Decomposing Covered-Interest Parity Deviations

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Preliminary & Comments Welcome

Abstract

Prevailing theories of financial intermediation face a challenge in explaining a striking feature of bank-intermediated arbitrage trades: that spreads on these trades exhibit substantial cross-sectional variation in sign and magnitude. We use confidential supervisory data—covering more than $25 trillion in daily notional exposures on average—to study covered-interest parity (CIP) deviations in currency markets. We uncover that three novel forces are important for explaining cross-sectional variation in CIP deviations: foreign safe asset scarcity, which makes CIP arbitrage imperfect and leads intermediaries to take risk; market segmentation, with banks specializing in different markets; and concentration of demand. Our findings highlight the presence and importance of segmentation and search frictions in even the most liquid markets.

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

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1 Introduction

Spreads on bank-intermediated arbitrage trades, called bases, have persisted in the post-global financial crisis (GFC) period, attracting substantial attention from academics and market participants alike.[1] The existence of bases is the clearest evidence that financial intermediaries are not simply a veil, as assumed in classical theories, and that the litany of constraints that intermediaries face are important determinants of asset prices. However, prevailing theories of intermediary asset pricing face a challenge in explaining a striking feature of the data – there is substantial cross-sectional variation in the signs and magnitude of different basis trades, even within the same asset class. For example, looking at Covered-Interest Parity (CIP) bases in 1-year currency forwards versus the US Dollar, the average annualized basis for the Japanese Yen is -50 basis points (bps), while the basis for the Australian Dollar is $+6$ bps annualized, where negative signs correspond with more expensive USD legs.

In this paper, we use confidential supervisory data to study the cross-section of covered interest rate parity bases, with an eye towards better understanding the role of intermediaries in asset prices. We find that three forces are especially important for the cross-section of CIP bases. First, banks are only able to imperfectly execute CIP arbitrage due to a scarcity of foreign safe assets, and take risk in their CIP trades. This force indicates the relevance of frictions on the *asset side* of banks' balance sheets, whereas previous work emphasizes the *liability side* in the form of borrowing costs. Second, markets are segmented, with banks specializing in different currencies and bases reflecting their specializing banks' constraints. Because CIP trades are risky, segmentation is also important because it reduces the elasticity of bases with respect to demand by reducing risk sharing. Third, in certain markets, demand is concentrated from a few counterparties, with intermediaries requiring additional compensation for taking on concentrated demand. Our results provide a new perspective on CIP deviations that emphasizes the importance of safe asset scarcity, risk, and investor composition.

We organize our empirical investigation with a stylized model where intermediaries satisfy

[1] There are several types of basis trades beyond the covered-interest parity bases we study, including the equity index futures/cash basis (Hazelkorn et al., 2022), 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 (Bai and Collin-Dufresne, 2019), and the CDX/CDS basis (Boyarchenko et al., 2018c).

customers' demand for dollars in exchange for foreign currency by engaging in basis trades. Intermediaries face a number of frictions in executing basis trades. These include: a leverage constraint; heterogeneous search costs (it is costly to locate scarce foreign safe bonds); and counterparty limits (intermediaries seek diverse counterparties).

The model reveals how each of the constraints may contribute to cross-sectional differences in bases and helps motivate empirical tests. Leverage constraints drive a common component of bases across currencies. Search costs for scarce foreign safe bonds makes CIP arbitrage imperfect, and leads intermediaries to hold risky bonds in their trades. In turn, this leads to differences in bases across currencies based on the amount of synthetic dollar borrowing demand from those currencies. Heterogeneity in search costs leads intermediaries to specialize in the currencies for which they have the lowest search costs, and makes segmentation a driver of the elasticity of the basis due to impeded risk-sharing. Counterparty limits mean that the composition of demand also contributes to the inelasticity of bases. While frictions akin to leverage constraints have occupied much of the attention of the literature, we examine and present evidence that each of the other frictions are important.

With the model predictions in hand, we turn to testing them. Our main data source is the Federal Reserve's FR2052a *Complex Institution Liquidity Monitoring Report*, which provides granular, high-frequency data on the assets and liabilities of the largest banks in the US. The data cover more than $25 trillion of daily notional exposure on average. Our analysis proceeds in two steps. First, we show that banks lend the most dollars in the same markets where the basis indicates dollar funding is most expensive. We argue that this fact is consistent with the banking sector facing increasing marginal (shadow) costs to meet dollar demand from each currency. Second, guided by our model, we seek to understand how each of the aggregate and bank-specific constraints contribute to these increasing marginal costs.

Our first result is that foreign safe asset scarcity is an important driver of CIP bases. To do the CIP basis arbitrage, an intermediary must hold the equivalent of $1 of foreign safe asset for every $1 lent; otherwise, they would not earn the foreign risk-free rate. In practice, banks hold less than $0.05 per dollar lent. In a regression, we find that a one standard deviation difference in foreign safe asset scarcity corresponds with a 20 to 30 basis point larger basis. In addition to helping explain the cross-section of CIP bases, this inability to hedge with foreign safe assets also may contribute to the sharp increase in the magnitude of bases in the post-GFC period. The GFC and accompanying recessions combined to exacerbate the global shortage of safe assets (e.g., see Caballero et al. (2017)). The effect of this shortage on CIP bases is amplified by a post-GFC reduction in collateral velocity – the amount of re-use of the same safe collateral in multiple transactions (Jank et al. (2022)).

Our second result is that currency market segmentation contributes to CIP bases. We define a *market* as a tenor by currency pair, so the 1-month EURUSD, 1-year EURUSD, and 1-year JPYUSD are all distinct markets. For each market, we calculate Herfindahl-Hirschman Index (HHI), which reflects the degree of segmentation in that market. Differences in HHI across markets indicate that different banks specialize in different markets. We find a strong relationship between relatively more concentrated markets and larger basis dislocations – a one standard deviation more segmented market has a 15 to 20 bp larger basis. Interpreted alongside our safe asset scarcity result, the relationship between segmentation and the magnitude of bases highlights the importance of risk – and intermediaries' (in)ability to share it.

Segmentation can also be observed by the extent to which bank-specific constraints are reflected in bases. We use a natural experiment to test the relationship between bank-specific shocks and the basis. Following the banking system turmoil in March 2023, there was a notable shift of deposits toward the largest U.S. banks. We show that currency markets intermediated by banks with comparatively large deposit inflows during this period have smaller basis dislocations. The result is consistent with the model's prediction about supply segmentation, indicating that specializing banks' constraints transmit to the markets in which they specialize.

Our third result is that currency markets have concentrated demand, and that markets with a less diverse mix of counterparties have larger basis dislocations. That is, the composition of demand impacts bases, with more concentrated demand corresponding with larger bases, consistent with banks managing counterparty risk. We find that one standard deviation more concentrated market has a 7 bp larger basis.

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)), and on 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)). Prior work primarily focuses on post-GFC increases in bank borrowing costs that give rise to CIP deviations, 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 light on the asset side of intermediaries' basis trades and indicates that that scarcity of foreign safe assets means that intermediaries must resort to holding riskier securities in the foreign legs of their basis trades. This result is complementary to the findings of Diamond and Van Tassel (2021), who suggest that convenience yields on foreign safe assets may help explain CIP bases. Moreover, given the real costs of CIP deviations (Du and Huber (2023)), our results that safe asset scarcity helps drive CIP deviations also contribute to literature on the real effects of safe asset scarcity (e.g., Caballero (2006), Caballero et al. (2017), Caballero and Farhi (2018)).

Our paper is unique in its focus on intermediation frictions that give rise to cross-sectional variation in bases.[2] This focus leads us to conclude that intermediary heterogeneity (Kargar (2021)), and the accompanying segmentation of intermediaries into different markets are important drivers of bases. Using supervisory regulatory data, we provide direct evidence of the impact that segmentation has in transmitting idiosyncratic, bank-specific constraints into asset prices. Moreover, relative to previous work suggesting the presence of segmentation in basis arbitrage trading (e.g., Rime et al. (2022); Siriwardane et al. (2022); Kloks et al. (2023)), because we find that CIP arbitrage is risky, our results indicate that segmentation decreases the elasticity of bases with respect to demand by reducing intermediary risk sharing.

Lastly our work contributes to the literature that studies the effect of intermediaries on asset prices (Brunnermeier and Pedersen (2009), He and Krishnamurthy (2013), Adrian et al. (2014), He et al. (2017), and Du et al. (2023)). Our results illustrate the importance of intermediary heterogeneity and segmentation for understanding asset prices. Our results indicate that segmentation, as well as the composition of demand, help explain the elasticity of bases with respect to demand. In this regard, our results provide direction for understanding the source of inelastic financial markets (e.g., Gabaix and Koijen (2021) and work that builds on their approach), suggesting that the composition of investors may be important for understanding price elasticities.

[2] An ingredient required of our explanation 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 et al. (2023)). Similar heterogeneity in demand also exists in other markets, for example equity index futures markets (Hazelkorn et al. (2022)).

2 Model

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

2.1 Model Setup

There are N_k foreign currencies (against the USD), indexed by $k = \{1, \ldots, N_k\}$. 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 payoffs are realized in period 2.

The U.S. offers safe bonds in perfectly elastic supply, with payoff normalized to zero. Each foreign currency features three types of assets: one period currency forwards, safe bonds, risky bonds. All foreign bonds are also in perfectly elastic supply, with price normalized to zero. Currency forwards are in zero net supply, and their price is endogenously determined as P_k^f, which also corresponds with the basis.

Customer Demand for Currency Forwards. 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 $\text{sign}(X_k) = \text{sign}(X_{c,k}), \forall c, k$.

Foreign Bonds and Safe Asset Scarcity. Risky bonds across countries are mutually uncorrelated and have payoff variance of σ^2. Safe bonds are in fixed supply. There is a sufficient supply of safe bonds to hedge all currency trades, but each intermediary i faces a search cost of $\frac{1}{2}\lambda_{s,i,k} s_{i,k}^2$ to locate safe bonds in currency k, where $s_{i,k}$ is the safe bond position of intermediary i in currency k and $\lambda_{s,i,k}$ is a coefficient that captures how quickly intermediary i's search costs increase with the demand they face. That is, safe bonds in currency k become increasingly difficult to locate as demand for them increases, with intermediaries facing heterogeneous search costs.

Intermediary Hedging and Safe Asset Choice. Financial intermediaries each maximize a quadratic utility function, $U_i = \mathbb{E}(W_{i,2}) - \frac{\gamma}{2}\mathbb{V}(W_{i,2})$, 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 is a coefficient of risk-aversion. 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 risk exposure in 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, all intermediaries allocate a proportion $\alpha_{i,k} \equiv \frac{\lambda_{s,i,k}}{\gamma\sigma^2+\lambda_{s,i,k}}$ to risky bonds and allocate the remainder of their hedge positions to the safe bond.

Each intermediary also faces a set of constraints that we detail below.[3]

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

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

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 (e.g., 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. We

[3]Conceptually, our results only depend on the fact that constraints are (weakly) convex. For example, explicit counterparty limits are convex constraints that would yield the same qualitative predictions as the quadratic counterparty costs that we assume.

express counterparty constraints as costs of the form:

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

2.2 Model Predictions

We can write financial intermediary i's problem as

$$\begin{aligned}
\max_{Z_{i,k},\alpha\forall k} & \sum_k \text{Basis}_k Z_{i,k} \\
& -\frac{\gamma}{2}(\alpha_{i,k}Z_{i,k})^2\sigma^2 && \text{(Risk)} \\
& -\frac{1}{2}\lambda_{s,i,k}\left((1-\alpha_{i,k})Z_{i,k}\right)^2 && \text{(Collateral Scarcity)} \\
& -\frac{1}{2}\lambda_{BS}\times \text{sign}(X_k)\left(\sum_{k'}|Z_{i,k'}|\right)^2 && \text{(Balance Sheet Costs)} \\
& -\frac{1}{2}\lambda_{CP}\times \text{sign}(X_k)\sum_c\left(\sum_{k'}|Z_{i,k',c}|\right)^2. && \text{(Counterparty Costs)}
\end{aligned}$$

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

$$\begin{aligned}
\text{Basis}_k = & \\
& \gamma\frac{1}{N_i}\sum_i \alpha_{i,k}^2\sigma^2 X_k && \text{(Risk)} \\
& +\frac{1}{N_i}\sum_i \lambda_{s,i,k}(1-\alpha_{i,k})^2 X_k && \text{(Collateral Scarcity)} \\
& +\frac{1}{N_i}\lambda_{BS}\times \text{Sign}(X_k)\sum_{k'}|X_{k'}| && \text{(Balance Sheet Cost)} \\
& +\frac{1}{N_i}\lambda_{CP}\times \text{Sign}(X_k)\left(\underbrace{|X_k|\sum_c\frac{X_{c,k}^2}{X_k^2}}_{\text{Demand Concentration in }k} + \underbrace{\sum_c\frac{X_{c,k}}{X_k}\sum_{k'\neq k}|X_{c,k'}|}_{\text{Importance of }c\text{ in other trades}}\right)
\end{aligned}$$

The basis, expressed from investors' first order conditions immediately yields a a number of empirical predictions.

Prediction 1 (Sign of the Basis)**.** *The sign 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}).

Prediction 3 (Collateral Scarcity)**.** *The magnitude of the basis for currency k is increasing in synthetic demand to borrow dollars from currency k.*

Prediction 3 is a novel, cross-sectional prediction that arises from the risk and collateral scarcity terms in the basis. The basis embeds the search cost that intermediaries pay to locate foreign safe bonds. The marginal search cost (and distaste for risk) is increasing in the amount of demand banks must intermediate. Hence, the basis in a market increases in the amount of demand that intermediaries face in the market.

Prediction 4 (Supply Segmentation and Size of the Basis)**.** *The basis for currency k is larger in magnitude when intermediary supply for currency k is more segmented.*

Prediction 4 arises from heterogeneous search costs for different intermediaries, and we derive it in the appendix. It is a distinctive prediction from other work on bases that suggests that funding markets may be segmented (e.g., Rime et al. (2022); Siriwardane et al. (2022)) and arises in our setting because CIP arbitrage is imperfect, and intermediaries take risk in their positions. Heterogeneous search costs, and the accompanying segmentation, impede the risk-sharing that intermediaries would do in their absence. In segmented markets where

[4] In principle, this is basically the total leverage of the financial system.

intermediaries are less able to share risk, they demand larger compensation for meeting customer forward demand.[5]

While we do not micro-found the potential sources of heterogeneous search costs in our stylized model, we discuss these sources in our empirical analysis. We document that the intermediaries that hold large market shares in a particular currency market also, for example, tend to hold larger loan portfolios in that market. The evidence indicates that lower search costs may be driven by greater familiarity with a given market, and a more easily accessible set of counterparties.[6]

Prediction 5 (Demand Concentration)**.** *The magnitude of the basis for currency k is increasing in the concentration of demand to swap foreign currency for dollars across counterparties c.*

Prediction 5 reflects the fact that intermediaries are sensitive when demand is concentrated from a particular counterparties and demand larger compensation for concentrated demand.

With our empirical predictions in hand, we next turn to discussing our data sources and our empirical analysis.

3 Data

We collect information on bank-specific FX positions from the FR 2052a *Complex Institution Liquidity Monitoring Report*, and we 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.[7] The data are confidential and not publicly available. The

[5]Segmentation may also be associated with market power, and correspondingly larger bases, as argued by Wallen (2022) in the context of CIP. While we cannot eliminate the potential contribution of the market power channel, we present empirical evidence consistent with the importance of our proposed channel.

[6]A similar idea is present in Bryzgalova et al. (2023), who show that intermediaries tend specialize in options markets that are their 'natural markets,' where they face lower fixed costs of entry due to economies of scale or related business areas.

[7]See `https://www.federalreserve.gov/supervisionreg/reglisting.htm`.

data provide information by asset class, outstanding balance, and purpose, each reported by maturity and date.[8] The data cover Global Systemically Important Banks (G-SIBs) and foreign banking organizations with more than $100 billion in assets at their U.S. broker-dealer. U.S. firms with at least $700 billion in assets or $10 trillion in assets under custody and certain foreign banking organizations must file the report each business day. Smaller banks report data monthly.[9] Banks have a strong incentive to report data fully and truthfully given the several consequences for making misrepresentations to government authorities, which may result in enforcement actions in some cases. Moreover, misreporting would likely be identified and corrected quickly given the high level of scrutiny these banks are subject to, unlike other public companies. Researchers have recently begun using this dataset to study bank behavior: for example, Infante and Saravay (2020), Cooperman et al. (2023), and—most related to our focus—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 and spans both OTC and centrally cleared transactions. Roughly 80 percent of the gross notional positions in our sample are settled bilaterally, while the rest is centrally cleared. Firms report FX transactions using 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 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.

