

Exchange Rate Expectations and Currency Demand

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Abstract

International exchange-traded funds (ETFs) generally allow investors to choose between a currency-hedged and unhedged product. I show how relative holdings between these products reveal the currency demand and exchange rate expectations of investors. Investors' allocations to currency-hedged versus unhedged ETFs are best explained by survey-based exchange rate expectations, but less so by expectations derived from macro models or currency pricing factors. Currency return expectations implied by relative ETF holdings predict future exchange rates more accurately than survey expectations or expectations based on macro or factor models. Dispersion in these portfolio-implied expectations accounts for 27% of FX volatility, consistent with models of heterogeneous beliefs.

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

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1 Introduction

Economists increasingly rely on survey expectations to explain asset prices and constrain macroeconomic models.¹ Yet, how well such survey expectations relate to investors' portfolio decisions remains an unsettled question.² A survey sample could diverge from the relevant group of investors that decides on financial allocation and the marginal group that influences prices. Moreover, surveys may fail to elicit investors' true beliefs and expectations inferred from equilibrium models or risk factors may be more informative.

An alternative promising path towards more accurate return expectations is to recover them directly from portfolio allocations. But inferring exchange rate expectations from currency holdings is particularly difficult, as currency is often held as a byproduct of foreign investment, making it hard to isolate the pure currency demand component of the investment decision. This paper addresses this challenge by exploiting the observable asset allocation between share classes of exchange-traded funds (ETF). For a given foreign index, many funds can be purchased currency-hedged or unhedged, allowing a clean separation of currency demand from asset demand. The analysis here combines two elements.

First, I construct a novel dataset covering the universe of international ETFs from 2014–2025. I match ETFs domiciled in six currency areas outside the US that track the same underlying US benchmark index but differ in their currency hedging strategy.³ My final dataset comprises 350 currency-hedged ETFs with their 350 paired unhedged twins, with aggregate holdings accounting for roughly 5% and 1% of total foreign holdings in USD-denominated equities and bonds, respectively.⁴

Second, I build on the mean-variance framework for optimal currency hedging pioneered by [Anderson and Danthine \(1981\)](#). This theory predicts that the relative size of two otherwise identical ETFs, differing only in their currency exposure, reflects two separable components: a hedging mo-

¹For example, survey expectations are used to identify the Uncovered Interest Parity (UIP) premium and explain the forward premium anomaly ([Kalemli-Özcan and Varela, 2021](#); [Dao et al., 2025](#)), isolate expected inflation from inflation risk premia ([Chernov and Mueller, 2012](#)), or quantify information rigidity to discipline expectations formation ([Coibion and Gorodnichenko, 2015](#)).

²[Cochrane \(2011\)](#) notes a disconnect between investors' portfolio choice and their survey responses, while recent research establishes a close connection between beliefs and holdings in equity markets ([Giglio et al., 2021](#)).

³International ETFs represent a substantial portion of global ETF investment. For example, in December 2024, ETFs domiciled in the euro-area that invest in international equity had assets under management totaling USD 482 billion, while those investing in European equity managed just under half of that, with USD 188 billion in assets.

⁴[Du and Huber \(2024\)](#) find that in June 2021 foreigners held USD 12 trillion USD-denominated equities and USD 20 trillion in USD-denominated bonds. Their sample includes all non-US based investors, while I focus on holdings by six currency areas.

tive, given by the covariance between currency and asset returns scaled by exchange rate volatility, and a speculative motive given by the risk-adjusted expected currency excess return. Based on this framework, I can map exchange rate expectations to investors' relative allocation between hedged and unhedged ETFs across the 350 pairs.

The combination of ETF holding data and financial theory linking relative holdings directly to exchange rate expectations allows me to address the following three research questions:

1. How well can survey-based exchange rate expectations account for the relative portfolio allocation of ETF investors compared to expectations derived from macroeconomic theory or asset pricing factors?
2. If we use relative EFT allocations as a new inference method to deduce exchange rate expectations, how accurate can such portfolio-implied expectations predict future returns relative to survey expectations or macro- or factor-based expectations?
3. Is a higher dispersion in portfolio-implied exchange rate expectations (across ETF pairs) related to higher foreign exchange (FX) volatility as predicted by heterogeneous belief models (Basak, 2005; Buraschi and Jiltsov, 2006)?

The answers to these three questions can be summarized as follows:

First, survey expectations outperform macro- or factor-based expectations when it comes to explaining the observed portfolio allocations between hedged and unhedged ETF pairs. I focus on two estimates of conditional currency returns for benchmarking: *macro* expectations that combine purchasing power parity-implied mean reversion in the real exchange rate with a trend signal from past returns as in Chernov et al. (2023), and *factor* expectations derived from the two most prominent currency pricing factors, the dollar and carry factor (Lustig et al., 2011; Verdelhan, 2018) as in Opie and Riddiough (2020). ETF investors' USD holdings show no significant sensitivity to either estimate of model-implied expectations, once controlling for aggregate time trends. In contrast, survey expectations are highly significant in the cross-section of currencies: Investors in currency areas that are expected to depreciate more against the USD (i.e., higher expected excess returns on USD investments) allocate a larger share of their portfolios to the unhedged ETF, increasing their exposure to USD fluctuations. This shows that FX survey expectations are indeed a suitable inference method for rationalizing international portfolio allocations.

Second, I show that the accuracy of FX survey expectations is still surpassed by expectations

deduced from the relative ETF allocations. A horse race between portfolio-implied exchange rate expectations, survey expectations and those embedded in macro and factor models shows that only the first have predicative power for future exchange rates, over the 11-year period under consideration. This suggests that trading by the average ETF investor is rational. I highlight that the predictive power of portfolio-implied expectations stems primarily from active flows into the unhedged ETF relative to the hedged ETF, however, the theory-guided portfolio-implied expectations contain incremental and stronger predictive information beyond flows.

Third, I find that the cross-sectional dispersion of portfolio-implied expectations increases significantly during volatile FX market periods, consistent with models of heterogeneous beliefs (Basak, 2005; Buraschi and Jiltsov, 2006). Specifically, the mean absolute deviation of portfolio-implied expectations can account for 27% of FX option-implied volatility and is positively correlated with it at 71% for the aggregate USD basket. Quantitatively, the explanatory power is comparable to that of order flow variables (e.g., Evans and Lyons (2002) document an R^2 between 40% and 67%) or macroeconomic variables (e.g., Koijen and Yogo (2020) attribute approximately 26% of exchange rate fluctuations to macro variables).

My paper provides an indicator with immediate practical use: By recovering expectations from daily ETF trading, I construct a high-frequency gauge of investors' sentiment towards the USD. As an illustrative example, following the announcement of US tariffs on April 2, 2025, portfolio-implied expectations as well as flows into unhedged relative to hedged ETFs fell sharply (see Figure A.1), consistent with expectations of a USD depreciation. This pattern aligns with Jiang et al. (2025) who argue, based on price movements, that investors started questioning the dominant role of the USD in the international financial system, following the day of the announcement.⁵ The example underscores that investors' traded quantities can deliver a near-real-time indicator of foreign investors' USD perceptions.

Finally, I acknowledge two measurement limitations in my analysis. First, I measure foreign currency holdings at the aggregate level for a representative investor per fund and rely on aggregate consensus forecasts for survey expectations. Individual investor holdings, combined with their survey responses, would provide a more comprehensive and granular picture. The aggregation

⁵Similarly, Shin et al. (2025) document increased hedging by non-US institutions in USD index futures during this period, using the Commodity Futures Trading Commission's (CFTC) weekly data.

process obscures the substantial heterogeneity in subjective beliefs among investors and might fail to capture the belief of the marginal agent. Second, cross-border ownership could bias the relative size of unhedged versus hedged share classes: investors outside the ETF’s domicile may not have a motive to hedge if their home currency coincides with the fund’s base currency. However, retail investors are generally legally constraint from buying ETFs outside their home market (e.g., euro-area investors cannot access US-listed ETFs) and institutional investors, who generally face no such restriction, hold only about one-quarter of the shares in my sample of funds. Any resulting bias should be modest.

2 Related Literature

My study relates to the literature on subjective beliefs derived from survey expectations ([Greenwood and Shleifer, 2014](#); [Adam and Nagel, 2023](#)), in particular, on the link between beliefs and portfolio decisions ([Amromin and Sharpe, 2014](#); [Giglio et al., 2021](#); [Ameriks et al., 2020](#)). I provide new evidence on how aggregate exchange rate beliefs from surveys map into currency portfolio holdings. In particular, similar to [Giglio et al. \(2021\)](#), who document a robust relationship between equity shares of individual investors’ portfolios and expected equity returns from surveys in both the cross-section and within individuals over time, I examine the analogous relationship for the USD currency share and expected currency returns. I find a strong relationship in currency markets in the cross-section of currencies: a one standard deviation increase in expected spot returns is linked to a 0.23 standard deviation increase in the USD share, a sensitivity quantitatively comparable to the investor-level evidence in equity markets (cf. 0.16). The strong connection between investors’ financial decisions and their expectations is also documented in [Nagel and Yan \(2022\)](#), who identify this relationship between inflation expectations and retail investors’ flows into TIPS ETFs.

Currency survey expectations are also explored in two other recent studies. [Stavrakeva and Tang \(2020\)](#) document that rational expectations are strongly rejected using FX futures positions. In contrast, [Kremens et al. \(2025\)](#) show that survey currency expectations can forecast realized currency returns, especially at horizons above one month, and are thus broadly rational. This study confirms the rationality of investors as portfolio-implied expectations significantly predict one-month currency returns. For the same period, I do not find predictive power of one-month

survey-based expectations.

By combining aggregate holding data with estimates of exchange rate expectations, this study also contributes to the expanding field of international asset pricing, where the number of currency pricing factors continues to grow beyond the well-known carry and dollar factors (Lustig et al., 2011; Verdelhan, 2018), with new additions such as momentum (Burnside et al., 2011; Menkhoff et al., 2012b), value (Menkhoff et al., 2017), volatility (Menkhoff et al., 2012a), illiquidity (Mancini et al., 2013), downside beta risk (Lettau et al., 2014), and economic momentum (Dahlquist and Hasseltoft, 2020). This study asks whether investors rely on the predictive signals implied by asset pricing models when deciding on global currency allocations, a question largely overlooked even though asset pricing models should not only replicate asset price behavior but also align with observable investor expectations. I show that aggregate investors do not systematically tilt their portfolio toward conditional expectations derived from the two most prominent factors (dollar and carry) to generate excess returns.

My paper complements recent work on recovering beliefs from holdings. Crescini et al. (2025) recover market return expectations from option holdings data, while Egan et al. (2022) infer those by exploiting demand for leveraged ETFs. Similarly, I recover exchange rate expectations from ETF holdings data. In contrast to the expectations recovered here, Egan et al. (2022) find that the average expected return of investors does not forecast future returns. However, consistent with my findings, both papers also document substantial and time-varying heterogeneity in beliefs among investors.

I also contribute to the literature on heterogeneous beliefs by providing new empirical evidence of a close link between differences in investor expectations and volatility. In Buraschi and Jiltsov (2006); Buraschi et al. (2014) volatility and belief dispersion move together as optimistic investors insure pessimists in high volatility states, earning a premium that rises with disagreement. Beber et al. (2010) confirm this theory for three currency pairs over the period 1993-2006 using dispersion in survey forecasts, and find that differences in beliefs explains on average 45% of option-implied FX volatility. I complement this evidence by showing that, for a cross-section of six currency pairs, in a much more recent time period, the correlation between differences in beliefs derived from portfolio holdings with implied volatility reaches up to 71% for the aggregate USD basket.

This study also relates to the growing empirical literature on currency hedging which builds

on theoretical work on optimal currency hedging by [Anderson and Danthine \(1980, 1981\)](#), or more recently by [Campbell et al. \(2010\)](#). [Du and Huber \(2024\)](#) is the first comprehensive study to examine global currency hedging at an aggregate level, comparing hedging quantities to mean-variance optimal benchmarks. With the growing availability of data, recent advances have shifted toward comparing optimal hedging strategies at the fund level. For example, [Greenwood and Cheema-Fox \(2024\)](#) and [Opie and Riddiough \(2024\)](#) analyze fund-level hedging behavior of US investment funds, while [Bräuer and Hau \(2024\)](#) focus on hedging by European investment funds. This study differs from the existing literature in one key aspect: rather than examining the hedging behavior of funds, I focus on investors of ETFs that are either fully hedged or completely unhedged. As a result, the optimal currency hedging problem transitions from the fund level to the investor level, placing the emphasis on investor decisions regarding hedging strategies rather than on the funds' hedging strategies. Furthermore, this study emphasizes the speculative component of foreign currency demand, the expectations about exchange rates implied by currency portfolios.

Lastly, this paper adds new evidence to the literature on ETF investment and its effect on prices ([Ben-David et al., 2017](#)). While the asset allocation is most often passive, when investing internationally, investors face an active decision regarding currency exposure. This paper shows that this decision is rational and forecasts currency returns. Thus, while ETF flows might be driven by individuals or unsophisticated institutions, on aggregate, ETF investors are informed about future currency returns.

3 Theory

3.1 Optimal Currency Demand

General Setup. Suppose there exist two ETFs that invest in the same foreign asset index. One does not hedge its currency risk and the other fully hedges its currency risk. Suppose further that there exists one risk-averse domestic investor i in a specific currency area, who decided to invest in the foreign asset index, i , and can choose between the two products. Her total wealth equals

$A_{i,t} = A_{i,t}^{unhedged} + A_{i,t}^{hedged}$ of which she can allocate $w_{i,t}$ to the unhedged ETF so that

$$w_{i,t} = \frac{A_{i,t}^{unhedged}}{A_{i,t}^{unhedged} + A_{i,t}^{hedged}} \quad (1)$$

where the assets under management, $A_{i,t}$, is the product of net asset value (NAV) and outstanding shares and $1 - w_{i,t}$ is the weight in the hedged ETF. The expected return on the hedged and unhedged ETF is equal to

$$\begin{aligned} \mathbb{E}_t[r_{i,t+1}^{unhedged}] &= \mathbb{E}_t[r_{i,t+1}] + \mathbb{E}_t[\Delta s_{t+1}] \\ \mathbb{E}_t[r_{i,t+1}^{hedged}] &= \underbrace{\mathbb{E}_t[r_{i,t+1}] + \mathbb{E}_t[\Delta s_{t+1}]}_{\text{Asset Return in Home Currency}} + \underbrace{f_t - \mathbb{E}_t[s_{t+1}]}_{\text{Forward Contract Return}} = \mathbb{E}_t[r_{i,t+1}] + f_t - s_t \end{aligned}$$

where $\mathbb{E}_t[r_{i,t+1}]$ represents the expected return of the foreign equity or bond index, s_t represents the log spot rate and f_t denotes the log forward rate. All exchange rates are denoted such that the base currency corresponds to the foreign currency and the quote currency corresponds to the domestic currency. The difference in return between the unhedged and hedged ETF equals the expected log currency excess from buying the dollar in the forward market and selling it in the spot market after one month against the foreign currency, defined as

$$\mathbb{E}_t[rx_{t+1}] = \mathbb{E}_t[s_{t+1}] - f_t = \underbrace{\mathbb{E}_t[\Delta s_{t+1}]}_{\text{Expected Spot Return}} - \underbrace{(f_t - s_t)}_{\text{Forward Premium}} \quad (2)$$

The expected currency excess return comprises the expected USD appreciation, $\mathbb{E}_t[\Delta s_{t+1}]$, and the forward premium, $f_t - s_t$. The forward premium represents the time- t known (deterministic) component of the expected excess return on the unhedged ETF and, under covered interest parity, equals the interest rate differential between the domestic and foreign (US) rate, $i^{dom} - i^* = f_t - s_t$. For investors hedging foreign denominated assets, the negative of this term ($s_t - f_t$) is often referred to as hedging cost, since empirically the domestic currency does not appreciate sufficiently to offset the negative interest differential between the domestic and foreign (US) interest rate.

The portfolio return and variance of a portfolio consisting of the two assets (unhedged and

hedged) are equal to

$$\begin{aligned}\mathbb{E}_t[r_{i,t+1}^p] &= \mathbb{E}_t[r_{i,t+1}] + w_{i,t} \mathbb{E}_t[\Delta s_{t+1}] + (1 - w_{i,t})(f_t - s_t) \\ \text{Var}_t[r_{i,t+1}^p] &= \text{Var}_t[r_{i,t+1}] + w_{i,t}^2 \text{Var}_t[\Delta s_{t+1}] + 2w_{i,t} \text{Cov}_t[r_{i,t+1}, \Delta s_{t+1}].\end{aligned}$$

where $\mathbb{E}_t[r_{i,t+1}^p]$ and $\text{Var}_t[r_{i,t+1}^p]$ denote the expected conditional (log) return and variance of a portfolio consisting of the hedged and unhedged ETF that both invest in the same foreign equity/bond index.

Sequential Optimization. The investor's optimal allocation to the unhedged index, $w_{i,t}$, versus the hedged index can be characterized by maximizing the following objective function

$$\max_{w_{i,t}} \mathbb{E}_{i,t}[r_{i,t+1}^p] - \frac{\gamma}{2} \text{Var}_{i,t}[r_{i,t+1}^p] \quad (3)$$

where γ is the level of risk aversion and $\mathbb{E}_{i,t}[\cdot]$ is the conditional subjective expectation of investor i . Crucially, and in contrast to the original model in [Anderson and Danthine \(1980, 1981\)](#), I allow investor-specific subjective beliefs about the first moment. Otherwise, the model follows the original model and assumes homogeneous beliefs about second moments and a common risk aversion parameter across investors. ⁶

The first-order condition of the (constrained) maximization problem in Eq. (3) for the optimal currency demand follows as

$$w_{i,t}^* = \underbrace{\frac{\mathbb{E}_{i,t}[\Delta s_{t+1}] - (f_t - s_t)}{\gamma \text{Var}_t[\Delta s_{t+1}]}}_{\text{Speculative term}} - \underbrace{\frac{\text{Cov}_t[r_{i,t+1}, \Delta s_{t+1}]}{\text{Var}_t[\Delta s_{t+1}]}}_{\text{Benchmark hedge}} \quad (4)$$

where $w_{i,t}^*$ is between zero and one. With zero value for the speculative term, full hedging ($w_{i,t}^* = 0$) is optimal when the correlation between exchange rates and local currency asset returns is zero, i.e., $\text{Cov}_t[r_{i,t+1}, \Delta s_{t+1}] = 0$, while zero hedging ($w_{i,t}^* = 1$) occurs when exchange rates and local currency asset returns are perfectly negatively correlated, i.e., $\text{Cov}_t[r_{i,t+1}, \Delta s_{t+1}] = -1$.

⁶In heterogeneous-beliefs models, it is standard to assume that agents can deduce volatility but must estimate the conditional mean (e.g., [Basak \(2005\)](#)) as mean returns are much harder to estimate than volatility ([Merton, 1980](#)), such that disagreement centers on the first moment. The baseline specification of [Egan et al. \(2022\)](#) likewise imposes common risk aversion and perceptions about risk. They also show that extending the model by allowing for heterogeneous risk aversion, or equivalently, for heterogeneous perceptions about second moments, yields qualitatively similar results.

Portfolio-implied Expectations. One of the paper’s key contribution is to recover investors’ exchange rate expectations from ETF holdings by inverting Eq. (4), using the observed portfolio weights, $w_{i,t}^{observed}$, as

$$\mathbb{E}_{i,t}^{PF}[rx_{t+1}] = \gamma(w_{i,t}^{observed} \mathbb{V}\text{ar}_t[\Delta s_{t+1}] + \mathbb{C}\text{ov}_t[r_{i,t+1}, \Delta s_{t+1}]). \quad (5)$$

The average portfolio-implied expectations are then equal to

$$\mathbb{E}_t^{PF}[rx_{t+1}] = \frac{1}{N_t} \sum_i^{N_t} \mathbb{E}_{i,t}^{PF}[rx_{t+1}] \quad (6)$$

and their dispersion, measured by the mean absolute deviation (MAD), is equal to

$$Disp_t^{PF} = \frac{1}{N_t} \sum_{i=1}^{N_t} |\mathbb{E}_{i,t}^{PF}[rx_{t+1}] - \mathbb{E}_t^{PF}[rx_{t+1}]| \quad (7)$$

where N_t equals the number of funds per time.⁷

Crucially, under homogeneous beliefs, we have

$$\mathbb{E}_t^{PF}[rx_{t+1}] = \mathbb{E}_{i,t}^{PF}[rx_{t+1}] \forall i \quad \text{and} \quad Disp_t^{PF} = 0 \quad (8)$$

where expectations are taken with respect to either the objective or a common subjective probability measure. Controlling for exchange rate volatility and the benchmark hedging term, the first-order condition in Eq. (4) then maps portfolio weights to a common expectation about exchange rates. Three such candidates for exchange rate expectations are given in the next section.

