Fund-Level FX Hedging Redux

Leonie Bräuer

University of Geneva, and Swiss Finance Institute[1]

Harald Hau

University of Geneva, CEPR, and Swiss Finance Institute[2]

November, 2024

Abstract

Using comprehensive new contract level data (EMIR) for the period 2019-2023, we explore how the FX derivative trading by European funds compares to a feasible theoretical benchmark of optimal hedging. We find that hedging behavior by all fund types is often partial, unitary (i.e., with a single currency focus), and sub-optimal. Overall, the observed FX derivative trading does not significantly reduce the return risk of the average European investment funds, even though optimal hedging strategies could do so without incurring substantial trading costs.

JEL Codes: E44, F31, F32, G11, G15, G23

Keywords: Global Currency Hedging, Institutional Investors, Mean-Variance Optimization

[1] 42 Bd du Pont d'Arve, Genève 4, Switzerland. Email: leonie.braeuer@unige.ch.

[2] 42 Bd du Pont d'Arve, Genève 4, Switzerland. Email: prof@haraldhau.com.

Acknowledgments and Disclaimer

The work in this paper has been carried out at the European Systemic Risk Board (ESRB) under the Alberto Giovannini Programme for Data Science 2022. We thank in particular Marco D'Errico and Tuomas Peltonen for their indispensible support. We also thank Tony Berrada, Ines Chaieb, Amy Huber, Christian Kubitza, Fabio Trojani as well as seminar participants at the University of Geneva.

The views expressed in this paper are those of the authors and do not represent the views of the ESRB or the institutions to which the authors are affiliated. The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

1 Introduction

Foreign investment funds have significantly increased their holdings of dollar-denominated assets, leading to a growing demand for foreign exchange (FX) derivatives to hedge the associated currency risk.[1] Yet, because of lack of fund-level derivative data, there is limited understanding of the extent to which institutional investors hedge their currency risk, what factors influence their actual hedging decisions, and how funds' hedging policies contribute to investment performance. Our paper fills this gap and contributes to the literature in three dimensions.

First, financial theory characterizes the optimal use of FX derivative contracts for a multi-currency investment strategy more than 50 years ago, e.g. Anderson and Danthine (1981) and Jorion (1994). But surprisingly little is known about whether theoretical solutions inform actual investment behavior. Do most international investment funds hold FX derivatives close to the theoretical benchmark? So far fund-level reporting on OTC derivative use has been too incomplete to address this question. Our paper uses comprehensive regulatory (EMIR) data and matches fund-level data for a large cross-section of $4,124$ European investment funds with OTC derivative data. Approximately $2,806$ (or 68%) of our sample of European investment funds use FX forward and FX swap contracts at least sporadically during the five-year period 2019-23.[2] We track their monthly equity and bond market investments in the seven most important currencies to characterize their underlying currency and investment risk. This allows us to predict their optimal hedging portfolio and compare the theoretical benchmark to the observed FX hedging positions.

Second, the previous empirical literature has highlighted the forward premium puzzle, whereby average realized exchange rate movements do not match interest rate differentials (Burnside et al. (2009); Boudoukh et al. (2016)). Recent research suggests that FX derivative contracts can be used to exploit pricing inefficiencies between spot and forward rates for speculative purposes (Opie and Riddiough (2020)). Our accurate data on fund derivative holding allows us to explore which factors influence institutional derivative use and return seeking through derivatives. In particular, we examine how institutional holdings of FX derivatives depend on the time-varying forward

[1] For example, Du and Huber (2024) document that non-US mutual funds more than doubled their USD portfolio share since 2005, reaching 6% and 43% in 2020 for equity funds and fixed-income funds, respectively. They also show that aggregate foreign holdings of USD-denominated assets amounts to 33.4 USD trillion by mid-2021, of which 4 USD trillion (or 12%) is held by mutual funds.

[2] We note that 68% reflects a lower bound as we cannot exclude that some of the remaining 32% of funds also use derivatives, but report their derivative positions through their parent company.

premium, namely the difference between the forward rate and the spot rate. We can also discern if FX derivative investments generate any systematic FX return premium and if trading costs in derivatives matter for funds.

Third, research on fund performance for a large cross-section of institutional investors has been very influential and has popularized the view that market efficiency is a good benchmark in competitive equity markets Malkiel (1995). Yet, how derivative trading by institutional investors influences fund performance is a largely unexplored question. Our data allows us to isolate the performance contribution of derivative contracts on average monthly returns and their standard deviations relative to a passive strategy that does not engage in FX risk hedging. We also entertain the counterfactual assumption that European investment funds engage in optimal multi-currency hedging contingent on their observed multi-currency equity and fixed income risk and evaluate the respective performance shortfall (after transaction costs) due to sub-optimal derivative use.

We summarize the main findings of our analysis as follows:

1. A minority of approximately 44% of European bond funds with discretionary FX hedging policies hold derivative positions that are close to those predicted by mean-variance optimization. The derivative positions of mixed funds and equity funds are generally even further removed from any optimal hedge and are uncorrelated with optimal hedging positions in an economic, though not a statistical, sense.

2. Even funds that implement hedging strategies that reduce FX exposure of their real international investment generally do not engage in cross-currency hedging as predicted by mean-variance optimization. They do *not* use all available forward rates to hedge the FX exposure in a particular currency and do not account for the correlation of each hedging instruments with the entire asset portfolio. Instead, funds engage in unitary hedging where the currency exposure in each currency is managed in isolation from the other exposures or hedging opportunities. In other words, there is no evidence for a portfolio approach to hedging conditional on the existing real investment portfolio.

3. We find that FX derivative trading by investment funds depends on the forward premium, which captures the expected return on the Euro long position if exchange rates follow a

random walk. Such a forward premium tilt is particularly pronounced among bond funds. We can interpret this as a price elastic hedging demand that decreases if the forward rate becomes more unfavorable relative to the existing spot rate.

4. Mean-variance optimization (under exogenous trading costs) predicts that funds should tilt their derivative positions toward positions with similar hedging benefits, but lower (or even negative) costs. This is generally not observed in the data, where larger derivative weights correlate with higher transaction costs. Funds therefore face higher trading costs for derivative positions also sought by other funds. The strong positive correlation between the expense ratio of a funds and its trading costs is indicative of adverse selection risk that dealer banks could face in their trading against funds specializing in FX trading.[3]

5. With respect to the fund performance contribution of FX derivative trading, we examine various counterfactual (partial equilibrium) scenarios that compare the observed FX trading strategies to alternative strategies. We find that the observed FX derivative trading behavior of European funds (including bond funds) during the period 20219-23 on average achieves no statistically or economically significant risk reduction (relative to a scenario where all funds abstained from any derivative trading).

6. Mean-variance optimal FX derivative trading could have reduced the portfolio risk of the average bond (equity) funds by 0.61% (1.47%) relative to the observed annualized risk of 5.94% (14.95%), which amounts to a 10% (10%) risk reduction and considerably improves on the performance of a unity hedge. Such reduction of FX exposure by funds comes with the possibility that the hedging strategy is loss-making whenever the Euro depreciates persistently against other currencies.

Our empirical analysis has a number of limitations upon which future research can improve upon. These mostly concern measurement issues. First, we observe fund asset holdings only at a monthly frequency so that our holding-based fund return inference is imprecise and does not exactly match the reported performance. Second, we also measure the existing FX derivative positions in the six

[3]The 20% of funds with largest foreign currency investment share feature a profitable correlation between their derivative position and spot rate changes in the following month, as illustrated in Figure 7. See in particular Burnside et al. (2009) on adverse selection risk in FX trading.

most important currencies only at month end to match the structure of the equity and bond data. We make the implicit assumption that all hedging decisions are taken at the end of each month and are maintained for one month.[4] Similarly, we estimate the transaction costs (relative to the interbank midprice) for one-monthly maturities. Again, any non-synchronicity can affect the cost and hedge returns. As a robustness check, we repeat the analysis only for a 50% subsample of funds for which the holding-imputed returns best match the reported return over the five-year period of our sample. Third, we note that our comparison of observed and optimal hedging depends on the estimation of two covariance matrices, namely the covariance matrix of exchange rate returns and the covariance matrix of exchange rates returns with bond and equity returns. We use two different methods of predicting these matrices for the month ahead: Realized covariance based on the last six (or three) months and two multivariate GARCH (MGARCH) models with a varying number of parameters. We only stress results that are robust across all methods. Notwithstanding these measurement problems, we think that our analysis is novel, as no previous paper has been able to analyze and evaluate the hedging behavior of the European fund investment industry at the asset holding level in the comprehensive manner in which we do.

We stress that a better understanding of funds' derivative trading and the implied currency risk is valuable for market and bank supervisors. The large increase of Europe's net investment position vis-à-vis the US and other countries (particularly in bond markets) has created a structural demand imbalance for Euro long positions in FX forward markets, which is mostly met by the largest dealer banks and their synthetic hedging. Aggregate net demand imbalances with respect to FX forward and swap contracts can have important repercussions of exchange rate determination as recently highlighted by Bräuer and Hau (2023). But in this paper, we take a partial equilibrium perspective that treats asset and exchange rate returns as exogenous and focuses on a fund's best response to its exogenous stochastic environment.

[4] There is trade clustering toward the end of each month. Investment funds in our sample change FX derivative holdings on average nine times per month, where 56% (41%) of their trades occur after day 20 (25) until the end of month.

2 Related Literature

We build on a long-standing literature on the theory of optimal currency hedging (Anderson and Danthine (1981); Jorion (1994); Glen and Jorion (1993)). These papers derive optimal hedging decisions by including derivative positions within a mean-variance framework of portfolio choice. Financial theory predicts that the optimal hedge portfolio features a pure hedging component (referred to as benchmark portfolio) and a speculative component related to currency return expectations and trading costs. The latter tilts the optimal hedge portfolio toward positions that increase the expected return. In spite of these rather sound theoretical foundations, empirical testing of the theory could not advance because of the absence of granular data on FX derivative positions. Accordingly, we still do not dispose of any evidence on the relative importance of the pure hedging motive relative to the speculative motive for the FX derivative demand of various types of investment funds.

While the existing theoretical solutions are readily available, they suffer from two major shortcomings that are of empirical relevance. First, most expositions of the multi-currency hedging problem consider only short positions in any foreign currency as an available hedge. This implies that the globally optimal hedging solution may not be available under this constraint. We do not want to impose this restriction in our analysis even though it is convenient: It guarantees a unique global optimal hedging policy even under transaction costs linear in position size. Second, transaction costs are usually discarded from the analysis of optimal hedging because they make the product of (cost-adjusted) expected returns and hedge portfolio weights a non-affine function. As a consequence, the global convexity property of the maximization problem is lost. While it is still possible to derive necessary conditions for the global optimum, these are no longer sufficient and do not guarantee uniqueness. However, we can still test these necessary first-order conditions, which is preferable to imposing invalid restrictions on the optimization domain. To our knowledge, the influence of transaction costs on optimal derivative positions has not been analyzed before.[5]

Previous financial research has discussed the benefits of holding currency forwards to the performance of a global bond and equity portfolio. For example, Campbell et al. (2010) argue that the risk-minimizing currency strategy for a global bond portfolio is close to a full hedge of its foreign

[5] Appendix A.1 discusses the optimal (conditional) hedge portfolio for the case of non-affine transaction costs (i.e., for a bid-ask spread).

currency positions. Our main contribution is to advance from such a normative prediction to a descriptive analysis of the actual investment behavior. Our analysis also marks a step forward toward the measurement of transaction costs associated with hedging. The previous research was unable to characterize the OTC trading costs with any precision, which renders normative portfolio recommendations somewhat fragile. The EMIR transaction data allows trade-by-trade calculation of transaction costs (relative to the interbank benchmark price) and enables us to infer fund-specific transaction costs. A comprehensive analysis of transaction costs in FX forward and swap transactions is available for corporate clients in Hau et al. (2021). In this paper we extend their cost analysis to derivative transactions between investment funds and dealer banks.[6]

Empirical research on currency hedging by funds has been scarce in the literature. An early exception is Levich et al. (1999), who surveys approximately 300 US institutional investors and documents that equity funds generally do not hedge their currency exposure. But with the gradual improvement of the electronic and regulatory infrastructure, more data becomes available for empirical work. A first comprehensive study of hedging practices by Du and Huber (2024) finds that mutual funds hedge on average only 21% of their foreign currency holdings. They also study hedging positions in the mean-variance framework based on aggregate positions averaged across investor groups at the currency-level. The authors emphasize the importance of the speculative motive proxied by currency return expectations and the cross-currency basis for the aggregate hedging demand over and above the risk-minimizing benchmark hedge. Our paper further develops this line of research by undertaking a disaggregated analysis at the fund level. Recent work by Kubitza et al. (2024) highlights the role of the cross-currency basis for international bond and derivative flows as well as US bond prices. The relation between aggregate currency hedging positions and exchange rate movements is documented by Bräuer and Hau (2023) based on FX derivative data from the US multi-currency settlement system CLS. The analysis here documents that institutional net hedging of currency risk strongly correlates with exchange rate movements.

Two other studies also document hedging behavior at the fund-level, namely Sialm and Zhu (2023) and Opie and Riddiough (2023). Sialm and Zhu (2023) document a hedge ratio of 18% for 400 US bond funds. Opie and Riddiough (2023) find that only 37% of funds hedge at all and

[6]Other relevant work based on EMIR data includes Abbassi and Bräuning (2021); Ferrara et al. (2022); Cenedese et al. (2021) for FX trading and Bahaj et al. (2023) on inflation swaps.

that among those only 14% hedge a significant portion of exchange rate risk. None of the previous empirical work interprets fund-level hedge ratios in the light of the existing theory or seeks to develop a benchmark for optimal hedging against which any hedging shortfall can be measured. We also note that the average hedge ratio on individual currencies is not a very meaningful measure of hedging shortfall once a fund operates in a multi-currency setting in which currency returns are correlated. This becomes clear in the following section where we develop our model framework.

3 Optimal Hedging Decisions

The following section characterizes optimal hedging decisions for a risk averse (European) investment funds with a predetermined global investment portfolio. Following Anderson and Danthine (1981), Glen and Jorion (1993) and Jorion (1994), we assume that the fund holds an international asset portfolio characterized by a $(N+1)\times 1$ vector of portfolio weights w_x with $w_x'\mathbf{1} = 1$, where N denotes the number of foreign countries with distinct currencies $c = 1, 2, 3, ..., N$, and corresponding asset markets. The last weight in row $N + 1$ is the home (Euro) investment currency for which the fund does not face any nominal exchange rate risk. For each currency, we model only one asset, which can itself be a portfolio of fixed income and equity investments. It is straightforward to extend the model to multiple distinct assets in each currency, but any empirical implementations then faces a curse of dimensionality.[7]

3.1 A Mean-Variance Model

The hedging problem of a European fund consists in the choice of a $(N \times 1)$ vector of optimal net foreign (non-Euro) currency short positions w_f in the N foreign currencies ordered like the corresponding real asset weights w_x in N foreign currencies. We define N spot exchange rates $S_{c,t}$ and forward rates $F_{c,t}$ between the quote currency c and the Euro as the base currency (for example EUR/USD) and express the (log) return on a long hedging position in foreign currency c (i.e., a Euro short position) as $r_{f,c,t+1} = \frac{S_{c,t+1}-F_{c,t}}{S_{c,t}} \approx s_{c,t+1} - f_{c,t}$, where we denote the end-of-month t log spot rate as $s_{c,t+1} = ln(S_{c,t+1})$ and the one-month log forward rate at the beginning of month t as $f_{c,t} = ln(F_{c,t})$, respectively. An increase in the spot rate $S_{c,t+1}$ corresponds to an depreciation

[7] To maintain empirical tractability, we group the assets of each fund into fixed income and equity investments and assume that the asset risk in each currency is a linear combination of a currency-specific bond and equity index.

of Euro against foreign currency c and generates a positive return $r_{f,c,t+1}w_{f,c,t} > 0$ on the long position $w_{f,c,t} > 0$ in foreign currency c. We denote the expected return vector on long positions in foreign currency as $E[r_{f,t+1}] = \mu_f$ and the covariance matrix of exchange rate returns as Σ_{ff}. The expected return vector (in Euros) on a fund's real asset positions in $N+1$ currencies is μ_x, the corresponding covariance matrix Σ_{xx}, and the covariance of asset and hedging returns Σ_{fx}.

For simplicity, we assume mean-variance preferences for the fund with a risk tolerance parameter γ. The optimization problem takes on the form

$$\max_{w_f} \quad w'\mu - \frac{1}{2\gamma} w'\Sigma w, \tag{1}$$

where the covariance matrix, the portfolio weights, and the expected returns can be written as

$$\Sigma = \begin{pmatrix} \Sigma_{xx} & \Sigma_{xf} \\ \Sigma_{fx} & \Sigma_{ff} \end{pmatrix}, \qquad w = \begin{pmatrix} w_x \\ w_f \end{pmatrix}, \qquad \mu = \begin{pmatrix} \mu_x \\ \mu_f + \tau \end{pmatrix},$$

respectively. We assume that the non-negative real portfolio weights $w_x \geq 0$ are exogenous (or predetermined) and that the optimal hedging problem consists in finding the optimal weights w_f conditional on w_x. The vector τ represents transaction costs linear in the portfolio weights.[8]

3.2 Solution and Interpretation

If transaction costs τ are zero, and the covariance matrix Σ_{ff} of exchange rate returns is a positive definite, there exists a unique global optimum given by

$$\Sigma_{ff} w_f^* = \gamma \mu_f - \Sigma_{fx} w_x. \tag{2}$$

Optimal derivative weights w_f^* can generally involve Euro long ($w_{f,c}^* < 0$) and/or Euro short positions ($w_{f,c}^* > 0$) in any currency c depending on expected exchange rate returns μ_f and the matrix Σ_{fx}.[9]

[8]Non-zero transaction costs complicate the analysis considerably and are therefore excluded from many expositions of the optimal hedging problem. We provide a detailed discussion of the general solution with non-zero transaction costs in Appendix A.2

[9]We refer to Euro long positions in derivatives as positions in FX swaps or forwards that promise Euro at maturity against a foreign currency with an additional (initial) reverse cash flow in the case of FX swaps.

Institutional risk management considerations can prevent some European funds from acquiring short Euro positions (with $w_{f,c} > 0$) as such trades are often deemed speculative. Theoretical expositions of the optimal hedging problem often impose a non-positivity constraint $w_{f,c} \leq 0$. This assumption then allows easy incorporation of constant (linear) transaction costs τ into the optimization problem.[10] The first-order condition of the (constrained) maximization problem in Eq. (1) follows as

$$\Sigma_{ff} w_f = \gamma \left(\mu_f + \tau - \lambda \right) - \Sigma_{fx} w_x, \tag{3}$$

where λ represents an $N \times 1$ vector of Lagrange multipliers related to the non-positivity constraint $w_f \leq 0$. The complementary slackness condition is $\lambda \geq 0$ and $\lambda w_f = 0$. If the net cost of hedging exceeds the net benefit from the risk reduction, i.e., $(\mu_{f,c} + \tau_c) > \frac{1}{\gamma}(\Sigma_{fx})_{c\bullet} w_x$, the fund chooses the corner solution of no hedging with $\lambda_c > 0$ and $w_{f,c} = 0$ in currency c. If the hedging costs are smaller than the benefits from hedging and the fund opts for hedging, we have an interior solution with $\lambda_c = 0$ and $w_{f,c} < 0$.

In the case where transaction costs are not binding ($\lambda = 0$), the optimal hedging position follows as

$$\begin{aligned} w_f^* &= \underbrace{\gamma \Sigma_{ff}^{-1} \left(\mu_f + \tau \right)}_{\text{Speculative Term}} - \underbrace{[\Sigma_{ff}^{-1} \Sigma_{fx}] w_x}_{\text{Benchmark Hedge}} \\ &= \underbrace{\gamma \Sigma_{ff}^{-1} \left(\mu_f + \tau \right)}_{\text{Speculative Term}} - \underbrace{[\Sigma_{ff}^{-1} \Sigma_{fx} - I_{+0}] w_x}_{\text{Cross-Currency Hedge}} - \underbrace{w_x}_{\text{Unitary Hedge}}, \end{aligned} \tag{4}$$

where the speculative term characterizes the shift of the hedging position due to transaction costs and return expectation on forward contracts, and the benchmark hedge seeks to minimize the portfolio risk. Positive return expectations for foreign currencies, long positions (i.e., $\mu_f > 0$) as well as higher transaction ($\tau > 0$) imply less hedging as indicated by the speculative term. A higher risk tolerance γ increases the role of the speculative term. The benchmark hedge depends on the real investment positions w_x in the $N + 1$ currencies multiplied by the matrix product $\Sigma_{ff}^{-1} \Sigma_{fx}$. In other words, the benchmark hedge generally depends both on the covariance structure of currency returns and the covariance of currency returns with real asset returns.

We can further decompose the benchmark hedge into a cross-currency hedge and a so-called

[10] Transaction costs τ measured by a spread flip their sign at $w_{f,c} = 0$. This makes $(\mu_f - \tau) w_f$ a non-affine function for $w_f \in \mathbb{R}^N$, but an affine function in the negative subdomain.

unitary hedge, where the matrix I_{+0} denotes an $N \times N$ identify matrix with a column vector of zeros added in column $N+1$. The unitary hedge matches each (long) real investment position w_x with a similar foreign currency short position in FX forward contracts. Optimal hedging generally deviates from unitary hedging by the cross-currency hedge term, which involves all the off-diagonal elements of the matrix $\Sigma_{ff}^{-1}\Sigma_{fx}$.

It is insightful to consider a special case. First, we assume that the home asset return is not correlated with any of the currency returns. Then, the last column in matrix Σ_{fx} is zero and we can write the remaining N columns as Σ_{fx}^N, which implies $\Sigma_{fx}w_x=\Sigma_{fx}^N w_x^N$. Second, we assume that the fund's foreign assets are risk-less bonds and their Euro denominated returns are therefore only subject to currency risk. It follows that $\Sigma_{fx}^N = \Sigma_{ff}$ and the optimal hedging weights simplify to

$$w_f = \underbrace{\gamma\Sigma_{ff}^{-1}(\mu_f + \tau)}_{\text{Speculative Term}} - \underbrace{w_x^N}_{\text{Unitary Hedge}} . \tag{5}$$

The cross-currency hedging term is zero in this special case. Under zero hedging cost with $\tau = 0$ and a zero return premium on forward positions with $\mu_f = 0$, the speculative term in Eq. (5) disappears as well. The optimal hedging policy then consists only of the unitary hedge $w_f = -w_x^N \leq 0$. In this special case, the optimal hedging policy consists in hedging each currency exposure individually and fully (Jorion (1994)).

3.3 Transaction Costs, Corner Solutions, and Positive Hedging Weights

Positive transaction costs can make it optimal not to hedge and the best hedging position in any currency can become zero. In this case the Lagrange multiplier element takes on a non-zero value and testing the validity of the first order condition in Eq. (2) becomes more complicated. Such corner solutions are more likely if the initial asset position in any currency is small (or zero), if the fund's risk tolerance is large, or if transaction costs are large. In these cases, the marginal benefit of hedging does not exceed the transaction cost and the unobserved vector of Lagrange multipliers has non-zero elements. We can circumvent this problem by focusing *only* on strictly (non-zero) hedging positions for which the Lagrange multiplier element is zero under the null hypothesis of optimal hedging, namely the rows for which $w_{f,c} \neq 0$.

In the case of high hedging costs and a zero-hedging position in a particular currency, the first-order condition degenerates to an equality featuring the non-zero Lagrange parameter in the vector λ. Without loss of generality, we can order currencies so that the first n currencies feature strictly negative hedging positions and a zero Lagrange parameter, while the remaining $N-n$ currencies and corresponding rows in Eq. (2) can be discarded. This reduces Eq. (2) to

$$\Sigma_{ff}^n w_f^n = \gamma\left(\mu_f^n + \tau^n\right) - \Sigma_{fx}^n w_x^n, \tag{6}$$

where we denote the first n components of the respective vectors and matrices with the superscript n. The Lagrange vector $\lambda^n = 0$ now disappears. In the following text, we suppress the superscript n even though we reduce the first-order condition for each fund and month to the n dimensions with non-zero FX forward positions ($w_{f,c,t} \neq 0$). Under the constrains $w_{f,c} \leq 0$ for $c = 1, 2, 3, ..., N$, Eq. (6) characterizes a unique global maximum.

A more general approach to the optimal hedging problem is to drop the non-positivity constraints and allow that European funds can also acquire Euro short positions ($w_{f,c} > 0$). We show in Appendix A.2 that for an extended domain $w_f \in \mathbb{R}^N$, Eq. (6) still represents a necessary condition for any global maximum. But the first-order condition is no longer a sufficient condition for the global maximum nor is uniqueness of the maximum assured. This is due to the non-convexity that bid-ask spreads introduce into the optimization problem and their non-affine nature. Finding the globally optimal hedge then involves a numerical approach that ranks potential global optima within each subspace of $\mathbb{R}^N$ for which the transaction costs are affine (i.e., proportional in $w_{f,c}$). [11]

3.4 Return Seeking Strategies

Next, we discuss various FX hedging strategies that seek to increase the expected return from hedging as the latter could be time varying. It is convenient to decompose the expected return $\mu_{f,c,t+1}$ on any short Euro position in currency c into an expected exchange rate change and the (ex ante observable) forward premium; hence

$$\mu_{f,c,t+1} = E\left(\frac{S_{c,t+1} - F_{c,t}}{S_{c,t}}\right) = E\left(\frac{S_{c,t+1}}{S_{c,t}} - 1\right) + 1 - \frac{F_{c,t}}{S_{c,t}} \approx E(s_{c,t+1} - s_{c,t}) - fp_{c,t}, \tag{7}$$

[11] Our regression analysis in Tables 3 and 4 distinguishes between the sample of all fund derivative positions and the smaller subsample of derivative positions that fulfill the non-positivity condition.

where $s_{c,t} = ln(S_{c,t})$ and $f_{c,t} = ln(F_{c,t})$ denote the (log) end-of-month t closing prices for the spot and forward rate, respectively. The forward premium is defined as $fp_{c,t} = f_{c,t} - s_{c,t}$.

