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 exposure 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 and uncovered 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 has highlighted 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. It 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. Specifically, 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 exogenous shocks to intermediary risk-bearing constraints following the granular instrumental variable (GIV) approach (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 have the potential to 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 exposure 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 earns returns on a (nonzero) net position, but such risky positions are subject to a convex

[1] These risk limits refer to the risk-bearing constraints of trading desks, imposed by internal management for both risk-management and regulatory purposes. The legal definition (according to 17 CFR Appendix A to Part 255) is "constraints that 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."

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, their 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 are faced with 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 to identify exogenous limit shocks builds on a striking institutional feature of the foreign exchange market: it is a highly concentrated dealer market, where 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.

As previewed above, we exploit two novel, detailed supervisory micro data 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 contains granular information on all trading desks of large US bank holding companies, including limits on their positions and usage of these positions at the daily level. 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. In order to understand the effects of these limits on individual currencies, we also leverage the supervisory Y-14F data, schedule F, which contains quarterly information on net currency exposures of trading desks, broken down by currency.[3] Our main sample covers the period from 2016 through 2022 for 32 currencies. Together, these data provide us with a comprehensive

[2]For example, the top 8 dealer banks have 92% market share in spot transactions, 81% market share in outright forwards, 74% market share in FX swaps, and 92% market share in options, see the Survey of North American Foreign Exchange Volume Market Share, NY Fed, October 2022.

[3]BHCs with average gross trading assets and liabilities over the prior four calendar quarters equal to $20 billion or more need to file VV-1. The Y-14F respondent panel is comprised of 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 datasets.

view of the risk limits and net currency exposures 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 dataset and the first to combine them together.

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: (i) the exchange rate change, (ii) changes in bid-ask spread, (iii) 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 default swap (CDS) spreads.[5] These spreads capture sovereign default risk, an increase of which generally implies sell-offs of domestic assets such as local-currency denominated government bonds (Augustin et al., 2016; Hébert and Schreger, 2017). This sell-off 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 0.33 percent. Aggregate net positions of US dealers towards the foreign currency also decrease by 0.5 percent (relative to the standard deviation of quarterly changes in net positions). Risk-limit shocks also prompt larger bid-ask spreads, regardless of the direction of currency flows. Specifically, a one-standard-deviation tighter risk-limit shock implies bid-ask spreads increase by 6%.[6] Focusing on the impact on the value of the dollar, we estimate an average increase in currency returns on the broad dollar index by about 17 basis points in response to a one-standard-deviation limit shock.

We also show that tighter limits shocks imply deviations from uncovered interest parity, as

[4] Both these data sets are collected by the Federal Reserve to support the stress testing exercise as mandated by the 2010 Dodd-Frank Act after the Great Financial Crisis. All information in these data sets refers to activities consolidated at the Bank Holding Company (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.

[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 beside sovereign CDS spread.

interest rates do not move in response to limit shocks, while exchange rates do. Furthermore, the shocks also cause changes in covered interest parity deviations, implying that dealers' intermediation function is impaired as a result of these shocks. Overall, these results substantiate how our limit shocks proxy well for market frictions in FX dealers markets. 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, suggestive that other dealer banks step in as time goes by and bring the exchange market back to the old equilibrium. It is important to highlight that the effects of aggregate—as opposed to idiosyncratic—limits shocks may be different, potentially leading to large and permanent exchange rate changes.

We provide further evidence that risk limit shocks to global banks' trading desks impair their critical intermediation function by examining the factors behind banks' profits from currency intermediation. Specifically, this intermediation profit can be thought of as a combination of volume and spread. Our analysis shows that that currency turnover, measured at either the currency-time level or 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 margin) 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% and an increase in margins of about 8% in response to a one-standard-deviation limit shock.

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. Firstly, 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 focus on the role of a financier who must 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 has tested this implication (Froot and Ramadorai, 2005; Hau, Massa and Peress, 2010; Pandolfi and Williams, 2019). However, a direct test of the effect of financier constraints on currency

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

returns has been difficult to achieve due to limited data availability, a problem we are able to confront using novel data sources.

There is a small strand of the literature that is able to relate 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 exchange rates. In contrast, our paper is the first that we know of to utilize trading desk-level limits and exposures to 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 also 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 because of fixed costs in doing business, e.g. inventory costs, or 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/dollar market to show that order flows (net-buying pressure on a particular currency) can explain up to 60% of daily FX volatility. In their model, order flows from better informed investors generate price concessions for the dealers. Our paper differs from this literature, as 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 have argued that post-financial crisis regulation have made banks' balance sheet capacity more costly leading to deviations from covered interest parity (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

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

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

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 implications of the trading-desk's role in the foreign exchange market, we start by introducing a basic model of a foreign exchange intermediary based on Gabaix and Maggiori (2015). 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 exposure at end of any trading day. However, the bank has a risk limit on currency exposure. 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 $2s$ around the mid-price point $\mathcal{E}$.

The bank takes as given the net dollar demand, $D(e+s)$, with $D' < 0$.[10] Financiers (non-dealers, e.g., hedge funds) absorb part of this imbalance according to $F(e-s)$, with $F' > 0$, similar to the financiers in Gabaix and Maggiori (2015).[11] Let δ be the foreign currency position that the bank holds at the end of the period, expressed in US Dollar terms (for example, the bank may hold 5 million US Dollars worth of Japanese Yen). We assume that the bank plans on selling all of this exposure 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 (i.e., nonzero δ) is costly to the bank. Risk aversion, volatility, regulations, or information asymmetries are some factors that may be behind exposure limits.

[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, similar to Gabaix and Maggiori (2015), we 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.

We model such cost in reduced form as a convex (quadratic) cost in δ; for simplicity, we assume the following functional form: $\delta^2/2$. 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 in more detail below.

The bank's profit (expressed in dollars) is equal to the sum of total margin from intermediation and the return of their non-zero net foreign currency position, δ. The bank takes as given the exchange rate, and chooses the spread and foreign currency exposure 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 exposure. In our empirical analysis, as we will discuss below, we will use shocks to trading desk limits as exogenous variation in γ.

The interior solution returns the bank foreign currency supply function and the spread pricing equation:

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

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

The bank's optimal foreign currency exposure thus increases if the foreign currency has a low value, i.e. 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 exposure. The spread depends on the demand and financier supply elasticities. 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 financier 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 (or, equivalently, a preference against holding foreign currency by the US). A positive value of a means that net demand for dollars increases. Our linear level-log specification of the demand function implies that the parameter $b > 0$ is the elasticity of demand for dollars. The parameter $\Gamma > 0$ represents the constraints of non-bank financiers, as in Gabaix and Maggiori (2015), which has a distinct role than the constraint on banks γ. We also follow the prior 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 bank holdings, exchange rate, and spread are:*

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

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

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

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

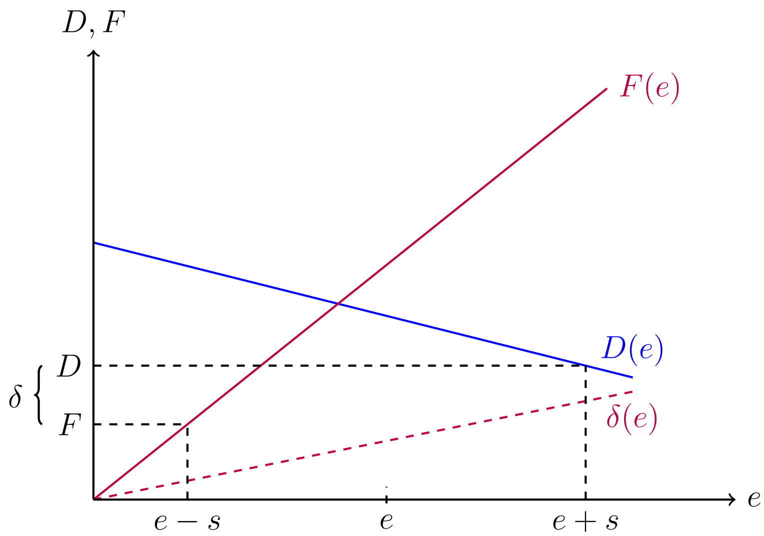
Crucially, the sign of the exchange rate, spread, and net position depends on the demand shifter, a. In the trivial case of no net demand shift, $a=0$, the (log) exchange rate equals the expectation, and net positions and spreads are 0. Moreover, the equilibrium exchange rate, net position, and spread are increasing functions in a, so when there is higher demand for dollars, the dollar appreciates more, banks' supply of dollars increases, and spread increases.

In the model of currency flows, D and F are not restricted to be positive in equilibrium.[13] Figure 1 summarizes the equilibrium graphically for a positive dollar demand shock, $a>0$. As with 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 foreign currency exposure, $\delta>0$. The bank also increases 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

[13] As discussed above, D and F simply refer 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 simply means that there is a negative demand for dollars, i.e. a positive demand for foreign currency by that sector. Likewise, when F is negative, this simply means that the financiers supply more foreign currency than dollars.

inelastic than the supply curve, for a given midpoint exchange rate, an increase in spread leads to a lower reduction in demand compared with supply.

