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**demand for dollars: evidence from
survey expectations**

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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 foreign exchange trading data, we show that forward-looking expectations accurately predict both currency returns and flows. Specifically, we show that the predictability of currency returns at long-horizons can be attributed to price pressure that originates from investors whose trading activity is aligned with survey expectations. To empirically establish the relevance of survey-based expectations for currency flows, we present three results: First, end-user investors increase their dollar holdings when they expect the US dollar to appreciate, whereas dealer banks supply dollar liquidity. Second, cross-sectionally, investors rebalance along the factor structure of currency risk into the US dollar following an expected dollar appreciation. Third, the predictive power of survey forecasts weakens when uncertainty or forecaster disagreement rises. Overall, our findings demonstrate that long-horizon expectations accurately predict dollar demand across spot, swap, and forward currency markets. To rationalise these empirical findings, we develop a model of currency demand.

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

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 30% of US Treasuries outstanding according to the Federal Reserve System,¹ whereas foreign banks borrow around 230 billion US dollar 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 US dollar demand across various groups of market participants as well as traded instruments.²

To this end, we leverage survey expectations for exchange rates and macroeconomic variables (i.e., interest rates, current account, inflation, and GDP) to uncover how these survey-based expectations predict US dollar demand across market participants (i.e., banks, corporations, investment funds, and non-bank financials) and traded instruments (i.e., spot and derivatives such as swaps and forwards). Whether survey expectations are useful for predicting dollar demand is not obvious since survey expectations are known to be weak predictors of exchange rates (e.g., Nagel and Xu, 2023; Dahlquist and Söderlind, 2022). In contrast to this earlier literature, Kremens, Martin, and Varela (2025) show that long-horizon exchange rate forecasts successfully predict realised currency returns.

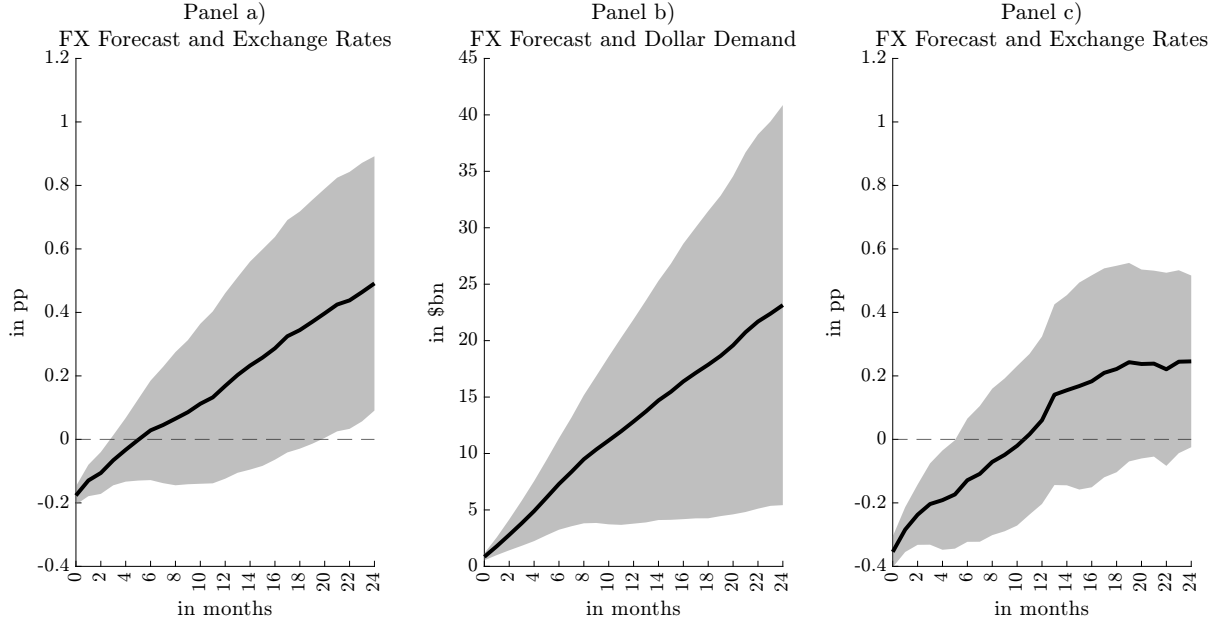
Figure 1 replicates these earlier results and shows that the component of currency returns predicted by long-run expectations materializes relatively gradually over a two-year horizon.³ Panel a) shows that an expected appreciation of the USD by 1 percentage point (pp) over the next 24 months is associated with a subsequent appreciation of around 49 bps over the next 24 months. Similarly, in Panel b) we find that an expected 1 pp appreciation of the USD is associated with an instantaneous dollar inflow, proxied by spot currency flows, which increases

¹Board of Governors of the Federal Reserve System, Financial Accounts of the United States (Z.1), Table L.210 (Treasury Securities), via Data Download Program at <https://www.federalreserve.gov/datadownload>.

²We focus on the role of FX dealer banks as liquidity providers rather than cross-market arbitrageurs and hence, measure dollar demand as currency transactions that either involve the purchase or borrowing of US dollars by investors (i.e., clients) from dealer banks.

³Compared to Kremens et al. (2025), our evidence for short-horizon predictability of long-term forecasts is somewhat weaker for three reasons: First, our sample period extends to 2025. Second, the cross-section of currencies is different as we focus on G10 currencies. Lastly, we include both currency and time fixed effects to control for global factors simultaneously affecting forecasts and currency flows.

up to 23 \$bn over two years. In sum, exchange rate expectations accurately predict both future exchange rate movements and currency flows at both short and long horizons. In light Figure 1: Predictability of Exchange Rates and Currency Flows with Exchange Rate Forecasts



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

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

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

of the evidence in Figure 1, one might ask whether some of the exchange rate predictability is related to currency flow-induced price pressure. To quantitatively address this question, we repeat the empirical exercise in Panel a), but include spot currency flows and their interaction with exchange rate forecasts as an additional control variable. Two insights emerge: First, currency flows subsume the predictive content of exchange rate forecasts for realized currency returns (see Panel c). Second, the interaction between flows and forecasts is negative and significant, implying that the information content of survey expectations diminishes precisely when currency flows exert stronger dollar price pressure (see Table 3).

The core focus of our paper is on quantities rather than prices and our primary goal is to shed light on the determinants of dollar demand across various groups of market participants and traded currency instruments. To guide our empirical analysis, we develop a model of currency demand that builds on the line of work by [Gabaix and Maggiori \(2015\)](#), [Itskhoki and Mukhin \(2021\)](#), and [Vayanos and Vila \(2021\)](#). We augment these models by the fact that exchange rates follow a strong factor structure ([Lustig, Roussanov, and Verdelhan, 2011](#); [Verdelhan, 2017](#)). The core idea is that investors learn about the expected returns associated with currency risk factors from professional forecasts. 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 dollar is going to appreciate. At the same time, she borrows fewer dollars synthetically via swaps. Large dealer banks take the opposite side of these trades to provide liquidity. Second, in the cross-section of currencies, investors rebalance from foreign currencies into USD along the factor structure of currency risk. Following an expected appreciation of the USD, investors sell more high risk foreign currencies (e.g., Australian dollar) and fewer low risk foreign currencies (e.g., Japanese yen). Third, investors respond less to professional forecasters' predictions about exchange rates and macroeconomic fundamentals when forecaster dispersion increases and/or in times of higher uncertainty.

To provide empirical support for these three predictions, we employ 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. Our cross-section includes the G10 currencies against the US dollar, which comprise more than 60% of global FX trading volume ([BIS, 2025](#)). To measure forward-looking expectations about exchange rates as well as macroeconomic variables, we use monthly surveys of finance professionals conducted by Consensus Economics. The forecasters interviewed are global banks, research institutes, and investors who actively participate in the currency market. With these data and the theoretical foundation 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-looking expectations matter for exchange rate flows. First, we show that an expected appreciation of the dollar over the horizon of the next two years predicts that investment funds and non-dealer banks buy dollars and sell foreign currency over the next month. Dealer banks and NBFIs take the opposite side by providing liquidity. In addition, we also find that the expected economic conditions in the US, proxied by GDP growth, CPI growth, and external positions accurately predict future FX spot transactions. In the cross-section of market participants, we find that funds and smaller non-dealer banks buy significantly more USD when the US dollar is expected to appreciate or when the US runs a larger current account deficit translating into a financial account surplus. While the current account reflects more structural economic differences, corporates strongly respond to macroeconomic business cycle variables such as GDP, for example, they purchase dollars when consensus expectations point towards faster economic growth in the US.

Comparing across forecast horizons, we find that long-horizon exchange rate expectations explain short-run currency flows much better than short horizon expectations. This result complements [Kremens et al. \(2025\)](#), who show that long-horizon exchange rate expectations also have a much stronger predictive power for realised short-run currency returns. [Kremens and Varela \(2026\)](#) provide a possible explanation for the poor performance of short-term forecasts. In particular, they decompose forecasts into a component shared with long-term expectations and a component that loads on lagged forecast errors. The former component strongly predicts exchange rates even at short horizons, while the latter predicts currency returns with the wrong sign, thereby offsetting the informative component contained in the overall short-term forecast. We observe a similar pattern for currency flows. Specifically, short-term (3-month) FX forecasts have only limited predictive power for spot currency flows. In contrast, short-term interest rate forecasts have substantial predictive power for currency flows, even at short-horizons.

Second, to assess funding currency flows in the FX swap market, we construct forecast-based expectations of covered interest parity (CIP) deviations. Consistent with our conceptual framework, we find that, conditional on the cost of synthetic dollar funding decreasing (i.e.,

synthetic dollar funding becoming more attractive), investment funds and non-dealer banks engage in more synthetic dollar borrowing. Furthermore, we find that the borrowing decisions of both funds and non-dealer banks are driven by exchange rate expectations: they reduce USD borrowing when the dollar is expected to appreciate, consistent with a widening of the basis (Avdjiev, Du, Koch, and Shin, 2019). Notably, smaller banks increase synthetic dollar borrowing when US interest rates rise relative to foreign rates, which is consistent with synthetic dollar funding becoming cheaper. In contrast, funds exhibit the opposite pattern, increasing USD lending following a rise in US interest rates. This divergence suggests that investment funds' FX swap trading is not solely driven by funding considerations. Dealer banks, on the other hand, again take the opposite side of the market and provide liquidity.

Third, focusing on long-dated forwards, we show that investment funds tend to purchase dollars forward when the dollar is expected to appreciate. This behaviour is consistent with hedging of foreign investment positions as well as directional bets on dollar appreciation.⁴ Our evidence here provides a new perspective on 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-horizon interest expectations, we find that an increase in the US short-rate in one year ahead is associated with funds and NBFIs selling more USD forward.

Regarding the second theoretical prediction, we study the cross-sectional heterogeneity across G10 currencies against the USD. We consider two key currency factor models: (i) the two-factor model by Lustig et al. (2011) and Verdelhan (2017) that includes both the dollar and the carry factor and (ii) the one-factor model by Chernov, Dahlquist, and Lochstoer (2023) that builds an unconditional mean variance efficient portfolio. To measure the riskiness of foreign currencies with respect to each of these factors, we consider their factor loading (i.e., betas). Focusing on the interaction terms between currency risk factors (i.e., dollar, carry, or UMVE betas) and our forecast variables, we find that, conditional on (i) expecting the USD to appreciate and/or (ii) expecting US interest rates to rise relative to abroad, investors exchange riskier currencies more heavily for USD than safe ones. With respect to funding US dollar via FX swaps, we find that, conditional on an expected increase in the cost of synthetic dollar

⁴Note that our goal is not to disentangle hedging from speculative trading motives as this would require us to make strong assumptions about investors' preferences.

funding, investment funds reduce their dollar funding less via high-carry-beta currencies (e.g., Australian dollar) than via low-carry-beta currencies (e.g., Japanese yen). Turning to long-dated forward currency flows, we find that all investor groups except for corporates hedge less in high relative to low beta currencies.

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

In sum, we provide evidence that expectations about exchange rates and the economic prospects of the US relative to foreign economies accurately predict dollar demand across various traded instruments. The paper is structured as follows: After providing an overview of the related literature, we introduce our data in Section 2 and provide motivating evidence in Section 3. We then introduce our theoretical framework in Section 4, which we then test empirically in Section 5. Section 6 provides robustness results and Section 7 concludes.

