Demand for Dollars: Evidence from Survey Expectations*

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Abstract

We study the determinants of US dollar demand across market participants and traded instruments using survey-based exchange rate and macroeconomic expectations. Leveraging granular foreign exchange (FX) trading data and forward looking expectations, we present three results. First, currency investors increase their dollar holdings when expecting US dollar appreciation or improved US macroeconomic fundamentals, whereas synthetic dollar funding is driven by forecasted deviations from covered interest parity. Second, cross-sectionally, investors rebalance along the factor structure of currency risk into dollars following an expected dollar appreciation. Third, the predictive power of professional forecasts weakens when uncertainty or forecaster disagreement rises. Our findings demonstrate that long-horizon expectations accurately predict dollar demand across spot, swap, and forward currency markets. To rationalise these empirical findings, we develop a model of currency demand.

J.E.L. classification: F31, G15, F37

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1. Introduction

The US dollar (USD) plays a pivotal role in the global monetary and financial system, as a currency for investments, funding, and hedging. For example, foreign investors hold 31% of US Treasuries outstanding (Treasury International Capital (TIC) system), whereas foreign banks borrow around 230 billion dollars via foreign exchange (FX) swaps each day (Kloks, Mattille, and Ranaldo, 2024), and more than 90 percent of international bond mutual funds use currency forwards for hedging (Sialm and Zhu, 2024). The goal of this paper is to provide a holistic overview of the determinants of dollar demand across various groups of market participants (i.e., banks, corporations, investment funds, and non-bank financials) as well as traded instruments (i.e., spot and derivatives such as swaps/forwards).[1]

To this end, we leverage survey expectations for exchange rates as well as macroeconomic fundamentals and financial variables (i.e., GDP, inflation, current account, interest rates) to uncover how these survey-based expectations predict dollar demand across market participants and traded instruments. Whether survey expectations are useful for predicting dollar demand is not obvious since survey expectations are known to be weak predictors of exchange rates, especially at shorter horizons (e.g., Nagel and Xu, 2023; Dahlquist and Söderlind, 2022). In contrast to this earlier literature Kremens, Martin, and Varela (2025) show that long-horizon exchange rate forecasts successfully predict realised currency returns.

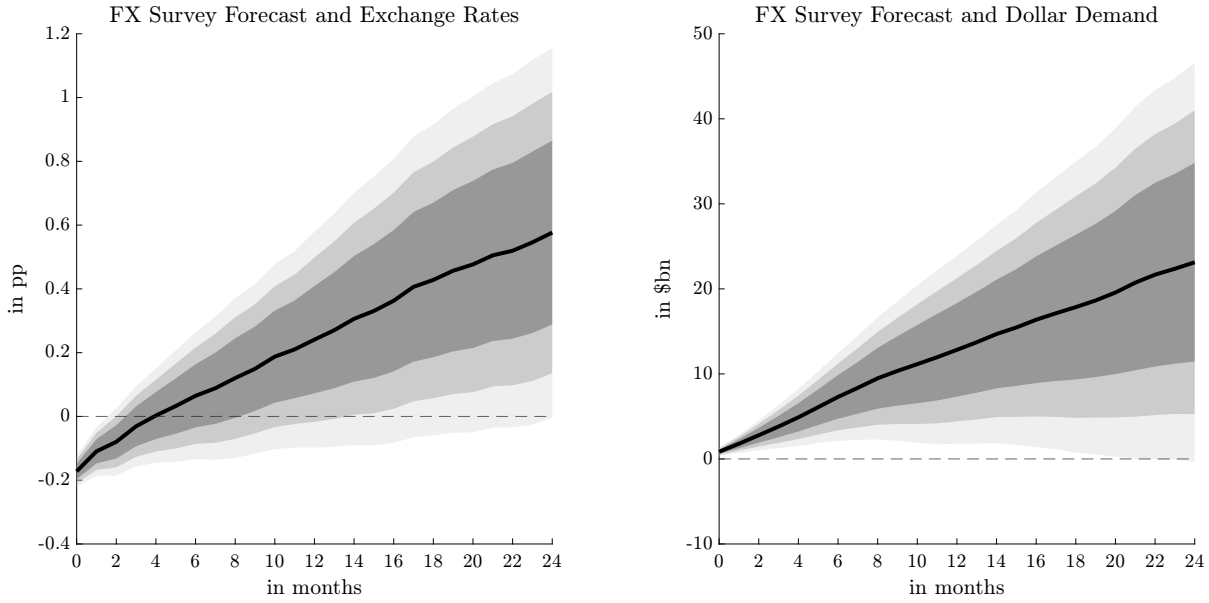
Figure 1 replicates these earlier results and shows that the component of currency returns predicted by long-run expectations materializes relatively gradually over a two year horizon.[2] For example, an expected appreciation of the USD by 1 percentage point (pp) over the next 24 months is associated with an initial depreciation of the dollar of 17 basis points (bps), followed by a subsequent appreciation of around 58 bps over the next 24 months. Similarly, we find that an expected 1 pp appreciation of the USD is associated with an instantaneous inflow into USD, proxied by spot currency flows, which increases up to 23 $bn over two

[1] We focus on the role of FX dealer banks as liquidity providers rather than cross-market arbitrageurs and hence, measure dollar demand as currency transactions that either involve the purchase or borrowing of US dollars by investors (i.e., clients) from dealer banks.

[2] Compared to Kremens et al. (2025) our evidence for short-horizon predictability is somewhat weaker for three reasons: First, our sample period extends to 2025. Second, the cross-section of currencies is different due to the availability of macroeconomic forecasts from Consensus Economics. Lastly, we include both currency and time fixed effects to control for global factors simultaneously affecting forecasts and currency flows.

years. Our takeaway from this is that exchange rate expectations successfully predict both future exchange rate movements and currency flows at both medium- and long-horizons.

Figure 1: Predictability of Exchange Rates and Currency Flows with Exchange Rate Forecasts



Note: This figure plots the impulse response functions of local projections of the form:

$$y_{i,(t;t+h)} = \mu_{i,h} + \alpha_{t,h} + \beta_h EFX_{i,t} + \gamma_h IRD_{i,t} + \epsilon_{i,t+h},$$

where the dependent variable in the left figure is the cumulative change in the exchange rate of foreign currency i against the USD after h months; and in the right figure it is the cumulative spot FX flow ($SPT_{i,(t;t+h)}$) from CLS Group in currency pair i after h months (see Section 3 for details). $EFX_{i,t}$ is the expected relative change in the FX rate based on survey forecasts from Consensus Economics, reflecting exchange rate expectations in the year after next. $IRD_{i,t}$ is the 2-year forward discount in month t. μ_i and α_t are currency and time fixed effects, respectively. The inference is based on robust standard errors (Driscoll and Kraay, 1998) correcting for heteroskedasticity and serial correlation, induced by overlapping observations in the local projection. The grey shaded areas denote the 90%, 95%, and 99% confidence bands (from dark to light grey). The sample spans from December 1994 (September 2012) to May 2025 for the left (right) figure.

In light of the evidence in Figure 1 one might ask whether some of the exchange rate predictability is related to order flow price pressure. To quantitively address this question we repeat the empirical exercise in Figure 1 but include spot currency flows and its interaction with exchange rate forecasts as an additional control variable. Two insights emerge: First, currency flows subsume the predictive content of exchange rate forecasts for realized currency returns. Second, the interaction between flows and forecasts is negative and significant, implying that the information content of survey expectations diminishes precisely when order flow exerts stronger dollar price pressure.

The core focus of our paper is on quantities rather than prices and our primary goal is to shed light on the determinants of dollar demand across various groups of market participants and traded currency instruments. To guide our empirical analysis, we develop a model of currency demand that builds on the line of work by Gabaix and Maggiori (2015), Itskhoki and Mukhin (2021), and Vayanos and Vila (2021). We augment these models by the fact that exchange rates follow a strong factor structure (Lustig, Roussanov, and Verdelhan, 2011; Verdelhan, 2017). The core idea is that investors learn about the expected returns associated with currency risk factors from forecasts made by professional forecasters. Consequently, investors allocate more assets to currencies that they expect to appreciate or more generally to countries that they expect to experience better economic prospects.

The model makes three key predictions. First, a mean-variance investor buys more dollars if she expects that the USD is going to appreciate (e.g., because she expects the US economy to grow faster). Second, in the cross-section of currencies, investors re-balance from foreign currencies into USD along the factor structure of currency risk. Following an expected appreciation of the USD investors sell more high risk foreign currencies (e.g., Australian dollar) and less low risk foreign currencies (e.g., Japanese yen). Third, investors respond less to professional forecasters' predictions about exchange rates and macroeconomic fundamentals when forecaster dispersion increases and/or in times of higher uncertainty.

We provide empirical support for these three predictions using quantity data on dollar demand and forward-looking forecast expectations. More precisely, we use a granular and comprehensive dataset on global FX spot, swap, and forward trading activity from CLS Group (CLS). CLS operates the world's largest currency cash settlement system, handling over 50% of the global spot, swap, and forward FX transaction volume. To measure forward-looking expectations about exchange rates as well as macroeconomic and financial variables, we use monthly surveys of finance professionals conducted by Consensus Economics. The forecasters interviewed are global banks, research institutes, and investors that actively participate in the currency market. With these data and theoretical foundations in place, our empirical findings can be summarized along four dimensions, corroborating the theoretical predictions.

Regarding the first and second prediction, we provide three pieces of evidence that are in line with the idea that forward-looking expectations matter for exchange rate flows. First, we

show that an expected appreciation of the USD over the horizon of the next two years is associated with a positive demand for USD in spot FX markets. Similarly, we find that expected economic conditions in the US, proxied by GDP growth, CPI growth, the trade balance, and interest rates also shape demand for USD in FX spot transactions over the next 24 months. In the cross-section of market participants, we find that funds, non-bank financials, and smaller non-dealer banks buy significantly more USD when US interest rates are projected to increase or when the US runs a larger current account deficit. By contrast, corporates strongly respond to macroeconomic variables such as GDP and inflation, for example, they purchase USD when consensus expectations point towards faster economic growth in the US. In addition, dealer banks take the opposite side in the market and provide liquidity to investors.

Comparing across forecast horizons, we find that long-horizon expectations explain short-run currency flows much better than short-horizon expectations. This result complements Kremens et al. (2025), who show that long-horizon expectations also have a much stronger predictive power for realised short-run currency returns. Kremens and Varela (2026) provide a possible explanation for the poor performance of short-term forecasts. In particular, they decompose forecasts into a component shared with long-term expectations and a component that loads on lagged forecast errors. The former component strongly predicts exchange rates even at short horizons, while the latter predicts currency returns with the wrong sign, thereby offsetting the informative component contained it the overall shor-term forecast.

Second, to assess funding currency flows in the FX swap market, we construct forward-looking expectations of covered interest parity (CIP) deviations. Consistent with our conceptual framework, we find that non-dealer banks (funds) operating in a positive (negative) CIP basis environment increase their synthetic dollar borrowing when synthetic funding is expected to become cheaper over the next six months, while dealer banks take the opposite side and provide liquidity. Notably, the trading behaviour of funds is regime-dependent: while they borrow USD in a negative CIP environment, they tend to supply additional USD funding to non-dealer banks via FX swaps when direct dollar funding is more expensive than synthetic borrowing. Furthermore, we find that the borrowing decisions of both funds and non-dealer banks are driven by exchange rate expectations — they expand USD borrowing when the dollar is expected to appreciate, but reduce their synthetic borrowing when US

interest rates are expected to rise relative to those abroad.

Third, focusing on long-dated currency swaps and forwards as instruments for hedging, we show that investment funds tend to purchase dollars forward if the USD is expected to appreciate, indicating hedging of foreign investment positions (or potentially directional bets on dollar appreciation). This evidence provides a new perspective to earlier work, showing that investment funds leave their foreign equity and bond positions largely unhedged (see, e.g., Bräuer and Hau, 2022, 2024; Opie and Riddiough, 2023; Sialm and Zhu, 2024). Regarding long-term interest expectations, we find that an increase in the US long-rate is associated with funds selling more USD forward. This behaviour is consistent with foreign investment funds (i) hedging their exposure to US assets and (ii) betting on a depreciation of the USD in the long-run (Lustig, Stathopoulos, and Verdelhan, 2019). The behaviour of non-bank financial investors is consistent with that of investment funds, whereas corporates respond stronger to macroeconomic fundamentals. More precisely, if US macroeconomic fundamentals are expected to weaken, corporates sell forward US dollars, whereas dealer banks, again, take the other side of the market by providing liquidity.

Regarding the third prediction, we study the cross-sectional heterogeneity across seven major currencies against the USD.[3] We consider two key currency factor models: (i) the two factor model by Lustig et al. (2011) and Verdelhan (2017) that includes both the dollar and the carry factor and (ii) the one factor model by Chernov, Dahlquist, and Lochstoer (2023) that builds an unconditional mean variance efficient portfolio. To measure the riskiness of foreign currencies with respect to each of these factors, we consider their factor loading (i.e., betas).

Focusing on the interaction terms between currency risk factors (i.e., dollar, carry, or UMVE betas) and our forecast measures, we find that conditional on (i) expecting the USD to appreciate, and/or (ii) expecting US interest rates and economic fundamentals to improve relative to abroad, investors exchange riskier currencies more heavily for USD than safe ones. With respect to funding dollars via FX swaps, we find that conditional on an expected increase in the cost of synthetic dollar funding, investment funds reduce their dollar funding via high carry beta currencies (e.g., Australian dollars) less relative to low carry beta (e.g., Japanese yen) currencies. Turning to hedging flows, we see that conditional on an expected

[3]Our cross-section includes the G10 currencies against the US dollar, which compromise more than 60% of global FX trading volume according to the 2025 Bank for International Settlements triennial central bank survey.

appreciation of the USD, funds hedge less in high relative to low carry beta currencies.

Regarding the fourth prediction of our theoretical framework, namely, that conditional on times of uncertainty, investors put a lower weight on consensus forecasts relative to their own forecast, we proceed along two dimensions: (i) we interact forecasts with measures of uncertainty such as the VIX index and (ii) we also look at interactions with measures of forecaster dispersion (i.e., disagreement). Along both dimensions, we find that conditional on times of higher uncertainty or disagreement, currency flows respond less to consensus forecasts relative to periods of low uncertainty or disagreement.