3.2 Common Estimates of Exchange Rate Expectations

This section introduces the three most prominent estimates for conditional currency excess return expectations from the literature. Estimates are given per currency area, c .

Survey Expectations. Building on the growing literature on subjective beliefs, which argues that objective return expectations differ from subjective return expectations, I construct expected

⁷I follow [Beber et al. \(2010\)](#) and define the dispersion using the *mean* absolute deviation rather than the *median* absolute deviation. The results in section 7 are robust to the alternative definition.

currency returns and excess returns from survey data, denoted as $\mathbb{E}_t^{survey}[rx_{c,t+1}]$. I compute the return using the estimate of expected future (one-month ahead) spot rates, $Spot_{c,t+1}^{survey}$. Formally,

$$\mathbb{E}_t^{survey}[rx_{c,t+1}] = \log(Spot_{c,t+1}^{survey}) - s_{c,t} - (f_{c,t} - s_{c,t}). \quad (9)$$

Macro Expectations. I construct conditional expected currency returns as in [Chernov et al. \(2023\)](#). They draw on prominent economic theories to derive their conditional expected currency excess returns. I refer to these expected currency returns as macro expectations, $\mathbb{E}_t^{macro}[rx_{c,t+1}]$. The macro expectations consist of three components. The first component is anchored in the random-walk hypothesis ([Meese and Rogoff, 1983](#)) that implies that expected currency excess returns are predictable using the forward discount: $s_{c,t} - f_{c,t}$, i.e., the carry factor. The second component is based on the purchasing power parity that implies that the real exchange rate (RER) is mean reverting in the long run and can thus be used to forecast movements in the nominal exchange rate ([Chernov and Creal, 2021](#); [Dahlquist and Pénasse, 2022](#)), akin to the value factor in the asset pricing literature. The mean-reversion component, z_{c,Q_t} , is built as the relative level of the current real exchange rate compared to its centered moving average from five years ago. The last component, the trend signal, builds on evidence from the forecasting literature that past returns predict future returns, echoing the momentum factor. Combining all three components, I compute the macro expectations as

$$\mathbb{E}_t^{macro}[rx_{c,t+1}] = \gamma_{c,t} \underbrace{(s_{c,t} - f_{c,t})}_{\text{Forward Discount}} + \delta_{c,t} \underbrace{z_{c,Q_t}}_{\text{RER}} + \phi_{c,t} \underbrace{(s_{c,t} - s_{c,t-12})}_{\text{Trend}}. \quad (10)$$

The regression is run month-by-month in an expanding window fashion. Following [Chernov et al. \(2023\)](#) I set $\gamma_{c,t} = 1$ to align with the random walk baseline; this choice has little impact on the results compared to leaving $\gamma_{c,t} = 1$ unrestricted. Details of the estimation technique are provided in Appendix [B.1](#), with coefficient estimates reported in Figure [B.1](#).

Factor Expectations. I construct expected currency returns based on the two most popular currency pricing factors, the dollar and carry factor ([Lustig et al., 2011](#)) and compute expected excess returns as in [Opie and Riddiough \(2020\)](#). The latter show that a hedging strategy that applies the mean-variance framework of the previous section with expected currency returns based on the

forecastable component of global factor returns can generate superior investment performance.

The key idea is that expected currency returns are determined using the linear beta pricing model

$$\mathbb{E}_t^{factor}[rx_{c,t+1}] = \lambda_t^{carry} \beta_{c,t}^{carry} + \lambda_t^{dollar} \beta_{c,t}^{dollar} \quad (11)$$

where λ_t^{carry} and λ_t^{dollar} are replaced by their expected components, $\mathbb{E}_t[\lambda_{t+1}^{carry}]$ and $\mathbb{E}_t[\lambda_{t+1}^{dollar}]$. These expected factor returns are the forecastable components of the risk premia, predicted using other variables that have been shown to successfully forecast factor returns. More precisely, in a first step, the factor loadings, $\beta_{c,t}$, are estimated by running a rolling OLS regression of excess returns on the dollar and carry factor using past data up to t . The dollar factor involves taking a long position in foreign currencies and a short position in the dollar, while the carry factor takes a long position in currencies with relatively high forward discounts and a short position in currencies with relatively low forward discounts. In a second step, the average forward discount, the foreign exchange volatility and the commodity index return are used to predict one-month ahead expected factor returns $\mathbb{E}_t[\lambda_{t+1}^{carry}]$ and $\mathbb{E}_t[\lambda_{t+1}^{dollar}]$. Combining the factor loadings and the expected factor returns yields what I refer to as *factor* expectations. Details of the estimation technique are provided in Appendix B.2, with coefficient estimates reported in Figure B.2.

Expected exchange rate returns, $\mathbb{E}_t[\Delta s_{c,t+1}]$, for all four estimates are then derived from expected excess returns by adding the forward premium (see Eq. (2)).

3.3 Covariance Estimation

I estimate conditional covariance matrices, Ω_t , from daily exchange rate changes and asset returns. For each fund i and currency c , I estimate the covariance matrix

$$\Sigma_{i,c,t} = \begin{bmatrix} \text{Var}_t[\Delta s_{c,t+1}] & \text{Cov}_t[\Delta s_{c,t+1}, r_{i,c,t+1}] \\ \text{Cov}_t[\Delta s_{c,t+1}, r_{i,c,t+1}] & \text{Var}_t[r_{i,c,t+1}] \end{bmatrix} \quad (12)$$

where the asset return $r_{i,c,t+1}$ corresponds to daily realized changes in net asset values of the unhedged ETF i , domiciled in currency area c and measured in local currency. The covariance is estimated over the preceding 25 trading days to arrive at monthly covariances for each day. I follow

Chernov et al. (2023) compute the exponential weighted average of the matrix using a decay factor of $\lambda = 0.94$. The conditional covariance matrix for month $t + 1$ is then equal to

$$\Omega_{i,c,t} = (1 - \lambda)\Sigma_{i,c,t} + \lambda\Omega_{i,c,t-1}. \quad (13)$$

I check whether the conditional variance is plausible and follow Chernov et al. (2023) by regressing the variance of realized currency excess returns on the estimated conditional variance.⁸ The variance of realized currency excess returns is constructed using the three different estimates of exchange rate expectations. Under the null hypothesis that the correct conditional means and variances are identified, the coefficient should equal unity. Results are reported in Table A.1. For the model-implied expectations (macro and factor) the coefficient is relatively close to one with macro expectations yielding a coefficient of 1.3. In contrast, the coefficient of survey expectations is 10 times larger, suggesting that the forecast error from surveys is much larger than the realized variance.

4 Data

4.1 Exchange-Traded Funds

I retrieve the universe of currently active and inactive ETFs from LSEG (formerly Refinitiv) Workspace’s Advanced Search. I restrict the sample to ETFs that invest in US equity and debt and are domiciled in one of six currency areas: the United Kingdom, the euro-area, Switzerland, Canada, Australia, and Japan. I keep only funds that have a currency-hedged and non-hedged share class. For example, my sample includes a Canada-domiciled ETF investing in the United States, such as the *BMO S&P 500 Hedged to CAD Index ETF*, along with its corresponding unhedged share class, the *BMO S&P 500 Index ETF*. For funds investing in a global index, the fund’s AUM is allocated proportionally across currencies based on its currency allocation. Only observations where the currency allocation exceeds 50% of the total AUM are retained, while smaller allocations are excluded.

The data for ETFs are more comprehensive and complete in Bloomberg, I thus rely on Bloomberg

⁸I add $(s_{c,t} - f_{c,t})^2$ to $\text{Var}_t[\Delta s_{c,t+1}]$ to get to $\text{Var}_t[rx_{c,t+1}]$.

for the underlying data of the ETFs. My sample covers 11 years starting in January 2014 until June 2025. ETFs have existed since early 2000 but currency-hedged funds have only begun holding significant assets under management since 2014. Panel A of Figure 1 plots the total assets under management (AUM) in billion USD for hedged and unhedged ETFs in blue and red, respectively, from 2014 to 2025. By the end of 2025, unhedged funds hold nearly five times the assets of currency-hedged funds, with totals reaching 600 billion USD for unhedged funds and 120 billion USD for currency-hedged funds.

I focus on investment by ETFs domiciled in six major non-US currency areas (EUR, GBP, CHF, CAD, JPY, AUD), investing in US equity and bond market, and thus having exposure to the USD. These ETFs make up the largest share of international currency-hedged ETFs, i.e., ETFs investing abroad and for which there exists a hedged counterpart to the unhedged ETFs. I also remove funds and observations for which assets under management are below USD 1 million. In total my sample covers 350 currency-hedged ETFs with their unhedged counterpart. For each fund-pair i domiciled in currency area c at time t , I calculate its weight in the unhedged index as

$$w_{i,c,t} = \frac{A_{i,c,t}^{unhedged}}{A_{i,c,t}^{unhedged} + A_{i,c,t}^{hedged}}. \quad (14)$$

where $A_{i,c,t}^{unhedged}$ and $A_{i,c,t}^{hedged}$ are the assets under management for the unhedged and hedged ETF in domestic currency, respectively.

Table 1, Panel A, reports summary statistics for the sample of funds, including assets under management, the weight in the unhedged index and the USD return of the hedged and unhedged ETF.

Additionally, I follow Curcuru et al. (2011) and define active flows into the unhedged ETF, $flow_{i,c,t}$, as the active change in the weight in USD as

$$flow_{i,c,t} = w_{i,c,t} - w_{i,c,t-1} \frac{1 + r_{i,c,t}^{unhedged}}{1 + r_{i,c,t}^p} \quad (15)$$

where $r_{i,c,t}^{unhedged}$ is the return of the unhedged ETF per currency and $r_{i,c,t}^p$ is the portfolio return of the unhedged and hedged ETF using weights $w_{i,c,t-1}$. As is standard practice in mutual fund flow analysis, I winsorize the flow distribution at the 1st and 99th percentiles. Furthermore, I define

aggregate flows per currency area as

$$flow_{c,t} = w_{c,t}^{agg} - w_{c,t-1}^{agg} \frac{1 + r_{c,t}^{unhedged}}{1 + r_{c,t}^p} \quad (16)$$

where returns are currency (AUM-weighted) averages across funds and aggregate weights, $w_{c,t}^{agg}$, are computed using currency-level aggregates of assets under management. Panel B of Figure 1 plots the average aggregate active flows over time.

4.1.1 Institutional Details of ETFs

Since this study analyzes holdings from ETFs, I provide a brief, self-contained ETF overview for context. I summarize the main concept here and refer to [Hill et al. \(2015\)](#) for details.

An exchange-traded fund is a pooled investment vehicle with shares that are traded throughout the day at stock exchanges in the secondary market at a price, P . This price stays close to the market value of the underlying securities, the net asset value, NAV , due to arbitrage by authorized participants (AP). APs are typically large financial institutions that have agreements with the ETF issuer. These agreements allow them to create and redeem ETF shares at the NAV at the end of each day in the primary market to arbitrage any difference between the NAV and the price of an ETF. The arbitrage process, when the ETF trades at a premium ($P > NAV$), is depicted in Figure A.2. The basic mechanism works as follows: (1) an AP buys the underlying securities of the ETF, (2) sells it to the ETF sponsor at the NAV in the primary market, receives the ETF shares, and (3) sells the ETF shares to the ETF investors in the secondary market at price P .

More precisely, the ETF sponsor publishes a daily creation basket, which details the specific securities and quantities that reflect the ETF’s target portfolio. The AP delivers this basket in-kind to the sponsor in order to receive a “creation unit” of ETF shares. Typically, one creation unit consists of a number of ETF shares that range between 25,000 to 200,000 shares. When the underlying securities are difficult and illiquid, the ETF may allow the AP, instead of in-kind delivery, to substitute cash or derivatives (total return swaps) for some or all of the assets in the creation basket. The value of the creation basket and any cash adjustment equals the value of the creation unit based on the ETF’s NAV at the end of the day on which the transaction was initiated. In practice, the ETF sponsor also charges a fee to the AP, which is higher when in-kind

delivery does not occur, to compensate for the transaction costs incurred when the sponsor has to purchase the underlying securities directly. Moreover, the AP does not need to sell all the shares, it can also hold some on its balance sheet. Per share sold in the secondary market the AP makes a profit of $P - NAV$. The increased supply of ETF shares puts downward pressure on the price of the ETF, so that the ETF trades again at a price close to the NAV . If the ETF trades at a discount to its NAV , the reverse arbitrage mechanism functions: the AP redeems ETF shares in the primary market in exchange for the underlying securities, which can then be sold in the asset market.

Importantly, the ETF fund flows present newly created or redeemed shares in the primary market. Unlike mutual funds, these flows do not represent end investors trading with the asset market. Instead, they represent APs transacting with the ETF sponsor to create or redeem ETF shares. However, as highlighted by [Converse et al. \(2023\)](#), when the ETF arbitrage mechanism functions effectively, the creation and redemption of shares directly mirrors the excess demand of end investors and can be interpreted as equivalent to investor dollar flows into or out of ETFs. If ETF arbitrage works well, the difference between NAV and the price (the mispricing) is small.

Mispricing is generally higher for my sample of international ETFs compared to a sample of domestic ETFs. This is due to the different trading hours between the ETF and the underlying assets. For example, an ETF trading at the Frankfurt Stock Exchange, that invests in US equity, trades at Frankfurt trading hours, while its underlying assets trade at US trading hours. The NAV of the ETF is thus stale for around 6.5 hours during Frankfurt trading hours, while the underlying assets of the ETF are still traded for 4.5 more hours when the Frankfurt exchange is already closed. This makes the arbitrage mechanism by APs more complicated and less efficient. In [Figure A.3](#) I plot the average relative percentage mispricing over time for hedged (red) and unhedged (blue) ETFs, respectively. The relative mispricing is defined as the difference between the last trading price of the ETF and the NAV divided by the NAV , i.e., $\epsilon = \frac{P_t - NAV_t}{NAV_t} \times 100$. The average mispricing is particularly pronounced during periods of market stress. For instance, at the onset of the COVID-19 crisis in March 2020, mispricing spikes to 3%. On average, hedged ETFs exhibit slightly higher mispricing than unhedged ETFs, with mean values of 0.036% and 0.019%, respectively. These figures are similar to those reported by [Petajisto \(2017\)](#), who document an average mispricing of 0.06% for all US-listed ETFs and 1 to 2% for the sample of US-listed international ETFs over the

period 2007-2014.

In the context of my study, it is important to verify that differences in flows between hedged and unhedged ETFs coming from AP activity are driven by investor demand rather than by supply-side constraints of APs. In other words, the willingness of APs to arbitrage the hedged ETF versus the unhedged ETF must be the same. The only difference between the constituents of the creation basket of a hedged and unhedged ETF is the forward contract, which the AP delivers in cash. Thus, the liquidity of the hedged and unhedged creation basket is essentially the same. Liquidity constraints of APs typically arise in highly volatile times. Thus, especially for these times, it is necessary to ensure that the mispricing of hedged and unhedged ETFs does not differ systematically. To check how mispricing between hedged and unhedged ETFs differs, in Table A.2 I report the results of regressing the hedged ETF premium/discount against the premium/discount of the unhedged ETF, where a premium is defined as $\epsilon > 0$ and a discount defined as $\epsilon < 0$. Column (1) and (4) show a clear positive relationship between the mispricing of the two ETFs. Importantly, this correlation increases when the VIX increases as documented in Column (3) and (6) where I add the VIX (as a proxy for liquidity constraints as in [Pan and Zeng \(2017\)](#)) and the interaction term. Thus, when constraints of APs are more likely to bind, the mispricing of hedged and unhedged ETFs comove even stronger. In less constraint times, the comovement is weaker and potentially driven by other demand-side factors. This provides evidence that investors' demand is transmitted to an AP's activity similarly for both types of ETFs, suggesting that the currency hedge of an ETF does not matter for an AP's willingness to arbitrage mispricing and that flows can be interpreted as investor demand.

4.2 Exchange Rate Prices and Expectations

Exchange rates for six currencies EUR, CAD, CHF, JPY, AUD, GBP against USD are sourced from Bloomberg. I use spot and 1-month forward rates and compute excess returns as defined in Eq. (2). I also obtain 1-month option-implied FX volatility. I compute the 1-month cross-currency basis using the Overnight Indexed Swaps (OIS) rate and construct the basis by closely following the currency derivative conventions outlined in [Du et al. \(2018\)](#). For the monthly sample, I use end-of-month observations.

Survey expectations for one-month future spot rates are obtained from Consensus Economics

(CE). The surveys are typically collected on the second Wednesday of each month. Accordingly, I align the monthly sample to each survey’s collection date. Data are available through August 2024.

Portfolio-implied expectations are computed according to Eq. (5), using conditional variance-covariance estimates and setting the risk aversion parameter to three as in other studies (e.g., [Opie and Riddiough \(2020\)](#)). Additionally, it is important to account for the fact that changes in expectations can arise solely from valuation effects. Specifically, portfolio-implied expectations based on the weight may shift over time due to exchange rate fluctuations, even in the absence of any in- or outflows. To address this, I compute a flow-only version of the weight using active flows into the unhedged ETF share class:

$$w_{i,c,t}^{flow} = w_{i,c,t-1} + flow_{i,c,t} \quad (17)$$

which I then use in the computation of $\mathbb{E}_{i,t}^{PF}[rx_{c,t+1}]$.⁹

In Table 1, Panel D, I report the average expected currency excess return for all four estimates. Notably, survey and factor expectations are much larger in scale. For example, portfolio-implied and macro expectations average +3 bp and −3 bp, respectively, with a s.d. of roughly 12 bp, while survey expectations average 19 bp with a s.d. of 162 bp. However, note that portfolio-implied expectations scale with the risk-aversion parameter and a higher value (e.g., $\gamma = 30$) would bring its magnitude closer to survey estimates. Figure 2 plots the four different estimates of expected currency excess returns over time averaged across all currency pairs in basis points, dividing survey and factor expectations by 10 for comparability. The four estimates of currency expectations feature some similar trends. For example, all exchange rate expectations drop in March 2020 during the onset of COVID-19. Quantitatively, in March 2020, the average ETF investor expected an annualized currency risk premium on the USD basket of about −4% ($= 12 \times 33$ bp).

5 Observed and Optimal Mean-Variance Currency Demand

While expectations derived from surveys or constructed from rational expectations models such as macro- or factor-based forecasts are widely used in the literature, it is not clear whether these

⁹Theoretically, the difference between w_t^{flow} and w_t is important, however, empirically, this difference is very small and amounts on average only to 1.14 basis points. Also, note that the value of the risk aversion parameter is merely a scaling factor in Eq. (5) and does not change the results qualitatively.

benchmarks correspond to investors' revealed currency demand. The theory of optimal currency demand provides a framework to test this link, as it specifies how expected returns and second moments map into observed portfolio holdings.

In Table 2 I present results of regressing monthly USD holdings, $w_{i,c,t}$, on the optimal currency demand components: the expected exchange rate change, $\mathbb{E}_t[\Delta s_{c,t+1}]$, the forward premium, $f_{c,t} - s_{c,t}$, and the covariance of real asset returns with exchange rates, $\text{Cov}_t[r_{i,c,t+1}, \Delta s_{c,t+1}]$. All terms are scaled by the exchange rate volatility, $\text{Var}_t[\Delta s_{c,t+1}]$. The regression is run separately for each of the three exchange rate expectations measures: survey, macro, factor. Moreover, I report the results for equity and debt funds in panels A and B, respectively, since hedging practices of equity and debt funds are found to differ considerably (Bräuer and Hau, 2024; Greenwood and Cheema-Fox, 2024).¹⁰ I first run the regression without any fixed effects, the baseline model, and show results in Column (1)-(3). The baseline model matches the data extremely well for equity and debt funds with an R^2 ranging between 51% and 56%. All components of optimal currency hedging yield the sign predicted by theory and all estimates of expected currency returns correlate highly significantly with currency demand in the baseline model. Specifically, a one standard deviation increase in (variance-adjusted) expected spot returns implied by surveys is associated with a 0.23 ($= 0.002 \times \frac{32.6}{0.28}$) standard deviation, or 6.5 percentage points, increase in investors' dollar share. The response to macro and factor expectations is slightly stronger and amounts to a 0.37 ($= 0.052 \times \frac{2}{0.28}$) and 0.33 ($= 0.003 \times \frac{31.5}{0.28}$) standard deviation increase in investors' dollar share, respectively. The estimated sensitivity of portfolio shares to beliefs is comparable to investor-level evidence in the equity market: Giglio et al. (2021) find that a one standard deviation increase in expected one-year stock returns increases the equity share by 0.16 standard deviations.¹¹

Consistent with theory, the forward premium enters the regression with a significantly negative coefficient for both asset classes. The size of the effect is also substantial in economic terms. Specifically, a one standard deviation increase in the forward premium comes with a 1.2 ($= 0.1 \times \frac{3.36}{0.28}$)

¹⁰Survey data is only available through August 2024. However, the results for the macro and factor expectations presented in Table 2 remain robust when the samples are truncated at the same endpoint.