Figure 1: Foreign Exchange Market Equilibrium

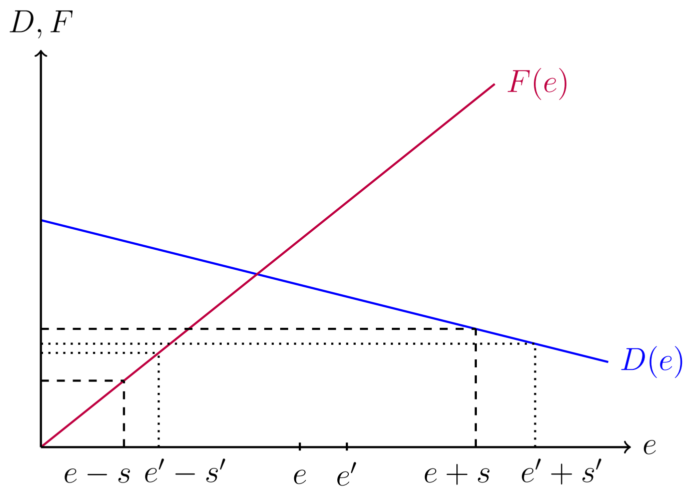


Note: Equilibrium for positive dollar demand shift, $a > 0$, in full model. For reference, the figure also includes the dashed red line, which corresponds to the banks' net foreign currency position (dollar supply). Note that, in general, the equilibrium exchange rate e (midpoint between bid and ask)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

We can benchmark the equilibrium exchange rate in our model, with the equilibrium exchange rates from different models that are nested within our structure. In particular, we can compute the exchange rate when the bank is not charging spread for intermediation ($s = 0$), or when the bank is not holding any currency exposure ($\delta = 0$), or either combination of the two. Clearly, without the bank intermediating or holding currency risk, the equilibrium exchange rate, denoted by $e^{\delta=0,s=0} = \frac{a\Gamma}{1+b\Gamma}$, would clear $F = D$. Graphically, this is the intersection of the red and blue curves. The resulting exchange rate would be lower than that in our model. Next, consider the case where the bank holds currency risk, but doesn't charge spread, thereby effectively being a financier. The exchange rate in this case is $e^{\delta=\delta^*,s=0} = \frac{a\Gamma}{1+\Gamma/\gamma+b\Gamma}$, which is also smaller than the equilibrium rate in the full model. If the bank is intermediating currency demand by charging spread, but is not holding any residual risk, we obtain the following equilibrium exchange rate: $e^{\delta=0,s=s^*} = \frac{a\Gamma(b\Gamma+3)}{b\Gamma(b\Gamma+6)+1}$. This exchange rate is again smaller than in our full model. Nevertheless, the presence of the spread-charging intermediary impacts the equilibrium exchange rate, even if they cannot hold a position themselves. Overall, this analysis highlights the role of intermediation (charging spread) vs risk holding (nonzero net exposure) in our model. Both frictions—holding cost of nonzero positions as well as intermediation spread—in turn lead to a stronger depreciation of the foreign currency after a net dollar demand shift.

The focus of our analysis is 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. When the bank is more constrained (γ increases to $\gamma' > \gamma$), the bank reduces its net position and provides less dollars in equilibrium (equation 2), the total supply of dollars decreases, and the foreign currency depreciates ($e > 0$). Moreover, given our assumption on the inelastic demand shifter, the bank increases the spread. Taking together equilibrium adjustments in spread and exchange rate, both the buy and sell prices increase, leading to a larger supply of dollars by the financiers, yet the increase in supply by the financiers 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]

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.

We can summarize the intuition behind Figure 2 in 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 financiers' supply (i.e., $1 - b\Gamma > 0$ holds), the following comparative statics with respect to the bank's cost of holding net position, γ,*

[14] Appendix Figure A.1 visualizes the corresponding comparative statics for a negative net dollar demand shift, $a < 0$.

hold:

$$\frac{\partial \delta^*}{\partial \gamma} \propto -a \tag{10}$$

$$\frac{\partial e^*}{\partial \gamma} \propto a \tag{11}$$

$$\frac{\partial s^*}{\partial \gamma} \propto |a|(1 - b\Gamma) > 0. \tag{12}$$

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 dollar increases ($a > 0$), larger limit shocks (tighter limits) lead to a stronger foreign currency depreciation and a reduction in net foreign currency exposure. For this reason, our empirical strategy focuses both on identifying exogenous limit shocks, γ, and proxying for the net demand flow, a, to correctly interpret our empirical results through the lens of the theoretical framework. Note that given our assumption that the currency in net demand has more inelastic demand, the spread always increases in response to tighter risk limits.[15]

Note that our highly stylized model is static in nature, 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 to the much larger gross flow intermediated (see the next section). Net positions (stock) are typically 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 impairs 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. 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 exposures (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. We will provide supportive evidence that indeed limit shocks reduce banks' turnover and gross notionals as proxies for total flow.

[15] The absolute value in the spread derivative comes from the fact that we redefined s to be the absolute value of s for $a < 0$.

2 Data

Our analysis utilizes two supervisory datasets: the Regulation VV Quantitative Measurements (henceforth VV-1) data and the FR Y-14F (henceforth Y-14) data.[16] The Federal Reserve System was mandated with the collection of both these supervisory dataset in the 2010 Dodd-Frank act that aimed at building a more resilient financial system against the backdrop of the 2008/09 Great Recession. Both datasets contain information about the consolidated global activity of the largest Bank Holding Companies (banks hereafter) domiciled in the United States.Therefore, we capture the banks' activity both from foreign and domestic offices (including branches and subsidiaries). Moreover, both data sets also cover the activities of foreign-owned intermediate holding companies (IHCs) with substantial presence in the United States. As discussed, for simplicity, we refer to these institutions collectively as "banks".

The VV-1 dataset originated under the 2013 Volcker rule of the Dodd-Frank Act in order to monitor compliance with restrictions on proprietary trading. Banks with average gross trading assets and liabilities over the prior four calendar quarters equal to $20 billion or more are required to submit 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 primarily are of two types: sensitivity (e.g., delta position, or cash equivalent position) and value-at-risk (VaR).[18] We focus on VaR-based limits in our main analysis, but our results are robust to using delta-based limits.[19] Our analysis is primarily based on risk limits. Because limits are desk-specific and not product-specific (e.g., foreign exchange, i.e. FX), 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 (e.g., FX, currency, foreign exchange).[20]

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

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

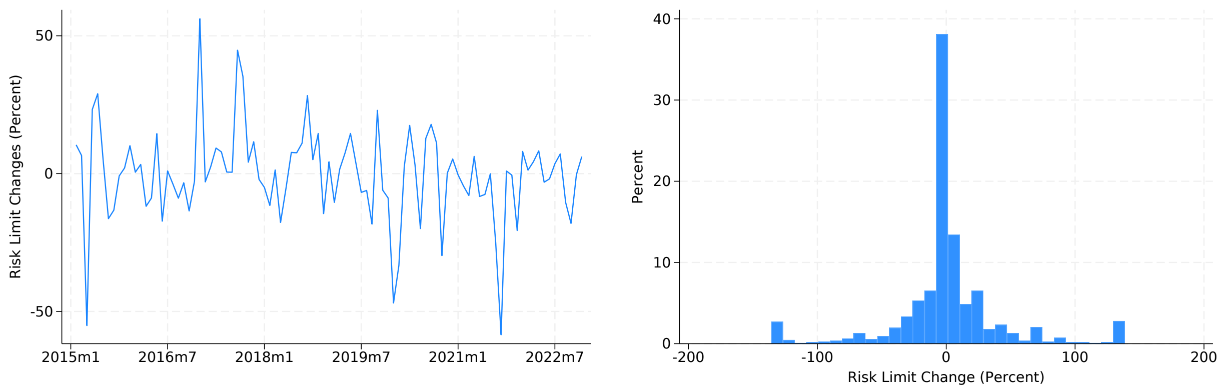
[18]The "cash equivalent" or the "delta position" of a derivative is the expected change in the value of a derivative for each dollar change in the price of the underlying asset, multiplied by the face value of the derivative. In exchange rate markets, it's also called the "spot equivalent position"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

[19]Often, a single desk has multiple limit types, for example, they 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", and "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. Specifically, we verify that a desk is trading FX as one of its primary activities and not just using FX 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.

Our final data includes 167 FX desks for 11 banks. 120 desks have delta limits and 165 have VaR limits. 118 desks report both delta and VaR limits. Since the reporting entity is the holding company, our dataset covers trading desks affiliated with large US banks outside of the US. For example, we capture FX desks in London. All desks declare the limit and limit use, in dollars, for each limit measure. Desks may also declare the maximum and minimum of two-sided limits, most relevant for delta limits. We focus in our analysis on the maximum absolute limit value (max limit), so for a bank that reports an upper limits of +\$100M (long exposure) and a lower limit of -\$120M (short exposure), the max limit would be +\$120M.[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' percent changes (log difference times 100) in risk limits . Panel (b) shows the histogram of percent 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%. *Source*: FR VV-1, authors' calculations.

