Dealer Risk Limits and Currency Returns*

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Abstract

We leverage supervisory micro data to uncover the role of global banks' risk limits in driving exchange rate dynamics. Consistent with a model of currency intermediation under risk constraints, shocks to dealers' risk limits lead to price and quantity adjustment in the foreign exchange market. We show that dealers adjust their net position and increase spread in response to granularly identified limit shocks, leading to lower turnover and an adjustment in currency returns. These shocks exacerbate effects of net currency demand on exchange rate movements, as predicted by theory, and trigger deviations from covered interest parity.

Keywords: exchange rates, currency returns, market making, risk constraints, financial intermediation

JEL Codes: F31, G15, G21

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Introduction

To what extent are exchange rates determined by the ability of market intermediaries to facilitate flows? An important recent theoretical literature highlights the role of financial intermediaries in foreign exchange markets (Gabaix and Maggiori, 2015; Itskhoki and Mukhin, 2021*a*). A common theme from this literature is that financial frictions, such as risk-bearing constraints of financial institutions, can affect exchange rate determination and dynamics. However, validating this theory empirically has proved elusive, due to difficulties in observing the constraints of the specific actors. Validation is further encumbered by the fact that risk-bearing constraints are endogenous to the broader market conditions that may govern exchange rates.

Our paper provides empirical support for the role of financial intermediaries in driving exchange rate dynamics by focusing on the constraints of the currency trading desks of global banks. We use a novel supervisory data set on risk limits *at the desk level* to show that movements in market-maker constraints do in fact impact exchange rates when there is a currency flow to be mediated.[1] For identification, we construct idiosyncratic shocks to intermediary risk-bearing constraints following an approach similar to the granular instrumental variable (GIV) in Gabaix and Koijen (2020).

Why the necessary focus on foreign exchange trading desks at global banks? These trading desks are the central market makers in the dealer-centric over-the-counter foreign exchange market (Chaboud, Rime and Sushko, 2023). Any cross-currency flow, which could be related to international trade in goods or financial assets, will ultimately be reflected in transactions with a few large currency dealers that intermediate supply and demand for foreign exchange. Regardless of the size of the residual risk held by dealers, shocks to their risk limits can undermine their currency mediation function, thereby impairing risk reallocation and triggering exchange rate adjustments. In fact, using an additional novel data set on trading desk currency holdings, we uncover the stylized fact that the currency position of these foreign exchange trading desks is typically small, consistent with the current regulatory framework, which limits proprietary trading in market-making trading desks.

We use this insight—that these trading desks are critical intermediaries of currency flows but do not themselves hold a large profit-making position—to build a stylized economic model that guides our empirical analysis. In the model, a representative currency dealer intermediates currency between supply and demand to earn a bid-ask spread. The dealer also

[1] These risk limits refer to the risk-bearing constraints of trading desks, imposed by internal managers for both risk-management and regulatory purposes. From a legal standpoint, risk-bearing constraints "define the amount of risk and the positions that a trading desk is permitted to take at a point in time, as defined by the banking entity for a specific trading desk" (17 CFR Appendix A to Part 255).

earns returns on a (nonzero) net position, but such risky positions are subject to a convex holding cost, which can also be micro-founded with a risk limit such as the ones we observe in the data. The equilibrium analysis shows that an exogenous change in the risk limit affects the spread and net currency position, thereby affecting intermediation and risk sharing and triggering a market adjustment in currency returns. Notably, the dealer's function as a necessary, spread-earning intermediary prompts adjustments in currency returns beyond what would be predicted by replacing the dealer with a standard financier. The size and sign of these effects intuitively depend on the shift in net demand for dollars. For example, if banks face exogenously tighter risk limits and the economy faces a positive net-dollar demand shock, our model predicts a stronger depreciation of the foreign currency, driven by a reduction in banks' foreign currency holdings and lower turnover.

In reality, risk limits are endogenous to market conditions. Our strategy for identifying exogenous limit shocks builds on a striking institutional feature of the foreign exchange market: It is a highly concentrated dealer market, in which a few large global banking institutions intermediate the vast share of supply and demand of foreign currency.[2] This institutional feature allows us to leverage the insights of the granular instrumental variable method (Gabaix and Koijen, 2020) to construct an aggregate limit shock from idiosyncratic changes in large dealers' risk limits as observed in supervisory micro data. The idea is that, because of their size, idiosyncratic shocks to individual dealers matter in the aggregate. We then use the identified limit shocks to US dealers to estimate the effect on their aggregate net positions, exchange rates, and other key quantities.

We exploit two novel, supervisory microdata sets to construct the limit shocks and trace their impact on exchange rates. First, we use the FR VV-1 data, collected by the Federal Reserve, which contain granular information on all trading desks of large US bank holding companies (BHCs), including limits on their positions and daily usage of these positions. We find that trading desks tend to face limits on their aggregate position across a basket of currencies, as opposed to positions on individual currencies. To understand the effects of these limits on individual currencies, we also leverage the supervisory Y-14F data, schedule F, which contain quarterly information on net currency positions of trading desks, broken down

[2]For example, the top eight dealer banks have 92 percent market share in spot transactions, 81 percent market share in outright forwards, 74 percent market share in FX swaps, and 92 percent market share in options; see the Survey of North American Foreign Exchange Volume Market Share, Federal Reserve Bank of New York, October 2022.

by currency.[3] Our main sample covers the period from 2016 through 2022 for 32 currencies. Together, these data provide us with a comprehensive view of the risk limits and net currency positions of the largest US banks across their currency trading desks globally.[4] We are thus able to tackle the question of how shocks to these risk limits impact currency returns via financial intermediation. To our knowledge, this paper is among the first to use either data set and the first to combine them.

We test the model predictions using a standard regression approach. Our key independent variable is the granularly identified limit shock, and, in line with the model, we focus on the following core response variables in our baseline analysis: (1) the exchange rate change, (2) changes in bid–ask spread, and (3) changes in US banks' net foreign currency positions. Because theory postulates that the directional effect of the limit shocks depends on net dollar demand, we proxy these net dollar demand shifts and compute conditional effects (interaction terms). Our baseline proxy measure is innovations in dollar-denominated sovereign credit default swap (CDS) spreads.[5] These spreads capture sovereign default risk, an increase of which generally implies selloffs of domestic assets such as local-currency-denominated government bonds (Augustin et al., 2016; Hébert and Schreger, 2017). This selloff constitutes a currency net demand, which is intermediated by the dealer banks in our sample.

Our empirical results are consistent with our model predictions. Shocks to banks' risk limits have sizable effects on exchange rates, exacerbating effects from shifts in net currency demand. A negative standard-deviation shock in net demand for a foreign currency implies a 1 percent depreciation of that currency within the quarter. If, simultaneously, US dealers experience a one-standard-deviation tighter risk-limit shock, the currency depreciates by an additional 33 basis points (an increase of about one-third). In line with impaired dealer intermediation capacity, tighter risk-limit shocks also prompt larger bid–ask spreads and a reduction in aggregate exposure of US dealers toward foreign currencies, regardless of the direction of currency flows. Specifically, a one-standard-deviation tighter risk-limit shock implies bid–ask spreads increase by 6 percent and exposure to foreign currency declines by

[3] BHCs with average gross trading assets and liabilities over the previous four calendar quarters equal to $20 billion or more need to file VV-1. The Y-14F respondent panel comprises BHCs with $100 billion or more in total consolidated assets. Both data sets also cover the activity of foreign banking operations (at the intermediate holding company level). Full reporting requirements are available on the corresponding Federal Reserve Board websites. Our final sample includes 11 BHCs observed in both data sets.

[4] Both these data sets are collected by the Federal Reserve to support the stress testing exercise mandated by the 2010 Dodd-Frank Act after the Great Financial Crisis. All information in these data sets refers to activities consolidated at the BHC. Thus, our data capture activity by foreign branches and subsidiaries of US BHCs. For brevity, however, we use the term "bank" instead of BHC throughout the rest of this paper.

[5] In our baseline analysis, we estimate innovations in the log CDS spread as the residual of an auto-regressive model, estimated for each country separately. We show robustness to different demand shift proxies.

8.7 percent.[6]

Our analysis shows that it is important to account for the endogenous response of risk limits to market conditions. In particular, while all our key results are robust to differently identified limit shocks, we do not find an exchange rate response when using (endogenous) limit changes. We also show robustness to alternative proxies for net demand shocks besides innovation to sovereign CDS spreads. While the significant effects of idiosyncratic limit shocks on impact are consistent with segmented markets, we also show that the effects on foreign exchange markets are transitory. Indeed, our dynamic analysis shows that the exchange rate effects dissipate after one quarter, suggesting that other dealer banks step in over time and bring the exchange market back to the previous equilibrium. Consistent with this mechanism, we find that dealers that do not experience tighter limits when other banks face such constraints take up some of the slack by increasing their positions.

The risk-limit shocks also cause changes in covered interest parity (CIP) deviations, further supporting impediments to the dealer's intermediation activity due to risk-limit tightening. We estimate a substantial widening of CIP deviations of 6 basis points in response to a one-standard-deviation tightening limit shock. We provide further evidence of intermediation impairment by examining the factors behind banks' profits from currency intermediation. This intermediation profit can be thought of as a combination of volume and spread. Our analysis shows that currency turnover, measured at either the currency-time level or the bank-time level, decreases as a result of limit shocks. Additionally, consistent with our earlier finding that bid–ask spreads increase at the currency level, intermediation spreads (trading margins) across all currencies at the bank level also increase.[7] Our estimates are also economically relevant, pointing to a reduction in turnover of up to 3 percent and an increase in margins of about 8 percent in response to a one-standard-deviation limit shock.

Finally, we estimate heterogeneous exchange rate responses to limit shocks for each currency in our sample. The results highlight that for the majority of currencies, limit shocks have significant and sizable effects, consistent with the strong average effect uncovered in our baseline analysis, although there is variation in the magnitude of the estimate response coefficient. In fact, we find that the strength of the exchange rate response is closely related to the volatility of the currency return (as measured by the average quarterly standard deviation): More volatile currencies exhibit stronger responses to limit shocks. This pattern is consistent with predictions from a multi-currency extension of our baseline model, in which—as in the case of the value-at-risk (VaR) limits exploited in our analysis—risk-sensitive constraints

[6] Consistent with the model, we also show that the sign of the exposure reduction (long versus short) depends intuitively on the net demand shifter.

[7] We measure bank-level spread as foreign exchange trading revenue over gross notional in foreign exchange trading instruments.

govern the heterogeneous adjustment of position and spread. However, a causal interpretation of this empirical relationship is not possible, as limit shocks themselves exacerbate exchange rate movements, thereby contributing to volatility.

Related Literature Overall, our findings underscore the importance of financial frictions in understanding exchange rate movements. In doing so, it fits into a few strands of the literature. First, it contributes to the literature that focuses on the role of market segmentation in exchange rate determination (Hau and Rey, 2006; Alvarez, Atkeson and Kehoe, 2009; Bruno and Shin, 2014). Specifically, this paper provides empirical support for theories that center on the role of financiers who mediate currency transactions (Gabaix and Maggiori, 2015; Greenwood et al., 2020; Gourinchas, Ray and Vayanos, 2022; Itskhoki and Mukhin, 2021*a*,*b*). These theories emphasize the role of financiers' risk-bearing constraints in determining currency returns. An implication of these theories is that gross currency flows should determine exchange rate returns, and a strand of the literature tests this implication (Froot and Ramadorai, 2005; Hau, Massa and Peress, 2010; Corte, Riddiough and Sarno, 2016; Pandolfi and Williams, 2019). However, a direct test of the effect of financier constraints on currency returns has been difficult to conduct due to limited data availability, a problem we confront using novel data sources.

A small strand of the literature relates bank-level information or speculator activity to currency returns. Adrian, Etula and Groen (2011) and Adrian, Etula and Shin (2015) use publicly available bank balance sheet data to understand how US bank funding liquidity can help forecast US dollar (USD) exchange rates. By contrast, our paper is the first that we know of to utilize trading desk-level limits and positions in specific currencies. A few papers focus on futures market positions in specific currencies: Hong and Yogo (2012) look at the impact of futures market contract open interest on exchange rate returns, and Kim, Liao and Tornell (2014) relate survey results on futures market positions to exchange rate returns. However, our paper considers all currency cash and derivative instruments (it is worth mentioning that futures constitute a tiny portion of currency derivatives). Additionally, in contrast to this literature, our paper uses granular shocks to achieve causal identification of the effects.

Our paper also relates to the literature studying the role of market micro-structure and order flows in asset pricing determination. In this literature, market makers influence prices either due to fixed costs of doing business (for example, inventory costs), information asymmetries (Glosten and Milgrom, 1985), or monopoly power (Duffie, Gârleanu and Pedersen, 2005). Evans and Lyons (2002) and Evans and Lyons (2007) use trading data of a large dealer in the Deutsche mark/US dollar market to show that order flows (net-buying pressure on a particular currency) can explain as much as 60 percent of daily foreign exchange (FX) volatility. In their model, order flows from better informed investors generate price concessions for the dealers. Our paper differs from this literature in that we focus on the effect of exogenous changes in the risk and inventory capacity of dealers.[8] We also focus on exchange rate returns over a quarterly horizon, rather than concentrating on intraday changes.

More broadly, our paper relates to the strand of literature studying the relationship between bank balance sheets and foreign exchange markets. In particular, several papers argue that post-financial-crisis regulation has made banks' balance sheet capacity more costly, leading to deviations from CIP (e.g., Du, Tepper and Verdelhan, 2018; Abbassi and Bräuning, 2020; Cenedese, Della Corte and Wang, 2021).[9] We provide support for desk-level risk limits as an additional bank constraint that impacts the foreign exchange market. While balance sheet capacity may inform risk limits, these limits are also informed by other factors such as internal risk aversion and regulatory bans on proprietary trading. Overall, however, our findings reinforce the idea that bank constraints are crucial for understanding the foreign exchange market.

The remainder of the paper is organized as follows. Section 1 presents a stylized model that guides the empirics. Section 2 discusses the data, and Section 3 focuses on the construction of limit shocks. Sections 4 present the empirical results. Section 5 concludes.

1 Model

To understand the effects of trading desks' risk limits in the foreign exchange market, we start by introducing a basic model of a foreign exchange intermediary. Consider a representative bank that intermediates demand and supply for currencies. The bank charges a spread on its intermediation activities and can hold nonzero currency position at the end of any trading day. However, the bank has a risk limit on currency position. The model is set up in one period and with two currencies: the dollar and the foreign currency. The exchange rate, $\mathcal{E} = \exp(e)$, is expressed as foreign currency per dollar—an increase in the exchange rate means the dollar appreciates and the foreign currency depreciates. Without loss of generality, we assume a symmetric bid–ask spread of $2\tilde{s}$ around the mid-price point $\mathcal{E}$.

[8] Huang et al. (2023) show how constraints, such as VaR, affect dealers' liquidity provision in the foreign exchange market.

[9] Our work also relates to papers arguing more broadly that investors' hedging of international portfolios is a driver of spot and forward exchange rates (e.g., Liao and Zhang, 2020).

The bank takes as given the net dollar demand, $D(e+s)$, with $D' < 0$.[10] Financiers (non-dealers, for example, hedge funds) absorb part of this imbalance according to $F(e-s)$, with $F' > 0$, similarly to the financiers in Gabaix and Maggiori (2015).[11] We define a dollar demand-financier spread $2s$, which we allow to be negative. Let δ be the foreign currency position that the bank holds at the end of the period, expressed in USD terms (for example, the bank may hold 5 million US dollars' worth of Japanese yen). The bank sells all of this position δ in the future at $\mathbb{E}[\mathcal{E}_1] = 1$, leading to a gain or loss that is not discounted. The profits expressed in US dollars from holding the δ position are $\left(\frac{\mathcal{E}}{\mathbb{E}[\mathcal{E}_1]} - 1\right)\delta \approx \delta e$.[12]

Importantly, holding risk (that is, nonzero δ) is costly to the bank. Factors including risk aversion, volatility, regulations, or information asymmetries may be behind position limits. We model such cost in reduced form as a convex (quadratic) cost in δ. Note that the risk limits are exogenous in the model, while they may respond endogenously to market conditions in the data—a key identification challenge for our empirics that we elaborate on later.

The bank's profit (expressed in dollars) is equal to the sum of total margin from intermediation and the return of its nonzero net foreign currency position, δ. The bank takes as given the exchange rate and chooses the spread and foreign currency position to maximize expected profits:

$$\max_{s,\delta} \ \pi = s\left(D(e+s) + F(e-s)\right) + \delta e - \frac{\gamma}{2}\delta^2, \tag{1}$$

where γ parameterizes the bank's cost of holding nonzero net positions. A larger γ means that it is more costly for the bank to hold a nonzero position.

The interior solution returns the bank's optimal net position (foreign currency supply) and the optimal spread pricing equation:

$$\delta = \frac{e}{\gamma} \tag{2}$$

$$s = \frac{D+F}{F'-D'}. \tag{3}$$

[10]Note that $\tilde{D}(\mathcal{E}) = \tilde{D}(e^{\log(\mathcal{E})})$, so any demand function $\tilde{D}(\mathcal{E})$ can be expressed as $D(e)$ with $D = \tilde{D} * e$. Also note that $\log(\mathcal{E}(1+s)) = e + \log(1+s) \approx e + s$.

[11]Demand and financiers' schedules are reduced form but can be micro-founded by carry traders (hedge funds) or exporters, etc. For example, similarly to Gabaix and Maggiori (2015), one may think of demand in our model as net demand from the real sector, and net supply as financiers who ultimately hold risk. The bank intermediates between those two segments.

[12]To derive this, note that the bank converts δ USD into $\delta\mathcal{E}$ foreign currency. In the future, the bank will convert this foreign currency position back to USD, receiving $\left(\frac{\mathcal{E}}{\mathbb{E}[\mathcal{E}_1]}\right)\delta$ USD in expectation. Their total expected profit in USD is thus $\left(\frac{\mathcal{E}}{\mathbb{E}[\mathcal{E}_1]} - 1\right)\delta$ USD. Assuming $\mathcal{E}_1 = 1$, this is equivalent to $(\mathcal{E} - 1)\,\delta$. Because $\mathcal{E} = \exp(e) \approx 1 + e$, this approximately equals δe.

The bank's optimal foreign currency position thus increases if the foreign currency has a low value, that is, if e is high. Intuitively, when the foreign currency is depreciated, future returns are positive, so the bank wants to hold more of the foreign currency. A higher cost of holding risk, on the other hand, decreases the bank's position. The spread depends on the elasticities of dollar demand and supply by the financier. For example, when supply and demand are both very elastic, the dealer will charge a smaller spread for intermediation.

For simplicity, assume linear demand and supply functions:

$$D(e+s) = a - b(e+s) \tag{4}$$

$$F(e-s) = \frac{1}{\Gamma}(e-s). \tag{5}$$

The parameter a is a net demand shifter, which we interpret as a shock in preference for holding dollars by the foreign country. A positive value of a means that net demand for dollars increases. The elasticity of demand is $b > 0$, while $\Gamma > 0$ represents the constraints of nonbank financiers, as in Gabaix and Maggiori (2015). We also follow the existing literature and study the effect of *inelastic* net demand shifts. In particular, we assume that $(1 - b\Gamma) > 0$, which means that the dollar demand (D) is more inelastic than the dollar supply (F).

The global market clearing condition is:

$$D(e+s) - F(e-s) - \delta = 0, \tag{6}$$

which states that the total dollar demand must be equal to the total dollar supply provided by the financiers and the bank.