¹¹Compared to Giglio et al. (2021), my main specification regresses the USD share on *variance-adjusted* expected exchange rate changes, which limits one-to-one comparability. In Appendix A.3 I replicate their specification in Eq. (1) and regress the USD share on expected spot rate changes only. Among the high statistically significant coefficients, the estimated sensitivity of USD allocations to beliefs shows that a one standard deviation increase in expected returns is associated with a 0.08 to 0.27 standard deviation increase in the USD share. Thus, using their regression specifications, the estimated sensitivity also closely matches the baseline specification of Table 2 and falls within the range reported by Giglio et al. (2021).

standard deviation decrease in investors' dollar share. Higher hedging costs (the negative of the forward premium) thus decrease USD-hedging and increase USD holdings substantially.

According to theory, the benchmark coefficient should be equal to one. Empirically, this holds more closely for debt funds than for equity funds: the estimated coefficient ranges from 0.31 for equity funds to 0.46 for debt funds. This is in line with [Bräuer and Hau \(2024\)](#) who also find a smaller coefficient for the benchmark hedge for equity funds compared to fixed-income funds. With zero speculation on future currency returns, the benchmark coefficient between 0.31 and 0.46 implies an average weight in the unhedged index between 15% ($= -0.47 \times -0.31$) and 22% ($= -0.47 \times -0.46$).

Columns (4)–(6) add time fixed effects, yielding a key result: only survey-based expectations remain statistically significant for both investor groups; macro- and factor-based measures do not. For equity investors, the forward premium remains highly significant. The result also shows that across funds the covariance term is irrelevant to both investor groups.

Columns (7) to (9) examine the relationship between observed and optimal currency demand within individual funds by adding fund fixed effects. The results show that equity investors respond only to changes in fund-specific covariances and do not speculate on expected currency returns. In contrast to theoretical predictions, the forward premium enters with a positive coefficient, but the effect is weak and only marginally significant at the 10% level. For debt fund investors none of the components of optimal currency exposure matter to their allocation of the unhedged and hedged share classes within a given fund.

In the Appendix I show results for two alternative specifications of the regression. First, I combine the expected spot change with the forward premium into the excess return and re-estimate the regression in order to obtain an estimate for the risk aversion parameter. Specifically, in the model of optimal currency demand, the estimated coefficient of the expected currency excess return equals the inverse of the risk-aversion parameter. Table [A.4](#) shows that macro expectations imply a risk-aversion parameter of ≈ 13.8 for equity investors and ≈ 15.6 for debt fund investors. These estimates are relatively close to estimates of the risk aversion parameter documented in the literature, which typically range from 3 to 10. In contrast, survey expectations imply a much higher risk aversion parameter of more than 300. This finding aligns with [Giglio et al. \(2021\)](#) who also find a higher risk aversion parameter using survey data of equity investors (of 36), compared to

usual estimates. Excess returns based on factor expectations yield a similarly high risk aversion parameter but are not significant in explaining USD allocations at conventional significance levels.

Second, in Table A.5, I run the regression at the currency level by aggregating the weights (AUMs) per currency. That is, instead of applying the theory at the fund-level, we can alternatively think of one representative agent per currency area that solves for the optimal currency demand. The results are very similar to the fund-level regression for the baseline model, with some interesting differences. In the baseline model, only survey expectations yield a significant coefficient, while the other two expectations estimates are only weakly significant. However, macro expectations turn significant for equity funds once controlling for average time effects in Column (5). At the currency level, aggregate investors demand more dollars in currency areas with a positive (less negative) covariance in Colum (4) to (6), which is in contrast to the fund-level regression. A possible explanation is measurement error in the covariance matrix at the aggregate level. An aggregate investor potentially holds the full portfolio of currencies. Consequently, portfolio risk depends on the entire FX covariance matrix, including cross-currency correlations, rather than the covariance of a single currency with the asset return. Consistent with this, Bräuer and Hau (2024) demonstrate that optimal hedging based on the full FX covariance structure yields substantially lower risk than hedging strategies that consider each currency in isolation.

In Figure 3, I visualize the cross-sectional relationship between USD holdings and expectations at the currency level. It plots the average weight in the unhedged ETF on the vertical axis against three estimates of the (variance-adjusted) expected excess returns (Panel A-C) per currency for equity funds (left column) and debt funds (right column), respectively. All variables are scaled by the inverse of the exchange rate variance and the benchmark hedge is subtracted as in Eq. (4). Panel A, using survey expectations, confirms prior regression-based evidence for a strong economic link between survey estimates for exchange rate expectations and the weight in the unhedged index. The correlation between the two variables across funds and time is positive and significant and amounts to 97% for equity and 98% bond funds. For example, while Swiss investors held their investment in the US almost completely unhedged, Japanese investors hedged more than half of their US investment, which aligns with higher survey expectations for currency excess returns on the USD against the CHF compared to the JPY. The correlation between return expectations and currency demand is lower for macro expectations with 60% or 76% for equity and debt funds,

respectively, while factor expectations are only weakly correlated and negative, around -8% .¹²

Taken together, the analysis highlights the following findings: Expected currency excess returns are only relevant in the cross-section of funds and currency areas, with survey expectations capturing best currency (USD) holdings. Time-variation in the estimates of currency expectations obtained from surveys or proposed by the literature does not determine investors' USD demand. Hedging costs, captured by the forward premium, play an especially important role for equity investors. Equity investors also tilt their currency positions with the FX-asset covariance, however, the direction of its effect is ambiguous and depends on the regression specification (fund versus currency-level). Abstracting from heterogeneity across funds, currencies, and time, the model of optimal currency demand explains in the baseline model the overall patterns in observed currency demand remarkably well.

5.1 Heterogeneity among ETFs

This section explores whether the currency demand of investors depends on some characteristics of ETFs. Specifically, I perform the previous baseline regression for each fund separately and sort the coefficients on the expected currency excess return, the forward premium and the benchmark hedge in quartiles of fund characteristics. In this section, I focus exclusively on survey expectations, i.e., $\mathbb{E}_t^{survey}[r_{c,t+1}]$, as the previous section found this estimate to be most statistically significant.

I sort the ETFs based on four characteristics: size, relative expense ratio, institutional investor share and hedging strategy. Summary statistics for the four characteristics are reported in Panel C of Table 1. The first characteristic is the log size which is the log of the sum of the hedged and unhedged assets under management. The second characteristic is the relative or net expense ratio that captures potential cost consideration when investors switch between the two ETFs. It is the difference between the expense ratio of the unhedged ETF and the hedged ETF, so that a lower ratio indicates a relatively costlier hedged product. On average, the hedged share class is 2.6 basis points more expensive than the unhedged share class, reflecting hedging costs associated with forward trading. The upper quartile of funds has a zero net expense ratio, with the hedged share class as expensive as the unhedged share class. The third characteristic is the institutional investor

¹²Note that the figure is virtually identical when using only expected exchange rate changes on the horizontal axis, i.e., without variance scaling and without subtracting the forward premium and the benchmark hedging term.

share, which captures the average (across time and share class) proportion of shares outstanding held by institutional investors for a given ETF-pair. Institutional investors typically own about one-quarter of the shares outstanding in most funds, with the average institutional share being 23% and the median at 17%. The last characteristic is the hedging strategy, which measures how much a fund's hedging strategy deviates from a naive hedging strategy that rolls over one-month forward contracts at the end of each month. Specifically, I take for each fund the one-month return difference between the unhedged and hedged share class and subtract the one-month realized excess return,

$$\Delta_{i,c,t}^{strategy} = \underbrace{r_{i,c,t}^{unhedged} - r_{i,c,t}^{hedged}}_{\text{return difference}} - \underbrace{(s_{c,t} - f_{c,t-1})}_{\text{realized excess return}} . \quad (18)$$

If a fund can trade the forward and spot rate at the mid rate and rolls over its forward contract at the end of the month, the deviation is equal to zero, $\Delta_{i,c,t}^{strategy} = 0$. Vice versa, the difference is non-zero if the fund incurs transaction costs or it itself optimizes the hedging, i.e., deviates from a naive end-of-month roll-over strategy, and strategically times its forward transaction. A positive (negative) difference indicates that a fund outperforms (underperforms) a naive hedging strategy with zero transaction costs. Table 1 shows that the average deviation is positive, $\Delta_{i,c,t}^{strategy} > 0$, and amounts to 4.4 basis points. Thus, on average funds' strategic timing more than compensates for transaction costs, resulting in a net gain relative to a naive hedge. For reference, the average quoted bid-ask spread on a one-month outright EUR/USD forward contract is about 3.1 basis points over the sample period 2014-2024.

Figure 4 presents results of the fund-level regression. The average of the estimated coefficient for the expected currency excess return in Column (1), the forward premium in Column (2) and the benchmark hedge in Column (3) per quartile. Column (1) shows that survey expectations are positively correlated with currency demand for larger funds (quartile 3 and 4), while they are negatively correlated for very small funds (quartile 1). Thus, survey expectations are most clearly reflected in the currency holdings of large funds. Funds with a relatively cheap hedged product (with a net expense ratio > 0) or a relatively expensive hedged product (with a net expense ratio < 2 bp) take positions most consistent with survey expectations. Conversely, funds with an average expensive hedged product do not load significantly on survey expectations. Furthermore, speculation based on survey expectations tends to be concentrated in funds with a relatively low

share of institutional investors (below 34%) and with medium hedging strategy profits (quartiles 2 and 3 with $-1.8 < \Delta_{i,c,t}^{strategy} < 5.5$).

Column (2) shows that the forward premium coefficient is stable and negative across characteristics: estimates are statistically indistinguishable across quartiles, with no evidence of heterogeneity. Thus, hedging costs play an important role for all types of investors and funds.

Column (3) presents the coefficient on the benchmark hedge. A coefficient that deviates further from -1 indicates that investors do not fully align their currency allocation with an optimal mean-variance strategy. Across characteristics, the coefficient averages about -0.4 and is slightly less negative (further away from the optimal hedge) for small funds, for funds with a low institutional ownership share, and funds with high hedging-strategy profits.

The heterogeneity analysis shows that benchmark hedging and forward-premium sensitivity are broadly similar across funds, whereas speculative behavior varies significantly across funds and drives the largest cross-sectional differences. This suggests that, when I study belief dispersions in portfolio-implied expectations later, those primarily reflect differences in speculative activity rather than benchmark hedging or cost sensitivity.

6 Predictability of Exchange Rate Expectations

The finding that agents' aggregate portfolios correlate with common expectation estimates only cross-sectionally, raises the question of what their actual time-varying expectations are, and what properties these portfolio-implied expectations exhibit. In particular, whether portfolio-implied expectations predict future returns, that is, whether they are rational, and how their predictive power compares to the other expectation estimates.

I therefore conduct a horse race across survey, macro, factor, and portfolio-implied expectations to assess their predictive content for future exchange rate movements. Formally, I test the forecasting power of each estimate with the following panel regression

$$rx_{c,t+1} = \alpha_t + \beta_1 \mathbb{E}_t[rx_{c,t+1}] + \beta_2(f_{c,t} - s_{c,t}) + \epsilon_{c,t} \quad (19)$$

where $rx_{c,t+1}$ are one-month realized currency excess returns, $\mathbb{E}_t[rx_{c,t+1}]$ is one of the four expecta-

tion estimates, $f_{c,t} - s_{c,t}$ is the one-month forward premium and α_t are time fixed effects. I remove currency-specific levels of expected excess returns by subtracting a within-currency trailing mean (based on data up to t) to avoid look-ahead bias.

According to the uncovered interest rate parity, the coefficient for the forward premium, β_2 , should equal zero. I also run regressions using the one-month realized exchange rate returns Δs_{t+1} as the dependent variable, in which β_2 should equal one.¹³

Table 3 reports the results. In Column (1) and (5) I report results for the advocated portfolio-implied return expectation, $\mathbb{E}_t^{PF}[rx_{c,t+1}]$, in Column (2) and (6) I use monthly survey expectations, $\mathbb{E}_t^{survey}[rx_{c,t+1}]$, in Column (3) and (7) macro expectations and Column (4) and (8) factor expectations. Portfolio-implied expectations can predict future monthly dollar excess returns with a highly significant coefficient of 1.12.¹⁴ In contrast, survey expectations cannot significantly predict future currency returns. Macro and factor expectations can also not significantly forecast future returns. In line with existing literature, the forward premium yields a non-zero coefficient in Column (1)-(4) and a coefficient that is not equal to one in Column (5)-(8), however, both not statistically significant.

It is important to note that the predictive power of the other three estimates increases when evaluated over a longer time period or at a different time horizon. Specifically, Chernov et al. (2023) show that their return expectation forecasts returns in the period from 1985-2020. Similarly, Kremens et al. (2025) find that survey-based expectations of currency returns can successfully predict realized currency appreciations at the two-year horizon. Generally, a shared predictive power of survey-based and portfolio-implied expectations is consistent with a common priced risk channel: Kremens et al. (2025) show that surveys are to a large extent explained by the covariance between the equity market and the (real) exchange rate, which is also a key ingredient for the construction of portfolio-implied expectations of equity ETFs.

As a robustness check for the advocated portfolio-implied expectations, I alternatively construct expectations based on representative equity and bond index returns. More precisely, in Eq. (5) the

¹³To assess rationality, in-sample predictive regressions are the right econometric specification. In rational expectation models, agents know the underlying data-generating process and its parameters (and do not, e.g., learn) so the econometrician's in-sample estimates approximate as close as possible the knowledge (parameters) held by rational investors.

¹⁴In unreported regressions, I find that daily portfolio-implied expectations also forecast future one-day ahead currency appreciations with a t -statistics of 2.081.

ETF-specific covariance matrices are replaced by covariance matrices from returns on a portfolio of the S&P aggregate sovereign bond index and the MSCI equity index, with an equity weight of 0.43 reflecting the fraction of equity ETF in the sample relative to debt ETFs. The results, not reported, show no statistically significant predictive power (t -statistic of 1.39) for these index-based expectations.

6.1 Do Portfolio-implied Expectations Add Information Beyond Flows?

Portfolio-implied expectations consist of three components: a weight in the unhedged ETF, a variance term and a covariance term. The weight in the unhedged ETF can further be decomposed into the active flows into the unhedged ETF (defined in Eq. (16)) and prior period’s weight. Formally, recall that

$$\begin{aligned}\mathbb{E}_t^{PF}[rx_{c,t+1}] &= \gamma \underbrace{w_{c,t}^{flow}}_{= w_{c,t-1} + flow_{c,t}} \text{Var}_t[\Delta s_{c,t+1}] + \gamma \text{Cov}_t[r_{c,t+1}, \Delta s_{c,t+1}]. \\ &= w_{c,t-1} + flow_{c,t}\end{aligned}$$

This section tests the predictive content of each component of the portfolio-implied expectation to determine whether predictability is driven by a single component or by their combination.

Columns (1)-(3), Table 4, show the results of regressing realized one-month currency excess returns on each of the components of portfolio-implied expectations separately. None of the components are significant on their own. Notably, however, once the weight is decomposed into its two components, Column (4) shows that monthly flows can significantly predict subsequent exchange rate excess returns. Specifically, a one standard deviation increase in active USD flows predicts a positive USD excess return of 13 basis points ($= 0.09 \times 0.014$). This estimate is similar in magnitude to the findings of Engel and Wu (2023). They show that a one standard deviation decrease in the US term spread, the only significant predictor in the in-sample monthly regressions, predicts an 18.3-basis-point appreciation of the USD. Furthermore, a back-of-the-envelope calculation suggests that a one standard deviation of active flows corresponds to USD 38 million in 2024.¹⁵ In contrast to flows, past weights have no predictive power for future returns. However, in the monthly sample, flows do not outperform the forecasting power of portfolio-implied expectations as shown in Column

¹⁵ Average assets under management in 2024 of hedged and unhedged ETFs correspond to USD 2.7 billion, multiplied by one standard deviation of active flows this yields USD 38 million.

(5), Table 4. When entered jointly, both variables are significant, but flows are only significant at the 10% level.

I further compare the predictive power of flows and portfolio-implied expectations across different forecasting horizons, using realized excess returns, $rx_{c,t+1}^k$, over $k \in \{1, 3, 12\}$ months. For example, for $k = 3$, the realized excess return is calculated as the difference between the (log) spot rate three months ahead and the (log) three-month forward rate observed at time t . To expand the sample size, I use daily data, constructing flow measures as one-month rolling averages of past flows. Standard errors are obtained via a moving-block bootstrap with block length set to 22, 66, and 264 for $k = 1, 3, 12$, respectively, to account for overlapping returns. Significance is based on bootstrap p-values. Table 5 presents the regression results for one-month returns in Panel A, three-month returns in Panel B, and twelve-month returns in Panel C.

For the one-month horizon (Panel A), the evidence echoes the finding of the monthly sample. Portfolio-implied expectations possess stronger predictive information than flows, but when both predictors are included, each remain statistically significant. At the three-month horizon (Panel B), overall predictability weakens, with portfolio-implied expectations being significant at the 10% level. In contrast, flows and portfolio-implied expectations both exhibit strong predictive power for twelve-month excess returns (Panel C). This pattern mirrors survey-based exchange rate expectations that also feature improved predictive power at longer horizons (Kremens et al., 2025).

In sum, flows provide a close proxy for portfolio-implied expectations. Nevertheless, the theory-guided portfolio-implied expectations contain incremental and stronger predictive information beyond flows.

In Appendix C I additionally compare several monthly trading strategies, including three built on the signal obtained from ETF portfolio-implied expectations or ETF active flows and traditional strategies such as the carry, dollar or momentum strategy. Over the period 2014-2025 the strategies based on ETF signals deliver the highest Sharpe ratios (up to 0.58), whereas the traditional strategies reach at most 0.24. This pattern suggests that signals based on ETF allocations (hedged vs. unhedged) contain incremental information about currency risk premia beyond traditional predictors.

7 Dispersion of Exchange Rate Beliefs

The unique feature of portfolio-implied expectations compared to most other estimates of exchange rate expectations is that they provide a cross-section of individual investor beliefs for each currency. This allows me to extract information about the dispersion of investor expectations, which may arise from differences in currency demand, $w_{i,c,t}$, and/or covariances, $\text{Cov}_{i,c,t}[r_{t+1}, \Delta s_{c,t+1}]$, (see Eq. (5), where both terms are fund-specific). Figure 5 visualizes the distribution of individual expectations, $\mathbb{E}_{i,t}^{PF}[rx_{c,t+1}]$ by currency, with each dot representing a fund-day observation. The figure documents substantial heterogeneity of exchange rate expectations across investors, which is in line with prior studies by MacDonald and Marsh (1996); Chionis and MacDonald (2002). The dispersion of expectations increases notably during periods of heightened market volatility, most prominently in March 2020 at the onset of the COVID-19 crisis and again in April 2025 following the announcement of US tariffs. Currency-specific spikes in dispersion are also evident around major shocks such as the third phase of the euro-area sovereign debt crisis in July 2015, the Brexit referendum in June 2016 or the Swiss National Bank’s decision to unpeg the Swiss franc from the euro in January 2015.

These patterns suggest a strong link between dispersion in beliefs and exchange rate volatility. Such a link can be rationalized by a simple consumption-based asset pricing model under heterogeneous beliefs. Specifically, in Appendix D I show that with heterogeneous beliefs, the standard stochastic discount factor (SDF) is augmented by a belief component which is a wealth-weighted average of how each investor tilts probabilities relative to a reference probability, e.g., the average belief.¹⁶ Holding the reference probability measure fixed, greater dispersion among beliefs thus increases the volatility of the SDF.¹⁷

State contingent equilibrium consumption shares can further amplify the volatility of the SDF as derived in Buraschi and Jiltsov (2006); Buraschi et al. (2014). They show that when investors can trade state contingent risk-sharing contracts (options), the optimistic investor insures the pessimistic investor in bad states of the world, such that the pessimist’s relative consumption share is

¹⁶The form of the SDF is similar to the one of Dumas et al. (2009, 2017) who develop a general equilibrium model with two groups of investors that hold different beliefs about the state of the economy. In these models heterogeneity arises because one group of investors overreacts to a public signal or because one group misinterpret the public signals of others. I abstract from the underlying reasons for differences in investors’ beliefs.

¹⁷Empirically, I hold the reference probability fixed by computing the mean absolute deviation which centers individual expectations around the average belief per time t .

higher in those states. The optimist earns a premium on these contracts that increases with the degree of heterogeneity in beliefs. As option-implied volatility is derived from the market price of these contracts, it also increases with the degree of belief dispersion. Thus, the model also predicts a strong correlation between differences in beliefs and (expected) exchange rate volatility.