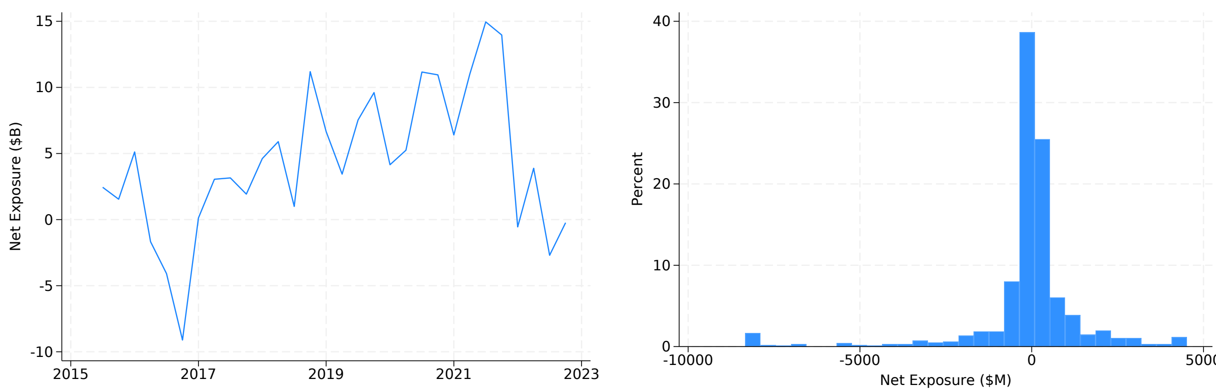
The observed changes in these trading desks' daily risk limits are at the core of our identification strategy. Based on the total of 1,071 nonzero limit changes observed in our data, we find substantial variation in limit changes over time and in the cross section of desks. Figure 4, Panel (a), depicts the monthly average of trading desks' daily risk limit changes (measured in percent). 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%. The risk limits are endogenous to macroeconomic conditions and subject to bank-level variation in the way they are declared (see Anderson,

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

McArthur and Wang, 2023). For this reason, section 3 develops a methodology to isolate the idiosyncratic risk limit shifts.

Our second data source is the 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 total consolidated assets are subject to the mandated Dodd-Frank Act Stress Testing (DFAST) and are required to file the Y-14 for stress-testing and supervisory purposes. Specifically, we exploit Y-14F Schedule F on Trading that contains information on banks' FX trading activity. The schedule reports for each bank and quarter the delta positions, i.e., the cash equivalent net exposures, in each currency. In what follows, for simplicity, we refer to this delta position as "net exposure" going forward. Again, because the reporting entities are bank holding companies, 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 Exposure to Foreign Currencies



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

Notes: Panel (a) shows the sum of net exposure across all banks and currencies, for each quarter (in $ billion). Positive values correspond to long exposure to foreign currency. Panel (b) shows the histogram of the net exposures at the bank-currency-quarter level (in $ million), winsorized at 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.5 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

[22]Submission types are further broken down into: (i) 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; (ii) AL Hedges are positions that are used to hedge held-for-investment (HFI) accrual loans; (iii) Credit Valuation Adjustment (CVA) refers to the market value of the credit risk due to any failure of the counterparty to deliver; and (iv) Trading. In most of our analysis, we focus on the Trading submission, given our research question.

also reveals that exposure to foreign currency has increased from about 2017 throughout 2021, but then fell thereafter. Moreover, exposures vary between -\$10 billion and \$15 billion. Panel (b) zooms in on the distribution of net exposures at the bank-quarter-currency level, revealing substantial cross-currency variation and fat tails, indicating that some large exposures exceed \$1 billion. Appendix Figure A.4 shows the evolution of the aggregate net exposures by currency over time and demonstrates additional time variation, which is significant for several currencies.[23]

Appendix Figure A.5, Panel (a), zooms in on the distribution of deltas by currency, across time and banks. The underlying data are at the currency-quarter-bank level. The majority of net exposures are rather small: in the order of tens to hundreds of millions, with maximum net exposure being \$1 billion. (Note that due to confidentiality reasons the data are winsorized at the top and bottom 5%.) The relatively small net exposures are in stark contrast to the average daily turnover from the BIS triennial survey, which is in the order of trillions (Panel b). Our model rationalized how, even while risk limits and net exposures are small, changes in limits have significant and sizable effects on exchange rates.

In addition to these supervisory micro datasets, we also 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 like asset size or capital ratios, the Y-9C also 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, credit default swap (CDS) spreads, forward exchange rates and settlement dates, and interest rates from Bloomberg and Haver. Additionally, we use turnover data at the currency-level from the NY Fed FX Volume Survey.

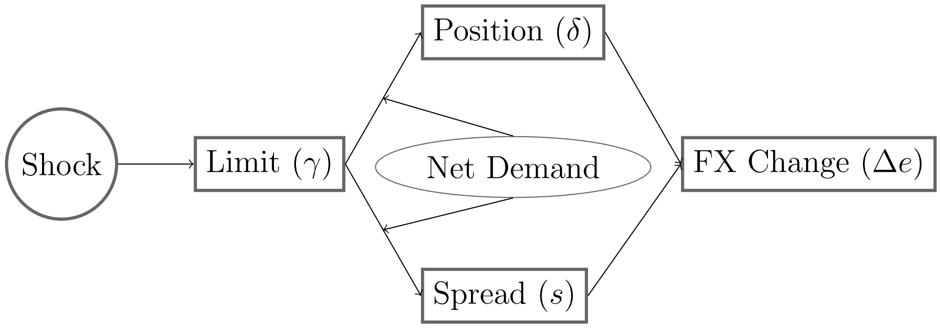
3 Identification

Figure 5 illustrates the core causal chain that is the focus of this paper: conditional on net currency demand, shifts in risk limit affects the spread and bank net exposures, 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. We therefore construct limit shocks that are exogenous to market conditions. In this section, we discuss how we identify

[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 Foreign Exchange Market



Note: The diagram 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.

such exogenous variation in risk limits from the data. Similarly, we discuss how we identify demand shifters given that our model predicts that the effect of limits shocks depends on net demand.

Risk Limit Shocks We exploit the supervisory micro data to construct currency-level and bank-level shocks to risk limits that are driven by idiosyncratic desk-time factors, i.e., they are exogenous to the aggregate dynamics in the foreign exchange market. 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. Second, the granularity of the dealer centric market, that is, the fact that 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.

The assumption that desk-level idiosyncratic risk limit changes are exogenous to broader market conditions is key to our identification strategy. In defending this assumption, it helps to consider why trading desks might change their risk limits ideosyncratically. As a motivating example, consider the Federal Reserve's enforcement actions against Deutsche Bank in April 2017.[24] Deutsche Bank was found to be in violation of the Volcker Rule, as it had failed to adequately monitor proprietary trading, and was required to improve oversight and controls. One might imagine that Deutsche Bank would tighten trading desk risk limits in an ideosyncratic manner after such an order.[25]

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

[25] Note that because of the confidential nature of our microdata, we cannot describe individual shocks in our data.

Our granular approach to isolating risk limit shocks is based on 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 for time-trends and dealer-specific effects. Specifically, in our baseline specification, we model the log limits changes at the desk-day (d,τ) level using a saturated fixed-effects model:

$$\Delta \log \text{Limit}_{d,\tau} = \sum_{h=1}^{20} \gamma_h \log \text{Limit}_{d,\tau-h} + \sum_{h=1}^{20} \omega_h \text{Usage}_{d,\tau-h} + \alpha_d + \alpha_{b,\tau} + e_{d,\tau}, \qquad (13)$$

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 (say New York and London desks) within a given bank. For example, 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 percent 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 quite some 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 went up in the recent past they tend to go down 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.

We further allow for a common factor structure in the residuals of equation (13) that may not be captured by our extensive set of fixed effects and controls:

$$e_{d,\tau} = \lambda_d' f_\tau + \epsilon_{d,\tau}, \qquad (14)$$

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

Table 1: Variation in Δ Log Limit

	Δ Log Limit				
	(1)	(2)	(3)	(4)	(5)
$\sum_{i=1}^{20} \beta_{t-i}^{Limit}$					-0.023***
					(0.002)
$\sum_{i=1}^{20} \beta_{t-i}^{LimitUse}$					1.930***
					(0.522)
Controls	-	-	-	-	Yes
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
N	98956	98956	98956	98956	98956

Notes: Explanatory power of different models for desk-day level (log) limit changes. Column (5) corresponds to equation (13). *Sources*: FR VV-1, FR Y-14F, authors' calculations.

of equation (13). In our baseline analysis we remove one common factor, but results are robust to removing more common factors.