The sample averages about $25 trillion in gross notional each day across foreign exchange swaps and forwards. This sample reflects only the subset of the data that has transactions in the seven other currencies against the dollar. 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) estimated 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

[8]See the FR 2052a instructions for additional details: `https://www.federalreserve.gov/apps/reportforms/reportdetail.aspx?sOoYJ+5BzDbpqbklRe3/1zdGfyNn/SeV`.

[9]See `https://www.federalreserve.gov/supervisionreg/large-institution-supervision.htm`.

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

($1 trillion). Generally speaking, the tenors with the largest notional amounts are at the weekly increments—7, 14, 21, 28 days—and steadily grow in total beyond beginning with 6 month tenors. We limit our sample to maturities with fewer than 5 years maturity, since the five year bucket contains all maturities at five years and beyond.

We also collect data on banks' safe assets. We focus on unencumbered assets (assets which 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 that are 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 assets that are level 1 high-quality liquid assets. HQLAs are the securities that are broadly considered the closest proxy for risk-free securities, so long as they are held to maturity.[11] While the data do not provide the CUSIPs of the assets banks hold, the data provides collateral categories. We also include a broader set of assets beyond just level 1 HQLA in some instances, which we describe later.

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 curve from 1 week to 5 years, which is the longest maturity bucket reported in the FR 2052a. We provide details on cleaning the OIS interest rates in the online appendix.[12] We calculate CIP violations following Du et al. (2018). Define s_t as 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. Then 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

[11]The rapid increase in interest rates in 2022 and 2023, for example, caused mark-to-market losses on long maturity U.S. Treasuries, which are themselves HQLAs.

[12]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 5 years and greater, so its average maturity is likely much more than 5 years.

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 and earning $y^{\$}_{t,t+n}$ and exchanging their USD for foreign currency, investing 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 also provide the average and standard deviation of the 1-year CIP bases in Table 2. The basis averages −24bps across all currencies, although it 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 (the period of our bank data sample).

We merge the Bloomberg basis panel with the FR 2052a panel using the days to maturity. For contracts with at least a month maturity, we merge the panels by focusing on the commonly reported days in the FR 2052a data.[13]

Table 1 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 6 months, while swaps are larger at six months and beyond. 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 begin by showing and discussing cross-sectional variation in currency's bases. After constructing a measure of dollar lending from different currencies, we show that banks lend the most dollars in the currency and maturity markets that exhibit the largest CIP deviations. We interpret this result (as in our model) as indicating that banks face increasing marginal

[13]Specifically, 1m is 28 days; 2m is 61 days; 3m is 83 days if the days to maturity is between 83 and 90, inclusive, and 91 days if the days to maturity is 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.

costs to meet currency- and maturity-specific demand for dollar borrowing.

We then use our model to guide us in decomposing these marginal costs to understand the role of safe asset scarcity, market segmentation, and counterparty concentration. Finally, we provide additional evidence on the impact of segmentation through an event-study methodology surrounding the March 2023 turmoil to show how shocks trace through net dollar lending and its effect on the bases.

4.1 Cross-sectional Heterogeneity 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 in a non-obvious pattern outside the financial crisis and Covid panic. Although an aggregate intermediary leverage constraint is important, the fact that we observe bases with different magnitudes and signs is *prima facie* evidence that forces beyond an aggregate intermediary constraint are major drivers of the basis cross-section.

We turn to our model predictions to help explore these other drivers. Prediction 1 notes that the sign of demand for dollars from a currency determines the sign of the basis. This prediction is supported by the summary statistics in Table 2. 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: AUD and CAD have the least dollar demand and JPY the most. That different foreign economies have different demand for dollars, 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, will have different demand for dollars than countries without similar commodity-related dollar inflows.[14]

Prediction 2 is that the magnitude of the basis—in absolute value—is decreasing in the banking system's balance sheet capacity across all basis trades. The magnitude of the basis reflects dislocations that prevent the banking system from pushing the basis back toward zero—from either a positive or negative direction. Such a prediction is consistent with work that studies the important role the aggregate intermediary sector plays in basis dynamics,

[14] 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.

for example Du et al. (2023).

In principle, Predictions 1 and 2 could explain all the variation in bases. We calculate the first principal component of the bases which we use to proxy for an intermediary-wide factor. In Figure 4 we show the variance across the bases in a given tenor that can be explained by the first principal component. The figure shows that the common comovement across all the bases is important but leaves variation to be explained. For the 1-week tenor shown in the first column, the principal component can explain 75 percent of the variation in the bases. The principal component explains less variation for longer maturities, falling to roughly 60 at tenors of 1-year and beyond. The figure shows that Predictions 1 and 2 together cannot explain at least one-third of the variation, on average, across the tenors. The remaining predictions try to understand the unexplained variation.

4.2 Net Dollar Lending

Our remaining predictions each depend upon the dollar lending behavior of different intermediaries across different currencies. Accordingly, we begin by constructing a measure of net dollar lending for each market. We discuss the construction and details of the variable below.

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 ccy via FX swaps using:

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

Table 3 provides a simple example to illustrate the logic underpinning $Net^{ccy}_{t,t+n}$ construction. Suppose the 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: $2.6\% = 5/195 = 5.23/204$.

Notice that the net variable is the same regardless of if it's based on the near or far leg flows.

When $Net_{t,t+n}^{ccy} > 0$, the bank lends out more dollars today than it borrows against currency ccy with maturity $t + n$. This is because the bank will receive more dollars in at maturity on $t + n$ than it pays out. We divide by the notional dollar flows because some markets are larger than others. Although such net lending is possible through swaps and a combination of spot transaction with forwards, we calculate net using only swaps since there is no upfront exchange of principal for forwards and futures, and we cannot necessarily connect forward transactions with spot transactions constituting basis trades.

We can calculate two flavors of our net lending measure by aggregating across different levels. $Net_{t,t+n}^{ccy}$is our primary measure, and it reflects the entire intermediary sector because it aggregates lending across all banks at the date × maturity × currency level. We also calculate $Net_{t,t+n}^{ccy,i}$, which is bank specific—the difference is the i superscript. It aggregates at the date × maturity × currency × bank level. Since banks only report non-zero values, we set $Net_{t,t+n}^{ccy} = 0$ when there is no lending or borrowing data for a given observation.

4.2.2 $Net_{t,t+n}^{ccy}$Summary Statistics

As an example, we plot the net variable for 1-week, 6-month, and 1-year EUR in Figure 5. At the 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 approached \$800 billion in 2023. The regular spikes in the shorter maturities reflect window dressing. However, since dollars in and dollars out both tend to increase during periods of window dressing, the $Net_{t,t+n}^{ccy}$variable exhibits no visually obvious window-dressing.

Figure 6 shows a histogram of $Net_{t,t+n}^{ccy}$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 $Net_{t,t+n}^{ccy}$to be near zero or tightly bounded around zero, rather than large long or short positions.

Table 4 gives the average and standard deviation of $Net^{ccy}_{t,t+n}$by currency and tenor.[15] With few exceptions, $Net^{ccy}_{t,t+n}$is small and near zero, indicating that the intermediary sector broadly matches its dollars in and dollars out. The table highlights three facts: first, the intermediary sector tends to borrow at shorter tenors and lend at longer tenors, with the average flipping from negative to positive 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 3.7 percent) and lend EUR (1.0 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 about 30 percent compared to less than 10 percent for maturities at least 6 months.

Appendix Table A3 shows $Net^{ccy}_{t,t+n}$'s correlations with several variables, and shows generally intuitive correlations with a number of variables. $Net^{ccy}_{t,t+n}$is increasing in maturity, size, and an analogous measure of net lending provided using the coarser data from the Traders in Financial Futures Report from the Commodity Futures Trading Commission (CFTC), as used in Hazelkorn et al. (2022). It is lower at quarter- and month-ends. Our measure is also positively related to the market's convenience yield—estimated using a Nelson-Siegel-Svensson yield curve model. Finally, $Net^{ccy}_{t,t+n}$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 $Net^{ccy}_{t,t+n}$and the SPX return.

4.3 $Net^{ccy}_{t,t+n}$vs. Bases

With the $Net^{ccy}_{t,t+n}$variable in hand, we next show how cross-sectional variation in $Net^{ccy}_{t,t+n}$captures cross-sectional variation in bases. This is a matter of understanding whether banks lend more where there are dollar shortages. We run the regression

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

where a negative basis indicates dollar shortage, and X_t is a vector of controls. Our model predicts that $\beta < 0$ – bases are the most negative in the markets with the most dollar demand. This arises from the increasing marginal (shadow) costs that intermediaries face to provide

[15] Appendix Table A2 shows the level of $Net^{ccy}_{t,t+n}$in billions of dollars.

additional dollar funding in different markets.[16] The alternative – $\beta > 0$ would mean that banks are lending USD exactly in the markets where there is the least USD shortage. This would coincide with opportunistic lending behavior by banks to profit from CIP deviations.

Table 5 shows the regression results. $\beta < 0$ across specifications with different controls. The first row shows a robust negative relationship between bases and $Net^{ccy}_{t,t+n}$ after including tenor and time fixed effects and weighting by the square root of the market's share of the total daily gross notional. Column (4) is the benchmark estimate which includes the full set of fixed effects and weights by notional share. The coefficient shows that when $Net^{ccy}_{t,t+n}$ is 1 percentage point (pp) larger then the basis is 0.4bps smaller. A one-standard deviation change in $Net^{ccy}_{t,t+n}$weighted by its daily notional share is about 10pp, corresponding to a basis that is 4.1bps lower using column 4's coefficient. Columns (5) and (6) split the sample into short- and long-term tenors, with a threshold of 1 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 $Net^{ccy}_{t,t+n}$for these longer tenors corresponds to a basis that is 9bps lower (5.9×-1.5).

In the online appendix, we provide additional results on the relationship between bases and lending. We show this two ways: first, Figure A1 scatterplots the average basis against the average $Net^{ccy}_{t,t+n}$ for a given currency and tenor, and Figure A2 shows the average basis and $Net^{ccy}_{t,t+n}$for each currency at several tenors. Second, we show the regression coefficients in Figure A3. The regression coefficient on $Net^{ccy}_{t,t+n}$ is near zero for maturities less than 3 months but is significant and negative for all longer maturities.

The cross-sectional relationship between $Net^{ccy}_{t,t+n}$and bases is consistent with the interpretation provided by our model – that cross-sectional variation in bases is driven by intermediaries facing (shadow) costs that increase with dollar funding demand from a particular currency. The remaining predictions of our model are based on decomposing the importance of different constraints in contributing to these costs.

[16] $\beta < 0$ is assumed in a number of other papers, for example, Greenwood et al. (2023) and Liao and Zhang (2020). An analogous result is also shown to be the case in equity index futures markets by Hazelkorn et al. (2022).

4.4 Sources of Increasing Marginal Costs

We identify three potential sources of costs that bind either at the market level or at the bank level: foreign safe asset shortages, dollar supply concentration, and dollar demand concentration. We construct proxies for each these measures, which we use together in a regression to jointly test their ability to explain the cross-section of bases.

4.4.1 Foreign Safe Asset Scarcity

A CIP arbitrage requires \$1 of foreign safe asset for every net dollar lent. The trade is not a risk-free arbitrage if the arbitrageur cannot find a perfectly maturity-matched security, denominated in that foreign currency, that pays the risk-free rate. Recent work has shown there is likely a scarcity of safe assets, often compelling agents to produce private substitutes (Sunderam (2015), Caballero et al. (2017), Aggarwal et al. (2021), Kacperczyk et al. (2021), Jank et al. (2022)). We find that CIP arbitrageurs also suffer from a scarcity of safe assets, so their CIP trades are not risk-free—they involve nontrivial risk.

We first define the set of securities that could be safe assets. Our primary measure of foreign safe asset collateral is the sum of level 1 HQLAs that are unencumbered assets, unsettled asset purchases, and assets that are pledged to the central bank. [17] 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

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

If Safe Asset $\text{Ratio}_{t,t+n}^{ccy} = 1$, then every dollar of net dollar lending for currency ccy on date t with maturity $t+n$ is perfectly matched to a dollar of foreign safe asset in the same currency and the same tenor. Such perfect matching is required by the definition of the CIP arbitrage.

[17] We include a full list of level 1 HQLA securities in the online appendix section A.2. Sovereign bonds constitute the majority of these securities.

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

We also calculate a broader definition

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

where Broad Asset Ratio$^{ccy}_{t,t+n}$ covers assets beyond HQLAs in the three categories listed above. It includes all assets denominated in ccy with maturity $t+n$ that are unencumbered assets, unsettled asset purchases, capacity, central bank deposits, reverse repurchases, or securities borrowings. For example, a German government bond would be in both coverage measures, but a German corporate bond would only show up the broader coverage measure since it is not a level 1 HQLA. Beginning in 2022, the data begins coverage of encumbered assets, and we treat this subsample separately as a point of comparison given the large value of the banking system's encumbered assets. 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 to be short one of these securities, their net long measure would be lower.[19]

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

The first two columns of Table 6 show the median safe asset ratio across currencies ranges from \$0.00 (CHF) to \$0.16 (EUR), and averaging across the currencies is \$0.06. For every \$1 of foreign currency received by net dollar lending trades, banks only hold \$0.06 of unencumbered foreign safe assets with a matched maturity. Including encumbered assets in the safe asset ratio increases the number on average—now ranging from \$0.00 (CHF) to \$0.19 (EUR)—but the ratio is well below one for each currency and averages \$0.07. Even for our

[19]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. As a 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 effects of any double counting are tiny.

broadest measures—broad assets including both unencumbered and encumbered assets—the ratios only are uniformly well below 1, ranging between 0.02 (CHF) and 0.80 (EUR), with an average of 0.32. The bottom of the table also shows the corresponding measures for instances in which the banks are net borrowing dollars—which means they need to hold USD-denominated safe assets. This number is consistently much higher than 1, ranging from 2 to 25, consistent with our prediction that U.S.-based G-SIBs hold substantially more dollar-denominated safe assets since they use these securities for much more than to cover interest rate trades.

Banks have higher ratios at longer maturities, though generally still below one. Figure 7 breaks out the median ratio by currency and tenor for unencumbered safe and broad assets.[20] Only in one case—4-year EUR—is the ratio greater than one. This is partly expected: the width of the maturity buckets are larger for the longer maturities, so the measurement error is higher for longer maturities because we require the trade to be perfectly matched.[21]

Little of the CIP trades are arbitrages since banks must hold something other than the matching foreign safe asset. Prediction 3 predicts just that: given a scarce foreign safe asset supply, each dollar of lending exhausts that foreign safe asset until, at last, it becomes too costly to search for additional safe assets, and the bank must place that foreign currency somewhere else.

Where could they place it? One way banks could invest the foreign currency is at shorter tenors—like central bank deposit facilities, money markets, or reverse repos. Such a trade is no longer an arbitrage: the bank is now exposed to rollover risk should interest rates on their short-maturity investments change during the duration of the dollar loan. While we include repos and central bank deposits in our measure of safe assets, their contribution to the ratios is small since most of these transactions occur at very short tenors, like overnight. Hence, they would not match to even our shortest CIP trade of 1 week.

Safe asset ratios increase somewhat if we loosen our arbitrage definition by no longer requiring matched lending and safe asset maturities, as shown in the right half of Table 6.

[20] Figure A4 is the plot of the ratios when including encumbered assets but is limited to the shorter time frame.

[21] Suppose the bank lends dollars in a 14 day swap, receives JPY, and buys a 12 day JGB. This is not an arbitrage, and we can perfectly measure whether or not the bank has matched its swap with its foreign risk-free rate investment since the maturity buckets are daily up to 60 days. If the bank has a 400 day swap and invests in a 365 day bond, our methodology would incorrectly infer that the trade is covered since data beyond 1 year is reported at yearly buckets. Therefore, our ratios are biased to be higher for longer tenors.

