Quantities and Covered-Interest Parity

Tobias J. Moskowitz, Chase P. Ross, Sharon Y. Ross, Kaushik Vasudevan*

July 11, 2024

Abstract

Studies of intermediated arbitrage argue that bank balance sheets are an important consideration, yet little evidence exists on banks' positioning in this context. Using confidential supervisory data (covering $25 trillion in daily notional exposures) we examine banks' positions in connection with covered-interest parity (CIP) deviations. Exploiting cross-sectional variation in CIP deviations that have largely challenged existing theories, we document three novel forces that drive bases: 1) foreign safe asset scarcity, 2) market power and segmentation of banks specializing in different markets, and 3) concentration of demand. Our findings shed empirical light on the interplay of frictions influencing banks' provision of dollar funding.

JEL Codes: F3, F31, F65, G1, G13, G15, G2, G23

Keywords: basis, covered-interest parity deviation, foreign exchange, safe assets

*T. Moskowitz is at the Yale School of Management, Yale University, NBER, and AQR Capital Management, email: tobias.moskowitz@yale.edu. C. Ross is at the Board of Governors of the Federal Reserve System, email: chase.p.ross@frb.gov. S. Ross is at the Board of Governors of the Federal Reserve System, email: sharon.y.ross@frb.gov. K. Vasudevan is at the Daniels School of Business, Purdue University, email: kvasude@purdue.edu. We thank Tristan D'Orsaneo for excellent research assistance. For comments and suggestions, we thank our discussants Rashad Ahmed, Will Diamond, Ben Golez, Piotr Orłowski, Stephen Szaura, and Mengbo Zhang, as well as Ricardo Correa, Wenxin Du, Nathan Foley-Fisher, Peter Hansen, Toomas Laarits, Jinsook Lee, Borghan Narajabad, Stas Nikolova, Junko Oguri, David Rappoport, Bryan Ricketts, Matt Seay, Alex Vardoulakis, Xiaochuan Xing, Chenzi Xu, Emre Yoldas, seminar participants at the University of Nebraska and Fed Board, and conference participants at the Wabash River Conference, 2024 ASSA, 2024 MFA, the Spring 2024 NBER Financial Market Frictions and Systemic Risks meeting, the 2024 Eastern Finance Association meeting, and the 2024 UCLA Fink Center Conference. AQR Capital is a global asset manager who may or may not use the insights and methods in this paper. The analysis and conclusions set forth are those of the authors and do not indicate concurrency by members of the Board of Governors of the Federal Reserve System, AQR, or their staffs.

1 Introduction

Spreads on bank-intermediated arbitrage trades, called bases, have persisted since the 2008 financial crisis, attracting substantial attention from academics and practitioners. The existence of bases is often cited as evidence that financial intermediaries are not simply a veil, as assumed in classical theories. The litany of frictions faced by intermediaries, therefore, may have import on asset prices and, by extension, the broader economy. Prior work focuses primarily on asset pricing data. In this paper, we use novel quantity data, to gain a better understanding of intermediaries' basis trading activity and of how intermediary constraints affect asset prices.

We focus on covered-interest parity (CIP) as a simple and clear arbitrage trade intermediated by banks.[1] CIP deviations have been used as a primary empirical laboratory to describe the importance of intermediation frictions. A CIP arbitrage trade consists of the following: 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. CIP implies that the return on this transaction should be zero. Deviations from CIP are important because they reflect frictions in the global provision of dollar funding, which occurs largely via currency swaps and forwards. 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)).

To better understand the role of intermediaries in asset prices and, specifically, the global provision of dollar funding, we use granular confidential supervisory data. We also exploit cross-sectional variation in CIP bases, whose existence is a puzzle for existing intermediary theories for the basis. Our unique quantity data provide bank positions in these markets, which when merged with prices, shed substantial light on what drives bases, including explaining their puzzling cross-sectional heterogeneity.

[1] There are several types of basis trades beyond covered-interest parity, 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 (J 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 bases because our data provide detailed bank exposure information to specific country interest rates and currencies, allowing a granular examination.

We find that three novel forces are important for driving bases. First, intermediaries purchase foreign risky assets, rather than safe assets, corresponding with their synthetic dollar lending to customers. Since CIP arbitrage requires a position in safe assets, banks only imperfectly execute CIP arbitrage and take on meaningful risk. Second, markets are segmented, with banks specializing in different currencies and tenors, so bases reflect bank-specific constraints. Segmentation also reduces the elasticity of bases to demand via reduced risk sharing and market power. Third, intermediaries face concentrated demand in some markets from certain counterparties and require compensation associated with counterparty risk. We break down and quantify how each of these channels generates time-series and cross-sectional variation in CIP deviations. Our results highlight the presence and importance of segmentation and search frictions in even the largest and most liquid markets.

To better interpret our findings and guide our empirical investigation, we build 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, foreign safe asset scarcity (difficulty in locating scarce foreign safe bonds with low yields), heterogeneous expertise in risky assets, and counterparty limits.

The model showcases how each friction contributes to bases. Balance sheet costs drive a common component of bases across all currencies, which is the primary focus of the literature. However, the other frictions we model have an impact, too, and, importantly, can capture the cross-sectional heterogeneity in the data. For example, scarce foreign safe bonds that are hard to find and have low yields lead intermediaries to hold risky bonds. In turn, we observe differences in bases across currencies based on the amount of synthetic dollar borrowing demand from those currencies. Heterogeneous expertise leads intermediaries to specialize in certain markets. This segmentation creates market power and impedes risk sharing, which affects the elasticity of the basis differentially across currencies. Counterparty limits also imply that the concentration of demand contributes to the inelasticity of bases. These frictions vary across banks and markets, generating cross-sectional variation in bases.

To test the model's implications and whether these channels can capture the variation in bases, 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 assets and liabilities side of banks' balance sheets, we obtain a novel 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 in the same markets where the basis indicates dollar funding is the most expensive. This fact is consistent with the banking sector facing increasing marginal costs to meet dollar demand from each currency. Guided by our model, we empirically investigate how the outlined frictions contribute to these increasing marginal costs.

First, we find foreign safe asset scarcity is an important driver of CIP bases. 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 \$0.05 per dollar lent when matching maturities perfectly. Even when employing a generous definition of maturity-matched safe assets that ignores counterparty risk and permits small maturity mismatches, banks hold only \$0.48 of foreign "safe" assets per \$1 lent. A significant component of intermediaries' currency exposure is, therefore, hedged with maturity-mismatched safe assets and with risky assets. The choice or constraint to execute imperfect CIP arbitrage explains why dollar funding is most expensive in markets where banks are doing the most dollar lending since those are the markets where intermediaries are taking the most risk.

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 7 to 9 bps.

Second, we find that currency market segmentation contributes to CIP bases. We define a *market* as a tenor $\times$ currency pair, so the 1-month EURUSD, 1-year EURUSD, and 1-year JPYUSD are all distinct markets. For each market, we calculate a Herfindahl-Hirschman Index (HHI) of bank exposure and find a strong relationship between more concentrated markets and larger bases: a one standard deviation more segmented market has a 10 to 14 bps larger basis. Combined with our results on safe asset scarcity, the relationship between segmentation and bases highlights the importance of risk—and intermediaries imperfectly sharing it—as drivers of CIP deviations, which may also be amplified by market power.

We also identify segmentation by examining the extent to which bank-specific constraints are reflected in bases. We use the March 2023 banking turmoil as a natural experiment to test the relationship between bank-specific shocks and the basis. There was a notable shift of deposits toward the largest US banks following the Silicon Valley Bank (SVB) turmoil. We show that currency markets intermediated by banks with comparatively larger deposit inflows had comparatively smaller basis dislocations. This result is consistent with the model's prediction that constraints facing banks who specialize in certain markets will transmit to prices in those markets, consistent with market segmentation on the supply side.

The presence and importance of segmentation are surprising in our setting since global currency markets are among the largest and most liquid markets in the world. We show that segmentation is persistent, with market shares displaying persistence and more segmented currency markets remaining so over time. Our model ascribes segmentation to heterogeneous expertise in executing arbitrage across markets, where banks specialize in markets where they have the most expertise. We provide support for this mechanism by showing 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 further show that banks hold more loans in the currencies in which they have large currency market shares in FX swap markets, suggesting that banks have market-specific expertise and a more readily available set of counterparties in the markets they specialize in.

Third, we find that some currency markets have concentrated demand. Markets with a less diverse mix of counterparties also have larger basis dislocations, controlling for foreign safe asset scarcity and segmentation. More concentrated demand is associated with larger bases, consistent with banks managing counterparty risk. A one standard deviation increase in demand concentration has a 7 bps larger basis.

Analysis of the cross-section of CIP deviations reveals several novel and important frictions affecting prices: scarcity of foreign safe assets and supply and demand segmentation. These frictions matter for arbitrage activity even in global currency markets, which are some of the largest and most liquid markets.

Related Literature Our work is most closely related to work 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. (2021), 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 bank regulation (Du et al. (2018)) or debt overhang frictions associated with the expansion of bank balance sheets (Andersen et al. (2019)).

In contrast, our work shines a light on the asset side of intermediaries' basis trades using unique data on quantities. Our findings indicate that either the difficulty in locating foreign safe assets for use in CIP trades or the choice to invest in higher-yielding assets results in intermediaries holding riskier securities in the foreign legs of their basis trades, thus making CIP arbitrage activity risky. This conclusion complements the findings of Diamond and Van Tassel (2021), 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. Furthermore, given the real costs of CIP deviations (Du and Huber (2023)), our result that safe asset scarcity may help drive CIP deviations highlights the real effects of safe asset scarcity consistent (e.g., Caballero (2006), Caballero et al. (2017), Caballero and Farhi (2018)).

Uniquely, we focus on cross-sectional variation in bases. We conclude that intermediary heterogeneity (Kargar (2021)) and the accompanying segmentation of intermediaries into different markets are important drivers of bases.[2] Using supervisory regulatory data, we provide direct evidence of segmentation's impact in transmitting idiosyncratic, bank-specific constraints into asset prices. This result is consistent with other work (e.g., Rime et al. (2022); Siriwardane et al. (2022); Kloks et al. (2023)). However, our empirical evidence uniquely sheds light on the source of segmentation. Because we find that CIP arbitrage is risky, our results

[2] A necessary ingredient is that there are differences in dollar demand via currency forwards, which, for example, may arise from differences in currency hedging demand across currencies (e.g., Liao and Zhang (2021) and Du and Huber (2023)). Similar heterogeneity in demand also exists in other markets, for example, equity index futures markets (Hazelkorn et al. (2023)).

highlight another channel through which segmentation affects bases—reduced risk sharing. The evidence supports the idea that investors specialize in "complex asset markets" due to market-specific expertise (e.g., Glode and Opp (2020), Eisfeldt et al. (2023), Bryzgalova et al. (2023)), emphasizing that the riskiness of arbitrage—and differences in intermediaries' abilities to reduce that risk—are key to understanding segmented arbitrage.

Lastly, our work contributes to the 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 utility of *specializing* intermediaries contributes to market risk premia and not just the intermediary sector in aggregate.

2 Model

We present a stylized model to organize and interpret our empirical investigation. The model yields a set of predictions on the cross-sectional drivers of CIP bases and illustrates how different frictions give rise to variation in bases.

2.1 Setup

There are N_k foreign currencies (against the USD), indexed by $k = \{1, \ldots, N_k\}$. For simplicity, each currency faces a unitary exchange rate versus the USD. There are two types of investors: N_i financial intermediaries, indexed by $i = \{1, 2, \ldots, N_i\}$ and N_c customers, indexed by $c = \{1, 2, \ldots, N_c\}$. There are two periods, $t = 1, 2$. All investors invest in period 1 and realize payoffs in period 2.

The U.S. offers safe bonds in perfectly elastic supply, with returns normalized to zero. Each foreign currency features three types of assets: one-period currency forwards, safe bonds, and 'risky' bonds, which are imperfect substitutes for safe bonds and which investors face idiosyncratic risk to invest in, as detailed below. All risky foreign bonds offer a return of r. Safe foreign bonds in currency k offer expected returns of $r_k \leq r$. Currency forwards are in zero net supply, and their price is endogenously determined.

Customer Demand for Currency Forwards and the Basis. Customers only transact in currency forwards. In period 1, customer c exogenously demands to synthetically swap $X_{c,k}$ dollars from currency k into USD via forwards. In aggregate, synthetic dollar demand to swap currency k for dollars is given by $X_k = \sum_{c=1}^{N_c} X_{c,k}$. For simplicity, we assume that customers' trades are netted out, such that $\text{sign}(X_k) = \text{sign}(X_{c,k}), \forall c, k$. The price of currency forwards for currency k is given as $P_{f,k}$.

The basis for currency k is the price of the forward contract minus the expected return from borrowing in USD and investing in foreign safe assets:

$$\text{Basis}_k \equiv P_{f,k} - r_k.$$

With exogenous risk-free rates, the basis is determined by the forward price.

Foreign Bonds and Safe Asset Scarcity. There is a sufficient supply of safe bonds to hedge all currency trades, 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. Intermediary i faces an idiosyncratic payoff variance of $\sigma_{i,k}^2$ when purchasing risky bonds in currency k. Intermediaries with lower $\sigma_{i,k}^2$ for a given market face less risk in their basis trades when substituting away from safe bonds in the cash legs of their basis trades. This feature can be interpreted as intermediaries having "market-specific expertise" in substituting away from safe assets. The heterogeneity in risk faced by different intermediaries may reflect, for example, differences in technologies across intermediaries in producing information about issuers in a given market, differences in access to counterparties, or alternatively differences in trade execution (Glode and Opp (2020), Eisfeldt et al. (2023)).

Intermediary Hedging and Safe Asset Choice. Each intermediary i maximizes a mean-variance objective function, $\mathbb{E}(W_{i,2}) - \frac{\gamma_i}{2}\mathbb{V}(W_{i,2})$, where $W_{i,2}$ is the terminal wealth of intermediary i, $\mathbb{E}(\cdot)$ and $\mathbb{V}(\cdot)$ are the expectations and variance operators, and γ_i is a coefficient that captures the risk-bearing capacity of intermediary i. Intermediaries take the other side of customer demand in synthetic funding markets. Intermediary i takes a position of $Z_{i,k}$ in currency forward k. Forward market clearing is given by $\sum_i Z_{i,k} + \sum_c X_{c,k} = 0, \forall k$.

Intermediaries are constrained to fully hedge their currency exposure from meeting forward demand via cash bonds. To satisfy their first-order conditions, intermediaries' allocations to safe and risky bonds in currency k must make them indifferent to obtaining marginal hedge positions in either. This means that given their total position of $-Z_{i,k}$ in cash bonds of currency k, intermediary i allocates a proportion $\alpha_{i,k} \equiv \frac{r - r_k + \lambda_{s,k}}{\lambda_{s,k} + \gamma_i \sigma_{i,k}^2}$ to risky bonds and allocates the remainder of their hedge position to the safe bond. Given their positions, intermediary i's profits in currency k are given by $-(\alpha_{i,k} r + (1 - \alpha_{i,k}) r_k - P_{f,k}) Z_{i,k}$.

Each intermediary also faces a set of constraints that we detail below.

Balance Sheet Cost: Intermediary i faces increasing marginal costs to expand its balance sheet (e.g., because of regulation or debt overhang). This is captured by each intermediary facing a cost of the form

$$\frac{1}{2}\lambda_{BS}\left(\sum_k |Z_{i,k}|\right)^2. \tag{1}$$

We assume quadratic costs for mathematical ease, but conceptually, our results depend only on the fact that constraints are (weakly) convex.

Counterparty Constraints: Intermediary i pays increasing marginal costs to meet demand from specific counterparties. All else equal, intermediaries prefer to equalize positions across different counterparties for diversification purposes.

Here, we assume that for each currency k and customer c, intermediaries' counterparty position is directly proportional to their holding in currency k, i.e.,

$$Z_{i,k,c} = Z_{i,k}\frac{X_{c,k}}{X_k} \tag{2}$$

where $Z_{i,k,c}$ is defined as intermediary i's position in currency k opposite customer c. For each counterparty c, intermediary i faces a cost of the form

$$\frac{1}{2}\lambda_{CP}\left(\sum_k |Z_{i,k,c}|\right)^2. \tag{3}$$

Fixed Participation Costs: Each intermediary pays a fixed participation cost of $\lambda_{PC,k}$ to trade in currency k. This can be thought of, for example, as the cost of setting up a trading desk for currency k.

2.2 Model Predictions

We can write financial intermediary i's problem as

$$\begin{aligned}
\max_{Z_{i,k},\alpha_{i,k}\forall k} & \sum_k -(\alpha_{i,k} r + (1-\alpha_{i,k}) r_k - P_{f,k}) Z_{i,k} \\
& - \sum_k \frac{\gamma_i}{2} (\alpha_{i,k} Z_{i,k})^2 \sigma_{i,k}^2 && \text{(Risk)} \\
& - \sum_k \frac{1}{2} \lambda_{s,k} \left((1-\alpha_{i,k}) Z_{i,k}\right)^2 && \text{(Safe Asset Scarcity)} \\
& - \sum_k \lambda_{PC,k} \mathbb{1}_{\{Z_{i,k} \neq 0\}} && \text{(Fixed Participation Costs)} \\
& - \frac{1}{2} \lambda_{BS} \left(\sum_k |Z_{i,k}| \right)^2 && \text{(Balance Sheet Costs)} \\
& - \frac{1}{2} \lambda_{CP} \sum_c \left(\sum_k |Z_{i,k,c}| \right)^2 . && \text{(Counterparty Costs)}
\end{aligned}$$

Our first set of predictions does not rely on intermediary heterogeneity, so for clarity of exposition, we (1) set fixed participation costs to zero and (2) assume there is no heterogeneity across intermediaries in risk-bearing capacity or in risk faced (i.e., $\sigma_{i,k} = \sigma_k$ for some value σ_k and $\gamma_i = \gamma$ for some value γ, $\forall i$, and $\forall k$).[3]

[3] In the appendix, we present an expression for the basis without this simplification, which results in a more complicated expression that yields the same predictions as presented here.

Taking the first order condition with respect to $Z_{i,k}$, and averaging across intermediaries,

$$\begin{aligned}
\text{Basis}_k =& \frac{(r-r_k)^2 + (r-r_k)\lambda_{s,k}}{\lambda_{s,k}+\gamma_i\sigma_k^2} + \frac{X_k}{N_i}\frac{(r-r_k)^2+\lambda_{s,k}\gamma\sigma_k^2}{\lambda_{s,k}+\gamma\sigma_k^2} && \text{(Safe Asset Scarcity)} \\
&+\lambda_{BS}\frac{\text{Sign}(X_k)}{N_i}\sum_{k'}|X_{k'}| && \text{(Balance Sheet Costs)} \\
&+\lambda_{CP}\frac{\text{Sign}(X_k)}{N_i}\left(\underbrace{|X_k|\sum_c \frac{X_{c,k}^2}{X_k^2}}_{\text{Demand Conc. in } k} + \sum_c \frac{X_{c,k}}{X_k}\sum_{k'\neq k}|X_{c,k'}|\right). && \text{(Counterparty Costs)}
\end{aligned}$$

This expression for the basis yields the following predictions:

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, $\sum_{k'}|X_{k'}|$.*[4]

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 that the intermediation sector faces 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}).

The model also yields novel, cross-sectional predictions:

Prediction 3 (Safe Asset Scarcity)**.** *The cost of synthetic dollar funding for currency k is increasing in demand to borrow dollars from currency k via forwards (more positive bases).*

Corollary 1 (Heterogeneity in Safe Asset Scarcity)**.** *All else equal, currencies where foreign safe assets are harder to find (high search costs, $\lambda_{s,k}$) have larger magnitude bases. On average, dollar funding is more expensive in currencies where safe rates (r_k) are lower.*

Prediction 3 is novel and makes a prediction about the cross-section of bases that arise from risk and safe asset scarcity. The basis embeds the search cost that intermediaries pay to

[4] In principle, this reflects the balance sheet usage of the financial system.

locate foreign safe bonds, where the marginal search cost (and distaste for risk) is increasing in the amount of demand banks must intermediate.

Corollary 1 extends this prediction to consider the possibility that search costs for foreign 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 must make. A related point is that in currencies where safe assets are scarce, foreign safe interest rates are low (Caballero (2006); Caballero et al. (2017)); and as a result, we expect more substantial CIP deviations in those currencies in the form of more expensive dollar funding, due to intermediaries optimally choosing to substitute into higher-yielding risky assets.

Prediction 4 (Demand Concentration)**.** *The magnitude of the basis for currency k increases in the concentration of demand to swap foreign currency for dollars across counterparties c.*

Prediction 4 reflects the fact that intermediaries demand larger compensation for concentrated demand from counterparties, due to more idiosyncratic counterparty risk.

