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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 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 CIP deviations. Second, cross-sectionally, investors rebalance along the factor structure of currency risk into dollars following an expected dollar appreciation. Third, responses to professional forecasts weaken when uncertainty or forecaster disagreement rises, and are lower for forecasters with poorer past accuracy. Our findings demonstrate that long-horizon expectations accurately predict dollar demand across spot, swap, and forward currency markets. We rationalize those finding in a theoretical model of currency demand.

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

Keywords: Exchange rate expectations, dollar demand, currency flows, FX swaps, survey forecasts.

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1. Introduction

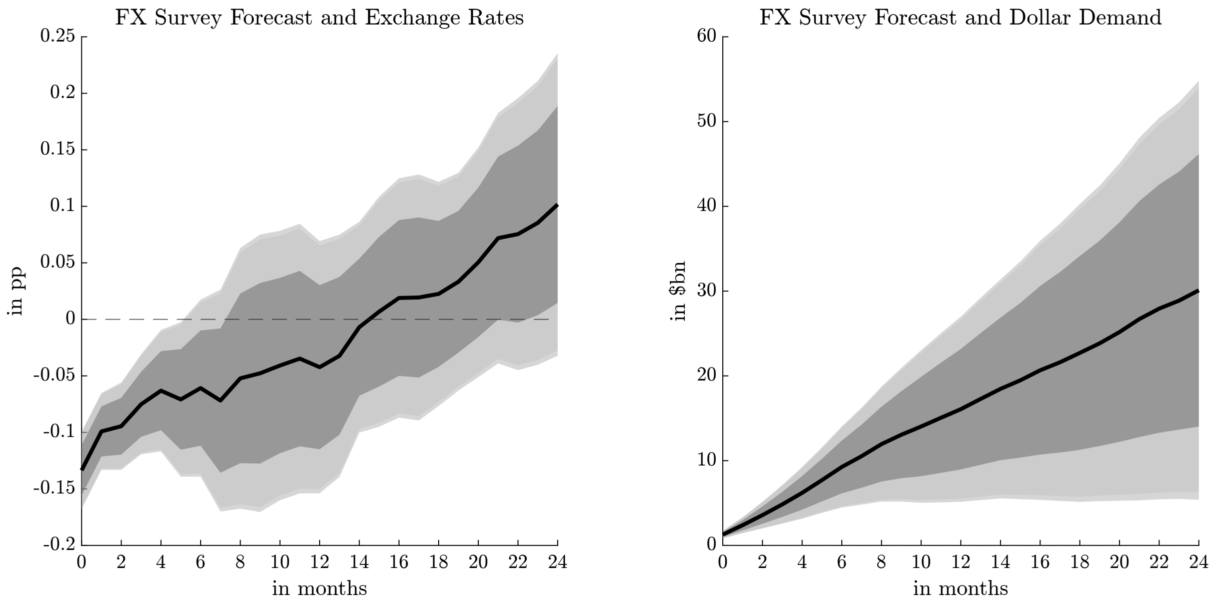
The US dollar (USD) plays a pivotal role in the global monetary and financial system, as a currency for investments, funding, and hedging. For example, foreign investors hold 31% of US Treasuries outstanding (Treasury International Capital (TIC) system), whereas foreign banks borrow around 20 trillion 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 shed light on 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, recent work by Kremens, Martin, and Varela (2025) shows that exchange rate forecasts are successful at forecasting long-horizon exchange rate movements. Figure 1 replicates these earlier results and shows that FX forecasts start to predict exchange rates over longer horizons beyond two years when forecasted exchange rate appreciations predict positive exchange rate returns. 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 13 basis points (bps), followed by a subsequent appreciation of around 23 bps over the next 24 months. At the same time, by looking at currency flows, we show that inflows into USD, proxied by spot FX flows, instantaneously pick up and increase up to 30 $bn over the next 24 months for a 1 pp expected appreciation of the USD. What we can learn from this is that exchange rate expectations successfully predict long- (but not

[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 USD by investors (i.e., clients) from dealer banks.

short-) horizon exchange rate movements, whereas the same exchange rate expectations are strong predictors of currency flows not only at long horizons but *also* over shorter horizons. Hence, it seems as if exchange rate expectations are strong predictors of dollar demand at both short *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:

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

where the dependent variable in the left figure is the cumulative change in 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. $\Delta \log RER_{i,(t;t+h)}$ is the (cumulative) change in the log of the real exchange rate after h months, and $IRD_{i,t}$ 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 50%, 70%, and 90% confidence bands (from dark to light grey). The sample spans from September 2012 to May 2025.

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 simple 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). Specifically, we augment the baseline model by the fact that exchange rates follow a strong factor structure (Lustig, Roussanov, and Verdelhan, 2011; Verdelhan, 2017). The core idea of the model is that investors learn about the expected returns associated with these 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. Specifically, following an expected appreciation of the USD investors sell more high risk foreign currencies (e.g., Canadian dollar) and less low risk foreign currencies (e.g., Japanese yen). And third, investors respond less to professional forecaster's 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 three dimensions, corroborating the theoretical predictions.

Regarding the first prediction, we provide three pieces of evidence that are in line with the idea that forward 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.

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 buyside 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 buyside 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 buyside 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 USD 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-banks as another group of institutional investors is consistent with that of funds, whereas corporates respond stronger to macroeconomic fundamentals. More precisely, if US macroeconomics fundamentals are expected to weaken, corporates sell forward US dollars. Dealer banks, again, take the other side of the market by providing liquidity.