We relax the requirement 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.[22] 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. There are advantages and disadvantages to this rounding: Whereas in the previous results we looked at the specific slices of net lending and safe assets that corresponded to the same tenors as our market-based measures of CIP violations, the rounding approach is no longer limited to those specific slices and instead captures volumes across all maturities. However, by rounding we are relaxing the definition of the arbitrage, allowing for maturity mismatch. For example, if a bank lends USD on a 1 week basis against JPY and invest its JPY in overnight markets, the bank is not trading an arbitrage because it is exposed to interest-rate risk and would stand to lose if interest rates changed over the week.

With the relaxed maturity matching, the average median safe asset ratio increases to 0.17 and 0.48p, with the latter estimate including encumbered assets. The average median broad asset ratio increases to 0.59 and 1.77, again the latter including encumbered assets. A quick scan of the mean rows within a currency—e.g., the mean unencumbered safe asset ratio for GBP is 3.10—indicates that banks hold substantially more safe assets denominated in AUD with roughly the correct maturity as their USD lending for some tenors. This much is clear in Figure 8 where we plot the rounded safe asset ratios by tenor and currency. In particular, the ratios tend to be very high at the 1w ratio—reflecting large short-term money-market lending, often overnight—and tapers off beyond that.

Figure 9 summarizes our estimates of safe and broad asset ratios. Three facts stand out: banks do not cover their net USD lending with foreign safe assets, they hold only \$0.06 of unencumbered foreign risk-free assets per dollar lent. They hold an incremental \$0.11 of unencumbered foreign safe asset with imperfect but roughly similar maturities. And they hold an incremental \$0.42 in riskier assets. As robustness, we also calculate 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 a FX

[22]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).

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.[23]

If they hold only \$0.06 in foreign safe assets per dollar lent, where does the rest of it go? Some of it goes to imperfectly-tenor matched foreign safe assets, and the rest of likely goes to riskier assets, much of which is encumbered. When a bank cannot perfectly match its FX lending, it ends up exposed to interest rate risk (because of imperfect matching), credit risk (because some of it is not held in safe assets), and counterparty risk (because much of their assets are encumbered).

The ratio estimates in Table 6 and Figure 7 are likely an upper bound on the ratios, not just because they include gross long positions. Banks have several reasons to hold foreign assets, most unrelated to CIP trades. We capture these other motives in a simple regression framework by regressing the banking system's level of foreign safe asset on the level of net lending:

$$Asset\ (Level)^{ccy}_{t,t+n} = \alpha + \beta Net^{ccy}_{t,t+n}(Level) + \gamma_i + \varepsilon^{ccy}_{t,t+n}$$

where γ_i is a currency fixed effect. In Table 7, we show the regression separately for when $Net^{ccy}_{t,t+n} > 0$ (columns 1 and 3) and when $Net^{ccy}_{t,t+n} < 0$ (columns 2 and 4), meaning the banks are borrowing dollars and lending foreign currency. When $Net^{ccy}_{t,t+n} < 0$, banks need to hold USD-denominated safe assets. CHF does not appear in the table because we set it as the base level of the currency fixed effects.

The sum of the regression's constant and the currency fixed effect indicates the dollar amount of foreign safe asset held when $Net^{ccy}_{t,t+n} = 0$, a proxy for the amount of safe assets the banks hold for reasons unrelated to CIP trades. Column 1 shows that banks hold an average of \$2.0 billion of unencumbered EUR-denominated safe assets across the tenors or \$4.0 billion including encumbered securities (column 5).

The main result is shown in the first row of the table: net lending higher by \$1 is associated with an increase of 2 cents (column 1) in unencumbered safe assets or 18 cents (column 3) when including encumbered safe assets. The regression shows that banks increase their unencumbered safe assets by a much smaller amount than suggested by the simple ratios

[23]We provide a table of these robustness ratios in Figure A4.

discussed earlier. In the bottom panel of the table, we repeat the regressions using the broad asset ratios. Columns 1 and 3 of Panel B show that banks increase their broad asset holdings by 19 cents in unencumbered assets and 30 cents of both encumbered and unencumbered.

The table also shows the coefficient when banks are borrowing dollars and $Net^{ccy}_{t,t+n} < 0$. In this case, banks hold more than \$1 of dollar denominated safe assets—\$1.3 of encumbered and \$2.3 of encumbered and unencumbered—likely indicating that at times when banks are borrowing dollars in one market, they are also borrowing in several others at the same time.

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-GFC increase in the magnitude of bases as well. Unfortunately, systematic data on collateral re-use are not readily available before the GFC. However, Gorton et al. (2020) use data the 10Qs of six broker-dealers and banks to show that collateral pledged halved between 2007 and 2009, amounting to a decline of more than \$2.5 trillion. The availability of foreign safe assets has also decreased following the GFC (e.g., see Caballero et al. (2017)). In addition to the reduction in the number of safe assets, there has also been 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% reduction in collateral re-use of European sovereign bonds from 2008 to 2017. As Inhoffen and van Lelyveld (2023) discuss and provide evidence for, this reduction in collateral velocity is likely linked to increased balance sheet costs in the post-GFC era, due to the balance sheet intensive nature of repos.

4.4.2 Supply Concentration

Prediction 4 shows that the basis for a given currency is more inelastic when banks' supply for that currency is more concentrated. If banks specialize in specific markets, then shocks to those specialists will affect *their* markets. We document that banks do specialize in certain markets and show that shocks to those banks have disproportionate effects on their markets.

Without frictions or market segmentation, banks' net exposures across tenors and currencies should be the same, although banks with larger foreign exchange books will hold proportionally more. In this case, banks face identical marginal costs to lend dollars in each market and have highly correlated net lending. But, if markets are segmented, a bank that lends increasing amounts in its own markets faces increasing marginal costs, pushing the basis increasingly negative—consistent with Prediction 4.

We empirically estimate dollar supply concentration by calculating an HHI of individual bank's notional exposure in each market using

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

where

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

Our HHI is not directly comparable with other HHI estimates: our sample is limited to the set of banks reporting data. Suppose there are 9 banks with data. Then the lowest possible HHI value is $9 \times [(1/9) \times 100]^2 \approx 1,111$. Typically, an HHI could approach lower values with low market concentration across more firms. The highest possible HHI remains the same.

Figure 10 plots the average measure by market against that market's size. Lower HHI values indicate more competition and less concentration. Larger markets are clearly less concentrated. Short-term contracts for CAD and AUD are very concentrated, and CHF is clearly the most segmented. The least concentrated markets are JPY and EUR at longer tenors, especially at 1 year.[24]

Why FX markets are segmented is an important question, and we provide suggestive evidence that shows banks specialize in certain markets. Markets that have higher supply segmentation rely on banks with larger FX books. Table 8 column 1 regresses 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. There is a strong relationship, indicating that more segmented markets rely on larger intermediaries.[25]

Segmentation is persistent. We show this two ways in Table 8. First, we show that markets that are more segmented remain segmented over time. We regress a market's supply HHI on its 1-month, 1-year, and 5-year lags. The coefficients are highly significantly related.

[24] We estimate similar supply HHI's looking just across tenors and currencies in the online appendix, see Figures A5 and A5.

[25] Figure A7 in the online appendix provides a scatterplot of these two variables in the online appendix.

The results are shown in the first four columns. 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 over time. We regress bank i's market share on lags of its market share. We calculate a bank's market share 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 different from zero, ranging from 0.87 at a 1-month lag to 0.74 at a 5-year lag.

Banks specialize not just in certain 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 show this by calculating 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 Bank FX Share$^{i,ccy}_{t,ctpty}$ where i denotes the bank and $ctpty$ denotes the counterparty. 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 Share$^{z,AUD}_{t,insurance} = 10\%$. We exclude bank counterparties since they are the largest counterparty by an order of magnitude in most markets and recall that FX counterparty data is available beginning in May 2022.

We calculate two related measures: first, we calculate the average market share of all banks except bank i, which we call Other Bank FX Share$^{i,ccy}_{t,ctpty}$. Second, we estimate a bank's Bank Loan Share$^{i,ccy}_{t,ctpty}$ 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.[26]

Table 9 shows how banks specialize in certain counterparty-currency markets. The first column shows that bank's specialization in counterparty-currency markets is persistent over time as the lag of Bank FX Share$^{i,ccy}_{t,ctpty}$ strongly predicts its current values. One possibility is

[26]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.

that all banks uniformly service the same set of counterparty-currency markets. Column two adds a variable, Other Bank FX $\text{Share}^{i,ccy}_{t,ctpty}$, and rejects this possibility since the coefficient on the other bank variable is not different from 0. Column three shows that banks specialize in currency currencies and counterparty across their lines of business. It regresses the bank FX share on Bank Loan $\text{Share}^{i,ccy}_{t,ctpty}$ and finds a strong positive relationship. Adding controls for other banks' loan shares (column 4) does not change the result. Column 5 adds Other Bank FX $\text{Share}^{i,ccy}_{t,ctpty}$ 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 own 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.

4.4.3 Demand Concentration

Demand concentration also affects the basis. Prediction 5 shows that the basis is increasing in the concentration of demand. A bank can manage its counterparty risk by lending to a wide set of counterparties in a given market. Lending is riskier when the bank trades with a small set of counterparties, because the bank's counterparty risk grows.

We empirically proxy for demand segmentation with another HHI, this time measuring the concentration of counterparties in a given market. The data does not provide firm-specific counterparty names, but it does provide about 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 assuming that firms within a category have highly correlated risks. Such an assumption is plausible: lending to exclusively levered funds is riskier than lending to a mix of levered funds and non-financial corporates given the two lines of business are exposed to different risks.

The demand HHI is calculated similarly to the supply HHI:

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

[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.

where

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

Figure 11 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 are among the most demand concentrated. The range of demand HHIs are much higher, partly reflecting banks' large share as counterparties to one another.

Since counterparty data is only available beginning in May 2022, we estimate the full sample demand concentration using two different items available during the full sample: loan counterparties and settlement types. The data for unsecured and secured loans includes counterparties, and we calculate loan demand concentration measure analogous to the previous method for the main demand HHI measure.

Banks also report what type of settlement their FX transaction use: bilateral, continuous linked settlement (CLS), or other. CLS transactions are settled payment-versus-payment to reduce Herstatt risk and cover roughly 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. For each market, we calculate that day's share of bilateral transactions compared to the total transactions in that market. The bilateral share is a rough measure for the relative importance of investors like hedge funds in a given market.

We estimate Demand $\text{HHI}^{ccy}_{t,t+n}$ for the full sample with

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

We show the estimated coefficients in the online appendix, Table A1. We then use the regression coefficients to estimate $\widehat{\text{Demand HHI}}^{ccy}_{t,t+n}$ 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—likely have considerably more error 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 now test the sources of marginal costs we have identified: collateral scarcity, supply concentration, and demand concentration. We run the following regression:

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

The dependent variable is the absolute value of the basis for a given market on a given day. A larger dislocation, either a shortage or a glut of dollars, will increase the absolute value of the basis. We use the absolute value of the basis because we expected larger frictions from any of our sources of marginal costs to push the basis away from zero. Moreover, we expect that a scarcity of safe assets denominated in the covering currency (e.g., the currency the investor borrows for the duration of the trade) will be the key friction, which changes from a foreign currency to USD when $Net^{ccy}_{t,t+n}$switches from positive to negative. Since we expect there may be differences in the frictions when the bank is net lending dollars or net borrowing dollars, we include dummies to capture this asymmetry. In particular, since the banks are U.S. banks, we expect foreign collateral scarcity to behave differently than USD collateral scarcity.

We include controls for the risk of a safe asset sovereign issuer, which we proxy 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 $Net^{ccy}_{t,t+n} \geq 0$ and the U.S spread when $Net^{ccy}_{t,t+n} < 0$. [29] We include tenor and date fixed effects, and we weight 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 Italy 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

square root of the market's share of the total daily gross notional. To make the coefficients directly comparable, we transform the marginal cost independent variables to modified z-scores using each variable's full sample median and standard deviation. We use the sample median rather than mean to control for the high skewness of the data.

Table 12 shows the main results from the regression, which is limited to the period from May 2022 to March 2023 by the demand concentration variable. The first two columns include encumbered asset ratios, and the last two columns include both unencumbered and encumbered asset ratios.

The first two rows show that supply concentration is an important friction and roughly symmetric across markets in which there are dollar gluts and dollar shortages. A one standard deviation increase in the supply HHI increases the absolute value of the basis by 25bps. Such a result is consistent with our expectation that markets relying on a more concentrated set of banks will have larger dislocation.

The next two rows show that demand concentration is not different from zero. It is not surprising the that these coefficients have larger standard errors given the supply concentration is measured perfectly—we observe the institution-specific universe of banks' transaction—but we only view the coarse counterparty type as an input to the demand HHI.

The next several rows include measures of collateral scarcity. The first column includes the unencumbered safe asset ratio: the coefficient is negative, large, and significant. A one standard deviation increase in the safe asset ratio pushes the basis toward zero by 35bps for markets with dollar shortages. In the next column we replace the safe asset ratio with the broad asset ratio, which includes both safe and risky assets. A one standard deviation increase in the broad asset ratio moves the basis towards zero by 54bps. Unencumbered safe assets are more efficient at reducing dislocations, which is clear by comparing the coefficients on the collateral scarcity rows.

The regression shows that both foreign safe asset scarcity and supply concentration are important sources of marginal costs that help describe the cross-section of bases, and foreign safe asset scarcity has the largest relationship. Its effect is 37 percent larger than the supply concentration effect, all else equal.

Table 11 repeats the same regression using the estimated value of demand concentration

value-weighting the individual bank's CDS spreads with quotes provided by Markit on that day based on their gross position in a given market as a share of the total gross positions in that market.

in order to expand the sample to January 2016 to March 2023. There is no encumbered asset data for this longer period, so the asset ratios cover only unencumbered assets.

The first two columns exclude demand concentration, and the results are similar to the last table. Supply concentration is a significant driver of basis deviations, and the effect is mostly symmetric for markets with dollar gluts and shortages. Foreign safe asset scarcity is important only in markets with dollar shortages. In this longer sample, the estimated coefficient on foreign safe asset scarcity is smaller at -16.

The last two columns include our estimate of demand concentration using loan and bilateral share data, and the results are consistent with the first two columns. The demand measure is significant and positive in this longer sample. The coefficient for demand concentration indicates that a one standard deviation increase in demand HHI increases the basis dislocation by 8.5bps for markets with dollar shortages. Although the demand concentration variables are measured with considerably more error than the other variables, the regression suggests that demand concentration plays a role in exacerbating basis dislocations. Columns 3 and 4 show that safe asset scarcity has the largest effect on the basis, followed by supply concentration, and demand concentration has the smallest effect.

5 March 2023 Event Study

The cross-sectional regressions reported in the previous are tests of equilibrium relationships that hold in the data. We also provide an additional test of supply segmentation using an event study methodology.

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 the event led to a shift of deposits from smaller banks 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 \$185bn.[30] The average large bank had deposit inflows of \$120/25 =\$4.8 billion, using the fact that the data spans the largest 25 domestically charted commercial banks. We can also get a sense of the deposit flows using publicly available call reports which are available quarterly. We calculate the change in total deposits between

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

December 31, 2022 and March 31, 2023 for the banks in our sample. Using this public call report data, the average deposit change was −\$11 billion, ranging from −\$44 billion to \$32 billion, with a standard deviation of \$21 billion.[31]

The unexpected deposit flows to large banks are an exogenous relaxing of those banks' funding constraints, at least in the short term. We use this plausibly exogenous variation in banks' abilities to intermediate FX markets to identify the effect of supply concentration.

For each of the banks in our sample, we calculate the change in their dollar-denominated deposits between March 9, one day before the event to two weeks after the event. We then calculate the value-weighted change in deposits for tenor and currency pair in our sample, which we define as $\Delta Deposits^{ccy}_{t+n}$. We calculate value-weights using a bank's gross notional in a given market relative to the total gross notional for the same market. We fix our value weights from March 9 to exclude the effects of banks rebalancing their activity after the SVB shock, hence the variable has no t subscript: it is fixed through the sample and varies only over tenor and currency, not by date. The method provides us with 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 $\Delta Deposits^{ccy}_{t+n}$ into a modified z-score using the median rather than the mean. The average deposit inflow to a given market was \$20.9 billion, with a standard deviation of \$6.6 billion.

