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Monetary policy transmission through the exchange rate factor structure ☆

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ABSTRACT

We show that US monetary policy is transmitted internationally through the factor structure of exchange rates. Following an easing of monetary policy, investment funds sell safe and buy risky currencies. Global US banks, similarly, tilt their distribution of foreign loan origination toward currencies with greater systematic currency risk. The effects of monetary policy on currency flows and loans persist for several months and feed into the leverage and real investment decisions of firms and, in particular, those that operate using a high-risk currency. We conclude that the risk factor exposure of currencies is a significant channel through which we can understand the international transmission of US monetary policy.

1. Introduction

The returns on currencies follow a strong factor structure (Lustig et al., 2011), that is, a few factors account for the bulk of the variation in the return and risk properties of bilateral exchange rates. In other words, exchange rate returns are largely explained by their exposure to a small group of factors. Currencies with low or negative betas are considered safe investments and earn small returns, whereas those with high betas are risky and their holders are compensated with large returns. These factors have an economic meaning in and of themselves (for example the carry factor or the dollar factor), but they are silent on other macroeconomic features of exchange rates. In this paper, we ask and answer how they explain the transmission of US monetary policy to foreign currencies and ultimately international capital flows.

To fix ideas, consider an unexpected easing in the policy rate of the Federal Open Market Committee (FOMC). Post-easing, we find that investment funds (mutual, pension, and hedge funds) pursue a "risk-on" strategy by rebalancing up the risk spectrum of exchange rates; that is, funds sell safe currencies like the Japanese yen to buy risky ones like the Australian dollar. Global US banks, similarly, reallocate their loan origination from low- to high-risk currencies. These responses have lasting real economic effects: foreign firms that mainly operate in a risky currency borrow (lever up) and invest more relative to firms that operate in safe currencies.

Our mechanism relates to the risk-taking channel of monetary policy (Borio and Zhu, 2012), which postulates that monetary policy impacts the willingness of market participants to take on risk exposures and thereby influences financial conditions and, ultimately, real economic outcomes (Bruno and Shin, 2015). Our novel contribution is to show that currency exposures provide a lens through which

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economists can understand how US monetary policy is transmitted to other economies. We formalize this intuition in Section 2 where we illustrate theoretically that an unexpected decline in the Federal Funds rate either lowers investors' risk aversion or expands the risk-taking capacity of global intermediaries, generating the risk-on patterns that we document in this paper. Our theoretical framework builds on Gabaix and Maggiori (2015), Itskhoki and Mukhin (2021), and Vayanos and Vila (2021). We extend their work by focusing on the interaction between systematic currency risk and the endogenously determined supply of intermediation capacity that global financial institutions provide to international firms.

We begin by analyzing the response of currency flows to US monetary policy announcements. One challenge we face in our analysis is that currency flows play a role in monetary policy. To overcome this, we use the high-frequency changes in Federal Funds futures prices surrounding FOMC announcements to identify changes in interest rates unrelated to currency flows (Kuttner, 2001; Bernanke and Kuttner, 2005). Measuring flows of currencies is difficult, because the FX market is complex in traded instruments, decentralized across players, and global in nature. Key to our analysis is thus, the use of relatively novel settlement data provided by Continuous Linked Settlement (CLS) Group, which covers around half of global currency trading volume for various players transacting in spot and FX derivative markets alike. We discuss these data along with our other auxiliary sources in Section 3.

In Section 4 we show that monetary shocks have a strong and directional impact on global currency flows, especially for investment funds and banks. For context, a typical 10 basis point (bp) expansionary monetary surprise induces fund flows into the Australian dollar of around $1904 mn. This is more than two-thirds of the standard deviation of monthly flows between the US Dollar and Australian Dollar. We interpret these coefficients as *flow betas* because, as we show, they align well with currency betas.

We then assess how currency flows vary across common measures of currency risk. For our baseline results we focus on two measures: carry and dollar betas. Verdelhan (2018) documents that these two factors account for a substantial fraction of bilateral exchange rate variation. These betas summarize the set of a country's characteristics that collectively determine its currency's risk. Among other things, currencies with large carry betas tend to possess high interest rates (Lustig and Verdelhan, 2007), whereas currencies with large dollar betas face greater impediments to trade in goods (Lustig and Richmond, 2019). Moreover, Chernov et al. (2023) show that from a mean–variance perspective the majority of dollar and carry returns are driven by unpriced risk. To account for this result, we also explore currencies' exposure to an unconditional mean–variance efficient portfolio and find that our results concerning currency flows and bank loans are driven by the priced rather than unpriced component of currency returns.

In our regressions, the key regressor is an interaction of currency risk with a monetary policy shock measure. We find that both carry and dollar exposures influence the direction and magnitude of investment funds' flows: funds reallocate positions from low- to high-risk currencies following a monetary easing in the US, and vice versa. And while the US monetary shock is transient, its effect is long-lived. We show that currencies with low carry betas tend to experience outflows over the following five months, whereas currencies with high carry betas face a lasting wave of demand, persisting beyond that period.

The currency market, and investment funds' currency flows more specifically, is not the only medium through which US monetary policy can impact foreign economies. In particular, monetary policy may also affect global economic activity via the credit channel (see, e.g., Bernanke and Gertler, 1995; Bernanke et al., 1999). Therefore, in Section 5 we study how US monetary policy affects global US banks' international loan origination. In line with Bräuning and Ivashina (2020a), we confirm that a reduction in the Federal Funds rate leads to less lending in foreign currencies by banks that are domiciled in the United States. However, we also show that the magnitude of this decrease is affected by the denomination of the loan's currency and how risky it is. Loans in safe currencies witness the largest decline, whereas loans in riskier currencies experience a smaller reduction or even loan growth. Thus, US banks tilt their foreign currency loan portfolios toward riskier currencies following a monetary easing.

Finally, in Section 6 we turn to study how firms themselves are impacted by the currency in which they primarily operate and borrow. We link our database on global US banks' lending to international firms' financial statements, allowing us to tie loan origination to real outcomes. In our regressions, we control for country-time fixed effects that absorb variation due to demand effects in foreign countries, isolating the effect of loan supply. In fact, our data allow us to distinguish a firm's operating currency from its country's currency, and hence, our estimates are identified from the variation that comes from firms borrowing in different currencies within the same country.

Eventually, we show that foreign firms that primarily operate using risky currencies are impacted differently by changes in US monetary policy than firms that mainly use safe currencies. Specifically, firms that use high-risk currencies experience a positive loan supply shock from global US banks following an unexpected easing in the Federal Funds rate. These firms, in turn, use the loans to expand the size of their balance sheets, increase leverage, and invest more in tangible assets.

In sum, our evidence indicates that expansionary US monetary policy causes both funds and banks to tilt their portfolios away from safe toward riskier currencies. Moreover, we find that these effects feed through to foreign firms' real decisions. Our main contribution is to show that the magnitude of these spillover effects to foreign economies is determined by the riskiness of different currencies. In other words, our empirical evidence highlights that the risk factor exposure of currencies is a significant channel through which we can understand the international transmission of US monetary policy.

Related literature

Since Fama (1984), an extensive literature in international finance has studied the economic reasons for uncovered interest rate parity (UIP) deviations. One enduring view is organized around systematic currency risk. Indeed, several papers have found support of this risk-based view of exchange rates, which posits that currencies' average excess returns should align with their systematic risk exposures. For instance, Verdelhan (2018) shows that dollar and carry betas are central in explaining bilateral exchange rate movements, whereas in recent work Liu et al. (2022) and Nucera et al. (2023) argue that the same two factors also explain a large cross-section of currency portfolio returns. However, Chernov et al. (2023) find that these principal components explain only a small share of the variation in a unconditional mean–variance efficient portfolio and hence, these portfolios are mainly driven by unpriced risk.[1] Moreover, the aforementioned currency risk exposures have been shown to be related to the fundamental characteristics of countries.[2] In contrast to much of the focus of this literature, we study whether the exchange rate factor structure has economic implications beyond a currency's expected return and risk.

[1] Throughout the paper, whenever we use the term "systematic" currency risk we refer to this as the exposure of bilateral exchange rates to a factor model rather than priced vs. unpriced components of a factor with respect to a mean–variance investor.

[2] For example, a country's characteristic like its interest rate (Lustig et al., 2011), exposure to global volatility (Menkhoff et al., 2012a), size (Hassan, 2013), external imbalances (Della Corte et al., 2016), capital–output ratios (Hassan et al., 2016), trade composition (Ready et al., 2017), global growth news exposure (Colacito et al., 2018), trade centrality (Richmond, 2019), geography of trade (Lustig and Richmond, 2019; Hassan et al., 2023), sovereign credit risk (Della Corte et al., 2022), and liquidity risk (Söderlind and Somogyi, 2024) have all been shown to impact its currency's risk.

Another vein of work in international macroeconomics studies how monetary policy shocks propagate across the global economy. The vector autoregression literature, for example, studies impulse responses of international macroeconomic variables to structural shocks (Eichenbaum and Evans, 1995; Stavrakeva and Tang, 2015; Schmitt-Grohé and Uribe, 2018). Instead, our work uses more recent techniques to achieve a cleaner identification by using high-frequency movements in futures prices surrounding monetary policy shocks (Kuttner, 2001; Bernanke and Kuttner, 2005). In robustness, we also consider some of the most recent advances in measuring monetary policy surprises (e.g., Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020; Kearns et al., 2022; Bauer and Swanson, 2023a,b).

Recent papers examine the dynamics of various assets that are driven by FOMC announcements. A select sample of papers that study equity, option, and bond returns around FOMC meetings are Savor and Wilson (2014), Lucca and Moench (2015), Ai and Bansal (2018), Cieslak et al. (2019), and Roussanov and Wang (2023). Notably, Mueller et al. (2017) study US dollar movements surrounding monetary policy announcements. They show that a simple trading strategy that shorts the dollar and buys foreign currencies earns high excess returns during days with announcements. Contemporaneously, Antolin-Diaz et al. (2023) document that currencies that are more exposed to US monetary policy yield positive average returns. They show that currency characteristics explain the cross-sectional heterogeneity of these exposures across currencies and time.

We contribute to this literature in three ways. First, we study the response of investment funds' currency flows (rather than currency returns) and global banks' loan origination to monetary policy shocks. Second, we relate the magnitudes of these flows and loans to measures of currency risk that go beyond just interest rate differentials. Finally, we tie the change in the distribution of loan origination to firms' real decisions, and in particular their leverage and investment choices.

Our study aims to connect the exchange rate factor structure to the real international transmission of US monetary policy.[3] Ottonello and Winberry (2020) assess the investment channel of monetary policy among US non-financial firms, though they do not study the channel in other countries. Zhang (2021) explores the role of trade invoicing currencies in the international spillover of monetary policy and shows that exchange rates, interest rates, and equity returns in countries with a larger dollar-invoicing share respond more to US monetary policy. We provide complementary insights to this line of reasoning by focusing on quantity flows induced by monetary policy and their real effects as well as by linking the differences across currencies to measures of currency risk. Bräuning and Ivashina (2020a) examine how changes in central banks' interest rates affect global banks' allocations of lending across domestic and foreign markets. Correa et al. (2021) analyze the impact of monetary policy on bilateral cross-border bank flows using the Bank for International Settlements (BIS) locational banking statistics database. Their focus is on policy rate changes abroad rather than in the US and they provide no link to measures of currency risk. We contribute to this branch of literature by studying the response of not only banks but also funds to monetary policy shocks, and we link these responses to the factor structure of exchange rates.

More broadly, our work connects to the global financial cycle (Rey, 2013; Miranda-Agrippino and Rey, 2020) and the risk-taking channel of monetary policy (e.g., Borio and Zhu, 2012; Bruno and Shin, 2015, 2017; Adrian et al., 2019; Bruno et al., 2022; Bauer et al., 2023). Parts of this literature focus on the implications for emerging market credit cycles and financial crises such as Gourinchas and Obstfeld (2012) and Bräuning and Ivashina (2020b). Different from these papers, we show evidence that the currency factor structure can provide a simple framework to better understand the international transmission of US monetary policy.

[3] Related is also the literature on international transmission of bank liquidity: for example, Schnabl (2012), Cetorelli and Goldberg (2012), and Temesvary et al. (2018).

2. Theoretical exposition

Our paper is primarily empirical and we leave a fully-fledged theoretical model for future work. A new finding of our paper is the relation between the supply of intermediated capital and currencies' systematic risk. In Appendix A we present a simple model of this mechanism, which we complement with a numerical solution and comparative statics that mimic the monetary policy shock in our empirical environment below. We summarize our key findings below, serving as a guide to the empirical analysis.

First, a decline in the US policy rate increases the supply of intermediation capital available for currency trading. Consequently, the lower interest rate increases the expected return on the carry trade, incentivizing traders to move capital into foreign currencies that have higher interest rates. As in Itskhoki and Mukhin (2021), intermediaries have constant absolute risk aversion and the new capital acts as a decrease in intermediaries' *effective* risk aversion. This decline in risk aversion loosens the constraint on the supply of intermediation capital, much like in Gabaix and Maggiori (2015) and Vayanos and Wang (2011). Our model provides a theoretical underpinning to the colloquial language of "risk-on" that we use in this paper (and that investors use in practice).

Second, the supply of intermediation capital is directed to different countries depending on their currencies' risk. In particular, currencies with higher levels of risk (and higher expected excess returns) will benefit the most from an increase in the supply of intermediation capital, and will typically see inflows of capital. Low risk currencies, on the other hand, will benefit the least and tend to see outflows of capital. In the cross-section, we see that intermediated capital flows out of low-risk currencies and into high-risk ones.

Finally, the shift in the supply of intermediated capital across countries affects the equilibrium rental rates of physical capital in each country. Countries with riskier currencies will see bigger inflows, and thus, a larger decline in their required return on capital, which subsequently will boost investments.

These patterns fit the core empirical findings of our paper. The key novelty is the equilibrium relation that links the supply of intermediation capacity to firms' investment decisions. To our knowledge, this explicit connection is new and provides a connection between topics in currency markets and corporate finance.

3. Data and summary statistics

Our four primary databases span exchange rates, currency flows, global loan origination, and corporate balance sheets. While some of the data are available at high frequency, we primarily analyze monthly and quarterly frequencies as we focus on the impact of monetary policy on real economic outcomes. The sample for the loan data spans from January 1999 to March 2024, whereas the flow data are only available from September 2012 to March 2024. We discuss these sources in turn.

3.1. Exchange rates and forward contracts

We collect hourly data on spot mid, bid, and ask 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. We use mid prices when calculating exchange rate changes, $\Delta \log S_{i,t}$, and compute relative bid–ask spreads to measure liquidity in the form of transaction costs.

During normal market periods, forward rates satisfy the covered interest rate parity condition (Du et al., 2018). Under this condition, interest rate differentials approximate the forward discount, the difference of the log forward price from the log spot price. We use forward and spot prices to compute interest rate differentials: $r_{i,t} - r_{US,t} \approx \log F_{i,t} - \log S_{i,t}$. The term of the interest rate depends on the maturity of the forward and, following the literature in currency asset pricing, we use one-month contracts unless otherwise noted.

3.2. Measures of currency risk

We focus on dollar and carry betas to capture systematic risk in currency returns. The currency betas quantify an asset's exposure to currency risk factors. Verdelhan (2018) 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. Moreover, the dollar and carry factor are highly correlated with the first and second principal components (PC) of carry trade returns (Lustig and Verdelhan, 2007; Lustig et al., 2011).

The dollar factor is the average change in all currencies with respect to the US dollar. The carry factor mimics the returns of the well-known carry trade strategy, which is the long-short portfolio return of a zero-cost trading strategy that borrows in low interest rate currencies to invest in high interest rate currencies. We create this portfolio by sorting, every month, currencies into five portfolios based on the one-month forward discount relative to the US dollar 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 (2018) but exclude Euro area countries as our main sample period runs from January 2000 to March 2024. This leaves us with 28 countries to construct the risk factors. Specifically, we estimate the dollar β_i^{DOL} and carry β_i^{CAR} betas following Verdelhan (2018) using a 60-month rolling window regression (starting in January 1995) of log changes in currency i's exchange rate $S_{i,t}$ on either the dollar or the carry factor:

$$\Delta \log S_{i,t} = a_i + \beta_i^{DOL} Dollar_t + \epsilon_{i,t}, \tag{1}$$

$$\Delta \log S_{i,t} = a_i + \beta_i^{CAR} Carry_t + \epsilon_{i,t}. \tag{2}$$

We estimate these betas separately but include both of them simultaneously in the cross-sectional analysis in the next section. Note that doing the latter is similar to estimating dollar and carry betas from a joint regression, including both the dollar and the carry factor. In fact our key results are unaffected by this modeling choice.

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 et al., 2017). Carry betas generally line up with interest rate differentials (Lustig et al., 2011). Countries with large dollar betas typically face large trade costs in goods, which relates to the gravity equation in international trade (Lustig and Richmond, 2019; Hassan et al., 2023). 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 Section 7 we investigate these deeper sources of country-level risk.

Analogous to a stock market beta, dollar betas record the incremental systematic currency risk that a US investor takes on when investing in foreign currency i, whereas carry betas measure currency i's exposure to the carry factor. Higher values of dollar and carry betas indicate greater exposure to currency risk.

3.3. Monetary policy shocks

The use of high-frequency identification to study the effect of monetary policy transmission has become standard in macroeconomics and asset pricing. Currency markets (Andersen et al., 2003), bank lending (Bräuning and Ivashina, 2020a), and firm-level investment (Ottonello and Winberry, 2020) are all known to react strongly to changes in central bank policy rates. We follow Kuttner (2001) to measure the surprise component in the monetary policy target rate around an FOMC announcement on day t as follows:

$$MPS_t = (\mathrm{ff}_t^0 - \mathrm{ff}_{t-1}^0)\frac{m}{m-t}, \tag{3}$$

where m is the number of days in a given month and ff_t^0 is the Fed Fund futures price for a contract that expires at the end of the current month. The date at which the target rate is changed is denoted by t, typically the second day of the FOMC meeting. On the last three days of a month (when $m-t$ gets small), we use $\mathrm{ff}_t^1 - \mathrm{ff}_{t-1}^1$ instead for stability, where ff_t^1 is the Fed Fund futures price for a contract that expires at the end of the next month. Hence, an increase in MPS_t corresponds to a reduction in rates, an easing of monetary policy, and a positive or an expansionary monetary policy shock.[4]

To aggregate high-frequency shocks to the monthly or quarterly frequency we simply sum all shocks in a given time period. As an alternative, we follow Ottonello and Winberry (2020) to aggregate the high-frequency shocks to the monthly frequency. Specifically, we construct a moving average of the high-frequency shocks weighted by the number of days in the month after the shock occurs. This type of aggregation ensures that we weigh shocks by the amount of time market participants have had to react to them. Our findings are robust to using this alternative form of time aggregation.

Table 1 indicates that the time aggregated shocks have similar features to the original high-frequency shocks. The average monthly and quarterly standard deviation across measures is around 10 basis points. The median realization for all shocks is zero.

