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RISK AND SPECIALIZATION IN COVERED-INTEREST ARBITRAGE

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ABSTRACT

Prevailing theories of financial intermediation assume an integrated financial sector with frictionless risk-sharing. However, we identify substantial risk-sharing frictions linked to intermediary specialization using the cross-section of covered-interest parity (CIP) deviations as a laboratory. Obtaining confidential supervisory data covering $25 trillion in daily bank exposures, we document that CIP arbitrage is risky for banks, which take on maturity mismatches and purchase risky assets to hedge their currency exposure from derivatives. These risks lead intermediaries to specialize in markets where they have expertise in managing them. Our results highlight the importance of intermediary specialization and its impact on risk premia.

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Introduction

A substantial body of work following the 2008 financial crisis highlights that financial intermediaries and the frictions they face may have a significant impact on asset prices and the broader economy. The predominant assumption made in prior work is that the financial sector is integrated, with intermediaries freely operating across markets and sharing risks. The validity of this assumption is central to understanding the effects of intermediation frictions on asset prices. For example, limited intermediary participation may increase the price impact of investor demand by limiting risk-sharing and creating market power. Additionally, specialization may disconnect prices across markets, and make a given market more susceptible to the idiosyncratic shocks of its specializing intermediaries.

In this paper, we show that the intermediary sector is not fully integrated, and identify the causes and consequences of the lack of integration by leveraging a confidential supervisory dataset on banks' balance sheets that covers over $25 trillion in daily exposures. We focus our study on covered-interest parity (CIP), a primary testing ground for showcasing the importance of financial intermediaries.[1] A riskless CIP arbitrage trade works as follows: to meet foreign customer demand to borrow dollars, an intermediary borrows dollars, enters into a foreign exchange swap with the customer to exchange the dollars for foreign currency, and invests the proceeds in foreign safe assets. At maturity, the intermediary receives dollars from the customer and repays the initial dollar loan. Under CIP, the return on this transaction should be zero. Most studies test and reject that CIP bases are zero and relate non-zero bases to measures of intermediary frictions (Du et al. (2018), Iida et al. (2018), Cenedese et al. (2021), Wallen (2022), Du and Schreger (2022), Augustin et al. (2022)).

Using our unique supervisory data, we closely study banks' behavior with respect to CIP arbitrage, and examine quantities as well as prices in the arbitrage trade. We document two important departures from the assumptions underlying prior work. First, banks bear substantial risk in their CIP trades by purchasing risky assets and maturity-mismatched

[1] There are several other types of 'basis' trades that seek to profit from price dislocations of assets with (nearly) identical cash flows, including the equity index futures/cash basis (Hazelkorn et al., 2023), the Treasury on-the-run/off-the-run spread (Krishnamurthy, 2002), the Treasury cash/futures basis (Barth and Kahn, 2021), the Treasury cash/swap basis (Jermann, 2020; Boyarchenko et al., 2018b), the bond/CDS basis (Bai and Collin-Dufresne, 2019), and the CDX/CDS basis (Boyarchenko et al., 2018c). We focus on CIP deviations, or "bases", because our data provide detailed bank exposure information to specific countries' interest rates and currencies, allowing a granular examination.

safe assets corresponding to their synthetic dollar lending to customers. This fact stands in contrast to the textbook assumptions of riskless CIP arbitrage, where intermediaries offset their synthetic lending with maturity-matched safe assets. Second, banks specialize in markets where they have strong counterparty relationships and large loan books; that is, where they are best able to manage risk. Specialization induces market segmentation and also makes CIP bases more inelastic to demand via reduced risk sharing. Our results highlight the presence, causes, and consequences of intermediary specialization for asset prices in even the largest and most liquid markets.

To guide our empirical investigation, we begin our analysis with a stylized model where risk-averse intermediaries meet customers' demand for dollars in exchange for foreign currency by engaging in basis trades, but face several frictions: costs to expand their balance sheets, search costs for safe bonds, and heterogeneous expertise in managing risks in different markets.

The model showcases how each friction contributes to CIP bases. Balance sheet costs drive a common component of bases across currencies, which is the primary focus of the prior literature. However, the other frictions we model have an impact too, and also capture cross-sectional heterogeneity in bases, a puzzling feature of the data for prior work. Search costs for safe bonds lead banks to hold either maturity-matched risky assets or safe assets at mismatched tenors, introducing risk. In turn, we observe differences in bases across currencies based on the amount of synthetic dollar borrowing demand from those currencies. The presence of risk in CIP arbitrage and heterogeneous expertise in managing that risk lead intermediaries to specialize in markets where they have expertise. This specialization induces price inelasticity, so that a given increase in customer demand produces a larger price impact due to reduced risk sharing. The frictions we highlight vary across banks and markets, contributing to cross-sectional variation that we use to identify the relevant effects.

To test the model's implications, we use the Federal Reserve's FR2052a *Complex Institution Liquidity Monitoring Report*, which provides granular, high-frequency data on the balance sheets of the largest banks in the US. The data cover \$25 trillion of daily notional exposure on average. Because the report provides detailed snapshots of derivative exposures as well as the asset and liability sides of banks' balance sheets, we obtain a view of the otherwise opaque positioning of intermediaries in currency markets. Analyzing the data, we find that banks net lend about \$100 billion on average through swaps in the markets we study, indicating their importance in meeting global demand for dollar funding. Moreover, we show that banks synthetically lend the most dollars precisely where bases indicate that dollar funding is costliest, consistent with the banking sector facing increasing marginal costs to meet dollar demand. Guided by our model, we empirically investigate how the outlined frictions contribute to these increasing marginal costs.

Our first main result is that banks have a foreign safe asset mismatch in their CIP trades, which introduces risk. To execute CIP basis arbitrage, an intermediary must hold the equivalent of $1 of maturity-matched foreign safe assets for every $1 it lends in order to earn the foreign risk-free rate. In practice, however, banks hold $0.07 per dollar lent when matching maturities perfectly. Even under a generous definition of maturity-matched safe assets that ignores counterparty risk and permits small maturity mismatches, banks hold only $0.30 of foreign "safe" assets per $1 lent. As we further document, a significant component of intermediaries' currency exposure is hedged with maturity-mismatched safe assets and with risky assets. We attribute this foreign safe asset mismatch to search costs. Consistent with this channel, we find that intermediaries have lower safe asset ratios when bonds of a given currency and maturity are in short supply, and accordingly are more difficult to locate.

In terms of magnitudes, we find that a one-standard-deviation change in dollar borrowing demand increases the magnitude of the basis by 4 to 9 bps, without accounting for any cross-currency differences in banks' abilities to access maturity-matched foreign safe assets. In addition, there are differences in the cost of locating maturity-matched safe assets across currencies. We capture this cost using cross-currency variation in the number of dollars of foreign safe assets held per dollar of swap exposure, which we call the *safe asset ratio*. We find that a one-standard-deviation difference in the safe asset ratio corresponds to a further increase in the basis of 9 to 16 bps.

Our second main result is that financial intermediaries specialize in different currency markets. This specialization causes risk to concentrate on the balance sheets of particular intermediaries. We measure the degree of concentration in a given market, defined as a tenor × currency pair, by the Herfindahl-Hirschman Index (HHI) of bank exposures. Using the HHI measures, we find that the effective number of banks, the number of equal-share banks that would generate the observed HHI, is around three. Given our sample consists of nine banks, the HHI measures indicate the presence of substantial concentration.

Our model predicts that more concentrated markets should have larger bases per unit of demand, stemming from reduced risk-sharing. We find a strong relationship between a market's concentration measured by HHI and the size of its basis: a one-standard-deviation more concentrated market has a 13 to 17 bps larger basis. Combined with our results on safe asset mismatch, the relationship between risk concentration and bases highlights the importance of risk and intermediaries' imperfect risk-sharing as drivers of CIP deviations. These effects may also be further amplified by market power.

We next provide evidence that banks' specialization is driven by their expertise in managing risk. We show that specialization is persistent, with market shares displaying persistence and more concentrated currency markets remaining so over time. Moreover, we show that banks specialize in counterparty segments. For example, a bank might specialize in Canadian insurance counterparties, while another may cater to Asian sovereign wealth funds. We also show that banks hold more loans in the currencies in which they have large currency market shares in FX swap markets. These results suggest that banks developed market-specific expertise from persistent activity and a more readily available set of counterparties. Finally, we test a unique implication of specialization driven by expertise in managing risk: intermediaries with higher market shares hold fewer foreign safe assets per dollar of net lending, because substituting away from safe assets is less risky for them. Analyzing the safe asset holdings of intermediaries, we confirm this prediction in the data.

We conclude our analysis by discussing a final implication of intermediary specialization—segmentation. Segmentation implies that bases for a given market should reflect the risk-bearing capacity of its specializing banks, and not of the overall intermediary sector. We use the March 2023 banking turmoil induced by the Silicon Valley Bank (SVB) run as a natural experiment that caused a notable shift of deposits toward the largest U.S. banks. We find that currency markets intermediated by banks with comparatively larger deposit inflows from this shock had comparatively smaller basis dislocations, consistent with these intermediaries' risk-bearing capacities being less impaired. This result matches the model's prediction regarding the transmission of idiosyncratic shocks.

Our results highlight the causes and consequences of intermediary specialization in covered-interest arbitrage. We link this specialization to the fact that banks take on maturity mismatches and invest in risky assets with the foreign cash from their forward trades, contrary to the riskless trade assumed by traditional theories. We show that specialization is driven by banks having heterogeneous expertise in managing risk across markets.

The rest of the paper is organized as follows. Section 1 discusses the relevant literature and where our paper fits in. Section 2 presents our stylized model of intermediation and CIP deviations, which guides and interprets our empirical investigation. Section 3 highlights the unique supervisory data we explore and other data to identify the channels driving CIP deviations. Section 4 presents our empirical tests and results focusing on the cross-sectional variation in bases. Section 5 analyzes intermediary specialization and uses the Silicon Valley Bank run as an experiment to identify the impact of financial constraints on bases arising from segmentation. Section 6 concludes.

1 Related Literature

Our work is closely related to work on segmentation and specialization in financial markets. Prior work documents evidence of segmentation in asset markets by studying the transmission of idiosyncratic, bank-specific constraints into asset prices (e.g., Rime et al. (2022); Siriwardane et al. (forthcoming); Kloks et al. (2023)), and contemporaneous works studying intermediaries' behavior in options markets (Bryzgalova et al. (2025)) and across stocks, bonds, and derivatives (Wittwer and Uthemann (2025)) present evidence of specialization. We find a similar result for CIP deviations, but importantly, we leverage supervisory regulatory data to shed light on the sources of intermediary specialization. We find that CIP arbitrage is risky and intermediaries specialize in the markets where they have expertise in managing these risks. Our results support the predictions of theoretical models of investor specialization due to market-specific expertise (e.g., Glode and Opp (2020), Eisfeldt et al. (2023)).

Our work also relates to the literature on CIP deviations (Du et al. (2018), Iida et al. (2018), Cenedese et al. (2021), Wallen (2022), Du and Schreger (2022), Augustin et al. (2022)) and bank-intermediated arbitrage spreads (e.g., Garleanu and Pedersen (2011), Pasquariello (2014), Boyarchenko et al. (2018a), Andersen et al. (2019), Anderson et al. (forthcoming), Foley-Fisher et al. (2020)). Previous work focuses primarily on increased bank funding costs that give rise to CIP deviations following the 2008 financial crisis, for example, due to banking regulation (Du et al. (2018)) or debt overhang frictions associated with the expansion of bank balance sheets (Andersen et al. (2019)). Our work instead sheds light on the asset side of intermediaries' basis trades using supervisory data. We document that, in contrast to the assumptions surrounding textbook CIP arbitrage, intermediaries do not invest in maturity-matched safe assets in the foreign cash legs of their trades; instead, they invest in higher-yielding, risky assets or maturity-mismatched safe assets, both of which introduce risk. This finding complements those of Diamond and Van Tassel (forthcoming), who suggest that convenience yields on foreign safe assets may help explain CIP bases; and those of Liao (2020), who documents a strong relationship between CIP deviations and differences in corporate credit spreads across currencies. Our results are also related to Du et al. (2023a), who find that the security holdings of the banking and insurance sectors in the Euro-area far exceed the amount of government debt, with institutions tilting their portfolios towards risky corporate debt.

Lastly, our paper contributes to the broader literature on intermediary asset pricing (Brunnermeier and Pedersen (2009), He and Krishnamurthy (2013), Adrian et al. (2014), Gabaix and Maggiori (2015), He et al. (2017), and Du et al. (2023b)) that emphasizes the intermediary sector's marginal utility as a state variable determining asset risk premia, due to households' limited participation in asset markets. Our findings indicate that limited participation is present even within the intermediary sector itself, and suggest that the marginal utilities of *specializing* intermediaries contribute to market risk premia.

2 Model

We present a stylized model to organize and interpret our empirical investigation. The model yields predictions regarding the drivers of CIP deviations and intermediaries' investment positions, and illustrates the contributions of various frictions to bases.

2.1 Setup

There are N_k foreign currencies, indexed by $k \in \{1, 2, \ldots, N_k\}$. For each currency k in period t, the spot exchange rate is $S_{k,t}$ (units of currency k per U.S. dollar) and the one-period forward rate is $F_{k,t}$ (with $log(S_{k,t}) = s_{k,t}$ and $log(F_{k,t}) = f_{k,t}$).

There are two types of investors: N_i *financial intermediaries*, indexed by $i \in \{1, \ldots, N_i\}$; and a mass of customers. All investors invest in period t and realize payoffs in period $t+1$.

For each currency k, three instruments trade: (i) a risk-free bond with gross return $1+y_{k,t}$; (ii) a risky bond with gross return $1 + r_{k,t}$, where $\mu_k \equiv \mathbb{E}_{t-1}(r_{k,t}) \geq y_{k,t}$; and (iii) a currency forward in zero net supply, trading at $F_{k,t}$. U.S. Treasury bonds supply a gross return $1 + y_{\$,t}$.

The (log) basis is

$$\text{Basis}_{k,t} = \Big(f_{k,t} - s_{k,t}\Big) - \Big(y_{k,t} - y_{\$,t}\Big). \tag{1}$$

The basis is the difference between the dollar interest rate and the synthetic dollar interest rate.

Customer Demand for Currency Forwards and the Basis. Customers trade only forwards and exogenously demand $X_{k,t}$ forward contracts of currency k in period t. A positive $X_{k,t}$ indicates that customers are synthetically borrowing dollars in period t.

Intermediaries' Foreign Bond Positions. Intermediaries meet customer demand for currency forwards in aggregate, and intermediary i takes a position of $Z_{i,k,t}$ in market k.

Intermediaries are constrained to invest the cash received from selling forwards in currency k into bonds of that currency, so they take no currency risk. They can choose to invest in the safe or risky bonds of currency k.

There is a sufficient supply of safe bonds for intermediaries to invest in, but each intermediary i faces a total search cost of $\frac{1}{2}\lambda_{s,k}s_{i,k}^2$ to locate safe bonds in currency k, where $s_{i,k}$ is the safe bond position of intermediary i in currency k and $\lambda_{s,k}$ is a coefficient that captures how quickly search costs increase in currency k. That is, safe bonds in currency k become increasingly difficult to locate as demand for them increases.

Intermediaries may also take positions in risky bonds of each currency, in perfectly elastic supply. In the context of our empirics, these risky bonds can be thought of as maturity-mismatched bonds or bonds with default risk. Intermediary i faces an idiosyncratic payoff variance of $\sigma_{i,k}^2$ when purchasing risky bonds in currency k. We define intermediary i's *expertise* in market k as $\pi_{i,k} \equiv \sigma_{i,k}^{-2}$. Intermediaries with higher expertise face less risk when substituting away from safe bonds in the cash legs of their basis trades. This market-specific expertise can be interpreted as reflecting, for example, more precise information about a given market, access to counterparties, or trade execution capabilities (Glode and Opp (2020), Eisfeldt et al. (2023)).

Intermediaries' Problem. Each intermediary i has mean-variance utility over its period $t+1$ wealth, given by $\mathbb{E}_t(W_{i,t+1}) - \frac{\gamma_i}{2}\mathbb{V}_t(W_{i,t+1})$, where $W_{i,t+1}$ is the wealth of intermediary

i in period $t+1$, $\mathbb{E}_t(\cdot)$ and $\mathbb{V}_t(\cdot)$ are the expectations and variance operators, and γ_i is a coefficient that captures the risk-bearing capacity of intermediary i.

In addition to risk and return considerations and the search costs that they pay for safe bonds, each intermediary i faces costs to expand its balance sheet (e.g., because of regulation or debt overhang), of the form $\frac{1}{2}\lambda_{BS}\left(\sum_k |Z_{i,k,t}|\right)^2$.

We can then write the objective function that intermediary i maximizes as

$$\mathbb{E}_t W_{i,t+1} - \frac{\gamma_i}{2}\mathbb{V}_t W_{i,t+1} \qquad \text{(Risk and Return)}$$
$$- \tfrac{1}{2}\,\lambda_{BS}\Big(\sum_{k=1}^{N_k} |Z_{i,k,t}|\Big)^2 \qquad \text{(Balance Sheet Costs)}$$
$$- \frac{\lambda_{s,k}}{2}\sum_{k=1}^{N_k}((1-\alpha_{i,k})Z_{i,k,t})^2 \qquad \text{(Safe Asset Search)}$$

Equilibrium. In equilibrium, all forward markets clear: $\sum_i Z_{i,k,t} + X_{k,t} = 0, \forall k$.

Intermediaries' Positions and Expression for the Basis. A first-order log approximation yields

$$W_{i,t+1} \approx \sum_{k=1}^{N_k} Z_{i,k,t}\Big[\text{Basis}_{k,t} - \alpha_{i,k,t}(r_{k,t} - y_{k,t})\Big],$$

so that

$$\mathbb{E}_t W_{i,t+1} \approx \sum_{k=1}^{N_k} Z_{i,k,t}\Big[\text{Basis}_{k,t} - \alpha_{i,k,t}(\mu_k - y_{k,t})\Big],$$
$$\mathbb{V}_t W_{i,t+1} \approx \sum_{k=1}^{N_k} \frac{Z_{i,k,t}^2\alpha_{i,k,t}^2}{\pi_{i,k}}.$$

Then, to a first-order approximation, the first-order condition for $\alpha_{i,k,t}$, the proportion that intermediary i allocates to risky bonds in currency k, yields

$$\alpha_{i,k,t} = -\frac{\pi_{i,k}(\mu_k - y_{k,t})}{Z_{i,k,t}\Big(\gamma_i + \lambda_{s,k}\pi_{i,k}\Big)} + \frac{\pi_{i,k}\lambda_{s,k}}{\gamma_i + \pi_{i,k}\lambda_{s,k}}. \qquad (2)$$

Substituting (2) into the first-order condition for $Z_{i,k,t}$ yields

$$Z_{i,k,t} = -\phi_{i,k}\lambda_{BS}\text{Sign}(Z_{i,k,t})\sum_{\ell\neq k}|Z_{i,\ell,t}| + \phi_{i,k}\text{Basis}_{k,t} - \tau_{i,k}(\mu_k - y_{k,t}), \tag{3}$$

where $\phi_{i,k} = \frac{\pi_{i,k}\lambda_{s,k}+\gamma_i}{\lambda_{BS}\pi_{i,k}\lambda_{s,k}+\gamma_i(\lambda_{BS}+\lambda_{s,k})}$ and $\tau_{i,k} = \frac{\pi_{i,k}\lambda_{s,k}}{\lambda_{BS}\pi_{i,k}\lambda_{s,k}+\gamma_i(\lambda_{BS}+\lambda_{s,k})}$. Summing Equation (3) across intermediaries, substituting in the market clearing condition, and re-writing in terms of the basis, we have that

$$\text{Basis}_{k,t} = \underbrace{-\frac{1}{\sum_i^{N_i}\phi_{i,k}}X_{k,t}}_{\text{Risk and Search}} \underbrace{-\lambda_{BS}\frac{\sum_i^{N_i}\phi_{i,k}\sum_{\ell\neq k}|Z_{i,\ell,t}|}{\sum_i^{N_i}\phi_{i,k}}\text{Sign}(X_{k,t})}_{\text{Balance Sheet Cost}} + \underbrace{\frac{\sum_i^{N_i}\tau_{i,k}}{\sum_i^{N_i}\phi_{i,k}}(\mu_k - y_{k,t})}_{\text{Risky Asset Returns}}. \tag{4}$$

2.2 Model Predictions

The first two predictions of the model rely only on balance sheet costs, and follow directly from the Balance Sheet Cost term of Equation (4). In the absence of all other frictions, Equation (4) simplifies to

$$\text{Basis}_{k,t} = -\lambda_{BS}\frac{\text{Sign}(X_{k,t})}{N_i}\sum_{j=1}^{N_k}|X_{j,t}|.$$

Prediction 1 (Sign of the Basis)**.** *The direction of synthetic demand for dollars from currency k determines the sign of the basis.*

Prediction 2 (Balance Sheet Costs)**.** *The magnitude of the basis is increasing in the total balance sheet usage of intermediaries across basis trades, $\sum_j^{N_k}|X_{j,t}|$.*

Predictions 1 and 2 are predictions of standard explanations for CIP deviations. The basis for each currency contains a common balance sheet cost component that reflects the marginal cost faced by the intermediation sector in expanding its balance sheet. The post-GFC increase in the magnitude of CIP bases reflects the increase in the magnitude of balance sheet costs (e.g., an increase in λ_{BS}).

Note that in the absence of other frictions, the basis is equalized in magnitude across all currencies, resulting in no cross-sectional variation. The next two predictions of the model are with respect to cross-sectional variation in bases, which arises from the assumption that intermediaries face search costs for safe assets and make risky substitutions. These predictions do not rely on heterogeneity across intermediaries; in the absence of heterogeneity (setting $\pi_{i,k} = \pi$ and $\gamma_i = \gamma$), Equation (4) simplifies to

$$\text{Basis}_{k,t} = \underbrace{-\frac{\lambda_{s,k}\gamma}{N_i(\gamma + \pi\lambda_{s,k})}X_{k,t}}_{\text{Risk and Search}} \underbrace{-\lambda_{BS}\frac{\text{Sign}(X_{k,t})}{N_i}\sum_{j}^{N_k}|X_{j,t}|}_{\text{Balance Sheet Cost}} + \underbrace{\frac{\pi\lambda_{s,k}}{\gamma + \pi\lambda_{s,k}}(\mu_k - y_{k,t})}_{\text{Risky Asset Returns}}.$$

Prediction 3 (Cross-Sectional Heterogeneity in Bases from Demand)**.** *The cost of synthetic dollar funding for currency k is increasing in demand to borrow dollars from currency k via forwards (more negative bases as $X_{k,t}$ increases).*

Prediction 3 is novel, and follows directly from the "Risk and Search" term in the expressions for the basis. It arises from the fact that as demand for forwards in a particular currency increases, intermediaries face increasing marginal costs to locate additional safe bonds, and increasingly substitute into risky bonds. These costs transmit to the basis.

Prediction 4 (Cross-Sectional Heterogeneity in Bases from Safe Asset Mismatch)**.** *When customers are net borrowing dollars, currencies where foreign safe assets are harder to find (high search costs, $\lambda_{s,k}$) have larger magnitude bases. Currencies where the proportion of foreign safe assets for each dollar of foreign synthetic lending is lower have more expensive dollar funding.*

Prediction 4 considers a different form of heterogeneity across currencies than demand: search costs for safe assets may systematically vary across currencies. For currencies with higher search costs, bases are larger per unit of demand, reflecting those costs and the additional risky substitutions that intermediaries make ($\frac{\partial \text{Basis}_{k,t}}{\partial \lambda_{s,k}} < 0$ when intermediaries are net dollar lending, as we derive in the Internet Appendix). In the data, markets where search costs for safe bonds are high can be observed from intermediaries' positions, where intermediaries substitute away more from safe bonds into risky bonds.

Our last set of predictions stems from intermediary heterogeneity. These predictions arise from the fact that intermediaries face heterogeneous risk in substituting away from safe assets. As a result, intermediaries will specialize and hold higher market shares in the markets where they have the most expertise in managing risk.

Prediction 5 (Risk Concentration and the Elasticity of the Basis)**.** *All else equal, holding aggregate expertise ($\sum_i^{N_i} \pi_{i,k}$) fixed, the basis for currency k is larger in magnitude for a given level of demand when intermediation is more concentrated in market k.*

Prediction 5 arises from the fact that when intermediation in a market is more concentrated, risk becomes more concentrated, which leads to a larger basis per unit of demand. From Equation (4), the aggregate supply elasticity of intermediaries in market k is determined by $\sum_i^{N_i} \phi_{i,k}$. As we show in the Internet Appendix, $\phi_{i,k}$ is a concave and increasing function of expertise, $\pi_{i,k}$, with differences in expertise determining differences in market shares. Holding aggregate expertise fixed, the market is most elastic when expertise, and hence, risk, is evenly distributed across intermediaries.[2] An additional channel that may amplify this risk-sharing effect when intermediation is concentrated is market power (Wallen (2022)), which would appear in a Cournot-style variant of our model where customer demand is not exogenous.[3]

While we do not micro-found the sources of heterogeneity in our stylized model, we discuss these sources in our empirical analysis. We document that intermediaries that hold large market shares in a particular currency market also tend to hold larger loan portfolios in that market. This evidence suggests that lower risk in substituting away from safe assets may be driven by expertise, such as informational advantages coming from greater familiarity with a given market or a more easily accessible set of counterparties.

Prediction 6 (Heterogeneous Expertise in Managing Risk and Safe Asset Ratios)**.** *Specializing intermediaries with a larger share in a given currency market hold fewer foreign safe bonds per dollar of lending (for currency k, intermediary i's allocation to risky bonds, $\alpha_{i,k}$, is larger when intermediary i's net dollar lending is larger in magnitude).*

Prediction 6 arises from the fact that intermediaries with a higher willingness and ability to substitute into risky foreign bonds have a higher capacity for meeting currency forward

[2] Interpreting expertise as reflecting the precision of intermediaries' information about risky asset returns in market k, holding aggregate expertise $\sum_i^{N_i} \pi_{i,k}$ fixed is naturally interpreted as holding the total amount of information about market k held by intermediaries fixed. In extensions of our model, we also often expect aggregate expertise to be lower in more concentrated markets, which would amplify inelasticity. For example, some intermediaries may not enter a market at all, simultaneously increasing concentration and decreasing aggregate expertise.

[3] Because market power and risk-sharing make the same directional predictions, we cannot empirically disentangle the roles they play. From a related perspective, Bryzgalova et al. (2025) argue that intermediaries tend to specialize in options markets that are their 'natural markets,' due to low fixed costs of entry from related business areas or economies of scale.

demand and, accordingly, have higher market shares (see Internet Appendix for derivation). Prediction 6 distinguishes expertise in managing risk as a driver of specialization from another form of expertise: lower search costs for safe bonds. A heterogeneous search-cost-based explanation would predict a similar or higher share of foreign safe asset holdings by specializing intermediaries.

Prediction 7 (Specializing Intermediaries and Segmentation)**.** *The basis for currency k reflects the frictions faced by intermediaries that specialize in currency k.*

Intermediaries specialize in different markets with those with greater expertise having higher market shares. The frictions faced by the *specializing* intermediaries in a market are the particularly relevant drivers of bases in that market, not those faced by the overall intermediary sector. For example, in computing the effects of balance sheet costs for the basis in market k, balance sheet usage is weighted by $\phi_{i,k}$ in Equation (4), which is increasing in expertise, and broadly captures how active intermediary i is in market k. An implication of this weighting is that bases should not perfectly co-move across markets. Siriwardane et al. (forthcoming) present suggestive evidence consistent with this prediction by examining the correlations of different arbitrage strategies across asset classes. We present direct evidence for this prediction *within* an asset class, using detailed and direct data on intermediaries' participation across markets.

We turn next to describing the data used to test these predictions.

3 Data

We collect information on bank-specific FX positions from the FR 2052a *Complex Institution Liquidity Monitoring Report* and from Bloomberg for exchange rates, prices, and interest rates.

3.1 FR 2052a Complex Institution Liquidity Monitoring Report

The Federal Reserve collects granular data on banks' liquidity in the FR 2052a as part of its capital adequacy framework, as required by the Dodd-Frank Act and implemented by the Federal Reserve's Regulation YY. The data are confidential and not publicly available. The data contain information by asset class, outstanding balance, and purpose, each reported by maturity and date, covering large U.S. and foreign banks. Global systemically important banks (G-SIBs), category II, and category III banks with a weighted average short-term funding of $75 billion must file the report each business day. Smaller banks report data monthly.[4] Banks have a strong incentive to report data fully and truthfully because of the possible consequences of making misrepresentations to government authorities, which could result in enforcement actions. Regulators closely scrutinize banks, so any misreporting is likely to be identified and corrected.[5]

We use the data on banks' foreign exchange swaps and forwards.[6] Our sample includes daily observations from January 2016 through March 2023, spanning over-the-counter (OTC) and centrally-cleared transactions. Roughly 85 percent of the gross notional positions in our sample are settled bilaterally on a value-weighted basis, while the rest clear centrally. Firms report FX transactions for eight currencies: AUD, CAD, CHF, EUR, GBP, JPY, USD, and other. The data cover cash-settled transactions settled with the physical exchange of currency, so they do not include contracts for difference or other non-deliverable transactions. The swaps in our sample include both FX forward swaps and cross-currency swaps, where the latter involve periodic interest payments in addition to the exchange of notional currencies at the beginning and end of the transaction. The data report maturities at daily increments up to 60 days, weekly increments from 61 days to 90, monthly increments to 180 days, 6-month increments to 1 year, and yearly increments beyond one year. We discuss additional data cleaning in Internet Appendix Section IA.B.