The shock is an inflow of dollars, so we expect markets in which banks lend dollars will have an effect. Therefore, we limit the sample to the markets in which $Net^{ccy}_{t,t+n}$was positive on average over the two weeks leading into the event. In Table 13, we run a regression:

$$|\text{Basis}^{ccy}_{t,t+n}| = \alpha + \gamma_1 \mathbb{I}(\text{Post}) + \gamma_2 \Delta Deposits^{ccy}_{t+n} + \gamma_3 \mathbb{I}(\text{Post}) \times \Delta Deposits^{ccy}_{t+n} + \varepsilon^{ccy}_{t,n}. \quad (7)$$

$\mathbb{I}(\text{Post})$ is equal to 1 for days after March 9, and 0 otherwise. Our window is the 2 weeks before and after the event, which gives us the longest time frame before the last week of March when quarter-end window-dressing could bias the estimates.

The first three columns of Panel A show the main results. The columns vary the fixed

[31] 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).

effects and whether the regression is weighted by the markets' sizes. The coefficient on the post dummy is positive and significant, indicating that basis dislocations worsened following the event, consistent with risk-off sentiment. The bases were larger on average in markets with larger deposit inflows. This is likely because deposit flows went toward banks perceived as the safest, and those same banks lend dollars most in markets with larger CIP dislocations.

The key result is the interaction row. After the stress, markets that relied more on banks that saw the largest inflows saw a comparatively smaller increase in the dislocation, indicated by the significant and negative coefficient. The result is robust across specifications. The specification with all the controls, column 3, shows that a 1 standard deviation increase in deposit inflows decreases the absolute value of the basis by 2 or 3bps after the event. The effect is economically large: the average basis absolute value is 30bps, so the coefficients imply a 7 percent decline.

Why would the basis relatively improve in the treated markets? In the last three columns of Panel A, we show that treated markets saw increased net dollar lending. It is likely the deposit inflows allowed banks to lend some marginal dollars. The panel runs the same event study regression except changes the dependent variable to $Net^{ccy}_{t,t+n}$. The main result is the third row: markets with larger deposit inflows were the same markets in which banks increased $Net^{ccy}_{t,t+n}$. The result holds when the markets are weighted by their size, so small markets behaved differently. Using column 6, a one standard deviation increase in deposit flows after the event increased $Net^{ccy}_{t,t+n}$by 0.6 percentage points.

Panel B runs a placebo event study using data from one month before. The regression is exactly the same except sets the post dummy equal to 1 for days after February 9. There was no salient market volatility in mid-February 2023, so we have no expectation that the interaction term has a significant effect. Moreover, the deposit flows captured by the variable had not yet occurred. The third row of Panel B shows that the placebo event had no clear effect on the basis, and if anything, the basis increased during the period. The last three columns of the table show no obvious pattern in the interaction term's effect on net lending.

6 Conclusion

CIP bases vary across currencies, a puzzle for prevailing theories of financial intermediation. We show that banks lend the most dollars in precisely the markets with the largest CIP violations. Why? We posit banks lend dollars subject to several types of shadow costs: foreign safe asset scarcity, demand concentration, and supply concentration. We empirically show that each of these frictions plays an important role in explaining CIP bases. Basis dislocations are strongly related to banks' foreign safe asset holdings; namely, the lack thereof. And the markets that rely on fewer banks or that trade against fewer counterparties have larger dislocations. Since banks specialize in some markets, shocks to those banks are shocks to those markets. Our results highlight the importance of safe assets and investor composition in understanding intermediaries' impact on asset prices.

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7 Figures

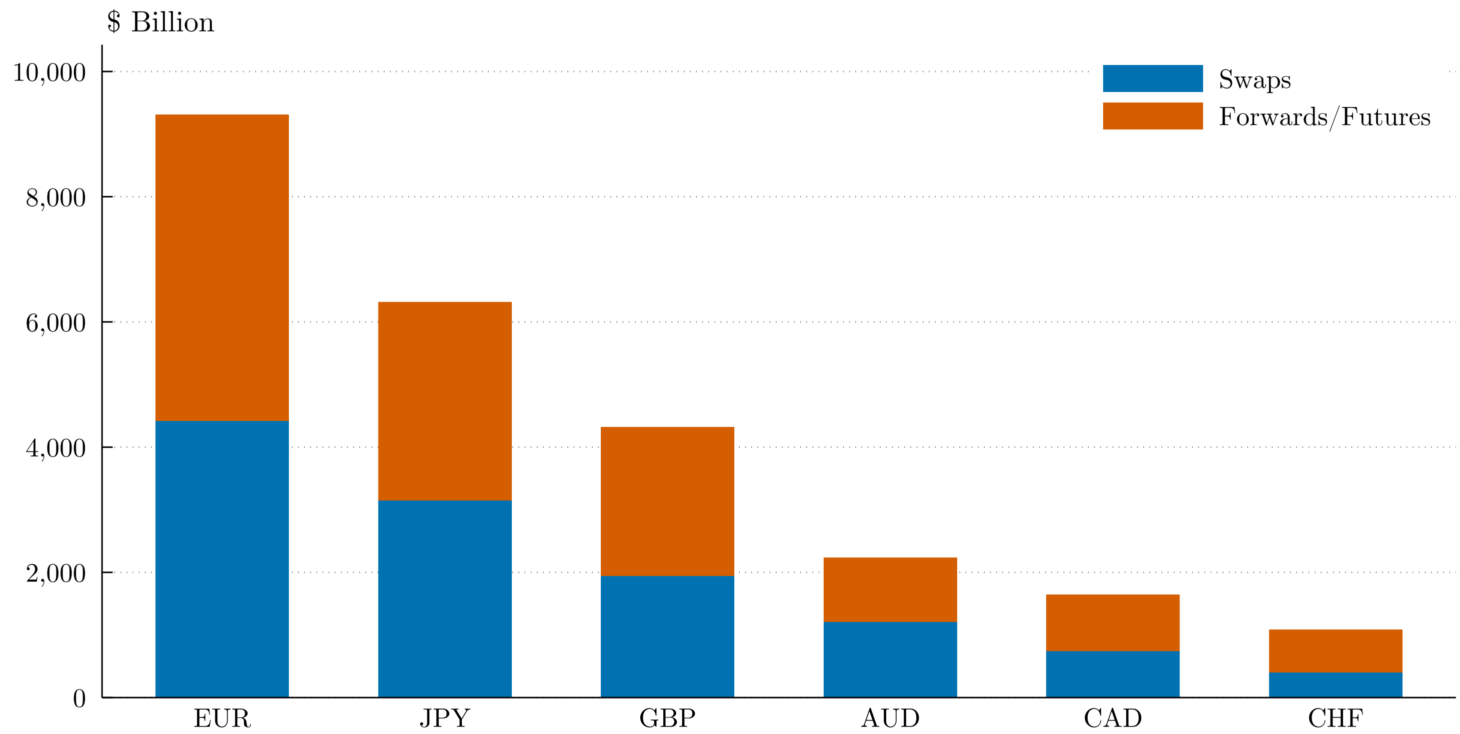

Figure 1: Foreign Exchange Notional Exposure. Figure provides the average notional FX exposures in our sample by currency across swaps and forwards/futures before limiting to the tenors with OIS rates. Sample includes only transactions in the six currencies versus the dollar.

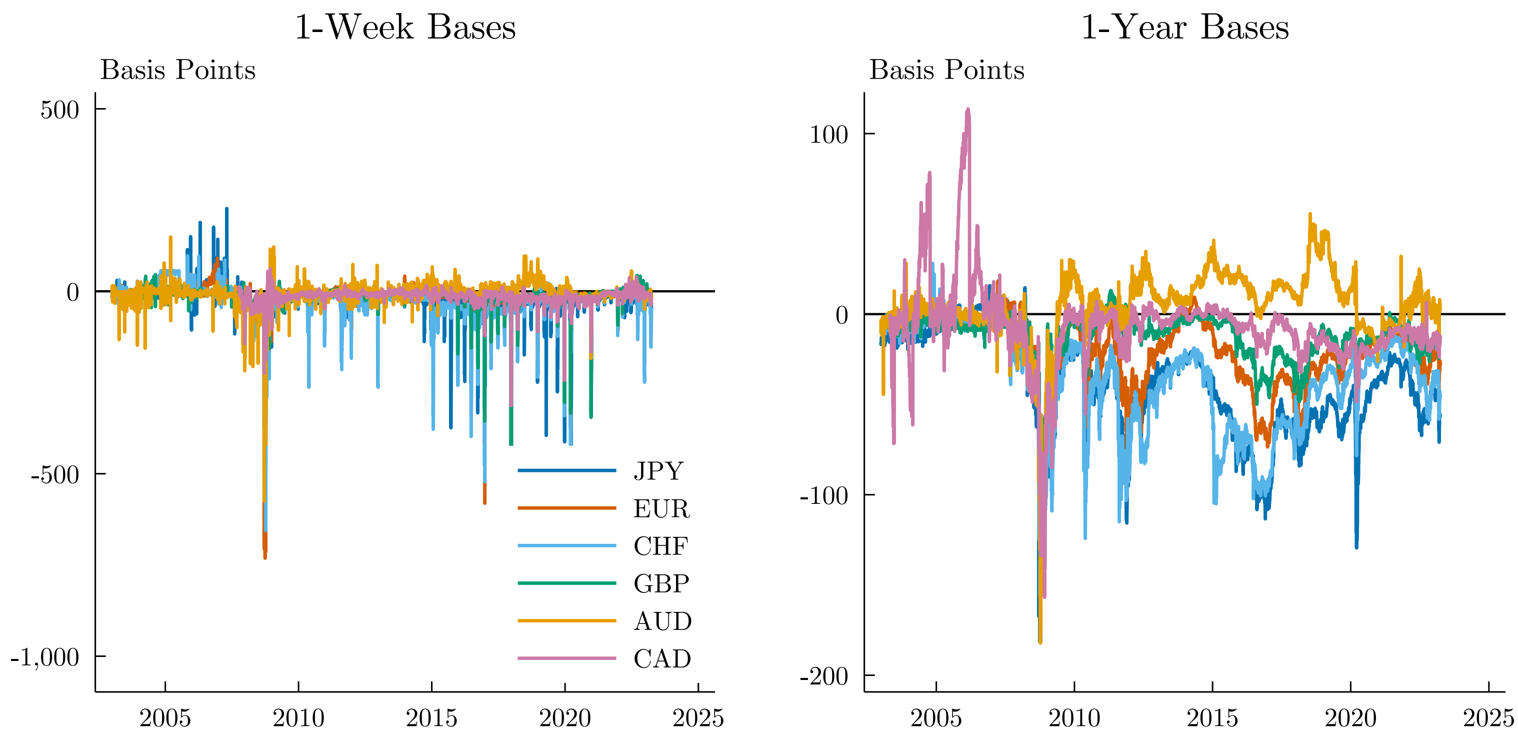

Figure 2: Covered-Interest Parity Violations. Figure plots the CIP bases across two tenors—1-week and 1-year—across several currencies.

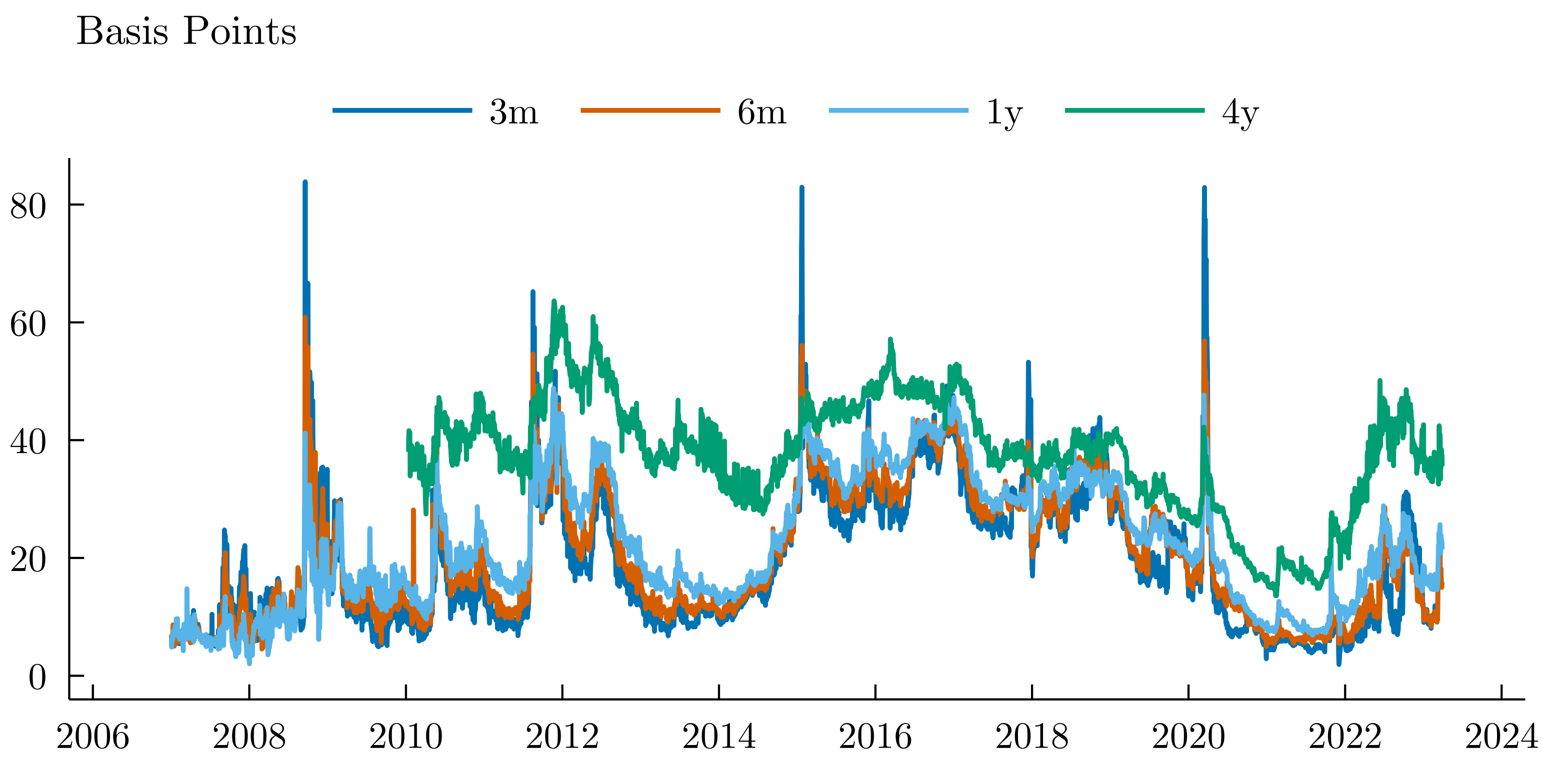

Figure 3: Cross-Sectional Standard Deviation of Covered-Interest Parity Violations. Figure plots the cross-sectional standard deviation of CIP bases for the given tenor.

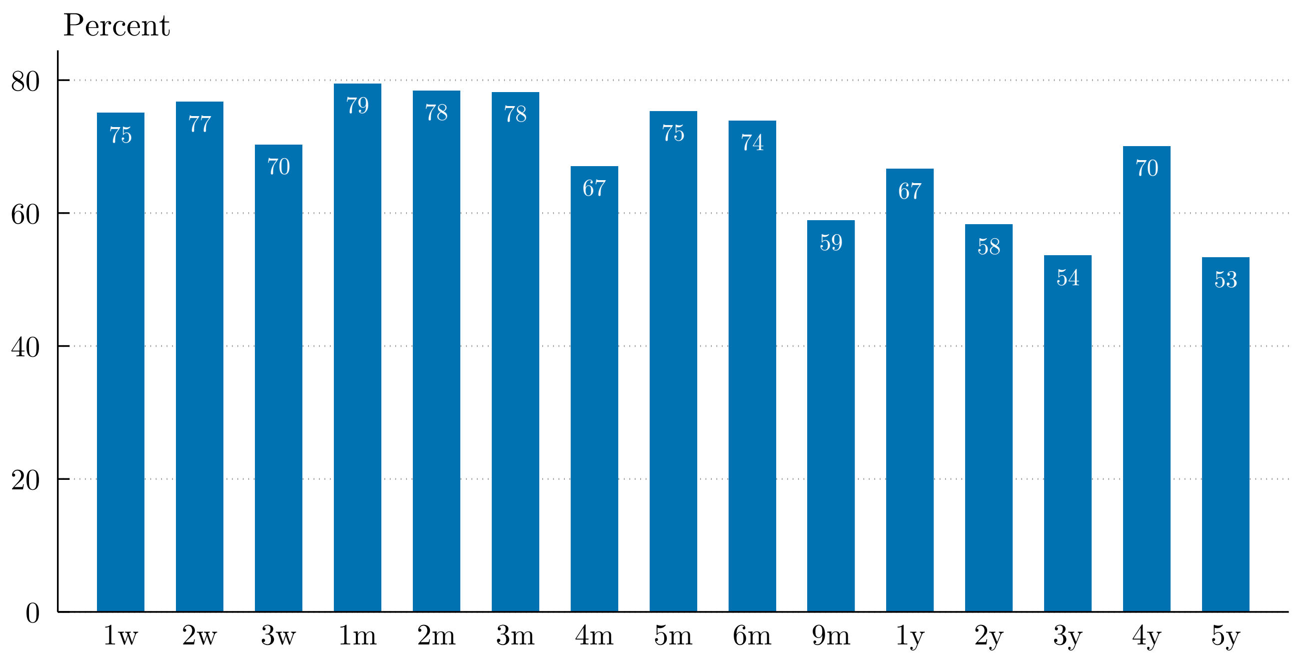

Figure 4: Proportion of CIP Deviation Variance Explained by First Principal Component. Figure plots the proportion of the variance explained by the first principal component after estimating 6 principal components across the signed CIP deviations by tenor.