The link between exchange rate volatility and disagreement is particularly salient in Figure 6. The figure plots the mean absolute deviation of the portfolio-implied expectations, defined in Eq. (7), (solid blue line) against the option-implied one-month FX volatility (red dashed line). The correlation between these two series is remarkably high, ranging from 47% (GBP) to 63% (JPY), suggesting that higher dispersion in expectations is systematically associated with higher exchange rate volatility. In Appendix Figure A.4, I present the daily dispersion of portfolio-implied expectations, calculated across all funds and currency areas. The disagreement measure exhibits an even stronger correlation with average FX volatility amounting to 71%.

To formally evaluate the link, I run monthly panel regressions of option-implied FX volatility on the mean absolute deviation of portfolio-implied expectations. Formally,

$$IVol_{c,t} = \alpha_t + \alpha_c + \beta_1 Disp_{c,t}^{PF} + \beta_2 IVol_{c,t-1} + \epsilon_{c,t} \quad (20)$$

where $IVol_{c,t}$ is the one-month option-implied FX volatility and $Disp_{c,t}^{PF}$ denotes the mean absolute deviation of portfolio-implied expectations, and α_t and α_c represent time and currency fixed effects, respectively. I also add the one-month lag of implied volatility $IVol_{c,t-1}$ to account for its persistence. I use a log-log specification to stabilize variance and scale across currencies.¹⁸ In Table 6 reports the results. In Column (1) and (2) I estimate the regression in levels, in Column (3) and (4), I run the regression using log differences, in Column (5) and (6) I run a predictive regression with lagged dispersion. In all specifications, I include both currency and time fixed effects.¹⁹

The results mirror the visual evidence from the previous figure: dispersion in portfolio-implied

¹⁸Since only one fund is available for AUD until 2015, the sample for this currency begins in 2015. For all other observations, the variables $Disp_{c,t}^{PF}$ and $IVol_{c,t}$ are strictly positive and taking logs is feasible. The results remain qualitatively unchanged when the regression is estimated in levels rather than logs. Note also that the results are robust when restricting the sample to observations with an above-average number of funds per currency-month, i.e., when $N_{c,t} > 27$.

¹⁹Note that the dynamic panel bias (Nickell, 1981) from including the lagged volatility with fixed effects that affects $\hat{\beta}_2$ is negligible. Using $T = 132$ implies a bias of about -0.013 on the persistence coefficient, raising $\hat{\beta}_2$ in Column (2) from 0.663 to 0.675 after correction. Alternatively, when I exclude time fixed effects in the first-difference specification (Columns 3–4), the results are qualitatively unchanged: coefficient magnitudes shift only modestly, signs are preserved, and statistical significance is unchanged.

expectations is strongly and positively associated with expected future exchange rate volatility, even after controlling for lagged volatility and time and currency specific variations. The point estimate in Column (1) implies that a one-standard deviation increase of dispersion raises the exchange rate volatility by roughly 0.122 points ($= 0.135 \times 0.9$), which is about half its standard deviation, indicating a economically sizable effect. Approximately 27% of the exchange rate volatility is explained by the dispersion of expectations alone.²⁰ Column (2) shows that the dispersion coefficient remains positive and significant at the 1% level when including lagged volatility. Estimating the specification in first differences (Columns (3) and (4)) still yields a statistically significant coefficient for dispersion, though the t -statistics decline to 2.75 and 3.49, respectively.

The explanatory power of differences in beliefs from portfolio-implied expectations for option-implied FX volatility is comparable to that of survey-based measures. In particular, [Beber et al. \(2010\)](#) use mean absolute deviations in survey forecasts to measure differences in beliefs between May 1993 to December 2006 for the currency pairs JPY, EUR and GBP against USD. In their most parsimonious regression (Table 5) difference in survey expectations explain on average 45% of the variance of the one-month option-implied volatility. In my sample, time-series regressions for the three currency pairs yield similar R^2 values, averaging 40%, with the GBP showing the lowest explanatory power as in [Beber et al. \(2010\)](#).

Columns (5)–(6) show that dispersion also predicts future implied volatility. On its own, dispersion strongly predicts future volatility (t -statistics of 4.3) and explains 19% of future volatility. Adding lagged volatility preserves a positive, significant coefficient, though the t -statistics falls to 2.42.

Overall, heterogeneity in beliefs inferred from portfolio holdings explains a significant share of exchange rate volatility. The explanatory power of 27% is comparable to that of order flow variables or macroeconomic variables: For order flows, [Evans and Lyons \(2002\)](#) document an R^2 between 40 and 67%, while for macro variables [Stavrakeva and Tang \(2025\)](#) document an R^2 of 23 – 37% and [Kojen and Yogo \(2020\)](#) attribute roughly 26% of exchange rate variations to macro variables.

²⁰Following [Beber et al. \(2010\)](#), the main regression employs implied volatility. Replacing FX option-implied volatility with realized monthly volatility increases the R^2 in Column (1) to 37%. Note that implied volatility correlates with realized volatility at 80%.

8 Conclusion

Survey-based exchange rate expectations are informative about aggregate investors' portfolio decisions and remain a defensible input for model calibration and asset pricing tests. Using the relative allocation decision of investors into hedged and unhedged ETFs, I find that investors' USD currency demand is strongly linked to survey-based expectations in the cross-section of currencies, unlike expectations derived from macroeconomic models or asset pricing factors. However, time-series variation in currency demand shows little sensitivity to common estimates of exchange rate expectations, leaving open what investors' actual time-varying expectations are.

I propose a simple and tractable method to recover exchange rate expectations directly from investors' currency positions. This approach yields a daily indicator of average expectations and disagreement about future exchange rates. Empirically, these portfolio-implied expectations are more accurate in predicting returns compared to other expectations estimates. They also capture cross-sectional dispersion in expectations, which comoves strongly with FX volatility, suggesting that disagreement across agents contributes to exchange rate fluctuations.

Applications for portfolio-implied expectations are straightforward. For policy makers, portfolio-implied expectations provide daily gauge of investors' sentiment about future currency returns. Specifically, they help assess how closely expectations align with planned policy actions, how quickly policy is transmitted to investors, and the extent to which a policy decision reduces or amplifies investor disagreement. Thus, expectations derived from holdings offer a promising alternative to survey-, macro- or factor-based measures for calibration, monitoring, and policy evaluation.

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Table 1: Summary Statistics

Panel A reports assets under management for hedged and unhedged ETFs, the weight in the unhedged index, and the index returns of hedged and unhedged ETFs. Panel B reports three different expected currency returns, along with the forward premium and the covariance between asset and currency returns all scaled by exchange rate volatility. Panel C reports the fund characteristics: the average log of assets under management, the difference between the expense ratio of the unhedged versus the hedged ETF, the share of number of shares held by institutional investors and the hedging strategy. Panel D (next page) reports aggregates per currency area for portfolio-implied expectations, survey expectations, macro expectations, factor expectations, currency excess returns, exchange rate changes, the one-month forward premium, active flows, dispersion in expectations and one-month option-implied FX volatility. For readability all variables in Panel D are multiplied by 100. The sample period spans from January 2014 to June 2025.

	Obs.	Mean	Std	Min	25%	50%	75%	Max
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Fund Sample								
$A_{i,t}^{hedged}$ (mil USD)	350	197	516	1	12	53	185	6,198
$A_{i,t}^{unhedged}$ (mil USD)	350	1,474	4,472	1	24	170	899	39,646
w_t	350	0.678	0.284	0.008	0.494	0.761	0.914	0.998
$r_{i,t}^{hedged}$	350	0.003	0.007	-0.022	-0.001	0.003	0.007	0.038
$r_{i,t}^{unhedged}$	350	0.005	0.006	-0.017	-0.000	0.004	0.009	0.028
Panel B: Explanatory Components								
$\frac{\mathbb{E}_t^{survey}[\Delta s_{c,t+1}]}{\text{Var}_t[\Delta s_{t+1}]}$	15,622	1.988	32.570	-136.003	-18.887	4.320	19.248	132.133
$\frac{\mathbb{E}_t^{macro}[\Delta s_{c,t+1}]}{\text{Var}_t[\Delta s_{t+1}]}$	20,429	1.394	1.996	-13.674	0.478	1.168	2.440	12.407
$\frac{\mathbb{E}_t^{factor}[\Delta s_{c,t+1}]}{\text{Var}_t[\Delta s_{t+1}]}$	20,429	3.478	31.343	-273.522	-8.214	6.046	21.104	114.186
$\frac{f_{c,t} - s_{c,t}}{\text{Var}_t[\Delta s_{t+1}]}$	20,429	-2.548	3.365	-38.533	-3.374	-1.669	-0.341	8.382
$\frac{\text{Cov}_t[r_{ic,t+1}, \Delta s_{t+1}]}{\text{Var}_t[\Delta s_{t+1}]}$	20,429	-0.465	0.669	-6.307	-0.790	-0.359	-0.049	7.304
Panel C: Fund Characteristics								
Log Average Size	350	5.664	2.209	0.874	4.091	5.760	7.153	12.122
Net Expense Ratio (%)	315	-0.026	0.065	-0.390	-0.050	-0.020	0.000	0.610
Institutional Share	290	0.225	0.202	0.000	0.071	0.168	0.339	0.935
$\Delta^{strategy}$ (in bp)	350	4.405	21.807	-58.321	-1.808	2.803	5.547	243.934

Table 1 continued.

	Obs.	Mean	Std	Min	25%	50%	75%	Max
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel D: Aggregates								
$\mathbb{E}_t^{PF}[rx_{c,t+1}]$	763	-0.034	0.140	-1.338	-0.100	-0.035	0.018	1.285
$\mathbb{E}_t^{survey}[rx_{c,t+1}]$	638	-0.192	1.622	-5.753	-1.179	-0.227	0.657	6.225
$\mathbb{E}_t^{macro}[rx_{c,t+1}]$	763	0.037	0.109	-0.384	-0.008	0.044	0.115	0.292
$\mathbb{E}_t^{factor}[rx_{c,t+1}]$	763	0.090	1.099	-4.957	-0.692	-0.004	0.847	3.870
$rx_{c,t+1}$	763	0.230	2.390	-7.126	-1.415	0.228	1.845	9.065
$\Delta s_{c,t+1}$	763	0.132	2.399	-7.424	-1.496	0.139	1.775	9.130
$f_{c,t} - s_{c,t}$	763	-0.098	0.134	-0.543	-0.162	-0.069	-0.015	0.228
$flow_{c,t}$	763	0.019	1.399	-11.102	-0.174	0.013	0.247	14.881
$Disp_{c,t}^{PF}$	748	-7.853	0.895	-12.860	-8.311	-7.846	-7.313	-5.116
$IVol_{c,t}$	748	2.053	0.274	1.342	1.858	2.029	2.241	2.963

Table 2: Observed and Optimal Mean-Variance Hedging

The table presents results of monthly panel regressions where the observed currency weight, $w_{i,c,t}$, is regressed on the optimal mean-variance components: three different expectations of currency returns, $E_t[\Delta s_{c,t+1}]$, the forward premium, $f_{c,t} - s_{c,t}$, and the covariance of real asset returns with exchange rates, $Cov_t[r_{i,c,t+1}, \Delta s_{c,t+1}]$. All terms are scaled by the exchange rate volatility, $Var_t[\Delta s_{c,t+1}]$. Panel A reports the result for equity ETFs and Panel B reports the results for debt ETFs. The sample covers the period January 2014 until May 2025 (for survey expectations only until August 2024). I double cluster standard errors at the time- and fund level and mark statistical significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

Dep. Variable:	$w_{i,c,t}$								
	Baseline Model			Across Funds			Within Funds		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Equity ETFs									
$\frac{E_t^{survey}[\Delta s_{c,t+1}]}{Var_t[\Delta s_{c,t+1}]}$	0.002** (0.001)			0.002*** (0.000)			0.000 (0.000)		
$\frac{E_t^{macro}[\Delta s_{c,t+1}]}{Var_t[\Delta s_{c,t+1}]}$		0.052*** (0.011)			0.004 (0.007)			0.002 (0.002)	
$\frac{E_t^{factor}[\Delta s_{c,t+1}]}{Var_t[\Delta s_{c,t+1}]}$			0.003*** (0.001)			-0.001 (0.001)			-0.000 (0.000)
$\frac{f_{c,t} - s_{c,t}}{Var_t[\Delta s_{c,t+1}]}$	-0.106*** (0.008)	-0.082*** (0.010)	-0.095*** (0.009)	-0.024*** (0.006)	-0.014*** (0.004)	-0.013*** (0.005)	0.003* (0.002)	0.003* (0.001)	0.002* (0.001)
$\frac{Cov_t[r_{i,c,t+1}, \Delta s_{c,t+1}]}{Var_t[\Delta s_{c,t+1}]}$	-0.360*** (0.029)	-0.314*** (0.029)	-0.333*** (0.029)	0.004 (0.019)	0.017 (0.017)	0.018 (0.017)	-0.013*** (0.004)	-0.009*** (0.003)	-0.009*** (0.003)
Time FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	No	No	No	No	Yes	Yes	Yes
R^2	0.562	0.549	0.541	0.055	0.019	0.023	0.008	0.005	0.005
No. Obs.	9,866	12,713	12,713	9,866	12,713	12,713	9,866	12,713	12,713
Panel B: Debt ETFs									
$\frac{E_t^{survey}[\Delta s_{c,t+1}]}{Var_t[\Delta s_{c,t+1}]}$	0.002** (0.001)			0.002*** (0.001)			-0.000 (0.000)		
$\frac{E_t^{macro}[\Delta s_{c,t+1}]}{Var_t[\Delta s_{c,t+1}]}$		0.078*** (0.012)			0.005 (0.009)			-0.005 (0.004)	
$\frac{E_t^{factor}[\Delta s_{c,t+1}]}{Var_t[\Delta s_{c,t+1}]}$			0.007*** (0.001)			-0.001 (0.001)			0.000 (0.000)
$\frac{f_{c,t} - s_{c,t}}{Var_t[\Delta s_{c,t+1}]}$	-0.088*** (0.009)	-0.057*** (0.010)	-0.082*** (0.008)	-0.014* (0.007)	-0.008 (0.006)	-0.007 (0.006)	0.002 (0.002)	0.000 (0.002)	0.001 (0.001)
$\frac{Cov_t[r_{i,c,t+1}, \Delta s_{c,t+1}]}{Var_t[\Delta s_{c,t+1}]}$	-0.460*** (0.064)	-0.440*** (0.066)	-0.405*** (0.062)	0.012 (0.040)	0.037 (0.044)	0.040 (0.045)	0.009 (0.009)	0.004 (0.006)	0.005 (0.006)
Time FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	No	No	No	No	Yes	Yes	Yes
R^2	0.512	0.513	0.518	0.028	0.008	0.008	0.001	0.003	0.000
No. Obs.	5,756	7,716	7,716	5,756	7,716	7,716	5,756	7,716	7,716

Table 3: Forecast Performance of Exchange Rate Expectations

The table presents results of monthly regressions where the realized excess currency return $rx_{c,t+1}$ (Column 1-4) or currency appreciation $\Delta s_{c,t+1}$ (Column 5-8) is regressed on estimates for average expected excess currency returns, $\mathbb{E}_t[rx_{c,t+1}]$, and the one-month forward premium, $f_{c,t} - s_{c,t}$. $\mathbb{E}_t^{PF}[rx_{c,t+1}]$ are the portfolio-implied expectations, $\mathbb{E}_t^{survey}[rx_{c,t+1}]$ are expectations obtained from surveys, $\mathbb{E}_t^{macro}[rx_{c,t+1}]$ are expectations derived from prominent predictors of exchange rates as in [Chernov et al. \(2023\)](#) and $\mathbb{E}_t^{factor}[rx_{c,t+1}]$ are expectations constructed from two currency factors as in [Opie and Riddiough \(2020\)](#). All regressions include time fixed effect. Expected currency returns are demeaned at the currency level using backward-looking averages. The sample covers the period January 2014 until June 2025 (for Column (4) only until August 2024). I cluster standard errors at the time-level and mark statistical significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

Dep. Variable:	$rx_{c,t+1}$				$\Delta s_{c,t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{E}_t^{PF}[rx_{c,t+1}]$	1.12** (0.497)				1.12** (0.497)			
$\mathbb{E}_t^{survey}[rx_{c,t+1}]$		0.097 (0.078)				0.097 (0.078)		
$\mathbb{E}_t^{macro}[rx_{c,t+1}]$			-0.370 (0.828)				-0.370 (0.828)	
$\mathbb{E}_t^{factor}[rx_{c,t+1}]$				0.112 (0.151)				0.112 (0.151)
$f_t - s_t$	-0.640 (0.699)	-0.600 (0.865)	-0.690 (0.719)	-0.776 (0.711)	0.360 (0.699)	0.400 (0.865)	0.310 (0.719)	0.224 (0.711)
R^2 (%)	1.19	0.00	0.08	0.21	1.00	0.00	0.11	0.19
No. Obs.	763	701	763	763	763	701	763	763

Table 4: Forecast Performance of Components of PF-implied Expectations

The table presents results of monthly regressions where the dependent variable is the realized one-month excess currency return, $rx_{c,t+1}$. In Column (1)-(3) the independent variable is one of the components of portfolio-implied expectations: weight in the unhedged ETF, $w_{c,t}^{flow}$, variance of spot returns, $\text{Var}_t[\Delta s_{c,t+1}]$, covariance of underlying average asset returns and spot returns, $\text{Cov}_t[r_{c,t+1}, \Delta s_{c,t+1}]$. In Column (4) and (5) the weight in the unhedged ETF is further decomposed into the active flows into the unhedged ETF, $flow_{c,t}$, and previous month's weight, $w_{c,t-1}$. All regressions control for the one-month forward premium, $f_{c,t} - s_{c,t}$, and include time fixed effect. Expected currency returns are demeaned at the currency level using backward-looking averages. The sample covers the period January 2014 until June 2025. I cluster standard errors at the time-level and mark statistical significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

Dep. Variable:	$rx_{c,t+1}$				
	(1)	(2)	(3)	(4)	(5)
$w_{c,t}^{flow}$	-0.005 (0.003)				
$\text{Var}_t[\Delta s_{c,t+1}]$		-0.541 (0.955)			
$\text{Cov}_t[r_{c,t+1}, \Delta s_{c,t+1}]$			2.306 (1.760)		
$flow_{c,t}$				0.090** (0.045)	0.088* (0.045)
$w_{c,t-1}$				-0.005 (0.003)	
$\mathbb{E}_t^{PF}[rx_{c,t+1}]$					1.079** (0.482)
$f_{c,t} - s_{c,t}$	-0.691 (0.707)	-0.660 (0.705)	-0.441 (0.728)	-0.735 (0.707)	-0.704 (0.700)
R^2 (%)	0.62	0.29	0.81	1.38	1.56
No. Obs.	763	763	763	763	763

Table 5: Forecast Performance at Different Horizons

The table presents results of daily regressions where the dependent variable is realized k -months excess currency return, $rx_{c,t+1}^k$, and the independent variable are active flows, $flow_{c,t}$, into the unhedged versus hedged ETF or portfolio-implied expectations, $\mathbb{E}_t^{PF}[rx_{c,t+1}]$. All regressions include the k -month forward premium, $f_{c,t}^k - s_{c,t}$. Each panel computes realized returns and forward premia for a different horizon. Standard errors are computed using a moving-block bootstrap (10,000 replications) to account for autocorrelation from overlapping observations and significance is based on bootstrap p-values. I denote by *, **, and ***, the significance levels at the 10%, 5%, and 1%, respectively.