We analyze robustness to other measures of monetary policy shocks in Section 7. In particular, our findings based on syndicated loans are robust to using the high-frequency shocks in Bauer and Swanson (2023b), which account for the FOMC adjusting to new macroeconomic information just prior to the FOMC announcement. For completeness, we also document in the Online Appendix (see Tables B.7 and B.16) that our findings are not driven by unscheduled monetary policy announcements, such as the two unscheduled meetings during the Covid-19 market turmoil in March 2020.

Given that our main analysis is at the monthly and quarterly frequencies, a possible concern is that market participants are responding to other central banks' decisions, preceding the FOMC announcement. We address this concern in Section 7 in two ways: First, we directly control for the monetary policy announcement surprise of foreign central banks in Table B.14.[5] Second, in Table 13 we provide evidence that foreign central banks' policy actions tend to be positively correlated with the Fed. Against this backdrop, controlling for foreign monetary policy announcement surprises is only a valid approach as long as foreign central banks' decisions are independent from the Fed and thus, their monetary surprises contain information that is not yet contained in US surprises.

3.4. Currency flow data

The currency flow data come from Continuous Linked Settlement (CLS) Group, which operates the world's largest multi-currency cash settlement system and handles nearly 50 percent of global FX volumes. These data are well-suited to our analysis as we observe currency volume and order flow on a global scale for a range of currency

[4] We download the original shock series (ending in June 2019) from Kenneth N. Kuttner's website https://econ.williams.edu/faculty-pages/research/ (accessed on March 31, 2026) and complement the series with our own computations starting July 2019.

[5] We are grateful to Nihar Shah for sharing his monetary policy shock series for G10 central banks with us. Note that the foreign central banks shock series in Shah (2022) ends in December 2016 and hence, we only utilize these data for the longer sample period pertaining to foreign currency lending.

Table 1
Summary statistics of monetary policy shocks.

		Monthly		Quarterly	
	High-frequency	Simple sum	Weighted sum	Simple sum	Weighted sum
Mean	1.18	1.20	0.81	2.43	1.20
Median	0.00	0.00	0.00	0.00	0.00
Std.	8.30	9.03	7.79	11.76	8.97
Min.	−24.89	−24.89	−24.89	−29.19	−23.50
Max.	74.06	83.24	72.43	66.55	51.47
#Obs	208	204	204	101	101

Note: This table reports summary statistics of monetary policy shocks following Kuttner (2001). All numbers are in basis points (bps), except for the row labeled "#Obs", which shows the number of monetary policy shocks over the sample period from 1 January 1999 to 31 March 2024. The first column labeled "High-frequency" refers to shocks that are estimated using the event study strategy in Eq. (3). The columns labeled "Simple sum" aggregate the high-frequency shocks by simply summing up all shocks within a month or quarter, whereas the columns labeled "Weighted sum" aggregate the shocks to a monthly or quarterly frequency using the weighted average method described in the main text.

instruments and players.[6] Currencies are traded in spot, forward, and swap markets. The latter two instruments are broken down into various maturity buckets.

The CLS data sample of currency flows covers the period from September 2012 to March 2024. We consider the G10 currencies of developed markets against the US dollar (USD): Australia (AUD), Canada (CAD), Euro area (EUR), Japan (JPY), New Zealand (NZD), Norway (NOK), Sweden (SEK), Switzerland (CHF), and United Kingdom (GBP).[7] In the Online Appendix we demonstrate that our results are robust to including the less heavily traded emerging market currencies of Israel (ILS), Mexico (MXP), and South Africa (ZAR).

To protect anonymity, CLS reports only hourly aggregates of trading volume and order flow by currency and customer (institution) type. There are two broad classifications of market participants: dealer banks and institutions. Dealer banks are market makers that quote prices,[8] whereas price-taking institutions (labeled "BuySide") are divided into four types: corporates (non-financial corporations), funds (e.g., mutual funds, pension funds, and high-frequency trading firms), non-bank financials (e.g., insurance companies and endowments), and non-dealer banks (banks that are not market makers in a specific currency). Note that flows between non-dealer and dealer banks are approximated as the difference between the total "BuySide" trading activity (see Fig. 1 for an example) and transactions between banks (including both dealer and non-dealer banks) and corporates, funds, and non-bank financials, respectively. This approximation underestimates the trading activity between non-dealer and dealer banks since corporates, funds, and non-bank financials trade with both dealer and non-dealer banks.

We compute directional currency flows as the net buying pressure (volume of purchase net of the volume of sales) of a foreign currency in US dollars. We first convert all volumes in the CLS data to dollars using our spot FX rates. For each hour, we then compute the difference between purchases and sales for each foreign currency i and institution type j,

$$OF(Y_{ij,t}) = \text{Buy Volume}_{ij,t} \text{ in } \$ - \text{Sell Volume}_{ij,t} \text{ in } \$, \tag{4}$$

where Y denotes the asset in question (e.g., either spot or forward).

A positive realization of order flow, $OF(Y)$, implies that the demand for a given foreign currency was larger than the demand for US dollars. Fig. 1 shows a sample of spot EURUSD transactions executed within 12 to 1 pm (hour 12) GMT on 2 January 2019. The flow attributed to funds in the last column ("Order Flow") is the largest in magnitude for this data sample. Specifically, the order flow to exchange euros for dollars by funds alone was $669 mn in that single hour.

Next, we aggregate hourly currency flows to the monthly frequency. We time-aggregate for two reasons. First, we are interested in the long-lasting impact of monetary policy on currency flows rather than the transitory high-frequency intraday response. Second, currency flows are quite noisy in the sense that the standard deviation of hourly flows is large compared to their mean. Cumulating them to a longer horizon reduces their volatility, allowing more precise measurement of directional currency flows. Note that all our key results (for both currency flows and syndicated loans) are qualitatively similar when aggregating to the weekly rather than monthly frequency.

Table 2 presents summary statistics for spot currency flows broken down by institution type and currency pairs. We report standard deviations and the share of each currency pair's trading volume that is accounted for by each institution. Funds and non-dealer banks generate, by far, the most directional flows as measured by their standard deviations. Across all currency pairs, trading activity by funds and non-dealer banks easily exceeds the combination of corporate or non-bank financial accounts. We also see that funds and, especially, non-dealer banks dominate currency markets as they collectively account for around 95 percent of the total trading volume across all currency pairs.

The large economic impact of funds is consistent with the findings from the currency market microstructure literature.[9] In contrast, both non-dealer banks and dealer banks are more likely to be providers of liquidity.

[6] Collectively, the papers by Hasbrouck and Levich (2017), Cespa et al. (2021), Ranaldo and Somogyi (2021), Hasbrouck and Levich (2021), and Khetan and Sinagl (2022) have comprehensively described the CLS data. Although CLS operates five-and-a-half days a week from 10 pm CET Sunday to 2 am Saturday, the vast majority of settlement instructions are received during the so-called London trading hours from 8 am to 5 pm GMT. The results that we report below are based on this subsample but are similar to those based on the 24-hour trading day.

[7] We restrict our sample by excluding currencies that are pegged (i.e., Denmark (DKK), Hong Kong (HKD), and Singapore (SGD)). We also exclude Hungary (HUF), entering the data set on 7 November 2015, and South Korea (KRW), due to insufficient amount of trades per institution type.

[8] Dealer banks are classified via network analysis done by CLS Group. By observing the frequency of trades over time across banks, CLS can create a set of banks that are connected to the majority of other banks in the *same* set. Dealer banks are those that remain in this set consistently over time. The network analysis is done independently for each currency pair using 24 months of data. Within this classification, one bank could be a market maker in one currency yet a price taker in another. Note that CLS data only report transactions between dealer banks and their customers and exclude trades between two dealer banks or two non-dealer banks.

[9] In particular, Menkhoff et al. (2016) and more recently (Czech et al., 2022) show that the currency flows of funds and real money investors constitute "smart money" that is highly predictive of future exchange rates. These funds trade strategically and have substantial permanent price impacts across currency pairs (Ranaldo and Somogyi, 2021).

Instrument	London Date	Hour	Price Taker	Market Maker	Buy CCY	Sell CCY	Buy Volume	Sell Volume	Net Volume	Order Flow
SPT	2019-01-02	12	BuySide	SellSide	EUR	USD	1,597,927,686	2,245,621,149	-647,693,463	-732,709,707
SPT	2019-01-02	12	Corporate	Bank	EUR	USD	88,656,999	9,786,333	78,870,666	89,223,229
SPT	2019-01-02	12	Fund	Bank	EUR	USD	42,308,060	634,132,478	-591,824,418	-668,828,535
SPT	2019-01-02	12	Non-Bank Financial	Bank	EUR	USD	51,267,386	132,102,521	-80,835,135	-91,445,554
SPT	2019-01-02	12	Non-Dealer Bank	Bank	EUR	USD	**1,415,095,242**	**1,469,599,817**	**-54,504,575**	**-61,658,846**

Fig. 1. Snapshot of CLS data.
Note: The values in bold denote the "residual" calculated to define non-dealer banks. For buy volume, it is calculated by subtracting the volume from corporates, funds, and non-bank financials from total buy-side (price taker) activity; there is a similar calculation for sell volume. The EURUSD exchange rate on 2 January 2019 is 1.13126 USD per EUR.

Table 2
Summary statistics — CLS.

	Corporates		Funds		NBFIs		Non-dealer banks	
	Std.	Share	Std.	Share	Std.	Share	Std.	Share
USDAUD	0.42	0.36	2.65	10.98	0.46	3.18	3.97	85.49
USDCAD	0.70	0.29	15.58	10.40	1.03	1.98	31.40	87.33
USDCHF	0.57	0.90	2.41	9.06	1.45	4.17	4.27	85.87
USDEUR	3.46	2.19	11.39	13.78	1.45	3.18	14.67	80.85
USDGBP	1.23	1.00	5.82	13.02	1.56	3.56	7.96	82.42
USDJPY	0.94	0.85	4.81	8.93	0.96	3.14	6.19	87.08
USDNOK	0.12	0.45	0.58	12.75	0.10	2.94	1.55	83.86
USDNZD	0.04	0.08	1.18	7.30	0.15	3.46	1.68	89.16
USDSEK	0.18	1.18	0.97	20.78	0.12	2.78	1.64	75.26

Note: This table collects summary statistics for the CLS order flow data. The columns labeled *Std.* report the standard deviation of monthly order flows (buy volume minus sell volume) in $bn broken down by four categories of market participants, namely, corporates, funds, non-bank financials (NBFIs), and non-dealer banks. The columns labeled *Share* are computed based on the sum of buy and sell volume and reflect the relative share (summing up to 100% for each currency pair) in percent of trading volume associated with each of the four groups of market participants. The sample covers the period from September 2012 to March 2024.

3.5. Global banks' loan origination

We use the Thomson Reuters DealScan database for global corporate loan issuances for a relatively long sample from January 2000 to March 2024. It covers syndicated loans, which are typically larger than non-syndicated loans. Bräuning and Ivashina (2020a) report that syndicated loans represented at least 45 percent of all US commercial and industrial lending in 2016. The database has information on borrowers, their home country, the syndicate's lenders, and loan details such as the amount (broken down by each lender) and currency. Appendix B includes a detailed step-by-step explanation of how we get from the raw data to our final dataset.

In our analysis, we focus on top-tier lenders within a syndicate by excluding lenders with smaller commitments (so-called "Participants"). We also drop observations with negative tranche amounts or if the tranche amount exceeds the deal amount.

Given that we study the transmission of US monetary policy we filter for syndicated loans that involve at least one US bank. We define global US banks as those that are domiciled in the US and are internationally active in the sense that they syndicate foreign currency loans. Specifically, it could be the case that either the bank holding company or the subsidiary is domiciled in the US. For example, we classify Mizuho Securities USA LLC as a global US bank. All our results are robust to a more restrictive definition of global US banks: (1) when both the parent bank and the subsidiary are domiciled in the US; or (2) when we only consider US based bank holding companies.[10]

For each global US bank in every month, we aggregate all loans denominated in the same foreign currency by leveraging information about the share that the bank has lent across every syndicate. Specifically, we follow Bräuning and Ivashina (2020a) and prorate the loan amount among lenders in our sample because information on the share held by individual banks is scarce in the DealScan database.

Fig. 2 shows that US banks' foreign lending is concentrated in a handful of currencies. For instance, US banks lend on average \$5832 mn in EUR and \$1991 mn in GBP each month. Our final data sample spans from January 1999 to March 2024 and contains the same G10 currencies as for the CLS currency flows.

3.6. Corporate borrowers and their balance sheets

Our data on international corporations come from their quarterly financial statements via Compustat North America and Compustat Global from January 1999 to March 2024. These data cover around eighty-thousand firms of which only about ten-thousand have ever borrowed via a syndicated loan.

We apply standard filters and exclude firms that are in finance, insurance, or real estate (SIC codes 6000 to 6799) and public administration (9100 to 9729) and remove observations of negative assets, property, plant, and equipment (PPE), and sales. We retain only non-US firms that report using a G10 currency and convert all balance sheet variables to US dollars.

For firms that do borrow from a syndicate, we aggregate all loans issued in the same currency within a quarter. If a firm borrows in more than one currency in any given quarter, we only keep the loans that are issued in the firm's reporting (i.e., operating) currency. After this filtering, we are left with 987 international firms.[11] It is worth noting that the distribution of firms across countries is similar to the distribution of loans across countries, suggesting that our select sample of firms is indeed representative of the broader market for syndicated loans (see Figure B.2 in the Online Appendix).

Table 3 presents summary statistics of the final sample. Total firm-quarter observations amount to over 50,000. The average firm has a current asset ratio of 34 percent and is around 30 percent debt financed. Firm debt, assets, PPE, and sales grow on average by around two percent nominally every quarter. The average loan amount that

[10] We also run a placebo test on a sample of foreign banks, that is, neither the parent bank nor the subsidiary is in the US. Unlike for global US banks we find no evidence that following an easing of US monetary policy foreign banks tilt their loan origination toward riskier currency loans. We are grateful to the editor for suggesting this placebo test.

[11] Note that the number of firms that we use in some regressions is less than 987 because we take first differences in firm-level outcome variables and thus, lose firms that are not reporting every quarter.

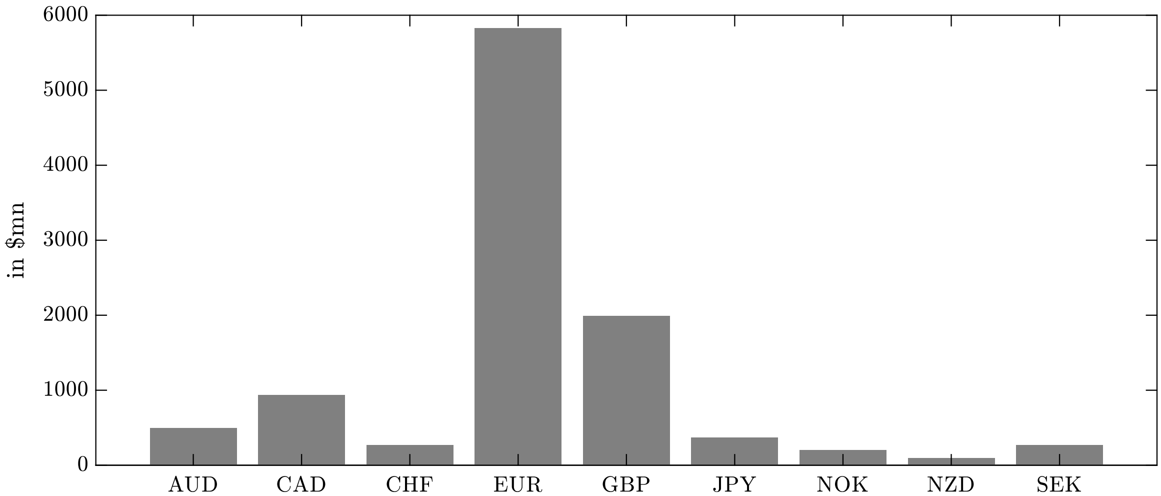

Fig. 2. Snapshot of DealScan data.
Note: This figure reports the average of the total aggregate loan amount in a given currency aggregated over a month. The sample covers the period from January 1999 to March 2024.

Table 3
Summary statistics — Compustat.

	#Obs	Mean	Std.	5%	25%	50%	75%	95%
Current asset ratio in %	50,494	34.4	19.6	5.9	19.1	32.5	47.9	68.8
Book leverage in %	50,498	30.0	21.0	4.7	18.7	28.0	39.0	59.2
$\Delta\log$ debt in %	50,498	1.8	34.3	−23.2	−4.5	0.0	4.8	32.4
$\Delta\log$ assets in %	50,498	1.7	13.8	−10.1	−2.5	0.9	4.4	15.2
$\Delta\log$ PPE in %	50,275	1.6	24.2	−11.3	−2.5	0.6	4.2	16.8
$\Delta\log$ sales in %	50,498	1.4	25.3	−28.1	−4.7	1.1	7.7	31.3
$\Delta\log$ leverage in %	50,498	0.0	4.4	−4.5	−1.0	0.0	0.9	4.6
$\Delta\log$ Tobin's Q in %	50,498	−0.2	20.6	−20.8	−4.8	0.3	5.2	19.2
Loan amount in $mn	2,116	382.9	686.8	26.8	72.3	159.7	391.2	1,402.2
log (loan amount)	2,116	19.0	1.2	17.1	18.1	18.9	19.8	21.1
Borrowing probability in %	N/A	3.1	3.4	0.0	1.0	2.2	4.3	9.2

Note: This table reports summary statistics for our sample of firms borrowing from US banks. It compiles the average *Mean*, standard deviation *Std.*, and the 5, 25, 50, 75 and 95 percentile of several firm-level variables: *current asset ratio* is the ratio of current to total assets, *book leverage* is book debt over total assets, $\Delta\log$ *debt* is the relative change in firm debt (short-term plus long-term liabilities), $\Delta\log$ *assets* is the relative change in total assets, $\Delta\log$ *PPE* is the relative change in property plant and equipment (PPE) net of depreciation, $\Delta\log$ *sales* is the relative change in total gross sales net of trade and cash discounts, $\Delta\log$ *leverage* is the relative change in leverage, $\Delta\log$ *Tobin's Q* is the relative change in Tobin's Q ([market value of equity + book value of debt]/book value of total assets), *loan amount* is the aggregate amount of the portion of all syndicated loans that a firm has borrowed in a given quarter from US banks, log *loan amount* is the log of *loan amount*, and *borrowing probability* is the share of quarters during which a firm borrows from US banks in the same currency as the reporting currency of the firm. *#Obs* counts the number of non-missing observations for each variable, except for *loan amount* where it counts non-zero observations. The sample covers the period from January 1999 to March 2024.

firms receive from US banks is around $383 mn with a sizable standard deviation of $687 mn per quarter. The average firm borrows from US banks around three times (101 quarters times 3.1%), translating to around $1149 mn in lending over our sample from January 1999 to March 2024.