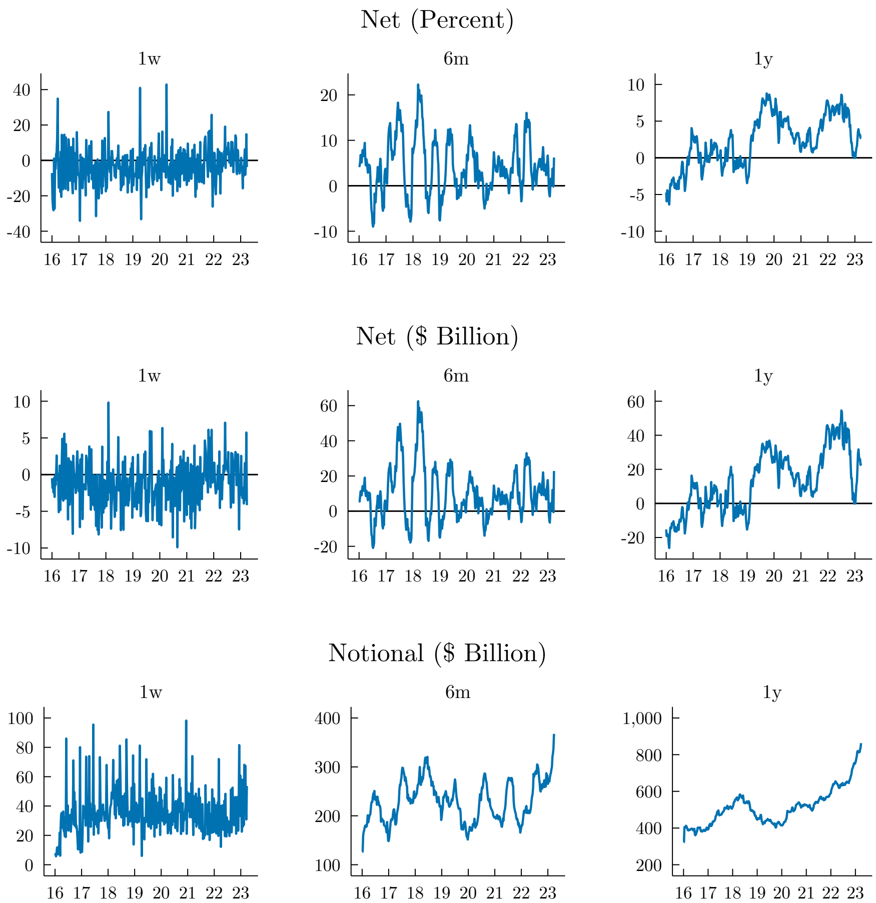

Figure 5: $Net_{t,t+n}^{ccy}$ **for EUR across several tenors**. Top panel plots our main measure, $Net_{t,t+n}^{ccy}$, for EUR contracts across various tenors. Middle panel plots the level of net dollar lending. Bottom panel plots the notional dollars across borrowing and lending transactions for EUR across the highlighted tenors. All figures plot weekly averages based on daily observations.

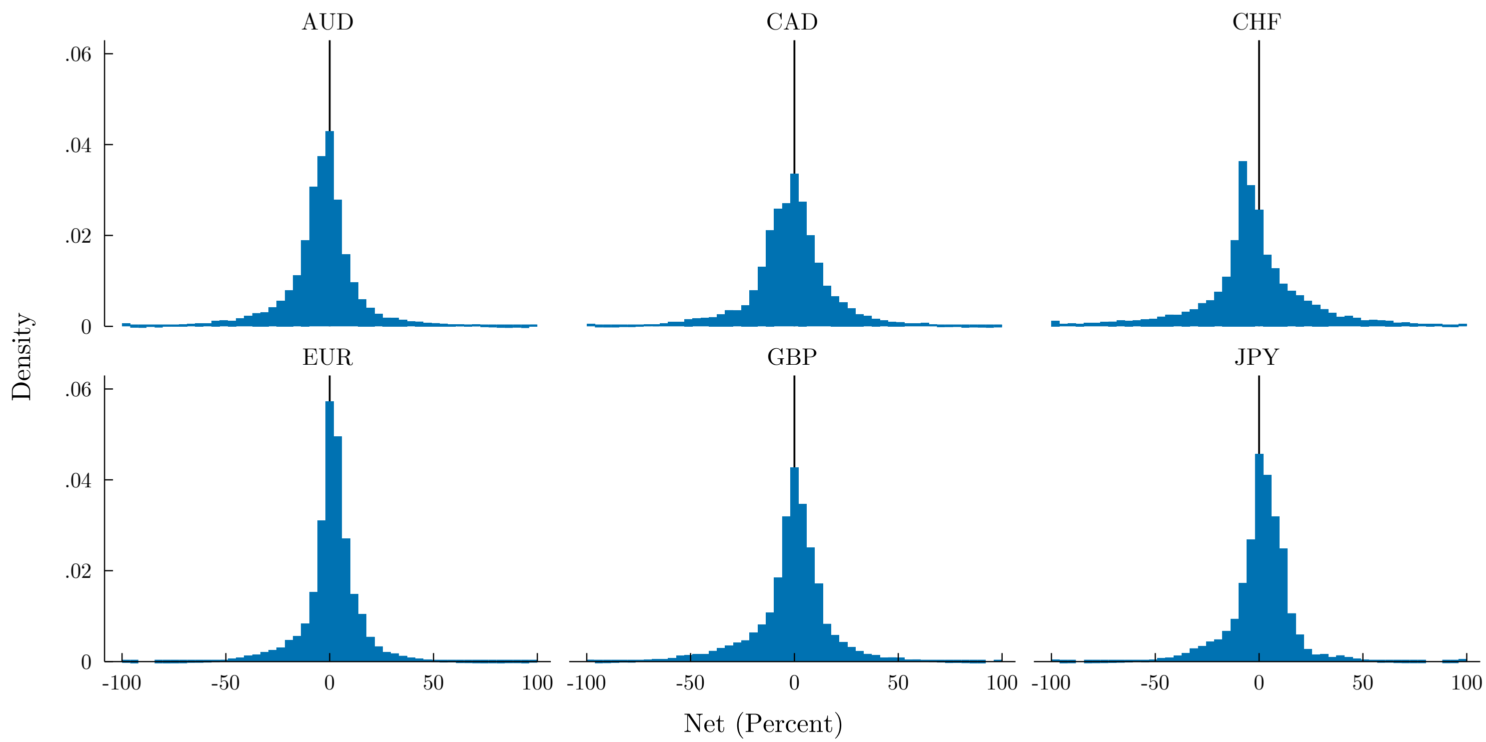

Figure 6: Most Markets are Nearly Matched Books. Figure plots the histogram of $Net^{ccy}_{t,t+n}$across all tenors within a given currency.

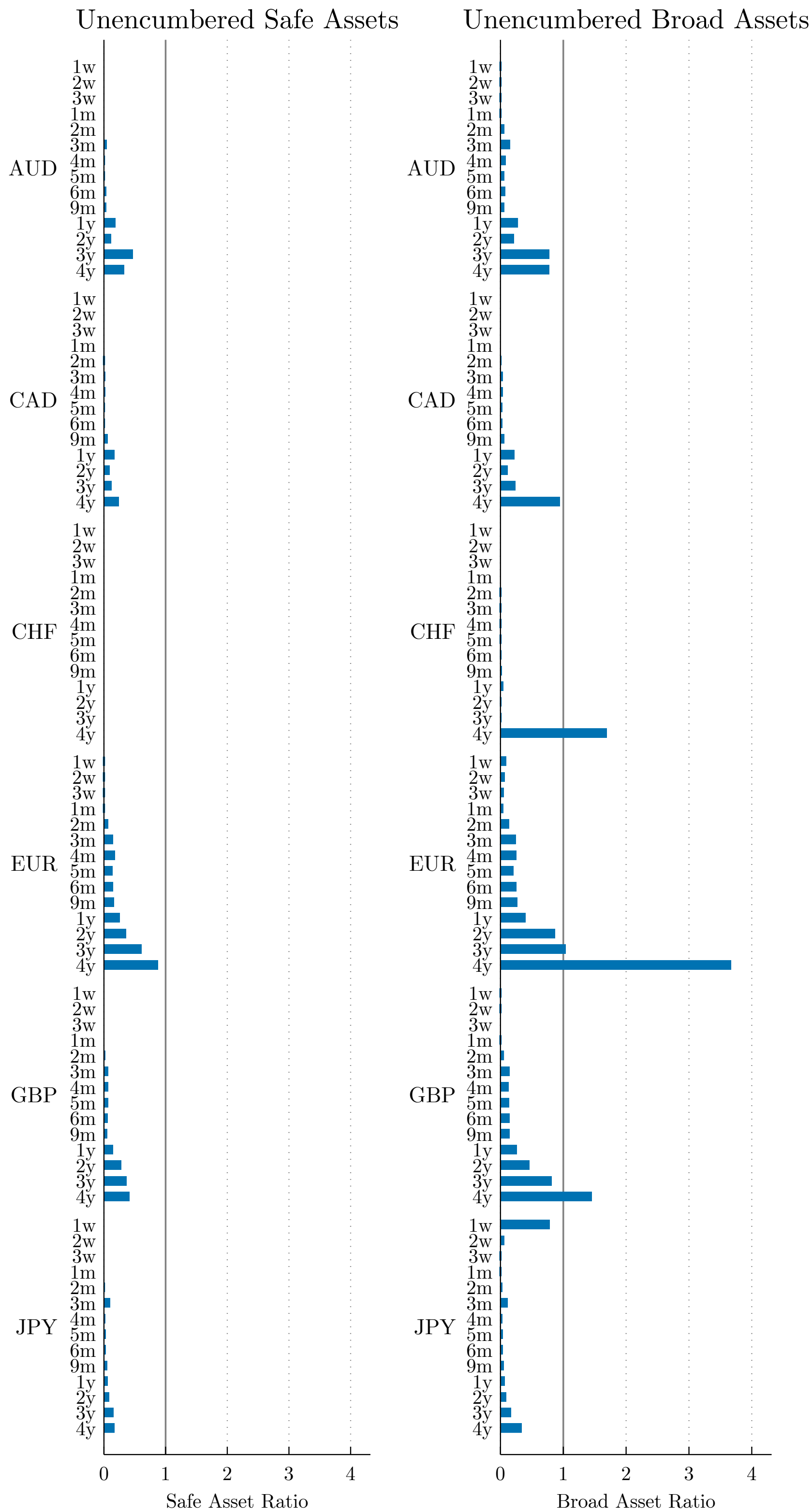

Figure 7: Safe Asset Scarcity by Market. Figure plots safe asset and broad asset ratios when $Net^{ccy}_{t,t+n}$ is positive when matching the tenor of the net dollar lending and the foreign safe asset.

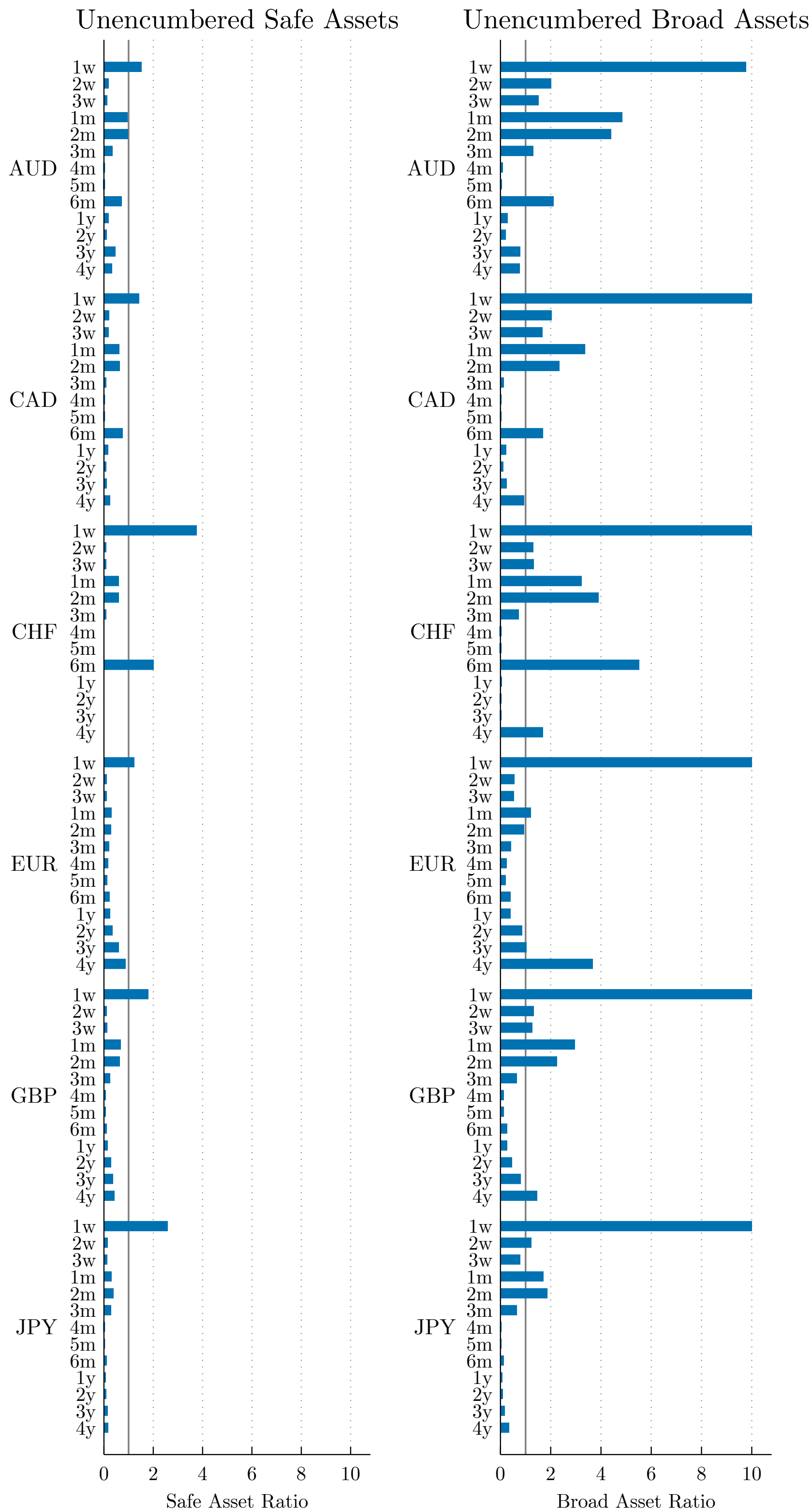

Figure 8: Safe Asset Scarcity by Market with Rounded Tenors. Figure plots safe asset and broad asset ratios when $Net^{ccy}_{t,t+n}$is positive when bucketing net dollar lending and foreign safe assets into the nearest benchmark tenor. Unlike Figure 7 this measure allows for some maturity mismatch in the trade.