Banks carry FX exposures both on- and off-balance sheet. Our data cover both. FX swaps, futures, and forwards are reported at fair value on banks' balance sheets, netted by counterparty. The fair value reflects the replacement cost or marked-to-market value of the FX derivatives, which is typically near zero at inception and fluctuates as prices move. Off-balance-sheet exposures typically refer to the gross notional value of the FX derivatives.

[4] For details on Regulation YY and FR 2052, see `https://www.federalreserve.gov/supervisionreg/reglisting.htm`. The reporting instructions for FR 2052a are available at `https://www.federalreserve.gov/apps/reportingforms/Report/Index/FR_2052a`. Additional details on which large financial institutions must report daily are at `https://www.federalreserve.gov/supervisionreg/large-institution-supervision.htm`.

[5] Researchers have recently begun using this dataset to study bank behavior: for example, Infante and Saravay (2020), Cooperman et al. (2025), and Correa et al. (2020).

[6] The data on forwards include forwards and futures. We will refer to them as forwards for brevity.

The fair value of a derivative is typically a small share of its notional value.

We focus on the subset of the data with transactions in the six currencies against the dollar. On average, our sample covers $25 trillion in gross notional daily contracts across foreign exchange swaps and forwards. We plot the daily sample average by currency in Figure 1. The sample is large and represents a material slice of the foreign exchange derivative market. While not an apples-to-apples comparison, Bank of International Settlements (2022) estimates the total notional amount of OTC foreign exchange derivatives at $110 trillion in 2022. Euro contracts are the largest ($9 trillion), and Swiss Franc contracts are the smallest ($1 trillion). The tenors with the largest notional amounts are at the weekly increments—7, 14, 21, 28 days—and steadily grow in total beginning with 6-month tenors. We limit our main sample to maturities less than 4 years since the 5-year bucket contains all maturities at five years and beyond.

The banks in our sample vary in terms of their business focus, and include money-center banks, legacy investment banks, and custodial banks. For example, Bank of New York Mellon's 10-K reported $2.9 million in FX value-at-risk at 2023 year-end, compared to Citi's $134 million, a 50-fold difference. Banks must report all FX exposures, including transactions in which they intermediate back-to-back offsetting trades for clients. These transactions increase the gross size of a market but leave our estimate of net dollar lending—our primary measure of interest—unaffected, since the inflows and outflows would offset. We aggregate exposures by summing across banks rather than averaging, which naturally reflects this variation by weighting each bank's contribution to net lending by the scale of its FX business.

Our data provide comprehensive coverage of U.S. banks and U.S. operations of foreign banks, with the former dominating notional exposures. U.S. banks account for 97 percent of total gross notional exposures across the broader set of banks that report at a monthly frequency.

U.S. banks play a central role in global dollar funding markets, making our data particularly informative. U.S. banks are likely the largest dollar suppliers globally, given their dollar deposit bases, access to a litany of dollar-based liquidity facilities from the central bank, and large footprint in foreign markets. This is consistent with evidence from Kubitza et al. (2024) who use regulatory data covering European banks and find that non-European banks—likely including U.S. banks—are the dominant suppliers of dollars in Europe. Our dollar-focused data likely represent a large share of global FX activity, as Borio et al. (2022) show that the dollar appears on one side of 88 percent of all outstanding FX swaps and similar contracts. However, foreign banks also play a significant role in intermediating these dollar flows globally (Du et al., 2018).

We also collect data on banks' safe assets. We focus on unencumbered assets (assets that face no restriction on use as collateral), assets pledged to central banks against which the bank could borrow, unrestricted central bank reserve balances, unsettled asset purchases, and encumbered assets (assets restricted from use as collateral). Encumbered assets are available only starting from mid-2022. Across these categories, we measure banks' safe assets as a subset of the level 1 high-quality liquid assets (HQLAs) and central bank liabilities. HQLAs are securities considered the closest proxy for risk-free securities if held to maturity. While the dataset does not provide the asset CUSIPs, it does provide collateral categories. In some instances, we include a broader set of assets beyond just level 1 HQLA.

3.2 Covered-Interest Parity Violations

We calculate covered-interest parity violations using interest rates, spot exchange rates, forward points, and forward maturity dates from Bloomberg. We use OIS interest rates across the maturity curve, ranging from 1 week to 4 years. Details on cleaning the OIS interest rate data are provided in the Internet Appendix.[7] We calculate CIP violations following Du et al. (2018). Define s_t as the spot exchange rate in units of foreign currency per U.S. dollar available at date t, $y^{\$}_{t,t+n}$ as the dollar interest rate available on date t and maturing at $t+n$, and $f_{t,t+n}$ as the n-period outright forward exchange rate in foreign currency per USD. The CIP basis is

$$\text{Basis}_{t,t+n} = y^{\$}_{t,t+n} - \left(y_{t,t+n} - \frac{1}{n}(f_{t,t+n} - s_t) \right). \tag{5}$$

When the basis is negative, $\text{Basis}_{t,t+n} < 0$, dollar arbitrageurs can profit by borrowing at USD interest rates, simultaneously converting their USD to foreign currency at s_t, buying a forward $f_{t,t+n}$ to exchange that foreign currency back into dollars at maturity, and investing abroad at the foreign interest rate. Intuitively, an investor should be indifferent between

[7] The specific tenors we use are 1w, 2w, 3w, 1m, 2m, 3m, 4m, 5m, 6m, 1y, 2y, 3y, and 4y. We exclude the 5y tenor because the longest maturity category in the FR 2052a data is five years and greater, so its average maturity is likely much more than five years.

holding USD to earn $y^{\$}_{t,t+n}$ and exchanging USD for foreign currency invested at the foreign risk-free rate and converting the foreign currency back to USD by buying a forward.

Figure 2 plots our estimates of CIP bases at the 1-week and 1-year tenors. Substantial dislocations are apparent during the 2008 financial crisis and the early stages of the Covid pandemic. We also provide the average and standard deviation of the 1-year CIP bases in Table 1. The basis averages −24 bps across all currencies but ranges from +6 for AUD to −50 for JPY. The first and second moments of the bases do not change much if we restrict the sample to begin in 2016 when our bank data sample starts.

We merge the Bloomberg basis panel data with the FR 2052a panel data using the days to maturity. For contracts with at least a month to maturity, we merge the panels using the commonly reported days to maturity in the FR 2052a data.[8]

Table 2 provides the daily average and standard deviation by currency and by tenor after merging with our estimates of CIP deviations using Bloomberg data, which limits the sample to the tenors of the OIS contracts. The daily average gross notional of the merged sample is $10.7 trillion. Forwards are larger at maturities less than six months, while swaps are larger beyond that. Shorter tenors also have more volatility in volumes. For example, the 1-week swap averages $91 billion with a standard deviation of $78 billion.

3.3 Net Dollar Lending

Our empirical analysis compares the amount of net dollar lending done by intermediaries across markets and relates this variation to cross-sectional variation in CIP deviations. We detail the construction of our measure of net dollar lending from supervisory regulatory data below.

3.3.1 Construction

We use the FR 2052a data to calculate banks' net dollar lending position for each market, where we define a market as a specific currency × tenor. Given our focus on dollar lending, we restrict the sample to transactions with USD in one leg and exclude other non-USD

[8]Specifically, 1m is 28 days; 2m is 61 days; 3m is 83 days if the days to maturity are between 83 and 90, inclusive, and 91 days if the days to maturity are greater than 90 days but less than 120 days; 4m is 121 days; 5m is 151 days; 6m is 181 days; 9m is 271 days; 1 year is 366 days; 2 years is 731 days; 3y is 1,096 days; 4y is 1,461 days.

currency pairs (e.g., EUR/JPY) unless otherwise specified. We calculate banks' net USD supplied from date t to $t+n$ for a given currency pair k via FX swaps using:

$$Net^k_{t,t+n} = \frac{(\text{USD in at } t+n) - (\text{USD out at } t+n)}{(\text{USD in at } t+n) + (\text{USD out at } t+n)}. \tag{6}$$

We define a market's gross notional as the denominator of (6)—the sum of dollar inflows and outflows against a specified currency at the specified maturity.

Table 3 provides a simple example to illustrate the logic underpinning the construction of $Net^k_{t,t+n}$. Suppose a bank is buying and selling JPY swaps, with spot rate $S_t = 115$ and forward exchange rate $F_{t,t+7} = 110$. In the first swap, the bank lends \$100 at the near leg and receives $\$100 \times S_t = ¥11,500$. Separately, and simultaneously, the bank receives \$95 in a second swap and pays $\$95 \times S_t = ¥10,925$. The bank has paid \$5 more than it received, equivalent to lending \$5. At maturity, the two swaps unwind at the forward price. The net variable is the ratio of the net dollars lent to the notional dollars: $2.56\% = 5/195 = 5.23/204$ at time $t+7$. The net variable is the same regardless of whether it's based on the near or far leg flows (t or $t+7$).

When $Net^k_{t,t+n} > 0$, the bank lends out more dollars today than it borrows against currency k with maturity $t+n$, because the bank will receive more dollars in at maturity on $t+n$ than it pays out. We normalize by notional dollar flows since the size of markets varies.[9]

We aggregate the net lending measure at two levels. $Net^k_{t,t+n}$is our primary measure, reflecting the entire intermediary sector by aggregating lending across all banks at the date $\times$ maturity $\times$ currency level. We also calculate a bank-specific measure (indicated by the i superscript), $Net^{k,i}_{t,t+n}$, that aggregates at the date $\times$ maturity $\times$ currency $\times$ bank level. Since banks report only non-zero values, we set net lending to zero when there are no lending or borrowing data for a given observation.

Our data provide a unique view into dollar lending in FX markets. Estimating lending through FX derivatives using public data, whether on- or off-balance-sheet, is challenging

[9] Although net lending is possible through swaps and a combination of spot transactions with forwards, we calculate net using only swaps since there is no upfront exchange of principal for forwards and futures, and we are unable to connect forward transactions with spot transactions forming basis trades. We expect our results to be unaffected if forward and futures demand is directionally similar to swap demand. We find little evidence that including forwards and futures meaningfully affects our results, for example, in our analysis of safe asset ratios in Table IA.6. Similarly, our net lending measure excludes intermediate interest payments since we are unable to match those payments to the underlying swap.

due to its coarseness and reliance on fair values. Lending through swaps—determined by the difference of off-balance-sheet notional inflows and outflows at maturity—appears on the balance sheet at near-zero fair value when the swap is first initiated. Later fluctuations in fair value reflect market movements, not the actual principal amount lent, thereby obscuring lending volumes. We compare our measure with public data in the Internet Appendix Section IA.C.2.

3.3.2 *Net* Summary Statistics

Table 4 gives the average and standard deviation of $Net^k_{t,t+n}$ by currency and tenor. With few exceptions, $Net^k_{t,t+n}$ is small and near zero, indicating that the intermediary sector broadly matches its dollars in and out. The table highlights three facts: first, the intermediary sector tends to net borrow dollars at shorter tenors and net lend at longer tenors, with the average flipping from negative (net borrowing) to positive (net lending) around 3 months. Second, there is considerable variation in net dollar lending across the currencies—averaging across all tenors, intermediaries tend to lend dollars against EUR (1.1 percent) and borrow dollars against AUD (3.6 percent). Third, net lending is more volatile at shorter maturities than it is at longer maturities. At less than a month, the average time-series standard deviation is 30 percent compared to less than 10 percent for maturities beyond 5 months.

Table IA.1 shows the level of $Net^k_{t,t+n}$ in billions of dollars. Average $Net^k_{t,t+n}$ is largest in level terms for JPY at \$5.4b, and smallest for AUD at −\$1.3b. Adding across the rows shows that banks net lend dollars most against JPY (\$75b) and EUR (\$44b) while borrowing the most against AUD (−\$18b). Adding the columns together yields the average net dollar provision by banks in these currencies and markets: \$98b.

The net dollar lending of the banks in our sample is substantial. One way to contextualize it is by comparing it to the total dollars the Fed provided through central bank swap lines during the worst stage of the COVID-19 pandemic, a period when the dollar shortage was particularly acute. The Fed's swap lines peaked at \$450 billion in May 2020, compared to our roughly \$100 billion of average lending, most of which occurred outside stressed periods.[10]

Table IA.2 shows that $Net^k_{t,t+n}$ is increasing in maturity, size, and an analogous measure of net lending provided using the coarser data from the Traders in Financial Futures Report

[10] The Federal Reserve's swaps are publicly released in the H.4.1, see `https://www.federalreserve.gov/releases/h41/`.

from the Commodity Futures Trading Commission, as used in Hazelkorn et al. (2023). It is lower at quarter- and month-ends. Finally, $Net^k_{t,t+n}$is weakly pro-cyclical, being larger when the VIX and the Baa-Aaa spread are lower. There is no obvious relationship between $Net^k_{t,t+n}$and the SPX return.

To illustrate the variation over time and across tenors, we plot the net variable for 1-week, 6-month, and 1-year EUR in Figure IA.1. At shorter maturities, net lending is normally negative but often turns positive for brief periods. The middle panel shows the level of net lending in billions of dollars. Average net lending at the 1-week tenor is −\$1.2 billion but grows to \$13 billion at the 1-year tenor. The bottom panel shows the gross notional dollar flows. There is an increasing trend across all tenors, but the trend is most obvious at the 1-year maturity, where notional values approached \$800 billion in 2023. The recurring spikes in the shorter maturities reflect window dressing.

Figure IA.2 shows a histogram of $Net^k_{t,t+n}$by currency across all tenors. The peaks near the zero net lending line indicate that the banking system generally runs a matched book, lending as much as it borrows. The figure makes clear that we expect $Net^k_{t,t+n}$to be near zero or tightly bounded around zero, rather than large directional positions, either long or short.[11]

$Net^k_{t,t+n}$'s small size is not unique to banks' USD-related FX activity. Banks primarily make markets and do not take large directional FX positions; they hedge most exposures with offsetting positions. We show this by calculating banks' net receivables, by currency, across all currency pairs. Unlike $Net^k_{t,t+n}$, which measures the net receivable of dollars against the six named currencies, this measure captures receivables by currency against all other currencies (including currencies beyond the six named currencies). We plot the average net receivable as a percent of gross payables and receivables in the same currency in Figure IA.4. Banks receive or pay less than 3 percent of the notional for each currency; hence, they hedge most FX exposures.

Given that U.S. and non-U.S. banks both may engage in dollar lending, and that U.S. banks may behave differently because of easier access to dollar funding sources, an important question is how different banks' behavior is represented in these patterns. We find that U.S. banks play a primary role in driving the observed relationships. In Table IA.3, we compare $Net^k_{t,t+n}$ and gross FX exposures across U.S. banks and foreign banks, insofar as foreign bank activity is included in our data. We calculate $Net^k_{t,t+n}$ separately for U.S. and foreign banks

[11]In the Internet Appendix, Figure IA.3 shows that net is closer to zero for the largest markets.

using monthly data, since monthly frequency data are available for a wider set of banks. The first two columns regress the overall $Net^k_{t,t+n}$ (e.g., calculated from the full sample of banks) separately on U.S. banks' and foreign banks' $Net^k_{t,t+n}$. The first column shows that a one percentage point (pp) increase in U.S. banks' $Net^k_{t,t+n}$ corresponds to a 0.97 pp increase in overall $Net^k_{t,t+n}$. The second column shows a one pp increase in foreign banks' $Net^k_{t,t+n}$ results in a 0.03 pp increase in overall $Net^k_{t,t+n}$. The last two columns compare notional exposures across U.S. and foreign banks; a \$1 increase in U.S. (foreign) banks' notional corresponds to a \$1.03 (\$15.02) increase in overall notional, confirming that U.S. banks dominate the notional exposures in our sample. However, our view into foreign bank activities is incomplete because the data do not include activities from the foreign banks' parent companies.

4 Empirical Strategy and Results

We turn to testing the predictions of our model. The first two predictions are about the sign of bases and time-series variation in them, as previously studied in the literature. Our remaining predictions study cross-sectional variation in currencies' bases, which has presented a puzzle for prior work. Using our measures of net dollar lending in each market, we show that banks lend the most dollars in the currency and maturity markets with the largest CIP deviations. As indicated by our model, this result is consistent with banks facing increasing marginal costs to meet currency- and maturity-specific demand for dollar borrowing. In our model, we identify two potential sources that influence cross-sectional variation in the basis: 1) foreign safe asset mismatch, stemming from search costs for bonds of the appropriate currency and maturity to meet customer dollar funding demand; and 2) intermediary specialization. We construct proxies for both and jointly test their ability to explain the cross-section of bases.

4.1 Predictions 1 and 2: Time-Series Variation in Bases

Prediction 1 states that the sign of demand for dollars from a currency determines the sign of the basis. The summary statistics in Table 1 support this prediction. The AUD basis is positive while the others are negative. The rank ordering is consistent across tenors: AUD is typically the largest, CAD the second largest, and JPY the smallest. Prediction 1 explains this rank order since AUD and CAD have the least dollar demand and JPY the most. It is intuitive that different foreign economies have different dollar demands and are willing to pay different prices for dollars. For example, countries with large commodity exports invoiced in dollars, like Australia and Canada, have different demand for dollars than countries without similar commodity-related dollar inflows.[12]

Prediction 2 states that the size of the basis, in absolute value, is decreasing in the banking system's balance sheet capacity across all basis trades. The size of the basis reflects dislocations that prevent the banking system from pushing the basis back toward zero. Such a prediction is consistent with work that studies the important role the aggregate intermediary sector plays in basis dynamics (e.g., Du et al. (2023b)). We discuss how regulatory constraints affect FX derivatives in the Internet Appendix section IA.C.1.

Predictions 1 and 2 reflect (signed) time-series variation in bases, the primary focus of earlier work. The first principal component of the bases, for example, explains a substantial share of variance across the bases in each tenor (about 70 percent), but there is significant unexplained variation. The focus of our paper is on the cross-sectional variation in the size of bases, which accounts for the remaining variation in bases.

Figure 3 plots the cross-sectional standard deviation across currencies on a given day. The variance across bases increases in tenor. The cross-sectional dispersion varies over time, with notable spikes during the financial crisis and Covid pandemic. The existence of bases with different magnitudes and signs across currencies and tenors at a point in time is *prima facie* evidence that forces beyond an aggregate intermediary balance sheet constraint matter for the bases. While aggregate leverage and other balance sheet constraints are important, they cannot capture the cross-sectional variation in bases observed in the data.

4.2 Prediction 3: *Net* vs. Bases

We test Prediction 3, that banks lend more in markets where dollar funding is most expensive, by testing whether cross-sectional variation in $Net^k_{t,t+n}$captures cross-sectional variation in bases. We run the regression,

$$\text{Basis}^k_{t,t+n} = \alpha + \beta Net^k_{t,t+n} + \gamma\prime X_t + \varepsilon^k_{t,t+n} \tag{7}$$

[12]Du et al. (2018) also discuss dollar demand in terms of interest rates—AUD is the highest interest rate currency, and therefore expected to have the least carry trade demand for dollars, and vice versa for JPY.

where a negative basis indicates that swapping foreign currency for dollars is expensive, and X_t is a vector of controls. Our model predicts $\beta < 0$, because bases should be more negative in markets with higher dollar demand. This relationship arises from the search costs and risks that intermediaries face when supplying dollars in different markets, due to the mismatch of foreign safe assets.[13]

Table 5 reports the regression results, with β reliably negative across all specifications using different controls. The first row shows a robust negative relationship between bases and $Net^k_{t,t+n}$ after including tenor and time fixed effects and weighting by the square root of the market's share of the total daily gross notional. We use weighted least squares regression since markets can differ substantially in size. Column 4 is the benchmark estimate, which includes the full set of fixed effects and weights by notional share. The coefficient shows that when $Net^k_{t,t+n}$ is one pp larger, the basis is 0.4 bps smaller. A one-standard-deviation change in $Net^k_{t,t+n}$weighted by its daily notional share is about 10 pp, corresponding to a basis that is 4.3 bps lower using column 4's coefficient.The last two columns split the sample into short- and long-term tenors, using a threshold of one year. The relationship is much stronger for longer-tenor lending, with a coefficient roughly 9 times larger than for short-dated tenors. A one-standard-deviation change in $Net^k_{t,t+n}$for these longer tenors corresponds to a basis that is 9 bps lower (5.9×-1.6).

Our preferred specification uses a weighted least squares regression because market sizes are extremely skewed. Out of a total of 84 markets (6 currencies times 14 tenors), the largest 12 markets account for more than half of the total notional, and the largest 44 markets capture more than 90 percent. The biggest market is close to 600 times larger than the smallest non-zero market on average, and we do not want to treat the $3 billion 1-week CHF market as having the same influence as the $500 billion 1-year EUR market.

Table 5 column 1 confirms our key finding holds in unweighted regressions, though the coefficient is smaller, consistent with noise from smaller markets attenuating the relationship. Results are robust across various sample restrictions and market size cutoffs, as detailed in the Internet Appendix. Column 5 sorts markets by gross size and reruns an unweighted OLS on the subset of the largest markets that cumulatively capture the top 90 percent of total

[13] $\beta < 0$ is implicitly assumed in several other papers, for example, Greenwood et al. (2023), Liao and Zhang (2025), and Du and Huber (2025). An analogous result is also shown to be the case in equity index futures markets by Hazelkorn et al. (2023).

notional, following the approach used by Asness et al. (2013) to create liquid stock samples. The coefficient estimated after restricting to the largest markets is -0.59, suggesting that the smaller markets introduce relatively more noise. Internet Appendix Section IA.C.3 provides details on the relationship between bases and lending.

Our analysis focuses on the relationship between bases and intermediaries' *net* positions, rather than their *gross* positions, with the former being the relevant feature of the data for the frictions that we focus on (intermediaries' search for safe bonds and risk). However, gross positions may also be important, for example, due to intermediaries facing non-risk-weighted leverage constraints. In Internet Appendix Table IA.4, we run the same analysis including intermediaries' gross positions in a market as an independent variable. The relationship between bases and $Net^k_{t,t+n}$remains similar, but gross positions also carry a significant negative coefficient, consistent with the importance of non-risk-weighted regulatory constraints binding swap activity.

The cross-sectional relationship between $Net^k_{t,t+n}$and bases is consistent with our model. Intermediaries' (shadow) costs, which increase with dollar funding demand from a particular currency, drive cross-sectional variation in bases. We next explore the importance of different frictions in contributing to the increasing marginal costs that intermediaries face to meet dollar funding demand.

4.3 Prediction 3: Foreign Safe Asset Mismatch

Prediction 3 links bases with dollar funding demand because intermediaries substitute away from safe assets into maturity-mismatched safe assets and risky assets to meet this demand. The increasing basis reflects the compensation that intermediaries require for making such substitutions.

We find that on average, intermediaries hold only 7 cents of perfectly maturity-matched foreign safe assets per dollar of net lending. Banks put the rest of the cash leg of their CIP trades toward maturity-mismatched safe assets and risky foreign currency assets, taking on risk to meet customer demand in currency swap markets. To illustrate this point, we first examine maturity-matched safe asset positions, then progressively relax our definitions to understand how banks actually deploy the cash leg of their CIP lending.

We define safe assets as the sum of level 1 HQLAs (including unencumbered assets, unsettled asset purchases, and assets pledged to the central bank), central bank reserves, and reverse repos with central banks. The BIS describes HQLAs as assets that "can be easily and immediately converted into cash at little or no loss of value."[14] The measure is specific to the market: there are daily observations for each currency and tenor. We define

$$\text{Safe Asset Ratio}^k_{t,t+n} = \frac{\text{FV}\left(\text{Safe Assets } (\$)^k_{t,t+n}\right)}{\text{Net } (\$)^k_{t,t+n}}.$$

Because some asset holdings are reported by market value, rather than maturity value, we apply a future value operation, FV(·), to convert market values into maturity cash flows using the tenor- and currency-specific risk-free rate. This allows direct comparison with $Net^k_{t,t+n}$. FV(·) multiplies asset classes reported by market values (the HQLA securities and central bank reserves) by $1 + rf^k_{t,t+n}$ but leaves asset classes already reported by maturity cash flows (central bank reverse repos) unchanged.[15]

If $\text{Safe Asset Ratio}^k_{t,t+n} = 1$, then banks perfectly match every dollar of net dollar lending for currency k on date t with maturity $t + n$ to a dollar of foreign safe asset in the same currency and the same tenor. Safe asset ratios less than one indicate that intermediaries' swap and cash positions do not offset one another and that the intermediary holds an imperfect CIP position involving some risk.[16]

To better understand where intermediaries might invest their foreign currency, we calculate a broader definition

$$\text{Broad Asset Ratio}^k_{t,t+n} = \frac{\text{FV}\left(\text{Broad Assets } (\$)^k_{t,t+n}\right)}{\text{Net } (\$)^k_{t,t+n}}.$$

This ratio includes asset classes beyond those captured in the safe assets ratio. It includes unencumbered assets, unsettled asset purchases, assets pledged to the central bank, central bank deposits, short-term investments, reverse repurchases, securities borrowings, and margin

[14]See `https://www.bis.org/basel_framework/chapter/LCR/30.htm`.

[15]Specifically, the expanded expression is $\text{Safe Asset Ratio}^k_{t,t+n} = (1/\text{Net } (\$)^k_{t,t+n})\times (\text{Safe Assets } (\$)^{k,MaturityValue}_{t,t+n} + \text{Safe Assets}(\$)^{k,MarketValue}_{t,t+n} \times (1 + rf^k_{t,t+n}))$. When there is no OIS risk-free rate with identical maturity, we use the rate with the nearest maturity.

[16]The ratio is an upper bound for the safe assets that intermediaries use to hedge swap exposures because intermediaries may hold safe assets for other reasons. Internet Appendix Section IA.C.4 provides details.

loans. Like the safe asset ratio, the broad asset ratio spans some assets that are reported by market value (unencumbered assets, unsettled asset purchases, assets pledged to the central bank, and central bank reserves) and other assets that are reported at maturity value (all others). We again convert market values to maturity values by multiplying them by $1+rf^{k}_{t,t+n}$, so the broad asset ratio compares cash flows at maturity for both broad asset holdings and net dollar lending.[17]

For example, a German government bond would appear in both ratios, but a German corporate bond would only show up in the broad asset ratio since it is not a level 1 HQLA. Beginning in 2022, the data include encumbered assets, and we treat this subsample separately as a point of comparison given the large value of the banking system's encumbered assets.[18] These measures are gross long positions, so they are an upper bound on the banking system's net position in these markets. If a bank were short the security, its net long measure would be lower.

We separately address cases when banks net lend dollars from cases when banks net borrow dollars. When $Net^{k}_{t,t+n} > 0$, banks lend dollars, receive foreign currency, and therefore have a demand for foreign safe assets. When $Net^{k}_{t,t+n} < 0$, banks lend foreign currency, receive dollars, and thus need USD-denominated safe assets. We separate these two cases in the following analysis since we have strong priors that USD safe asset holdings differ for U.S.-based G-SIBs.

Figure 4 summarizes our estimates of safe and broad asset ratios, which illustrate the presence of foreign safe asset mismatch. This analysis focuses particularly on the case where $Net^{k}_{t,t+n} > 0$, where intermediaries have demand for foreign safe assets. The top panel shows that, with perfect maturity matching, banks hold only 7 cents of safe assets per dollar lent. Including encumbered assets, which entail counterparty risk, brings the ratio to 20 cents. The results are similar if we include forwards and net short positions (see Figure IA.5).

[17]Many assets included in the broad asset ratio are not risk-free, and so likely carry yields above the risk-free rate, but the data do not provide yield information. We therefore estimate their expected cash flows at maturity using the risk-free rate. The approximation has a small effect: interest rates were low during most of our sample period, and most tenors are short. For example, if we add 400 basis points to the risk-free rates—the largest Baa-10-year Treasury spread in our sample—the average safe asset ratio only increases from 7.3 to 7.6 cents, and the broad asset ratio increases from 54.4 to 56.3 cents. We provide a sample breakdown of broad assets for the 1-year tenor in Internet Appendix Section IA.C.5.

[18]Beginning in 2022, the data include a new category of asset, short-term investments, which includes time deposits held with other financial counterparties. We include this category in the post-2022 subsample, although it is small compared to the other asset categories included in our definition of broad assets.

The maturity-matched safe asset ratio is restrictive because it requires the maturities of the safe asset and the swap to match. A 6-day maturity safe asset does not count as hedging a 7-day maturity swap lending. We relax this restriction by rounding the tenor of safe assets and FX lending to the nearest benchmark tenor for which we have estimated CIP violations, and we round tenors less than 7 days to the 1-week bucket. The rounded tenors raise the average safe asset ratio to 12 cents, or 30 cents if we include encumbered assets. Still, even with these more liberal definitions of safe asset matching, intermediaries hold only 30 cents of foreign safe assets per dollar lent. What do banks do with the remaining unaccounted-for 70 cents?

We turn to broad asset ratios, which include risky assets. With exact maturity matching, banks hold 54 cents of assets per dollar lent, with the ratio exceeding 1 when we include encumbered assets. While banks do not hold enough maturity-matched safe assets to hedge currency exposures from their CIP trades, they do hold enough risky assets to do so, with broad asset ratios of 1.06 when including encumbered assets (with only 0.20 of that ratio composed of safe assets). When considering broad asset ratios, intermediaries' foreign currency exposures are largely hedged, though a large part of this hedging relies on maturity-mismatched assets that are either encumbered or risky.

The safe asset and broad asset ratios vary substantially across currencies. The median safe asset ratio across currencies ranges from \$0.00 (CHF) to \$0.21 (EUR), with broad asset ratios ranging from 0.02 (CHF) to 1.3 (GBP).[19] Heterogeneity is relevant for understanding cross-sectional variation in bases as well. Corollary 4 shows that differences in safe asset ratios—stemming from differences in intermediaries' ability to source safe bonds in foreign currency—amplify cross-sectional variation in bases, even after we control for differences in net dollar lending across currencies. This is because differences in safe asset ratios across currencies indicate different riskiness associated with CIP trades. All else equal, lower safe asset ratios imply riskier CIP trades. When banks are net borrowing dollars, their safe asset ratios range from 3 to 20, consistent with our prediction that U.S.-based G-SIBs hold substantially more dollar-denominated safe assets.