4. Global currency flows

We first study how institutions' transactions of various currencies respond to US monetary policy surprises. We then examine how currency risk governs this response before analyzing the persistence of the effect over time.

4.1. Immediate response of currency flows to US monetary policy

In this section, we examine the contemporaneous response of various institutions' currency transactions in response to an FOMC announcement. In contrast to much of the literature that focuses on intra-day dynamics (for example, Savor and Wilson, 2014; Mueller et al., 2017; Ai and Bansal, 2018), we analyze flows during the whole calendar month that includes the days preceding and succeeding the announcement.

We begin by estimating regressions of an institution's order flow for each currency on our measure of monetary policy surprises to understand how each type of institution responds to policy surprises. We run the following time series regression

$$OF(S_{ij,t}) = a_{ij} + \beta_{ij} MPS_t + \epsilon_{ij,t}. \tag{5}$$

We call the estimated slope coefficients, β_{ij}, *flow betas*. They measure in US dollars the magnitude of flows into foreign currency i by institution type j in response to an unexpected one basis point decline in the Federal Funds rate. Because an expansionary shock raises Federal Funds futures prices, we would expect that an easing of US monetary policy induces a positive inflow into foreign currencies as the opportunity cost of holding dollars increases. Hence, we expect that β_{ij} is positive.

Table 4 tabulates flow betas across our set of nine dollar-based currency pairs and institution types. We order currency pairs by their average carry betas, which approximate their interest rate differentials

Table 4
Flow betas for G10 currency pairs.

	Corporates	Funds	NBFIs	Non-dealer banks	Dealer banks	Carry beta	Dollar beta	FX beta
USDJPY	8.04	35.88	14.42	−246.79***	188.45***	−0.26	0.51	−0.13
	[0.56]	[0.74]	[1.03]	[4.73]	[4.25]			
USDCHF	7.08	23.51	−10.85	−15.52	−4.22	−0.10	0.98	−0.15
	[0.76]	[0.42]	[0.67]	[0.57]	[0.10]			
USDEUR	31.47	−580.18***	16.15*	−62.86	595.42**	−0.09	1.11	−0.25
	[0.95]	[4.57]	[1.86]	[0.40]	[2.44]			
USDGBP	−72.82***	210.39***	−25.46*	27.04	−139.15	0.04	0.87	0.03
	[2.90]	[3.38]	[1.76]	[0.18]	[1.29]			
USDSEK	4.17**	−30.21***	−2.18	20.67	7.55	0.05	1.34	−0.15
	[2.54]	[3.14]	[1.38]	[1.03]	[0.51]			
USDNOK	−4.39**	−13.99***	−1.19	−47.26***	66.84***	0.21	1.57	0.15
	[2.12]	[3.33]	[1.15]	[4.60]	[6.47]			
USDCAD	2.18	537.22***	25.06	500.92	−1,065.39***	0.28	0.96	−0.30
	[0.46]	[5.67]	[1.51]	[1.62]	[3.30]			
USDNZD	−1.67	23.94	1.32	−49.58**	26.00***	0.51	1.42	0.50
	[1.59]	[1.13]	[1.55]	[2.11]	[2.96]			
USDAUD	−0.02	190.42***	1.03	−213.38***	21.95	0.58	1.44	0.37
	[0.00]	[5.23]	[0.20]	[3.42]	[0.64]			

Note: This table reports the β_{ij} regression coefficients from $OF(S_{ij,t}) = a_{ij} + \beta_{ij} MPS_t + \epsilon_{ij,t}$, where $OF(S_{ij,t})$ is the currency flow in \$mn in currency pair i customer group j in month t and MPS_t is our monetary policy shock measure in basis points that we extract from Fed Fund futures rate changes following Kuttner (2001). Currency pairs are sorted by carry betas in ascending order. By market clearing, the column labeled "Dealer banks" is equal to the sum of the first four columns times minus one. The penultimate two columns report the average carry and dollar beta that we compute based on rolling window regressions. The last column reports the exchange rate response to a standard deviation easing surprise of MPS_t (Mueller et al., 2017); positive estimates indicate an appreciation of the foreign currency. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels. The numbers inside the brackets are the corresponding test statistics based on robust standard errors (Newey and West, 1987), correcting for heteroskedasticity and serial correlation up to 3 lags. The sample covers the period from September 2012 to March 2024.

relative to the US. Specifically, we compute the full-sample averages of the rolling-window carry and dollar betas (see Eq. (1)). In the table's penultimate two columns we list each country's average carry and dollar betas. The table's last column reports the exchange rate response to a one standard deviation easing surprise of MPS_t. In line with Mueller et al. (2017) we find that foreign currencies with higher carry risk tend to appreciate when US monetary policy eases, whereas the effect goes the opposite direction for low carry beta currencies.

We start by looking at flow betas across currencies for investment funds. Low carry beta currencies tend to possess negative flow betas, at least in cases when the betas are statistically significant. As carry betas turn from negative to positive, flow betas also switch from negative to positive. Thus, funds sell low-risk currencies and purchase high-risk currencies during periods of expansionary US monetary policy. For example, a one basis point unexpected decline in US rates leads to a \$190 mn inflow into the Australian dollar. Relative to the USDAUD currency pair's monthly variability of fund flows of \$2650 mn, this amounts to around 7 percent of a standard deviation per basis point surprise.

Funds' response to monetary policy is consistent with their strategic, risk-taking behavior. Fig. 3 provides a visualization for their "risk-on" response by scattering carry betas on fund betas. As carry betas shift from negative to positive, so does the direction of foreign currency flows, changing from outflows to inflows. In sum, we find that funds rebalance across currencies by shifting out of safe, low interest rate currencies (e.g., euros) into risky, high interest rate currencies (e.g., Australian dollars) following expansionary US monetary policy. This heterogeneity of fund flows across currencies is also consistent with the evidence for exchange-traded funds: Kroencke et al. (2021) show that equity fund flows respond significantly to FOMC announcements, which is in line with investors reacting heterogeneously to monetary policy news.

Turning to other institution types, we do not find evidence of such a "risk-on" response. In particular, corporations tend to have flows that appear to move oppositely to fund flows, that is, when US rates fall unexpectedly, corporations appear to buy low interest rate currencies and sell high-rate ones. The economic magnitude of these corporate flows, moreover, is much smaller than those generated by funds.

Among all types of institutions, flows of non-bank financials are the least responsive to monetary policy shocks. All coefficients are statistically insignificant. This is despite their flows being greater in magnitude than those of corporates on average (see Table 2). We conjecture that differences in investment mandates or horizons could potentially explain why non-bank financials respond differently than investment funds.

Finally, we turn to banks. We distinguish smaller, non-dealer banks from large, dealer banks. We find that non-dealer banks have a statistically significant response for currencies only with negative flow betas. As we expect a lower US rate to induce purchases of foreign currencies, this indicates these banks tend to take the other side of the trade, regardless of the currency's risk. That is, they seem to provide aggregate liquidity. For dealer banks, we find that they tend to purchase low carry beta and sell high carry beta currencies, exactly the opposite of what investment funds do. In this sense, they, too, provide market liquidity, but mainly to funds. Evans and Lyons (2002a,b) show that dealer banks collectively work to offset currency and other exposures by trading with other dealer banks in the inter-dealer market. The CLS data, however, do not allow us to directly study inter-dealer transactions.

4.2. *Currency flows by investment funds and the FX factor structure*

In the previous section, we have identified investment funds as a major contributor to currency flows surrounding monetary policy announcements. Funds, in particular, appear to rebalance up the spectrum of currency risk following easing shocks.

We now proceed to decompose the determinants of investment funds' currency flows. We do this by regressing flows on an interaction of country characteristics, $X_{i,t}$, with monetary policy shocks, MPS_t:

$$OF(S_{i,t}) = \mu_i + \alpha_t + \gamma X_{i,t} + \beta MPS_t + \varphi(X_{i,t} \times MPS_t) + \kappa \mathbf{W}_{i,t} + \epsilon_{i,t}, \quad (6)$$

where the dependent variable is funds' order flow of currency i at time t. We include both country- and time-fixed effects, μ_i and α_t, to control for unobserved heterogeneity at the country-level and for time variation in global factors.

In $\mathbf{W}_{i,t}$ we control for currency liquidity, measured by log change in the relative bid–ask spread, and the exchange rate's log return. Because our construction of currency flows is in dollars, movements in the exchange rate could introduce mechanical variation. To separate changes in currency flows driven by exchange rates from actual flows,

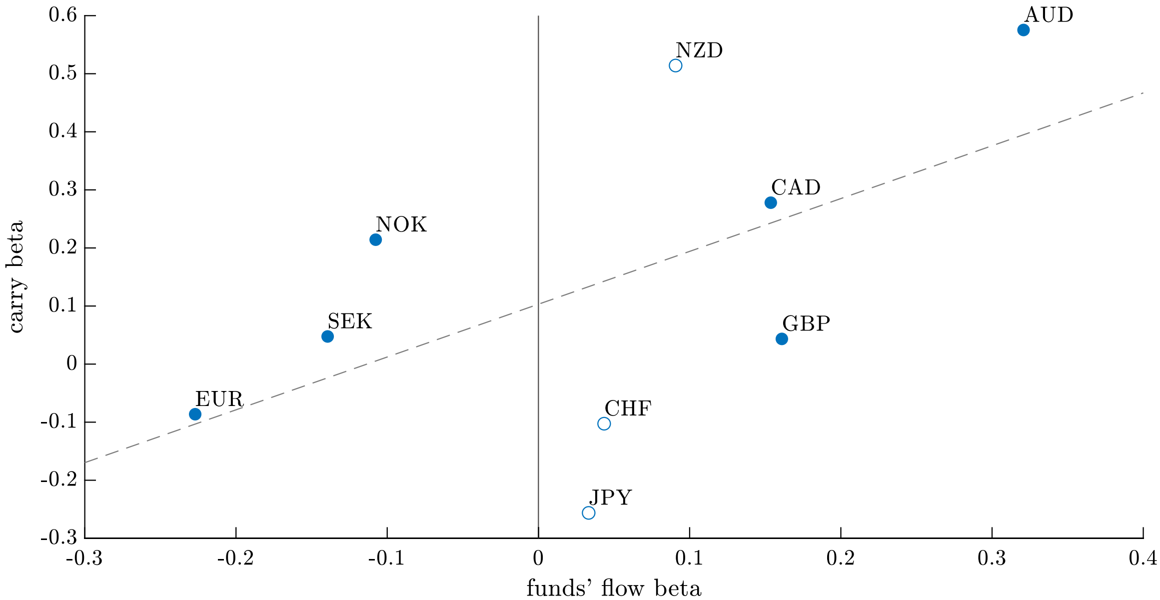

Fig. 3. Funds' currency flow betas and carry betas.

Note: This figure plots the β regression coefficient estimates from $OF(S_{i,t}) = a_i + \beta_i MPS_t + \epsilon_{i,t}$, where $OF(S_{i,t})$ is the currency flow in \$mn in currency pair i by investment funds in month t and MPS_t is our monetary policy shock measure in basis points against the average carry beta. For the regression, both dependent and independent variables are measured in units of standard deviations. Filled dots indicate point estimates that are statistically significant at the 10% confidence level. The inference is based on robust standard errors (Newey and West, 1987), correcting for heteroskedasticity and serial correlation up to 3 lags. The sample spans from September 2012 to March 2024.

Table 5
Currency flows of funds and the FX factor structure.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
carry $\text{beta}_{i,t}$		0.02			−0.01		−0.15	
		[0.39]			[0.05]		[1.10]	
dollar $\text{beta}_{i,t}$			0.13			0.14	0.20	
			[0.70]			[0.76]	[0.97]	
UMVE $\text{beta}_{i,t}$				−0.19				−0.13
				[1.55]				[1.02]
MPS_t	0.03	0.01	−0.04	0.08				
	[0.86]	[0.26]	[0.43]	[1.61]				
carry $\text{beta}_{i,t} \times \text{MPS}_t$		0.09***			0.09***		0.17***	
		[2.73]			[2.61]		[4.18]	
dollar $\text{beta}_{i,t} \times \text{MPS}_t$			0.08			0.07	−0.36***	
			[1.13]			[0.95]	[3.68]	
UMVE $\text{beta}_{i,t} \times \text{MPS}_t$				0.08***				0.08***
				[3.76]				[4.92]
$\Delta \log$ bid-ask $\text{spread}_{i,t}$		−0.03	−0.03	−0.03	−0.01	−0.02	0.03	−0.01
		[1.34]	[1.57]	[1.52]	[0.67]	[0.87]	[0.92]	[0.95]
$\Delta \log S_{i,t}$		−0.01	−0.02	−0.03	−0.02	−0.03	−0.02	−0.03
		[0.38]	[0.52]	[0.97]	[0.44]	[0.59]	[0.47]	[0.74]
Overall R^2 in %	18.76	19.45	19.25	21.33	30.80	30.64	31.88	31.24
Total # of Obs.	1251	1242	1242	1242	1242	1242	1242	1242
Avg. #Time periods	139	138	138	138	138	138	138	138
#Currencies	9	9	9	9	9	9	9	9
Currency FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time series FE	No	No	No	No	Yes	Yes	Yes	Yes

Note: This table reports results from fixed effects panel regressions of the form $OF(S_{i,t}) = \mu_i + \alpha_t + \gamma X_{i,t} + \beta MPS_t + \varphi(X_{i,t} \times MPS_t) + \kappa \mathbf{W}_{i,t} + \epsilon_{i,t}$, where $OF(S_{i,t})$ is the order flow by *funds* in \$bn in currency pair i in month t. $X_{i,t}$ denotes either the *carry* $\textit{beta}_{i,t}$, *dollar* $\textit{beta}_{i,t}$, or *UMVE* $\textit{beta}_{i,t}$ that are based on rolling window regressions of currency returns on the carry, dollar, and UMVE factor, respectively. MPS_t is our monetary policy shock in basis points that we extract from Fed Fund futures rate changes following Kuttner (2001). $\mathbf{W}_{i,t}$ may include the following control variables: $\Delta \log$ *bid-ask* $\textit{spread}_{i,t}$ is the log change in the monthly average relative bid-ask spread and $\Delta \log S_{i,t}$ is the log change in the spot exchange rate expressed as the number of foreign currency units per unit of US dollar. Both dependent and independent variables are measured in units of standard deviations. The test statistics based on double clustered (by currencies and time) standard errors, allowing for serial correlation up to 3 lags are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels. The sample covers the period from September 2012 to March 2024.

we include the exchange rate return to control for this mechanical relationship.

More formally, the coefficient φ on the interaction term between monetary policy surprises MPS_t and country characteristics (e.g., carry betas) is what we are most interested in, as it captures the cross-sectional differences in the way how currency flows respond to US monetary policy. Thus, these variables indicate which country-level characteristics drive the contemporaneous responses in currency flows, and we consider, for instance, dollar and carry betas that are known to capture systematic currency risk.

Before proceeding to our results, we address two econometric concerns that arise when regressing traded quantities on risk measures derived from asset prices. First, endogeneity could arise if quantities (e.g., currency flows) themselves affect exchange rates and thus the currency betas that we use as regressors. We mitigate this concern in three ways: (i) our currency betas are estimated using 60-month rolling windows, making them econometrically predetermined relative to monthly flows, (ii) we document in Table B.4 (in the Online Appendix) that carry and dollar betas show virtually no response to monetary policy shocks at monthly frequencies and (iii) in additional robustness tests (see Table B.6 in the Online Appendix), we use cross-sectional rankings of betas rather than the betas themselves, highlighting that our results are driven by cross-sectional rather than by time series variation in the currency betas.

Second, omitted variable bias is a concern if unobserved factors drive both currency risk and quantities. Our specification addresses this through: (i) the inclusion of currency fixed effects μ_i that absorb time-invariant country characteristics (ii) time fixed effects α_t that control for global factors, and (iii) we use high-frequency monetary policy surprises, which are plausibly exogenous to traded quantities, interacted with measures of currency risk to trace out the differential response across currencies. Thus, for an omitted variable to bias our results it would have to correlate not just with currency risk but also directly affect how quantities respond to monetary policy surprises.

Table 5 tabulates the results of estimating Eq. (6) with standardized coefficients. Column (1) shows that, as expected, a surprise decline in the Fed Funds rate (an increase in MPS_t) causes an outflow from the US. And vice versa, a surprise tightening induces dollar inflows. The effect, by itself, is statistically insignificant, however.

Column (2) measures this effect once controlling for countries' carry betas. For a country that has a carry beta near zero, like the United Kingdom, the effect of the monetary policy shock on currency flows is 0.01 and hence, effectively zero. That is, despite an easing of US monetary policy, we find no evidence of currency outflows to countries with similar risk characteristics.

Next, we analyze how systematic currency risk impacts the cross-section of currency flows. Raising the carry beta by one standard deviation substantially brings out the effect of the response. The effect of the monetary policy shock contributes to $0.01 + 0.09 = 0.10$ of a standard deviation of flows, a multiple of the baseline response. In the context of the Australian dollar, this amounts to a directional flow of $0.1 \times \$2.65$bn $= \$0.265$bn per one standard deviation move in our monetary policy shock measure.

The more positive the carry beta, the larger is the flow into that foreign currency. This response provides a detailed account of the Fama (1984) regression. Fama showed that currencies with higher interest rates tend to appreciate, counter to UIP holding. We report evidence on the underlying quantities that may contribute to this price appreciation. Subsequent to a reduction in US interest rates, investment funds' currency flows may further push up the price of riskier, high interest rate currencies. These findings are also in line with Mueller et al. (2017), showing that foreign currencies tend to systematically appreciate around FOMC announcements.

If the carry beta of the country in question is negative, like Japan's, then the foreign currency experiences an outflow that moves into US dollars following the cut in the Federal Funds rate. For example, a country with a carry beta that is one standard deviation below the mean experiences a net flow of $0.01 - 0.09 = -0.08$ standard deviations, which is therefore an outflow. We emphasize that if the currency's carry beta is sufficiently negative, it can result in net *inflows* to the dollar despite a reduction in US rates.

The evidence in Table 5 highlights the mechanism of the risk-taking channel of monetary policy. This is because, if funds were simply "reaching for yield" (i.e., higher interest rates), we would not expect them to sell out of low risk currencies (e.g., Japanese yen) and buy US dollars following an *easing* of US monetary policy. Moreover, by virtue of being a long-short dollar neutral trading strategy, the ex-ante efficacy of the carry trade, which, for instance, buys Australian dollars and sell Japanese yen is unaffected by the level of US interest rates. Thus, our findings are consistent with a broader interpretation of reach for yield, which assumes that investors' risk appetite increases when rates fall.

Collectively, the evidence supports a systematic rebalancing of funds' currency positions and is consistent with the risk-taking channel of monetary policy. Following an unexpected easing in the Federal Funds rate, funds' reshuffle their portfolios by selling low-risk currencies and instead buying high-risk ones, as measured by carry betas.