Proposition 1. *Given the bank supply and spread pricing equation* (2)–(3)*, the demand and financiers equations* (4)–(5)*, and the global market clearing condition* (6)*, the general equilibrium equations for the bank's net position, exchange rate, and spread are:*

$$\delta^* = \frac{a\Gamma(3+b\Gamma)}{A} \tag{7}$$

$$e^* = \gamma\frac{a\Gamma(3+b\Gamma)}{A} \tag{8}$$

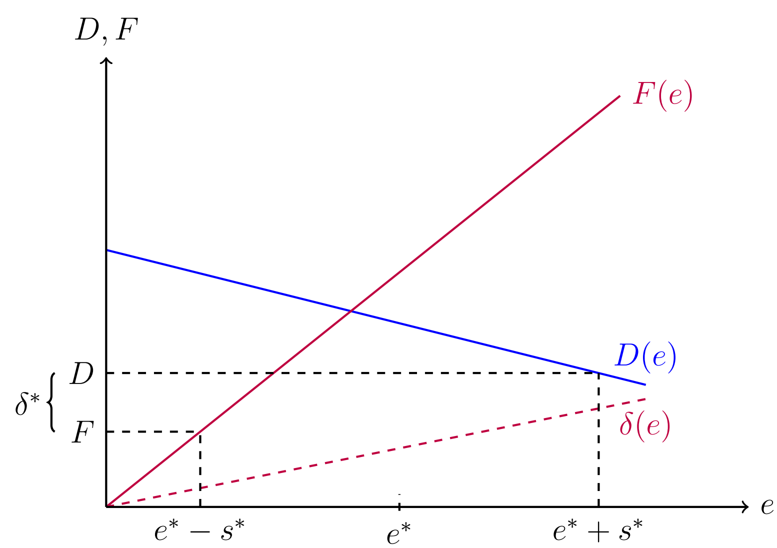
$$\tilde{s}^* = \frac{|a|\Gamma(\Gamma+2\gamma)}{A}, \tag{9}$$

where $A = \gamma + 2\Gamma(1+b\Gamma) + b\gamma\Gamma(6+b\Gamma) > 0$.

Crucially, the sign of the equilibrium exchange rate and net position depends on the demand shifter, a. In the trivial case of no net demand shift, $a = 0$, the (log) exchange rate equals the expectation, and net positions and spreads are zero. Moreover, the equilibrium exchange rate, net position, and spread are increasing functions in a, so when there is greater demand for dollars, the dollar appreciates more, banks' supply of dollars increases, and the spread increases. The absolute value in the bid-ask spread derivative comes from the fact that in our model of currency flows, D and F are not restricted to being positive in equilibrium, and the demand-financier spread s is negative whenever $a < 0$.[13]

Figure 1 illustrates the equilibrium for a positive dollar demand shock, $a > 0$. Similarly to the financiers in Gabaix and Maggiori (2015) or Itskhoki and Mukhin (2021*a*), the bank accommodates a demand growth for dollars in equilibrium by selling dollars and holding long the foreign currency position, $\delta > 0$. The bank also increases the spread, which, on net with the foreign currency depreciation, leads to an increase in the dollar supply from financiers and a reduction in dollar demand. Note that because, by assumption, the demand curve is more inelastic than the supply curve, for a given midpoint exchange rate, an increase in the spread leads to a lower reduction in demand compared with supply.

Figure 1: Foreign Exchange Market Equilibrium



Note: Equilibrium for positive dollar demand shift, $a > 0$, in full model. For reference, the figure also includes the dashed red line, which corresponds to the banks' net foreign currency position (dollar supply). Note that, in general, the equilibrium exchange rate e (midpoint between bid and ask) in our model is not equal to the equilibrium exchange rates that clears $D = F$.

We can compare the equilibrium exchange rate in our full model, $e^{\delta=\delta^*, s=s^*} := e^*$, with the equilibria that would emerge if we prevent the bank from either charging a spread or

[13] As discussed earlier, D and F refer simply to the net dollar demand by sector D and the dollar supply by sector F. We interpret these sectors as the real side and financiers. When D is negative, this means that there is a negative demand for dollars, that is, a positive demand for foreign currency by that sector. Likewise, when F is negative, this means that the financiers supply more foreign currency than dollars.

holding net position. The following inequality compares the exchange rate under four different models:

$$e^{\delta=0,s=s^*} > e^{\delta=\delta^*,s=s^*} > e^{\delta=0,s=0} > e^{\delta=\delta^*,s=0}.$$

Without the bank intermediating or holding any currency risk ($e^{\delta=0,s=0}$), the model collapses to Gabaix and Maggiori (2015). By comparison, our full model generates a larger depreciation than in Gabaix and Maggiori (2015) after a demand shock because the spread limits some of the financiers' capacity for demand absorption. If we allow banks to hold a foreign currency position but forbid them to charge a spread ($e^{\delta=\delta^*,s=0}$), the depreciation would instead be lower than under Gabaix and Maggiori (2015) since banks would be equivalent to an additional financier. By contrast, the foreign currency depreciates the most when banks are allowed to charge only a spread. In this case, banks do not take any position to absorb demand, and they charge a spread, limiting financiers' willingness to buy foreign currency. A risk-limit tightening is equivalent to a movement toward the latter equilibrium.

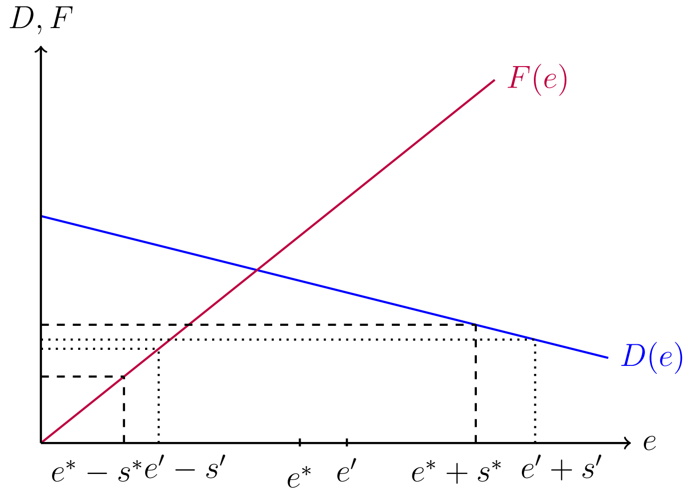
We next turn to the central focus of our analysis: the effects of changes in trading desks' risk limits on the foreign exchange market. Figure 2 illustrates the impact of an increase in γ on the equilibrium with a positive net dollar demand shifter. When the bank is more constrained (γ increases to $\gamma' > \gamma$), the bank reduces its net position and provides fewer dollars in equilibrium (equation 2), the total supply of dollars decreases, and the foreign currency depreciates ($e > 0$). Moreover, given our assumption about the inelastic demand shifter, the bank increases the spread. Taking together equilibrium adjustments to the spread and exchange rate, both the buy and sell prices increase, leading to a larger supply of dollars by the financiers, yet the increase does not make up for the reduction in the bank's position, leading to an overall decline in dollar supply (movement down the demand curve).[14]

We can summarize the intuition behind Figure 2 with the following testable proposition.

Proposition 2. *Given the general equilibrium exchange rate, bank position, and spread, and assuming that dollar demand is more inelastic than the financiers' supply (that is,* $1 - b\Gamma > 0$ *holds), the following comparative statics with respect to the bank's cost of holding the net*

[14] Appendix Figure A.2 illustrates the corresponding comparative statics for a negative net dollar demand shift, $a < 0$.

Figure 2: Effect of Tighter Risk Limits (increase from γ to γ')



Note: Comparative statics showing the effect of tighter risk limits on the currency market equilibrium. After the increase in γ, conditional on positive dollar demand shift ($a > 0$), the foreign currency depreciates more, spread increases, and banks' net position decreases, leading to an overall reduction in dollar intermediation.

position, γ, hold:

$$\frac{\partial \tilde{s}^*}{\partial \gamma} \propto |a|(1 - b\Gamma) > 0 \tag{10}$$

$$\frac{\partial \delta^*}{\partial \gamma} \propto -a \quad \textit{and} \qquad \frac{\partial^2 \delta^*}{\partial \gamma \partial a} < 0 \tag{11}$$

$$\frac{\partial e^*}{\partial \gamma} \propto a \qquad \textit{and} \qquad \frac{\partial^2 e^*}{\partial \gamma \partial a} > 0. \tag{12}$$

These comparative statics highlight that the sign of the effect of an increase in γ on the exchange rate and net position depends on the dollar demand shifter. Only when demand for dollars increases ($a > 0$) do larger limit shocks (tighter limits) lead to a stronger foreign currency depreciation and a reduction in the net foreign currency position. For a negative dollar demand shift ($a < 0$), the opposite holds. Note that given our assumption that the currency in net demand has greater inelastic demand, the spread always increases in response to tighter risk limits.

To obtain testable predictions for the exchange rate and net position change, we proceed in two steps. First, we proxy for the net demand flow, a, and test the interaction between limit shocks and demand shifts to correctly interpret our empirical results through the lens of the theoretical framework (equations 11 and 12). Second, we flatten the direction of the exchange rate and position change by looking at the response of the absolute value of the currency return and the absolute value of the position. Indeed, some basic algebra shows that the sign of the derivatives of the absolute value of the currency return and position to limit shocks is unambiguous, as summarized in the following proposition.

Proposition 3. *Given the general equilibrium exchange rate and bank position, the following comparative statics with respect to the bank's cost of holding net position, γ, hold:*

$$\frac{\partial|\delta^*|}{\partial\gamma} < 0 \tag{13}$$

$$\frac{\partial|e^*|}{\partial\gamma} > 0. \tag{14}$$

Tighter limit shocks exacerbate exchange rate movements—with the direction of the movement determined by the net demand shift—as banks reduce their position size and increase the spread, thereby impairing their intermediation capacity.

Note that our highly stylized model is static, hence flow equals stock, and the bank's net position δ equals the net flow. In the data, banks' net exposure to currency risk, measured at the end of each quarter, is small, especially when compared with the much larger gross flow intermediated (see the next section). Typically, net positions (stock) are closely linked to order flow, which reflects broader market conditions. We take the view that shocks to banks' cost of holding residual risk at any moment in time impair the banks' currency intermediation between ultimate supply and demand (order flow), thereby impairing risk sharing and changing currency returns to induce ultimate risk holders to absorb the risk.[15]

2 Data

Our analysis utilizes two supervisory data sets: the Regulation VV Quantitative Measurements (henceforth VV-1) data and the FR Y-14F (henceforth Y-14) data.[16] The 2010 Dodd–Frank Act mandated that the Federal Reserve System collect both these supervisory data, with the aim of building a more resilient financial system against the backdrop of the 2008–2009 Great Recession. Both data sets contain information about the consolidated global activity of the largest BHCs domiciled in the United States. Therefore, we capture the banks' activities from both foreign and domestic offices (including branches and subsidiaries). Moreover, both data sets cover the activities of foreign-owned intermediate holding companies (IHCs) with

[15]While not adding to the conceptional insights, one way to model this in our setup would be to introduce a function that maps the net positions (net stock) into a net flow going through the bank balance sheet. This net flow, during any time interval, is likely several magnitudes larger than the end-of-period stock.

[16]The reported data are confidential supervisory information, but the reporting forms and instructions, including the list of variables collected by the Federal Reserve, are publicly available at `https://www.federalreserve.gov/apps/reportforms/Default.aspx`.

substantial presence in the United States. As discussed, for simplicity, we refer to these institutions collectively as "banks."

The VV-1 data set originated under the 2013 Volcker rule of the Dodd–Frank Act to monitor compliance with restrictions on proprietary trading. Banks with average gross trading assets and liabilities over the previous four calendar quarters equal to or more than $20 billion are required to submit trading-desk names and descriptions and report a variety of metrics for each desk, including daily desk-specific internal risk limits and usage.[17] Risk limits are primarily of two types: sensitivity (for example, delta position, or cash equivalent position) and value-at-risk.[18] We focus on VaR-based limits in our main analysis, but our results are robust to using delta-based limits.[19] Because limits are desk-specific and not product-specific (for example, foreign exchange), we limit our analysis to desks that trade currencies as one of their primary products. We do so by selecting desks that match specific strings in their desk names or desk descriptions (for example, FX, currency, foreign exchange).[20]

It is worth noting that not all foreign exchange products were included in the original Volcker rule; while FX derivatives were included, FX cash was exempt. Furthermore, FX derivatives became exempt with the 2020 amendment to the Volcker rule, which became effective in January 2021. In practice, however, banks continue to report their internal risk limits for their FX desks through the end of our sample. Regardless of the regulation on FX limits, banks still limit exposure based on internal risk-management practices, and the Volcker rule reporting requirement gives us a unique window into these limits.

Our final data include 167 FX desks for 11 banks. Of these, 120 desks have delta limits, and 165 have VaR limits. One hundred eighteen desks report both delta and VaR limits. Since the reporting entity is the holding company, our data set covers trading desks affiliated with large US banks outside of the United States. For example, we capture FX desks in London. All desks declare the limit and limit use, in dollars, for each limit measure. Desks

[17]According to the Volcker rule, a "desk" is a unit of organization that purchases or sells financial instruments for a bank's trading account. Desks are structured according to a business strategy and to set and monitor trading limits, losses, and strategies. See 12 CFR § 248.3(e)(14)(ii).

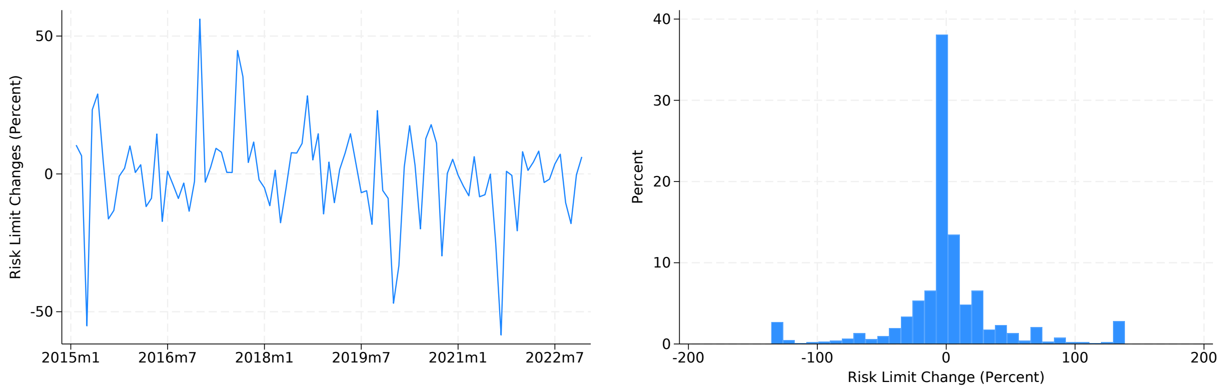
[18]The "cash equivalent" or the "delta position" of a derivative is the expected change in the value of a derivative for each dollar change in the price of the underlying asset, multiplied by the face value of the derivative. In exchange rate markets, it is also called the "spot equivalent position" and is used as a summary measure of the overall position to a given exchange rate across spot and derivative instruments.

[19]Often, a single desk has multiple limit types; for example, the desk may report both VaR-based and delta-based limits. VaR limits and delta limits are highly correlated.

[20]Banks record desk names and descriptions along with their internal desk IDs. We select desks whose names include one of the following strings: "FX," "currency," or "foreign exchange." We also include desks for review whose description includes "FX" or "currency," regardless of their desk name. We hand-verify all selected desks; that is, we verify that a desk is trading FX as one of its primary activities, not using FX just to hedge positions in other primary activities (such as equities or commodities). We do not include interest rate trading desks that trade cross-currency swaps as one of their products if they do not trade other FX products as one of their primary products.

may also declare the maximum and minimum of two-sided limits, which are most relevant for delta limits. Our analysis focuses on the maximum absolute limit value, so for a bank that reports an upper limit of +\$100 million (long position) and a lower limit of –\$120 million (short position), this value would be +\$120 million.[21]

Figure 3: Risk-limit Changes of Trading Desks



(a) Average Limit Change

(b) Distribution at Desk-Day Level

Notes: Panel (a) shows the monthly average of trading desks' percentage changes (log difference times 100) in risk limits. Panel (b) shows the histogram of percentage changes (log difference times 100) in risk limits at the desk-day level. Both data series are winsorized at the top and bottom 2.5 percent. *Source*: FR VV-1, authors' calculations.

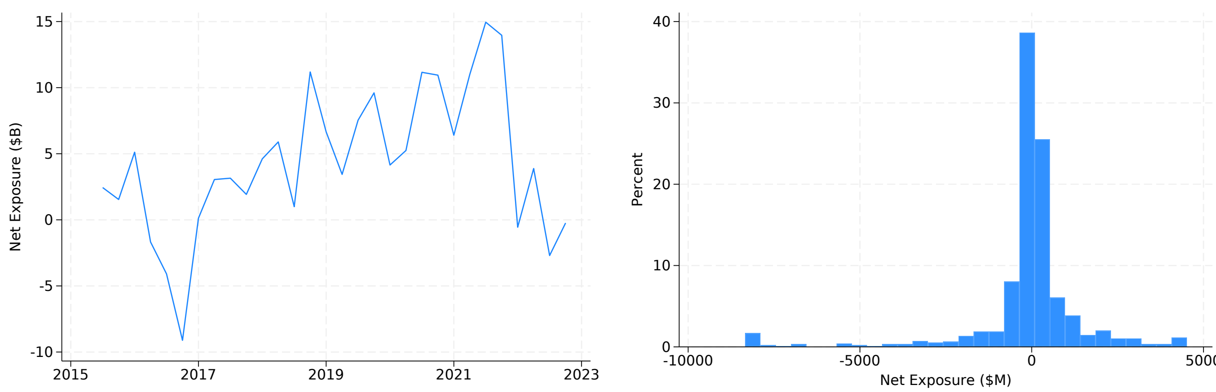
The observed changes in these trading desks' daily risk limits are at the core of our identification strategy. Based on the total of 1,071 nonzero limit changes observed in our data, we find substantial variation in limit changes over time and in the cross section of desks. Figure 4, panel (a), depicts the monthly average of trading desks' daily risk limit changes (measured in percentages). Large limit shocks stand out throughout the sample period exceeding +/–50 percent on average in some months. There is also a decline in limit increases throughout the sample. Panel (b) shows the histogram of corresponding desk-day level limit changes. The distribution exhibits substantial kurtosis. For confidentiality, the data in the graphs are winsorized at the top and bottom 2.5 percent. The risk limits are endogenous to macroeconomic conditions and subject to bank-level variation in the way they are declared (see Anderson, McArthur and Wang, 2023). For this reason, section 3 develops a method for isolating the idiosyncratic risk-limit shifts.

Our second data source is the FR Y-14. The Y-14 dataset includes detailed information on the portfolio holdings of the largest US banks. Banks with more than \$100 billion in

[21]In most cases, limits and limit changes are symmetric, thus preventing a separate analysis of asymmetric limit changes.

total consolidated assets are subject to the mandated Dodd–Frank Act Stress Test (DFAST) and are required to file the Y-14 for stress-testing and supervisory purposes. Specifically, we exploit Y-14 Schedule F on trading that contains information on banks' FX trading activity. For each bank and quarter, the schedule reports the delta positions, that is, the cash equivalent net exposures, in each currency. In what follows, for simplicity, we refer to this delta position as "net position" or "net exposure." Again, because the reporting entities are BHCs, we capture all consolidated positions, irrespective of whether they come from a trading desk in the Unites States or abroad.[22]

Figure 4: Trading Desks' Net Position in Foreign Currencies



(a) Aggregate Position (b) Distribution at bank-quarter-currency

Notes: Panel (a) shows the sum of net position across all banks and currencies, for each quarter (in \$ billion). Positive values correspond to long position in foreign currency. Panel (b) shows the histogram of the net positions at the bank-currency-quarter level (in \$ million), winsorized at the top and bottom by 1 percent. We exclude Korean won exposure from panel (a) because some desks have large net short positions with an outsized effect on aggregate exposure. Appendix Figure A.6 shows full details on the net exposures for each currency. *Source*: FR Y-14F, BIS, authors' calculations.

Figure 4, panel (a), shows the evolution of aggregate net positions (total delta positions across banks and currencies) over time. The series reveals that US banks are generally long in foreign currencies, thus providing dollars to the rest of their trading counterparties. The figure also reveals that positions in foreign currency increased from about 2017 through 2021 but then fell. Moreover, positions vary from –\$10 billion to \$15 billion. Panel (b) zooms in on the distribution of net positions at the bank-quarter-currency level, revealing

[22]Submission types are further broken down into the following: (1) FVO hedges are positions that are used to hedge loan assets that are held for sale (HFS) or held under fair value option (FVO) accounting; (2) AL hedges are positions that are used to hedge held-for-investment (HFI) accrual loans; (3) Credit valuation adjustment (CVA) refers to the market value of the credit risk due to any failure of the counterparty to deliver; and (4) trading. In most of our analysis, we focus on the trading submission, given our research question.

substantial cross-currency variation and fat tails, which indicate that some large positions exceed \$1 billion. Appendix Figure A.5 shows the evolution of the aggregate net positions by currency over time and demonstrates additional time variation, which is significant for several currencies.[23]

Appendix Figure A.6, panel (a), zooms in on the distribution of positions by currency, across time and banks. The majority of net positions are rather small, in the order of tens to hundreds of millions, with maximum net position being \$1 billion. This insight is consistent with trading desks focusing on intermediation rather than proprietary trading. (Note that to maintain confidentiality, the data are winsorized at the top and bottom 5 percent.) The relatively small net positions contrast starkly with the average daily turnover from the BIS triennial survey, which is in the order of trillions (panel b). Our model rationalizes how changes in limits have significant and sizable effects on exchange rates—even when risk limits and net positions are small.