Additionally, we find substantial variation in safe asset ratios across maturities. In particular, the rounded safe asset ratios are large for very short tenors—39 for GBP, 37 for EUR, and 18 for JPY—reflecting substantial short-maturity balances of reserves and

[19]See Table IA.5; Table IA.6 calculates the ratios including forwards and short positions.

reverse repos with central banks.[20] Such a high ratio suggests that banks may also offset their currency risk in CIP lending by investing in very short-term assets.

Ignoring maturity and aggregating across all tenors, banks hold enough foreign-denominated safe assets to hedge their foreign currency exposure, i.e., maturity-agnostic ratios exceed one, as shown in Figure 5. For example, banks hold 8 times more JPY-denominated safe assets than their CIP lending. The maturity-agnostic ratios, however, embed maturity transformation: the average maturity of net dollar lending averages one year while safe assets average 0.6 years. Banks have enough safe assets to hedge their currency exposures from their swap positioning, but only at unmatched maturities.[21]

The analysis of safe and broad asset ratios indicates that intermediaries' currency swap transactions entail significant risk. Intermediaries do not execute textbook CIP arbitrage; they do not hold a sufficient amount of maturity-matched safe assets to offset their synthetic dollar exposure. Instead of holding maturity-matched foreign safe assets, they invest in risky or maturity-mismatched foreign safe assets. Importantly, banks hold *enough* assets denominated in the same currency, but they are either in the form of risky assets or assets with mismatched maturities. Interpreted through the lens of our model, this imperfect hedging shows why $Net^k_{t,t+n}$(intermediaries' net dollar lending) helps explain cross-sectional variation in bases.

4.4 Prediction 4: Search Costs and Bases

Prediction 4 suggests another source of cross-sectional variation in bases: that search costs may vary systematically across currencies. Currencies with higher search costs should have larger magnitude bases.

The first implication of Prediction 4 is that markets where intermediaries make more substitutions from maturity-matched safe assets into unmatched safe assets and risky assets will have larger magnitude bases. These are markets where safe asset ratios are lower and search costs are larger. We test this implication and find evidence in support of it in Section 4.6.

Additionally, the search cost mechanism has another implication for intermediaries'

[20] See Figures IA.6 (maturity matched ratio by currency and tenor), IA.7 (rounded maturity ratio by currency and tenor), and IA.8 (maturity matched ratio by currency and tenor, including encumbered assets).

[21] Figure IA.9 plots the maturity mismatch over time.

behavior. When bonds of a particular currency and maturity are in short supply, it may be costly or outright impossible for banks to find safe assets to hedge CIP lending. Accordingly, intermediaries may substitute across maturities or into risky assets, resulting in lower safe asset ratios for that currency-maturity pair.

To test this prediction, we use prices from ICE Data Pricing & Reference Data to calculate the face value of sovereign bonds by currency and maturity, and match these to the safe asset ratio panel.[22] We define a currency- and maturity-specific bond supply measure, $BondsOut^k_{t,t+n}$. To account for cross-country scale differences, we standardize bond supply by total sovereign bonds outstanding in the same currency on the same day. We also exclude asset ratios and bonds with maturities less than 7 days, since we are interested in comparing the supply of securities against asset ratios. The vast majority of very short-maturity safe assets are reserves and reverse repos with central banks rather than sovereign bonds.

We confirm the basic intuition by regressing safe asset ratios on bonds outstanding in Table 6. Columns 1 through 4 show that there is a positive relationship between safe asset ratios and bonds outstanding: a 1 pp increase in $BondsOut^k_{t,t+n}$—meaning that bonds with tenor $t+n$ account for 1 pp more of the currency's total sovereign bonds—is associated with an increase in asset ratios of 0.1 for unencumbered sovereign bonds and 0.3 if we include both unencumbered and encumbered bonds. The R^2 in the regression is near zero because the odds of a sovereign bond with maturity $t+n$ existing are low, so most $BondsOut^k_{t,t+n}$ observations are zeros. We include currency and date fixed effects in most specifications to control for differences in the level of safe asset ratios within a currency stemming from differences in the level of supply. The table requires two caveats: the ICE data may understate bond supply if its coverage is incomplete. Second, greater supply does not necessarily imply higher safe asset ratios—only that they are possible.

One limitation is that we only observe consolidated balance sheets for U.S. banks, potentially understating foreign safe asset holdings if foreign banks hold more. While we cannot directly test this, two factors suggest it may not be a major concern. First, U.S. GSIBs have large maturity-agnostic safe asset ratios. Second, U.S. banks have large operations in major foreign markets, suggesting comparable access to foreign safe assets. For example, Morgan

[22] Internet Appendix Section IA.B provides details on the data cleaning. The results are similar if we use market values rather than face values, but we prefer face value since it is more consistent with the safe asset ratio's focus on cash flows at maturity.

Stanley is a primary dealer in the U.K., Japan, and more than a dozen European countries. Since we have good reason to believe U.S. banks are the largest dollar suppliers through CIP trades, the risk of net dollar lending depends on how well U.S. banks, specifically, rather than foreign banks, hedge their lending with foreign safe assets.

4.5 Prediction 5: Risk-Concentration and Elasticity of Bases

Prediction 5 states that variation in intermediaries' expertise in substituting away from safe assets leads intermediaries to specialize in particular markets, giving rise to the risks associated with CIP arbitrage being concentrated among fewer intermediaries. The basis for a given currency is more inelastic when intermediary supply is more concentrated, due to reduced risk-sharing, an effect that is potentially amplified by intermediary market power.

We show that banks specialize in markets. Without frictions or market concentration, banks' net exposures across tenors and currencies should be in equal proportion to the size of their FX books. In this case, banks face the same marginal search costs and risks across markets when lending dollars, with their net lending being highly correlated. But, with specialization, a bank lending more in its own market faces increasing marginal costs and risk, reflected in larger magnitude bases.

We empirically estimate dollar supply concentration by calculating a Herfindahl-Hirschman index (HHI) of an individual bank's notional exposure in each market using

$$\text{Supply HHI}^{k}_{t,t+n} = \sum_{i \in \text{bank}} (\text{Market Share}^{k,i}_{t,t+n})^2,$$

$$\text{Market Share}^{k,i}_{t,t+n} \equiv \frac{\text{Bank } i\text{'s USD In} + \text{Bank } i\text{'s USD Out}}{\text{Industry USD In} + \text{Industry USD Out}}.$$

Our HHI measure is not directly comparable to HHI measures in other settings because our sample is limited to nine banks, and therefore, the lowest possible value is $9 \times [(1/9) \times 100]^2 \approx 1,111$.

Figure 6 illustrates the cross-sectional variation in HHI, plotting the average measure by market against that market's size. Higher HHIs indicate more concentration. Short-term contracts for CAD and AUD are more segmented, and CHF is the most concentrated. The least segmented markets are JPY and EUR at longer tenors, especially at 1-year.[23]

We can quantify concentration across markets by asking what effective number of equally sized banks would generate the observed supply HHIs: we can calculate this using 10,000 divided by the supply HHI. Most markets cluster around 3,000—equivalent to three equally sized banks. The most concentrated markets, the short-dated CHF markets, operate as if they had fewer than two equally sized banks. Given that the main sample includes nine banks, these effective-bank numbers are small by comparison, indicating substantial concentration of activity in any given market among a small fraction of banks.

In the next section, we directly test Prediction 5 in regression form, showing that cross-sectional variation in market concentration across markets, or equivalently, cross-sectional variation in the number of effective intermediaries operating in a market, explains cross-sectional variation in bases.

4.6 Decomposing Deviations from CIP

We compare how each of the frictions measured above contributes to cross-sectional variation in bases. We run the following regression:

$$
\begin{aligned}
|\text{Basis}^k_{t,t+n}| = \alpha &+ \beta_1 \left(\text{Supply HHI}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)\right) \\
&+ \beta_2 \left(\text{Supply HHI}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)\right) \\
&+ \beta_3 \left(\text{Safe Asset Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)\right) \\
&+ \beta_4 \left(\text{Safe Asset Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)\right).
\end{aligned}
$$

The dependent variable is the absolute value of the basis for a given market on a given day. A larger basis dislocation—either expensive or cheap dollar funding compared to benchmark rates—increases the absolute value of the basis. We use the absolute value of the basis because we expect increases in the magnitude of any of the frictions to push the basis away from zero. Since we expect potential differences in the frictions when the bank is net lending dollars or net borrowing dollars, we include dummies to capture this asymmetry. We expect foreign safe asset mismatch to behave differently from USD safe asset mismatch since the

[23] We estimate similar supply HHIs looking just across tenors and currencies in the Internet Appendix; see Figures IA.10 and IA.11.

banks we study are based in the U.S.

We include controls for the risk of a safe asset sovereign issuer, which we proxy for using the country's CDS spread, and the value-weighted average CDS spread for the banks lending in that market. We merge government CDS spreads based on which safe asset an arbitrageur would hold, the foreign government CDS when $Net^k_{t,t+n} \geq 0$, and the U.S. spread when $Net^k_{t,t+n} < 0$.[24] We include tenor and date fixed effects and weight the regression by the square root of the market's share of the total daily gross notional in some specifications.[25] To make the coefficients directly comparable, we transform the independent variables to modified z-scores using each variable's full sample median and standard deviation. We use the sample median rather than the mean to mitigate the influence of the high skewness of the data.

Table 7 reports our main regression results using the sample from January 2016 to March 2023 and using safe or broad asset ratios estimated with unencumbered assets and matched maturities. Columns 2 and 4 are our preferred specifications, with the full battery of controls and weights based on market size.[26]

The first set of rows illustrates the importance of foreign safe asset mismatch and banks' search costs for foreign safe bonds, consistent with Prediction 3. The coefficients on $Net^k_{t,t+n}$ are positive and significant, with values ranging from around 5 to 7 bps in the weighted specifications, indicating that a one-standard-deviation increase in $Net^k_{t,t+n}$ corresponds to a 5 to 7 bps higher basis, consistent with the results presented in Table 5. Interpreted through the lens of our model, these coefficients capture the effect of foreign safe asset mismatch if safe asset ratios are the same across markets and if differences across markets stem from the total amount of dollar demand.

However, there are also meaningful differences in safe asset ratios across markets. Predic-

[24] CDS spreads are from Markit. For both banks and sovereigns, we use CDS spreads for the 5y tenor of senior unsecured tier for the primary curves and coupons, as identified by Markit. The euro CDS spread is a simple average of Italian and German CDS spreads (both quoted in USD). We use the MM14 contract for DB since Markit denotes both MM and MM14 as primary curves. We create a market-specific bank CDS spread by value-weighting the individual banks' CDS spreads based on their gross position in the market as a share of the total gross positions across all banks with CDS quotes from Markit in that market on that day. CDS quotes for two banks in our sample are comparatively sparse. In the regression results, coefficients on the bank CDS controls carry large and negative values, due to the fact that the banks with smaller CDS spreads do more net dollar lending in markets with the largest basis dislocations.

[25] The right panel of Figure IA.12 plots a binscatter of residuals on market size for the unweighted regression in column 1 of Table 7, showing that smaller markets have higher unweighted regression residuals.

[26] Table IA.9 shows the unweighted regression results, which are similar.

tion 4 indicates that these differences arise from differences in search costs across markets. Markets where there are higher search costs for safe bonds—and accordingly, that have lower safe asset ratios—should have more expensive dollar funding. The next four rows account for the effect of variation in foreign safe asset mismatch across different markets, stemming, for example, from differences in search costs for foreign safe assets across markets. Focusing on markets where there is net dollar demand, we observe significant negative coefficients of 9 to 16 bps in columns 1 and 2 on the safe asset ratio, indicating that a one-standard-deviation decrease in the safe asset ratio moves the basis by an additional 9 to 16 bps. When using the broad asset ratios in the regressions rather than safe asset ratios (in columns 3 and 4), these coefficients fall in magnitude to 5 bps.

The next two rows test Prediction 5: markets with more concentrated intermediary activity should have bases that are less elastic to demand, due to lower risk-sharing. A one-standard-deviation increase in our measure of concentration, supply HHI, increases the absolute value of the basis by 10 to 13 bps, depending on the controls. This result is consistent with our prediction that markets relying on a more concentrated set of banks will have larger dislocations. The elasticity of bases is affected by the concentration of intermediaries that meet dollar funding demand in each market.

The regression evidence indicates the importance of safe asset mismatch and supply concentration in explaining cross-sectional variation in CIP deviations.[27] We interpret the importance of supply concentration as arising from heterogeneous expertise across intermediaries and explore that theme further in the next section.

5 Intermediary Specialization

We next turn to exploring the final two predictions of our model, specifically those related to intermediary specialization. First, we provide evidence consistent with Prediction 6, that intermediaries specialize in markets based on their ability to manage the risk associated with

[27]In Table IA.10, we also present regression results with additional controls, including the supply of safe assets and the convenience yield. Table IA.11 separately considers each independent variable. The results are similar to those reported in the main regression, suggesting an even stronger relationship between the independent variables and bases. The results are also robust to swapping the matched asset ratios for rounded asset ratios. In Table IA.12, we show that larger and safer banks tend to intermediate markets of currencies from relatively riskier sovereign issuers.

substituting away from safe assets. Second, we use an event study analysis around the Silicon Valley Bank run to better identify the impact of financial constraints and test an additional implication arising from segmentation (Prediction 7): specializing intermediaries' constraints should help explain cross-sectional variation in bases.

5.1 Prediction 6: Specialization and Expertise in Managing Risk

Prediction 6 of our model is that intermediary specialization is driven by heterogeneous expertise in managing risk. Intermediaries better able to manage risk in a market should be more active in intermediating that market. We argue that banks gain market-specific expertise from other business areas, providing better access to counterparties in those markets.

First, we show that markets with higher supply concentration rely on banks with larger FX books. If larger banks have better risk management and access to counterparties, this provides one piece of evidence that specialization may be driven by the ability to manage risk. Column 1 of Table 8 reports results from a regression of a market's supply HHI on (log of 1 plus) the FX swap notional of the banks active in that market, weighted by their market share. The independent variable in the regression estimates the FX book size of the average bank in that market.[28]

Second, we show that concentration exhibits persistence. Markets that are more concentrated remain so over time, and banks with larger market shares retain them over time. This persistence is consistent with banks building and using expertise over time in particular markets. Columns 2 through 4 of Table 8 report results from regressions of a market's supply HHI on 1-month, 1-year, and 5-year lags. A 1-point increase in the supply HHI is associated with a 0.62-point increase in the supply HHI one year later. The relationship is stronger at shorter lags, but the coefficient is still large and significantly different from zero even with a 5-year lag.

We find that individual banks' market shares are also persistent. We regress bank i's market share on lags of its market share. A bank's market share is calculated as its share of the total gross notional of swaps in that market. The last three columns of Table 8 show the regression results using a panel at the bank-tenor-currency-date level. These persistence coefficients are similarly large and reliably different from zero, ranging from 0.87 at a 1-month

[28]Figure IA.13 in the Internet Appendix provides a scatterplot of these two variables.

lag to 0.74 at a 5-year lag. This evidence indicates that banks specialize in the same markets over time, consistent with developing and having market-specific expertise.

Third, we show that banks specialize not just in specific markets—currency and tenor—but also in counterparty segments. One bank, for example, may have a large Rolodex of Canadian insurance counterparties, while another may cater more to Asian sovereign funds. We calculate a bank's market share of a given counterparty and currency, collapsing across all maturities. We calculate the market share as the notional FX swap exposures with that counterparty-currency pair as a share of the bank's total notional FX swaps on that day. We denote this measure Bank FX $\text{Share}^{i,k}_{t,ctpty}$, where i denotes the bank and *ctpty* denotes the counterparty.[29]

We calculate two related measures: 1) we calculate the average market share of all banks except bank i, which we call Other Bank FX $\text{Share}^{i,k}_{t,ctpty}$; 2) a bank's Bank Loan $\text{Share}^{i,k}_{t,ctpty}$, to study how concentration works across a bank's lines of business. We define bank loans as the items reported by the bank in its inflows-secured and inflows-unsecured tables in the FR 2052a data.[30]

Table 9 shows that banks specialize in counterparty-currency markets, and that they also tend to hold large FX market shares in markets where they carry larger loan books. That is, banks specialize in markets where they may be able to best manage risk. The first column shows that the bank's specialization in counterparty-currency markets is persistent over time as the lag of Bank FX $\text{Share}^{i,k}_{t,ctpty}$ strongly predicts its current values. However, one concern is that banks all uniformly service the same counterparty-currency markets. Column 2 adds a variable, Other Bank FX $\text{Share}^{i,k}_{t,ctpty}$, and rejects such a possibility since the coefficient on the other bank variable is not different from 0. Column 3 shows that banks specialize in currencies and counterparties across their lines of business. We regress the bank FX share on Bank Loan $\text{Share}^{i,k}_{t,ctpty}$ and find a strong positive relationship. Adding

[29]For example, if bank z had \$100 of gross notional swaps outstanding and had \$10 of gross notional with insurance companies denominated in AUD, we would set Bank FX $\text{Share}^{z,AUD}_{t,insurance} = 10\%$. We exclude bank counterparties as they are the largest counterparty type by an order of magnitude in most markets, and we exclude two counterparty types that were removed in 2022. Recall that FX counterparty data are available beginning in May 2022.

[30]Values are reported on a gross basis and not netted. We exclude collateral swaps. These tables include offshore and onshore placements, operational balances, outstanding draws on unsecured or secured revolving facilities, other unsecured loans, short-term investments, reverse repos, securities borrowing, dollar rolls, margin loans, other secured loans, synthetic customer longs, and synthetic firm sourcing.

controls for other banks' loan shares (column 4) does not change the result. Column 5 adds Other Bank FX Share$_{t,ctpty}^{i,k}$ along with the loan share variables, showing that the bank's loan book is still informative above and beyond what other banks' FX activities are in predicting a bank's FX activities. The last column (column 6) includes the bank's lagged FX share, which dominates the results. Note, however, that the bank's loan share variable is the only other variable with a positive coefficient, even if not statistically significant.

Finally, we provide evidence that uniquely ties specialization to expertise in managing risk, as opposed to other forms of expertise. Prediction 6 indicates that banks with larger market shares hold fewer foreign safe bonds per dollar of net lending. Because substituting away from maturity-matched safe assets is risky, this prediction is specifically tied to the fact that such banks are better able to manage the risks associated with substituting away from safe assets.

We test this idea by calculating bank-specific safe-asset ratios for each market. Table 10 shows the regression results of bank-specific safe-asset ratios on the same bank's market share when banks are net borrowers of foreign currency ($Net_{t,t+n}^{k} > 0$). The latter condition matters because it indicates times when banks receive foreign currency and have a demand for foreign safe assets. The market share is defined as the bank's notional FX swap exposure in that market as a share of all banks' total notional FX swaps in the market on that day. The results show that there is a strong negative relationship between the two variables across several specifications. Using the third column, which controls for date and bank fixed effects, a one-standard-deviation increase in Bank FX Share$_{t,t+n}^{i,k}$ (15pp) corresponds to a decline in that bank's safe asset ratio of 0.16, an economically large relationship given that the average bank-specific safe asset ratio is 0.43.

The evidence supports the notion that banks specialize in particular markets because they have expertise and easier access to counterparties in those markets, stemming, for example, from other parts of their business. This expertise and access likely make it easier to manage risky assets and lower operating costs, and are distinct from other potential forms of expertise, for example, lower search costs for foreign safe assets.

5.2 Prediction 7: Evidence from the Silicon Valley Bank Run

We analyze the final prediction of our model, Prediction 7: pricing in a particular market should reflect the risk-bearing capacity of intermediaries that specialize in that market. We use the shock from the Silicon Valley Bank run of 2023, which differentially affected the risk-bearing capacity of various banks, to help identify this specialization channel.

In March 2023, Silicon Valley Bank suffered a bank run following disclosures about losses on its hold-to-maturity portfolio. Data from the publicly available H.8 show that some depositors moved from smaller to larger banks, including the G-SIBs in our sample. Between March 8 and March 15, the H.8 data show that large banks gained \$120bn of deposits while small banks lost \$108bn.[31] The average large bank had deposit inflows of \$120/25 =\$4.8 billion since H.8 data span the largest 25 domestically chartered commercial banks. Publicly available call report data show that the average bank in our sample lost \$11 billion in deposits between 2022 Q4 and 2023 Q1, ranging from −\$44 billion to \$32 billion, with a standard deviation of \$21 billion.[32]

The unexpected flow of deposits to large banks is an exogenous increase in those banks' risk-bearing capacity, at least in the short term. We use this plausibly exogenous variation in banks' abilities to intermediate FX markets to test Prediction 7 of our model: that markets should reflect the risk-bearing capacity of *their* specializing banks. The particular source of variation exploited by the shock is the cross-sectional variation in deposit inflows corresponding with the shock.

We calculate the change in dollar-denominated deposits between March 9, one day before the event, and two weeks after the event for each bank. We calculate the value-weighted change in deposits for each market (tenor and currency pairs) in our sample, which we define as $\Delta Deposits^{k}_{t+n}$, where value weights are a bank's gross notional in a given market relative to the total gross notional for that market. We fix value weights on March 9, 2023, to exclude the effects of banks rebalancing after the SVB shock. Hence, the variable has no t subscript: it is fixed through the sample and varies only over tenor and currency. Our measure provides a market-specific deposit inflow. For example, if two banks each had half of the 1-year JPY

[31] See `https://www.federalreserve.gov/releases/h8/20230324/`.

[32] We match the banks in our FX data with their main affiliated banks using the following RSSDs: JPM (852218), BAC (480228, 1443266), WFC (2362458, 451965, 1225761), C (476810), GS (2182786), BK (934329, 398668, 541101), MS (370271, 1456501, 2489805), STT (35301), and DB (214807). We calculate the change in deposits using RCON2200 (domestic deposits) and RCFN2200 (foreign deposits).

gross notional on March 9, and bank 1 had deposit flows of x and bank 2 had deposit flows of y, then the value-weighted deposit flow we assign to 1-year JPY would be $(x+y)/2$. We transform $\Delta Deposits^k_{t+n}$ into a modified z-score using the median rather than the mean. To give a sense of magnitudes, the average deposit inflow to a given market was \$20.3 billion, with a standard deviation of \$6.5 billion.

The shock is an inflow of dollars, so we expect markets where banks lend dollars will be affected. Therefore, we limit the sample to the markets where $Net^k_{t,t+n}$was positive on average over the two weeks leading into the event. In Table 11, we run a regression:

$$|\text{Basis}^k_{t,t+n}| = \alpha + \gamma_1 \mathbb{I}(\text{Post}) + \gamma_2 \Delta Deposits^k_{t+n} + \gamma_3 \mathbb{I}(\text{Post}) \times \Delta Deposits^k_{t+n} + \varepsilon^k_{t,n}. \quad (8)$$

$\mathbb{I}(\text{Post})$ is equal to 1 for days after March 9 and 0 otherwise. Our window is the two weeks before and after the event, providing the longest time frame before the last week of March, to avoid any quarter-end window-dressing that might confound the estimates.

The first three columns of Table 11 Panel A show the main results, with specifications that vary in fixed effects and whether the regression is weighted by market size. The coefficient on the post dummy is positive and significant, indicating that basis dislocations worsened following the SVB event, consistent with a risk-off sentiment. The bases are larger on average in markets with larger deposits. This finding is likely because deposit flows go to banks perceived as the safest, who lend the most dollars in markets with larger CIP dislocations.

The key result is the interaction term between the post dummy and the change in deposits. After the event, markets that relied more on banks with the largest inflows had smaller dislocations, as indicated by the significant and negative coefficient. The result is robust across specifications. The specification with all controls (column 3) finds that a one-standard-deviation increase in deposit inflows decreases the absolute value of the basis by 2 bps after the event. The effect is economically large: the average absolute value of the basis is 31 bps, so the coefficients imply a 6 percent decline.

Why would the basis relatively improve in the treated markets? The last three columns of Panel A show that treated markets experienced increased net dollar lending. The deposit inflows likely allowed banks to lend some marginal dollars. The panel runs the same event study regression except that it changes the dependent variable to $Net^k_{t,t+n}$. The main result is the third row: markets with larger deposit inflows were the same ones in which banks increased $Net^k_{t,t+n}$. The result holds when markets are weighted by their size, so small markets do not drive the results. Using column 6, a one-standard-deviation increase in deposit flows after the event increased $Net^k_{t,t+n}$by 0.6 percentage points.

Panel B runs a placebo event study using data from one month before the actual SVB event. The regression is the same except the post dummy equals 1 for days after February 9. With no salient market volatility in mid-February 2023 or abnormal deposit flows, we do not expect the interaction term to have a significant effect. The third row of Panel B shows that the placebo event had no effect on the basis, and if anything, the basis increased during the period. The last three columns of the table also show no obvious pattern in the interaction term's effect on net lending.

The evidence from the SVB bank run supports the notion that segmented markets reflect their specializing banks' risk-bearing capacity, which appears to be important for intermediaries' impact on asset prices.

6 Conclusion

Prevailing theories of financial intermediation assume an integrated financial sector with frictionless risk-sharing. Using covered-interest parity deviations as an empirical setting, we shed light on the causes and consequences of the failure of this assumption. Leveraging confidential supervisory data and cross-sectional variation in CIP deviations, we show that, contrary to its textbook treatment, covered-interest arbitrage by intermediaries entails risk. Intermediaries face search costs for the maturity-matched safe bonds required for textbook CIP arbitrage and substitute into maturity-mismatched and risky assets in their trades. The presence of risk and differences in intermediaries' expertise in managing that risk induce specialization, with intermediaries specializing in the markets in which they are better able to manage risk. Such specialization leads idiosyncratic shocks to intermediaries operating in a market to be transmitted to that market's prices, as evidenced by the Silicon Valley Bank run of March 2023. Our findings highlight the importance of risk and intermediary specialization in banks' provision of global dollar funding.

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7 Figures

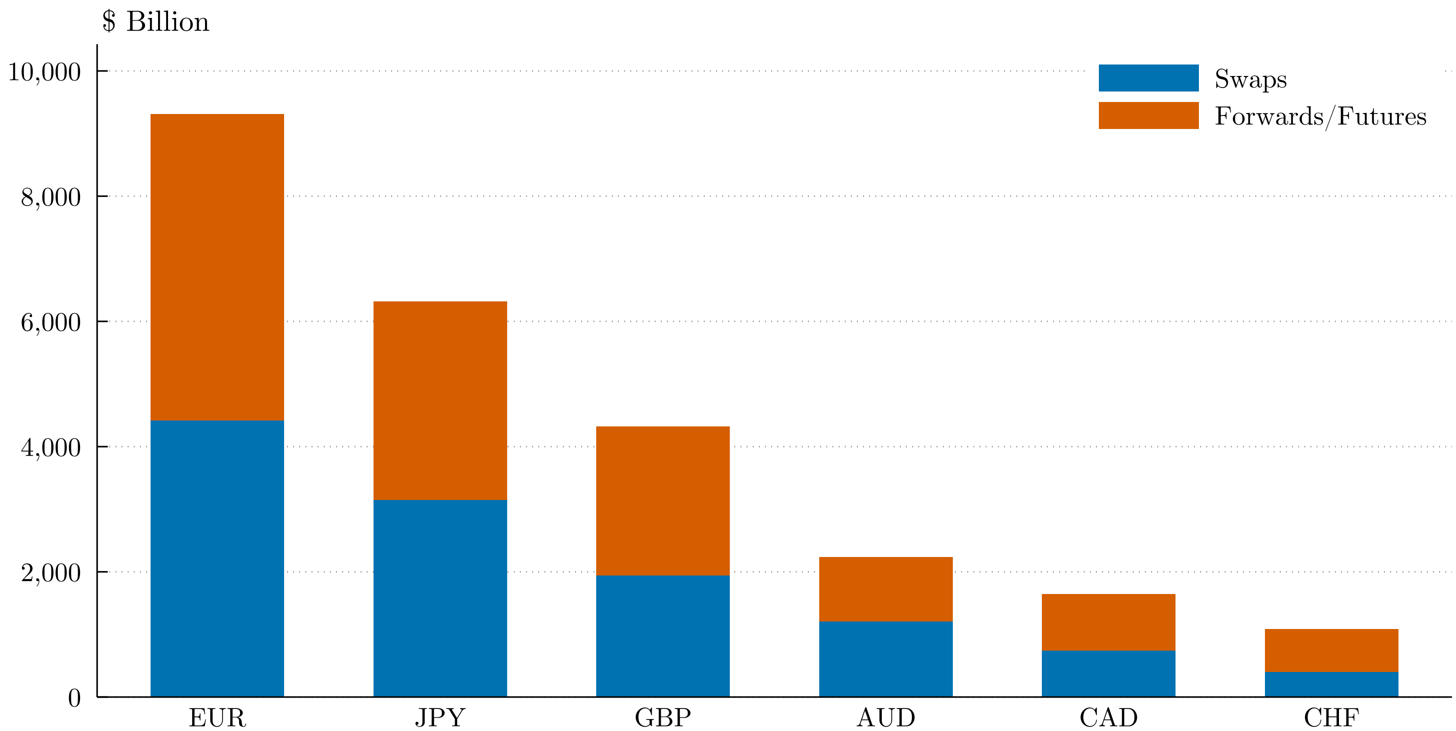

Figure 1: Foreign Exchange Notional Exposure. Figure provides the average notional FX exposures in our sample by currency across swaps and forwards/futures before limiting to the tenors with OIS rates. Sample includes only transactions in the six currencies versus the dollar.