Hedging Without Return Seeking. If funds believe that the forward rate $F_{c,t}$ reflects rational expectations about the future spot rate $S_{c,t+1}$, then the expected return $\mu_f, c, t+1$ on any forward contract is zero. Funds that operate under this assumption ignore the speculative component of the hedging strategy and only focus on risk minimization. We refer to this as hedging without return seeking.

Forward Premium Effect. Generally, a negative forward premium ($f_{c,t} - s_{c,t} < 0$) comes with foreign money market rates above the corresponding Euro rate. Conditional on a choice of real investments and a zero expected exchange rate change, $E(\Delta s_{c,t}) = 0$, a negative (positive) forward premium makes hedging more (less) attractive because of a positive (negative) expected hedging return $\mu_{f,c,t+1} w_{f,i,c,t}$.

Exchange Rate Predictability. Private information about future currency returns implies that the optimal hedging positions correlate positively with future currency returns. If funds receive a private signal ζ_t about future currency returns $s_{c,t+1} - s_{c,t}$, we expect their currency return expectations to be tilted toward the realized future currency, that is

$$\mu_{f,c,t+1} \approx E[s_{c,t+1} - s_{c,t} \mid \zeta_t] + fp_{c,t} = \kappa \Delta s_{c,t+1} - fp_{c,t}, \tag{8}$$

where the coefficient $0 \leq \kappa \leq 1$ depends positively on the precision of the signal and we define the currency return vector $\Delta s_{t+1} = s_{t+1} - s_t$. [12]

Transaction Costs. As fund-specific transaction prices in forward markets generally deviate from the benchmark (interbank) rate, funds should adjust their derivative trading to account for these costs. We benchmark the price F_T of any forward trade T against the contemporaneous (same minute) mid-price Mid_T in the interbank market. For bid (sell Euro, i.e., Euro short) and ask (buy Euro, i.e., Euro long) transactions, we define a dummy as $d(T = sell) = -1$ and $d(T = buy) = 1$,

[12] Private information about future currency moves could also alter the conditional covariances as perceived by a fund, but we ignore this effect in our empirical setup.

respectively. The transaction spread relative to the interbank mid-price then follows as

$$Spread_T = d(T)\frac{F_T - Mid_T}{Mid_T}, \tag{9}$$

where the dummy $d(T)$ flips signs between buy and sell transactions.

Next, we regress the spread on forward contract T on four trade characteristics,

$$Spread_T = \theta_t + \theta_c + \theta_{Buy\ c} + \theta_i + \eta_T, \tag{10}$$

where θ_t is a month fixed effect, θ_c represents a currency fixed effect (for buy and sell trades) in currency c, $\theta_{Buy\ c}$ is a fixed effect for all buy trades (of funds) in currency c, and θ_i is a fixed effect for each fund i. The predicted transaction costs (defined as negative value) for the forward positions $w_{f,i,t}$ by fund i in month t then follow as vector product $\tau_{t,i}w_{f,t,c}$ with currency-specific transaction costs

$$\tau_{c,t,i} = \begin{cases} \theta_t + \theta_c + \theta_i & \text{if } w_{f,c,t,i} < 0 \\ 0 & \text{if } w_{f,c,t,i} = 0 \\ -(\theta_t + \theta_c + \theta_{Buy\ c} + \theta_i) & \text{if } w_{f,c,t,i} > 0, \end{cases} \tag{11}$$

that can differ between buy and sell trades in each month t. The dummy $\theta_{Buy\ c}$ captures the differential (asymmetric) transaction costs that funds incur on average for Euro short positions (relative to Euro long positions). Section 4.4 takes up the measurement of currency and fund specific transaction costs with further details in Appendix A.3.

4 Data and Measurement

Three main data sources enter into our analysis. First, we use the supervisory data on FX derivatives from the European Central Bank that are collected under the European Markets Infrastructure Regulation (EMIR). Under EMIR each European legal entity is obliged to report all its trades in derivatives, which ensures that we do not miss any contracts for European reporting entities. One drawback of this data source is the short time span of the derivative data collection. We can use only a five-year period from January 2019 to December 2023, but benefit from the comprehensive reporting for each FX Forward and Swap contract.[13] Based on the EMIR data, we construct end-of-month net FX derivative positions for any European investment fund in the six most relevant foreign currencies against the EUR (i.e., net EUR short positions get a positive sign in $w_{f,i,c}$). In addition, we use the transaction data to infer monthly measures of transaction costs by fund, currency, and trade direction.

Second, we match the FX derivative data with the Refinitiv Lipper Funds Holdings database that reports monthly asset holdings with the corresponding currency denomination per fund. In total we identify $6,930$ European funds that are relevant for our analysis of Euro hedging practices. We consider as relevant funds those that (i) have Euro as their base currency, (ii) have more than 90% of their liabilities denominated in Euros, and (iii) have no strict mandate to hedge their equity and bond positions in a foreign currency.[14]

Among the relevant European funds, we have $4,124$ funds that never report any FX derivative positions during the period 2019-23. Such funds are presumably barred from derivative investments or are not considered a good investment option. Table 1, Panel A, provides summary statistics on these funds, which never hedge. We also provide a breakdown by funds type and distinguish bond, equity, and mixed funds.

Table 1, Panel B, reports on the remaining $2,806$ European funds that acquire FX derivative contracts at least once during the period 2019-23. We deduce that these funds have a discretionary mandate that allows them to engage in derivative trading. They are the focus of our analysis. These funds are on average larger and also tend to have a larger foreign investment share compared to the funds in Panel A.

Among the funds in Panel B with a discretionary mandate, we distinguish 806 bond funds (with no equity positions), $1,109$ equity funds (without fixed income holdings) and 891 mixed funds. Panel C reports the monthly fund-currency positions in the six foreign currencies (expressed in Euros) for the funds in Panel B. Appendix B provides more details on the initial fund type selection, including the treatment of share classes, the matching of EMIR derivative data, and the filtering of the matched fund-derivative data.

[13] In the EMIR dataset FX forwards and FX swaps are reported under the same identifier so that it is not possible to distinguish between the two instruments. Accordingly, we use the term FX derivatives or FX forwards for both FX forwards and FX swaps.

[14] Funds labeled "currency hedged" do not dispose of any discretionary mandate so an analysis of their derivative trading is less interesting.

Third, we draw on end-of-the-month closing prices for spot and forward rates obtained via Refinitiv Eikon. Our analysis focuses on six exchange rates quoted with the Euro as the base currency: EUR/AUD, EUR/CHF, EUR/GBP, EUR/JPY, EUR/SEK, EUR/USD. The six underlying currencies account for 40% of the aggregate asset value of the $2,654$ funds in Panel B.

4.1 Fund Asset Holdings by Currency and Forward Positions

In our sample of $2,806$ European equity and fixed income funds in Panel B, we find the following aggregate real investment shares by currency denomination (not reported in the table): On average 51% of all assets are invested in Euro denominated assets, followed by 29% US Dollar assets (USD), 7% in British Pounds (GBP), 6% in Japanese Yen (JPY), 4%in Swiss Francs (CHF), 3% in Swedish Krona (SEK), and 1% in Australian Dollars (AUD). All other currency shares represent less than 9% of the aggregate investments. We exclude these less liquid currencies from our analysis as hedging here is relatively rare due to the small contribution of exchange rate risk to fund returns.

Figure 1 characterizes the evolution of the aggregate real investments and the net outstanding interest of FX derivative positions in the six main foreign investment destinations for the period January 2019 to December 2023. Total aggregate asset values (in equity and fixed income instruments) are presented by the solid blue line (left scale) and the corresponding net outstanding notional value in long Euro forward positions by the dashed black line (right scale). The aggregate derivative positions track the underlying asset values, but tend to be much smaller. For example, net long Euro derivative positions amount on average to roughly 17% of real US dollar investments and 11% of British Pound investments.

Figure 2 provides a disaggregate picture of holding and hedging behavior at the fund level by major foreign investment destination. Here we plot the (exposure-scaled) average foreign investment shares of funds $\Sigma_{ff}^{-1}\Sigma_{fx}w_{x,ic}$ referred to as "benchmark hedges" on the horizontal axis and the corresponding long Euro forward position $-w_{f,ic}$ on the vertical axis. Bond funds are represented by a blue dot, equity funds by a yellow cross, and mixed funds by a green triangle. First, large foreign investment shares at the fund level are observed mostly for dollar assets. Many European funds invest exclusively in dollar assets apart from Euro assets. Second, bond funds tend to feature more hedging compared to mixed or equity funds as their blue dots are closer to the 45 degree line. For some funds, their average long positions in Euros closely mirrors the optimal hedged portfolio on the vertical axis.

4.2 Fund Level Currency Exposure

Given the large number of funds and the heterogeneity of their fixed income and equity positions, we track the investment return only of a representative fixed income and equity position in each of the six currencies. A disaggregate analysis for the 316,000 different assets (ISINs) and their individual daily asset returns in Euros is technically infeasible and would also run into a "curse of dimensionality" with respect to robust covariance estimation.[15]

We reduce the dimensions of the covariance inference by grouping assets only by asset class (equity or fixed income) and by currency. Then we estimate covariances between asset and FX returns only for representative bond and equity portfolios in each currency. We proxy bond returns with S&P Sovereign Bond index returns and proxy equity returns with MSCI equity index returns by country.[16] For example, a fund i may hold investment weights $w_{x,i,c,t}$ in currency c at the end of month t, where a share $\omega_{c,t}$ is invested in bonds and $1-\omega_{c,t}$ in equity. We can represent the covariance of a fund's real assets returns (in Euros) with the currency returns as

$$\Sigma_{fx,i,t+1} = \Sigma_{fb,t+1} D(\omega_{i,c,t}) + \Sigma_{fe,t+1} D(1-\omega_{i,c,t}), \tag{12}$$

where $\Sigma_{fb,t+1}$ and $\Sigma_{fe,t+1}$ denotes the $n \times (n+1)$ covariance matrices between the currency returns and the bond and equity returns in month $t+1$, respectively. The $(n+1) \times (n+1)$ diagonal matrices $D(\omega_{i,c,t})$ and $D(1-\omega_{i,c,t})$ feature the relative share of bonds and equity investments of fund i in currency c, respectively, as diagonal element c. This ensures that the analysis accounts for the fund-specific mix of fixed income and equity instruments in each currency. The covariance of currency return in currency c with the asset holdings of fund i then follows as $[\Sigma_{fx,i,t+1}]_{c\bullet} w_{x,i,t}$, where the index $c\bullet$ refers to row c of the respective matrix.

[15] This implies that the covariance structure of fund returns and exchange rate returns is estimated with measurement error. Such measurement error translates into an attenuation bias for the inferred benchmark hedge position.

[16] A robustness analysis in Section 6 sorts funds based on the validity of this approximation. We compare the inferred fund return to the reported fund return and exclude funds for which the reporting mismatch is large.

4.3 Estimation of Currency and Asset Risk

An important input to the analysis is the determination of the currency risk captured by the covariance matrix $\Sigma_{ff,t+1}$ and the currency-asset covariance risk represented by the covariance matrices $\Sigma_{fb,t+1}$ and $\Sigma_{fe,t+1}$ for bond and equity returns, respectively. We use two different (out-of-sample) methods to predict future covariances.

Lagged Realized Covariance. Here we measure the realized covariance based on daily returns for either a previous 3-month or 6-month period. This simple and direct approach assumes that the recently observed realized covariance structure is a good predictor of the covariance structure in the coming month $t+1$. We use a triangular kernel which gives more weight to the most recent daily return observations. The estimated realized covariance matrices $\Sigma_{ff,t+1}$ are all positive definite, which ensures a unique optimal hedging portfolio if transaction costs are ignored.[17]

MGARCH Models. Alternatively, we estimate two multivariante GARCH models using a dynamic conditional correlation (DCC) specification. An unconstrained MGARCH(5,1) uses five daily ARCH innovations (L1-L5) and one GARCH term (L6). The first model (MGARCH1) estimates a total of $2+6\times(2N+1)=80$ parameters to capture the dynamics of the covariance structure of the $N+1$ asset and N currency returns. A more parsimonious specification restricts the coefficients of the five ARCH terms for each currency or asset to be identical. This reduces the number of free parameters to be only $2+2\times(2N+1)=28$ (MGARCH2). Both GARCH models implicitly use covariance shrinkage by constraining the off-diagonal covariance elements to a time-invariant correlation.

We estate the all four covariances based on daily returns data. For the MGARCH models the data starts five years prior to the month of prediction. Appendix A.4 provides details about the predicted covariance matrices obtained from the MGARCH specifications. We find again that the monthly predicted covariance matrix $\Sigma_{ff,t+1}$ is positive definite so that convexity of the optimization problem is guaranteed for the entire five-year sample period.

We provide in Figure 3 a graphical illustration of the average covariance structure observed (in-sample) for the full five-year period 2019-23. Graph A shows the estimated covariance of

[17] For quantitatively small transaction costs, we can assume that this unique hedge portfolio is at least close to the optimal hedge under transaction costs.

daily realized currency returns ($\overline{\Sigma}_{ff}$), Graph B shows the covariance of currency returns with equity returns ($\overline{\Sigma}_{fx,e}$), and Graph C the corresponding covariance with bond returns by investment destination ($\overline{\Sigma}_{fx,b}$). The intensity of the green color implies large positive covariance and the red color large negative covariance terms. The average covariance matrix $\overline{\Sigma}_{ff}$ is also positive definite similar to the monthly predicted covariances.

Figure 4 depicts by currency the time-varying variance of currency returns (black dashed line), the covariance of currency and equity returns (yellow line with crosses) and between currency and foreign bond returns (blue line with dots). The FX volatility and covariances with real asset spike for most countries around the outbreak of Covid-19 and the Russian-Ukrainian war at the beginning of 2022. The figure highlights that the covariance between currency returns and equity returns can be larger than with bond returns and often spikes when FX volatility is also high.

In the Appendix, we compare in Figure D.2 the time variation of the diagonal elements of the FX covariance matrix according to the four different inference methods, namely lagged realized variances for a 3-month and 6-month period, respectively, and the corresponding unconstrained and constrained MGARCH estimates, respectively. The overall correlation between different (one-month-ahead) predictions of all covariance elements is provided in Appendix Table D.1 and varies between 0.63 for the correlation between MGARCH1 and LRC 3-month and 0.96 for the correlation between MGARCH1 and MGARCH2. Different inference methods generate different covariance estimates, which in turn imply different optimal hedge portfolios. Our main analysis therefore shows results for different inference methods for the covariance matrices and stress results that are robust across these different methods.

4.4 What Explains Transaction Costs?

Next, we explore transaction costs in the forward market. For the period 2019-23, the EMIR data provides roughly $2,268,283$ transactions between funds and dealer banks. We select all transactions involving the 2,806 funds in our sample and search for a contemporaneous interbank trade in the same minute, with the same (one month) maturity in the same currency pair. In total we identify $74,344$ transaction prices F_T that can be benchmarked against synchronous interbank trades Mid_T for the calculation of the effective spread as defined in Eq. 9.

We regress the spreads (in basis points) measured for these $74,344$ forward trades on a time (day) fixed effect, a currency fixed effect, a fixed effect marking only buy trades in a foreign currency c (i.e., Euro short positions), and fund fixed effect for funds. The $74,344$ trades feature a total of $1,120$ different funds. For $1,685$ funds in our sample we do not have trades because their transactions occurred in a currency or with a maturity or at a time when no synchronous interbank trade is available to provide a suitable benchmark for the spread measurement. For these funds we rely on their fund characteristics rather than fund fixed effects for the prediction of the fund-specific transaction costs.

Appendix Table C.2 presents the regression results and Figure 5 plots the average transaction costs for buy and sell transactions in each of the six currency pairs deduced from Column (1). A positive coefficient $\theta_{USD} = 1.641$ implies a cost of 1.641 basis points for each Euro of notional in a forward USD sell trade (Euro long position). If a fund applies a unitary (full) hedge to a real USD dollar ($c = USD$) investment of $w_{x,c} = 10\%$ of fund assets, these transaction costs reduce the monthly portfolio return by $\Delta r = -\tau_c w_{f,c} = -0.0001641 \times 0.1\%$ or $12 \times 0.1 \times -0.01641\%$ annually. Hedging a USD exposure fully thus implies (unconditionally) average annual costs of 0.197% or roughly 20 basis points.

While hedging USD and GBP exposures through Euro long positions has moderate costs, selling the Euro for the USD and aqcuiring Euro short positions generates *negative* transaction costs. In other words, interdealer transactions occur on average at a lower forward price than the fund-dealer Euro sell transactions (i.e., $Mid_T < F_T$, $d(T) = -1$). As shown in Appendix A.3 and Figure C.2, this data feature is related to a strongly negative currency basis for the USD, which makes the acquisition of Euro short positions very desirable because of the relatively higher dollar interest rates in our sample period.

For the fund characteristics, we find that funds with a higher *Expense Ratio* also face higher transaction costs and that equity funds have lower average transaction costs. Funds with higher expenses might invest in FX research particularly if their foreign investment share is large. Their higher trading costs indicate that dealer banks quote these funds at less favourable prices because of the adverse selection risk (Burnside et al. (2009)). The overall explanatory power of the various fixed effects and fund characteristics in Columns (3)-(4) is modest at an overall R^2 of 2.3%. Including fund fixed effects in Column (5) does not increases the regression fit, which suggests that there is no evidence for fund-specific price discrimination. This contrasts with evidence of strong discriminatory pricing found for corporate clients in the same OTC market (Hau et al. (2021)).

5 Empirical Analysis

5.1 Observed versus Optimal Hedge Positions

In this section, we compare the observed FX derivative positions of European investment funds with discretionary hedging policies to the optimal benchmark hedge derived under mean-variance optimization. The optimal hedging position of each fund depends on the funds' mix of equity and bond positions in each of the seven currencies summarized in the asset weights $w_{x,i,t}$. These real investments determine a fund's currency exposure in month $t+1$ captured by the covariance matrix $\Sigma_{fx,i,t+1}$ that follows from Eq. (12).

To test the first order condition in Eq. (6), we regress a fund's FX derivative positions $w_{f,i,c,t}$ on the expected returns effect $\Sigma^{-1}_{ff,t+1}\mu_{f,c,t+1}$ and the benchmark hedge $\Sigma^{-1}_{ff,t+1}\Sigma_{fx,i,t+1}w_{x,i,c,t}$. To simplify notation, we suppress the superscript n in Eq. (6) even though covariance matrices have fund-specific dimensions given by the number of non-zero hedging positions $w_{f,i,c,t}$.

Table 3 reports our baseline results for two different estimation procedures for the covariance matrices. Panel A uses Lagged Realized Covariances (for the last six months) and uses this estimation as the predicted covariances for month t+1. The results in Panel B are based on the MGARCH1 model described in Appendix A.4. We also report analogous results for two additional estimation methods in Appendix Table F.2. Our discussion focuses on coefficients that are robust across different estimation procedures. We consider the derivative positions of bond, equity, and mixed funds separately and distinguish for each fund type the sample of all positions in Columns (1)-(3) and the subsample of only Euro long positions in Columns (4)-(6).

Speculative Terms in the Optimal Hedge. The positive coefficient for $\Sigma^{-1}_{ff,t+1}\Delta s_{t+1}$ indicates that Euro long positions are more frequent under Euro appreciations (i.e., a decrease of s_{t+1}), but statistical significance is modest. Bond funds in Panel A and B show statistical significance at the 5% and 10% level, respectively. Mixed funds also show some weak evidence for FX predictability in Table 3, Column (6) where only Euro long positions are taken into account. No statistical evidence of systematic FX predictability can be discerned among equity funds.[18]

Under the random walk assumption for exchange rate movements, a positive forward premium in currency c amounts to a lower price on the long Euro position and a positive expected return $-w'_{f,i,t} fp_t > 0$. This should tilt the optimal hedge portfolio $w_{f,i,t}$ toward more hedging (i.e., make the vector more negative) and generate a negative coefficient for the regression coefficient. This is what we observe for the realized covariance in Panel A in Columns (1)-(6). The same coefficients are statistically insignificant and even positive for mixed funds in Panel B where we infer covariance risk from the MGARCH model. The evidence for the forward premium tilt is thus fragile and depends on the estimation method for covariance risk. Du and Huber (2024) forego the estimation of a time-varying covariance matrix and find that the interest rate differential, which we proxy with the forward premium, can by itself significantly explain investors' hedging positions.

The forward premium closely correlates with deviations from covered-interest rate parity (CIP), commonly referred to as the cross-currency basis.[19] The latter is often interpreted as the cost of hedging. We find that replacing the forward premium with the cross-currency basis yields qualitatively very similar results, implying that higher hedging costs correlate with reduced hedging positions. The results also suggest that bond and mixed funds are more cost-sensitive than equity funds in their hedging behavior.

The adjustment of the optimal hedge portfolio to (exogenous) transaction costs is captured by the coefficient on $\Sigma^{-1}_{ff,t+1}\tau_{i,t}$. Positive transaction costs $\tau_{i,t} > 0$ from a positive spread should generally tilt the optimal hedge portfolio toward smaller notional positions and imply a positive coefficient. However, all of the measured coefficients in Panels A and B for the sample of all derivative positions in Columns (1)-(3) are negative and statistically significant. This implies that the average portfolio tilt is toward derivative positions with higher transaction costs rather than lower ones, which is surprising.

Average transaction costs across all funds are generally low and do not exceed 20 basis point per year for a full dollar investment position. This could explains why funds might consider hedging

[18] We find additional evidence that funds with high expense ratios (i.e., in the upper quintile of the expense ratio) make speculative profits in their FX derivative trading before transaction costs. The coefficient of the predictability term is 0.012 with a t-statistics of 1.973. However, these funds also face higher trading costs as shown in Appendix Table C.4 as dealer banks increase their spread in protection against adverse selection risk.

[19] CIP deviations are mostly driven by the forward premium rather than the interest rate differential. For example, in our period 2019-23 the forward premium is correlated with the cross-currency basis at 53% for the EURUSD.

costs as negligible, potentially leading to a statistically insignificant coefficient. But a statistically significant negative coefficient requires a different explanation and points to an endogenous cost effects: The higher the net aggregate FX derivative demand in any currency, the more adverse the price response and the higher the transaction costs charged by dealer banks. A price elastic currency supply features both in theoretical and empirical work on the FX market (Gabaix and Maggiori (2015); Hau and Rey (2006); Hau et al. (2010)) and can rationalize the negative coefficients for the transaction cost effect for all fund types in Table 3, Columns (1)-(3).

Benchmark Hedge Component. The coefficient for the optimal benchmark hedge portfolio in Table 3 is of the greatest interest. Tracking of the benchmark hedge implies that a fund implements mean-variance optimization with covariance estimates close to ours. A coefficient of -1 implies a perfect fit with theory for all funds. A zero coefficient suggests that the derivative positions of the average funds do not achieve any risk reduction and that the funds engages in exchange rate speculation only. Unlike the return-seeking components, the magnitude of the expected coefficient does not depend on the risk tolerance of the respective fund.

The overall coefficient for bond funds in Column (1) is -0.426 and -0.588 in Panels A and B, respectively. In the sample with only Euro long positions, this coefficient is even larger at -0.691 and -0.942, respectively. This means that the benchmark portfolio is a reasonable proxy for bond funds without Euro short positions. By contrast, the same coefficient is close to zero in the sample of equity funds in Column(2) and also low for mixed funds in Column (3), respectively. In other words, European equity funds and mixed funds generally do not hedge their exchange rate exposure.

In Appendix Table F.2, Panels A and B, we replace the covariance matrices with a 3-month lagged realized covariance matrix and a covariance matrix based on the MGARCH2 model with fewer free parameters, respectively. The results do not change significantly for these two different covariance estimation techniques. In Appendix Table F.3 we add fund$\times$currency fixed effects to the regression and find a smaller coefficient for the benchmark effect. This is not surprising, as funds' real asset positions can be relatively stable and the fund fixed effects can capture some of the explanatory power of the benchmark hedge if the latter does not change much over time. More noteworthy is that the evidence for the forward premium effect for bond and mixed funds in Table F.3, Panel A, Columns (1) and (3) are robust to fund fixed effects.

5.2 Unitary versus Cross-Currency Hedge Positions

Table 4 repeats the regression in Table 3 with the addition that the benchmark hedge is decomposed into the unitary hedge and the cross-currency hedge as described in Eq. (4). The speculative terms have very similar coefficients as in Table 3. The interesting observation is that the cross-currency hedging term $[\Sigma^{-1}_{ff,t+1}\Sigma_{xf,i,t+1} - I_{+0}]w_{x,i,t}$ is statistically insignificant even for bond funds although theory predicts a value of -1. Only the unitary hedge component of the optimal benchmark portfolio has a coefficient close to -1 at -0.910 and -0.914 in Column (4) of Panels A and B, respectively. The predominance of unitary hedging suggests that bond funds rarely engage in cross-currency hedging where they consider the entire cross-section of available forward rates to simultaneous hedge a cross-section of exposures. Instead, they hedge each currency exposure in isolation with a one-to-one hedge $w_{f,i,c,t} = -w_{x,i,c,t}$ in each currency c.

An advantage of the unitary hedge is that it is easy to determine and does not depend on the estimation of any covariance, unlike the benchmark hedge. But from a theoretical perspective, unitary hedging is clearly second-best for two reasons. First, it ignores the marginal hedging benefits of forward positions in other currencies if the same-currency hedge itself is imperfectly correlated with real asset risk. Second, it fails to account for the correlation between the domestic asset position and hedging instruments.