For our last set of predictions, we focus on heterogeneity across intermediaries. We reintroduce non-zero fixed participation costs, heterogeneous risk in substituting away from safe bonds, and heterogeneous risk-bearing capacity. For clarity of exposition, set $\lambda_{BS} = \lambda_{CP} = 0$ and $r = r_k$.

Given fixed participation costs, intermediary i participates in currency k in equilibrium only when it faces sufficiently low risk ($\sigma_{i,k}$) in substituting away from risk-free assets in currency k.[5] The basis can be expressed as

$$\text{Basis}_k = \frac{X_k}{\frac{N_{p,k}}{\lambda_{s,k}} + \sum_i^{N_{p,k}} \frac{1}{\gamma_i \sigma_{i,k}^2}},$$

where $N_{p,k} \leq N_i$ is the number of participating intermediaries. Segmentation arises because some intermediaries cannot justify the fixed participation costs given the risk they face in substituting away from currency k safe assets.

[5]Derivations contained in Appendix A.1. In the main specification, as a consequence of customer demand being perfectly inelastic, bases are exactly equal to intermediaries' marginal costs including risk. Hence, intermediaries with too low $\sigma_{i,k}$ will also avoid participation because their capacity to execute the trade at low risk may drive profits toward zero. However, this lower bound on $\sigma_{i,k}$ disappears when customer demand is price sensitive, as in an extension presented in the appendix.

Prediction 5 (Supply Segmentation)**.** *The basis for currency k is larger in magnitude when intermediary supply for currency k is more segmented (smaller $N_{p,k}$).*

Prediction 5 arises from a combination of foreign safe asset scarcity, heterogeneity in the risk faced by intermediaries in different markets, and fixed participation costs. It is a novel and distinct prediction from other work on bases that suggests that funding markets may be segmented (e.g., Rime et al. (2022); Siriwardane et al. (2022)). This prediction arises in our model because CIP arbitrage is imperfect, and intermediaries take risks in their positions. With segmentation, intermediaries are less able to share risk and accordingly demand larger compensation for meeting customer demand.[6] An additional channel that amplifies the risk-sharing effect is market power (Wallen (2022)), which also appears in a simple Cournot-style variant of our model presented in the appendix. Segmentation may be symptomatic of intermediary market power, which can create larger bases via markups.[7]

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.[8]

Prediction 6 (Specializing Intermediaries' Risk-Bearing Capacity)**.** *The basis for currency k reflects the risk-bearing capacity of intermediaries that specialize in currency k.*

When intermediaries specialize in different markets, the risk-bearing capacity of the *specializing* intermediaries in a market is the relevant driver of bases in that market, not the risk-bearing capacity of the overall intermediary sector. Siriwardane et al. (2022) 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.

[6]This prediction is related to an implication of Eisfeldt et al. (2023), that participation should be lower in markets that have higher Sharpe ratios.

[7]Because market power and risk-sharing make the same directional predictions, we cannot empirically disentangle the roles they play. Neuhann and Sockin (2023) present a dynamic model to study the 'risk-rent' tradeoff faced by large strategic traders (e.g., intermediaries).

[8]Bryzgalova et al. (2023) similarly 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.

Corollary 2 (Safe Asset Ratios Across Intermediaries). *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 position, $Z_{i,k}$, is larger in magnitude).*

Corollary 2 arises from the fact that intermediaries hold larger positions in markets where they face lower risk in substituting away from safe assets in the cash legs of their basis trades. Intermediaries with a higher willingness and ability to substitute into risky foreign bonds have a higher capacity for meeting currency forward demand and, accordingly, have higher market shares. We note that Corollary 2's prediction of lower shares of foreign safe bonds for specializing intermediaries is distinctive from the prediction of another form of expertise by specializing intermediaries: lower search costs for safe bonds. An alternative search-cost-based explanation would predict, if anything, a higher share of foreign safe asset holdings by specializing intermediaries.

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 use 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 provide information by asset class, outstanding balance, and purpose, each reported by maturity and date. The data cover 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.[9] Banks have a strong incentive to report data fully and truthfully because of the

[9] 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.`

possible consequences of making misrepresentations to government authorities, which could result in enforcement actions. Unlike other public companies, regulators closely scrutinize banks, so any misreporting would likely be identified and corrected quickly. Researchers have recently begun using this dataset to study bank behavior: for example, Infante and Saravay (2020), Cooperman et al. (2023), and—more related to our work—Correa et al. (2020).

We use the data on banks' foreign exchange swaps and forwards.[10] 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 it does 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 that. We discuss additional data cleaning in Appendix A.2.

We focus on the subset of the data with transactions in the seven 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 sample to maturities less than 4 years since the 5-year bucket contains all maturities at five years and beyond.

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.

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

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 from mid-2022. Across these categories, we measure banks' safe assets as the subset of the level 1 high-quality liquid assets (HQLAs). 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 from 1 week to 4 years. Details on cleaning the OIS interest rate data are provided in the online appendix.[11] We calculate CIP violations following Du et al. (2018). Define s_t as the spot exchange rate in units of foreign currency per US 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,

$$\text{Basis}_{t,t+n} = y^{\$}_{t,t+n} - \left(y_{t,t+n} - \frac{1}{n}(f_{t,t+n} - s_t) \right). \tag{4}$$

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 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 tenor. Dislocations are apparent during the 2008 financial crisis and the early stages of the Covid pandemic. We

[11] 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 FR2052a data is five years and greater, so its average maturity is likely much more than five years.

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 of maturity, we merge the panels using the commonly reported days to maturity in the FR 2052a data.[12]

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.

4 Empirical Strategy and Results

We focus on the cross-sectional variation in currencies' bases. Constructing a measure of dollar lending against different currencies, 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, or with banks seeking higher returns from lending in specific currencies and maturities.

We use the model to guide an empirical decomposition of the basis into safe asset scarcity, segmentation, and counterparty concentration in giving rise to bases. Finally, we use the event surrounding the March 2023 Silicon Valley Bank (SVB) turmoil to show how demand shocks trace through net dollar lending and their effects on bases.

[12]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 1096 days; 4y is 1461 days.

4.1 Signed Time-series Variation of 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.

Our model offers insights into other drivers of the basis that help explain the cross-sectional variation. 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 the 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. That different foreign economies have different dollar demands and are willing to pay different prices for dollars, is intuitive. 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.[13]

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)).

Predictions 1 and 2 reflect (signed) time-series variation in bases, the primary focus of earlier work. We calculate the first principal component of the bases which we use to proxy for an intermediary-wide factor. Figure A1 plots the variance across the bases in each tenor that can be explained by the first principal component. The figure shows that the common comovement across all the bases is important, but there is significant variation left to be explained. The focus of our paper is on the cross-sectional variation in the size of bases,

[13]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.

which accounts for the remaining variation in bases.

4.2 Net Dollar Lending

Our remaining predictions depend upon the intermediaries' dollar lending across currencies. We begin by constructing a measure of net dollar lending for each market.

4.2.1 Construction

We use the FR 2052a data to calculate banks' net lending position for each market, where we define a market as a specific currency × tenor. We calculate banks' net USD supplied from date t to $t+n$ for a given currency pair k via FX swaps using:

$$Net^{k}_{t,t+n} = \frac{(\text{USD in at } t+n) - (\text{USD out at } t+n)}{(\text{USD in at } t+n) + (\text{USD out at } t+n)}. \tag{5}$$

Table 3 provides a simple example to illustrate the logic underpinning $Net^{k}_{t,t+n}$ construction. 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 dollars 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 $t+7$. Notice that 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.[14]

[14]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 future 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 Appendix Table A4. Similarly, our net lending measure excludes intermediate interest payments since we are unable to match those payments to the underlying swap.

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 × maturity × 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 × maturity × currency × bank level. Since banks report only non-zero values, we set net lending to zero when there is no lending or borrowing data for a given observation.

4.2.2 *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 borrow in AUD (on average $Net^{AUD}_{t,t+n}$ of 3.6 percent) and lend EUR (at 1.1 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.

Appendix Table A1 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.[15]

Appendix Table A2 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

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

Report 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, given that it is 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 A2. 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 \$12 billion at the 1-year tenor. The bottom panel shows the gross notional dollar flows—the denominator of our net variables. 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 A3 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.[16]

4.3 *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,

$$\text{Basis}^k_{t,t+n} = \alpha + \beta Net^k_{t,t+n} + \gamma\prime X_t + \varepsilon^k_{t,t+n} \tag{6}$$

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 the most negative in markets with the most dollar demand. This relationship arises from the search costs and risks that intermediaries face when supplying dollars in different markets, due to the scarcity of foreign safe assets.[17]

[16] In the online appendix, Figure A4 shows that net is closer to zero for the largest markets.

[17] $\beta < 0$ is implicitly assumed in several other papers, for example, Greenwood et al. (2023), Liao and Zhang (2021) and Du and Huber (2023). An analogous result is also shown to be the case in equity index

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 1 percentage point (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 10pp, corresponding to a basis that is 4.3 bps lower using column 4's coefficient. Columns (5) and (6) split the sample into short- and long-term tenors, with a threshold of one year. The relationship is much stronger for longer-tenor lending, with a coefficient roughly 9 times larger than 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×-1.5).

In the online appendix, we provide additional results on the relationship between bases and lending. Figure A5 scatterplots the average basis against the average $Net^k_{t,t+n}$ for a given currency and tenor, and Figure A6 shows the average basis and $Net^k_{t,t+n}$for each currency at several tenors. Second, we show the regression coefficients in Figure A7. 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.

The cross-sectional relationship between $Net^k_{t,t+n}$and bases is consistent with our model. Intermediaries' (shadow) costs that increase with dollar funding demand from a particular currency drive cross-sectional variation in bases. The remaining predictions of our model explore the importance of different constraints in contributing to these costs.

4.4 Frictions Contributing to the Basis

We identify three potential sources that influence the size of the basis: foreign safe asset scarcity, intermediary segmentation, and demand concentration. We construct proxies for each measure, which we use together in a regression to jointly test their ability to explain the cross-section of bases.

futures markets by Hazelkorn et al. (2023).

4.4.1 Foreign Safe Asset Scarcity

Prediction 3 links bases with dollar funding demand because it is either difficult for intermediaries to find foreign safe assets or because they seek higher returns by taking on some risk. In this case, CIP arbitrage will be executed imperfectly if dollars lent are not matched \$1 for \$1 with foreign risk-free assets at the same maturity.

Intermediaries do not appear to be executing perfectly hedged CIP arbitrages. We find that on average, intermediaries hold only 5 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 foreign currency risky assets, taking on risk to meet customer demand in currency swap markets.

To illustrate this point, we define foreign safe assets as the sum of level 1 HQLAs that are unencumbered assets, unsettled asset purchases, and assets pledged to the central bank. We include a full list of types of level 1 HQLA securities in the online appendix section A.2. Sovereign bonds make up most of these securities. The BIS describes HQLAs as assets that "can be easily and immediately converted into cash at little or no loss of value."[18] The measure is specific to the market: there are daily observations for each currency and tenor. We define

$$\text{Safe Asset Ratio}^k_{t,t+n} = \frac{\text{Level 1 HQLAs } (\$)^k_{t,t+n}}{\text{Net } (\$)^k_{t,t+n}}.$$

If 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.[19]

To better understand where intermediaries may place their foreign currency, we calculate

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

[19]The denominator of safe asset ratios uses the maturity value of net swap lending rather than the present value, and the numerator is the market value of the securities. Discounting this maturity value of net swap lending to present value does not substantively affect the computed safe asset ratios due to the short maturity of the assets and low interest rates in the sample.

a broader definition

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

where Broad Asset Ratio$^k_{t,t+n}$ covers assets beyond HQLAs in the three categories listed above. It includes unencumbered assets, unsettled asset purchases, capacity, central bank deposits, reverse repurchases, or securities borrowings.[20] For example, a German government bond would be in both ratios, but a German corporate bond would show up only in the broad asset ratio since it is not a level 1 HQLA. Beginning in 2022, the data includes encumbered assets, and we treat this subsample separately as a point of comparison given the large value of the banking system's encumbered assets.[21] Note that 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, their net long measure would be lower.[22]

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 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 are different for U.S.-based G-SIBs.

[20] Unencumbered assets, unsettled asset purchases, capacity, and central bank deposits are market values. Reverse repurchases and securities borrowings—along with short-term investments and firm shorts, which we use later for robustness—are reported by amounts due at maturity rather than market value; since these are short-term with negligible credit risk, we do not discount them into present value terms and instead, we follow market convention to report these instruments at carrying value since it closely approximates fair value (see JP Morgan 10-K, 2022, pg 186).

[21] Beginning in 2022, the data also begins including 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.

[22] The broad asset ratio measure may include double counting when the bank pre-positions collateral it receives from a secured financing transaction, like a reverse repo, with a central bank. For example, if a bank lent AUD in a 1-month repo and pre-positioned the AUD-denominated collateral (say with a 2-year maturity) it received with a central bank, then our broad ratios for 1-month and 2-year AUD would reflect this exposure. The data does not allow us to distinguish if the pre-positioned securities are received through a secured financing transaction. For robustness, we calculate the broad asset ratios excluding pre-positioned securities. The correlation between the broad asset ratios, including and excluding capacity is 0.997, so the effect of any double counting is tiny.

Figure 4 summarizes our estimates of safe and broad asset ratios, which illustrate the presence of foreign safe asset scarcity. 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 reports the average median Safe Asset Ratio across currencies, which is 0.05. Intermediaries hold 5 cents of unencumbered, maturity-matched safe assets per dollar of net lending. The panel plots the ratios constructed using two alternative methods. First, plotted in orange, we include forwards in the estimate of FX net lending, since a spot transaction paired with a forward transaction can be economically similar to an FX swap. The data don't allow us to pair these two separate transactions together, so including forwards will likely overestimate the amount of net lending. Second, plotted in light blue, we calculate asset ratios net of the banks' short positions in those securities. Both methods yield nearly identical results.

The definition of maturity-matching used in the construction of the safe asset ratio is restrictive because it requires the maturity of safe assets to exactly match the maturity of net swap lending. For example, a 6-day maturity safe asset does not count as hedging 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.[23] For example, we round a 2-day swap to the 1-week bucket, a 10-day swap to the 1-week bucket, and a 9-month swap to the 1-year bucket. The resulting safe asset ratios allow small deviations in intermediaries' cash positions to count toward hedging their swap market positioning.

Figure 4 reports the rounded tenor results for safe asset ratios in the top panel. The average median safe asset ratio increases to 0.17, indicating that small maturity mismatches can account for an additional 12 cents of safe asset positioning, but is still markedly below 1.

We further relax the definition of safe assets to include encumbered assets—which cannot be used as collateral, entail counterparty risk, and are not counted as level 1 HQLAs—but which may help intermediaries hedge the currency exposure coming from their net lending. Figure 4 illustrates that this more permissive definition of the safe asset ratio has an average median value of 0.13 across currencies when requiring strict maturity matching, and the value

[23]Recall, the tenors in the confidential supervisory data are 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 that. The benchmark tenors for which we estimate CIP violations are 1w (7d), 2w (14d), 3w (21d), 1m (28d), 2m (61d), 3m (91d), 4m (121d), 5m (151d), 6m (181d), 1y (366d), 2y (731d), 3y (1096d), and 4y (1461d).

jumps to 0.48 with maturity rounding. Still, even with these more liberal definitions of safe asset matching, intermediaries hold only 48 cents of foreign safe assets per dollar lent. What do banks do with the remaining unaccounted for 52 cents?

We turn to broad asset ratios, which include riskier foreign assets in addition to safe assets in the numerator of the ratio calculation. The bottom panel of Figure 4 plots the same values as the top panel, except for broad asset ratios. Focusing on unencumbered assets, the average median broad asset ratio requiring exact maturity matching for broad assets and net lending is 0.11, indicating that intermediaries hold only maturity-matched assets against approximately 11 cents per dollar of net lending they perform. Using the rounded tenor approach, the broad asset ratio jumps to 0.59, indicating that we can account for 59 cents per dollar of net lending by relaxing the perfect maturity matching requirement. Finally, the broad asset ratios jump to over 1 after we further add encumbered assets. Although intermediaries hedge foreign currency exposures, a large part of their hedging relies on maturity-mismatched assets that are either encumbered or risky.

The analysis of safe and broad asset ratios indicates that intermediaries' currency swap transactions entail significant risk. Intermediaries, unable to, or choosing not to, take positions in foreign safe assets that textbook CIP arbitrage requires, end up taking positions in risky foreign assets. Interpreted through the lens of our model, imperfect hedging shows why $Net^{k}_{t,t+n}$(intermediaries' net dollar lending) helps explain cross-sectional variation in bases.

Figure 4 plots safe and broad asset ratio medians across markets. There is substantial variation in safe asset ratios across currencies and maturities, as we present in more detail in the appendix. Heterogeneity is relevant for understanding cross-sectional variation in bases as well. Corollary 1 shows that differences in safe asset ratios—stemming from differences in intermediaries' ability to source safe bonds in foreign currency—amplifies 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.

Appendix Table A3 reports details on safe and broad asset ratios across currencies and shows the median safe asset ratio across currencies ranges from \$0.00 (CHF) to \$0.16 (EUR). For our broadest measures—broad assets including both unencumbered and encumbered assets—the ratios range between 0.01 (CHF) and 0.80 (EUR). The bottom of the table also shows the corresponding measures for instances in which the banks are net borrowing dollars, which implied demand to hold USD-denominated safe assets. This number is consistently much higher than 1, ranging from 2 to 29, consistent with our prediction that U.S.-based G-SIBs hold substantially more dollar-denominated safe assets. Figure A8 breaks out the median ratio by currency and tenor for unencumbered safe and broad assets, and Figure A9 plots the median ratio when using the rounded tenor method. Across the maturity dimension, the takeaway is that safe asset ratios are slightly higher at longer maturities than shorter maturities, partially because the width of the maturity buckets is larger for the longer maturities.

For robustness, Appendix Table A4 calculates the ratios using two different methods. First, we include forwards in the estimate of FX net lending, since a spot transaction paired with a forward transaction can be economically similar to an FX swap. The data doesn't allow us to pair these two separate transactions together, so including forwards will likely overestimate the amount of net lending. Second, we calculate asset ratios net of the banks' short positions in those securities.

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 Appendix Table A5, 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 $1.8 billion of unencumbered EUR-denominated safe assets across the tenors, after controlling for $Net^k_{t,t+n}$.[24]

More closely analyzing intermediaries' motivations for substituting away from safe assets, Corollary 1 indicates that we might expect intermediaries to substitute away from safe assets and into risky assets particularly when safe asset yields are low. We provide evidence consistent with this dynamic by regressing the safe asset ratio on convenience yields. 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 from Diamond and Van Tassel (2021). The convenience yields are monthly and span the

[24] 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.

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,

$$\text{Safe Asset Ratio}_{t,t+n}^{k} = \alpha + \beta_1 CY_{t,t+n}^{k} + \beta_2 \text{Risky Asset Ratio}_{t,t+n}^{k} + \varepsilon_{t,t+n}^{k} \tag{7}$$

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 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 6 shows that banks hold fewer safe assets and more risky assets when convenience yields are higher. The positive and significant coefficients on the risky asset ratio in the first three columns, and the safe asset ratio in the last three, indicate that banks tend to increase both ratios simultaneously. Hence, when safe asset ratios fall, it is not because banks are moving to maturity-matched risky assets, but instead to unmatched assets. [25]

4.4.2 Supply Segmentation

Prediction 5 states that variation in intermediaries' expertise in substituting away from safe assets in a market leads to market segmentation. The basis for a given currency is more inelastic when intermediary supply is more segmented since the risk is more concentrated, an

[25] Our discussion of foreign safe asset scarcity primarily focuses on cross-sectional variation. However, we also note that foreign safe asset scarcity 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.

effect that is potentially amplified by intermediary market power.

We show that banks specialize in markets and provide some evidence consistent with heterogeneous bank expertise across markets. Without frictions or market segmentation, 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, if markets are segmented, a bank lending more in its own market faces increasing marginal costs and risk, pushing the basis increasingly negative—consistent with Prediction 5.

We empirically estimate dollar supply concentration by calculating a Hirschman-Herfindahl 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 5 illustrates the cross-sectional variation in HHI, plotting the average measure by market against that market's size. Higher HHI indicates more concentration and segmentation. Larger markets are clearly less segmented. Short-term contracts for CAD and AUD are more segmented, and CHF is the most segmented. The least segmented markets are JPY and EUR at longer tenors, especially at 1-year.[26]

Why FX markets are segmented is an important question. We provide support for heterogeneous expertise as a possible mechanism using cross-sectional variation in HHI in Section 5, where we also discuss another implication of segmentation—that shocks to the specialists in a market should particularly impact *that* market.

[26] We estimate similar supply HHI's looking just across tenors and currencies in the online appendix, see Figures A11 and A12.