The residual of equation (14) is our baseline measure of idiosyncratic (desk-level) limit innovations. We extensively discuss and show results on alternative models to construct limit innovations in Appendix B. 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:

$$\text{Limit Shock}_{b,t} = -\sum_{\tau \in t} \sum_{d \in b} w_{d,\tau-1}^{b} \hat{\epsilon}_{d,\tau}, \tag{15}$$

where $w_{d,\tau}^{b} = \text{Limit}_{d,\tau-1} / \sum_{d \in b} \text{Limit}_{d,\tau-1}$ is the relative limit size of desk d (the summation occurs over all desks affiliated to a given bank, $d \in b$). The outer summation then aggregates these daily bank level shocks to the quarterly frequency, by summing across all days within a given quarter. Importantly, note the negative sign in equation (15). An increase in the limit shock variable thus corresponds to a tightening of limits, similar to an increase in γ in our model.

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

$$\text{Limit Shock}_{c,t} = \sum_b w^c_{b,t} \text{Limit Shock}_{b,t} = -\sum_b w^c_{b,t-1} \sum_{\tau \in t} \sum_{d \in b} w^b_{d,\tau-1} \hat{\epsilon}_{d,\tau}, \tag{16}$$

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 exposure 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 how our identification hinges on the random shocks, while exposure shares are allowed to be endogenous (Borusyak, Hull and Jaravel, 2021).

Appendix Figure A.7 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 (and other variables in the regressions) are winsorized at the 5th and 95th percentile. Finally, we standardize the limit shocks in each estimation sample to have mean zero and unit variance.

Demand Shifters Our theory suggests that the directional effect of limit shocks on exchange rates depends on the direction of currency demand. Specifically, when limits are tightened in the presence of net dollar demand, theory suggests the exchange rate should depreciate. In order to proxy for shifts in net dollar demand, we use innovations in spread of credit default swaps (CDS) written on sovereign debt. An increase of sovereign-default risk generally implies foreign sell-offs 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:

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

and use the residuals of this regression as CDS innovations.[26] Our demand shift measure is then given as

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

[26] 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.

We winsorize this variable at the top and bottom one percent so that results are not driven by outliers. In the robustness analysis, we also compute innovations to one-month at-the-money implied volatility as well as innovations to sovereign credit ratings.[27]

By construction, limit shocks and the demand shifter are likely unrelated. Indeed, Appendix Figure A.8 shows that the two variable 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.

Summary Statistics Our main analysis is based on a currency-quarter level dataset, which covers data on 30 currencies observed for 30 quarters each. Table 2 reports summary statistics of the key variables. We winsorize all outcome variables and shock variables at the bottom 5 percent and top 5 percent. On average 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 exposure is negative, indicating that US banks on average are short in foreign currency on their trading books. However, there is substantial variation in net exposures.

[27]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.

Table 2: Summary Statistics

	(1) Mean	(2) Std. Dev.	(3) P5	(4) P25	(5) P50	(6) P75	(7) P95	(8) N
Δ Log(px)$_t$	1.08	5.94	-6.50	-2.15	0.19	3.60	10.45	960
Net Exposure/L.Maxlimit	-2.37	30.50	-34.03	-2.23	0.31	3.10	23.94	928
Net Exposure/Turnover	-0.21	2.72	-3.04	-0.16	0	0.19	2.09	660
BA Spread (Pct.)	24.84	47.76	0.96	4.25	11.78	27.26	79.66	959
Limit Shock	-149.02	9529.92	-5045.31	-429.71	41.48	322.27	4641.98	960
Limit Change	127.34	9375.87	-3392.59	-125.70	78.53	385.16	4566.40	960
Demand Shifter (CDS Innovation)	0	0.23	-0.34	-0.13	-0.01	0.08	0.43	731
CDS Change	0	0.29	-0.38	-0.15	-0.02	0.07	0.45	827
Demand Shifter (Vola Innovation)	0	0.21	-0.31	-0.14	-0.03	0.09	0.40	832
Vola Change	0	0.29	-0.39	-0.15	-0.02	0.11	0.48	928
CIP Deviations	-16.32	181.69	-192.97	-52.31	-20.16	0.74	103.68	745
UIP Deviations	110.04	2282.18	-2898.24	-1046.80	50.80	1078.75	3470.02	723

Notes: Summary statistics for key variables at the currency-quarter level. Log difference in exchange rate is multiplied by 100. BA spread is as percent of the mid price. Limit Shocks and Changes as well as CDS Innovations and Changes and Vola Innovations and Changes are measured in log differences. CIP and UIP deviations are measured in basis points. The sample covers data from 2015q3 through 2022q4 and 32 currencies. *Sources*: FR VV-1, FR Y-14F, Bloomberg, BIS, authors' calculations.

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 implications for interest parity conditions. Finally, we present results on turnover and margin.

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

$$\begin{aligned}\Delta y_{c,t} = \beta_1 \text{Limit Shock}_{c,t} + \beta_2 \text{Limit Shock}_{c,t} \times \text{Demand Shifter}_{c,t} \\ + \alpha_i + \alpha_t + \gamma' X_{c,t} + u_{c,t},\end{aligned} \tag{17}$$

where $y_{c,t}$ is the outcome variable, which in our baseline analysis is either (i) the log spot exchange rate of currency c, multiplied by 100, (ii), the aggregate US banks' net exposure to currency c normalized by the sum of the limits across all US banks, or (iii) the bid-ask spread in percent of the mid point.[28] Limit Shock is the granular limit shock as identified in the

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

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 outbreak in 2020q1 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 2020q1, thereby effectively removing the impact of 2020q1 on our estimates. In line with our model predictions, our key parameters of interest are the coefficients on the limit shock, β_1, and 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 level to account for correlation of residuals within each cluster.

Baseline Results Table 3 shows the estimation results of regression model (17). The respective response variable (change in exchange rate, net position, or bid-ask spread) is indicated in the super-column titles. In the columns with odd numbers, we report the average effect of limit shocks. In the even-numbered columns, we report the differential effect of limit shocks depending on net demand shifts.

When we investigate the average effect of limit shocks, we find that, on their own, they have an insignificant effect on currency returns and the net positions of banks (columns 1 and 3). 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 or not banks' net positions increase or decrease after a limit shock is dependent on the direction of net dollar demand.

On the other hand, column (5) shows that, on average, bid-ask spreads increase by about 6% 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 predictions, given our assumption of inelastic demand shifters. 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.

Our theory crucially predicts that limit shocks interact with demand shifters to affect the exchange rate and net position of banks. We test this prediction in the evenly-numbered columns that include the interaction term. Given our standardized limit shock variable, the

Table 3: Effects of Dealers Risk-Limit Shocks on FX, Exposure, and Bid-Ask spread

	Δ FX Rate		Δ Net Exposure		Δ Bid-Ask Spread	
	(1)	(2)	(3)	(4)	(5)	(6)
Limit Shock	0.038	0.103**	-0.065	-0.228	0.062**	0.069*
	(0.057)	(0.050)	(0.321)	(0.374)	(0.026)	(0.034)
Demand Shifter		0.991**		-0.191		0.083**
(CDS Innovation)		(0.370)		(0.564)		(0.037)
Limit Shock × Demand Shifter		0.330***		-0.458**		0.015
		(0.108)		(0.205)		(0.034)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Currency FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Within R-squared	0.037	0.080	0.329	0.368	0.430	0.457
N	800	702	768	675	758	660

Notes: This table shows the effect of shocks to banks' risk limits on key endogenous variables in the foreign exchange market. In columns (1) and (2), the dependent variable, Δ FX Rate, is the quarterly log difference in the spot exchange rate, multiplied by 100. In columns (3) and (4), the dependent variable, Δ Net Exposure, 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. In columns (5) and (6), the dependent variable, Δ Bid-Ask Spread, is the quarterly change in the (log) bid-ask spread relative to the mid point. 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 2016q3 through 2022q4 for 32 currencies. 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.

coefficient estimate on Demand Shifter represents the average effect of a demand shift in our sample. For this average effect, we find that an increase in net dollar demand (decrease in foreign currency demand) leads to an 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 points, this implies a one-third larger effect on exchange rates after a limit shock. This effect is statistically significant and in line with our theoretical predictions.[29]

[29]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 in order to achieve narrow identification. We also found these narrowly limit shocks to be weak instruments for (aggregate) limit changes, which is why we estimate reduced form models throughout.

In column (4), which estimates the response of banks' net exposure, 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 exposure in foreign currency after a limit shock. (The level effect of Demand Shifter captured by the uninteracted variable is negative but statistically insignificant.) The coefficient estimate of –0.458 implies that, in response to a one standard deviation limit shock and conditional on a unit dollar demand shifter, net foreign currency exposure falls by 63% relative to the mean value of net exposure of 0.727 in the regression sample. If we express the effect relative to the standard deviation of quarterly net exposure changes (value of 9.54), the coefficient implies a reduction of about 4.8%.

Column (6) shows that there is no significant heterogeneity of the effect on limits shocks on bid-ask spreads depending on net demand shifters. However, the point estimate on the interaction term is positive. In fact, when using alternative proxies for demand shifters, we find a significantly positive interaction term in line with our model prediction.