Turning to dollar betas, we find positive but insignificant effects, at least initially. Column (3) shows that currencies with greater dollar betas are *not* differentially affected by monetary policy compared to currencies with smaller dollar betas. Thus, dollar betas, by themselves, do not seem to explain the response of flows to monetary policy.

Carry betas therefore appear to be the primary source of currency risk that explains the response of funds' flows across currencies to *monetary policy shocks*. We find similar point estimates in columns (5) and (6) when including both currency and time fixed effects in the same specification.

In column (7) we include both dollar and carry betas in addition to time fixed effects. Carry betas retain their explanatory power and the interaction coefficient is boosted from 0.09 to 0.17. The interaction coefficient with dollar betas, however, now displays a statistically significant, negative effect, once we control for carry betas.

The negative interaction coefficient with dollar betas in the last column seems to contradict the risk-on/risk-off interpretation that we have invoked for the carry betas. This apparent puzzle can be explained by the positive correlation between dollar and carry betas in our sample period: following the global financial crisis, the correlation between dollar and carry betas has increased by approximately 70% relative to the pre-crisis episode. This high positive correlation explains why, once we control for carry betas in column (7), the interaction with dollar betas turns negative. Specifically, including carry betas in column (7) effectively orthogonalizes dollar betas against carry betas. The "residual" variation (i.e., the part of the dollar betas that is not driven by carry betas) is highly correlated with gravity variables in international trade such as the physical distance between two countries (Lustig and Richmond, 2019). In other words, in our post-crisis sample, dollar betas are largely subsumed by carry betas and therefore, dollar betas offer limited additional explanatory power. We provide additional evidence supporting this interpretation in the Online Appendix (see Tables B.2 and B.3).

Finally in column (4) (and column (8)), we consider the beta on the unconditional mean–variance efficient (UMVE) portfolio of currencies that we create following Chernov et al. (2023). Specifically, UMVE is constructed such that it solely accounts for the priced risk component of currency returns. As for the carry and dollar factor, we similarly estimate the currency beta with respect to the UMVE factor from

$$\Delta \log S_{i,t} = a_i + \beta_i^{\mathrm{UMVE}} \mathrm{UMVE}_t + \epsilon_{i,t}. \tag{7}$$

The coefficient on the interaction of UMVE with the monetary policy shock is 0.08, which is close to that on the interaction of carry betas with monetary policy surprises, indicating a strong role for the priced component of currency returns. Overall, our results suggests that the priced component of currency returns plays an important role in shaping global currency flows across countries.

4.3. Persistent response of funds' FX flows to US monetary policy

We previously established that investment funds respond contemporaneously to monetary policy surprises. We now examine the response of funds' currency flows to a change in US monetary policy at longer horizons. The persistence of this response is plausibly more informative regarding the transmission of monetary policy.

We study the cumulative impact of spot market flows.[12] To isolate the impact of currency risk on flows, we form three groups of currencies — low, medium, and high — based on their carry betas and then sum all flows within each group. The point of grouping is to isolate common drivers of currency flows, which will be useful for thinking about persistent responses. By contrast, focusing on individual currencies would allow idiosyncratic noise to contaminate the confidence intervals of the long-run impulse responses.

We estimate the impulse responses of currency flows to monetary policy shocks by using local projections (Jordà, 2005). For each group g, the local projections are as follows:

$$OF(S^g_{t,t+h}) = \alpha^g_h + \sum_{m=0}^{3} \beta^g_{h,m} MPS_{t-m} + \epsilon^g_{t+h}, \tag{8}$$

where $OF(S^g_{t,t+h})$ is the cumulative currency flow within a group observed h months ahead of the monetary policy shock that occurred at time t.

In Fig. 4 we plot the cumulative impulse responses of funds' spot currency flows by reporting the coefficient $\beta^g_{h,0}$ separately for both the low- and high-carry-beta groups. We see that currencies with low carry betas experience an outflow following an easing of US monetary policy. The plots are cumulative flows, so following the initial outflow we see a series of smaller outflows before returning to the average flow. The effect is statistically significant for around four months.

The group of currencies with high carry betas displays a different dynamic: an unexpected easing shock causes an enduring flow from the US into high-risk currencies. The average effect is quite persistent, lasting beyond 12 months in our data sample.

Taken together, there is evidence that the safest and riskiest currencies are differentially impacted by US monetary policy. Investment funds sell safe and buy risky currencies. This rebalancing up the risk spectrum of currencies is persistent, despite the fact that monetary policy and macroeconomic news gets incorporated quickly (within hours) into exchange rates (Andersen et al., 2003).

5. International bank lending

In Section 4, we have focused on the short and medium-run response of capital flows to a change in US monetary policy. Specifically, our results highlight the differential response across investments funds' currency flows that follow a risk-on pattern following an easing of monetary policy. To draw a fuller picture of the international transmission of US monetary policy, we turn to the credit channel. A large body of literature in macroeconomics studies the allocation of credit (see, e.g., Bernanke and Gertler, 1995; Bernanke et al., 1999), which operates through the banking sector.

To study how currency risk impacts monetary policy transmission via the credit channel, we focus on how globally active US banks tilt their currency risk exposure in the market for foreign currency loans. The market for foreign currency loans is large (several trillion dollars drawn each year) and global bank loans constitute nearly half of external liabilities of emerging economies (Bräuning and Ivashina, 2020b). Moreover, banks originate loans in the primary market, which eventually allows us to study how these loan originations impact the real economy by studying how firm-level outcomes (such as investment) change in response to monetary policy induced changes in the supply of foreign currency loans. We control for demand effects in the next section when estimating changes in loan origination at the borrower level.

[12] In the Online Appendix in Section A we study differences in order flow for forward contracts following a monetary policy shock. We find that purchases of forwards are concentrated in near-maturities, consistent with Lustig et al. (2019). These results do not imply that carry trade activity only has a short-term impact, however, our data do not allow us to see if initial carry trade positions are rolled over to lengthen the horizon of the trade.

5.1. International lending in response to US monetary policy

We first explore the response of foreign currency lending to changes in US monetary policy by running the following regression:

$$\log Loan_{i,t} = a_i + \beta_i MPS_t + \gamma_i \Delta \log S_{i,t} + \epsilon_{i,t}, \tag{9}$$

where $\log Loan_{i,t}$ is the log of the total cumulative amount lent by all US banks in our sample to corporations domiciled abroad during month t in currency i. Since all loan activity in DealScan is reported in US dollars, movements in the dollar exchange rate could mechanically influence loan volumes, so we include log changes in the bilateral spot rate, $\Delta \log S_{i,t}$, to mitigate this mechanical effect.

Our coefficient of interest is β_i, which we call a currency's *credit beta*. It measures the rate of loan growth in a particular foreign currency, such as the Japanese yen, conditional on a positive monetary policy shock of one basis point.

We run Eq. (9) for each currency and plot credit betas on carry betas in Fig. 5. We first note that four out of nine currencies display negative credit betas in response to a loosening of US monetary policy. This result supports the findings of Bräuning and Ivashina (2020a), who show that foreign currency lending decreases following a narrowing of the spread for interest on reserves between the United States and abroad. Intuitively, as the opportunity cost of holding reserves falls domestically, US banks substitute away from making international loans toward domestic ones. While Bräuning and Ivashina (2020a) document this effect for a small set of currencies (i.e., British pound, Canadian dollar, euro, Japanese yen, and Swiss franc), our results support this mechanism for the broader set of G10 currencies.

The regression line in Fig. 5 is upward sloping and hence, similar to the risk-on pattern that we have seen for investment funds.[13] While funds sell out of low-risk currencies to invest in risky ones following an expansionary shock (see Fig. 3), we see that banks, similarly, tilt their lending toward risky currencies following a similar risk-on impetus. The key novelty here is that banks' risk-taking behavior occurs in the primary market.

5.2. International lending and the FX factor structure

We further decompose the drivers of how US banks' foreign currency lending responds to changes in monetary policy using panel regressions. We examine how lending is impacted by country-level characteristics, $X_{i,t}$, that measure currencies' systematic exposures; namely, dollar and carry betas. Thus, we estimate the following panel regression:

$$\log Loan_{i,t} = \mu_i + \alpha_t + \gamma X_{i,t} + \beta MPS_t + \varphi (X_{i,t} \times MPS_t) + \psi \Delta \log S_{i,t} + \epsilon_{i,t}, \tag{10}$$

where we include both country- and time-fixed effects, μ_i and α_t. Our interaction term φ is the coefficient of interest and, as before, $X_{i,t}$ captures cross-sectional differences in the way how the monetary policy shock MPS_t is transmitted to foreign loan origination. It is worth noting that the dependent variable $\log Loan_{i,t}$ captures both extensive and intensive margin effects because, except for the EUR, there are months where the variable is zero.[14]

[13] The primary purpose of this figure is to illustrate the positive relation between credit betas and carry betas. Specifically, to evaluate statistical significance we rely on the panel regression in Eq. (10), including both fixed effects and controls.

[14] To disentangle the extensive and intensive margin effects we rerun our analysis in Table 6 but (1) replace the dependent variable with a dummy that is equal to 1 if $\log Loan_{i,t} > 0$ and 0 otherwise and (2) estimate Eq. (10) for a sample that only includes loan months that are non-zero. Tables B.18 and B.19 in the Online Appendix collect the results for the (1) extensive margin and (2) intensive margin, respectively. While the interaction effects with carry betas are positive and significant in Table B.19 they are insignificant in Table B.18, suggesting that the combined effect in Table 6 is predominantly driven by the extensive margin.

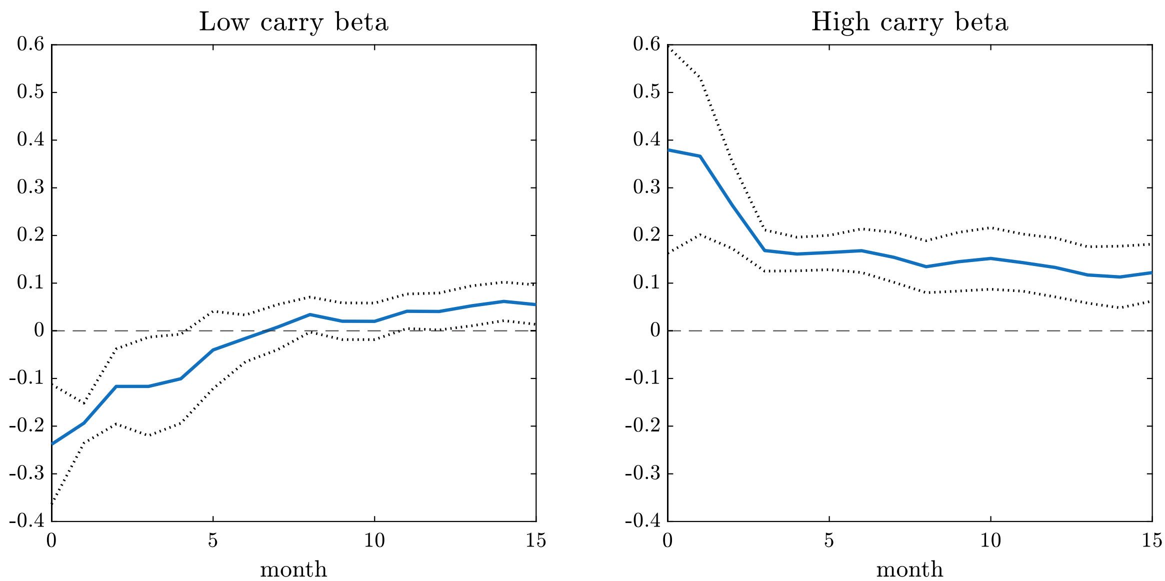

Fig. 4. Persistent effect of monetary policy on spot currency flows.
Note: This figure plots the impulse response function of currency flows to monetary surprises with local projections (Jordà, 2005) from $OF(S^g_{t,t+h}) = \alpha^g_h + \sum_{m=0}^{3} \beta^g_{h,m} MPS_{t-m} + \epsilon^g_{t+h}$, where $OF(S^g_{t,t+h})$ is the cumulative order flow in currency group g in \$bn after h months. Both dependent and independent variables are in standardized units. Currency groups are formed based on country i's carry beta and MPS_t is our monetary policy shock. The dotted lines mark the 90% confidence bands based on Newey and West (1987) standard errors, correcting for the autocorrelation induced by overlapping periods. The sample covers the period from September 2012 to March 2024.

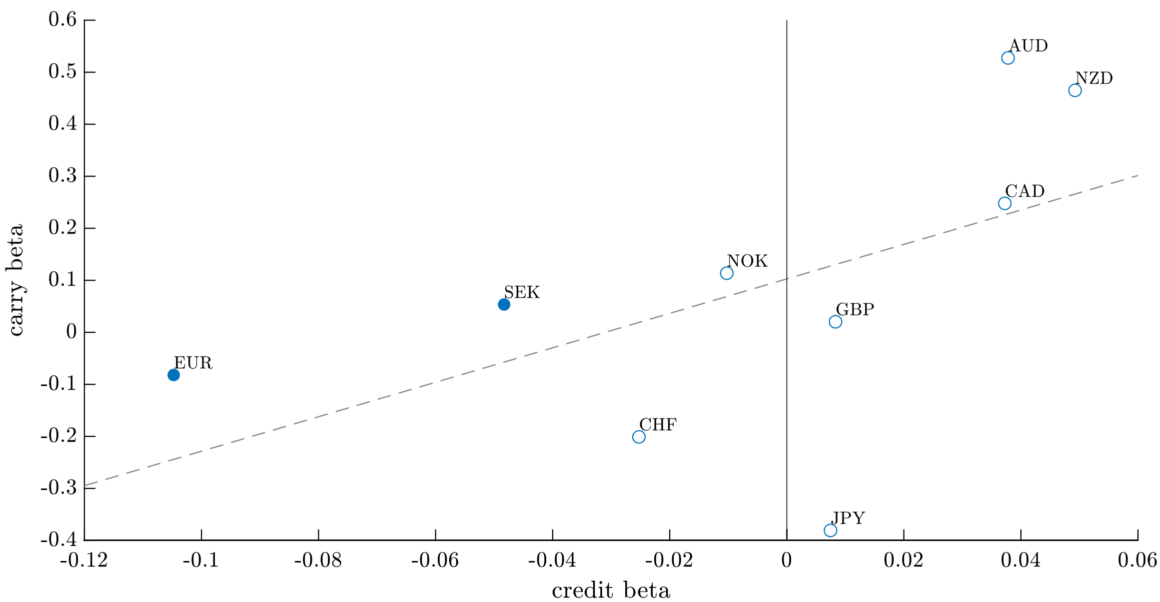

Fig. 5. Foreign credit betas and carry betas.
Note: This figure plots the β_i regression coefficient estimates from $\log Loan_{i,t} = a_i + \beta_i MPS_t + \gamma_i \Delta \log S_{i,t} + \epsilon_{i,t}$ against the average carry beta. $\log Loan_{i,t}$ is the natural log of the dollar amount lent by global banks headquartered in the US to corporations domiciled abroad in foreign currency i during month t. MPS_t is our monetary policy shock measure in basis points (Kuttner, 2001). $\Delta \log S_{i,t}$ is the log change in the spot exchange rate expressed as the number of foreign currency units per unit of US dollar. For the regression, both dependent and independent variables are measured in units of standard deviations. Filled dots indicate point estimates that are statistically significant at the 10% confidence level. The inference is based on robust standard errors (Newey and West, 1987), correcting for heteroskedasticity and first-order serial correlation. The sample spans from January 1999 to March 2024.

Table 6 tabulates the results with standardized regressors. Column (1) produces the average point estimate of the results displayed visually in Fig. 5. The coefficient of 0.02 is modestly positive but statistically insignificant. Column (2) controls for the monetary policy shock interacted with carry betas. As we saw with funds, lending in a currency that has a zero carry beta, and therefore, possesses a similar interest rate as the US, appears to be relatively unresponsive to a change in US monetary policy.

The growth in foreign lending, however, is influenced by the degree of currency risk. Conditional on an unexpected easing of US monetary policy, foreign currencies with greater carry betas experience a marked increase in lending. For example, shifting up across the distribution of countries' carry betas by one-standard deviation raises foreign currency lending by $0.05 + 0.14 = 19$ percent. Conversely, lower carry betas are associated with a decline in lending. Hence, carry betas impact the intensity of banks' loan origination: banks take on more currency

Table 6
International lending and the FX factor structure.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
carry $\text{beta}_{i,t}$		−0.24			−0.80**		−1.53*	
		[0.82]			[1.99]		[1.94]	
dollar $\text{beta}_{i,t}$			0.62*			0.58	0.97*	
			[1.70]			[1.53]	[1.67]	
UMVE $\text{beta}_{i,t}$				0.30				0.01
				[1.13]				[0.03]
MPS_t	0.02	0.05	0.57***	0.05				
	[0.40]	[1.35]	[3.44]	[1.51]				
carry $\text{beta}_{i,t} \times \text{MPS}_t$		0.14***			0.15**		0.21**	
		[4.86]			[1.97]		[2.36]	
dollar $\text{beta}_{i,t} \times \text{MPS}_t$			−0.56**			−0.67**	−0.87***	
			[2.33]			[2.51]	[2.82]	
UMVE $\text{beta}_{i,t} \times \text{MPS}_t$				0.15***				0.19**
				[2.87]				[2.36]
$\Delta \log S_{i,t}$	−0.06	−0.05	−0.07	−0.06	0.00	−0.03	−0.02	0.01
	[0.52]	[0.47]	[0.63]	[0.51]	[0.02]	[0.14]	[0.11]	[0.04]
Overall R^2 in %	57.16	57.21	57.36	57.26	62.36	62.42	62.73	62.26
Total # of Obs.	2727	2727	2727	2727	2727	2727	2727	2727
Avg. #Time periods	303	303	303	303	303	303	303	303
#Currencies	9	9	9	9	9	9	9	9
Currency FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time series FE	No	No	No	No	Yes	Yes	Yes	Yes

Note: This table reports results from fixed effects panel regressions of the form $\log Loan_{i,t} = \mu_i + \alpha_t + \gamma X_{i,t} + \beta MPS_t + \varphi(X_{i,t} \times MPS_t) + \psi \Delta \log S_{i,t} + \epsilon_{i,t}$, where $\log Loan_{i,t}$ is the natural log of the dollar amount lent by banks domiciled in the US (either bank holding company or subsidiary) to firms domiciled abroad in currency i during month t. We winsorize the dependent variable at the 1% level. $X_{i,t}$ denotes either the ***carry*** $\text{beta}_{i,t}$, ***dollar*** $\text{beta}_{i,t}$, or ***UMVE*** $\text{beta}_{i,t}$ that are based on rolling window regressions of currency returns on the carry, dollar, and UMVE factor, respectively. MPS_t is our monetary policy shock in basis points that we extract from Fed Fund futures rate changes following Kuttner (2001). $\Delta s_{i,t}$ is the log change in the spot FX rate expressed as the number of foreign currency units per US dollar. The independent variables are measured in units of standard deviations. The test statistics based on double clustered (by currencies and time) standard errors, allowing for first-order serial correlation are shown in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels. The sample spans from January 1999 to March 2024.

risk in primary markets by tilting their loan origination toward riskier currencies as measured by their carry exposure.