In sum, we provide evidence that expectations about exchange rates and economic prospects of the US relative to foreign economies are an accurate predictor of dollar demand. The remainder of the paper is structured as follows: After providing an overview of the related literature, we introduce our theoretical framework in Section 2. Section 3 provides an overview of the data employed for the empirical analysis in Section 4. Section 6 concludes.

Related Literature. Our paper contributes to the strand of research that aims to understand the determinants of dollar demand. First, there is a large literature in currency markets that studies the role of buying and selling pressure (i.e., order flow) in explaining exchange rates. This literature has been pioneered by Evans and Lyons (2002); Evans (2002), inspiring a vast literature on exchange rates and order flow dynamics (see, e.g., Froot and Ramadorai, 2005; Bacchetta and van Wincoop, 2006; Rime, Sarno, and Sojli, 2010; Menkhoff, Sarno, Schmeling, and Schrimpf, 2016). The core focus of these papers is to contemporaneously explain exchange rates using order flows or to illustrate the contemporaneous link between order flows and macroeconomic news. We contribute to this strand of literature by showing that long-horizon exchange rate and macroeconomic expectations successfully predict spot currency flows. To the best of our knowledge, we are the first paper to link currency flows and forward-looking expectations about exchange rates and macroeconomic fundamentals.

Second, our work relates to a broad literature that explores the determinants of synthetic dollar funding in the context of covered interest rate parity deviations. Due to the paucity of quantity data, this literature has so far largely focused on explaining CIP deviations with intermediary and funding constraints[4] and only recently has started to jointly study prices

[4]See, for example, Baba, Packer, and Nagano (2008); Mancini-Griffoli and Ranaldo (2011); Du, Tepper, and

(the CIP basis) and quantities (the amount of synthetic dollar borrowing).[5] We add to this literature by showing that an expected increase in the cost of synthetic dollar funding is associated with less synthetic dollar borrowing by investment funds. Moreover, in the cross-section of currencies we find that investment funds reduce synthetic dollar borrowing less via currencies that are more exposed to the dollar and carry factor, respectively.

Finally, we add to a growing body of literature that studies the prevalence and determinants of currency hedging for investment funds. Du and Huber (2023) show that mutual funds hedge on average only 21% of their foreign currency denominated asset holdings. Bräuer and Hau (2022, 2024) explore the relation between aggregate currency hedging positions and exchange rate movements based on FX derivatives data from CLS and EMIR, respectively. In addition, three other studies also analyse currency hedging behaviour at the fund-level, namely, Opie and Riddiough (2023), Sialm and Zhu (2024), and Cheema-Fox and Greenwood (2024). Contemporaneously, Hacıoğlu-Hoke, Ostry, Rey, Planat, Stavrakeva, and Tang (2025) leverage regulatory data for the UK and show that pension and investment funds, insurers, and non-financial corporations use FX derivatives primarily to hedge. In contrast to this evidence on advanced economy currencies, De Leo, Keller, and Zou (2024); De Leo, Keller, Simoncelli, Villamizar-Villegas, and Williams (2025) focus on FX derivatives against emerging market currencies, where trading activity is dominated by speculative rather than hedging motives. We contribute to this literature by providing empirical evidence that investment funds buy USD in forward contracts if professional forecasters either expect that the USD will appreciate or key US macroeconomic indicators will increase relative to abroad.

2. Theoretical Framework

We present a model of currency demand with heterogeneous investors and financial intermediaries. The framework builds on Gabaix and Maggiori (2015) and Itskhoki and Mukhin (2021), augmented by the fact that exchange rates follow a strong factor structure (Lustig

Verdelhan (2018b); Du, Im, and Schreger (2018a); Avdjiev, Du, Koch, and Shin (2019); Andersen, Duffie, and Song (2019); Cenedese, Della Corte, and Wang (2021); Jiang, Krishnamurthy, and Lustig (2021); Rime, Schrimpf, and Syrstad (2022); Augustin, Chernov, Schmid, and Song (2024); Georgievska, Karner, and Syrstad (2026)

[5] See, e.g., Ivashina, Scharfstein, and Stein (2015); Puriya and Bräuning (2020); Correa, Du, and Liao (2020); Becker, Schmeling, and Schrimpf (2023); Kloks, Mattille, and Ranaldo (2023); Kloks et al. (2024); Krohn and Sushko (2022); Kubitza, Sigaux, and Vandeweyer (2024); Ben Zeev and Nathan (2024); Du, Strasser, and Verdelhan (2025); Moskowitz, Ross, Ross, and Vasudevan (forthcoming 2025).

et al., 2011; Verdelhan, 2017). The model links investors' expectations about future currency returns to portfolio allocation decisions across countries, while intermediaries absorb order flow imbalances subject to balance sheet constraints.

2.1. *Environment*

Investors. There are J types of investors (e.g., funds, corporates, non-bank financial institutions, and smaller non-dealer banks), indexed by $j \in \{1, \ldots, J\}$. Each type has mass θ_j in the market, where $\sum_{j=1}^{J} \theta_j = 1$. Investors decide how to allocate wealth across N currencies, with the US dollar being the home currency for all investors. The model is agnostic about investors' trading motives (e.g., speculation or hedging) and investment horizon (e.g., spot or forward). Each investor type j maximizes expected utility over their investment portfolio:

$$\max_{\mathbf{w}_j} \; E_j \left[-\frac{1}{\gamma_j} e^{-\gamma_j \mathbf{w}_j' \mathbf{R}^e} \right], \tag{1}$$

where $\mathbf{w}_j$ is a vector of portfolio weights across currencies, $\gamma_j > 0$ captures constant absolute risk aversion for investor type j, and $\mathbf{R}^e$ is a vector of currency excess returns.

Intermediaries. Dealer banks act as market makers, absorbing order flow imbalances from investors. Unlike investors, dealers face balance sheet costs that limit their risk-bearing capacity and the dealer sector solves:

$$\max_{\mathbf{w}_D} \; \mathbf{w}_D' E_D[\mathbf{R}^e] - \frac{\gamma_D}{2} \mathbf{w}_D' \mathbf{\Sigma} \mathbf{w}_D - \frac{\tau}{2} \mathbf{w}_D' \mathbf{w}_D, \tag{2}$$

where $E_D[\mathbf{R}^e]$ denotes dealers' expectations, γ_D is their risk aversion, and $\tau > 0$ captures intermediation costs arising from capital requirements, risk limits, or funding constraints.

2.2. *Heterogeneous Beliefs*

Investors form expectations about currency risk premia by combining private information with publicly available survey forecasts. Investor type j forms expectations as follows:

$$E_j[\boldsymbol{\lambda}] = (1 - \omega_j) \boldsymbol{\lambda}^j + \omega_j \boldsymbol{\lambda}^F, \tag{3}$$

where λ^j represents investor j's private belief about currency risk premia, λ^F is the consensus forecast from professional forecasters, and $\omega_j \in [0,1]$ is the weight placed on public information. The weight ω_j may vary across investor types, reflecting differences in information processing capabilities, attention allocation, or confidence in public signals.

2.3. Optimal Portfolio Choice

Investors. The above utility function implies mean-variance preferences when utility is approximated by the first two moments (i.e., mean and variance). Thus, investor type j solves:

$$\max_{\mathbf{w}_j} \ \mathbf{w}_j' E_j[\mathbf{R}^e] - \frac{\gamma_j}{2}\mathbf{w}_j'\mathbf{\Sigma}\mathbf{w}_j, \tag{4}$$

where $\mathbf{\Sigma}$ is the covariance matrix of currency returns. The first-order condition yields:

$$\mathbf{w}_j^* = \frac{1}{\gamma_j}\mathbf{\Sigma}^{-1}E_j[\mathbf{R}^e]. \tag{5}$$

The above solution implies that investors allocate more to currencies that they expect to appreciate and less to those expected to depreciate against the US dollar, which delivers our first theoretical prediction:

Proposition 1: *The mean-variance investor buys more US dollar if they expect that the dollar will appreciate. This is because* $\mathbf{w}^*$ *is increasing in* $E[\mathbf{R}^e]$.

The above prediction applies to spot, forward, and swap trades alike. Forward and spot transactions differ only in terms of maturity, whereas swaps involve both a spot and a forward leg. Swaps are frequently used for synthetic dollar funding, that is, investors swap foreign currency for dollars at the prevailing spot rate and then unwind their dollar position at a forward price that is agreed upon today. The price of synthetic dollar borrowing is measured by the cross-currency basis (Du et al., 2018b). In particular, a stronger dollar is associated with a widening of the basis (Avdjiev et al., 2019), making synthetic dollar funding more expensive and thereby reducing investors' net dollar borrowing. As a result, we expect market participants to buy rather than sell US dollars in the forward leg of FX swaps, reducing their net synthetic dollar borrowing. In sum, our model predicts that an expected appreciation of

the US dollar is associated with dollar purchases across all three traded instruments.

Intermediaries. The dealer's first-order condition is:

$$E_D[\mathbf{R}^e] - \gamma_D \mathbf{\Sigma} \mathbf{w}_D - \tau \mathbf{w}_D = \mathbf{0}. \tag{6}$$

Solving for optimal dealer positions:

$$\mathbf{w}_D^* = (\gamma_D \mathbf{\Sigma} + \tau \mathbf{I})^{-1} E_D[\mathbf{R}^e]. \tag{7}$$

The term $\tau \mathbf{I}$ captures the additional cost dealers incur when expanding their balance sheets, reducing their willingness to absorb large order flow imbalances.

2.4. Market Clearing

In equilibrium, aggregate demand from all investor groups must equal the supply provided by dealer banks and hence, it must hold that

$$\sum_{j=1}^{J} \theta_j \mathbf{w}_j^* + \mathbf{w}_D^* = \mathbf{0}. \tag{8}$$

Next, we define the aggregate risk tolerance of all investor groups as:

$$\Gamma \equiv \sum_{j=1}^{J} \frac{\theta_j}{\gamma_j}, \tag{9}$$

and the belief-weighted average expectation as:

$$\bar{E}[\mathbf{R}^e] \equiv \frac{1}{\Gamma} \sum_{j=1}^{J} \frac{\theta_j}{\gamma_j} E_j[\mathbf{R}^e]. \tag{10}$$

With the above definitions, aggregate investor demand can then be re-written as:

$$\mathbf{w}_B^* \equiv \sum_{j=1}^{J} \theta_j \mathbf{w}_j^* = \Gamma \mathbf{\Sigma}^{-1} \bar{E}[\mathbf{R}^e]. \tag{11}$$

Substituting Eqs (5) and (7) into the market clearing condition Eq. (8):

$$\Gamma\boldsymbol{\Sigma}^{-1}\bar{E}[\mathbf{R}^e] + (\gamma_D\boldsymbol{\Sigma} + \tau\mathbf{I})^{-1} E_D[\mathbf{R}^e] = \mathbf{0}. \tag{12}$$

2.5. Equilibrium Characterisation

Dealers as pure liquidity providers. Consider the benchmark case where dealers have no private view on currency returns, i.e., $E_D[\mathbf{R}^e] = \mathbf{0}$. Market clearing then requires that

$$\mathbf{w}_D^* = -\mathbf{w}_B^* = -\Gamma\boldsymbol{\Sigma}^{-1}\bar{E}[\mathbf{R}^e]. \tag{13}$$

In equilibrium, dealers simply absorb whatever order flow imbalance the investors create, taking the opposite position. This delivers our second key prediction:

Proposition 2: *When dealers act as pure liquidity providers, they take positions opposite to aggregate investors demand. If investors expect the dollar to appreciate and purchase dollars, dealer banks sell dollars to accommodate this demand.*

Dealers with beliefs and constraints. When $E_D[\mathbf{R}^e] \neq \mathbf{0}$ and $\tau > 0$, rearranging the market clearing condition yields:

$$(\gamma_D\boldsymbol{\Sigma} + \tau\mathbf{I})^{-1} E_D[\mathbf{R}^e] = -\Gamma\boldsymbol{\Sigma}^{-1}\bar{E}[\mathbf{R}^e]. \tag{14}$$

To build intuition, assume for simplicity a diagonal covariance matrix $\boldsymbol{\Sigma} = \sigma^2\mathbf{I}$:

$$E_D[\mathbf{R}^e] = -\frac{\Gamma(\gamma_D\sigma^2 + \tau)}{\sigma^2}\bar{E}[\mathbf{R}^e]. \tag{15}$$

For dealers to willingly absorb investors' order flows, their beliefs must be negatively related to aggregate investor beliefs. The magnitude of this relationship is amplified by intermediation costs τ: higher balance sheet costs require dealers to expect larger compensating returns to take the opposite side of customer trades. The intuition here directly follows from Gabaix and Maggiori (2015); when investors buy dollars, the dollar appreciates on impact beyond its fundamental value. This overshooting generates expected dollar depreciation in the future, which compensates intermediaries for absorbing customer flows.

2.6. *Factor Structure and Cross-Sectional Predictions*

To shed light on the cross-sectional differences across currencies, we follow the empirical literature (e.g., Lustig et al., 2011; Verdelhan, 2017) and assume that expected currency excess returns follow a factor structure, that is, $E_j[\mathbf{R}^e] = \boldsymbol{\beta}' E_j[\boldsymbol{\lambda}]$, where $\boldsymbol{\beta}$ is an $N \times K$ matrix of factor loadings (e.g., dollar beta, carry beta) and $E_j[\boldsymbol{\lambda}]$ is investor j's expectation of factor risk premia. Since $E_j[\mathbf{R^e}]$ is increasing in $\boldsymbol{\beta}$ Eq. (5) implies that investors re-balance from foreign currencies into US dollars along the factor structure of currency risk ($\frac{\partial \mathbf{w}^*}{\partial \boldsymbol{\beta}} > 0$), which leads to our third theoretical prediction:

Proposition 3: *In the cross-section of currencies, investors re-balance from foreign currencies into US dollar along the factor structure of currency risk. Following an expected appreciation of the dollar, investors sell more out of higher risk (i.e., large $\boldsymbol{\beta}$) but less out of safer (i.e., small $\boldsymbol{\beta}$) foreign currencies.*

2.7. *State-Dependent Attention to Public Forecasts*

Following the empirical findings in Egan, MacKay, and Yang (2021), we assume that the more risk averse investors are, the more weight they put on their own expectations and the less on professional forecasters' expectations due to rational inattention. The weight on public forecasts depends on the prevailing level of uncertainty, that is, $\omega_j = \omega_j(\xi)$, with $\frac{\partial \omega_j}{\partial \xi} < 0$, where ξ measures uncertainty, such as the VIX index or forecast dispersion among professional forecasters. When uncertainty rises, investors discount public forecasts and rely more heavily on their private signals.