4.4.3 Demand Concentration

Demand concentration also affects the basis. Prediction 4 claims that the basis is increasing in demand concentration, which maps to high counterparty risk. A bank can manage its counterparty risk by lending to a wide set of counterparties in each market. Lending becomes riskier when a bank deals with fewer counterparties, increasing its exposure to idiosyncratic counterparty risk. Intermediaries may require compensation for this risk.

We proxy for demand concentration with a separate HHI measuring counterparty concentration. The data does not provide firm-specific counterparty names but instead provides two dozen counterparty types—e.g., broker-dealer, non-financial corporate, non-regulated fund.[27] Since we do not view individual counterparties, we calculate demand concentration across counterparty types, assuming that firms within a category have highly correlated risks. Such an assumption is plausible: lending exclusively to levered funds is riskier than lending to a mix of levered funds and non-financial companies, given the two lines of business are likely exposed to different risks.

We calculate the demand HHI similarly to the supply HHI:

$$\text{Demand HHI}^{k}_{t,t+n} = \sum_{j \in (\text{c.p. type})} (\text{Counterparty Market Share}^{k,j}_{t,t+n})^2$$

,

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

Figure 6 plots demand concentration by market. There is no clear pattern between the market size and its demand concentration, although currencies tend to bunch together—longer maturity CAD is among the most demand-concentrated. The range of demand HHIs is much higher, partly reflecting banks' large share as counterparties to one another.

Counterparty data are available only beginning in May 2022. We estimate the full sample demand concentration using two different items available for the full sample: loan counterparties and settlement types. The data for unsecured and secured loans includes

[27] The full list of FX counterparties: Bank, Broker Dealer, Central Bank, Debt Issuing Special Purpose Entity, Financial Market Utility, Government Sponsored Entity, Investment Company or Advisor, Multilateral Development Bank, Non-Financial Corporate, Non-regulated Fund, Other, Other Supervised Non-Bank Financial Entity, Other Supranational, Pension Fund, Public Sector Entity, Retail, Small Business, Sovereign.

counterparty types, and we calculate loan demand concentration HHI analogously. Banks also report FX settlement types: bilateral, continuous linked settlement (CLS), or other. CLS transactions are settled payment-versus-payment to reduce Herstatt risk and cover 30 percent of all FX transactions.[28] Bilateral trades are often, but not exclusively, transactions that banks do with their clients, like hedge funds. Hedge funds trade through their prime brokers using *give up trades*, which are typically bilateral. The bilateral share is a rough measure of the relative importance of investors like hedge funds in each market. For each market, we calculate that day's share of bilateral transactions compared to the total transactions in that market. We estimate Demand $\text{HHI}^k_{t,t+n}$ for the full sample by running a regression of Demand $\text{HHI}^k_{t,t+n}$ on loan and bilateral demand in the short sample for which we have counterparty market share data, and then use the estimated coefficients to project Demand $\text{HHI}^k_{t,t+n}$ over the full sample period where we do not have counterparty data.

$$\text{Demand HHI}^k_{t,t+n} = \alpha + \beta_1 \text{Loan Demand HHI}^k_{t,t+n} + \beta_2 \text{Bilateral Share}^k_{t,t+n} + \varepsilon^k_{t,t+n}.$$

We show the estimated coefficients in the online appendix, Table A6. Both loan and bilateral concentration of demand are strongly positively related to counterparty concentration. We use the regression coefficients to estimate $\widehat{\text{Demand HHI}}^k_{t,t+n}$ for the full sample. Both measures of demand concentration—directly measured using the shorter sample with counterparty information, or the longer sample that uses settlement type and loan counterparties to project counterparty demand concentration—are less precise than the supply concentration measure.

[28]See `https://www.newyorkfed.org/medialibrary/microsites/fxc/files/2020/FX_settlement_risk_CLS.pdf`.

4.5 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:

$$
\begin{aligned}
|\text{Basis}^k_{t,t+n}| = \alpha &+ \beta_1 \left(\text{Demand HHI}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)\right) \\
&+ \beta_2 \left(\text{Demand HHI}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)\right) \\
&+ \beta_3 \left(\text{Supply HHI}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)\right) \\
&+ \beta_4 \left(\text{Supply HHI}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)\right) \\
&+ \beta_5 \left(\text{Safe Asset Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)\right) \\
&+ \beta_6 \left(\text{Safe Asset Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)\right).
\end{aligned}
$$

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 scarcity to behave differently than USD safe asset scarcity since the 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 $Net^k_{t,t+n} < 0$.[29] We include tenor and date fixed effects and weigh the regression by the

[29] CDS spreads are from Markit. For both banks and sovereigns, we use CDS spreads for 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.

square root of the market's share of the total daily gross notional. 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. Due to data availability, the regressions use estimated demand concentration rather than the directly measured demand concentration HHI, and we compute safe asset ratios, including unencumbered assets with matched maturities. The first two columns in the table exclude estimated demand concentration, while the last two columns include it.

The first two rows show that supply concentration is an important friction and is symmetric across markets with long or short dollar demand. A one standard deviation increase in the supply HHI increases the absolute value of the basis by 10 to 14 bps. This result is consistent with our expectation 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 next set of rows illustrates the importance of foreign safe asset scarcity and banks' search costs for foreign safe bonds. The coefficients on $Net^k_{t,t+n}$are positive and significant, with values ranging from around 4 to 7.5 bps, indicating that a one standard deviation increase in $Net^k_{t,t+n}$corresponds with a 4 to 7.5 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 scarcity 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. The next four rows account for the effect of variation in foreign safe asset scarcity 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 8 to 9 bps in columns (1) and (3) on the safe asset ratio, indicating that a one standard deviation decrease in the safe asset ratio moves the basis by an additional 8 to 9 bps. When using the broad asset ratios in the regressions rather than safe asset ratios (in columns (2) and (4)), these coefficients increase in magnitude to 11 and 14.

The next two rows examine the effect of demand concentration on the basis. We observe that in markets where banks are net lending dollars, a one standard deviation increase in demand concentration coincides with an approximately 7 bps higher basis. This effect is limited to dollar net lending, and the coefficients are insignificant when looking at markets where banks are borrowing in dollars.

The regression evidence indicates the importance of safe asset scarcity and supply concentration in explaining cross-sectional variation in CIP deviations. In addition, and despite demand concentration being measured with more error, the regression suggests that demand concentration may play a role in amplifying basis dislocations.

We also present additional variations of our regressions in Appendix Table A7, where we present analysis including encumbered assets and using directly measured demand concentration from the shorter sample. In Appendix Table A8, we also present regression results separately considering 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 show that both foreign safe asset scarcity and intermediary segmentation are important frictions that help describe the cross-section of bases. We interpret these frictions as arising from heterogeneous expertise across intermediaries and explore that theme further in the next section.

5 Intermediary Segmentation

The data supports the idea that intermediary segmentation is a key driver of bases, making them more inelastic to demand.

In this section, we take a deeper dive to try to understand the drivers of this segmentation. First, we provide evidence that segmentation arises from heterogeneous expertise across intermediaries in 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 6): specializing intermediaries' constraints should help explain cross-sectional variation in bases.

5.1 Sources of Intermediary Segmentation

We present several facts consistent with intermediary segmentation being driven by heterogeneity in banks' expertise in different markets. In particular, we argue that banks gain market-specific expertise from other business areas, providing better access to counterparties in those markets.

We show that markets with higher supply segmentation rely on banks with larger FX books. 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. There is a strong relationship between more segmented markets and larger intermediaries.[30]

Segmentation is persistent. The first four columns of Table 8 report regression results from a market's supply HHI on its 1-month, 1-year, and 5-year lags. A 1-point increase in the supply HHI is associated with a 0.51-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.

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 four 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 lag to 0.74 at a 5-year lag. This evidence suggests that segmentation is present, with banks specializing in the same markets over time, consistent with having and developing market-specific expertise.

We present further evidence supporting this story by showing 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 $\text{Share}^{i,k}_{t,ctpty}$,

[30]Figure A13 in the online appendix provides a scatterplot of these two variables.

where i denotes the bank and $ctpty$ denotes the counterparty.[31]

We calculate two related measures: first, we calculate the average market share of all banks except bank i, which we call Other Bank FX $\text{Share}_{t,ctpty}^{i,k}$. Second, we estimate a bank's Bank Loan $\text{Share}_{t,ctpty}^{i,k}$ to study how segmentation works across a bank's lines of business. We define bank loans as the items reported by the bank in their inflows-secured and inflows-unsecured tables in the FR2052a data.[32]

Table 9 shows how banks specialize in specific counterparty-by-currency markets. The first column shows that the bank's specialization in counterparty-currency markets is persistent over time as the lag of Bank FX $\text{Share}_{t,ctpty}^{i,k}$ strongly predicts its current values. However, one concern is that banks all uniformly service the same counterparty-currency markets. Column two adds a variable, Other Bank FX $\text{Share}_{t,ctpty}^{i,k}$, and rejects such a possibility since the coefficient on the other bank variable is not different from 0. Column three shows that banks specialize in currencies and counterparties across their lines of business. We regress the bank FX share on Bank Loan $\text{Share}_{t,ctpty}^{i,k}$ and find a strong positive relationship. Adding controls for other banks' loan shares (column 4) does not change the result. Column 5 adds Other Bank FX $\text{Share}_{t,ctpty}^{i,k}$ 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.

Providing additional support for the idea that intermediary specialization may be driven by expertise in reducing risk, Corollary 2 indicates that banks with larger market shares hold fewer foreign safe bonds per dollar of net lending. This is because 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.

[31] 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 $\text{Share}_{t,insurance}^{z,AUD} = 10\%$. We exclude bank counterparties since they are the largest counterparty by an order of magnitude in most markets, and we exclude two counterparty types that were removed in 2022. Recall that FX counterparty data is available beginning in May 2022.

[32] 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.

Table 10 shows the regression results of bank-specific safe-asset ratios on the same bank's market share when banks are net borrowing foreign currency ($Net^k_{t,t+n}> 0$). The latter condition matters because it indicates 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 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 $\text{Share}^{i,k}_{t,t+n}$ (16pp) corresponds to a decline in that bank's safe asset ratio of 0.15, an economically large relationship given the average bank-specific safe asset ratio is 0.42.

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 other potential forms of expertise, for example lower search costs for foreign safe assets.

5.2 Event Study: Silicon Valley Bank Run

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 shows 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 shows that large banks gained \$120bn of deposits while small banks lost \$108bn.[33] The average large bank had deposit inflows of \$120/25 =\$4.8 billion since H.8 data spans the largest 25 domestically charted commercial banks. Publicly available call report data shows 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.[34]

The unexpected flow of deposits to large banks is an exogenous increase in those banks'

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

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

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 6 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 the 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 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 have an effect. 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, when quarter-end window-dressing could confound the estimates.

The first three columns of Panel A show the main results, with specifications that vary 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 dollars most 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 of the 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 basis absolute value is 30 bps, so the coefficients imply a 7 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 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 in which banks increased $Net^{k}_{t,t+n}$. The result holds when markets are weighted by their size, so small markets behave differently. 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

In this paper, we shed new light on the role of intermediaries in covered interest parity arbitrage and the global provision of dollar funding using granular confidential supervisory data. Exploiting cross-sectional variation in CIP bases that is puzzling to prevailing theories, we uncover three key forces that drive these bases: imperfect execution of CIP arbitrage due to foreign safe asset scarcity, market segmentation resulting from intermediaries' specialization in different currencies and tenors, and concentrated demand from certain types of counterparties in some markets. More closely studying intermediary segmentation, the March 2023 banking turmoil following the Silicon Valley Bank run provides a natural experiment, demonstrating how bank-specific shocks transmit to prices in the markets where those banks specialize. Intermediary segmentation persists over time and is linked to banks' heterogeneous expertise and specialization in different counterparty segments. Our findings highlight the importance of specialized supply and demand forces in banks' provision of global dollar funding.

References

Tobias Adrian, Erkko Etula, and Tyler Muir. Financial intermediaries and the cross-section of asset returns. *Journal of Finance*, 69(6):2557–2596, 2014.

Leif Andersen, Darrell Duffie, and Yang Song. Funding value adjustments. *Journal of Finance*, 74(1):145–192, 2019.

Alyssa G Anderson, Wenxin Du, and Bernd Schlusche. Arbitrage capital of global banks. Technical report, National Bureau of Economic Research, 2021.

Patrick Augustin, Mikhail Chernov, Lukas Schmid, and Dongho Song. The term structure of covered interest rate parity violations. *Journal of Finance, forthcoming*, 2022.

Jennie Bai and Pierre Collin-Dufresne. The cds-bond basis. *Financial Management*, 48(2): 417–439, 2019.

Bank of International Settlements. Otc derivatives statistics at end-december 2022. 2022.

Daniel Barth and R Jay Kahn. Hedge funds and the treasury cash-futures disconnect. *OFR WP*, pages 21–01, 2021.

Nina Boyarchenko, Thomas M Eisenbach, Pooja Gupta, Or Shachar, and Peter Van Tassel. Bank-intermediated arbitrage. *FRB of New York Staff Report*, (858), 2018a.

Nina Boyarchenko, Pooja Gupta, Nick Steele, Jacqueline Yen, et al. Negative swap spreads. *Federal Reserve Bank of New York Economic Policy Review*, 24(2):1–14, 2018b.

Nina Boyarchenko, Pooja Gupta, Nick Steele, Jacqueline Yen, et al. Trends in credit basis spreads. *Economic Policy Review*, 24(2):15, 2018c.

Markus K Brunnermeier and Lasse Heje Pedersen. Market liquidity and funding liquidity. *Review of Financial Studies*, 22(6):2201–2238, 2009.

Svetlana Bryzgalova, Anna Pavlova, and Taisiya Sikorskaya. Strategic arbitrage in segmented markets. 2023.

Ricardo J Caballero. On the macroeconomics of asset shortages. Technical report, National Bureau of Economic Research, 2006.

Ricardo J Caballero and Emmanuel Farhi. The safety trap. *Review of Economic Studies*, 85 (1):223–274, 2018.

Ricardo J Caballero, Emmanuel Farhi, and Pierre-Olivier Gourinchas. The safe assets shortage conundrum. *Journal of Economic Perspectives*, 31(3):29–46, 2017.

Gino Cenedese, Pasquale Della Corte, and Tianyu Wang. Currency mispricing and dealer balance sheets. *Journal of Finance*, 76(6):2763–2803, 2021.

Harry R Cooperman, Darrell Duffie, Stephan Luck, Zachry Z Wang, and Yilin Yang. Bank funding risk, reference rates, and credit supply. Technical report, National Bureau of Economic Research, 2023.

Ricardo Correa, Wenxin Du, and Gordon Y Liao. Us banks and global liquidity. 2020.

William Diamond and Peter Van Tassel. Risk-free rates and convenience yields around the world. *Jacobs Levy Equity Management Center for Quantitative Financial Research Paper*, 2021.

Wenxin Du and Amy Huber. Dollar asset holding and hedging around the globe. 2023.

Wenxin Du and Jesse Schreger. Cip deviations, the dollar, and frictions in international capital markets. In *Handbook of International Economics*, volume 6, pages 147–197. Elsevier, 2022.

Wenxin Du, Alexander Tepper, and Adrien Verdelhan. Deviations from covered interest rate parity. *Journal of Finance*, 73(3):915–957, 2018.

Wenxin Du, Alessandro Fontana, Petr Jakubik, Ralph SJ Koijen, and Hyun Song Shin. International portfolio frictions. Technical report, Bank for International Settlements, 2023a.

Wenxin Du, Benjamin Hebert, and Amy Wang Huber. Are intermediary constraints priced? *Review of Financial Studies*, 36(4):1464–1507, 2023b.

Andrea L Eisfeldt, Hanno Lustig, and Lei Zhang. Complex asset markets. *Journal of Finance*, 78(5):2519–2562, 2023.

Nathan Foley-Fisher, Borghan Narajabad, and Stephane Verani. Who limits arbitrage? *Available at SSRN 3361902*, 2020.

Xavier Gabaix and Matteo Maggiori. International liquidity and exchange rate dynamics. *The Quarterly Journal of Economics*, 130(3):1369–1420, 2015.

Nicolae Garleanu and Lasse Heje Pedersen. Margin-based asset pricing and deviations from the law of one price. *Review of Financial Studies*, 24(6):1980–2022, 2011.

Vincent Glode and Christian C Opp. Over-the-counter versus limit-order markets: The role of traders' expertise. *The Review of Financial Studies*, 33(2):866–915, 2020.

Gary B Gorton, Andrew Metrick, and Chase P Ross. Who ran on repo? *AEA Papers and Proceedings*, 2020.

Robin Greenwood, Samuel Hanson, Jeremy C Stein, and Adi Sunderam. A quantity-driven theory of term premia and exchange rates. *Quarterly Journal of Economics*, page qjad024, 2023.

Todd M Hazelkorn, Tobias J Moskowitz, and Kaushik Vasudevan. Beyond basis basics: Liquidity demand and deviations from the law of one price. *The Journal of Finance*, 78(1): 301–345, 2023.

Zhiguo He and Arvind Krishnamurthy. Intermediary asset pricing. *American Economic Review*, 103(2):732–770, 2013.

Zhiguo He, Bryan Kelly, and Asaf Manela. Intermediary asset pricing: New evidence from many asset classes. *Journal of Financial Economics*, 126(1):1–35, 2017.

Tomoyuki Iida, Takeshi Kimura, and Nao Sudo. Deviations from covered interest rate parity and the dollar funding of global banks. *55th issue (September 2018) of the International Journal of Central Banking*, 2018.

Sebastian Infante and Zack Saravay. What drives us treasury re-use? 2020.

Justus Inhoffen and Iman van Lelyveld. Safe asset scarcity and re-use in the european repo market. 2023.

Urban J Jermann. Negative swap spreads and limited arbitrage. *Review of Financial Studies*, 33(1):212–238, 2020.

Stephan Jank, Emanuel Moench, and Michael Schneider. Safe asset shortage and collateral reuse. 2022.

Mahyar Kargar. Heterogeneous intermediary asset pricing. *Journal of Financial Economics*, 141(2):505–532, 2021.

Pēteris Kloks, Patrick McGuire, Angelo Ranaldo, and Vladyslav Sushko. Bank positions in fx swaps: insights from cls. 2023.

Arvind Krishnamurthy. The bond/old-bond spread. *Journal of Financial Economics*, 66 (2-3):463–506, 2002.

Gordon Liao and Tony Zhang. The hedging channel of exchange rate determination. 2021.

Gordon Y Liao. Credit migration and covered interest rate parity. *Journal of Financial Economics*, 138(2):504–525, 2020.

Daniel Neuhann and Michael Sockin. Wealth dynamics and financial market power. 2023.

Paolo Pasquariello. Financial market dislocations. *Review of Financial Studies*, 27(6): 1868–1914, 2014.

Dagfinn Rime, Andreas Schrimpf, and Olav Syrstad. Covered interest parity arbitrage. *Review of Financial Studies*, 35(11):5185–5227, 2022.

Emil Siriwardane, Adi Sunderam, and Jonathan L Wallen. Segmented arbitrage. Technical report, National Bureau of Economic Research, 2022.

Jonathan Wallen. Markups to financial intermediation in foreign exchange markets. 2022.

7 Figures

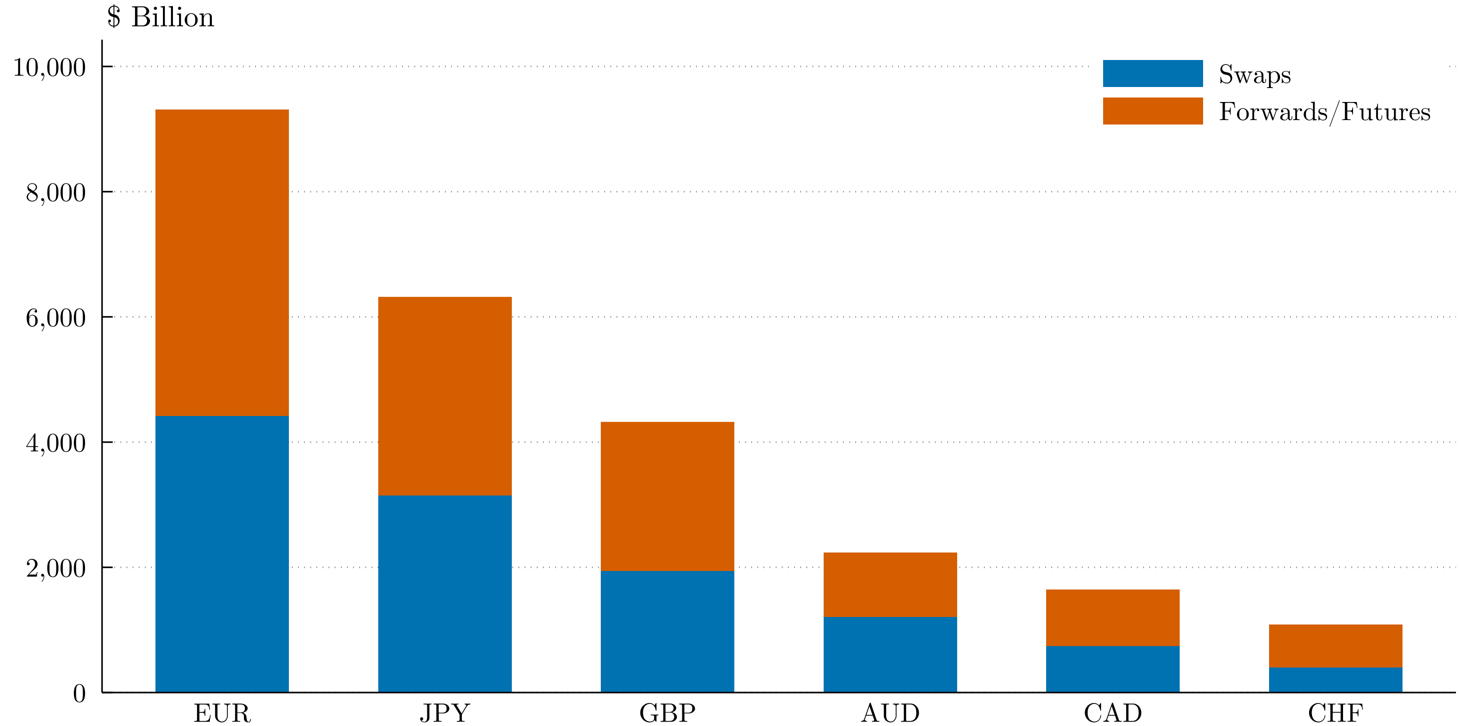

Figure 1: Foreign Exchange Notional Exposure. Figure provides the average notional FX exposures in our sample by currency across swaps and forwards/futures before limiting to the tenors with OIS rates. Sample includes only transactions in the six currencies versus the dollar.