Lastly, we comment on the overall regression fit in Table 4. Mean variance optimization explains 25% of all variation in hedging weights for bond funds in both Panels A and B. The share rises to 68% if we consider only Euro long positions of bond funds. This explanatory power drops below 5% if we consider all derivative positions of equity funds. Thus, the derivative trading policies of equity funds are not well explained by an FX hedging motive.

5.3 Heterogeneity in Hedging by Fund Type

We can replace the pooled regressions for all funds in Tables 3 and 4 by fund-specific regressions that estimate the respective coefficients for each fund separately. In light of the evidence in favor of unitary hedging among bond funds in Table 4, we estimate the respective coefficient for the 805 bond funds with at least 60 monthly positions. Figure 6 provides the distribution of the coefficients in Panel A. For comparison, we plot the corresponding distribution for all equity funds and mixed funds in Panels B and C, respectively.

For our sample of European bond funds with discretionary FX derivative trading, we find that roughly 44% feature a coefficient estimate in the range $[-1.5, -.5]$, which means that their average hedge shows less than a 50% deviation from the unitary hedge with $w_{f,i,c} = -w_{x,i,c}$. Such a large coefficient interval should account generously for various types of measurement error. The corresponding percentages are only 7% and 28% for equity and mixed funds, respectively. The disaggregate evidence confirms the previous conclusion that active currency hedging is concentrated in bond funds. But even among bond funds with a discretionary mandate, a large percentage of funds deviate from a derivative position that can provide a meaningful FX risk reduction. Bond funds in the right tail of the distribution systematically increase their FX risk exposure through derivative trades and these are not rare cases. Approximately 12% of bonds funds hold derivative positions that increase their FX risk exposure by more than 50%.

5.4 Heterogeneity in Derivative Trading by Fund Characteristics

This section further explores fund-level heterogeneity in derivative trading by fund characteristics. We report not only the coefficient distribution for the unitary hedge, as in Figure 6, but also for the exchange rate predictability effect, the forward premium effect, and the transaction cost effect. To characterize fund heterogeneity in a simple manner, we sort all funds along different characteristics into quintiles and only report the quintile average with a standard error bar around the mean. The fund characteristics considered are (i) the number of currencies a fund invests in (ranging from 1 to 6), (ii) the fund size measures as assets under management, (iii) the turnover ratio, (iv) the expense ratio, and (v) the portfolio share of foreign currency (real) asset. As expense ratios are fund type dependent, we rank bond, equity, and mixed funds separately, and take a constant share of each fund type into the respective quintile.

Figure 7 presents the mean coefficient of all funds-level regression after funds are sorted into quintiles according to their characteristics. Column (1) suggests that profitable speculative derivative positions tend to be concentrated in larger funds (quintiles 4 and 5), higher expense ratios (quintiles 3 and 4), and a high share of assets invested in foreign currency (quintile 5). Column (2) of Figure 7 describes the average tilt of the derivative holdings toward capturing the forward premium. Such speculative gains are sought mostly by funds that hold assets in only one or two currencies (quintiles 1 and 2), that have a large asset turnover (quintile 5), and feature a large share of assets in foreign currency (quintile 5). Column (3) characterizes the sensitivity of the derivative portfolio toward transaction costs. A portfolio tilt toward lower costs is observed for funds with a larger number of investment currencies and for funds of larger size across all quintiles. However, a larger expense ratio and a larger foreign investment share both imply on average more negative fund coefficients for the transaction cost effect. No particular fund type pattern emerges in Column (4) for the mean fund coefficient for unitary hedging.

The heterogeneity analysis shows that the 20% of funds with the highest share of foreign currency investment use FX derivatives most actively in pursuit of higher investment returns. They also face roughly six times greater transaction costs compared to funds in the lowest quintile. This supports a model of discriminatory derivative pricing where market makers face adverse selection risk, as in Burnside et al. (2009).

5.5 Ex-Post Fund Performance by Trading Strategy

The previous sections suggest that observed derivative trading behavior in the European investment industry substantially deviates from what a mean-variance model predicts. In particular we find that derivative positions by investment funds are very heterogeneous with respect to the forward premium and transaction costs, and generally ignore cross-currency hedging benefits in their trading policies. In this section we explore how different hedging policies influence long-run fund performance in four different scenarios.

First, we infer their baseline performance using their (end-of-month) observed equity and fixed income shares in the seven different currencies and their (end-of-month) observed hedging positions. This performance benchmark is necessarily coarse as it calculates fund returns based on asset returns at the currency-asset class level rather than the level of the individual stock or bond. Furthermore, it ignores portfolio adjustments that occur within any month. However, we can compare the inferred fund returns to the self-reported fund returns over the five-year period and eliminate all funds for which this approximation is not within a certain range of tolerable error. Such a robustness check is undertaken as a last step in Section 6.

Second, we define four different alternative hedging scenarios to check if such alternative derivative trading policies (for fixed real investments) improve the average performance of European investment funds. We focus on four different performance measures, namely the in-sample (i) implied mean fund return over the five year sample period (Mean), (ii) its standard deviation (St.D.), (iii) the so-called certainty equivalence (CEQ), and (iv) the total (annualized) transaction costs incurred through FX derivative trades. The CEQ calculates the value of the objective function and represents the equivalent mean return without risk that makes the funds indifferent to the any risky outcome. Formally,

$$CEQ = \mu - \frac{1}{2\gamma}\sigma^2, \tag{13}$$

where μ and σ^2 are the average realized monthly excess return (relative to the EONIA rate) and variance, respectively. The value of the CEQ depends on the risk tolerance of the fund and we consider two different values in our performance simulations. We chose a risk tolerance parameter $\gamma = 0.2$ as a plausible parameter value. Equity funds feature an annualized standard deviation for monthly returns of 14.6%. The parameter $\gamma = 0.2$ then implies an annualized equity premium of $\frac{1}{2\gamma}(0.146)^2 = 5.3\%$.[20]

Baseline: Fund Returns for Observed Derivative Trading. This benchmark case calculates the fund returns under the observed (end-of-month) asset and derivative holding and includes transaction costs for the derivative portfolio. We can decompose the (7×1) vector portfolio weights $w_{x,i,t} = w_{b,i,t} + w_{e,i,t}$ of fund i at the end of month t into bond weights $w_{b,i,t}$ and equity weights $w_{e,i,t}$, respectively. Let $r_{e,t+1}$ and $r_{b,t+1}$ represent the corresponding (7×1) vectors of asset returns in month $t+1$ expressed in Euros. We define observed monthly fund returns as

$$r_{i,t+1}^{Observed} = w'_{b,i,t} r_{b,t+1} + w'_{e,i,t} r_{e,t+1} + w'_{f,i,t}(s_{t+1} - f_t + \tau_{i,t}), \tag{14}$$

where $s_{t+1} = ln(S_{t+1})$ represents the log spot rate vector at the end of month $t+1$ and $f_t = ln(F_t)$ the one month log forward rate at the end of month t.[21] The vector of (derivative) transactions costs $\tau_{i,c}$ is calculated as stated in Eq. (11) and generally differs between short and long Euro positions.

Scenario 1: Fund Returns without FX Derivatives. Here we simply ignore the contribution

[20] Our parameter choice is also close to $\gamma = 1/3$ picked by Opie and Riddiough (2020).

[21] We measure prices at the end of each month t as the last available closing prices in month t and use the mid-price in the interdealer market.

of the hedging return to a fund's portfolio return in any given month. Formally, fund returns are

$$r_{i,t+1}^{Nohedge} = w_{b,i,t}' r_{b,t+1} + w_{e,i,t}' r_{e,t+1}. \tag{15}$$

Scenario 2: Unitary Hedge without Return Seeking. An interesting scenario is unitary hedging because it is prevalent among bond funds. This hedging policy ignores the covariance structure of FX and asset returns and matches any foreign currency exposure from real investments with an equally large forward short position currency by currency (i.e., $w_{f,i,t} = -w_{x,i,t}$). We exclude any return seeking behavior, but account for transaction costs so that returns follow as

$$r_{i,t+1}^{Unitary} = w_{b,i,t}' r_{b,t+1} + w_{e,i,t}' r_{e,t+1} - w_{x,i,t}'(s_{t+1} - f_t + \tau_{i,t}). \tag{16}$$

Scenarios 3: Optimal Hedge without Return Seeking. This hedging policy follows from mean-variance optimization characterized in Eq. (4) and includes cross-currency hedging. Formally,

$$r_{i,t+1}^{Optimal} = w_{b,i,t}' r_{b,t+1} + w_{e,i,t}' r_{e,t+1} + w_{f,i,t}^{*\prime}(s_{t+1} - f_t + \tau_{i,t}). \tag{17}$$

Scenarios 4: Optimal Hedge with Return Seeking. The benchmark hedge is the same as in Scenario 3, but the policy includes additional speculative terms, which tilts the hedge portfolio toward long Euro positions in currencies with a positive forward premium and low (or even negative) transaction costs.

Table 5 reports performance statistics for the observed benchmark hedge and the four hedge scenarios for the period 2019-23. Columns (1)-(3) provide (i) the (annualized) average return of all bond, equity, and mixed funds, respectively, (ii) the (annualized) average standard deviation (St.D.) of the monthly returns by fund type, (iii) the average of the certainty equivalent (CEQ) by fund type for a risk tolerance parameter of $\tau = 0.2$, and (iv) the average (annualized) transaction costs in basis points. Columns (4)-(6) report the performance improvements of each scenario relative to the observed baseline, where we measure a reduced standard deviation and smaller transaction cost as positive improvements.

The baseline case in Table 5 states that bond funds had (ex-post) a disappointing annualized mean performance of -3.316% (in Euros) during the period 2019-23 relative to 6.905% for equity funds. The average annualized transaction costs are relatively small for equity funds of one basis point compared to equity and mixed funds, which incur three times larger transaction costs.

For the different alternative scenarios, we focus on Columns (4)-(6), which state the changes in fund outcomes relative to the baseline case. Scenario 1 considers the (counterfactual) case of no derivative trading by any fund. Column (4) shows that this would have improved the (annualized) mean return of bond funds by 0.339% without changing the average standard deviation of bond fund returns. Interestingly, derivative trading did not change the average return risk of bonds funds or mixed funds either. We therefore summarize that the observed derivative trading behavior did not achieve any economically or statistically significant reduction in the FX exposure for the average European investment fund. Only the annualized average bond fund performance would have increased by 34 basis points (ex-post) if no derivative trading had taken place. Derivative transaction costs do not explain this difference as they account for only three basis points in annualized returns. Instead, we can point to the average dollar appreciation over the period 2019-23 which generated negative returns on the average Euro long position held by European bond funds.

Unitary hedging in Scenario 2 reduces the standard deviation of portfolio risk for bond funds by 0.277% relative to the baseline risk of 5.935%, which represents only a very modest risk reduction of 4.6%. A risk increase is observed for equity funds, while there is no change for mixed funds. Hence, unitary hedging is disappointing in its reduction of FX exposure. The unitary hedging strategy involves only slightly higher average costs of 0.6 basis points annualized compared to the observed benchmark. This means that unitary hedging does not involve absolutely larger derivative positions, but derivative trades that better match the fund's FX exposure currency by currency.

Scenarios 3 and 4 consider mean-variance optimal hedging strategies without and with return seeking, respectively. The return seeking strategies differ by their portfolio tilt toward low-cost hedging and toward currencies with a negative forward premium, but implement the same benchmark hedge with the same cross-currency term. We find that optimal hedging provides a more significant improvement in terms of risk reduction. The standard deviation of portfolio returns for bond funds decreases by an annualized 0.61% under both strategies, which amounts to a 10% risk reduction. An even larger absolute risk reduction could have been achieved by equity and mixed funds of 1.47% and 1.025%, respectively, if they had implemented the benchmark hedge for their foreign asset position. The associated costs are again very small at two basis points and 0.5 basis points of annualized fund performance, respectively. In fact, optimal hedging is slightly cheaper than unitary hedging and provides an average absolute risk reduction of the monthly standard deviation of fund returns, which is twice as large.

We find that the return seeking element in Scenario 4, which tilts the optimal benchmark portfolio toward lower transaction costs and the forward premium, makes no difference to the average fund performance. The latter is negative and almost identical for both Scenarios 3 and 4 across all fund types. Ex-post the fund returns would have been lower by 1.25%, 1.17%, and 1.17% basis points for bond, equity, and mixed funds, respectively. These lower ex-post returns should not be confused with negative expected returns. But it is also clear that optimal hedging can generate a significant relative performance risk against similar funds that do not hedge; it thus relies on investors able to distinguish expected returns from ex-post realized returns.

6 Robustness

A shortcoming of our analysis consists in the imperfect measurement of a fund's asset returns. We replace the actual returns by inferred returns that map the bond and equity positions dispersed over roughly 300,000 individual assets into only 12 asset classes, namely one representative bond and equity portfolio for each of the six currencies. How critical is this simplification of the hedging problem to our results?

If the true asset returns in foreign currency deviate from the return of the reference asset only by an idiosyncratic error $\epsilon_{c,i,t+1} = r^{true}_{x,c,t+1} - r_{x,c,t+1}$ that is independent of vector of currency returns Δs_t, then the benchmark hedge $\Sigma_{ff,i,t+1}\Sigma_{fx,i,t}w_{x,i,t+1}$ remains unchanged. In other words, foreign asset return deviations from our representative asset class return that are orthogonal to the currency returns do not matter for the optimal hedging policy. Such orthogonal errors imply an inference error for a fund's mean return and also its SD and certainty equivalence. However, the improvement of the mean return stated in Table 5, Columns (4) is again unaffected for all alternative hedge scenarios as they depend only on the return of the invariant optimal hedging policy.

But the measurement errors in funds' local asset returns may not always be orthogonal to the currency returns. In this case, it is important for our inference that the true asset return in any of the 12 asset classes is well approximated by the representative asset class (or index) return. The more diversified a fund invests in any of the 12 asset classes, the better the respective index return approximates a fund's return history. Table F.4 in Appendix A.5 tabulates the absolute value of the average monthly difference between our inferred monthly portfolio returns (i.e., the baseline case in Table 5) and the monthly return that funds report. A total of 25% of funds feature an average monthly difference of more than 1.9%. As a robustness exercise, we identify these 25% (non-representative) funds and exclude them from our analysis.

Table F.5 repeats the analysis in Table 3 for the 75% of funds for which the holding-inferred and reported fund returns coincide best. The results are very similar to the baseline regression results. The coefficient for the benchmark hedge is on average slightly larger in absolute terms and increases for the regression with the best fit in Column (4) of Panel B from -0.94 to -0.95.

Table F.6 reproduces the scenario analysis in Table 5 for the 75% of funds with the least absolute deviation of holding-inferred and reported returns. Again, the results do not change significantly. A marginally lower risk for equity funds in the optimal hedging portfolio (Scenarios 3 and 4) compared to full sample regression in Table 5 is the most noticeable difference.

7 Conclusion

The decentralized over-the-counter (OTC) structure of the global FX derivative market left this market largely out of the scope of empirical research so that little was known about the derivative trading at the institutional investor level. Following the 2007-8 financial crisis, new financial regulation (EMIR) has increased the reporting requirements for all European counterparties in this market. As these data become more readily available to researchers at regulatory institutions, it is possible to confront the established theory of optimal FX hedging (in the mean-variance framework) with contract-level microdata reported by institutional investors.

We find that 68% of our sample of European investment funds use FX forward and FX swap contracts at least sporadically during the five-year period 2019-23. Yet, their trading in FX derivatives generally does not correspond to the theoretical predictions implied by mean-variance optimization.

Even among fixed income funds, only a minority of 44% of bond funds hold derivative positions that are broadly consistent with a hedging behavior designed to reduce the FX exposure of portfolio return variance in Euro terms. This share is even lower for equity and mixed funds at 7% and 28%, respectively.

Most of the observed hedging behavior does not involve a comprehensive portfolio approach that seeks to hedge all foreign currency exposures simultaneously with all available derivative contracts. Instead, we find evidence for unitary hedging (mostly by bond funds) that reduces each exchange rate exposure separately on a currency by currency base. We show that such an approach deprives European investment funds of half of their risk reduction opportunities that a more comprehensive approach would permit at similar or even lower trading costs.

Overall, the observed derivative trading does *not* function as an important tool for the reduction of currency risk in foreign asset holdings of European funds with a discretionary hedging mandate. In the counterfactual scenario without any FX derivative trading, the average European investment fund would hold an economically indistinguishable overall return risk. This finding contrasts with a feasible (partial equilibrium) scenario of optimal hedging, which suggests that the overall investment risk of both bond and equity funds could be reduced through FX derivatives by approximately 10% without incurring significantly higher transaction costs. But we also note that such absolute risk reduction can easily be costly in terms of relative underperformance with respect to non-hedging funds if the Euro depreciates relative to foreign currencies and Euro long positions incur losses.

Our findings suggest that international risk trading through FX derivative markets is incomplete if US-based funds with the inverse FX exposure show a similar shortfall in FX risk hedging as European funds. In this case a considerable amount of FX risk is maintained in the investment portfolios even though this risk could be jointly eliminated through FX derivative trading. Such trading (as opposed to market) incompleteness is consistent with a previous macro literature that fails to find evidence of international risk-sharing in aggregate consumption data (Lewis (1996)). But imperfect international risk trading at the fund level is a much starker finding and in many ways a stronger challenge to financial theory as it occurs for financially sophisticated fund managers with access to cheap risk trading instruments.

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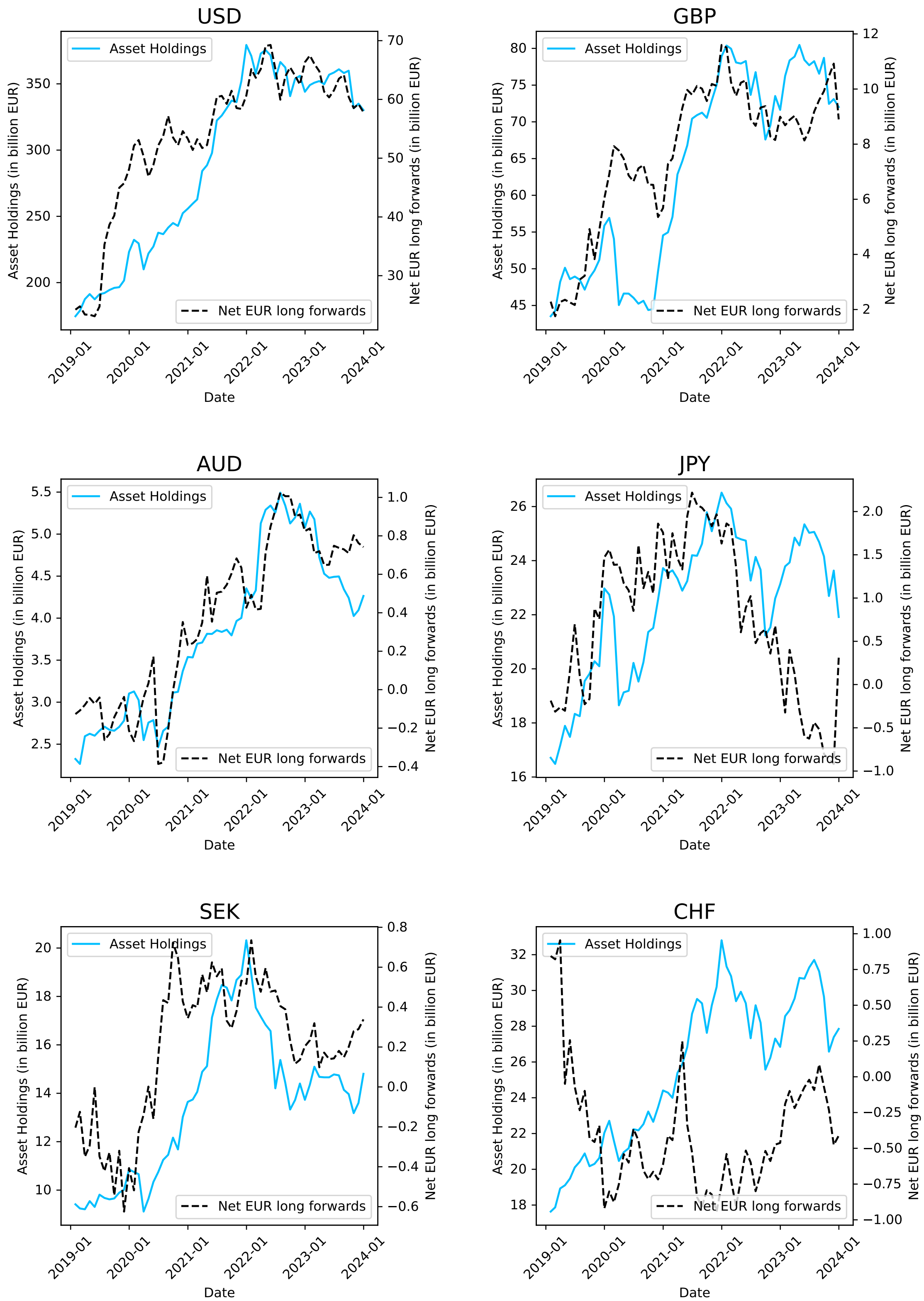
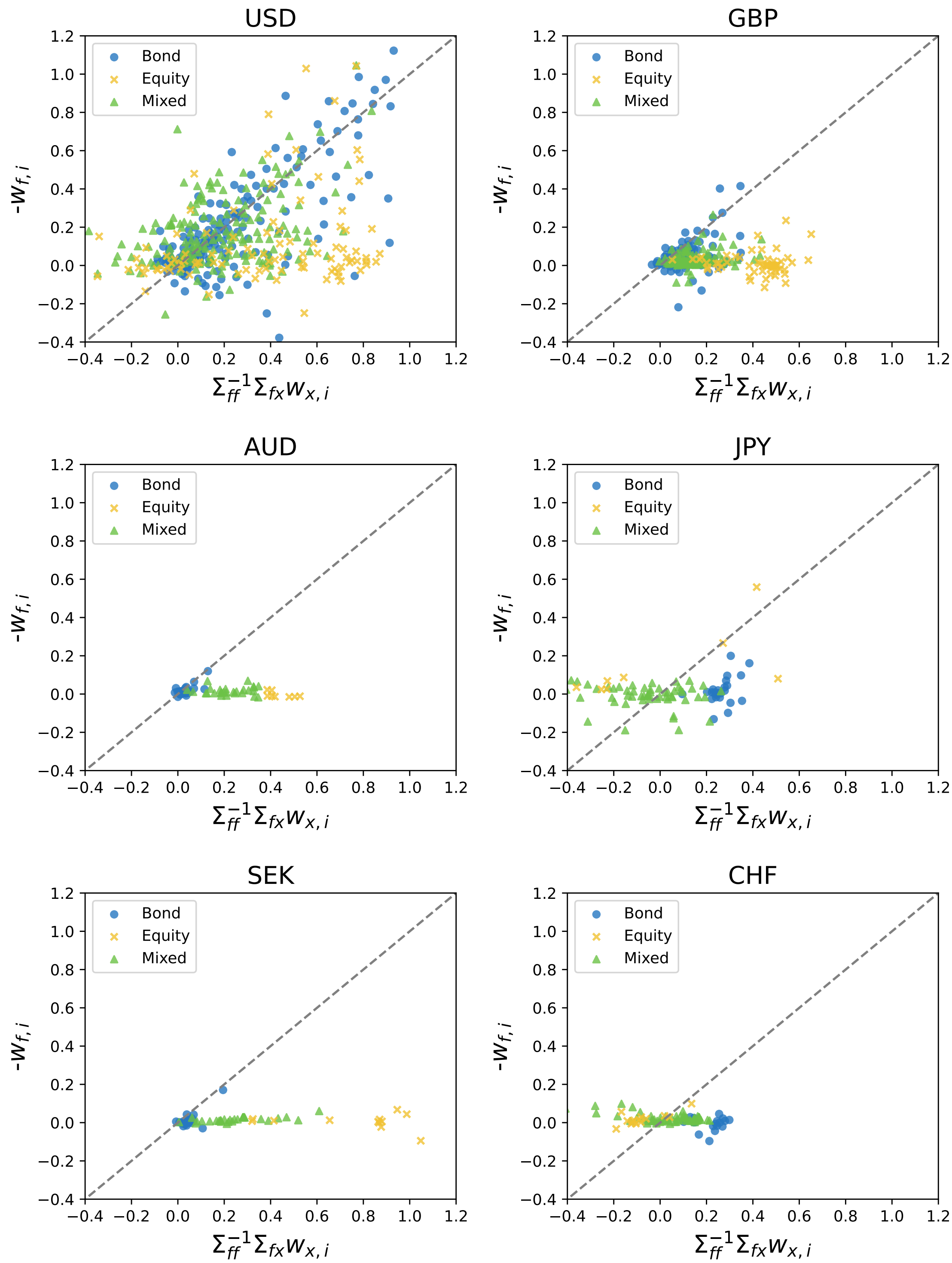
Figure 1: Aggregate Asset Value and Notional Value of Net Forward Positions by Currency



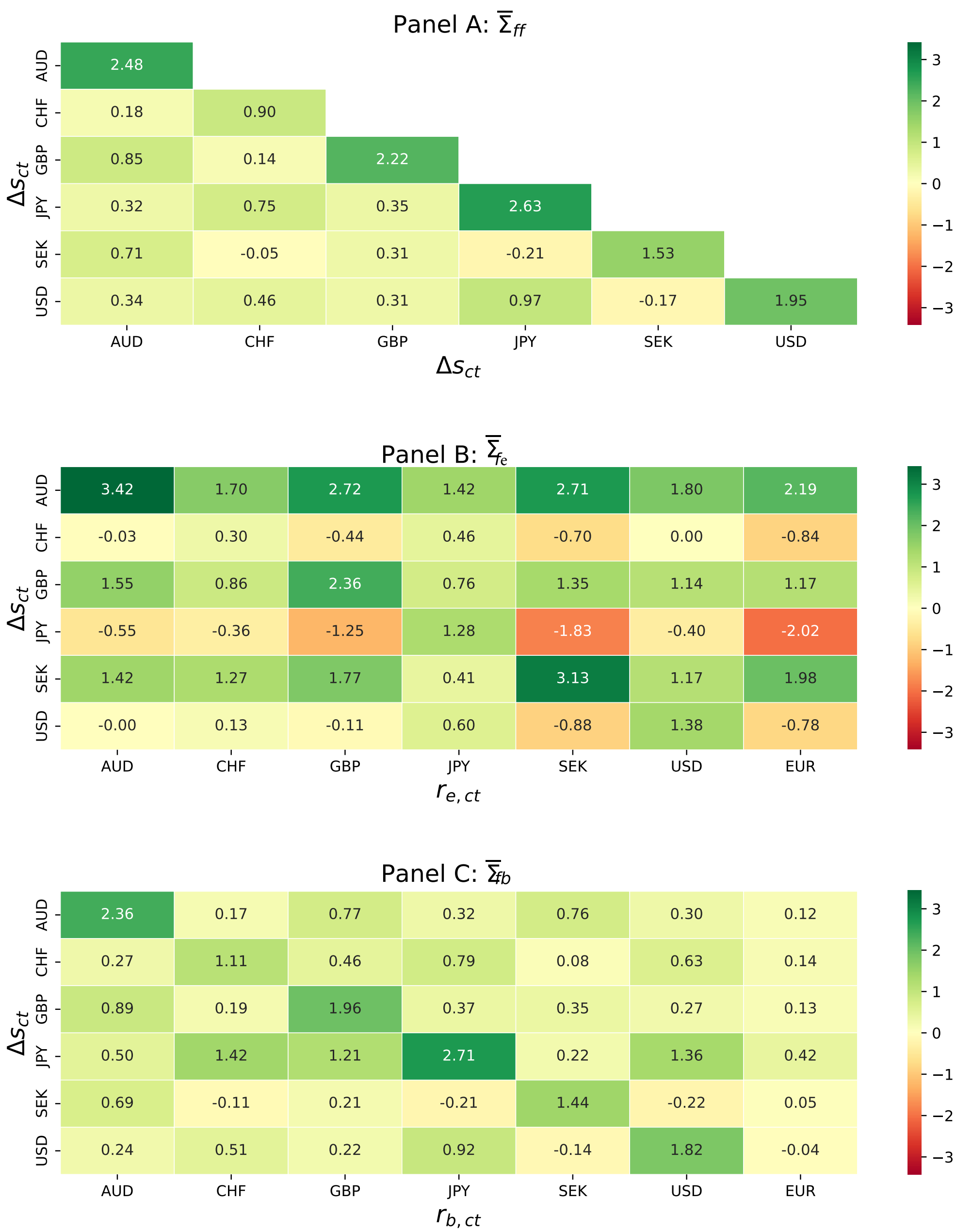
Notes: We plot the aggregate value of real investment asset positions (in Euros, solid line, left axis) and the notional value of net forward positions (i.e., long positions in Euros, dashed line, right scale) for the sample of 2,806 European investment funds by currency.