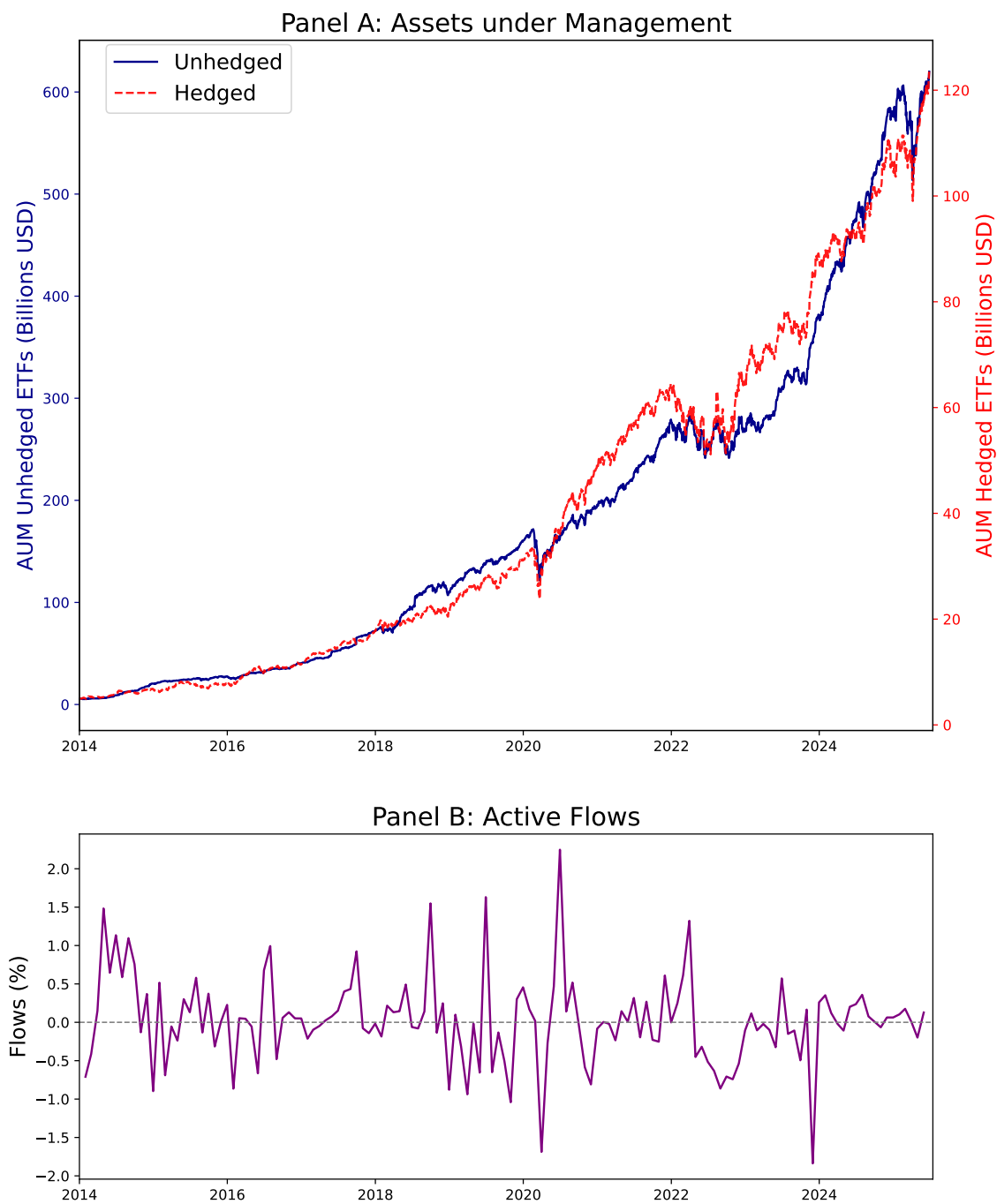
Dep. Variable:	$rx_{c,t+1}^k$		
	(1)	(2)	(3)
Panel A: 1-month horizon ($k = 1$)			
$flow_{c,t}$	0.214* (0.110)		0.188* (0.109)
$\mathbb{E}_t^{PF}[rx_{c,t+1}]$		1.006*** (0.275)	0.937*** (0.272)
$f_{c,t}^k - s_{c,t}$	-0.787 (0.618)	-1.422** (0.675)	-1.296* (0.657)
R^2 (%)	0.97	1.38	1.89
Panel B: 3-months horizon ($k = 3$)			
$flow_{c,t}$	0.394 (0.255)		0.350 (0.254)
$\mathbb{E}_t^{PF}[rx_{c,t+1}]$		1.783* (0.838)	1.655* (0.830)
$f_{c,t}^k - s_{c,t}$	-0.605 (0.566)	-0.986 (0.660)	-0.911 (0.645)
R^2 (%)	1.48	1.91	2.59
Panel C: 12-months horizon ($k = 12$)			
$flow_{c,t}$	1.173*** (0.361)		1.051*** (0.300)
$\mathbb{E}_t^{PF}[rx_{c,t+1}]$		4.929** (2.410)	4.538** (2.309)
$f_{c,t}^k - s_{c,t}$	-0.670 (0.412)	-0.934* (0.490)	-0.879* (0.465)
R^2 (%)	5.45	6.05	7.75
No. Obs.	14,389	14,389	14,389

Table 6: Dispersion in Portfolio-implied Expectations and FX volatility

The table presents results of monthly regressions where the dependent variable is the log of the one-month option-implied FX volatility, $IVol_{c,t}$. The independent variable is the log mean absolute deviation of portfolio-implied expectations, $Disp_{c,t}^{PF}$, and the lagged one-month option-implied volatility, $IVol_{c,t-1}$. In Column (1) and (2) the regression is performed in levels, in Column (3) and (4) the regression is performed in changes. The sample covers the period January 2014 until June 2025 (for AUD I start in 2015 as there are not enough observations to compute MAD). In all regressions I add currency and time fixed effects. I cluster standard errors by time and currency and mark statistical significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

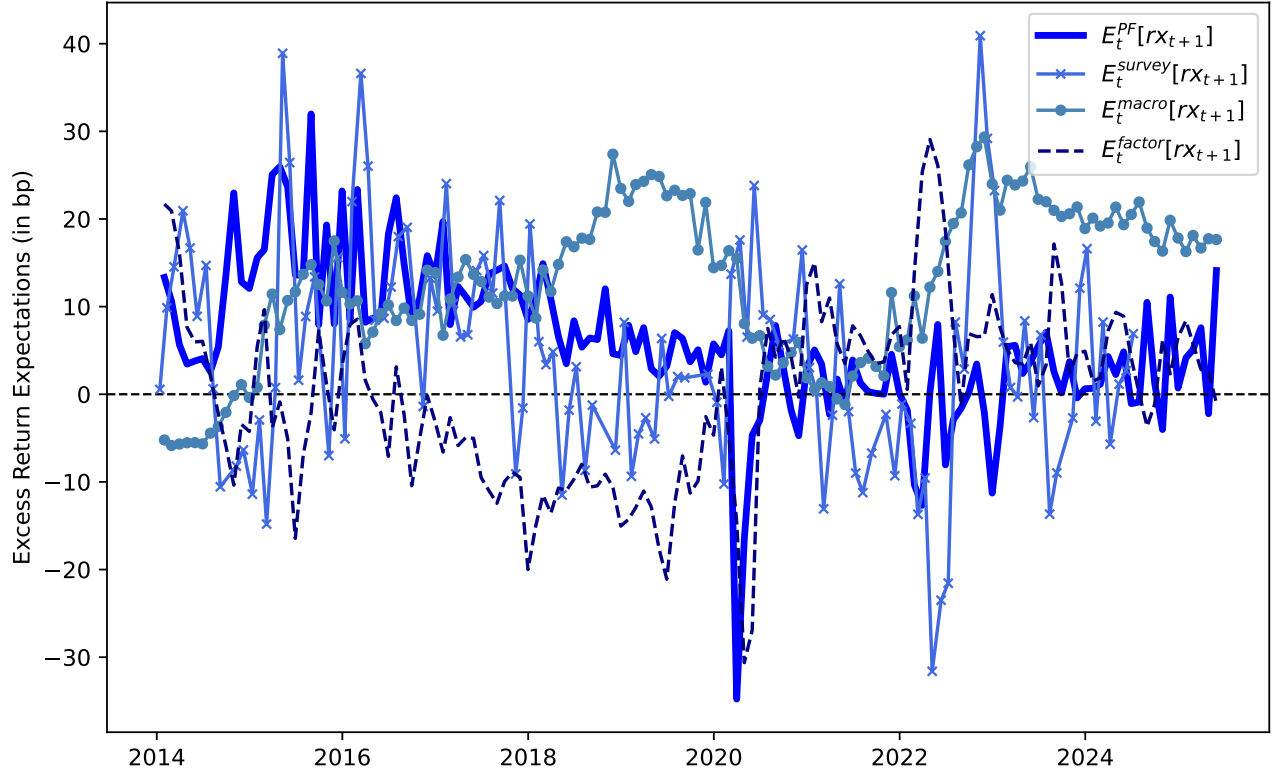
Dep. Variable:	$IVol_{c,t}$		$\Delta IVol_{c,t}$		$IVol_{c,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$Disp_{c,t}^{PF}$	0.134*** (0.025)	0.055*** (0.009)				
$Disp_{c,t-1}^{PF}$					0.112*** (0.026)	0.019* (0.008)
$IVol_{c,t-1}$		0.662*** (0.045)				0.721*** (0.038)
$\Delta Disp_{c,t}^{PF}$			0.027** (0.009)	0.027** (0.007)		
$\Delta IVol_{c,t-1}$				-0.269*** (0.038)		
Overall R^2	0.81	0.90	0.68	0.70	0.78	0.89
Within R^2	0.27	0.61	0.03	0.10	0.19	0.58
No. Obs.	749	749	749	749	742	742

Figure 1: Assets Under Management and Flows for FX-hedged and unhedged ETFs



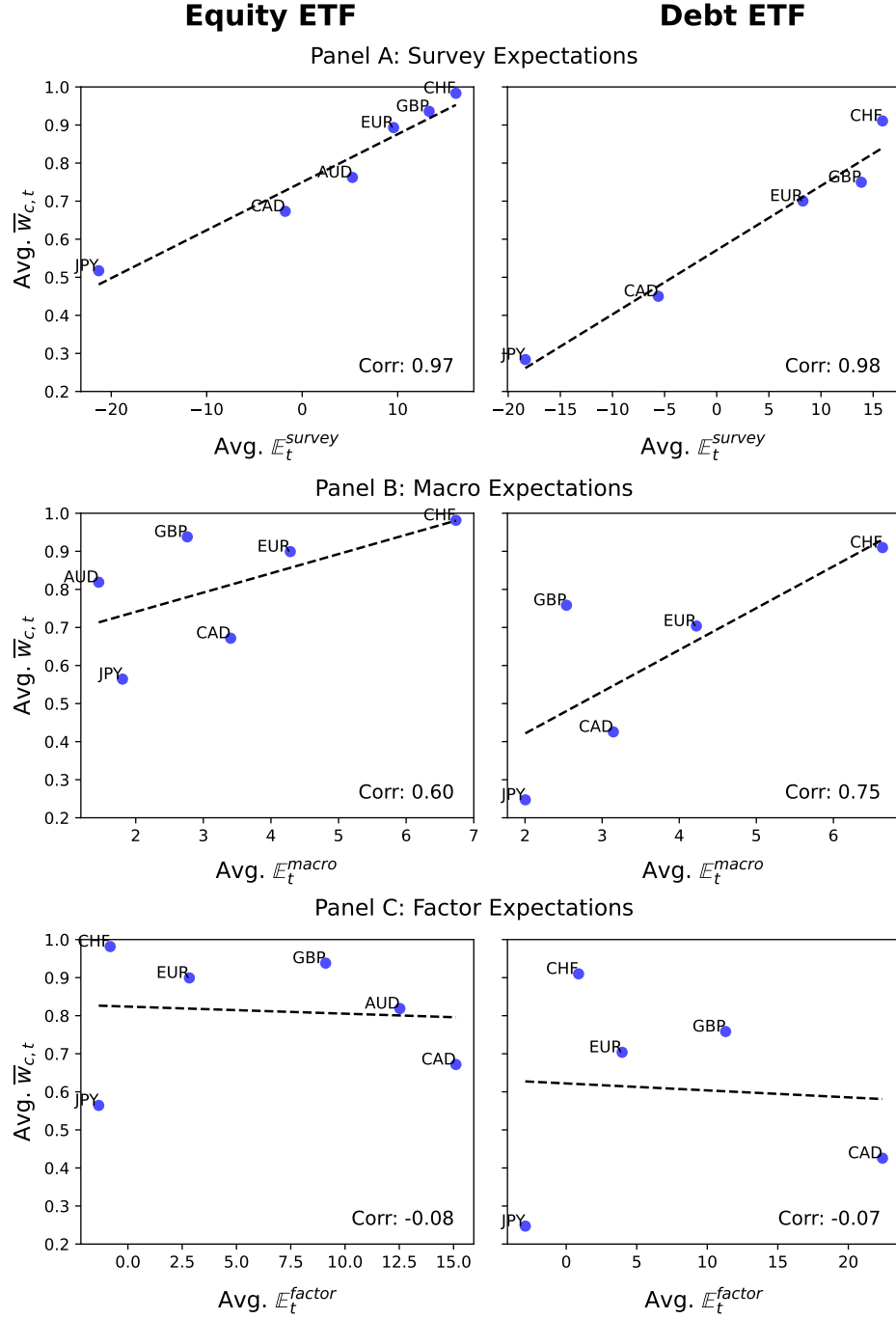
Notes: The figure depicts the assets under management in billion USD in Panel A and active flows in Panel B of currency-hedged ETFs (red) and their unhedged counterpart (blue) over the period 2014-2025.

Figure 2: Expected Currency Excess Returns



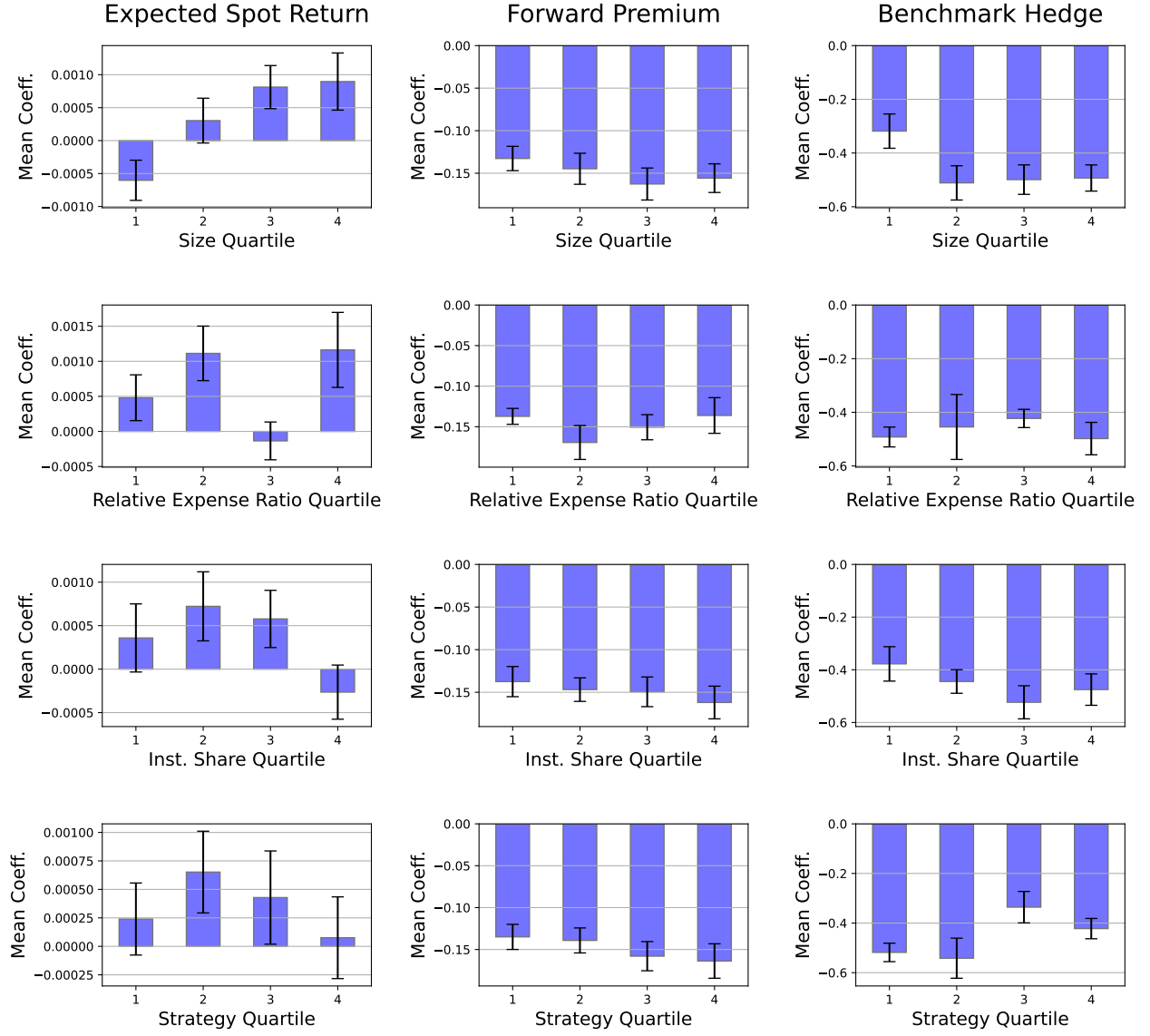
Notes: The figure plots four different estimates of monthly expected currency excess returns over the period 2014-2025 averaged across currency areas. The estimates include portfolio implied expectation (solid line), survey expectations (crosses on line), macro expectations (dots on line) and factor expectations (dashed line). The survey and factor expectations are divided by 10 to match the scale of the other expectation estimates.

Figure 3: Currency Demand and Optimal Hedging Components



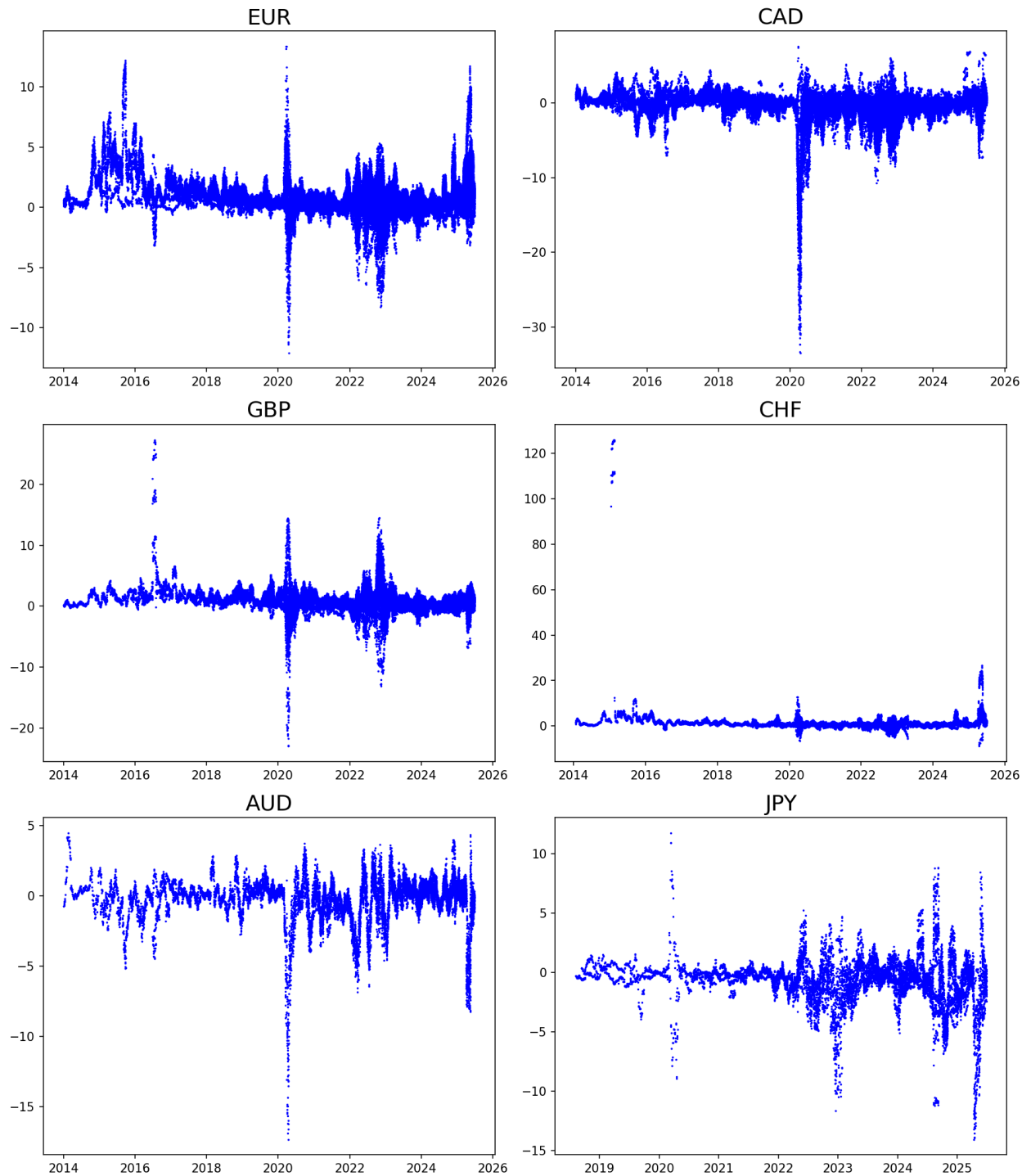
Notes: The figure shows the time-averaged weight in the unhedged ETF on the vertical axis against three estimates of the expected excess returns (Panel A-C) per currency for equity funds (left column) and debt funds (right column). All variables are scaled by the inverse of the exchange rate variance and the benchmark hedge is subtracted as in Eq. (4). Panel A uses survey-based, Panel B macro-based and Panel C factor-based expectations of currency excess returns. The dashed line is the trendline.