In column (3) we examine the impact of dollar betas on loan growth. The coefficient estimate is negative and statistically significant, again plausibly reflecting the gravity effects of international trade that we have already referenced in the context of funds' currency flows (see Section 4.2). This is because our sample here involves several years before the global financial crisis during which the correlation between dollar betas and physical distance is high, exceeding 50%. In columns (5) and (6), we run more stringent specifications that include time-fixed effects, controlling for omitted time-varying global factors. Both interaction coefficients retain their sign as well as statistical significance.

In column (7) we project loan growth onto interactions of the monetary policy shock with both carry and dollar betas. The magnitudes of coefficients for both betas has grown by about 50 percent from when evaluated separately. Statistical significance for both coefficients, too, has strengthened. Overall, the results are consistent with carry betas measuring the risk aspect of the loan allocation, whereas dollar betas capture how gravity effects impede these loan origination flows.

Finally in column (4) (and column (8)), we repeat the exercise from Table 5 and evaluate the effect of the priced component of currency risk on foreign lending. We find a positive and strong effect of currencies with a larger UMVE beta, suggesting that priced risk matters for lending as much as it does for global currency flows.

There are two complementary channels here. First, global US banks syndicate more loans in high-risk currencies but at lower, more favorable interest rate spreads. Second, following an easing of US monetary policy, interest rates in high-risk countries fall more than the rates in low risk countries. Both channels suggest that the impact is on prices rather than on quantities.

To address the first channel, we rerun our analysis in Table 6 but replace loan growth with the average interest rate spread that US banks charge in a given foreign currency i within month t. We consider both equal and loan value weighted averages. In Table B.17 we show that an unexpected easing of US monetary policy is associated with higher rather than lower interest rate spreads in high-risk currencies. This finding is also in line with the corporate bond market, where Richers (2019) finds that corporate bonds denominated in, for instance, Japanese yen have substantially lower yields than bonds denominated in Australian dollars.

Addressing the second channel, we show that an easing of US monetary policy predicts a drop in foreign policy rates, however these declines are not significantly stronger for countries with high-risk currencies (see Table 13). This is especially the case when using key benchmark rates (e.g., LIBOR) that constitute the main reference rate for syndicate loans instead of actual policy rates. Taken together, these result are not consistent with a narrative that attributes the increase in foreign currency lending in high-risk countries to more favorable credit conditions.

In sum, global US banks reshuffle their foreign currency lending in response to changes in US monetary policy. Specifically, we see that banks tilt their loan origination toward currencies that are riskier in the carry sense. In cases in which currency risk is particularly pronounced, the risk-taking channel could completely offset and even reverse the decline of foreign loans driven by the reduced opportunity cost of holding US reserves.

6. Firm-level outcomes

In Sections 4 and 5, we have documented evidence that is consistent with the risk-taking channel of monetary policy: following an unexpected easing of monetary policy, both funds and banks tilt away from currencies that are safe toward ones that are risky. However, so far we have stayed away from the international transmission of US monetary policy to the real side of foreign economies. To fill this gap, we use the fact that banks reallocate in the primary market for loan originations, allowing us to test for real effects within the set of firms borrowing from US banks.

Our empirical strategy is to test whether foreign firms domiciled outside of the US that are more "exposed" to high-risk currencies are impacted differently than firms exposed to low-risk currencies. We do this in two steps. We first estimate how much firms are borrowing following an unexpected easing of US monetary policy and conditional on the firm's currency exposure. We then maintain the high- relative to low-risk focus and provide evidence that firms that are mainly exposed to high risk currencies via their borrowing experience different firm-level outcomes compared to firms that mainly borrow in low risk currencies.

To do this, we first need to define what a firm's currency exposure is. We choose to measure exposure based on the reporting currency of the firm. A firm's reporting currency is the currency in which the firm primarily generates its cash flows, basically its operating currency. We expect that firms that report in high-risk currencies and borrow from a global US bank are more likely to respond more to US monetary policy than firms that report in low-risk currencies given that on aggregate lending increases in high- relative to low-risk currencies (see previous section).

The now-standard approach of identifying the impact of credit supply shocks in the financial intermediation literature, pioneered by Khwaja and Mian (2008), is to control for credit demand using firm-time fixed effects. In our setup it is not possible to include firm-time fixed effects because our principal source of variation is at the firm-time level. To include firm-time fixed effects we would require that firms borrow in multiple currencies from US banks within a given quarter. However, in our sample there is effectively no variation across borrowing currencies within a given firm-quarter cell and hence, including firm-time fixed effects absorbs all the relevant variation that we seek to identify.

With the above caveat in mind, the only way for us to control for demand factors is at the country (rather than firm) level and industry level with country-time and industry-time fixed effects. We are able to do so because for around 11 percent of the firms in our sample the reporting currency (which we use to match currency betas) is not the same as the currency of their domicile country. This distinction allows us to control for country specific time-varying effects and isolate the impact of a firm's currency, rather than its country, on its borrowing. Though our results are qualitatively similar when identifying a firm's currency exposure based on their domicile currency.

To be consistent with the quarterly balance sheet data from Compustat, all loans are aggregated at the firm-quarter level. For firms that borrow more than once per quarter, we keep only the loan(s) issued in the firm's reporting currency. But our results are robust to excluding these firm-quarter observations from our sample.

6.1. How firms' borrowings responds to US monetary policy

We start by focusing on how currency risk affects the likelihood of borrowing via a syndicated loan. In particular, we aim to test whether US monetary policy has a differential impact on syndicated loan originations to firms that are more exposed to high-risk currencies relative to firms that are mainly exposed to low-risk currencies. To test this hypothesis we focus only on syndicated loans that involve at least one US bank (either bank holding company or subsidiary) in a given quarter t and currency i. And for any given firm j in country c we only consider loans that are issued in the same currency as the reporting currency of the firm. We do so because we want to distinguish between firms borrowing in high- relative to low-risk currencies. Specifically, we run a regression that explains the probability of borrowing in a foreign currency via a syndicated loan conditional on changes in US monetary policy:

$$D_{j,i,c,t} = \mu_j + \alpha_{c,t} + \nu_{n,t} + \gamma X_{i,t} + \varphi(X_{i,t} \times MPS_t) + \psi \Delta \log S_{i,t} + \kappa \mathbf{W}_{j,i,t} + \epsilon_{j,i,c,t}, \tag{11}$$

where the dependent variable $D_{j,i,c,t}$ is a dummy variable that is equal to unity if firm j has borrowed via a syndicate, which involves at least one bank that is domiciled in the US in quarter t and currency i, where currency i is equal to the reporting currency of the firm. As before, our currency risk measures of dollar and carry betas are in $X_{i,t}$, which we attribute to each firm based on its reporting currency and MPS_t is our monetary policy shock measure based on Kuttner (2001). Our control variables are the change in the log of the spot exchange rate, $\Delta \log S_{i,t}$, and $\mathbf{W}_{j,i,t}$, which includes log assets, current ratio, changes in log sales, changes in log leverage, and changes in log Tobin's Q.[15] We always control for firm fixed effects, μ_j, and we either use country-times-quarter fixed effects, $\alpha_{c,t}$, to control for time-variation in a given country's macroeconomic conditions and/or industry-times-quarter fixed effects,[16] $\nu_{n,t}$, to control for time-varying loan demand at the industry level.

With country-times-quarter fixed effects, $\alpha_{c,t}$, we can isolate the monetary transmission that comes through the supply of bank loans. The fixed effect absorbs all the variation due to a country's specific economic conditions. Hence, the only effect remaining will come from the supply of the new syndicated loans involving a global US bank. Importantly, a firm's country c does not necessarily align with its reporting currency i. Hence, our main coefficient of interest, φ, will be identified based on firms borrowing in different currencies in the *same* country. The coefficient captures the differences in syndicated loan origination to firms exposed to high- relative to low-risk currencies following an unexpected easing of US monetary policy.

Table 7 reports the results from estimating Eq. (11) across various specifications as a panel logit with fixed effects. We find that following an easing of US monetary policy firms that are mainly exposed to high carry beta currencies (e.g., Australian dollars) are more likely to receive a loan compared to firms that are primarily exposed to low carry beta currencies (e.g., Japanese yen). Specifically, we find that a one standard deviation easing of US monetary policy is associated with a 4.5 to 5.4 percentage point increase in the average marginal effect of obtaining syndicated loans for firms borrowing in currencies with carry betas that are one standard deviation above average.

The interaction effects with respect to dollar betas are either negative or statistically insignificant. This underscores our earlier finding that dollar betas do not line up with foreign currency flows in terms of their response to an easing of US monetary policy. When including both carry and dollar betas in the same specification, the carry betas drive out the dollar betas when examining the response within a country-quarter.

6.2. How borrowing impacts a firm's leverage and investment

After establishing that firms that are more exposed to high-risk currencies experience a positive loan supply shock following an easing of US monetary policy, we now turn to testing what impact borrowing has on a firm's outcomes. Specifically, our goal is to show that firm-level outcomes are different for firms that are mainly exposed to high relative to low risk currencies via their syndicated loan borrowing. We run the following firm-level panel regression:

$$\begin{aligned}\Delta \log y_{j,i,c,t} = {} & \mu_j + \alpha_{c,t} + \nu_{n,t} + \gamma X_{i,t} + \varphi(X_{i,t} \times MPS_t) + \psi \Delta \log S_{i,t} \\ & + \kappa \mathbf{W}_{j,i,t} + \epsilon_{j,i,c,t},\end{aligned} \tag{12}$$

where $\log y_{j,i,c,t}$ is the log value of a firm-level outcome variable y for firm j domiciled in country c and borrowing in currency i in quarter t. Our controls in $\mathbf{W}_{j,i,t}$ are the same as in Eq. (11) and $\Delta \log S_{i,t}$ is the log change in the FX rate. We include firm-fixed effects, μ_j, in all

[15] We compute Tobin's Q as the ratio of the market value of equity plus liabilities and book value of assets. For firms that have missing market value of equity we fill the Tobin's Q with the industry average.

[16] We follow the SIC manual and group firms into 11 divisions that are similar to the Fama–French 12 industry classification. The SIC manual is accessible here: https://www.osha.gov/data/sic-manual (accessed on March 31, 2026).

Table 7
Firm-level foreign currency borrowing and the FX factor structure.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
carry $\text{beta}_{\text{i,t}}$	−0.23*		−0.06	−0.91*		−0.84	−1.14*		−1.10*
	[1.85]		[0.44]	[1.87]		[1.52]	[1.85]		[1.68]
dollar $\text{beta}_{\text{i,t}}$		−0.31***	−0.31***		−0.47	−0.30		−0.42	−0.24
		[4.04]	[3.72]		[1.05]	[0.62]		[0.83]	[0.46]
carry $\text{beta}_{\text{i,t}} \times \text{MPS}_{\text{t}}$	0.09***		0.09**	0.71***		0.92***	0.99***		1.19***
	[2.73]		[2.17]	[3.94]		[2.97]	[4.00]		[3.10]
dollar $\text{beta}_{\text{i,t}} \times \text{MPS}_{\text{t}}$		−0.30***	−0.24***		0.01	1.67		0.12	1.70
		[3.37]	[3.06]		[0.01]	[1.37]		[0.05]	[1.25]
$\Delta \log S_{i,t}$	0.07	0.09	0.04	0.02	−0.02	0.12	−0.23	−0.20	−0.16
	[0.28]	[0.34]	[0.14]	[0.03]	[0.02]	[0.13]	[0.26]	[0.24]	[0.19]
log $\text{assets}_{j,i,t-1}$	0.61***	0.67***	0.67***	0.79***	0.78***	0.79***	0.79***	0.78***	0.79***
	[4.08]	[4.49]	[4.51]	[4.99]	[4.95]	[4.97]	[4.56]	[4.49]	[4.53]
current asset $\text{ratio}_{j,i,t-1}$	0.02	0.06	0.05	0.07	0.07	0.07	0.05	0.06	0.06
	[0.18]	[0.59]	[0.55]	[0.70]	[0.72]	[0.71]	[0.52]	[0.55]	[0.53]
Δ log $\text{sales}_{j,i,t}$	0.08***	0.08***	0.08***	0.10***	0.10***	0.10***	0.10***	0.11***	0.10***
	[2.88]	[2.80]	[2.83]	[3.05]	[3.07]	[3.05]	[2.94]	[2.96]	[2.94]
Δ log $\text{leverage}_{j,i,t}$	0.13**	0.13**	0.13**	0.14**	0.14**	0.13**	0.14**	0.14**	0.14**
	[2.32]	[2.29]	[2.30]	[2.33]	[2.35]	[2.33]	[2.36]	[2.38]	[2.36]
Δ log Tobin's $\text{Q}_{j,i,t}$	−0.10**	−0.10**	−0.10**	−0.09**	−0.10**	−0.09**	−0.17**	−0.17**	−0.17**
	[2.14]	[2.04]	[2.05]	[2.16]	[2.18]	[2.16]	[2.50]	[2.52]	[2.50]
AME in %	0.36	−1.11	0.35	2.91	0.04	3.77	4.50	0.53	5.40
Odds-Ratio	1.10	0.74	1.10	2.04	1.01	2.52	2.70	1.12	3.30
Total # of Obs.	50498	50498	50498	50498	50498	50498	50498	50498	50498
Avg. #Time periods	51	51	51	51	51	51	51	51	51
#Firms	987	987	987	987	987	987	987	987	987
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	No	No	No	No	No	No
Country × quarter FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry × quarter FE	No	No	No	No	No	No	Yes	Yes	Yes

Note: This table reports results from panel logit regressions with fixed effects of the form $D_{j,i,c,t} = \mu_j + \alpha_{c,t} + \nu_{n,t} + \gamma X_{i,t} + \varphi(X_{i,t} \times MPS_t) + \psi \Delta \log S_{i,t} + \kappa \mathbf{W}_{j,i,t} + \epsilon_{j,i,c,t}$, where the dependent variable $D_{j,i,c,t}$ is a dummy variable that is equal to unity if firm j in country c has borrowed via a syndicate, which involves at least one bank that is domiciled in the US (either bank holding company or subsidiary) in quarter t and currency i, where currency i is equal to the reporting currency of the firm. As before, $X_{\text{i,t}}$ denotes either the *carry* $\textit{beta}_{\text{i,t}}$ or *dollar* $\textit{beta}_{\text{i,t}}$ and we also attribute these dollar and carry betas to each firm based on the reporting currency of the firm. MPS_t is our monetary policy shock in basis points following Kuttner (2001). $\Delta \log S_{i,t}$ is the change in the log of the spot FX rate and $\mathbf{W}_{j,i,t}$ includes the same controls as in Equation 11 in the paper. μ_j, $\alpha_{c,t}$, and $\nu_{n,t}$ denote firm, quarter times country c, and quarter times industry n fixed effects, respectively. *AME in %* is the average marginal effect for the point estimate concerning either the interaction of dollar or carry betas and MPS_t. *Odds-Ratio* is computed as the exponential of the estimated interaction effects. Columns 2, 5, and 8 report the *AME in %* and *Odds-Ratio* for the point estimate of *dollar* $\textit{beta}_{i,t} \times \textit{MPS}_t$, whereas all other columns report the AME for *carry* $\textit{beta}_{i,t} \times \textit{MPS}_t$. The independent variables are measured in units of standard deviations. The test statistics based on double clustered standard errors (by firm and time) are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels. The sample spans from January 1999 to March 2024.

specifications as well as country-times-quarter, $\alpha_{c,t}$, and/or industry-times-quarter, $\nu_{n,t}$, fixed effects to control for unobserved heterogeneity at the firm-level and for differences in demand that stem from time-varying local macroeconomic conditions and unobservable factors at the industry level, respectively.

Table 8 shows the results of estimating Eq. (12) for three firm-level outcome variables (in log differences): total debt (short- plus long-term liabilities), total assets, and PPE net of depreciation. In line with our result in Table 7, we find in columns (1) and (4) that firms that are mainly exposed to high carry beta currencies (e.g., firms that report earnings in Australian dollars; hereinafter "high carry beta firms") experience an additional 1.5 percent increase in their total borrowings (relative to a firm with a carry beta of zero) conditional on a one standard deviation easing of US monetary policy. The opposite holds for firms that are mainly exposed to low carry beta currencies (e.g., Japanese yen; hereinafter "low carry beta firms"). Moreover, in columns (2) and (5) we also find that high carry beta firms are expanding the overall size of their balance sheet relative to low carry beta firms, suggesting that the new loans are not just simply used to refinance existing borrowing. Lastly, columns (3) and (6) show that property plant and equipment (net of depreciation) increases by an additional 1.1–1.2 percent for high carry beta firms, whereas low carry beta firms invest less.

Taken together, the evidence in Tables 7 and 8 corroborates the notion that (i) US monetary policy has a differential effect on loan supply in high- relative to low-risk currencies and (ii) that firms that are mainly exposed to high-risk currencies (i.e., high carry beta firms) expand their balance sheet more and invest more into tangible assets relative to low carry beta firms.

7. Extensions and robustness

Here we summarize robustness checks and additional analyses supporting our main findings. Specifically, we study (i) economic sources of currency risk, (ii) persistence in currency risk factors, (iii) other FX risk factors, (iv) contractionary vs. expansionary monetary policy shocks, (v) alternative measures of monetary policy shocks, (vi) other central banks' reactions to US monetary policy, and (vii) European monetary policy shocks.

7.1. Deeper economic sources of currency risk

We go beyond the PC motivated dollar and carry exposures and explore their economic determinants. We estimate the panel regressions of Sections 4 and 5 with country-level risk characteristics known to account for the effect of monetary policy across currencies. In particular, we focus on the more recent literature that considers interest rate differentials (Lustig et al., 2011), size (Hassan, 2013), downside betas (Lettau et al., 2014), global imbalances (IMB) betas (Della Corte et al., 2016), trade composition (Ready et al., 2017), trade network centrality (Richmond, 2019), and term premia (Andrews et al., 2024). Table 9 presents the results from extending our findings in Table 5 to these sources of country-level risk.

Countries that have higher interest rates as measured by their forward discount ($f_i - s_i$), that are more peripheral in the global trade network, that have a greater carry slope expected return, that are smaller economies, and that tend to export commodities and import

Table 8
Firm-level outcomes and the FX factor structure.