Figure 2: Optimal Benchmark Hedge and Observed FX Derivative Holdings by Currency



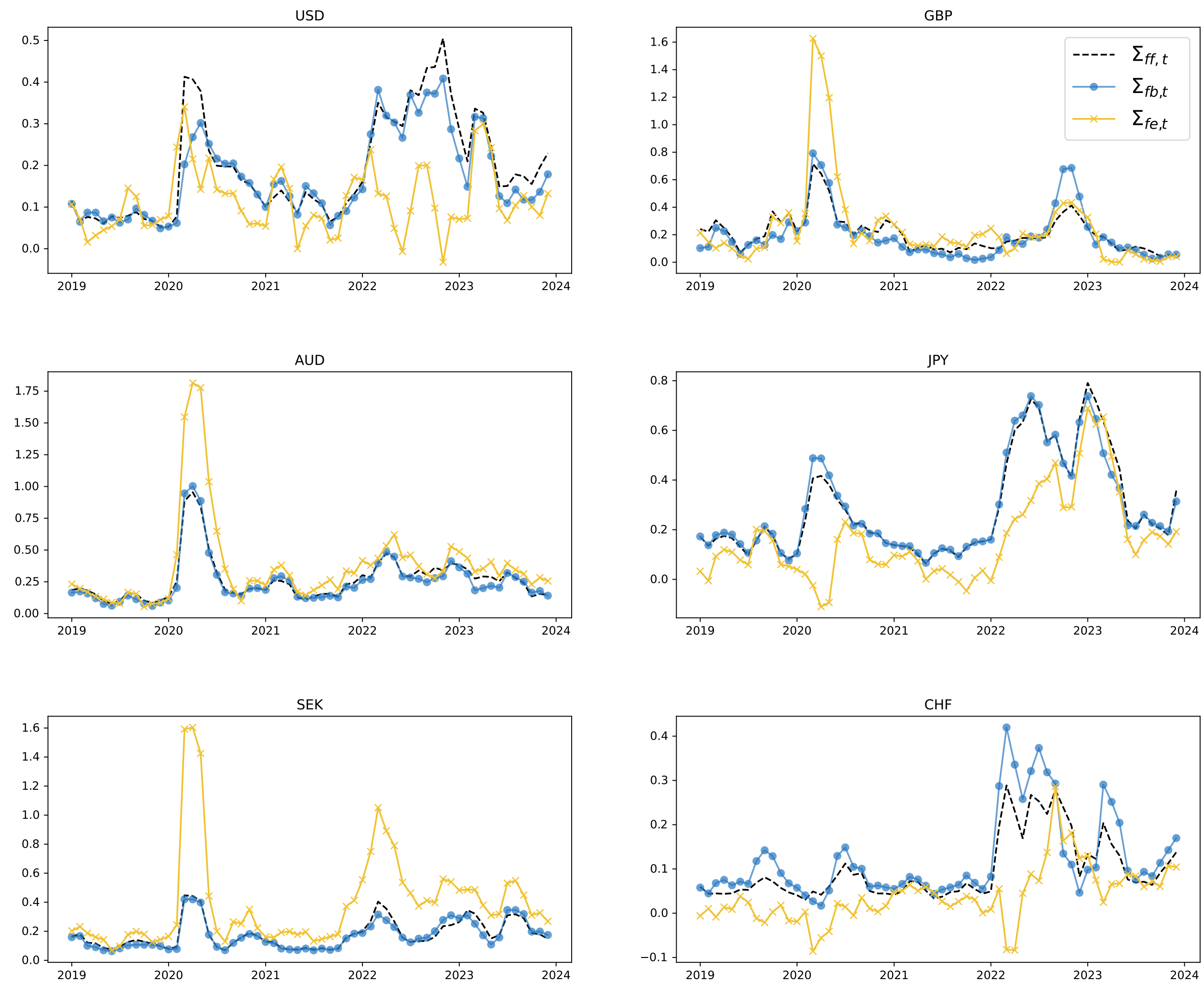
Notes: We plot the optimal fund-level (time-average) benchmark hedging weights in Euro long positions (as implied by mean-variance optimization) on the horizontal axis against the corresponding observed (time-averaged) FX derivative weights in Euro long positions (i.e., outstanding interest relative to total real investment value) on the vertical axis for bond funds (blue dot), equity funds (yellow cross) and mixed funds (green triangle). For confidentiality reasons we group funds together that have similar x and y values and plot the average of the group. We have at least four funds per group and do not plot groups that do not pass the confidentiality requirements. The number of funds with investment positions in currency c are 2,516 (USD), 2,253 (GBP), 936 (AUD), 1,080 (JPY), 1,403 (SEK), and 1,593 (CHF), respectively.

Figure 3: Average Covariance Matrices



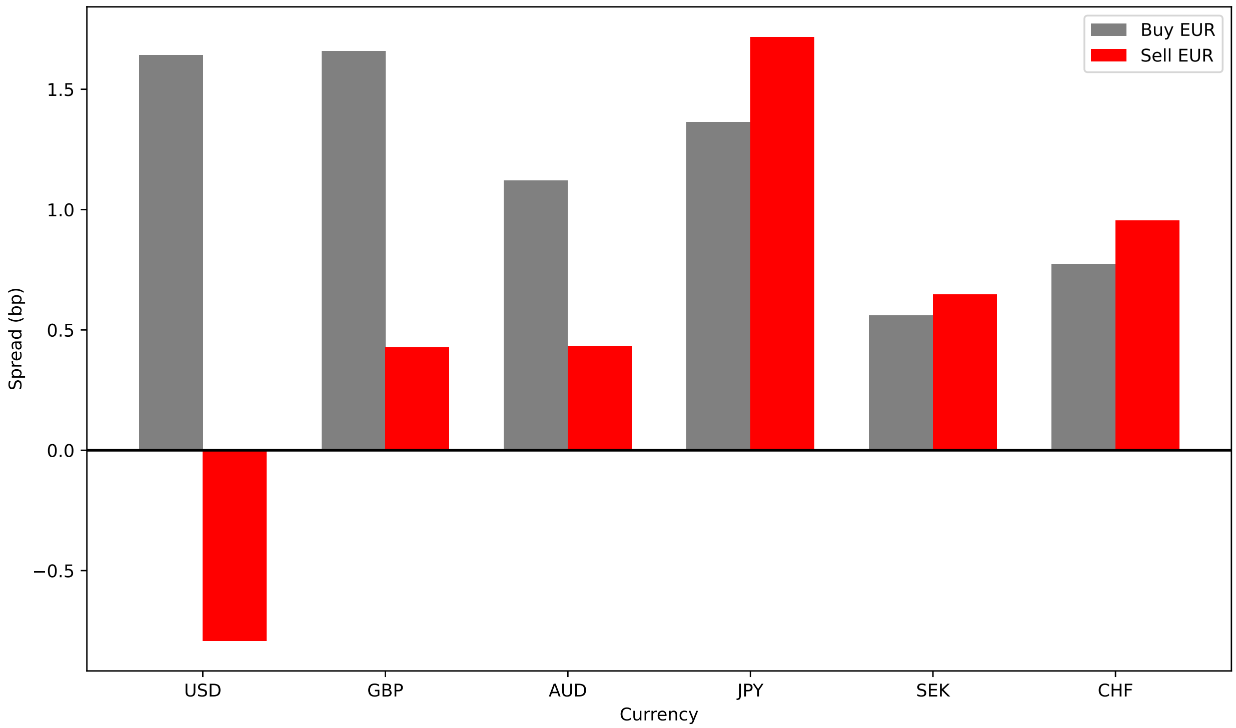
Notes: For the period 2019-23, we plot in Panel A the average (in-sample) covariance matrix $\overline{\Sigma}_{ff}$ of daily exchange rate returns, in Panel B the average covariance $\overline{\Sigma}_{fe}$ of the daily exchange rate returns and equity returns, and in Panel C the average covariance $\overline{\Sigma}_{fb}$ of daily exchange rate returns and bond returns. All covariance terms are scaled by a factor of 10,000.

Figure 4: Time-varying Covariance Matrices



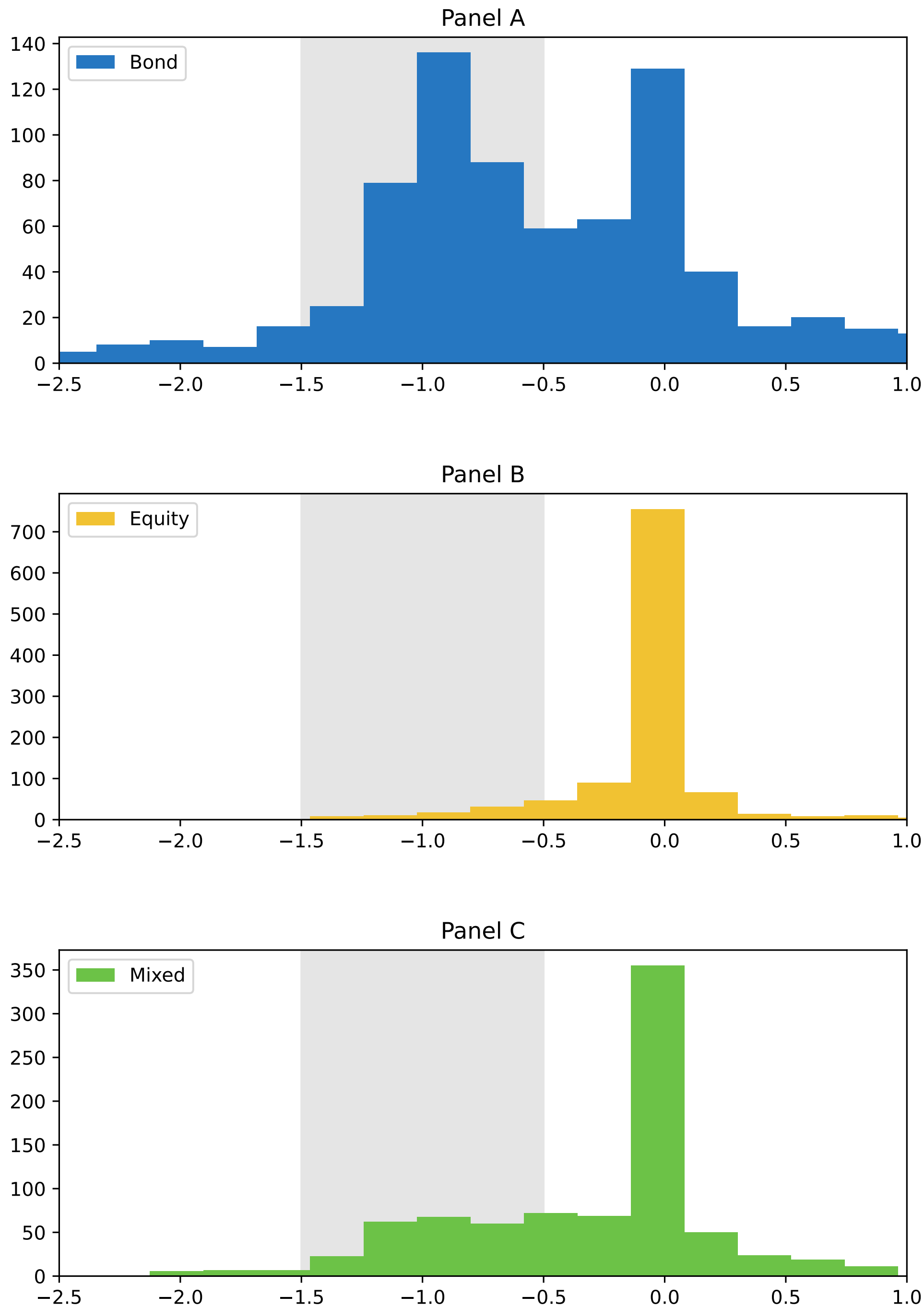
Notes: We depict by currency the time-varying variance of currency returns $[\Sigma_{ff,t}]_{cc}$ (black dashed line), the covariance of currency and equity returns $[\Sigma_{fxe,t}]_{cc}$ (yellow line with crosses) and between currency and foreign bond returns $[\Sigma_{fxb,t}]_{cc}$ (blue line with dots). The covariance is calculated as lagged realized covariance (LRC) for a 6-month rolling window (see Appendix A.4) using daily returns (in Euros). We scale by a factor of 100,000.

Figure 5: Average Transaction Costs of Forward Contracts



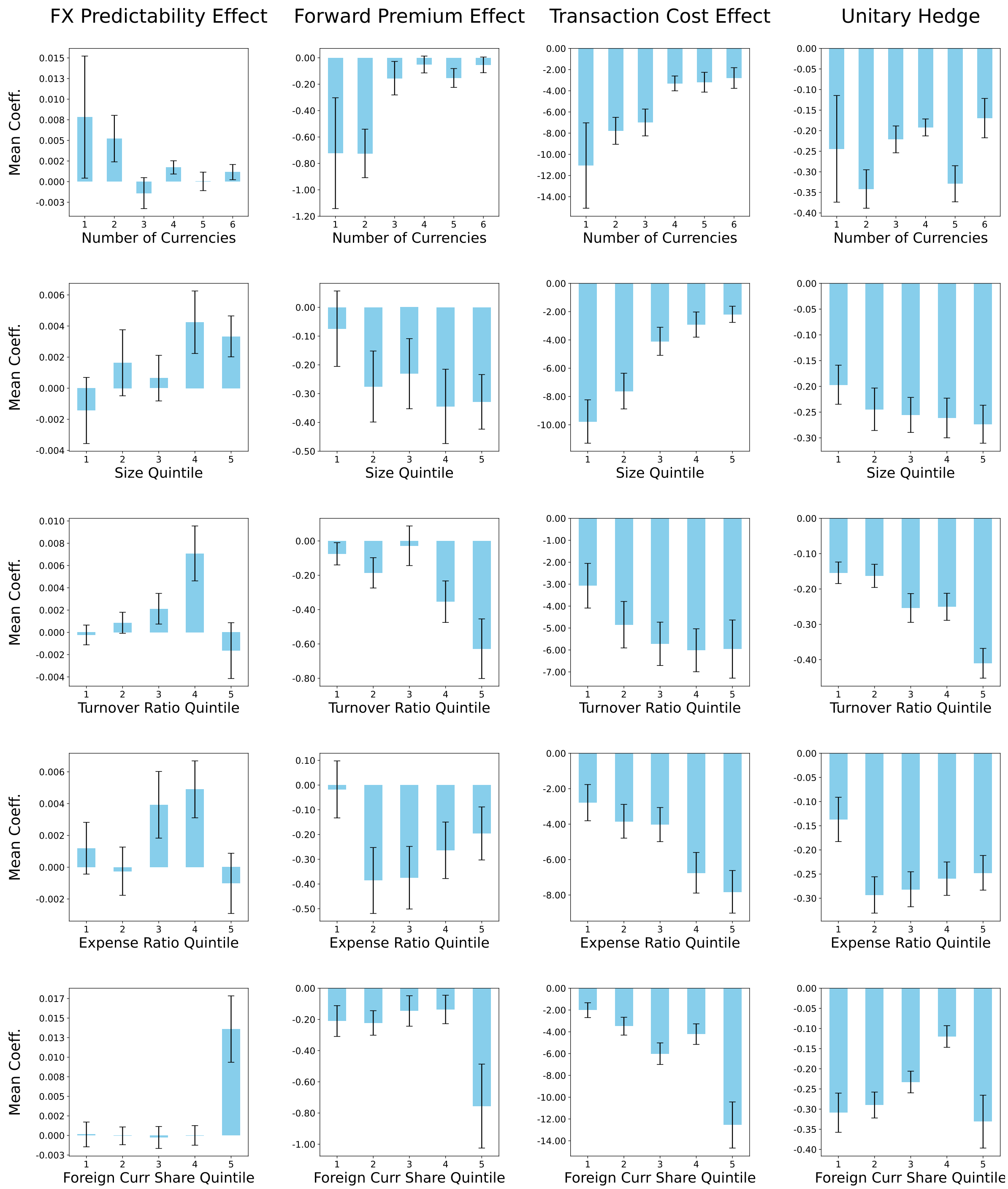
Notes: We depict by currency the average transaction cost spread deduced from regression 10 reported in Column (1) of Table C.2. The grey bars are average spreads for buying Euros and the red bars are the average spread for selling Euros at maturity of the forward contract. The spread is defined in Eq. (9).

Figure 6: Prevalence of (Unitary) Hedging by Fund Type



Notes: We undertake the regression in Table 4, Panel A, for each fund and record the regression coefficient for the unitary hedging term, which captures a fund's degree of currency hedging with full hedging represented by a value of -1. Panel A shows that 44% of bond funds feature a coefficient in the interval $[-1.5, -0.5]$. This share is only 7% for equity funds and 28% for mixed funds in Panels B and C, respectively. The plotted distribution for bond funds ignores extreme coefficients below -2.5 and above 1, which represents roughly 7% of bond funds.

Figure 7: Heterogeneity in Fund Hedging



Notes: We undertake funds-level hedging regressions and report the mean of the coefficient distribution for the FX Predictability Effect in Column (1), the Forward Premium Effect in Column (2), the Transaction Cost Effect in Column (3), and the Unitary Hedge in Column (4) by fund characteristics. The coefficients are winsorized at the 1% level. The black bar indicates the standard errors of the mean, i.e., the standard deviation divided by the square root of the number of observations. We sort funds by the number of currencies invested, and quintiles for fund size, for the turnover ratio, for the expense ratio, and for the portfolio share invested in foreign currency.

Table 1: European Fund Sample and Foreign Investment Positions

We report summary statistics on monthly asset positions, the foreign (non-Euro) investment share, and foreign currency positions for European investment funds by fund type for the period 2019-23. Panel A reports the asset statistics for $7,133$ funds that do not report any (end-of-month) FX derivative positions in the entire sample period, whereas Panel B presents the same asset statistics for $2,521$ funds that report at least one FX derivative position during the same period. In Panel C, we report the pooled foreign investment positions in six different currencies (USD, GBP, AUD, JPY, SEK, CHF) for all fund-months in Panel B. The hedge ratio $-w_{f,i,c,t}/w_{x,i,c,t}$ provides the weight on Euro long positions relative to the foreign asset weight in currency c in month t by fund i. The fund data are from Lipper and the derivative positions come from regulatory EMIR data at the European Systematic Risk Board.

Panel A: European Funds without FX Derivative Positions, Monthly Observation 2019-23

			Fund Assets (mil)					Foreign Investment Share (%)				
	No. Funds	Obs.	Mean	St.D.	Q25	Q50	Q75	Mean	St.D.	Q25	Q50	Q75
Bond	630	44,763	279.2	622	35	92.9	246.4	16.8	24.7	2.7	6.4	18.4
Equity	2,233	354,417	186.6	538.4	18	57.1	159.8	44	33.5	9.5	40.8	76.6
Mixed Assets	1,261	193,451	132.8	428.2	12.9	32.4	90.6	28.5	23.7	9.1	22.9	42.7
All Funds	4,124	592,631	184.3	523.6	17.1	50.6	152.9	36.8	31.3	7.4	29.4	61.2

Panel B: European Funds with FX Derivative Positions, Monthly Observation 2019-23

			Fund Assets (mil)					Foreign Investment Share (%)				
	No. Funds	Obs.	Mean	St.D.	Q25	Q50	Q75	Mean	St.D.	Q25	Q50	Q75
Bond	806	118,328	441.6	819.6	81.7	195.2	467.6	28.3	28.6	4.6	18	46.1
Equity	1,109	230,844	406.4	815.4	45.7	149.2	437.7	50.9	29.1	30.2	46.8	77.5
Mixed Assets	891	174,080	317.7	798.6	38.9	113.5	279.5	35.1	21.9	17.1	32.6	52.1
All Funds	2,806	523,252	388.4	812.6	51.3	146.6	399.7	39.4	28.6	14.4	36.2	61.3

Panel C: Foreign Currency Position for European Funds with FX Derivative Positions

			Foreign Currency Asset Value (mil)					Hedge Ratio $-w_{f,i,c,t}/w_{x,i,c,t}$ (%)				
	No. Funds	Obs.	Mean	St.D.	Q25	Q50	Q75	Mean	St.D.	Q25	Q50	Q75
Bond	795	66,503	122.6	384.7	8	32.3	98.6	51.4	49.6	9.4	63	95.2
Equity	1,109	173,911	249.5	636	17.4	66.9	234.9	4.4	19.3	−0.3	0	0.9
Mixed Assets	884	121,240	117.4	464	9.7	30.9	92.1	25.1	35.8	0	9.2	43.7
All Funds	2,788	361,654	171.4	524.6	11.2	40.8	138.4	24.4	40.3	0	2.4	49.8

Table 2: Summary Statistics

We report summary statistics of predicted monthly components of optimal hedging weights in six foreign currencies of 2,806 European investment funds with at least one FX forward position in the period 2019-23. Panel A provides the hedging and investment weights of fund i in currency c in month t denoted by $w_{f,i,c,t}$ and $w_{x,i,c,t}$, respectively. Panel B reports the same statistic for Euro long positions only ($w_{f,i,c,t} < 0$). Panel C states the components for the optimal hedging weights. For the construction of the matrices $\Sigma_{ff,t}$ and $\Sigma_{fx,t}$, we alternatively calculate the (i) Lagged Realized Covariances (LRC 6-month) over the previous 6-month period or (ii) or the predicted MGARCH1 covariance as explained in Appendix C. The subscript $X_{c\bullet}$ refers to row c of the matrix X and a superscript X^{-1} denotes the inverse of matrix X. The (6×1) vector Δs_{t+1} denotes the (log) currency return for the next month $t+1$ and $fp_t = f_{c,t} - s_{c,t}$ the vector of forward premia at the end of month t.