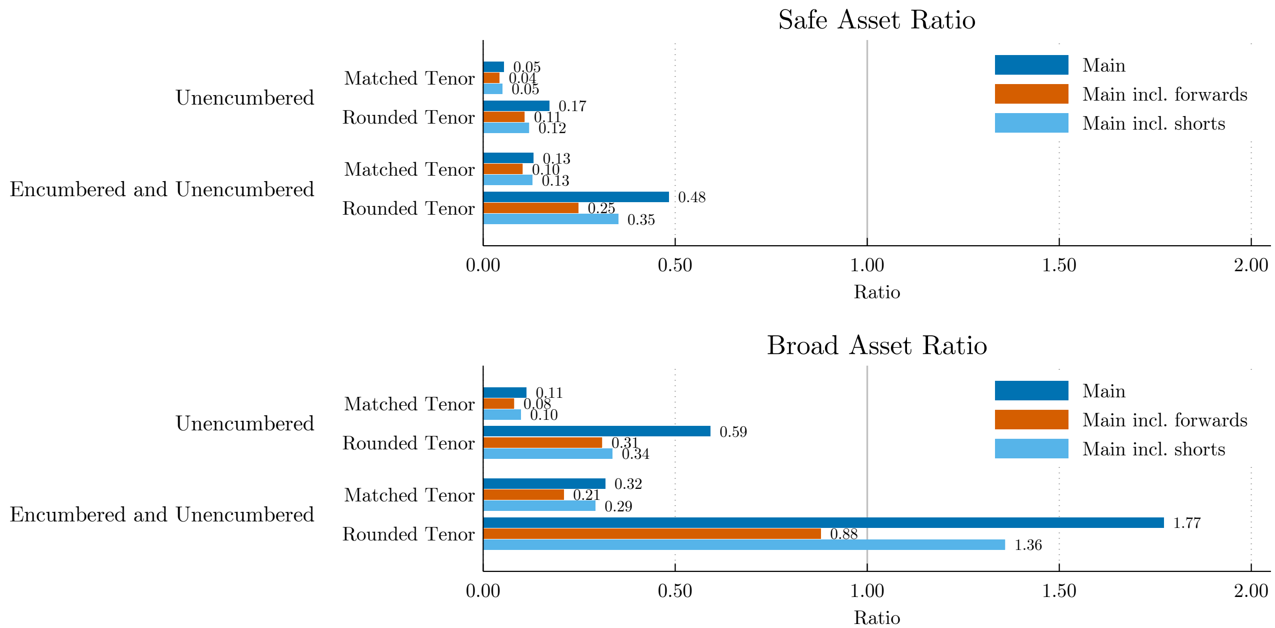

Figure 9: Summary of Safe Asset Ratios Figure plots the average median safe and broad asset ratio across all currencies when $Net^{ccy}_{t,t+n}$is positive excluding the USD. Matched tenor shows the asset ratio when the tenor of the underlying asset and the swap have the same maturity. Rounded tenor 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).

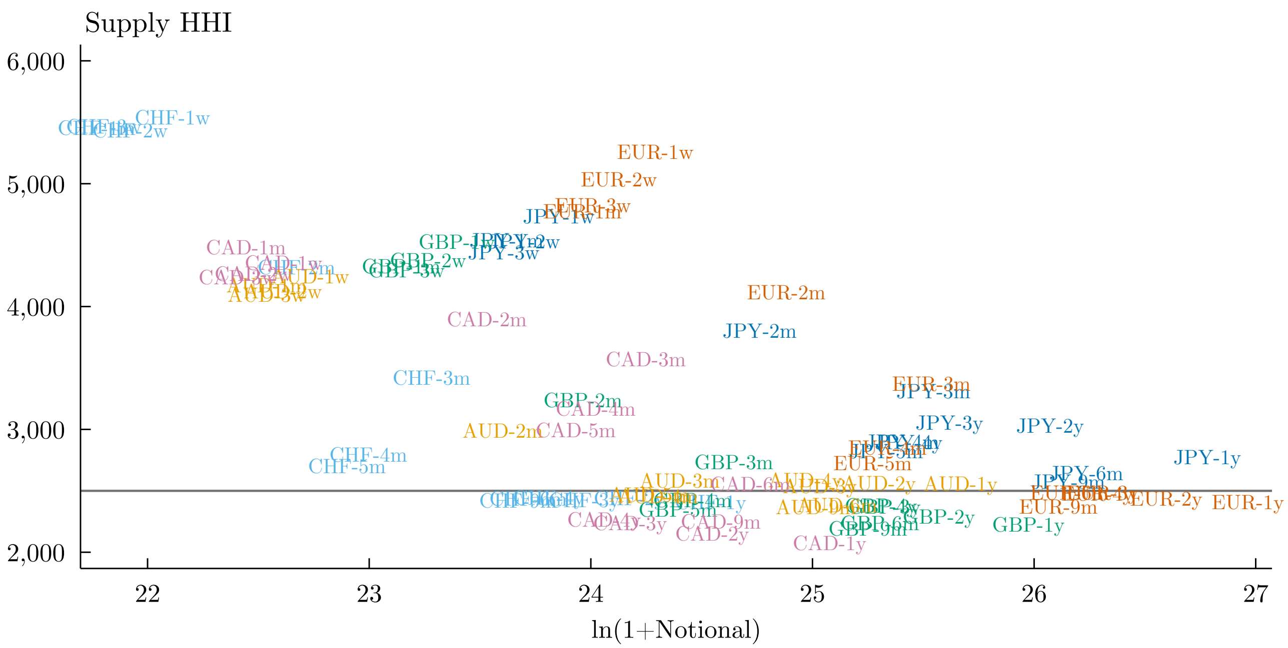

Figure 10: Supply Segmentation. Figure plots the average of daily Supply $\text{HHI}^{ccy}_{t,t+n}$ against the (log of 1 plus) the average notional of that market.

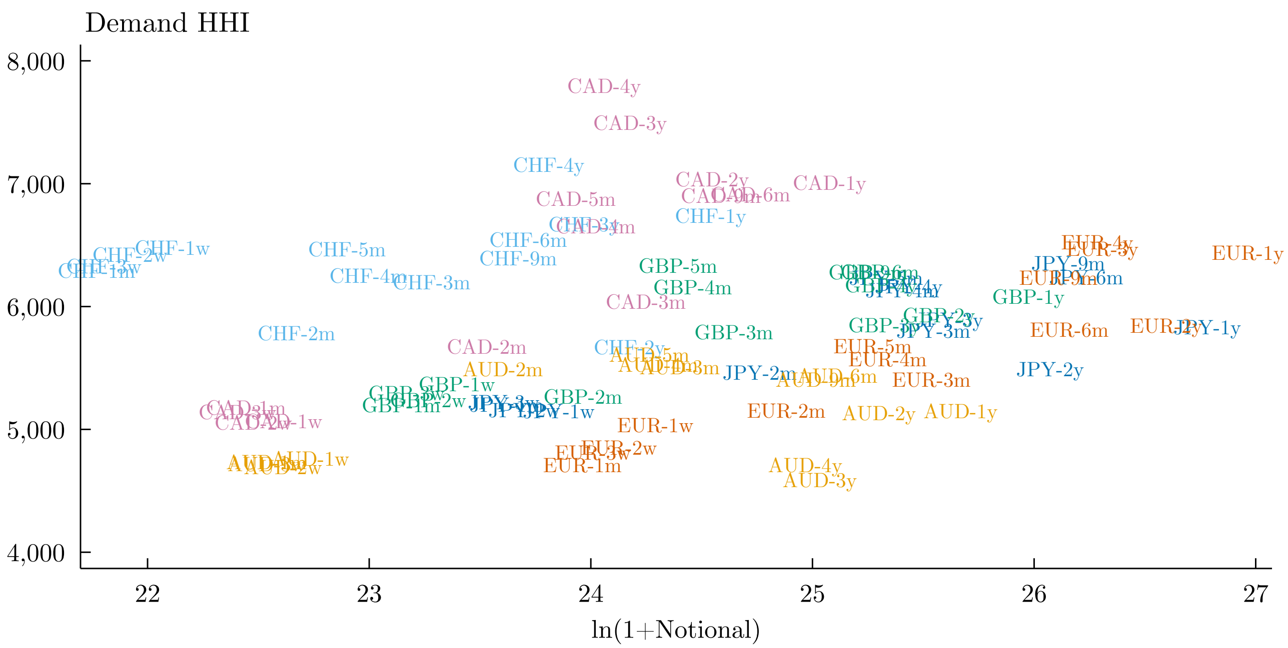

Figure 11: Demand Segmentation. Figure plots the average of daily Demand $\text{HHI}^{ccy}_{t,t+n}$ against the (log of 1 plus) the average notional of that market.

8 Tables

by currency	Swaps		Forwards & Futures	
	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	
	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 1: Average daily gross FX notional across all banks. Table shows average daily notional in USD billions across all banks and tenors for the matched covered-interest parity tenors by currency.

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 2: 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.

Bank's Cash Flows		t	$t+7$
Swap #1: lend USD vs. JPY			
	USD pay	$-$\$100	
	JPY receive	¥11,500	
	USD receive		\$105
	JPY pay		$-$¥11,500
Swap #2: lend JPY vs. USD			
	USD receive	\$95	
	JPY pay	$-$¥10,925	
	USD pay		$-$\$99
	JPY receive		¥10,925
Total			
(a)	Net Dollars Lent	\$5	\$5.23
(b)	Notional Dollars	\$195	\$204
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. Table assumes that the spot exchange rate $S_t = 115$ and the forward exchange rate is $F_{t,t+7} = 110$.

Mean (%)							
	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 (%)							
	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: $\boldsymbol{Net^{ccy}_{t,t+n}}$ **Summary Statistics**. Top panel plots the average daily $Net^{ccy}_{t,t+n}$ for a given currency ccy and maturity $t+n$. Bottom panel plots the time-series standard deviation of $Net^{ccy}_{t,t+n}$.

	All Tenors				Short-Term	Long-Term
	(1)	(2)	(3)	(4)	(5)	(6)
$Net^{ccy}_{t,t+n}$	-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 $Net^{ccy}_{t,t+n}$: $\text{Basis}^{ccy}_{t,t+n} = \alpha + \beta Net^{ccy}_{t,t+n} + \gamma\prime X_t + \varepsilon^{ccy}_{t,t+n}$. 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. $Net^{ccy}_{t,t+n}$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 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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

Panel A: Safe Assets.				
	Unencumbered Safe Assets		Unencumbered & Encumbered Safe Assets	
	(1)	(2)	(3)	(4)
$Net^{ccy}_{t,t+n}$($ 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)
$Net^{ccy}_{t,t+n}$($ 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 7: Net vs. Safe Asset Ratios. Table presents the regression of the level of $Net^{ccy}_{t,t+n}$on the level of the assets—either HQLAs or broad assets—with the same maturity and currency in millions of dollars: $Asset\ (Level)^{ccy}_{t,t+n} = \alpha + \beta Net^{ccy}_{t,t+n}(\text{Level}) + \gamma_i + \varepsilon^{ccy}_{t,t+n}$ where γ_i is a currency fixed effect. Columns 1 and 3 limit the sample to observations with net dollar lending (e.g., $Net^{ccy}_{t,t+n} > 0$). Columns 2 and 4 limit the sample to observations with net dollar borrowing (e.g., $Net^{ccy}_{t,t+n} < 0$). Base level is CHF. Within R^2 reported. t-statistics shown using robust standard errors clustered by market and date where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	HHI Supply$^{ccy}_{t,t+n}$				Market Share$^{ccy,i}_{t,t+n}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln(1 + \text{Avg. Book Size}^{ccy}_{t,t+n})$	122.6***						
	(35.63)						
HHI Supply$^{ccy}_{t-1m,t-1m+n}$		0.510***					
		(20.18)					
HHI Supply$^{ccy}_{t-1y,t-1y+n}$			0.510***				
			(22.36)				
HHI Supply$^{ccy}_{t-5y,t-3y+n}$				0.377***			
				(15.78)			
Market Share$^{ccy,i}_{t-1m,t-1m+n}$					0.866***		
					(24.09)		
Market Share$^{ccy,i}_{t-1y,t-1y+n}$						0.838***	
						(18.23)	
Market Share$^{ccy,i}_{t-5y,t-5y+n}$							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

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. Regression includes date fixed effects. Constant omitted. 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$^{i,ccy}_{t,ctpty}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Bank FX Share$^{i,ccy}_{t-6m,ctpty}$	0.951***	0.938***				0.927***
	(43.50)	(32.10)				(24.60)
Other Bank FX Share$^{i,ccy}_{t,ctpty}$		0.0539			0.571***	0.0211
		(1.50)			(4.41)	(0.66)
Bank Loan Share$^{i,ccy}_{t,ctpty}$			0.234***	0.174**	0.155**	0.108
			(3.95)	(2.36)	(2.33)	(1.19)
Other Bank Loan Share$^{i,ccy}_{t,ctpty}$				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$^{i,ccy}_{t,ctpty}$ on several variables. Bank FX Share$^{i,ccy}_{t,ctpty}$ 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$^{i,ccy}_{t,ctpty}$ is the average market share of all banks except bank i. Bank Loan Share$^{i,ccy}_{t,ctpty}$ and Other Bank Loan Share$^{i,ccy}_{t,ctpty}$ are calculated analogously using secured and unsecured loans rather than FX positions. Within R^2 reported. t-statistics shown using robust standard errors clustered by date and bank where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Unencumbered Assets		Unencumbered & Encumbered Assets	
	(1)	(2)	(3)	(4)
Supply Concentration				
Supply $\text{HHI}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} \geq 0)$	21.73***	21.67***	21.71***	21.67***
	(4.93)	(4.94)	(4.93)	(4.94)
Supply $\text{HHI}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} < 0)$	20.29***	20.27***	20.29***	20.27***
	(5.63)	(5.63)	(5.63)	(5.63)
Demand Concentration				
Demand $\text{HHI}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} \geq 0)$	4.54	4.56	4.55	4.57
	(1.39)	(1.40)	(1.39)	(1.40)
Demand $\text{HHI}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} < 0)$	2.72	2.72	2.72	2.72
	(0.85)	(0.85)	(0.85)	(0.85)
Collateral Scarcity				
Safe Asset $\text{Ratio}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} \geq 0)$	−27.02*		−18.42**	
	(−1.76)		(−2.49)	
Safe Asset $\text{Ratio}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} < 0)$	−0.37		−0.20	
	(−1.40)		(−1.36)	
Broad Asset $\text{Ratio}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} \geq 0)$		−57.00***		−42.22***
		(−2.64)		(−3.38)
Broad Asset $\text{Ratio}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} < 0)$		−0.19		−0.17
		(−1.29)		(−1.30)
Controls				
$\text{Net}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} \geq 0)$	1.65	1.48	1.58	1.45
	(0.35)	(0.31)	(0.33)	(0.31)
$\text{Net}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} < 0)$	3.06	3.05	3.06	3.05
	(0.96)	(0.96)	(0.96)	(0.96)
Bank $\text{CDS}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} \geq 0)$	−84.28***	−83.97***	−84.22***	−83.99***
	(−2.85)	(−2.84)	(−2.85)	(−2.84)
Bank $\text{CDS}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} < 0)$	−88.45***	−88.21***	−88.42***	−88.23***
	(−3.01)	(−3.00)	(−3.01)	(−3.00)
Govt $\text{CDS}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} \geq 0)$	−1.41	−1.42	−1.40	−1.41
	(−1.50)	(−1.52)	(−1.50)	(−1.51)
Govt $\text{CDS}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} < 0)$	−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 10: 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 marginal cost 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)
Supply Concentration				
Supply $\text{HHI}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} \geq 0)$	10.81^{***}	10.81^{***}	10.12^{***}	10.12^{***}
	(6.00)	(6.00)	(6.05)	(6.05)
Supply $\text{HHI}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} < 0)$	13.75^{***}	13.76^{***}	11.65^{***}	11.65^{***}
	(6.63)	(6.63)	(6.23)	(6.23)
Demand Concentration				
$\widehat{\text{Demand HHI}}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} \geq 0)$			7.42^{***}	7.42^{***}
			(3.37)	(3.38)
$\widehat{\text{Demand HHI}}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} < 0)$			1.27	1.26
			(0.82)	(0.82)
Collateral Scarcity				
Safe Asset $\text{Ratio}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} \geq 0)$	-7.77^{*}		-9.34^{*}	
	(−1.94)		(−1.97)	
Safe Asset $\text{Ratio}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} < 0)$	−0.50		−0.36	
	(−1.39)		(−1.15)	
Broad Asset $\text{Ratio}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} \geq 0)$		-10.82^{*}		-13.52^{**}
		(−1.94)		(−2.24)
Broad Asset $\text{Ratio}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} < 0)$		−0.25		−0.17
		(−1.06)		(−0.87)
Controls				
$\text{Net}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} \geq 0)$	5.22^{**}	5.22^{**}	4.35^{**}	4.34^{**}
	(2.11)	(2.11)	(2.00)	(2.00)
$\text{Net}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} < 0)$	7.14^{***}	7.14^{***}	7.50^{***}	7.50^{***}
	(3.13)	(3.12)	(3.23)	(3.23)
Bank $\text{CDS}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} \geq 0)$	-97.97^{***}	-97.97^{***}	-97.35^{***}	-97.34^{***}
	(−6.50)	(−6.50)	(−6.86)	(−6.86)
Bank $\text{CDS}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} < 0)$	-99.21^{***}	-99.22^{***}	-98.13^{***}	-98.13^{***}
	(−6.47)	(−6.47)	(−6.85)	(−6.85)
Govt $\text{CDS}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} \geq 0)$	-2.14^{***}	-2.14^{***}	-1.71^{**}	-1.71^{**}
	(−2.85)	(−2.85)	(−2.43)	(−2.43)
Govt $\text{CDS}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} < 0)$	−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 11: Regression of the absolute value of the basis on marginal cost measures using estimated demand concentration. Table presents the regression described in section 4.5 using demand HHI measures estimated from Table A1. The dependent variable is the absolute value of the basis. To make the coefficients directly comparable, we transform the marginal cost independent variables to modified z-scores each variable's full sample median and standard deviation. Sample includes markets in which $Net^{ccy}_{t,t+n}$was positive on average over the two weeks leading into the event. 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 Concentration						
Supply $\text{HHI}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} \geq 0)$	18.27***					
	(4.55)					
Supply $\text{HHI}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} < 0)$	17.18***					
	(4.87)					
Demand Concentration						
Demand $\text{HHI}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} \geq 0)$		−0.25				
		(−0.07)				
Demand $\text{HHI}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} < 0)$		−0.57				
		(−0.16)				
$\widehat{\text{Demand HHI}}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} \geq 0)$			12.19***			
			(3.07)			
$\widehat{\text{Demand HHI}}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} < 0)$			3.40			
			(1.58)			
Collateral Scarcity						
Safe Asset $\text{Ratio}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} \geq 0)$				−17.35**		
				(−2.04)		
Safe Asset $\text{Ratio}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} < 0)$				−0.60		
				(−1.55)		
Broad Asset $\text{Ratio}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} \geq 0)$					−23.29*	
					(−1.91)	
Broad Asset $\text{Ratio}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} < 0)$					−0.36	
					(−1.23)	
$\text{Net}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} \geq 0)$						8.13**
						(2.28)
$\text{Net}^{ccy}_{t,t+n} \times \mathbb{I}(Net^{ccy}_{t,t+n} < 0)$						4.29**
						(2.07)
N	149,337	18,755	149,293	149,337	149,337	149,337
R^2	0.08	0.00	0.04	0.00	0.00	0.02
Tenor FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Weighted	Yes	Yes	Yes	Yes	Yes	Yes