Next, we substitute Eq. (3) into Eq. (5) and derive the marginal effect of the public forecasts on currency demand as:

$$\frac{\partial w^*_{ji}}{\partial \boldsymbol{\lambda}^F} = \frac{\omega_j(\xi)}{\gamma_j \sigma_i^2} \boldsymbol{\beta}'_i, \tag{16}$$

which is decreasing in ξ, yielding our fourth prediction:

Proposition 4: *Investors place a lower weight on professional forecasters' expectations during periods of elevated uncertainty. Consequently, the response of currency flows to public forecasts weakens when uncertainty or forecaster disagreement increases.*

3. Data

Here, we introduce the data on currency flows and survey forecasts that we employ to empirically test the four theoretical predictions derived in the previous section.

3.1. Currency flow data

Our data on currency flows by market participants come from CLS Group (CLS), which operates the world's largest FX settlement system, mitigating both principal and operational risks by simultaneously settling both sides of the FX transaction (Hasbrouck and Levich, 2018). This dataset possesses several characteristics that make it well-suited for research on currency flows. First, CLS records the buy and sell trading volume in the base currency alongside the number of transactions on an hourly basis, spanning from Sunday at 9 pm to Friday at 9 pm (London time, GMT), thereby covering the full FX trading week. Second, CLS covers different groups of currency market participants: corporates, funds, non-bank financial firms (NBFIs), and banks. Third, the data covers spot, swap, and forward currency flows. Consequently, significant heterogeneity exists in the motivations of the market participants FX trading across different instruments.

In a first step, CLS reports transactions between corporates/banks, funds/banks, and non-banks financial firms/banks. This categorization is purely based on the identity of the trading counterparties and provides no information on who initiated the transaction and it assumes that banks acted as liquidity providers. In a second step, CLS performs a proprietary network analysis that allows them to categorize all market participants into price takers (buyside) and market makers (sellside). Given the two tier market structure of the currency market (see, e.g., Schrimpf and Sushko, 2019), it appears fair to assume that almost all sellside market participants will be comprised by either large FX dealer banks (e.g., UBS) or non-bank liquidity providers (e.g., XTX). In contrast, the buyside market participants will mainly consist of corporates, funds, non-banks financial firms plus smaller, non-dealer banks acting as price takers. CLS does not directly report transactions between price taker banks and market maker banks. However, the reporting structure above allows us to indirectly infer these transactions by computing the difference between total buyside trading activity and transactions

between banks and corporates, funds, and non-bank financial firms, respectively. Note that this approximation will generally *underestimate* the trading activity between price taker banks (in the following classified as smaller, non-dealer banks, which we abbreviate as "Buyside Banks") and market maker or dealer banks since the three aforementioned groups may trade with both buyside and sellside banks.

In each hourly interval, CLS logs buy volume as the amount of the base currency acquired by price takers from market makers. Conversely, the sell volume denotes the volume of the base currency sold by price takers to market makers. Note that whenever we study flows between buyside and sellside market participants, we take the perspective of the liquidity providers (that is, we compute net flows as sellside minus buyside flow). The Online Appendix provides further institutional insights and details on CLS's classification of market participants into price takers and market makers.

Our main variable of interest is the net currency flow (i.e., total buy volume less total sell volume), denominated in billions of USD (positive values indicate net purchases of USD). Our sample period spans from September 2012 to May 2025, and we focus on G10 currency pairs: the USD versus AUD, CAD, CHF, EUR, GBP, JPY, NOK, NZD, and SEK. Trading volumes are separately recorded for buyside and sellside market participants after trade instructions are received from both counterparties. Within the data, CLS logs the transaction time as if it had taken place at the moment the first instruction was received. CLS obtains confirmation for over 90% of trade instructions from settlement members within two minutes of execution. The majority of the 72 existing settlement members are large multinational banks. Additionally, there are more than 25,000 "third-party" clients of these settlement members, encompassing other banks, funds, non-bank financial firms, and corporations.

Table 1 tabulates the average monthly net trading volumes of each currency pair by market participant and traded instruments. Specifically, for our empirical analysis, we focus on short-term swaps with maturities of less than 35 trading days and long-dated forwards with maturities beyond 35 trading days to capture synthetic dollar funding and hedging flows, respectively. Overall, trading activity in the FX market is dominated by swap transactions, which consistently exhibit the largest average volumes and standard deviations across all currencies. spot transactions exceed forward transactions in average volume, while both are

Table 1: Summary Statistics - Monthly Net FX Trading Volume

Currency		Dealer Banks			Corporates			Funds			NBFIs			Buyside Banks		
		Spot	Swap	Fwd	Spot	Swap	Fwd	Spot	Swap	Fwd	Spot	Swap	Fwd	Spot	Swap	Fwd
AUD	Mean	-2.13	-10.29	1.39	-0.62	-0.07	0.42	3.15	-23.73	-3.12	-0.01	0.77	0.05	-0.39	23.46	0.19
	SD	5.23	87.45	2.86	0.81	0.24	0.60	4.23	16.70	3.62	0.59	4.64	0.19	5.65	88.12	0.92
CAD	Mean	-2.77	-25.03	-0.03	-0.21	0.29	0.64	7.34	-18.41	-0.15	0.43	0.99	-0.19	-4.79	35.28	0.13
	SD	38.41	58.29	2.52	1.06	0.69	0.83	20.25	18.74	2.42	1.94	6.06	0.35	29.73	59.27	1.14
CHF	Mean	-3.03	-86.27	1.42	-1.09	-0.66	0.01	2.53	-30.02	-1.10	0.91	-9.47	-0.03	0.75	110.94	-0.47
	SD	5.31	123.33	2.25	1.47	1.51	0.10	3.39	23.32	2.13	1.68	7.41	0.22	4.99	126.98	1.70
EUR	Mean	-22.42	-552.94	1.69	-0.24	-6.73	2.94	10.25	76.33	-9.58	0.27	-0.52	0.52	11.99	447.01	0.43
	SD	18.89	272.10	6.16	4.01	4.78	2.98	12.98	182.42	7.16	1.98	27.71	0.89	18.81	265.09	2.95
GBP	Mean	-8.25	-57.89	-0.04	-0.86	0.18	1.06	9.29	-67.98	-4.40	0.53	0.99	0.32	-0.46	96.17	0.77
	SD	9.88	114.61	4.22	1.76	1.28	1.14	7.87	40.30	3.27	1.89	9.94	0.41	8.62	114.41	2.60
JPY	Mean	2.81	-273.66	1.05	-0.87	0.50	0.77	0.53	-4.49	-2.86	0.71	0.46	-2.46	-3.18	270.32	-0.04
	SD	11.97	219.91	4.56	1.09	1.23	1.45	7.67	27.70	4.79	1.91	10.20	3.05	10.80	216.98	2.82
NOK	Mean	0.32	12.81	0.03	0.08	-0.16	0.01	0.19	-3.29	-0.20	-0.02	-0.05	-0.01	-0.48	-10.11	0.01
	SD	1.69	42.38	0.80	0.24	0.36	0.09	0.69	1.93	0.55	0.15	0.33	0.03	1.68	41.47	0.59
NZD	Mean	-0.19	1.28	0.01	-0.07	-0.01	0.03	0.70	-1.40	0.02	-0.01	0.08	0.01	-0.03	-1.08	-0.05
	SD	2.85	29.99	1.09	0.09	0.03	0.05	1.53	2.94	0.74	0.14	1.46	0.06	2.77	29.69	0.78
SEK	Mean	0.06	-37.03	0.20	-0.03	-0.18	0.02	0.01	-2.14	-0.17	-0.03	-0.17	0.01	0.20	36.07	-0.10
	SD	1.80	51.17	0.85	0.53	0.66	0.20	1.30	3.32	0.68	0.17	0.64	0.09	1.74	48.79	0.51

Note: This table reports mean and standard deviation of the monthly currency flows (spot, swap with maturities of less than 35 days, and forward flows with maturities beyond 35 days) by trading counterparty (in billions of USD) and by currency pairs quoted against the USD. Trading counterparties include dealer banks, corporates, funds, non-bank financial firms (NBFIs), and non-dealer banks (buyside banks). The sample covers G10 currencies quoted against the USD. The data are monthly from September 2012 to May 2025.

smaller and less volatile than swaps. Forward transactions, while the smallest part of the market, on average, still represent a significant share of activity. Comparing the different market participants, we observe that trading activity is dominated by dealer and non-dealer banks (i.e., buyside banks) as well as investment funds. Corporates and NBFIs represent a smaller share of trading with forwards playing a relatively more important role for corporates.

3.2. FX and economic forecasts

We obtain forecasts from Consensus Economics. The data contain monthly forecasts covering exchange rates and macroeconomic fundamentals, such as interest rates, current account balances, consumer prices, and real GDP growth, and span from September 2012 to May 2025. Again, we focus on the G10 currencies and the corresponding economies. For exchange rates, we obtain forecasts for 3-, 12-, and 24-month horizons.[6] Interest rate projections for three-

[6]Note that survey forecasts for CHF, NOK, and SEK are expressed relative to the EUR rather than the USD. Since, for any dollar currency pair USD/X, it holds that $\mathbb{E}[S_{USD/X}] = \mathbb{E}[S_{USD/EUR} \cdot S_{EUR/X}] = \mathbb{E}[S_{USD/EUR}] \cdot \mathbb{E}[S_{EUR/X}] + \text{Cov}(S_{USD/EUR}, S_{EUR/X})$, we convert these forecasts to dollar expectations using the prevailing USDEUR spot rate and we account for the covariance term using rolling historical covariances.

month interest rates and ten-year government bond yields cover 3- and 12-month forecast periods.[7]. Forecasts for key economic indicators such as consumer prices, current account balances, and real GDP growth are for the current and subsequent year-end.

Data for macroeconomic fundamentals are at the individual forecaster-level. We construct *consensus* forecasts by aggregating individual forecaster-level data, providing an average forecast that reflects the collective outlook of multiple forecasters. Measures of forecaster disagreement, such as the highest and lowest forecasts and the standard deviation of predictions, help us to assess the level of uncertainty in economic projections. For the main part of our analysis, we focus on consensus forecasts, however, we also look at individual forecaster-level outcomes, for example, with regard to forecaster disagreement.

Based on those forecasts, we construct our key forecast measures to assess the predictive power of forecasts for currency flows. Motivated by Kremens et al. (2025), who document the higher predictive power of longer-term exchange rate forecasts on currency returns, we mainly focus on longer-term horizon forecasts. Since FX transactions always involve two currencies and relate to the economic conditions in two countries, we express our forecast measures as differentials. For example, the FX rate change is calculated as the percentage change in the exchange rate over 24 months, using the USD as the base currency. Accordingly, the interest rate differential is computed as the difference between 3-month (annualized) interest rates in the US and the corresponding foreign rates projected 12 months ahead. The current account to GDP (CA to GDP) differential, consumer price differential, and real GDP growth differential are all calculated as the differences between US and foreign forecasts for external balances, inflation, and real economic growth, respectively, at the end of the subsequent year. To assess the importance of shorter-term horizon forecasts, we apply the same methodology to construct corresponding measures over shorter horizons.

The price of synthetic dollar borrowing is measured by the CIP basis. In line with Du et al. (2018b), we define the CIP basis as $CIP = i_{us} - (i_{foreign} - FD_{annualized})$, where FD is the forward discount defined as the relative difference between the forward rate F and the spot rate S (i.e., $(F - S)/S$). If CIP > 0 ($CIP < 0$), the direct USD interest rate is higher (*lower*) than the synthetic dollar interest rate, implying that synthetic dollar funding is cheaper (*more*

[7]Since there are no specific forecasts for euro area interest rates, German interest rate forecasts are used as a proxy for euro interest rate predictions.

expensive) relative to the cash market. Our innovation is to consider the *forecasted CIP basis*. For this purpose, we consider forecasts of 3-month interest rates projected three months ahead, together with the corresponding forward discount for the 3-month period starting in three months.[8]

Table 2: Summary Statistics - Forecast Variables

Currency	FX Rate Change in PP	Interest Rate Diff. in PP	CA to GDP Diff. in PP	Cons. Prices Diff. in PP	GDP Diff. in PP	CIP Deviation in PP
AUD	−0.909	−0.398	−1.526	−0.199	−0.277	−0.097
CAD	−2.366	0.141	−1.163	0.197	0.142	−0.064
CHF	1.660	1.915	−12.592	1.594	0.590	−0.445
EUR	−1.286	1.230	−5.425	0.603	0.599	−0.389
GBP	−1.983	0.233	0.220	−1.042	0.374	−0.206
JPY	−1.608	1.600	−6.053	1.146	1.070	−0.627
NOK	−7.124	−0.092	−12.834	0.183	0.238	−0.318
NZD	−0.056	−1.002	1.502	0.189	−0.313	−0.131
SEK	−6.224	0.912	−8.228	0.423	0.134	−0.375

Note: FX Rate Change is defined as $(\text{FX}_{24mo} - \text{FX})/\text{FX} \times 100$, with USD as the base currency. Interest Rates, CA to GDP, Consumer Prices, and real GDP growth are differentials between the US and the quote country, forecasted 12 months ahead (for interest rates) or at the end of the subsequent year (for the other variables), measured in percentage points. The CIP deviation is defined as the difference between the annualized forward discount and the annualized interest rate differential between the quote country and the US, with the USD being the base currency. The forward discount is computed as $(F - S)/S \times (360/90) \times 100$ where S is today's spot exchange rate and F is the implied forward rate for the period from month 3 to month 6. This forward rate is constructed as $F = S \times (F_{0,6}/F_{0,3})$, where $F_{0,3}$ and $F_{0,6}$ denote today's 3-month and 6-month forward rates, respectively. The interest rate differential embedded in the CIP deviation is based on 3-month interest rates forecasted three months ahead. The sample covers G10 currencies quoted against the USD. The data are monthly from September 2012 to May 2025.