Our baseline results on exchange rates, net exposures, and bid ask spread are robust to a variety of different approaches which we present in the Appendix. Table B.2 confirms that our estimates hold when using a different proxy for demand shifter. Specifically, we use innovation to the (log) implied volatility. Table B.3 shows qualitatively similar results using sovereign credit rating innovations (ratings are coded such that higher integers correspond to better rating grades), but results lack statistical significance, likely due to the lack of variation in sovereign ratings in our sample.

Tables B.5 and B.5 show that results are robust to using differently constructed limit shocks. For example, columns (1) through (3) show 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. Results are also robust to using delta-based limit shocks (instead of VaR-based limit shocks) as columns (4) through (6) show. On the other hand, when we use the (endogenous) raw changes in limits instead of idiosyncratic innovations, we find attenuated coefficient estimates, highlighting the importance to isolate variation in limits that are orthogonal to market conditions (columns 10 through 12).

As an application of our findings, we zoom in on the US Dollar. Our baseline results focus on a panel of bilateral exchange rates against the dollar. How do limit shocks impact the US Dollar defined as a broad dollar index? We first collect the trade weights underlying the Broad Index of the Foreign Exchange Value of the Dollar published by the Federal Reserve Board. Table 4 reports the results of the trade-weighted analysis in columns (1) and (2) and

Table 4: Implications for Broad Dollar Index

	Trade-Weighted		Unweighted	
	(1)	(2)	(3)	(4)
Limit Shock	0.165***	0.221**	-0.026	0.154**
	(0.035)	(0.081)	(0.055)	(0.063)
Demand Shifter		0.575		1.082***
(CDS Innov.)		(0.337)		(0.341)
Limit Shock × Demand Shifter		0.215		0.355**
		(0.203)		(0.135)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Currency FE	Yes	Yes	Yes	Yes
Within R-squared	0.094	0.158	0.049	0.142
N	600	514	600	514

Notes: This table shows the effect of shocks to banks' risk limits on the Federal Reserve's Broad Index of the Foreign Exchange Value of the Dollar. The dependent variable in all columns is the log difference in the exchange rate. In columns (1) and (2), the observations are weighted with the trade-weights underlying the index. For comparison, columns (3) and (4) show unweighted regression for the same sample of observations of columns (1) and (2). 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 2016q3 through 2022q4 for 24 currencies with available dollar index weights information. 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, Haver, authors' calculations.

unweighted analysis in columns (3) and (4). The unweighted estimates are very close to our baseline effects reported in Table 3. Note that the number of observations falls from Table 3, as we drop currencies in this analysis that have a zero weight in the Broad Index of the Foreign Exchange Value of the Dollar. In contrast, when using weighted regression in columns (1) and (2), we estimate smaller and insignificant coefficients on the demand shifter and its interaction with the limits shock. This could be a consequence of low amount of CDS spread shocks for the largest trade partners. Importantly, however, we now find a significant and positive level effect of Limit Shocks, indicating that the broad dollar appreciates when Limit Shocks are tighter. The point estimate suggests a depreciation of foreign currencies by about 17 basis points in response to a one-standard-deviation limit shock (recall that the dependent variable is a log difference). Through the lens of our model, the positive level term means that US trade partners tend to have positive net dollar demand shifts ($a > 0$). (Appendix Figure A.6 shows that tightening limits changes are associated with an increase in the dollar's value even without fixed effects, i.e., unconditionally.) For full transparency, Appendix Figure A.9 reports country-specific estimates on the interaction term (using unweighted regressions).

Dynamic Effects We next zoom in on the dynamics effects of limit shocks on the exchange rate. Our limit shocks and net exposure vary at the quarterly frequency, the frequency that we are using 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 (17) for the daily log exchange rate as the dependent variable using our dataset 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 $\tau = -90, ..., 120$. As before our regression model controls for four (quarterly) lags as controls 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.

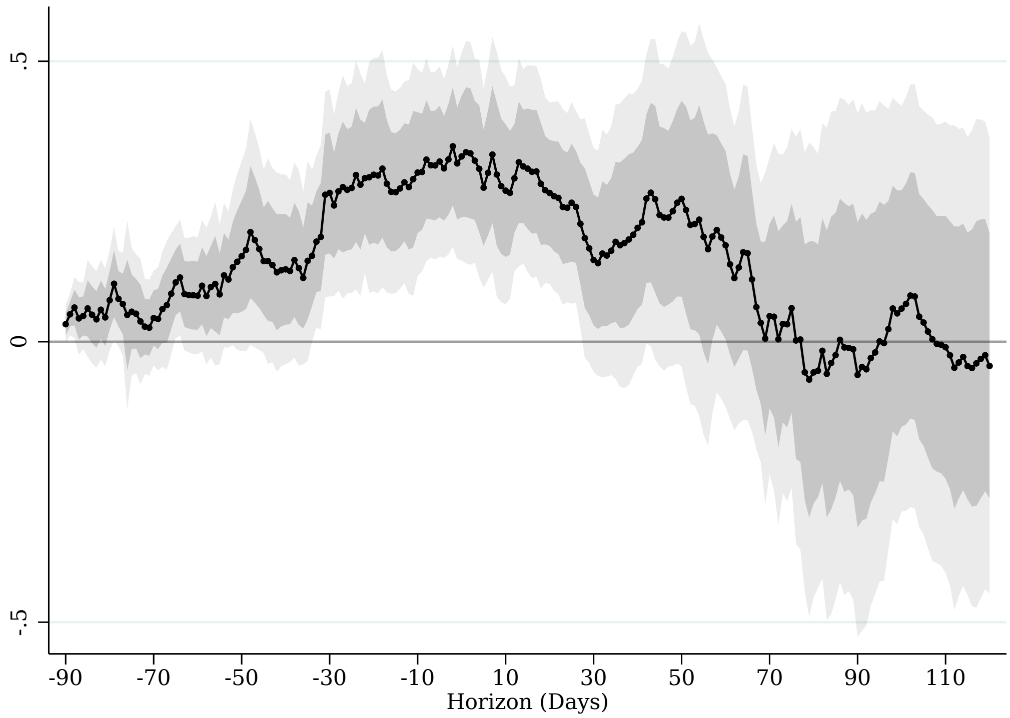
Figure 6 depicts the exchange rate response for different daily horizons on the horizontal axis. The figure shows that the limit shock leads to an exchange rate appreciation (conditional on a one-standard-deviation dollar demand shifter) for about 60 days (from $\tau = -30$ through $\tau = +30$) and the exchange reverts back to its pre-shock level after about 1 quarter (at $\tau = 90$).[30] We confirm the transitory effects of limit shocks on delta positions and bid-ask spread in Table B.6, 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 rates effect are consistent with segmented market frictions prevailing in the short run. Because of 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 old equilibrium. Importantly, it is possible that aggregate limit shocks—shocks that tighten the limits of *all* dealer banks—have persistent and larger effects on the exchange rate than those of our *granular* limit shocks identified from idiosyncratic limit changes.

Deviations from Interest Parity Because limit shocks affect exchange rates, we next investigate whether they also trigger violations from interest parity conditions. Interest parity conditions link exchange rates to interest rates using some form of no arbitrage conditions. Specifically, uncovered interest parity (UIP) states that the expected currency return must be equal to the interest rate differential, while covered interest parity (CIP) states that the

[30] Appendix Figure A.10 shows the responses to the 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 (17) for the exchange rate as dependent variable using our dataset 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 $\tau = -90, ..., 120$. 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 with black dots. The dark gray area represents a standard error band and the light gray area represents the 90% confidence interval. *Sources*: FR VV-1, FR Y-14F, Bloomberg, authors' calculations.

forward premium (i.e., the forward exchange rate relative to spot exchange rate) is equal to the interest rate differential. While our model does not explicitly include interest rates, the exchange rate movements due to market frictions necessarily constitute a deviation from UIP.[31] The effect on CIP can shed light on whether bank intermediation ability is a key

[31]Note that interest rates may also adjust in response to our limit shocks, for example, if, in general equilibrium, central banks may respond to exchange rate movements by adjusting monetary policy. Also remember that by construction limit shocks are orthogonal to bank-time factors, so changes in banks' interest rate trading desk that potentially could move rates are accounted for. We confirm using the Y-14 data that interest rate sensitivity to a specific currency is not significantly correlated with delta sensitivity to that currency at the bank-currency-quarter level.

mechanism behind our baseline findings, as CIP constitutes a riskless arbitrage opportunity and deviations are often associated with impaired intermediation.