Figure 4: Heterogeneity in Currency Speculation and Hedging



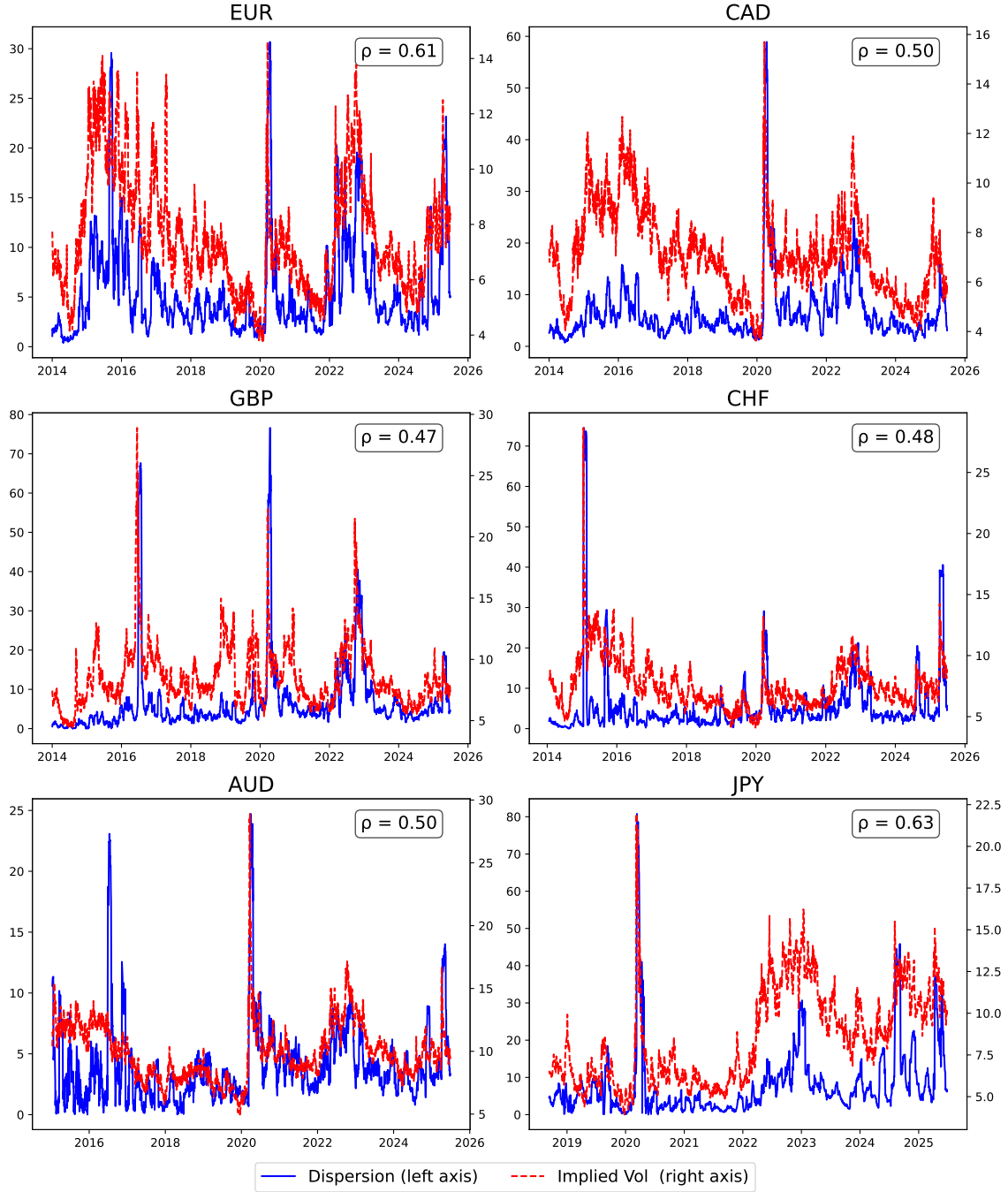
Notes: The figure presents the mean coefficient per quartile of the expected currency return in Column (1), the forward premium in Column (2) and the benchmark hedge in Column (3), categorized by fund characteristics, when running the baseline regression in Table 2 for each fund separately. The black bar indicates the standard errors of the mean, i.e., the standard deviation divided by the square root of the number of observations. Funds are sorted into quartiles by log total assets, net expense ratio, average institutional share, and average hedging strategy of the hedged and unhedged ETFs.

Figure 5: Portfolio-implied Expectations



Notes: The figure shows the portfolio-implied expectations per currency. Each dot represents a fund-day observation.

Figure 6: Dispersion in Portfolio-implied Expectations and FX volatility



Notes: The figure shows the mean absolute deviation of portfolio-implied expectations across funds defined in Eq. (7) in blue (left axis) against the option-implied FX volatility in red (right axis) for each currency area.

Appendix

Exchange Rate Expectations and Currency Demand

A Additional Tables and Figures

Table A.1: Predictive Ability of Conditional Variance

The table presents results of monthly regressions where the variance of realized currency excess returns is regressed on the estimated conditional variance $Var_t(rx_{c,t+1})$. In Column (1) the realized variance is computed using surveys, in Column (2) using macro expectations, and in Column (3) using factor expectations. All regressions include currency and time fixed effects. I double cluster standard errors by time and currency and mark statistical significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

Dep. Variable:	$(rx_{c,t+1} - \mathbb{E}_t^{survey}[rx_{c,t+1}])^2$ (1)	$(rx_{c,t+1} - \mathbb{E}_t^{macro}[rx_{c,t+1}])^2$ (2)	$(rx_{c,t+1} - \mathbb{E}_t^{factor}[rx_{c,t+1}])^2$ (3)
$Var_t(rx_{c,t+1})$	11.690* (6.688)	1.175 (1.142)	1.407* (0.806)
R^2	0.032	0.001	0.002
No. Obs.	701	763	763

Table A.2: Mispricing between Hedged and Unhedged ETFs

The table presents results of daily panel regressions where the premia and discounts of the hedged ETF is regressed on the premia and discounts of its unhedged counterpart, the VIX and the interaction term. The premia and discounts of an ETF are calculated using the mispricing of an ETF $\epsilon = \frac{P_t - NAV_t}{NAV_t} \times 100$, where a premium corresponds to a positive value of ϵ and a discount to a negative value of ϵ . The VIX is normalized to have mean zero. All regressions include fund fixed effects. I double cluster standard errors by time and currency and mark statistical significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

Dep. Variable:	$Premium_{i,t}^{hedged}$			$Discount_{i,t}^{hedged}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$Premium_{i,t}^{unhedged}$	0.313*** (0.048)		0.222*** 0.034***	0.255*** (0.044)		0.182*** 0.035
VIX_t		0.023*** (0.003)	0.015*** (0.001)		-0.019*** (-8.737)	-0.012*** 0.002***
$Premium_{i,t}^{unhedged} \times VIX_t$			1.077*** (0.350)			0.722*** (0.128)
R^2	0.09	0.05	0.14	0.06	0.04	0.09
No. Obs.	194,223	194,223	194,223	159,097	159,097	159,097

Table A.3: Expected Currency Returns and Portfolio USD Shares

The table presents results of monthly panel regressions where the observed currency weight, $w_{i,c,t}$, is regressed on three different expectations of currency returns, $\mathbb{E}_t[\Delta s_{c,t+1}]$. Panel A reports the result for equity ETFs and Panel B reports the results for debt ETFs. The row *Sensitivity* reports the change in the USD share in terms of standard deviations to a one standard deviation change in expected currency returns, computed as $\hat{\beta} * (\text{std}(\mathbb{E}_t[\Delta s_{c,t+1}]) / \text{std}(w_{i,c,t}))$. The sample covers the period January 2014 until May 2025 (for survey expectations only until August 2024). I double cluster standard errors at the time- and fund level and mark statistical significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

Dep. Variable:	$w_{i,c,t}$								
	Baseline Model			Across Funds			Within Funds		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Equity ETFs									
$\mathbb{E}_t^{survey}[\Delta s_{c,t+1}]$	1.457*** (0.455)			4.097*** (0.887)			0.379* (0.220)		
$\mathbb{E}_t^{macro}[\Delta s_{c,t+1}]$		26.842** (12.993)			33.846** (16.255)			7.452 (6.415)	
$\mathbb{E}_t^{factor}[\Delta s_{c,t+1}]$			-0.263 (0.674)			-3.236 (2.712)			-0.496 (0.866)
Sensitivity	0.08	0.08	-0.01	0.22	0.10	-0.13	0.02	0.02	-0.02
Time FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	No	No	No	No	Yes	Yes	Yes
R^2	0.006	0.006	0.000	0.019	0.007	0.003	0.001	0.001	0.000
No. Obs.	10006	12713	12713	10006	12713	12713	10006	12713	12713
Panel B: Debt ETFs									
$\mathbb{E}_t^{survey}[\Delta s_{c,t+1}]$	0.971* (0.534)			5.046*** (1.389)			0.092 (0.261)		
$\mathbb{E}_t^{macro}[\Delta s_{c,t+1}]$		17.979 (21.917)			45.004** (20.783)			-10.309 (14.600)	
$\mathbb{E}_t^{factor}[\Delta s_{c,t+1}]$			-3.859*** (1.172)			-5.252 (4.723)			-1.410 (1.851)
Sensitivity	0.05	0.05	-0.13	0.27	0.13	-0.18	0.00	-0.03	-0.05
Time FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	No	No	No	No	Yes	Yes	Yes
R^2	0.003	0.003	0.018	0.021	0.013	0.005	0.000	0.002	0.001
No. Obs.	5818	7716	7716	5818	7716	7716	5818	7716	7716

Table A.4: Observed and Optimal Mean-Variance Hedging Using Excess Returns

The table presents results of monthly panel regressions where the observed currency weight, $w_{i,c,t}$, is regressed on the optimal mean-variance components: three different expectations of currency excess returns, $E_t[rx_{c,t+1}]$, and the covariance of real asset returns with exchange rates, $Cov_t[r_{i,c,t+1}, \Delta s_{c,t+1}]$. All terms are scaled by the exchange rate volatility, $\text{Var}_t[\Delta s_{c,t+1}]$. Panel A reports the result for equity ETFs and Panel B reports the results for debt ETFs. The sample covers the period January 2014 until May 2025 (for survey expectations only until August 2024). I double cluster standard errors at the time- and fund level and mark statistical significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

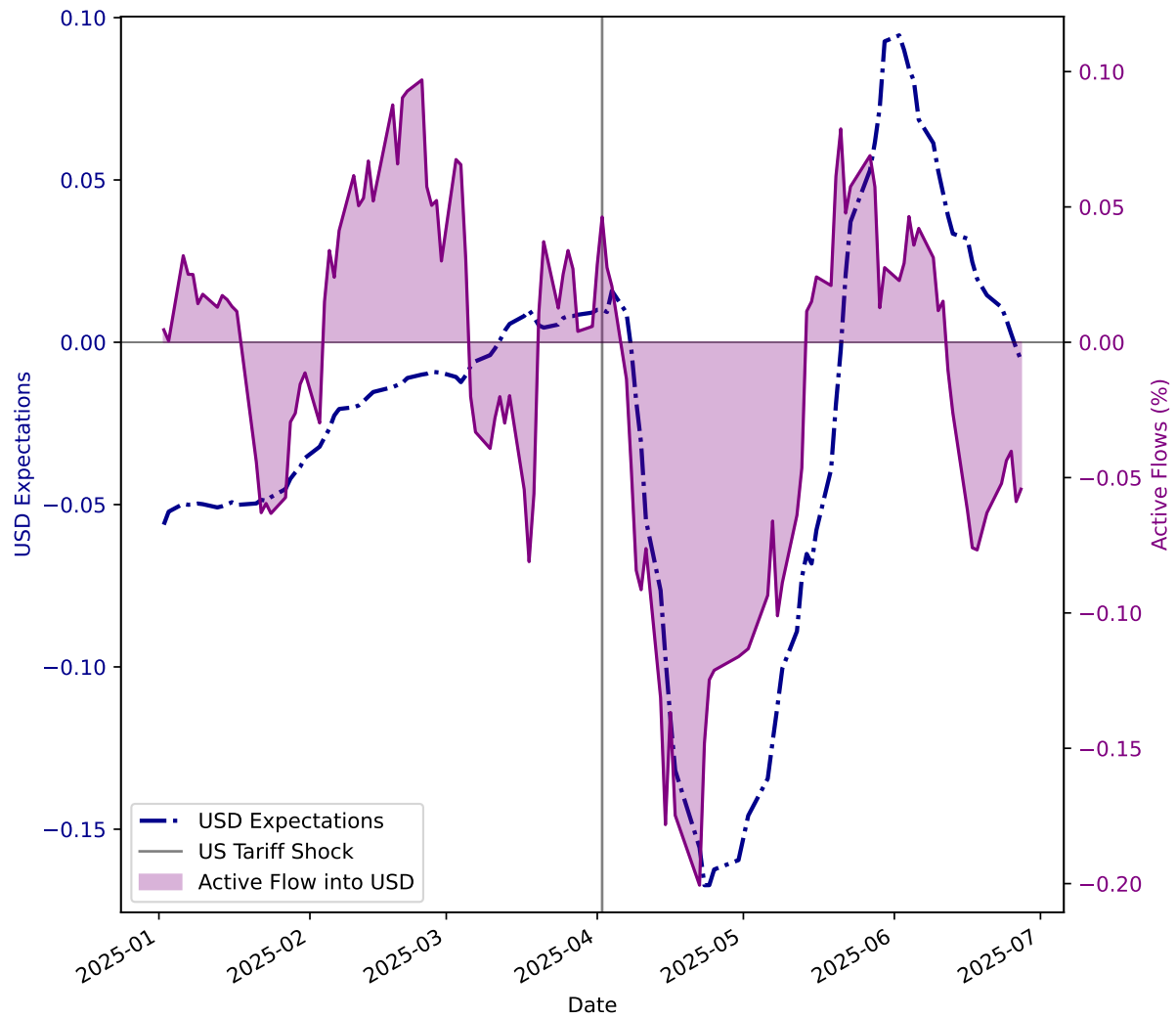
Dep. Variable:	$w_{i,c,t}$								
	Baseline Model			Across Funds			Within Funds		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Equity ETFs									
$\frac{E_t^{survey}[rx_{c,t+1}]}{\sqrt{\text{Var}_t[\Delta s_{c,t+1}]}}$	0.003*** (0.001)			0.002*** (0.000)			0.000 (0.000)		
$\frac{E_t^{macro}[rx_{c,t+1}]}{\sqrt{\text{Var}_t[\Delta s_{c,t+1}]}}$		0.072*** (0.007)			0.011*** (0.003)			-0.001 (0.001)	
$\frac{E_t^{factor}[rx_{c,t+1}]}{\sqrt{\text{Var}_t[\Delta s_{c,t+1}]}}$			0.001 (0.001)			-0.002** (0.001)			-0.000 (0.000)
$\frac{Cov_t[r_{i,c,t+1}, \Delta s_{c,t+1}]}{\sqrt{\text{Var}_t[\Delta s_{c,t+1}]}}$	-0.441*** (0.034)	-0.303*** (0.030)	-0.425*** (0.034)	0.020 (0.020)	0.020 (0.018)	0.028 (0.018)	-0.013*** (0.004)	-0.009*** (0.003)	-0.009*** (0.003)
Time FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	No	No	No	No	Yes	Yes	Yes
R^2	0.351	0.546	0.305	0.027	0.017	0.013	0.005	0.003	0.003
No. Obs.	9866	12713	12713	9866	12713	12713	9866	12713	12713
Panel B: Debt ETFs									
$\frac{E_t^{survey}[rx_{c,t+1}]}{\sqrt{\text{Var}_t[\Delta s_{c,t+1}]}}$	0.003*** (0.001)			0.002*** (0.001)			-0.000 (0.000)		
$\frac{E_t^{macro}[rx_{c,t+1}]}{\sqrt{\text{Var}_t[\Delta s_{c,t+1}]}}$		0.064*** (0.008)			0.007 (0.005)			-0.002 (0.002)	
$\frac{E_t^{factor}[rx_{c,t+1}]}{\sqrt{\text{Var}_t[\Delta s_{c,t+1}]}}$			0.002 (0.002)			-0.002 (0.001)			0.000 (0.000)
$\frac{Cov_t[r_{i,c,t+1}, \Delta s_{c,t+1}]}{\sqrt{\text{Var}_t[\Delta s_{c,t+1}]}}$	-0.790*** (0.071)	-0.445*** (0.068)	-0.838*** (0.068)	0.004 (0.041)	0.035 (0.046)	0.036 (0.045)	0.009 (0.009)	0.004 (0.006)	0.005 (0.006)
Time FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	No	No	No	No	Yes	Yes	Yes
R^2	0.303	0.511	0.271	0.018	0.007	0.005	0.000	0.002	0.000
No. Obs.	5756	7716	7716	5756	7716	7716	5756	7716	7716

Table A.5: Observed and Optimal Mean-Variance Hedging at the Currency Level

The table presents results of monthly panel regressions where the observed aggregate currency weight, $w_{c,t}$, is regressed on the optimal mean-variance components: three different expectations of currency returns, $\mathbb{E}_t[\Delta s_{c,t+1}]$, the forward premium, $f_{c,t} - s_{c,t}$, and the covariance of real asset returns with exchange rates, $\text{Cov}_t[r_{c,t+1}, \Delta s_{c,t+1}]$. All terms are scaled by the exchange rate volatility, $\text{Var}_t[\Delta s_{c,t+1}]$. Panel A reports the result for equity ETFs and Panel B reports the results for debt ETFs. The sample covers the period January 2014 until May 2025 (for survey expectations only until August 2024). I double cluster standard errors at the time- and currency level and mark statistical significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

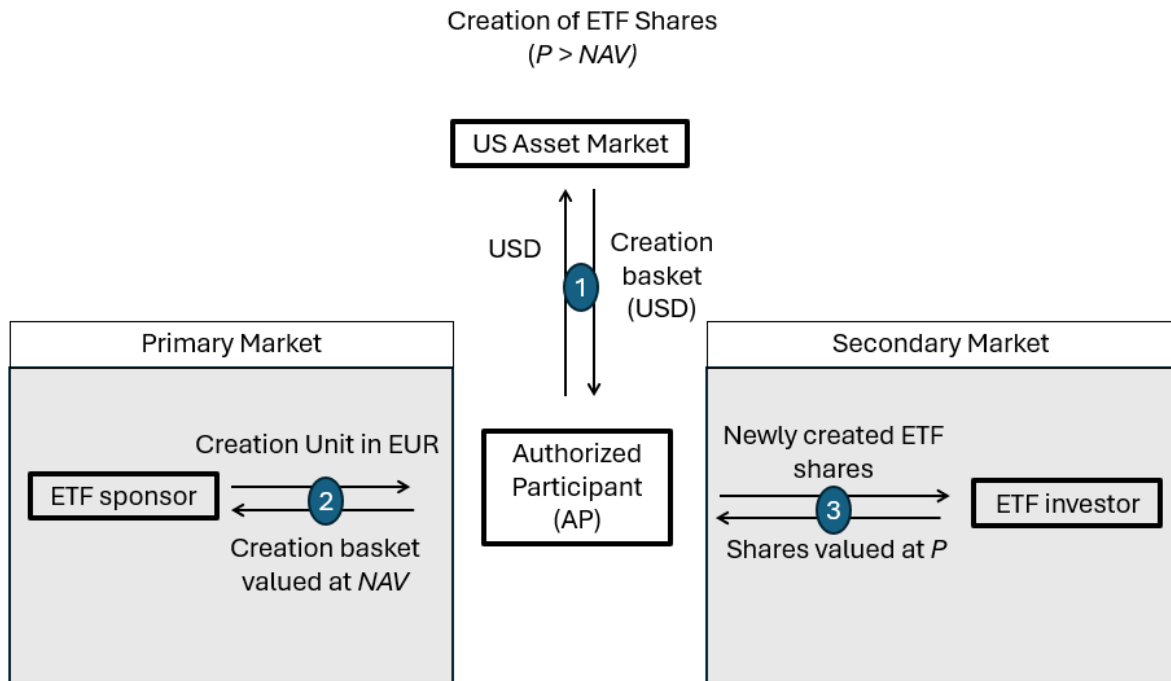
Dep. Variable:	$w_{c,t}$								
	Baseline Model			Across Currency Areas			Within Currency Areas		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Equity ETFs									
$\frac{\mathbb{E}_t^{\text{survey}}[\Delta s_{c,t+1}]}{\text{Var}_t[\Delta s_{c,t+1}]}$	0.005*** (0.001)			0.002** (0.001)			0.000 (0.000)		
$\frac{\mathbb{E}_t^{\text{macro}}[\Delta s_{c,t+1}]}{\text{Var}_t[\Delta s_{c,t+1}]}$		0.050* (0.029)			0.019*** (0.004)			0.007 (0.002)	
$\frac{\mathbb{E}_t^{\text{factor}}[\Delta s_{c,t+1}]}{\text{Var}_t[\Delta s_{c,t+1}]}$			0.003 (0.002)			0.002* (0.001)			0.000 (0.000)
$\frac{f_{c,t} - s_{c,t}}{\text{Var}_t[\Delta s_{c,t+1}]}$	-0.100*** (0.015)	-0.075*** (0.011)	-0.096*** (0.020)	-0.011 (0.009)	-0.003 (0.008)	-0.010 (0.007)	-0.004 (0.006)	-0.001 (0.004)	-0.003 (0.003)
$\frac{\text{Cov}_t[r_{i,c,t+1}, \Delta s_{c,t+1}]}{\text{Var}_t[\Delta s_{c,t+1}]}$	-0.517*** (0.098)	-0.480*** (0.099)	-0.471*** (0.120)	0.075*** (0.021)	0.111*** (0.016)	0.107*** (0.013)	0.004 (0.011)	0.004 (0.011)	0.002 (0.011)
Time FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Currency FE	No	No	No	No	No	No	Yes	Yes	Yes
R^2	0.540	0.507	0.494	0.176	0.191	0.142	0.017	0.083	0.010
No. Obs.	636	763	763	636	763	763	636	763	763
Panel B: Debt ETFs									
$\frac{\mathbb{E}_t^{\text{survey}}[\Delta s_{c,t+1}]}{\text{Var}_t[\Delta s_{c,t+1}]}$	0.004** (0.002)			0.002*** (0.001)			0.000 (0.000)		
$\frac{\mathbb{E}_t^{\text{macro}}[\Delta s_{c,t+1}]}{\text{Var}_t[\Delta s_{c,t+1}]}$		0.023 (0.022)			0.002 (0.010)			-0.009 (0.007)	
$\frac{\mathbb{E}_t^{\text{factor}}[\Delta s_{c,t+1}]}{\text{Var}_t[\Delta s_{c,t+1}]}$			0.005* (0.002)			0.002 (0.001)			-0.000 (0.001)
$\frac{f_{c,t} - s_{c,t}}{\text{Var}_t[\Delta s_{c,t+1}]}$	-0.093*** (0.009)	-0.064*** (0.014)	-0.087*** (0.015)	-0.016 (0.014)	-0.009 (0.014)	-0.015 (0.012)	-0.003 (0.006)	-0.002 (0.005)	-0.000 (0.003)
$\frac{\text{Cov}_t[r_{i,c,t+1}, \Delta s_{c,t+1}]}{\text{Var}_t[\Delta s_{c,t+1}]}$	-0.472** (0.211)	-0.374* (0.200)	-0.286 (0.179)	0.245 (0.159)	0.378** (0.169)	0.372** (0.175)	-0.019 (0.058)	-0.012 (0.035)	0.002 (0.039)
Time FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Currency FE	No	No	No	No	No	No	Yes	Yes	Yes
R^2	0.447	0.365	0.386	0.193	0.212	0.224	0.004	0.035	0.002
No. Obs.	451	579	579	451	579	579	451	579	579