Regarding the second prediction, we study the cross-sectional heterogeneity across seven major currencies against the USD.[2] Specifically, 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 respective 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 synthetic dollar funding via FX swaps, we find that conditional on an expected increase in the cost of synthetic dollar funding, investment funds reduce their synthetic dollar funding via high carry beta currencies (e.g., Canadian dollars) less relative to low carry beta (e.g., Japanese yen) currencies. Regarding hedging flows, we observe that conditional on an expected appreciation of the USD, investment funds hedge less in high relative to low carry beta currencies.

Regarding the third prediction of our theoretical framework, namely, that conditional on times of uncertainty, investors put a lower weight on consensus forecast 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 high uncertainty or disagreement, currency flows respond less to consensus forecast relative to periods of low uncertainty or disagreement.

Lastly, we show that investors' trading responses to professional forecasts depend on the individual forecaster's past forecasting accuracy. Using forecaster-level regressions, we show that currency flows react strongly when economic indicators signal an improving US outlook,

[2]Our cross-section includes the Canadian Dollar (CAD), the Swiss Franc (CHF), the Euro (EUR), the British Pound (GBP), the Japanese Yen (JPY) as well as the Norwegian (NOK) and Swedish Krona (SEK), and is limited by the availability of forecasting data from Consensus Economics rather than by currency trading activity in spot and derivative markets.

but this reaction is noticeably weaker when forecasts come from forecasters with a history of large prediction errors. Overall, more accurate forecasters generate stronger and more reliable currency-flow responses, as evidenced by higher "flow betas," whereas forecasters with larger past errors have lower betas and thus lower predictive power. These results suggest that investors place greater weight on forecasts they view as more credible based on their past trading performance.

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 5 concludes.

Related Literature. Our paper contributes to the strand of research that aims to understand the determinants of dollar demand along various dimensions. 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 either contemporaneously explain exchange rates using order flows or 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. Put differently, 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[3] and only recently has started to jointly study prices

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

(the CIP basis) and quantities (the amount of synthetic dollar borrowing).[4] 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 derivative 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 to 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 et al., 2011; Verdelhan, 2017). The model links investors' expectations about future currency

Syrstad (2022); Augustin, Chernov, Schmid, and Song (2024)

[4]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).

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:

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

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 $\boldsymbol{\lambda}^j$ represents investor j's private belief about currency risk premia, $\boldsymbol{\lambda}^F$ 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:

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

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

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

The above solution implies that investors allocate more to foreign currencies that they expect to appreciate, and vice versa allocate less to foreign currencies that are 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* $E[\mathbf{R}^\mathbf{e}]$.

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, the price of which is determined by the cross-currency basis (Du et al., 2018b). A stronger dollar is associated with a widening of the basis, making synthetic dollar funding more expensive and thereby reducing investors' net dollar borrowing (i.e., increasing net dollar purchases in the forward leg of FX swaps). 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):

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

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

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

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:

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

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

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

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 $E_j[\mathbf{R}^{\mathbf{e}}]$ 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 depend on the prevailing level of uncertainty, that is, $\omega_j = \omega_j(\xi), \quad \text{with} \quad \frac{\partial \omega_j}{\partial \xi} < 0$, 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 third 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). The data cover spot, swap, and forward currency flows. 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, and banks.

CLS classifies FX market participants into four categories: corporates, funds, non-bank financial firms (NBFIs) and banks. In a first step, CLS reports transactions between corporates/banks, funds/banks, and non-banks financials/banks. This categorization is purely based on the identity of the trading counterparties and provides no information 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 financials, 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 base currency acquired by price takers from market makers. Conversely, sell volume denotes the quantity of base currency sold by price takers to market makers (i.e., banks or sellside). 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 seven major currencies pairs: the USD versus CAD, CHF, EUR, GBP, JPY, NOK, and SEK. Trading volumes are separately recorded for buyside and sellside market participants after trade instructions are received from both counterparties. Within the dataset, 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 institutions, and corporations.

Table 1 tabulates the average monthly net trading volumes of each currency pair by market participant. 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 and forward transactions are generally smaller and less volatile, though forwards still represent a significant share of activity. Comparing the different market participants, we observe that corporates and non-banks represent a smaller share of trading, in particular in swaps and forwards, as trading activity is dominated by dealer and non-dealer banks (i.e., buyside banks) as well as investment funds.

Table 1: Monthly Net FX Trading Volume Summary Statistics

Currency		**Dealer Banks**			**Corporates**			**Funds**			**NBFIs**			**Buyside Banks**		
		Spot	Swap	Fwd	Spot	Swap	Fwd	Spot	Swap	Fwd	Spot	Swap	Fwd	Spot	Swap	Fwd
CAD	Mean	-2.77	-25.03	18.33	-0.21	0.29	0.66	7.34	-18.41	-22.39	0.43	0.99	-0.30	-4.79	35.28	-1.89
	SD	38.41	58.29	13.99	1.06	0.69	0.83	20.25	18.74	17.68	1.94	6.06	0.64	29.73	59.27	5.38
CHF	Mean	-3.03	-86.27	13.02	-1.09	-0.66	-0.18	2.53	-30.02	-16.21	0.91	-9.47	-1.46	0.75	110.94	0.19
	SD	5.31	123.33	12.58	1.47	1.51	0.43	3.39	23.32	14.14	1.68	7.41	2.07	4.99	126.98	8.39
EUR	Mean	-22.42	-552.94	20.62	-0.24	-6.73	-0.06	10.25	76.33	-111.07	0.27	-0.52	-0.90	11.99	447.01	35.71
	SD	18.89	272.10	32.14	4.01	4.78	4.29	12.98	182.42	42.39	1.98	27.71	7.73	18.81	265.09	24.78
GBP	Mean	-8.25	-57.89	17.26	-0.86	0.18	1.13	9.29	-67.98	-62.14	0.53	0.99	0.83	-0.46	96.17	14.13
	SD	9.88	114.61	14.94	1.76	1.28	1.18	7.87	40.30	24.51	1.89	9.94	0.84	8.62	114.41	11.47
JPY	Mean	2.81	-273.66	13.83	-0.87	0.50	0.47	0.53	-4.49	-46.36	0.71	0.46	-4.19	-3.18	270.32	21.24
	SD	11.97	219.91	30.90	1.09	1.23	1.60	7.67	27.70	35.68	1.91	10.20	4.65	10.80	216.98	18.50
NOK	Mean	0.32	12.81	-1.63	0.08	-0.16	0.00	0.19	-3.29	-8.05	-0.02	-0.05	-0.01	-0.48	-10.11	1.71
	SD	1.69	42.38	4.50	0.24	0.36	0.09	0.69	1.93	3.69	0.15	0.33	0.06	1.68	41.47	2.85
SEK	Mean	0.06	-37.03	2.32	-0.03	-0.18	-0.03	0.01	-2.14	-16.30	-0.03	-0.17	-0.17	0.20	36.07	-0.23
	SD	1.80	51.17	4.81	0.53	0.66	0.26	1.30	3.32	7.55	0.17	0.64	0.45	1.74	48.79	2.59