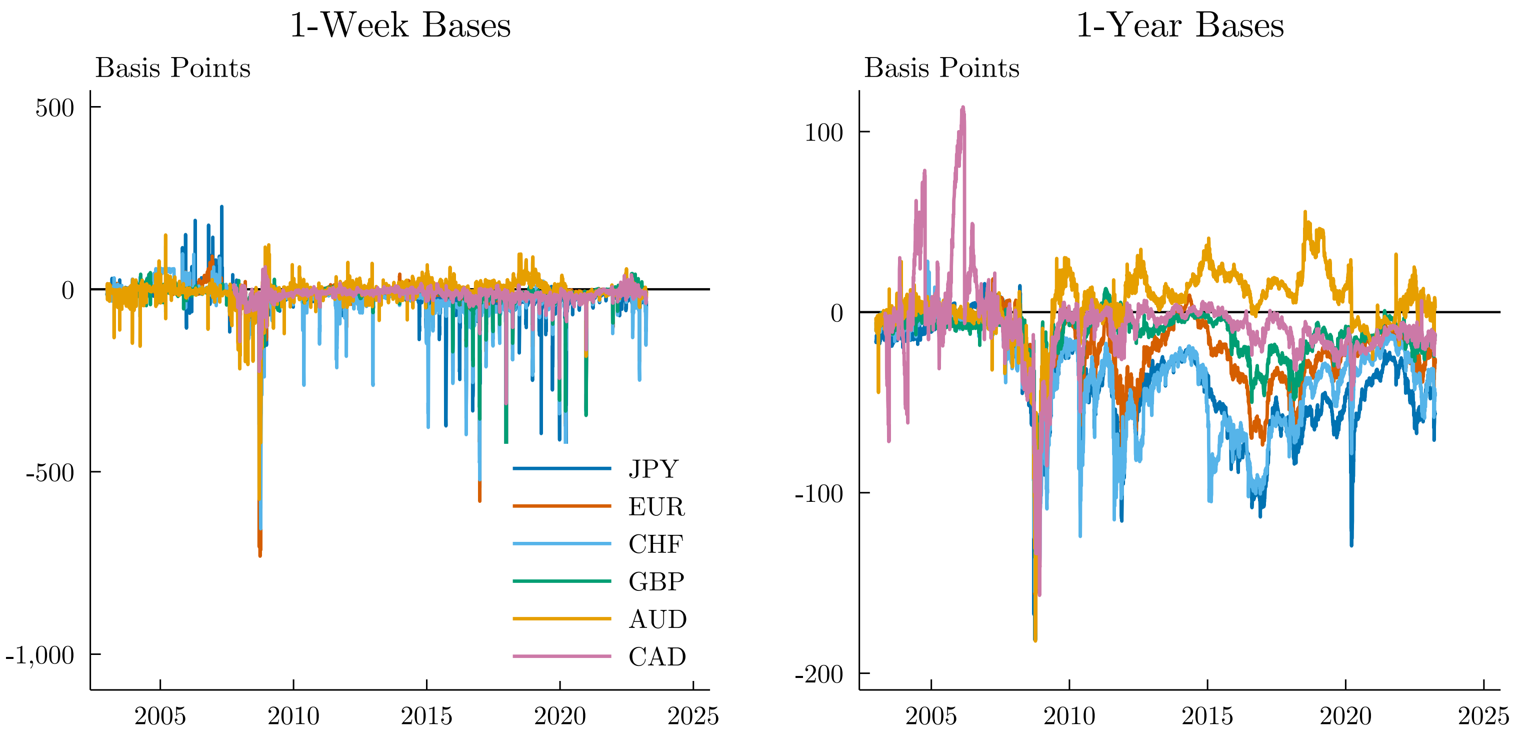

Figure 2: Covered-Interest Parity Violations. Figure plots the CIP bases across two tenors—1-week and 1-year—across several currencies.

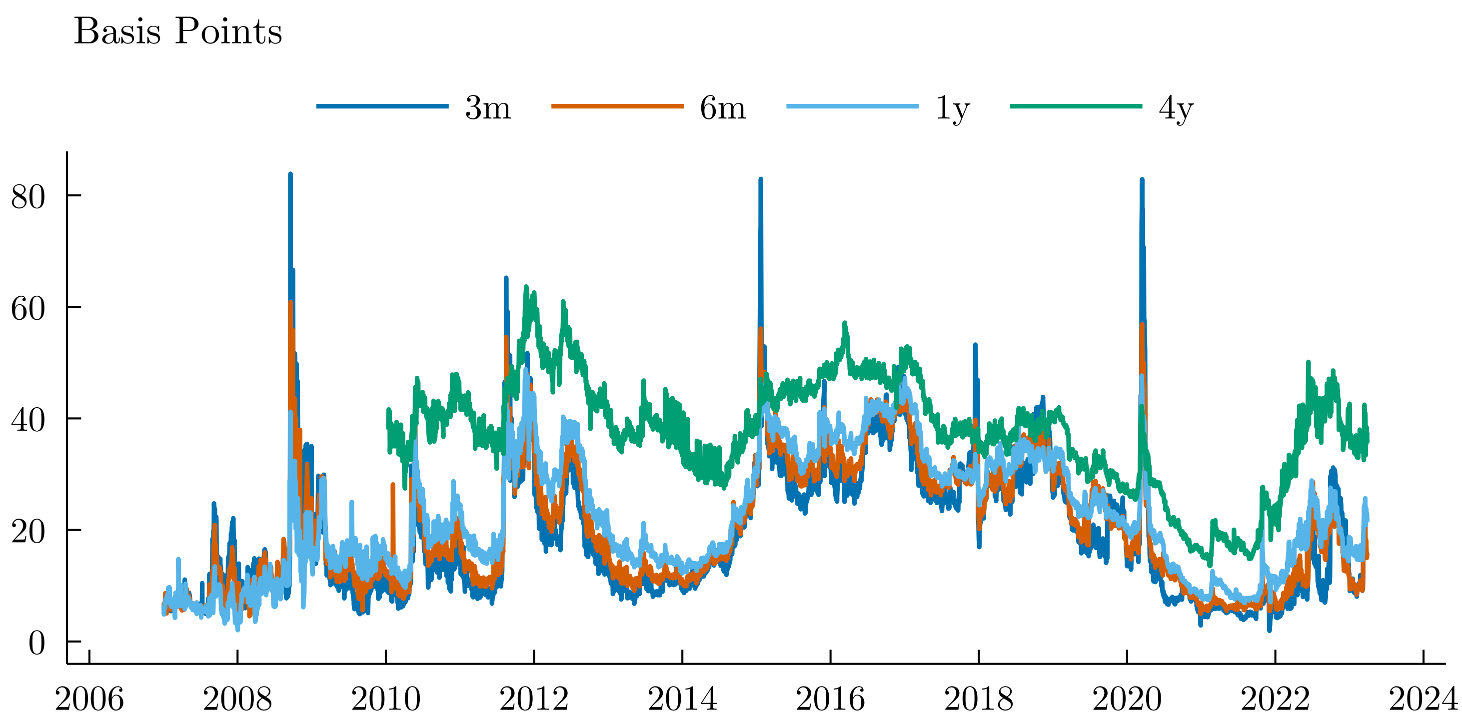

Figure 3: Cross-Sectional Standard Deviation of Covered-Interest Parity Violations. Figure plots the cross-sectional standard deviation of CIP bases for the given tenor. Sample includes only periods when we have observations for all of the six currencies against the dollar.

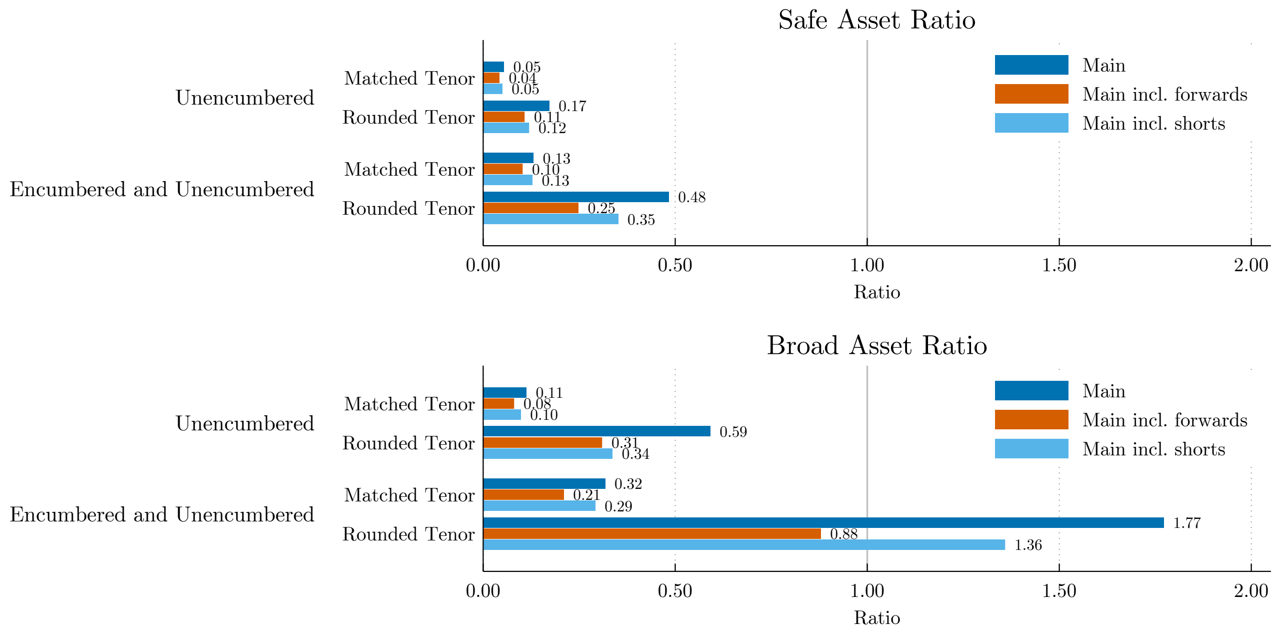

Figure 4: Summary of Safe Asset Ratios Figure plots the average median safe and broad asset ratio across all currencies when $Net^{k}_{t,t+n}$ is positive excluding the USD. Matched tenor shows the asset ratio when the tenor of the underlying asset and the swap have the same maturity. Rounded tenor buckets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

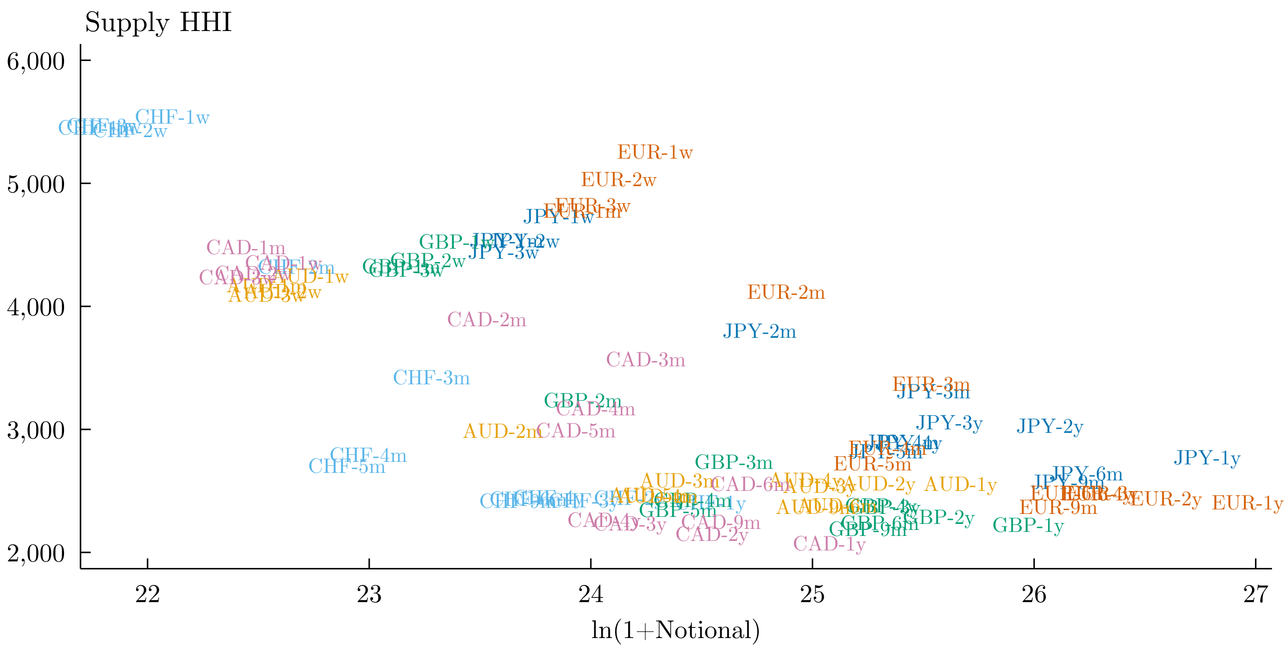

Figure 5: Supply Segmentation. Figure plots the average of daily Supply $\text{HHI}^k_{t,t+n}$ against the (log of 1 plus) the average notional of that market.

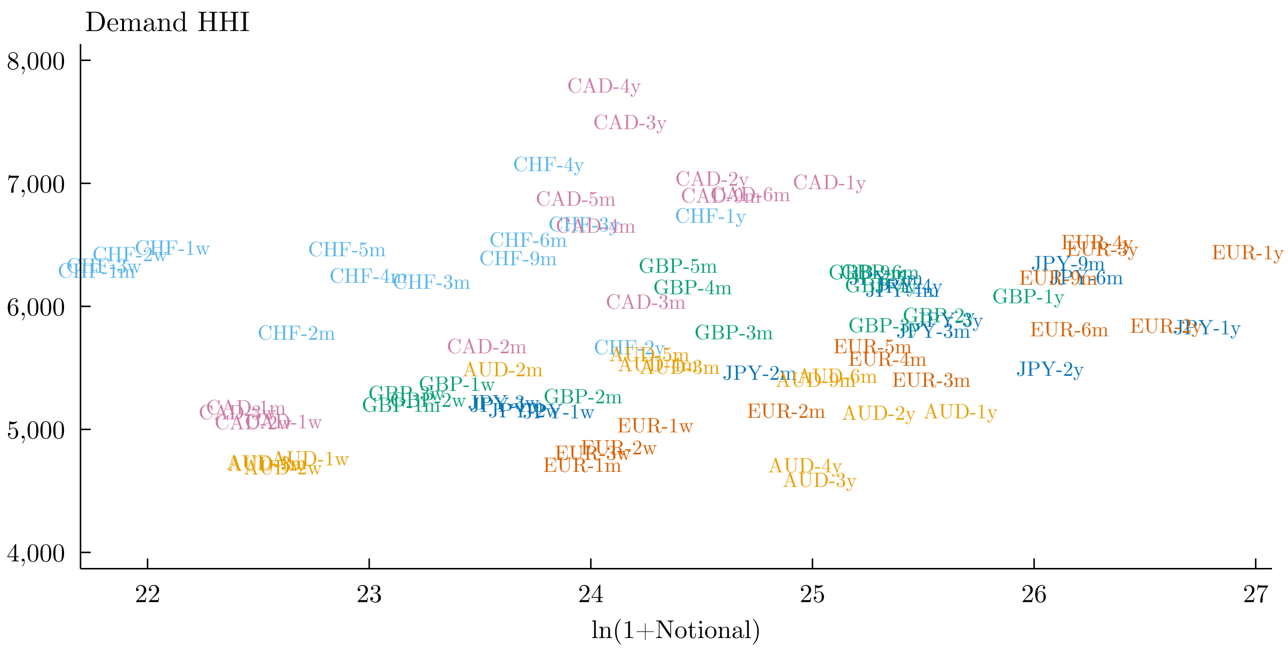

Figure 6: Demand Segmentation. Figure plots the average of daily Demand $\text{HHI}^{k}_{t,t+n}$ against the (log of 1 plus) the average notional of that market.

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	345	1,610	270
GBP	914	172	729	166
JPY	1,827	180	1,146	181

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	201	277	43
2y	868	133	109	9
3y	632	101	53	6
4y	589	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	$Net^{JPY}_{t,t+7}$	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 the forward exchange rate is $F_{t,t+7} = 110$.

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	−0.5	−1.6	−7.3	−5.1	−4.0
3w	−6.2	−3.3	−1.0	−1.6	−8.1	−4.1	−4.0
1m	−5.8	−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	0.1
4m	−3.5	1.8	−0.1	2.5	2.5	2.5	0.9
5m	−3.6	0.9	0.0	3.2	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	−3.7	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	1.1	

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	22.9	31.0	24.7	31.4
3w	34.1	34.6	45.8	24.0	31.6	25.5	32.6
1m	34.2	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	12.7
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 plots the average daily $Net^k_{t,t+n}$ for a given currency k and maturity $t + n$. Bottom panel plots the time-series standard deviation of $Net^k_{t,t+n}$.