Related literature. Our paper contributes to the strand of research that aims to understand the determinants of dollar demand. First, there is a large literature in currency markets that studies the role of buying and selling pressure (i.e., order flow) in explaining exchange rates. This literature has been pioneered by [Evans and Lyons \(2002\)](#) and [Evans \(2002\)](#), inspiring a vast literature on exchange rates and order flow dynamics (see, e.g., [Froot and Ramadorai, 2005](#); [Bacchetta and van Wincoop, 2006](#); [Rime, Sarno, and Sojli, 2010](#); [Menkhoff, Sarno, Schmeling, and Schrimpf, 2016](#)). The core focus of these papers is to contemporaneously explain exchange rates using order flows or to illustrate the contemporaneous link between order flows and macroeconomic news. [Stavrakeva and Tang \(2025\)](#) show that FX survey expectations align with aggregate open interest positions in CFTC futures. We, instead, measure dollar flows via spot, swap, and forward markets and show that not only exchange rate expectations but also expectations about macroeconomic fundamentals predict global currency flows across a granular set of market participants and traded instruments.

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 constraints⁵ and only recently has started to jointly study prices (the CIP basis) and quantities (the amount of synthetic dollar borrowing).⁶ 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 groups such as investment funds and smaller non-dealer banks. 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, carry, and UMVE factor, respectively.

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

⁵See, for example, [Baba, Packer, and Nagano \(2008\)](#); [Mancini-Griffoli and Rinaldo \(2011\)](#); [Du, Tepper, and Verdelhan \(2018b\)](#); [Du, Im, and Schreger \(2018a\)](#); [Avdjiev et al. \(2019\)](#); [Andersen, Duffie, and Song \(2019\)](#); [Cenedese, Della Corte, and Wang \(2021\)](#); [Jiang, Krishnamurthy, and Lustig \(2021\)](#); [Rime, Schrimpf, and Syrstad \(2022\)](#); [Augustin, Chernov, Schmid, and Song \(2024\)](#); ?

⁶See, e.g., [Ivashina, Scharfstein, and Stein \(2015\)](#); [Puriya and Bräuning \(2020\)](#); [Correa, Du, and Liao \(2020\)](#); [Becker, Schmeling, and Schrimpf \(2023\)](#); [Kloks, Mattille, and Rinaldo \(2023\)](#); [Kloks et al. \(2024\)](#); [Krohn and Sushko \(2022\)](#); [Kubitza, Sigaux, and Vandeweyer \(2024\)](#); [Ben Zeev and Nathan \(2024\)](#); [Du, Strasser, and Verdelhan \(2025\)](#); [Moskowitz, Ross, Ross, and Vasudevan \(forthcoming 2025\)](#).

2. Data

We begin by introducing our data on currency flows, survey forecasts, exchange rates, and forward contracts that we employ for the empirical analysis in Sections 3 and 5.

2.1. *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 majority of the 72 existing settlement members are large multinational banks. Additionally, there are more than 25,000 “third-party” clients of these settlement members, encompassing other banks, funds, non-bank financial firms, and corporations.

This dataset possesses several characteristics that make it well-suited for research on currency flows. First, CLS accurately 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, as mentioned before, CLS covers different groups of currency market participants: corporates, funds, non-bank financial firms (NBFIs), and banks. Third, the data cover spot, swap, and forward currency flows and account for approximately 50% of global FX trading volume as reported in the BIS Triennial Surveys.

CLS constructs its final dataset in two steps. In a first step, CLS reports transactions between corporates/banks, funds/banks, and non-bank financial firms/banks. This categorization is purely based on the identity of the trading counterparties and provides no information on who initiated the transaction and implicitly assumes that banks act as liquidity providers. In a second step, CLS performs a proprietary network analysis that allows it 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 composed of 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-bank 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 buy-side trading activity and transactions between banks and corporates, funds, and non-bank financial firms, respectively. Note that this approximation will generally *underestimate* the trading activity between price taker banks (in the following classified as smaller, non-dealer banks, which we abbreviate as “Buy-side Banks”) and market maker or dealer banks since the three aforementioned groups may trade with both buy-side and sell-side banks. More precisely, CLS only reports aggregate trading activity between say funds and banks but not a separate breakdown of funds trading with buy-side and sell-side banks, respectively.

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

Our main variable of interest is the net currency flow (i.e., total buy volume less total sell volume), denominated in billions of USD (positive values indicate net purchases of USD). Our sample period spans from September 2012 to May 2025, and we focus on G10 currency pairs: the USD versus AUD, CAD, CHF, EUR, GBP, JPY, NOK, NZD, and SEK.

Table 1 tabulates the average monthly net trading volumes of each currency pair by market participant and traded instruments. Short-term swaps tend to be driven by currency funding needs, whereas long-term forwards are driven by hedging needs (see, e.g., [Kloks et al., 2023](#); [Ranaldo, 2023](#)). Hence, for our empirical analysis, we focus on short-term swaps with maturities of less than 35 trading days and long-dated forwards with maturities beyond 35 trading days to capture synthetic dollar funding and hedging flows, respectively.

Overall, currency flows in the FX market are dominated by swap transactions, which consistently exhibit the largest average net flow imbalances and standard deviations across all currency pairs. Spot FX transactions exceed forward transactions in terms of average

Table 1: Summary Statistics - Monthly Net FX Trading Volume

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

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

net flows but are an order of magnitude smaller and less volatile compared to FX swaps. Overall, forward transactions comprise the smallest part of the market, which is consistent with the evidence in the BIS Triennial Surveys. Comparing across different groups of market participants, directional currency flows are dominated by dealer and non-dealer banks (i.e., buyside banks) as well as investment funds. In contrast, corporates and NBFIs account for a much smaller share of overall net currency flows.

2.2. FX and economic forecasts

We obtain forecasts from Consensus Economics. The data contain monthly forecasts covering exchange rates and macroeconomic fundamentals, such as interest rates, current account balances, consumer prices, and real GDP growth. Our sample spans from September 2012 to May 2025. Again, we focus on the G10 currencies and the corresponding economies. For ex-

change rates, we obtain forecasts for 3-, 12-, and 24-month horizons.⁷ Interest rate projections for three-month interest rates and ten-year government bond yields cover 3- and 12-month forecast periods.⁸ Forecasts for key economic indicators such as consumer price changes, current account balances, and real GDP growth are for the current and subsequent year-end.⁹

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

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

⁷Note that survey forecasts for CHF, NOK, and SEK are expressed relative to the EUR rather than the USD. Since, for any dollar currency pair USD/X , it holds that $\mathbb{E}[S_{USD/X}] = \mathbb{E}[S_{USD/EUR} \cdot S_{EUR/X}] = \mathbb{E}[S_{USD/EUR}] \cdot \mathbb{E}[S_{EUR/X}] + \text{Cov}(S_{USD/EUR}, S_{EUR/X})$, we convert these forecasts to dollar expectations using the prevailing USDEUR spot rate and we account for the covariance term using expanding historical covariances starting in January 2000.

⁸Since there are no specific forecasts for euro area interest rates, German interest rate forecasts are used as a proxy for euro interest rate predictions.

⁹Consensus Economics provides forecasts for current account *balances* which we scale by the previous year's GDP to ensure comparability across countries and over time.

The price of synthetic dollar borrowing is measured by the CIP basis. In line with [Du et al. \(2018b\)](#), we define the CIP basis as $CIP = i_{us} - (i_{foreign} - FD_{annualized})$, where FD is the forward discount defined as the log difference between the forward rates $F_{0,6}$ and $F_{0,3}$, annualized according to the maturity between the forward rates. If $CIP > 0$ ($CIP < 0$), the direct USD interest rate is higher (*lower*) than the synthetic dollar interest rate, implying that synthetic dollar funding is cheaper (*more expensive*) relative to the cash market. Our innovation is to consider the *forecasted CIP basis*. For this purpose, we consider forecasts of 3-month interest rates projected three months ahead, together with the corresponding forward discount for the 3-month period starting in three months.¹⁰

Table 2: Summary Statistics - Forecast Variables

Currency	FX Rate Change in PP	Interest Rate Diff. in PP	CA to GDP Diff. in PP	Cons. Prices Diff. in PP	GDP Diff. in PP	CIP Deviation in PP
AUD	-0.909	-0.398	-1.526	-0.199	-0.277	-0.100
CAD	-2.366	0.141	-1.163	0.197	0.142	-0.065
CHF	1.686	1.915	-12.592	1.594	0.590	-0.454
EUR	-1.286	1.230	-5.425	0.603	0.599	-0.393
GBP	-1.983	0.233	0.220	-1.042	0.374	-0.207
JPY	-1.608	1.600	-6.053	1.146	1.070	-0.637
NOK	-7.090	-0.092	-12.834	0.183	0.238	-0.319
NZD	-0.056	-1.002	1.502	0.189	-0.313	-0.135
SEK	-6.368	0.912	-8.228	0.423	0.134	-0.378

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

Table 2 tabulates the average values of our forecast variables across currencies. On average, all foreign currencies in our sample are expected to appreciate against the USD over the subsequent 24 months with the exception of the Swiss franc. The predicted 3-month interest rate differentials are mostly small and positive, indicating slightly higher US interest rates. Notable exceptions are Australia and New Zealand, which are high-interest-rate currencies

¹⁰As 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.

that frequently end up in the long-leg of the carry trade. The current-account-to-GDP differentials are negative for most currencies, reflecting the fact that the US is projected to run negative CA / GDP balances. Consumer-price and GDP differentials are slightly positive, on average, indicating higher real growth and inflation forecasts for the US. Finally, the CIP basis is typically negative, which implies that, in accordance with existing literature (e.g., [Du et al., 2018b](#)), the cost of synthetic dollar funding is more expensive relative to the cash market.¹¹ Online Appendix Section B provides detailed graphical illustrations of survey-based forecasts for exchange rate changes and CIP deviations, respectively, alongside their realization.

Consensus Economics forecasts are widely used by policymakers, investors, and businesses to inform decision-making and strategic planning¹². A common criticism of survey forecasts is that they are biased by strategic incentives (see, e.g., [Coibion and Gorodnichenko \(2012\)](#), [Coibion and Gorodnichenko \(2015\)](#), [Bordalo, Gennaioli, Ma, and Shleifer \(2020\)](#), [De Marco, Macchiavelli, and Valchev \(2021\)](#), and [Gemmi and Valchev \(2026\)](#)). Our results do not imply that the forecasts themselves are rational, but rather that the trading flows of the marginal investor in currency markets are predicted by consensus forecasts.¹³

2.3. *Exchange Rates and Forward Contracts*

We collect hourly data on spot mid quotes and daily forward prices for various maturities from Bloomberg. We denote the spot price for country i at time t by $S_{i,t}$ and forward prices by $F_{i,t}$. An increase in F or S corresponds to an appreciation of the US dollar relative to the foreign currency, i.e., F and S are quoted with the USD as the base currency. We use mid prices when calculating exchange rate changes $\Delta \log S_{i,t}$.

In normal times, forward rates satisfy the covered interest rate parity condition ([Du et al., 2018b](#)). Under this condition, interest rate differentials approximate the forward discount, the difference of the log forward price from the log spot price. We use 2-year forward rates and spot prices to compute interest rate differentials: $r_{i,t} - r_{US,t} \approx \log F_{i,t} - \log S_{i,t}$.

¹¹The basis is negative in more than 90% of the sample observations, with heterogeneity across currencies.

¹²Consider, for example, [Devereux, Smith, and Yetman \(2012\)](#).

¹³An alternative to survey forecasts would be to use option-implied expectations, which reflect beliefs under risk-neutral pricing. However, since our goal is to capture investors' subjective beliefs under the physical measure, we employ survey-based forecasts.

2.4. 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. We construct the dollar and carry factors from currency excess returns, which we define as $\log S_t - \log F_{t-1,t}$, and hence, a higher factor return corresponds to an appreciation of the dollar. The dollar factor is the average change in all currencies with respect to the US dollar. It is akin to the capital asset pricing model’s market portfolio. The carry factor mimics the returns of a self-financing long-short trading strategy that borrows in low-interest-rate currencies to invest in high-interest-rate ones. We create this portfolio by sorting, every month, currencies into five portfolios based on the one-month forward discount relative to the USD prevailing over the previous month. The “long” portfolio consists of currencies with the highest interest rates relative to the US, whereas low-interest-rate currencies constitute the “short” portfolio.