Table 2 illustrates the average values of our forecast variables across currencies. On average, the sample currencies are forecasted to appreciate against the USD over the subsequent 24 months with the exception of the Swiss franc. The predicted 3-month interest rate differentials are mostly small and positive, indicating slightly higher US interest rates. Notable exceptions are Australia and New Zealand, which are typically high-interest-rate currencies and, therefore, attractive for carry trades. The current-account-to-GDP differentials are negative for most currencies, reflecting the fact that the US runs (and is, therefore, projected to run) negative CA/GDP balances. Consumer-price and GDP differentials are slightly positive,

[8]The forward discount is computed as $(F - S)/S \times (360/90) \times 100$ where S is today's spot rate and F is the implied forward rate for the period from month 3 to month 6. This forward rate is constructed as $F = S \times (F_{0,6}/F_{0,3})$, where $F_{0,3}$ and $F_{0,6}$ denote today's 3- and 6-month forward rates, respectively. As an alternative, we could also employ FX rate forecasts to derive the forecasted forward discount. However, those forecasts are only available at 3- and 12-month horizons, hence, we would need to interpolate any forecasts to match the interest rate horizon.

on average, indicating higher real growth and inflation forecasts for the US. Finally, the CIP basis is typically negative, which implies that, in accordance with existing literature (e.g., Du et al., 2018b), the cost of synthetic dollar funding is more expensive relative to the cash market.

Our forecasts are widely used by policymakers, investors, and businesses to inform decision-making and strategic planning[9]. A common criticism of survey forecasts is that they are biased by strategic incentives (see, e.g., Coibion and Gorodnichenko (2012), Coibion and Gorodnichenko (2015), Bordalo, Gennaioli, Ma, and Shleifer (2020), De Marco, Macchiavelli, and Valchev (2021), and Gemmi and Valchev (2026) for recent evidence). Our results do not imply that the forecasts themselves are rational, but rather that the trading flows of the marginal investor in currency markets are predicted by consensus forecasts.

3.3. Measures of currency risk

To study the cross-sectional differences across currencies, we construct measures of currency risk (i.e., currency betas) based on two factor models: i) the bivariate model by Lustig et al. (2011) and Verdelhan (2017) that includes the dollar and the carry factor and ii) the one factor model by Chernov et al. (2023) that builds an unconditional mean variance efficient portfolio. The currency betas quantify an asset's exposure to currency risk factors.

Verdelhan (2017) shows that the dollar and carry factors jointly account for the majority of variation in bilateral FX rates relative to the dollar, explaining between 19 and 91 percent of the exchange rate variation among developed countries. The dollar factor is the average change in all currencies with respect to the USD. It is akin to the capital asset pricing model's market portfolio. The carry factor mimics the returns of a self-financing long-short trading strategy that borrows in low interest rate currencies to invest in high interest rate ones. We create this portfolio by sorting, every month, currencies into five portfolios based on the one-month forward discount relative to the USD prevailing over the previous month. The "long" portfolio consists of currencies with the highest interest rates relative to the US, whereas low interest rate currencies constitute the "short" portfolio.

We consider the same cross-section of 39 countries as in Verdelhan (2017) but exclude euro

[9]Consider, for example, Devereux, Smith, and Yetman (2012).

area countries; this leaves us with 28 countries to construct the risk factors. Specifically, we estimate dollar β_i^{DOL} and carry β_i^{CAR} betas using a 60-month rolling window regression of log changes in currency i's exchange rate $S_{i,t}$ on either the dollar or the carry factor:

$$\Delta \log S_{i,t} = a_i + \beta_i^{DOL} Dollar_t + \epsilon_{i,t}, \tag{17}$$

$$\Delta \log S_{i,t} = a_i + \beta_i^{CAR} Carry_t + \epsilon_{i,t}. \tag{18}$$

Dollar and carry betas summarize the assortment of a country's characteristics that collectively determine its currency's risk. For example, countries with large carry betas tend to be on the periphery of the global trade network (Richmond, 2019) and typically export commodities and import finished goods (Ready, Roussanov, and Ward, 2017). Carry betas align with interest rate differentials (Lustig et al., 2011). Countries with large dollar betas typically face large trade costs in goods, which relates, for instance, to the gravity equation in international trade. These economic sources of currency risk are not mutually exclusive. Thus, the carry and dollar betas are useful as they proxy for deeper economic phenomena but are defined by their ability to capture a currency's exposure to these FX risk factors.

In addition to the dollar and carry betas, we also consider the beta on the unconditional mean-variance efficient (UMVE) portfolio of currencies that we create following Chernov et al. (2023). UMVE is constructed such that it solely accounts for the priced risk component of currency returns. As for the carry and dollar factor, we similarly estimate the currency beta with respect to the UMVE factor from a rolling window regression (see Eq. (17)):

$$\Delta \log S_{i,t} = a_i + \beta_i^{\text{UMVE}} \text{UMVE}_t + \epsilon_{i,t}. \tag{19}$$

Table 1 in the Online Appendix summarizes the betas by currency. Analogous to a stock market beta, dollar betas record the incremental systematic currency risk that a US investor takes on when investing in foreign currency i. Carry and UMVE betas measure currency i's exposure to the carry and UMVE factor, respectively.[10]

[10]Since the dollar beta has a mean close to one, we standardize the dollar beta by the cross-sectional mean and standard deviation.

4. Empirical Analysis

4.1. Currency flow predictability

We begin our analysis by exploring whether survey expectations about exchange rates and macroeconomic variables have predictive power for currency flows. For this, we estimate predictive regressions of currency flows on survey forecasts. In doing so, we consider the three most heavily traded currency instruments: spot, swap, and forward trades.

To ease the interpretation of the sign of the point estimates, we leverage our theoretical framework (see Section 2) which predicts that higher expected US dollar returns are associated with buying more US dollars in the future (either via spot or forward contracts). A similar intuition applies to synthetic dollar borrowing via currency swaps: an expected appreciation of the US dollar is associated with a widening of the CIP basis (Avdjiev et al., 2019), making synthetic dollar funding more expensive and thus reducing net dollar borrowing via FX swaps (i.e., selling fewer dollars forward). Several remarks are in order. First, the link between macroeconomic variables (e.g., interest rates and GDP growth) and exchange rates is both theoretically and empirically ambiguous (see, e.g., Obstfeld and Rogoff, 2000). Second, we interpret the regression coefficients as the revealed preferences of the marginal investor who may trade currencies for various reasons (e.g., investment, speculation, or hedging). Therefore, if we find that an expected increase in these macroeconomic variables is associated with a given investor group buying more US dollars, then this indicates that the group interprets these expectations as a sign of (future) dollar appreciation.

Investment flows: The FX spot market facilitates the immediate exchange of one currency for another at the prevailing market rate. For instance, spot FX transactions are widely used by investors seeking to obtain foreign currencies for portfolio allocation and investment purposes. The FX spot market, therefore, plays a central role in enabling investors to gain direct exposure to foreign assets and to adjust their currency holdings in response to market conditions. As a first step, we seek to understand how currency flows in the spot FX market are related to forecasts of exchange rates as well as macroeconomic variables.

Table 3 reports the results of regressing spot FX flows at time $t+1$ on a set of forecasts

formed at time t. Specifically, we run regressions of the form:

$$SPT_{i,t+1} = \mu_i + \alpha_t + \beta' \mathbf{X}_{i,t} + \epsilon_{i,t}, \tag{20}$$

where the dependent variable is the spot FX flow ($SPT_{i,t+1}$) from CLS in currency pair i and month $t+1$. The key regressors are in $X_{i,t}$ containing forecasts of exchange rates and macroeconomic variables. Specifically, in panel (a), $X_{i,t}$ includes forecasts of FX rate changes over the following 24 months ("FX Change"). Panel (b) adds the forecasted interest rate differentials between the US and a given foreign country i (e.g., Canada for the USDCAD exchange rate) in 12 months ("Interest Rate"), the difference in the CA / GDP ratio between the US and a given foreign country i ("CA / GDP"), as well as the first principal component of forecasted differentials in inflation and real GDP growth between the US and the foreign country at the end of the subsequent year ("Macro PC1"). This setup allows the underlying macroeconomic variables to capture different economic dimensions. For example, CA-to-GDP likely reflects more persistent, structural differences across economies, whereas GDP growth and inflation capture more cyclical, short-run conditions. Panel (c) replaces the Macro PC1 with individual forecasted differentials in inflation ("Inflation") and real GDP growth ("GDP").The inference is based on Driscoll and Kraay's (1998) robust covariance matrix, which allows for cross-sectional and serial correlation.

In all regression specifications, we include currency μ_i and time α_t fixed effects. Currency fixed effects control for time-invariant unobserved heterogeneity at the currency level, while time fixed effects absorb variation in global factors common to all currencies (e.g., US monetary policy cycle, general market uncertainty). As a result, the β coefficient in Eq. (20) captures the relative sensitivity of dollar demand to, for instance, an expected dollar depreciation: within a given period, foreign currencies, whose expected depreciation against the dollar exceeds the cross-sectional average, see differentially higher outflows, over and above what global factors alone would predict.

Panel (a) shows a clear difference between customer flows (i.e., funds and buyside banks) on the one hand and dealer banks on the other. Customer flows, particularly those of funds and small banks, are positive and significant, reflecting forecast-following or directional trading behaviour. In other words, an expected appreciation of the USD over the horizon of the

Table 3: Forecasting Investment Currency Flows

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
(a) Exchange rate forecasts					
FX Change	−0.753***	−0.033*	0.330***	−0.089***	0.548**
	(0.270)	(0.017)	(0.111)	(0.030)	(0.233)
Overall R^2	0.335	0.241	0.319	0.185	0.267
(b) Exchange rate, interest rate, CA / GDP, and PCA of macro forecasts					
FX Change	−0.776***	−0.025	0.461***	−0.071***	0.399*
	(0.260)	(0.019)	(0.150)	(0.023)	(0.225)
Interest Rates	−0.034	0.103	1.061	0.131	−1.392
	(1.194)	(0.080)	(0.728)	(0.099)	(0.892)
CA / GDP	0.693***	0.026	−0.261**	−0.097***	−0.335*
	(0.258)	(0.027)	(0.118)	(0.028)	(0.202)
Macro PC1	1.150	0.640***	−0.688	−0.127	−0.875
	(1.177)	(0.149)	(0.722)	(0.103)	(0.878)
Overall R^2	0.340	0.276	0.325	0.200	0.271
(c) Exchange rate, interest rate, CA / GDP, and macro forecasts					
FX Change	−0.759***	−0.023	0.438***	−0.071***	0.402*
	(0.254)	(0.019)	(0.139)	(0.023)	(0.223)
Interest Rates	0.168	0.127	0.786	0.139	−1.358
	(1.165)	(0.083)	(0.696)	(0.103)	(0.883)
CA / GDP	0.620**	0.017	−0.162	−0.100***	−0.347*
	(0.252)	(0.026)	(0.106)	(0.028)	(0.208)
Inflation	−0.437	0.314***	1.234	−0.147	−0.852
	(1.201)	(0.108)	(0.852)	(0.128)	(1.142)
GDP	1.650*	0.624***	−1.498***	−0.079	−0.632
	(0.948)	(0.153)	(0.565)	(0.090)	(0.805)
Overall R^2	0.342	0.278	0.334	0.201	0.271
Observations	1′368	1′368	1′368	1′368	1′368
Currencies	9	9	9	9	9
FEs	Yes	Yes	Yes	Yes	Yes

Note: This table reports forecasting regressions of investment currency flows (spot market) by trading counterparty (in billions of USD) at $t+1$ on the set of forecasts available at t. Panel (a) includes forecasts of FX rate changes. Panel (b) adds the forecasted interest rate and CA / GDP differentials and the first principal component of forecasted differentials in inflation and real GDP growth between the US and the foreign country at the end of the subsequent year (Macro PC1). Panel (c) replaces the Macro PC1 with individual forecasted differentials in inflation and GDP growth. All regressions include currency and time fixed effects. Standard errors in parentheses are computed using the spatial estimator of Driscoll and Kraay (1998), which allows for cross-sectional and serial correlation as well as heteroskedasticity. Stars indicate significance at the 10% (*), 5% (**), and 1% (***) levels. The sample covers G10 currencies quoted against the USD. The data are monthly from September 2012 to May 2025.

next two years is associated with a positive demand for USD in FX spot markets. For example, when the consensus forecast indicates an appreciation of 1% of the USD, then trading volume for buying USD and selling foreign currency by buyside banks increases, on average, by 0.55 billion USD over the following month. In contrast, dealer banks display the opposite behaviour, that is, the coefficient is negative and significant, indicating that they sell USD when the USD is expected to appreciate. This is consistent with dealer banks acting as liquidity providers in the currency market.

Panel (b) performs a horse race between forecasts for exchange rates and macroeconomic variables. First, the coefficient on 3-month interest rate differentials is not significant. However, we expect interest rate differentials to align with carry betas (Lustig et al., 2011), which we show in Section 4.2. Second, we find that expected changes in the current account to GDP ratio differential have a strong predictive power for currency flows. Note that an increase in the CA / GDP differential is associated with a relatively smaller US current account deficit compared to abroad, implying an associated decrease in the US financial account. During our sample period, the US has experienced a current account deficit, which the US government has financed by the issuance of new debt. The fact that institutional investors purchase USD as the US current account deficit is expected to increase is consistent with foreign investors playing an important role in US Treasury markets (Somogyi, Wallen, and Xu, 2025). The results confirm that investors (i.e., funds, NBFIs, and smaller banks) tend to buy USD when they expect the US current account deficit to rise relative to abroad. For example, a one percentage point expected decrease in the CA / GDP differential is associated with investment funds buying an additional 0.26 billion USD over the next month. In line with Panel (a), dealer banks take the other side of the trade and sell USD when current account deficits in the US are expected to rise relative to abroad. Third, while the CA / GDP ratio reflects more structural economic differences, the Macro PC1 captures more business cycle dynamics. As expected, those considerations are particularly relevant for corporates.

Panel (c) decomposes the principal component into its individual components. In line with the positive loading on the Macro PC1, corporates increase their USD purchases when US inflation and GDP growth are expected to rise. This result is intuitive, since corporate trading is largely driven by the import and export prices of purchases and sales in foreign

currency. For example, a European firm that exports to the US may find it optimal to buy USD today to insure itself against a depreciation of the dollar in response to rising inflation expectations. Other investor groups follow those business cycle dynamics less, the only exception are funds who sell USD when US GDP growth is expected to rise.

The results suggest that macroeconomic variables contain additional information for spot FX flows that goes beyond exchange rate expectations. This is in line with Kremens et al. (2025), who find that FX forecasts have lower predictive power for exchange rates when controlling for variation in current account and real FX rate.