			Obs	Mean	St.D.	Q10	Q25	Q50	Q75	Q90
			(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Hedging and Investment Weights										
$w_{f,i,c,t}$		$\times 100$	402,171	−2.93	13.91	−7.49	−0.52	0.00	0.00	0.27
$w_{x,i,c,t}$		$\times 100$	402,171	12.99	20.44	0.35	1.30	4.20	14.06	41.56
Panel B: Hedging and Investment Weights for Euro Long Positions only ($w_{f,i,c,t} < 0$)										
$w_{f,i,c,t}$		$\times 100$	121,511	−11.89	21.6	−35.32	−12.12	−3.25	−0.94	−0.19
$w_{x,i,c,t}$		$\times 100$	121,511	16.37	23.27	0.32	1.53	5.43	21.17	51.78
Panel C: Explanatory Components										
FX Predictability Effects										
$[\Sigma^{-1}_{ff,t+1}]_{c\bullet}\Delta s_{t+1}$	LRC 6-month	$\times 0.01$	402,171	1.07	15.1	−15.61	−8.07	0.59	8.94	20.16
$[\Sigma^{-1}_{ff,t+1}]_{c\bullet}\Delta s_{t+1}$	MGARCH1	$\times 0.01$	402,171	0.41	10.95	−13.25	−7.12	0.74	7.53	14.78
Forward Premium Effects										
$[\Sigma^{-1}_{ff,t+1}]_{c\bullet}fp_t$	LRC 6-month	$\times 0.01$	402,171	−0.31	1.2	−1.35	−0.67	−0.3	0.07	0.84
$[\Sigma^{-1}_{ff,t+1}]_{c\bullet}fp_t$	MGARCH1	$\times 0.01$	402,171	−0.12	0.75	−1.05	−0.47	−0.16	0.1	0.74
Transaction Cost Effects										
$[\Sigma^{-1}_{ff,t+1}]_{c\bullet}\tau_{i,t}$	LRC 6-month	$\times 0.01$	402,171	0.02	0.3	−0.07	−0.00	0.00	0.04	0.15
$[\Sigma^{-1}_{ff,t+1}]_{c\bullet}\tau_{i,t}$	GARCH1	$\times 0.01$	402,171	0.01	0.18	−0.06	−0.00	0.00	0.03	0.11
Benchmark Hedge										
$[\Sigma^{-1}_{ff,t+1}\Sigma_{fx,t+1}]_{c\bullet}w_{x,i,t}$	LRC 6-month	$\times 100$	402,171	16.62	49.37	−34.05	−2.18	14.35	38.47	72.74
$[\Sigma^{-1}_{ff,t+1}\Sigma_{fx,t+1}]_{c\bullet}w_{x,i,t}$	MGARCH1	$\times 100$	402,171	18.92	37.94	−32.38	−0.77	15.83	43.42	69.82
Panel D: Transaction Data on One-Month FX Forward Contracts										
Spread		$\times 10,000$	74,473	0.69	7.65	−4.89	−0.26	0.12	2.36	6.22
Log Assets Under Mgmt			74,473	19.39	1.64	17.41	18.45	19.59	20.41	21.33
Turnover Ratio			74,473	0.12	0.23	0.02	0.03	0.07	0.12	0.21
Expense Ratio			74,473	1.35	0.85	0.25	0.62	1.34	1.87	2.72

Table 3: Comparing Observed and Optimal Mean-Variance Hedging

We regress the currency derivative positions $w_{f,ict}$ of European investment funds labeled i, in currency c, and in month t (measured as share of total assets invested) on future exchange rate changes (FX predictability effect), the optimal forward premium tilt, the optimal transaction cost tilt, and the optimal benchmark hedge. We report in Columns (1)-(3) and Columns (4)-(6) the results for all derivative positions and only (dollar) short positions, respectively. For the the calculation of the (time-varying) covariances $\Sigma_{ff,t+1}$ and $\Sigma_{fx,t+1}$, we use in Panels A and B the (in-sample) lagged realized covariance (estimated for daily returns over the previous 6 months) and the predicted covariance based on the MGARCH1 model, respectively. We include currency fixed effects in all regressions. We double cluster standard errors at the time- and fund-currency level and mark statistical significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

Dep. Variable:	$w_{f,i,c,t}$					
Sample:	All Derivative Positions			Euro Long Positions Only ($w_{f,i,c,t} < 0$)		
Fund Type:	Bonds	Equity	Mixed	Bonds	Equity	Mixed
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Lagged Realized Covariances (6-Month Period)						
FX Predictability Effect $[\Sigma^{-1}_{ff,t+1}]_{c\bullet}\Delta s_{t+1}$	0.042^{**}	0.002	0.010	0.083^{**}	0.012	0.029^{**}
	(0.021)	(0.002)	(0.006)	(0.034)	(0.009)	(0.012)
Forward Premium Effect $[\Sigma^{-1}_{ff,t+1}]_{c\bullet}fp_t$	-1.649^{***}	-0.139	-0.490^{**}	-1.329^{***}	-0.232	-0.581^{*}
	(0.441)	(0.094)	(0.198)	(0.505)	(0.381)	(0.338)
Transaction Cost Effect $[\Sigma^{-1}_{ff,t+1}]_{c\bullet}\tau_{i,t}$	-1.520^{**}	-1.978^{***}	-2.081^{***}	-0.102	0.243	0.924^{*}
	(0.659)	(0.749)	(0.752)	(0.366)	(0.410)	(0.493)
Benchmark Hedge $[\Sigma^{-1}_{ff,t+1}\Sigma_{fx,t+1}]_{c\bullet}w_{x,i,t}$	-0.426^{***}	-0.011^{***}	-0.040^{***}	-0.691^{***}	-0.058^{***}	-0.137^{***}
	(0.040)	(0.003)	(0.009)	(0.039)	(0.015)	(0.024)
Adj. R^2	0.192	0.006	0.014	0.467	0.020	0.062
No. Observations:	82,822	182,568	136,781	48,300	28,242	44,969
No. Funds:	805	1109	891	728	809	705
Panel B: Predicted Covariances based on MGARCH1 Model (DCC, 80 Parameters)						
FX Predictability Effect $[\Sigma^{-1}_{ff,t+1}]_{c\bullet}\Delta s_{t+1}$	0.032^{*}	0.004	0.007	0.049^{*}	0.017	0.028^{*}
	(0.019)	(0.003)	(0.009)	(0.027)	(0.011)	(0.015)
Forward Premium Effect $[\Sigma^{-1}_{ff,t+1}]_{c\bullet}fp_t$	-0.313	0.141	0.736^{**}	1.018	0.760	1.341^{***}
	(0.701)	(0.156)	(0.295)	(0.827)	(0.720)	(0.487)
Transaction Cost Effect $[\Sigma^{-1}_{ff,t+1}]_{c\bullet}\tau_{i,t}$	-2.863^{**}	-3.747^{***}	-4.766^{***}	0.211	0.733	1.607^{*}
	(1.230)	(1.315)	(1.500)	(0.396)	(0.850)	(0.891)
Benchmark Hedge $[\Sigma^{-1}_{ff,t+1}\Sigma_{fx,t+1}]_{c\bullet}w_{x,i,t}$	-0.588^{***}	-0.037^{***}	-0.082^{***}	-0.942^{***}	-0.174^{***}	-0.268^{***}
	(0.049)	(0.008)	(0.018)	(0.036)	(0.033)	(0.039)
Adj. R^2	0.262	0.015	0.023	0.639	0.065	0.113
No. Observations:	82,822	182,568	136,781	48,300	28,242	44,969
No. Funds:	805	1,109	891	728	809	705

Table 4: Cross-Currency versus Unitary Hedging

We regress the currency derivative positions $w_{f,i,c,t}$ of European investment funds labeled i, in currency c, and in month t (measured as share of total assets invested) on future exchange rate changes (FX predictability effect) and the optimal forward premium tilt as in Table 3, but decompose the optimal benchmark hedge into a cross-currency hedge and the unitary hedge. In Panels A and B, we use lagged realized covariances and predicted covariance based on the MGARCH1 model, respectively. We double cluster standard errors at the time- and fund-currency level and mark statistical significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

Dep. Variable:	$w_{f,i,c,t}$					
Sample:	All Derivative Positions			Euro Long Positions Only ($w_{f,i,c,t} < 0$)		
Fund Type:	Bonds	Equity	Mixed	Bonds	Equity	Mixed
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Lagged Realized Covariances (6-Month Period)						
FX Predictability Effect						
$[\Sigma^{-1}_{ff,t+1}]_{c\bullet}\Delta s_{t+1}$	0.008	0.001	0.005	0.010**	0.001	0.015***
	(0.009)	(0.001)	(0.004)	(0.005)	(0.006)	(0.005)
Forward Premium Effect						
$[\Sigma^{-1}_{ff,t+1}]_{c\bullet}fp_t$	−1.197***	−0.100	−0.352**	−0.638***	0.219	−0.259
	(0.323)	(0.074)	(0.143)	(0.219)	(0.300)	(0.180)
Transaction Cost Effect						
$[\Sigma^{-1}_{ff,t+1}]_{c\bullet}\tau_{i,t}$	−1.452**	−1.929***	−1.915***	0.203	0.180	0.780**
	(0.625)	(0.720)	(0.689)	(0.210)	(0.380)	(0.366)
Cross-Currency Hedge						
$[\Sigma^{-1}_{ff,t+1}\Sigma_{fx,t+1} - I_{+0}]_{c\bullet}w_{x,i,t}$	−0.011	0.004**	0.004	−0.022*	0.015*	0.003
	(0.015)	(0.002)	(0.003)	(0.012)	(0.009)	(0.007)
Unitary Hedge						
$w_{x,i,c,t}$	−0.571***	−0.095***	−0.353***	−0.910***	−0.315***	−0.634***
	(0.047)	(0.017)	(0.044)	(0.035)	(0.050)	(0.059)
Adj. R^2	0.283	0.040	0.114	0.682	0.138	0.300
No. Observations:	82,822	182,568	136,781	48,300	28,242	44,969
No. Funds:	805	1,109	891	728	809	705
Panel B: Predicted Covariances based on MGARCH1 Model (DCC, 80 Parameters)						
FX Predictability Effect						
$[\Sigma^{-1}_{ff,t+1}]_{c\bullet}\Delta s_{t+1}$	0.011	−0.000	0.002	0.014**	0.000	0.013**
	(0.009)	(0.000)	(0.004)	(0.006)	(0.005)	(0.005)
Forward Premium Effect						
$[\Sigma^{-1}_{ff,t+1}]_{c\bullet}fp_t$	−1.508***	−0.034	0.052	−0.919**	−0.152	−0.360
	(0.523)	(0.144)	(0.206)	(0.398)	(0.690)	(0.356)
Transaction Cost Effect						
$[\Sigma^{-1}_{ff,t+1}]_{c\bullet}\tau_{i,t}$	−2.842**	−3.708***	−4.313***	0.367	0.410	1.451**
	(1.255)	(1.271)	(1.355)	(0.383)	(0.836)	(0.671)
Cross-Currency Hedge						
$[\Sigma^{-1}_{ff,t+1}\Sigma_{fx,t+1} - I_{+0}]_{c\bullet}w_{x,i,t}$	−0.039	0.012***	0.035***	−0.068*	0.026	0.044***
	(0.047)	(0.004)	(0.007)	(0.038)	(0.021)	(0.012)
Unitary Hedge						
$w_{x,i,c,t}$	−0.574***	−0.093***	−0.350***	−0.914***	−0.313***	−0.632***
	(0.048)	(0.017)	(0.044)	(0.035)	(0.050)	(0.060)
Adj. R^2	0.282	0.041	0.118	0.682	0.137	0.302
No. Observations:	82,822	182,568	136,781	48,300	28,242	44,969
No. Funds:	805	1,109	891	728	809	705

Table 5: Fund Performance by Hedging Strategy

We report summary statistics on European fund returns, namely the mean return (Mean), the standard deviation of the return (St.D.), and the certainty equivalent (CEQ) under different hedging scenarios. Columns (1)-(3) report the sample averages of the three performance statistics separately for bond, equity, and mixed funds, respectively. Columns (4)-(6) state the corresponding improvements of the sample averages under four different scenarios relative to the baseline case given by the fund returns on the observed hedge. We test for the equality of means between the baseline case and the scenario performance and mark the rejection of equality (null hypothesis) at the 10%, 5%, and 1% level by *, **, and ***. We exclude funds that fall within the lowest tenth percentile of observation counts to ensure that our standard deviation estimates are reliable.

	Sample Average			Improvement (Relative to Baseline)		
Fund Type	Bond	Equity	Mixed	Bond	Equity	Mixed
	(1)	(2)	(3)	(4)	(5)	(6)
Baseline: Fund Returns on Observed Derivative Trading						
Mean (% annualized)	−3.316	6.905	1.689			
St.D. (% annualized)	5.935	14.944	9.857			
CEQ Ratio	−4.837	0.314	−1.917			
Transaction Costs (bp annualized)	2.989	0.874	2.728			
Scenario 1: Fund Returns without Derivative Trading						
Mean (% annualized)	−2.977	6.949	1.898	0.339***	0.044	0.209
St.D. (% annualized)	5.865	14.848	9.596	0.070	0.096	0.261
CEQ Ratio	−4.468	0.430	−1.574	0.369***	0.116	0.343**
Transaction Costs (bp annualized)				2.989***	0.874***	2.728***
Scenario 2: Fund Returns for Unitary Hedge without Return Seeking Seeking						
Mean (% annualized)	−3.627	6.255	1.315	−0.311***	−0.650***	−0.374*
St.D. (% annualized)	5.658	15.331	10.098	0.277***	−0.387**	−0.241
CEQ Ratio	−5.064	−0.629	−2.434	−0.227	−0.943***	−0.517***
Transaction Costs (bp annualized)	3.596	2.580	3.799	−0.607	−1.706***	−1.071***
Scenario 3: Optimal Hedge without Return Seeking Seeking						
Mean (% annualized)	−4.566	5.733	0.518	−1.250***	−1.172***	−1.171***
St.D. (% annualized)	5.328	13.474	8.832	0.607***	1.470***	1.025***
CEQ Ratio	−5.914	0.216	−2.581	−1.077***	−0.098	−0.664***
Transaction Costs (bp annualized)	3.373	2.865	3.230	−0.384	−1.991***	−0.502
Scenario 4: Optimal Hedge with Return Seeking (for risk tolerance $\gamma = 0.2$)						
Mean (% annualized)	−4.572	5.732	0.518	−1.256***	−1.173***	−1.171***
St.D. (% annualized)	5.328	13.476	8.834	0.607***	1.468***	1.023***
CEQ Ratio	−5.920	0.214	−2.583	−1.083***	−0.100	−0.666***
Transaction Costs (bp annualized)	3.400	2.877	3.260	−0.411	−2.003***	−0.532
No. Funds	660	1,038	796			
Observations	80,966	183,505	136,291			

Internet Appendix

Not for Journal Publication

A Optimal Hedge Portfolios

A.1 Conditional Quadratic Optimization

Let Σ be a symmetric $n \times n$ covariance matrix of real and currency returns, vectors w, $\mu \in \mathbb{R}^n$ denote portfolio weights and expected returns, and γ a positive scalar for the risk tolerance. For any positive definite matrix Σ, the quadratic function

$$U(w) = w'\mu - \tfrac{1}{2\gamma} w'\Sigma w \tag{A.1}$$

has a unique global maximum w^* characterized by $\frac{1}{\gamma}\Sigma w^* = \mu$.

We can partition the matrix Σ and the vectors w, μ as follows

$$\Sigma = \begin{pmatrix} \Sigma_{xx} & \Sigma_{xf} \\ \Sigma_{fx} & \Sigma_{ff} \end{pmatrix}, \qquad w = \begin{pmatrix} w_x \\ w_f \end{pmatrix}, \qquad \mu = \begin{pmatrix} \mu_x \\ \mu_f \end{pmatrix}, \tag{A.2}$$

where w_x represents the portfolio weights in $N+1$ real assets (N foreign and 1 home asset) and w_f the corresponding portfolio weights in N FX forward contracts.

Next, we make the assumption that the real asset portfolio w_x is already determined, i.e., $w_x = \overline{w}_x \geq 0$. The quadratic function in Eq. (A.1) can then be reformulated as

$$U^C(w_f) = w_f'\mu_f^C - \tfrac{1}{2\gamma} w_f'\Sigma_{ff} w_f + k, \tag{A.3}$$

with a constant term $k = w_x'\mu_x - \frac{1}{2\gamma}\overline{w}_x \Sigma_{xx} \overline{w}_x$ irrelevant to the maximization and a modified (constant) vector $\mu_f^C = \mu_f - \frac{1}{2\gamma}[\Sigma_{fx}\overline{w}_x + (\overline{w}_x'\Sigma_{xf})'] = \mu_f - \frac{1}{\gamma}\Sigma_{fx}\overline{w}_x$. The conditional function $U^c(w_f)$ is defined for the $w_f \in \mathbb{R}^N$ with $N = (n-1)/2$. If Σ_{ff} is positive definite, a unique global maximum w_f^* is characterized by the condition

$$\tfrac{1}{\gamma}\Sigma_{ff} w_f^* = \mu_f^C - \tfrac{1}{\gamma}\Sigma_{fx}\overline{w}_x \qquad \Leftrightarrow \qquad w_f^* = \gamma \Sigma_{ff}^{-1}\mu_f - \Sigma_{ff}^{-1}\Sigma_{fx}\overline{w}_x. \tag{A.4}$$

We note that the approximations $\mu_f \simeq 0$ and $\Sigma_{ff} \simeq \Sigma_{fx}$ imply a strictly negative solution $w_f^* = -\overline{w}_x < 0$ with all components negative if the real portfolio weights are strictly positive, $\overline{w}_x > 0$.

A.2 Optimal Hedging with Bid and Ask Spreads

Generally, any asymmetric bid-ask spread implies a non-linearity in the transaction costs at $w_f = 0$. As a consequence it is more difficult to characterize the optimal hedge portfolio. Let c denote one of the N currency components of the vectors w_f and μ_f. We define transaction costs (linear in portfolio weights) in currency c as a bid and ask spread

$$\tau_c(w_f) = \begin{cases} \tau_c^A & \text{if} \quad w_f < 0 \\ 0 & \text{if} \quad w_f = 0 \\ \tau_c^B & \text{if} \quad w_f > 0 \end{cases}, \tag{A.5}$$

where $\tau_c^A, \tau_c^B \in \mathbb{R}$ are arbitrary (non-zero) values and the expected return changes to

$$\mu_f^m = \mu_f + \tau(w_f). \tag{A.6}$$

As transaction costs can take on three different values in each of the N currencies, we have 3^N different combinations that correspond to 3^N different partitions of the domain $\mathbb{R}^N$ according to the values for w_f. For example, given only three currencies ($N = 3$), a transaction cost vector $\tau' = (0, \tau_c^A, \tau_c^B)$ corresponds to a domain for the hedge $w_f \in \mathbb{R}^3$ with $w_{f,1} = 0$, $w_{f,2} < 0$, and $w_{f,3} > 0$.

For $N = 6$, we obtain $M = 3^6 = 729$ cases or subdomains for w_f. We number these (non-intersecting) convex subdomains for w_f by $m = 1, 2, 3, ..., M$ and denote them by $\mathbb{R}_m$. Formally, $\mathbb{R}_1 \cup \mathbb{R}_2 \cup ... \cup \mathbb{R}_M = \mathbb{R}^N$. A special subdomain containing a single point corresponds to the null vector $\tau' = (0, 0, ..., 0)$ of transaction costs for which we need $w_{f,c} = 0$ for all c. This means no hedging occurs in any currency. This special case is also a potential solution and defines a lower bound for the global optimum given by

$$U^C(w_f = 0) = k = w_x' \mu_x - \frac{1}{2\gamma} \overline{w}_x \Sigma_{xx} \overline{w}_x. \tag{A.7}$$

The solution algorithm for the global maximum proceeds in three steps:

1. We find candidate solutions $w_f^m \in \mathbb{R}^N$ for all 3^N combinations of transaction costs τ^m. If a transaction cost vector m has $j < N$ currencies for which the transaction costs are assumed

to be zero ($\tau_c = 0$), we impose the constraint $w_{f,c} = 0$, which is the only value compatible with $\tau_c = 0$. Thus, we reduce the number of dimensions of the optimization problem to a vector $w_f \in \mathbb{R}^{N-j}$ in the remaining $N - j$ currencies c with $\tau_c \neq 0$. The matrix Σ_{ff} becomes $(N - j) \times (N - j)$ and is still positive definite, which would guarantee a unique maximum if μ^m and τ^m were constant for all $w_f \in \mathbb{R}^N$. The candidate solution follows as

$$w_{f,c}^m = \begin{cases} 0 & \text{for} \quad c \quad \text{with} \quad \tau_c = 0 \\ \gamma \left[\Sigma_{ff}^{-1}\right]_{c\bullet} \mu_f^m - \left[\Sigma_{ff}^{-1}\Sigma_{fx}\right]_{c\bullet} \overline{w}_x & \text{for} \quad c \quad \text{with} \quad \tau_c \neq 0. \end{cases}, \tag{A.8}$$

where the subscript $_{c\bullet}$ denotes row c of a matrix.

2. We discard all candidate solutions w_f^m that are incompatible with the assumed transaction costs, that is $w_f^m \notin \mathbb{R}_m$. We define the set of transaction costs consistent (local) maxima as

$$S = \{w_f^m \mid w_f^m \in \mathbb{R}_m\}. \tag{A.9}$$

3. We select the global optimum as the vector that maximizes $U^C(w_f^m)$ with $w_f^m \in S$:

$$w_f^{m*} = \arg\max_{w_f^m \in S} U^C(w_f^m). \tag{A.10}$$

It is possible that multiple local optima produce the same value $U^C(w_f^{m_1}) = U^C(w_f^{m_2})$ for $w_f^{m_1} \neq w_f^{m_2}$. Uniqueness of the global maximum cannot be guaranteed. Moreover, every global optimum fulfills the necessary condition that

$$w_f^{m*} = \gamma \left[\Sigma_{ff}^{-1}\right]_{c\bullet} (\mu_f + \tau) - \left[\Sigma_{ff}^{-1}\Sigma_{fx}\right]_{c\bullet} \overline{w}_x \quad \text{if} \;\; w_{f,c} \neq 0, \tag{A.11}$$

where the vector elements $\tau_c = \tau_c(w_f)$ depend on the sign of $w_{f,c}$ as assumed in Eq. (A.5).

B Fund Holding Data

B.1 Selection of the Fund Universe

Our source for the bond and equity positions of European investment funds is the Refinitiv Lipper dataset. As funds can have multiple fund shares that can differ in characteristics such as base currency or expense ratios, we focus only on the fund share class with the largest asset value.[22] We select funds that (i) have EUR as their base currency, (ii) have more than 90% of their liabilities denominated in EUR, (iii) have no mandate to hedge (recognizable by the term "hedged" in the fund name), (iv) hold on average more than 90% of their portfolio in equity and bond type securities, (v) are based in the Euro-area, and (vi) report at least 10% of the maximum number of monthly observations.

These six filters generate a universe of $7,029$ European funds, of which 10% hold no assets denominated in foreign currencies. In this universe of European international funds, we find that $2,806$ (or 40%) engage in a least one FX forward trade and hold at least one asset denominated in a foreign (non-Euro) currency in the period 2019-23 in our six currencies under consideration. For our final dataset we also trim our dataset based on the upper and lower 0.1% of the distribution of forward net long EUR positions (i.e., $w_{f,i,c,t}$).

The Refinitiv Lipper dataset reports asset holdings of funds on a monthly or quarterly basis. For funds that report quarterly, which represent 25% of all funds, we forward fill the asset holdings with the previous values.

We group all reported real investments by funds into either equity or fixed income (debt) instruments. Table B.1 states which assets are assigned to the equity and debt security bucket, respectively. Our analysis assumes that different equity and debt instruments in the same currency feature identical covariances estimated by the representative return process, which are the equity index for equity-like assets and the government bond price index for all debt-like assets in each currency.

[22]For August 2023, we dispose of a detailed breakdown of all share classes of European funds. The largest fund share class by value accounts for an average of 85% of the total net asset value of a fund and the median is 100%.

Table B.1: Asset Categories

The table shows how we categorized different types of assets as Bond, Equity, Derivatives, and Other.

Category	Asset Types
Bond	CORP, Commercial Paper, Mortgages, Corporate Medium Term Notes, Sovereign Bond, Certificate of Deposit, Agencies, Credit Card Receivables, CMO Whole Loan, Commercial Mortgage-Backed Security, Fixed Income, MUNI, CMOs, Home Equity Loan, Certificates, Global Bonds, Bank Debt, Auto/Installment Loans, ABSY, Mortgage Pools, Student Loan, Convertible Bond, Treasury Bills, Agency Notes/Bonds, Convertible, Auto Lease Loans, Asset Backed Tranches, Loan Participation Note, Equipment Backed Loan, Linked Notes and Deposits, Corporate Intermediate and Long Term Debt, Manufactured Housing Loan, Collateralized Debt Obligation, Aircraft Lease, Auto Floorplan/Wholesale Loans, Small Business Administration, Treasury STRIPS, Collateralized Loan Obligation, Eurobonds, CMO Tranches, Mortgage Pass-Thru Generics, Collateralized Bond Obligation, Motorcycle Lease, Bankers Acceptance, Marine Loans, Agency Medium Term Notes, Recreational Vehicle Loan, CMO Agricultural MBS, Muni Other
Equity	Common Shares, Depository Receipts, Preferred Stock, Equity, Cumulative Preferred
Derivative	Equity Option, Cash Options, Futures, Commodity Future Option, Interest Rate Swap, Credit Default Swap, OTC Derivatives, Listed Derivatives, Commodity Future, Futures - Financial, Swap Contract for Differences, Forward Other, FX Forward, Swap Other
Other	Warrant, Cash Equivalent, Structured Other, Rights, Supranational, Unit, Unknown, REITs, Commodity, Closed End Funds, Convertible Preference, Participation, Index, ETF, Collective Investments, Swaption, Cash, Insurance Funds, Net Interest Margin Securities, Fund, Hedge Funds

B.2 FX Derivative Holdings at Month End

The European Central Bank collects derivative positions from residents in the Euro Area under the European Markets Infrastructure Regulation (EMIR). We obtain data access under the 2022 Alberto Giovannini Programme for Data Science by the ESRB.

For the period 2019-23, we retrieve daily net foreign currency short positions in FX forward and swaps for $13,381$ funds. The matching of FX derivative trades to individual funds is undertaken based on the Legal Entity Identifier (LEI), which features both in the Refinitiv Lipper fund and transaction data. All daily derivative transactions are aggregated to daily net new positions and based on their maturity date to the aggregate outstanding net FX derivative position by fund, currency, and day.