We consider the same cross-section of 39 countries as in [Verdelhan \(2017\)](#) but exclude euro 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:

$$\Delta \log S_{i,t} = a_i + \beta_i^{DOL} \text{Dollar}_t + \epsilon_{i,t}, \quad (1)$$

$$\Delta \log S_{i,t} = a_i + \beta_i^{CAR} \text{Carry}_t + \epsilon_{i,t}. \quad (2)$$

Dollar and carry betas summarize the assortment of a country’s characteristics that collectively determine its currency’s risk. For example, countries with large carry betas tend to be on the periphery of the global trade network ([Richmond, 2019](#)) and typically export commodities and import finished goods ([Ready, Roussanov, and Ward, 2017](#)). Carry betas

align with interest rate differentials (Lustig et al., 2011). Countries with large dollar betas typically face large trade costs in goods, which relates, for instance, to the gravity equation in international trade. These economic sources of currency risk are not mutually exclusive. Thus, the carry and dollar betas are useful as they proxy for deeper economic phenomena but are defined by their ability to capture a currency’s exposure to these FX risk factors.

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

$$\Delta \log S_{i,t} = a_i + \beta_i^{\text{UMVE}} \text{UMVE}_t + \epsilon_{i,t}. \quad (3)$$

Table C.1 in the Online Appendix summarizes the betas by currency pair. Analogous to a stock market beta, dollar betas record the incremental systematic currency risk that a US investor takes on when investing in foreign currency i . Carry and UMVE betas measure currency i ’s exposure to the carry and UMVE factor, respectively.¹⁴

3. Motivating Evidence

Given our motivating results in Figure 1 and the evidence that long-horizon exchange rate forecasts predict future exchange rates, one might wonder whether some of this predictability reflects flow-induced price pressure. To empirically address this question, we estimate the following regression:

$$y_{i,(t;t+24)} = \mu_i + \alpha_t + \beta \text{EFX}_{i,t} + \gamma \text{IRD}_{i,t} + \zeta \text{SPT}_{i,t} + \rho(\text{SPT}_{i,t} \times \text{EFX}_{i,t}) + \epsilon_{i,t+h}, \quad (4)$$

where the dependent variable is either the cumulative change in the exchange rate of foreign currency i against the USD after 24 months (columns 1, 3, and 4) or the cumulative spot FX flow ($\text{SPT}_{i,(t;t+24)}$) from CLS Group in currency pair i after 24 months. $\text{EFX}_{i,t}$ is the expected

¹⁴Since, by construction, dollar betas average to one in the cross-section, we rescale them to have zero mean and unit standard deviation, to ease the interpretation of our regression coefficients.

relative change in the FX rate based on survey forecasts from Consensus Economics, reflecting exchange rate expectations in the year after next. $IRD_{i,t}$ is the 2-year forward discount in month t . $SPT_{i,t}$ is spot FX flow from CLS Group in currency pair i and month t . μ_i and α_t are currency and time fixed effects, respectively. Our key coefficient of interest is ρ , the interaction term between spot currency flows and exchange rate forecasts.

Table 3: Exchange Rate Predictability and Order Flow Price Pressure

	(1)	(2)	(3)	(4)
	FX Rate Change	Spot FX Flow	FX Rate Change	FX Rate Change
EFX	0.491** (0.250)	23.148** (10.776)	0.246 (0.169)	0.185 (0.154)
IRD	-0.476 (0.600)	-1.843 (19.794)	-0.147 (0.634)	-0.047 (0.627)
SPT			-0.031* (0.017)	-0.032** (0.013)
EFX \times SPT				-0.011*** (0.004)
Overall R^2	0.70	0.58	0.65	0.66
Total # of Obs.	2'943	1'143	1'368	1'368
#Currencies	9	9	9	9
Currency FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Note: This table reports forecasting regressions of the form

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

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

Table 3 reports the results for various specifications of Eq. (4). Specifically, columns 1 (“FX Rate Change”) and 2 (“Spot FX Flow”) replicate the point estimates in Figure 1, whereas columns 3 and 4 (focusing on FX rate changes) include spot currency flows and their interaction with exchange rate forecasts as additional explanatory variables. The core insight is

twofold: First, exchange rate forecasts are not statistically significant predictors of currency flows when controlling for currency flows. Second, the interaction between currency flows and exchange rate forecasts is negative and significant, that is, the predictive power of exchange rate forecasts declines conditional on currency flows exerting dollar price pressure. Put differently, conditional on large dollar inflows from foreign currencies, exchange rate forecasts are weaker predictors of realised currency returns.

Taken together, these findings highlight a novel link between exchange rate predictability using survey expectations and currency flows. Against this backdrop, it is natural to ask how currency flows are related to survey forecasts. To address this question, we first develop a simple theoretical framework, which we then test empirically using data on currency flows and survey expectations.

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

4.1. Environment

Investors. There are J types of investors (e.g., funds, corporates, non-bank financial institutions, and smaller non-dealer banks), indexed by $j \in \{1, \dots, J\}$. 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:

$$\max_{\mathbf{w}_j} E_j \left[-\frac{1}{\gamma_j} e^{-\gamma_j \mathbf{w}_j' \mathbf{R}^e} \right], \quad (5)$$

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's problem is:

$$\max_{\mathbf{w}_D} \mathbf{w}'_D E_D[\mathbf{R}^e] - \frac{\gamma_D}{2} \mathbf{w}'_D \boldsymbol{\Sigma} \mathbf{w}_D - \frac{\tau}{2} \mathbf{w}'_D \mathbf{w}_D, \quad (6)$$

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.

4.2. *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:

$$E_j[\boldsymbol{\lambda}] = (1 - \omega_j) \boldsymbol{\lambda}^j + \omega_j \boldsymbol{\lambda}^F, \quad (7)$$

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.

4.3. *Optimal Portfolio Choice*

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

$$\max_{\mathbf{w}_j} \mathbf{w}'_j E_j[\mathbf{R}^e] - \frac{\gamma_j}{2} \mathbf{w}'_j \boldsymbol{\Sigma} \mathbf{w}_j, \quad (8)$$

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

$$\mathbf{w}_j^* = \frac{1}{\gamma_j} \boldsymbol{\Sigma}^{-1} E_j[\mathbf{R}^e]. \quad (9)$$

This solution implies that investors tilt more toward currencies expected to appreciate against the dollar and away from those expected to depreciate, yielding our first prediction:

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

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

Intermediaries. The dealer's first-order condition and optimal position \mathbf{w}_D^* are as follows:

$$E_D[\mathbf{R}^e] - \gamma_D \Sigma \mathbf{w}_D - \tau \mathbf{w}_D = \mathbf{0}. \quad (10)$$

$$\mathbf{w}_D^* = (\gamma_D \Sigma + \tau \mathbf{I})^{-1} E_D[\mathbf{R}^e]. \quad (11)$$

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.

4.4. Market Clearing

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

$$\sum_{j=1}^J \theta_j \mathbf{w}_j^* + \mathbf{w}_D^* = \mathbf{0}. \quad (12)$$

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

$$\Gamma \equiv \sum_{j=1}^J \frac{\theta_j}{\gamma_j}, \quad (13)$$

and the belief-weighted average expectation as:

$$\bar{E}[\mathbf{R}^e] \equiv \frac{1}{\Gamma} \sum_{j=1}^J \frac{\theta_j}{\gamma_j} E_j[\mathbf{R}^e]. \quad (14)$$

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

$$\mathbf{w}_B^* \equiv \sum_{j=1}^J \theta_j \mathbf{w}_j^* = \Gamma \Sigma^{-1} \bar{E}[\mathbf{R}^e]. \quad (15)$$

Substituting Eqs (9) and (11) into the market clearing condition Eq. (12):

$$\Gamma \Sigma^{-1} \bar{E}[\mathbf{R}^e] + (\gamma_D \Sigma + \tau \mathbf{I})^{-1} E_D[\mathbf{R}^e] = \mathbf{0}. \quad (16)$$

4.5. 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

$$\mathbf{w}_D^* = -\mathbf{w}_B^* = -\Gamma \Sigma^{-1} \bar{E}[\mathbf{R}^e]. \quad (17)$$

In equilibrium, dealers simply absorb whatever order flow imbalance the investors create, taking the opposite position. This adds to our first prediction:

Proposition 1 (continued): *When dealers act as pure liquidity providers, they take positions opposite to aggregate investors demand. If investors expect the US 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:

$$(\gamma_D \Sigma + \tau \mathbf{I})^{-1} E_D[\mathbf{R}^e] = -\Gamma \Sigma^{-1} \bar{E}[\mathbf{R}^e]. \quad (18)$$

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

$$E_D[\mathbf{R}^e] = -\frac{\Gamma(\gamma_D \sigma^2 + \tau)}{\sigma^2} \bar{E}[\mathbf{R}^e]. \quad (19)$$

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 US 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.

4.6. 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, UMVE beta) and $E_j[\boldsymbol{\lambda}]$ is investor j 's expectation of factor risk premia. Since $E_j[\mathbf{R}^e]$ is increasing in $\boldsymbol{\beta}$, Eq. (9) implies that investors rebalance 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 second theoretical prediction:

Proposition 2: *In the cross-section of currencies, investors rebalance 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.*

4.7. State-Dependent Attention to Public Forecasts

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

sional forecasters. When uncertainty rises, investors discount public forecasts and rely more heavily on their private signals.

Next, we substitute Eq. (7) into Eq. (9) and derive the marginal effect of the public forecasts on currency demand as:

$$\frac{\partial w_{ji}^*}{\partial \lambda^F} = \frac{\omega_j(\bar{\zeta})}{\gamma_j \sigma_i^2} \beta_{i'}' \quad (20)$$

which is decreasing in $\bar{\zeta}$, yielding our third prediction:

Proposition 3: *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.*

5. Empirical Analysis

We now turn to the empirical analysis that aims to test our theoretical predictions.

5.1. Currency flow predictability

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

To ease the interpretation of the sign of the point estimates, we leverage our theoretical framework (see Proposition 1). The framework predicts that higher expected US dollar returns are associated with investors buying more US dollars in the future (either via spot or forward contracts). A similar intuition applies to synthetic dollar borrowing via currency swaps: an expected appreciation of the US dollar is associated with a widening of the CIP basis (Avdjiev et al., 2019), making synthetic dollar funding more expensive and thus reducing net dollar borrowing by investors via FX swaps (i.e., selling fewer dollars forward). We expect dealers to take the opposite position to aggregate investor demand.

Several remarks are in order. 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). Hence, we interpret the regression coefficients as the

revealed preferences of the marginal investor who may trade currencies for various reasons (e.g., investment, speculation, or hedging). For example, if we find that an expected increase in these macroeconomic variables is associated with a given investor group buying more US dollars, then, through the prism of our theoretical framework, this indicates that the group views 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, investors can use spot FX transactions to obtain foreign currencies for portfolio allocation and investment purposes. The FX spot market, therefore, enables investors to gain direct exposure to foreign assets and to adjust their currency holdings in response to market conditions. As a first step, we seek to understand how currency flows in the spot FX market are related to forecasts of exchange rates as well as macroeconomic variables.

Table 4 reports the results of regressing spot FX flows at time $t + 1$ on a set of forecasts formed at time t . Specifically, we run regressions of the form:

$$SPT_{i,t+1} = \mu_i + \alpha_t + \beta'X_{i,t} + \epsilon_{i,t}, \quad (21)$$

where the dependent variable is the spot FX flow ($SPT_{i,t+1}$) from CLS in currency pair i and month $t + 1$. The key regressors are in $X_{i,t}$, which contains 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”). Panel (c) adds the forecasted difference in the CA / GDP ratio (“CA / GDP”), inflation (“Inflation”), and real GDP growth (“GDP”) between the US and a given foreign country i at the end of the subsequent year. This setup allows the underlying macroeconomic variables to capture different economic dimensions. For example, the CA / GDP ratio likely reflects more persistent, structural differences across economies, whereas GDP growth and inflation capture more cyclical, short-run conditions.¹⁵

In all regression specifications, we include currency μ_i and time α_t fixed effects. Cur-

¹⁵The inference is based on Driscoll and Kraay’s (1998) robust covariance matrix which allows for cross-sectional and serial correlation.