Next, we replicate our analysis in Table 3 with short-term forecasts. Consensus Economics offers forecasts at different horizons, with macroeconomic variables being predicted for the end of the current year as well as the end of the subsequent year, while interest rate and FX forecasts are predicted 3, 12 (and 24) months ahead. Kremens et al. (2025) show that long-term FX forecasts tend to be more accurate predictors of short-term FX returns than short-term FX forecasts. We provide complementary evidence to their findings for currency flows. In particular, when we use 3-month ahead forecasts for FX rates, we find no evidence of predictability of currency flows over the subsequent month. By contrast, interest rate forecasts appear to be more relevant at shorter horizons (3 months). In particular, funds and smaller banks tend to sell USD following an expected relative increase in US interest rates. The results for the other macroeconomic variables are consistent with our previous findings. Hence, we confirm that short-term FX rate forecasts offer less predictive information compared to long-term FX forecasts, however, we also show that short-term forecasts for other macroeconomic variables are still relevant in explaining FX order flow.

In sum, our evidence on spot FX flows indicates that there is heterogeneity in the way currency flows of various groups of market participants relate to expectations about future exchange rates and macroeconomic conditions. Specifically, investment funds, NBFIs, and non-dealer banks tend to purchase USD (i) when the USD is expected to appreciate, (ii) when US short-term interest rates are expected to rise, and (iii) when the US financial account surplus is expected to decrease. In the cross-section of market participants, corporates' currency flows are strongly related to expectations about macroeconomic variables such as GDP and inflation but less so to changes in the current account deficit. Lastly, dealer banks' currency

Table 4: Forecasting Investment Currency Flows with Short-term Forecasts

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
(a) Exchange rate forecasts					
FX Change	−0.183	0.035	−0.020	−0.032	0.199
	(0.321)	(0.031)	(0.196)	(0.040)	(0.263)
Overall R^2	0.322	0.239	0.312	0.161	0.256
(b) Exchange rate, interest rate, CA / GDP, and PCA of macro forecasts					
FX Change	0.003	0.060*	−0.103	−0.004	0.036
	(0.302)	(0.031)	(0.193)	(0.028)	(0.242)
Interest Rates	1.881*	0.185***	−0.876*	0.412**	−1.743*
	(1.092)	(0.068)	(0.453)	(0.120)	(0.892)
CA / GDP	0.581***	0.004	−0.261***	−0.062***	−0.232
	(0.188)	(0.020)	(0.093)	(0.020)	(0.149)
Macro PC1	−0.465	0.276*	0.310	−0.053	0.014
	(1.046)	(0.143)	(0.734)	(0.089)	(0.858)
Overall R^2	0.331	0.251	0.318	0.198	0.263
(c) Exchange rate, interest rate, CA / GDP, and macro forecasts					
FX Change	−0.009	0.056*	−0.083	−0.006	0.035
	(0.298)	(0.031)	(0.185)	(0.027)	(0.242)
Interest Rates	2.041*	0.244***	−1.136**	0.440***	−1.735*
	(1.098)	(0.085)	(0.520)	(0.127)	(0.903)
CA / GDP	0.524***	−0.017	−0.168*	−0.072***	−0.235
	(0.191)	(0.021)	(0.094)	(0.023)	(0.155)
Inflation	−0.758	−0.074	1.027*	−0.120	−0.019
	(0.728)	(0.073)	(0.564)	(0.076)	(0.617)
GDP	0.159	0.327***	−0.525	0.045	0.029
	(0.708)	(0.124)	(0.458)	(0.056)	(0.569)
Overall R^2	0.332	0.265	0.326	0.203	0.263
Observations	1'368	1'368	1'368	1'368	1'368
Currencies	9	9	9	9	9
FEs	Yes	Yes	Yes	Yes	Yes

Note: This table reports forecasting regressions of investment currency flows (spot market) by trading counterparty (in billions of USD) at $t+1$ on the set of forecasts available at t. Forecasts are for shorter horizons than the results in Table 3. Panel (a) includes forecasts of FX rate changes at the 3-month horizon. Panel (b) adds the forecasted interest rate differentials 3-month ahead and CA / GDP differential at the end of the same year and the first principal component of forecasted differentials in inflation and real GDP growth between the US and the foreign country at the end of the same year (Macro PC1). Panel (c) replaces the Macro PC1 with individual forecasted differentials in inflation and GDP growth for the current year. All regressions include currency and time fixed effects. Standard errors in parentheses are computed using the spatial estimator of Driscoll and Kraay (1998), which allows for cross-sectional and serial correlation as well as heteroskedasticity. Stars indicate significance at the 10% (*), 5% (**), and 1% (***) levels. The sample covers G10 currencies quoted against the USD. The data are monthly from September 2012 to May 2025.

flows similarly correlate with survey forecasts but with the opposite sign, that is, dealer banks supply dollar liquidity when their customers demand USD.

Price pressure. Given our results in Figure 1 and the evidence on long-horizon exchange rate forecasts, one might wonder whether some of the exchange rate predictability is related to order flow price pressure. To empirically address this question, we estimate the following regression:

$$y_{i,(t;t+24)} = \mu_i + \alpha_t + \beta EFX_{i,t} + \gamma IRD_{i,t} + \xi SPT_{i,t} + \rho(SPT_{i,t} \times EFX_{i,t}) + \epsilon_{i,t+h}, \qquad (21)$$

where the dependent variable is the cumulative change in the exchange rate of foreign currency i against the USD after two years. Our key coefficient of interest is ρ, the interaction term between spot currency flows and exchange rate forecasts.

Table 5 estimates various specifications of Eq. (21). Specifically, columns 1 ("FX Rate" Change) and 2 ("Spot FX Flow") replicate the point estimates in Figure 1, whereas columns 3 and 4 (focusing on FX rate changes) include spot currency flows and their interaction with exchange rate forecasts as additional explanatory variables. The core insight is twofold: First, exchange rate forecasts are not statistically significant predictors of currency flows when controlling for currency flows. Second, the interaction between currency flows and exchange rate forecasts is negative and significant, that is, the predictive power of exchange rate forecasts declines conditional on currency flows exerting dollar price pressure. Put differently, conditional on large dollar inflows from foreign currencies, exchange rate forecasts are weaker predictors of realised currency returns.

Funding flows: Currency swaps enable the simultaneous exchange of two currencies at the spot rate and the agreement to reverse the transaction at a predetermined forward rate in the future. Unlike spot markets, which are frequently used for portfolio allocation and investment motives, FX swap markets are primarily used for short-term funding. In particular, financial institutions such as non-dealer banks, but also funds, rely on FX swaps to obtain USD funding. For instance, a Dutch investment fund could borrow dollars and lend euro by engaging in an FX swap that exchanges euros for dollars today and receives euros in the "forward leg." This mechanism allows investors to "synthetically" borrow in foreign currencies

Table 5: Exchange Rate Predictability and Order Flow Price Pressure

	(1)	(2)	(3)	(4)
	FX Rate Change	Spot FX Flow	FX Rate Change	FX Rate Change
EFX	0.577**	21.616**	0.246	0.186
	[2.465]	[2.165]	[1.402]	[1.151]
IRD	−0.460	−0.617	−0.147	−0.047
	[0.721]	[0.031]	[0.222]	[0.072]
SPT			−0.031*	−0.032**
			[1.646]	[2.131]
SPT × EFX				−0.011***
				[2.661]
Overall R^2 in %	73.53	57.44	65.27	65.61
Total # of Obs.	2516	1152	1368	1368
Avg. #Time periods	280	128	152	152
#Currencies	9	9	9	9
Currency FE	yes	yes	yes	yes
Time series FE	yes	yes	yes	yes

Note: This table reports forecasting regressions of the form

$$y_{i,(t;t+24)} = \mu_i + \alpha_t + \beta EFX_{i,t} + \gamma IRD_{i,t} + \xi SPT_{i,t} + \rho(SPT_{i,t} \times EFX_{i,t}) + \epsilon_{i,t+h},$$

where the dependent variable is either the cumulative change in the exchange rate of foreign currency i against the USD after 24 months (columns 1, 3, and 4) or the cumulative spot FX flow ($SPT_{i,(t;t+24)}$) from CLS Group in currency pair i after 24 months. $EFX_{i,t}$ is the expected relative change in the FX rate based on survey forecasts from Consensus Economics, reflecting exchange rate expectations in the year after next. $IRD_{i,t}$ is the 2-year forward discount in month t. $SPT_{i,t}$ is spot FX flow from CLS Group in currency pair i and month t. μ_i and α_t are currency and time fixed effects, respectively. The inference is based on robust standard errors (Driscoll and Kraay, 1998) correcting for heteroskedasticity and serial correlation, induced by overlapping observations. Stars indicate significance at the 10% (*), 5% (**), and 1% (***) levels. The sample covers G10 currencies quoted against the USD. The data spans from December 1994 (September 2012) to May 2025 for column 1 (columns 2, 3, and 4).

without accessing foreign funding markets (e.g., Repo markets) directly (Borio, McCauley, and McGuire, 2022). CLS records the second leg of the swap, i.e., a negative order flow corresponds to borrowing USD in the first leg and repaying it in the second leg.

The price of synthetic dollar borrowing is typically measured by the CIP basis. In brief, CIP states that the interest rate differential between two countries should equal the forward–spot exchange rate differential, ensuring that a hedged foreign investment earns the same return as a domestic investment. In frictionless markets, CIP holds because arbitrage capital can freely exploit any pricing gap between money and FX markets. However, since the Global Financial Crisis, persistent CIP deviations have emerged (see, e.g., Du et al., 2018b). Specifically, synthetic dollar funding via FX swaps has become more expensive relative to direct funding via the cash market. We define the CIP basis as $CIP = i_{us} - (i_{foreign} - FD_{annualized})$. Interest rates and forward discount are annualized. If CIP > 0 ($CIP < 0$), the direct USD interest rate is higher (*lower*) than the synthetic dollar interest rate, implying that synthetic dollar funding is cheaper (*more expensive*) relative to the cash market.

Given our interest in understanding how expectations predict currency flows, we construct a forward-looking measure of CIP. Specifically, we use three-month-ahead forecasts of US and foreign three-month cash market interest rates, together with the three-to-six-month forward discount implied by today's forward rates, to compute the expected CIP basis. We use these implied CIP forecasts to predict future swap currency flows. Our prior is that an expected increase in the CIP basis (i.e., synthetic dollar funding becomes cheaper) is associated with more synthetic USD borrowing via FX swaps. Put differently, we expect to see more trading activity in FX swaps that sell USD in the second leg of the swap contract.

Table 6 reports the results of regressing swap currency flows at time $t+1$ on CIP forecasts formed at time t. Specifically, we run regressions of the form:

$$SWP_{i,t+1} = \mu_i + \alpha_t + \beta CIP_{i,t} + \epsilon_{i,t}, \tag{22}$$

where the dependent variable is the swap currency flow ($SWP_{i,t+1}$) in a given foreign currency i and month $t+1$. A positive swap flow implies that the amount of synthetic dollar lending exceeds the amount of borrowing. The key regressor is the CIP forecast $CIP_{i,t}$. As before, we include both currency μ_i and time α_t fixed effects.

Panel (a) includes forecasts of the CIP deviation over the next six months ("CIP Deviation") as regressor. The point estimate for funds is negative and economically large, amounting to an additional 53 billion (bn) USD synthetic borrowing for a 1 percentage point (pp) expected contraction of the CIP basis. Note that we record the second leg of the swap and hence, a negative coefficient means that, conditional on the cost of synthetic dollar funding decreasing (i.e., the basis becomes less negative), investment funds sell more USD forward, which is equivalent to doing more synthetic dollar funding. The same holds true for smaller buyside banks who might be restricted from accessing direct dollar funding. In contrast, dealer banks supply USD to meet swap funding demand as they have a large positive coefficient with respect to the expected CIP basis of 123 billion (bn) USD, covering both the demand by funds and buyside banks. This means that they lend out USD in the first leg and receive them back in the second leg.

Panel (b) differentiates between periods when the CIP basis is positive ("CIP^+") and negative ("CIP^-"), respectively. As has been shown in Table 2, and in line with with Du et al. (2018b), the CIP basis is mostly negative, hence, the results with the negative CIP interaction term mostly mimic the results in Panel (a). A few additional results emerge. First, non-dealer banks increase their synthetic dollar borrowing in times when synthetic dollar funding is cheaper than the cash market rate (i.e., "CIP^+"). Second, funds appear to be the most elastic group of synthetic dollar borrowers. Specifically, they lend dollars when the basis is positive, but borrow dollars when it is negative. Lastly, dealer banks supply dollar funding irrespective of the sign of the CIP basis, which is consistent with their role as global liquidity providers. However, coefficients associated with positive CIP environments are not statistically significant, which likely reflects the small number of observations in this regime during the sample.

Panel (c) replaces the expected CIP basis with its individual components — forecasted exchange rate changes at the three-month horizon ("FX Change") and expected three-month interest rate differentials between the US and the foreign country 3-month ahead ("Interest Rate"). An expected appreciation of the US dollar is associated with a widening of the CIP basis (Avdjiev et al., 2019), i.e., a more negative basis, which raises the cost of synthetic dollar funding and, in turn, reduces net USD borrowing via FX swaps by both funds and buy-side

banks (i.e., selling fewer dollars forward). In contrast, responses to expected interest rate differentials differ across investor types. Smaller banks increase synthetic USD borrowing when US interest rates rise relative to foreign rates, consistent with a contraction in the CIP basis. Funds, however, exhibit the opposite behavior and increase USD lending following a rise in US interest rates, suggesting that their activity in FX swap markets is not solely driven by funding considerations.