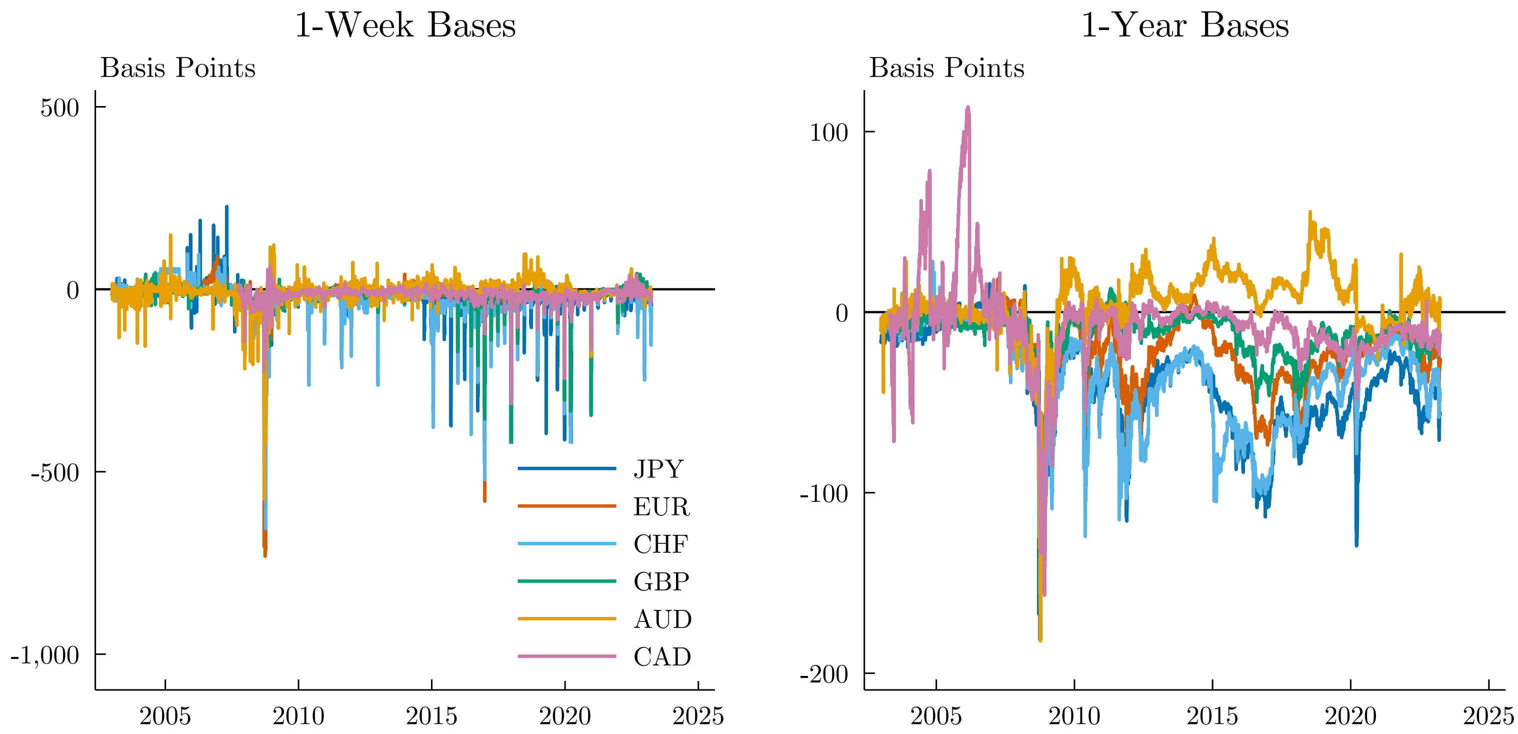

Figure 2: Covered-Interest Parity Violations. Figure plots the CIP bases across two tenors—1-week and 1-year—across several currencies.

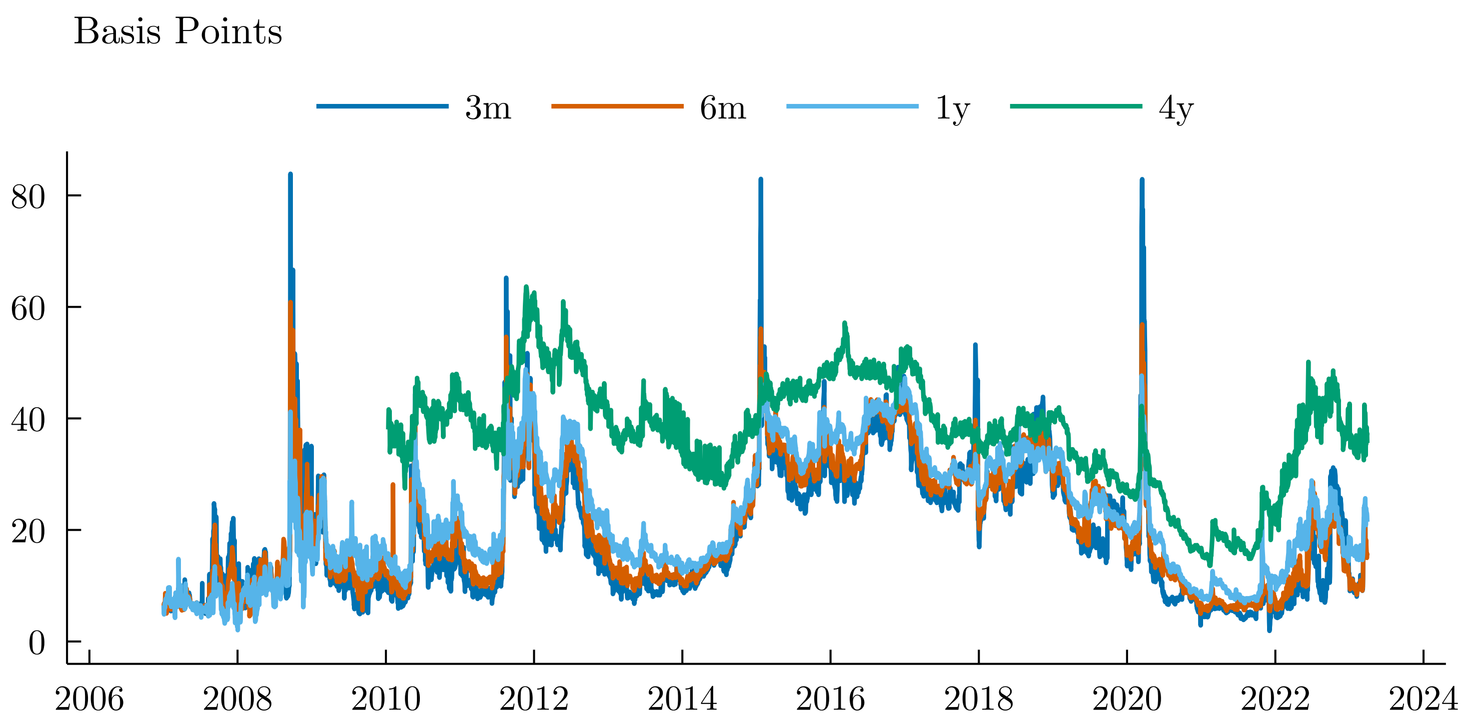

Figure 3: Cross-Sectional Standard Deviation of Covered-Interest Parity Violations. Figure plots the cross-sectional standard deviation of CIP bases for the given tenor. Sample includes only periods when we have observations for all of the six currencies against the dollar.

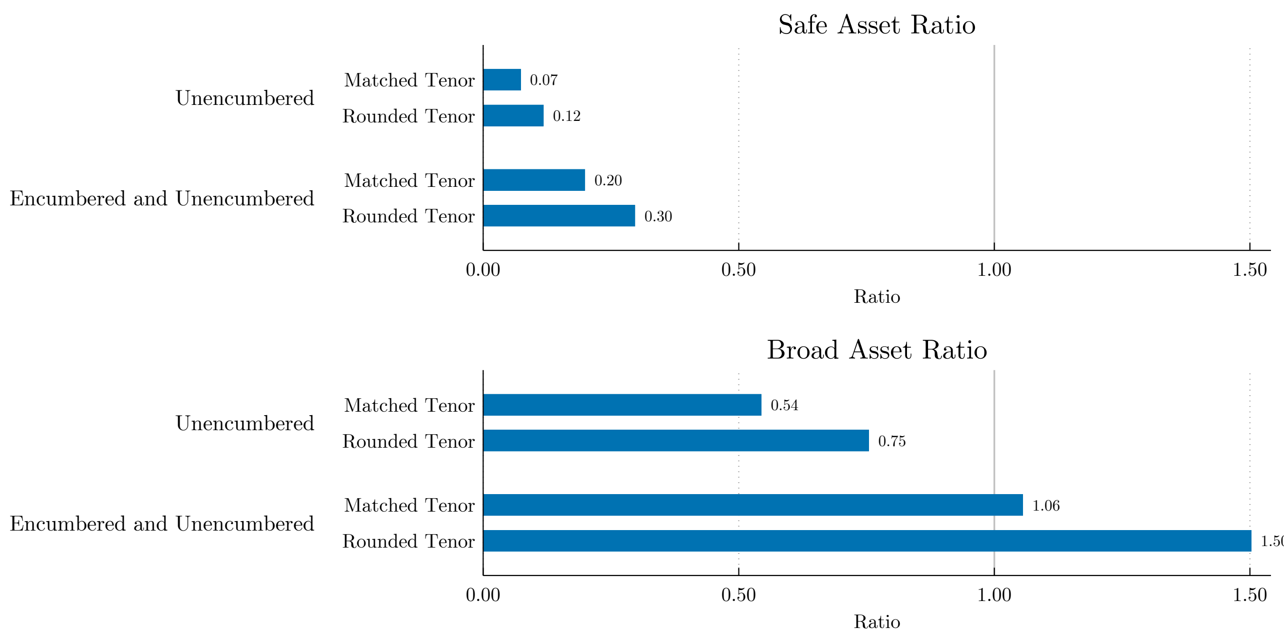

Figure 4: Summary of Safe Asset Ratios. Figure plots the average median safe and broad asset ratios across all currencies when $Net^k_{t,t+n}$is positive, excluding the USD. Matched tenor shows the asset ratio when the tenor of the underlying asset and the swap have the same maturity. Rounded tenor buckets swaps and the assets into the nearest benchmark tenor.

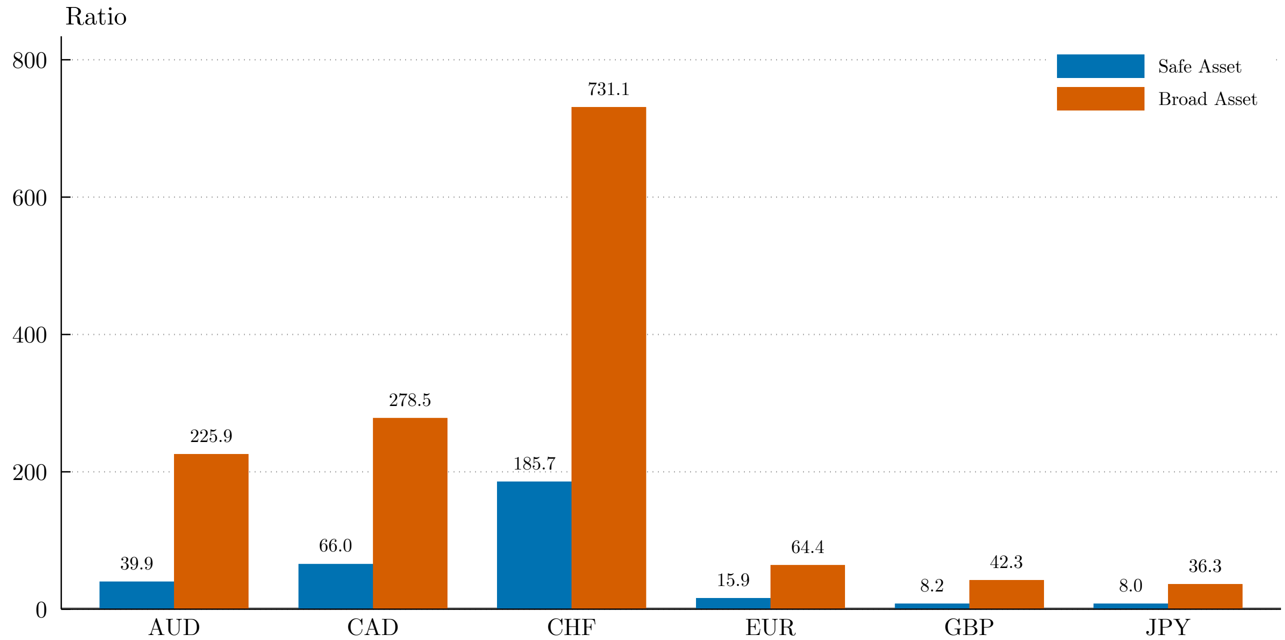

Figure 5: Safe Asset Ratios Aggregated Across All Tenors. Figure plots median safe asset and broad asset ratios when aggregating net lending and asset holdings across all tenors and the aggregated $Net^{k}_{t,t+n}$ is positive. We include all tenors, including those that do not correspond to a matching Bloomberg basis estimate as well as those with maturities of 5 years or greater.

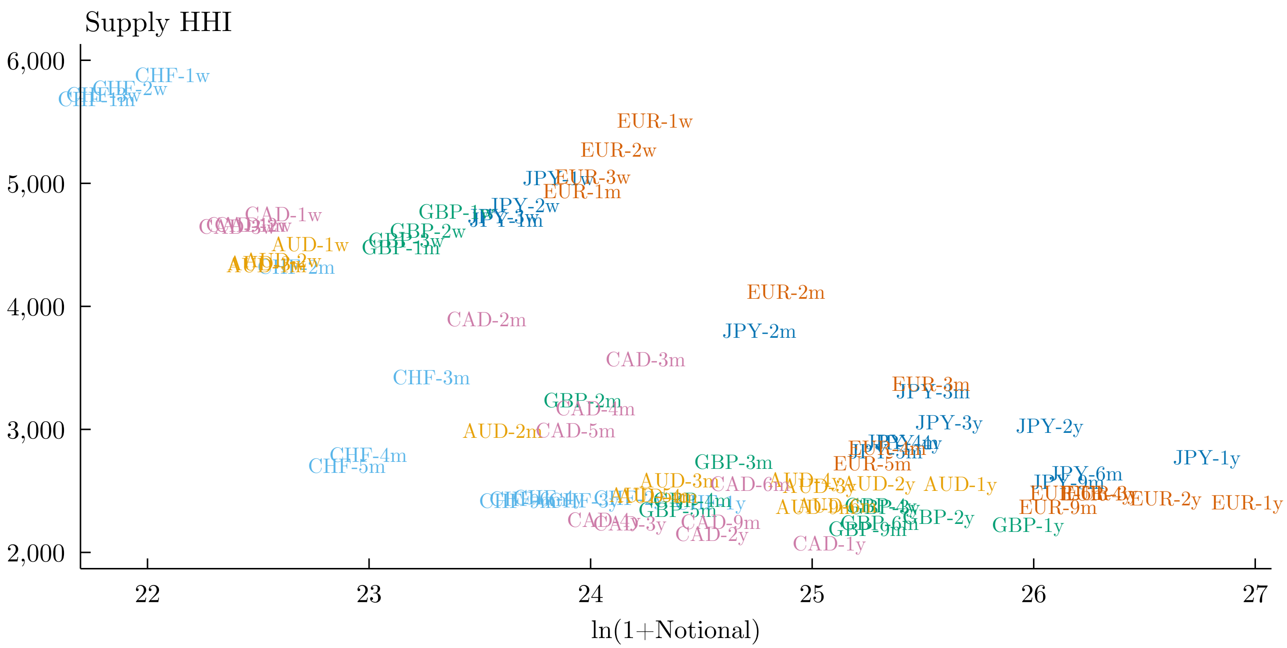

Figure 6: Supply Concentration. Figure plots the average of daily Supply $\text{HHI}^k_{t,t+n}$ against (log of 1 plus) the average notional of that market.

8 Tables

Summary Statistics, bps	All	AUD	CAD	CHF	EUR	GBP	JPY
2008–2023							
Mean	−24.1	6.2	−12.8	−46.6	−26.8	−14.7	−49.9
Std. Dev.	28.4	21.9	16.9	24.3	20.3	14.8	23.3
2016–2023							
Mean	−26.3	9.6	−14.3	−45.6	−30.9	−19.4	−57.5
Std. Dev.	27.0	14.8	6.6	22.9	15.1	9.9	20.5

Table 1: 1-Year Covered-Interest Parity Violations. Table shows mean and standard deviation of the CIP deviations at a one-year tenor. See section 3.2 for the calculation details.

by currency	Swaps		Forwards & Futures	
$ billions	Mean	Std. Dev.	Mean	Std. Dev.
AUD	689	92	331	137
CAD	411	92	290	99
CHF	215	28	207	55
EUR	2,344	344	1,610	270
GBP	914	171	729	166
JPY	1,828	179	1,146	180

by tenor	Swaps		Forwards & Futures	
$ billions	Mean	Std. Dev.	Mean	Std. Dev.
1w	91	78	308	295
2w	78	72	251	260
3w	71	67	222	240
1m	69	68	208	226
2m	188	120	456	334
3m	384	147	721	338
4m	324	78	420	122
5m	302	67	338	94
6m	730	104	564	127
9m	679	101	352	71
1y	1,396	199	277	43
2y	868	132	109	9
3y	632	101	53	6
4y	590	92	34	7

Table 2: Average daily gross FX notional across all banks. Table shows average daily notional across all banks and tenors for the matched covered-interest parity tenors by currency.

Bank's Cash Flows		t	$t+7$
Swap #1: lend USD vs. JPY			
	USD pay	−$100.00	
	JPY receive	¥11,500	
	USD receive		$104.55
	JPY pay		−¥11,500
Swap #2: lend JPY vs. USD			
	USD receive	$95.00	
	JPY pay	−¥10,925	
	USD pay		−$99.32
	JPY receive		¥10,925
Total			
(a)	Net Dollars Lent	$5.00	$5.23
(b)	Notional Dollars	$195.00	$203.87
a/b	$Net_{t,t+7}^{JPY}$	2.6%	2.6%

Table 3: Net Calculation Example. Table shows the bank's cash flows across two swaps, one receiving dollars and the other paying dollars with spot exchange rate $S_t = 115$ and forward exchange rate $F_{t,t+7} = 110$.

Mean (Percent)							
	AUD	CAD	CHF	EUR	GBP	JPY	Mean
1w	−5.2	−4.3	−4.2	−3.0	−6.6	−6.6	−5.0
2w	−5.5	−4.3	−0.6	−1.6	−7.3	−5.1	−4.1
3w	−6.2	−3.3	−1.0	−1.6	−8.1	−4.1	−4.0
1m	−5.9	−3.9	−2.0	−1.6	−8.2	−3.2	−4.1
2m	−5.6	−0.2	−7.0	2.4	−2.1	−3.8	−2.7
3m	−3.7	3.0	−1.6	2.0	−0.2	0.8	0.0
4m	−3.5	1.8	−0.1	2.5	2.5	2.5	0.9
5m	−3.6	0.9	0.0	3.1	2.4	2.1	0.8
6m	−3.9	−0.6	−1.5	4.3	2.3	4.5	0.8
9m	−2.8	−5.0	−2.4	4.8	3.5	3.5	0.3
1y	−1.9	−3.1	−3.8	2.3	3.4	5.7	0.4
2y	0.3	−3.4	−6.1	1.4	1.1	5.4	−0.2
3y	−1.9	−1.4	−7.3	1.2	0.3	5.0	−0.7
4y	−1.2	−0.3	−3.1	−1.2	1.2	7.9	0.5
Mean	−3.6	−1.7	−2.9	1.1	−1.1	1.0	

Standard Deviation (Percent)							
	AUD	CAD	CHF	EUR	GBP	JPY	Mean
1w	30.2	30.2	41.4	21.3	28.9	23.5	29.3
2w	32.3	33.1	44.3	22.8	31.0	24.7	31.4
3w	34.1	34.6	45.8	24.0	31.6	25.5	32.6
1m	34.3	35.7	45.9	23.6	31.9	26.0	32.9
2m	18.8	20.4	27.6	12.9	18.3	12.8	18.5
3m	11.2	13.7	20.1	8.5	12.8	9.7	12.6
4m	10.6	14.1	19.8	8.2	14.3	9.5	12.8
5m	11.2	15.2	19.6	8.8	14.7	9.9	13.2
6m	7.4	9.8	12.5	6.1	8.0	9.0	8.8
9m	9.0	10.5	12.7	6.3	8.4	8.5	9.2
1y	5.6	7.2	6.1	3.4	5.1	5.8	5.5
2y	6.9	7.5	5.5	3.2	5.8	7.2	6.0
3y	4.6	8.6	3.3	3.2	4.1	6.0	4.9
4y	4.6	8.2	4.4	3.3	4.9	6.7	5.4
Mean	15.8	17.8	22.1	11.1	15.7	13.2	

Table 4: *Net* Summary Statistics. Top panel reports the average daily $Net^k_{t,t+n}$ for a given currency k and maturity $t+n$. Bottom panel reports the time-series standard deviation of $Net^k_{t,t+n}$.

	All Tenors					Short-Term	Long-Term
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Net^k_{t,t+n}$	-0.054^{*}	-0.600^{***}	-0.432^{***}	-0.431^{***}	-0.587^{***}	-0.172^{**}	-1.547^{***}
	(-1.82)	(-3.97)	(-3.36)	(-3.40)	(-3.23)	(-2.55)	(-3.67)
N	151,704	149,381	149,381	149,381	74,090	106,037	43,344
R^2	0.00	0.04	0.03	0.02	0.03	0.01	0.11
Tenor FE	No	No	No	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	Yes	Yes	Yes
Weighted	No	Yes	Yes	Yes	No	Yes	Yes
Sample	All	All	All	All	Top 90	All	All

Table 5: Net and Bases. Table presents the regression of the basis on $Net^k_{t,t+n}$: $\text{Basis}^k_{t,t+n} = \alpha + \beta Net^k_{t,t+n} + \gamma\prime X_t + \varepsilon^k_{t,t+n}$. Currencies include AUD, CAD, CHF, EUR, GBP, and JPY and tenors include: 1w, 2w, 3w, 1m, 2m, 3m, 4m, 5m, 6m, 9m, 1y, 2y, 3y, and 4y. Constant omitted from table. Columns with weights are weighted by the square root of the market's daily gross notional share. Short-term column limits swaps to less than 1-year maturities, and long-term is greater than or equal to 1-year maturities. $Net^k_{t,t+n}$is in percent and basis is in basis points. The top 90 sample restricts the sample by sorting markets by gross size in descending order and including the markets that cumulatively account for 90 percent of total gross across all markets. Within R^2 reported. t-statistics shown using robust standard errors clustered by market and date where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Safe Asset Ratio$^k_{t,t+n}$				Risky Asset Ratio$^k_{t,t+n}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BondsOut$^k_{t,t+n}$	0.106***	0.103***	0.253**	0.266**	−0.439***	−0.529***	−0.135	−0.168
	(3.90)	(3.49)	(1.99)	(2.08)	(−4.38)	(−3.93)	(−0.88)	(−0.93)
N	177,726	177,726	33,387	33,387	177,726	177,726	33,387	33,387
R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Currency FE	No	Yes	No	Yes	No	Yes	No	Yes
Incl. Encumbered	No	No	Yes	Yes	No	No	Yes	Yes

Table 6: Asset Ratios and Sovereign Bond Supply. Table presents the regression of asset ratios on BondsOut$^k_{t,t+n}$ when $Net^k_{t,t+n}$is positive and for maturities greater than seven days. BondsOut$^k_{t,t+n}$ is the face value of currency k's sovereign bonds with a maturity of $t+n$ standardized by the total face value of sovereign bonds outstanding denominated in the same currency on the same day. Sovereign bond data are from ICE Data and Reference Pricing; see appendix for details. Within R^2 reported. t-statistics shown using robust standard errors clustered by market and date, where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)
Safe Asset Mismatch				
$\text{Net}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$	5.17	5.25**	5.19	5.26**
	(1.59)	(2.12)	(1.59)	(2.13)
$\text{Net}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$	4.68**	7.15***	4.66**	7.14***
	(2.11)	(3.13)	(2.11)	(3.13)
$\text{Safe Asset Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$	−15.95**	−9.45**		
	(−2.13)	(−2.07)		
$\text{Safe Asset Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$	−0.44	−0.50		
	(−1.40)	(−1.35)		
$\text{Broad Asset Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$			−5.05	−4.50*
			(−1.64)	(−1.71)
$\text{Broad Asset Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$			−0.90	−1.02
			(−1.29)	(−1.25)
Supply Concentration				
$\text{Supply HHI}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$	15.62***	10.44***	15.62***	10.44***
	(4.55)	(6.01)	(4.55)	(6.01)
$\text{Supply HHI}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$	17.17***	13.41***	17.17***	13.41***
	(5.11)	(6.65)	(5.11)	(6.65)
Controls				
$\text{Bank CDS}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$		−92.94***		−92.94***
		(−6.55)		(−6.55)
$\text{Bank CDS}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$		−94.04***		−94.05***
		(−6.52)		(−6.52)
$\text{Govt CDS}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$		−2.13***		−2.13***
		(−2.87)		(−2.87)
$\text{Govt CDS}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$		−2.63		−2.62
		(−1.26)		(−1.25)
N	149,381	149,290	149,381	149,290
R^2	0.09	0.22	0.09	0.22
Tenor FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Weighted	Yes	Yes	Yes	Yes

Table 7: Regression of the absolute value of the basis on frictions. Table presents the regression described in section 4.6. The dependent variable is the absolute value of the basis. To make the coefficients directly comparable, we transform the independent variables to modified z-scores using each variable's full sample median and standard deviation. Regression includes tenor and date fixed effects and weights by the square root of the market's share of the total daily gross notional. Within R^2 reported. t-statistics shown using robust standard errors clustered by market and date where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	HHI $\text{Supply}^k_{t,t+n}$				Market $\text{Share}^{k,i}_{t,t+n}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln(1 + \text{Avg. Book Size}^k_{t,t+n})$	3461.9***						
	(10.33)						
HHI $\text{Supply}^k_{t-1m,t-1m+n}$		0.637***					
		(29.22)					
HHI $\text{Supply}^k_{t-1y,t-1y+n}$			0.624***				
			(30.63)				
HHI $\text{Supply}^k_{t-5y,t-3y+n}$				0.470***			
				(19.08)			
Market $\text{Share}^{k,i}_{t-1m,t-1m+n}$					0.866***		
					(24.09)		
Market $\text{Share}^{k,i}_{t-1y,t-1y+n}$						0.838***	
						(18.23)	
Market $\text{Share}^{k,i}_{t-5y,t-5y+n}$							0.736***
							(9.39)
N	149,381	145,276	126,973	45,447	1,408,437	1,230,588	441,360
R^2	0.22	0.41	0.41	0.29	0.75	0.72	0.57
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Specialization Persistence. Table presents the regression of measures of specialization on its lags as well as (1 plus the log of the) average notional book size of banks in that market, which is the notional book size of the banks active in that market, weighted by their market share in that market. Lag for 1 month is 21 business days, for 1 year is 250 business days, and for 5 years is 1,250 business days. Within R^2 reported. t-statistics shown using robust standard errors clustered by market and date for the first four columns and clustered by bank and date for the last three columns, where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Bank FX Share$^{i,k}_{t,ctpty}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Bank FX Share$^{i,k}_{t-6m,ctpty}$	0.951***	0.938***				0.927***
	(43.50)	(32.10)				(24.60)
Other Bank FX Share$^{i,k}_{t,ctpty}$		0.0539			0.571***	0.0211
		(1.50)			(4.41)	(0.66)
Bank Loan Share$^{i,k}_{t,ctpty}$			0.234***	0.174**	0.155**	0.108
			(3.95)	(2.36)	(2.33)	(1.19)
Other Bank Loan Share$^{i,k}_{t,ctpty}$				0.265***	0.0332	−0.00849
				(3.39)	(0.74)	(−0.28)
N	93,636	93,636	208,386	208,386	208,386	93,636
R^2	0.59	0.59	0.05	0.06	0.14	0.60

Table 9: Specialization in Counterparties. Table presents the regression of Bank FX Share$^{i,k}_{t,ctpty}$ on several variables. Bank FX Share$^{i,k}_{t,ctpty}$ is the bank's notional FX swap exposures with that counterparty-currency pair as a share of the bank's total notional FX swaps on that day. Other Bank FX Share$^{i,k}_{t,ctpty}$ is the average market share of all banks except bank i. Bank Loan Share$^{i,k}_{t,ctpty}$ and Other Bank Loan Share$^{i,k}_{t,ctpty}$ are calculated analogously using secured and unsecured loans rather than FX positions. Constant omitted from the table. Within R^2 reported. t-statistics shown using robust standard errors clustered by date and bank where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Bank Safe Asset Ratio$^{i,k}_{t,t+n}$			
	(1)	(2)	(3)	(4)
Market Share$^{k,i}_{t,t+n}$	-0.114^{***}	-0.112^{***}	-0.054^{**}	-0.010^{***}
	(-3.07)	(-3.10)	(-2.57)	(-4.12)
N	891,057	891,057	891,057	502,684
R^2	0.00	0.00	0.00	0.00
Time FE	No	Yes	Yes	Yes
Bank FE	No	No	Yes	Yes
Weighted	No	No	No	Yes

Table 10: Banks with larger market shares have lower safe asset ratios. Table presents the regression of Bank Safe Asset Ratio$^{i,k}_{t,t+n}$ on the bank's FX market share, Bank FX Share$^{i,k}_{t,t+n}$ when $Net^{k}_{t,t+n} > 0$, which corresponds to times when banks receive foreign currency and have demand for foreign safe assets. The market share is defined as the bank's notional FX swap exposures in that market as a share of all banks' total notional FX swaps in the market on that day. Regression includes date, bank, and tenor fixed effects, and we weight the regression by the square root of the market's share of the total daily gross notional. Constant omitted from the table. Within R^2 reported. t-statistics shown using robust standard errors clustered by date and bank where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Event Study.						
	Dependent Var.: $\lvert \text{Basis}^k_{t,t+n} \rvert$			Dependent Var.: $Net^k_{t,t+n}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{I}$(Post)	14.59***	14.96***	14.52***	−1.78***	−1.89***	−1.90***
	(7.82)	(7.94)	(7.47)	(−3.93)	(−3.30)	(−3.13)
$\Delta\text{Deposits}^k_{t+n}$	16.38***	23.70***	21.11***	−0.26	1.65	1.63
	(6.10)	(6.96)	(5.21)	(−0.29)	(1.51)	(1.34)
$\mathbb{I}(\text{Post}) \times \Delta\text{Deposits}^k_{t+n}$	−2.11***	−2.37**	−1.95*	0.53**	0.60*	0.60
	(−3.21)	(−2.23)	(−1.98)	(2.52)	(1.73)	(1.61)
Supply $\text{HHI}^k_{t,t+n}$			11.25			0.10
			(1.54)			(0.05)
Constant	10.07***	3.56	7.79*	5.66***	4.01***	4.04**
	(4.72)	(1.06)	(1.80)	(4.63)	(3.10)	(2.55)
N	959	959	959	959	959	959
R^2	0.51	0.54	0.55	0.01	0.04	0.04
Tenor FE	No	Yes	Yes	No	Yes	Yes
Weighted	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Placebo Event Study.						
	Dependent Var.: $\lvert \text{Basis}^k_{t,t+n} \rvert$			Dependent Var.: $Net^k_{t,t+n}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{I}$(Post)	−1.46***	−1.64***	−1.76***	1.44**	1.72***	1.70***
	(−5.66)	(−41.16)	(−9.70)	(2.73)	(2.93)	(2.91)
$\Delta\text{Deposits}^k_{t+n}$	15.61***	20.26***	17.91***	0.01	1.95	1.54
	(7.19)	(7.81)	(5.57)	(0.01)	(1.54)	(1.01)
$\mathbb{I}(\text{Post}) \times \Delta\text{Deposits}^k_{t+n}$	0.47	0.62**	0.70***	0.19	0.00	0.02
	(1.31)	(2.81)	(3.35)	(0.71)	(0.00)	(0.05)
Supply $\text{HHI}^k_{t,t+n}$			10.88			1.88
			(1.62)			(0.73)
Constant	12.49***	8.36***	12.47***	2.49	0.70	1.42
	(6.50)	(3.15)	(3.38)	(1.59)	(0.47)	(0.71)
N	910	910	910	910	910	910
R^2	0.60	0.57	0.59	0.01	0.04	0.05
Tenor FE	No	Yes	Yes	No	Yes	Yes
Weighted	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: March 2023 Event Study. Table shows the results of the regression $\lvert \text{Basis}^k_{t,t+n} \rvert = \alpha + \gamma_1 \mathbb{I}(\text{Post}) + \gamma_2 \Delta\text{Deposits}^k_{t+n} + \gamma_3 \mathbb{I}(\text{Post}) \times \Delta\text{Deposits}^k_{t+n} + \varepsilon^k_{t,t+n}$. We transform $\Delta\text{Deposits}^k_{t+n}$ to a modified z-score using its median and standard deviation; supply HHI is transformed to a modified z-score using its full sample median and standard deviation. $\mathbb{I}$(Post) is equal to 1 for days after March 9, and 0 otherwise. The window is the 2 weeks before and after the event. Panel B is a placebo test which shifts the treatment date to February 9. Regression includes tenor fixed effects and we weight the regression by the square root of the market's share of the total daily gross notional. Within R^2 reported. t-statistics shown using robust standard errors clustered by market and date where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Internet Appendix to

Risk and Specialization in Covered-Interest Arbitrage

(Not intended for publication)

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The Internet Appendix consists of four sections. Section IA.A provides derivations for predictions of the model. Section IA.B provides additional details about the data. Section IA.C provides additional discussion and results to supplement the main text. Section IA.D presents supplemental tables and figures.