Table 4: Forecasting Investment Currency Flows

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
(a) Exchange rate forecasts					
FX Change	-0.744*** (0.225)	-0.029* (0.015)	0.322*** (0.097)	-0.085*** (0.024)	0.538*** (0.192)
Overall R^2	0.335	0.240	0.319	0.182	0.266
(b) Exchange rate and interest rate forecasts					
FX Change	-0.770*** (0.226)	-0.015 (0.017)	0.454*** (0.128)	-0.065*** (0.021)	0.383** (0.190)
Interest Rates	-0.228 (0.908)	0.123 (0.082)	1.125* (0.602)	0.172** (0.076)	-1.331* (0.713)
Overall R^2	0.335	0.241	0.322	0.185	0.269
(c) Exchange rate, interest rate, CA / GDP, and macro forecasts					
FX Change	-0.747*** (0.222)	-0.019 (0.017)	0.432*** (0.122)	-0.065*** (0.020)	0.385** (0.188)
Interest Rates	0.181 (0.941)	0.138* (0.078)	0.781 (0.592)	0.151* (0.084)	-1.391* (0.735)
CA / GDP	0.611*** (0.207)	0.017 (0.022)	-0.157* (0.093)	-0.100*** (0.023)	-0.343** (0.173)
Inflation	-0.442 (1.023)	0.313*** (0.112)	1.237* (0.716)	-0.148 (0.103)	-0.846 (0.942)
GDP	1.673** (0.812)	0.625*** (0.121)	-1.512*** (0.501)	-0.077 (0.087)	-0.644 (0.715)
Overall R^2	0.341	0.278	0.333	0.199	0.271
Total # of Obs.	1'368	1'368	1'368	1'368	1'368
#Currencies	9	9	9	9	9
Currency FE	Yes	Yes	Yes	Yes	Yes
Time FE	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 differential between the US and the foreign country in twelve months. Panel (c) adds the forecasted differentials in CA / GDP, inflation, and GDP growth between the US and the foreign country at the end of the subsequent year. All regressions include currency and time fixed effects. Standard errors in parentheses are computed using the spatial estimator of [Driscoll and Kraay \(1998\)](#), which allows for cross-sectional and serial correlation as well as heteroskedasticity. Stars indicate significance at the 10% (*), 5% (**), and 1% (***) levels. The sample covers G10 currencies quoted against the USD. The data are monthly from September 2012 to May 2025.

rency fixed effects control for time-invariant unobserved heterogeneity at the currency level, while time fixed effects absorb variation in global factors common to all currencies (e.g., US monetary policy cycle, general market uncertainty). As a result, the β coefficient in Eq. (21)

captures the *relative* sensitivity of dollar demand to expected exchange rate changes. In particular, within a given period, foreign currencies whose expected depreciation against the dollar exceeds the cross-sectional average see differentially higher outflows relative to what global factors alone would predict.

Panel (a) shows a clear difference between customer flows (i.e., funds and buy-side banks) on the one hand and dealer banks on the other. The coefficients on customer flows, particularly for funds and small banks, are positive and significant, reflecting forecast-following or directional trading behaviour. In other words, an expected appreciation of the USD over the horizon of the next two years is associated with a positive demand for USD in FX spot markets. For example, when the consensus forecast indicates an appreciation of 1% of the USD, then trading volume for buying USD and selling foreign currency by buy-side banks increases, on average, by 0.54 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. Similarly, the coefficient for NBFIs is negative and significant, revealing that non-bank financial institutions also provide liquidity to investors.

Panel (b) incorporates interest rate forecasts. The coefficient on the three-month interest rate differential is not statistically significant. However, building on [Lustig et al. \(2011\)](#), we expect interest rate differentials to play a more important role when interacted with carry betas, a relationship we explore in [Section 5.2](#).

Panel (c) performs a horse race between forecasts for exchange rates and macroeconomic variables. First, we find that expected changes in the current account to GDP ratio differential have a strong predictive power for currency flows. Note that an increase in the CA / GDP differential is associated with a relatively smaller US current account deficit compared to abroad, implying an associated decrease in the US financial account. During our sample period, the US has experienced a current account deficit, which the US government has financed by the issuance of new debt. The fact that institutional investors purchase USD as the US current account deficit is expected to increase is consistent with foreign investors playing an important role in US Treasury markets ([Somogyi, Wallen, and Xu, 2025](#)). The results

confirm that investors (i.e., NBFIs, and smaller banks) tend to buy USD when they expect the US current account deficit to rise relative to abroad. For example, a one percentage point expected decrease in the CA / GDP differential is associated with smaller buy-side banks purchasing an additional 0.34 billion USD over the next month. In line with Panel (a), dealer banks take the other side of the trade and sell USD when current account deficits in the US are expected to rise relative to abroad. Moreover, while the CA / GDP ratio reflects more structural economic differences, inflation and real GDP growth capture more business cycle dynamics. As expected, those considerations are particularly relevant for corporates. More specifically, corporates increase their USD purchases when US inflation and GDP growth are expected to rise. This result is intuitive, since corporate trading is largely driven by the import and export prices of purchases and sales in foreign currency. For example, a European firm that exports to the US may find it optimal to buy USD today to insure itself against a depreciation of the dollar in response to rising inflation expectations. Other investor groups follow such business cycle dynamics less. The only exception is investment funds who sell the dollar when US GDP growth is expected to rise.

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

Next, we replicate our analysis in Table 4 with short-term forecasts. Consensus Economics offers forecasts at different horizons. Macroeconomic variables are being predicted for the end of the current year and the end of the subsequent year, while interest rate and FX forecasts are predicted 3, 12, and 24 months ahead. [Kremens et al. \(2025\)](#) show that long-term FX forecasts tend to be more accurate predictors of short-term FX returns than short-term FX forecasts. We provide complementary evidence to their findings for currency flows. In particular, in panel (a), when we use 3-month ahead forecasts for FX rates, we find no evidence of predictability of currency flows over the subsequent month.

By contrast, in panel (b), interest rate forecasts appear to be more relevant at shorter horizons (3 months). In particular, funds and smaller banks tend to sell USD following an expected relative increase in US interest rates. This is consistent with uncovered interest rate

parity, which predicts that currencies with higher yields tend to depreciate. The results for the other macroeconomic variables in panel (c) are consistent with our previous findings. Hence, we confirm that short-term FX rate forecasts offer less predictive information compared to long-term FX forecasts, however, we also show that short-term forecasts for other macroeconomic variables are still relevant in explaining currency flows.

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

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 ([Rinaldo, 2023](#)). For instance, a Dutch investment fund could borrow US dollars and lend euros by engaging in an FX swap that exchanges euros for dollars today and receives euros in the “forward leg.” This mechanism allows investors to “synthetically” borrow in foreign currencies 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 and FX markets. How-

Table 5: Forecasting Investment Currency Flows with Short-term Forecasts

	Dealer Banks	Corporates	Funds	NBFIs	Buy-side Banks
(a) Exchange rate forecasts					
FX Change	-0.136 (0.281)	0.049* (0.027)	-0.052 (0.167)	-0.017 (0.033)	0.155 (0.236)
Overall R^2	0.322	0.240	0.312	0.160	0.256
(b) Exchange rate and interest rate forecasts					
FX Change	0.022 (0.278)	0.066** (0.027)	-0.126 (0.171)	0.020 (0.026)	0.003 (0.231)
Interest Rates	1.800** (0.851)	0.196*** (0.065)	-0.847** (0.395)	0.430*** (0.095)	-1.726** (0.727)
Overall R^2	0.326	0.245	0.314	0.191	0.262
(c) Exchange rate, interest rate, CA / GDP, and macro forecasts					
FX Change	0.055 (0.269)	0.069** (0.027)	-0.117 (0.162)	0.009 (0.025)	-0.024 (0.226)
Interest Rates	2.071** (0.902)	0.251*** (0.075)	-1.154** (0.447)	0.447*** (0.101)	-1.762** (0.758)
CA / GDP	0.528*** (0.158)	-0.015 (0.017)	-0.171** (0.085)	-0.071*** (0.018)	-0.238* (0.132)
Inflation	-0.748 (0.609)	-0.071 (0.072)	1.020** (0.453)	-0.118* (0.062)	-0.028 (0.514)
GDP	0.164 (0.599)	0.327*** (0.097)	-0.526 (0.373)	0.046 (0.054)	0.024 (0.492)
Overall R^2	0.332	0.266	0.326	0.203	0.263
Total # of Obs.	1'368	1'368	1'368	1'368	1'368
#Currencies	9	9	9	9	9
Currency FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports forecasting regressions of investment currency flows (spot market) by trading counterparty (in billions of USD) at $t + 1$ on the set of forecasts available at t . Forecasts are for shorter horizons than the results in Table 4. Panel (a) includes forecasts of FX rate changes at the 3-month horizon. Panel (b) adds the forecasted interest rate differentials 3-month ahead between the US and the foreign country. Panel (c) adds the forecasted differentials in CA / GDP, inflation, and GDP growth between the US and the foreign country at the end of the same year. All regressions include currency and time fixed effects. Standard errors in parentheses are computed using the spatial estimator of Driscoll and Kraay (1998), which allows for cross-sectional and serial correlation as well as heteroskedasticity. Stars indicate significance at the 10% (*), 5% (**), and 1% (***) levels. The sample covers G10 currencies quoted against the USD. The data are monthly from September 2012 to May 2025.

ever, since the Global Financial Crisis, persistent CIP deviations have emerged (see, e.g., Du et al., 2018b). Specifically, synthetic dollar funding via FX swaps has become more expensive relative to direct funding via the cash market. We define the CIP basis as $CIP =$

$i_{us} - (i_{foreign} - FD_{annualized})$. Interest rates and forward discount are annualized. If $CIP > 0$ ($CIP < 0$), the direct USD interest rate is higher (*lower*) than the synthetic dollar interest rate, implying that synthetic dollar funding is cheaper (*more expensive*) relative to the cash market.

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

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

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

where the dependent variable is the swap currency flow ($SWP_{i,t+1}$) in a given foreign currency i and month $t + 1$. Note that CLS records the second leg of the swap, hence a negative currency flow corresponds to borrowing USD in the first leg and repaying it in the second leg. Therefore, a positive swap flow implies that the amount of synthetic dollar lending exceeds the amount of borrowing. The key regressor is the CIP forecast $CIP_{i,t}$. As before, we include both currency μ_i and time α_t fixed effects.

Panel (a) includes forecasts of the CIP deviation over the next six months (“CIP Deviation”) as regressor. The point estimate for funds is negative and economically large, amounting to an additional 55 billion (bn) USD synthetic borrowing for a 1 percentage point (pp) expected tightening of the CIP basis. Note that we record the second leg of the swap and hence, a negative coefficient means that, conditional on the cost of synthetic dollar funding decreasing (i.e., the basis becomes less negative), investment funds sell more USD forward, which is equivalent to doing more synthetic dollar funding. The same holds true for smaller buy-side banks that might be restricted from accessing direct dollar funding. In contrast, dealer banks supply dollars to meet swap funding demand as they have a large positive co-

efficient with respect to the expected CIP basis of 131 bn USD, which amounts to almost the entire demand by funds and buyside banks.

Panel (b) differentiates between periods when the CIP basis is positive (“CIP⁺”) and negative (“CIP⁻”), respectively. As has been shown in Table 2, and in line with Du et al. (2018b), the CIP basis is mostly negative, hence, the results with the negative CIP interaction term mostly mimic the results in Panel (a). Three results emerge. First, non-dealer banks increase their synthetic dollar borrowing in times when synthetic dollar funding is cheaper than the cash market rate (i.e., “CIP⁺”). Second, funds appear to be the most elastic group of synthetic dollar borrowers. Specifically, they lend dollars when the basis is positive, but borrow dollars when it is negative. Lastly, dealer banks supply dollar funding irrespective of the sign of the CIP basis, which is consistent with their role as global liquidity providers. However, the coefficients in positive CIP environments are statistically insignificant, likely due to the small number of observations in this regime.

Panel (c) replaces the expected CIP basis with its individual components — forecasted exchange rate changes at the three-month horizon (“FX Change”) and expected three-month interest rate differentials between the US and the foreign country 3-month ahead (“Interest Rate”). An expected appreciation of the US dollar is associated with a widening of the CIP basis (Avdjiev et al., 2019), i.e., a more negative basis, which raises the cost of synthetic dollar funding and, in turn, reduces net USD borrowing via FX swaps by both funds and buy-side banks (i.e., selling fewer dollars forward). In contrast, responses to expected interest rate differentials differ across investor types. Smaller banks increase synthetic USD borrowing when US interest rates rise relative to foreign rates, consistent with a contraction in the CIP basis. Funds, however, exhibit the opposite behaviour and increase USD lending following a rise in US interest rates, suggesting that their activity in FX swap markets is not solely driven by funding considerations.

Hedging flows: Long-dated currency forwards are widely used for hedging purposes, allowing investors and firms to protect themselves against exchange rate fluctuations (Du and Huber, 2023). 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.