Table 6: Forecasting Funding Currency Flows

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
(a) CIP forecasts					
CIP Deviation	123.263***	0.001	−54.388***	1.298	−78.498*
	(36.728)	(0.387)	(17.848)	(1.261)	(43.534)
Overall R^2	0.699	0.637	0.387	0.187	0.637
(b) Positive and negative CIP levels					
$CIP^+ \times$ CIP Deviation	127.231	0.498	21.743	−0.984	−143.788
	(94.655)	(0.809)	(24.955)	(3.859)	(96.507)
$CIP^- \times$ CIP Deviation	126.535***	0.060	−63.188***	1.892	−71.917
	(40.654)	(0.460)	(20.119)	(1.356)	(47.378)
Overall R^2	0.699	0.637	0.388	0.187	0.637
(C) FX and interest rate forecasts					
FX Change	−3.448***	−0.002	0.429*	0.003	3.036**
	(1.301)	(0.013)	(0.246)	(0.085)	(1.276)
Interest Rates	11.400	0.123	12.668***	0.974**	−22.625**
	(10.616)	(0.101)	(2.289)	(0.469)	(10.239)
Overall R^2	0.698	0.637	0.392	0.189	0.640
Observations	1'368	1'368	1'368	1'368	1'368
Currencies	9	9	9	9	9
FEs	Yes	Yes	Yes	Yes	Yes

Note: This table reports forecasting regressions of funding currency flows (swap flows with maturities shorter than 35 days) by trading counterparty (in billions of USD) at $t+1$ on the set of forecasts available at t. Panel (a) includes the forecasted CIP deviations. Panel (b) interacts the forecasted CIP deviations with a dummy variable indicating positive respectively negative CIP levels. Panel (c) replaces the CIP deviations with forecasted FX rate changes at the 3-month horizon and forecasted three-month interest rate differentials 3-month ahead. All regressions include currency and time fixed effects. Standard errors in parentheses are computed using the spatial estimator of Driscoll and Kraay (1998), which allows for cross-sectional and serial correlation as well as heteroskedasticity. Stars indicate significance at the 10% (*), 5% (**), and 1% (***) levels. The sample covers G10 currencies quoted against the USD. The data are monthly from September 2012 to May 2025.

Hedging flows: Long-dated currency forwards are widely used for hedging purposes, allowing investors and firms to protect themselves against exchange rate fluctuations. An FX

forward is a contractual agreement to buy or sell a specific amount of foreign currency at a predetermined rate on a future date. By locking in this forward rate, market participants can eliminate uncertainty about future exchange rate movements. For instance, a US investment fund expecting to receive large dividend payments in euros three months from now can enter a forward contract to sell euros for dollars at a fixed rate, thereby hedging against the risk of euro depreciation. In this way, FX forwards serve as a key risk management tool. As a next step in our analysis, we want to understand how currency flows in forwards are predicted by forecasts about exchange rates and macroeconomic fundamentals.

Table 7 reports forecasting regressions of long-dated forward flows by trading counterparty at time $t+1$ on a set of forecasts available at time t. The empirical setup closely follows our earlier analysis on the spot market in Eq. (20). In Panel (a), we see that corporates, funds, and NBFIs exhibit large and positive coefficients, which is consistent with buying USD at predefined rates when expecting a dollar appreciation. This suggests that the marginal investor across these groups of investors is likely to have foreign currency exposures that they seek to hedge. In contrast, dealer banks sell forward USD conditional on survey forecasts predicting a dollar appreciation, thereby providing dollar liquidity.

Panel (b) adds the interest rate differential, the CA / GDP differential, and the Macro PC1 as additional explanatory variables to the regression in Panel (a). Regarding long-term interest rates, an increase in US interest rates is associated with corporates, funds, and NBFIs selling forward USD, suggesting that these institutions hedge against potential long-term dollar depreciation driven by the uncovered interest parity condition (Lustig et al., 2019). Interestingly, corporates have a strong, negative loading on the Macro PC1, while funds have an opposite positive loading. As Panel (c) confirms, this effect is mostly driven by forecasts of real GDP growth compared to inflation expectations. More precisely, corporates (funds) sell (buy) forward USD when GDP growth is expected to rise, the opposite reactions to their trading in the spot market. Overall, our findings highlight that professional investors integrate both financial and macroeconomic outlooks when managing currency risk.

Table 7: Forecasting Hedging Currency Flow

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
(a) Exchange rate forecasts					
FX Change	−0.127***	0.025**	0.192***	0.069***	0.001
	(0.034)	(0.012)	(0.046)	(0.025)	(0.019)
Overall R^2	0.181	0.492	0.543	0.446	0.128
(b) Exchange rate, interest rate, CA / GDP, and PCA of macro forecasts					
FX Change	−0.084**	0.001	0.110***	0.027	0.026
	(0.041)	(0.012)	(0.039)	(0.020)	(0.022)
Interest Rates	0.374	−0.234***	−0.652***	−0.349***	0.226*
	(0.252)	(0.083)	(0.227)	(0.127)	(0.134)
CA / GDP	−0.076*	−0.029	0.106	0.044**	−0.004
	(0.039)	(0.022)	(0.073)	(0.020)	(0.027)
Macro PC1	0.226	−0.356***	0.860***	0.049	0.056
	(0.227)	(0.066)	(0.235)	(0.093)	(0.151)
Overall R^2	0.188	0.511	0.557	0.465	0.131
(c) Exchange rate, interest rate, CA / GDP, and macro forecasts					
FX Change	−0.087**	−0.001	0.118***	0.028	0.027
	(0.041)	(0.012)	(0.039)	(0.020)	(0.022)
Interest Rates	0.334	−0.252***	−0.555***	−0.342***	0.237*
	(0.251)	(0.081)	(0.209)	(0.130)	(0.137)
CA / GDP	−0.062*	−0.023	0.071	0.041**	−0.008
	(0.036)	(0.022)	(0.072)	(0.020)	(0.027)
Inflation	0.414*	−0.145	0.011	−0.004	−0.031
	(0.218)	(0.089)	(0.309)	(0.133)	(0.118)
GDP	0.061	−0.363***	1.056***	0.062	0.085
	(0.224)	(0.069)	(0.221)	(0.069)	(0.161)
Overall R^2	0.189	0.513	0.562	0.465	0.132
Observations	1'368	1'368	1'368	1'368	1'368
Currencies	9	9	9	9	9
FEs	Yes	Yes	Yes	Yes	Yes

Note: This table reports forecasting regressions of hedging currency flows (forward flows with maturities longer than 35 days) by trading counterparty (in billions of USD) at $t+1$ on the set of forecasts available at t. Panel (a) includes forecasts of FX rate changes. Panel (b) adds the forecasted interest rate and CA / GDP differentials and the first principal component of forecasted differentials in inflation and real GDP growth between the US and the foreign country at the end of the subsequent year (Macro PC1). Panel (c) replaces the Macro PC1 with individual forecasted differentials in inflation and GDP growth. All regressions include currency and time fixed effects. Standard errors in parentheses are computed using the spatial estimator of Driscoll and Kraay (1998), which allows for cross-sectional and serial correlation as well as heteroskedasticity. Stars indicate significance at the 10% (*), 5% (**), and 1% (***) levels. The sample covers G10 currencies quoted against the USD. The data are monthly from September 2012 to May 2025.

4.2. *Heterogeneity across currencies*

Next, we explore how the predictive power of survey forecasts for currency flows varies across currencies. Specifically, we want to understand whether (predicted) currency flows propagate through the exchange rate factor structure, that is, whether riskier currencies experience larger outflows following an expected appreciation of the US dollar relative to safer currencies. More precisely, we consider currencies' exposure to three tradeable risk factors, the dollar, carry, and UMVE, respectively. We estimate the following regression:

$$y_{i,t+1} = \mu_i + \alpha_t + \beta' \mathbf{X}_{i,t} + \varphi(\mathbf{X}_{i,t} \times \mathbf{Z}_{i,t}) + \delta' \mathbf{Z}_{i,t} + \epsilon_{i,t}, \tag{23}$$

where the dependent variable is either the spot, swap, or forward currency flow in currency pair i and month t. The key regressors are in $X_{i,t}$ containing forecasts of exchange rates and macroeconomic variables, and in $Z_{i,t}$ containing the respective FX risk factor betas by currency pair. Our main coefficient of interest is φ which identifies the cross-sectional differences across currency pairs through the interaction term. A positive coefficient implies that, for instance, an expected appreciation of the dollar is associated with larger outflows from riskier relative to safer currencies into US dollars. In all regression specifications, we include both currency μ_i and time α_t fixed effects to control for unobserved heterogeneity at the currency-level and for time variation in global factors. As before, the inference is based on Driscoll and Kraay's (1998) robust covariance matrix, which allows for cross-sectional and serial correlation.

Investment flows: We start by regressing future spot currency flows on exchange rate forecasts as well as the interaction of exchange rate forecasts and currency betas. Table 8 reports the results of regressing spot FX flows at time $t+1$ on FX forecasts at time t and their interaction with currency betas (i.e., dollar, carry, and UMVE betas).

Panel (a) confirms our earlier result: following an expected appreciation of the dollar, funds and smaller buyside banks buy US dollars, whereas dealer banks provide liquidity by selling dollars. Turning to the interaction between expected dollar appreciation (i.e., "FX Change") and carry betas, we find that funds, NBFIs, and buyside banks exchange riskier, high carry beta currencies more heavily for US dollars than safer ones. Put differently, customers of large dealer banks unwind their exposure to the carry factor by increasing their

dollar purchases in times when survey forecasts predict a dollar appreciation and, in turn, reduce their exposure to high-risk currencies (e.g., Australian Dollar and New Zealand Dollar).

Panels (b) and (c) extend the analysis in Panel (a) by examining how dollar and UMVE betas, respectively, shape spot currency flows. Panel (b) shows that the interaction terms with dollar betas are also positive and significant across most investor groups, indicating that an expected dollar appreciation predicts a larger outflow from foreign currencies (into dollars) that are more exposed to the dollar factor. Panel (c) shows a similar and consistent pattern for the UMVE beta, implying that the priced component of currency returns also plays an important role in shaping global currency flows across countries.

Table 9 extends the analysis by incorporating forecasts of interest rate differentials between the US and the foreign economy. Specifically, we extend the previous specification by adding the interest rate differential (i.e., "Interest Rates") and its interaction term with the currency betas. The results reveal different patterns across high- and low- (negative-) beta currencies. On average, investor groups such as funds and NBFIs increase USD purchases when US interest rates are expected to rise, consistent with USD-denominated investments becoming more attractive. However, the interaction with currency betas is negative and statistically significant for NBFIs and smaller buyside banks. This indicates that, conditional on higher expected US rates, these investors tilt toward high-beta currencies — selling USD and increasing exposure to higher-yielding currencies. As in previous specifications, dealer banks take the opposite side of these trades, thereby supplying liquidity to the market.

Funding flows: Next, we repeat our analysis above but replace the dependent variable in Eq. (23) by short-term swaps. Table 10 reports the results of regressing swap currency flows at time $t+1$ on CIP forecasts at time t in currency pair i and the interaction with various measures of currency risk (i.e., dollar, carry and UMVE betas).

Panels (a)–(c) highlight how funds' relative to other banks' synthetic dollar borrowing relates to an expected increase in the CIP basis. Specifically, funds exhibit a positive interaction coefficient with carry and UMVE betas, respectively. Therefore, an expected increase in the cost of synthetic dollar funding (i.e., a more negative CIP basis) is associated with a stronger reduction in synthetic dollar borrowing via low risk currencies (e.g., Japanese yen) relative to high risk currencies (e.g., Canadian dollars). This result is intuitive, given that the size of

Table 8: Investment Currency Flows and the FX Factor Structure

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
(a) Exchange rate forecasts and carry beta					
FX Change	−0.505**	−0.042**	0.294**	−0.094***	0.353*
	(0.233)	(0.018)	(0.113)	(0.031)	(0.212)
FX Change × Carry Beta	−0.847***	−0.033**	0.372***	0.075***	0.421***
	(0.139)	(0.013)	(0.101)	(0.028)	(0.119)
Overall R^2	0.354	0.250	0.326	0.198	0.285
(b) Exchange rate forecasts and dollar beta					
FX Change	−0.519**	−0.021	0.190*	−0.103***	0.459**
	(0.231)	(0.015)	(0.100)	(0.032)	(0.203)
FX Change × Dollar Beta	−0.570***	−0.017*	0.299***	0.039***	0.244**
	(0.110)	(0.009)	(0.072)	(0.014)	(0.102)
Overall R^2	0.355	0.265	0.342	0.204	0.275
(c) Exchange rate forecasts and UMVE beta					
FX Change	−0.757**	−0.072***	0.299***	−0.036	0.569**
	(0.292)	(0.015)	(0.093)	(0.025)	(0.258)
FX Change × UMVE Beta	−0.224	−0.069**	0.125	0.116***	0.036
	(0.261)	(0.029)	(0.181)	(0.037)	(0.202)
Overall R^2	0.341	0.242	0.331	0.205	0.266
Observations	1′368	1′368	1′368	1′368	1′368
Currencies	9	9	9	9	9
FEs	Yes	Yes	Yes	Yes	Yes

Note: This table reports forecasting regressions of investment currency flows (spot market) by trading counterparty (in billions of USD) at $t+1$ on the set of forecasts available at t, interacted with common FX risk factor betas by currency pair. Panel (a) includes forecasts of FX rate changes and the interaction with the carry beta. Panel (b) replicates Panel (a) with the dollar beta. And Panel (c) replicates Panel (a) with the UMVE beta. The dollar beta is standardized by the cross-sectional mean and standard deviation. All regressions include currency and time fixed effects. Standard errors in parentheses are computed using the spatial estimator of Driscoll and Kraay (1998), which allows for cross-sectional and serial correlation as well as heteroskedasticity. Stars indicate significance at the 10% (*), 5% (**), and 1% (***) levels. The sample covers G10 currencies quoted against the USD. The data are monthly from September 2012 to May 2025.