From the daily net foreign currency short positions we remove net short foreign currency positions that fall outside the 1st and 99th percentiles for each currency on each day. We also remove days that fall on a weekend or a bank holiday. As the Refinitiv fund holdings in real assets are reported for each end of the month, we synchronize the derivative positions and retain only the last observation of each month.

C Transaction Costs

This section describes how transaction costs are calculated using EMIR price data. We report the filtering process for the transaction in Section C.1, the calculation of the effective spread in Section C.2, and determination of fund-specific transaction costs in Section C.5. Lastly, we relate average transaction costs to covered interest rate parity (CIP) deviations in Section C.6.

C.1 Filtering

For the calculation of transaction costs, we filter the reported derivative contracts as follows. First, we consider all new transactions in a month with a notional value above 1,000 EUR. Second, we retain only one observation if a trade is reported twice by the buyer and the seller in the case that both entities are reporting. In case of double reporting, we check that the forward rate and the notional value match up to a rounding error. Third, we drop transactions with extremely large notional values above the 99% quantile. Fourth, we filter price outliers by requiring that the forward rate occurs within a 3% difference of the daily forward (benchmark) rate available from Refinitiv. Fifth, we we retain in each currency only transactions with a spread relative to the Refinitiv benchmark between the 1% and 99% quantile. For some of the analysis, we focus on FX derivative contracts with a monthly maturity. Accordingly, only transactions with a maturity of 20 to 25 business days are retained.

C.2 Effective Spreads Using Interdealer Transactions

The transaction costs are computed using EMIR price data of fund-to-dealer transactions and of dealer-to-dealer transactions.[23] Specifically, we compute spreads for fund i as the difference between the transaction price F_T for buying (selling) the Euro against the foreign currency and the median price in the same minute for the same maturity for a dealer-to-dealer transaction, Mid_T.[24] We define a dummy $d_T = 1$ for an ask side (buy) transaction T and $d_T = -1$ for a bid side (sell) transaction for a forward currency contract that goes long EUR against a foreign currency.

[23] For each trade, we identify the European System of Accounts (ESA) sector of both the reporting counterparty and the other counterparty.

[24] Dealer banks are in the best position to undertake arbitrage and therefore their between transaction price can be regarded as a good competitive benchmark. In contrast, relying on quotes has the drawback of using prices that are often not executed.

Formally,

$$Spread_T = d(T)\frac{F_T - Mid_T}{Mid_T}, \tag{C.1}$$

All exchange rates are expressed with the EUR as the base currency. This construction of the spread is used in the main paper.

C.3 Effective Spreads Using Refinitive Quotes

As interdealer transactions in 1-month forwards can be sparse in rates other than the EURUSD rate, we also propose an alternative method of spread calculation based on (indicative) Refinitive quote data available at the one minute interval. Yet, Refinitiv tick data provides an indicative interbank quote for 1-month forwards at the one-minute interval. Moreover, the EMIR data does not distinguish between outright forwards and forward swaps. Generally, forward swaps have narrower bid-ask spreads as they are mechanically collateralized due to the currency exchange at the near leg of the contract. We adjust the Refinitiv quote price Mid_T^q by adding the median daily difference between the interdealer mid price and the Refinitiv quote reported at the same minute. Formally,

$$Spread_T^{adj} = d(T)\frac{F_T - Mid_T^{adj}}{Mid_T^{adj}} \quad \text{with} \quad Mid_T^{adj} = Mid_T^q + \Delta_T, \tag{C.2}$$

where Mid_T^{adj} denotes the adjusted interdealer price, and $\Delta_T = \overline{Mid_{T\pm x} - Mid_{T\pm x}^q}$ the adjustment term for transaction T calculated as the average daily deviation of all interbank transactions (in the same currency) from the synchronous quoted interbank midprice. Eqs. (C.2) and (C.1) yield the same spread if an average interbank transaction price and the average corresponding quoted midprice are the same so that $\Delta_T = 0$. However, funds trade on average (over all days) at a 2.5% lower ask price and a 0.6% higher bid price relative to Refinitiv quotes. The advantage of the spread definition in Eq. (C.2) over Eq. (C.1) is that it allows us to construct spreads even if a benchmark interbank trade (MID_T) is not readily available.

C.4 Summary Statistics on Effective Spreads

Table C.1 reports summary statistics for both spread definitions, $Spread_T$ and $Spread_T^{adj}$, and the subsample of spread $Spread_T^{Fund}$ involving fund-dealer transaction by one of the 2,806 funds used in our main analysis.

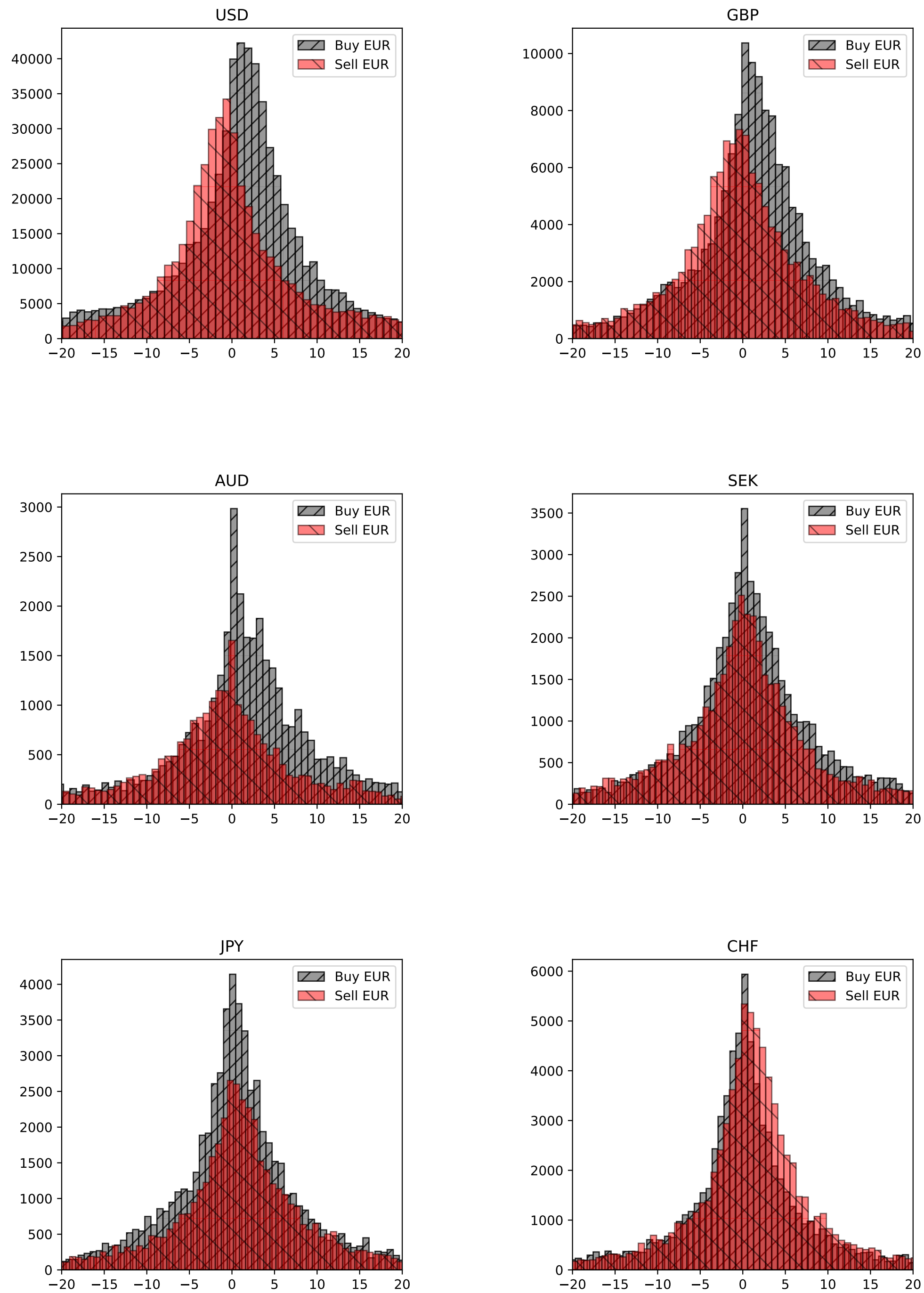
Figure C.1 plots a histogram of all spreads using the spread definition in Eq. (C.2) for all six currency pairs, in blue for trades that involve buying the EUR (Euro long positions) and in brown for trades that involve selling the EUR (Euro short positions) against the foreign currency. Three observations stand out. First, the EUR/USD and EUR/GBP rates feature more Euro long positions than short positions, illustrated by the area of the blue and brown histograms, respectively. Second, spreads for individual trades are very dispersed in all currency pairs and can be positive or negative relative to the interbank benchmark. Third, average transaction prices in the FX derivative market relative to the interbank price depend on the direction of the trade for the EUR against foreign currencies. To illustrate this, we can observe that buying the EUR in typical high-yield currencies such as the USD, GBP, AUD is more expensive relative to the interbank price than selling the EUR. For low-yield currencies such as the CHF or JPY the spreads for selling the EUR are more positive than buying the EUR. For the SEK we do not see a significant difference between the spreads of buying and selling. The average spread is 0.47, −0.33, 1.30 basis points for buying the EUR against USD, GBP, AUD compared to −3.35, −3.23, −3.25 basis points when selling the EUR against USD, GBP, AUD, respectively. In contrast, the average spread is −2.08, 0.45 basis points for buying the EUR against CHF and JPY compared to −0.81, 0.45 basis points when selling the EUR against CHF and JPY, respectively.

Table C.1: Summary Statistics for Transaction Costs

We report summary statistics for fund-dealer FX forward and swap transaction cost spreads. $Spread_T$ is defined as in Eq. (C.1) and computes the spread for all EMIR funds whenever a close interbank transactions is available, $Spread_T^{adj}$ is defined as in Eq. (C.2) and computes the spread relative to Refinitiv tick-data for all fund-dealer trades, and $Spread_T^{Funds}$ computes the spread as in Eq. (C.1) for a subsample of transactions involving one of the 2,806 funds used in the main analysis.

		Obs	Mean	St.D.	Q10	Q25	Q50	Q75	Q90
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Spread_T$	$\times 10,000$	$973,588$	0.41	8.1	-6.08	-0.81	0.00	2.06	7.03
$Spread_T^{adj}$	$\times 10,000$	$1,514,494$	0.58	5.38	-6.54	-2.71	0.51	3.89	7.71
$Spread_T^{Funds}$	$\times 10,000$	$74,344$	0.69	7.65	-4.89	-0.26	0.12	2.36	6.22

Figure C.1: Histograms of Ask and Bid Spreads per Currency



Notes: We plot FX transaction costs in 2,360,400 FX forward and swap contracts in which funds buy the EUR (grey) or sell the EUR (red) at maturity involving six currencies $c \in$ {USD, GBP, AUD, JPY, SEK, CHF} relative to the Euro (c/EUR). We define the spread in each trade relative to the price of an interbank quote reported by Refinitiv and defined in Eq. (C.2).

C.5 Determinants of Transaction Costs

Next we estimate Eq. (10), where we regress the spread on forward contract T on several trade characteristics. Columns (1)-(5) reports the regressions for transactions involving sample funds from the main analysis, while Column (6) reports the result for all fund-dealer transactions.

Column (1) reports the average transaction costs for Euro buy (i.e., foreign sell) transactions as fixed effects θ_c where $c \in \{$USD, GBP, AUD, SEK, JPY, CHF$\}$ denotes the currency that is shortened. All Euro long trades feature positive average spreads. The fixed effects $\theta_{Buy\ c}$ capture the average differential costs of Euro short transactions with respect to currency c. Euro sell trades (i.e., Euro short positions) have negative average transaction costs in the three high yield currencies USD, GBP, and AUD. Columns (3) and (4) suggest that funds with a high expense ratio face considerably higher transactions. Generally, hedge funds with FX research feature higher expense ratios and dealer banks may discriminate against "sophisticated clients" out of adverse selection concerns.

We use the regression specifications in Columns (4) and (5) to predict the fund-specific hedging costs by fund, currency, trade direction, and month. We can only compute the spread for funds in our sample for which we find a suitable benchmark interbank transaction in the same minute, for the same maturity (number of days) and the same currency pair. Out of our sample of $2,806$ funds we can compute a spread for $1,120$ funds. For these funds we predict the transaction costs using fund fixed effects as in Column (5); for the rest of the sample we rely on their fund characteristics reported in Column (4) rather than fund fixed effects for the prediction of the fund-specific transaction costs by trade direction and currency. In Column (6) we use a much larger sample including all trades in which the reporting entity is considered as a fund according to the European System of Accounts (ESA) classification.

Table C.2: Transaction Cost Regression

We report determinants of transaction costs in 74,344 FX forward and swap contracts involving six currencies $c \in$ {USD, GBP, AUD, JPY, SEK, CHF} relative to the Euro as the base currency (EUR/c). We define the spread in each trade relative to the corresponding interbank price and regress the spread on currency fixed effects θ_c, currency fixed effects $\theta_{Buy\ c}$ specific to buy trades in currency c, month fixed effects θ_t, fund fixed effects θ_i, dummies for trades involving equity and mixed funds, respectively, and other fund characteristics. Column (6) reports the same specification as Column (5) for a larger sample of all fund-dealer transactions, where the spread is defined as $Spread_T^{adj}$.

Dep. Variable:	$Spread_T$					
	(1)	(2)	(3)	(4)	(5)	(6)
θ_{USD}	1.641***	1.613***	1.132**	1.116**	1.624***	1.414***
	(0.153)	(0.141)	(0.551)	(0.552)	(0.144)	(0.083)
θ_{GBP}	1.658***	1.649***	1.190**	1.179**	1.664***	1.108***
	(0.168)	(0.170)	(0.560)	(0.558)	(0.265)	(0.141)
θ_{AUD}	1.122***	1.182***	0.695	0.671	1.317***	1.232***
	(0.164)	(0.175)	(0.553)	(0.548)	(0.223)	(0.176)
θ_{JPY}	1.364***	1.195***	0.600	0.593	1.039***	0.237
	(0.312)	(0.172)	(0.547)	(0.544)	(0.199)	(0.258)
θ_{SEK}	0.561***	0.637***	0.210	0.255	0.874***	0.658***
	(0.111)	(0.147)	(0.550)	(0.545)	(0.178)	(0.140)
θ_{CHF}	0.775***	0.731***	0.212	0.257	0.738***	0.357***
	(0.119)	(0.146)	(0.553)	(0.550)	(0.234)	(0.098)
$\theta_{Buy\ USD}$	−2.433***	−2.339***	−2.356***	−2.344***	−2.400***	−2.443***
	(0.286)	(0.294)	(0.293)	(0.292)	(0.323)	(0.192)
$\theta_{Buy\ GBP}$	−1.230***	−1.272***	−1.236***	−1.216***	−1.151*	−1.115***
	(0.325)	(0.335)	(0.331)	(0.330)	(0.654)	(0.307)
$\theta_{Buy\ AUD}$	−0.689**	−0.841***	−0.857***	−0.837***	−0.778*	−1.593***
	(0.322)	(0.316)	(0.309)	(0.310)	(0.399)	(0.300)
$\theta_{Buy\ JPY}$	0.353	0.406	0.379	0.365	0.367	0.562
	(0.393)	(0.286)	(0.284)	(0.285)	(0.261)	(0.366)
$\theta_{Buy\ SEK}$	0.087	0.102	0.196	0.166	0.080	−0.488**
	(0.296)	(0.325)	(0.321)	(0.324)	(0.409)	(0.196)
$\theta_{Buy\ CHF}$	0.180	0.241	0.331	0.283	0.276	0.166
	(0.197)	(0.219)	(0.217)	(0.219)	(0.301)	(0.126)
Log Asset Under Management			−0.009	−0.009		
			(0.027)	(0.027)		
Turnover Ratio			0.002	−0.096		
			(0.236)	(0.248)		
Expense Ratio			0.496***	0.565***		
			(0.070)	(0.076)		
$D_{Equity\ Fund}$				−0.264**		
				(0.134)		
$D_{Mixed\ Fund}$				0.034		
				(0.157)		
$D_{TurnoverR\ Missing}$			−1.472	−1.303		
			(1.140)	(1.144)		
$D_{ExpenseR\ Missing}$			0.372	0.456		
			(0.284)	(0.281)		
Time FEs	No	Yes	Yes	Yes	Yes	Yes
Fund FEs	No	No	No	No	Yes	Yes
Adj. R^2	0.019	0.019	0.023	0.023	0.019	0.016
Obs.	74,344	74,344	74,344	74,344	74,344	973,588

C.6 Transaction Costs and Covered Interest Rate Parity Deviations

This section shows how the asymmetry of buy and sell transaction costs relative to the interdealer quotes in each currency is systematically related to contemporaneous deviations from covered interest rate parity (CIP).

Covered interest rate parity postulates that one should not earn risk-free profit by borrowing in one currency and lending in another, while hedging the FX risk. The recent literature shows that this parity condition does not hold any longer and that the cross-currency basis widened up after the Great Financial Crisis in 2008. The literature usually takes the USD as the reference currency against which CIP deviations are computed. But CIP deviations also exist in currency pairs that do not involve the USD. As we focus on EUR derivatives, we define CIP deviations in terms of forward and spot rates expressed in Euros per unit of foreign currency. Formally, we define the cross-currency basis as

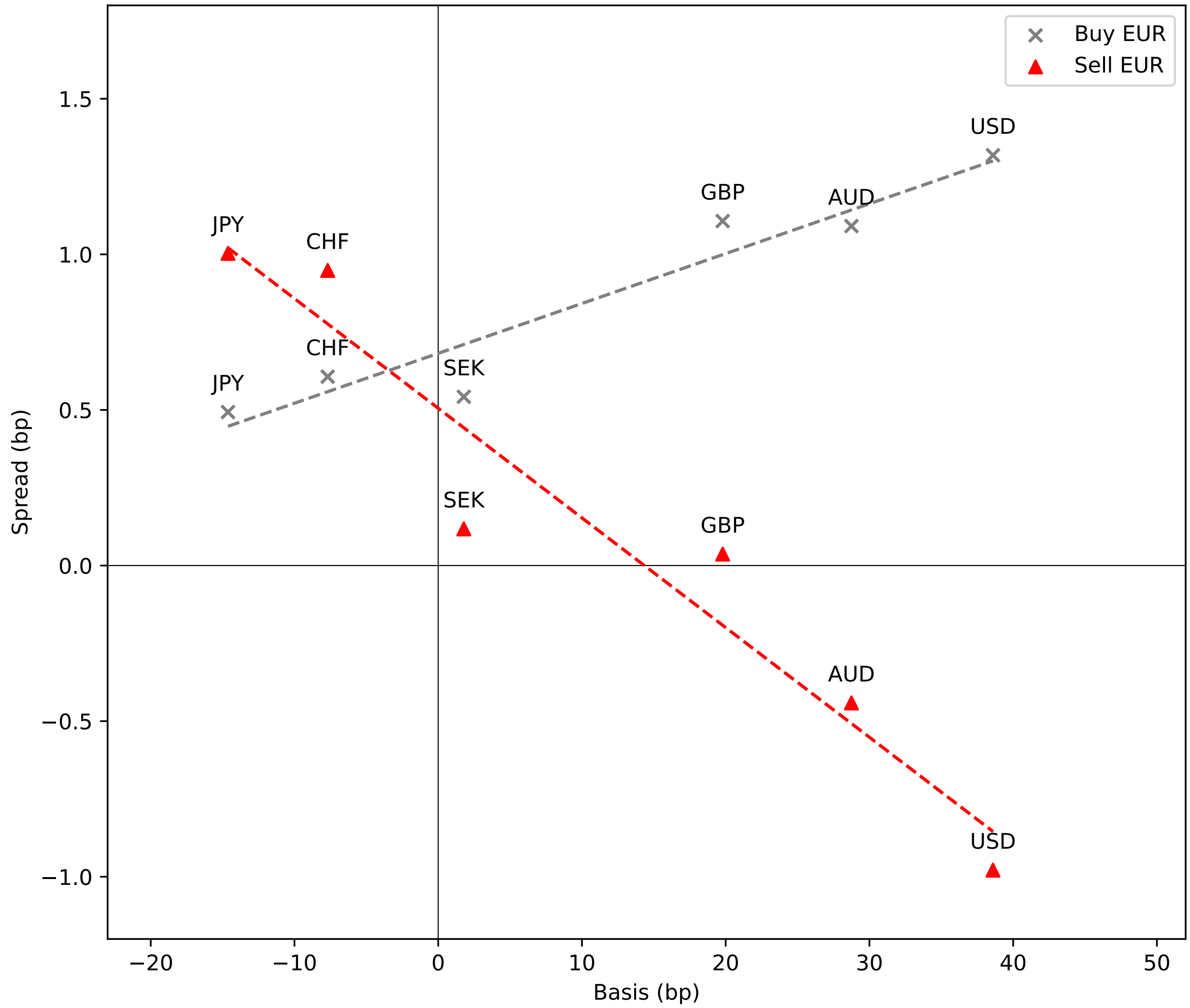
$$Basis_{c,t} = i_{c,t}^{EUR} - (f_{c,t} - s_{c,t}) - i_{c,t}^{*} \; , \tag{C.3}$$

where $i_{c,t}^{EUR}$ is the log EUR interest rate in the cash market, $i_{c,t}^{*}$ the log foreign currency interest rate, $f_{c,t}$ the log forward rate and $s_{c,t}$ the log spot rate defined in Euros per foreign currency unit. As the default interest rates we take the overnight index swap rate, which is the rate for overnight lending between banks. The CIP deviations change only marginally if we use, for example, the LIBOR rates, the commercial paper rate, or the short-term government bond rate.

Figure C.2 plots the average effective spread relative to interdealer prices for EUR buy and sell trades as a function of the (negative) cross-currency basis for all six currency pairs. A negative cross-currency basis for a foreign currency (represented by values to the right on the x-axis) implies that the direct foreign interest rate is higher than the synthetic foreign interest rate, which is the case for the USD against the EUR. Banks find it expensive to supply Euro long positions in this case as they synthetically hedge any net supply, which results in a higher interbank price the EUR buy trades and a lower EUR buy spread. The reverse is true for EUR sell trades, which are cheap to supply under a negative cross-currency base. For funds, only the forward rate itself is decision relevant if hedging decisions occur based on existing real investments. [25]

[25] We note that the same pattern emerges if we compute average spreads $Spread_T^{adj}$ based on the Refinitiv quote data.

Figure C.2: Average Ask and Bid Spreads and CIP Deviations by Currency



Notes: We plot the average covered interest rate parity (CIP) deviations in basis points on the horizontal axis and the average bid (red) and ask (grey) spreads defined in Eq. (C.1) on the vertical axis for six currencies against the EUR. Ask (bid) spreads are defined as spreads from a forward transaction that involves buying (selling) the EUR at maturity against a foreign currency. The sample consists of $731,395$ (USD), $98,307$ (GBP), $16,875$ (AUD), $33,070$ (JPY), $36,559$ (SEK), $57,382$ (CHF) FX forward and swap transactions.

To test the relationship between transactions costs and the cross-currency basis at the contract level we regress the spread of transaction T by fund i and with dealer bank d on a buy dummy variable that is $\theta_T^{Buy\ EUR} = 1$ for an ask (buy) side transaction T that buys EUR, and zero for a bid side (sell) transaction that sells EUR at maturity, a sell dummy that is $\theta_T^{Sell\ EUR} = 1$ for any bid (sell) side transaction T that sells EUR, and zero for an ask side (buy) transaction that buys EUR at maturity, and on the interaction term between the two dummy variables and the contemporaneous cross-currency basis, $Basis_{c,t}$. We also include contract specific $Controls_T$ and fund-dealer fixed effects, $\alpha_{i,d}$, to capture arbitrary spread variation across fund-dealer trading relationship.[26] Formally,

$$Spread_T = \beta_1 \theta_T^{Buy\ EUR} + \beta_2 \theta_T^{Sell\ EUR} + \beta_3(\theta_T^{Buy\ EUR} \times Basis_{c,t}) + \beta_4(\theta_T^{Sell\ EUR} \times Basis_{c,t}) + Controls_T + \alpha_{i,d} + \alpha_t + \epsilon_T. \tag{C.4}$$

In Table C.3, Panel A, we reports the results using the interbank EMIR transactions for computing spreads as in Eq. (C.1) and in Panel B the results using Refinitiv quote data for the spread computation as defined in Eq. (C.2). On average, buying the EUR is one basis point (= 1.332 − 0.329) more expensive than selling the EUR against the foreign currency as shown in Column (1) of Panel A, which is robust to including fund-dealer fixed effects in Column (2). Column (3) documents that CIP deviations measured by $Basis_{c,t}$ correlates positively with the spread for buy side transactions. For example, an average basis of 40 basis points (as for the USD) yields an average transaction cost spread of 1.538 ($= 1.098 + 0.011 \times 40$) basis points when buying the EUR. Controlling for cross-dealer and cross-fund fixed effects as in Column (4) does not significantly change the results. Panel B shows that the results are even statistically stronger when constructing the spreads relative to Refinitiv quote data. This shows that OTC transaction costs for funds in FX forward contracts are systematically related to CIP deviations.

[26] We include fund-dealer dummies only if there are at least 20 trade observations available for a fund-dealer pair.

Table C.3: Transaction Costs and CIP Deviations

We reports results of the panel regressions in Eq. (C.4), which includes a dummy $\theta_T^{Buy\ EUR} = 1$ for any ask (buy) side transaction and a dummy $\theta_T^{Sell\ EUR} = 1$ for an bid (sell) side transaction and their respective interaction terms with the contemporaneous cross-currency basis, $Basis_{c,t}$. Panel A reports the results for spreads benchmarked against synchronous interbank trades as defined in Eq. (C.1) and Panel B reports the results using Refinitiv quote data for the spread computation as defined in Eq. (C.2). The control variable $Customization_T$ measures deviations from standard maturity dates as in Hau et al. (2021). Standard errors are clustered at the fund-bank and time (day) level and shown in parentheses. Time fixed effects are day fixed effects. We denote by *, ** and *** the significance levels at the 10%, 5% and 1%, respectively.