Table 6: Forecasting Funding Currency Flows

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
(a) CIP forecasts					
CIP Deviation	130.899*** (29.645)	0.016 (0.346)	-55.198*** (14.584)	1.259 (1.201)	-85.192** (34.592)
Overall R^2 in	0.699	0.637	0.387	0.187	0.637
(b) Positive and negative CIP levels					
$CIP^+ \times CIP$ Deviation	134.730 (106.229)	0.471 (0.959)	19.933 (23.235)	-1.141 (3.341)	-149.852 (107.354)
$CIP^- \times CIP$ Deviation	136.284*** (32.353)	0.077 (0.420)	-64.370*** (16.924)	1.825 (1.308)	-80.341** (37.306)
Overall R^2 in	0.699	0.637	0.389	0.187	0.637
(c) FX and interest rate forecasts					
FX Change	-3.448*** (1.044)	-0.002 (0.011)	0.429** (0.195)	0.003 (0.070)	3.036*** (1.021)
Interest Rates	11.400 (8.246)	0.123 (0.081)	12.668*** (1.798)	0.974** (0.413)	-22.625*** (7.992)
Overall R^2	0.698	0.637	0.392	0.189	0.640
Total # of Obs.	1'368	1'368	1'368	1'368	1'368
#Currencies	9	9	9	9	9
Currency FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

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

For instance, a US investment fund expecting to receive large dividend payments in euros three months from now can enter a forward contract to sell euros for dollars at a fixed rate, thereby hedging against the risk of euro depreciation. In this way, FX forwards serve as a key risk management tool. As a next step in our analysis, we want to understand how forward currency flows are predicted by forecasts about exchange rates and macroeconomic fundamentals.

Table 7 reports forecasting regressions of long-dated forward flows by trading counterparty at time $t + 1$ on a set of forecasts available at time t . The empirical setup closely follows

our earlier analysis on the spot market in Eq. (21). In Panel (a), we see that corporates, funds, and NBFIs exhibit large and positive coefficients, which is consistent with buying USD at pre-defined rates when expecting a dollar appreciation. This suggests that the marginal investor across these groups of investors is likely to have foreign currency exposures that they seek to hedge. In contrast, dealer banks sell forward USD conditional on survey forecasts predicting a dollar appreciation, thereby providing dollar liquidity.

Panel (b) adds the interest rate differential as additional explanatory variable to the regression in Panel (a). An increase in US interest rates is associated with corporates, funds, and NBFIs selling forward USD, suggesting that these institutions hedge against potential long-term dollar depreciation driven by the uncovered interest parity condition (Lustig, Stathopoulos, and Verdelhan, 2019). In panel (c), we add the forecasted differentials in CA / GDP, inflation, and real GDP growth. Interestingly, real GDP growth dominates both CA / GDP and inflation expectations as a predictor. More precisely, corporates (funds) sell (buy) forward USD when GDP growth is expected to rise. These responses are opposite to what we see in the spot market. In sum, our findings highlight that professional investors seem to consider both financial and macroeconomic expectations when managing currency risk.

5.2. *Heterogeneity across currencies*

Next, we explore how the predictive power of survey forecasts for currency flows varies across currencies. Our theoretical framework suggests that, in the cross-section of currencies, investors rebalance from foreign currencies into US dollars along the factor structure of currency risk (see Proposition 2). Hence, we want to empirically understand whether (predicted) currency flows propagate through the exchange rate factor structure, that is, whether riskier currencies experience larger outflows following an expected appreciation of the US dollar relative to safer currencies. More precisely, we consider currencies' exposure to three tradeable risk factors, the dollar, carry, and UMVE, respectively. We estimate the following regression:

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

Table 7: Forecasting Hedging Currency Flow

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
(a) Exchange rate forecasts					
FX Change	-0.132*** (0.034)	0.026** (0.011)	0.197*** (0.040)	0.069*** (0.020)	0.001 (0.021)
Overall R^2	0.182	0.492	0.543	0.446	0.128
(b) Exchange rate and interest rate forecasts					
FX Change	-0.086** (0.041)	-0.001 (0.011)	0.121*** (0.041)	0.027 (0.017)	0.028 (0.021)
Interest Rates	0.388* (0.215)	-0.233*** (0.070)	-0.650*** (0.197)	-0.362*** (0.098)	0.232* (0.132)
Overall R^2	0.185	0.498	0.548	0.462	0.131
(c) Exchange rate, interest rate, CA / GDP, and macro forecasts					
FX Change	-0.094** (0.040)	0.000 (0.011)	0.123*** (0.039)	0.028 (0.017)	0.029 (0.021)
Interest Rates	0.316 (0.224)	-0.251*** (0.070)	-0.540*** (0.190)	-0.342*** (0.104)	0.241* (0.136)
CA / GDP	-0.063* (0.035)	-0.023 (0.018)	0.073 (0.060)	0.042*** (0.015)	-0.008 (0.024)
Inflation	0.416** (0.195)	-0.145* (0.085)	0.010 (0.283)	-0.004 (0.105)	-0.032 (0.114)
GDP	0.064 (0.218)	-0.363*** (0.076)	1.052*** (0.198)	0.061 (0.058)	0.084 (0.161)
Overall R^2	0.190	0.513	0.562	0.465	0.132
Total # of Obs.	1'368	1'368	1'368	1'368	1'368
#Currencies	9	9	9	9	9
Currency FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

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

where the dependent variable is either the spot, swap, or forward currency flow in currency pair i and month t . The key regressors are in $X_{i,t}$ containing forecasts of exchange rates and macroeconomic variables, and in $Z_{i,t}$ containing the respective FX risk factor betas by currency

pair. Our main coefficient of interest is φ , which identifies the cross-sectional differences across currency pairs through the interaction term. A positive coefficient implies that, for instance, an expected appreciation of the dollar is associated with larger outflows from riskier relative to safer currencies into US dollar. In all regression specifications, we include both currency μ_i and time α_t fixed effects to control for unobserved heterogeneity at the currency-level and for time variation in global factors. As before, the inference is based on [Driscoll and Kraay's \(1998\)](#) robust covariance matrix.

Investment flows: We start by regressing future spot currency flows on exchange rate forecasts as well as the interaction of exchange rate forecasts and currency betas. Table 8 reports the results of regressing spot FX flows at time $t + 1$ on FX forecasts at time t and their interaction with currency betas (i.e., dollar, carry, and UMVE betas).¹⁶

Panel (a) confirms our earlier result: following an expected appreciation of the dollar, funds and smaller buy-side banks buy US dollars, whereas dealer banks provide liquidity by selling dollars. Turning to the interaction between expected dollar appreciation (i.e., “FX Change”) and carry betas, we find that funds, NBFIs, and buy-side banks exchange riskier, high-carry-beta currencies more heavily for US dollars than safer ones. Put differently, customers of large dealer banks unwind their exposure to the carry factor by increasing their dollar purchases in times when survey forecasts predict a dollar appreciation and, in turn, reduce their exposure to high-risk currencies (e.g., Australian dollar and New Zealand dollar).

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

Table 9 extends the analysis by incorporating forecasts of interest rate differentials between the US and the foreign economy. Specifically, we extend the previous specification by adding the interest rate differential (i.e., “Interest Rates”) and its interaction term with the currency

¹⁶Throughout the paper, we estimate the full regression specifications but, for ease of presentation, we only report the main interaction coefficients of interest.

Table 8: Investment Currency Flows and the FX Factor Structure

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
(a) Exchange rate forecasts and carry beta					
FX Change	-0.495** (0.205)	-0.038** (0.016)	0.288*** (0.100)	-0.089*** (0.025)	0.339* (0.183)
FX Change \times Carry Beta	-0.819*** (0.117)	-0.033*** (0.012)	0.362*** (0.086)	0.073*** (0.023)	0.405*** (0.101)
Overall R^2	0.354	0.249	0.325	0.195	0.285
(b) Exchange rate forecasts and dollar beta					
FX Change	-0.515** (0.201)	-0.019 (0.014)	0.193** (0.091)	-0.099*** (0.026)	0.446** (0.174)
FX Change \times Dollar Beta	-0.571*** (0.087)	-0.017** (0.008)	0.298*** (0.061)	0.039*** (0.012)	0.246*** (0.081)
Overall R^2	0.354	0.264	0.342	0.201	0.274
(c) Exchange rate forecasts and UMVE beta					
FX Change	-0.672*** (0.231)	-0.064*** (0.015)	0.297*** (0.095)	-0.032 (0.020)	0.477** (0.195)
FX Change \times UMVE Beta	-0.109 (0.243)	-0.061** (0.027)	0.198 (0.167)	0.120*** (0.034)	-0.148 (0.188)
Overall R^2	0.336	0.247	0.323	0.203	0.267
Total # of Obs.	1'368	1'368	1'368	1'368	1'368
#Currencies	9	9	9	9	9
Currency FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

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

betas. The results reveal different patterns across high- and low-beta (including negative beta) currencies. On average, investor groups such as funds and NBFIs increase USD purchases when US interest rates are expected to rise, consistent with USD-denominated investments becoming more attractive. However, the interaction with currency betas is negative and statistically significant for NBFIs and buyside banks. This suggests that, conditional on higher expected US interest rates, investors sell *negative* carry beta currencies in exchange for USD, consistent with viewing the USD as a higher-yielding currency. As in previous specifications,

dealer banks take the opposite side of these trades, thereby supplying liquidity.

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

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
(a) Exchange rate forecasts, interest rates, and carry beta					
FX Change	-0.717*** (0.220)	-0.020 (0.017)	0.455*** (0.128)	-0.063*** (0.021)	0.334* (0.187)
Interest Rates	-1.282 (0.789)	0.136 (0.091)	1.208** (0.595)	0.183** (0.082)	-0.404 (0.668)
Interest Rates \times Carry Beta	1.496*** (0.549)	0.515*** (0.058)	-0.677** (0.339)	-0.230** (0.088)	-1.047** (0.441)
Overall R^2	0.347	0.284	0.324	0.195	0.283
(b) Exchange rate forecasts, interest rates, and dollar beta					
FX Change	-0.667*** (0.212)	-0.002 (0.016)	0.430*** (0.121)	-0.065*** (0.021)	0.291 (0.176)
Interest Rates	-0.828 (0.791)	0.160* (0.086)	0.946 (0.575)	0.223*** (0.081)	-0.634 (0.678)
Interest Rates \times Dollar Beta	2.964*** (0.569)	0.086** (0.037)	0.107 (0.332)	-0.126** (0.062)	-3.040*** (0.389)
Overall R^2	0.353	0.266	0.328	0.198	0.299
(c) Exchange rate forecasts, interest rates, and UMVE beta					
FX Change	-0.677*** (0.232)	-0.030 (0.019)	0.382*** (0.123)	-0.051** (0.022)	0.369* (0.193)
Interest Rates	-0.624 (0.981)	0.217** (0.085)	1.526** (0.658)	-0.034 (0.075)	-1.164 (0.726)
Interest Rates \times UMVE Beta	-0.820 (0.986)	0.248** (0.117)	0.715 (0.653)	-0.568*** (0.155)	0.555 (0.802)
Overall R^2	0.337	0.249	0.327	0.209	0.270
Total # of Obs.	1'368	1'368	1'368	1'368	1'368
#Currencies	9	9	9	9	9
Currency FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

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

Funding flows: Next, we repeat our analysis above but replace the dependent variable in Eq. (23) by short-term swaps. Table 10 reports the results of regressing swap currency flows

at time $t + 1$ on CIP forecasts at time t in currency pair i and the interaction with various measures of currency risk (i.e., dollar, carry and UMVE betas).

Panels (a)–(c) highlight how investment funds’ synthetic dollar borrowing relates to an expected increase in the CIP basis. Specifically, funds exhibit a positive interaction coefficient with carry and UMVE betas, respectively. Therefore, an expected increase in the cost of synthetic dollar funding (i.e., a more negative CIP basis) is associated with a stronger reduction in synthetic dollar borrowing via low-risk-currencies (e.g., Japanese yen) relative to high-risk-currencies (e.g., Canadian dollar). 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 positive bases (Du et al., 2018b). The results suggest that funds follow forecasts of CIP deviations in their funding flows, however, this sensitivity is weaker for currencies with higher risk exposure. In contrast to funds, smaller buy-side banks are less sensitive to the interaction of the CIP basis with carry or UMVE betas.