In addition to these supervisory micro data sets, we use banks' income and balance sheet information at the quarterly frequency as reported in the publicly available FR Y-9C data. In addition to standard variables such as asset size or capital ratios, the Y-9C contains information on income from FX trading as well as gross notional in FX trading. Moreover, we collect bilateral exchange rates, bid–ask spreads, implied volatility, CDS spreads, forward exchange rates and settlement dates, and interest rates from Bloomberg. Additionally, we use turnover data at the currency level from the Federal Reserve Bank of New York's Foreign Exchange Volume Survey.

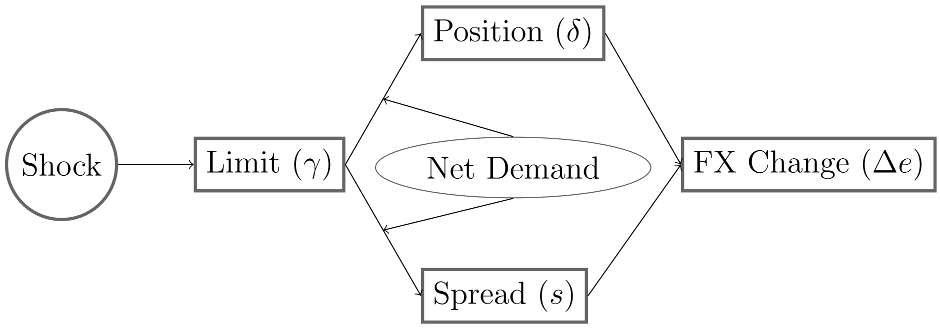
3 Identification

Figure 5 illustrates the core causal chain that is the focus of this paper: Conditional on net currency demand, shifts in dealers' risk limits affects the spread and net positions, thereby affecting intermediation and risk sharing, triggering a market adjustment in currency returns.

While risk limits were assumed to be exogenous in our stylized model, in reality they may respond endogenously to market conditions, including exchange rates, dealers' net positions, and bid–ask spread. Neglecting the endogeneity of risk limits generally leads to biased estimates of the effect of risk limits on exchange markets. In this section, we discuss how we use our confidential data to identify exogenous variation in risk limits that is exogenous to market conditions. Similarly, we discuss how we identify demand shifters given that our model predicts that the effect of limit shocks depends on net demand.

[23] The figure also reveals large short positions in the South Korean won (KRW), which is why we have excluded the KRW exposure from panel (a) of Figure 4.

Figure 5: The Effect of Limit Shocks on the Foreign Exchange Market



Note: The figure highlights the key causal relationship in our model. The rectangles represent endogenous variables, which depend on each other and on supply and demand in the currency market.

Risk-limit Shocks We exploit the supervisory microdata to construct currency-level and bank-level shocks to risk limits. To do so, we combine two insights from Gabaix and Koijen (2020). First, we identify desk-level idiosyncratic risk-limit changes, that is, changes in limits that are exogenous to the overall evolution of the foreign exchange market and its own bank. We provide supporting evidence of this exogeneity in the next subsection. Second, the granularity of the dealer-centric market—a few large dealers account for a large share of FX intermediation—allows exogenous idiosyncratic limit changes to affect aggregate quantities. The aggregated idiosyncratic limit changes weighted by bank currency exposure constitute an exogenous shock to dealers' trade limit in each currency.

Our granular approach to isolating risk-limit shocks involves two steps. First, we recover dealer-day-level idiosyncratic limit shocks as the residuals from a saturated regression of dealer-day-level limits, controlling for time trends and dealer-specific effects. Specifically, in our baseline specification, we model the log limit changes at the desk-day (d,τ) level using a saturated fixed-effects model:

$$\Delta \log \text{Limit}_{d,\tau} = \sum_{h=1}^{20} \gamma_h \log \text{Limit}_{d,\tau-h} + \sum_{h=1}^{20} \omega_h \text{Usage}_{d,\tau-h} + \alpha_d + \alpha_{b,\tau} + e_{d,\tau}, \qquad (15)$$

where d indexes desks, τ indexes days, and $\alpha_{b,\tau}$ is a bank-time effect to control for common changes of limits across different desks (for example, New York and London desks) within a given bank. For instance, the fixed effects would control for changes in the bank's equity capital or applicable banking regulation. We also include desk fixed effects to account for heterogeneity in limits across desks. In addition to these fixed effects, we control for 20 lags of the limit and the percentage usage of the limit to isolate surprise changes in limits orthogonal to limit and usage history. This is important because limits may adjust endogenously with usage; for example, when expected currency returns are high, limit usage may be high, and banks may increase risk limits to benefit from the expected exchange rate change.

To understand the variation in changes in (log) limits, Table 1 shows the R^2 of the different sets of fixed effects included in our baseline model, as well as the explanatory power of the full model. Column (3) shows that time fixed effects alone can explain only about 2 percent of the variation. On the other hand, column (4) shows that bank-day fixed effects alone can explain about 13 percent of the variation in limit changes, meaning that common bank factors, such as changes in total bank equity, have considerable explanatory power. The most saturated model in column (5) can explain about 44 percent of the variation. Moreover, the reported coefficients (sum of lags) on the control variables suggest a negative correlation between current and past limit changes—if limits increased in the recent past, they tend to decline again. Moreover, the positive coefficient on the lagged limit usage shows that risk limits respond endogenously to usage, with higher usage triggering increases in risk limits.

Table 1: Variation in Δ Log Limit

	Δ Log Limit					
	(1)	(2)	(3)	(4)	(5)	(6)
Past Limits ($\sum_{h=1}^{20} \gamma_h$)					-0.022***	-0.002***
					(0.001)	(0.000)
Past Usage ($\sum_{i=1}^{20} \omega_h$)					1.930***	1.943***
					(0.522)	(0.284)
Bank FE	Yes	-	-	-	Yes	-
Desk FE	-	Yes	-	-	Yes	-
Time FE	-	-	Yes	-	Yes	-
Bank $\times$ Time FE	-	-	-	Yes	Yes	-
R-squared	0.000	0.000	0.024	0.125	0.437	0.331
N	98956	98956	98956	98956	98956	98956

Notes: Explanatory power of different models for desk-day level (log) limit changes. Column (5) corresponds to equation (15). *Sources*: FR VV-1, FR Y-14F, authors' calculations.

We further allow for a common factor structure in the residuals of equation (15) that may not be captured by our extensive set of fixed effects and controls:

$$e_{d,\tau} = \lambda_d' f_\tau + \epsilon_{d,\tau}, \tag{16}$$

where f_τ is a vector of common factors, and λ_d are the associated loadings of desk d. The residual $\epsilon_{d,\tau}$ represents the truly idiosyncratic components. We estimate the factor structure using principal component analysis of the residuals obtained from a least-squares regression of equation (15). In our baseline analysis we remove one common factor, but results are robust to removing more common factors.

The residual of equation (16) is our baseline measure of idiosyncratic (desk-level) limit innovations. In Appendix B, we show results from alternative models for constructing limit innovations. To compute bank-level limit shocks, we aggregate the desk-level limit innovations to the bank level and currency level as weighted means. Specifically, we roll up the innovations to the bank-quarter (b, t) level as:

$$\text{Limit Shock}_{b,t} = -\sum_{\tau \in t} \sum_{d \in b} w^b_{d,t-1} \hat{\epsilon}_{d,\tau}, \tag{17}$$

where $w^b_{d,\tau} = \text{Limit}_{d,\tau} / \sum_{d \in b} \text{Limit}_{d,\tau}$ is the relative limit size of desk d (the summation occurs over all desks affiliated with a given bank, $d \in b$) on the last day of the previous quarter. The outer summation then aggregates these daily bank-level shocks to the quarterly frequency by summing across all days within a given quarter. Note the negative sign in equation (17); an increase in the limit shock variable thus corresponds to a tightening of limits, similarly to an increase in γ in our model.

Finally, we compute currency-quarter-level limit shocks by aggregating the bank-level shocks using position (delta) weighted means:

$$\text{Limit Shock}_{c,t} = \sum_b w^c_{b,t-1} \text{Limit Shock}_{b,t} = -\sum_b w^c_{b,t-1} \sum_{\tau \in t} \sum_{d \in b} w^b_{d,t-1} \hat{\epsilon}_{d,\tau}, \tag{18}$$

where $w^c_{b,t-1} = \text{abs}(\delta_{b,c,t-1}) / \sum_b \text{abs}(\delta_{b,c,t-1})$ is the share of net position held by bank b in the aggregate net position of all banks in our sample. Thus, currency-level shocks are constructed as a weighted mean of bank-level shocks, with the weights capturing the importance of a bank's net position in a given currency. The idea here is that limit shocks to banks that have a larger position, relative to other banks, in a given currency should matter more to that currency market. Note that our identification hinges on the random shocks, while position shares are allowed to be endogenous (Borusyak, Hull and Jaravel, 2021).[24]

Appendix Figure A.8 depicts our baseline limit shocks at the currency-quarter level. The shocks are symmetric and recurrent for most considered currencies. All shocks are transitory and not clustered around any specific quarter, in line with our identification of idiosyncratic innovations. For robust inference, all shocks are winsorized at the 5th and 95th percentiles. Finally, we standardize the limit shocks in each estimation sample to have mean zero and unit variance.

[24]Appendix Figure A.7 shows the distribution of the weights used in equation (18) by currency, and Appendix Table B.2 shows that the weights are fairly persistent over time.

Narrative Analysis The assumption that desk-level idiosyncratic risk-limit changes are exogenous to broader market conditions is key to our identification strategy. We provide support for this assumption in two ways: first, through conversations with traders and industry specialists, and second, through a quantitative textual analysis of bank earning calls. Note that due to the confidential nature of our microdata, we cannot describe individual shocks in our data.

Anecdotally, VaR limits indeed do not move in anticipation of specific future exchange rate changes. Rather, according to conversations, risk limits tend to change due to routine changes to the VaR methodology or recalibration, changes in business strategy (that is, top-down decision to reduce the activity of a set of desks), regulatory compliance, or occasionally, trading scandals that cause rethinking of the bank's underlying risk models. For example, consider the Federal Reserve's enforcement actions against Deutsche Bank in April 2017.[25] Deutsche Bank was found to have violated the Volcker rule, as it had failed to adequately monitor proprietary trading, and was required to improve oversight and controls. In general, traders view VaR risk metrics as slow-moving historical metrics, rather than forward-looking or news-sensitive metrics.

Additionally, a textual analysis of banks' earnings calls finds that risk-limit shocks are not correlated with institutional or macro events in our sample. We focus on the 20 largest bank-quarter risk-limit shocks in our sample, as defined in equation (17), because they are more likely related to sizeable macro or bank-related events. Figures A.9 and A.10 plot the currency-level idiosyncratic shocks and the variation driven by the 20 largest bank-quarter shocks. The largest bank-quarter-level shocks impact all currencies throughout the sample period, and they correspond to most of the largest movements of our aggregate currency-quarter-level idiosyncratic limit shocks.[26]

We use a large language model (LLM) to summarize and rank the most important topics discussed in each bank's earnings call. Appendix D outlines the method used to summarize the most important topics. We compare topics discussed when we observe large idiosyncratic risk-limit changes and all other calls in the sample. Figure A.11 presents a word cloud of the most relevant topics, as perceived by the LLM, in the large-shock sample versus all other bank-quarter observations.[27] We do not find any evidence of global or bank-related events being prominent in the large-shock sample. In fact, we can test that there is no significant difference in topics being discussed across a wide range of topic categories. Figure A.12 shows

[25] These enforcement actions were publicly listed on the Federal Reserve website and reported in the news.

[26] Note that we do not need our risk-limit shocks to have a granular distribution because all the banks in our sample are granular intermediaries in the foreign exchange market.

[27] This approach is similar in spirit to Balduin Bippus and Ostry (2023), although we rely on the LLM to summarize the textual content and minimize researcher bias.

the mean testing estimates in the two samples for the mention of 15 general topic clusters. The only (borderline) significant result is that there is less talk of future outlook under large risk-limit shocks. We find similar results when we explore the correlation between earnings calls sentiment and either raw limit shocks or idiosyncratic risk-limit shocks (see Appendix Table B.3). Overall, these results confirm the exogeneity of idiosyncratic risk-limit changes to market events, in line with our anecdotal evidence.

Demand Shifter Our theory suggests that the directional effect of limit shocks on exchange rates depends on the direction of currency demand. When limits are tightened in the presence of net dollar demand, theory suggests that the exchange rate will depreciate. To proxy for shifts in net dollar demand, we use innovations in the spread of five-year credit default swaps written on sovereign debt. An increase of sovereign default risk generally implies foreign selloffs of domestic assets, such as local currency-denominated government bonds, putting downward pressure on the local currency (Augustin et al., 2016; Hébert and Schreger, 2017). Thus, such a shift represents an increase in (net) demand for dollars. Because changes in sovereign credit risk can, in principle, be related to macroeconomic conditions more broadly, we compute surprise innovations to CDS spreads by estimating, for each country/currency c, the following autoregressive model:

$$\log CDS_{c,t} = \alpha_c + \sum_{j=1}^{4} \phi_{c,j} \log CDS_{c,t-j} + u_{c,t},$$

We use the residuals of this regression as CDS innovations.[28] Our demand shift measure is thus:

$$\text{Demand Shifter}_{c,t} = \hat{u}_{c,t}.$$

In the robustness analysis, we also compute innovations to one-month at-the-money implied volatility.[29] By construction, limit shocks and the demand shifter are likely unrelated. Indeed, Appendix Figure A.13 shows that the two variables exhibit no relationship. More formally, when regressing the limit-shock factor on the demand shifter in our quarter-currency panel, we find an insignificant slope coefficient and an R^2 close to zero.

[28]These CDS innovations are indeed negatively correlated with both changes and innovations in log total inflows, as computed from the IMF Balance of Payments data.

[29]Implied volatility is a measure of the market's expectation of the forward risk of a currency. It is calculated using currently outstanding over-the-counter (OTC) options contracts on currency futures.

4 Empirical Results

In this section, we present our empirical model to test the theoretical predictions of limit shocks. We then discuss our baseline results, focusing on the effects on exchange rates, bid–ask spread, and net positions. Then, we zoom in on dynamic effects and mechanisms supporting intermediation impediment.

Empirical Model To test the model predictions, we regress the three key dependent variables—exchange rate, net position, and bid–ask spread—on the limit shock interacted with the net demand shock. Formally, we use the following regression model:

$$\begin{aligned}\Delta y_{c,t} = \beta_1 \text{Limit Shock}_{c,t} + \beta_2 \text{Limit Shock}_{c,t} \times \text{Demand Shifter}_{c,t} \\ + \alpha_i + \alpha_t + \gamma' X_{c,t} + u_{c,t},\end{aligned} \tag{19}$$

where $y_{c,t}$ is the outcome variable, which in our baseline analysis is either (1) the log spot exchange rate of currency c, multiplied by 100; (2) the aggregate US banks' net position to currency c normalized by the sum of the limits across all US banks; or (3) the bid-ask spread in percent of the mid-point.[30] We also estimate similar models for the nondirectional variables that flatten out the direction (sign) of the position and exchange rate change. Specifically, as additional outcome variables, we use (4) the absolute value of the exchange rate change and (5) the change in the absolute value of the net position. Limit Shock is the granular limit shock, as identified in the last section. It represents exogenous shifts in limit changes, with an increase corresponding to a tightening of limits. Demand Shifter is the innovation to the CDS spread. An increase in Demand Shifter proxies for a decrease in foreign currency demand and an increase in dollar demand. The vector of controls $X_{c,t}$ contains four lags of $y_{c,t}$. It also includes the level (uninteracted) term of Demand Shifter. Moreover, α_t is a quarter-year fixed effect, and α_c is a currency fixed effect. Because the COVID-19 outbreak in 2020:Q1 triggered significant turmoil in financial markets, including the foreign exchange market, we interact the currency fixed effects in our baseline results with a dummy variable indicating 2020:Q1, thereby removing the impact of 2020:Q1 on our estimates. In line with our model predictions, our key parameters of interest are the coefficients on the limit shock, β_1, and, for the directional analysis, on the interaction term between the limit shock and the demand shifter, β_2. For statistical inference, we compute robust standard errors two-way clustered at the currency and quarter levels to account for correlation of residuals within each cluster.

[30] We normalize aggregate net position to currency c by lagged total limits (that is, we sum both net positions and lagged limits across banks/desks and then divide the sums), but results are robust to different normalizations of the net position, such as the total gross flow reported by the BIS.

Summary Statistics Our main analysis is based on a currency-quarter-level data set, which covers data on 30 currencies observed for 30 quarters each. Table 2, Panel A reports summary statistics of the key variables in this datasets. To ensure confidentiality of supervisory information, we winsorize all shock variables, as well as our measure of aggregate US banks' net currency positions, at the bottom 5 percent and top 5 percent. During our sample period, foreign currencies tended to depreciate slightly against the dollar, with an average depreciation rate of 1.08 percent. More importantly, fluctuations in exchange rates are sizable, with a standard deviation of 5.9 percent. In 5 percent of the observations, the foreign currency depreciates by more than 10 percent over the quarter, while for the bottom 5 percent of observations, the appreciation is larger than 6.5 percent. The table also reveals that the average net position is negative, indicating that US banks, on average, are short in foreign currency on their trading books. However, there is substantial variation in net positions.

Table 2: Summary Statistics

	(1) Mean	(2) Std. Dev.	(3) P5	(4) P25	(5) P50	(6) P75	(7) P95	(8) N
Panel A: Currency-Quarter Data								
Δ FX Rate	1.08	5.94	-6.50	-2.15	0.19	3.60	10.45	960
Norm. Net Position (Pct.)	-0.10	12.02	-34.06	-2.23	0.31	3.14	25.28	928
Δ Net Position	-0.01	8.08	-10.95	-2.02	0	2.18	9.76	896
Bid-Ask Spread (Pct.)	0.25	0.48	0.01	0.04	0.12	0.27	0.80	959
Δ Bid-Ask Spread	0.05	1.06	-1.70	-0.57	0.02	0.69	1.81	904
Limit Shock (Pct.)	0.03	0.39	-1.12	-0.03	0.12	0.20	0.66	960
Limit Change (Pct.)	0.01	0.94	-0.32	-0.04	-0.02	0.02	0.51	960
Demand Shifter (CDS Innovation)	0	0.26	-0.34	-0.13	-0.01	0.08	0.43	731
Demand Shifter (Vola Innovation)	0	0.23	-0.31	-0.14	-0.03	0.09	0.40	832
CIP Deviation 1m (B.P.)	11.26	302.06	-162.41	-1.16	20.54	60.55	262.98	888
Δ Log(Turnover)	0.01	0.38	-0.39	-0.12	0.02	0.18	0.48	268
Panel B: Bank-Quarter Data								
Δ Log(Gross Notional)	0	0.23	-0.29	-0.08	0.01	0.11	0.30	256
Δ Margin	-0.16	6.84	-4.18	-0.32	0.09	0.31	1.92	198

Notes: Panel A presents summary statistics for key variables in our baseline currency-quarter level data. Log difference in exchange rate is multiplied by 100. Aggregate US banks' net positions are normalized by the sum of limits across banks. Bid–ask spread is presented as a percentage of the mid-price. Limit Shocks and Changes as well as CDS and Volatility Innovations are measured in log differences. CIP deviations are measured in basis points. The sample covers data from 2015:Q3 through 2022:Q4 and 32 currencies. Panel B shows summary statistics for key variables at the bank-quarter level. The sample covers seven banks from 2014:Q3 through 2022:Q. *Sources*: FR VV-1, FR Y-14F, FR Y-9C, Bloomberg, NY Fed FX Volume Survey, authors' calculations.