	$\Delta\log \text{debt}_{j,i,c,t}$	$\Delta\log \text{assets}_{j,i,c,t}$	$\Delta\log \text{PPE}_{j,i,c,t}$	$\Delta\log \text{debt}_{j,i,c,t}$	$\Delta\log \text{assets}_{j,i,c,t}$	$\Delta\log \text{PPE}_{j,i,c,t}$
carry $\text{beta}_{\text{i,t}}$	2.25*	0.65	0.93	2.24*	0.78	0.79
	[1.74]	[0.77]	[0.90]	[1.69]	[0.91]	[0.72]
carry $\text{beta}_{\text{i,t}} \times \text{MPS}_\text{t}$	1.54**	1.16**	1.19***	1.50**	1.03**	1.05***
	[2.02]	[2.39]	[7.41]	[2.29]	[2.41]	[5.83]
$\Delta\log S_{i,t}$	7.66***	−0.21	0.75	7.34***	−0.35	0.74
	[4.76]	[0.35]	[1.37]	[4.54]	[0.60]	[1.30]
log $\text{assets}_{j,i,t-1}$	−8.36***	−6.74***	−3.00***	−8.64***	−6.73***	−2.86***
	[7.07]	[11.48]	[5.75]	[7.04]	[11.59]	[5.80]
current asset $\text{ratio}_{j,i,t-1}$	−0.38	−0.73**	3.39***	−0.48	−0.81***	3.34***
	[0.85]	[2.39]	[8.39]	[1.07]	[2.63]	[8.24]
$\Delta\log$ $\text{sales}_{j,i,t}$	3.32***	2.69***	2.47***	3.30***	2.67***	2.39***
	[8.36]	[14.42]	[7.51]	[8.54]	[14.42]	[8.06]
$\Delta\log$ $\text{leverage}_{j,i,t}$	19.90***	1.52***	2.76***	19.88***	1.55***	2.71***
	[8.65]	[4.42]	[4.95]	[8.80]	[4.67]	[5.14]
$\Delta\log$ Tobin's $\text{Q}_{j,i,t}$	−3.46***	−1.99***	−1.40***	−4.87***	−2.82***	−1.97***
	[3.64]	[4.45]	[3.75]	[3.49]	[4.29]	[3.79]
Overall R^2 in %	48.66	27.61	17.82	49.87	29.89	20.69
Total # of Obs.	50498	50498	50275	50498	50498	50275
Avg. #Time periods	51	51	51	51	51	51
#Firms	987	987	985	987	987	985
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Country × quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × quarter FE	No	No	No	Yes	Yes	Yes

Note: This table reports results from fixed effects panel regressions of the form $\Delta\log y_{j,i,c,t} = \mu_j + \alpha_{c,t} + \nu_{n,t} + \gamma X_{i,t} + \varphi(X_{i,t} \times MPS_t) + \psi\Delta\log S_{i,t} + \kappa \mathbf{W}_{j,i,t} + \epsilon_{j,i,t}$, where $\Delta\log y_{j,i,c,t}$ is the quarterly growth rate (in percentage points, that is, point estimates are multiplied times 100) of a firm-level outcome variable y (see column header) for firm j in country c borrowing in currency i at time t. We winsorize the dependent variable at the 0.5% level. $X_{\text{i,t}}$ denotes the *carry* $\textit{beta}_{\text{i,t}}$ that is based on a rolling window regression of currency returns on the carry factor. MPS_t is our monetary policy shock in basis points that we extract from Fed Fund futures rate changes following Kuttner (2001). $\Delta\log S_{i,t}$ is the log change in the spot FX rate expressed as the number of foreign currency units per US dollar and $\mathbf{W}_{j,i,t}$ includes the same controls as in Equation 11 in the paper. μ_j, $\alpha_{c,t}$, and $\nu_{n,t}$ denote firm, quarter times country c, and quarter times industry n fixed effects, respectively. The independent variables are measured in units of standard deviations. The test statistics based on double clustered (by currencies and time) standard errors are shown in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels. The sample spans from January 1999 to March 2024.

finished goods all display responses that are economically comparable to our baseline results in column (1) in terms of economic magnitude. For our sample, we do not find an identifiable response emanating from heterogeneous exposures to global trade imbalances (i.e., IMB beta) or downside risk (i.e., downside beta). The result concerning global imbalances is in line with Della Corte et al. (2016), showing that the riskiest countries in terms of net foreign asset positions are not necessarily the countries with the highest interest rates. Moreover, in unreported results we show that the carry betas drive out any other economic sources of risk, except for size, in a horse race.

In sum, all of these measures above confirm that currency flows are guided by currency risk, and that these flows are governed by the magnitude of risk. Collectively, they are consistent with our paper's central idea that heterogeneous exposure to currency risk shapes the response of currency flows to monetary policy.

7.2. Persistence in currency exposures

One possible concern is that currency risk characteristics are endogenous and quickly respond to monetary policy shocks. These characteristics of currency risk, however, are persistent over time. In particular, Lustig et al. (2011) and Hassan and Mano (2018) show that more than half of the carry trade return is driven by an unconditional sorting based on interest rate differentials. Furthermore, Lustig and Richmond (2019) report that dollar betas are well-explained by time-invariant variables with a gravity interpretation like geographic distance and common languages.

We treat dollar and carry betas as pre-determined in the econometric sense. The evidence we give in the Online Appendix support this view. First, we document in Table B.1 that exposures are persistent. First-order autocorrelation coefficients cluster around 0.98 for both dollar and carry betas. Moreover, there is compelling evidence that the cross-sectional ranking of currencies is stable over time. For instance, the Swiss franc spends 91 percent of its time in the lowest carry-beta portfolio, whereas the Australian dollar is always part of the highest. Similar patterns prevail for dollar betas.

Second, we show in Table B.4 that carry and dollar betas are virtually uncorrelated with monetary policy shocks at the monthly frequency. In particular, we find that none of the dollar betas responds significantly to changes in US monetary policy at the monthly frequency. Turning to carry betas, we see that only the USDNZD responds significantly negatively to an easing of US monetary policy.

Third, we replicate our analysis in Tables 5 and 6, but instead of using carry and dollar betas themselves, we transform the betas into a relative cross-sectional rank score (where a higher beta corresponds to a higher rank score). We show in Tables B.6 and B.15 that our key results are qualitatively unchanged. Thus the ordering of currency risk across the cross-section is at the heart of our results.

7.3. Other currency risk factors

The currency asset pricing literature has identified several sources of currency risk that are not subsumed by carry: Menkhoff et al. (2012b) create portfolios based on past winner and loser currencies (we consider one-, three-, and twelve-month momentum), Menkhoff et al. (2017) sort currencies into portfolios based on changes in the real exchange rate, Colacito et al. (2020) form portfolios based on the difference between the actual and potential output (industrial production), and Rafferty (2012) sorts currencies based on their exposure to a global skewness measure. We replicate these portfolio sorts and compute individual currencies' exposure to these factors using rolling window regressions in the spirit of Eq. (1); where we replace the carry factor by one of the aforementioned portfolios.

Table 10 shows that currency risk factors that are orthogonal to the carry trade cannot explain the cross-sectional differences in how investment funds' currency flows respond to monetary policy shocks. Specifically, the interaction terms for currency momentum are negative and statistically significant for the one-month maturity, confirming that the

Table 9
Currency flows of funds and economic sources of currency risk.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MPS_t	0.01	0.01	0.04	0.10**	−0.03	0.09**	0.12***	−0.03
	[0.26]	[0.53]	[1.12]	[2.07]	[0.46]	[2.06]	[2.83]	[1.10]
carry $beta_{i,t} \times MPS_t$	0.09***							
	[2.73]							
IMB $beta_{i,t} \times MPS_t$		−0.01						
		[0.48]						
downside $beta_{i,t} \times MPS_t$			0.01					
			[0.72]					
$f_{i,t} - s_{i,t} \times MPS_t$				0.09**				
				[2.01]				
$centrality_{i,t} \times MPS_t$					−0.08			
					[1.40]			
term $premium_{i,t} \times MPS_t$						0.09		
						[1.60]		
$size_{i,t} \times MPS_t$							−0.14***	
							[12.90]	
import $ratio_{i,t} \times MPS_t$								0.07***
								[4.91]
$\Delta\log$ bid-ask $spread_{i,t}$	−0.03	0.00	−0.03	−0.03	−0.04	−0.03	−0.04*	−0.01
	[1.34]	[0.52]	[1.47]	[1.56]	[1.62]	[1.62]	[1.69]	[1.04]
$\Delta\log S_{i,t}$	−0.01	−0.03	−0.02	−0.02	−0.02	−0.02	−0.01	−0.02
	[0.38]	[0.72]	[0.44]	[0.52]	[0.50]	[0.49]	[0.39]	[0.63]
Overall R^2 in %	19.45	34.52	19.19	19.22	19.73	19.34	21.69	33.57
Total # of Obs.	1242	846	1242	1242	1242	1242	1215	891
Avg. #Time periods	138	94	138	138	138	138	135	99
#Currencies	9	9	9	9	9	9	8	9
Currency FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports results from fixed effects panel regressions of the form $OF(S_{i,t}) = \mu_i + \gamma X_{i,t} + \beta MPS_t + \varphi(X_{i,t} \times MPS_t) + \kappa \mathbf{W}_{i,t} + \epsilon_{i,t}$, where $OF(S_{i,t})$ is the order flow by *funds* in \$bn in currency pair i in month t. $X_{i,t}$ denotes various measure of country level risk characteristics. For conciseness, we only report the β and φ coefficients. MPS_t is our monetary policy shock in basis points that we extract from Fed Fund futures rate changes following Kuttner (2001). $\mathbf{W}_{i,t}$ may include the following control variables: $\Delta\log$ *bid-ask* $spread_{i,t}$ is the log change in the monthly average relative bid-ask spread and $\Delta\log S_{i,t}$ is the log change in the spot FX rate expressed as the number of foreign currency units per US dollar. Both dependent and independent variables are measured in units of standard deviations. The test statistics based on double clustered (by currencies and time) standard errors, allowing for serial correlation up to 3 lags are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels. The sample spans from September 2012 to March 2024.

risk-on pattern in Fig. 3 cannot be explained by a simple trend-chasing behavior that is long past winner and short past loser currencies. We find a similar pattern for business cycle strength (i.e., output gap beta). Moreover, the risk-on pattern is largely unrelated to differences in real exchange rate value, exposure to global skewness risk, and longer bouts of momentum (three and twelve months).

7.4. Expansionary and contractionary monetary policy

Here, we split our sample into periods of positive and negative monetary policy shocks. Specifically, we replicate Fig. 3 for investment funds, distinguishing between periods of easing and tightening of US monetary policy. The key observation is that monetary policy shocks have a stronger impact on currency flows when US monetary policy is easing. This is visually apparent as the flow betas of both high- and low-carry-beta currencies are closer to zero conditional on times of monetary policy tightening. This asymmetry is consistent with the intermediary asset pricing literature: a tightening of US monetary policy is associated with higher balance sheet costs for a financial intermediary operating under a Value-at-Risk constraint, resulting into a deterioration of market liquidity and higher transaction costs (Huang et al., 2025).

7.5. Alternative measures of monetary policy shocks

For robustness, we consider alternative measures of monetary policy shocks. Our main analysis has employed high-frequency changes in Federal Fund futures prices around FOMC announcements (Kuttner, 2001; Bernanke and Kuttner, 2005). These shocks primarily capture the surprise in the policy target rate. There is a large literature on measuring different components of monetary policy surprises and we consider some recent contributions. Kearns et al. (2022) build on the work by Swanson (2021) but take a simpler approach and construct target rate, path, and long-rate surprises.[17] Jarociński and Karadi (2020) decompose monetary policy surprises into monetary policy (MP) and central bank information (CBI) shocks using the high frequency co-movement between interest rates and stock prices. Bauer and Swanson (2023b) follow Nakamura and Steinsson (2018) (NS) and extract monetary policy surprises from changes in Eurodollar futures contracts at different horizons around FOMC meetings. In addition, they also construct a shock series (ORT) that is orthogonal to macroeconomic and financial data that pre-dates the monetary policy announcement and thereby accounts for the "Fed response to news" channel in Bauer and Swanson (2023a). We evaluate these other monetary policy shocks to confirm the robustness of our findings (see Fig. 6).

Tables 11 and 12 replicate our results in Tables 5 and 6 but using various measures of monetary policy shocks. The evidence can be summarized along two dimensions: First, focusing on the interaction effects with carry and dollar betas we find that only the target factor shocks by Kearns et al. (2022), Jarociński and Karadi (2020), and Bauer and Swanson (2023b) deliver consistent results with our baseline estimates in the first column. Second, path and long-rate (Kearns et al., 2022) shocks as well as central bank information shocks (Jarociński and Karadi, 2020) are not associated with any significant foreign currency flows or syndicated loans.

7.6. Other central banks' response to US monetary policy

It could be that what we find is not consistent with the risk-taking channel of US monetary policy. Rather, it could be that foreign central

[17] We are sincerely grateful to Andreas Schrimpf for providing access to several of these shock series.

Table 10
Currency flows of funds and a comparison of currency risks.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MPS_t	0.01	0.01	0.02	0.01	−0.01	0.05*	0.00
	[0.26]	[0.34]	[0.35]	[0.11]	[0.23]	[1.76]	[0.05]
carry $\text{beta}_{i,t}$ × MPS_t	0.09***						
	[2.73]						
1M momentum $\text{beta}_{i,t}$ × MPS_t		−0.03**					
		[2.00]					
3M momentum $\text{beta}_{i,t}$ × MPS_t			−0.04				
			[0.91]				
1Y momentum $\text{beta}_{i,t}$ × MPS_t				−0.05			
				[1.28]			
value $\text{beta}_{i,t}$ × MPS_t					0.06		
					[1.15]		
output gap $\text{beta}_{i,t}$ × MPS_t						−0.03***	
						[6.47]	
skewness $\text{beta}_{i,t}$ × MPS_t							0.05
							[1.50]
$\Delta\log$ bid-ask $\text{spread}_{i,t}$	−0.03	−0.03*	−0.02	−0.03	−0.03*	−0.02	−0.02
	[1.34]	[1.68]	[1.09]	[1.32]	[1.67]	[1.19]	[1.50]
$\Delta\log S_{i,t}$	−0.01	−0.02	−0.02	−0.03	−0.02	−0.02	−0.02
	[0.38]	[0.60]	[0.59]	[0.84]	[0.59]	[0.59]	[0.70]
Overall R^2 in %	19.45	19.57	19.50	21.78	19.15	19.70	20.25
Total # of Obs.	1242	1242	1242	1242	1242	1242	1242
Avg. #Time periods	138	138	138	138	138	138	138
#Currencies	9	9	9	9	9	9	8
Currency FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports results from fixed effects panel regressions of the form $OF(S_{i,t}) = \mu_i + \gamma X_{i,t} + \beta MPS_t + \varphi(X_{i,t} \times MPS_t) + \kappa \mathbf{W}_{i,t} + \epsilon_{i,t}$, where $OF(S_{i,t})$ is the order flow by *funds* in \$bn in currency pair i in month t. $X_{i,t}$ denotes the exposure (i.e., beta) to various FX risk factors. For conciseness, we only report the β and φ coefficients. MPS_t is our monetary policy shock in basis points that we extract from Fed Fund futures rate changes following Kuttner (2001). $\mathbf{W}_{i,t}$ may include the following control variables: $\Delta\log$ *bid-ask spread*$_{i,t}$ is the log change in the monthly average relative bid-ask spread and $\Delta\log S_{i,t}$ is the log change in the spot exchange rate expressed as the number of foreign currency units per unit of US dollar. Both dependent and independent variables are measured in units of standard deviations. The test statistics based on double clustered (by currencies and time) standard errors, allowing for serial correlation up to 3 lags are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels. The sample spans from September 2012 to March 2024.

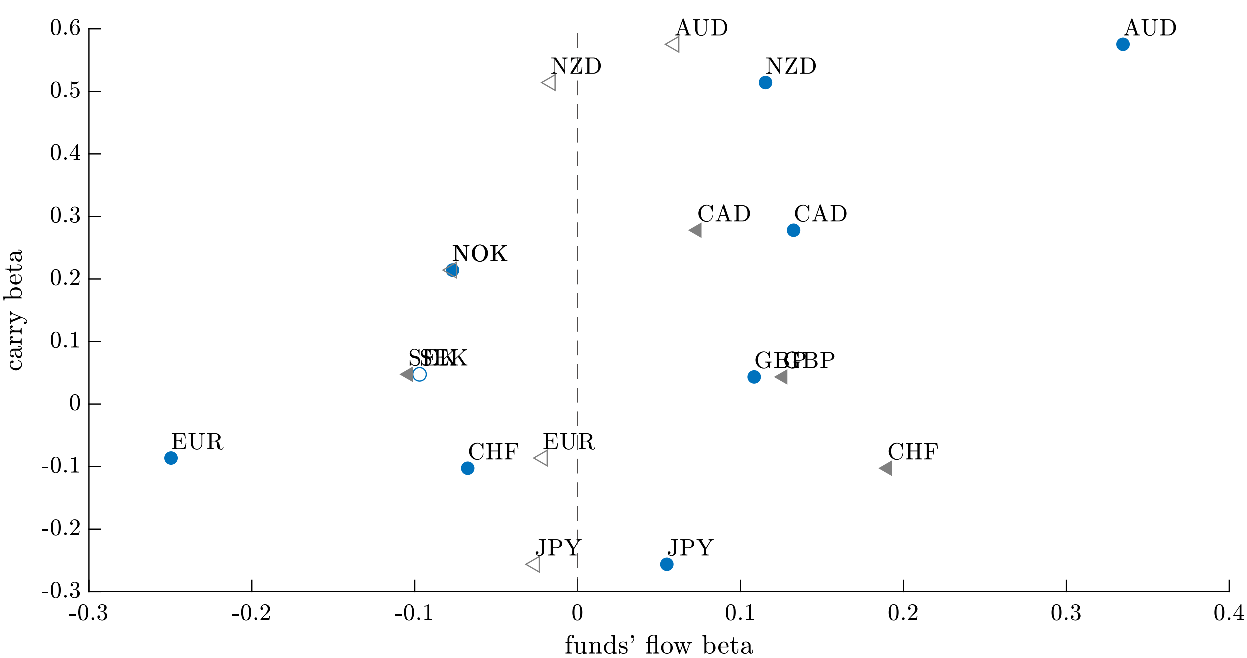

Fig. 6. Currency flow betas and carry betas — monetary easing and tightening.
Note: This figure plots the β_i and γ_i regression coefficients from $OF(S_{i,t}) = a_i + \beta_i MPS_t \times (MPS_t \geq 0) + \gamma_i MPS_t \times (MPS_t \leq 0) + \epsilon_{i,t}$ against the average carry beta. $OF(S_{i,t})$ is the spot order flow in \$mn in currency pair i by investment funds in month t and MPS_t is our monetary policy shock measure in basis points. For the regression, both dependent and independent variables are measured in units of standard deviations. The β and γ coefficients are shown as blue dots and gray triangles, respectively. Filled dots or diamonds indicate point estimates that are statistically significant at the 10% confidence level. The inference is based on robust standard errors (Newey and West, 1987), correcting for heteroskedasticity and serial correlation up to 3 lags. The sample covers the period from September 2012 to March 2024.

Table 11
Currency flows of funds in response to alternative monetary policy shocks.