Table 12: 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 marginal cost 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 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Event Study.						
	Dependent Var.: $\lvert Basis^{ccy}_{t,t+n}\rvert$			Dependent Var.: $Net^{ccy}_{t,t+n}$		
	(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)
$\Delta Deposits^{ccy}_{t+n}$	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) $\times$ $\Delta Deposits^{ccy}_{t+n}$	−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 $\text{HHI}^{ccy}_{t,t+n}$			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.: $\lvert Basis^{ccy}_{t,t+n}\rvert$			Dependent Var.: $Net^{ccy}_{t,t+n}$		
	(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)
$\Delta Deposits^{ccy}_{t+n}$	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) $\times$ $\Delta Deposits^{ccy}_{t+n}$	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 $\text{HHI}^{ccy}_{t,t+n}$			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 13: March 2023 Event Study. Table shows the results of the regression $|\text{Basis}^{ccy}_{t,t+n}| = \alpha + \gamma_1 \mathbb{I}(\text{Post}) + \gamma_2 \Delta Deposits^{ccy}_{t+n} + \gamma_3 \mathbb{I}(\text{Post}) \times \Delta Deposits^{ccy}_{t+n} + \varepsilon^{ccy}_{t,n}$. We transform $\Delta Deposits^{ccy}_{t+n}$ to a modified z-score using the median rather than mean to account for outliers. $\mathbb{I}$(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 Prediction 4

Prediction 4 is most clearly observed by considering the case where there are only collateral scarcity and participation costs.

The first order condition with respect to $Z_{i,k}$ yields:

$$\text{Basis}_k = (\gamma\alpha^2\sigma^2 + \lambda_S(1-\alpha)^2)Z_{i,k} + \lambda_{PC,i,k}Z_{i,k}, \tag{8}$$

which can be equivalently written as

$$Z_{i,k} = \frac{\text{Basis}_k}{\gamma\alpha^2\sigma^2 + \lambda_S(1-\alpha)^2 + \lambda_{PC,i,k}}. \tag{9}$$

Summing Equation (8) across intermediaries and substituting Equation (9) for $Z_{i,k}$, we get that

$$\begin{aligned}\text{Basis}_k =& (\gamma\alpha^2\sigma^2 + \lambda_S(1-\alpha)^2)X_k + \frac{1}{N_i}\sum_i \lambda_{PC,i,k}Z_{i,k} \\ =& (\gamma\alpha^2\sigma^2 + \lambda_S(1-\alpha)^2)X_k + \frac{1}{N_i}\sum_i \lambda_{PC,i,k}\frac{\text{Basis}_k}{(\gamma\alpha^2\sigma^2 + \lambda_S(1-\alpha)^2 + \lambda_{PC,i,k}}.\end{aligned}$$

This yields that

$$\text{Basis}_k = (\gamma\alpha^2\sigma^2 + \lambda_S(1-\alpha)^2)X_k\left(1 - \frac{1}{N_i}\sum_i \frac{\lambda_{PC,i,k}}{\gamma\alpha^2\sigma^2 + \lambda_S(1-\alpha)^2 + \lambda_{PC,i,k}}\right)^{-1}. \tag{10}$$

From Equation (8), we see that heterogeneous $\lambda_{PC,i,k}$ values give rise to segmentation. To consider the effects of segmentation on the basis for currency k, we want to shift the distribution of $Z_{i,k}$ across intermediaries while holding the impact of participation costs fixed. We can do this by assuming that

$$\sum_i \frac{1}{\lambda_{PC,i,k}} = \Lambda_{PC}, \tag{11}$$

where Λ_{PC} is a constant. Assuming the sum of inverses is constant is appropriate for measuring the effect of segmentation, since $\lambda_{PC,i,k}$ multiplies $Z_{i,k}$ in determining intermediary i's marginal shadow cost. It is straightforward to verify that subject to Equation (11) as a constraint, Equation (10) is minimized when $\lambda_{PC,i,k}$ is equalized across intermediaries, i.e., when all intermediaries hold the same position and there is no segmentation.

Derivation of Prediction 5

$$\frac{1}{N_i}\lambda_{CP} \times \text{Sign}(X_k) \sum_i \sum_c \left(\frac{X_{c,k}^2}{X_k^2} |Z_{i,k}| + \frac{X_{c,k}}{X_k} \sum_{k' \neq k} \frac{X_{c,k'}}{X_k'} |Z_{i,k'}| \right)$$

$$\frac{1}{N_i}\lambda_{CP} \times \text{Sign}(X_k) \sum_i \sum_c \left(\frac{X_{c,k}^2}{X_k^2} |Z_{i,k}| + \frac{X_{c,k}}{X_k} \sum_{k' \neq k} \frac{X_{c,k'}}{X_k'} |Z_{i,k'}| \right)$$

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

$$= \frac{1}{N_i}\lambda_{CP} \times \text{Sign}(X_k) \left(\underbrace{|X_k| \sum_c \frac{X_{c,k}^2}{X_k^2}}_{\text{Demand Concentration in } k} + \underbrace{\sum_c \frac{X_{c,k}}{X_k} \sum_{k' \neq k} |X_{c,k'}|}_{\text{Importance of } c \text{ in other trades}} \right)$$

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 have 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 subset of the largest banks that have consistently been daily reporters over the whole sample.[32] The data collection instructions were modestly updated in April 2022 to provide additional

[32] 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.

details on certain segments—for example, on FX counterparties—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 US 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
- 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 timeseries 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 EONIA 3-week OIS rate until November 21, 2019 when ESTR 3-week OIS rates are first available.

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.

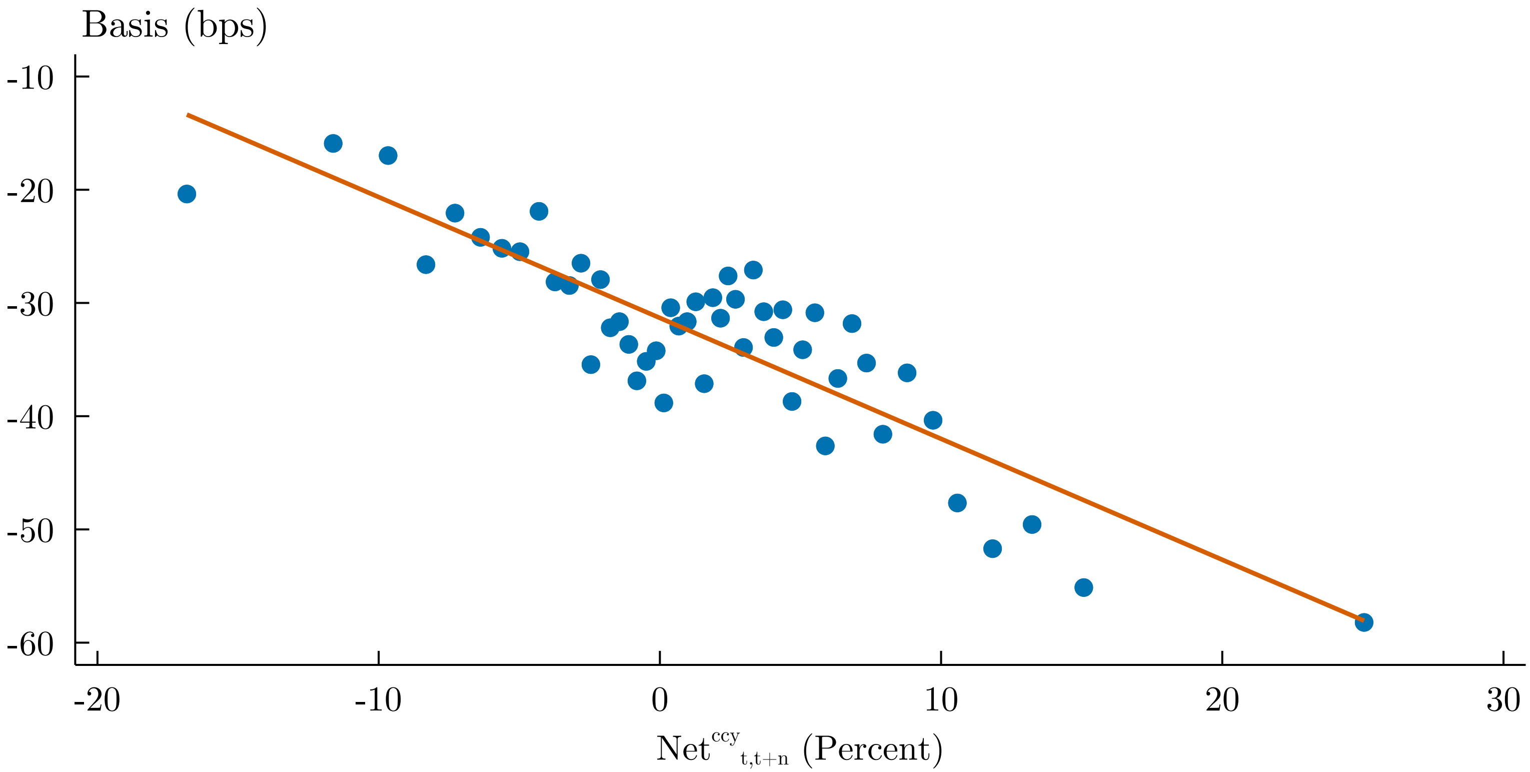

Figure A1: Basis vs. $Net^{\boldsymbol{ccy}}_{t,t+n}$ Figure presents the binscatter of the basis on $Net^{ccy}_{t,t+n}$after averaging on a monthly frequency. $Net^{ccy}_{t,t+n}$is at the month by currency by tenor level. Binscatter has 50 buckets.

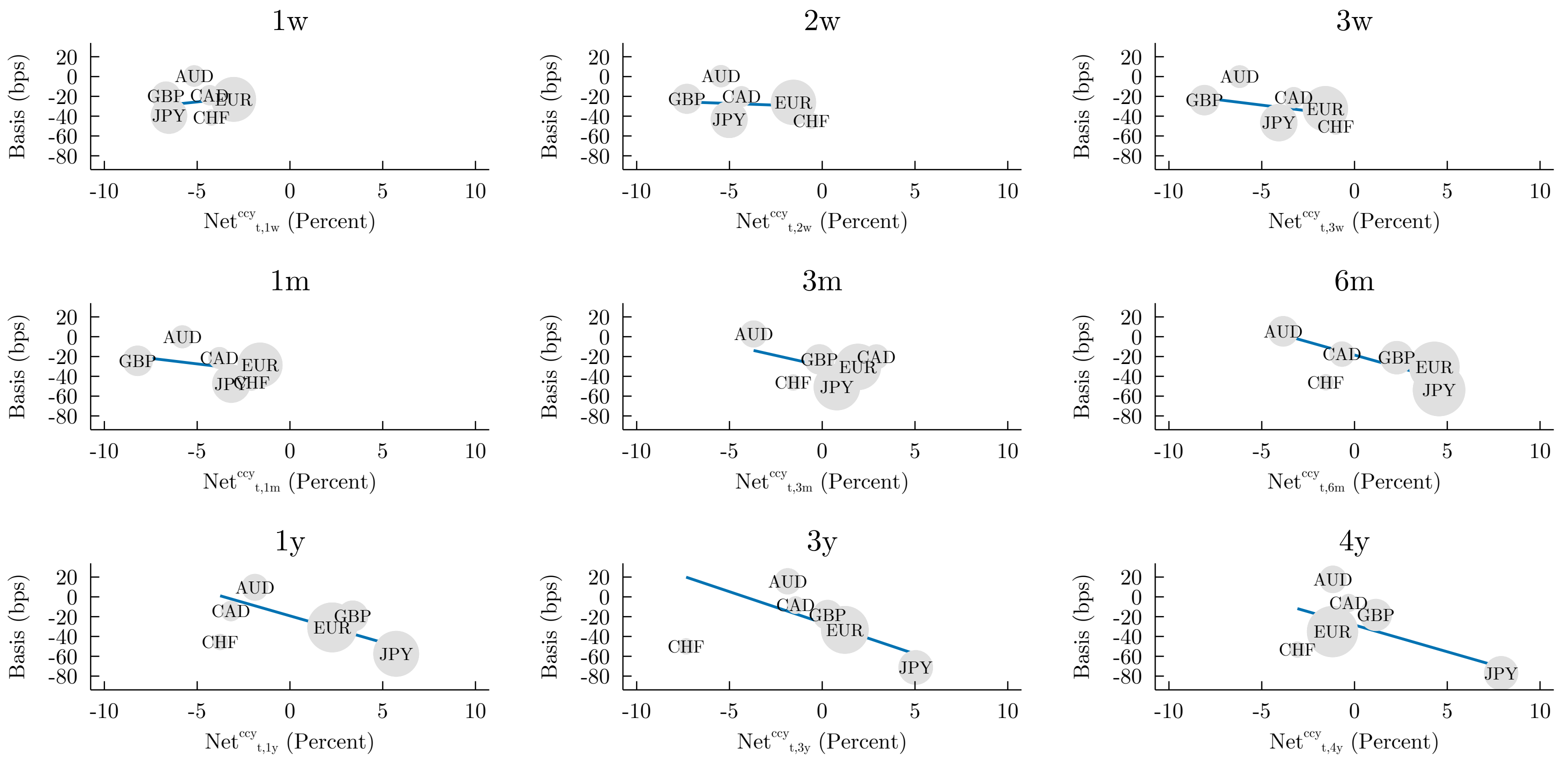

Figure A2: By Tenor: Basis vs. $Net^{ccy}_{t,t+n}$ Figure presents the scatter of the average basis on the average $Net^{ccy}_{t,t+n}$.