Baseline Results Table 3, panel A, presents the estimation results of equation (19) for our main response variables, that is, the exchange rate change, net position change, and bid-ask spread. When we investigate the average effect of limit shocks in columns (1) and (3), we find that, on their own, they have an insignificant effect on currency returns and the net positions of banks. As discussed in the model section, this result is theoretically justified: Because limit shocks prompt currency changes in the direction of net demand, theory predicts an ambiguous effect of limit shocks on exchange rates when net demand is not accounted for. Similarly, because bank net positions absorb some of the excess demand for dollars or foreign currency, and because limit shocks cause banks to reduce this absorption, whether banks' net positions increase or decrease after a limit shock depends on the direction of net dollar demand.

Crucially, our theory predicts that the response of exchange rates and banks' net positions depends on the demand shifter. We test this prediction in columns (2) and (4), which include the interaction term between limit shock and demand shifter.[31] For this average effect, we find that an increase in net dollar demand (decrease in foreign currency demand) leads to a depreciation of the foreign currency by about 1 percent (column 2). Focusing on the interaction term, we find that the foreign currency depreciates even more after a demand shock when banks' risk limits become tighter. Specifically, relative to the average effect of a demand shift of about 1 percentage point, this implies a one-third larger effect on exchange rates after a limit shock (a differential effect of 33.1 basis points). This effect is statistically significant and in line with our theoretical predictions.[32] Furthermore, these price movements are isolated to the foreign exchange market; Appendix Table B.8 shows that interest rate differentials do not seem to be affected by limit shocks, regardless of whether they are interacted with demand shifters.[33]

In column (4), which estimates the response of banks' net position, we estimate a significant and negative coefficient on the interaction term, indicating that, conditional on a positive net dollar demand shift, banks reduce their long position in foreign currency after a limit

[31] Given our standardized limit shock variable, the coefficient estimate on Demand Shifter represents the average effect of a demand shift in our sample; see also Table B.4, which shows specifications with only CDS Shock and Limit Shock as uninteracted variables.

[32] Note that the explanatory power of our limit shocks for our outcome variables is small throughout all regressions. Within R^2's are small and include the explanatory power of the control variables. This is not surprising because, by construction, we focus on idiosyncratic limit shocks and remove any common factors that explain the bulk of variation of our outcome variables. We sacrifice explanatory power to achieve narrow identification. We also find these narrow limit shocks to be weak instruments for (aggregate) limit changes, which is why we estimate reduced-form models throughout.

[33] Remember that, by construction, limit shocks are orthogonal to bank-time factors, so changes in banks' interest rate trading desk that could move rates are accounted for. Using the Y-14 data, we confirm that interest rate sensitivity to a specific currency is not significantly correlated with delta sensitivity to that currency at the bank-currency-quarter level.

Table 3: Limit Shock Effects on FX and Position Depending on Net Demand Shifter

	Δ FX Rate		Δ Net Position		Δ Bid-Ask Spread	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Directional (Baseline) Results						
Limit Shock	0.045	0.142	0.130	-0.096	0.069***	0.073**
	(0.115)	(0.104)	(0.341)	(0.371)	(0.023)	(0.034)
Demand Shifter		1.009***		-0.384		0.115***
(CDS Innovation)		(0.292)		(0.442)		(0.032)
Limit Shock × Demand Shifter		0.331**		-0.316**		0.000
		(0.137)		(0.118)		(0.032)
Within R-squared	0.035	0.091	0.345	0.385	0.429	0.463
N	800	702	768	675	758	660
Panel B: Undirectional Results						
Limit Shock	0.382***	0.476***	-0.087*	-0.091*		
	(0.115)	(0.136)	(0.047)	(0.050)		
Demand Shifter		0.381		-0.090**		
(CDS Innovation)		(0.324)		(0.035)		
Limit Shock × Demand Shifter		0.215		0.008		
		(0.151)		(0.026)		
Within R-squared	0.470	0.434	0.435	0.447		
N	800	702	768	675		
Dep. Variable Lags	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Currency FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the directional effect of (tightening) shocks to banks' risk limits on key endogenous variables in the foreign exchange market depending on net demand shifts. In columns (1) through (3), the dependent variable, Δ FX Rate, is the quarterly log difference in the spot exchange rate, multiplied by 100. In columns (4) through (6), the dependent variable, Δ Net Position, is the quarterly change in the aggregate US banking system's net (long) position in foreign currency, normalized with the total limit value in the last quarter. The independent variables Limit Shock and Demand Shifter are constructed as described in the main text, and they are standardized to have zero mean and unit variance in each regression sample. Controls include four lags of the dependent variable. Quarter fixed effects and currency fixed effects are included. The sample is at the quarterly frequency and includes data from 2016:Q3 through 2022:Q4 for 32 currencies. Robust standard errors are two-way clustered at the currency and quarter levels and are shown in parentheses. *Sources*: FR VV-1, FR Y-14F, Bloomberg, authors' calculations.

shock. (The level effect of Demand Shifter captured by the uninteracted variable is negative but statistically insignificant.) The coefficient estimate of –0.316 implies that, in response to a one-standard-deviation limit shock and conditional on a unit dollar demand shifter, the net foreign currency position falls differentially by about 4 percentage points more, relative to the standard deviation of quarterly net position changes (value of 8.08).

While the limit shock interacts with demand shifts to affect currency returns and dealer positions, column (5) shows that limit shocks have, on average, a significant impact on bid-ask spreads. The estimated coefficient indicates that spreads increase by 6.9 percent in response to a one-standard-deviation limit shock (recall that bid–ask spreads are measured in logs). This response is also consistent with our theoretical predictions. On the other hand, bid–ask spreads do not respond differentially to limit shocks depending on the demand shifter.

In panel B, we extend our baseline analysis by looking at the effects of limit shocks on nondirectional, or flattened out, variables, for which our model predicts average responses that do not depend on the sign of the net demand shift. We examine the effect of limit shocks on (1) the absolute value of the change in the (log) exchange rate and (2) the change in the (log) absolute value of banks' net positions. Consistent with our theoretical predictions from Proposition 3, we find that tightening limit shocks, on average, exacerbate exchange rate movements (column 1) and lead to a reduction in banks' foreign currency net positions (column 3). Columns (2) and (4) show that there is no differential effect depending on the demand shifter.

Similarly to our baseline analysis, our estimates of the flattened variables imply sizable economic effects. Specifically, a one-standard-deviation limit shock prompts a change in the exchange rate of 38.2 basis points (equivalent to 6 percent of the exchange rate standard deviation) and a decrease in the size of the (absolute value of) net positions of 8.7 percent. Recall also that the bid–ask spread increases by about 7 percent. Intuitively, a wider bid–ask spread around the mid-point (which changes depending on net demand shifters) allows the bank to manage its order flow in a way that its net currency position decreases in response to a tighter limit. Taking the ratio between the estimates, a limit shock that decreases bank positions in a currency by 1 percent will prompt a 4.39 (=0.382/-0.087) basis point movement in that currency. Similarly, a limit shock that increases bid–ask spreads by 1 percent will prompt a 5.54 (=0.382/0.069) basis point movement in that currency.

Our baseline results on exchange rates, net positions, and bid–ask spreads are robust to a variety of different approaches, which we present in the Appendix. Table B.5 confirms that our estimates hold when we use a different proxy for the demand shifter: innovations to the (log) implied volatility. Table B.6 shows that results are similar when we remove three common factors (instead of one) from the limit innovations. This shows that we indeed identify idiosyncratic (desk-level) limit innovations that are orthogonal to general market conditions and other common factors and hence qualify as exogenous limit shocks. On the other hand, Table B.6 also shows that when we use (endogenous) raw changes in limits—instead of granularly identified limit shocks—we find attenuated and insignificant coefficient estimates (columns 4 through 6). This bias is intuitive since we find that limit changes are pro-cyclical; that is, limits tend to increase when utilization is high (Table 1). For example, risk limits may increase endogenously during times of higher net dollar demand, which is when the foreign currency *depreciates*. Using exogenous loosening of limits, we find that the foreign currency actually *appreciates* during times of higher net dollar demand. Overall, this analysis highlights the importance of isolating variation in limit changes that are orthogonal to market conditions.

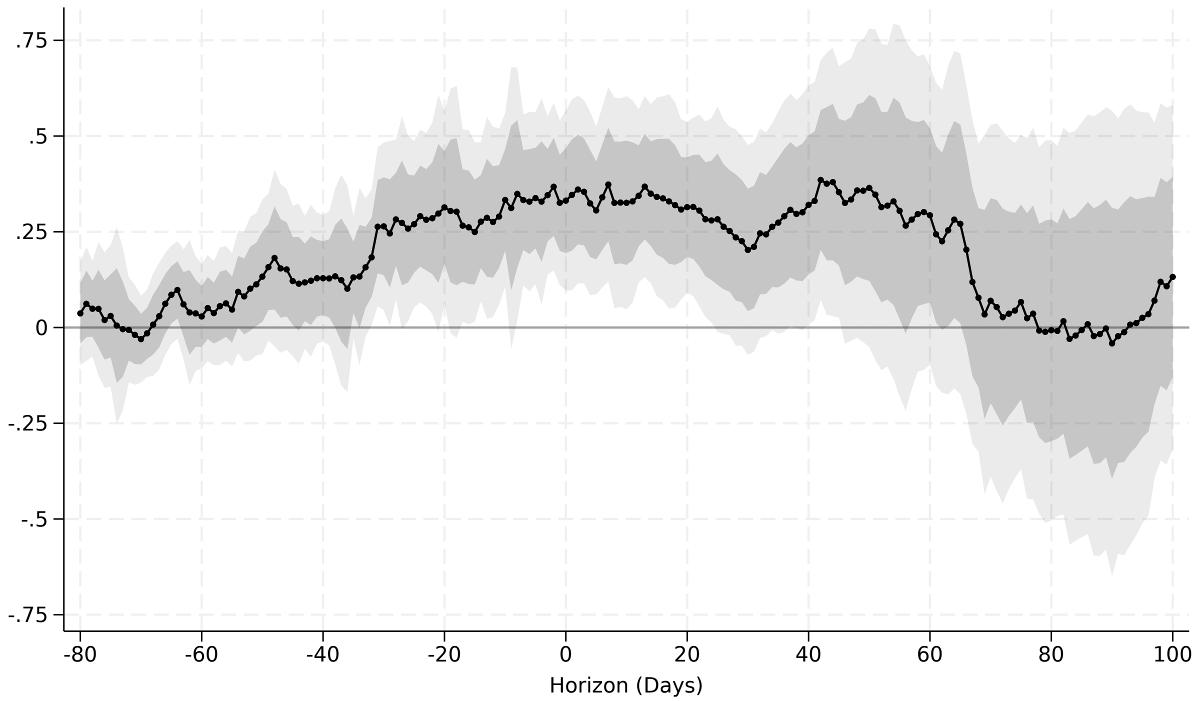
Dynamic Effects We next zoom in on the dynamic effects of limit shocks on the exchange rate. Our limit shocks and net positions vary at the quarterly frequency, which dictates the frequency we use throughout our main analysis. However, we can collect data on exchange rates at the daily frequency to estimate the higher frequency response of exchange rates. Formally, we do this by estimating equation (19) for the daily log exchange rate as the dependent variable using our data set at the quarterly frequency and focus on the estimate of β, as before. To better understand the dynamics, we now shift the LHS variable (daily log currency return) from the last day of the quarter (quarter-end) by τ days back or forward, with $\tau = -80, ..., 100$. As before, our regression model controls for four (quarterly) lags as control variables, so the estimated coefficients represent exchange rate changes relative to the last quarter-end exchange rate level. The limit shocks materialize in quarter t.

Figure 6 depicts the exchange rate response for different daily horizons on the horizontal axis. The figure shows that the limit shock leads to a significant exchange rate depreciation (conditional on a one-standard-deviation dollar demand shifter) for about two months (from $\tau = -32$ through $\tau = +24$), with point estimates above zero for almost five months (from $\tau = -68$ through $\tau = +77$).[34] We confirm the transitory effects of limit shocks on delta positions and bid–ask spread in Table B.7, which mimics our baseline Table 3 but uses as dependent variables the change in the outcome from the next quarter $(t + 1)$ relative to the last quarter $(t - 1)$.

The dynamics of the exchange rate effect are consistent with segmented market frictions prevailing in the short run. Due to such frictions, granular limit shocks have an effect on the exchange rate on impact. However, this effect is transitory, likely because, over time, other dealers step in such that the exchange rate is pushed back to the previous equilibrium. Indeed, Appendix Table B.10 shows that banks increase their positions when *other* banks' limits become tighter, with an increase in the absolute value of the net position by about 15 percent in response to a one-standard-deviation tighter limit at other banks. The increase in positions of unaffected banks may reduce the magnitude and persistence of granular limit shocks. Importantly, it is possible that aggregate limit shocks—shocks that tighten the limits

[34] Appendix Figure A.14 shows the responses to both the Limit Shock and the Demand Shifter (uninteracted).

Figure 6: Dynamic (Daily) Exchange Rate Response to Limit Shock



Notes: This figure depicts the dynamic response of the exchange rate to a limit shock happening during quarter t, conditional on a one-standard-deviation net demand shift. Responses are reported at several daily horizons (on the horizontal axis). Horizon 0 indicates the last day of the quarter during which the limit shock occurred. Formally, we estimate equation (19) for the exchange rate as the dependent variable using our data set at the quarterly frequency and focus on the estimate of β, as before. However, we now shift the LHS variable (log currency return) from the last day of the quarter (quarter-end) by τ days back or forward, with $\tau = -80, ..., 100$. That is, assuming a quarter with 90 days, $\tau = -90$ corresponds to the previous quarter end, $t-1$, and $\tau = 0$ corresponds to the current quarter end, t. Thus, the estimate reported at $\tau = 0$ corresponds to the estimate shown in Table 3, column 2 (see the caption of this table for additional information). For each τ, estimated coefficients are presented as black dots. The dark gray area represents a standard error band, and the light gray area represents the 90 percent confidence interval. *Sources*: FR VV-1, FR Y-14F, Bloomberg, authors' calculations.

of *all* dealer banks—have more persistent and larger effects on the exchange rate than those of our *granular* limit shocks identified from idiosyncratic limit changes.

Deviations from Covered Interest Parity To provide additional evidence of the mechanism driving our results, we next examine covered interest parity (CIP) deviations. CIP states that the forward premium (that is, the forward exchange rate relative to the spot exchange rate) is equal to the interest rate differential. Because CIP constitutes a riskless arbitrage opportunity, deviations are associated with limits to arbitrage. The risk-limit shocks that we identify constitute constraints to the intermediation capacity of banks in the foreign exchange market; thus, we should expect these shocks to result in CIP deviations.

We define the (log approximate) n-month CIP deviation between USD LIBOR and country c's XIBOR on day t as:

$$\Phi_{c,n,t}^{CIP} = r_{c,n,t} - r_{USD,n,t} - \rho_{c,n,t}^{CIP},$$

where $\rho_{c,n,t}$ is the n-month market-implied forward premium for hedging currency c against the US dollar. Specifically, the forward premium is constructed as

$$\rho_{c,n,t}^{CIP} = \frac{360}{d_{c,n,t}}(\ln F_{c,n,t} - \ln S_{c,t}),$$

where $S_{c,t}$ is again the spot exchange rate at time t, $F_{c,n,t}$ is the forward foreign exchange rate for tenor n (both expressed in units of foreign currency per units of US dollars), and $d_{c,n,t}$ is the number of days until maturity of the forward rate contract of tenor n for the given currency on date t.[35]

Table 4 confirms that limit shocks trigger CIP deviations in the direction of net dollar demand (column 2). Because the direction of CIP deviations is correlated to net dollar demand, this corresponds to CIP deviations widening after limit shocks. Specifically, looking at the absolute value of CIP deviations, one-month CIP deviations widen by 6.02 basis points in response to a one-standard-deviation limit shock. Appendix Table B.9 shows similar responses across the tenor curve. This widening of CIP deviations in response to our shocks is evidence that bank intermediation ability is a key mechanism behind our baseline findings.

Turnover and Margin Limit shocks affect exchange rates because they impair banks' ability to hold and intermediate currency risk, and we have shown the effect of limit shocks on banks' net positions (delta position) and bid–ask spreads. Because our model focuses on net dollar demand, the notion of total turnover is not defined in our model. However, we can show that tighter limit shocks lead to a reduction in net supply (intermediated by financiers and the bank) of the currency in positive net demand; that is, $\frac{\partial |D^*|}{\partial \gamma} < 0$. While this object cannot be directly observed in the data, we next empirically study the response of turnover to limit shocks as an additional proxy for intermediation.

Unfortunately, turnover data at the bank level by currency are not available in either the VV-1 or the Y-14F data we use in our main analysis. We therefore resort to additional, more aggregate data sources. To start, we examine turnover at the *currency level* using information provided in the (publicly available) biannual Federal Reserve Bank of New York's FX Volume

[35] Overall, the CIP deviation expressed in this way gives the difference between the synthetic borrowing cost in foreign currency and the direct borrowing cost in US dollars. Thus, a positive CIP basis means that the synthetic US dollar rate is more expensive than the direct USD rate.

Table 4: Effect of Limit Shocks on Covered Interest Parity Deviations

	Δ CIP Dev.		Δ ||CIP Dev.||	
	(1)	(2)	(3)	(4)
Limit Shock	-1.866	-2.674	6.018***	7.039
	(2.301)	(3.827)	(0.924)	(4.133)
Demand Shifter		-72.465***		54.341***
(CDS Innovation)		(23.953)		(16.870)
Limit Shock $\times$ Demand Shifter		-16.158**		2.682
		(7.484)		(5.560)
Dep. Variable Lags	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Currency FE	Yes	Yes	Yes	Yes
Within R-squared	0.272	0.104	0.301	0.050
N	727	658	727	658

Notes: This table shows the effect of shocks to banks' risk limits on CIP deviations, measured in basis points. In columns (1) and (2), the dependent variable is the change in the one-month CIP deviation. In columns (3) and (4), the dependent variable is the change in the absolute value of the one-month CIP deviation. Interest differential are computed using XIBOR rates. The independent variables Limit Shock and Demand Shifter are constructed as described in the main text, and they are standardized to have zero mean and unit variance in each regression sample. Controls include four lags of the dependent variable. Quarter fixed effects and currency fixed effects are included. Robust standard errors are two-way clustered at the currency and quarter level and are shown in parentheses. *Sources*: FR VV-1, FR Y-14F, Bloomberg, authors' calculations.

Survey. This survey captures the size and structure of foreign exchange activity in North America, and we use these data from 2016 onward, in line with the availability of our other variables. The most recent survey builds on responses from 21 leading institutions active in the North American market.[36] Our key response variable is the log difference in dealer turnover. Turnover is based on total interdealer turnover in all foreign exchange instruments (spot, forward, swap, options). Limit shocks are quarterly and survey dates are matched to the corresponding quarter of the limit shock.

We use the same regression model of equation (19) to study turnover responses in this data set. Table 5, columns 1 and 2, presents the estimation results. Given the small sample, we present results without (column 1) and with (column 2) currency fixed effects. The results show that tighter limit shocks indeed reduce turnover: The coefficient estimates indicate that

[36] These data are compiled by the NY Fed in collaboration with the Foreign Exchange Joint Standing Committee in London. The FXC agreed to collect one month's foreign exchange turnover data covering customer, product, currency pair, and execution data in April and October. See `https://www.newyorkfed.org/fxc/fx-volume-survey` for full details.

turnover falls by about 3 percent in response to a one-standard-deviation risk-limit shock. To put this number into perspective, the average daily turnover in our sample equals about $19 billion; hence, the estimated reduction of 3 percent translates into a sizable reduction in average daily turnover by about $573 million.[37]

Table 5: Response of Turnover, Gross Notional, and Margin to Limit Shocks

	Currency-Time		Bank-Time	
	(1)	(2)	(3)	(4)
	Δ Log(Turnover)	Δ Log(Turnover)	Δ Log(Gross Notional)	Δ Margin
Limit Shock	-0.038**	-0.028*	-0.011*	0.075*
	(0.016)	(0.013)	(0.006)	(0.038)
Dep. Variable Lags	No	No	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Currency FE	No	Yes	-	-
Bank FE	-	-	Yes	Yes
Within R-squared	0.009	0.004	0.250	0.223
N	268	268	144	144

Notes: This table shows the response of turnover, gross notional, and margin to limit shocks at the currency level and bank level. In columns (1) and (2), the dependent variable is the log difference in dealer turnover reported in the biannual public NY Fed FX Volume Survey from 2016 through 2022. Estimates are based on total turnover across all instruments of reporting dealers. Limit shocks are quarterly, and survey dates are matched to the corresponding quarter of the limit shock. Columns (3) and (4) are based on Y-9C bank-quarter-level data. In column (3), the dependent variable is the change in the (logarithm of) adjusted gross notional outstanding. In column (4), the dependent variable is the change in total FX trading revenue (from cash instruments and derivative instruments) relative to the adjusted gross notional (in basis points). The sample includes a constant set of seven banks from 2014:Q3 through 2022:Q4. Limit shocks are standardized to have mean zero and unit variance in each regression. *Sources*: NY Fed FX Volume Survey, FR Y-9C, FR VV-1, FR Y-14F, authors' calculations.