In Table 5, which follows the structure of our baseline table, first examine the effect of limit shocks on interest rate differentials and UIP. In columns (1) and (2) we start by examining whether our baseline results are affected by including interest rate differentials as additional regressors. We find that when we include XIBOR interest rate differentials between the foreign country and the US, as well as four lags of these interest rate differentials, our point estimate on the interaction between limit shock and demand shifter remains significant and very similar in size. Furthermore, it seems that interest rate differentials are not themselves affected by limit shocks, whether or not they are interacted with demand shifters (columns 3 and 4). We next test the specific impact of exchange rate movements on one-month UIP deviations, calculated using ex-post realized excess returns (columns 5 and 6):

$$\Phi^{UIP}_{c,n,t} \approx r_{c,n,t} - r_{USD,n,t} - \frac{360}{d_{c,n,t}}(\ln S_{c,t+n} - \ln S_{c,t}),$$

where $r_{c,n,t}$ is country c's XIBOR interest rate, $r_{USD,n,t}$ is the USD LIBOR interest rate, $S_{c,t}$ is the spot exchange rate at time t (expressed in units of foreign currency per units of US Dollars), and $d_{c,n,t}$ allows for annualization of the exchange rates. UIP deviations move following exchange rate returns in the baseline results: limit shocks in the presence of net dollar demand prompt an increase in the excess return to local currency assets. This makes sense given the lack of movement in interest rates in response to the shocks.

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

$$\Phi^{CIP}_{c,n,t} = r_{c,n,t} - r_{USD,n,t} - \rho^{CIP}_{c,n,t}$$

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

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

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

Table 5: Effect of Limit Shocks on Uncovered Interest Parity

	Δ FX Rate		Δ Interest Diff.		Δ UIP Dev.	
	(1)	(2)	(3)	(4)	(5)	(6)
Limit Shock	0.059	0.141*	0.026	0.031	-0.978**	-0.266
	(0.094)	(0.073)	(0.020)	(0.024)	(0.350)	(0.584)
Demand Shifter		0.899**		0.052		1.706
(CDS Innovation)		(0.386)		(0.034)		(1.245)
Limit Shock × Demand Shifter		0.361***		0.016		2.195***
		(0.125)		(0.023)		(0.772)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Interest Diff.	Yes	Yes	No	No	No	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Currency FE	Yes	Yes	Yes	Yes	Yes	Yes
Within R-squared	0.127	0.153	0.195	0.200	0.626	0.635
N	740	671	740	671	738	669

Notes: This table shows the effect of including interest rate differentials in our baseline regression in column (2) of Table 3, as well as the effect of shocks to banks' risk limits on interest rate differentials and one-month UIP deviations. In columns (1) and (2), the dependent variable, Δ FX Rate, is the quarterly log difference in the spot exchange rate, multiplied by 100. In columns (3) and (4), 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 (5) and (6), the dependent variable is the 1-month UIP deviation, calculated using ex-post returns and defined to be the excess return to local currency assets. 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. Columns (1) and (2) control for the current 3-month interest rate differentials, as well as four lags. 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.

given currency on date t.[32]

Panel A in Table 6 confirms that limit shocks trigger covered interest parity deviations across multiple tenors in the direction of net dollar demand. Because the direction of CIP deviations is correlated to net dollar demand, this corresponds to CIP deviations widening after limit shocks. Specifically, Panel B shows how the absolute value of CIP deviation increases with limit shocks across multiple tenors, evidence that limit shocks weaken banks' intermediation abilities.

[32] 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 6: Effect of Limit Shocks on Covered Interest Parity Deviations

	Δ CIP Dev. 1m		Δ CIP Dev. 3m		Δ CIP Dev. 6m	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: CIP Deviations						
Limit Shock	0.623	-5.332	-0.576	-8.991	1.129	-7.832
	(6.196)	(6.880)	(3.175)	(5.810)	(3.258)	(4.663)
Demand Shifter		-73.517**		-57.102**		-55.725**
(CDS Innovation)		(30.568)		(25.199)		(23.642)
Limit Shock × Demand Shifter		-26.204**		-19.258**		-16.992**
		(11.306)		(7.529)		(6.847)
Within R-squared	0.254	0.093	0.267	0.095	0.229	0.138
N	727	658	714	645	628	563
Panel B: Absolute Value of CIP Deviations						
Limit Shock	10.378*	12.882	6.841*	9.045	5.010**	7.524*
	(5.454)	(8.388)	(3.422)	(6.854)	(1.962)	(3.888)
Demand Shifter		55.790*		45.512*		44.048*
(CDS Innovation)		(29.716)		(24.280)		(21.604)
Limit Shock × Demand Shifter		7.805		7.468		10.594
		(9.885)		(8.521)		(7.767)
Within R-squared	0.277	0.068	0.271	0.076	0.225	0.117
N	727	658	714	645	628	563
Controls	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. 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.

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 exposures (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 a proxy for intermediation.

Unfortunately, turnover data by currency are not available in either the FR VV-1 or the FR Y-14F data that 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 NY Fed FX Volume Survey. This survey captures the size and structure of foreign exchange activity in North America, and we use this data from 2016 onward in line with the availability of our other variables. The most recent survey builds on responses by twenty-one leading institutions active in the North American market.[33] Our key response variable is the log difference in dealer turnover. Turnover is based on total interdealer turnover in all FX instruments (spot, forward, swap, options). Limit Shock are quarterly and survey dates are matched to the corresponding quarter of the limit shock.

Table 7: Foreign Exchange Turnover Response

	Δ Log Turnover			
	(1)	(2)	(3)	(4)
Limit Shock	-0.033***	-0.029*	-0.026**	-0.024
	(0.008)	(0.014)	(0.011)	(0.016)
Demand Shifter		-0.003		-0.011
(Innovation)		(0.017)		(0.018)
Limit Shock $\times$ Demand Shifter		0.010		0.009
		(0.016)		(0.016)
Time FE	Yes	Yes	Yes	Yes
Currency FE	No	No	Yes	Yes
Within R-squared	0.007	0.011	0.004	0.009
N	268	215	268	215

Notes: This table shows the response of turnover to limit shocks at the currency-level. The dependent variable is the log difference in interdealer turnover reported in the biannual public NY Fed FX Volume Survey from 2016 through 2022. Estimates are based on total turnover and broken down by instrument (spot, forward, swap, options). Limit Shock are quarterly and survey dates are matched to the corresponding quarter of the limit shock. Regressions control for time fixed effects and currency fixed effects, as indicated. The sample includes a constant set of seven banks from 2014q3 through 2022q4. *Sources*: NY Fed FX Volume Survey, FR VV-1, FR Y-14F, authors' calculations.

We use the same regression model of equation (17) to study turnover responses in this data set. Table 7—which follows the same structure as our main table (Table 3)—presents

[33] These data are compiled by the NY Fed in collaboration with 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.

the estimation results. Given the small sample, we present results without (columns 1 and 2) and with (columns 3 and 4) currency fixed effects. The results show that tighter limit shocks reduce turnover (columns 1 and 3). The coefficient estimates indicate that turnover falls by about 3% 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% translates into a sizable reduction in average daily turnover by about $573 million. Columns (2) and (4) show that the turnover response does not depend on the net dollar demand shifter—the interaction term between Limit Shock and Demand Shifter is close to zero and insignificant. Note that the turnover response hence resembles the bis-ask spread response, for which we also find an average effect of limits shocks but no differential effect depending on demand shifters.

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 variable from the Y-9C. First, we proxy turnover using gross notional values of foreign exchange trading. 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 which differ in maturity to estimate the implied turnover, see Tables A.2 and A.3 for details. Second, we compute margins from foreign exchange trading as total trading revenue (from cash instruments and derivative instruments) relative to adjusted gross notional values. This income includes intermediation income from bid-ask spreads as well as gains or losses from net exposures.[34]

We use the follow 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 Shock$_{b,t}$ is defined in equation 15. The regression also include bank fixed effects (α_b) and quarter fixed effects (α_t) as well as four lags of the dependent variable.

The estimation results presented in Table 8 show that, in response to tighter limit shocks, total turnover at the bank level decreases, consistent with our findings from the cross-currency

[34]Foreign exchange trading income information is only available 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.

analysis. The estimated coefficient suggests turnover decreases by about 1.6% in response to a one standard deviation limit shock. Columns (2) shows that total foreign exchange margin increases, consistent with the findings on currency-level bid-ask spreads. The estimate implies an increase of about 5.1/100 basis points in response to a one standard deviation limit shock, which equals about 8% 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.

Table 8: Bank-Level Gross Notional and Margin Response to Limit Shock

	(1) Δ Gross Notional	(2) Δ Trading Margin
Limit Shock	-0.016*	0.051*
	(0.009)	(0.028)
Controls	Yes	Yes
Bank FE	Yes	Yes
Time FE	Yes	Yes
Within R-squared	0.337	0.220
N	177	144

Notes: This table shows the response of turnover and margin to limit shocks at the bank-level. In column (1), the dependent variable is the change in the (logarithm of) adjusted gross notional outstanding. In column (2), the dependent variable is the change in total FX trading revenue (from cash instruments and derivative instruments) relative to adjusted gross notional (in basis points). Both dependent variables in columns (1) and (2) are computed from the Y-9C. The sample includes a constant set of seven banks from 2014q3 through 2022q4. *Sources*: FR Y-9C, FR VV-1, 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. For identification of these effects, we exploit an array of detailed supervisory micro data that 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 exposure in different currencies, thereby being able 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. In response to tighter limits, theory predicts that, in response to a net dollar demand shift, banks reduce their net positions, increase bid-ask spreads and intermediate less 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 finding highlights the role of market makers, which may hold only a small share of the total FX risk. Yet, because of their central intermediation function, shocks to their risk limits have sizable implication for currency pricing.