Panel A: Spreads Benchmarked Against Synchronous Interbank Trades

Dep. Variable:	$Spread_T$			
	(1)	(2)	(3)	(4)
$\theta_T^{Buy\ EUR}$	1.252***	0.943***	1.042***	0.763***
	(0.148)	(0.169)	(0.163)	(0.175)
$\theta_T^{Sell\ EUR}$	0.250	−0.122	0.647***	0.266
	(0.169)	(0.192)	(0.182)	(0.207)
$\theta_T^{Buy\ EUR} \times Basis_{c,t}$			0.013***	0.013***
			(0.003)	(0.003)
$\theta_T^{Sell\ EUR} \times Basis_{c,t}$			−0.009**	−0.008*
			(0.004)	(0.004)
$LogNotional_T$	−0.028***	−0.002	−0.041***	−0.017
	(0.011)	(0.013)	(0.011)	(0.014)
$Customization_T$	0.071***	0.058**	0.015	0.023
	(0.025)	(0.026)	(0.017)	(0.016)
Time FEs	Yes	Yes	No	No
Fund × Dealer FEs	No	Yes	No	Yes
Adj. R^2	0.004	0.004	0.005	0.005
Obs.	510,653	510,653	510,653	510,653

Panel B: Spreads Benchmarked Against Refinitiv Quoted Midprices

Dep. Variable:	$Spread_T^{adj}$			
	(1)	(2)	(3)	(4)
θ_T^{BuyEUR}	1.159***	0.937***	0.907***	0.704***
	(0.087)	(0.100)	(0.094)	(0.102)
$\theta_T^{SellEUR}$	−0.138	−0.339***	0.275**	0.045
	(0.114)	(0.130)	(0.119)	(0.134)
$\theta_T^{BuyEUR} \times Basis_{c,t}$			0.014***	0.014***
			(0.002)	(0.002)
$\theta_T^{SellEUR} \times Basis_{c,t}$			−0.013***	−0.012***
			(0.003)	(0.003)
$LogNotional_T$	0.002	0.019**	−0.005	0.010
	(0.006)	(0.008)	(0.007)	(0.008)
$Customization_T$	0.002	−0.010	−0.002	0.003
	(0.014)	(0.013)	(0.010)	(0.010)
Time FEs	Yes	Yes	No	No
Fund × Dealer FEs	No	Yes	No	Yes
Adj. R^2	0.014	0.012	0.018	0.016
Obs.	1,282,806	1,282,806	1,282,806	1,282,806

D Covariance Estimation

Here we describe the estimation procedure for the various covariances used in the analysis. We denote with t the calendar month for which a covariance matrix is estimated. Let $d(t)$ be the first day of the month and $d(t)-1$ the last trading day of the previous month, and $n(t)$ the number of trading days in month t. The 6×1 vector Δs_d denotes the log currency returns in the six Euro exchange rates between end of day $d-1$ and end of day d and the 7×1 vector r_d represents the fund returns for assets in the seven currencies all expressed in Euros.

Lagged Realized Covariance (LRC). These is an (out-of sample) covariance estimate for month t based on realized covariances for the previous 6 months (or 3-months) period prior to month t and defined as

$$\begin{aligned}
\Sigma^{LRC}_{ff,t} &= \sum_{j=0}^{N(t)-1} w_j \left(\Delta s_{d(t)-j} - \Delta\overline{s}\right)\left(\Delta s_{d(t)-j} - \Delta\overline{s}\right)' \\
\Sigma^{LRC}_{fx,t} &= \sum_{j=0}^{N(t)-1} w_j \left(\Delta s_{d(t)-j} - \Delta\overline{s}\right)\left(r_{d(t)-j} - \overline{r}\right)',
\end{aligned}$$

with means defined as

$$\Delta\overline{s} = \sum_{j=0}^{N(t)-1} w_j \Delta s_{d(t)-j} \quad \text{and} \quad \overline{r} = \sum_{j=0}^{N(t)-1} w_j r_{d(t)-j},$$

and where $N(t) = \sum_{k=1}^{6\ (3)} n(t-k)$ denotes the number of trading days in the last 6 month (3 months). The triangular weights of the kernel put more weight on the most recent observations, that is $w_j = \frac{2}{N(t)}\left(1 - \frac{j}{N(t)}\right)$.

MGARCH Covariance Estimation. Here we estimate a dynamic conditional correlation (DCC) multivariate generalized autoregressive conditionally heteroskedastic model to predict the covariance for month (t). Daily currency and bond (or equity) returns are alternatively stacked into a $2N+1$ vector to estimate a (time-varying) matrix Σ in Eq. (1) for equity and bond returns separately. The unconstrained version of the model (MGARCH1) involves five ARCH innovations (with lags L1 to L5) and one GARCH term (L6) that govern the variance dynamics of the exchange rates and the asset returns. We use the STATA mgarch ddc procedure to implement the rolling estimation of the covariance in month t. Following the notation in STATA, we define the 13×1 vector $y_t = [\Delta s_t, r_t]$' of exchange rate and equity (or bond) returns, which is characterized by the stochastic process

$$\begin{aligned}
y_t &= \overline{y} + \epsilon_t = \overline{y} + H_t^{1/2}\nu_t \\
H_t &= D_t^{1/2} R_t D_t^{1/2} \\
R_t &= \text{diag}(Q_t)^{-1/2} Q_t \text{diag}(Q_t)^{-1/2} \\
Q_t &= (1-\lambda_1-\lambda_2)R + \lambda_1 \widetilde{\epsilon}_{t-1}\widetilde{\epsilon}'_{t-1} + \lambda_2 Q_{t-6},
\end{aligned}$$

where $H_t^{1/2}$ is the Cholesky factor of the time-varying conditional covariance matrix H_t, ν_t is a 13×1 vector of normal, independent, and identically distributed innovations, D_t is a diagonal matrix of conditional variances, R_t is a matrix of conditional quasicorrelations, $\widetilde{\epsilon}_{t-1}$ is a 13×1 vector of standardized residuals, D_t is a diagonal matrix of conditional variances, and λ_1 and λ_2 are parameters that govern the dynamics of conditional quasicorrelations. Each conditional variance element $\sigma^2_{i,t}$ of the diagonal matrix D_t follows a univariate GARCH(5,1) process given by

$$\sigma^2_{i,t} = \sum_{j=1}^{5} \alpha_{i,j}\epsilon^2_{i,t-j} + \beta_i \sigma_{i,t-6}. \tag{D.1}$$

The unconstrained model features $2 + (6 \times 13) = 80$ free parameters and is estimated separately for a vector y_t of currency and equity returns and of currency and bond returns, respectively. We also estimate a constrained version of the model (MGARCH2) for which we assume that $\alpha_{i,j} = \alpha_i$ for $j = 1, 2, 3.., 5$. This reduces the number of free parameters to $2 + (2 \times 13) = 28$. We estimate both the constrained and unconstrained model for 60 months of daily return data prior to month t. The predicted covariances $\Sigma_{ff,t+1}$, $\Sigma_{fb,t+1}$, and $\Sigma_{fe,t+1}$ are the cumulative expected daily variance for all trading days in month $t + 1$.

Average In-Sample Covariance. Let $j = 1, 2, 3, ...N$ denote the N trading days for the entire five-year sample. We define the insample covariance as

$$\overline{\Sigma}_{ff} = \sum_{j=1}^{N} w_j \left(\Delta s_j - \Delta\overline{s}\right)\left(\Delta s_j - \Delta\overline{s}\right)'$$

$$\overline{\Sigma}_{fx} = \sum_{j=1}^{N} w_j \left(\Delta s_j - \Delta\overline{s}\right)\left(r_j - \overline{r}\right)'$$

with empirical means

$$\Delta\overline{s} = \sum_{j=1}^{N} w_j \Delta s_j \quad \text{and} \quad \Delta\overline{r} = \sum_{j=1}^{N} w_j r_j$$

and an equal-weighted kernel given by $w_j = \frac{1}{N}$.

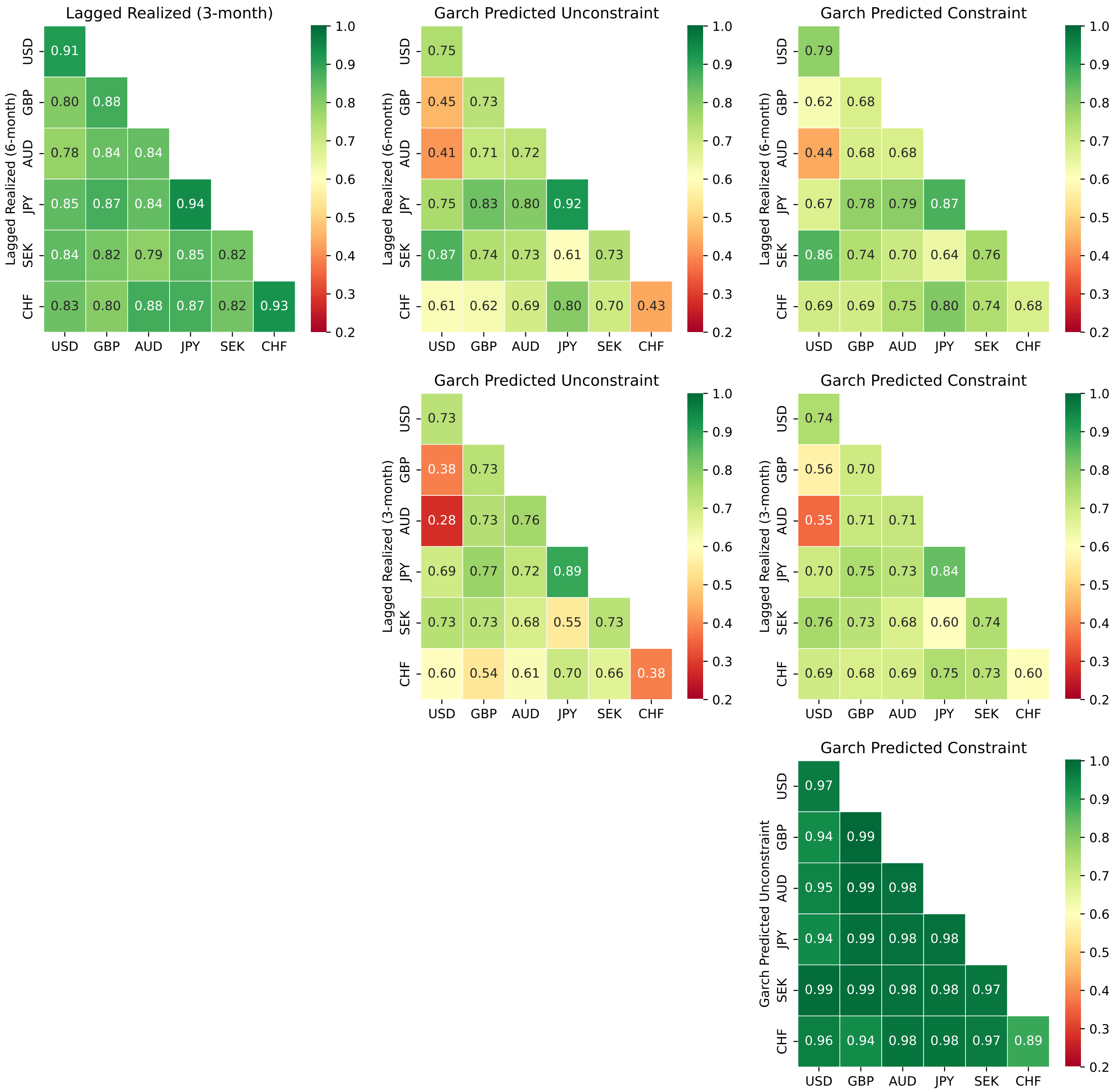
Comparison of Variances Estimates. The correlation between the different covariances matrices is reported in Table D.1, or in greater detail in Figure D.1. Figure D.2 plots for each currency the variances component of the Lagged Realized 6-month (black solid line), Lagged Realized 3-month (black dashed line), MGARCH1 unconstrained (orange solid line), MGARCH2 constrained (orange dashed line) covariance matrices.

Table D.1: Average Correlation between Covariance Terms

We report the average correlations between all monthly covariance terms obtained by four different estimation methods: Lagged Realized 6-month, Lagged Realized 3-month, MGARCH1 unconstrained, MGARCH2 constrained covariance matrices.

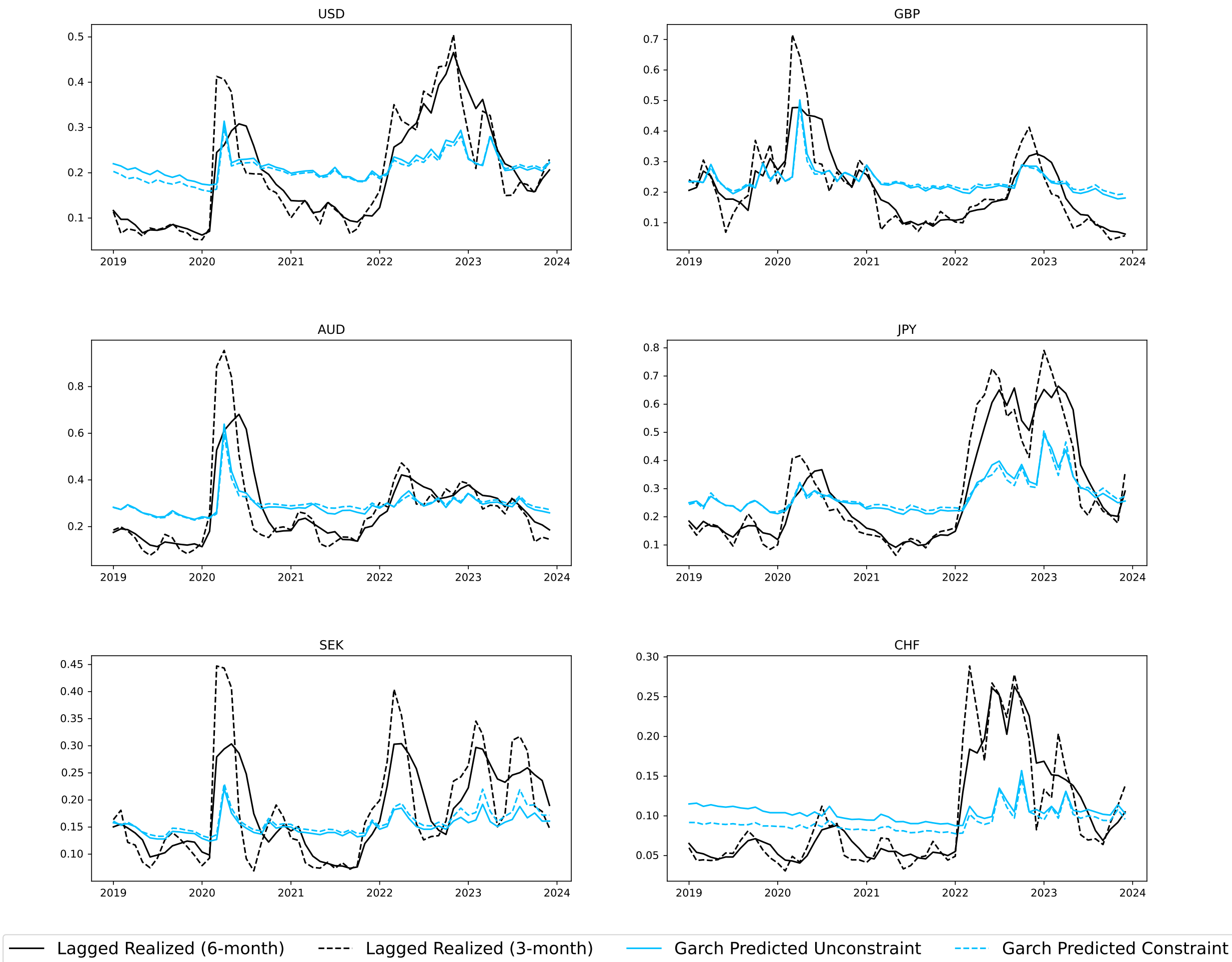
	LRC 6-month	LRC 3-month	MGARCH1	MGARCH2
LRC 6-month	1	0.841	0.692	0.712
LRC 3-month		1	0.638	0.682
MGARCH1			1	0.969
MGARCH2				1

Figure D.1: Correlation of Covariance Terms by Matrix Element



Notes: We report the correlation matrices between time series of the four different covariance matrices: Lagged Realized 6-month, Lagged Realized 3-month, MGARCH1 unconstrained, MGARCH2 constrained covariance matrices.

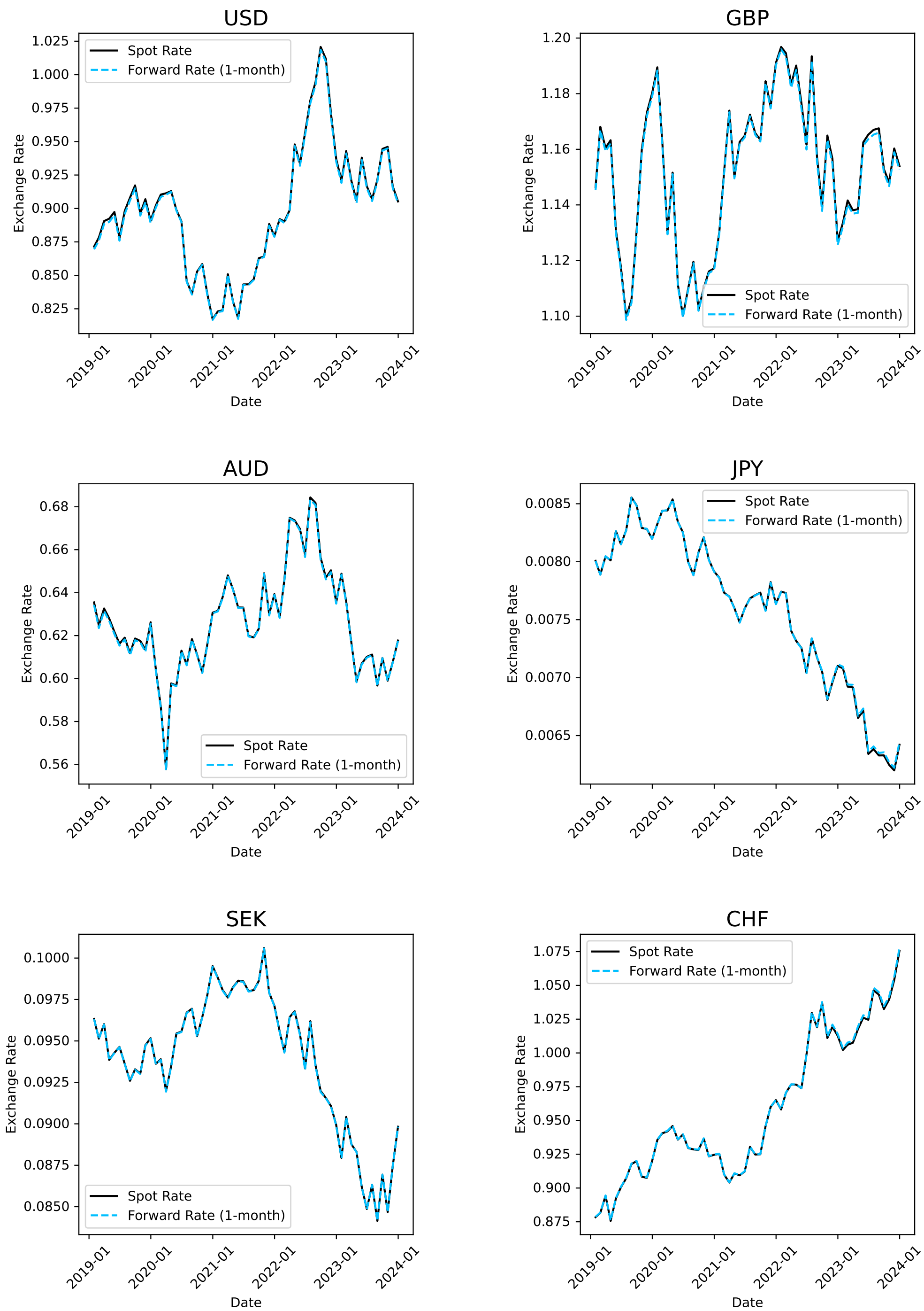
Figure D.2: Predicted Time-Varying Covariance Matrices Covariance



Notes: We plot the time-varying variances of currency returns $[\Sigma_{ff,t}]_{cc}$ computed as the Lagged Realized 6-month (black solid line), Lagged Realized 3-month (black dashed line), MGARCH1 unconstrained (orange solid line), MGARCH2 constrained (orange dashed line) covariance estimation. The covariances are computed using daily returns and are multiplied by a factor of 1e4.

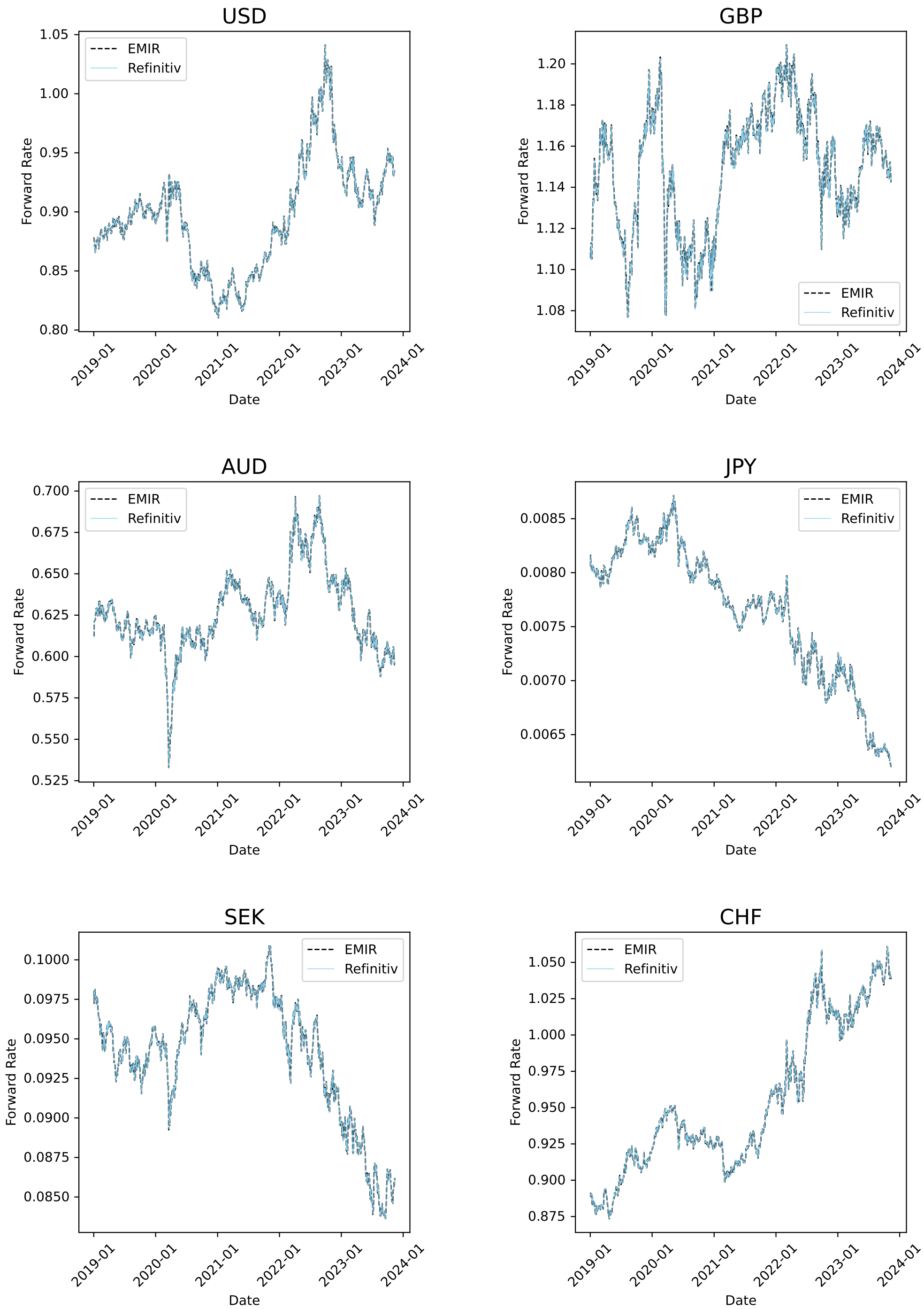
E Additional Figures

Figure E.1: Monthly Spot and Forward Rates by Currency



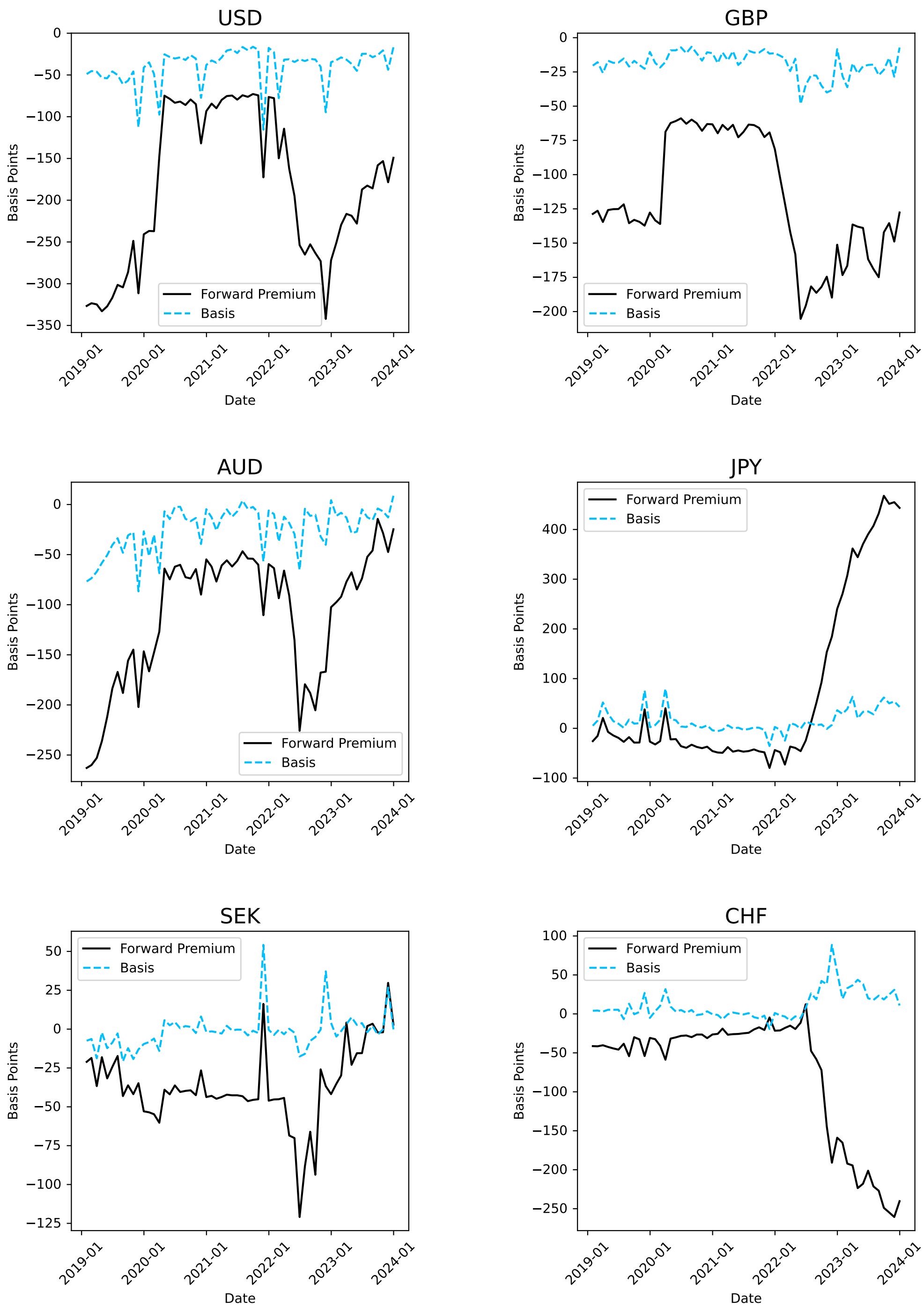
Notes: We show by currency the monthly spot rates for our sample period from January 2019 to December 2023. The exchange rate is defined in terms of Euros per unit of foreign currency c (i.e., EUR/c), such that an increase in S_t corresponds to an depreciation of EUR against foreign currency c.