Next, we study turnover and margin at the *bank level* using the public Y-9C data. These data are at the BHC-quarter level (but consistent with the rest of the paper, we use the term "banks" to refer to BHCs), and they contain information on banks' foreign exchange trading activity. Unfortunately, the data do not break down foreign exchange activity by currency. We use two key variables from the Y-9C. First, we proxy turnover using gross notional values of foreign exchange trading.[38] Second, we compute margins from foreign exchange trading as total trading revenue (from cash instruments and derivative instruments) relative to adjusted

[37]The turnover response does not depend on the net demand shifter, thereby resembling the bid–ask spread response, for which we also find an average effect of limit shocks but no differential effect depending on demand shifters.

[38]These gross notional values capture all contracts (spot and all derivatives) that are outstanding at the quarter-end reporting date. We adjust the reported raw quarter-end gross notional value for cross-bank differences in the shares in different instruments that differ in maturity to estimate the implied turnover; see Figures A.3 and A.4 for details.

gross notional values. This income includes intermediation income from bid–ask spreads as well as gains or losses from net positions.[39]

We use the following linear regression model to estimate the effect of limit shocks on bank-level turnover and margin:

$$\Delta y_{b,t} = \beta_1 \text{Limit Shock}_{b,t} + \alpha_b + \alpha_t + \gamma' X_{b,t} + u_{b,t},$$

where $y_{b,t}$ is either the (log) adjusted gross notional value or the margin measure (in basis points). Limit $\text{Shock}_{b,t}$ is defined in equation 17. The regression also includes bank fixed effects (α_b) and quarter fixed effects (α_t) as well as four lags of the dependent variable. Summary statistics of the bank-quarter variables are presented in Panel B of Table 2.

The estimation results are presented in Table 5, columns (3) and (4). Column (3) shows that, in response to tighter limit shocks, total gross notionals at the bank level decrease, consistent with our findings from the cross-currency analysis in columns (1) and (2). The estimated coefficient suggests that gross notionals decrease by about 1.1 percent in response to a one-standard-deviation limit shock. Column (4) shows that the total foreign exchange margin increases, consistent with the findings on currency-level bid–ask spreads. The estimate implies an increase of about 7.5 per 100 basis points in response to a one-standard- deviation limit shock, which equals about 13 percent relative to the average trading margin of 0.59 basis points. Together, both the quantity decline and the price increase in response to limit shocks are evidence that the adjustments in currency returns are driven by a contraction of global banks' currency intermediation.

Currency Heterogeneity Our baseline analysis focuses on testing predictions derived from a two-currency model. How would the dealer bank choose the spread and net position in a multi-currency setup? In such a setting, the bank has to decide for each currency i, the spread s_i and net position δ_i to maximize expected income from intermediation services and returns on net positions, net of holdings. For notation, stack the currency-specific scalars x_i in the vector x, with $x = e, s, \delta$. In our data, the VaR constraints typically limit the variance of the portfolio of net positions at the trading-desk level rather than by individual currencies. Thus, the banks' problem can be stated as a modified version of a standard mean-variance optimization problem:

$$\max_{s,\delta} \sum_i s_i \left(D_i + S_i\right) - e\delta - \frac{\gamma}{2}\delta' \Sigma \delta, \tag{20}$$

[39] Foreign exchange trading income information is available only for holding companies with \$5 billion or more in total assets that reported total trading assets of \$10 million or more for any quarter of the preceding calendar year.

where the holding cost is a scaled version of the net positions' return variance, Σ. As before, a larger γ means holding costs increase, for a given covariance of currency returns.[40]

Rearranging the first-order conditions gives the the vector of optimal net positions

$$\delta = \frac{1}{\gamma}\Sigma^{-1}e. \tag{21}$$

Thus, the optimal net positions depend on the inverse of the return covariance, the expected return, and the scaling parameter capturing the risk tolerance of the bank. While this equation (and the general equilibrium) can be solved analytically assuming linearity in demand and supply, the solutions become algebraically involved. Yet, we can gain some understanding of the basic additional forces that come into play in the multi-currency setting. For example, suppose that the covariance terms are small. Then, each net positions would be:

$$\delta_i = \frac{e_i}{\gamma\sigma_i^2},$$

such that a higher variance decreases the holding. In fact, with zero covariances, the risk-tolerance parameter γ enters multiplicatively with σ_i^2, meaning that larger variances exacerbate the effects of limit shocks. More intuitively, in the general model, expected returns on positions that have higher variance and/or are highly correlated with other positions are down weighted by more in the optimal allocation.

We estimate currency-specific exchange rate effects using the following extension of our baseline regression model for the unidirectional exchange rate change:

$$|\Delta e_{c,t}| = \beta_{c,1}\text{Limit Shock}_{c,t} + \alpha_i + \alpha_t + \gamma' X_{c,t} + u_{c,t};$$

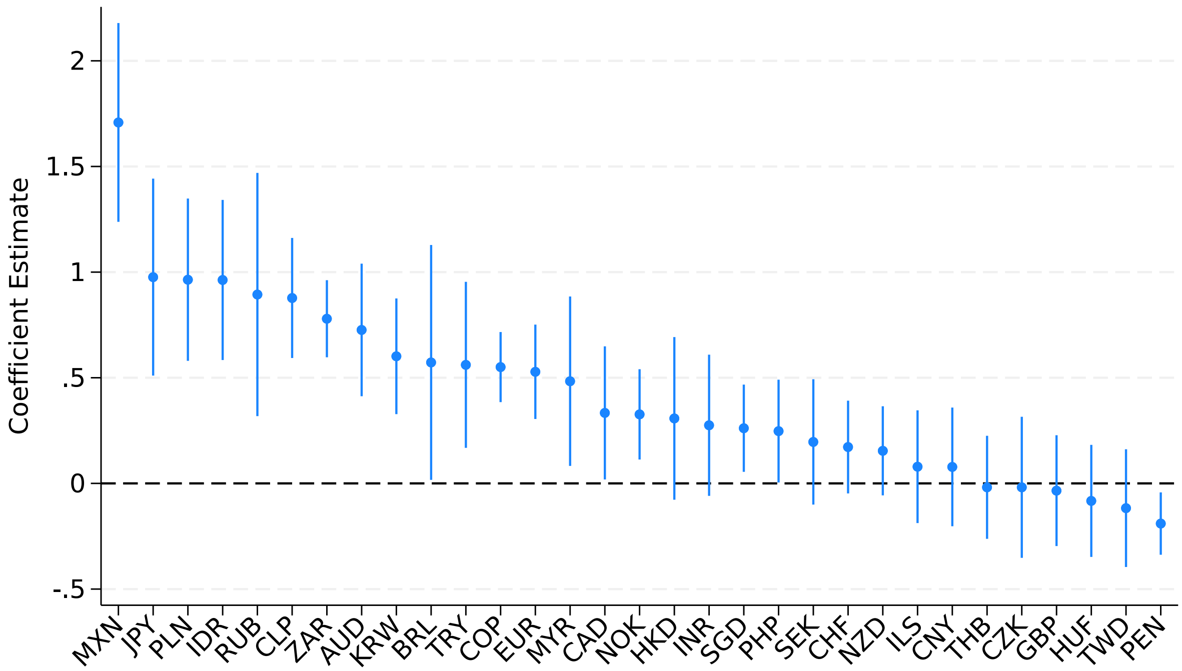
that is, we allow the slope coefficient on the limit shock to be currency-specific, while pooling all other parameters. The controls include four lags of the dependent variable.

Figure 7 reports the country-specific estimates along with 95 percent confidence intervals. For the large majority of currencies, we estimate significant and positive coefficients, confirming that the average effect reported in the previous section holds across a wide variety of currencies. Most of the significant effects are in the order of magnitude of 0.25 to 1.5, suggesting that some currency limit shocks lead to movements in the exchange rate that are as large as 1.5 percent (Mexico).

To better understand the drivers of the currency heterogeneity, we use the insights from our model extension suggesting that limits shocks should be larger for more volatile currencies.

[40]Note that the formulation of the intermediation income implicitly assumes zero cross-price elasticities of demand and supply.

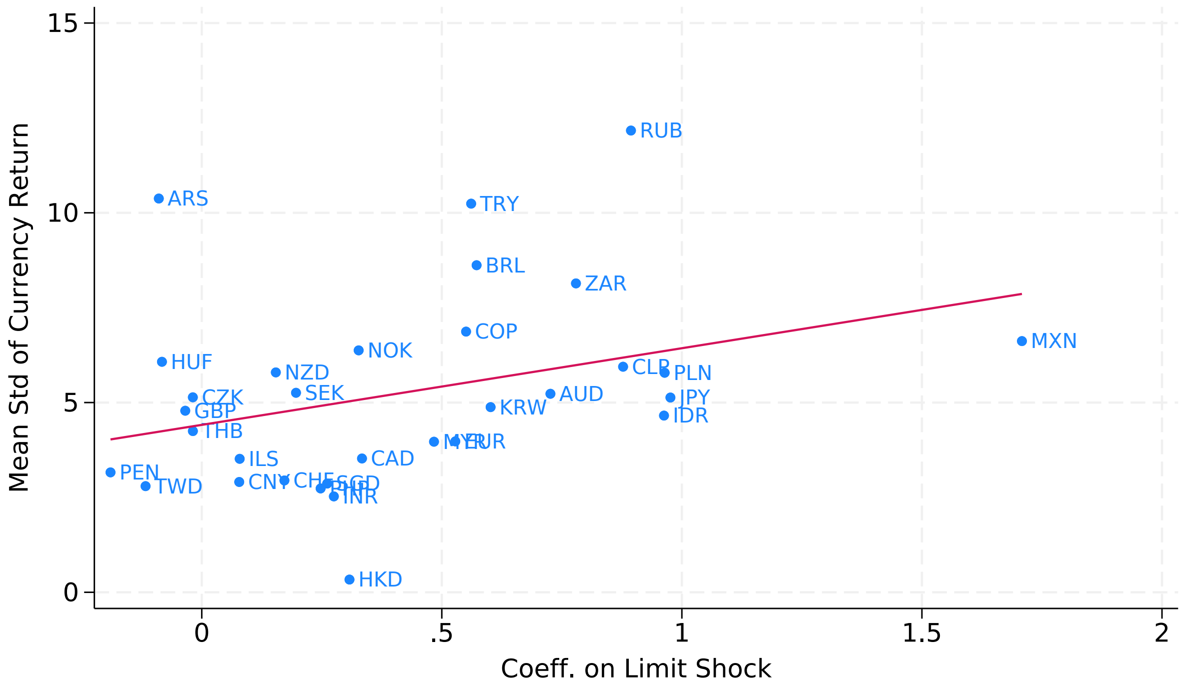
Figure 7: Effects of Limit Shock on Absolute Value of Exchange Rate Change, by Currency



Notes: This figure depicts currency-specific estimates of the effect of limit shocks on the absolute value of the currency return. The regression equation is $|\Delta e_{c,t}| = \beta_{1,c}\text{Limit Shock}_{c,t} + \alpha_i + \alpha_t + \gamma' X_{c,t} + u_{c,t}$. Limit Shock is standardized by currency to have mean zero and unit variance within each currency. Point estimates are shown as dots, and the bars represent 95 percent confidence intervals. *Sources*: FR VV-1, FR Y-14F, Bloomberg, authors' calculations.

Figure 8 presents a scatter plot of the estimated country-specific limit shock effect against the standard deviation of the quarterly currency return during our sample period. The results show that indeed the limit shock effects are larger for currencies that are more volatile (a correlation of about 0.5). That said, this result cannot be interpreted causally due to a lack of exogenous variation in foreign exchange volatility. In fact, reverse causality could be at play—at least to some degree—as a large sensitivity to limit shocks could lead to higher FX volatility, as suggested by our earlier findings.

Figure 8: Heterogeneous Limit Shock Effects and FX Rate Volatility



Notes: This scatter plot shows the relationship between currency-specific limit shock effects reported in Figure 7 and the standard deviation of quarterly currency returns during our sample period. *Sources*: FR VV-1, FR Y-14F, Bloomberg, authors' calculations.

5 Conclusion

Understanding exchange rate dynamics is one of the major research topics in international macroeconomics and finance. In line with recent theoretical papers highlighting the potential role of financial intermediaries in currency returns, this paper shows that changes in global banks' risk-taking capacity have a statistically and economically sizable effect on exchange rates. We exploit an array of detailed supervisory microdata, which provide a unique window into global banks' currency trading activities and allow us to identify exogenous risk-limit shocks.

Specifically, using desk-level risk-limit information from supervisory data, we construct exogenous risk-limit shocks of global banks' trading desks—the central intermediaries in the foreign exchange market. We also exploit supervisory information on global banks' net position in different currencies, thereby enabling us to draw a detailed picture of their FX trading activity and its impact on exchange rates.

Our empirical results are consistent with a model of currency intermediation under risk constraints. Theory predicts that in response to tighter limits and a net dollar demand shift, banks reduce their net positions, increase bid–ask spreads, and intermediate fewer dollars, such that the exchange rate adjusts to ensure market clearing in the new equilibrium.

Compared to prior literature that has focused on constraints on the holders of ultimate risk, our key finding highlights the role of market makers, which may hold only a small share of the total foreign exchange risk. Yet, due to these market makers' central intermediation function, shocks to their risk limits have sizable implications for currency pricing.

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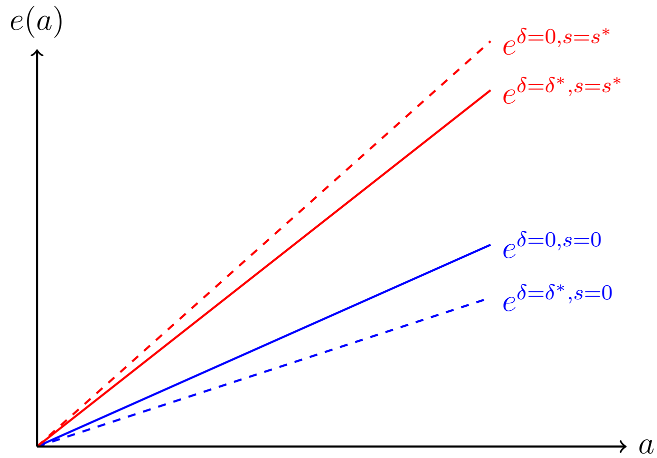
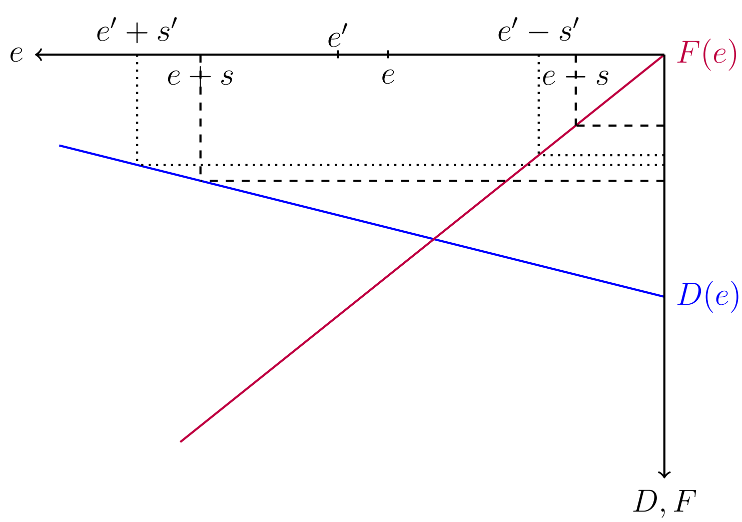
A Additional Figures

Figure A.1: Effect of Demand Shift on Equilibrium Rates in Different Models



Note: This figures shows the effect of demand shifts (a) on the equilibrium exchange rates in different models nested in our full model with a spread-charging intermediary that can hold some risk. For each model, the superscripts on the graph labels indicate whether the intermediary can charge spread and/or hold positions. $e^{\delta=\delta^*,s=0}$ indicates the model without the intermediary. $e^{\delta=\delta^*,s=s^*}$ indicates our full model.

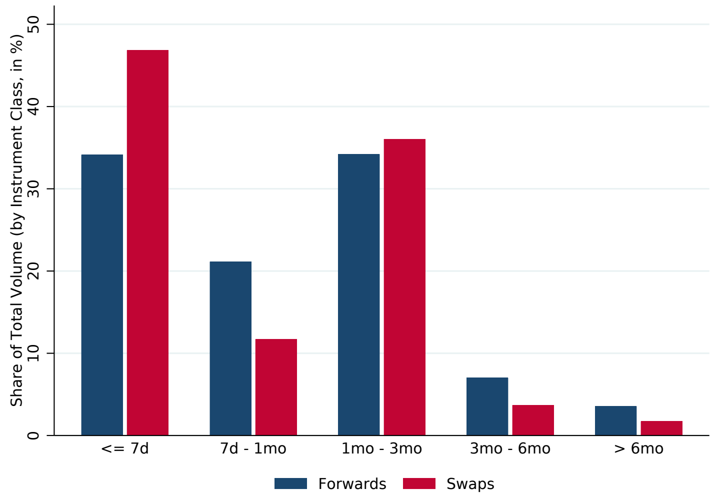
Figure A.2: Effects of Limit Shock for $a < 0$



(a) $\frac{b}{\Gamma} < 1$

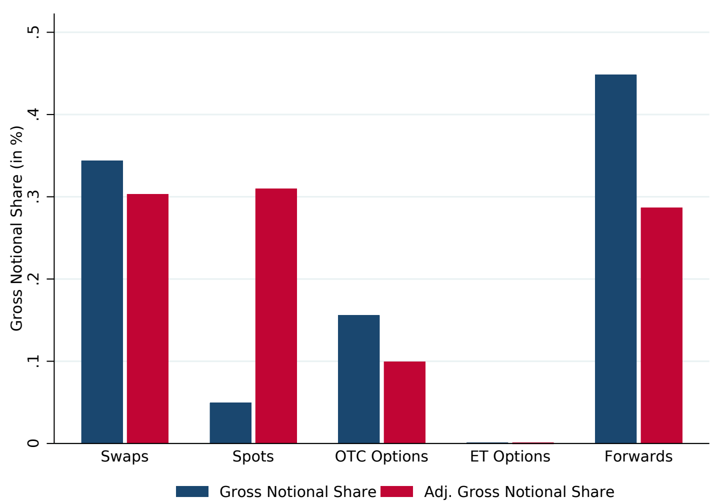
Note: Comparative statics of currency market equilibrium with respect to an increase in position holding cost, γ, condition on negative net dollar demand shock. Dotted line show equilibrium for tighter limits.