IA.A Model Derivations

For Predictions 4, 5, and 6, we consider a currency k where intermediaries are net dollar lending ($X_{k,t} > 0$, which implies $Z_{i,k,t} < 0, \forall i$), and assume the following regularity conditions:

1. intermediary i has a non-trivial position in currency k ($\frac{\mu_k - y_{k,t}}{\gamma_i \sigma^2_{i,k}} < |Z_{i,k,t}|$), where $Z_{i,k,t}$ is the dollar amount of their forward position (Predictions 4 and 6);

2. balance sheet costs are not so large that they dominate search costs and risk considerations: $0 < \lambda_{BS} < \min_{i,k} \frac{1}{2(N_k-1)\phi_{i,k}\left(1-\frac{\phi_{i,k}}{\sum_m^{N_i}\phi_{m,k}}\right)}$ (Predictions 5 and 6).

Derivation of Prediction 4.

We want to show that $\frac{\partial \text{Basis}_{k,t}}{\partial \lambda_{s,k}} < 0$ when $X_{k,t} > 0$, i.e. when customers are net borrowers of dollars in currency k.

In the expression without intermediary heterogeneity, we can write

$$\begin{aligned}
\frac{\partial \text{Basis}_{k,t}}{\partial \lambda_{s,k}} &= \frac{\partial}{\partial \lambda_{s,k}}\Big[-\frac{\lambda_{s,k}\gamma}{N_i(\gamma+\pi\lambda_{s,k})}X_{k,t} - \lambda_{BS}\frac{\text{Sign}(X_{k,t})}{N_i}\sum_j^{N_k}|X_{j,t}| + \frac{\pi\lambda_{s,k}}{\gamma+\pi\lambda_{s,k}}(\mu_k - y_{k,t}).\Big] \\
&= -\frac{\gamma^2}{(\gamma+\pi\lambda_{s,k})^2}\frac{X_{k,t}}{N_i} + \frac{\gamma\pi}{(\gamma+\pi\lambda_{s,k})^2}(\mu_k - y_{k,t}) \\
&= -\frac{\gamma^2\sigma^4}{(\lambda_{s,k}+\gamma\sigma^2)^2}\frac{X_{k,t}}{N_i} + \frac{\gamma\sigma^2}{(\lambda_{s,k}+\gamma\sigma^2)^2}(\mu_k - y_{k,t}) \\
&<^* \ 0,
\end{aligned}$$

where the inequality * follows from the assumption $\frac{\mu_k - y_{k,t}}{\gamma\sigma^2} < |Z_{i,k,t}|$, where $|Z_{i,k,t}| = \frac{X_{k,t}}{N_i}, \forall i$ in the homogeneous intermediary case. Hence, higher search costs ($\lambda_{s,k}$) make synthetic dollar funding more expensive (more negative basis).

Derivation of Prediction 5.

Note that $\phi_{i,k}$ is a concave and increasing function of $\pi_{i,k}$, which can be observed by

$$\begin{aligned}\frac{\partial \phi_{i,k}}{\partial \pi_{i,k}} &= \frac{\gamma_i \lambda_{s,k}^2}{(\lambda_{BS}\pi_{i,k}\lambda_{s,k} + \gamma_i(\lambda_{BS} + \lambda_{s,k}))^2} > 0, \text{ and} \\ \frac{\partial^2 \phi_{i,k}}{\partial \pi_{i,k}^2} &= \frac{-2\gamma_i \lambda_{BS} \lambda_{s,k}^3}{(\lambda_{BS}\pi_{i,k}\lambda_{s,k} + \gamma_i(\lambda_{BS} + \lambda_{s,k}))^3} < 0.\end{aligned}$$

By the concavity of $\phi_{i,k}$, holding $\sum_{i=1}^{N_i} \pi_{i,k} = \Pi_k$ fixed and assuming all else equal among intermediaries (e.g., holding $\gamma_i = \gamma$ fixed $\forall i$), Jensen's inequality implies that $\sum_{i=1}^{N_i} \phi_{i,k}$ is maximized at $\pi_{i,k} = \frac{\Pi_k}{N_i}, \forall i$. Moreover, the concavity of $\phi(\pi_{i,k})$ also implies that for any $\pi_{i,k} > \pi_{j,k}$, any transfer of expertise from i to j (e.g., subtracting $\delta \in (0, \pi_{i,k} - \pi_{j,k})$ expertise from intermediary i and providing it to intermediary j) strictly increases $\sum_{i=1}^{N_i} \phi(\pi_{i,k})$, i.e., $\phi(\pi_{i,k}) + \phi(\pi_{j,k}) < \phi(\pi_{i,k} - \delta) + \phi(\pi_{j,k} + \delta)$. Hence, redistribution towards parity in $\pi_{i,k}$ strictly increases the supply elasticity.

Lastly, we show that in equilibrium, differences in expertise give rise to differences in market shares. In particular, for two otherwise identical intermediaries i and j where $\pi_{i,k} > \pi_{j,k}$, we show that i has a larger market share than j, by showing that $\frac{\partial Z_{i,k,t}}{\partial \pi_{i,k}} < 0$, i.e., market shares rise with expertise (noting that $X_{k,t} > 0$ and so $Z_{i,k,t} < 0$). For this exercise, given that we are comparing two intermediaries in the same equilibrium, we hold the basis in market k fixed and compute partial derivatives, without considering the equilibrium feedback effects that changing $\pi_{i,k}$ has on the basis.

To proceed, we denote

$$\mathbf{Z}_{i,t} \equiv (Z_{i,1,t}, \ldots, Z_{i,N_k,t})^T.$$

We can express intermediary i's first-order condition from Equation (3) as

$$0 = G_{i,k}(\mathbf{Z}_{i,t}, \pi_{i,k}) \equiv Z_{i,k,t} - \phi_{i,k}\left(\text{Basis}_{k,t} + \lambda_{BS}\sum_{\ell \neq k}|Z_{i,\ell,t}|\right) + \tau_{i,k}(\mu_k - y_{k,t}).$$

We can stack the $N_i N_k$ first-order conditions across intermediaries and currencies into the system $F(\mathbf{Z}_t, \boldsymbol{\pi}) = 0$, where $\mathbf{Z}_t = (\mathbf{Z}_{1,t}, \ldots, \mathbf{Z}_{N_i,t})^T$. The Jacobian of this system is

$$\tilde{J} \equiv \frac{\partial F}{\partial Z} = I - \lambda_{BS}(B - C),$$

where, noting that $\text{Sign}(Z_{i,\ell,t}) = -\text{Sign}(X_{\ell,t})$, the block matrices B and C are defined by

$$B_{(i,k),(j,\ell)} \;=\; \text{Sign}(X_{\ell,t})\phi_{i,k}\,\mathbf{1}_{\{j=i\}}\mathbf{1}_{\{\ell\neq k\}}, \qquad C_{(i,k),(j,\ell)} \;=\; \text{Sign}(X_{\ell,t})\phi_{i,k}\,\frac{\phi_{j,k}}{\sum_{m=1}^{N_i}\phi_{m,k}}\,\mathbf{1}_{\{\ell\neq k\}}.$$

We want $\tilde{J}$ to be invertible, and for $\tilde{J}^{-1}$ to have positive diagonal entries. Both of these conditions are met under the assumption $\lambda_{BS} < \min_{i,k} \frac{1}{2(N_k-1)\phi_{i,k}\left(1-\frac{\phi_{i,k}}{\sum_m^{N_i}\phi_{m,k}}\right)}$. Letting $\mathcal{M} \equiv B - C$, because

$$\sum_{(j,\ell)\neq(i,k)} |\tilde{J}_{(i,k),(j,\ell)}| < \lambda_{BS}\,2(N_k-1)\phi_{i,k}\left(1-\frac{\phi_{i,k}}{\sum_m^{N_i}\phi_{m,k}}\right) < 1 \qquad \forall (i,k),$$

each row of $\tilde{J} = I - \lambda_{BS}\mathcal{M}$ is strictly diagonally dominant. Hence $\tilde{J}$ is nonsingular with positive diagonal entries, which implies

$$0 < \left[\tilde{J}^{-1}\right]_{(i,k),(i,k)} < \frac{1}{1-\lambda_{BS}\,2(N_k-1)\phi_{i,k}\left(1-\frac{\phi_{i,k}}{\sum_m^{N_i}\phi_{m,k}}\right)},$$

so every diagonal entry of $\tilde{J}^{-1}$ is strictly positive. Then note that by the Implicit Function Theorem,

$$\frac{\partial \mathbf{Z}_t}{\partial \pi_{i,k}} \;=\; -\,\tilde{J}^{-1}\,\underbrace{\frac{\partial F}{\partial \pi_{i,k}}}_{\mathbf{d}_{(i,k)}}, \qquad \left[\mathbf{d}_{(i,k)}\right]_{(j,\ell)} \;=\; \begin{cases} \dfrac{\partial G_{j,k}}{\partial \pi_{i,k}}, & \text{if } \ell = k, \\ 0, & \text{otherwise.} \end{cases}$$

Consequently,

$$\begin{aligned} \frac{\partial Z_{i,k,t}}{\partial \pi_{i,k}} &= -\sum_{j=1}^{N_i}\left[\tilde{J}^{-1}\right]_{(i,k),(j,k)}\frac{\partial G_{j,k}}{\partial \pi_{i,k}} \\ &= -\left[\tilde{J}^{-1}\right]_{(i,k),(i,k)}\frac{\partial G_{i,k}}{\partial \pi_{i,k}}. \end{aligned}$$

Hence it is sufficient to show that $\frac{\partial G_{i,k}}{\partial \pi_{i,k}} > 0$. Differentiating $G_{i,k}$ with respect to $\pi_{i,k}$ and evaluating at $G_{i,k} = 0$ gives

$$\begin{aligned}\frac{\partial G_{i,k}}{\partial \pi_{i,k}} &= -\frac{\partial \phi_{i,k}}{\partial \pi_{i,k}} \left(\text{Basis}_{k,t} + \lambda_{BS} \sum_{\ell \neq k} |Z_{i,\ell,t}| \right) + \frac{\partial \tau_{i,k}}{\partial \pi_{i,k}} (\mu_k - y_{k,t}) \\ &= -\frac{\partial \phi_{i,k}}{\partial \pi_{i,k}} \left(\frac{Z_{i,k,t} + \tau_{i,k}(\mu_k - y_{k,t})}{\phi_{i,k}} \right) + \frac{\partial \tau_{i,k}}{\partial \pi_{i,k}} (\mu_k - y_{k,t}) \\ &= -\frac{\partial \phi_{i,k}}{\partial \pi_{i,k}} \frac{Z_{i,k,t}}{\phi_{i,k}} + (\mu_k - y_{k,t}) \left(\frac{\partial \tau_{i,k}}{\partial \pi_{i,k}} - \frac{\tau_{i,k}}{\phi_{i,k}} \frac{\partial \phi_{i,k}}{\partial \pi_{i,k}} \right) \\ &= \underbrace{-\frac{\partial \phi_{i,k}}{\partial \pi_{i,k}} \frac{Z_{i,k,t}}{\phi_{i,k}}}_{>0} + \underbrace{(\mu_k - y_{k,t}) \left(\frac{\gamma_i \lambda_{s,k}}{(\gamma_i + \pi_{i,k}\lambda_{s,k})(\lambda_{BS}\pi_{i,k}\lambda_{s,k} + \gamma_i(\lambda_{BS} + \lambda_{s,k}))} \right)}_{>0} \\ &> 0. \end{aligned}$$

Derivation of Prediction 6.

Consider an equilibrium with two identical intermediaries i and j, except that $\pi_{i,k} > \pi_{j,k}$. Holding the basis fixed (since we are making cross-sectional comparisons in the same equilibrium), we show that

(i) $\frac{\partial Z_{i,k,t}}{\partial \pi_{i,k}} < 0$ (intermediary shares in a market rise with expertise $\pi_{i,k}$, noting $Z_{i,k,t} < 0$ since $X_{k,t} > 0$), and

(ii) $\alpha_{i,k,t} > \alpha_{j,k,t}$ (i has a higher risky asset share; $\frac{d\alpha_{i,k,t}}{d\pi_{i,k}} > 0$).

The derivation of (i) is shown in the derivation of Prediction 5. For (ii), differentiating $\alpha_{i,k}$ with respect to $\pi_{i,k}$ yields

$$\begin{aligned}\frac{d\alpha_{i,k,t}}{d\pi_{i,k}} &= \frac{\partial \alpha_{i,k,t}}{\partial \pi_{i,k}} + \frac{\partial \alpha_{i,k,t}}{\partial Z_{i,k,t}} \frac{\partial Z_{i,k,t}}{\partial \pi_{i,k}} \\ &= \underbrace{-\frac{\gamma_i(\mu_k - y_{k,t} - Z_{i,k,t}\lambda_{s,k})}{Z_{i,k,t}\left(\gamma_i + \pi_{i,k}\lambda_{s,k}\right)^2}}_{\equiv T_1} + \underbrace{\frac{\pi_{i,k}(\mu_k - y_{k,t})}{Z^2_{i,k,t}(\gamma_i + \pi_{i,k}\lambda_{s,k})} \frac{\partial Z_{i,k,t}}{\partial \pi_{i,k}}}_{\equiv T_2}. \end{aligned}$$

Note that $T_1 > 0$ and $T_2 < 0$, so $\frac{d\alpha_{i,k}}{d\pi_{i,k}}$ is positive if and only if $T_1 > |T_2|$. Observe from the proof of (i) that

$$
\begin{aligned}
\frac{\partial Z_{i,k,t}}{\partial \pi_{i,k}} \leq & \frac{1}{1-\lambda_{BS}\, 2(N_k-1)\phi_{i,k}\left(1-\frac{\phi_{i,k}}{\sum_m^{N_i}\phi_{m,k}}\right)} \frac{\partial G_{i,k}}{\partial \pi_{i,k}} \\
= & \frac{1}{1-\lambda_{BS}\, 2(N_k-1)\phi_{i,k}\left(1-\frac{\phi_{i,k}}{\sum_m^{N_i}\phi_{m,k}}\right)} \left(-\frac{\partial \phi_{i,k}}{\partial \pi_{i,k}} \frac{Z_{i,k,t}}{\phi_{i,k}} + (\mu_k - y_{k,t}) \left(\frac{\partial \tau_{i,k}}{\partial \pi_{i,k}} - \frac{\tau_{i,k}}{\phi_{i,k}} \frac{\partial \phi_{i,k}}{\partial \pi_{i,k}}\right)\right) \\
= & \frac{1}{1-\lambda_{BS}\, 2(N_k-1)\phi_{i,k}\left(1-\frac{\phi_{i,k}}{\sum_m^{N_i}\phi_{m,k}}\right)} \frac{\gamma_i \lambda_{s,k}(\mu_k - y_{k,t} - \lambda_{s,k} Z_{i,k,t})}{(\gamma_i + \pi_{i,k}\lambda_{s,k})(\lambda_{BS}\pi_{i,k}\lambda_{s,k} + \gamma_i(\lambda_{BS} + \lambda_{s,k}))} \\
= & \frac{\phi_{i,k}}{1-\lambda_{BS}\, 2(N_k-1)\phi_{i,k}\left(1-\frac{\phi_{i,k}}{\sum_m^{N_i}\phi_{m,k}}\right)} \frac{\gamma_i \lambda_{s,k}(\mu_k - y_{k,t} - \lambda_{s,k} Z_{i,k,t})}{(\gamma_i + \pi_{i,k}\lambda_{s,k})^2}.
\end{aligned}
$$

Hence, we can bound $|T_2|$ by

$$
\begin{aligned}
|T_2| \leq & \frac{\pi_{i,k}(\mu_k - y_{k,t})}{Z_{i,k,t}^2(\gamma_i + \pi_{i,k}\lambda_{s,k})} \frac{\phi_{i,k}}{1-\lambda_{BS}\, 2(N_k-1)\phi_{i,k}\left(1-\frac{\phi_{i,k}}{\sum_m^{N_i}\phi_{m,k}}\right)} \frac{\gamma_i \lambda_{s,k}(\mu_k - y_{k,t} - \lambda_{s,k} Z_{i,k,t})}{(\gamma_i + \pi_{i,k}\lambda_{s,k})^2} \\
= & \frac{\phi_{i,k}\pi_{i,k}\lambda_{s,k}(\mu_k - y_{k,t})}{Z_{i,k,t}^2(\gamma_i + \pi_{i,k}\lambda_{s,k})^3} \frac{\gamma_i(\mu_k - y_{k,t} - \lambda_{s,k} Z_{i,k,t})}{1-\lambda_{BS}\, 2(N_k-1)\phi_{i,k}\left(1-\frac{\phi_{i,k}}{\sum_m^{N_i}\phi_{m,k}}\right)}.
\end{aligned}
$$

Then, we can observe that

$$
\begin{aligned}
\frac{|T_2|}{T_1} \leq & \frac{\phi_{i,k}\pi_{i,k}\lambda_{s,k}(\mu_k - y_{k,t})}{|Z_{i,k,t}|(\gamma_i + \pi_{i,k}\lambda_{s,k})} \frac{1}{1-\lambda_{BS}\, 2(N_k-1)\phi_{i,k}\left(1-\frac{\phi_{i,k}}{\sum_m^{N_i}\phi_{m,k}}\right)} \\
= & \frac{\mu_k - y_{k,t}}{|Z_{i,k,t}|} \frac{\tau_{i,k}}{1-\lambda_{BS}\, 2(N_k-1)\phi_{i,k}\left(1-\frac{\phi_{i,k}}{\sum_m^{N_i}\phi_{m,k}}\right)} \\
= & \frac{\mu_k - y_{k,t}}{|Z_{i,k,t}|} \frac{\lambda_{s,k}}{\left(\gamma_i\sigma_{i,k}^2\lambda_{s,k} + \lambda_{BS}(\lambda_{s,k} + \gamma_i\sigma_{i,k}^2)\right)\left(1-\lambda_{BS}\, 2(N_k-1)\phi_{i,k}\left(1-\frac{\phi_{i,k}}{\sum_m^{N_i}\phi_{m,k}}\right)\right)} \\
< & \frac{\mu_k - y_{k,t}}{|Z_{i,k,t}|} \frac{\lambda_{s,k}}{\left(\gamma_i\sigma_{i,k}^2\lambda_{s,k} + \lambda_{BS}(\lambda_{s,k} + \gamma_i\sigma_{i,k}^2)\right)(1-\lambda_{BS}\, 2(N_k-1)\phi_{i,k})} \\
= & \frac{\mu_k - y_{k,t}}{|Z_{i,k,t}|} \frac{\lambda_{s,k}}{\gamma_i\sigma_{i,k}^2\lambda_{s,k} - (2(N_k-1)-1)\,\lambda_{BS}(\lambda_{s,k} + \gamma_i\sigma_{i,k}^2)} \\
< & \frac{\mu_k - y_{k,t}}{\gamma_i\sigma_{i,k}^2} \frac{1}{|Z_{i,k,t}|} \\
< & 1 \text{ by assumption.}
\end{aligned}
$$

Hence, $|T_2| < T_1$, yielding that $\frac{d\alpha_{i,k}}{d\pi_{i,k}} > 0$.

IA.B Data Details

FR 2052a Complex Institution Liquidity Monitoring Report

We limit the sample to firms that report daily data throughout the sample, focusing on the largest consolidated entity rather than individual material entities. We exclude transactions with internal counterparties. We drop foreign exchange options except when it appears that the foreign exchange flag is a data entry error. Foreign exchange options represent a small share of the notional positions for banks in our sample, so including foreign exchange options that could provide dollar lending in our sample does not meaningfully change the results. Unless otherwise specified, we drop transactions in which one leg's currency is denominated as "other" and keep transactions that include USD; in a handful of tables and figures, we include the full set of currency pairs, including other currencies. We exclude transactions where the first leg has not yet settled, since we are interested in actual lending rather than future obligations to lend. We include transactions that have likely already settled, as is the case for a handful of transactions when the forward start date and maturity date are reported to be the same, although this convention typically indicates a forward transaction that will have an open maturity. We drop roughly half a dozen dates with outliers, and we drop dates where fewer than seven filers' data are available. Since the set of banks reporting daily has changed over time, we focus on a subset of the largest banks that have consistently reported daily over the whole sample.[33] The data collection instructions were modestly updated in April 2022 to provide additional details on certain segments, and we clean the data so the data before and after 2022 are directly comparable. During the brief period that banks reported two sets of data, one to satisfy the pre-April 2022 instruction data and the other to satisfy post-April 2022 instructions, we use the data reported under the previous instructions. We also adjust the maturities of the contracts to be consistent through the sample as the maturity buckets for some maturities increased by 1 day with the updated instructions (e.g., 1- to 2-year contracts, previously reported at 366 days, started being reported at 365), and we assign assets with perpetual maturities to the 5-year maturity bucket.

Level 1 HQLA Assets

The following security types are considered level 1 HQLAs so long as they meet the asset-specific tests in section 20 of Regulation WW:

- Cash

[33] Over time, a handful of firms move from daily to monthly filing, or vice versa. Including these firms does not materially affect our results since the firms changing their filing frequency account for a comparatively small share of dollar lending.

- Debt issued by the U.S. Treasury
- U.S. Government Agency-issued debt (excluding the U.S. Treasury) with a U.S. Government guarantee
- Vanilla debt (including pass-through MBS) guaranteed by a U.S. Government Agency, where the U.S. Government Agency has a full U.S. Government guarantee
- Structured debt (excluding pass-through MBS) guaranteed by a U.S. Government Agency, where the U.S. Government Agency has a full U.S. Government guarantee
- Other debt with a U.S. Government guarantee
- Debt issued by non-U.S. sovereigns (excluding central banks) with a 0% RW
- Debt issued by multilateral development banks or other supranationals with a 0% RW
- Debt with a non-U.S. sovereign (excluding central banks) or multilateral development bank or other supranational guarantee, where the guaranteeing entity has a 0% RW
- Debt issued or guaranteed by a non-U.S. sovereign (excluding central banks) that does not have a 0% RW, but supports outflows that are in the same jurisdiction as the sovereign and are denominated in the home currency of the sovereign
- Securities issued or guaranteed by a central bank with a 0% RW
- Securities issued or guaranteed by a non-U.S. central bank that does not have a 0% RW, but support outflows that are in the same jurisdiction as the central bank and are denominated in the home currency of the central bank

OIS and FX Rates

We adjust the OIS rates for two currencies: CHF and EUR. CHF OIS rates were based on TOIS fixings until December 29, 2017, when they switched to SARON fixings. As a result, we split the CHF OIS rates to use the TOIS swaps before that date and the SARON swaps after that date. Bloomberg also does not have a full time-series for the 3w, 4m, and 5m OIS rates; when they are missing, we linearly interpolate the rates by estimating the curve each day. For the 3w CHF tenor, we estimate it based on CHF OIS tenors with fewer than 100 days to maturity; for the 4m and 5m, we use CHF OIS tenors with maturities between 28 and 181 days, exclusive. Euro OIS rates were based on EONIA until January 2, 2022, when the benchmark changed to ESTR. ESTR was introduced in October 2019 but Bloomberg provides backfilled rates for all tenors in our sample except for 3 weeks. We use the ESTR OIS rates when they are available, otherwise we use EONIA OIS rates.

We clean five data points for JPY forward points in April 2019 that appear incorrect because the days to maturity for consecutive contracts are the same. For example, the 2w and 3w forwards list the same days to maturity on April 11, 2019. In these five cases, we manually change the days to maturity to 7 × the contract's maturity in weeks.

ICE Reference Data

We use ICE Data Pricing and Reference Data to calculate sovereign bond market values by maturity. We use daily observations from November 2017 to March 2023, and the dataset provides prices along with several characteristics for a wide set of fixed income securities. We manually identify sovereign bond issuers for the currencies in our sample (AUD, CAD, CHF, EUR, GBP, JPY) based on the security's description. We exclude bonds issued by quasi-governmental and municipal government entities. We clean the data several ways: we require that a bond have a non-zero price, non-missing maturity and issuance dates, non-zero amounts outstanding, and non-missing coupon rate data. We exclude a subset of bonds that do not have consistent price data and appear infrequently: specifically, we require that a bond issue have prices for at least half of the weekly observations that it could. We exclude one bond that has outlier data. We calculate days to maturity as the difference between the price date and the maturity date, and we round maturities to the nearest tenor that is reported in the confidential data, including tenors that do not have corresponding Bloomberg CIP basis estimates.

IA.C Additional Discussion and Results

IA.C.1 Regulatory Treatment of FX Derivatives

Several regulatory constraints affect banks' FX activity, making it challenging to precisely isolate the effect of each because of their complex interactions. They fall into three categories: risk-weighted, non-risk-weighted, and other constraints (Du et al., 2018). Risk-weighted constraints, like the common equity tier 1 (CET1) capital ratios, require banks to hold capital proportional to their risk-weighted assets (RWA), with FX derivatives contributing to RWA primarily through their market risk, as measured by value-at-risk (VaR).

Market risk capital charges constrain FX exposures by requiring capital proportional to their VaR. At a high level, the market-based capital charge is the greater of the previous day's VaR or three times the average VaR, plus other add-ons. Unhedged FX positions face higher capital charges because of their higher VaR, while hedged positions that offset market risk face minimal VaR-based capital requirements.