	All Tenors				Short-Term	Long-Term
	(1)	(2)	(3)	(4)	(5)	(6)
$Net^k_{t,t+n}$	-0.0544^{*}	-0.601^{***}	-0.432^{***}	-0.431^{***}	-0.171^{**}	-1.548^{***}
	(-1.82)	(-3.97)	(-3.36)	(-3.40)	(-2.55)	(-3.67)
N	151,655	149,337	149,337	149,337	106,005	43,332
R^2	0.00	0.04	0.03	0.02	0.01	0.11
Tenor FE	No	No	No	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	Yes	Yes
Weighted	No	Yes	Yes	Yes	Yes	Yes

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. 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. 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			Risky Asset Ratio		
	(1)	(2)	(3)	(4)	(5)	(6)
$CY^k_{t,t+n}$	-0.490^{**}	-0.568^{**}	-0.319	0.120^{***}	0.143^{***}	0.134^{***}
	(-2.64)	(-2.63)	(-1.50)	(3.07)	(3.29)	(3.20)
Risky Asset Ratio$^k_{t,t+n}$	4.072^{***}	4.067^{***}	3.047^{***}			
	(4.25)	(4.31)	(2.84)			
Safe Asset Ratio$^k_{t,t+n}$				0.196^{***}	0.198^{***}	0.219^{***}
				(16.92)	(15.69)	(6.95)
N	321	321	321	321	321	321
R^2	0.80	0.81	0.67	0.80	0.81	0.68
Tenor FE	No	Yes	Yes	No	Yes	Yes
Time FE	No	Yes	Yes	No	Yes	Yes
Weighted	No	No	Yes	No	No	Yes

Table 6: 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 Ratio$^k_{t,t+n} = \alpha + \beta_1 CY^k_{t,t+n} + \beta_2$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 (2021) and in basis points. Panel merges monthly averages of asset ratios with the convenience yield measures, matched by currency and tenor. t-statistics shown using robust standard errors clustered by month where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)
Supply Segmentation				
Supply $\text{HHI}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$	10.81***	10.81***	10.12***	10.12***
	(6.00)	(6.00)	(6.05)	(6.05)
Supply $\text{HHI}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$	13.75***	13.76***	11.65***	11.65***
	(6.63)	(6.63)	(6.23)	(6.23)
Safe Asset Scarcity				
$\text{Net}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$	5.22**	5.22**	4.35**	4.34**
	(2.11)	(2.11)	(2.00)	(2.00)
$\text{Net}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$	7.14***	7.14***	7.50***	7.50***
	(3.13)	(3.12)	(3.23)	(3.23)
Safe Asset $\text{Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$	−7.77*		−9.34*	
	(−1.94)		(−1.97)	
Safe Asset $\text{Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$	−0.50		−0.36	
	(−1.39)		(−1.15)	
Broad Asset $\text{Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$		−10.82*		−13.52**
		(−1.94)		(−2.24)
Broad Asset $\text{Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$		−0.25		−0.17
		(−1.06)		(−0.87)
Demand Concentration				
$\widehat{\text{Demand HHI}}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$			7.42***	7.42***
			(3.37)	(3.38)
$\widehat{\text{Demand HHI}}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$			1.27	1.26
			(0.82)	(0.82)
Controls				
Bank $\text{CDS}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$	−97.97***	−97.97***	−97.35***	−97.34***
	(−6.50)	(−6.50)	(−6.86)	(−6.86)
Bank $\text{CDS}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$	−99.21***	−99.22***	−98.13***	−98.13***
	(−6.47)	(−6.47)	(−6.85)	(−6.85)
Govt $\text{CDS}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$	−2.14***	−2.14***	−1.71**	−1.71**
	(−2.85)	(−2.85)	(−2.43)	(−2.43)
Govt $\text{CDS}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$	−2.55	−2.53	−4.32*	−4.31*
	(−1.22)	(−1.21)	(−1.75)	(−1.75)
N	149,337	149,337	149,293	149,293
R^2	0.21	0.21	0.23	0.23
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 marginal cost measures. Table presents the regression described in section 4.5 using demand HHI measures estimated from Table A6. 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 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 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	HHI $\text{Supply}^{k}_{t,t+n}$				Market $\text{Share}^{k,i}_{t,t+n}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln(1 + \text{Avg. Book Size}^{k}_{t,t+n})$	122.6***						
	(35.63)						
HHI $\text{Supply}^{k}_{t-1m,t-1m+n}$		0.510***					
		(20.18)					
HHI $\text{Supply}^{k}_{t-1y,t-1y+n}$			0.510***				
			(22.36)				
HHI $\text{Supply}^{k}_{t-5y,t-3y+n}$				0.377***			
				(15.78)			
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	151,655	149,595	130,487	46,655	1,408,437	1,230,588	441,360
R^2	0.08	0.26	0.28	0.19	0.75	0.72	0.57
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Segmentation Persistence. Table presents the regression of segmentation measures on its lags as well as (1 plus the log of the) average notional book size of banks in that market. The notional book size of the banks active in that market, weighted by their market share in that market. Lags for 1 month are 21 business days, 1 year is 250 business days, and 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: Segmentation across 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. 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 $\text{Ratio}^{i,k}_{t,t+n}$			
	(1)	(2)	(3)	(4)
Market $\text{Share}^{k,i}_{t,t+n}$	-0.159^{***}	-0.169^{***}	-0.087^{***}	-0.010^{***}
	(-3.02)	(-2.91)	(-3.00)	(-4.08)
N	693,041	693,041	693,041	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 $\text{Ratio}^{i,k}_{t,t+n}$ on the bank's FX market share, Bank FX $\text{Share}^{i,k}_{t,t+n}$ 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. 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)
$\mathbb{I}$(Post) × $\Delta\text{Deposits}^k_{t+n}$	-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 $\text{HHI}^k_{t,t+n}$			11.60			0.10
			(1.54)			(0.05)
Constant	10.07^{***}	3.56	7.68^{*}	5.66^{***}	4.01^{***}	4.04^{**}
	(4.72)	(1.06)	(1.79)	(4.63)	(3.10)	(2.57)
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)
$\mathbb{I}$(Post) × $\Delta\text{Deposits}^k_{t+n}$	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 $\text{HHI}^k_{t,t+n}$			11.22			1.94
			(1.62)			(0.73)
Constant	12.49^{***}	8.36^{***}	12.37^{***}	2.49	0.70	1.40
	(6.50)	(3.15)	(3.40)	(1.59)	(0.47)	(0.70)
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 $\lvert \text{Basis}^k_{t,t+n} \rvert = \alpha + \gamma_1 \mathbb{I}(\text{Post}) + \gamma_2 \Delta\text{Deposits}^k_{t+n} + \gamma_3 \mathbb{I}(\text{Post}) \times \Delta\text{Deposits}^k_{t+n} + \varepsilon^k_{t,n}$. We transform $\Delta\text{Deposits}^k_{t+n}$ to a modified z-score using their 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 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A Online Appendix

A.1 Model

Derivation of Expression for the Basis (No Heterogeneity)

First, we observe that

$$\begin{aligned}\frac{\partial}{\partial Z_{i,k}}(P_{f,k} - \alpha_{i,k} r - (1-\alpha_{i,k}) r_k) Z_{i,k} =& P_{f,k} - \alpha_{i,k} r - (1-\alpha_{i,k}) r_k \\ =& P_{f,k} - \frac{(r-r_k)^2 + r\lambda_{s,k} + r_k \gamma_i \sigma_{i,k}^2}{\lambda_{s,k} + \gamma_i \sigma_{i,k}^2}\end{aligned}$$

For risk, and safe asset scarcity, the relevant part of the first-order condition can be expressed as

$$\frac{\partial}{\partial Z_{i,k}} \sum_{k'} \frac{\gamma}{2} (\alpha_{i,k'} Z_{i,k'})^2 \sigma_{i,k'}^2 + \frac{\lambda_{s,k'}}{2} \left((1-\alpha_{i,k'}) Z_{i,k'}\right)^2 = \alpha_{i,k}^2 \gamma \sigma_{i,k}^2 Z_{i,k} + \lambda_{s,k} (1-\alpha_{i,k})^2 Z_{i,k}.$$

We combine the risk and safe asset scarcity terms by noting that

$$\gamma \sigma_{i,k}^2 \alpha_{i,k}^2 Z_{i,k} + \lambda_{s,k} (1-\alpha_{i,k})^2 Z_{i,k} = \frac{(r-r_k)^2 + \lambda_{s,k} \gamma \sigma_{i,k}^2}{\lambda_{s,k} + \gamma_i \sigma_{i,k}^2} Z_{i,k}.$$

When intermediaries are identical, this reduces to:

$$-\frac{(r-r_k)^2 + \lambda_{s,k} \gamma \sigma_k^2}{\lambda_{s,k} + \gamma \sigma_k^2} \frac{X_k}{N_i} \tag{9}$$

For balance sheet costs, the relevant part of the first-order condition can be expressed as

$$\frac{\partial}{\partial Z_{i,k}} \left(\sum_{k'} |Z_{i,k'}| \right)^2 = \text{Sign}(Z_{i,k}) \sum_{k'} |Z_{i,k'}| = -\text{Sign}(X_k) \sum_{k'} |Z_{i,k'}|.$$

Averaging across intermediaries yields $-\text{Sign}(X_k) \sum_{k'} |X_{k'}|$. For counterparty costs, the relevant part of the first-order condition is

$$\begin{aligned}\frac{\partial}{\partial Z_{i,k}} \frac{1}{2} \lambda_{CP} \sum_c \left(\sum_{k'} |Z_{i,k',c}| \right)^2 =& \frac{\partial}{\partial Z_{i,k}} \frac{1}{2} \lambda_{CP} \sum_c \left(\sum_{k'} \frac{X_{c,k'}}{X_{k'}} |Z_{i,k'}| \right)^2 \\ =& -\lambda_{CP} \text{Sign}(X_k) \sum_c \frac{X_{c,k}}{X_k} \sum_{k'} \frac{X_{c,k'}}{X_{k'}} |Z_{i,k'}| \\ =& -\lambda_{CP} \text{Sign}(X_k) \sum_c \left(\frac{X_{c,k}^2}{X_k^2} |Z_{i,k}| + \frac{X_{c,k}}{X_k} \sum_{k' \neq k} \frac{X_{c,k'}}{X_{k'}} |Z_{i,k'}| \right).\end{aligned}$$

Averaging across intermediaries, we observe that:

$$\begin{aligned}
&\frac{1}{N_i}\lambda_{CP} \times \text{Sign}(X_k)\sum_i \sum_c \left(\frac{X_{c,k}^2}{X_k^2}|Z_{i,k}| + \frac{X_{c,k}}{X_k}\sum_{k'\neq k}\frac{X_{c,k'}}{X_{k'}}|Z_{i,k'}|\right) \\
=&\frac{1}{N_i}\lambda_{CP} \times \text{Sign}(X_k)\left(\underbrace{|X_k|\sum_c \frac{X_{c,k}^2}{X_k^2}}_{\text{Demand Concentration in } k} + \sum_c \frac{X_{c,k}}{X_k}\sum_{k'\neq k}|X_{c,k'}|\right).
\end{aligned}$$

Putting everything together, we have that

$$\begin{aligned}
P_{f,k} =& \frac{(r-r_k)^2 + r\lambda_{s,k} + r_k\gamma\sigma_k^2}{\lambda_{s,k}+\gamma_i\sigma_k^2} \\
&+\frac{X_k}{N_i}\frac{(r-r_k)^2+\lambda_{s,k}\gamma\sigma_k^2}{\lambda_{s,k}+\gamma\sigma_k^2} && \text{(Risk and Safe Asset Scarcity)} \\
&+\lambda_{BS}\frac{\text{Sign}(X_k)}{N_i}\sum_{k'}|X_{k'}| && \text{(Balance Sheet Costs)} \\
&+\lambda_{CP}\frac{\text{Sign}(X_k)}{N_i}\left(\underbrace{|X_k|\sum_c \frac{X_{c,k}^2}{X_k^2}}_{\text{Demand Conc. in } k} + \sum_c \frac{X_{c,k}}{X_k}\sum_{k'\neq k}|X_{c,k'}|\right).
\end{aligned}$$

Note that $\text{Basis}_k = P_{f,k} - r_k$. Observing that

$$\frac{(r-r_k)^2 + r\lambda_{s,k} + r_k\gamma_i\sigma_{i,k}^2}{\lambda_{s,k}+\gamma_i\sigma_{i,k}^2} - r_k = \frac{(r-r_k)^2 + (r-r_k)\lambda_{s,k}}{\lambda_{s,k}+\gamma_i\sigma_{i,k}^2},$$

we get the expression provided in the main text.

Derivation of Segmentation Predictions

For the segmentation predictions, for simplicity, we set $\lambda_{CP} = \lambda_{BS} = 0$ and $r_k = r$. We first derive equilibrium quantities in the model focusing only on intermediaries that participate in the basis trade. Based on these quantities, we then turn to financial intermediaries' participation decisions based on the fixed participation costs.

Equilibrium for Participating Intermediaries. Assuming they participate ($Z_{i,k} \neq 0$), intermediary i's first order condition can be written as

$$\text{Basis}_k = -\frac{\lambda_{s,k}\gamma\sigma_{i,k}^2}{\lambda_{s,k}+\gamma\sigma_{i,k}^2}Z_{i,k}. \tag{10}$$

This holds for each participating intermediary i, meaning that for any two intermediaries i

and j,

$$\frac{\lambda_{s,k}\gamma_i\sigma_{i,k}^2}{\lambda_{s,k}+\gamma_i\sigma_{i,k}^2}Z_{i,k} = \frac{\lambda_{s,k}\gamma_j\sigma_{j,k}^2}{\lambda_{s,k}+\gamma_j\sigma_{j,k}^2}Z_{j,k}, \tag{11}$$

or equivalently,

$$Z_{j,k} = \frac{\lambda_{s,k}\gamma_i\sigma_{i,k}^2}{\lambda_{s,k}+\gamma_i\sigma_{i,k}^2}\frac{\lambda_{s,k}+\gamma_j\sigma_{j,k}^2}{\lambda_{s,k}\gamma_j\sigma_{j,k}^2}Z_{i,k}. \tag{12}$$

The market clearing condition is $\sum_j Z_{j,k} = -X_k$, which can be written as

$$Z_{i,k}\frac{\lambda_{s,k}\gamma_i\sigma_{i,k}^2}{\lambda_{s,k}+\gamma_i\sigma_{i,k}^2}\sum_j \frac{\lambda_{s,k}+\gamma_j\sigma_{j,k}^2}{\lambda_{s,k}\gamma_j\sigma_{j,k}^2} = -X_k, \tag{13}$$

which provides a solution for $Z_{i,k}$:

$$Z_{i,k} = -\frac{X_k}{\sum_j \frac{\lambda_{s,k}+\gamma_j\sigma_{j,k}^2}{\lambda_{s,k}\gamma_j\sigma_{j,k}^2}} \times \frac{\lambda_{s,k}+\gamma_i\sigma_{i,k}^2}{\lambda_{s,k}\gamma\sigma_{i,k}^2}. \tag{14}$$

We can substitute this into the first-order condition to derive an expression for the basis.

$$\text{Basis}_k = \frac{X_k}{\sum_j \frac{\lambda_{s,k}+\gamma_j\sigma_{j,k}^2}{\lambda_{s,k}\gamma_j\sigma_{j,k}^2}}. \tag{15}$$

We can further write $\sum_j \frac{\lambda_{s,k}+\gamma_j\sigma_{j,k}^2}{\lambda_{s,k}\gamma_j\sigma_{j,k}^2}$ as

$$\begin{aligned}\sum_i \frac{\lambda_{s,k}+\gamma_i\sigma_{i,k}^2}{\lambda_{s,k}\gamma_i\sigma_{i,k}^2} =& \frac{\sum_i(\lambda_{s,k}+\gamma_i\sigma_{i,k}^2)\prod_{j\neq i}\lambda_{s,k}\gamma_i\sigma_{j,k}^2}{\prod_i \lambda_{s,k}\gamma_i\sigma_{i,k}^2} \\ =& \lambda_{s,k}\sum_i \frac{\prod_{j\neq i}\lambda_{s,k}\gamma_j\sigma_{j,k}^2}{\prod_j \lambda_{s,k}\gamma_j\sigma_{j,k}^2} + \sum_i \frac{\gamma_i\sigma_{i,k}^2\prod_{j\neq i}\lambda_{s,k}\gamma_j\sigma_{j,k}^2}{\prod_j \lambda_{s,k}\gamma_j\sigma_{j,k}^2} \\ =& \frac{N_{p,k}}{\lambda_{s,k}} + \sum_i \frac{1}{\gamma_i\sigma_{i,k}^2},\end{aligned}$$

where $N_{p,k} \leq N_i$ is the number of intermediaries participating in the basis trade. Hence, we can write the basis as

$$\text{Basis}_k = \frac{X_k}{\frac{N_p}{\lambda_{s,k}} + \sum_i \frac{1}{\gamma_i\sigma_{i,k}^2}}. \tag{16}$$

Intermediaries' Participation Decisions. We focus on Nash equilibria. In order to participate in the basis trade in currency k, intermediaries must find it worthwhile to pay the fixed cost of participation in equilibrium. Using the equilibrium quantities previously derived, this means that, assuming intermediary i participates,

$$\begin{aligned}\lambda_{PC,k} <& -\text{Basis}_k Z_{i,k} - \frac{\gamma_i}{2}(\alpha_{i,k} Z_{i,k})^2 \sigma_{i,k}^2 - \frac{\lambda_{s,k}}{2}(1-\alpha_{i,k})^2 Z_{i,k}^2 \\ =& \underbrace{\frac{\lambda_{s,k}\gamma_i\sigma_{i,k}^2}{\lambda_{s,k}+\gamma_i\sigma_{i,k}^2} Z_{i,k}^2}_{\text{Basis}_k Z_{i,k}} - \underbrace{\frac{1}{2}\frac{\lambda_{s,k}\gamma_i\sigma_{i,k}^2}{\lambda_{s,k}+\gamma_i\sigma_{i,k}^2} Z_{i,k}^2}_{\text{Risk and Safe Asset Scarcity}} \\ =& \frac{1}{2}\frac{\lambda_{s,k}\gamma_i\sigma_{i,k}^2}{\lambda_{s,k}+\gamma_i\sigma_{i,k}^2} Z_{i,k}^2.\end{aligned}$$

For ease of notation, we denote $A \equiv \frac{\lambda_{s,k}+\gamma_i\sigma_{i,k}^2}{\lambda_{s,k}\gamma_i\sigma_{i,k}^2} = \frac{1}{\lambda_{s,k}} + \frac{1}{\gamma_i\sigma_{i,k}^2}$, and $B \equiv \sum_{j\neq i} \frac{\lambda_{s,k}+\gamma_j\sigma_{j,k}^2}{\lambda_{s,k}\gamma_j\sigma_{j,k}^2}$, where j are the participating intermediaries (other than intermediary i). We want to solve for A to characterize i's participation threshold (where a higher A indicates that substitution from safe assets is less risky for intermediary i). We can re-write our participation condition as:

$$\begin{aligned}\lambda_{PC,k} <& \frac{1}{2}\frac{\lambda_{s,k}\gamma_i\sigma_{i,k}^2}{\lambda_{s,k}+\gamma_i\sigma_{i,k}^2} Z_{i,k}^2 \\ =& \frac{1}{2A}\frac{A^2 X_k^2}{(A+B)^2}.\end{aligned}$$

This yields a quadratic inequality for A to justify intermediary i's participation:

$$\lambda_{PC,k} A^2 + \left(2B\lambda_{PC,k} - \frac{1}{2}X_k^2\right) A + \lambda_{PC,k} B^2 < 0.$$

This yields a lower and upper bound for A:

$$\begin{aligned}&\frac{\frac{1}{2}X_k^2 - 2B\lambda_{PC,k} - \sqrt{\left(\frac{1}{2}X_k^2 - 2B\lambda_{PC,k}\right)^2 - 4\lambda_{PC,k}^2 B^2}}{2\lambda_{PC,k}} \leq A \\ &\leq \frac{\frac{1}{2}X_k^2 - 2B\lambda_{PC,k} + \sqrt{\left(\frac{1}{2}X_k^2 - 2B\lambda_{PC,k}\right)^2 - 4\lambda_{PC,k}^2 B^2}}{2\lambda_{PC,k}}.\end{aligned}$$

Denoting the lower and upper bounds as $\underline{A}$ and $\overline{A}$, we note that the bounds imply that intermediary i enters if and only if

$$\underline{A} \leq \frac{1}{\lambda_{s,k}} + \frac{1}{\gamma_i\sigma_{i,k}^2} \leq \overline{A},$$

which implies that

$$\frac{1}{(\overline{A} - 1/\lambda_{s,k})} \leq \gamma_i\sigma_{i,k}^2 \leq \frac{1}{(\underline{A} - 1/\lambda_{s,k})}. \tag{17}$$

The upper bound for $\gamma_i \sigma_{i,k}^2$ means that intermediary i must not face too much risk in substituting into risky assets (relative to participating intermediaries); otherwise, the fixed participation cost is too high for them. The lower bound for $\gamma_i \sigma_{i,k}^2$ means that intermediary i cannot have a risky alternative that is *too* close to risk-free; otherwise, they could drive the profits of the basis trade to zero, making the trade sufficiently unprofitable to justify their participation.

Importantly, with sufficient heterogeneity in $\sigma_{i,k}^2$ across intermediaries, we have limited participation in market k.

Basis with Balance Sheet Costs, Counterparty Costs, and Heterogeneity

In currency k, we denote the number of participating intermediaries as $N_{p,k}$. We take participating intermediary i's first order condition with respect to $Z_{i,k}$. We let $r_k = r$ for simplicity.