Table 9: Investment Currency Flows, Interest Rates, and the FX Factor Structure

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
(a) Exchange rate forecasts, interest rates, and carry beta					
FX Change	−0.727***	−0.024	0.459***	−0.070***	0.350
	(0.250)	(0.019)	(0.147)	(0.025)	(0.221)
Interest Rates	−1.259	0.130	1.196*	0.169*	−0.394
	(0.936)	(0.102)	(0.696)	(0.097)	(0.751)
Interest Rates × Carry Beta	1.524**	0.515***	−0.650	−0.235**	−1.096**
	(0.636)	(0.068)	(0.399)	(0.105)	(0.470)
Overall R^2	0.347	0.284	0.324	0.197	0.283
(b) Exchange rate forecasts, interest rates, and dollar beta					
FX Change	−0.665***	−0.005	0.432***	−0.070***	0.297
	(0.237)	(0.018)	(0.135)	(0.025)	(0.208)
Interest Rates	−0.807	0.154*	0.937	0.212**	−0.626
	(0.938)	(0.092)	(0.669)	(0.096)	(0.784)
Interest Rates × Dollar Beta	2.930***	0.085**	0.127	−0.131*	−3.020***
	(0.724)	(0.038)	(0.407)	(0.072)	(0.465)
Overall R^2	0.353	0.267	0.328	0.200	0.300
(c) Exchange rate forecasts, interest rates, and UMVE beta					
FX Change	−0.700**	−0.038*	0.414***	−0.055*	0.374
	(0.275)	(0.020)	(0.149)	(0.028)	(0.235)
Interest Rates	−0.178	0.220**	1.420*	−0.030	−1.476*
	(1.191)	(0.101)	(0.836)	(0.079)	(0.866)
Interest Rates × UMVE Beta	−0.054	0.293**	0.075	−0.504***	0.330
	(1.046)	(0.130)	(0.719)	(0.161)	(0.879)
Overall R^2	0.341	0.244	0.335	0.208	0.269
Observations	1'368	1'368	1'368	1'368	1'368
Currencies	9	9	9	9	9
FEs	Yes	Yes	Yes	Yes	Yes

Note: This table reports forecasting regressions of investment currency flows (spot market) by trading counterparty (in billions of USD) at $t+1$ on a set of forecasts available at t, interacted with common FX risk factor betas by currency pair. Panel (a) includes forecasts of FX rate changes, and forecasts of interest rates and the interaction with the carry beta. Panel (b) replicates Panel (a) with the dollar beta. And Panel (c) replicates Panel (a) with the UMVE beta. The dollar beta is standardized by the cross-sectional mean and standard deviation. All regressions include currency and time fixed effects. Standard errors in parentheses are computed using the spatial estimator of Driscoll and Kraay (1998), which allows for cross-sectional and serial correlation as well as heteroskedasticity. Stars indicate significance at the 10% (*), 5% (**), and 1% (***) levels. The sample covers G10 currencies quoted against the USD. The data are monthly from September 2012 to May 2025.

the CIP basis is correlated with the level of interest rates, which in turn is correlated with carry betas. Specifically, low interest rate currencies tend to exhibit the most negative bases and high interest rate currencies tend to have less negative bases or sometimes even positive bases (Du et al., 2018b). The results suggest that funds follow forecasts of CIP deviations in their funding flows, however, this is less prevalent in currencies with higher risk exposure. In contrast to funds, smaller buyside banks are less sensitive to the interaction of the CIP basis with carry or UMVE betas, mostly following movements in the CIP basis in general.

Table 10: Funding Currency Flows and the FX Factor Structure

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
(a) Forecasts of CIP deviations and carry beta					
CIP Deviation	129.575***	0.040	−56.637***	1.429	−82.653**
	(35.791)	(0.402)	(17.794)	(1.523)	(40.677)
CIP Deviation × Carry Beta	−135.354	−1.747**	71.412***	−0.338	61.570
	(82.260)	(0.720)	(24.123)	(4.377)	(82.356)
Overall R^2	0.711	0.644	0.391	0.202	0.654
(b) Forecasts of CIP deviations and dollar beta					
CIP Deviation	116.073***	−0.094	−57.848***	1.622	−68.376
	(41.823)	(0.369)	(18.245)	(1.437)	(48.844)
CIP Deviation × Dollar Beta	56.045*	0.180	−0.055	−0.663	−57.844*
	(32.753)	(0.202)	(10.092)	(1.106)	(32.083)
Overall R^2	0.704	0.645	0.423	0.192	0.639
(c) Forecasts of CIP deviations and UMVE beta					
CIP Deviation	151.314***	−0.275	−24.377	2.781	−135.864***
	(51.494)	(0.432)	(17.885)	(2.165)	(50.872)
CIP Deviation × UMVE Beta	68.183	−1.086	80.642***	3.966	−147.688
	(101.317)	(1.012)	(29.311)	(5.393)	(92.391)
Overall R^2	0.698	0.637	0.421	0.189	0.632
Observations	1'368	1'368	1'368	1'368	1'368
Currencies	9	9	9	9	9
FEs	Yes	Yes	Yes	Yes	Yes

Note: This table reports forecasting regressions of funding currency flows (swap flows with maturities shorter than 35 days) by trading counterparty (in billions of USD) at $t+1$ on the set of forecasts available at t, interacted with common FX risk factor betas by currency pair. Panel (a) includes the forecasted CIP deviations and the carry beta. Panel (b) replicates Panel (a) with the dollar beta. And Panel (c) replicates Panel (a) with the UMVE beta. The dollar beta is standardized by the cross-sectional mean and standard deviation. All regressions include currency and time fixed effects. Standard errors in parentheses are computed using the spatial estimator of Driscoll and Kraay (1998), which allows for cross-sectional and serial correlation as well as heteroskedasticity. Stars indicate significance at the 10% (*), 5% (**), and 1% (***) levels. The sample covers G10 currencies quoted against the USD. The data are monthly from September 2012 to May 2025.

Hedging flows: Lastly, we study the implications of the currency factor structure for long-dated forwards which investors can employ to hedge foreign currency exposures. Again, our key focus is on the interaction term between exchange rate forecasts and various measures of currency risk (i.e., carry, dollar, and UMVE betas).

Table 11 reports the results from a regression that is analogous to the one in Table 8 but replaces the dependent variable with long-dated forward currency flows. A positive coefficient indicates that, following an expected dollar appreciation, a given investor group buys US dollars and sells foreign currency in the forward leg. Across all panels, funds, NBFIs, and smaller buyside banks sell forward foreign currency when the dollar is expected to appreciate, while dealer banks provide liquidity by selling dollars forward. Turning to the cross-section of currencies, the negative interaction terms with currency betas imply that, following an expected appreciation of the dollar, those investor groups sell forward safe rather than risky currencies (i.e., the ones with larger carry, dollar, and UMVE betas). Overall, our evidence corroborates the notion that investment managers hedge less against exchange rate fluctuations in currencies with higher expected returns (i.e., higher factor betas). By contrast, corporates buy USD by particularly selling riskier currencies (positive interaction term) following an expected USD appreciation to hedge potential business risk.

4.3. Forecaster disagreement and global uncertainty

Following our theoretical framework in Section 2, investors form expectations about currency risk premia by combining their own expectations with professional forecasters' expectations about exchange rates and macroeconomic variables. The weight that investors put on their own relative to the public signal increases with uncertainty around the forecasts themselves (dispersion across professional forecasters) and general macroeconomic uncertainty. To test this empirically, we proceed along two dimensions: (i) we interact forecasts with forecaster dispersion, and (ii) we also consider interactions with the VIX and gold price changes to proxy for global uncertainty.

Forecaster disagreement: We begin by regressing spot currency flows at time $t+1$ on a set of consensus forecasts formed at time t. The dependent variable is the spot currency flow ($SPT_{i,t+1}$) from CLS in currency pair i and month $t+1$. The key explanatory variables are the

Table 11: Hedging Currency Flows and the FX Factor Structure

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
(a) Exchange rate forecasts and carry beta					
FX Change	−0.149***	0.016	0.218***	0.110***	0.026
	(0.033)	(0.014)	(0.045)	(0.023)	(0.022)
FX Change × Carry Beta	0.030	0.064***	−0.199***	−0.121***	−0.054***
	(0.036)	(0.015)	(0.049)	(0.029)	(0.020)
Overall R^2	0.185	0.500	0.551	0.524	0.143
(b) Exchange rate forecasts and dollar beta					
FX Change	−0.150***	0.009	0.247***	0.095***	0.018
	(0.038)	(0.012)	(0.051)	(0.021)	(0.021)
FX Change × Dollar Beta	0.049**	0.035***	−0.123***	−0.080***	−0.040***
	(0.025)	(0.006)	(0.025)	(0.011)	(0.013)
Overall R^2	0.186	0.505	0.558	0.575	0.136
(c) Exchange rate forecasts and carry beta					
FX Change	−0.096***	0.052***	0.054	0.027	−0.012
	(0.034)	(0.012)	(0.044)	(0.018)	(0.022)
FX Change × UMVE Beta	0.096	0.081***	−0.326***	−0.161***	−0.067*
	(0.074)	(0.020)	(0.068)	(0.042)	(0.035)
Overall R^2	0.188	0.501	0.560	0.466	0.129
Observations	1′368	1′368	1′368	1′368	1′368
Currencies	9	9	9	9	9
FEs	Yes	Yes	Yes	Yes	Yes

Note: This table reports forecasting regressions of hedging currency flows (forward flows with maturities longer than 35 days) by trading counterparty (in billions of USD) at $t+1$ on the set of forecasts available at t, interacted with common FX risk factor betas by currency pair. P Panel (a) includes forecasts of FX rate changes and the carry beta. Panel (b) replicates Panel (a) with the dollar beta. And Panel (c) replicates Panel (a) with the UMVE beta. The dollar beta is standardized by the cross-sectional mean and standard deviation. All regressions include currency and time fixed effects. Standard errors in parentheses are computed using the spatial estimator of Driscoll and Kraay (1998), which allows for cross-sectional and serial correlation as well as heteroskedasticity. Stars indicate significance at the 10% (*), 5% (**), and 1% (***) levels. The sample covers G10 currencies quoted against the USD. The data are monthly from September 2012 to May 2025.

forecast differentials between the US and a given foreign country i for interest rates ("Interest Rates"), the current account-to-GDP ratio ("CA / GDP"), inflation ("Inflation"), and real GDP growth ("GDP"). Interest rate forecasts are measured at the three-month horizon, while the remaining macroeconomic variables correspond to expectations at the end of the subsequent year.

Our primary interest lies in understanding how order flows respond to these forecasts during periods of elevated forecaster disagreement. Disagreement may arise from differing views about US fundamentals or those of the foreign country, and may vary across forecast variables. To capture these dimensions, we measure disagreement as the difference between the 90th and 10th percentiles of the cross-sectional distribution of forecasts, computed separately (i) for each variable and (ii) for the US and the foreign country. We then extract the first principal component of the absolute differences for the US and the foreign country, separately for each forecast variable. Based on this, we define a dummy variable ("High Disagr") that equals one when the corresponding principal component (for each variable) exceeds its sample median. Our main coefficients of interest are those on the interaction terms between the forecast variables and the disagreement indicator. All other aspects of the regression specification follow the baseline setup.[11]

Table 12 examines how investment currency flows relate to expected macroeconomic conditions and how these relationships vary with the degree of forecaster disagreement. Two main findings emerge. First, for most investor groups such as funds, NBFIs, and smaller buy-side banks, the interaction terms are statistically significant and exhibit signs opposite to the baseline effects of the forecasts on order flow. For instance, buy-side banks tend to sell USD when (i) US interest rates are expected to rise, (ii) the US current account deficit is expected to narrow, (iii) US inflation is expected to increase, and (iv) US real GDP growth is expected to decline. However, during periods of elevated disagreement, these relationships are substantially muted, suggesting that these investor groups rely more heavily on consensus forecasts in periods of low uncertainty. Second, the effects of forecast variables on order flow during periods of low disagreement are stronger and more precisely estimated than in the

[11] In all regression specifications, we include both currency μ_i and time α_t fixed effects to control for unobserved heterogeneity at the currency-level and for time variation in global factors. The inference is based on Driscoll and Kraay's (1998) robust covariance matrix, which allows for cross-sectional and serial correlation.

baseline specification. This is consistent with the notion that, when pooling across regimes, the opposing effects associated with low- and high-disagreement periods partially offset each other.

We also examine how individual forecasters' past performance (i.e., forecast error) correlates with the trading behaviour of different investor groups. Specifically, we move beyond the consensus-based analysis and estimate forecaster-level regressions. This approach allows us to capture how each investor group's currency flows are related to the forecasting performance of specific forecasters. Overall, and in line with the previous results, we show that the forecasts made by forecasters with larger past errors have less predictive power for investors' currency flows. The detailed results can be found in the Online Appendix.

Global uncertainty: Next, to capture the effect of global uncertainty, we regress spot currency flows at time $t+1$ on FX rate forecasts formed at time t, interacted with measures of uncertainty and the carry beta. The dependent variable is the spot currency flow ($SPT_{i,t+1}$) from CLS in currency pair i and month $t+1$. In Panel (a) we consider interactions with a dummy variable that is equal to one when the VIX is above its median realization ("High VIX"), whereas in Panel (b) we focus on an interaction with a dummy variable that is equal to one when the gold return is above its sample median, capturing periods of relatively high gold price increases ("High Gold"). The remaining regression set-up is unchanged.

Table 13 reports how investment currency flows relate to expected exchange rate changes and how this relation changes during periods of heightened uncertainty. Across both panels, we find that (i) FX rate forecasts are more relevant for high-beta currencies, and (ii), at the same time, during periods of elevated uncertainty, particularly for these high-beta currencies, the relevance of FX forecasts diminishes.

5. Robustness

To ensure the robustness of our results, we perform a number of additional tests that are reported in the Online Appendix. Specifically, we i) explore a rich set of fixed effects and control variables, ii) replicate our core results for the same cross-section as in Kremens et al. (2025). Overall, the results remain economically and statistically consistent.