Large banks face a Global Systemically Important Bank (G-SIB) capital surcharge based on components like complexity, size, interconnectedness, and short-term wholesale funding—each potentially affected by FX swap activities. The foreign-currency proceeds from CIP dollar lending can increase the bank's cross-jurisdictional G-SIB surcharge component. The 2022 rollout of the Standardized Approach for Counterparty Credit Risk (SA-CCR) increased capital requirements for FX derivatives, in part because many are not centrally cleared. FX swaps, typically short-maturity contracts, are often used to manage RWAs or G-SIB scores.

The largest U.S. banks' capital ratios also include a Stress Capital Buffer based on the results of the Federal Reserve's stress tests, designed to ensure banks have enough capital to absorb losses in periods of stress. Since 2020, the Federal Reserve has supplemented VaR-based capital requirements with a Global Market Shock (GMS), which is included in the Stress Capital Buffer.

Non-risk-weighted constraints, such as the supplementary leverage ratio (SLR), require banks to hold capital against total on- and off-balance sheet exposures, including FX derivatives. Other constraints include the Volcker Rule's restrictions on proprietary trading.

IA.C.2 Comparison with Public Y-9C Data

We collect data for the banks in our sample that provide Y-9C reports to construct quarterly, bank-level proxies for net lending based on public data. The first variable is derived from on-balance-sheet data based on fair values (FV), which we call "Net All Derivatives Fair Value":

$$\frac{\text{Derivatives with pos. FV} - \text{Derivatives with neg. FV}}{\text{Derivatives with pos. FV} + \text{Derivatives with neg. FV}}.$$

The measure captures net on-balance-sheet derivatives positions, but spans all derivatives, not just FX, and it incorporates counterparty netting. The Y-9C variables are BHCM3543 (Trading assets: derivatives with positive fair value) and BHCM3547 (Trading liabilities: derivatives with negative fair value).

We also construct an off-balance-sheet proxy, which we call "Net Gross FX FV":

$$\frac{\text{Gross FV of FX derivatives with pos. FV} - \text{Gross FV of FX Derivatives with neg. FV}}{\text{Gross FV of FX derivatives with pos. FV} + \text{Gross FV of FX Derivatives with neg. FV}},$$

which focuses on FX derivatives and does not reflect counterparty netting. The Y-9C variables for the gross FV of FX derivatives with positive FV are the sum of BHCK8734 (Gross fair values of derivatives contracts held for trading, positive value) and BHCK8742 (Gross fair values of derivatives contracts held for purposes other than trading, positive value). The gross FV of FX derivatives with negative FV is the sum of the analogous BHCK8738 and BHCK8746. We also use Y-9C data on notional FX exposures, which is the sum of swaps (BHCK3826), futures (BHCK8694), and forwards (BHCK8698).

In Table IA.13, we compare the confidential data and public data at the bank-by-quarter level. The first two columns regress $Net^k_{t,t+n}$ on the two variables and find no clear relationship. The third and fourth columns replace $Net^k_{t,t+n}$ with the broader measure of net FX lending used in Figure IA.4 which captures receivables by currency against all other currencies (including currencies beyond the six named currencies). These columns again show no strong relationship. The fifth column compares gross notional exposures with the gross notional exposures in Y-9C and finds a nearly perfect relationship, with the gross notional in the confidential and public data lining up closely. The table underscores the importance of the granular FX data: net lending and net fair values measure related but distinct things.

IA.C.3 Additional Results: Net vs. Basis

We find suggestive evidence that the smallest markets have more idiosyncratic noise. We compare the residual from the unweighted regression in column (1) with market size: the standard deviation of residuals is smaller in larger markets. Figure IA.12 provides a binscatter of the standard deviation of regression residuals on market size.

We also provide additional results on the relationship between bases and lending. Figure IA.14 scatterplots the average basis against the average $Net^k_{t,t+n}$ for a given currency and tenor, and Figure IA.15 shows the average basis and $Net^k_{t,t+n}$for each currency at several tenors. Second, we show the regression coefficients in Figure IA.16. The regression coefficient on $Net^k_{t,t+n}$ is near zero for maturities less than 3 months but is significant and negative for all longer maturities.

IA.C.4 Additional Results: Asset Ratios

Our analysis of safe asset ratios provides an upper bound for the safe assets that intermediaries hold corresponding with their swap exposure, because intermediaries may hold safe assets for reasons unrelated to meeting customer demand and hedging CIP trades. We explore this dimension in a regression framework presented in Table IA.14, which estimates the extent to which intermediaries may hold foreign currency assets even if their net lending exposure is zero. For example, Column 1 of the table shows that banks hold an average of $2 billion of unencumbered EUR-denominated safe assets across the tenors, after controlling for $Net^k_{t,t+n}$.[34]

IA.C.5 Additional Results: Broad Asset Composition

One question of interest is what is the composition of assets that intermediaries hold to hedge their net dollar lending to customers. Answering this question is challenging as there is no clear way to link the exact assets held by intermediaries with their net dollar lending. Banks hold enough safe assets of mismatched maturities and risky assets to hedge their currency exposures. As discussed in the main text and illustrated in Figure IA.9, the maturity of banks' safe asset holdings is shorter than their net dollar lending, indicating the nature of the maturity mismatch. We also shed light on the nature of the risky assets that may hedge banks' currency exposures by computing the asset composition in our broad asset ratios, focusing on the 1-year tenor. We focus on the 1-year tenor because asset holdings at that maturity are relatively dense and more comparable across currencies.

To do so, first, we collapse the asset classes to a handful of the largest categories since the data can span scores of granular asset classes.[35] The categories are government, quasi-government, investment-grade corporate debt, non-investment-grade and other assets, financial debt, and securitized debt. Below, we describe how we match granular asset categories to broader classes of assets. The asset types vary substantially by currency, so we standardize them into asset class categories by matching them to their nearest ICE (or S&P for CHF IG corporate) index.

- We set the category to government for A-1 (Treasuries), S-1 (foreign sovereign debt), and any central bank security or central bank guaranteed security (CB-1, CB-2, etc.). Any of the remaining asset classes in A (other debt with a U.S. government guarantee), S (e.g., debt issued or guaranteed by foreign sovereigns or supranationals), and any asset class in G (agency debt or agency MBS) is mapped to quasi-government.

- We identify the securitized category as any asset class from IG-3, IG-4, ..., IG-7 (spanning IG ABS, private label CMBS/RMBS, and covered bonds), as well as their non-IG equivalents N-3, N-4, ..., N-7.

- We identify the investment grade category as any asset class from IG that was not categorized as securitized.

[34]Moreover, the currency fixed effects in the regression are lower bounds since we merge safe asset holdings to the net lending data based on the net borrowing currency. Observations where the bank holds safe assets in a currency but is not net borrowing that currency are not included in the panel.

[35]For a full list of categories, see pages 98 to 100 in the filing instructions `https://www.federalreserve.gov/reportforms/forms/FR_2052a20220429_f.pdf`.

- We identify the financial category as any asset class from Y (financial debt).
- All the remaining categories we bucket into the non-investment grade category, which could include N (broadly non-investment grade bonds), E (equities), L (loans), P (property), and Z (all other assets).
- For Switzerland, we set any CHF-denominated asset in the A, S, G, or CB category to the government category and everything else to the investment grade category.

Table IA.7 displays the asset compositions. Averaging across currencies and ordering by weight, the weights of the categories are about 50% for government, 20% for investment grade, 15% for non-investment grade, 10% for quasi-government (e.g., agency debt), and less than 5% each for for financial and securitized assets. The patterns are similar when looking at USD and non-USD holdings.

IA.C.6 Additional Results: Convenience Yields

One implication of our model is that intermediaries should substitute away from safe bonds when safe asset yields are low (Equation 2).

We regress the safe asset ratio on convenience yields, and we find that banks hold fewer safe assets and more risky assets when the convenience yield is high. We test this dynamic by using convenience yields estimated from derivative prices by Diamond and Van Tassel (forthcoming). The convenience yields are monthly and span the six currencies in our sample. Each currency has a 1-year convenience yield estimate, except JPY, which also has a 3m convenience yield. We merge the monthly convenience yields with monthly asset ratios. The merged sample runs from 2016 to 2020.

We run the regression,

$$\text{Safe Asset Ratio}^k_{t,t+n} = \alpha + \beta_1 CY^k_{t,t+n} + \beta_2 \text{Risky Asset Ratio}^k_{t,t+n} + \varepsilon^k_{t,t+n} \tag{9}$$

where *risky asset ratio* is defined as the difference between the broad asset ratio and safe asset ratio (since the broad asset ratio includes both safe and risky assets). We include the risky asset ratio variable to control for banks' propensities to maturity-match over time or across currencies. Both safe asset and risky asset ratios are maturity-matched, so they are not required to sum to 1—this would be the case only if the bank invests all its foreign currency proceeds from net lending in maturity-matched assets, risky or safe.

Table IA.8 shows the regression results. Banks hold fewer safe assets and more risky assets when convenience yields are higher and safe asset yields are lower. The positive and significant coefficients on the risky asset ratio in the first three columns and the safe asset ratio in the last three columns show that safe and risky ratios move together. Banks shift to maturity-mismatched positions rather than substituting between maturity-matched safe and risky assets.[36] These results suggest that banks actively manage their safe and risky asset holdings based on returns and that these substitutions by banks may lead to risk related to a maturity mismatch.

[36]Our discussion of foreign safe asset mismatch primarily focuses on cross-sectional variation. However, we also note that foreign safe asset mismatch may be important for understanding the dramatic post-2008 increase in the size of bases as well. There has been a steep drop in the foreign safe assets available to intermediaries because of decreases in the supply of safe assets (e.g., see Caballero et al. (2017)) and decreases in their re-use as collateral in transactions. Systematic data on collateral re-use are not readily available before the 2008 financial crisis, but to the extent they are available, the evidence indicates a reduction. Gorton et al. (2020) use data from the 10Qs of six broker-dealers and banks to show that collateral pledged was halved between 2007 and 2009, amounting to a decline of more than $2.5 trillion. Along these lines, the existing evidence indicates there has been a large reduction in collateral velocity—the amount of re-use of the same safe asset in multiple transactions. For example, per the numbers reported in Jank et al. (2022), there has been an approximate 30 percent reduction in collateral re-use of European sovereign bonds from 2008 to 2017. As Inhoffen and van Lelyveld (2023) note, the decrease in collateral velocity connects to higher balance sheet costs after the crisis, attributed to the balance sheet-intensive nature of repos.

IA.D Appendix Figures and Tables

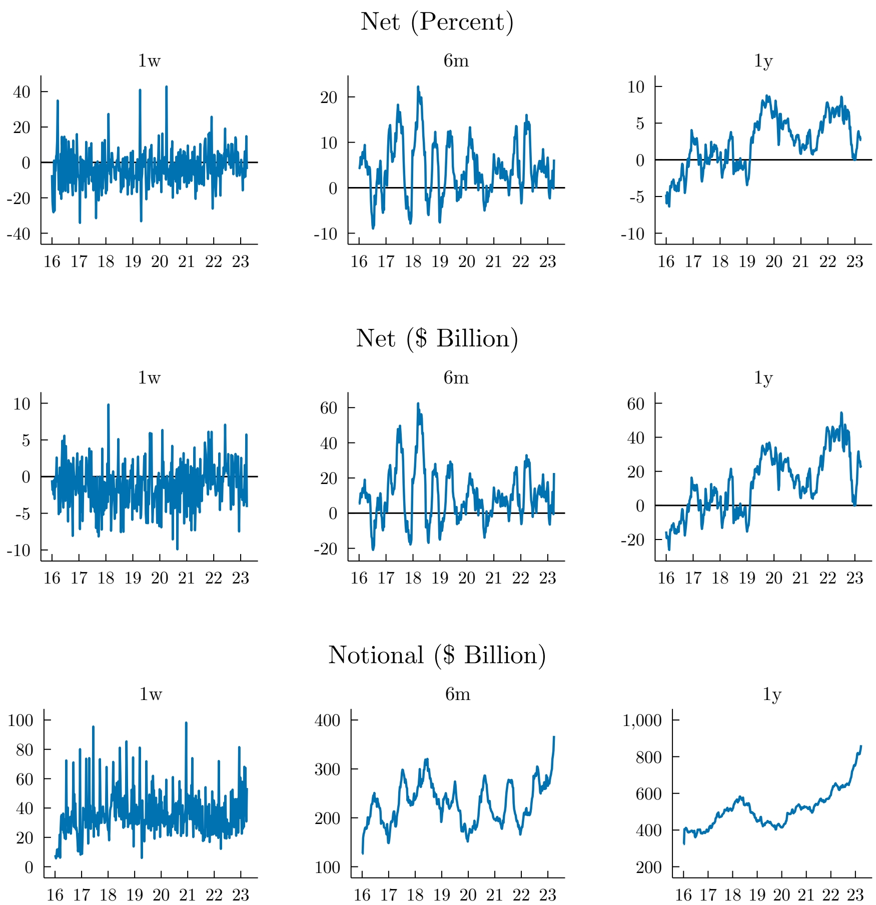

Figure IA.1: *Net* for EUR across several tenors. Top panel plots our main measure, $Net^k_{t,t+n}$, for EUR contracts across various tenors. Middle panel plots the level of net dollar lending. Bottom panel plots the notional dollars across borrowing and lending transactions for EUR across the highlighted tenors. All figures plot weekly averages based on daily observations.

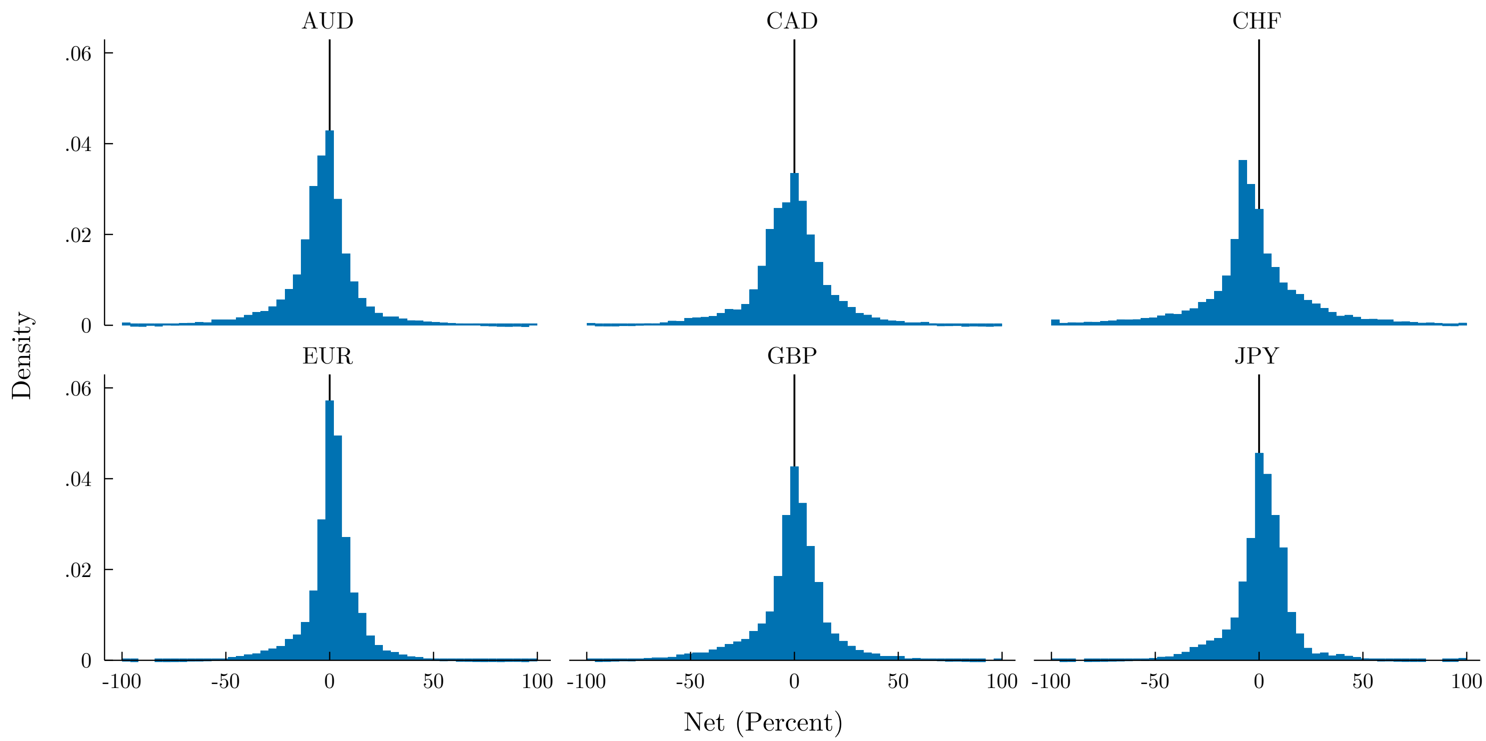

Figure IA.2: Most Markets are Nearly Matched Books. Figure plots the histogram of $Net^{k}_{t,t+n}$across all tenors within a given currency.

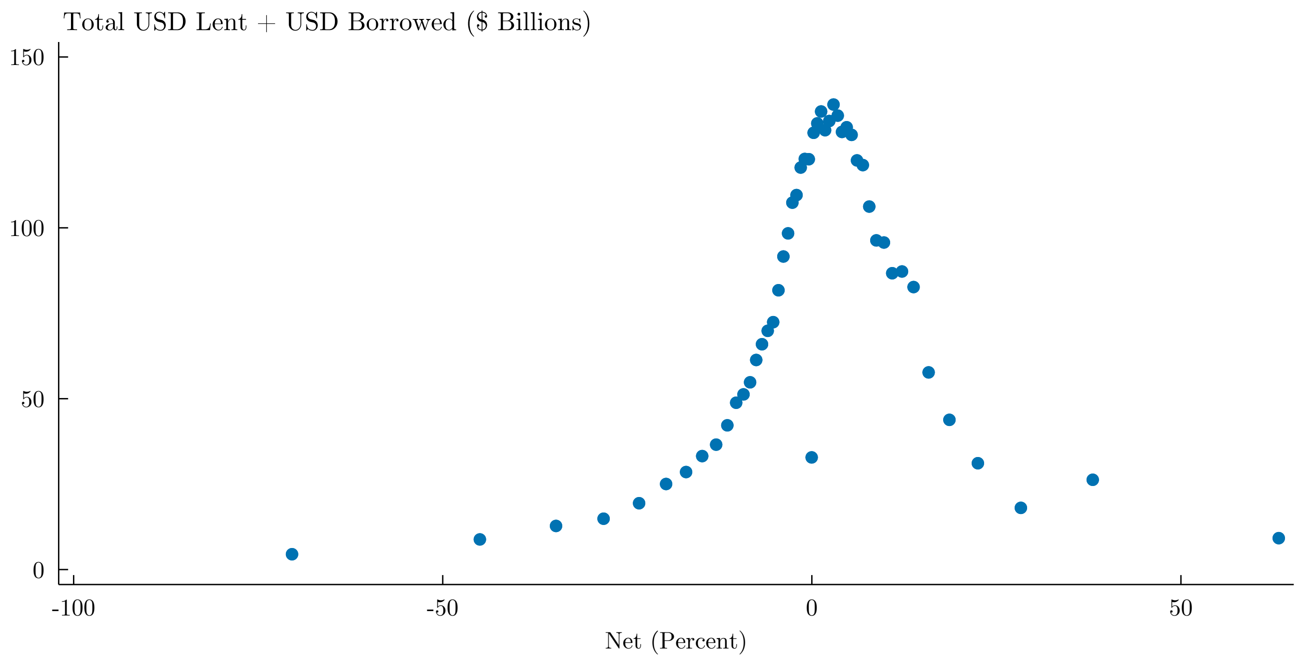

Figure IA.3: Size vs. *Net*. Figure presents the binscatter of the size of the market—defined as the sum of dollars lent and borrowed in billions—at the daily-currency-tenor level.

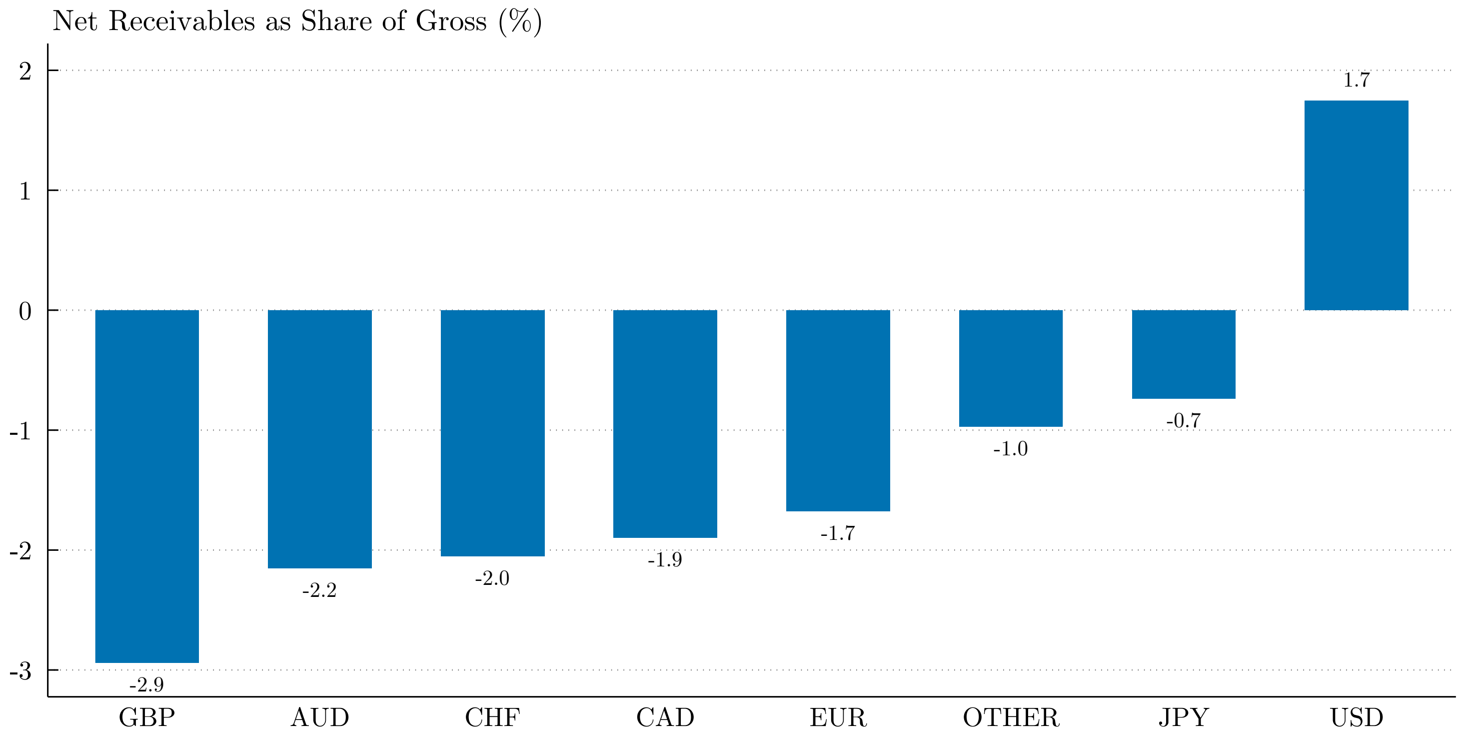

Figure IA.4: Net Receivables across All Currencies. Figure plots median daily net receivables by currency across all currency pairs (not just the six currencies against the dollar) and tenors (not just those with Bloomberg OIS risk-free rates), expressed as a percentage of gross payables and receivables in the same currency, aggregated across all banks.

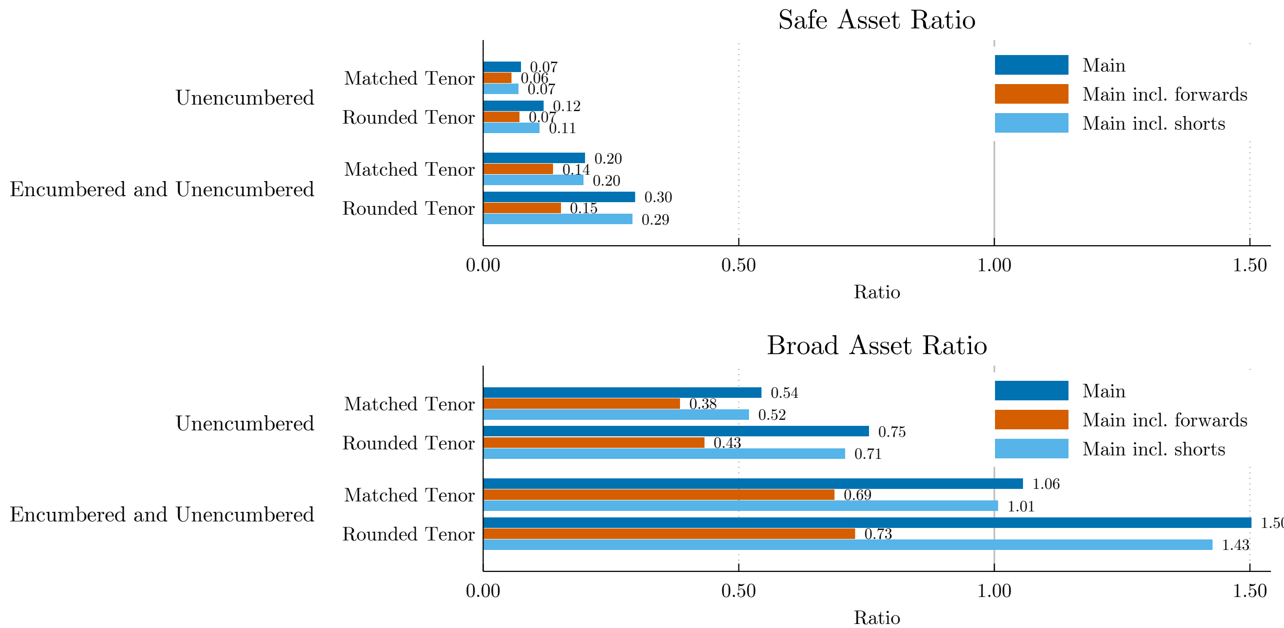

Figure IA.5: Summary of Safe Asset Ratios. Figure plots the average median safe and broad asset ratios across all currencies when $Net^k_{t,t+n}$ is positive, excluding the USD. Matched tenor shows the asset ratio when the tenor of the underlying asset and the swap have the same maturity. Rounded tenor buckets the swaps and assets into the nearest benchmark tenor. Figure also shows the analogous net measurement when including forwards and futures (affecting the denominator of the ratios) and when netting out the firms' short positions in the asset (affecting the numerator).

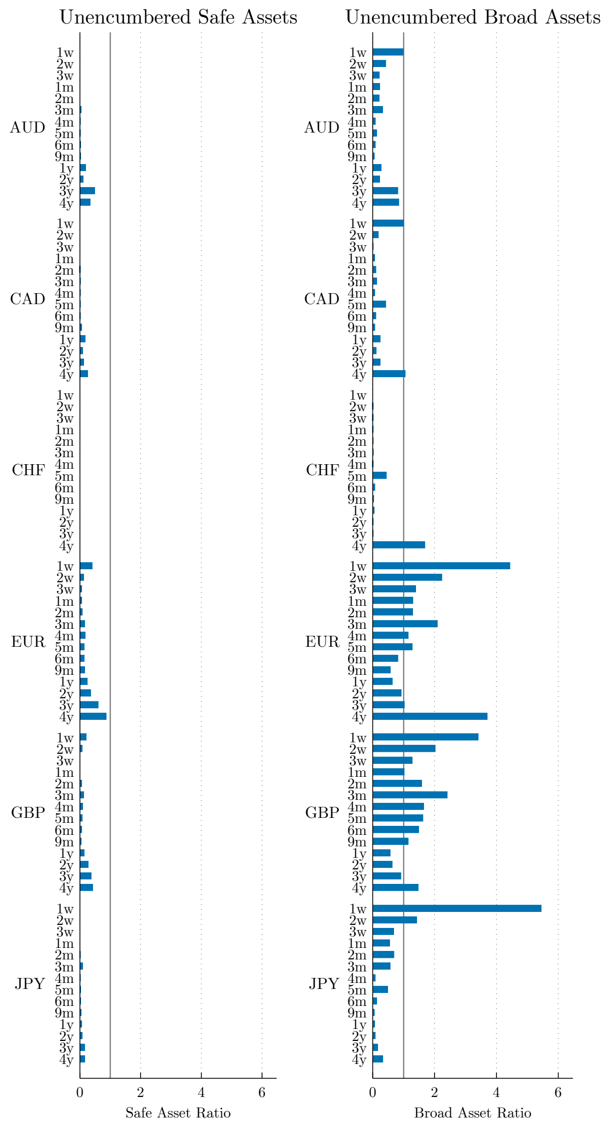

Figure IA.6: Safe Asset Ratio by Market. Figure plots median safe asset and broad asset ratios when $Net^{k}_{t,t+n}$is positive and matching the tenor of the net dollar lending and the foreign safe asset.