Note: This table reports mean and standard deviation of the monthly currency flows (spot, swap, 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 data are monthly from September 2012 to May 2025.

3.2. *FX and economic forecasts*

We obtain forecasts from Consensus Economics. The data contain monthly forecasts covering FX rates and macroeconomic fundamentals for various economies and span from September 2012 to May 2025. For exchange rates, it includes FX rate predictions for 3-, 12-, and 24-month horizons. Forecasts for key economic indicators such as consumer prices, current account balances, and GDP growth are for the current and subsequent year-end. Interest rate projections, including three-month interest rates and ten-year government bond yields, covering 3- and 12-month forecast periods.[5]

Data 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. These forecasts are widely used by policymakers, investors, and businesses to inform decision-making and strategic planning[6]. For the main part of our

[5]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. We find similar results when using French or euro area average interest rates, instead.

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

analysis, we focus on consensus forecasts, however, we also look at individual forecaster-level prediction errors and, therefore, run *forecaster-level* regressions.

Based on those forecasts, we construct our key forecast measures in order to assess the predictive power of forecasts for currency flows. 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 consumer prices differential, current account to GDP (CA to GDP) differential, and real GDP growth differential are all calculated as the differences between US and foreign forecasts for inflation, external balances, and real economic growth, respectively, at the end of the subsequent year.

The price of synthetic dollar borrowing is measured by the CIP basis. In line with (see, e.g., Du et al., 2018b), we define the CIP basis as $CIP = (i_{us} - i_{foreign}) + FD_{annualized}$. 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 relative to the cash market. Our innovation is to consider the forecasted CIP basis. For this, we consider forecasts of 3-month interest rates projected 3 months ahead and the corresponding forward discount over the subsequent 6-months embedded in today's forward and spot FX rates. More precisely, the forward discount is computed as $(F - S)/F \times (360/90) \times 100$ 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.[7]

Table 2 illustrates the average values of our forecast variables across currencies. On average, the sample currencies are forecasted to experience a moderate appreciation against the USD over the subsequent 24 month. Interest rate differentials are small and positive, indicating slightly higher US interest rates. Consumer-price and GDP differentials are also slightly

[7] 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.

Table 2: Summary Statistics

Currency	FX Rate Change in PP	Interest Rate Diff. in PP	Cons. Prices Diff. in PP	CA to GDP Diff. in PP	GDP Diff. in PP	CIP Deviation in PP
CAD	−2.366	0.141	0.197	−1.163	0.142	−0.065
CHF	1.755	1.915	1.594	−12.592	0.590	−0.462
EUR	−1.286	1.230	0.603	−5.425	0.599	−0.397
GBP	−1.983	0.233	−1.042	0.220	0.374	−0.208
JPY	−1.608	1.600	1.146	−6.053	1.070	−0.646
NOK	−7.239	−0.092	0.183	−12.834	0.238	−0.320
SEK	−6.300	0.912	0.423	−8.228	0.134	−0.382

Note: FX Rate Change is defined as $(\text{FX}_{24mo} - \text{FX})/\text{FX} \times 100$, with USD as the base currency. Interest Rates, Consumer Prices, CA to GDP, 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 sum of the annualized forward discount and the annualized interest rate differential between the US and the quote country, with USD as the base currency. The forward discount is computed as $(F - S)/F \times (360/90) \times 100$ 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 is based on 3-month interest rates forecasted three months ahead. Data are monthly from September 2012 to May 2025 for CAD, CHF, EUR, GBP, JPY, NOK, and SEK.

positive, on average, indicating higher real growth and inflation forecasts for the US. The current-account-to-GDP differentials are negative for all currencies, reflecting the fact that the US runs (and is, therefore, projected to run) negative CA/GDP balances. Finally, the forward discount is typically negative, implying that forward rates are, on average, below spot rates in USD terms, in line with the forecasted USD depreciation during our sample period.

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 the well-known carry trade strategy which is the long-short portfolio return of a zero-cost trading strategy that borrows in low interest rate currencies to invest in high interest rate currencies. 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 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 generally line up 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). Specifically, 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)):

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

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, whereas carry and UMVE betas measure currency i's exposure to the carry and UMVE factor, respectively. Higher values of dollar, carry, and UMVE betas indicate greater exposure to currency risk.