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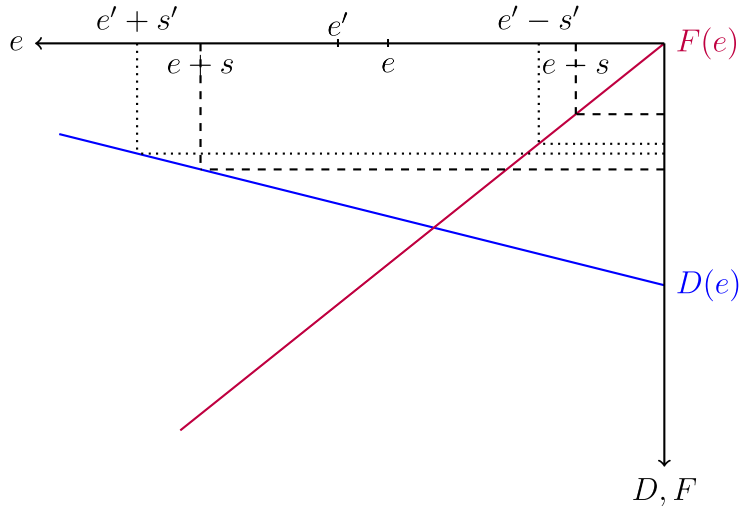
A Additional Figures

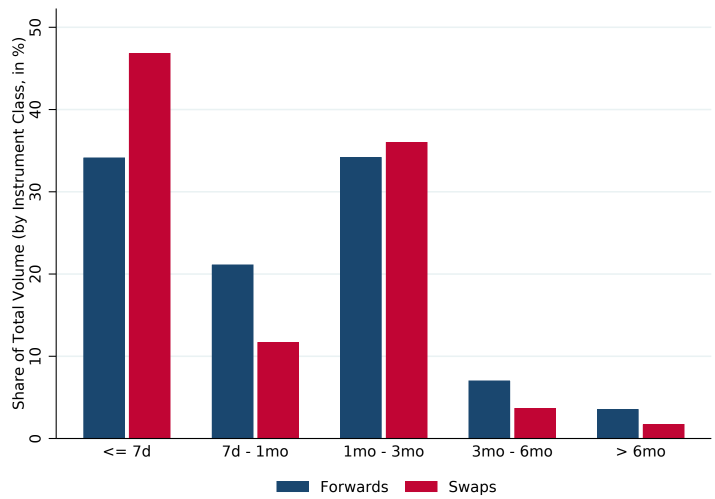
Figure A.1: Effects of Limit Shock for $a < 0$



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

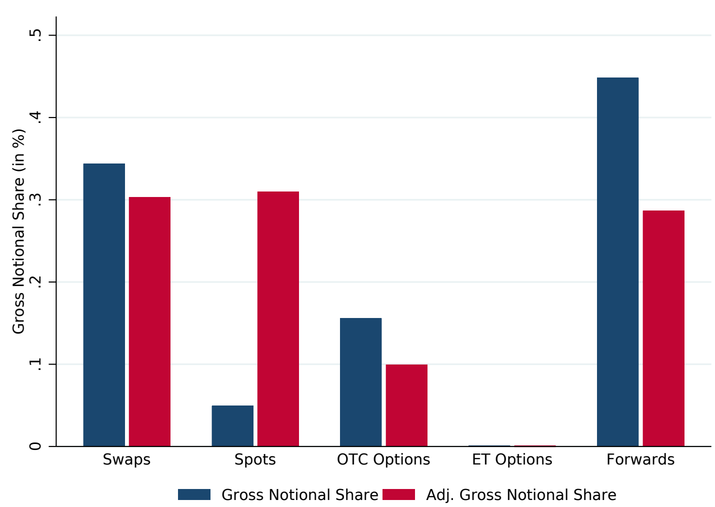
Note: Comparative statics of currency market equilibrium with respect to an increase in position holding cost, γ, condition on negative net dollar demand shock. Dotted line show equilibrium for tighter limits.

Figure A.2: Maturity Breakdown of Derivatives and Adjustments of Notionals Values



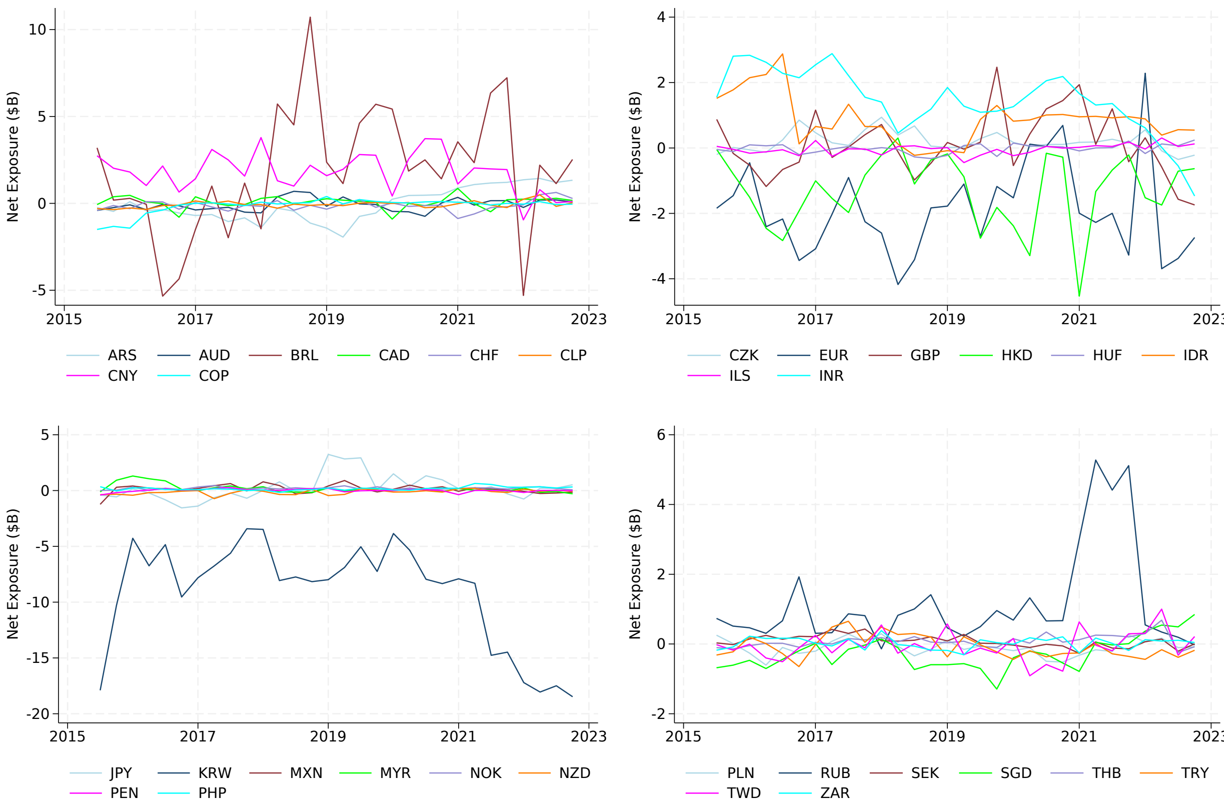
Notes: The figure shows the within-instrument (forwards, swaps) share of daily average turnover in 2019 for every given maturity class as reported by the Bank for International Settlements. To adjust the end-of quarter gross notional values we proceed as follows: Under the assumption that the maturities 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.3: 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.2. The shares for adjusted and unadjusted gross notionals are calculated by dividing by the adjusted/unadjusted total gross notional, across banks and instruments.