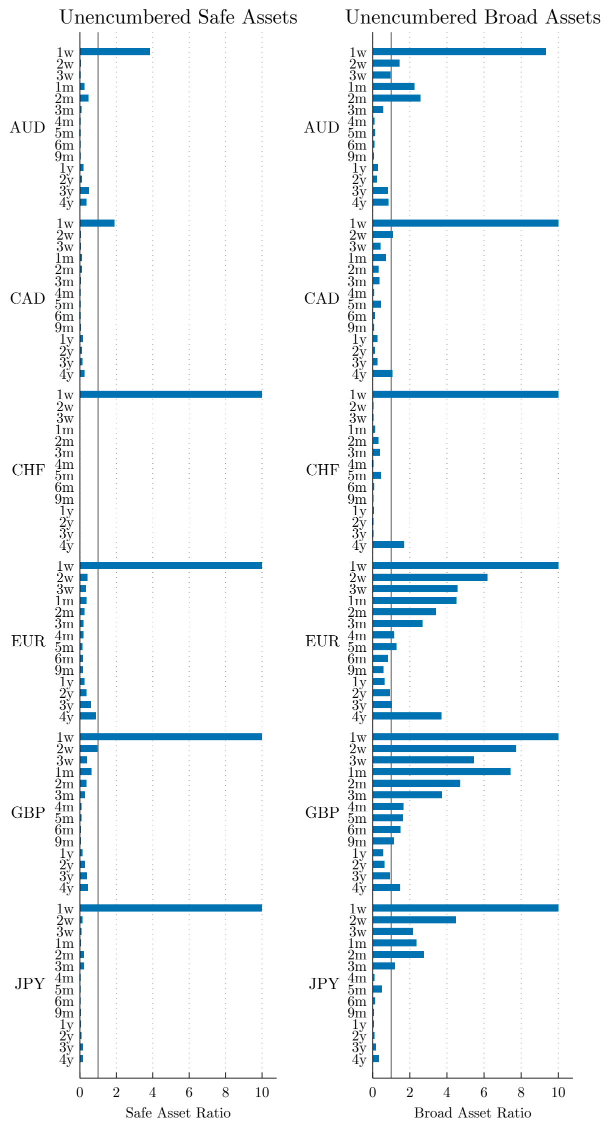

Figure IA.7: Safe Asset Ratios by Market with Rounded Tenors. Figure plots median safe asset and broad asset ratios when $Net^k_{t,t+n}$ is positive and when bucketing net dollar lending and foreign safe assets into the nearest benchmark tenor. Unlike Figure IA.6, this measure allows for some maturity mismatch in the trade. Values are truncated at 10.

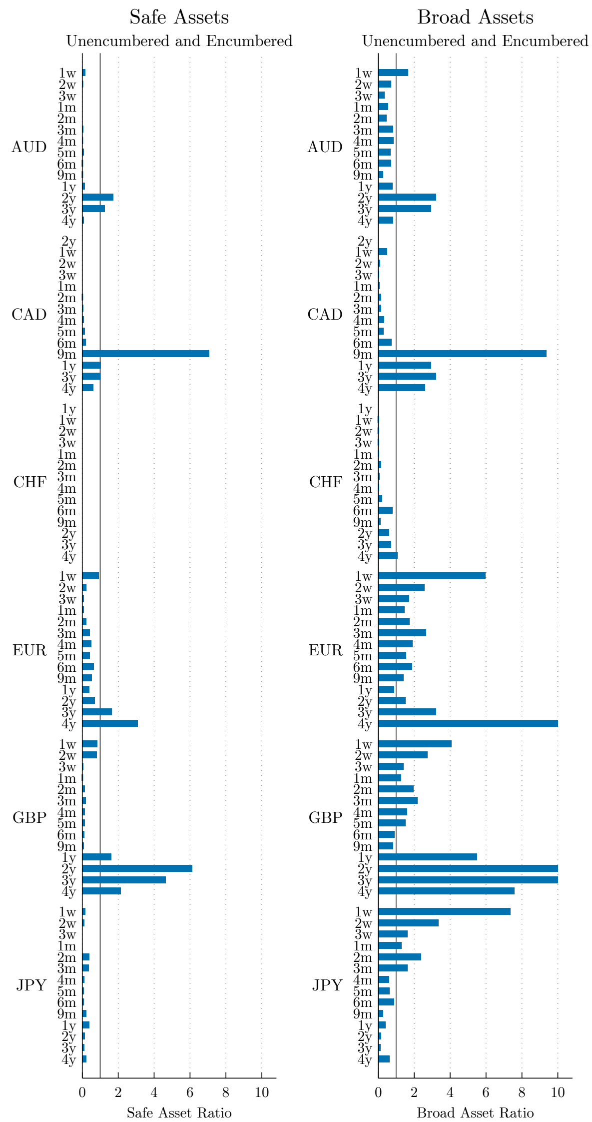

Figure IA.8: Safe Asset Ratios by Market, including encumbered assets. Figure plots median safe asset and broad asset ratios when $Net^{k}_{t,t+n}$ is positive, matching the tenor of the net dollar lending and the foreign safe assets, including encumbered assets. Values are truncated at 10.

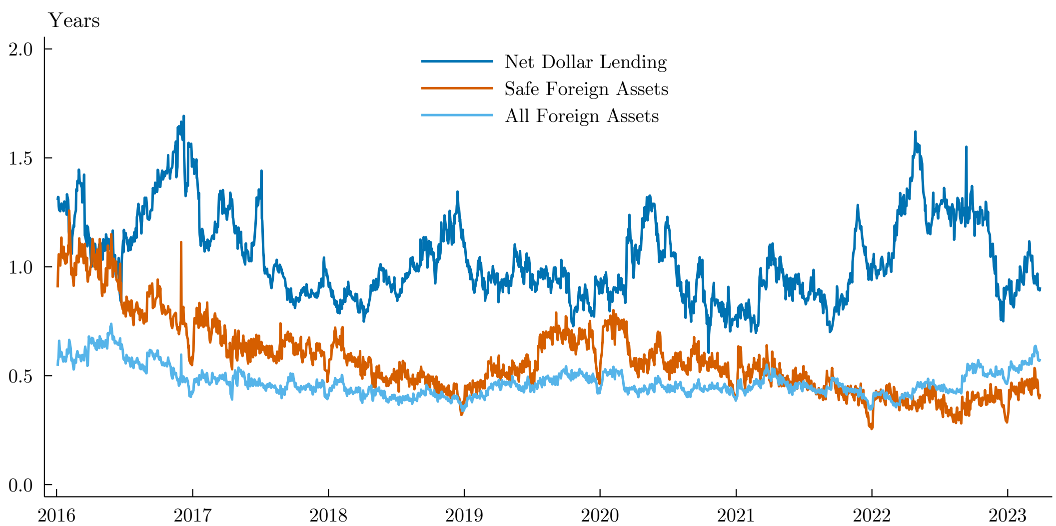

Figure IA.9: Average Maturity of Lending and Assets. Figure plots the value-weighted average maturity of net dollar lending, foreign safe assets, and all foreign assets. We include tenors that are 5 years or greater and set their tenor to 5 years.

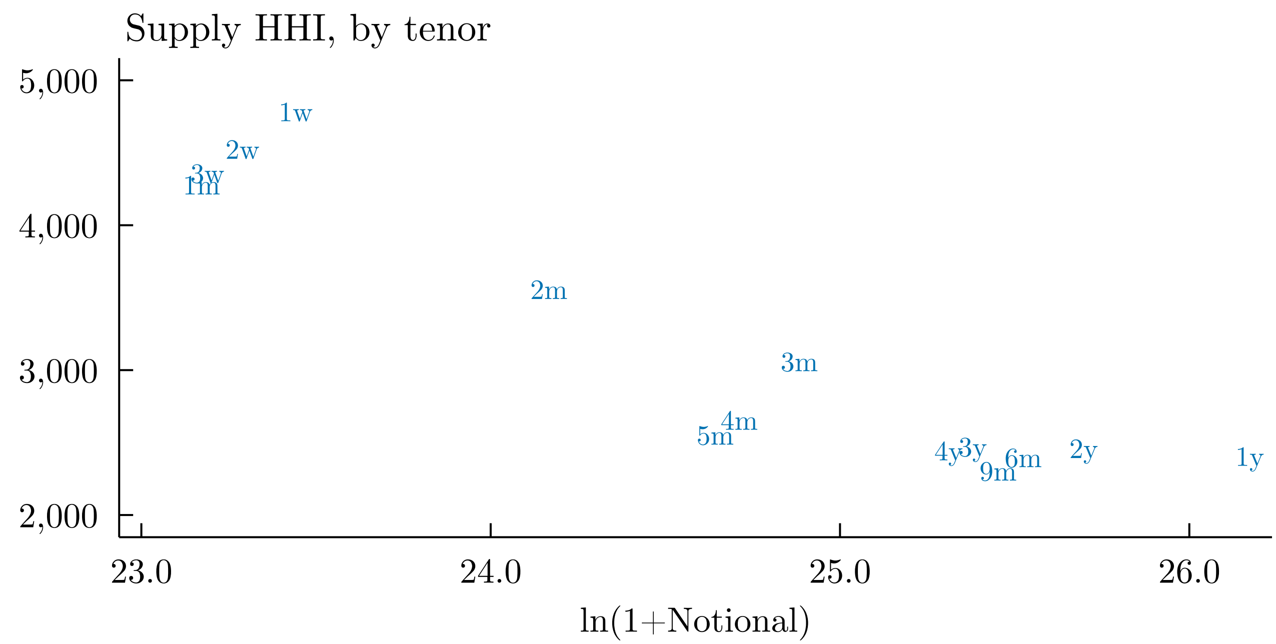

Figure IA.10: Supply Specialization. Figure plots the average of daily Tenor Supply $\text{HHI}_{t,t+n}$ against (log of 1 plus) the average notional of that market.

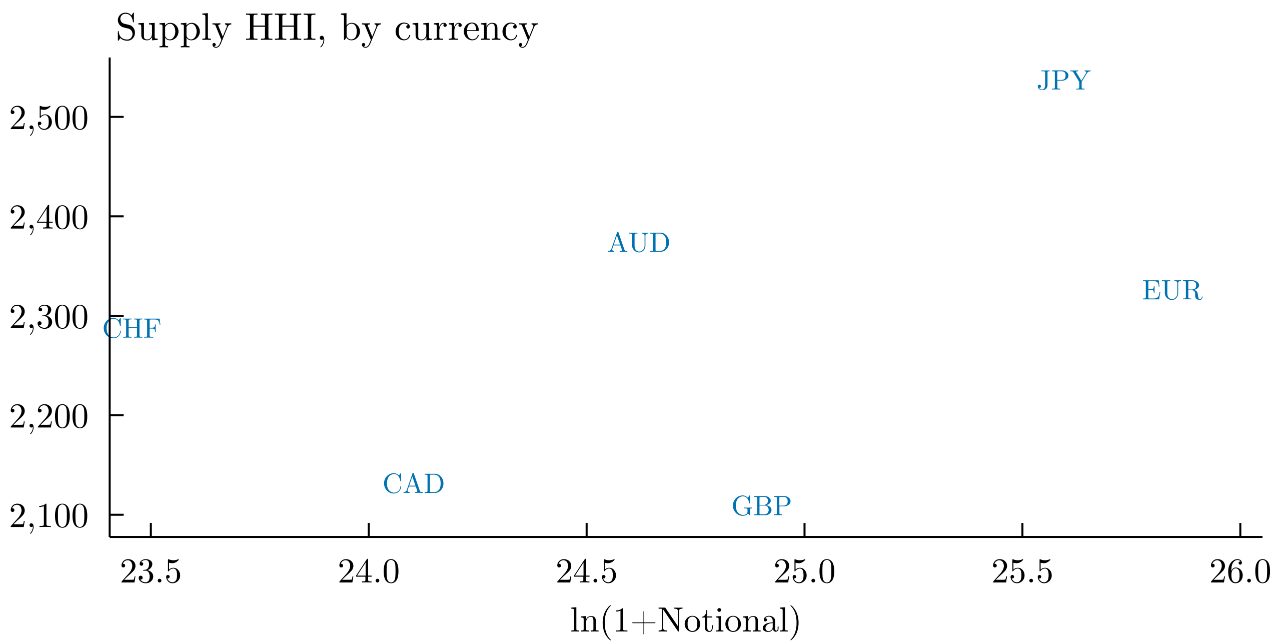

Figure IA.11: Supply Specialization by Currency. Figure plots the average of daily Currency Supply HHI_t^k against (log of 1 plus) the average notional of that market.

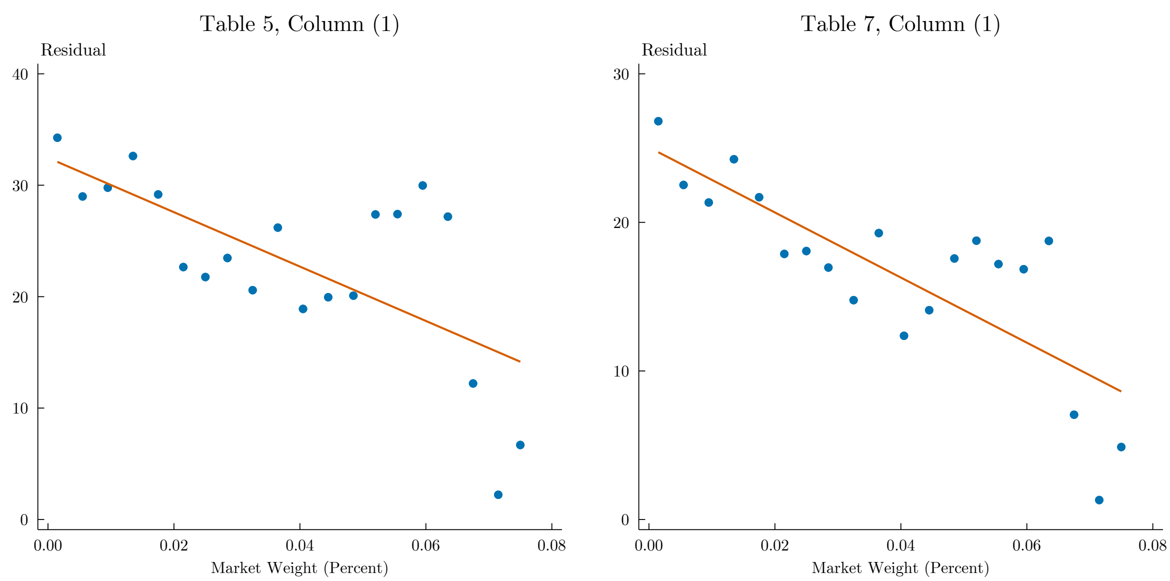

Figure IA.12: Unweighted Regression Residuals. Both panels are binscatters of market size against the standard deviation of regression residuals. We sort markets into buckets by rounding their share (in percent) to the nearest 0.1% and then calculate the standard deviation of residuals within each rounded share. Left panel is a binscatter of the regression residuals from Table 5 column (1) on notional market size; right panel is a binscatter of regression residuals from Table 7 column (1).

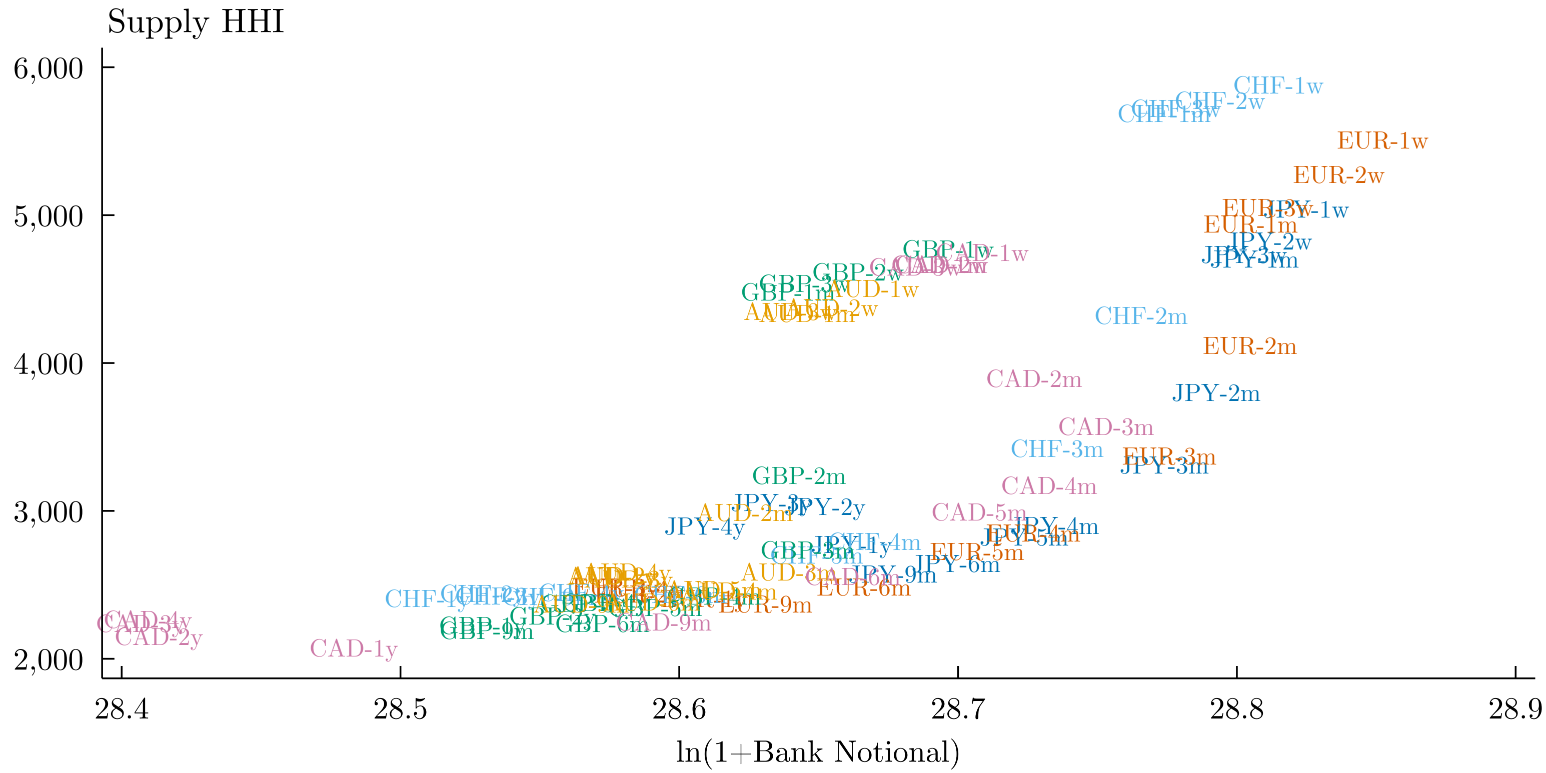

Figure IA.13: Supply Concentration vs. Bank Size. Figure plots the average of daily Supply $\text{HHI}^{k}_{t,t+n}$ against (log of 1 plus) the notional book size of the banks active in that market weighted by their market share.

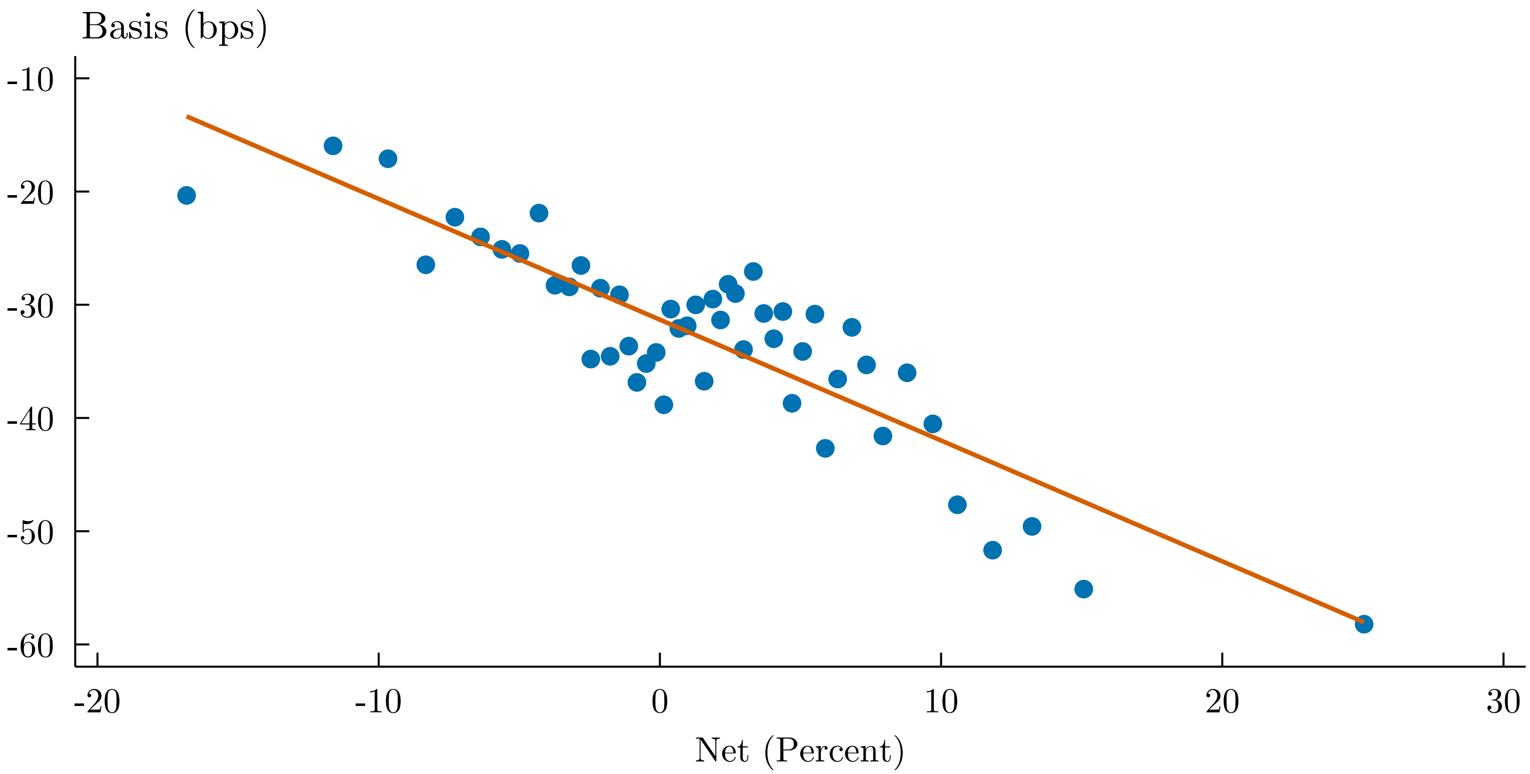

Figure IA.14: Basis vs. *Net*. Figure presents the binscatter of the basis on $Net^k_{t,t+n}$ after averaging on a monthly frequency weighted by market sizes. $Net^k_{t,t+n}$ is at the month-by-currency by tenor level.

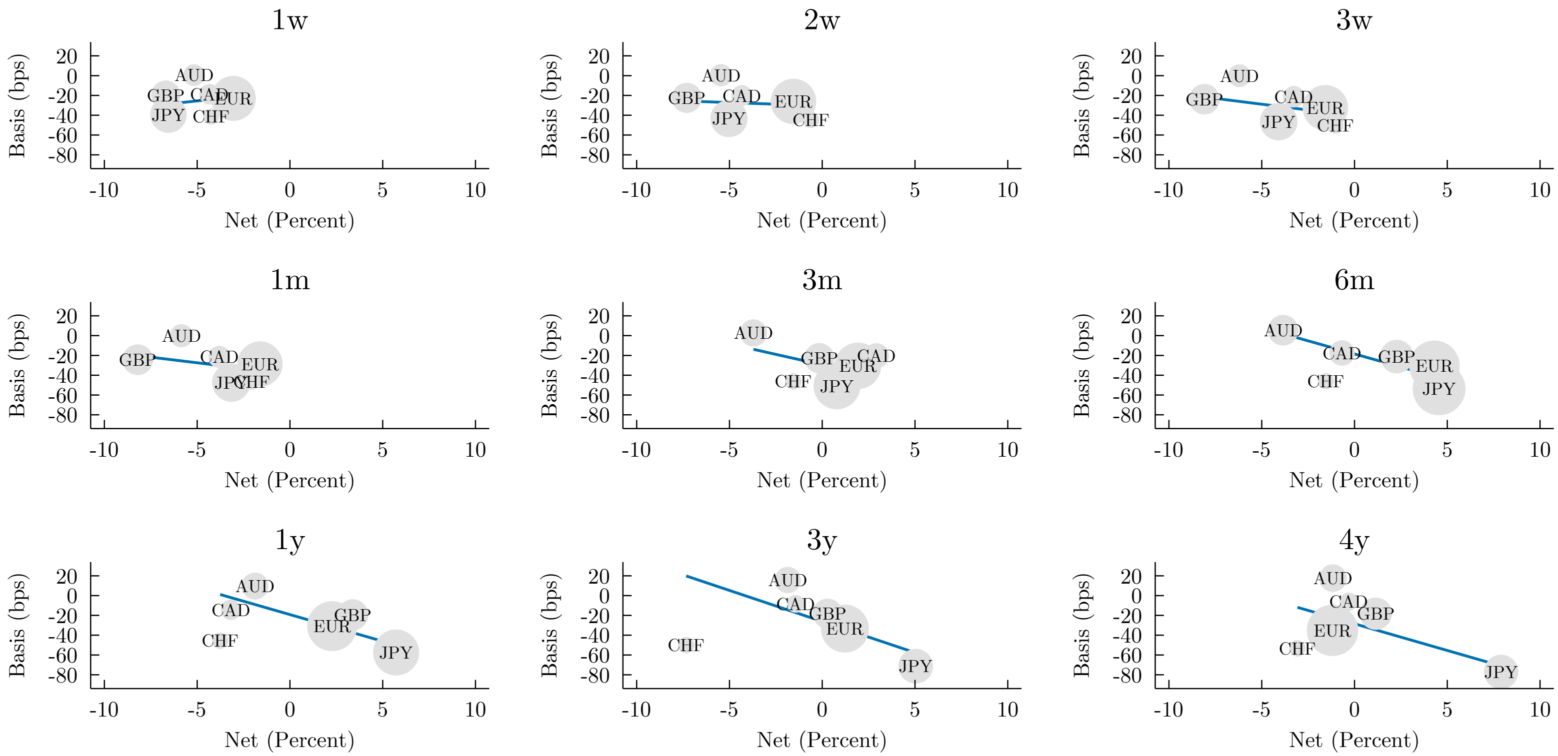

Figure IA.15: By Tenor: Basis vs. *Net*. Figure presents the scatter of the average basis on the average $Net^{k}_{t,t+n}$weighted by market sizes.

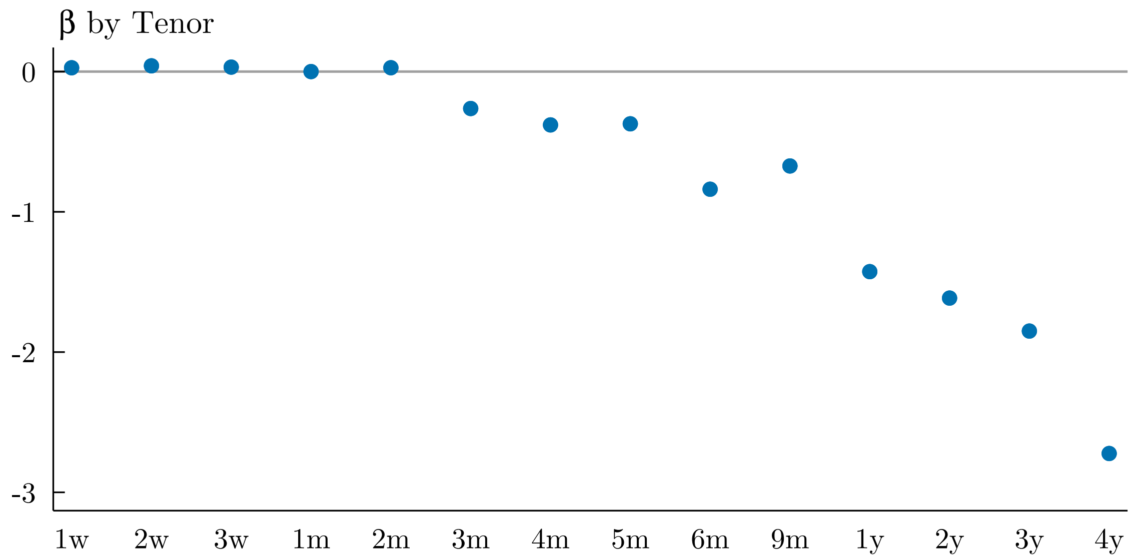

Figure IA.16: Regression Coefficient by Tenor: Basis vs. *Net*. Figure displays the β estimated by running the following regression separately for each tenor: $\text{Basis}^k_{t,t+n} = \alpha + \beta Net^k_{t,t+n} + \varepsilon^k_{t,t+n}$.

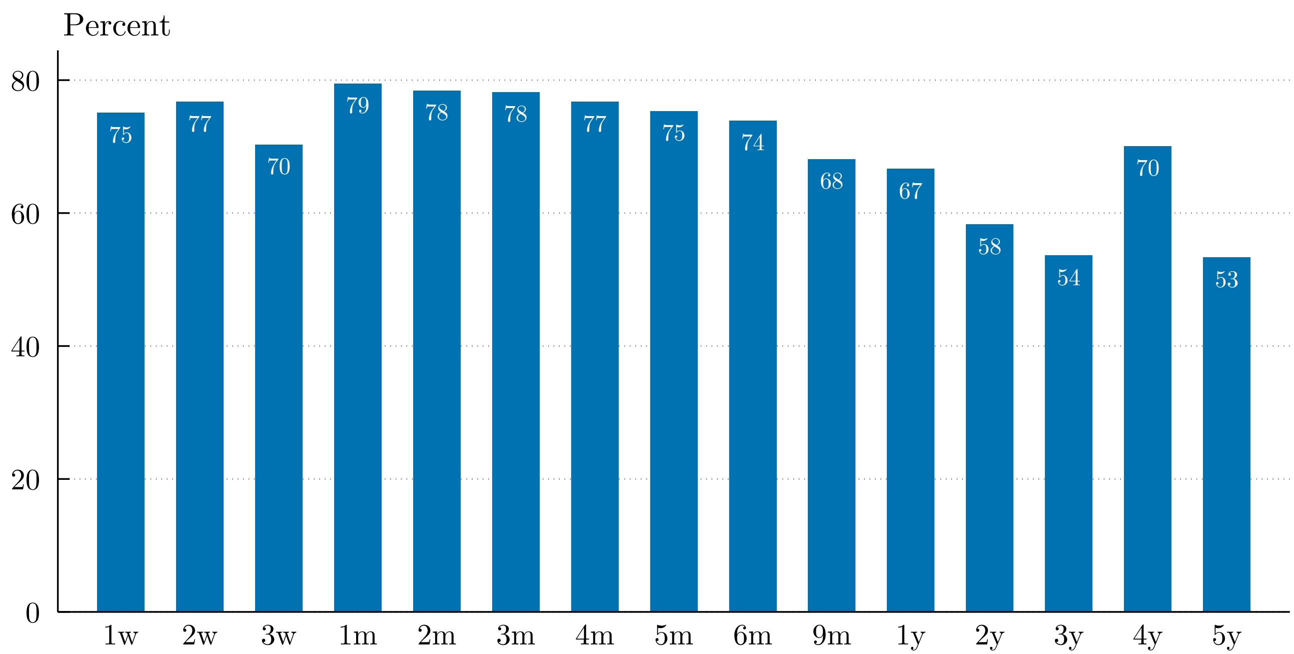

Figure IA.17: Proportion of CIP Deviation Variance Explained by First Principal Component. Figure plots the proportion of the variance explained by the first principal component after estimating 6 principal components across the signed CIP deviations by tenor.