4. Empirical Analysis

4.1. *Currency flow predictability*

We begin our analysis by exploring whether survey expectations about exchange rates, macroeconomic, and financial variables have any predictive power for currency flows. In doing so, we consider the three most heavily traded currency instruments: spot, forward, and swap trades. Specifically, we estimate predictive regressions of currency flows on survey forecasts. 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 covered interest rate parity (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). Thus, to ease the comparison with exchange rate and interest rate forecasts, we focus on the first principal component of macroeconomic variables. Second, we interpret the regression coefficients as the revealed preferences of the marginal investor who may trade currencies for various reasons (e.g., hedging, investment, and speculation). 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 evolving market conditions. As a first step in our analysis, we want to understand how currency flows in the spot FX market are related to forecasts of exchange rates as well as macroeconomic and financial variables.

Table 3 reports the results of regressing spot FX flows at time $t+1$ on a set of forecast formed at time t. Specifically, we run regressions of the form:

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

where the dependent variable is the spot FX flow ($SPT_{i,t+1}$) from CLS in currency pair i and month t. 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") as well as 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"). Panel (c) replaces the Macro PC1 with individual forecasted differentials in inflation ("Inflation"), CA / GDP ("CA / GDP"), and real GDP growth ("GDP").[8] Thus, all else equal, a higher Macro PC1 reading reflects stronger expected US fundamentals: higher financial account surplus, higher GDP growth, and higher short-term interest rates driven by inflation pressure. In all regression specifications, we include the log real exchange rate $\log RER_{i,t}$ as well as 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.

Panel (a) shows a clear difference between customer flows (e.g., funds) on the one hand

[8]We multiply the CA / GDP difference by minus 1 to account for the negative CA / GDP ratio in the US.

and dealer banks on the other. Customer flows, particularly those of corporates 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 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 (USD) and selling foreign currency by non-dealer banks increases on average by 0.7 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 rate, macroeconomic variables, and interest rates. Specifically, we compute the first principal component of consumer prices, CA to GDP, and GDP growth to measure expectations about macroeconomic variables. Adding interest differentials and macroeconomic forecasts almost doubles the within R2 of our predictive regressions. This suggests 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 limited predictive power for exchange rates when controlling for variation in current account and real exchange rate.

The coefficient on interest rate differentials is positive for funds and non-banks financials, indicating that these institutional portfolio managers tend to buy USD when they expect US interest rates to rise relative to abroad. For example, a one percentage point expected increase in the interest rate differential is associated with investment funds buying an additional 2.2 billion USD over the next month. In line with Panel (a), dealer banks take the other side of the trade and sell USD when interest rates in the US are expected to rise relative to abroad.

Panel (c) decomposes the principal component of macroeconomic variables (i.e., inflation, CA/GDP, and GDP growth) into its individual constituents. Across all five groups of market participants, we see that CA/GDP is the most important driver of our macro variable results in Panel (b). The only exception to this are corporates, who 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.

Unlike for corporates, we find that expected changes in the current account to GDP (i.e., CA/GDP) ratio differential have a strong predictive power for currency flows by institutional investors (funds, NBFIs, and non-dealer banks). Note that since we multiply CA/GDP times minus 1, an increase in the CA/GDP differential is associated with a relatively larger US current account deficit compared to abroad, implying an increase in the financial account. During our sample period from September 2012 until May 2025 the US has experienced a current account deficit, which the US government has financed by the issuance of government debt. The fact that institutional investors purchase USD as the US current account deficit is expected to increase is consistent with foreign investor playing an important role in US Treasury markets.

In sum, our evidence on spot FX flows indicates that there is heterogeneity in the way how the currency flows of various groups of market participants relate to expectations about future exchange rates, macroeconomic conditions, and financial variables. Specifically, investment funds, NBFIs, and non-dealer banks tend to purchase USD (i) when the USD is expected to appreciate, (ii) when US interest rates are expected to increase, and (iii) when macroeconomic conditions in the US are expected to improve relative to abroad. For instance, an expected appreciation of the USD is associated with a positive demand for USD in the FX spot market by non-dealer banks and investment funds. In addition to exchange rate forecasts, expectations about macroeconomic conditions in the US also predict dollar demand. In the cross-section of market participants, funds, non-bank financials, and non-dealer banks buy significantly more USD when US interest rates are expected to increase or when the US is expected to reduce its primary deficit. In contrast, corporates' currency flows 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 flows similarly correlate with survey forecasts but with the opposite sign, that is, dealer banks supply dollar liquidity when their customers demand USD (e.g., in anticipation of a stronger dollar)

Table 3: Forecasting Investment Currency Flows

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
(a) Exchange rate forecasts					
FX Change	−0.674*	0.041**	−0.064	−0.019	0.715**
	(0.384)	(0.021)	(0.200)	(0.036)	(0.322)
Overall R^2	0.366	0.271	0.348	0.250	0.313
(b) Exchange rate, interest rate, and PCA of macro forecasts					
FX Change	−0.967***	0.033	0.149	0.015	0.757**
	(0.365)	(0.025)	(0.200)	(0.035)	(0.333)
Interest Rates	−2.934*	−0.085	2.150**	0.344**	0.408
	(1.578)	(0.146)	(0.847)	(0.163)	(1.345)
Macro PC1	−3.986***	0.371**	1.566*	0.400**	1.674*
	(1.154)	(0.180)	(0.866)	(0.176)	(1.004)
Overall R^2	0.377	0.279	0.357	0.267	0.315
(c) Exchange rate, interest rate, and macro forecasts					
FX Change	−0.933**	0.033	0.148	0.011	0.727**
	(0.363)	(0.026)	(0.201)	(0.034)	(0.331)
Interest Rates	−3.619**	0.078	1.889*	0.424**	1.116
	(1.724)	(0.174)	(0.980)	(0.163)	(1.448)
Inflation	−0.584	0.503***	0.661	0.052	−0.600
	(1.035)	(0.142)	(0.911)	(0.138)	(1.065)
CA / GDP	−1.406***	−0.024	0.376**	0.144***	0.909**
	(0.458)	(0.034)	(0.177)	(0.043)	(0.363)
GDP	−0.191	0.806***	−0.995	0.045	0.371
	(1.479)	(0.198)	(0.794)	(0.127)	(1.019)
Overall R^2	0.384	0.318	0.362	0.277	0.322
Observations	1’064	1’064	1’064	1’064	1’064
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. Panel (a) includes forecasts of FX rate changes. Panel (b) adds the forecasted interest rate differentials 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). Panel (c) replaces the Macro PC1 with individual forecasted differentials in inflation, CA / GDP, and GDP growth. In all regression, we control for the logarithm of the real exchange rate. The sample covers seven currencies quoted against the USD. 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.