Figure A.1: USD Expectations around US Tariff Shock 2025



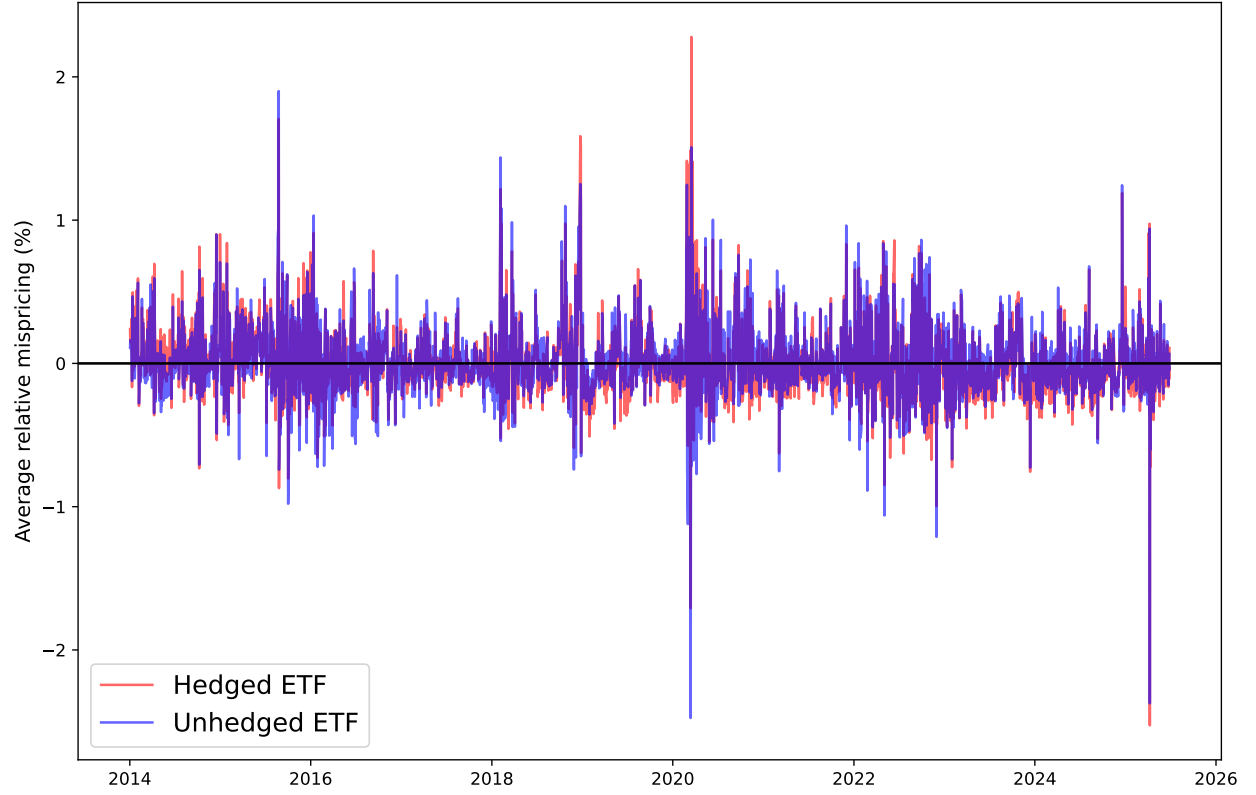
Notes: The figure shows portfolio-implied expectations extracted from ETF trading (blue dashed line, left axis) and active flows into unhedged ETFs relative to their hedged counterparts expressed in percent (purple shaded area, right axis). Expectations are plotted as a two-week rolling mean, flows are plotted as a two-week rolling sum. The gray vertical line marks the event date of April 2, 2025. The sample period spans from January to June 2025.

Figure A.2: ETF Arbitrage Mechanism



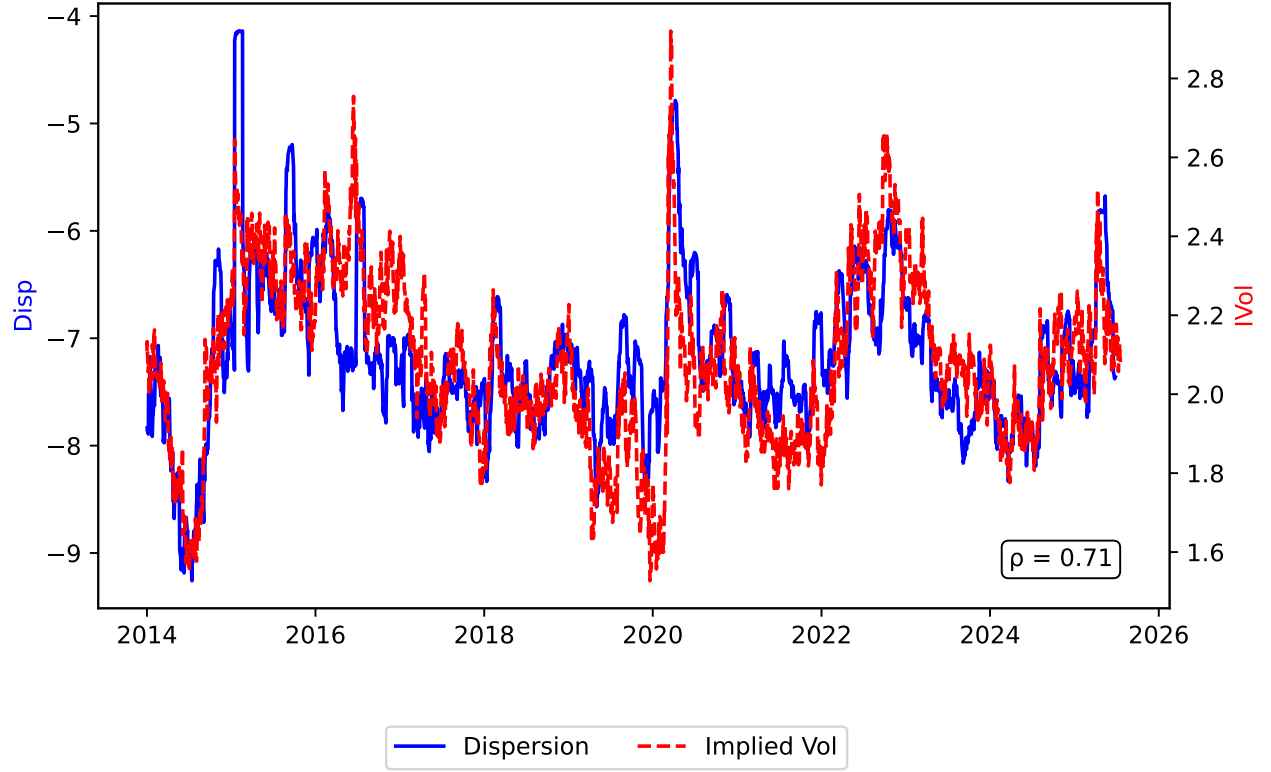
Notes: The figure shows the arbitrage mechanism for ETFs when the ETF trades at a premium and the Authorized Participant (AP) creates new shares.

Figure A.3: Time-series of relative Mispricing of ETFs



Notes: The figure plots the relative mispricing averaged across hedged ETFs (red) and unhedged ETFs (blue). Relative mispricing is defined as the difference between the last trading price of the ETF and the net asset value (NAV) divided by the NAV, i.e., $\epsilon = \frac{P_t - NAV_t}{NAV_t} \times 100$.

Figure A.4: Dispersion of PF-implied Expectations and FX volatility USD basket



Notes: The figure shows the mean absolute deviation of portfolio-implied expectations defined in Eq. (7) for each day across all funds in all currency areas in blue (left axis) against the log of the average option-implied FX volatility in red (right axis).

B Estimation Details for Expected Returns

This section details the estimation techniques and results for the construction of macro and factor expectations.

B.1 Macro Expectations

The macro expectations, $\mathbb{E}_t^{macro}[rx_{c,t+1}]$, are estimated following [Chernov et al. \(2023\)](#). I present the key equations for estimating expected currency excess returns and refer to the original paper for further details, in particular the underlying motivation behind each step. For comparability with [Chernov et al. \(2023\)](#), I define exchange rates as USD per unit of foreign currency and estimate expected excess currency returns in percentage changes in this section. The expectations used in the main paper correspond to the negative of these estimates. Furthermore, the sample covers all G10 currencies: AUD, CAD, EUR (or DEM before 1999), JPY, NZD, NOK, SEK, CHF, GBP and USD and starts in 1990. I source consumer price indices from Datastream and, for AUD and NZD, forward-filled to obtain monthly observations.

First, I compute an estimate of the mean-reversion component, z_{c,Q_t} , using the real exchange rate (RER)

$$Q_{c,t} = S_{c,t}P_{c,t}/P_t$$

where $P_{c,t}$ and P_t are the foreign and US consumer price index (CPI), respectively. In a next step RER is divided by its five-year smoothed lag (the average RER from 4.5 and 5.5 years ago)

$$\tilde{Q}_{c,t} = Q_{c,t} \left(\frac{1}{13} \sum_{j=-6}^6 Q_{c,t-60+j} \right)^{-1}$$

and cross-sectionally demeaned

$$z_{c,Q_t} = \tilde{Q}_{c,t} - \frac{1}{N} \sum_{i=1}^N \tilde{Q}_{c,t}.$$

Second, I run monthly panel regressions of realized spot exchange rate changes on the real exchange rate signal and the trend signal:

$$S_{c,t+1}/S_{c,t} - 1 = \bar{\delta}_t z_{c,Q_t} + \bar{\phi}_t (S_{c,t}/S_{c,t-12} - 1) + \epsilon_{c,t+1} \quad (1)$$

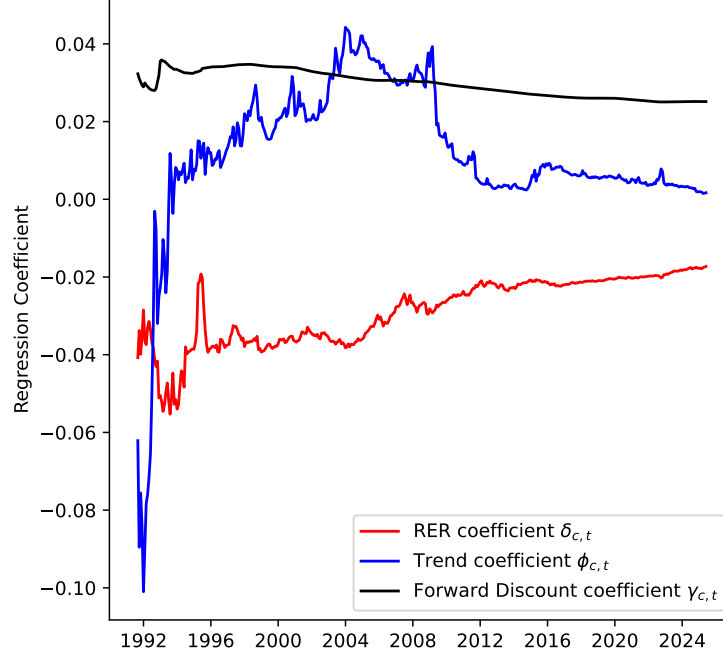
in an expanding window setup month by month. To get to expected excess returns, I multiply the coefficients by the forward discount

$$\begin{aligned}\mathbb{E}_t^{macro}[rx_{c,t+1}] &= (S_{c,t}/F_{c,t}) \mathbb{E}_t^{macro}[S_{c,t+1}/S_{c,t}] - 1 \\ \mathbb{E}_t^{macro}[rx_{c,t+1}] &= (S_{c,t}/F_{c,t} - 1) + (S_{c,t}/F_{c,t})\overline{\delta}_t z_{c,Q_t} + (S_{c,t}/F_{c,t})\overline{\phi}_t(S_{c,t}/S_{c,t-12} - 1)\end{aligned}$$

where $(S_{c,t}/F_{c,t})\overline{\delta}_t$ and $(S_{c,t}/F_{c,t})\overline{\phi}_t$ correspond to $\delta_{c,t}$ and $\phi_{c,t}$ in Eq. (10).

Figure B.1 replicates Figure 1 of [Chernov and Creal \(2021\)](#) and plots the standardized values of cross-sectional averages of the annualized estimated coefficients of the RER, $\delta_{c,t}$, and trend component, $\phi_{c,t}$, together with the standardized unit coefficient of the forward discount, $\gamma_{c,t}$. The figure shows that the estimated coefficients are very similar to those reported in [Chernov et al. \(2023\)](#); small differences arise at the beginning of the sample (which is not used in the main paper) since they start their estimation already from 1973. The coefficients stabilize by the time the sample period of the main paper begins in 2014. By then, the average annualized coefficients across the seven currency pairs used in the main paper are approximately -0.173 for the RER coefficient, 0.047 for the trend coefficient and 0.026 for the forward discount.

Figure B.1: Loadings on signals in expected excess currency returns.



Notes: The figure shows the standardized values of cross-sectional averages of the annualized estimated coefficients of the RER, $\delta_{c,t}$, and trend component, $\phi_{c,t}$, together with the standardized unit coefficient of the forward discount, $\gamma_{c,t}$. The sample period spans from 1990 to 2025.

B.2 Factor Expectations

For the construction of factor expectations, $\mathbb{E}_t^{factor}[rx_{c,t+1}]$, I proceed in two steps following [Opie and Riddiough \(2020\)](#). I present the key equations for estimating expected currency excess returns and refer to the original paper for further details, in particular the underlying motivation behind each step. As for the macro expectation, I define exchange rates as USD per unit of foreign currency. The expectations used in the main paper correspond to the negative of these estimates. The sample covers all G10 currencies: AUD, CAD, EUR (or DEM before 1999), JPY, NZD, NOK, SEK, CHF, GBP and USD and starts in 1990.

First, I estimate rolling betas of currency excess returns with respect to the carry and dollar factors. The carry factor corresponds to a strategy that goes long high-interest-rate currencies and

short low-interest-rate currencies. More precisely, a rank weight is given to each currency as

$$w_{c,t} = \text{rank}(s_{c,t} - f_{c,t}) - N^{-1} \sum_{c=1}^N \text{rank}(s_{c,t} - f_{c,t}) \quad (2)$$

where $s_{c,t} - f_{c,t}$ is the forward discount and $N = 9$. With nine currencies versus the USD, the possible weight values are $+0.4, +0.3, +0.2, +0.1, 0, -0.1, -0.2, -0.3$ and -0.4 . The carry factor then equals $R_{t+1}^{pf} = \sum_{c=1}^N w_{c,t} R_{c,t+1}$. The dollar factor is defined as the average return of a basket of currencies against the USD. To obtain time-varying loadings, $\hat{\beta}_{c,t}$, I regress excess returns, $rx_{c,t} = s_t - f_{t-1}$, on the two factors using a 60-month rolling window. The estimated carry and dollar beta for each currency are plotted in Panel A and B in Figure B.2, respectively.

Second, I forecast the factor prices of risk, λ_t , using predictor variables, X_{t-1} , in a rolling window regression. The predictors include the average forward discount, foreign exchange volatility, $\Delta\sigma_t^{FX}$, and commodity returns from the Commodity Research Bureau's raw industrials index, constructed as $\Delta CRB_t = \frac{1}{3} \log \left(\frac{CRB_t}{CRB_{t-3}} \right)$, together with a constant. This yields expected factor prices of risk, $\mathbb{E}_t[\lambda_{t+1}^{carry}]$ and $\mathbb{E}_t[\lambda_{t+1}^{dollar}]$ that are shown in Panel C and Panel D of Figure B.2, respectively.

To summarize, first, run

$$rx_{c,t} = \beta_{c,t}^{carry} \lambda_t^{carry} + \beta_{c,t}^{dollar} \lambda_t^{dollar} + \epsilon_{c,t}$$

and get $\hat{\beta}_{c,t}^{carry}$ and $\hat{\beta}_{c,t}^{dollar}$. Then run

$$\begin{aligned} \lambda_t^{carry} &= \alpha_t^{carry} + \phi_t^{carry} X_{t-1} + \epsilon_t^{carry} \\ \lambda_t^{dollar} &= \alpha_t^{dollar} + \phi_t^{dollar} X_{t-1} + \epsilon_t^{dollar} \end{aligned}$$

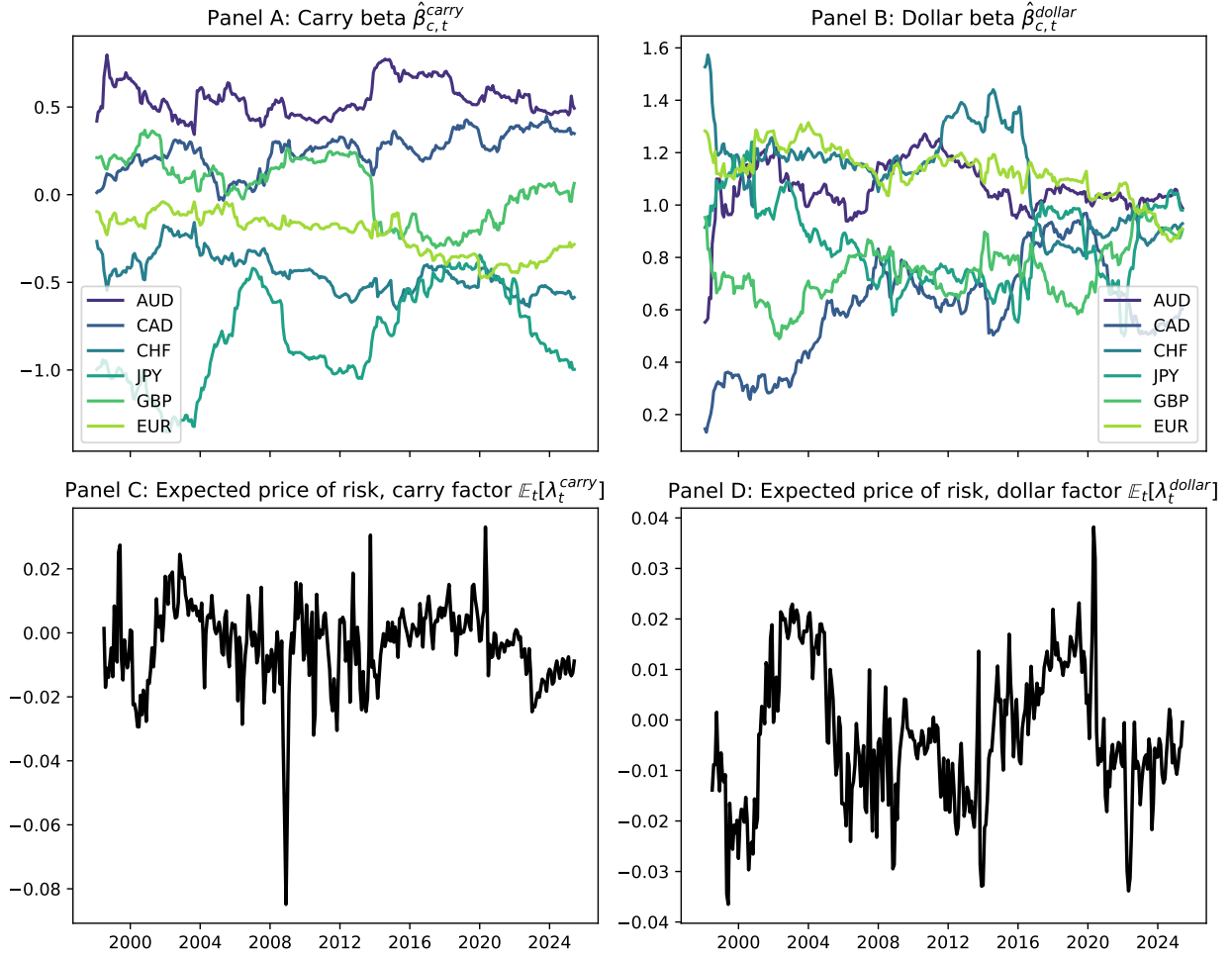
and get predicted values $\hat{\lambda}_{t+1}^{carry}$ and $\hat{\lambda}_{t+1}^{dollar}$ as estimates of the conditional expectations, $\mathbb{E}_t[\lambda_{t+1}^{carry}]$ and $\mathbb{E}_t[\lambda_{t+1}^{dollar}]$, respectively.