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

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

Table 10: Funding Currency Flows and the FX Factor Structure

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
(a) Forecasts of CIP deviations and carry beta					
CIP Deviation	135.286*** (28.929)	0.065 (0.353)	-57.435*** (14.512)	1.276 (1.368)	-87.299*** (32.638)
CIP Deviation \times Carry Beta	-136.356** (63.584)	-1.692*** (0.628)	74.283*** (19.257)	-0.069 (3.652)	59.929 (63.884)
Overall R^2	0.712	0.643	0.392	0.201	0.655
(b) Forecasts of CIP deviations and dollar beta					
CIP Deviation	124.182*** (33.296)	-0.078 (0.330)	-58.613*** (14.880)	1.568 (1.345)	-75.559* (38.460)
CIP Deviation \times Dollar Beta	53.540** (26.412)	0.184 (0.188)	0.271 (8.379)	-0.630 (0.990)	-55.688** (26.089)
Overall R^2	0.705	0.645	0.424	0.192	0.640
(c) Forecasts of CIP deviations and UMVE beta					
CIP Deviation	139.074*** (37.022)	-0.357 (0.377)	-23.541* (13.090)	2.243 (1.839)	-123.498*** (37.938)
CIP Deviation \times UMVE Beta	52.869 (75.429)	-1.127 (0.832)	96.858*** (24.095)	0.829 (5.148)	-140.712* (71.752)
Overall R^2	0.701	0.643	0.409	0.193	0.638
Total # of Obs.	1'368	1'368	1'368	1'368	1'368
#Currencies	9	9	9	9	9
Currency FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

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

sell risky currencies with positive factor betas (cf. positive interaction coefficient) following an expected USD appreciation.

5.3. Forecaster disagreement and global uncertainty

Following our theoretical framework (see [Proposition 3](#)), 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

Table 11: Hedging Currency Flows and the FX Factor Structure

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
(a) Exchange rate forecasts and carry beta					
FX Change	-0.155*** (0.035)	0.017 (0.012)	0.224*** (0.040)	0.109*** (0.018)	0.026 (0.023)
FX Change \times Carry Beta	0.028 (0.037)	0.061*** (0.013)	-0.191*** (0.044)	-0.115*** (0.022)	-0.051** (0.021)
Overall R^2	0.187	0.500	0.551	0.522	0.144
(b) Exchange rate forecasts and dollar beta					
FX Change	-0.153*** (0.038)	0.011 (0.011)	0.249*** (0.044)	0.097*** (0.017)	0.017 (0.023)
FX Change \times Dollar Beta	0.049** (0.023)	0.035*** (0.006)	-0.122*** (0.024)	-0.080*** (0.009)	-0.040*** (0.013)
Overall R^2	0.187	0.505	0.558	0.576	0.136
(c) Exchange rate forecasts and carry beta					
FX Change	-0.107*** (0.035)	0.049*** (0.011)	0.059* (0.036)	0.036** (0.014)	-0.011 (0.022)
FX Change \times UMVE Beta	0.023 (0.066)	0.091*** (0.019)	-0.286*** (0.063)	-0.133*** (0.035)	-0.039 (0.034)
Overall R^2	0.182	0.498	0.557	0.465	0.127
Total # of Obs.	1'368	1'368	1'368	1'368	1'368
#Currencies	9	9	9	9	9
Currency FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

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

investors put on their own relative to the public signal increases with uncertainty around the forecasts (dispersion across professional forecasters) and general macroeconomic uncertainty. To test this empirically, we proceed along two dimensions: (i) we interact forecasts with the VIX¹⁷ and gold price changes to proxy for global uncertainty, and (ii) we also consider interactions with forecaster dispersion.

¹⁷The VIX is a forward-looking measure of expected stock market volatility, computed from S&P 500 index option prices following the methodology of the Chicago Board Options Exchange.

Global uncertainty: To capture the effect of global uncertainty, we regress spot currency flows at time $t + 1$ on the FX rate forecasts formed at time t , interacted with the uncertainty measures and the carry beta. The dependent variable is the spot currency flow ($SPT_{i,t+1}$) from CLS in currency pair i and month $t + 1$. In Panels (a) and (b), 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 (c), we focus on an interaction with a dummy variable that is equal to one when the gold return is above its sample median, capturing periods of relatively high gold price increases (“High Gold”). All other aspects of the regression specification follow the baseline setup.¹⁸

Table 12 examines how investment currency flows relate to expected exchange rate changes and how this relationship varies during periods of heightened uncertainty. In Panel (a), we find that currency flows respond to FX forecasts in line with our previous results: for example, funds and smaller buy-side banks tend to purchase USD when the US dollar is expected to appreciate. This baseline relationship appears robust during periods of elevated uncertainty. Panel (b) extends this specification by interacting FX forecasts with the carry beta at the currency-pair level. Prior results indicate that customer flows are more sensitive to FX forecasts for riskier currencies (i.e., those with higher carry betas). Consistent with this, we find that (i) FX forecasts are more relevant for high-beta currencies, and (ii), at the same time, during periods of elevated uncertainty, particularly for these high-beta currencies, the relevance of FX forecasts diminishes.

Panel (c) replaces the VIX-based uncertainty measure with a proxy based on large increases in the price of gold. The results confirm that during periods of sharp increases in the price of gold, the relevance of FX forecasts declines, especially for high-risk currencies.

Forecaster disagreement: Next, we analyse the impact of forecaster disagreement instead of overall market uncertainty. To do so, we again regress spot currency flows at time $t + 1$ on a set of consensus forecasts formed at time t . The dependent variable is the spot currency flow ($SPT_{i,t+1}$) from CLS in currency pair i and month $t + 1$. The key explanatory variables are the forecast differentials between the US and a given foreign country i for interest rates (“Interest

¹⁸In all regression specifications, we include both currency μ_i and time α_t fixed effects to control for unobserved heterogeneity at the currency-level and for time variation in global factors. The inference is based on Driscoll and Kraay’s (1998) robust covariance matrix, which allows for cross-sectional and serial correlation.

Table 12: Investment Currency Flows in Periods of Uncertainty

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
(a) Forecasts and uncertainty (VIX)					
FX Change	-0.605** (0.262)	-0.024 (0.019)	0.214** (0.101)	-0.065** (0.027)	0.477** (0.217)
FX Change \times High VIX (=1)	-0.326* (0.180)	-0.012 (0.021)	0.254** (0.098)	-0.047** (0.023)	0.145 (0.160)
Overall R^2	0.336	0.240	0.321	0.186	0.267
(b) Forecasts, uncertainty (VIX), and carry beta					
FX Change	-0.300 (0.232)	-0.037* (0.019)	0.185* (0.104)	-0.063** (0.027)	0.215 (0.203)
FX Change \times High VIX (=1)	-0.461*** (0.176)	-0.003 (0.020)	0.237** (0.101)	-0.060** (0.027)	0.300* (0.161)
FX Change \times Carry Beta	-0.995*** (0.141)	-0.040*** (0.014)	0.381*** (0.095)	0.063*** (0.019)	0.574*** (0.130)
FX Change \times High VIX (=1) \times Carry Beta	0.548** (0.221)	0.019 (0.022)	-0.081 (0.221)	0.035 (0.040)	-0.509** (0.205)
Overall R^2	0.357	0.249	0.327	0.202	0.288
(c) Forecasts, uncertainty (gold price), and carry beta					
FX Change	-0.571** (0.274)	-0.032* (0.018)	0.342*** (0.118)	-0.082*** (0.025)	0.346 (0.238)
FX Change \times High Gold (=1)	0.149 (0.194)	-0.009 (0.018)	-0.095 (0.088)	-0.013 (0.025)	-0.030 (0.171)
FX Change \times Carry Beta	-0.995*** (0.142)	-0.051*** (0.012)	0.305*** (0.115)	0.075*** (0.022)	0.651*** (0.131)
FX Change \times High Gold (=1) \times Carry Beta	0.442** (0.213)	0.040* (0.023)	0.114 (0.157)	-0.009 (0.042)	-0.580*** (0.208)
Overall R^2	0.355	0.249	0.326	0.195	0.287
Total # of Obs.	1'368	1'368	1'368	1'368	1'368
#Currencies	9	9	9	9	9
Currency FE	Yes	Yes	Yes	Yes	Yes
Time FE	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. Panel (a) includes forecasts of FX rate changes interacted with a VIX dummy for high uncertainty periods, i.e., VIX above median VIX over the sample period. Panel (b) adds the carry beta by currency pair and its interaction terms. Panel (c) employs a dummy for high gold price changes, i.e., gold return above its sample median, instead of the VIX dummy. All regressions include currency and time fixed effects. We estimate the full regression specification, but for ease of presentation, we only report the main interaction coefficients of interest. Standard errors in parentheses are computed using the spatial estimator of [Driscoll and Kraay \(1998\)](#), which allows for cross-sectional and serial correlation as well as heteroskedasticity. Stars indicate significance at the 10% (*), 5% (**), and 1% (***) levels. The sample covers G10 currencies quoted against the USD. The data are monthly from September 2012 to May 2025.

Rates”), the current account-to-GDP ratio (“CA / GDP”), inflation (“Inflation”), and real GDP growth (“GDP”). Interest rate forecasts are measured at the three-month horizon, while the remaining macroeconomic variables correspond to expectations at the end of the next year.

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

Table 13 examines how investment currency flows relate to expected macroeconomic conditions and how these relations vary with the degree of forecaster disagreement. Two main findings emerge. First, for most investor groups such as funds, NBFIs, and smaller buy-side banks, the interaction terms are statistically significant and exhibit signs opposite to the baseline effects of the forecasts on currency flows. For instance, buy-side banks tend to sell USD when (i) US interest rates are expected to rise, (ii) the US current account deficit is expected to narrow, (iii) US inflation is expected to increase, and (iv) US real GDP growth is expected to decline. However, during periods of elevated disagreement, these relations are substantially muted, suggesting that these investor groups rely more heavily on consensus forecasts in periods of low uncertainty. Second, the effects of forecast variables on currency flows during periods of low disagreement are stronger and more precisely estimated than in the baseline specification. This is consistent with the notion that, when pooling across regimes, the opposing effects across low- and high-disagreement periods partially offset each other.

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

Table 13: Investment Currency Flows and Forecaster Disagreement

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
FX Change	-0.607*** (0.210)	-0.012 (0.017)	0.289*** (0.111)	-0.048*** (0.017)	0.358** (0.178)
Interest Rates	1.196 (1.090)	0.121 (0.131)	0.344 (0.604)	0.156* (0.092)	-1.917** (0.851)
Interest Rates \times High Disagr (=1)	-0.512 (0.731)	0.097 (0.085)	-0.956** (0.398)	0.162** (0.065)	1.104* (0.560)
CA / GDP	1.026*** (0.225)	0.026 (0.025)	-0.305*** (0.103)	-0.132*** (0.030)	-0.579*** (0.197)
CA / GDP \times High Disagr (=1)	-0.564*** (0.137)	-0.007 (0.012)	0.241*** (0.069)	0.023 (0.018)	0.307*** (0.112)
Inflation	0.879 (1.430)	0.285** (0.139)	2.489*** (0.834)	-0.458*** (0.174)	-3.058** (1.202)
Inflation \times High Disagr (=1)	-1.885** (0.926)	0.022 (0.115)	-0.922** (0.453)	0.347** (0.143)	2.407*** (0.852)
GDP	0.126 (1.163)	0.876*** (0.204)	-3.107*** (0.808)	0.151 (0.132)	2.044** (0.996)
GDP \times High Disagr (=1)	1.663 (1.209)	-0.304 (0.205)	1.982** (0.823)	-0.224 (0.143)	-3.188*** (1.061)
Overall R^2	0.355	0.285	0.345	0.223	0.285
Total # of Obs.	1'368	1'368	1'368	1'368	1'368
#Currencies	9	9	9	9	9
Currency FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

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

currency flows. The detailed results can be found in the Online Appendix.

6. Robustness

Online Appendix (see Section E) provides a range of robustness checks that confirm our baseline results across alternative empirical specifications. First, we report several alternative

fixed effects structures. For instance, we explore specifications that only include currency fixed effects, which control for time-invariant cross-currency heterogeneity but not for variation in unobservable global factors. Across all specifications, we find qualitatively similar results relative to our baseline, which includes both currency and time fixed effects.

Second, we restrict the cross-section of currencies to align with prior work (e.g., [Kremens et al., 2025](#)) and find consistent results in terms of both statistical and economic significance (see Table E.5). The core finding — exchange rate expectations accurately predict investors’ demand for dollars — remains robust across various specifications. Overall, our results support the notion that survey-based expectations contain economically meaningful information for predicting currency flows across market participants and traded instruments.

7. Conclusion

This paper studies how expectations about exchange rates and macroeconomic fundamentals predict global demand for US dollars across market participants and traded instruments. Using detailed currency flow data for spot, swap, and forward markets combined with survey-based forecasts, we show that investors increase dollar purchases in spot markets when they expect the dollar to appreciate. Dealer banks, in turn, take the opposite side of these trades, acting as liquidity providers. Cross-sectionally, investors rebalance along the factor structure of currency risk, reallocating from riskier foreign currencies into the dollar following an expected appreciation. However, currency flows respond less to forecasts during periods of elevated uncertainty or greater disagreement among forecasters. Across derivative markets, we document two novel findings. First, synthetic dollar borrowing via FX swaps declines as the forecasted cross-currency basis widens. Second, expected dollar appreciation and macroeconomic forecasts accurately predict dollar purchases in long-dated FX forwards.