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 to dollar today and receives euros in the "forward leg." This mechanism allows investors to "synthetically" borrow in foreign currencies without accessing foreign funding markets (e.g., Repo markets) directly (Borio, McCauley, and McGuire, 2022).

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 markets and FX forward 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.[9].

Given our interest in understanding how expectations influence future 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 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 4 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:

$$SWP_{i,t+1} = \mu_i + \alpha_t + \beta CIP_{i,t} + \gamma \log RER_{i,t} + \epsilon_{i,t}, \tag{21}$$

[9] The CIP basis is defined as $CIP = (i_{us} - i_{foreign}) + FD$. 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 relative to the cash market

where the dependent variable is the swap currency flow ($SWP_{i,t}$) in a given foreign currency i and month t. 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 regressors. The point estimate for funds is negative and economically large, amounting to and additional 117 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. 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. 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. Three results emerge, relative to the average effect in Panel (a). First, buyside banks heavily increase their synthetic dollar borrowing, but only in times when synthetic dollar funding is cheaper than the cash market rate. This result appears to be in line with the intuition that even non-dealer buyside banks have access to the wholesale funding market via, for instance, repos. 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. In light of this, funds appear to supply at least some of the dollar liquidity in currency pairs like the CAD and GBP to non-dealer banks during periods when the CIP basis is positive. Lastly, we find that dealer banks supply dollar funding irrespective of the sign of the CIP basis, which is consistent with their role as global liquidity providers.

Panel (c) replaces the expected CIP basis with its individual components — expected exchange rate changes ("FX Change") and expected 12-month interest rate differentials between the US and the foreign country ("Interest Rate"). Interestingly, the borrowing behaviour of buyside banks and funds in positive and negative CIP environments, respectively, as documented in Panel (b), appears to be driven by the exchange rate component. When the USD is expected to appreciate (i.e., when the CIP basis increases), both buyside banks and funds increase their USD borrowing in the corresponding environments. In contrast, both groups reduce their synthetic dollar borrowing when US interest rates are expected to rise relative to those abroad.

Table 4: Forecasting Funding Currency Flows

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
(a) CIP forecasts					
CIP Deviation	152.539***	–0.242	–117.086***	–1.123	–57.872
	(48.912)	(0.886)	(30.161)	(2.589)	(48.924)
Overall R^2	0.713	0.646	0.450	0.211	0.663
(b) Positive and negative CIP levels					
$CIP^+ \times$ CIP Deviation	231.506*	1.561	57.214**	2.176	–283.675*
	(134.569)	(0.994)	(27.001)	(3.565)	(144.513)
$CIP^- \times$ CIP Deviation	149.613***	–0.377	–139.013***	–0.867	–35.188
	(55.453)	(1.056)	(35.950)	(2.872)	(52.310)
Overall R^2	0.713	0.646	0.456	0.212	0.664
(C) FX and interest rate forecasts					
$CIP^+ \times$ FX Change	279.376**	1.732	54.005	3.683	–329.665**
	(131.361)	(1.115)	(41.072)	(5.110)	(141.989)
$CIP^- \times$ FX Change	143.124***	0.038	–62.815**	2.081	–88.572*
	(42.887)	(0.519)	(27.778)	(1.729)	(48.203)
$CIP^+ \times$ Interest Rates	–32.203	0.381	27.968**	0.400	9.850
	(27.241)	(0.253)	(13.882)	(2.002)	(24.013)
$CIP^- \times$ Interest Rates	–50.257***	0.048	12.175***	0.104	38.171***
	(10.801)	(0.147)	(4.362)	(0.578)	(11.275)
Overall R^2	0.724	0.646	0.431	0.212	0.677
Observations	1’064	1’064	1’064	1’064	1’064
Currencies	7	7	7	7	7
FEs + RER	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 standardized by the exchange rate. Panel (b) interacts the forecasted CIP deviations with a dummy variable indicating positive respectively negative CIP levels. Panel (c) replaces the CIP deviations with individual forecasted FX rate changes and interest rate differentials. In all regression, we control for the logarithm of the real exchange rate. The sample covers seven currencies quoted against the USD. 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.

Hedging flows: Currency forwards and long-dated currency swaps 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 payment 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 and long-dated currency swaps are predicted by forecasts about exchange rates, macroeconomic fundamentals, and financial variables.

Table 5 reports forecasting regressions of long-dated forward and swap currency 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 funds and NBFIs exhibit large and positive coefficients, which is consistent with buying at pre-defined rates when expecting a dollar appreciation. This suggests that the marginal investor across these two groups of investors is likely to have foreign currency exposures that they seek to hedge. In contrast, both dealer and non-dealer banks sell forward USD conditional survey forecasts predicting a dollar appreciation, thereby providing dollar liquidity to funds and NBFIs.

Panel (b) adds the interest rate 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 both 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).