Combining the estimated betas with the expected factor prices of risk, factor expectations of currency excess returns are given by

$$\mathbb{E}_t^{factor}[rx_{c,t+1}] = \hat{\beta}_{c,t}^{carry} \hat{\lambda}_{t+1}^{carry} + \hat{\beta}_{c,t}^{dollar} \hat{\lambda}_{t+1}^{dollar}$$

as in Eq. (11).

Figure B.2: Factor Loadings and Expected Prices of Risk for Dollar and Carry Factors



Notes: The figure reports rolling estimates of currency betas with respect to the carry and dollar factors for each currency used in the main paper (Panels A and B) and the expected factor prices of risk (Panels C and D). Betas are estimated from 60-month rolling regressions of currency excess returns on the carry and dollar factors. Expected factor prices of risk are obtained from predictive regressions using forward discounts, FX volatility, and commodity returns as predictors. The sample period spans 1990–2025.

C Trading Strategies Built on ETF Signals

This section reports statistics for several monthly cross-sectional and time-series strategy returns. I replicate all major trading strategies outlined in [Chernov et al. \(2023\)](#) and additionally add strategies based on active flows into the USD obtained from trading in international ETFs. Specifically, the portfolio excess return of a trading strategy is given by $R_{t+1}^{pf} = \sum_{c=1}^N w_{c,t} R_{c,t+1}$ where $w_{c,t}$ is the weight in currency c at time t and N are the number of currencies.

I construct cross-sectional (CS) strategies with rank weights

$$w_{c,t} = \text{rank}(z_{c,t}) - N^{-1} \sum_{c=1}^N \text{rank}(z_{c,t}) \quad (\text{C1})$$

where $z_{c,t}$ is the signal. The net exposure to the USD in cross-sectional strategies is thus zero. Weights for time-series (TS) strategies are equal to +1 or -1, depending on the sign of the signal. The net exposure to the USD in time-series strategies can be positive or negative. Returns and rebalancing is monthly. Table C.1 defines all strategies with the corresponding signals. The strategies based on ETF portfolio-implied expectations (denoted *ETF-Exp*) and active ETF flows (denoted *ETF-Flow*) are novel and derived from the mechanism analyzed in the main paper. All other strategies are standard.

Table C.2 presents average annualized returns in percentage, t -statistics (of non-zero average returns), and annualized Sharpe ratios (SR) from all trading strategies. In Column (1)-(3) the time period of the main paper is used 2014-2025, in Column (4)-(6) the period starts already in 1990, for which no data exist for the ETF trading strategies.

I note three main observations. First, for a given portfolio construction (cross-sectional, time-series, dollar) ETF strategies based on portfolio-implied expectations and on flows yield comparable performances, with the largest difference for the ETF-dollar strategy. Second, ETF strategies achieve an average excess return of 3.25%, substantially exceeding that of traditional strategies. Among traditional strategies the CS-Carry strategy also yields high average returns of 1.64%. However, only the CS-ETF strategies have an average excess return statistically different from zero. Third, the Sharpe ratios are highest for the cross-sectional ETF trading strategies, and reach up to 0.58 for the strategy based on portfolio-implied ETF expectations. The highest Sharpe Ratio

in the full sample is obtained by the TS-Carry strategy (of 0.46) as in [Chernov et al. \(2023\)](#).

Table C.1: Currency Trading Strategy Definitions

CS-ETF-Exp	Goes long (short) currencies with relatively low (high) active flows into the USD, i.e., it buys (sells) the USD whenever there are relatively high (low) portfolio-implied expectations in the previous month.
TS-ETF-Exp	Goes long (short) currencies with negative (positive) active flows, i.e., it buys (sells) the USD whenever there are positive (negative) portfolio-implied expectations in the previous month.
Dollar-ETF-Exp	Goes (short) long all currencies versus the USD, whenever average portfolio-implied expectations are negative (positive).
CS-ETF-Flow	Goes long (short) currencies with relatively low (high) active flows into the USD, i.e., it buys (sells) the USD whenever there are relatively high (low) active flows into the USD (unhedged vs. hedged share class) in the previous month.
TS-ETF-Flow	Goes long (short) currencies with negative (positive) active flows, i.e., it buys (sells) the USD whenever there are positive (negative) active flows into the USD (unhedged vs. hedged share class) in the previous month.
Dollar-ETF-Flow	Goes (short) long all currencies versus the USD, whenever average active flows are negative (positive).
Dollar	Goes long all currencies versus the USD.
Dollar-Carry	Goes (short) long all currencies versus the USD, whenever the average forward discount is positive (negative).
CS-Carry	Goes long (short) currencies with relatively high (low) forward discounts.
TS-Carry	Goes long (short) currencies with a positive (negative) forward discount.
CS-Mom 1	Goes long (short) currencies that have performed relatively well in the past month.
CS-Mom 12	Goes long (short) currencies that have performed relatively well in the past year.
TS-Mom 1	Goes long (short) currencies that had positive (negative) returns in the past 12 months.
TS-Mom 12	Goes long (short) currencies that had positive (negative) returns in the past 12 months.

Table C.2: Currency Trading Strategy Statistics

The table presents average annualized returns (%), t -statistics (of non-zero average returns) and annualized Sharpe ratios (SR) from trading strategies outlined in Table C.1. Column (1)-(3) report results for the sample from January 2014 until May 2025, Column (4)-(6) report results for the sample from January 1990 until May 2025. For the latter sample no results are reported for the ETF strategies as data starts only 2014. t -statistics test whether the mean monthly return equals zero, using Newey–West (lag 3) heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. The sample includes all currencies used in the main paper: AUD, GBP, EUR, CHF, JPY, CAD against the USD.

	Period 2014-2025			Period 1990-2025		
	Avg. Return (%)	t -statistics	SR	Avg. Return (%)	t -statistics	SR
	(1)	(2)	(3)	(4)	(5)	(6)
CS-ETF-Exp	3.25	2.01	0.58	-	-	-
TS-ETF-Exp	0.89	0.73	0.20	-	-	-
Dollar-ETF-Exp	0.12	0.07	0.02	-	-	-
CS-ETF-Flow	3.03	1.90	0.53	-	-	-
TS-ETF-Flow	1.13	0.95	0.27	-	-	-
Dollar-ETF-Flow	1.51	0.75	0.23	-	-	-
Dollar	-2.34	-1.22	-0.36	0.82	0.60	0.10
Dollar-Carry	-0.30	-0.15	-0.05	2.64	2.02	0.33
CS-Carry	1.64	1.03	0.24	2.96	2.15	0.34
TS-Carry	0.75	0.51	0.14	2.03	2.94	0.46
CS-Mom 1	-2.10	-1.07	-0.33	0.48	0.35	0.06
CS-Mom 12	-0.34	-0.20	-0.05	0.37	0.32	0.05
TS-Mom 1	-1.07	-0.78	-0.21	1.36	1.72	0.27
TS-Mom 12	-0.69	-0.44	-0.14	0.60	0.78	0.13

D Heterogeneous Beliefs in Asset Pricing

This section briefly outlines the main mechanism by which heterogeneous beliefs in complete markets can affect exchange rate volatility, built on [Back \(2010\)](#).

General Setup. A model with heterogeneous beliefs can be re-expressed to one with homogeneous beliefs and state-dependent utility. This can be done by defining some reference probability, for example, the average belief as

$$\mathbb{P}(\omega) = \frac{1}{N} \sum_{i=1}^N \mathbb{P}_i(\omega) \quad (\text{C1})$$

over N investors for a finite number of states ω where $\mathbb{P}_i$ and $\mathbb{P}$ are two σ -finite measures defined on a measurable space $(X, \mathcal{F}_t)$. The Radon-Nikodym theorem states that if $\mathbb{P}_i$ is absolutely continuous with respect to $\mathbb{P}$ ($\mathbb{P}_i \ll \mathbb{P}$), there exists a nonnegative random variable $\Lambda_{i,t}$, such that for any measurable set $A \in \mathcal{F}_t$

$$\mathbb{P}_i(A) = \int_A \Lambda_{i,t} d\mathbb{P} \text{ over all } A \in \mathcal{F}_t \quad (\text{C2})$$

where $\Lambda_{i,t}$ is a strictly positive martingale process and is called the Radon-Nikodym derivative of $\mathbb{P}_i$ with respect to $\mathbb{P}$. It can be written as

$$\Lambda_{i,t} = \left. \frac{d\mathbb{P}_i}{d\mathbb{P}} \right| \mathcal{F}_t. \quad (\text{C3})$$

The change of measure, $\Lambda_{i,t}$, transforms the belief of any investor i about a random variable x as

$$\mathbb{E}_t^{\mathbb{P}_i}[x_{t+1}] = \mathbb{E}_t^{\mathbb{P}} \left[\frac{\Lambda_{i,t+1}}{\Lambda_{i,t}} x_{t+1} \right]. \quad (\text{C4})$$

with the one-step likelihood ratio defined as $\xi_{i,t+1} = \frac{\Lambda_{i,t+1}}{\Lambda_{i,t}}$.

In a consumption-based asset pricing model, heterogeneous beliefs thus transform the stochastic discount factor (SDF) to

$$m_{i,t+1} = \kappa_t \beta \frac{u'_i(C_{i,t+1})}{u'_i(C_{i,t})} \frac{\Lambda_{i,t+1}}{\Lambda_{i,t}} \quad (\text{C5})$$

where κ_t is a scaling factor, β is the discount factor, $u'_i(C_{i,t})$ is investor i 's marginal utility of consumption $C_{i,t}$.

Example with Log Utility. With log-utility and aggregate consumption $\sum_i C_{i,t} = C_t$, the

first-order condition of the social planner's problem yields equilibrium consumption shares that satisfy

$$C_{i,t} = C_t \left(\frac{\lambda_i \Lambda_{i,t}}{\sum_i \lambda_i \Lambda_{i,t}} \right) \quad (\text{C6})$$

where λ_i denotes pareto weights assigned by the planner. The SDF then equals

$$m_{t+1} = \beta \frac{C_t \left(\frac{\lambda_i \Lambda_{i,t}}{\sum_i \lambda_i \Lambda_{i,t}} \right)}{C_{t+1} \left(\frac{\lambda_i \Lambda_{i,t+1}}{\sum_i \lambda_i \Lambda_{i,t+1}} \right)} \frac{\Lambda_{i,t+1}}{\Lambda_{i,t}} = \beta \frac{C_t}{C_{t+1}} \frac{BI_{t+1}}{BI_t} \quad (\text{C7})$$

where $BI_t = \sum_i \lambda_i \Lambda_{i,t}$ is the wealth-weighted average belief index (BI). Thus, compared to a model of homogenous beliefs, the SDF also depends on the time variation in wealth-weighted average beliefs $\frac{BI_{t+1}}{BI_t}$.

Dispersion in Beliefs. When investors disagree more about probabilities of future states, the wealth-weighted belief index, $\frac{BI_{t+1}}{BI_t}$, features greater variation. To see this, define

$$\frac{BI_{t+1}}{BI_t} = \sum_i \alpha_{i,t} \xi_{i,t+1} \quad \text{with } \alpha_{i,t} = \frac{\lambda_i \Lambda_{i,t}}{\sum_k \lambda_k \Lambda_{k,t}} \quad \text{and } \xi_{i,t+1} = \frac{\Lambda_{i,t+1}}{\Lambda_{i,t}} \quad (\text{C8})$$

then, assuming a discrete state space, its conditional variance under $\mathbb{P}$ is given by

$$\mathbb{V}\text{ar}_t^{\mathbb{P}} \left[\frac{BI_{t+1}}{BI_t} \right] = \mathbb{V}\text{ar}_t^{\mathbb{P}} \left[\sum_i \alpha_{i,t} \xi_{i,t+1} \right] \quad (\text{C9})$$

$$= \sum_s p(s) \left(\frac{\sum_i \alpha_{i,t} p_i(s)}{p(s)} - 1 \right)^2 \quad (\text{C10})$$

$$= \sum_s \frac{(\sum_i \alpha_{i,t} p_i(s) - p(s))^2}{p(s)} \quad (\text{C11})$$

where $p(s)$ and $p_i(s)$ are the time- t conditional probabilities under $\mathbb{P}$ and $\mathbb{P}_i$, respectively, such that $\xi_{i,t+1}(s) = \frac{p_i(s)}{p(s)}$. The second line follows from the martingale property of the Radon-Nikodym derivative under $\mathbb{P}$, i.e., $\mathbb{E}_t^{\mathbb{P}}[\sum_i \alpha_{i,t} \xi_{i,t+1}] = \mathbb{E}_t^{\mathbb{P}} \left[\frac{\sum_i \alpha_{i,t} p_i}{p} \right] = 1$ since $\sum_i \alpha_{i,t} = 1$. Thus, the larger the difference between the wealth-weighted mean beliefs (probabilities), $\sum_i \alpha_{i,t} p_i(s)$, from the reference probability, $p(s)$, the higher the variance of $\mathbb{V}\text{ar}_t[BI_{t+1}/BI_t]$.

As an example, consider a two-agent two-state model: an optimist and a pessimist who hold different beliefs about the parameters of a random variable that follows a Bernoulli distribution.

Specifically, the optimist assigns a probability of $p^{opti}(u) \in [0.1, 1]$ to the up state while the pessimist always assigns a probability of $p^{pessi}(u) = 0.1$ to the up state. The equilibrium share of the optimist takes a value of $\lambda^{opti} \in \{0.2, 0.5, 1\}$ with the pessimist taking $\lambda^{pessi} = 1 - \lambda^{opti}$. The reference probability is the equal-weighted average belief as defined in Eq. (C1). Figure D.1 shows the difference in beliefs (probabilities) between the agents on the horizontal axis against the variance in the belief index on the vertical axis, computed as²¹

$$\mathbb{V}\text{ar} \left[\frac{BI_{t+1}}{BI_t} \right] = \sum_{s \in \{u, d\}} p(s) \left(\lambda^{opti} \frac{p^{opti}(s)}{p(s)} + \lambda^{pessi} \frac{p^{pessi}(s)}{p(s)} - 1 \right)^2. \quad (\text{C12})$$

The figure shows that as the belief gap, $|p^{opti} - p^{pessi}|$, widens, the variance of the wealth-weighted belief update increases whenever $\lambda^{opti} \neq \lambda^{pessi}$ (lines marked with diamonds and circles). If agents hold equal shares $\lambda^{opti} = \lambda^{pessi} = 0.5$, the wealth-weighted average belief equals the reference probability and thus any difference in beliefs does not affect the variance of the belief update.

Dispersion in Exchange Rate Expectations. The log change in the nominal exchange rate between the home country and foreign country (*) is equal to the difference in the stochastic discount factors (see, e.g., Backus et al. (2001))

$$\Delta s_{t+1} = \log(m_{t+1}) - \log(m_{t+1}^*) \quad (\text{C13})$$

where I define an increase in Δs_{t+1} as a USD appreciation and refer to the home country as US. Note that if the SDF is in real terms, one needs to additionally subtract the inflation differential between countries in Eq. (C13).

In the log-utility example before, the exchange rate change then equals

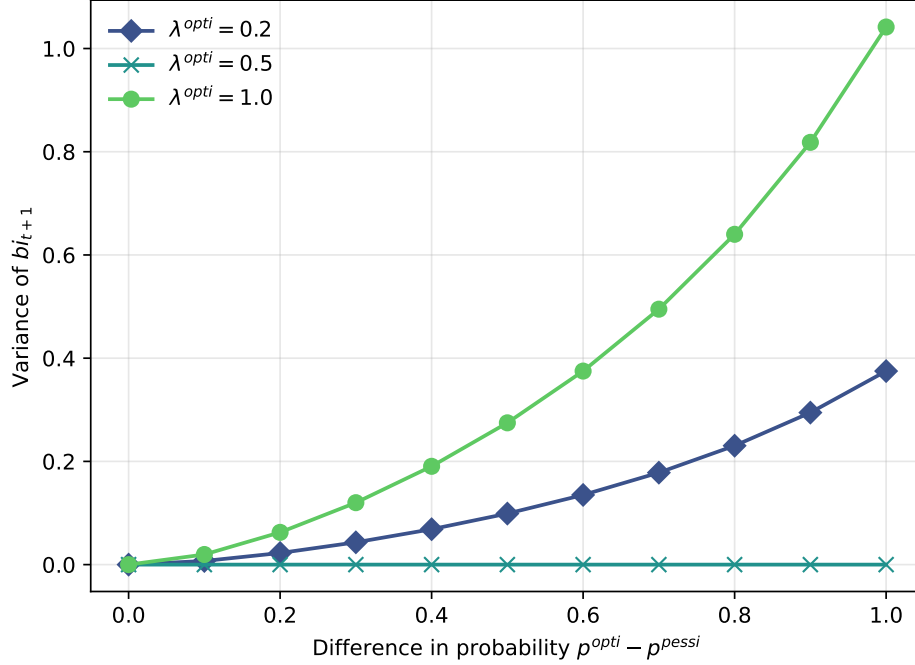
$$\Delta s_{t+1} = [\Delta c_{t+1}^* - \Delta c_{t+1}] + [\Delta bi_{t+1} - \Delta bi_{t+1}^*] \quad (\text{C14})$$

where small letters denote logs and I assume no difference in foreign and home discount factors, i.e., $\beta^* = \beta$. Excluding the belief index (the second term), Eq. (C14) equals the standard Backus-Smith condition (Eq. (4.8) in Backus and Smith (1993)).

²¹Note that in this example $\alpha_{i,t} = \lambda_i$ as I normalize $\Lambda_{i,t} = 1$, such that $\alpha_{i,t} = \frac{\lambda_i \Lambda_{i,t}}{\sum_k \lambda_k \Lambda_{k,t}} = \lambda_i$ as $\sum_k \lambda_k = 1$.

Eq. (C14) shows that under heterogeneous beliefs, the exchange rate depends on the random variables Δbi_{t+1}^* and Δbi_{t+1} , the average belief indices of the home and foreign country. In the main paper, I argue that dispersion in beliefs among foreign investors (here, e.g., euro-area ETF investors) varies with the volatility of the USD exchange rate. By Eq. (C11), an increase in dispersion among foreign investors raises $\text{Var}_t [BI_{t+1}^*/BI_t^*]$. Under a first-order log approximation, this also raises $\text{Var}_t [\Delta bi_{t+1}^*]$, and thus increases $\text{Var}_t [\Delta s_{t+1}]$ for fixed consumption and a fixed US belief index.

Figure D.1: Difference in Beliefs and Average Belief Index



Notes: The figure depicts the difference in beliefs (probabilities) between the two agents on the horizontal axis against the variance in the belief index on the vertical axis. The variance of the belief index is computed as in Eq. (C12). The figure shows three different values for the equilibrium share of the optimist $\lambda^{opti} \in \{0.2, 0.5, 1\}$.