	Kuttner (2001)	Kearns et al. (2022)			Jarociński and Karadi (2020)		Bauer and Swanson (2023b)	
		Target	Path	Long-rate	MP	CBI	NS	ORT
carry $\text{beta}_{i,t}$	−0.15	−0.13	−0.13	−0.13	−0.14	−0.12	−0.12	−0.10
	[1.10]	[1.01]	[1.00]	[1.04]	[1.05]	[0.94]	[0.99]	[0.87]
dollar $\text{beta}_{i,t}$	0.20	0.17	0.18	0.18	0.18	0.18	0.17	0.15
	[0.97]	[0.90]	[0.91]	[0.95]	[0.95]	[0.94]	[0.97]	[0.87]
carry $\text{beta}_{i,t} \times \text{MPS}_t$	0.17***	0.11**	−0.03	−0.03	0.01	0.04*	0.05	−0.02
	[4.18]	[2.07]	[1.20]	[0.95]	[0.40]	[1.91]	[1.12]	[0.79]
dollar $\text{beta}_{i,t} \times \text{MPS}_t$	−0.36***	−0.12*	0.04	0.05	0.05	0.04	−0.01	−0.08
	[3.68]	[1.79]	[0.76]	[0.69]	[0.72]	[0.59]	[0.17]	[1.36]
$\Delta \log$ bid-ask $\text{spread}_{i,t}$	0.03	0.00	−0.02	−0.02	−0.02	−0.01	−0.01	−0.01
	[0.92]	[0.07]	[0.76]	[0.82]	[0.83]	[0.75]	[0.78]	[0.26]
$\Delta \log S_{i,t}$	−0.02	−0.03	−0.04	−0.05	−0.04	−0.05	−0.05	−0.06
	[0.47]	[0.62]	[0.98]	[1.00]	[0.94]	[1.02]	[1.23]	[1.53]
Overall R^2 in %	31.88	32.43	31.75	31.72	31.70	31.78	32.06	32.78
Total # of Obs.	1242	1233	1233	1233	1233	1233	1224	1161
Avg. #Time periods	138	137	137	137	137	137	136	129
#Currencies	9	9	9	9	9	9	9	9
Currency FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time series FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports results from fixed effects panel regressions of the form $OF(S_{i,t}) = \mu_i + \alpha_t + \gamma X_{i,t} + \varphi(X_{i,t} \times MPS_t) + \kappa \mathbf{W}_{i,t} + \epsilon_{i,t}$, where $OF(S_{i,t})$ is the order flow by *funds* in \$bn in currency pair i in month t. $X_{i,t}$ denotes either the *carry* $\textit{beta}_{i,t}$ or *dollar* $\textit{beta}_{i,t}$ that are based on rolling window regressions of currency returns on the carry and dollar factor, respectively. MPS_t is a monetary policy shock shown in the column headers. $\mathbf{W}_{i,t}$ includes the following control variables: $\Delta \log$ *bid-ask* $\textit{spread}_{i,t}$ is the log change in the monthly average relative bid-ask spread and $\Delta \log S_{i,t}$ is the log change in the spot exchange rate expressed as the number of foreign currency units per unit of US dollar. Both dependent and independent variables are measured in units of standard deviations. The test statistics based on double clustered (by currencies and time) standard errors, allowing for serial correlation up to 3 lags are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels. The sample spans from September 2012 to March 2024.

Table 12
Foreign currency loans in response to alternative monetary policy shocks.

	Kuttner (2001)	Kearns et al. (2022)			Jarociński and Karadi (2020)		Bauer and Swanson (2023b)	
		Target	Path	Long-rate	MP	CBI	NS	ORT
carry $\text{beta}_{i,t}$	−1.53*	−1.50*	−1.51*	−1.50*	−1.51*	−1.54*	−1.48*	−1.48*
	[1.94]	[1.89]	[1.87]	[1.87]	[1.89]	[1.95]	[1.86]	[1.81]
dollar $\text{beta}_{i,t}$	0.97*	0.94	0.94	0.93	0.93	0.96*	0.91	0.95
	[1.67]	[1.62]	[1.60]	[1.60]	[1.60]	[1.65]	[1.56]	[1.59]
carry $\text{beta}_{i,t} \times \text{MPS}_t$	0.21**	0.20**	0.16***	−0.14***	0.23*	0.14	0.22*	0.37***
	[2.36]	[2.24]	[4.29]	[2.69]	[1.83]	[0.96]	[1.84]	[4.35]
dollar $\text{beta}_{i,t} \times \text{MPS}_t$	−0.87***	−0.37	0.33***	−0.06***	−0.13	−1.13***	−0.65	0.24
	[2.82]	[1.16]	[4.68]	[2.69]	[0.25]	[3.62]	[0.94]	[0.36]
$\Delta \log S_{i,t}$	−0.02	−0.01	−0.03	−0.02	−0.02	−0.06	−0.01	−0.06
	[0.11]	[0.03]	[0.13]	[0.09]	[0.11]	[0.34]	[0.04]	[0.35]
Overall R^2 in %	62.73	62.69	62.68	62.67	62.69	62.77	62.71	62.77
Total # of Obs.	2727	2727	2727	2727	2727	2727	2727	2727
Avg. #Time periods	303	303	303	303	303	303	303	303
#Currencies	9	9	9	9	9	9	9	9
Currency FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time series FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports results from fixed effects panel regressions of the form $\log Loan_{i,t} = \mu_i + \alpha_t + \gamma X_{i,t} + \varphi(X_{i,t} \times MPS_t) + \gamma \Delta \log S_{i,t} + \epsilon_{i,t}$, where $\log Loan_{i,t}$ is the natural log of the dollar amount lent by global banks headquartered in the US to corporations domiciled abroad in currency i during month t. $X_{i,t}$ denotes either the *carry* $\textit{beta}_{i,t}$ or *dollar* $\textit{beta}_{i,t}$ that are based on rolling window regressions of currency returns on the carry and dollar factor, respectively. MPS_t is a monetary policy shock shown in the column headers. $\Delta \log S_{i,t}$ is the log change in the spot exchange rate expressed as the number of foreign currency units per unit of US dollar. The independent variables are measured in units of standard deviations. The test statistics based on double clustered (by currencies and time) standard errors, allowing for first-order serial correlation are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels. The sample spans from January 1999 to March 2024.

banks tend to react shortly after FOMC announcements in a predictable, systematic way and that this explains our results. For instance, if in response to an easing surprise central banks of high currency risk countries were to hike interest rates, whereas central banks of low-risk countries were to cut rates, then this could generate a similar pattern to the one in Fig. 3. Funds would be simply chasing expected risk-free returns, rather than taking on exposure to currency risk.

To test this alternative story, we predict foreign policy rate changes using changes in the Federal Funds target rate interacted with our currency risk exposures:

$$\Delta y_{i,t} = \mu_i + \alpha_t + \beta \Delta FFR_{t-1} + \gamma X_{i,t} + \varphi(X_{i,t} \times \Delta FFR_{t-1}) + \epsilon_{i,t}, \tag{13}$$

where the dependent variable is the change in the policy rate by the foreign central bank of country i at time t and ΔFFR_{t-1} is the change in the Federal Fund target rate last month. We include both country- and time-fixed effects μ_i and α_t, respectively.

Table 13 presents the results from estimating Eq. (13) and provides evidence against the alternative story. This is because the interaction coefficients are either statistically insignificant (columns 3, 4, and 5) or positive (column 2). When the Fed cuts rates, countries with higher carry exposures, like Australia, tend to cut more, all else equal; whereas countries with negative carry exposures, like Japan, tend to cut less or even raise rates. These patterns are opposite of what the alternative story would predict.

Table 13
Predicting foreign policy rates with Fed Fund rates.

	(1)	(2)	(3)	(4)	(5)
Δ FFR$_{t-1}$	0.22**	0.22**	0.23		
	[2.00]	[2.26]	[0.62]		
carry beta$_{i,t}$		−0.08**		−0.12*	
		[2.17]		[1.88]	
dollar beta$_{i,t}$			0.02		0.01
			[0.26]		[0.11]
carry beta$_{i,t}$ × Δ FFR$_{t-1}$		0.11**		0.07	
		[2.37]		[0.78]	
dollar beta$_{i,t}$ × Δ FFR$_{t-1}$			−0.01		0.03
			[0.02]		[0.07]
Overall R^2 in %	5.23	6.90	5.25	43.35	42.76
Total # of Obs.	2745	2745	2745	2745	2745
Avg. #Time periods	305	305	305	305	305
#Currencies	9	9	9	9	9
Currency FE	Yes	Yes	Yes	Yes	Yes
Time series FE	No	No	No	Yes	Yes

Note: This table reports results from monthly fixed effects panel regressions of the form $\Delta y_{i,t} = \mu_i + \alpha_t + \beta \Delta FFR_{t-1} + \gamma X_{i,t} + \varphi(X_{i,t} \times \Delta FFR_{t-1}) + \epsilon_{i,t}$, where the dependent variable is the change in the policy rate by foreign central bank i one period ahead and ΔFFR_t is the change in the Federal funds target rate. We include both country- and time-fixed effects μ_i and α_t, respectively. $X_{i,t}$ denotes either the *carry beta*$_{i,t}$ or *dollar beta*$_{i,t}$ that are based on rolling window regressions of currency excess returns on the carry and dollar factor, respectively. Both dependent and independent variables are measured in units of standard deviations. The test statistics based on double clustered (by currencies and time) standard errors, allowing for serial correlation up to 3 lags are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels. The sample spans from January 1999 to March 2024.

In the Online Appendix we document similar results for estimating Eq. (13) using interbank lending rates (e.g., LIBOR). A key difference is that the interaction coefficient are all statistically indistinguishable from zero, suggesting that lower interest rates in the US are not associated with significantly lower interbank lending rates in say Japan relative to Australia. We find similar results when studying contemporaneous correlations.

7.7. European monetary policy shocks

The evidence so far has focused on US monetary policy shocks and US dollar-based currency pairs. A natural question to ask is whether other central banks' monetary policy shocks matter for dollar-based currency flows and whether euro-based currency pairs respond similarly to monetary shocks from the European Central Bank (ECB).

We find no evidence for either of these two hypotheses. In particular, we replace US monetary policy shocks with ECB monetary policy shocks from Jarociński and Karadi (2020) and find that global currency flows are largely unresponsive to changes in European monetary policy. We interpret this as evidence that the Fed is leading the global financial cycle (Brusa et al., 2019; Miranda-Agrippino and Rey, 2020).

In Table 14 we replicate the results of Table 4 but replace dollar-based currency pairs with euro-based (e.g., EURCAD) ones and employ ECB monetary policy shocks from Jarociński and Karadi (2020) instead of Fed shocks based on Kuttner (2001). Our sample period is shorter due to the availability of the ECB monetary policy shock series. Euro-based pairs do not seem to respond systematically to ECB monetary policy shocks.

8. Conclusion

The transmission of monetary policy is a central question in economics and finance. A central bank's decisions are often made for the benefit of their own domestic economy, but countless studies have documented the spillover effects of central banks housed in large and developed markets having a material impact on the fortunes of other economies.

We study if the currency factor structure can provide a lens through which we can understand this international transmission and provide evidence in favor of this idea. First, we show that investment funds direct flows from low-risk to high-risk currencies in response to an unexpected easing of US monetary policy. Second, global US banks tilt their foreign currency lending toward currencies that are more exposed to the currency carry trade. Both facts are consistent with the risk-taking channel of monetary policy. Third, these currency flows and syndicated bank loans persist for several months. We track bank loans to firms' borrowing and investment, and therefore the real effects of monetary policy. These real effects are more pronounced in countries that have currencies that are more exposed to the carry factor such as Australia.

To the best of our knowledge, we are the first to show that US monetary policy is transmitted internationally through measures of systematic currency risk. Rather than being narrowly confined to explaining the risk, return, and co-movement of currencies, our evidence supports the view that the exchange rate factor structure can be used as a lens through which we can study the international transmission of US monetary policy.

We hope our findings spur work into similar ideas concerning other macroeconomic phenomena that can be simply and better understood through risk exposures that have been studied so extensively in the asset pricing literature.

CRediT authorship contribution statement

Erik Loualiche: Writing – review & editing, Writing – original draft, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Alexandre R. Pecora:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Fabricius Somogyi:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Colin Ward:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Table 14
Flow betas for euro currency pairs.

	Corporates	Funds	NBFIs	Non-dealer banks	Dealer banks	Carry beta	Euro beta
EURCHF	−0.22***	−0.12	−0.17*	−0.07	0.19*	−0.17	0.64
	[4.14]	[0.78]	[1.89]	[1.09]	[1.78]		
EURJPY	0.08	0.18	0.05	−0.22*	0.11*	−0.03	1.21
	[1.09]	[1.34]	[1.06]	[1.86]	[1.69]		
EURDKK	0.04	0.06	0.14	−0.16***	0.09*	0.00	0.01
	[0.23]	[0.89]	[1.52]	[2.79]	[1.81]		
EURGBP	−0.09	0.12	−0.07	−0.15*	0.11	0.10	0.99
	[1.01]	[1.63]	[0.85]	[1.84]	[1.38]		
EURSEK	−0.03	−0.07	0.01	0.12	−0.06	0.17	0.59
	[0.42]	[0.98]	[0.07]	[1.19]	[0.66]		
EURUSD	−0.10	−0.15	0.09	−0.04	0.16*	0.18	1.26
	[0.90]	[1.30]	[1.20]	[0.74]	[1.79]		
EURNOK	0.06	−0.07	0.04	0.03	0.02	0.33	1.10
	[0.71]	[1.12]	[0.71]	[0.40]	[0.35]		
EURCAD	−0.04	−0.21	0.15**	0.12*	0.02	0.45	1.49
	[0.82]	[0.94]	[2.33]	[1.91]	[0.12]		
EURAUD	0.02	−0.02	−0.12*	0.17	−0.14	0.68	1.71
	[0.23]	[0.21]	[1.93]	[1.37]	[0.93]		

Note: This table reports the β_{ij} regression coefficients from $OF(S_{ij,t}) = a_{ij} + \beta_{ij} MPS_t + \epsilon_{ij,t}$, where $OF(S_{ij,t})$ is the currency flow in €mn in currency pair i customer group j in month t and MPS_t is our monetary policy shock measure based on Jarociński and Karadi (2020). Both dependent and independent variables are measured in units of standard deviations. Currency pairs are sorted by carry betas in ascending order. By market clearing, the column labeled "Dealer banks" is equal to the sum of the first four columns times minus one. The last two columns report the average carry and euro beta that we compute based on rolling window regressions. For both the carry and euro factor (average exchange rate change against the euro) we are only using the nine euro-currency pairs displayed in the first column. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels. The numbers inside the brackets are the corresponding test statistics based on robust standard errors (Newey and West, 1987) correcting for heteroskedasticity and serial correlation up to 3 lags. The sample spans from September 2012 to October 2023.

Appendix A. Theoretical appendix

We present a simple model on the interaction between currency markets and the intermediation done by global banks to finance international firms. We abstract from household decisions, imperfections in capital markets, and issues of sovereign default risk. The sole friction is that currency markets are subject to constraints on intermediation.

Global intermediaries. Global intermediaries, which could be funds or banks, choose to supply capital to firms in different countries. There is a continuum of intermediaries of measure one, but not all may choose to enter. We describe the entry decision that determines the endogenous supply of intermediation capacity below.

Following Itskhoki and Mukhin (2021), each intermediary has constant absolute risk aversion with risk aversion parameter $\gamma > 0$. An intermediary solves an allocation problem for N different countries, each with their own currency. Within each country, intermediaries diversify across a continuum of measure one of firms that operate in riskless and perfect markets. Consequently, the relative supply of equity or debt does not matter (Modigliani-Miller holds) for a particular firm in a particular country.

Intermediaries' choice to supply capital, $\mathbf{s} \in \mathbb{R}^N$, can have both positive and negative elements, reflecting an increase or a decrease in the net supply of funding to a country. Intermediaries can borrow at their domestic risk-free rate, r, and invest risk-free in a foreign firm, which pays r_i^K. This return on foreign capital is endogenized below. The only source of uncertainty that intermediaries face stems from the currency risk. The realized currency excess return of supplying one unit of capital is

$$R_i^e = r_i^K - r + \Delta e_i \tag{14}$$

Following Verdelhan (2018), we posit that exchange rates follow a factor structure, that is, the return of investing in currency i is

$$\Delta e_i = \beta_i' f + \epsilon_i \tag{15}$$

where $f \in \mathbb{R}^F$ represents F globally priced risk factors that affect currency returns and $\boldsymbol{\beta}_i$ summarizes currency i's exposure to these factors. These betas are constant, as are the prices of risk of the factors. The systematic components are determined by the country's characteristics, like its GDP or interest rate. The idiosyncratic component ϵ_i has zero mean and reflects country-level risk.

We further assume that both f and ϵ_i are normally distributed with variances $\Sigma_f \in \mathbb{R}^{F\times F}$ and σ_i^2, respectively. Furthermore, we define $\mathbb{E}[\mathbf{R}^e] = (\mathbb{E}[R_1^e], \ldots, \mathbb{E}[R_N^e])'$ and $\Sigma = \mathbb{E}\left[(\mathbf{R}^e - \mathbb{E}[\mathbf{R}^e])(\mathbf{R}^e - \mathbb{E}[\mathbf{R}^e])'\right]$, as the expected excess return and its variance.

The intermediary chooses the supply of intermediation capacity according to the following problem:

$$\max_{\mathbf{s}} V = \mathbb{E}\left[-\frac{1}{\gamma}\exp\{-\gamma \mathbf{s}'\mathbf{R}^e\}\right]. \tag{16}$$

The optimization problem has the following solution:

$$\mathbf{s} = \frac{1}{\gamma}\Sigma^{-1}\mathbb{E}[\mathbf{R}^e]. \tag{17}$$

The intermediaries trade off risk and return, accounting for the covariance across currencies. Risk aversion therefore acts as a constraint on intermediaries' supply of funds. Gabaix and Maggiori (2015) use limited commitment to constrain the supply of intermediation, whereas Vayanos and Vila (2021) use risk aversion.

Intermediary entry decision. We follow Gabaix and Maggiori (2015) to endogenize the supply of intermediation capacity. We posit that intermediaries decide to enter immediately after the central bank changes the short rate and before the excess return is known. The potential intermediary j enters if and only if $V \geq \kappa_j$, where κ_j is a cost drawn from a distribution with the cumulative distribution function $\mathrm{CDF}(x) = \mathbb{P}(\kappa_j \leq x)$.[18] This implies that the mass of intermediaries that chooses to enter, w, is

$$w = \mathrm{CDF}(V) \tag{18}$$

An unexpected easing lowers r and because $\partial\mathbb{E}[\mathbf{R}^e]/\partial r < 0$, the fall in r raises the expected excess return. There are two interpretations to this.

[18] The cost could be psychological in the sense that some intermediaries inherit a larger stock of knowledge on foreign economies and so can afford to invest less in information acquisition.