Panel (c) extends the analysis by incorporating individual macroeconomic forecasts alongside exchange rate and interest rate expectations. Two key results emerge: First, investment funds and NBFIs sell forward USD when inflation and GDP growth are expected to rise, suggesting that growth expectations outweigh inflationary depreciation pressure on the dollar. Second, an expected rise in interest rates as well as a decline in the current account deficit are both associated with funds and NBFIs buying more dollars in forward contracts and long-dated swaps, likely reflecting an expected appreciation of the USD. Overall, our findings highlight that professional investors integrate both financial and macroeconomic outlooks when managing currency risk, while dealer banks act as liquidity providers by supplying dollar liquidity in forwards and swaps.

4.2. *Heterogeneity across currencies*

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

$$y_{i,t+1} = \mu_i + \alpha_t + \beta' \mathbf{X}_{i,t} + \varphi(\mathbf{X}_{i,t} \times \mathbf{Z}_{i,t}) + \delta' \mathbf{Z}_{i,t} + \gamma \log RER_{i,t} + \epsilon_{i,t}, \tag{22}$$

where the dependent variable is either the spot, swap, or forward currency flow from in currency pair i and month t. The key regressors are in $X_{i,t}$, containing forecasts of exchange rates and macroeconomic variables. Our main coefficient of interest is φ, which identifies the cross-sectional differences across currency pairs. 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 the log real exchange rate $\log RER_{i,t}$ as well as 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 forecast as well as the interaction of exchange rate forecasts and currency betas (see, e.g., Eq. (17)). Table 6 reports the results of regressing spot FX flows at time $t+1$ on exchange rate forecasts at time t and their interaction with currency betas (i.e., dollar, carry, and UMVE betas).

Table 5: Forecasting Hedging Currency Flow

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
(a) Exchange rate forecasts					
FX Change	−1.468***	0.012	2.384***	0.255***	−0.367**
	(0.356)	(0.019)	(0.430)	(0.066)	(0.179)
Overall R^2	0.296	0.240	0.823	0.306	0.603
(b) Exchange rate, interest rate, and PCA of macro forecasts					
FX Change	−0.467	−0.040*	1.529***	0.163**	−0.233
	(0.357)	(0.021)	(0.490)	(0.068)	(0.189)
Interest Rates	10.119***	−0.523***	−8.732***	−0.948***	1.340
	(2.002)	(0.173)	(1.769)	(0.318)	(1.098)
Macro PC1	6.761***	−0.459**	−0.141	0.084	1.856
	(1.912)	(0.178)	(2.207)	(0.238)	(1.189)
Overall R^2	0.352	0.262	0.831	0.317	0.605
(c) Exchange rate, interest rate, and macro forecasts					
FX Change	−0.546	−0.038*	1.570***	0.164**	−0.229
	(0.361)	(0.022)	(0.428)	(0.063)	(0.185)
Interest Rates	13.153***	−0.631***	−8.167***	−0.710	0.763
	(2.016)	(0.175)	(1.968)	(0.448)	(1.256)
Inflation	2.189	−0.359**	5.033***	0.543*	0.811
	(1.351)	(0.163)	(1.837)	(0.316)	(1.085)
CA / GDP	2.042***	−0.059**	−1.821***	−0.149***	0.423
	(0.335)	(0.029)	(0.621)	(0.057)	(0.307)
GDP	7.127***	−0.432***	7.329***	1.245	−1.931
	(1.461)	(0.129)	(2.701)	(0.844)	(1.315)
Overall R^2	0.376	0.269	0.845	0.347	0.609
Observations	1’064	1’064	1’064	1’064	1’064
Currencies	7	7	7	7	7
FEs + RER	Yes	Yes	Yes	Yes	Yes

Note: This table reports forecasting regressions of hedging currency flows (swap and 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 differentials 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). Panel (c) replaces the Macro PC1 with individual forecasted differentials in inflation, CA / GDP, and GDP growth. In all regression, we control for the logarithm of the real exchange rate. The sample covers seven currencies quoted against the USD. 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.

Panel (a) confirms our earlier observation that customers and dealer banks trade in opposite directions: following an expected appreciation of the dollar, customers buy US dollars, whereas dealer banks provide liquidity by selling US dollars. Turning to the interaction between expected dollar appreciation (i.e., "FX Change") and carry betas, we find that all four customer segments exchange riskier, high carry beta currencies more heavily for US dollars than safer ones. Put differently, customers of large dealer banks increase their dollar purchases when the dollar is expected to appreciate according to the survey forecasts and, in turn, reduce exposure to high-risk currencies (e.g., Canadian dollars).

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 and UMVE betas, respectively, are 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: the interaction term is positive and significant for most customer segments, implying that the priced component of currency returns plays an important role in shaping global currency flows across countries.

Funding flows: Next, we repeat our analysis above but replace the dependent variable in Eq. (22) by short-term swaps. Table 7 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 the differences in how funds' relative to dealer banks' synthetic dollar borrowing relates to an expected increase in the CIP basis. Specifically, investment funds exhibit a positive interaction coefficient with carry and UMVE betas, respectively, whereas the interaction terms are negative for dealer banks. 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 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