For risk, and safe asset scarcity, the relevant part of the first-order condition can be expressed as

$$\frac{\partial}{\partial Z_{i,k}} \sum_k \frac{\gamma}{2} (\alpha_{i,k} Z_{i,k})^2 \sigma_{i,k}^2 + \frac{\lambda_{s,k}}{2} \left((1-\alpha_{i,k}) Z_{i,k}\right)^2 = \alpha_{i,k}^2 \gamma \sigma_{i,k}^2 Z_{i,k} + \lambda_{s,k} (1-\alpha_{i,k})^2 Z_{i,k}.$$

We combine the risk and safe asset scarcity terms by noting that

$$\gamma \sigma_{i,k}^2 \alpha_{i,k}^2 Z_{i,k} + \lambda_{s,k} (1-\alpha_{i,k})^2 Z_{i,k} = \frac{\lambda_{s,k} \gamma \sigma_{i,k}^2}{\lambda_{s,k} + \gamma_i \sigma_{i,k}^2} Z_{i,k}.$$

For balance sheet costs, the relevant part of the first-order condition can be expressed as

$$\begin{aligned} \frac{\partial}{\partial Z_{i,k}} \frac{1}{2} \lambda_{BS} \left(\sum_{k'} |Z_{i,k'}| \right)^2 =& \lambda_{BS} Z_{i,k} + \lambda_{BS} \text{Sign}(Z_{i,k}) \sum_{k' \neq k} |Z_{i,k'}| \\ =& \lambda_{BS} Z_{i,k} - \lambda_{BS} \text{Sign}(X_k) \sum_{k' \neq k} |Z_{i,k'}|. \end{aligned}$$

For counterparty costs, the relevant part of the first-order condition is

$$\begin{aligned} \frac{\partial}{\partial Z_{i,k}} \frac{1}{2} \lambda_{CP} \sum_c \left(\sum_{k'} |Z_{i,k',c}| \right)^2 =& \frac{\partial}{\partial Z_{i,k}} \frac{1}{2} \lambda_{CP} \sum_c \left(\sum_{k'} \frac{X_{c,k'}}{X_{k'}} |Z_{i,k'}| \right)^2 \\ =& -\lambda_{CP} \text{Sign}(X_k) \sum_c \frac{X_{c,k}}{X_k} \sum_{k'} \frac{X_{c,k'}}{X_{k'}} |Z_{i,k'}| \\ =& \lambda_{CP} Z_{i,k} \sum_c \frac{X_{c,k}^2}{X_k^2} - \lambda_{CP} \text{Sign}(X_k) \sum_c \sum_{k' \neq k} \frac{X_{c,k}}{X_k} \frac{X_{c,k'}}{X_{k'}} |Z_{i,k'}|. \end{aligned}$$

So, the first order condition can be expressed as

$$\begin{aligned}\text{Basis}_k = & -\left(\frac{\lambda_{s,k}\gamma\sigma_{i,k}^2}{\lambda_{s,k}+\gamma_i\sigma_{i,k}^2}+\lambda_{BS}+\lambda_{CP}\sum_c\frac{X_{c,k}^2}{X_k^2}\right)Z_{i,k} \\ & +\lambda_{BS}\text{Sign}(X_k)\sum_{k'\neq k}|Z_{i,k'}|+\lambda_{CP}\text{Sign}(X_k)\sum_c\sum_{k'\neq k}\frac{X_{c,k}}{X_k}\frac{X_{c,k'}}{X_{k'}}|Z_{i,k'}|,\end{aligned}$$

which we can re-write in terms of $Z_{i,k}$:

$$\begin{aligned}Z_{i,k} = & \left(-\text{Basis}_k+\lambda_{BS}\text{Sign}(X_k)\sum_{k'\neq k}|Z_{i,k'}|+\lambda_{CP}\text{Sign}(X_k)\sum_c\sum_{k'\neq k}\frac{X_{c,k}}{X_k}\frac{X_{c,k'}}{X_{k'}}|Z_{i,k'}|\right) \\ & \times\left(\frac{\lambda_{s,k}\gamma\sigma_{i,k}^2}{\lambda_{s,k}+\gamma_i\sigma_{i,k}^2}+\lambda_{BS}+\lambda_{CP}\sum_c\frac{X_{c,k}^2}{X_k^2}\right)^{-1}.\end{aligned}$$

Summing over participating intermediaries,

$$X_k=\sum_i^{N_{p,k}}\frac{\text{Basis}_k-\lambda_{BS}\text{Sign}(X_k)\sum_{k'\neq k}|Z_{i,k'}|-\lambda_{CP}\text{Sign}(X_k)\sum_c\sum_{k'\neq k}\frac{X_{c,k}}{X_k}\frac{X_{c,k'}}{X_{k'}}|Z_{i,k'}|}{\frac{\lambda_{s,k}\gamma\sigma_{i,k}^2}{\lambda_{s,k}+\gamma_i\sigma_{i,k}^2}+\lambda_{BS}+\lambda_{CP}\sum_c\frac{X_{c,k}^2}{X_k^2}}.$$

This can then be re-written as:

$$\begin{aligned}\text{Basis}_k = & X_k\left(\sum_i^{N_{p,k}}\frac{1}{\frac{\lambda_{s,k}\gamma\sigma_{i,k}^2}{\lambda_{s,k}+\gamma_i\sigma_{i,k}^2}+\lambda_{BS}+\lambda_{CP}\sum_c\frac{X_{c,k}^2}{X_k^2}}\right)^{-1} \\ & +\underbrace{\lambda_{BS}\text{Sign}(X_k)\left(\sum_i^{N_{p,k}}\sum_{k'\neq k}|Z_{i,k'}|\right)}_{\text{Balance Sheet Usage of Participating Intermediaries}}\left(\sum_i^{N_{p,k}}\frac{1}{\frac{\lambda_{s,k}\gamma\sigma_{i,k}^2}{\lambda_{s,k}+\gamma_i\sigma_{i,k}^2}+\lambda_{BS}+\lambda_{CP}\sum_c\frac{X_{c,k}^2}{X_k^2}}\right)^{-1} \\ & +\underbrace{\lambda_{CP}\text{Sign}(X_k)\left(\sum_c\sum_{k'\neq k}\frac{X_{c,k}}{X_k}\frac{X_{c,k'}}{X_{k'}}|Z_{i,k'}|\right)}_{\text{Counterparty Exposure of Participating Intermediaries}}\left(\sum_i^{N_{p,k}}\frac{1}{\frac{\lambda_{s,k}\gamma\sigma_{i,k}^2}{\lambda_{s,k}+\gamma_i\sigma_{i,k}^2}+\lambda_{BS}+\lambda_{CP}\sum_c\frac{X_{c,k}^2}{X_k^2}}\right)^{-1}.\end{aligned}$$

The expression for the basis yields the same predictions as the main text. In addition, we note that the expression highlights the logic behind Prediction 6 in a more general sense: the balance sheet usage and counterparty exposure of the *participating* intermediaries are the features that are relevant for understanding the basis in currency k, not the balance sheet usage and counterparty exposure of the overall financial sector.

Segmentation with Markups

We illustrate how segmentation also gives rise to a larger basis via a markup channel, in addition to the risk and safe asset scarcity channels that we focus on in our main analysis.

Rather than assuming exogenous customer demand, as in the main analysis, we assume that customer demand can be represented by an aggregate inverse demand curve of the form

$$\text{Basis}_k = \pi_k - \beta X_k.$$

This form can represent, for example, currency hedging demand via forwards from customers who adjust their amount of hedging based on the cost of hedging (the basis), as studied in Du and Huber (2023).

To simplify our analysis, as before, we consider the case where $\lambda_{BS} = \lambda_{CP} = 0$ and $r_k = r$. The financial intermediary i's problem is

$$\max_{Z_{i,k},\alpha_{i,k}\forall k} \sum_k -\text{Basis}_k Z_{i,k} - \sum_k \frac{\gamma}{2}(\alpha_{i,k}Z_{i,k})^2\sigma_{i,k}^2 - \sum_k \frac{1}{2}\lambda_{s,k}\left((1-\alpha_{i,k})Z_{i,k}\right)^2,$$

which can be re-written as

$$\max_{Z_{i,k}\forall k} \sum_k -(\pi_k + \beta \sum_j Z_{j,k})Z_{i,k} - \frac{1}{2}\sum_k a_i Z_{i,k}^2, \text{ where } a_i \equiv \frac{\lambda_{s,k}\gamma_i\sigma_{i,k}^2}{\lambda_{s,k} + \gamma\sigma_{i,k}^2}.$$

Taking the first order condition with respect to $Z_{i,k}$, we get that

$$(a_i + \beta)Z_{i,k} = -\pi_k - \beta \sum_j Z_{j,k}.$$

The right-hand side of the equation is common for all participating intermediaries, so $\forall i, j$,

$$Z_{j,k} = \frac{a_i + \beta}{a_j + \beta} Z_{i,k}.$$

Then, we have that

$$(a_i + \beta)Z_{i,k} = -\pi_k - \beta(a_i + \beta)Z_{i,k} \sum_j \frac{1}{a_j + \beta},$$

which provides a solution for $Z_{i,k}$:

$$Z_{i,k} = -\frac{\pi_k}{(a_i + \beta)\left(1 + \beta \sum_j \frac{1}{a_j + \beta}\right)}. \tag{18}$$

The market clearing condition is $X_k = -\sum_j Z_{j,k}$, so

$$X_k = \frac{\pi_k}{1+\beta\sum_j \frac{1}{a_j+\beta}} \sum_i \frac{1}{a_i+\beta}.$$

Plugging this into customers' inverse demand functions, we can solve for the basis:

$$\begin{aligned}\text{Basis}_k =& \pi_k - \beta X_k \\ =& \frac{\pi_k}{1+\beta\sum_j^{N_{p,k}} \frac{1}{a_j+\beta}}.\end{aligned}$$

To consider the impact of markups on the basis, we can compare the basis with intermediary i's marginal costs:

$$\begin{aligned}\text{Markup}_k =& \text{Basis}_k - (-a_i Z_{i,k}) \\ =& \frac{\pi_k}{1+\beta\sum_j \frac{1}{a_j+\beta}} - a_i \frac{\pi_k}{(a_i+\beta)\left(1+\beta\sum_j \frac{1}{a_j+\beta}\right)} \\ =& \frac{\beta\pi_k}{(a_i+\beta)\left(1+\beta\sum_j^{N_{p,k}} \frac{1}{a_j+\beta}\right)}.\end{aligned}$$

We observe that Basis_k increases with segmentation, as we decrease the number of participating intermediaries. Part of this effect comes from risk and safe asset scarcity, captured by the a_i terms, which are the focus of our analysis in the main text. An additional component of the effect arises from oligopolistic pricing, with intermediaries using their market power to charge markups.

A.2 Data Details

FR 2052a Complex Institution Liquidity Monitoring Report

We limit the sample to firms that report daily data through the sample, focusing on the largest consolidated entity firm rather than individual material entities. We exclude transactions with internal counterparties. We drop foreign exchange options except when it appears 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. We drop transactions in which one leg's currency is denominated as "other" and keep transactions that include USD. 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 there are fewer than seven filers' data available. Since the set of banks reporting daily has changed over time, we focus on a subset of the largest banks that have consistently been daily reporters over the whole sample.[35] 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 previous instruction data. We also adjust the maturities of the contracts to be consistent through the sample as the maturity buckets for some 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).

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
- Debt issued by the U.S. Treasury
- U.S. Government Agency-issued debt (excluding the U.S. Treasury) with a US 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

[35] 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 with a non-U.S. sovereign (excluding central banks) or multilateral development bank or other supranational guarantee, where 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 of 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 supports outflows that are in the same jurisdiction of 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 it 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 rate; when it is missing, we linearly interpolate the rate by estimating the curve each day. For the 3w CHF tenor, we estimate it based CHF OIS tenors with fewer than 100 days 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 $\times$ the contract's maturity in weeks.

A.3 Figures

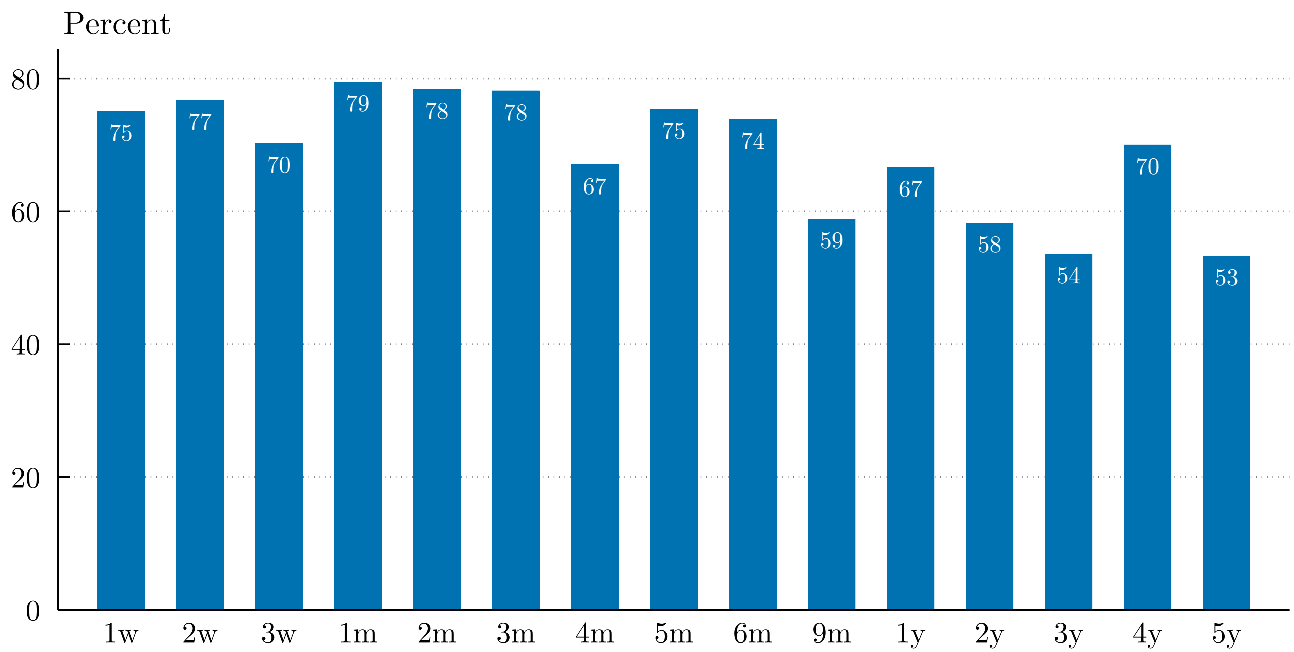

Figure A1: Proportion of CIP Deviation Variance Explained by First Principal Component. Figure plots the proportion of the variance explained by the first principal component after estimating 6 principal components across the signed CIP deviations by tenor.

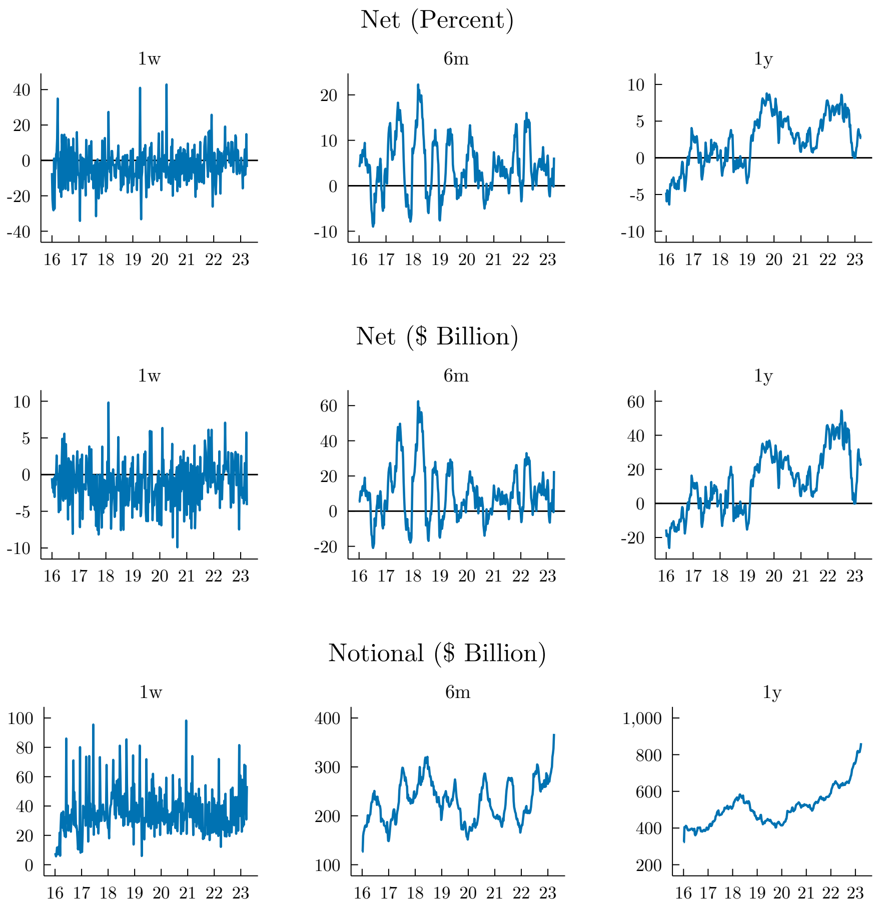

Figure A2: *Net* for EUR across several tenors. Top panel plots our main measure, $Net^k_{t,t+n}$, for EUR contracts across various tenors. Middle panel plots the level of net dollar lending. Bottom panel plots the notional dollars across borrowing and lending transactions for EUR across the highlighted tenors. All figures plot weekly averages based on daily observations.

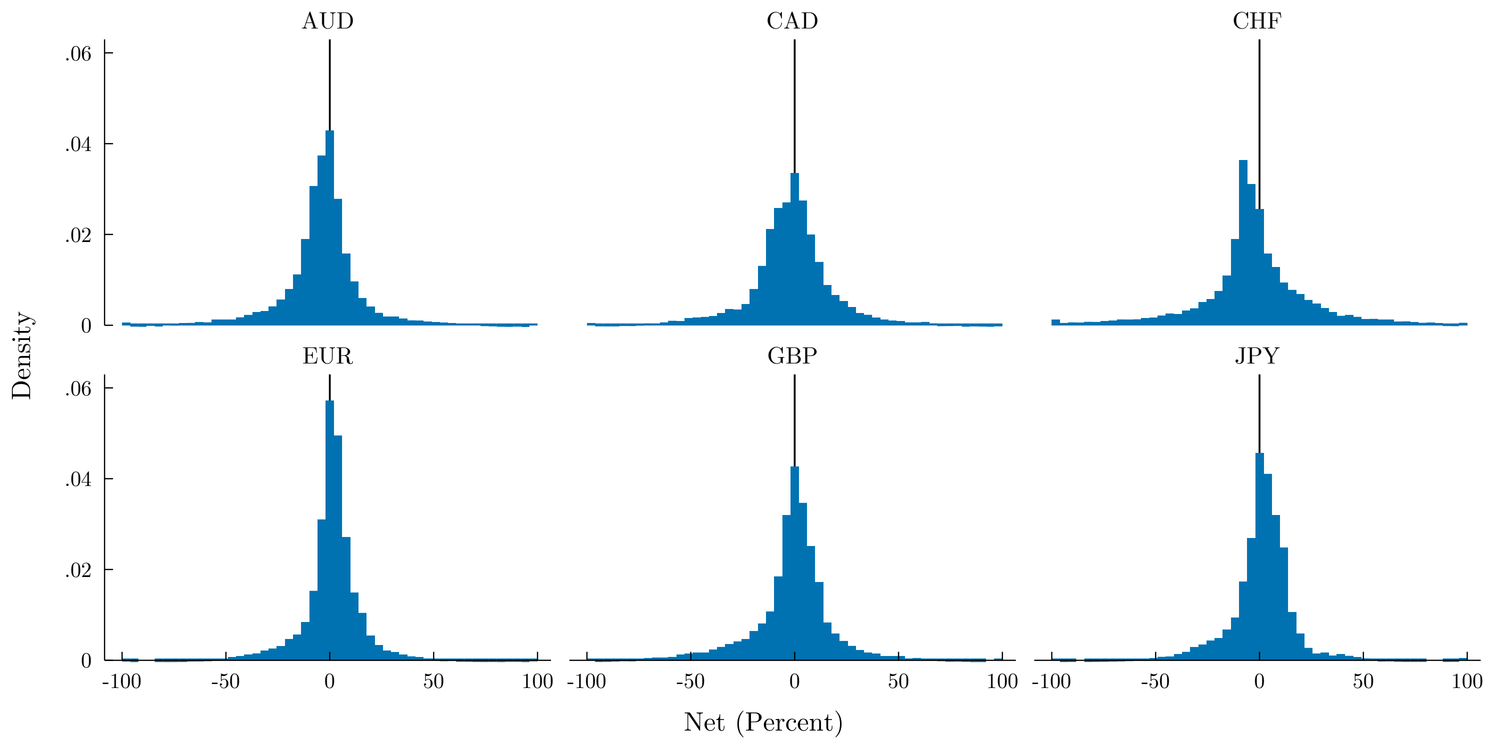

Figure A3: Most Markets are Nearly Matched Books. Figure plots the histogram of $Net^{k}_{t,t+n}$across all tenors within a given currency.