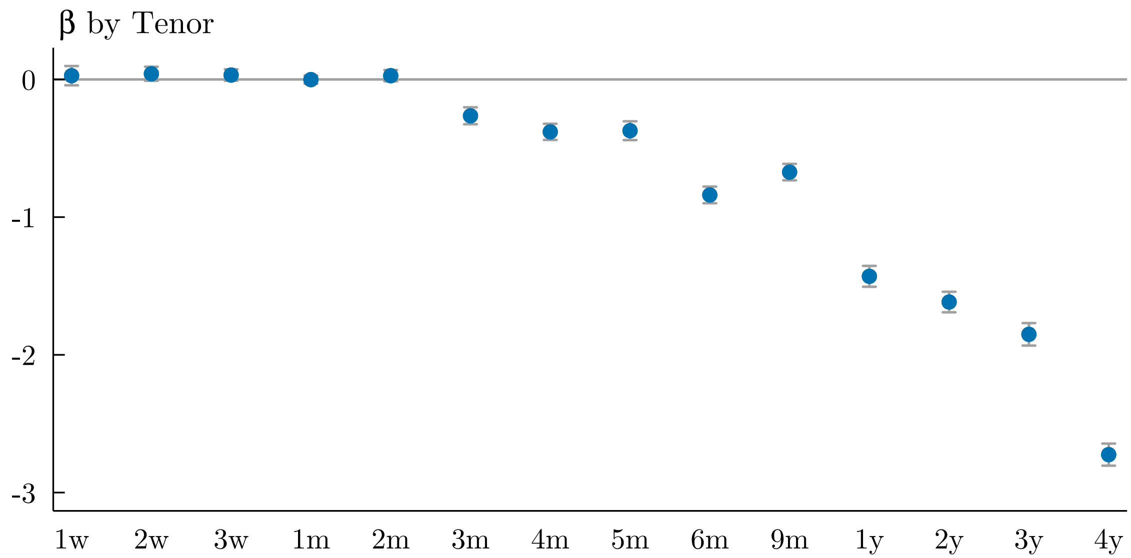

Figure A3: Regression Coefficient by Tenor: Basis vs. $Net^{ccy}_{t,t+n}$ Figure the β estimated by running the following regression separately for each tenor: $\text{Basis}^{ccy}_{t,t+n} = \alpha + \beta Net^{ccy}_{t,t+n} + \varepsilon^{ccy}_{t,t+n}$.

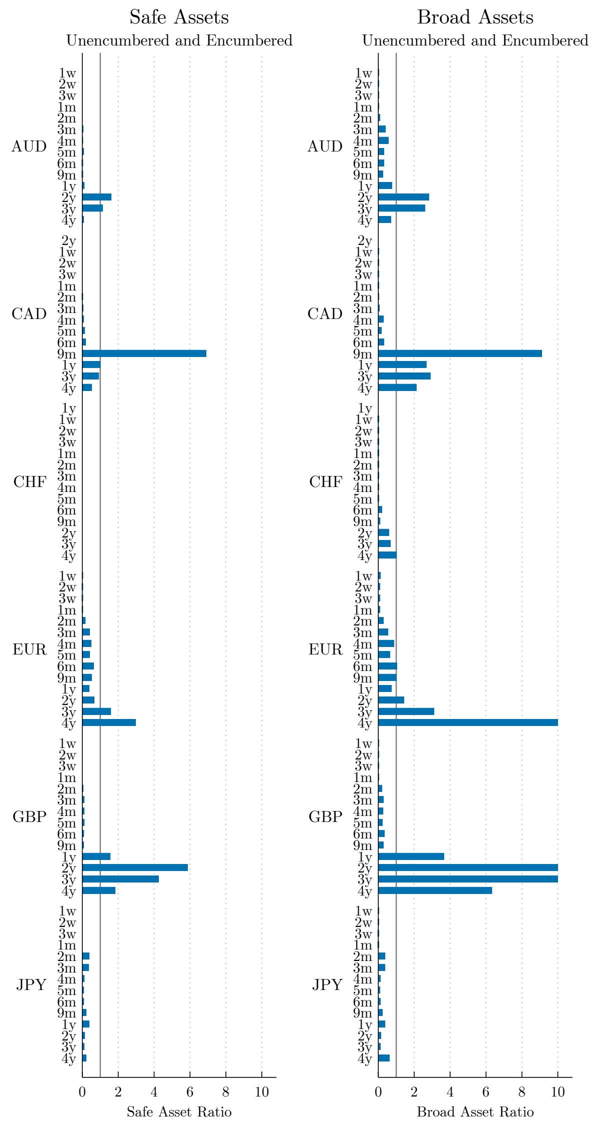

Figure A4: Safe Asset Scarcity by Market, including encumbered assets. Figure plots safe asset and broad asset ratios when $Net^{ccy}_{t,t+n}$is positive when matching the tenor of the net dollar lending and the foreign safe asset. Values are truncated at 10.

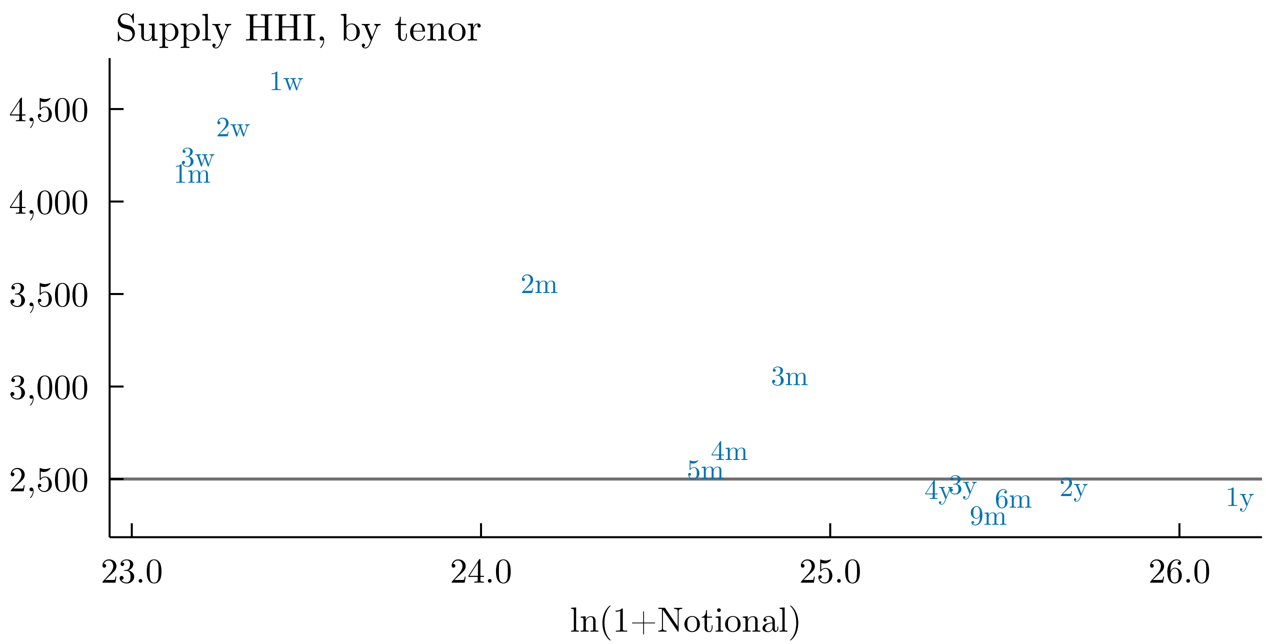

Figure A5: Supply Segmentation. Figure plots the average of daily Tenor Supply $\text{HHI}_{t,t+n}$ against (log of 1 plus) the average notional of that market.

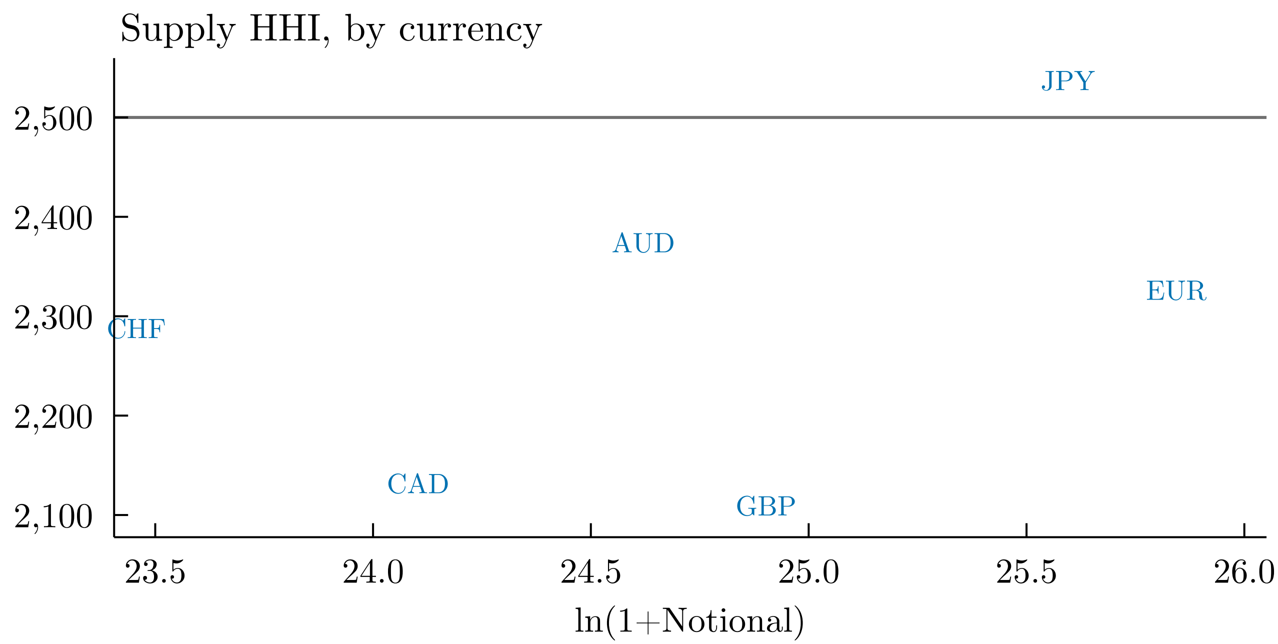

Figure A6: Supply Segmentation by Currency. Figure plots the average of daily Currency Supply HHI_t^{ccy} against (log of 1 plus) the average notional of that market.

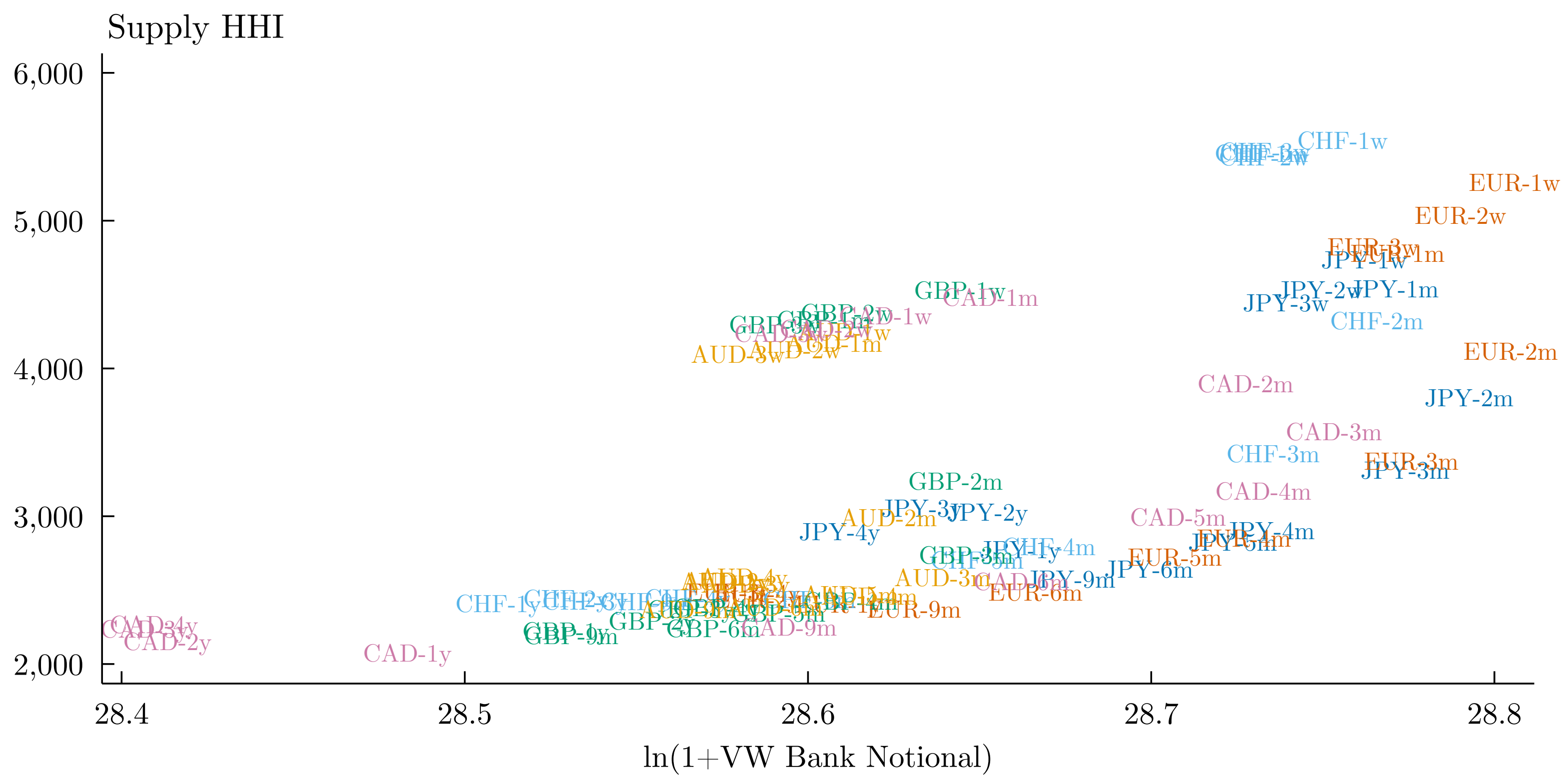

Figure A7: Supply Segmentation vs. Bank Size Figure plots the average of daily Supply $\mathrm{HHI}^{ccy}_{t,t+n}$ against (log of 1 plus the) the notional book size of the banks active in that market weighted by their market share in that market.

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

Table A1: Demand HHI estimate for full sample. Table presents the regression of Demand $\text{HHI}^{ccy}_{t,t+n} = \alpha + \beta_1 \text{Loan Demand HHI}^{ccy}_{t,t+n} + \beta_2 \text{Bilateral Share}^{ccy}_{t,t+n} + \varepsilon^{ccy}_{t,t+n}$, where Loan Demand $\text{HHI}^{ccy}_{t,t+n}$ 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.

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 A2: Level of $Net^{ccy}_{t,t+n}$ **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 $Net^{ccy}_{t,t+n}$ for a given currency ccy and maturity $t+n$. Bottom panel plots the time-series standard deviation of $Net^{ccy}_{t,t+n}$.

	Days to Maturity	$\ln(1 + \text{Gross Notional})$	$\mathbb{I}$(Quarter End)	$\mathbb{I}$(Year End)	HMV_t^{ccy}
$Net_{t,t+n}^{ccy}$	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

	$CY_{t,t+n}^{ccy}$	R_t^{SPX}	VIX_t	$Baa_t - Aaa_t$
$Net_{t,t+n}^{ccy}$	0.020^{***}	-0.002	-0.017^{***}	-0.012^{***}
	(0.00)	(0.38)	(0.00)	(0.00)
N	151,655	143,507	143,507	143,507

Table A3: Correlations. Table presents the correlation of $Net_{t,t+n}^{ccy}$at the day, by currency, by tenor level on days to maturity, $\ln(1 + \text{Gross Notional})$, dummies equal to 1 for month or year ends and 0 otherwise, and HMV_t^{ccy} which is a measure of net lending by dealers from CFTC data analogous to Hazelkorn et al. (2022)'s measure. Bottom panel compares with the convenience yield—estimated using the relevant currency's OIS rates and the Nielsen-Siegel-Svensson yield curve model—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, 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 includes 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).