Figure A.3: Maturity Breakdown of Derivatives and Adjustments of Notionals Values



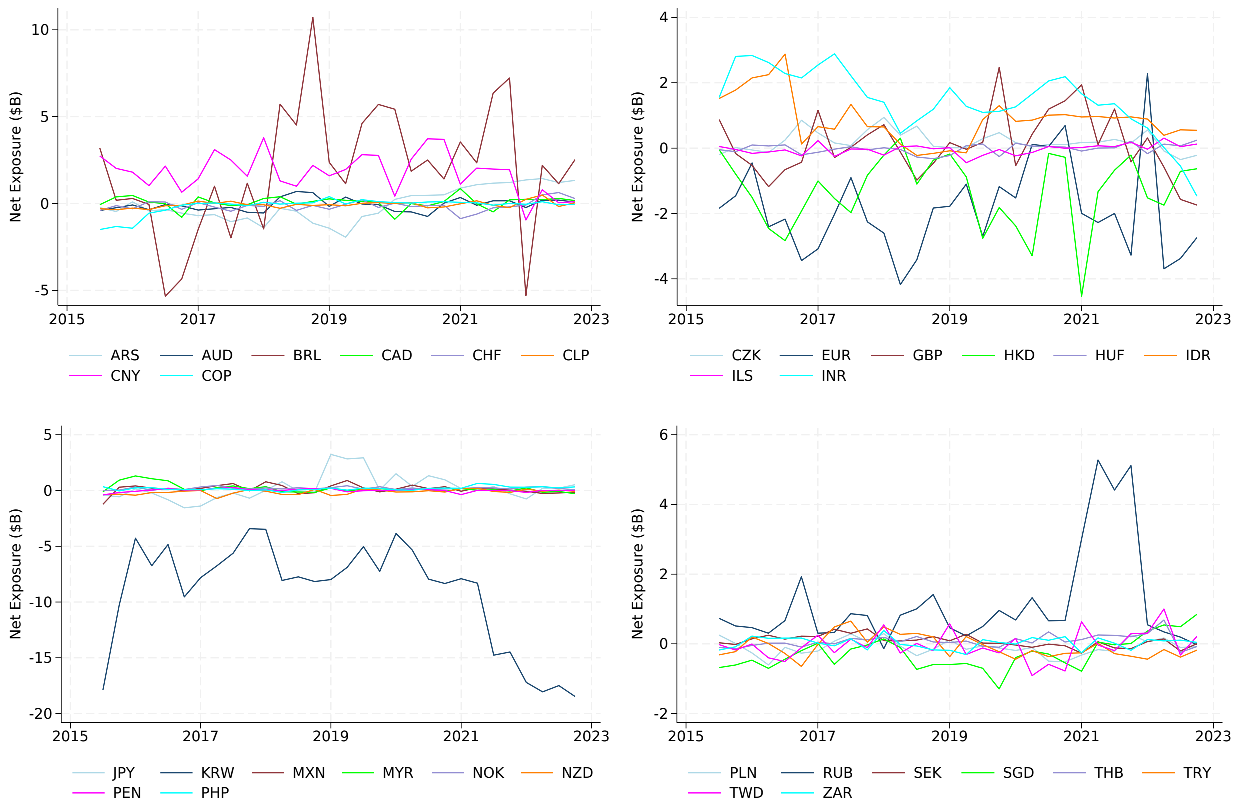
Notes: The figure shows the within-instrument (forwards, swaps) share of daily average turnover in 2019 for every given maturity class as reported by the Bank for International Settlements. To adjust the end-of quarter gross notional values we proceed as follows: Under the assumption that the maturities within each maturity class follow a uniform distribution, we estimate the average maturity in each bucket as the midpoint between the start- and enddate (for example, the midpoint for the class "over 7 days and up to 1 month" is (30d - 8d)/2 = 11d). For the class ">6mo", we assume a midpoint of 360 days. Finally, we estimate the maturity for each instrument class as the turnover-weighted average of midpoints. We then divide the length of 1 quarter (90 days) by the maturity estimates. Multiplying the result with end-of-quarter gross notionals allows us to estimate gross notional values for the entire quarter.

Figure A.4: Gross Notional Shares vs. Adj. Gross Notional Shares



Notes: The figure shows the share of total gross notional volume for each instrument class in 2019q1. Adjusted gross notionals are calculated following the steps outlined in the footnote for figure A.3. The shares for adjusted and unadjusted gross notionals are calculated by dividing by the adjusted/unadjusted total gross notional, across banks and instruments.

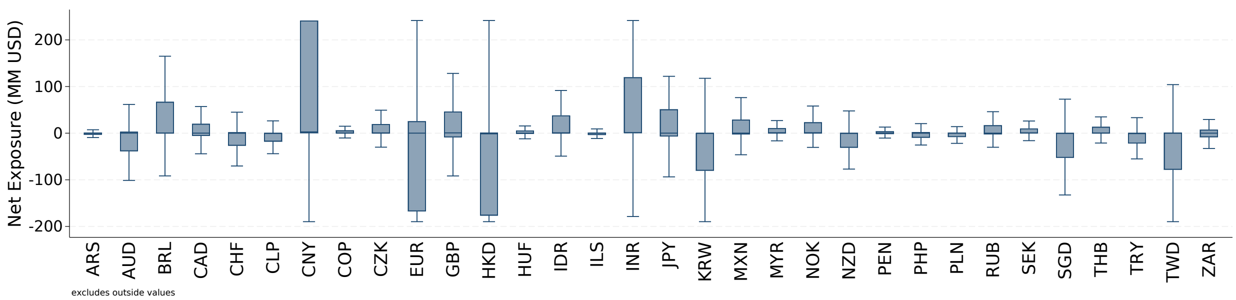
Figure A.5: Net Positions over Time, by Currency



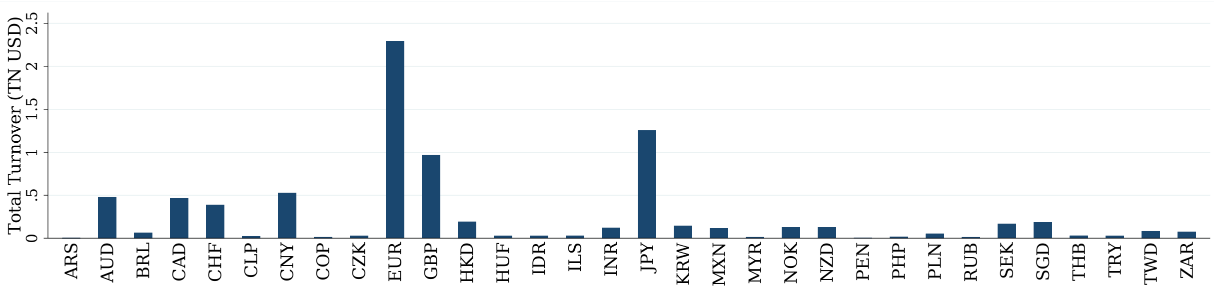
Notes: This figure shows the sum of net position across all banks, by currency, for each quarter. Positive values correspond to long position to foreign currency. *Source*: FR Y-14F, authors' calculations.

Figure A.6: Net Positions and Turnover, by Currency

(a) Net Positions

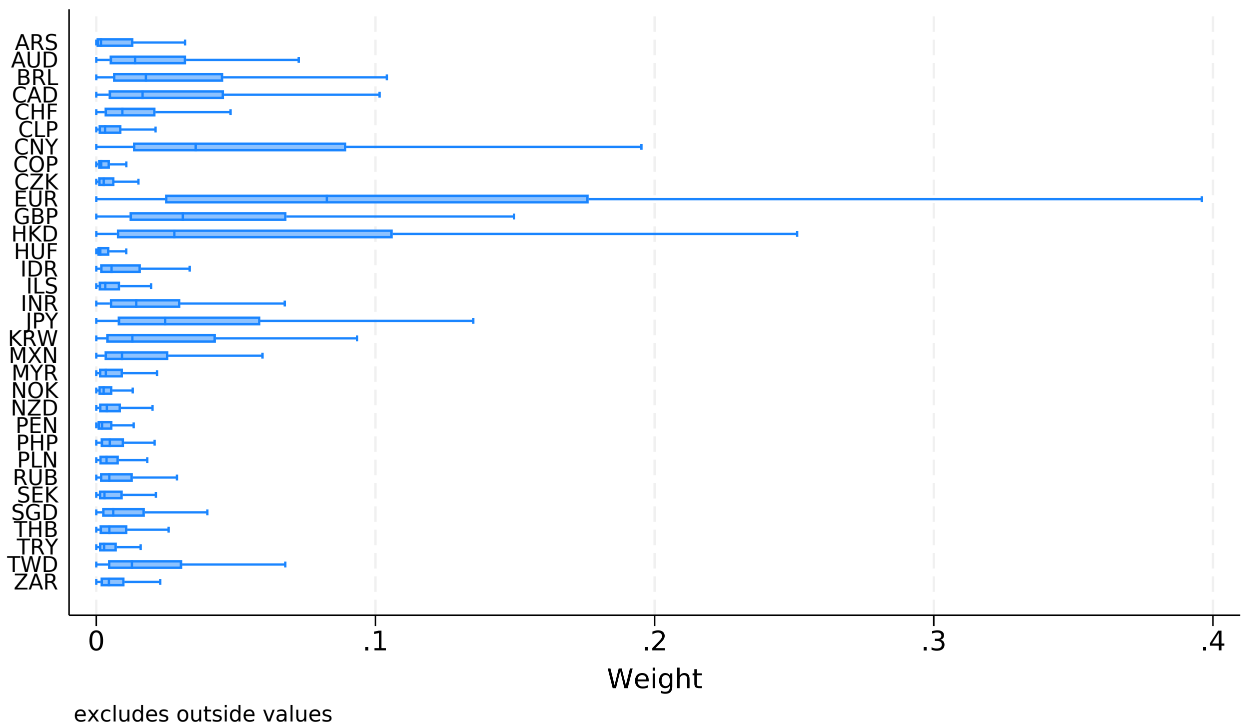


(b) Global Turnover



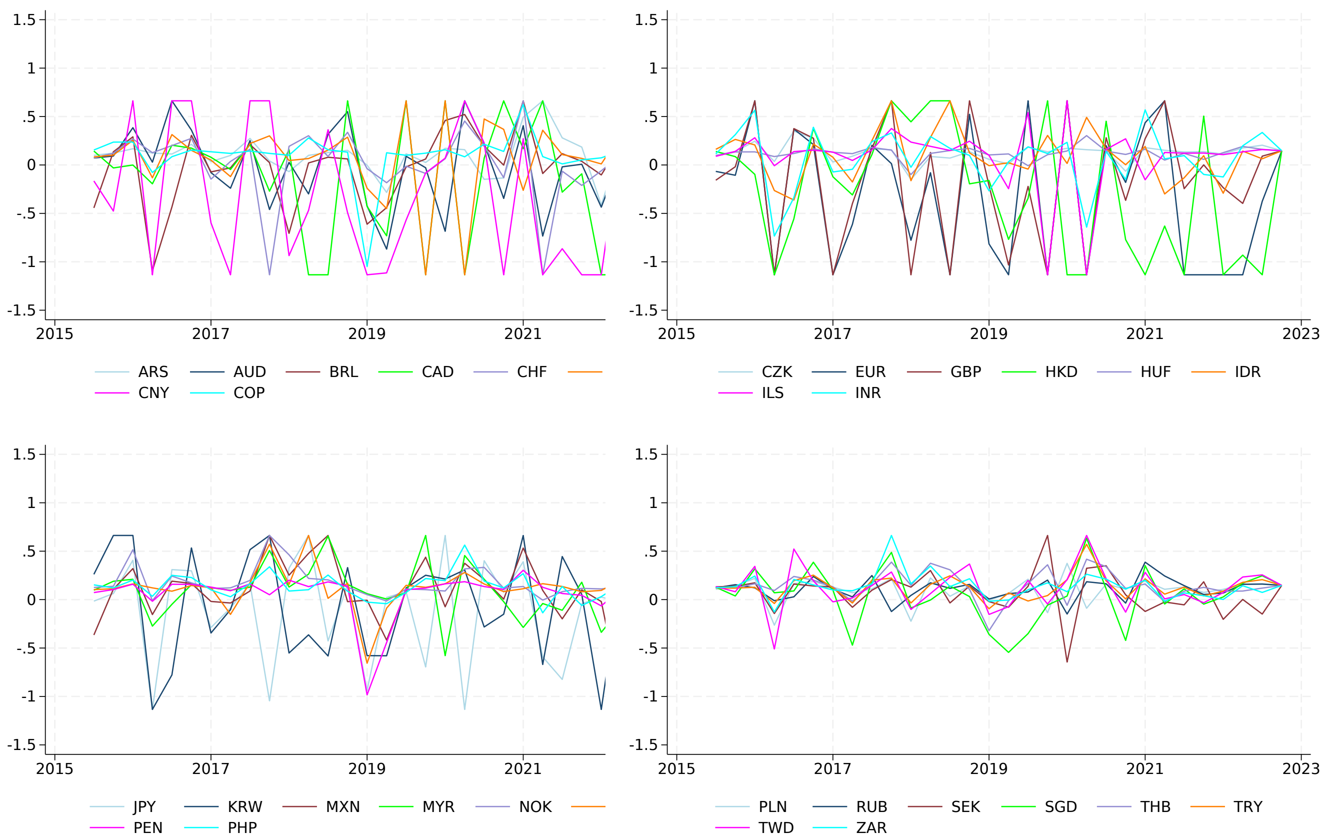
Note: Panel (a) shows box plots summarizing the distribution of net positions for each currency at the bank-quarter level from FR Y-14F. The underlying data are winsorized at the 5th and 95th percentile. Panel (b) shows the daily average turnover by currency in April 2022, in trillions of US dollars from the Triennial Central Bank Survey of foreign exchange and over-the-counter (OTC) derivatives markets. *Source*: FR Y-14F, BIS, authors' calculations.

Figure A.7: Weights Used in Shock Aggregation



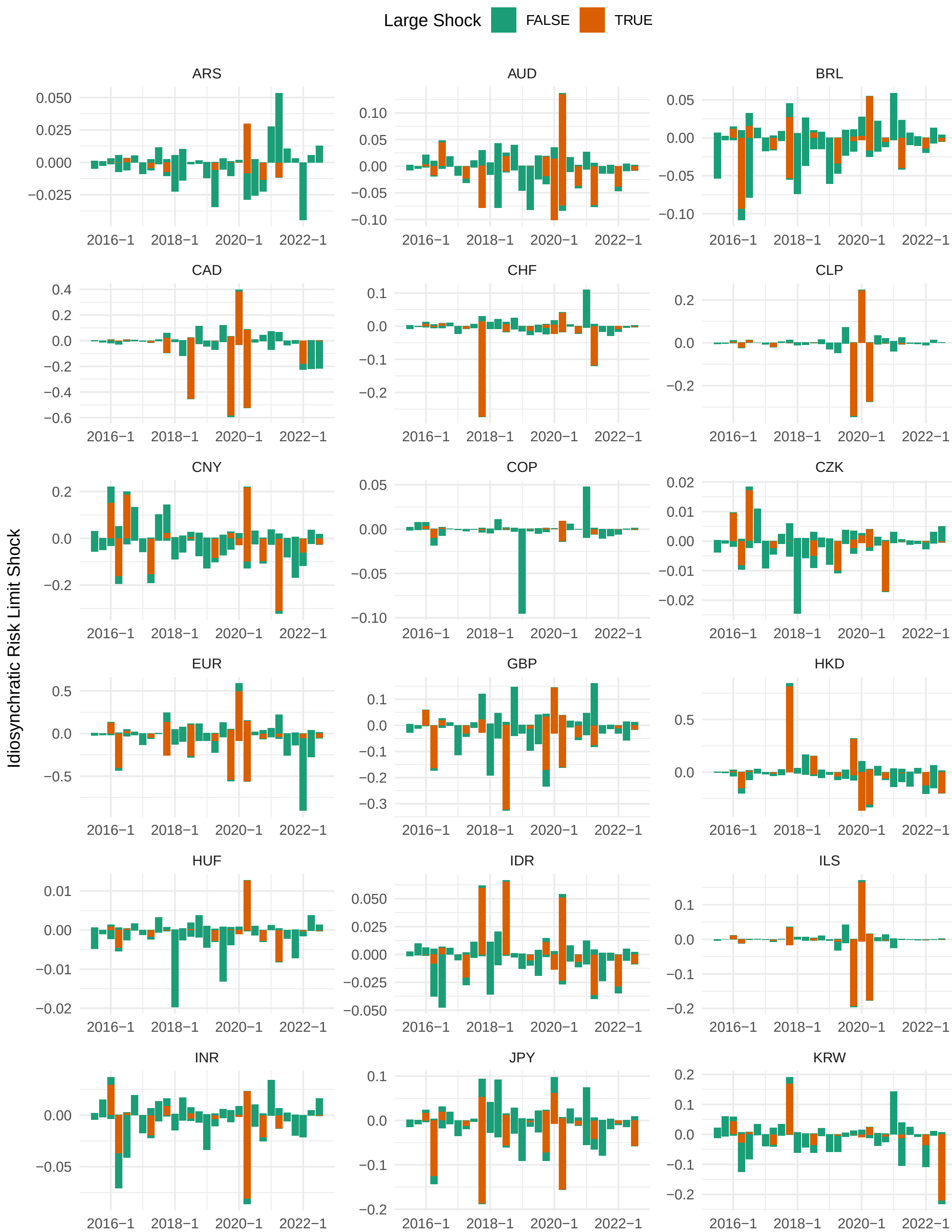
Notes: Distribution of weights used in the aggregation from bank-quarter limit innovations to currency-quarter shocks.

Figure A.8: Limit Shocks over Time



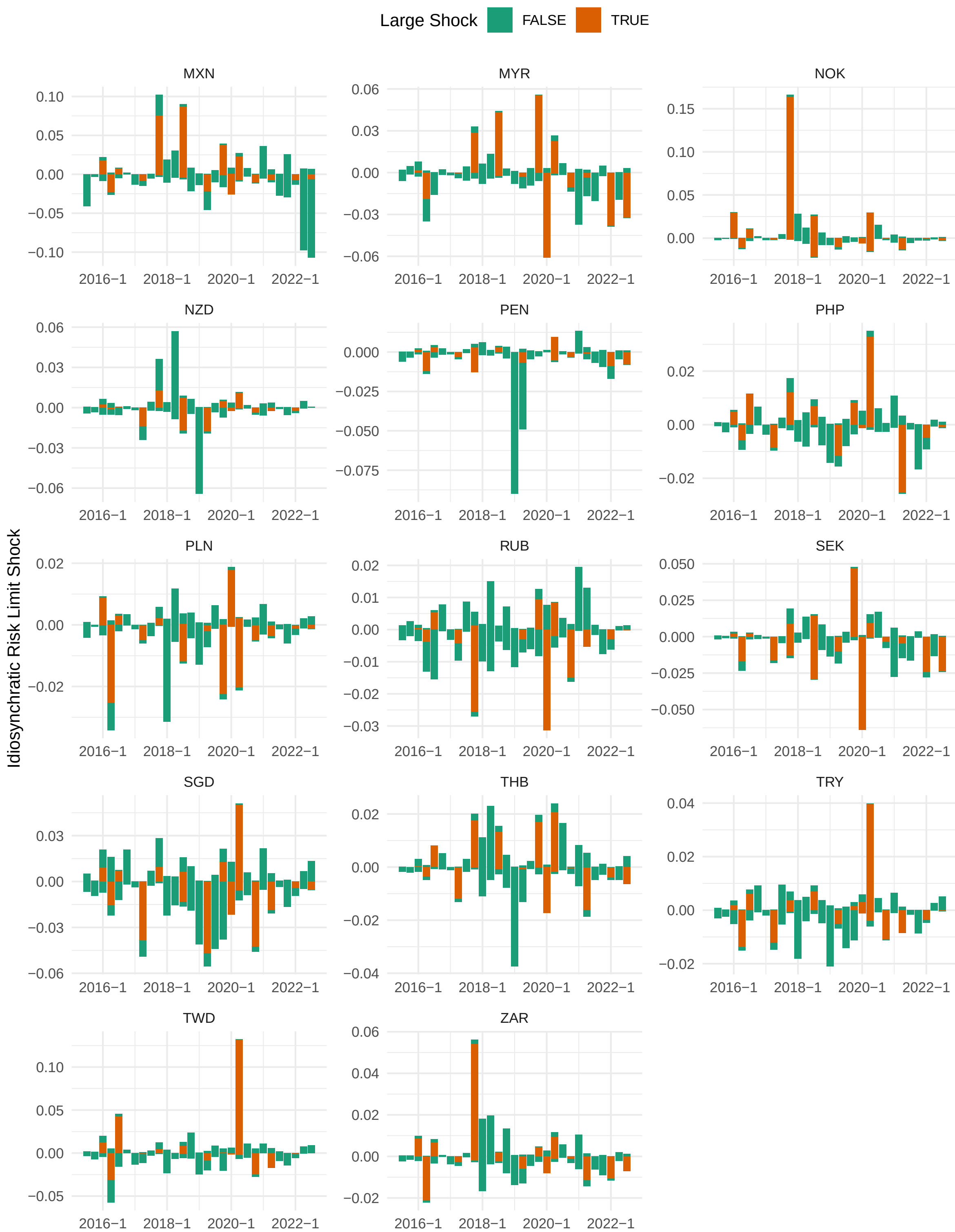
Notes: Baseline currency-level risk limit shocks over time identified from idiosyncratic dealer-level limit changes. *Sources*: FR VV-1, FR Y-14F, authors' calculations.