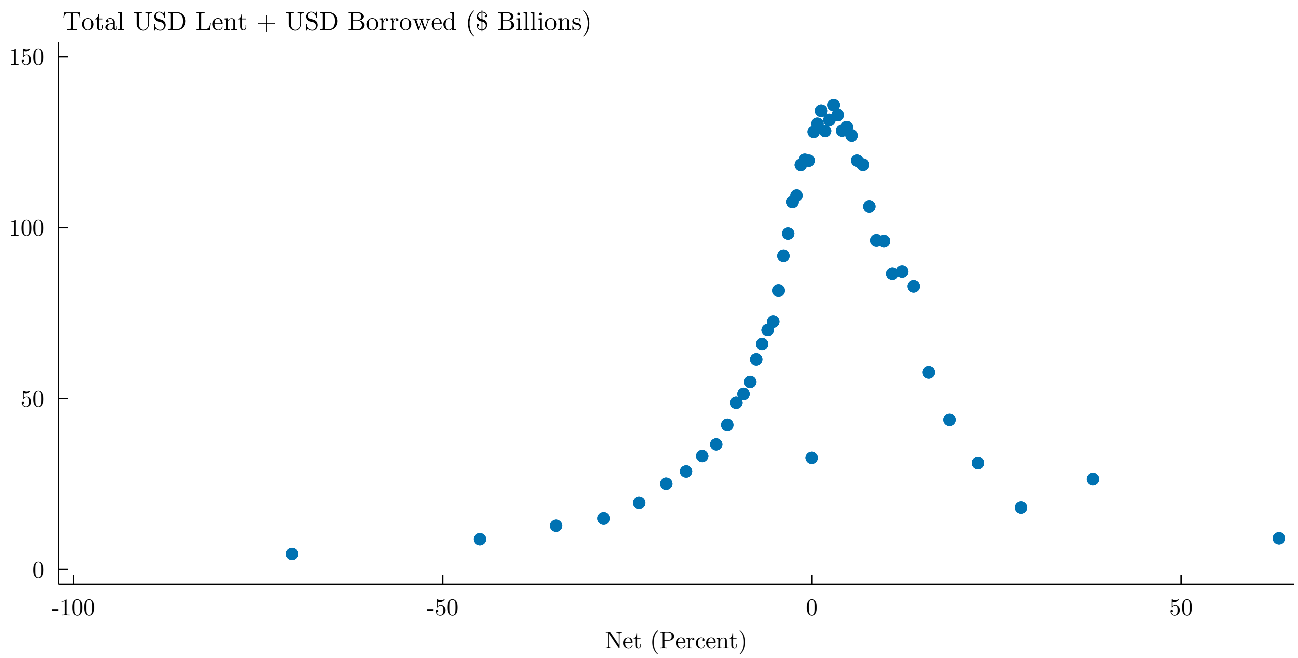

Figure A4: Size vs. *Net.* Figure presents the binscatter of the size of the market—defined as the sum of dollars lent and borrowed in billions—at the daily-currency-tenor level.

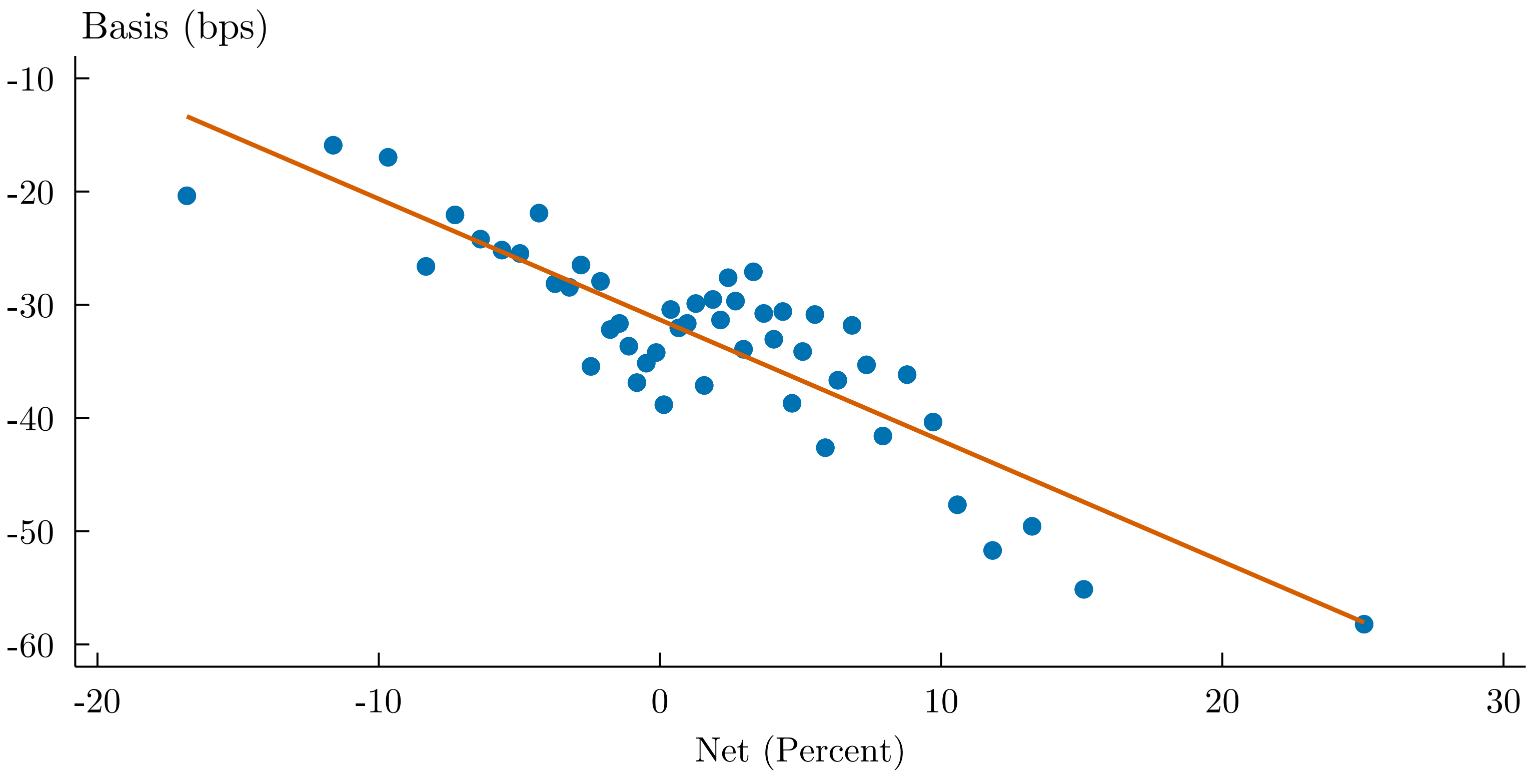

Figure A5: Basis vs. *Net*. Figure presents the binscatter of the basis on $Net^k_{t,t+n}$ after averaging on a monthly frequency. $Net^k_{t,t+n}$ is at the month by currency by tenor level.

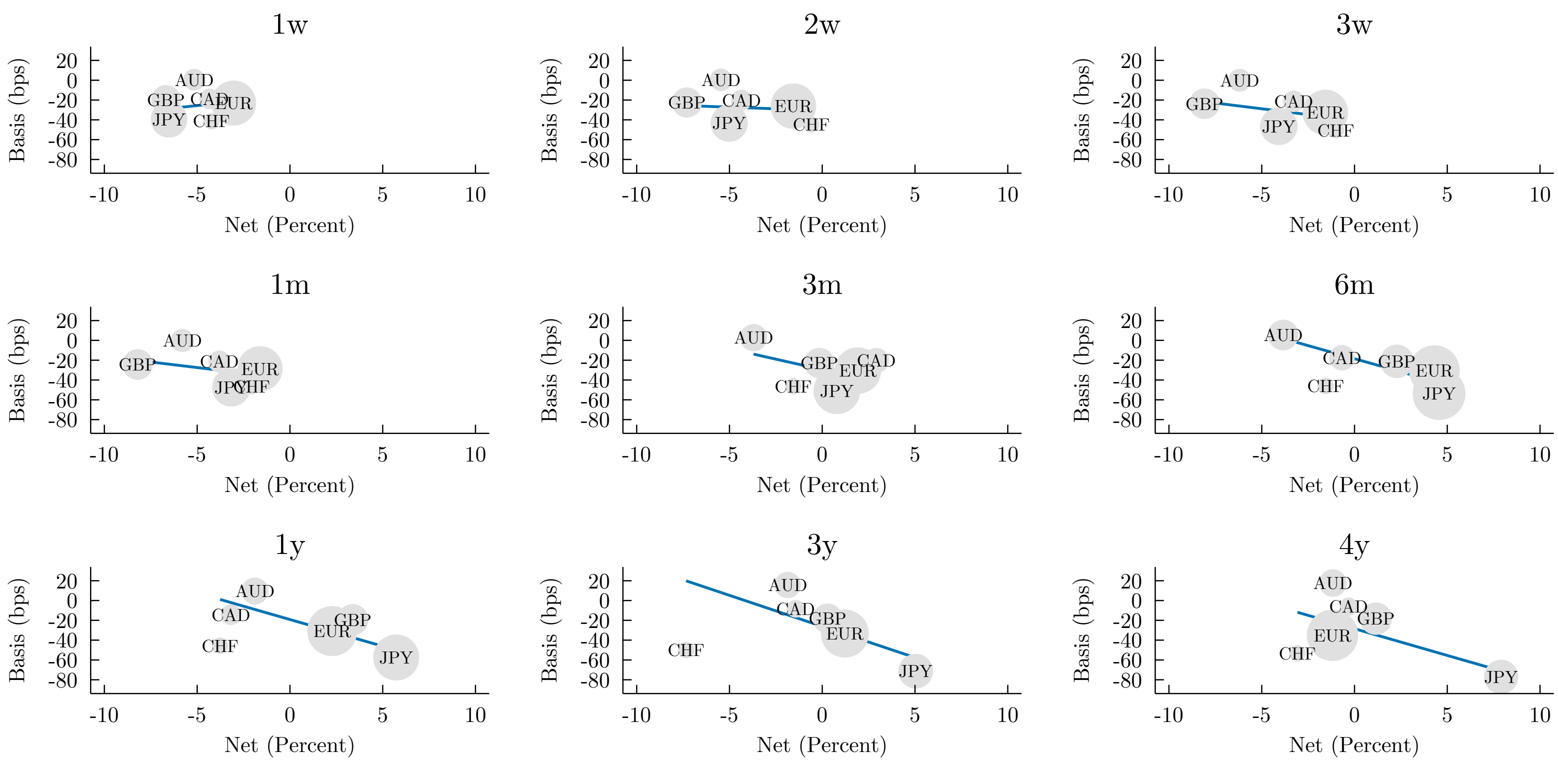

Figure A6: By Tenor: Basis vs. *Net*. Figure presents the scatter of the average basis on the average $Net^k_{t,t+n}$.

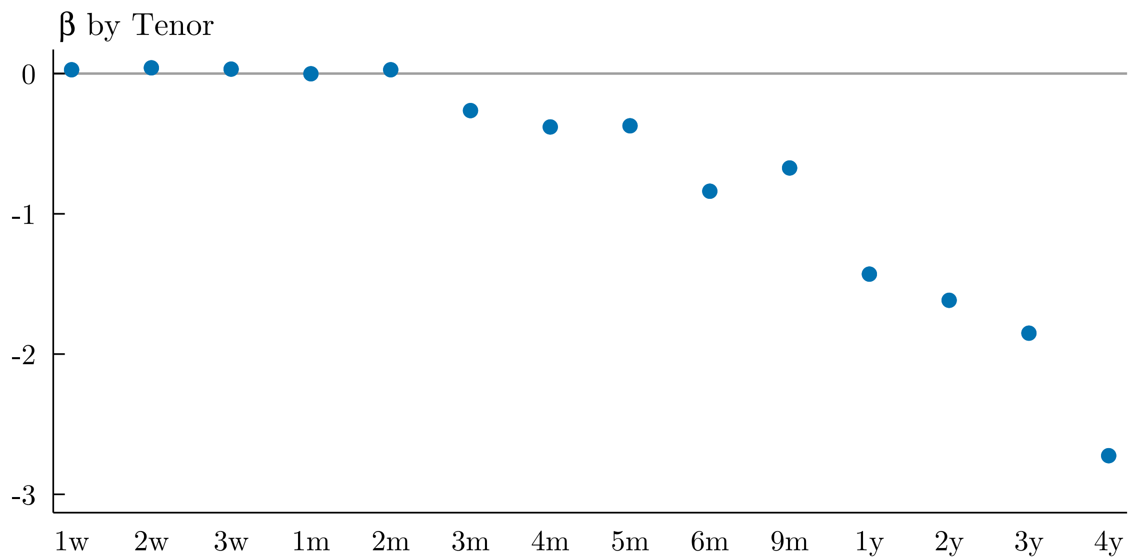

Figure A7: Regression Coefficient by Tenor: Basis vs. *Net*. Figure the β estimated by running the following regression separately for each tenor: $\text{Basis}_{t,t+n}^{k} = \alpha + \beta Net_{t,t+n}^{k} + \varepsilon_{t,t+n}^{k}$.

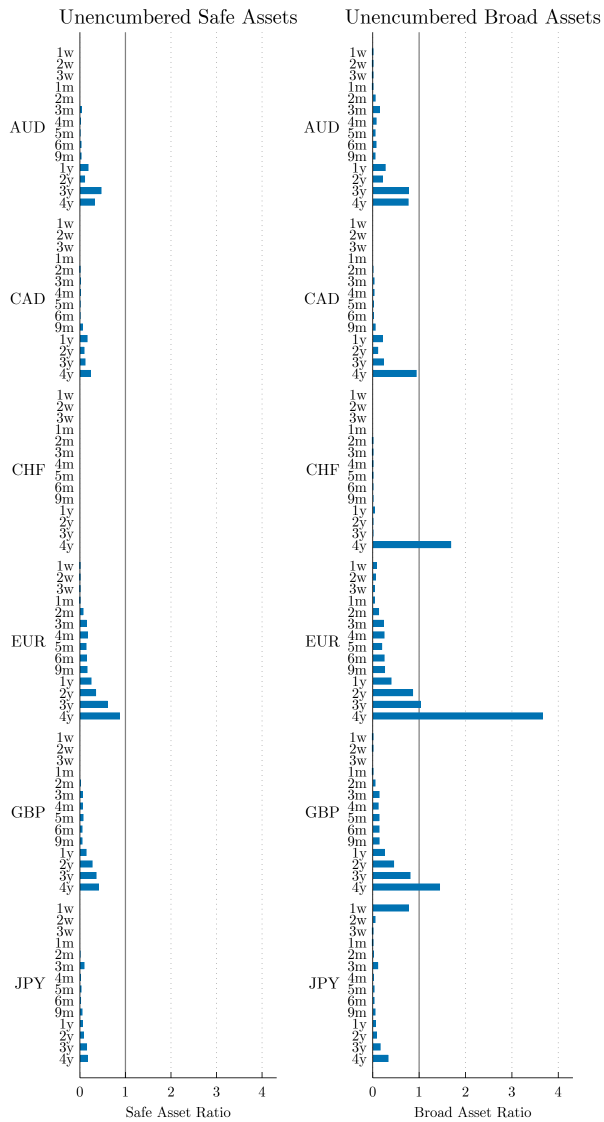

Figure A8: Safe Asset Scarcity by Market. Figure plots median safe asset and broad asset ratios when $Net^k_{t,t+n}$is positive and matching the tenor of the net dollar lending and the foreign safe asset.

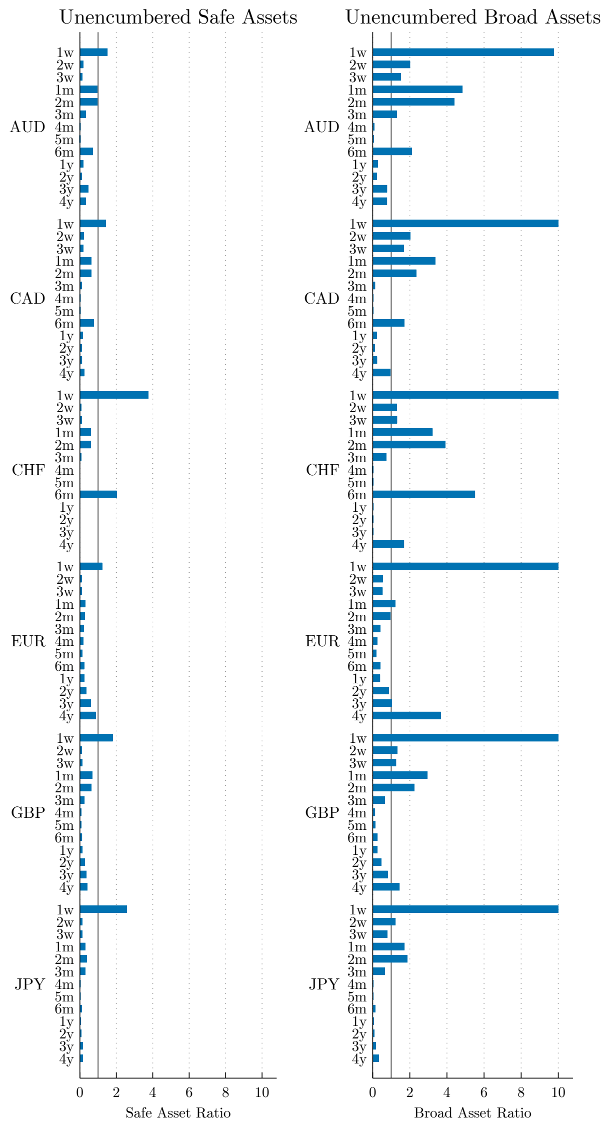

Figure A9: Safe Asset Scarcity by Market with Rounded Tenors. Figure plots median safe asset and broad asset ratios when $Net^k_{t,t+n}$is positive and when bucketing net dollar lending and foreign safe assets into the nearest benchmark tenor. Unlike Figure A8 this measure allows for some maturity mismatch in the trade. Values are truncated at 10.

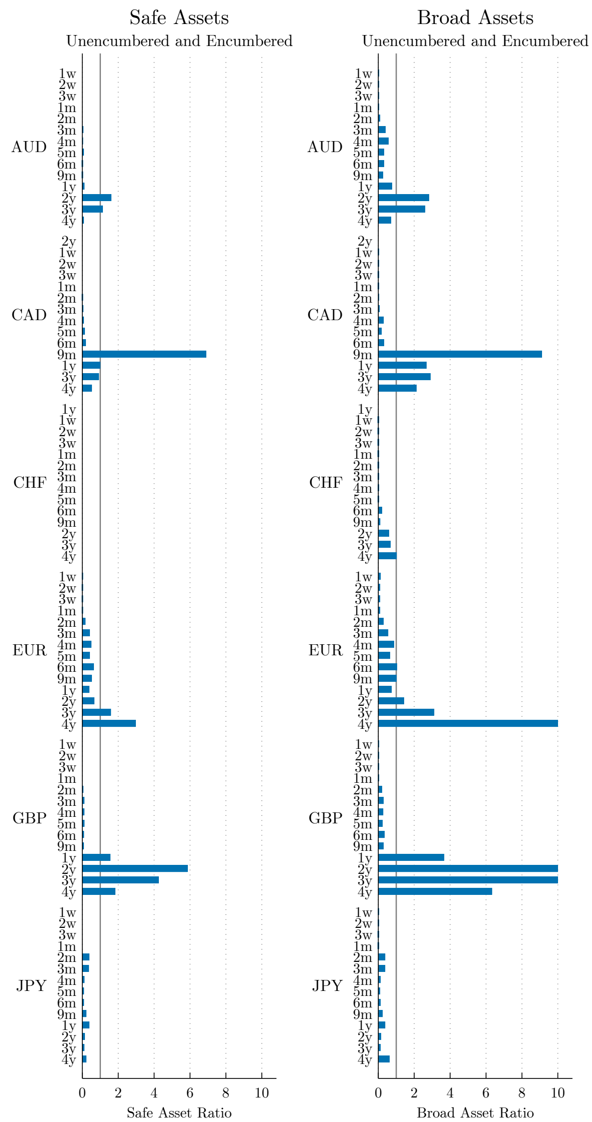

Figure A10: Safe Asset Scarcity by Market, including encumbered assets. Figure plots median safe asset and broad asset ratios when $Net^{k}_{t,t+n}$is positive when matching the tenor of the net dollar lending and the foreign safe asset. Values are truncated at 10.