In sum, our results highlight that expectations play a pivotal role in shaping global currency flows. Specifically, expectations about macroeconomic fundamentals and exchange rates accurately predict dollar demand across market participants and traded instruments. A better understanding of the determinants of currency flows is crucial, as these flows not only reflect investors’ expectations but also shape how those expectations are incorporated into future exchange rate dynamics.

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Online Appendix to
“Demand for Dollars: Evidence from Survey Expectations”

Appendix A. Additional Information on Data

The goal of this section is to describe how CLS categorizes market participants into price takers and market-makers and how this impacts the relative coverage of the currency flow data. CLS uses two distinct methods of categorizing market participants, namely, the identity-based and behaviour-based approaches.

For the first, CLS classifies market participants into corporates, funds, non-bank financial firms, and banks based on static identity information. The corporate category comprises any non-financial organisation. The fund category includes pension funds, hedge funds, and sovereign wealth funds, whereas non-bank financials (NBFIs) are insurance companies, brokers, and clearing houses. The fund category may also include principal trading firms (PTFs) such as high-frequency trading firms and electronic non-bank market-makers (e.g., XTX Markets or Jump Trading). The majority of these PTFs rely on prime brokers to gain access to the FX market (Schrimpf and Sushko, 2019). Hence, if PTFs settle a trade via a prime broker who is a CLS member, then this trade would appear as a bank-to-bank transaction. However, such inter-bank trades are excluded from the flow dataset unless one of the counterparties is classified as a non-dealer bank. More generally, CLS does not report any transactions between two market-makers or two price takers to avoid double counting.

The above labels refer to the identities of the entities trading and not to the behaviour they exhibit. This is because CLS is a payment-versus-payment platform that solely observes the executed trade price used for settlement and does not see the market behaviour of bids and offers that precede the execution or any other such details. Hence, the identity-based classification leads to three possible transactor pairings between end-user investors and banks (both sell-side and buy-side banks): corporate-to-bank, fund-to-bank, and non-bank-to-bank.

The above pairings account for about 10–15% of the total activity in the FX market.¹⁹ Most activity in this market is bank-to-bank. Therefore, CLS carries out a second analysis focusing on bank-to-bank transactions to determine which banks are market-makers and which banks are price takers. CLS maps all FX activity as a network. Market participants are nodes, while FX transactions are edges. Nodes that are mutually tightly interlinked and maintain a

¹⁹See “Triennial central bank survey — global foreign exchange market turnover in 2022,” Bank for International Settlements, September 2022, Hasbrouck and Levich (2018) and Ranaldo and Somogyi (2021).

consistently high coreness over time are considered market-makers, while all other nodes are considered price takers.

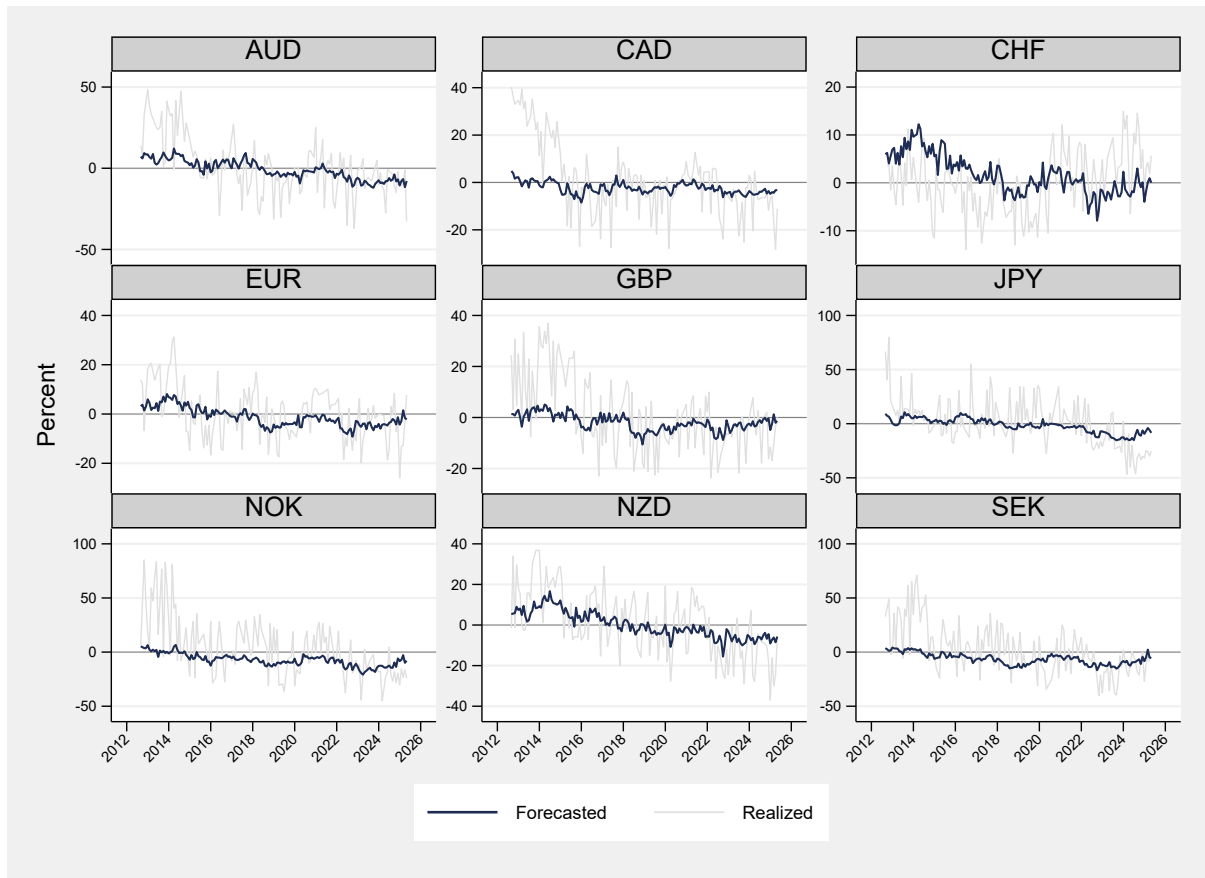
Based on our conversations with CLS, we know that the sellside almost exclusively comprises banks that were identified to be market-makers, whereas the buy-side involves corporates, funds, NBFIs and smaller non-dealer (price taker) banks. Unfortunately, CLS does not directly report transactions between price taker banks and market maker banks but only total trading activity between buy-side and sellside market participants. However, the reporting structure of the CLS data allows us to indirectly infer these transactions by computing the difference between total buy-side trading activity and transactions between banks and corporates, funds, and NBFIs, respectively. Note that this approximation will generally underestimate the trading activity between price taker banks and market maker or dealer banks since the three aforementioned groups may trade with both buy-side and sellside banks.²⁰

Empirically, transactions between market-makers make up most of the activity in the FX market. Typically, a price taker does an initial trade with one market-maker, and that market-maker hedges the resulting risk by trading with other market-makers. A single initial trade can lead to a chain of downstream transactions where various market-makers pass the “hot potato” around or slice up the risk in various ways. Consequently, the activity among market-makers will be higher than that between price takers and market-makers. There are three further reasons why transactions between non-bank price takers and market-maker banks represent a relatively low share of total FX turnover settled by CLS. First, many hedge funds and proprietary trading firms settle through prime brokers. CLS does not have look-through on these trades, and hence, they appear as bank-to-bank transactions. If those prime brokers are also market-makers, the transactions would be excluded from the order flow dataset. Second, CLS has relatively low client penetration among corporates and real money funds that trade FX infrequently and do not need a dedicated third-party settlement service. Third, market-maker banks may engage in price taking activity, but price taker banks are unlikely to ever engage in market-making activity.

²⁰More precisely, CLS only reports the total trading activity between say funds and buy-side as well as sellside banks but not separate breakdowns of funds trading with buy-side and sellside banks, respectively.

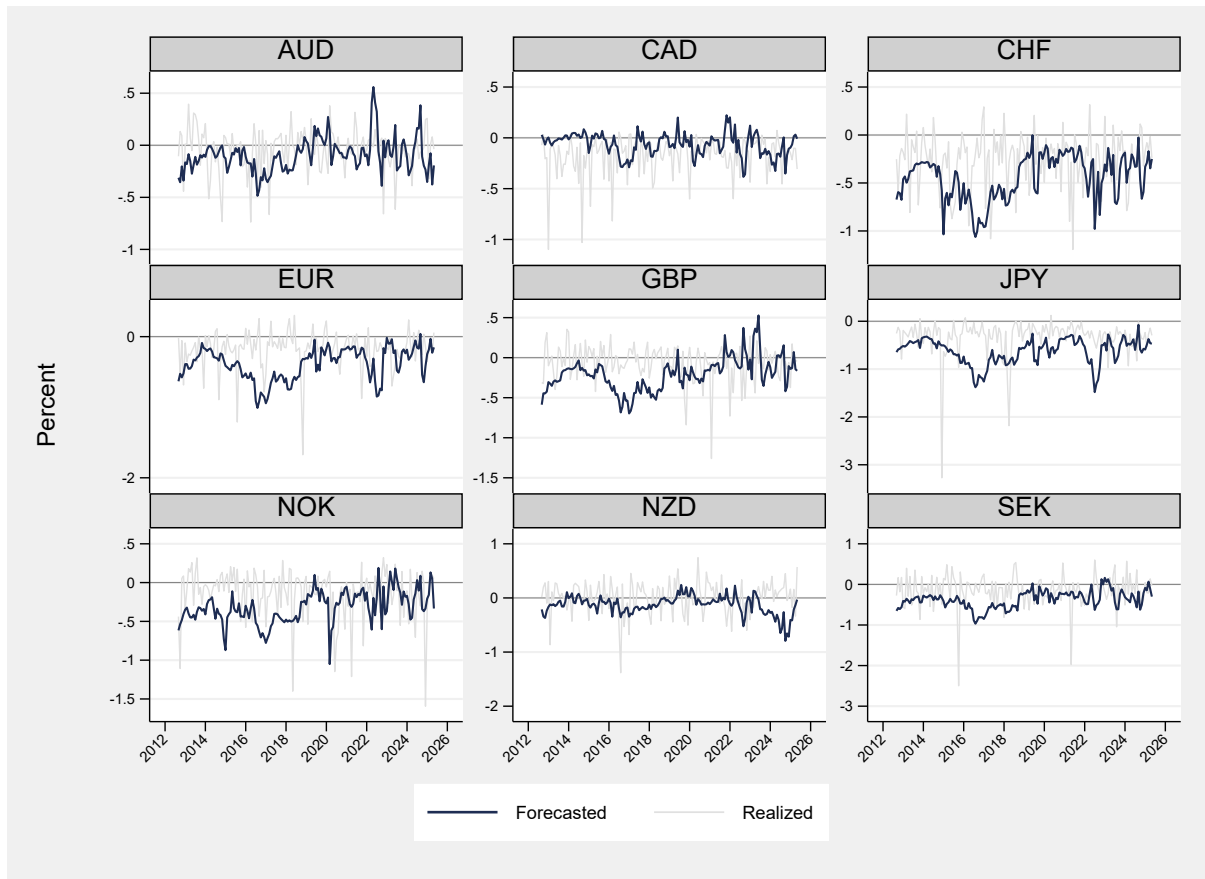
Appendix B. Summary Statistics - Forecasts

Figure B.1: Forecasted vs. realized FX Rate Change, 24-Month Horizon (in %)



Note: This figure plots, for each currency, the time-series of forecasted FX rate changes over a 24-month horizon. FX Rate Change is defined as $(FX_{24mo} - FX)/FX \times 100$, with USD as the base currency. For comparison, the realized exchange rate return over the matched forward-looking time period is also depicted. The sample covers G10 currencies quoted against the USD. The data are monthly from September 2012 to May 2025.

Figure B.2: Forecasted vs. realized 3-month CIP Deviation, 3-Month Horizon



Note: This figure plots, for each currency, the time-series of forecasted 3-month CIP deviations starting three months ahead. The CIP deviation is defined as the difference between the annualized forward discount and the annualized interest rate differential between the quote country and the US, with the USD being the base currency. The forward discount is computed as $(\log(F_{0,6}) - \log(F_{0,3})) \times \frac{360}{90} \times 100$. The interest rate differential embedded in the CIP deviation is based on 3-month interest rates forecasted three months ahead. For comparison, we plot the period-matched realized CIP deviation. The sample covers G10 currencies quoted against the USD. The data are monthly from September 2012 to May 2025.