First, a simple discounting argument indicates that the present value of the intermediated return will grow with a lower domestic discount rate. Second, this could arise as the marginal cost of risk-bearing capital, which is typically funded in short-term and often overnight markets, has declined. The optimal response, in equilibrium, would be to raise the amount of capital at risk to the point where its marginal benefit is reduced to equal its marginal cost. Both of these interpretations imply that w is decreasing in r.

Since all intermediaries choose the same $\mathbf{s}$, the total supply of intermediated funds is

$$\frac{w}{\gamma}\Sigma^{-1}\mathbb{E}[\mathbf{R}^e]. \tag{19}$$

For a given Σ and $\mathbb{E}[\mathbf{R}^e]$, the *effective risk aversion* is given as (γ/w): more intermediated capital effectively lowers risk aversion. Thus, the decline in risk aversion caused by an unexpected easing can be interpreted as arising from a downward-sloping demand curve for risk-bearing by financial intermediaries. Note that a similar mechanism operates in Itskhoki and Mukhin (2021).

Furthermore, Oskolkov (2025) shows that under ambiguity aversion, an intermediary's behavior can be described as being subject to a value-at-risk (VaR) constraint. This is because the VaR of a given trading position increases with the likelihood of adverse scenarios, on which ambiguity aversion would place a greater weight. In this sense, more intermediation capacity w in our model can be also interpreted as a relaxation of an intermediary's VaR constraint. Hence, a reduction in a central bank's policy rate would be consistent with a reduced likelihood of adverse scenarios, a smaller VaR, and a greater capacity all else equal to take on risk, all of which are consistent with the "risk-on" language used in our paper.

Firms' investment. In each country i, there is a continuum of firms of measure one, each indexed by j. Firms raise capital from intermediaries to finance production that has decreasing returns to scale. Firms are charged a rental cost of capital denoted by r_i^K. Each firm's problem and capital decision are given by (omitting subscripts i and j):

$$\max_k \; k^\alpha - r^K k \Rightarrow k = \left(\frac{\alpha}{r^K}\right)^{\frac{1}{1-\alpha}} \tag{20}$$

Total capital raised by country i's firms is therefore $K_i = \int_0^1 k_{ij}\,dj = \left(\frac{\alpha}{r^K}\right)^{\frac{1}{1-\alpha}}$.

Equilibrium. Intermediaries supply capital subject to foreign exchange rate risk and firms use this capital to produce goods and services. The equilibrium rental costs, $\mathbf{r}^K = (r_1^K, \ldots, r_N^K)'$, of capital satisfies the following set of N equations:

$$\underbrace{\theta_0^S + \frac{w}{\gamma}\Sigma^{-1}\mathbb{E}[\mathbf{R}^e]}_{\text{Supply}} = \underbrace{\theta_0^D - \theta K_i(\mathbf{r}^K)}_{\text{Demand}}, \tag{21}$$

where θ_0^i are intercepts that stand for other sources of supply and demand that are not in the model, for both supply ($i = S$) and demand ($i = D$) of intermediated capital; θ is the slope of demand.

This is the key equation. It creates a link between monetary policy rates, intermediated capital characterized by systematic currency risk, and the return on invested capital across countries. It is thus an equilibrium restriction on capital flows subject to foreign exchange rate risk.

Numerical example. We use our currency data for the G10 currencies (9 currencies against the US dollar) for monthly data from January 1999 to March 2024 for Australia, Canada, Euro area, Japan, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom. The covariance matrix and expected currency excess return vector are estimated from excess returns over the full sample. We report the average expected excess *currency* return and its covariance matrix below, both multiplied by 12×100 (see the equations in Box I).

Table A.1
Model calibration and comparative statics.

Panel A: Calibration		
Parameter	Value	Interpretation
γ	3	Risk aversion
$U(a,b)$	$U(-0.334, -0.284)$	CDF$(\cdot)$ is uniformly distributed
α	1/3	Decreasing returns to capital
$\theta_0^S - \theta_0^D$	35	Difference in intercepts of supply and demand
θ	2	Slope of the demand curve
r	0.045	Domestic interest rate
Panel B: Comparative statics illustration		
Pre-shock	Post-shock	Variable
8.66	11.64	Norm of supply per intermediary, $\mathbf{s}$
0.5	0.937	Intermediary capital, w

Note: This table reports the model calibration in Panel A. In Panel B the pre-shock and post-shock values of two variables are reported following a 25 basis point decline in the domestic interest rate.

Given these estimates of Σ and $\mathbb{E}[\mathbf{R}^e] = r^K - r + \mathbb{E}[\mathbf{R}^e_{FX}]$ and our calibration, we solve for $\mathbf{s}$ by finding the fixed point in Eq. (21) that solves for the equilibrium vector $\mathbf{r}^K$. We tabulate our calibration in Table A.1.

To mimic "risk-on" sentiment in financial markets, we add 25 basis points (bps) to the expected currency excess return vector and call the equilibrium solution $\mathbf{s}'$. Note that the norm of $\mathbf{s}'$ is greater than the norm of $\mathbf{s}$, indicating the average position is larger, consistent with more capital at risk.

Looking at Fig. A.1, the top-left figure shows the initial distribution of financial intermediaries' capital supply across countries, $\mathbf{s}$. We see that, ex ante, currencies with greater expected excess returns receive more capital, and vice versa. In the top-right panel, we show that the average currency excess returns align well with carry betas, consistent with the risk-based view of currency markets.

In the bottom-left panel, we implement our 25 bps decline and we see positive demand changes for countries that have currencies that are more risky with respect to the carry factor, like New Zealand. Conversely, countries with low currency risk, like Sweden, tend to see negative changes in demand to or outflows from their currencies. In sum, an unexpected easing of US monetary policy is associated with a "risk-on" sentiment in financial markets that corresponds to intermediaries selling out of low-risk currencies and increasing their positions in high-risk currencies.

The bottom-left panel connects these changes in currency flows to changes in the required return on capital. We see that currencies that experience a supply inflow also see a decline in their required return. Because firms' capital choice k increases when r^K falls, then this also increases their investment $(k' - k)$, as we see in the data.

Appendix B. DealScan data appendix

This section describes how we clean the DealScan loan data to derive our final sample, which we then merge with Compustat Global and NA using the linking table by Michael R. Roberts (all data are available via WRDS).[19] After loading the raw DealScan data from June 15, 1981 until March 31, 2024 we remove duplicate observations by filtering for unique observations at the `Lender_Id`, `Borrower_Id`, `LPC_Deal_ID`, `Deal_Input_Date`, `Deal_Active_Date`, `LPC_Tranche_ID`, and `Tranche_Active_Date` level. The original raw dataset has 3,150,264 rows (each row is one observation) and we are left with 2,835,262 observations after this filtering (i.e., we lose 315,002 observations). Note that the classification into parent bank (i.e., bank holding company) and subsidiary is done by k DealScan and there are separate fields provided for `Lender_Operating_Country` and `Lender_Parent_Operating_Country`, respectively.

[19] See https://wrds-www.wharton.upenn.edu/ (accessed on March 31, 2026).

$$\mathbb{E}[\mathbf{R}^{e}_{FX}] \times 1200 = \begin{bmatrix} 1.760 \\ 0.536 \\ -0.062 \\ -1.040 \\ -0.744 \\ -3.354 \\ -0.708 \\ 2.468 \\ -1.664 \end{bmatrix} \begin{pmatrix} \text{AUD} \\ \text{CAD} \\ \text{CHF} \\ \text{EUR} \\ \text{GBP} \\ \text{JPY} \\ \text{NOK} \\ \text{NZD} \\ \text{SEK} \end{pmatrix}$$

$$\Sigma \times 1200 = \begin{bmatrix} 0.924 & 0.448 & 0.365 & 0.440 & 0.363 & 0.125 & 0.612 & 0.765 & 0.596 \\ 0.448 & 0.397 & 0.176 & 0.231 & 0.221 & 0.041 & 0.356 & 0.363 & 0.322 \\ 0.365 & 0.176 & 0.609 & 0.496 & 0.330 & 0.265 & 0.469 & 0.392 & 0.490 \\ 0.440 & 0.231 & 0.496 & 0.588 & 0.379 & 0.206 & 0.532 & 0.436 & 0.573 \\ 0.363 & 0.221 & 0.330 & 0.379 & 0.526 & 0.108 & 0.425 & 0.382 & 0.422 \\ 0.125 & 0.041 & 0.265 & 0.206 & 0.108 & 0.621 & 0.173 & 0.125 & 0.203 \\ 0.612 & 0.356 & 0.469 & 0.532 & 0.425 & 0.173 & 0.840 & 0.542 & 0.642 \\ 0.765 & 0.363 & 0.392 & 0.436 & 0.382 & 0.125 & 0.542 & 0.945 & 0.567 \\ 0.596 & 0.322 & 0.490 & 0.573 & 0.422 & 0.203 & 0.642 & 0.567 & 0.767 \end{bmatrix}$$

Box I.

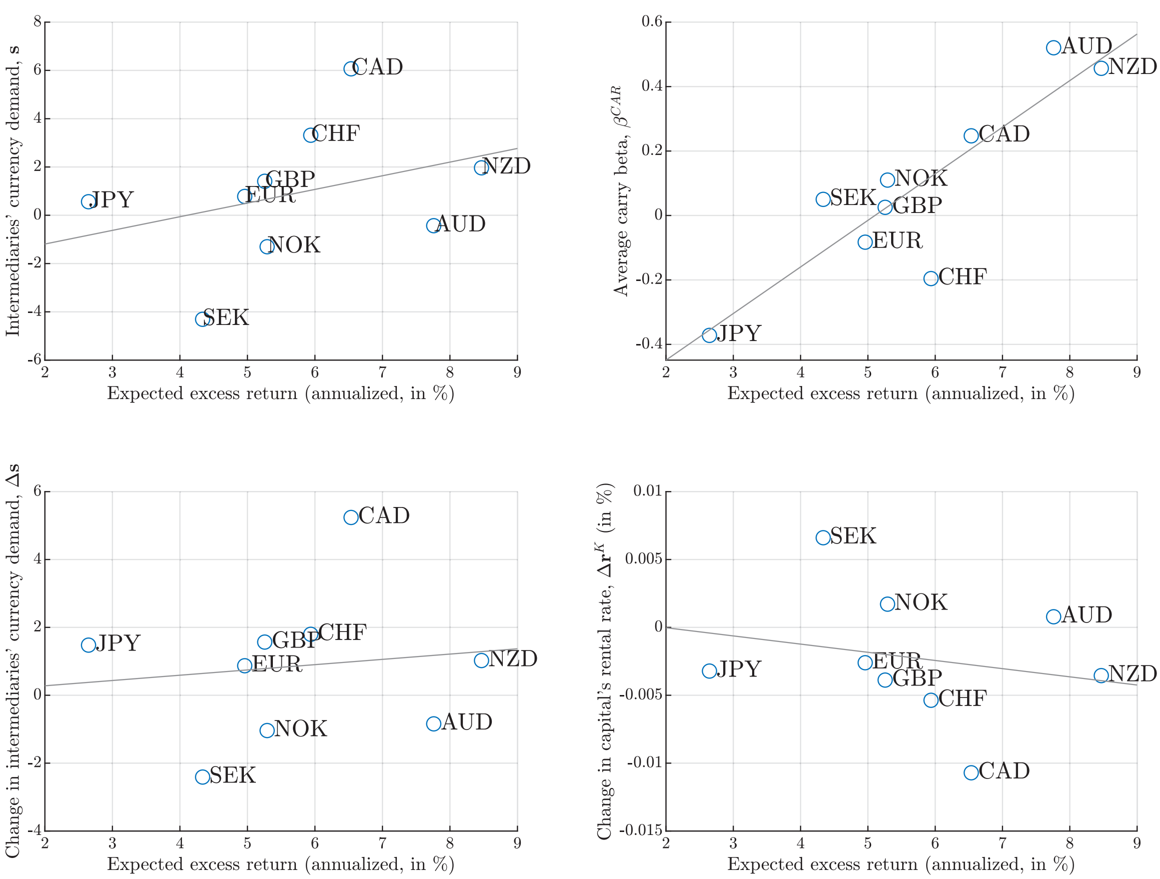

Fig. A.1. Equilibrium following a 25 bps decline in the Fed Funds rate.
Note: All x-axes are the model's pre-shock equilibrium excess returns on capital. The top-left figure plots intermediaries' capital supply across countries, **s**. The top-right figure scatters the average carry betas in the data. The bottom two panels illustrate the comparative statics in response to subtracting 25 basis points from the domestic interest rate r. The bottom-left panel shows the change in demand $w's' - ws$ and the bottom-right panel shows the change in equilibrium excess returns.

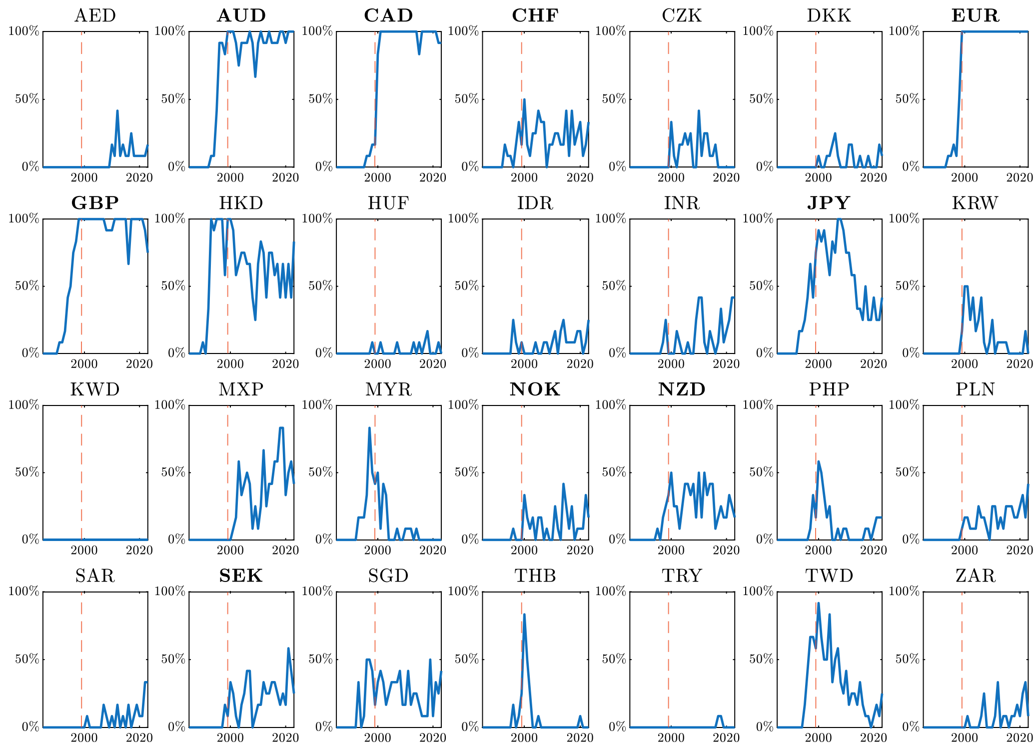

Fig. B.1. DealScan data coverage over time and currencies.
Note: This figure summarizes the share of non missing loan-month observations in the DealScan data. A loan-month observations is the sum of loans aggregated across all global US banks within a given currency. A share of 100% (0%) implies that in every given month within a year there was at least one (not a single) syndicated loan that involved at least one global US bank. The dotted red line corresponds to the year 2000. The sample is yearly and spans from 1988 to 2023.

Next, we apply the following additional filters based on Bräuning and Ivashina (2020a) in the following order:

1. Focus on *originations* only, that is, we only look at tranches that are new loan *originations* (i.e., Tranche_O_A equals "Origination") and we ignore any loan *amendments*. We lose 728,808 observations.
2. Remove any lender types that are *participants* (i.e., we remove observations for which Primary_Role equals "Participant"). We keep all other lender types (e.g., lead arranger, bookrunner, co-arranger, etc.). We lose an additional 685,065 observations.
3. We remove any observations for which either the Tranche_Amount_Converted or Deal_Amount_Converted is missing, equal to zero, less than zero (i.e., negative) and we also remove observations for which Tranche_Amount_Converted exceeds the Deal_Amount_Converted. We lose an additional 19,177 observations.

After applying the three filters above we are left with 1,402,212 observations. Next, we compute the number of lenders per Tranche and we do so at the Borrower_Id, Borrower_Country, Tranche_Active_Date, Deal_Active_Date, LPC_Tranche_ID, and Deal_Currency level. We use the number of lenders per tranche to pro-rate the tranche amount equally across lenders. For instance, if a given tranche involves four lenders, we would attribute 25% to each of them and hence, the Lender_Share would be equal to 25% for this particular tranche. A concrete example of this is LPC_Tranche_ID 486086 consisting of the following four lenders: ISP, Credit Agricole CIB, Banco BPM SPA, and BPER Banca Spa. Note that the variable Lender_Share is missing for about 70% of all observations in our sample.

To identify the portion of the tranche that is intermediated by global US banks we multiply the Lender_Share with the Tranche_Amount_Converted, and a dummy that equals one if either Lender_Operating_Country or Lender_Parent_Operating_Country equals "United States". We call this variable "Loan_Amount_US" and use the monthly aggregate version of this for our analysis in Section 5, that is, we aggregate Loan_Amount_US within a given month across all syndicated loans and US lenders. For concreteness, consider LPC_Tranche_ID #484505 consisting of 8 lenders (4 global US banks and 4 foreign banks): Royal Bank of Canada, BNP Paribas SA, Deutsche Bank AG, Sumitomo Mitsui Banking Corp, JP Morgan, Morgan Stanley, Goldman Sachs & Co, Bank of America NA. The total tranche amount is 4200 mn euros, with half of it being attributable to global US banks.

In the penultimate step, we exclude any tranches for which the Borrower_Name or Borrower_Id is not unique, losing an additional 98 observations (the sample has now 1,402,114 rows).

In the final step, we aggregate the DealScan loan data to the deal level, that is we aggregate the data to the Borrower_Name, LPC_Deal_ID, Tranche_Active_Date, Tranche_Currency level by summing up Loan_Amount_US across tranches within a given "deal". After this aggregation our dataset has 257,437 rows, where each row corresponds to approximately one "deal".[20] Within the same step we also compute the average interest rate margin within a given deal by computing both equal and tranche amount weighted averages across tranches within a given "deal". Lastly, to merge the DealScan loan data with balance sheet information from Compustat we aggregate the Loan_Amount_US to the quarter-borrower-currency level.

Fig. B.1 visualizes the coverage of the DealScan loan data across currencies and over time. Specifically, the figure shows the share of months

[20] The reason why this is only approximately the case is because some deals have tranches issued in different currencies and within a given deal there is often heterogeneity across tranche active dates.

with non-zero loan observations (i.e., monthly `Loan_Amount_US` is positive) for every year from 1988 to 2023. There is a clear structural break in terms of data coverage around 2000. Take for instance the Pound sterling (GBP) or the Japanese Yen (JPY): it appears quite implausible to believe that US banks have not been syndicating loans in these currencies prior to 2000; instead, we believe that this reflects the sparse reporting of the loan data.

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