Figure E.2: Daily Forward Rates of EMIR and Refinitiv by Currency



Notes: We show by currency the daily median 1-month forward rates obtained from EMIR and Refinitiv tick-data for our sample period from January 2019 to December 2023. The exchange rate is defined in terms of Euros per unit of foreign currency, such that an increase in S_t corresponds to an depreciation of EUR against foreign currency c.

Figure E.3: Forward Premium and CIP Deviations by Currency



Notes: We show by currency the annualized forward premium $fp_{c,t} = f_{c,t} - s_{c,t}$ (blue, solid line) and the negative cross-currency basis (also termed CIP deviations) $-Basis_{c,t} = -(i^{EUR}_{c,t} - (f_{c,t} - s_{c,t}) + i^{*}_{c,t})$. The exchange rate is defined as in terms of Euros per unit of foreign currency, such that an increase in S_t corresponds to an depreciation of EUR against foreign currency c. The monthly data are expressed in basis points.

F Additional Tables

Table F.1: Summary Statistics for Transaction Costs

We report summary statistics for spot exchange rate changes, Δs_{t+1} and the forward premium $f_t - s_t$ per currency pair. We define all exchange rates in terms of Euros per unit of foreign currency, such that an increase in s_t corresponds to an appreciation of the foreign currency against the EUR.

		Obs	Mean	St.D.	Q10	Q25	Q50	Q75	Q90
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: USD									
Δs_{t+1}	×100	60	0.06	2.09	−0.02	−1.55	0.17	1.41	0.03
$f_t - s_t$	×100	60	−0.15	0.07	−0.00	−0.21	−0.14	−0.07	−0.00
Panel B: GBP									
Δs_{t+1}	×100	60	0.06	1.53	−0.02	−0.96	0.22	1.07	0.02
$f_t - s_t$	×100	60	−0.09	0.04	−0.00	−0.12	−0.1	−0.05	−0.00
Panel C: AUD									
Δs_{t+1}	×100	60	0.01	2.26	−0.03	−1.49	−0.17	1.51	0.03
$f_t - s_t$	×100	60	−0.09	0.05	−0.00	−0.13	−0.07	−0.05	−0.00
Panel D: JPY									
Δs_{t+1}	×100	60	−0.36	2.06	−0.02	−1.64	−0.56	1.19	0.02
$f_t - s_t$	×100	60	0.06	0.15	−0.00	−0.03	−0.02	0.09	0.00
Panel E: SEK									
Δs_{t+1}	×100	60	−0.16	1.68	−0.02	−1.57	−0.37	0.99	0.02
$f_t - s_t$	×100	60	−0.03	0.02	−0.00	−0.04	−0.03	−0.02	−0.00
Panel F: CHF									
Δs_{t+1}	×100	60	0.32	1.17	−0.01	−0.38	0.33	1.04	0.02
$f_t - s_t$	×100	60	0.06	0.07	0.00	0.02	0.03	0.07	0.00

Table F.2: Robustness of Table 3 to Different Covariance Matrices

We repeat the baseline regression in Table 3 with different covariance matrices. In Panel A we use the 3-month lagged realized covariance matrix, in Panel B the covariance matrix based on the MGARCH2 model, and in Panel C and average in-sample covariance matrix, respectively. We regress the currency derivative positions $w_{f,ict}$ of European investment funds labeled i, in currency c, and in month t (measured as share of total assets invested) on future exchange rate changes (FX predictability effect), the optimal forward premium tilt, the optimal transaction cost tilt, and the optimal benchmark hedge. We double cluster standard errors at the time- and fund-currency level and mark statistical significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

Dep. Variable:	$w_{f,ict}$					
Sample:	All Derivative Positions			Euro Long Positions Only ($w_{f,ict} < 0$)		
Fund Type:	Bonds	Equity	Mixed	Bonds	Equity	Mixed
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Lagged Realized Covariances (3-Month Period)						
FX Predictability Effect						
$[\Sigma^{-1}_{ff,t+1}]_{c\bullet}\Delta s_{t+1}$	0.032*	0.002	0.008*	0.062**	0.009	0.025***
	(0.018)	(0.002)	(0.005)	(0.030)	(0.007)	(0.009)
Forward Premium Effect						
$[\Sigma^{-1}_{ff,t+1}]_{c\bullet}fp_t$	−1.199***	−0.101	−0.368**	−0.885*	−0.158	−0.366
	(0.370)	(0.071)	(0.148)	(0.469)	(0.293)	(0.245)
Transaction Cost Effect						
$[\Sigma^{-1}_{ff,t+1}]_{c\bullet}\tau$	−1.326**	−1.935***	−1.979***	0.186	0.219	1.032**
	(0.560)	(0.570)	(0.587)	(0.380)	(0.405)	(0.428)
Benchmark Hedge						
$[\Sigma^{-1}_{ff,t+1}\Sigma_{fx,t+1}]_{c\bullet}w_{x,it}$	−0.366***	−0.008***	−0.029***	−0.604***	−0.041***	−0.101***
	(0.037)	(0.002)	(0.007)	(0.041)	(0.011)	(0.020)
Adj. R^2	0.164	0.005	0.011	0.409	0.014	0.045
No. Observations:	82,822	182,568	136,781	48,300	28,242	44,969
No. Funds:	805	1,109	891	728	809	705
Panel B: Predicted Covariances based on MGARCH2 Model (DCC, 28 parameters constrained)						
FX Predictability Effect						
$[\Sigma^{-1}_{ff,t+1}]_{c\bullet}\Delta s_{t+1}$	0.034*	0.004	0.008	0.053*	0.018*	0.029*
	(0.020)	(0.003)	(0.009)	(0.028)	(0.011)	(0.015)
Forward Premium Effect						
$[\Sigma^{-1}_{ff,t+1}]_{c\bullet}fp_t$	−0.983	0.056	0.517*	0.117	0.460	0.944*
	(0.755)	(0.156)	(0.297)	(0.867)	(0.704)	(0.483)
Transaction Cost Effect						
$[\Sigma^{-1}_{ff,t+1}]_{c\bullet}\tau$	−2.748**	−3.358***	−4.342***	0.279	0.713	1.508*
	(1.148)	(1.227)	(1.445)	(0.398)	(0.749)	(0.842)
Benchmark Effect						
$[\Sigma^{-1}_{ff,t+1}\Sigma_{fx,t+1}]_{c\bullet}w_{x,i,t}$	−0.572***	−0.035***	−0.078***	−0.923***	−0.168***	−0.259***
	(0.048)	(0.008)	(0.017)	(0.035)	(0.032)	(0.038)
Adj. R^2	0.260	0.015	0.022	0.639	0.063	0.111
No. Observations:	82,822	182,568	136,781	48,300	28,242	44,969
No. Funds:	805	1,109	891	728	809	705

Table F.2 continued.

Dep. Variable:	$w_{f,ict}$					
Sample:	All Derivative Positions			Euro Long Positions Only ($w_{f,ict} < 0$)		
Fund Type:	Bonds	Equity	Mixed	Bonds	Equity	Mixed
	(1)	(2)	(3)	(4)	(5)	(6)
Panel C: Average In-Sample Covariance Matrix						
FX Predictability Effect						
$[\overline{\Sigma}^{-1}_{ff,t+1}]_{c\bullet}\Delta s_{t+1}$	0.001	0.001**	0.004	−0.003	0.007*	0.015***
	(0.009)	(0.001)	(0.006)	(0.007)	(0.004)	(0.005)
Forward Premium Effect						
$[\overline{\Sigma}^{-1}_{ff,t+1}]_{c\bullet}fp_t$	−0.292	−0.065	0.539**	1.026**	−0.842	0.113
	(0.488)	(0.155)	(0.239)	(0.420)	(0.794)	(0.423)
Transaction Cost Effect						
$[\overline{\Sigma}^{-1}_{ff,t+1}]_{c\bullet}\tau$	−2.719**	−4.128***	−5.154***	−0.044	−0.105	0.720
	(1.193)	(1.450)	(1.593)	(0.372)	(0.809)	(0.761)
Benchmark Effect						
$[\overline{\Sigma}^{-1}_{ff,t+1}\overline{\Sigma}_{fx,t+1}]_{c\bullet}w_{x,it}$	−0.595***	−0.047***	−0.124***	−0.960***	−0.189***	−0.328***
	(0.050)	(0.011)	(0.021)	(0.036)	(0.045)	(0.043)
Adj. R^2	0.270	0.018	0.045	0.662	0.058	0.153
No. Observations:	82,822	182,568	136,781	48,300	28,242	44,969
No. Funds:	805	1,109	891	728	809	705

Table F.3: Cross-Sectional Hedging Patterns with Fund-Currency FEs

We repeat the baseline regression in Table 3, but add fund × currency fixed effects. We regress the currency derivative positions $w_{f,ict}$ of European investment funds labeled i, in currency c, and in month t (measured as share of total assets invested) on future exchange rate changes (FX predictability effect), the optimal forward premium tilt, the optimal transaction cost tilt, and the optimal benchmark hedge. All regressions include fund × currency fixed effects. We double cluster standard errors at the time- and fund-currency level and mark statistical significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

Dep. Variable:	$w_{f,ict}$					
Sample:	All Derivative Positions			Euro Long Positions Only ($w_{f,ict} < 0$)		
Fund Type:	Bonds	Equity	Mixed	Bonds	Equity	Mixed
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Lagged Realized Covariances (6-Month Period)						
FX Predictability Effect						
$[\Sigma^{-1}_{ff,t+1}]_{c\bullet}\Delta s_{t+1}$	0.011	0.001	0.002	0.013**	0.002	0.008**
	(0.009)	(0.001)	(0.003)	(0.006)	(0.003)	(0.004)
Forward Premium Effect						
$[\Sigma^{-1}_{ff,t+1}]_{c\bullet}fp_t$	−1.163***	−0.038	−0.405***	−0.229	0.015	−0.455***
	(0.329)	(0.053)	(0.133)	(0.202)	(0.157)	(0.170)
Transaction Cost Effect						
$[\Sigma^{-1}_{ff,t+1}]_{c\bullet}\tau$	−0.764*	−0.672**	−0.813**	−0.031	0.130	0.324*
	(0.434)	(0.291)	(0.327)	(0.161)	(0.177)	(0.182)
Benchmark Hedge						
$[\Sigma^{-1}_{ff,t+1}\Sigma_{fx,t+1}]_{c\bullet}w_{x,i,t}$	−0.044***	0.000	−0.000	−0.087***	0.003	−0.016*
	(0.013)	(0.001)	(0.003)	(0.019)	(0.003)	(0.009)
Adj. R^2	0.010	0.001	0.004	0.016	0.000	0.004
Panel B: Predicted Covariances based on MGARCH1 Model (DCC, 80 Parameters)						
FX Predictability Effect						
$[\Sigma^{-1}_{ff,t+1}]_{c\bullet}\Delta s_{t+1}$	0.020	0.001	0.004	0.025**	0.005	0.014*
	(0.013)	(0.001)	(0.004)	(0.013)	(0.004)	(0.008)
Forward Premium Effect						
$[\Sigma^{-1}_{ff,t+1}]_{c\bullet}fp_t$	−0.856	0.064	−0.072	0.483	0.306	0.195
	(0.587)	(0.086)	(0.187)	(0.493)	(0.331)	(0.298)
Transaction Cost Effect						
$[\Sigma^{-1}_{ff,t+1}]_{c\bullet}\tau$	−1.515*	−1.615**	−2.257***	−0.039	0.105	0.488
	(0.813)	(0.638)	(0.796)	(0.267)	(0.223)	(0.310)
Benchmark Hedge						
$[\Sigma^{-1}_{ff,t+1}\Sigma_{fx,t+1}]_{c\bullet}w_{x,i,t}$	−0.223***	0.000	−0.018	−0.407***	−0.015	−0.102***
	(0.041)	(0.004)	(0.011)	(0.055)	(0.013)	(0.029)
Adj. R^2	0.017	0.002	0.004	0.079	0.001	0.014
No. Observations:	82,822	182,568	136,781	48,300	28,242	44,969
No. Funds:	805	1,109	891	728	809	705

Table F.4: Difference between Inferred and Reported Monthly Returns

We report the distribution of the time averaged absolute differences between the reported and inferred returns for bond, equity, and mixed funds. The sample covers the period January 2019 to December 2023.

	Absolut Return Difference (in %)							
	Obs (1)	Mean (2)	St.D. (3)	Q10 (4)	Q25 (5)	Q50 (6)	Q75 (7)	Q90 (8)
Bond Funds	797	1.590	1.933	0.181	0.468	0.954	2.077	3.620
Equity Funds	1,097	1.495	1.692	0.169	0.443	0.993	1.938	3.349
Mixed Funds	881	1.425	1.705	0.140	0.355	0.955	1.820	3.395
All Funds	2,775	1.500	1.769	0.163	0.420	0.969	1.952	3.472

Table F.5: Robustness of Table 3 for Fund Sample with Low Return Mismatch

We regress the currency derivative positions $w_{f,ict}$ of European investment funds labeled i, in currency c, and in month t (measured as share of total assets invested) on future exchange rate changes (FX predictability effect), the optimal forward premium tilt, the optimal transaction cost tilt, and the optimal benchmark hedge. We report in Columns (1)-(3) and Columns (4)-(6) the results for all derivative positions and only (USD) short positions, respectively. For the the calculation of the (time-varying) covariances $\Sigma_{ff,t+1}$ and $\Sigma_{fx,t+1}$, we use in Panels A and B the (in-sample) lagged realized covariance (estimated for daily returns over the previous 6 months) and the predicted covariance based on the MGARCH1 model, respectively. We double cluster standard errors at the time- and fund-currency level and mark statistical significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

Dep. Variable:	$w_{f,i,c,t}$					
Sample:	All Derivative Positions			Euro Long Positions Only ($w_{f,i,c,t} < 0$)		
Fund Type:	Bonds	Equity	Mixed	Bonds	Equity	Mixed
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Lagged Realized Covariances (6-Month Period)						
FX Predictability Effect $[\Sigma^{-1}_{ff,t+1}]_{c\bullet}\Delta s_{t+1}$	0.042**	0.003	0.009	0.086**	0.019**	0.033**
	(0.021)	(0.002)	(0.006)	(0.034)	(0.009)	(0.014)
Forward Premium Effect $[\Sigma^{-1}_{ff,t+1}]_{c\bullet}fp_t$	−1.815***	−0.236**	−0.576***	−1.252**	−0.656	−0.791**
	(0.478)	(0.107)	(0.199)	(0.532)	(0.417)	(0.366)
Transaction Cost Effect $[\Sigma^{-1}_{ff,t+1}]_{c\bullet}\tau_{i,t}$	−2.155***	−1.887***	−2.226***	−0.004	0.551	0.830*
	(0.646)	(0.679)	(0.779)	(0.525)	(0.492)	(0.485)
Benchmark Hedge $[\Sigma^{-1}_{ff,t+1}\Sigma_{fx,t+1}]_{c\bullet}w_{x,i,t}$	−0.435***	−0.011***	−0.038***	−0.703***	−0.048***	−0.141***
	(0.048)	(0.003)	(0.009)	(0.045)	(0.016)	(0.026)
Adj. R^2	0.194	0.007	0.014	0.470	0.017	0.066
No. Observations:	60,732	127,566	120,655	34,603	19,923	38,402
No. Funds:	585	730	766	532	536	606
Panel B: Predicted Covariances based on MGARCH1 Model (DCC, 80 Parameters)						
FX Predictability Effect $[\Sigma^{-1}_{ff,t+1}]_{c\bullet}\Delta s_{t+1}$	0.032	0.003	0.007	0.049*	0.018	0.033*
	(0.020)	(0.004)	(0.009)	(0.026)	(0.012)	(0.018)
Forward Premium Effect $[\Sigma^{-1}_{ff,t+1}]_{c\bullet}fp_t$	−0.592	−0.001	0.602*	0.944	0.319	1.251**
	(0.782)	(0.184)	(0.307)	(0.868)	(0.833)	(0.540)
Transaction Cost Effect $[\Sigma^{-1}_{ff,t+1}]_{c\bullet}\tau_{i,t}$	−4.377***	−3.738***	−4.994***	0.267	1.025	1.496*
	(1.233)	(1.282)	(1.547)	(0.673)	(1.017)	(0.893)
Benchmark Hedge $[\Sigma^{-1}_{ff,t+1}\Sigma_{fx,t+1}]_{c\bullet}w_{x,i,t}$	−0.604***	−0.033***	−0.080***	−0.953***	−0.141***	−0.284***
	(0.059)	(0.009)	(0.018)	(0.046)	(0.035)	(0.042)
Adj. R^2	0.267	0.015	0.024	0.641	0.052	0.129
No. Observations:	60,732	127,566	120,655	34,603	19,923	38,402
No. Funds:	585	730	766	532	536	606

Table F.6: Robustness of Table 5 for Fund Sample with Low Return Mismatch

We report summary statistics on European fund returns, namely the mean return (Mean), the standard deviation of the return (St.D.), and the certainty equivalent (CEQ) under different hedging scenarios. Columns (1)-(3) report the sample averages of the three performance statistics separately for bond, equity, and mixed funds, respectively. Columns (4)-(6) state the corresponding improvements of the sample averages under four different scenarios relative to the baseline case given by the fund returns on the observed hedge. We test for the equality of means between the baseline case and the scenario performance and mark the rejection of equality (null hypothesis) at the 10%, 5%, and 1% level by *, **, and ***. We exclude funds that fall within the lowest 10th percentile of observation counts to ensure that our standard deviation estimates are reliable.

	Sample Average			Improvement (Relative to Baseline)		
Fund Type	Bond	Equity	Mixed	Bond	Equity	Mixed
	(1)	(2)	(3)	(4)	(5)	(6)
Baseline: Fund Returns on Observed Derivative Trading						
Mean (% annualized)	−3.282	7.122	1.777			
St.D. (% annualized)	5.875	15.328	9.834			
CEQ Ratio	−4.764	0.345	−1.797			
Transaction Costs (bp annualized)	3.229	0.883	2.746			
Scenario 1: Fund Returns without Derivative Trading						
Mean (% annualized)	−2.921	7.174	1.966	0.361^{***}	0.052	0.189
St.D. (% annualized)	5.798	15.242	9.575	0.077	0.086	0.259
CEQ Ratio	−4.371	0.465	−1.474	0.393^{**}	0.120	0.323^{*}
Transaction Costs (bp annualized)				3.229^{***}	0.883^{***}	2.746^{***}
Scenario 2: Fund Returns for Unitary Hedge without Return Seeking						
Mean (% annualized)	−3.592	6.482	1.373	-0.310^{**}	-0.640^{***}	-0.404^{**}
St.D. (% annualized)	5.582	15.756	10.080	0.293^{***}	-0.428^{**}	−0.246
CEQ Ratio	−4.986	−0.628	−2.346	−0.222	-0.973^{***}	-0.549^{***}
Transaction Costs (bp annualized)	3.627	2.598	3.872	−0.398	-1.715^{***}	-1.126^{***}
Scenario 3: Optimal Hedge without Return Seeking						
Mean (% annualized)	−4.532	5.836	0.531	-1.250^{***}	-1.286^{***}	-1.246^{***}
St.D. (% annualized)	5.266	13.829	8.825	0.609^{***}	1.499^{***}	1.009^{***}
CEQ Ratio	−5.843	0.162	−2.543	-1.079^{***}	−0.183	-0.746^{***}
Transaction Costs (bp annualized)	3.414	2.941	3.303	−0.185	-2.058^{***}	−0.557
Scenario 4: Optimal Hedge with Return Seeking (for risk tolerance $\gamma = 0.2$)						
Mean (% annualized)	−4.539	5.834	0.531	-1.257^{***}	-1.288^{***}	-1.246^{***}
St.D. (% annualized)	5.266	13.831	8.828	0.609^{***}	1.497^{***}	1.006^{***}
CEQ Ratio	−5.850	0.159	−2.544	-1.086^{***}	−0.186	-0.747^{***}
Transaction Costs (bp annualized)	3.442	2.953	3.334	−0.213	-2.070^{***}	−0.588
No. Funds	482	696	691			
Observations	59,174	127,372	119,653			

Table F.7: Fund Performance Comparison for Funds with High Foreign Investment Share

We repeat Table 5 for the 20% of funds with the highest foreign investment share for each fund type. We test for the equality of means between the baseline case and the scenario performance and mark the rejection of equality (null hypothesis) at the 10%, 5%, and 1% level by *, **, and ***. We exclude funds that fall within the lowest 10th percentile of observation counts to ensure that our standard deviation estimates are reliable.

	Sample Average			Improvement (Relative to Baseline)		
Fund Type	Bond	Equity	Mixed	Bond	Equity	Mixed
	(1)	(2)	(3)	(4)	(5)	(6)
Baseline: Fund Returns on Observed Hedge						
Mean (% annualized)	−3.129	8.492	3.455			
St.D. (% annualized)	6.207	15.274	11.083			
CEQ Ratio	−4.836	1.875	−0.726			
Transaction Costs (bp annualized)	7.958	2.380	4.522			
Scenario 1: Fund Returns without Hedge						
Mean (% annualized)	−2.203	8.592	3.751	0.926***	0.100	0.296
St.D. (% annualized)	6.169	15.092	10.767	0.038	0.182	0.316
CEQ Ratio	−3.869	2.128	−0.254	0.967***	0.253	0.472
Transaction Costs (bp annualized)				7.958***	2.380***	4.522***
Scenario 2: Fund Returns for Unitary Hedge without Return Seeking						
Mean (% annualized)	−3.906	7.526	2.587	−0.777***	−0.966***	−0.868*
St.D. (% annualized)	5.471	16.285	11.572	0.736***	−1.011***	−0.489
CEQ Ratio	−5.370	0.073	−1.950	−0.534*	−1.802***	−1.224***
Transaction Costs (bp annualized)	9.446	6.063	6.648	−1.488	−3.683***	−2.126**
Scenario 3: Optimal Hedge without Return Seeking						
Mean (% annualized)	−4.844	6.936	1.896	−1.715***	−1.556***	−1.559***
St.D. (% annualized)	5.151	15.177	10.386	1.056***	0.097	0.697
CEQ Ratio	−6.222	0.333	−1.947	−1.386***	−1.542***	−1.221***
Transaction Costs (bp annualized)	8.464	4.405	5.163	−0.506	−2.025***	−0.641
Scenario 4: Optimal Hedge and Return Seeking (for risk tolerance $\gamma = 0.2$)						
Mean (% annualized)	−4.851	6.932	1.893	−1.722***	−1.560***	−1.562***
St.D. (% annualized)	5.152	15.180	10.389	1.055***	0.094	0.694
CEQ Ratio	−6.229	0.326	−1.952	−1.393***	−1.549***	−1.226***
Transaction Costs (bp annualized)	8.491	4.419	5.191	−0.533	−2.039***	−0.669
No. Funds	143	204	155			
Observations	11,860	22,143	20,907			