Figure A.9: How the 20 largest bank-quarter shocks impact the currency-level shock



Notes: Each panel represents the variation of the currency-level risk limit shock defined as in equation (18). The red bars represent the contribution of the twenty largest bank-quarter risk-limit shocks defined as in equation 17 to the currency-level shock variation. The green bars represent all the residual variation. *Sources*: FR VV-1, FR Y-14F, authors' calculations.

Figure A.10: How the 20 largest bank-quarter shocks impact the currency-level shock



Notes: Each panel represents the variation of the currency-level risk limit shock defined as in equation (18). The red bars represent the contribution of the twenty largest bank-quarter risk-limit shocks defined as in equation 17 to the currency-level shock variation. The green bars represent all the residual variation. *Sources*: FR VV-1, FR Y-14F, authors' calculations.

Figure A.11: Word Cloud of Relevant Topics in Banks' Earnings Calls

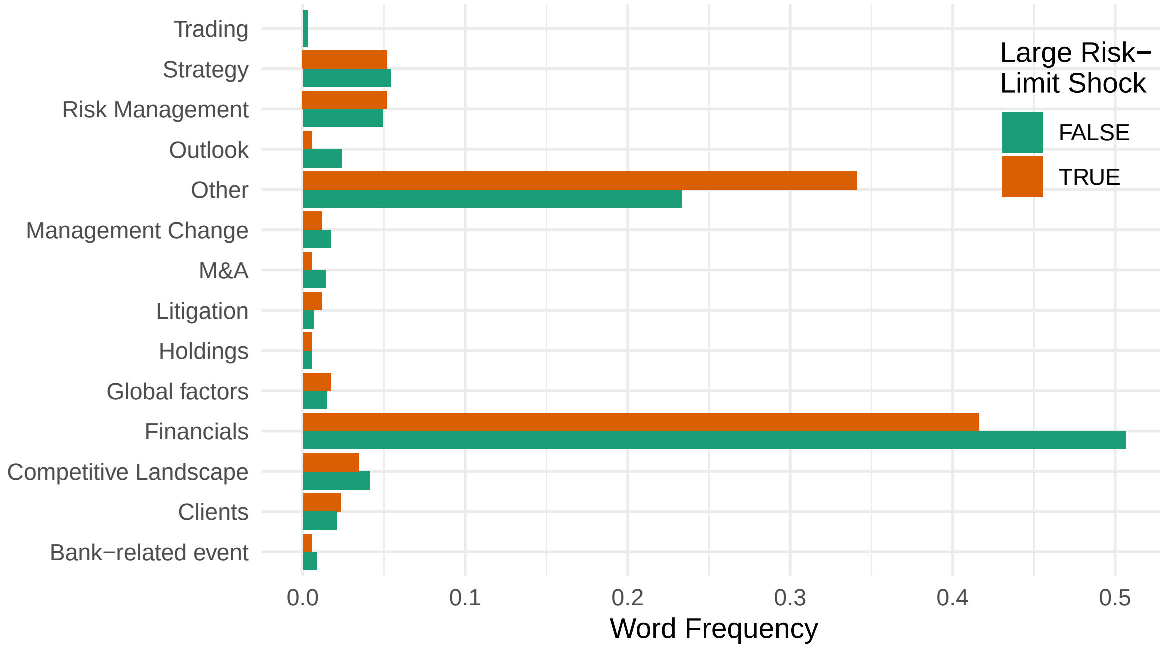
(a) Large Risk-Limit Shock Sample

(b) All other Earnings Calls

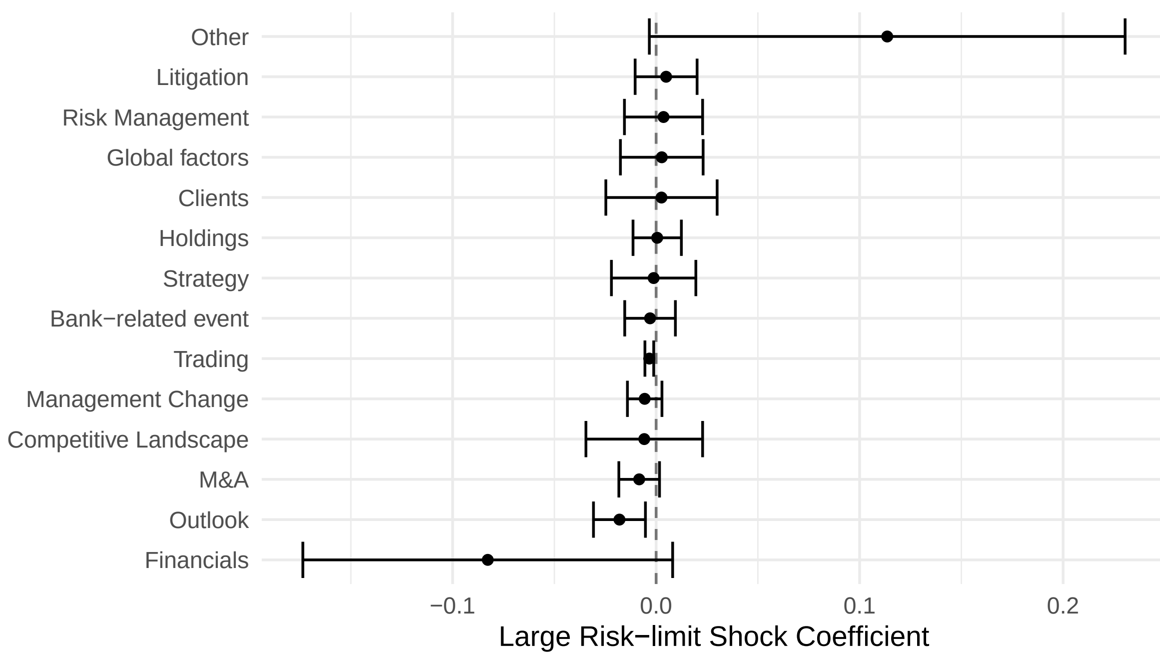
Notes: Both panels show a word cloud of the most important topics covered in the earnings calls of the 11 banks in our sample from 2015q3 to 2022. The most important topics were summarized and selected by a large language model (LLM). The LLM selected 10 'topics' from each earnings call. The size of the word cloud represent the frequency of each topic in the sample. Panel (a) shows the frequency of topic discussion in the sample of earnings calls corresponding to the twenty largest risk limit shocks, defined as in equation (17). Panel (b) shows the frequency of topic discussion in all other earnings calls. *Sources*: FR VV-1, FR Y-14F, authors' calculations.

Figure A.12: Comparison of Topic Frequency for Large vs Small Risk-limit Shock Sample

(a) Frequency of Topics in Earnings Calls for Large vs. Small Risk-limit Shocks

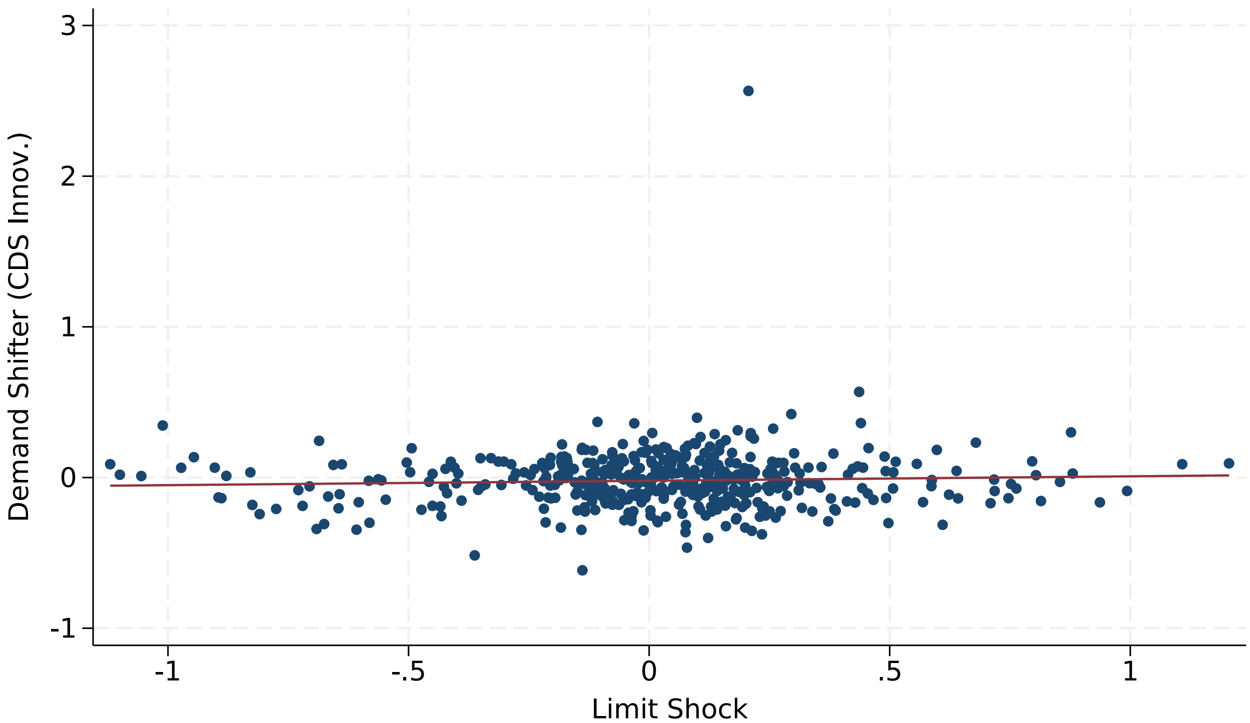


(b) Mean-testing of Topics Frequency for Large vs. Small Risk-limit Shocks



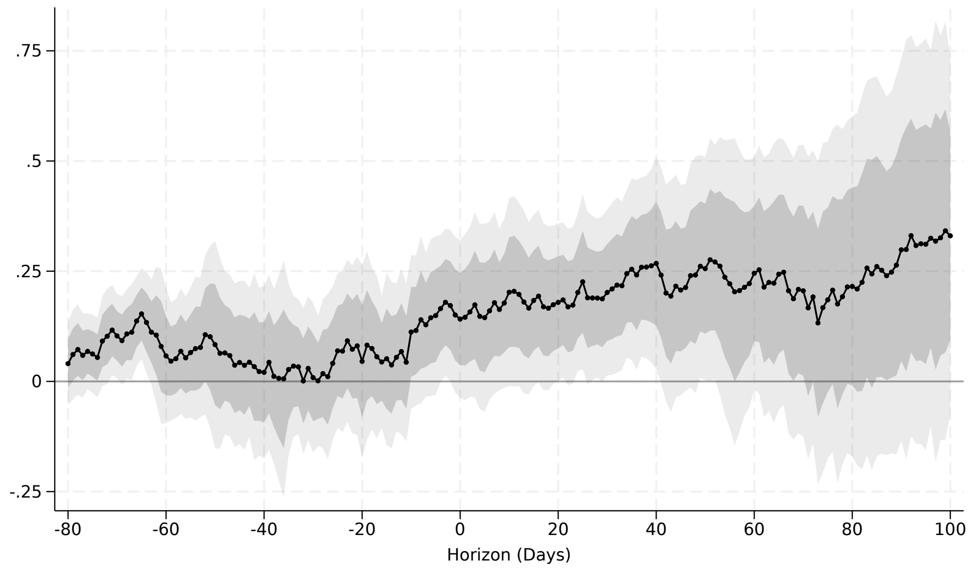
Notes: Panel (a) shows the frequency in which 14 categories of topics appear in the 11 banks' earnings calls from 2015q3 to 2022. The red bars represent the topic frequency in earnings calls for bank-quarters corresponding to the top-20 risk limit shocks defined as in equation (17). The green bars represent the topic frequency for all other earnings calls. The clustering of each topic within the 14 main categories above was implemented by a large language model, with the summarized topics in Figure A.11 provided as input. Panel (b) tests whether the difference in topic frequency between the two samples is significant. The point estimates and confidence interval for each topic category c are estimated from the following logit model: $\mathbb{1}(\text{word} = c)_{bt} = \alpha + \beta(\text{Large Shock Dummy})_{bt} + \epsilon_{bt}$. Standard errors are clustered by bank.*Sources*: FR VV-1, FR Y-14F, authors' calculations.

Figure A.13: Relationship between Limit Shocks over Demand Shifter

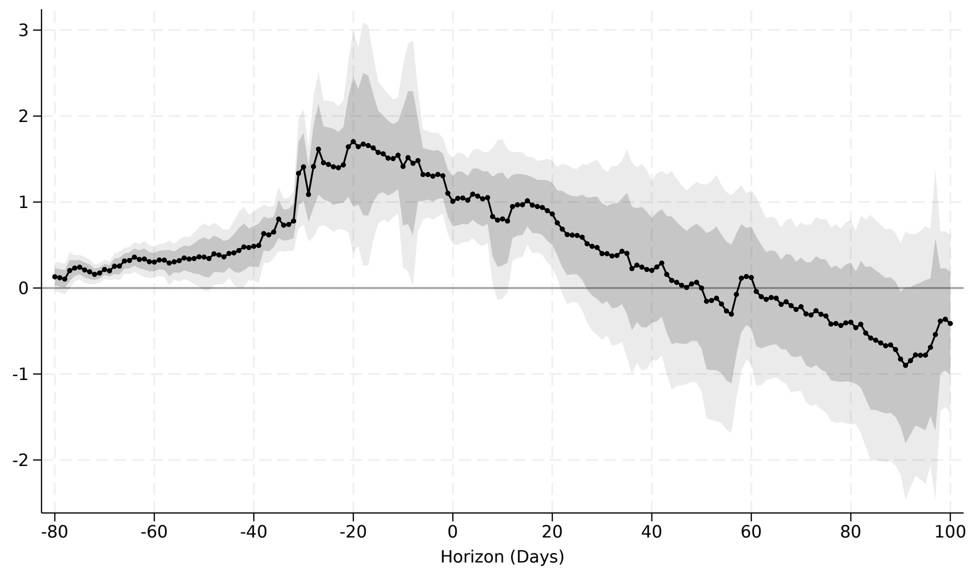


Notes: The binned scatter plot between limit shocks and CDS innovation demand shifter shows that the two variables are uncorrelated. The binned scatter plot absorbs date and currency fixed effects and controls for four lags of the exchange rate. *Sources*: FR VV-1, FR Y-14F, Bloomberg, authors' calculations.

Figure A.14: Dynamic FX Rate Response to Limit Shock and Demand Shifter



(a) Response to Limit Shock



(b) Response to Demand Shifter

Notes: Panel (a) shows the exchange rate response to the Limit Shock. Panel (b) shows the exchange rate response to the Demand Shifter. For further details, see Table 6.

B Additional Tables

Table B.1: US Dealers' Share in Total Gross Notional, by Currency, in Percent

Currency/Year	2010	2013	2016	2019	2022
AUD	15.7	17.9	18.9	14.1	20.8
BRL	34.8	43.8	47.7	27.4	36.3
CAD	32.0	34.4	36.3	28.3	32.8
CHF	18.7	17.7	17.0	15.5	20.4
CNY	7.1	5.8	9.5	8.3	12.4
EUR	19.1	17.6	19.4	18.2	18.8
GBP	16.5	17.4	22.3	19.2	19.1
HUF	10.5	11.9	18.0	17.0	18.5
JPY	15.0	19.7	18.4	13.5	17.1
KRW	4.6	7.0	9.4	10.8	16.2
MXN	36.5	44.8	43.6	33.3	41.0
NOK	10.7	16.6	21.7	19.5	21.7
NZD	16.3	22.0	18.7	15.2	20.2
PLN	10.8	12.8	17.5	18.7	16.8
RUB	2.4	7.0	7.5	11.8	8.0
SEK	8.6	16.6	21.6	15.6	14.6
SGD	7.4	15.3	13.4	9.5	13.2
TRY	1.8	10.6	14.2	13.7	12.1
TWD	6.7	8.3	6.8	8.3	6.6
USD	18.2	19.2	19.2	16.6	19.6
ZAR	7.2	16.4	17.0	14.7	20.1

Note: Based on BIS Triennial FX Data.

Table B.2: Persistence of Weights

	Weights	
	(1)	(2)
Lagged Weight	0.717***	0.628***
	(0.008)	(0.009)
Currency FE	No	Yes
Time FE	No	Yes
Bank FE	No	Yes
R^2	0.512	0.538
R^2 within	0.512	0.394
N	8,049	8,049

Note: Autoregressive coefficients of the weights used in the aggregation of bank-quarter limit shocks to currency-quarter limit shocks.

Table B.3: Correlation between Limit Shocks and Earnings Calls Text Characteristics

Dependent Variables:	Text Similarity			Text Sentiment		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Raw Limit	0.1822			2.168		
	(0.1001)			(1.513)		
Limit Shock		-0.0872			-1.231	
		(0.1371)			(1.123)	
Large Shock Dummy			-0.1518			-1.242
			(0.2336)			(1.314)
Fixed-effects						
Bank	Yes	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	213	213	213	213	213	213
R^2	0.52450	0.50406	0.50366	0.46005	0.41947	0.41694
Within R^2	0.04340	0.00227	0.00147	0.07505	0.00553	0.00120

Notes: The table shows the correlation between measures of banks' earnings calls similarity and sentiment with our measure of risk-limit shocks. Each bank's earnings calls has a unique similarity score representing the average similarity between the earnings call's text and all other earnings calls' texts within the same quarter. Text similarity is defined as the cosine similarity score between two texts. Text sentiment is defined as the net amount of positive minus negative sentences over the total number of sentences in each earnings calls. The sentiment is assigned according to FinBERT: a sentiment analysis model pre-trained on financial texts. The 'Raw limit' variable contains the raw sum of maximum VaR limits of all desks for each bank-quarter in the sample. The Limit Shock variable is defined as in equation (17). The 'Large Shock Dummy' is one only for the twenty largest limit shocks. Standard errors are two-way clustered by bank and quarter. *Sources*: FR VV-1, FR Y-14F, authors' calculations.

Table B.4: Table 3 using CDS spread innovation as Demand Shifter

	Δ FX Rate			Δ Net Position			Δ Bid-Ask Spread		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Limit Shock	0.045	0.081	0.142	0.130	-0.038	-0.096	0.069***	0.073**	0.073**
	(0.115)	(0.112)	(0.104)	(0.341)	(0.384)	(0.371)	(0.023)	(0.032)	(0.034)
Demand Shifter		1.052***	1.009***		-0.424	-0.384		0.115***	0.115***
(CDS Innovation)		(0.273)	(0.292)		(0.451)	(0.442)		(0.032)	(0.032)
Limit Shock × Demand Shifter			0.331**			-0.316**			0.000
			(0.137)			(0.118)			(0.032)
Dep. Variable Lags	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Currency FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R-squared	0.035	0.087	0.091	0.345	0.384	0.385	0.429	0.463	0.463
N	800	702	702	768	675	675	758	660	660

Notes: Same as Table 3 but with additional columns.

Table B.5: Table 3 using Implied Vola as Demand Shifter

	Δ FX Rate			Δ Net Position			Δ Bid-Ask Spread		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Limit Shock	0.045	-0.070	0.009	0.130	0.141	-0.055	0.069***	0.058**	0.067**
	(0.115)	(0.111)	(0.090)	(0.341)	(0.358)	(0.352)	(0.023)	(0.025)	(0.026)
Demand Shifter		1.357***	1.321***		-0.120	-0.032		0.133***	0.128***
(Vola. Innovation)		(0.400)	(0.390)		(0.404)	(0.372)		(0.036)	(0.034)
Limit Shock × Demand Shifter			0.333***			-0.768***			0.043***
			(0.045)			(0.253)			(0.015)
Dep. Variable Lags	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Currency FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R-squared	0.035	0.111	0.116	0.345	0.345	0.352	0.429	0.447	0.448
N	800	800	800	768	768	768	758	758	758

Notes: Same as Table 3 but with Demand Shifter computed from implied volatility instead of CDS spreads.