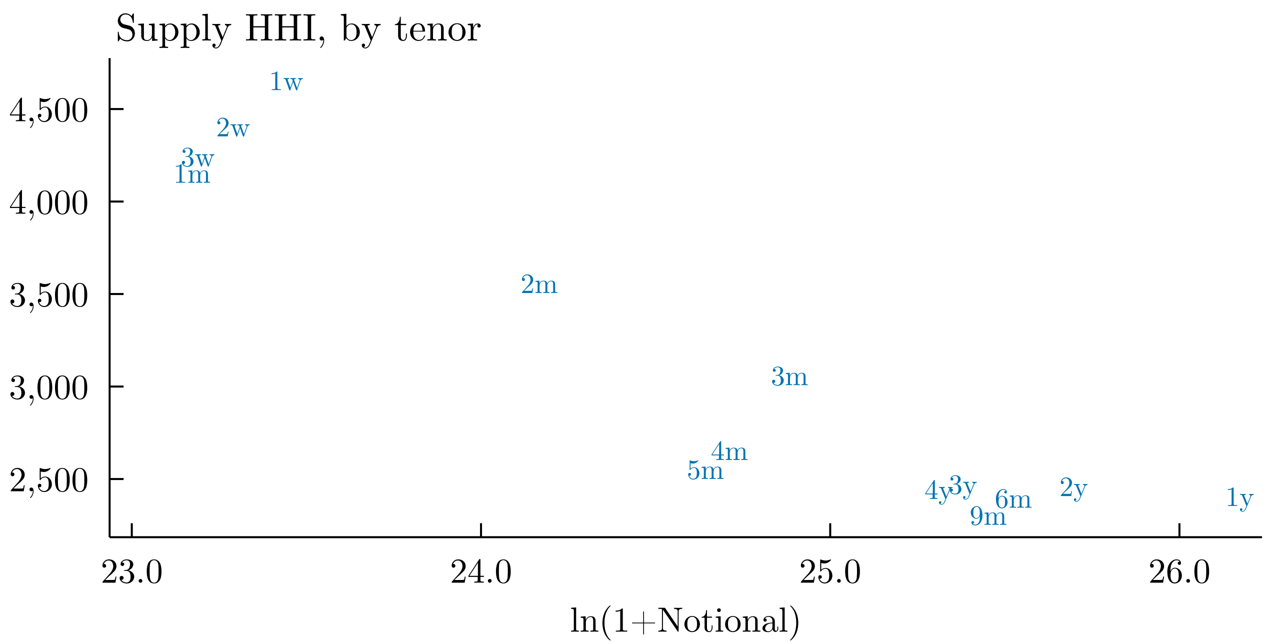

Figure A11: Supply Segmentation. Figure plots the average of daily Tenor Supply $\text{HHI}_{t,t+n}$ against (log of 1 plus) the average notional of that market.

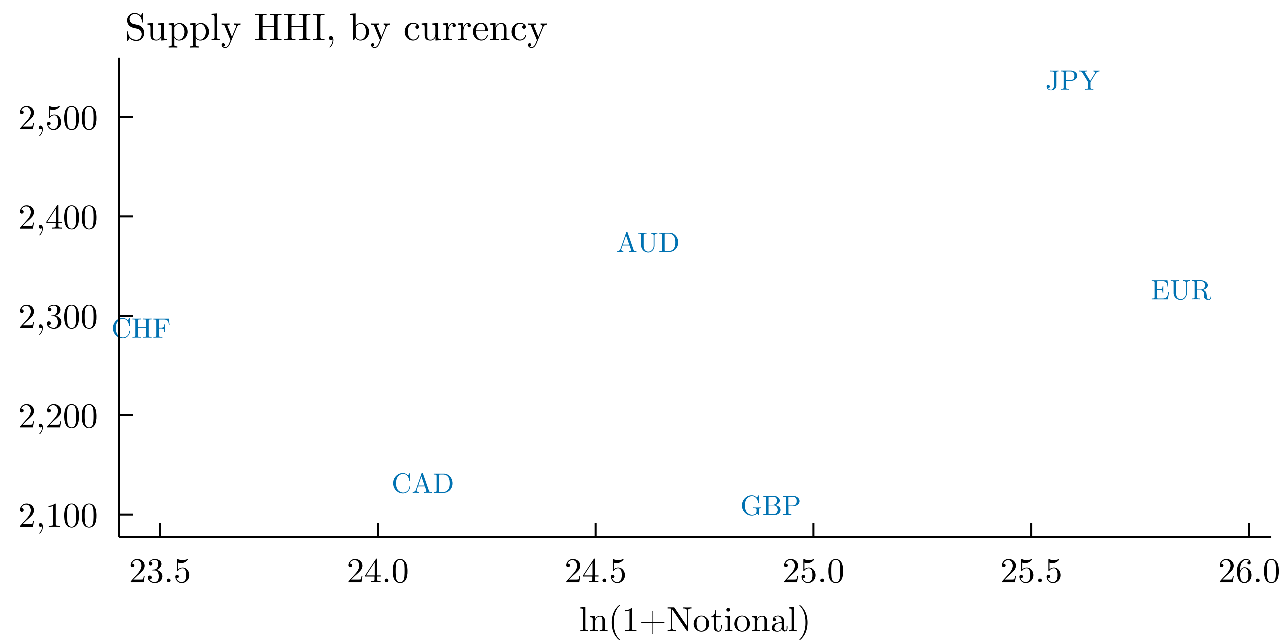

Figure A12: Supply Segmentation by Currency. Figure plots the average of daily Currency Supply HHI_t^k against (log of 1 plus) the average notional of that market.

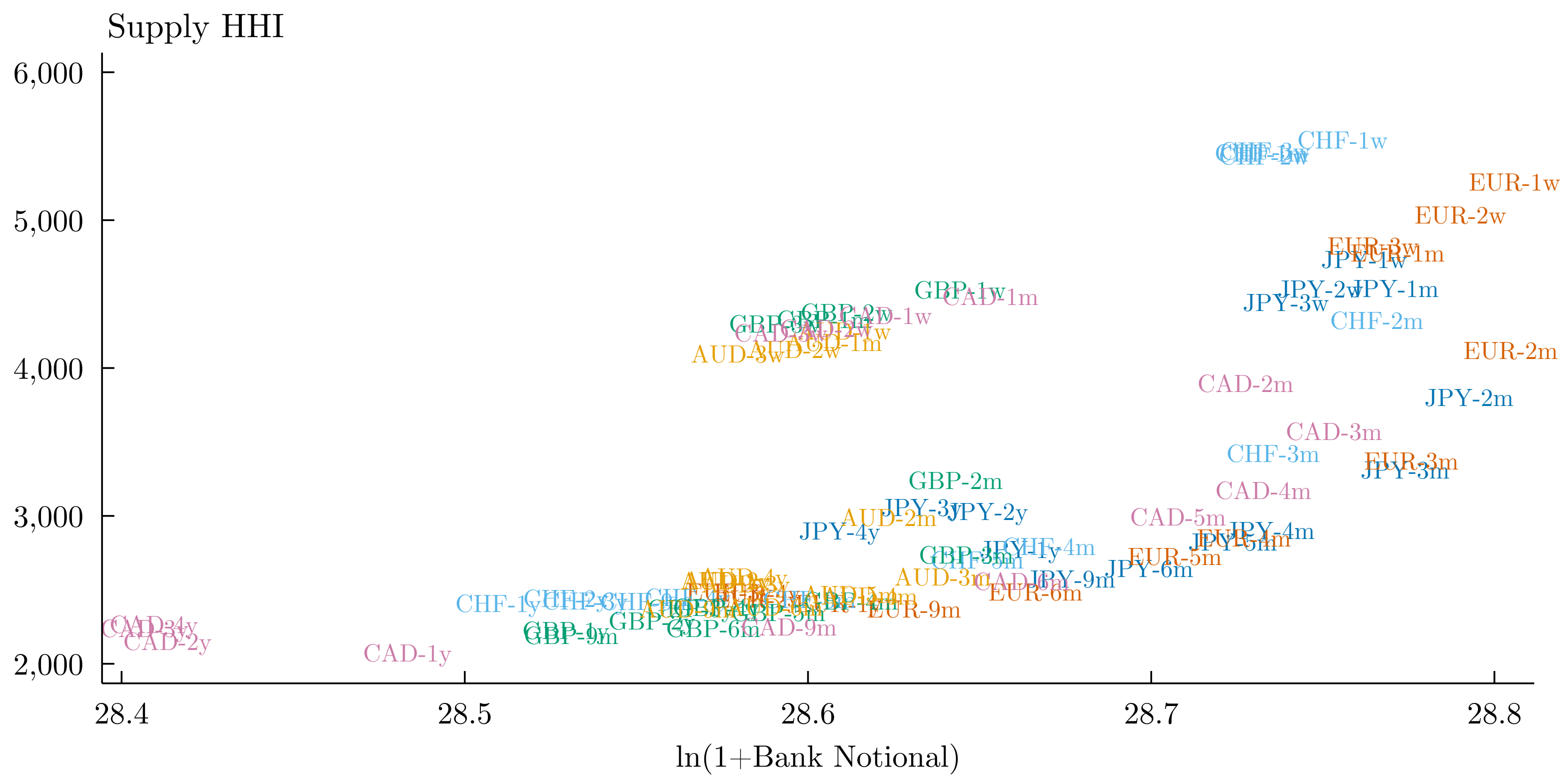

Figure A13: Supply Segmentation vs. Bank Size Figure plots the average of daily Supply $\text{HHI}^{k}_{t,t+n}$ against (log of 1 plus the) the notional book size of the banks active in that market weighted by their market share.

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	0.2	−0.8	−1.2	−1.1	−0.6
3w	−0.4	−0.2	0.1	−0.8	−1.2	−0.9	−0.5
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	8.9	4.7	7.3	4.6
Mean	4.1	3.2	1.8	9.6	5.9	12.9	

Table A1: *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	151,655	151,655	151,655	151,655	129,059

	R_t^{SPX}	VIX_t	$Baa_t - Aaa_t$
$Net_{t,t+n}^k$	-0.002	-0.017^{***}	-0.012^{***}
	(0.38)	(0.00)	(0.00)
N	143,507	143,507	143,507

Table A2: Correlations. Table presents the correlation of $Net_{t,t+n}^k$at the day, by currency, by tenor level on 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 years) 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 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

		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	0.03	0.04	0.10	0.46	0.25	0.60	0.84	2.46
	Mean	0.73	0.67	1.44	2.47	6.46	14.76	31.98	119.42
	Std. Dev.	18.40	3.69	32.79	11.73	87.41	165.50	676.37	1,924.34
CAD	Median	0.01	0.06	0.03	0.13	0.17	0.45	0.64	1.93
	Mean	0.61	2.06	1.01	3.20	5.55	3.12	24.05	17.74
	Std. Dev.	18.78	60.50	26.70	79.98	73.17	30.69	438.50	163.84
CHF	Median	0.00	0.00	0.00	0.01	0.00	0.00	0.53	1.21
	Mean	0.02	0.00	0.73	0.68	9.73	45.01	34.78	118.54
	Std. Dev.	0.53	0.02	34.88	6.73	179.17	866.07	608.15	2,054.87
EUR	Median	0.16	0.44	0.29	0.80	0.28	0.70	0.64	1.57
	Mean	1.02	2.16	2.12	4.49	2.54	3.87	16.91	33.77
	Std. Dev.	11.21	19.84	21.00	35.41	36.93	25.71	705.19	835.99
GBP	Median	0.07	0.10	0.18	0.32	0.21	0.91	0.66	3.05
	Mean	0.93	2.85	2.11	7.58	3.10	5.55	13.08	37.85
	Std. Dev.	31.64	23.69	55.94	59.49	49.81	31.45	211.45	535.56
JPY	Median	0.05	0.14	0.08	0.18	0.12	0.25	0.23	0.41
	Mean	0.44	0.61	1.19	0.89	3.32	3.53	13.34	24.13
	Std. Dev.	5.46	5.18	19.53	7.63	136.16	57.34	328.15	666.67
USD	Median	2.01	8.56	5.38	24.79	2.19	7.80	7.25	28.72
	Mean	50.12	94.32	107.77	234.33	55.67	97.10	335.44	342.05
	Std. Dev.	1,394.56	1,142.77	2,982.31	3,123.05	4,609.31	1,187.54	60,064.85	5,107.52
Average of All excl. USD	Median	0.05	0.13	0.11	0.32	0.17	0.48	0.59	1.77
	Mean	0.63	1.39	1.43	3.22	5.12	12.64	22.36	58.57
	Std. Dev.	14.34	18.82	31.81	33.49	93.77	196.13	494.63	1,030.21

Table A3: 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.

		Matched, incl. Swaps and Forwards				Matched, incl. Firm Shorts			
		Safe Asset		Broad Assets		Safe Asset		Broad Assets	
Borrowing Currency		Unencumbered	Unencumbered & Encumbered	Unencumbered	Unencumbered & Encumbered	Unencumbered	Unencumbered & Encumbered	Unencumbered	Unencumbered & Encumbered
AUD	Median	0.01	0.02	0.05	0.13	0.03	0.04	0.09	0.36
	Mean	0.52	1.57	1.25	4.26	0.72	0.67	1.18	2.12
	Std. Dev.	10.90	27.26	23.64	64.98	18.38	3.69	23.08	10.74
CAD	Median	0.01	0.04	0.01	0.10	0.01	0.06	0.03	0.13
	Mean	0.19	0.32	0.39	0.86	0.60	2.05	0.89	3.15
	Std. Dev.	1.91	1.59	3.91	3.94	18.74	60.50	25.96	79.98
CHF	Median	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01
	Mean	0.47	0.00	0.91	1.82	0.02	0.00	0.18	0.18
	Std. Dev.	40.98	0.00	45.30	43.28	0.51	0.02	5.31	0.95
EUR	Median	0.12	0.30	0.20	0.55	0.15	0.43	0.24	0.78
	Mean	1.11	0.70	2.68	1.47	0.95	2.08	1.88	4.20
	Std. Dev.	10.57	1.93	44.88	3.91	10.49	19.20	20.02	34.28
GBP	Median	0.06	0.11	0.15	0.29	0.07	0.10	0.15	0.31
	Mean	2.49	9.21	5.53	22.44	0.90	2.75	1.95	7.19
	Std. Dev.	109.26	226.64	207.99	512.93	31.62	23.34	55.74	57.98
JPY	Median	0.05	0.15	0.08	0.18	0.05	0.14	0.07	0.16
	Mean	0.80	0.68	1.16	0.79	0.40	0.59	0.81	0.82
	Std. Dev.	42.26	13.44	43.91	14.63	4.99	5.17	11.49	7.61
USD	Median	1.39	5.45	3.72	16.48	1.62	8.15	4.25	24.02
	Mean	51.31	91.14	108.04	225.04	44.16	91.63	77.27	210.52
	Std. Dev.	1,398.32	963.80	2,900.46	2,396.41	1,328.84	1,100.99	2,612.97	2,407.17
Average of All excl. USD	Median	0.04	0.10	0.08	0.21	0.05	0.13	0.10	0.29
	Mean	0.93	2.08	1.99	5.27	0.60	1.36	1.15	2.94
	Std. Dev.	35.98	45.14	61.60	107.28	14.12	18.65	23.60	31.92

Table A4: 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 two columns include net forward positions in addition to net swap lending (which changes the denominator of asset ratios), and last two columns net out firm shorts from banks' net long position in the assets (which changes the numerator).

Panel A: Safe Assets.				
	Unencumbered Safe Assets		Unencumbered & Encumbered Safe Assets	
	(1)	(2)	(3)	(4)
$Net^{k}_{t,t+n}$($ Level)	0.020**	−1.149**	0.166***	−2.325
	(2.18)	(−2.01)	(4.74)	(−1.60)
AUD	265.068***		180.328*	
	(3.33)		(1.91)	
CAD	175.109***		96.310	
	(3.40)		(0.56)	
EUR	1803.268***		3899.425***	
	(4.11)		(3.94)	
GBP	592.817***		901.963	
	(3.59)		(1.36)	
JPY	735.252***		530.823	
	(3.88)		(1.32)	
Constant	−27.346*	22557.509***	−214.863***	61711.154***
	(−1.71)	(5.12)	(−4.91)	(5.17)
N	74,997	76,658	10,145	8,923
R^2	0.29	0.01	0.49	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)	0.187***	−4.749*	0.303***	−5.599*
	(3.87)	(−1.76)	(3.72)	(−1.78)
AUD	822.035**		986.092**	
	(2.20)		(2.59)	
CAD	239.727		369.490	
	(0.79)		(0.73)	
EUR	4492.373***		8279.851***	
	(3.16)		(3.31)	
GBP	2040.245*		2593.438	
	(1.83)		(1.65)	
JPY	18.434		66.421	
	(0.03)		(0.08)	
Constant	−117.260	126810.843***	−264.553*	145684.497***
	(−1.10)	(5.37)	(−1.97)	(5.40)
N	10,099	8,885	10,099	8,885
R^2	0.38	0.01	0.41	0.01
Time FE	Yes	Yes	Yes	Yes
Sample	USD	Non-USD	Non-USD	USD

Table A5: 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: $\textit{Asset (Level)}^{k}_{t,t+n} = \alpha + \beta Net^{k}_{t,t+n}(\text{Level}) + \gamma^{k} + \varepsilon^{k}_{t,t+n}$ 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 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)
Loan Demand $\text{HHI}^k_{t,t+n}$	0.0704^{***}
	(10.76)
Bilateral $\text{Share}^k_{t,t+n}$	2165.9^{***}
	(22.47)
Constant	3640.6^{***}
	(38.99)
N	18,752
R^2	0.06

Table A6: Demand HHI estimate for full sample. Table presents the regression of Demand $\text{HHI}^k_{t,t+n} = \alpha + \beta_1\text{Loan Demand HHI}^k_{t,t+n} + \beta_2\text{Bilateral Share}^k_{t,t+n} + \varepsilon^k_{t,t+n}$, where Loan Demand $\text{HHI}^k_{t,t+n}$ is the unsecured and secured loan counterparty HHI calculated over the full sample, 2016 to 2023, and bilateral share is the share of bilateral FX transactions compared to the total FX transactions in that market.

	Unencumbered Assets		Unencumbered & Encumbered Assets	
	(1)	(2)	(3)	(4)
Supply Segmentation				
Supply $\text{HHI}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$	21.73***	21.67***	21.71***	21.67***
	(4.93)	(4.94)	(4.93)	(4.94)
Supply $\text{HHI}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$	20.29***	20.27***	20.29***	20.27***
	(5.63)	(5.63)	(5.63)	(5.63)
Safe Asset Scarcity				
$\text{Net}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$	1.65	1.48	1.58	1.45
	(0.35)	(0.31)	(0.33)	(0.31)
$\text{Net}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$	3.06	3.05	3.06	3.05
	(0.96)	(0.96)	(0.96)	(0.96)
Safe Asset $\text{Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$	−27.02*		−18.42**	
	(−1.76)		(−2.49)	
Safe Asset $\text{Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$	−0.37		−0.20	
	(−1.40)		(−1.36)	
Broad Asset $\text{Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$		−57.00***		−42.22***
		(−2.64)		(−3.38)
Broad Asset $\text{Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$		−0.19		−0.17
		(−1.29)		(−1.30)
Demand Concentration				
Demand $\text{HHI}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$	4.54	4.56	4.55	4.57
	(1.39)	(1.40)	(1.39)	(1.40)
Demand $\text{HHI}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$	2.72	2.72	2.72	2.72
	(0.85)	(0.85)	(0.85)	(0.85)
Controls				
Bank $\text{CDS}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$	−84.28***	−83.97***	−84.22***	−83.99***
	(−2.85)	(−2.84)	(−2.85)	(−2.84)
Bank $\text{CDS}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$	−88.45***	−88.21***	−88.42***	−88.23***
	(−3.01)	(−3.00)	(−3.01)	(−3.00)
Govt $\text{CDS}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$	−1.41	−1.42	−1.40	−1.41
	(−1.50)	(−1.52)	(−1.50)	(−1.51)
Govt $\text{CDS}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$	−3.94	−3.98	−3.96	−3.99
	(−1.30)	(−1.31)	(−1.30)	(−1.31)
N	18,755	18,755	18,755	18,755
R^2	0.28	0.28	0.28	0.28
Tenor FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Weighted	Yes	Yes	Yes	Yes

Table A7: Regression of the absolute value of the basis on measures of frictions. Table presents the regression described in section 4.5 using the sample where our demand concentration measure is available. 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 each variable's full sample median and standard deviation. Regression includes tenor and date 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 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
Supply Segmentation						
Supply $\text{HHI}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$	18.27***					
	(4.55)					
Supply $\text{HHI}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$	17.18***					
	(4.87)					
Safe Asset Scarcity						
$\text{Net}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$		8.13**				
		(2.28)				
$\text{Net}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$		4.29**				
		(2.07)				
Safe Asset $\text{Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$			−17.35**			
			(−2.04)			
Safe Asset $\text{Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$			−0.60			
			(−1.55)			
Broad Asset $\text{Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$				−23.29*		
				(−1.91)		
Broad Asset $\text{Ratio}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$				−0.36		
				(−1.23)		
Demand Concentration						
Demand $\text{HHI}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$					−0.25	
					(−0.07)	
Demand $\text{HHI}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$					−0.57	
					(−0.16)	
$\widehat{\text{Demand HHI}}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} \geq 0)$						12.19***
						(3.07)
$\widehat{\text{Demand HHI}}^k_{t,t+n} \times \mathbb{I}(Net^k_{t,t+n} < 0)$						3.40
						(1.58)
N	149,337	149,337	149,337	149,337	18,755	149,293
R^2	0.08	0.02	0.00	0.00	0.00	0.04
Tenor FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Weighted	Yes	Yes	Yes	Yes	Yes	Yes

Table A8: Regression of the absolute value of the basis on marginal cost measures. Table presents the regression described in section 4.5. 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 each variable's full sample median and standard deviation. Regression includes tenor and date 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 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.