Table 12: Investment Currency Flows and Forecaster Disagreement

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
FX Change	−0.617***	−0.017	0.298**	−0.055***	0.372*
	(0.230)	(0.017)	(0.119)	(0.019)	(0.204)
Interest Rates	1.176	0.105	0.364	0.138	−1.881*
	(1.333)	(0.138)	(0.675)	(0.106)	(1.001)
Interest Rates × High Disagr (=1)	−0.497	0.100	−0.966**	0.168**	1.089*
	(0.865)	(0.086)	(0.456)	(0.069)	(0.625)
CA / GDP	1.030***	0.025	−0.306***	−0.132***	−0.581**
	(0.276)	(0.029)	(0.113)	(0.038)	(0.236)
CA / GDP × High Disagr (=1)	−0.562***	−0.007	0.240***	0.024	0.305**
	(0.159)	(0.013)	(0.073)	(0.020)	(0.128)
Inflation	0.870	0.288*	2.491***	−0.455**	−3.058**
	(1.719)	(0.146)	(0.948)	(0.188)	(1.394)
Inflation × High Disagr (=1)	−1.871*	0.020	−0.927**	0.346**	2.403**
	(1.122)	(0.112)	(0.451)	(0.145)	(0.987)
GDP	0.097	0.876***	−3.093***	0.150	2.061*
	(1.377)	(0.258)	(0.899)	(0.140)	(1.135)
GDP × High Disagr (=1)	1.681	−0.305	1.974**	−0.224	−3.196***
	(1.437)	(0.248)	(0.918)	(0.150)	(1.219)
Overall R^2	0.356	0.285	0.345	0.224	0.285
Observations	1'368	1'368	1'368	1'368	1'368
Currencies	9	9	9	9	9
FEs	Yes	Yes	Yes	Yes	Yes

Note: This table reports forecasting regressions of investment currency flows (spot market) by trading counterparty (in billions of USD) at $t+1$ on the set of forecasts available at t. It includes forecasts of FX rate changes as well as forecasted differentials in interest rate, CA / GDP, inflation and real GDP growth between the US and the foreign country in three month (for interest rates) and at the end of the subsequent year for the other variables. In addition, we measure forecaster disagreement as the first principal component of the absolute differences between the 90th and 10th percentiles of the cross-sectional distribution of forecasts for the US and the foreign country, respectively, calculated separately for each variable. We then define a dummy variable that is one when the first principal component (for each variable) is above its sample median. All regressions include currency and time fixed effects. Standard errors in parentheses are computed using the spatial estimator of Driscoll and Kraay (1998), which allows for cross-sectional and serial correlation as well as heteroskedasticity. Stars indicate significance at the 10% (*), 5% (**), and 1% (***) levels. The sample covers G10 currencies quoted against the USD. The data are monthly from September 2012 to May 2025.

Table 13: Investment Currency Flows in Periods of Uncertainty

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
(a) Forecasts and uncertainty (VIX)					
FX Change	−0.311	−0.042*	0.191	−0.068*	0.229
	(0.259)	(0.023)	(0.119)	(0.035)	(0.229)
FX Change × High VIX (=1)	−0.457**	−0.001	0.233**	−0.060**	0.298*
	(0.181)	(0.022)	(0.110)	(0.027)	(0.168)
FX Change × Carry Beta	−1.033***	−0.041***	0.395***	0.065***	0.597***
	(0.175)	(0.015)	(0.100)	(0.023)	(0.162)
FX Change × High VIX (=1) × Carry Beta	0.569**	0.023	−0.091	0.036	−0.525**
	(0.252)	(0.024)	(0.245)	(0.039)	(0.215)
Overall R^2	0.357	0.250	0.328	0.203	0.287
(b) Forecasts and uncertainty (Gold Price)					
FX Change	−0.586*	−0.037*	0.351***	−0.088***	0.363
	(0.301)	(0.020)	(0.128)	(0.029)	(0.267)
FX Change × High Gold (=1)	0.157	−0.008	−0.099	−0.012	−0.035
	(0.195)	(0.018)	(0.086)	(0.023)	(0.165)
FX Change × Carry Beta	−1.036***	−0.052***	0.317**	0.078***	0.678***
	(0.158)	(0.014)	(0.130)	(0.025)	(0.156)
FX Change × High Gold (=1) × Carry Beta	0.467**	0.043*	0.109	−0.009	−0.602**
	(0.214)	(0.024)	(0.155)	(0.042)	(0.243)
Overall R^2	0.355	0.251	0.326	0.198	0.287
Observations	1'368	1'368	1'368	1'368	1'368
Currencies	9	9	9	9	9
FEs	Yes	Yes	Yes	Yes	Yes

Note: This table reports forecasting regressions of investment currency flows (spot market) by trading counterparty (in billions of USD) at $t+1$ on the set of forecasts available at t interacted with measures of uncertainty and the carry beta by currency pair. Panel (a) includes forecasts of FX rate changes and the carry beta, interacted with a dummy for high uncertainty periods, i.e., VIX above median VIX over the sample period. Panel (b) employs a dummy for high gold price changes, i.e., gold return above its sample median. All regressions include currency and time fixed effects. Standard errors in parentheses are computed using the spatial estimator of Driscoll and Kraay (1998), which allows for cross-sectional and serial correlation as well as heteroskedasticity. Stars indicate significance at the 10% (*), 5% (**), and 1% (***) levels. The sample covers G10 currencies quoted against the USD. The data are monthly from September 2012 to May 2025.

6. Conclusion

In this paper, we examine how expectations about exchange rates and macroeconomic fundamentals predict global demand for US dollars across market participants and traded instruments. Using detailed currency flow data for spot, swap, and forward markets combined with survey-based forecasts, we show that investors increase dollar purchases in spot markets when they expect the US dollar to appreciate, and more generally adjust their positions in response to expectations about key macroeconomic fundamentals. Dealer banks, in turn, act as liquidity providers by taking the opposite side of these trades. Investors also account for the factor structure of currency risk, reallocating from riskier foreign currencies into the dollar following an expected dollar appreciation. However, currency flows respond less to forecasts during periods of uncertainty and/or disagreement among forecasters. Across instruments, we provide two novel empirical insights. First, synthetic dollar borrowing via FX swaps declines as the forecasted cross-currency basis widens. Second, expected dollar appreciation as well as other macroeconomic forecasts also predicts dollar purchases via long-dated FX forwards. In sum, our results highlight the central role of expectations in shaping currency flows and emphasize that demand for US dollars is tightly related to expectations about exchange rates and macroeconomic fundamentals. Overall, studying order flows is crucial as we show that order flows not only reflect investor expectations but also determine how these expectations are incorporated into exchange rate dynamics.

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Online Appendix to

"Demand for Dollars: Evidence from Survey Expectations"

Appendix A. Summary Statistics - Currency Betas

Table 1: Summary Statistics - Currency Betas

Currency	Dollar Beta Beta	Carry Beta Beta	UMVE Beta Beta
AUD	1.432	0.539	−0.059
CAD	0.940	0.263	−0.164
CHF	0.968	−0.125	−0.263
EUR	1.106	−0.095	−0.446
GBP	0.897	0.048	−0.521
JPY	0.561	−0.276	−0.395
NOK	1.582	0.210	−0.284
NZD	1.430	0.475	0.025
SEK	1.350	0.028	−0.451

Note: Dollar β_i^{DOL} and carry β_i^{CAR} betas are estimated using a 60-month rolling window regression of log changes in currency i's exchange rate $S_{i,t}$ on either the dollar or the carry factor. We consider the same cross-section of 39 countries as in Verdelhan (2017) but exclude euro area countries; this leaves us with 28 countries to construct the risk factors. The dollar factor is the average change in all currencies with respect to the USD. The carry factor is created as a portfolio return by sorting, every month, currencies into five portfolios based on the one-month forward discount relative to the USD prevailing over the previous month. As for the carry and dollar factor, we estimate the currency beta with respect to the UMVE factor from a rolling window regression. We create the mean-variance efficient UMVE portfolio following Chernov et al. (2023).

Appendix B. Heterogeneity Across Forecasters

Here, we examine how individual forecasters' past performance (i.e., forecast error) correlates with the trading behaviour of different investor groups. Specifically, we move beyond the consensus-based analysis and estimate forecaster-level regressions. This approach allows us to capture how each investor groups' currency flows are related to the forecasting performance of specific forecasters.

We focus on forecasts for the US, as our interest lies in whether and how past forecasting accuracy shapes investor demand for US dollars. For each forecaster and point in time, we compute the median forecast error across their US forecasts for interest rates, inflation, the current account-to-GDP ratio, and real GDP growth.[12] We then construct a dummy variable, *High Error*, that equals one if a forecaster's median forecast error during the preceding 12–24 months is above the cross-sectional median forecast error among all forecasters over the preceding 24–72 months.[13]

Table B.1 shows how spot currency flows correlate with forecasters' past forecasting errors. On average, investors purchase US dollar when key US economic indicators (proxied by the first principal component of macroeconomic forecasts, labelled "Macro PC1") are expected to strengthen. However, this response weakens when forecasts come from forecasters with a history of large past errors. Non-dealer banks, in particular, show a strong positive reaction to fundamentals, but this effect is significantly smaller when forecasts originate from less accurate forecasters, indicating that they adjust their trading behaviour conditional on forecaster accuracy. Dealer banks display the opposite pattern: given their central role as liquidity providers, they sell US dollars when US economic indicators are expected to improve. However, their currency flows are less predictable by forecasts made by forecasters that exhibit above median forecast errors.

Next, we build on the above intuition and estimate the response of all price taker investors' (i.e., total buyside) spot currency flows to macroeconomic forecasts (i.e., Macro PC1) made by

[12] Forecast errors are standardized. We calculate them as the absolute difference between the forecast and the realization, standardized by the realization and expressed in percentage points.

[13] We use the 12–24-month window because forecast errors can only be observed with a lag. Since forecasts pertain to the subsequent year, this structure ensures that we use forecast errors that would have been known to market participants at the time they made their trading decisions.

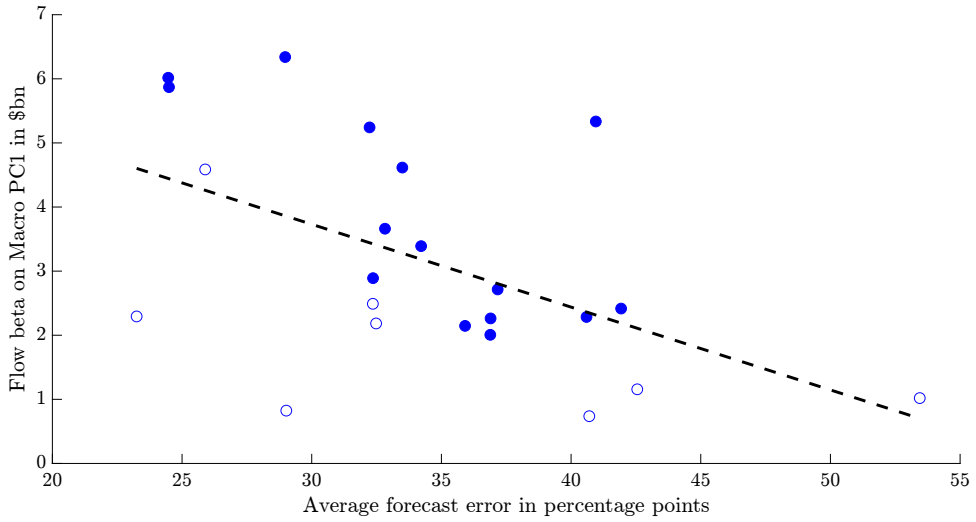
Table B.1: Investment Currency Flows and Forecast Accuracy

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
FX Change	−0.426	0.034**	−0.214	0.009	0.601**
	(0.278)	(0.017)	(0.143)	(0.032)	(0.255)
Macro PC1	−2.223***	0.157***	0.150	0.201***	1.708***
	(0.687)	(0.060)	(0.292)	(0.064)	(0.591)
Macro PC1 × High Error (=1)	1.844***	0.010	−0.149	−0.052	−1.619***
	(0.552)	(0.035)	(0.250)	(0.062)	(0.487)
Overall R2	0.452	0.335	0.425	0.310	0.361
Observations	13'825	13'825	13'825	13'825	13'825
Currencies	7	7	7	7	7
FEs + RER	Yes	Yes	Yes	Yes	Yes

Note: This table reports forecasting regressions of investment currency flows (spot market) by trading counterparty (in billions of USD) at $t+1$ on the set of forecasts available at t, interacted with a measure of forecaster-level errors. It includes forecasts of FX rate changes and the first principal component of forecasted differentials in inflation, CA/GDP, and real GDP growth between the US and the foreign country at the end of the subsequent year (Macro PC1), interacted with a dummy variable for high forecaster-level errors. This dummy takes the value of one if a forecaster's forecast error during the preceding 12 to 24 months exceeds the cross-sectional median forecast error among all forecasters over the preceding 24 to 72 months. Each forecaster's forecast error is computed as the median of their forecast errors across US interest rates, inflation, CA/GDP, and real GDP growth. In all regression, we control for the logarithm of the real exchange rate. All regressions include currency and time fixed effects. Standard errors in parentheses are computed using the spatial estimator of Driscoll and Kraay (1998), which allows for cross-sectional and serial correlation as well as heteroskedasticity. Stars indicate significance at the 10% (*), 5% (**), and 1% (***) levels. The data are monthly from September 2012 to May 2025.

individual forecasters.[14] Moreover, each forecaster's forecast error is computed as the average of the time-series mean absolute error across their US forecasts for inflation, CA/GDP, and real GDP growth.

Figure B.1: Flow Beta and Average Forecast Error



Note: This figure plots, for each forecaster, the time-series average forecast error against the sensitivity (i.e., flow beta) of investors' spot currency flows to the Macro PC1. The beta on the Macro PC1 is obtained from regressing the total currency flows by all price taker investor groups (i.e., total buyside) at time $t+1$ on FX forecasts and the Macro PC1 at time t:

$$SPT_{i,t+1} = \mu_i + \alpha_t + \beta' \mathbf{X}_{i,t,f} + \gamma \log RER_{i,t} + \epsilon_{i,t},$$

where $SPT_{i,t+1}$ denotes total buyside spot currency flow in currency pair i in month $t+1$. We estimate this regression for each forecaster f. The regressor set $X_{i,t,f}$ includes FX forecasts and the first principal component of forecasted differentials in inflation, CA/GDP, and real GDP growth between the US and the foreign country for the subsequent year ("Macro PC1"). The Macro PC1 is constructed at the forecaster level from individual forecaster data. Each forecaster's forecast error is computed as the average of the time-series mean absolute error across their US forecast for inflation, CA/GDP, and real GDP growth. All regressions control for $\log RER_{i,t}$ and include currency and time fixed effects. Standard errors in parentheses use the spatial estimator of Driscoll and Kraay (1998), which allows for cross-sectional and serial correlation and heteroskedasticity. Filled dots indicate point estimates that are statistically significant at the 10% confidence level. The sample spans from September 2012 to May 2025.

Figure B.1 plots, for each forecaster, the average forecast error against the sensitivity (i.e., flow beta) of investors' currency flows to the Macro PC1. We observe a strong negative relation between forecasters' average forecast errors and investors' flow betas. Forecasters with smaller forecast errors tend to have higher flow betas. In contrast, forecasters with larger past errors exhibit lower betas, implying that their forecasts carry less predictive power for investors' currency flows. One possible interpretation of this pattern is that investors

[14] Note that we compute the Macro PC1 at the forecaster level from individual forecaster data.

place a greater weight on information from more accurate forecasters, reflecting a possible link between forecast "credibility" and the degree to which forecasts predict currency flows.