Mean ($ Billions)							
	AUD	CAD	CHF	EUR	GBP	JPY	Mean
1w	−0.4	−0.2	0.0	−1.2	−1.1	−1.7	−0.8
2w	−0.4	−0.2	0.1	−0.8	−1.2	−1.1	−0.6
3w	−0.4	−0.2	0.1	−0.8	−1.2	−0.9	−0.6
1m	−0.4	−0.2	0.1	−0.7	−1.2	−0.8	−0.5
2m	−1.0	0.0	−0.4	1.1	−0.9	−1.9	−0.5
3m	−1.6	1.2	0.0	2.4	0.0	2.3	0.7
4m	−1.5	0.7	0.0	2.6	1.3	3.6	1.1
5m	−1.5	0.4	−0.1	3.1	1.2	2.7	1.0
6m	−3.7	−0.9	−0.3	10.0	2.3	12.9	3.4
9m	−2.8	−2.9	−0.5	10.2	3.1	9.7	2.8
1y	−3.0	−2.0	−1.8	12.9	6.3	24.3	6.1
2y	0.7	−1.2	−2.0	6.1	0.5	11.0	2.5
3y	−1.2	−0.4	−1.9	2.9	−0.1	6.6	1.0
4y	−0.8	0.0	−0.7	−3.6	0.6	8.3	0.6
Mean	−1.3	−0.4	−0.5	3.2	0.7	5.4	

Standard Deviation ($ Billions)							
	AUD	CAD	CHF	EUR	GBP	JPY	Mean
1w	2.0	1.8	1.7	6.9	4.0	4.4	3.5
2w	1.9	1.7	1.5	6.7	4.0	4.1	3.3
3w	1.8	1.7	1.4	6.1	3.8	4.0	3.2
1m	1.9	1.8	1.4	5.8	3.9	4.1	3.1
2m	3.2	3.1	1.9	7.6	5.0	6.8	4.6
3m	4.2	4.4	2.5	10.0	6.4	14.1	6.9
4m	3.9	3.8	2.0	8.3	6.4	14.5	6.4
5m	4.0	3.5	1.8	8.3	6.1	12.7	6.1
6m	6.1	5.0	2.4	15.1	8.6	31.1	11.4
9m	6.9	4.9	2.3	13.9	8.1	28.1	10.7
1y	7.9	5.2	3.1	17.7	9.9	25.5	11.5
2y	6.6	3.0	1.8	11.5	7.4	15.5	7.6
3y	3.1	2.6	1.0	8.3	4.0	8.5	4.6
4y	3.4	2.3	1.0	8.8	4.7	7.3	4.6
Mean	4.1	3.2	1.8	9.6	5.9	12.9	

Table IA.1: *Net* Level Summary Statistics. Top panel plots the average level of daily net dollar lending aggregated across all intermediaries in the sample, equal to the numerator of $Net^k_{t,t+n}$for a given currency k and maturity $t+n$. Bottom panel plots the time-series standard deviation of $Net^k_{t,t+n}$.

	Days to Maturity	$\ln(1 + \text{Gross Notional})$	$\mathbb{I}$(Quarter End)	$\mathbb{I}$(Year End)	HMV_t^k
$Net_{t,t+n}^k$	0.046***	0.046***	−0.006**	−0.008***	0.007**
	(0.00)	(0.00)	(0.01)	(0.00)	(0.02)
N	151,704	151,704	151,704	151,704	129,108

	$CY_{t,t+n}^k$	R_t^{SPX}	VIX_t	$Baa_t - Aaa_t$
$Net_{t,t+n}^k$	0.056***	−0.002	−0.017***	−0.012***
	(0.00)	(0.39)	(0.00)	(0.00)
N	151,314	143,556	143,556	143,556

Table IA.2: Correlations. Table presents the correlation of $Net_{t,t+n}^k$at the date-by currency-by tenor level with days to maturity, $\ln(1 + \text{Gross Notional})$, dummies equal to 1 for quarter or year ends (defined as the last week of the quarter or year) and 0 otherwise and HMV_t^k which is a measure of net lending by dealers from CFTC data analogous to Hazelkorn et al. (2023)'s measure. Bottom panel compares the return on the SPX, and the levels of the VIX and Baa-Aaa spread. Correlations given with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Overall $\text{Net}^k_{t,t+n}$		Overall $\text{Notional}^k_{t,t+n}$	
	(1)	(2)	(3)	(4)
Net, $\text{US}^k_{t,t+n}$	0.971***			
	(538.25)			
Net, $\text{Foreign}^k_{t,t+n}$		0.0332***		
		(9.18)		
Notional, $\text{US}^k_{t,t+n}$			1.027***	
			(317.05)	
Notional, $\text{Foreign}^k_{t,t+n}$				15.02***
				(7.03)
Constant	0.134***	−2.053***	89.60*	13124.9***
	(3.37)	(−7.40)	(1.82)	(8.25)
N	39,150	39,150	39,150	39,150
R^2	0.97	0.00	1.00	0.41

Table IA.3: U.S. vs. Foreign Net and Gross Exposures using Monthly Data. First two columns present the regression of the overall $Net^k_{t,t+n}$(e.g., including all banks) separately on $Net^k_{t,t+n}$calculated from only U.S. banks or only foreign banks. Last two columns regress overall notional FX swaps gross exposures (e.g., including all banks) on gross exposure of U.S. banks or foreign banks. Sample is created using the same cleaning procedure described in the appendix applied to monthly data—which spans a wider set of firms than is used elsewhere in the paper. For each firm, we use data from the largest subsidiary when ranking the subsidiaries within a firm based on their gross FX exposure for that month. Data are at the month-by-currency-by-days-to-maturity level, and not limited to tenors that have a matching Bloomberg CIP violation. $Net^k_{t,t+n}$is in percent and notional is in millions. t-statistics shown using robust standard errors clustered by market and date where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	All Tenors					Short-Term	Long-Term
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Net^k_{t,t+n}$	-0.054^{*}	-0.479^{***}	-0.279^{***}	-0.270^{**}	-0.313^{**}	-0.054	-1.232^{***}
	(-1.94)	(-3.80)	(-2.71)	(-2.36)	(-2.00)	(-1.49)	(-2.87)
$\ln(1 + Gross^k_{t,t+n})$	0.006	-5.668^{**}	-6.772^{***}	-11.957^{***}	-17.911^{***}	-12.720^{***}	-9.878^{*}
	(0.02)	(-2.40)	(-2.94)	(-3.99)	(-3.90)	(-3.92)	(-2.02)
N	151,704	149,381	149,381	149,381	74,090	106,037	43,344
R^2	0.00	0.07	0.09	0.13	0.18	0.15	0.18
Tenor FE	No	No	No	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	Yes	Yes	Yes
Weighted	No	Yes	Yes	Yes	No	Yes	Yes
Sample	All	All	All	All	Top 90	All	All

Table IA.4: Gross Market Size and Net vs. Basis. Table presents the regression of the basis on $Net^k_{t,t+n}$and $\ln(1 + Gross^k_{t,t+n})$: $\text{Basis}^k_{t,t+n} = \alpha + \beta_1 Net^k_{t,t+n} + \beta_2 \ln(1 + Gross^k_{t,t+n}) + \gamma' X_t + \varepsilon^k_{t,t+n}$. Currencies include AUD, CAD, CHF, EUR, GBP, and JPY and tenors include: 1w, 2w, 3w, 1m, 2m, 3m, 4m, 5m, 6m, 9m, 1y, 2y, 3y, and 4y. Constant omitted. Columns with weights are weighted by the square root of the market's daily gross notional share. Short-term column limits swaps to less than 1-year maturities, and long-term is greater than or equal to 1-year maturities. $Net^k_{t,t+n}$is in percent and basis is in basis points. The top 90 sample restricts the sample by sorting markets by gross size in descending order and including the markets that cumulatively account for 90 percent of total gross across all markets. Within R^2 reported. t-statistics shown using robust standard errors clustered by market and date where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

		Matched				Rounded			
		Safe Asset		Broad Assets		Safe Asset		Broad Assets	
Borrowing Currency		Unencumbered	Unencumbered & Encumbered	Unencumbered	Unencumbered & Encumbered	Unencumbered	Unencumbered & Encumbered	Unencumbered	Unencumbered & Encumbered
AUD	Median	0.04	0.08	0.27	0.89	0.10	0.16	0.46	1.34
	Mean	0.83	0.88	2.81	4.83	1.72	2.94	4.95	8.55
	Std. Dev.	19.25	4.17	43.20	25.81	25.94	23.42	58.22	49.27
CAD	Median	0.02	0.06	0.20	0.29	0.07	0.12	0.34	0.54
	Mean	0.64	2.10	2.49	3.77	0.82	0.92	3.89	3.83
	Std. Dev.	18.90	60.81	58.68	82.45	7.91	5.09	42.72	24.22
CHF	Median	0.00	0.00	0.02	0.12	0.00	0.00	0.08	0.20
	Mean	0.02	0.00	1.47	1.13	1.28	0.41	2.88	2.14
	Std. Dev.	0.52	0.02	42.56	7.57	20.09	5.95	45.45	16.62
EUR	Median	0.21	0.52	1.22	1.89	0.28	0.60	1.68	2.62
	Mean	1.23	2.55	7.85	9.68	6.54	15.09	25.00	52.76
	Std. Dev.	11.67	20.97	160.49	77.46	329.21	471.37	1,067.27	1,493.43
GBP	Median	0.12	0.37	1.32	2.62	0.18	0.69	1.68	3.75
	Mean	1.31	3.46	12.12	12.52	3.51	10.75	16.73	29.25
	Std. Dev.	34.13	25.37	458.58	66.42	69.77	164.46	481.41	356.65
JPY	Median	0.06	0.16	0.23	0.53	0.08	0.22	0.29	0.56
	Mean	0.47	0.75	12.96	14.27	2.58	8.36	9.84	26.70
	Std. Dev.	5.62	6.27	974.27	425.65	118.26	310.77	345.74	961.48
USD	Median	2.50	9.38	19.68	45.42	4.47	18.05	30.07	79.04
	Mean	55.50	102.68	327.92	302.99	180.64	170.85	715.21	558.84
	Std. Dev.	1,561.52	1,286.36	13,176.71	3,656.85	22,390.96	2,289.39	83,703.07	7,676.74
Average of All excl. USD	Median	0.07	0.20	0.54	1.06	0.12	0.30	0.75	1.50
	Mean	0.75	1.62	6.62	7.70	2.74	6.41	10.55	20.54
	Std. Dev.	15.01	19.60	289.63	114.23	95.20	163.51	340.13	483.61

Table IA.5: Safe Asset Ratios. Table presents the average ratio of safe assets and broad assets, which reflect the value of assets (either unencumbered or both unencumbered and encumbered) relative to the level of net lending in the given market. Unencumbered and encumbered asset column data begin in May 2022.

Borrowing Currency		Matched, incl. Swaps and Forwards				Matched, incl. Firm Shorts			
		Safe Asset		Broad Assets		Safe Asset		Broad Assets	
		Unencumbered	Unencumbered & Encumbered	Unencumbered	Unencumbered & Encumbered	Unencumbered	Unencumbered & Encumbered	Unencumbered	Unencumbered & Encumbered
AUD	Median	0.02	0.03	0.13	0.27	0.04	0.08	0.26	0.84
	Mean	0.59	2.08	2.09	7.10	0.82	0.88	2.54	4.47
	Std. Dev.	11.99	32.05	39.89	97.17	19.23	4.17	36.26	25.31
CAD	Median	0.01	0.05	0.13	0.24	0.02	0.06	0.19	0.29
	Mean	0.21	0.37	0.99	2.27	0.63	2.09	2.37	3.72
	Std. Dev.	2.19	2.07	13.81	34.64	18.85	60.81	58.27	82.45
CHF	Median	0.00	0.00	0.01	0.04	0.00	0.00	0.02	0.08
	Mean	0.47	0.00	1.45	2.07	0.02	0.00	0.92	0.63
	Std. Dev.	40.73	0.00	51.96	46.59	0.50	0.02	25.80	3.09
EUR	Median	0.15	0.33	0.81	1.17	0.19	0.51	1.16	1.85
	Mean	3.24	0.83	15.34	2.91	1.16	2.47	7.62	9.39
	Std. Dev.	116.47	2.90	569.75	14.48	10.98	20.35	159.44	76.58
GBP	Median	0.10	0.25	1.03	1.91	0.12	0.37	1.29	2.59
	Mean	2.66	10.24	12.39	30.81	1.28	3.37	11.96	12.13
	Std. Dev.	111.07	237.37	388.52	639.05	34.10	25.02	458.52	64.88
JPY	Median	0.05	0.16	0.20	0.48	0.05	0.16	0.20	0.38
	Mean	0.80	0.71	3.16	2.00	0.43	0.73	12.57	14.20
	Std. Dev.	42.16	13.45	149.94	16.15	5.16	6.25	974.14	425.62
USD	Median	1.69	5.92	13.90	30.82	2.07	8.88	18.39	44.36
	Mean	56.36	100.38	299.95	274.77	49.54	99.99	297.44	279.18
	Std. Dev.	1,559.93	1,068.55	12,372.71	2,724.77	1,475.78	1,244.32	12,507.86	2,954.91
Average of All excl. USD	Median	0.06	0.14	0.38	0.69	0.07	0.20	0.52	1.01
	Mean	1.33	2.37	5.90	7.86	0.72	1.59	6.33	7.43
	Std. Dev.	54.10	47.97	202.31	141.35	14.80	19.44	285.40	112.99

Table IA.6: Safe Asset Ratios. Table presents the average ratio of safe assets and broad assets, which reflect the value of assets (either unencumbered or both unencumbered and encumbered) relative to the level of net lending in the given market. Unencumbered and encumbered asset column data begins in May 2022. First four columns include net forward positions in addition to net swap lending (which changes the denominator of asset ratios), and last four columns net out firm shorts from banks' net long position in the assets (which changes the numerator).

Percent	AUD	CAD	CHF	EUR	GBP	JPY	USD	Non-USD Avg.	All Avg.
Government	44	61	13	57	36	94	59	51	52
Quasi-Government	26	16	0	8	15	0	5	11	10
Investment Grade	12	8	87	6	6	1	7	20	18
Non-Investment Grade	18	13	0	19	26	4	25	13	15
Financial	1	3	0	2	1	1	2	1	1
Securitized	0	0	0	7	17	0	1	4	4

Table IA.7: Broad Asset Composition. Table provides the average weight of a given category in the securities held by banks with 1-year tenor across the same types of assets as in the broad asset ratio calculation, including unencumbered assets, unsettled asset purchases, capacity, and unrestricted reserve balances and the collateral backing reverse repurchases and securities borrowing. Values calculated based on sum of market and maturity values. Section IA.C.5 provides discussion for how we map the data's asset classes to the broad categories.

	Safe Asset Ratio			Risky Asset Ratio		
	(1)	(2)	(3)	(4)	(5)	(6)
$CY^k_{t,t+n}$	-0.389	-0.583^{*}	-0.272	0.203^{*}	0.321^{***}	0.329^{***}
	(-1.64)	(-1.81)	(-1.04)	(1.99)	(2.68)	(2.70)
Risky Asset $\text{Ratio}^k_{t,t+n}$	1.896^{***}	1.890^{***}	1.233^{**}			
	(2.79)	(2.84)	(2.23)			
Safe Asset $\text{Ratio}^k_{t,t+n}$				0.345^{***}	0.355^{***}	0.404^{***}
				(13.51)	(12.31)	(5.41)
N	321	321	321	321	321	321
R^2	0.65	0.67	0.50	0.66	0.68	0.52
Tenor FE	No	Yes	Yes	No	Yes	Yes
Time FE	No	Yes	Yes	No	Yes	Yes
Weighted	No	No	Yes	No	No	Yes

Table IA.8: Safe Asset Ratios and the Convenience Yield. Table presents the regression of the asset holdings as a share of the banking system's total assets on that day on the convenience yield with the matching currency and tenor, both in percentage points: Safe Asset $\text{Ratio}^k_{t,t+n} = \alpha + \beta_1 CY^k_{t,t+n} + \beta_2 \text{Risky Asset Ratio}^k_{t,t+n} + \varepsilon^k_{t,t+n}$. Asset ratios are the matched tenor version that uses unencumbered assets. Convenience yield is from Diamond and Van Tassel (forthcoming) and in basis points. Panel merges monthly averages of asset ratios with the convenience yield measures, matched by currency and tenor. Within R^2 reported. t-statistics shown using robust standard errors clustered by month where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)
Safe Asset Mismatch				
$\text{Net}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$	−0.57	−0.62	−0.56	−0.62
	(−0.63)	(−0.74)	(−0.62)	(−0.73)
$\text{Net}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$	1.10	1.28*	1.09	1.28*
	(1.53)	(1.80)	(1.52)	(1.79)
$\text{Safe Asset Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$	−10.97**	−10.13**		
	(−1.99)	(−2.01)		
$\text{Safe Asset Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$	−0.13	−0.12		
	(−1.53)	(−1.52)		
$\text{Broad Asset Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$			−1.37**	−1.47***
			(−2.54)	(−2.80)
$\text{Broad Asset Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$			0.01	0.02
			(0.19)	(0.37)
Supply Concentration				
$\text{Supply HHI}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$	5.59***	5.54***	5.59***	5.54***
	(8.13)	(8.54)	(8.12)	(8.54)
$\text{Supply HHI}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$	5.99***	5.95***	5.97***	5.94***
	(6.35)	(6.71)	(6.35)	(6.71)
Controls				
$\text{Bank CDS}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$		−14.85**		−14.85**
		(−2.36)		(−2.36)
$\text{Bank CDS}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$		−15.91**		−15.92**
		(−2.40)		(−2.40)
$\text{Govt CDS}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$		−1.12*		−1.12*
		(−1.86)		(−1.86)
$\text{Govt CDS}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$		1.56		1.56
		(0.91)		(0.91)
N	149,381	149,290	149,381	149,290
R^2	0.02	0.03	0.02	0.03
Tenor FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Weighted	No	No	No	No

Table IA.9: Regression of the absolute value of the basis on frictions, unweighted. Table presents the regression described in section 4.6. The dependent variable is the absolute value of the basis. To make the coefficients directly comparable, we transform the independent variables to modified z-scores using each variable's full sample median and standard deviation. Regressions include tenor and date fixed effects and are unweighted. Within R^2 reported. t-statistics shown using robust standard errors clustered by market and date where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Safe Asset Mismatch								
$\text{Net}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$	−0.57	−1.10**	5.17	0.17	−0.56	−1.10**	5.19	0.17
	(−0.63)	(−2.10)	(1.59)	(0.09)	(−0.62)	(−2.09)	(1.59)	(0.09)
$\text{Net}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$	1.10	1.39***	4.68**	5.64***	1.09	1.39***	4.66**	5.64***
	(1.53)	(2.78)	(2.11)	(2.99)	(1.52)	(2.77)	(2.11)	(2.98)
$\text{Safe Asset Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$	−10.97**	−15.05**	−15.95**	−21.26***				
	(−1.99)	(−2.04)	(−2.13)	(−2.69)				
$\text{Safe Asset Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$	−0.13	−0.08**	−0.44	−0.96***				
	(−1.53)	(−2.06)	(−1.40)	(−2.87)				
$\text{Broad Asset Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$					−1.37**	−8.94**	−5.05	−24.14**
					(−2.54)	(−2.14)	(−1.64)	(−2.03)
$\text{Broad Asset Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$					0.01	0.08	−0.90	−3.06***
					(0.19)	(1.41)	(−1.29)	(−2.66)
Supply Concentration								
$\text{Supply HHI}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$	5.59***	3.74***	15.62***	10.00***	5.59***	3.73***	15.62***	9.99***
	(8.13)	(4.52)	(4.55)	(4.85)	(8.12)	(4.52)	(4.55)	(4.85)
$\text{Supply HHI}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$	5.99***	3.44***	17.17***	10.18***	5.97***	3.41***	17.17***	10.18***
	(6.35)	(4.77)	(5.11)	(4.18)	(6.35)	(4.76)	(5.11)	(4.18)
Controls								
$\text{Bank CDS}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$		−27.79***		−79.94***		−27.80***		−79.96***
		(−2.90)		(−4.67)		(−2.89)		(−4.67)
$\text{Bank CDS}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$		−28.78***		−81.33***		−28.78***		−81.35***
		(−2.93)		(−4.78)		(−2.93)		(−4.78)
$\text{Govt CDS}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$		−2.65***		−3.36***		−2.65***		−3.36***
		(−4.50)		(−4.19)		(−4.50)		(−4.19)
$\text{Govt CDS}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$		−1.20		−6.31**		−1.21		−6.30**
		(−0.81)		(−2.48)		(−0.81)		(−2.48)
$\text{BondOut}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$		2.90**		3.38***		2.89**		3.38***
		(2.21)		(3.14)		(2.21)		(3.14)
$\text{BondOut}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$		−0.74		−1.94*		−0.75		−1.94*
		(−0.58)		(−1.69)		(−0.58)		(−1.69)
$\text{CY}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$		6.87***		3.32**		6.87***		3.32**
		(8.78)		(2.16)		(8.78)		(2.16)
$\text{CY}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$		7.45***		5.21***		7.45***		5.21***
		(10.19)		(4.16)		(10.19)		(4.16)
N	149,381	102,807	149,381	102,807	149,381	102,807	149,381	102,807
R^2	0.02	0.13	0.09	0.24	0.02	0.13	0.09	0.24
Tenor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weighted	No	No	Yes	Yes	No	No	Yes	Yes

Table IA.10: Regression of the absolute value of the basis on frictions, including sovereign bond supply control and convenience yield control. Table presents the regression described in section 4.6. The dependent variable is the absolute value of the basis. To make the coefficients directly comparable, we transform the independent variables to modified z-scores using each variable's full sample median and standard deviation. Convenience yield is matched to currency regardless of whether banks are net borrowing that currency. Regression includes tenor and date fixed effects and some specifications weight the regression by the square root of the market's share of the total daily gross notional. Within R^2 reported. t-statistics shown using robust standard errors clustered by market and date where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Safe Asset Mismatch										
$\text{Net}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$	0.60	8.13**								
	(0.70)	(2.28)								
$\text{Net}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$	0.10	4.29**								
	(0.17)	(2.07)								
Safe Asset $\text{Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$			−11.40**	−21.08**						
			(−2.01)	(−2.12)						
Safe Asset $\text{Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$			0.04	−0.61						
			(0.60)	(−1.51)						
Broad Asset $\text{Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$					−1.59**	−8.95*				
					(−2.41)	(−1.87)				
Broad Asset $\text{Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$					0.22**	−1.31				
					(2.47)	(−1.40)				
Supply Concentration										
Supply $\text{HHI}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$							5.61***	17.66***		
							(6.83)	(4.56)		
Supply $\text{HHI}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$							5.67***	16.73***		
							(7.57)	(4.86)		
$\text{BondOut}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$									2.32	4.05***
									(1.44)	(2.74)
$\text{BondOut}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$									−0.31	0.40
									(−0.24)	(0.32)
N	151,704	149,381	149,381	149,381	149,381	149,381	149,381	149,381	104,598	102,834
R^2	0.00	0.02	0.00	0.00	0.00	0.00	0.02	0.08	0.01	0.03
Tenor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weighted	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Table IA.11: Regression of the absolute value of the basis on frictions. Table presents the regression described in section 4.6. The dependent variable is the absolute value of the basis. To make the coefficients directly comparable, we transform the independent variables to modified z-scores using each variable's full sample median and standard deviation. Regression includes tenor and date fixed effects and some specifications weight the regression by the square root of the market's share of the total daily gross notional. Within R^2 reported. t-statistics shown using robust standard errors clustered by market and date where $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

	(1)	(2)	(3)
Avg. Bank CDS_t^k	-0.0615		-0.165^{***}
	(-1.40)		(-4.20)
$\ln(1 + \text{Avg. Book Size}_{t,t+n}^k)$		0.111^{***}	0.114^{***}
		(7.50)	(7.82)
N	605,867	605,867	605,867
R^2	0.00	0.02	0.02
Time FE	Yes	Yes	Yes

Table IA.12: Matching between banks and markets. Table presents the regression of government bond CDS spreads for a market on the weighted average bank CDS for banks active in that market and the weighted average size of banks active in that market. Panel is at the date-by-currency-by-tenor level, spanning all tenors including those without Bloomberg basis estimates. The left-hand side is the government CDS spread for 5-year senior unsecured debt from Markit. Within R^2 reported. t-statistics shown using robust standard errors clustered by market and date where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Net USD Lending		Net FX Exposure		Gross FX (Level)
	(1)	(2)	(3)	(4)	(5)
Net All Derivatives Fair Value	0.02		−0.01		
	(0.26)		(−0.25)		
Net Gross FX Fair Value		−0.03		0.01	
		(−0.31)		(0.51)	
Gross FX (Level)					0.99^{***}
					(113.21)
N	232	232	232	232	232
R^2	0.00	0.00	0.00	0.00	0.98

Table IA.13: Comparison of Confidential and Public FX Measures. This table presents regressions comparing confidential data and public data at the bank-quarter level, as described in section IA.C.2. The dependent variables are $Net^k_{t,t+n}$(columns 1 and 2), a broader measure of net FX lending (columns 3 and 4) from confidential data, and gross notional exposures (column 5). The independent variables are derived from Y-9C data. The on-balance sheet measure, "Net All Derivatives Fair Value," is calculated using the fair value of all derivatives and incorporates counterparty netting. The off-balance sheet measure, "Net Gross FX FV," is calculated using the fair value of FX derivatives only and does not incorporate counterparty netting. Gross notional exposures are the sum of FX swaps, futures, and forwards. See section IA.C.2 for details on the variables' construction. t-statistics shown using robust standard errors clustered by date where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Safe Assets

	Unencumbered Safe Assets		Unencumbered & Encumbered Safe Assets	
	(1)	(2)	(3)	(4)
$Net^k_{t,t+n}$($ Level)	0.018**	−1.156*	0.158***	−2.459
	(2.10)	(−1.97)	(4.50)	(−1.55)
AUD	284.404***		236.747**	
	(3.51)		(2.43)	
CAD	187.190***		133.134	
	(3.52)		(0.74)	
EUR	1980.489***		4405.444***	
	(4.91)		(4.51)	
GBP	753.200***		1353.896**	
	(5.13)		(2.08)	
JPY	769.104***		630.551	
	(4.16)		(1.57)	
Constant	−25.218	23652.102***	−202.183***	66946.261***
	(−1.58)	(5.19)	(−4.64)	(5.17)
N	75,002	76,702	10,145	8,923
R^2	0.33	0.01	0.51	0.01
Time FE	Yes	Yes	Yes	Yes
Sample	Non-USD	USD	Non-USD	USD

Panel B: Broad Assets

	Unencumbered Broad Assets		Unencumbered & Encumbered Broad Assets	
	(1)	(2)	(3)	(4)
$Net^k_{t,t+n}$($ Level)	0.104**	−5.821**	0.221***	−6.728**
	(2.11)	(−2.22)	(2.84)	(−2.18)
AUD	1282.197***		1463.182***	
	(3.26)		(3.68)	
CAD	700.362**		866.665	
	(2.19)		(1.58)	
EUR	11723.416***		15661.998***	
	(8.85)		(7.34)	
GBP	7361.575***		7976.473***	
	(5.76)		(4.77)	
JPY	3751.602***		3800.903***	
	(3.88)		(3.33)	
Constant	93.423	159833.404***	−53.795	180679.273***
	(0.81)	(6.49)	(−0.38)	(6.36)
N	10,099	8,885	10,099	8,885
R^2	0.54	0.02	0.58	0.02
Time FE	Yes	Yes	Yes	Yes
Sample	Non-USD	USD	Non-USD	USD

Table IA.14: Net vs. Safe Asset Ratios. Table presents the regression of the level of $Net^k_{t,t+n}$on the level of the assets—either HQLAs or broad assets—with the same maturity and currency in millions of dollars: $\text{Asset (Level)}^k_{t,t+n} = \alpha + \beta Net^k_{t,t+n}(\text{Level}) + \gamma^k + \varepsilon^k_{t,t+n}$ where γ^k is a currency fixed effect. Columns 1 and 3 limit the sample to observations with net dollar lending (e.g., $Net^k_{t,t+n} > 0$). Columns 2 and 4 limit the sample to observations with net dollar borrowing (e.g., $Net^k_{t,t+n} < 0$). Base level is CHF. Within R^2 reported. t-statistics shown using robust standard errors clustered by market and date where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.