Table 6: Investment Currency Flows and the FX Factor Structure

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
(a) Exchange rate forecasts and carry beta					
FX Change	−0.843**	0.045**	0.072	0.016	0.709**
	(0.396)	(0.021)	(0.186)	(0.036)	(0.331)
FX Change × Carry Beta	−0.312***	0.031***	0.094*	0.042**	0.149*
	(0.089)	(0.010)	(0.049)	(0.017)	(0.079)
Overall R^2	0.373	0.301	0.361	0.269	0.329
(b) Exchange rate forecasts and dollar beta					
FX Change	−0.830**	0.038**	0.009	−0.005	0.786**
	(0.413)	(0.019)	(0.216)	(0.038)	(0.340)
FX Change × Dollar Beta	−0.550***	0.005	0.207***	0.055***	0.284***
	(0.116)	(0.008)	(0.067)	(0.015)	(0.100)
Overall R^2	0.386	0.288	0.363	0.278	0.322
(c) Exchange rate forecasts and UMVE beta					
FX Change	−0.688*	0.025	−0.101	0.029	0.743**
	(0.416)	(0.020)	(0.208)	(0.039)	(0.350)
FX Change × UMVE Beta	−0.074	0.019**	−0.019	0.062***	0.014
	(0.110)	(0.009)	(0.056)	(0.014)	(0.089)
Overall R^2	0.374	0.275	0.356	0.279	0.315
Observations	1’064	1’064	1’064	1’064	1’064
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 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. Each factor beta is standardized by the cross-sectional mean and standard deviation. 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.

positive bases (Du et al., 2018b). In contrast to funds, dealer banks exhibit negative and significant interaction coefficients with respect to dollar, carry, and UMVE betas, respectively. In other words, dealer banks’ synthetic dollar lending is less sensitive to variation in the expected CIP basis in high relative to low risk currencies.

Hedging flows: Lastly, we study the implications of the currency factor structure for long-dated forwards and swaps, 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 7: 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	107.820**	−0.635	−89.433***	−0.315	−42.501
	(47.626)	(0.778)	(26.394)	(2.657)	(49.113)
CIP Deviation × Carry Beta	−158.684***	−1.113	94.147***	1.644	60.958
	(50.228)	(0.795)	(24.138)	(2.463)	(48.927)
Overall R^2	0.723	0.656	0.477	0.224	0.668
(b) Forecasts of CIP deviations and dollar beta					
CIP Deviation	150.822***	−0.250	−131.751***	−0.762	−44.831
	(56.806)	(0.898)	(32.242)	(2.758)	(53.248)
CIP Deviation × Dollar Beta	−41.907	0.720	−53.273*	−0.592	84.166*
	(52.917)	(0.585)	(27.510)	(3.128)	(45.881)
Overall R^2	0.715	0.653	0.483	0.217	0.665
(c) Forecasts of CIP deviations and UMVE beta					
CIP Deviation	145.965***	−0.233	−103.530***	−1.483	−63.360
	(46.409)	(0.899)	(31.026)	(2.516)	(46.915)
CIP Deviation × UMVE Beta	−57.423*	−0.397	48.919***	−1.978	16.837
	(30.672)	(0.332)	(8.554)	(2.235)	(29.391)
Overall R^2	0.722	0.645	0.482	0.212	0.662
Observations	1’064	1’064	1’064	1’064	1’064
Currencies	7	7	7	7	7
FEs + RER	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 forecasted CIP deviation 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. CIP deviation is standardized by the exchange rate, each factor beta is standardized by the cross-sectional mean and standard deviation. In all regression, we control for the logarithm of the real exchange rate. The sample covers seven currencies quoted against the USD. 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.

Table 8 reports the results from a regression that is analogous to the one in Table 6 but replaces the dependent variable with long-dated forward and swap 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 and NBFIs 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 funds and NBFIs first and foremost 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 fluctuation in currencies with higher expected returns (i.e., higher factor betas).

Table 8: Hedging Currency Flows and the FX Factor Structure

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
(a) Exchange rate forecasts and carry beta					
FX Change	−1.101***	0.015	1.635***	0.165***	−0.223
	(0.309)	(0.019)	(0.428)	(0.054)	(0.194)
FX Change × Carry Beta	0.683***	0.011	−0.897***	−0.144***	0.057
	(0.143)	(0.010)	(0.149)	(0.028)	(0.090)
Overall R^2	0.327	0.242	0.836	0.339	0.611
(b) Exchange rate forecasts and dollar beta					
FX Change	−1.340***	0.018	2.043***	0.225***	−0.275*
	(0.354)	(0.019)	(0.400)	(0.055)	(0.161)
FX Change × Dollar Beta	0.662***	0.013**	−1.141***	−0.128***	0.268***
	(0.122)	(0.006)	(0.122)	(0.020)	(0.068)
Overall R^2	0.336	0.244	0.843	0.337	0.610
(c) Exchange rate forecasts and carry beta					
FX Change	−1.276***	0.020	1.691***	0.231***	−0.158
	(0.375)	(0.020)	(0.460)	(0.062)	(0.177)
FX Change × UMVE Beta	0.155	0.020***	−0.830***	−0.078***	0.126
	(0.149)	(0.007)	(0.116)	(0.030)	(0.090)
Overall R^2	0.297	0.240	0.834	0.306	0.608
Observations	1'064	1'064	1'064	1'064	1'064
Currencies	7	7	7	7	7
FEs + RER	Yes	Yes	Yes	Yes	Yes

Note: This table reports forecasting regressions of hedging currency flows (swap and 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. Each factor beta is standardized by the cross-sectional mean and standard deviation. In all regression, we control for the logarithm of the real exchange rate. The sample covers seven currencies quoted against the USD. 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.

4.3. *Forecaster disagreement and forecast errors*

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 itself (dispersion across professional forecasters) and general macroeconomic uncertainty. To test this empirically, we proceed along two dimensions: i) we interact forecasts with the VIX index, which is a common measure of investor "fear"; and ii) we also consider interactions with measures of forecaster dispersion.