Appendix C. Summary Statistics - Currency Betas

Table C.1: Summary Statistics - Currency Betas

Currency	Dollar Beta	Carry Beta	UMVE Beta
AUD	1.432	0.547	-0.059
CAD	0.939	0.265	-0.169
CHF	0.968	-0.124	-0.249
EUR	1.105	-0.091	-0.433
GBP	0.897	0.046	-0.523
JPY	0.560	-0.280	-0.372
NOK	1.582	0.218	-0.281
NZD	1.429	0.482	0.017
SEK	1.350	0.037	-0.445

Note: Dollar β_i^{DOL} and carry β_i^{CAR} betas are estimated using a 60-month rolling window regression of log changes in currency i 's exchange rate $S_{i,t}$ on either the dollar or the carry factor. We consider the same cross-section of 39 countries as in [Verdelhan \(2017\)](#) but exclude euro area countries; this leaves us with 28 countries to construct the risk factors. The dollar factor is the average change in all currencies with respect to the USD. The carry factor is created as a portfolio return by sorting, every month, currencies into five portfolios based on the one-month forward discount relative to the USD prevailing over the previous month. As for the carry and dollar factor, we estimate the currency beta with respect to the UMVE factor from a rolling window regression. We create the mean-variance efficient UMVE portfolio following [Chernov et al. \(2023\)](#). The sample covers G10 currencies quoted against the USD. The data are monthly from September 2012 to May 2025 (for UMVE beta until March 2025).

Appendix D. Heterogeneity Across Forecasters

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

To measure forecast errors, 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.²¹ 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.²²

Table D.1 shows how spot currency flows correlate with forecasters' past forecasting errors. On average, investors purchase US dollars in relation to forecasts about macroeconomic variables. However, this response weakens when forecasts come from forecasters with a history of large past errors. For example, smaller buy-side banks tend to sell USD when (i) US interest rates are expected to rise relative to foreign interest rates, (ii) the US CA/GDP deficit is expected to widen, and (iii) the US is forecasted to have higher inflation rates relative to foreign inflation rates. However, this effect is significantly smaller when forecasts originate from less accurate forecasters, indicating that these banks adjust their trading behaviour conditional on forecaster accuracy. Dealer banks display the opposite pattern.

²¹Forecast 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.

²²We use the 12–24-month window because forecast errors can only be observed with a lag. Since forecasts pertain to the subsequent year, this structure ensures that we use forecast errors that would have been known to market participants at the time they made their trading decisions.

Table D.1: Investment Currency Flows and Forecast Accuracy

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
(a) Exchange and interest rate forecasts					
FX Change	-0.762*** (0.249)	-0.018 (0.018)	0.413*** (0.128)	-0.064** (0.026)	0.423** (0.213)
Interest Rates	0.343 (0.880)	0.167** (0.071)	0.743 (0.471)	0.098 (0.061)	-1.425** (0.653)
Interest Rates \times High Error (=1)	-0.501* (0.271)	-0.149*** (0.046)	0.048 (0.171)	0.035 (0.035)	0.546*** (0.204)
Overall R^2	0.374	0.281	0.376	0.225	0.262
(b) Full set of variables					
FX Change	-0.589** (0.253)	-0.006 (0.017)	0.232* (0.121)	-0.035* (0.019)	0.388* (0.205)
Interest Rates	1.440 (1.062)	0.191*** (0.072)	-0.354 (0.418)	0.243** (0.109)	-1.644* (0.835)
Interest Rates \times High Error (=1)	-0.905* (0.494)	-0.107** (0.041)	0.225 (0.203)	0.008 (0.037)	0.788* (0.429)
CA / GDP	0.858*** (0.253)	0.035 (0.025)	-0.199** (0.097)	-0.107*** (0.024)	-0.572*** (0.208)
CA / GDP \times High Error (=1)	-0.517*** (0.195)	-0.016* (0.008)	-0.003 (0.072)	0.023** (0.010)	0.519*** (0.163)
GDP	0.330 (0.702)	0.484*** (0.139)	-0.883** (0.339)	-0.021 (0.054)	0.126 (0.601)
GDP \times High Error (=1)	0.370 (0.548)	-0.236** (0.110)	-0.201 (0.295)	0.084 (0.058)	-0.035 (0.471)
Inflation	0.942 (0.892)	0.192** (0.075)	1.339*** (0.340)	-0.159* (0.083)	-2.339*** (0.855)
Inflation \times High Error (=1)	-1.668** (0.768)	-0.043 (0.066)	-0.527 (0.330)	0.077 (0.108)	2.249*** (0.748)
Overall R^2	0.408	0.321	0.391	0.263	0.293
Total # of Obs.	18'009	18'009	18'009	18'009	18'009
#Currencies	9	9	9	9	9
Currency FE	Yes	Yes	Yes	Yes	Yes
Time FE	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 as well as forecasted differentials in interest rate, CA / GDP, inflation and real GDP growth between the US and the foreign country in three months (for interest rates) and at the end of the subsequent year for the other variables. We then define 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. All regressions include currency and time fixed effects. Standard errors in parentheses are computed using the spatial estimator of [Driscoll and Kraay \(1998\)](#), which allows for cross-sectional and serial correlation as well as heteroskedasticity. Stars indicate significance at the 10% (*), 5% (**), and 1% (***) levels. The sample covers G10 currencies quoted against the USD. The data are monthly from September 2012 to May 2025.

Appendix E. Robustness

Appendix E.1. Fixed effects specifications

Table E.1: Forecasting Investment Currency Flows — Time FE

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
FX Change	−0.883*** (0.142)	−0.095*** (0.011)	0.437*** (0.069)	0.005 (0.019)	0.526*** (0.124)
Interest Rates	−2.284*** (0.637)	−0.316*** (0.052)	1.892*** (0.384)	0.324*** (0.055)	0.269 (0.450)
CA / GDP	0.111 (0.138)	0.019*** (0.007)	0.176*** (0.047)	0.005 (0.013)	−0.303*** (0.116)
Inflation	3.054*** (0.659)	0.261*** (0.076)	−1.919*** (0.496)	−0.057 (0.078)	−1.273** (0.550)
GDP	0.953 (0.950)	0.367*** (0.103)	−1.022** (0.467)	−0.020 (0.069)	−0.230 (0.728)
Overall R^2	0.182	0.233	0.214	0.151	0.169
Total # of Obs.	1'368	1'368	1'368	1'368	1'368
#Currencies	9	9	9	9	9
Currency FE	No	No	No	No	No
Time FE	Yes	Yes	Yes	Yes	Yes

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

Table E.2: Forecasting Investment Currency Flows — Quarter \times Year FE

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
FX Change	-0.624*** (0.177)	-0.023 (0.014)	0.351*** (0.100)	-0.042** (0.016)	0.317** (0.146)
Interest Rates	0.552 (0.889)	0.116 (0.074)	0.522 (0.518)	0.191** (0.082)	-1.530** (0.695)
CA / GDP	0.634*** (0.200)	0.018 (0.021)	-0.158* (0.087)	-0.100*** (0.021)	-0.365** (0.167)
Inflation	-0.516 (0.948)	0.311*** (0.104)	1.265* (0.669)	-0.164* (0.098)	-0.789 (0.837)
GDP	1.677** (0.732)	0.605*** (0.112)	-1.500*** (0.461)	-0.089 (0.081)	-0.626 (0.657)
Overall R^2	0.313	0.232	0.299	0.141	0.231
Total # of Obs.	1'368	1'368	1'368	1'368	1'368
#Currencies	9	9	9	9	9
Currency FE	No	No	No	No	No
Quarter-Year FE	Yes	Yes	Yes	Yes	Yes

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

Table E.3: Forecasting Investment Currency Flows — Currency FE

	Dealer Banks	Corporates	Funds	NBFIs	Buy-side Banks
FX Change	−0.030 (0.084)	0.028** (0.011)	−0.180*** (0.056)	0.024** (0.009)	0.129* (0.068)
Interest Rates	−1.359*** (0.498)	−0.123** (0.059)	−0.436 (0.267)	0.118** (0.050)	1.715*** (0.392)
CA / GDP	0.881*** (0.164)	0.024 (0.017)	−0.611*** (0.109)	−0.072*** (0.018)	−0.222* (0.130)
Inflation	−1.851*** (0.654)	0.078 (0.085)	1.056** (0.406)	0.031 (0.069)	0.733 (0.694)
GDP	2.948*** (0.626)	0.493*** (0.111)	−1.965*** (0.389)	0.071 (0.071)	−1.527** (0.616)
Overall R^2	0.220	0.132	0.208	0.066	0.128
Total # of Obs.	1'368	1'368	1'368	1'368	1'368
#Currencies	9	9	9	9	9
Currency FE	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No

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

Table E.4: Forecasting Investment Currency Flows - without FE

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
FX Change	-0.234*** (0.062)	-0.023*** (0.008)	0.050 (0.047)	0.036*** (0.010)	0.149*** (0.046)
Interest Rates	-2.830*** (0.277)	-0.366*** (0.045)	1.160*** (0.209)	0.184*** (0.034)	1.786*** (0.227)
CA / GDP	-0.095 (0.080)	-0.004 (0.005)	0.175*** (0.042)	-0.007 (0.009)	-0.061 (0.068)
Inflation	0.963** (0.484)	0.090 (0.071)	-0.794** (0.350)	-0.007 (0.066)	-0.208 (0.483)
GDP	2.715*** (0.728)	0.426*** (0.092)	-1.466*** (0.369)	0.084 (0.062)	-1.769*** (0.567)
Overall R^2	0.040	0.079	0.036	0.040	0.029
Total # of Obs.	1'368	1'368	1'368	1'368	1'368
#Currencies	9	9	9	9	9
Currency FE	No	No	No	No	No
Time FE	No	No	No	No	No

Note: This table reports forecasting regressions of investment currency flows (spot market) by trading counterparty (in billions of USD) at $t + 1$ on the set of forecasts available at t . It includes forecasts of FX rate changes, the forecasted interest rate differential between the US and the foreign country in twelve months, and the forecasted differentials in CA / GDP, inflation, and GDP growth between the US and the foreign country at the end of the subsequent year. Standard errors in parentheses are computed using the spatial estimator of [Driscoll and Kraay \(1998\)](#), which allows for cross-sectional and serial correlation as well as heteroskedasticity. Stars indicate significance at the 10% (*), 5% (**), and 1% (***) levels. The sample covers G10 currencies quoted against the USD. The data are monthly from September 2012 to May 2025.

Appendix E.2. Cross-section

Table E.5: Forecasting Investment Currency Flows — [Kremens et al. \(2025\)](#) cross-section

	Dealer Banks	Corporates	Funds	NBFIs	Buyside Banks
FX Change	-0.351 (0.254)	0.032 (0.021)	0.378*** (0.140)	-0.082*** (0.024)	0.032 (0.225)
Interest Rates	2.531* (1.493)	0.351*** (0.117)	-1.084 (0.752)	0.437*** (0.135)	-2.355** (1.165)
CA / GDP	1.432*** (0.517)	0.153*** (0.040)	-1.454*** (0.376)	-0.047 (0.049)	-0.086 (0.379)
Inflation	0.174 (1.307)	0.389*** (0.144)	1.293 (0.891)	-0.105 (0.150)	-1.708 (1.283)
GDP	2.167** (0.860)	0.617*** (0.132)	-2.298*** (0.621)	-0.026 (0.103)	-0.475 (0.886)
Overall R^2	0.379	0.317	0.373	0.241	0.322
Total # of Obs.	1'368	1'368	1'368	1'368	1'368
#Currencies	6	6	6	6	6
Currency FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports forecasting regressions of investment currency flows (spot market) by trading counterparty (in billions of USD) at $t + 1$ on the set of forecasts available at t . It includes forecasts of FX rate changes, the forecasted interest rate differential between the US and the foreign country in twelve months, and the forecasted differentials in CA / GDP, inflation, and GDP growth between the US and the foreign country at the end of the subsequent year. All regressions include time and currency fixed effects. Standard errors in parentheses are computed using the spatial estimator of [Driscoll and Kraay \(1998\)](#), which allows for cross-sectional and serial correlation as well as heteroskedasticity. Stars indicate significance at the 10% (*), 5% (**), and 1% (***) levels. The sample covers the [Kremens et al. \(2025\)](#) cross-section, i.e., AUD, CAD, EUR, GBP, JPY, and KRW currencies quoted against the USD. The data are monthly from September 2012 to May 2025.

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