Table B.6: Table 3 using Alternative Limit Shocks

	Limit Shock: 3 Factors			Limit Shock: Raw Changes		
	(1) Δ FX Rate	(2) Δ Net Position	(3) Δ Bid-Ask Spread	(4) Δ FX Rate	(5) Δ Net Position	(6) Δ Bid-Ask Spread
Limit Shock	0.059	0.044	0.068	0.134	0.149	-0.054*
	(0.119)	(0.322)	(0.043)	(0.122)	(0.496)	(0.031)
Demand Shifter	1.034***	-0.407	0.115***	1.065***	-0.556	0.118***
(CDS Innovation)	(0.286)	(0.439)	(0.032)	(0.275)	(0.482)	(0.032)
Limit Shock $\times$ Demand Shifter	0.329**	-0.445*	-0.020	0.009	-0.263	0.008
	(0.125)	(0.226)	(0.034)	(0.089)	(0.519)	(0.018)
Dep. Variable Lags	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Currency FE	Yes	Yes	Yes	Yes	Yes	Yes
Within R-squared	0.090	0.386	0.462	0.088	0.385	0.460
N	702	675	660	702	675	660

Notes: Same as Table 3 but using alternative limit shocks. In columns (1) to (3), we purge three common factors (instead of one in our baseline) from desk-level limit innovations. Columns (4)-(6) use raw changes in log limits to construct the shock.

Table B.7: Table 3 using Next Period's Dependent Variable

	Δ FX Rate$_{t+1}$		Δ Net Position$_{t+1}$		Δ Bid-Ask Spread$_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Limit Shock	0.193	0.348	0.228	0.058	0.030	0.029
	(0.158)	(0.246)	(0.333)	(0.406)	(0.029)	(0.031)
Demand Shifter		-0.936		-0.517		0.065**
(CDS Innovation)		(0.824)		(0.425)		(0.029)
Limit Shock × Demand Shifter		0.022		-0.010		0.011
		(0.351)		(0.415)		(0.029)
Dep. Variable Lags	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Currency FE	Yes	Yes	Yes	Yes	Yes	Yes
Within R-squared	0.884	0.775	0.167	0.139	0.047	0.041
N	768	674	736	647	727	633

Notes: Same as Table 3 but with dependent variables measuring changes from t-1 over t+1.

Table B.8: Effect of Limit Shocks on Interest Rate Differentials

	Δ Interest Diff. 1m		Δ Interest Diff. 3m		Δ Interest Diff. 6m	
	(1)	(2)	(3)	(4)	(5)	(6)
Limit Shock	0.031	0.032	0.031	0.027	0.027	0.027
	(0.028)	(0.049)	(0.034)	(0.053)	(0.032)	(0.053)
Demand Shifter		0.390**		0.413**		0.466**
(CDS Innovation)		(0.187)		(0.191)		(0.210)
Limit Shock × Demand Shifter		0.054		0.064		0.072
		(0.049)		(0.055)		(0.062)
Dep. Variable Lags	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Currency FE	Yes	Yes	Yes	Yes	Yes	Yes
Within R-squared	0.155	0.257	0.165	0.275	0.172	0.301
N	740	671	740	671	655	590

Notes: This table shows the effect of shocks to banks' risk limits on interest rate differentials. In columns (1) and (2), the dependent variable is the change in the interest differential between a country's 1-month XIBOR rate and the US 1-month LIBOR. In columns (3) and (4), the dependent variable is the change in the interest differential between a country's 3-month XIBOR rate and the US 3-month LIBOR. In columns (5) and (6), the dependent variable is the change in the interest differential between a country's 6-month XIBOR rate and the US 6-month LIBOR. The independent variables Limit Shock and Demand Shifter are constructed as described in the main text, and they are standardized to have zero mean and unit variance in each regression sample. Controls include four lags of the dependent variable. Quarter fixed effects and currency fixed effects are included. Robust standard errors are two-way clustered at the currency and quarter level and are shown in parentheses. *Sources*: FR VV-1, FR Y-14F, Bloomberg, authors' calculations.

Table B.9: Effect of Limit Shocks on Covered Interest Parity Deviations of Different Tenors

	Δ CIP Dev. 1m		Δ CIP Dev. 3m		Δ CIP Dev. 6m	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: CIP Deviations						
Limit Shock	-1.866	-2.674	-2.329	-2.801	-0.261	-0.388
	(2.301)	(3.827)	(3.558)	(3.530)	(4.226)	(4.664)
Demand Shifter		-72.465***		-54.830***		-52.056***
(CDS Innovation)		(23.953)		(18.368)		(13.042)
Limit Shock × Demand Shifter		-16.158**		-10.539**		-9.490**
		(7.484)		(4.809)		(3.508)
Within R-squared	0.272	0.104	0.253	0.076	0.191	0.120
N	727	658	714	645	628	563
Panel B: Absolute Value of CIP Deviations						
Limit Shock	6.018***	7.039	5.584*	6.698	6.212*	7.074**
	(0.924)	(4.133)	(3.020)	(4.955)	(3.251)	(3.197)
Demand Shifter		54.341***		38.358***		33.883***
(CDS Innovation)		(16.870)		(12.780)		(9.991)
Limit Shock × Demand Shifter		2.682		4.311		4.797
		(5.560)		(4.590)		(4.061)
Within R-squared	0.301	0.050	0.267	0.074	0.210	0.143
N	727	658	714	645	628	563
Dep. Variable Lags	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Currency FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the effect of shocks to banks' risk limits on covered intered parity deviations, measured in basis points. In columns (1) and (2) of Panel A, the dependent variable is the change in the 1-month covered interest parity violation. In columns (3) and (4) of Panel A, the dependent variable is the change in the 3-month covered interest parity violation. In columns (5) and (6) of Panel A, the dependent variable is the change in the 6-month covered interest parity violation. Panel B is identical, except dependent variables are replaced with their absolute values. Interest differential are computed using XIBOR rates. The independent variables Limit Shock and Demand Shifter are constructed as described in the main text, and they are standardized to have zero mean and unit variance in each regression sample. Controls include four lags of the dependent variable. Quarter fixed effects and currency fixed effects are included. Robust standard errors are two-way clustered at the currency and quarter level and are shown in parentheses. *Sources*: FR VV-1, FR Y-14F, Bloomberg, authors' calculations.

Table B.10: Response of Bank-Currency-Level Positions to Other Banks' Limit Shocks

	Δ Log Abs Exposure		
	(1)	(2)	(3)
Limit Shock	0.143**	0.159***	0.179***
	(0.054)	(0.050)	(0.064)
Currency*Time FE	Yes	Yes	Yes
Currency*Bank FE	No	Yes	Yes
Bank*Time FE	No	No	Yes
Within R-squared	0.829	0.132	0.121
N	11547	11500	11500

Notes: This table show the response of banks' net position (absolute value) to limit shocks of other banks. The dependent variable is the change in the logarithm of the absolute value of the delta position, at the bank-currency-quarter level. The key independent variable is Limit Shock, which is, as before, the aggregated idiosyncratic limit changes, but now only aggregated for other banks, excluding the bank under consideration. Fixed effects are included or not as indicated. The regression includes four quarterly lags of the dependent variable. Standard errors are two-way clustered at the currency and quarter level.

C Model Appendix

We define the bid–ask spread in the foreign exchange market as $2\tilde{s}$: the mid-price point around $\mathcal{E}$. To outline the bank's profit function, we define the dollar demand-financier spread $2s$, which represents the spread between the price paid by the net buyers of dollars and the price paid by the financiers.

$$\max_{s,\delta} \ \pi = s\left(D(e+s) + F(e-s)\right) + \delta e - \frac{\gamma}{2}\delta^2,$$

Crucially, we allow s to be negative. When net dollar demand is positive, $a > 0$, then $s > 0$ because dollar net demand agents are buyers, and financiers are sellers. Hence, when $a > 0$, then $\tilde{s} = s$. When net dollar demand is negative, $a < 0$, the real side of the economy has an excess of dollars and wants to buy foreign currency. Therefore, the net demand agents are the sellers, and the financiers are the buyers. Hence, when $a < 0$, then $\tilde{s} = -s$ and $s < 0$. To summarize:

$$\tilde{s} = \begin{cases} s & \text{when } a \geq 0 \\ -s & \text{when } a < 0 \end{cases} \tag{22}$$

Proof of Proposition 1. The two partial equilibrium first-order conditions of the bank in equations (2) and (3) and the global market clearing condition (6) form a system of three equations with three unknowns. The unique closed-form solution is:

$$\delta = \frac{a\Gamma(b\Gamma + 3)}{b\gamma\Gamma(b\Gamma + 6) + 2\Gamma(b\Gamma + 1) + \gamma}$$
$$e = \frac{a\gamma\Gamma(b\Gamma + 3)}{b\gamma\Gamma(b\Gamma + 6) + 2\Gamma(b\Gamma + 1) + \gamma}$$
$$s = \frac{a\Gamma(2\gamma + \Gamma)}{b\gamma\Gamma(b\Gamma + 6) + 2\Gamma(b\Gamma + 1) + \gamma}$$

The latter equation and the definition in (22) imply that:

$$\tilde{s} = \frac{|a|\Gamma(2\gamma + \Gamma)}{b\gamma\Gamma(b\Gamma + 6) + 2\Gamma(b\Gamma + 1) + \gamma}$$

□

Proof of Proposition 2. The full derivatives behind the comparative statics in Proposition 2 are:

$$\frac{\partial \delta}{\partial \gamma} = -\frac{a\Gamma(b\Gamma+3)(b\Gamma(b\Gamma+6)+1)}{(b\gamma\Gamma(b\Gamma+6)+2\Gamma(b\Gamma+1)+\gamma)^2} \qquad \propto -a \tag{23}$$

$$\frac{\partial e}{\partial \gamma} = \frac{2a\Gamma^2(b\Gamma+1)(b\Gamma+3)}{(b\gamma\Gamma(b\Gamma+6)+2\Gamma(b\Gamma+1)+\gamma)^2} \qquad \propto a \tag{24}$$

$$\frac{\partial s}{\partial \gamma} = -\frac{a\Gamma^2(b\Gamma-1)(b\Gamma+3)}{(b\gamma\Gamma(b\Gamma+6)+2\Gamma(b\Gamma+1)+\gamma)^2} \qquad \propto a(1-b\Gamma) \tag{25}$$

$$\frac{\partial \delta}{\partial \gamma \partial a} = -\frac{\Gamma(b\Gamma+3)(b\Gamma(b\Gamma+6)+1)}{(b\gamma\Gamma(b\Gamma+6)+2\Gamma(b\Gamma+1)+\gamma)^2} \qquad < 0 \tag{26}$$

$$\frac{\partial e}{\partial \gamma \partial a} = \frac{2\Gamma^2(b\Gamma+1)(b\Gamma+3)}{(b\gamma\Gamma(b\Gamma+6)+2\Gamma(b\Gamma+1)+\gamma)^2} \qquad > 0 \tag{27}$$

$$\frac{\partial s}{\partial \gamma \partial a} = -\frac{\Gamma^2(b\Gamma-1)(b\Gamma+3)}{(b\gamma\Gamma(b\Gamma+6)+2\Gamma(b\Gamma+1)+\gamma)^2} \qquad \propto (1-b\Gamma) \tag{28}$$

Equations (25) and (22) imply:

$$\frac{\partial \tilde{s}}{\partial \gamma} \propto |a|(1-b\Gamma)$$

□

Proof of Proposition 3. For practical purposes, we treat the derivative of the absolute value function to behave like the signum function. In practice, this allows us to define the derivative of the absolute value in the full domain of the variables considered in this proof. This is acceptable in our model because when $a = 0$, then $\delta = e = 0$. Therefore,

$$\frac{\partial |\delta|}{\partial \gamma} = \mathrm{sgn}(\delta)\frac{\partial \delta}{\partial \gamma}$$
$$\frac{\partial |e|}{\partial \gamma} = \mathrm{sgn}(e)\frac{\partial e}{\partial \gamma}$$

From the solutions in equation (7) and (8):

$$\mathrm{sgn}(\delta) = \mathrm{sgn}(e) = \begin{cases} +1 & \text{when } a > 0 \\ 0 & \text{when } a = 0 \\ -1 & \text{when } a < 0 \end{cases} \tag{29}$$

The rest of the proof follows from proposition 2. □

D Narrative Analysis

D.1 Summarization via Large Language Model

To summarize the most important topics discussed by the banks in our sample we proceed as follows:

1. We retrieve all earnings calls between 2015q3 to 2022 of all banks in our sample. We consider the full text of the earnings calls, both speeches and Q&A session. We only purge the operator messages.

2. We download the open-source pre-trained 9B-paramter large language model (LLM) called *Faro-Yi-9B-200K*. One of the advantages of this model is its large context window necessary to incorporate the entire body of the earnings calls to the prompt. For each earnings call, we provide the following prompt to the model:

```
LLM_SYSTEM_DIRECTIVE_SUMMARY = (
    "You are a financial analyst with a PhD in finance,
       specialized in the banking and trading sector, who
       is particularly attentive to major and/or unusual
       pieces of  news related to large banks."
)
LLM_PROMPT_SUMMARY = (
    "Summarize the most important facts, decisions, or news
        discussed in the earnings call as it relates to the
        particular bank in the earnings call. Summarize in
       ten  bullet points, ranked from most to least
       important to you. Use as few words as  possible
       without sacrificing meaning. Put a bullet point
       title at the beginning.  This is an example of how
```

```
        the output should look like: '1. *litigation*: the
        litigation with BlaBla has come to an end with only
        $1Billion losses.\n2.  **fixed-income**: our fixed-
        income trading division has made abnormal profits
        ...'  and so on for all bullet points. Do not make
        up any information and be truthful to what is
        contained in the earnings call. The text of the
        earnings call is: <...>"
)
```

We manually verify the quality of the LLM output for a small sample of earnings calls. The ten words contained between the characters '**' of the LLM output are shown in the word cloud of Figure A.11.

3. The same LLM model generates the topics clusters associated to the previous topics' summary and shown in Figure A.12. The clusters are manually selected given the frequent topics discussed in each earnings calls. We also selected the topics to make sure that any macro-related or bank-related news should stand out. This is because our aim in this section is to verify whether risk-limits move with institutional or global events.

   For each earnings call, we provide the following prompt to the model:

```
    LLM_SYSTEM_DIRECTIVE_LABEL = (
    "You are a financial analyst with a PhD in finance,
       specialized in the banking and trading sector, who
       has a deep understanding of the meaning and
       implication of financial jargon"
)

LLM_PROMPT_LABEL = (
    "Categorize the words that appear in the input text
       under new umbrella cluster words based on their
       meaning. The input text is a summary, in bullet
       points, of what a bank has mostly talked about
       during an earnings call. The input text has the
       following repeated format: 'number *word-to-
       categorize*: summary of what that word implies and
```

```
means in the text'. You should use both the *word-to
-categorize* and the sentence that comes after to
assign each word to a category. Do not make up any
information and assign each of the terms betwen '*'
according to the rules I give you. There are only 15
 categories: Management Change, Global factors,
Strategy, Competitive Landscape, Risk Management,
Financials, M&A, Clients, Exchange Rate Market, Bank
-related event, Litigation, Regulation, Trading,
Holdings, Outlook. You must pick one between them,
do not create one yourself.  The **categories**, and
 the rules for assignment are as follows:\n**
Management Change**: anything related to the bank's
own change of management or transition, not only for
 the CEO but of any kind of lower management
position.\n**Global factors**: any talk of global
event like COVID, economic crises, geo-political
events, trade-related events, political events in
foreign countries and similar.\n**Strategy**: any
talk of business strategy like entering/exiting a
new market, cutting costs, etc.\n**Competitive
Landscape**: any talk of competitors or the position
 of the bank compared to competitors.\n**Risk
Management**: any talk of change in risk position of
 the bank, note that if the bank simply presents
some risk metric, that is not an explicit change and
 it should instead fall into financials.\n**
Financials**: any talk about standard financial
metrics like earnigns, dividends, ROE, revenues, etc
. If, together with the financial metric, there is
also an explanation of why the financial indicator
has fallen or increased, then see if you can assign
to another category according to the explanation.\n
**M&A**: any talk of M&A of the bank in the earnings
 call.\n**Clients**: any talk about change in
clients landscape.\n**Exchange Rate Market**: any
```

```
talk about FX, FOREX, exchange market, or exchange-
related risk.\n**Bank-related event**: any event
that affected the earnings call's bank specifically
and that does not fall into any other category, for
instance bankrupcy, very large, surprising, or
sudden losses/gains, anniversaries, scandals etc.\n
**Litigation**: talk of specific litigations or
litigation issue.\n**Regulation**:any talk about
regulatory compliance.\n**Trading**: any event or
change specifically related to the trading activity
of the bank, this should not include standard
presentations of the trading activity of the bank,
that should instead fall into financials.\n**
Holdings**: any presentation of the asset portfolio
of the bank, either bonds, or equities, or
derivatives. Returns on holdings should go on
financials but any info on composition of portoflio
should go here instead.\n **Outlook**: talk about
the future in a very general way, without giving
information that could help categorizing the record
in any other category.\nThe following is an example
of input and output that I want (the following
example input does not necessarily span the full set
 of categories above): Input: '1. **CEO transition
**: New CEO James takes over with John Adams and
Rita Pavone on his team.\n2. **Competitive landscape
**: We aim at being number one, two, or three in all
 businesses.\n3. **Institutional Securities** (ISG):
 Revenues of $3.2 billion, 39percent compensation
ratio for the quarter, 40percent for the year.\n4.
**Investment Banking**: Top global M&A advisor in
2009, advised four of the top 10 announced
transactions.\n5. **Equity Sales and Trading**:
Revenue of $722 million, lower than expected due to
reduced client activity.\n6. **Fixed Income and
other sales and trading**: Revenue of $963 million,
```

```
        losses of $380 million from credit spreads.\n7. **
        Commodities**: Lower revenues due to lower
        volatility.\n8. **Value-at-Risk (VaR)**: Total VaR
        increased to $187 million from $168 million.\n9. **
        Global Wealth Management (GWM)**: Revenues up 4
        percent sequentially, net profit of $231 million,
        pretax margin of 7%.\n10. **Impairment**: The bank
        credit conditions look benign, and they expect
        impairment to be low in Q1 and high in Q4.\n11. **
        Cost flexibility**: The bank is prepared to flex
        costs where appropriate to deal with revenue
        pressure.\n12. **Leadership changes**: The bank
        announced leadership changes to help execute their
        plans in the global consumer banking and payments
        businesses.\n13**Funding**: Basel III net stable
        funding ratio at 100%, Swiss regulatory leverage
        ratio at 4.7%.\n14. **Litigation**: Litigation with
        RMBS repurchase claims transferred out CHF 2 billion
         into litigation.' Output: '1. **Management change
        **\n2. **Competitive Landscape**\n3. **Financials**\
        n4. **Competitive Landscape**\n5. **Financials**\n6.
         **Financials**\n7. **Global factors and events**\n8
        . **Risk Management**\n9. **Financials**\n10. **
        Outlook**\n11. **Strategy**\n12. **Management Change
        **.\n13. **Financials**\n14. **Litigation**'. Given
        this information, generate the output text from the
        input text I provided in the beginning. This is the
        text to categorize: <...>"
)
```

Sometimes, the model does not categorize the words according to the instructions in the prompt. Given that these cases do look peculiar, we manually force such cases to fall under an 'Other' category.

D.2 Sentiment and Similarity Analysis

Table B.3 contains earnings calls' similarity and sentiment scores. To compute the similarity score between each earnings within the same quarter we computed the cosine similarity score between each combination of texts. To do so, we use the cosine similarity functionality of the sentence-transformer model *paraphrase-MiniLM-L6-v2*. We define text sentiment as the net amount of positive minus negative sentences over the total number of sentences in each earnings calls. The sentence sentiment is assigned according to the *FinBERT* model: a sentiment analysis model pre-trained on financial texts.