We start by regressing spot currency flows at time $t + 1$ on a set of survey 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. The key regressors are the first principal component of forecasted differentials in inflation, CA/GDP, and real GDP growth between the US and a given foreign country i measured at the end of the subsequent year ("Macro PC1"), and its interaction with measures of uncertainty. 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 continuous variable that captures US forecaster disagreement ("Disagreement"). Specifically, 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 each macroeconomic variable for the US. We focus on the dispersion in US forecasts as we are particularly interested in how forecast dispersion is associated with US dollar currency flows.[10]

Table 9 reports how investment currency flows relate to expected macroeconomic conditions and how this relation changes during periods of heightened uncertainty and forecaster disagreement. Across both panels, we find that all four groups of investors tend to buy more US dollars over the next month if they expect US macroeconomic fundamentals to strengthen over the next two years. However, investment managers (i.e., funds and NBFIs) buy fewer US dollars during periods of elevated market uncertainty and forecaster disagreement, respectively. A possible interpretation of this result is that i) investors put a smaller weight on consensus forecasts during periods of uncertainty and/or ii) they scale back directional trading based on their own signal. Dealer banks, once again, take the opposite side of the market,

[10]In all regression specifications, we include the log real exchange rate $\log RER_{i,t}$ as well as 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.

acting as liquidity providers, that is, they tend to sell dollars when US macroeconomic fundamental are expected to strengthen, accommodating investors' demand for dollars. Moreover, consistent with their role as liquidity providers, dealer banks also reduce their supply of dollars during periods of heightened uncertainty or volatility.

Table 9: Investment Currency Flows in Periods of Uncertainty and Forecaster Disagreement

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
(a) Forecasts and uncertainty					
FX Change	−0.649*	0.041**	−0.077	−0.020	0.702**
	(0.369)	(0.019)	(0.200)	(0.037)	(0.313)
Macro PC1	−6.810***	0.456**	2.840**	0.454**	3.156**
	(1.822)	(0.188)	(1.128)	(0.194)	(1.567)
Macro PC1 × High VIX (=1)	3.315***	−0.081	−1.581***	−0.093	−1.623
	(1.183)	(0.080)	(0.601)	(0.123)	(1.016)
Overall R^2	0.382	0.279	0.357	0.261	0.319
(b) Forecasts and disagreement					
FX Change	−0.620	0.040**	−0.093	−0.022	0.694**
	(0.390)	(0.020)	(0.199)	(0.038)	(0.323)
Macro PC1	−5.752***	0.421**	2.430**	0.476***	2.420**
	(1.380)	(0.174)	(0.994)	(0.182)	(1.220)
Macro PC1 × Disagreement	1.053***	−0.022	−0.551***	−0.056*	−0.404
	(0.310)	(0.037)	(0.185)	(0.033)	(0.282)
Overall R^2	0.381	0.279	0.358	0.263	0.317
Observations	1'064	1'064	1'064	1'064	1'064
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 measures of uncertainty and forecaster disagreement. Panel (a) 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 for high uncertainty periods, i.e., VIX above median VIX over the sample period. Panel (b) employs the US forecaster disagreement instead of the VIX dummy. 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.

Finally, 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.[11] 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.[12]

Table 10 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. Buyside 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 *individual* forecasters.[13] 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 2 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

[11]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.

[12]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.

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

Table 10: 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

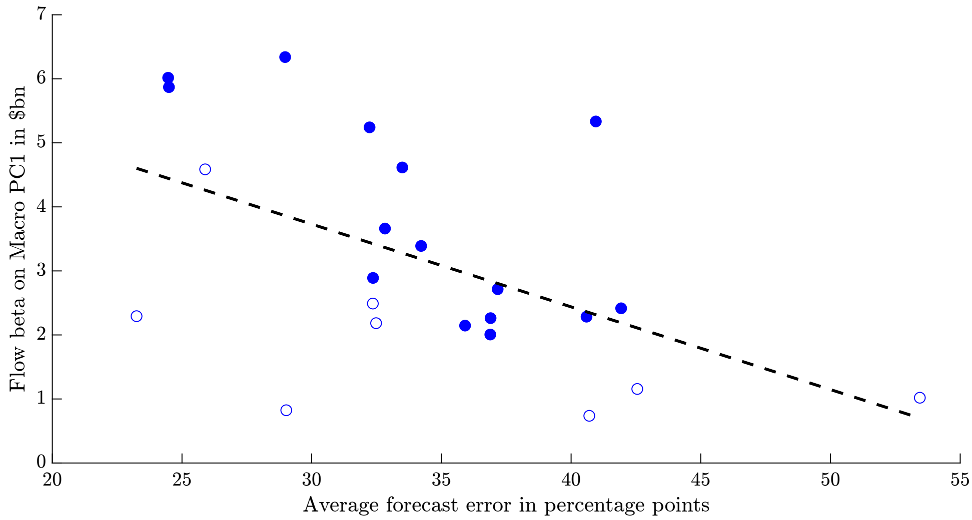
Note: This table reports forecasting regressions of investment currency flows (spot market) by trading counterparty (in billions of USD) at $t+1$ on the set of forecasts available at t, interacted with a measure of forecaster-level errors. It includes forecasts of FX rate changes and the first principal 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.

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 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.

5. Conclusion

In this paper, we examine how expectations about exchange rates and macroeconomic fundamentals predict global demand for the 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 anticipate an appreciation of the US dollar or when they expect key US macroeconomic indicators to strengthen. Dealer banks, in turn, act as liquidity providers by taking the opposite side of these trades. Investors also account for the factor structure of cur-

Figure 2: 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 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.

rency risk, reallocating from riskier foreign currencies into the dollar following an expected dollar appreciation. However, currency flows are less predictable by macroeconomic 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 cross-currency basis widens. Second, expected dollar appreciation also predicts dollar purchases via long-dated FX forwards. We conclude by documenting that not all forecasts are created equal. Specifically, the predictability of currency flows by survey forecasts positively hinges on forecasters' (historical) accuracy. 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.

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