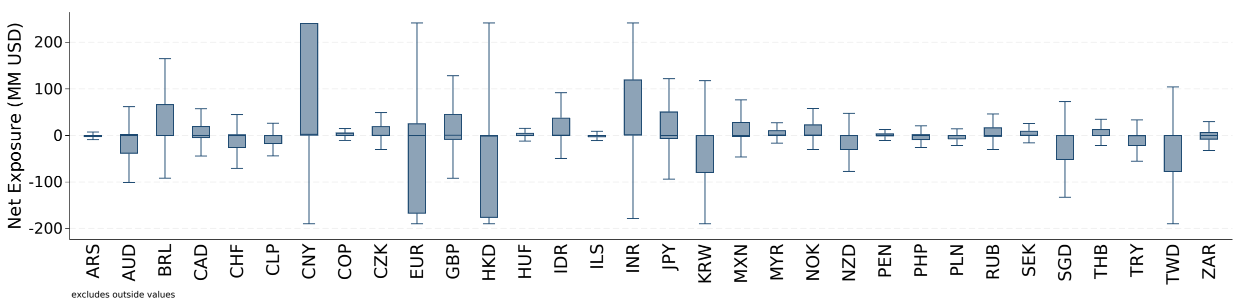
Figure A.4: Net Exposures over Time, by Currency



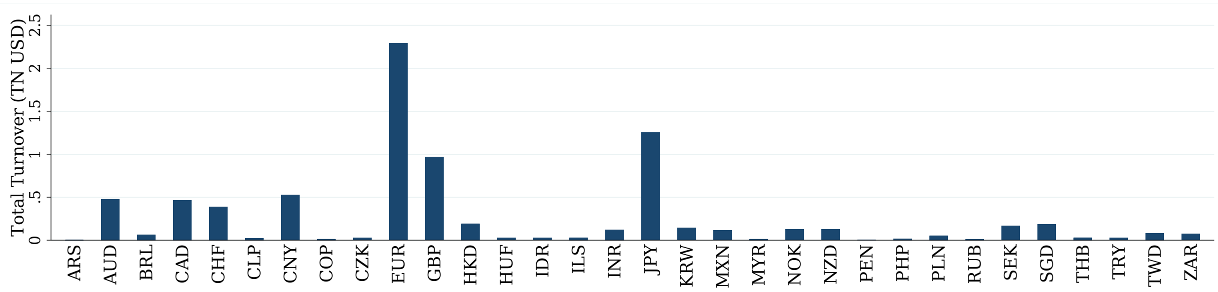
Notes: This figure shows the sum of net exposure to across all banks, by currency, for each quarter. Positive values correspond to long exposure to foreign currency. *Source*: FR Y-14F, authors' calculations.

Figure A.5: Net Exposures and Turnover, by Currency

(a) Net Exposures

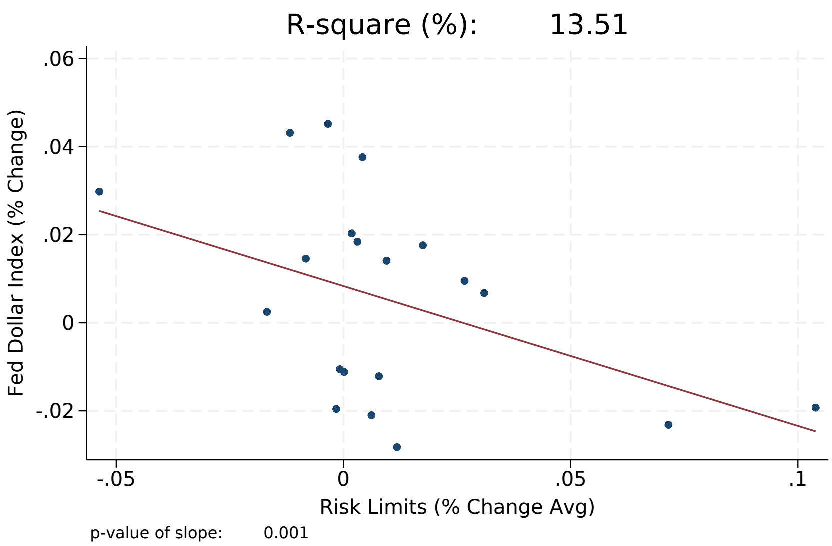


(b) Global Turnover



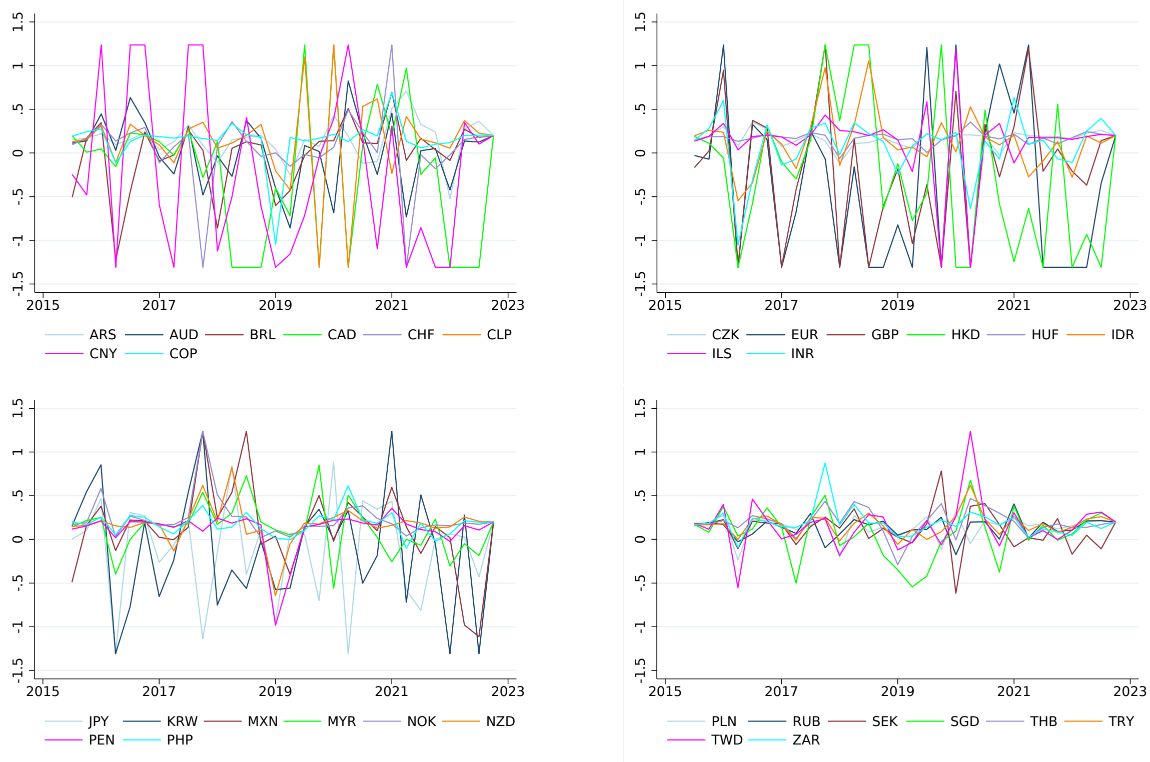
Note: Panel (a) shows box plots summarizing the distribution of net exposures for each currency at the bank-quarter level from FR Y-14F. The underlying data are winsorized at the 5th and 95th percentile. Panel (b) shows the daily average turnover by currency in April 2022, in trillions of US dollars 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.6: Time Series Relationship Between Dollar Index and Risk Limits



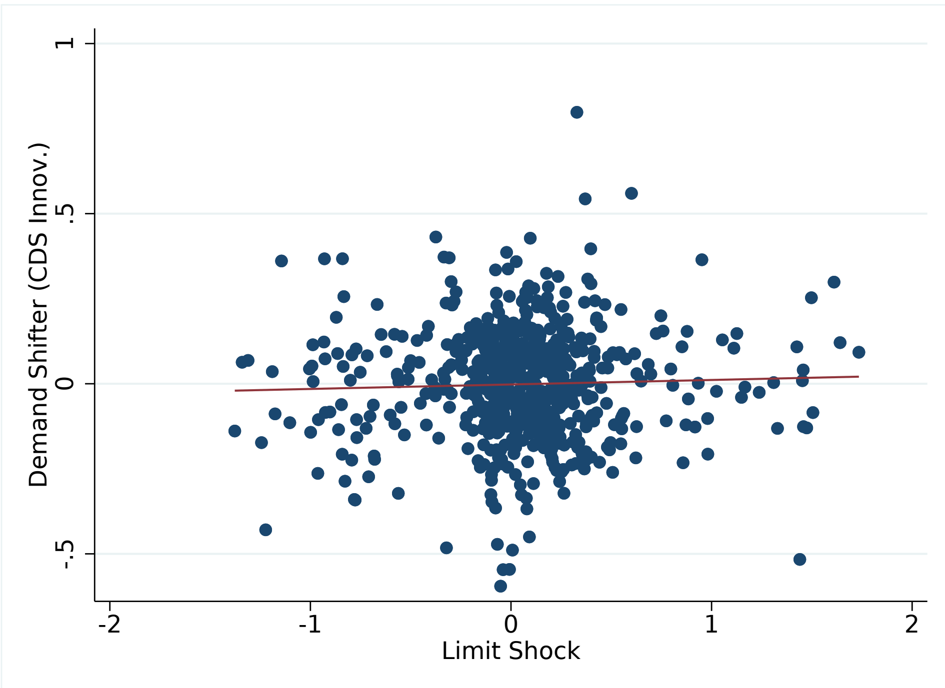
Notes: Binned scatter plot. Data are at quarterly frequency. The dollar index is the broad trade-weighted dollar index from the Federal Reserve Board. Risk Limit Changes are presenting average log limit change across desks. An increase in the dollar index means the dollar's value increases.

Figure A.7: Limit Shocks over Time



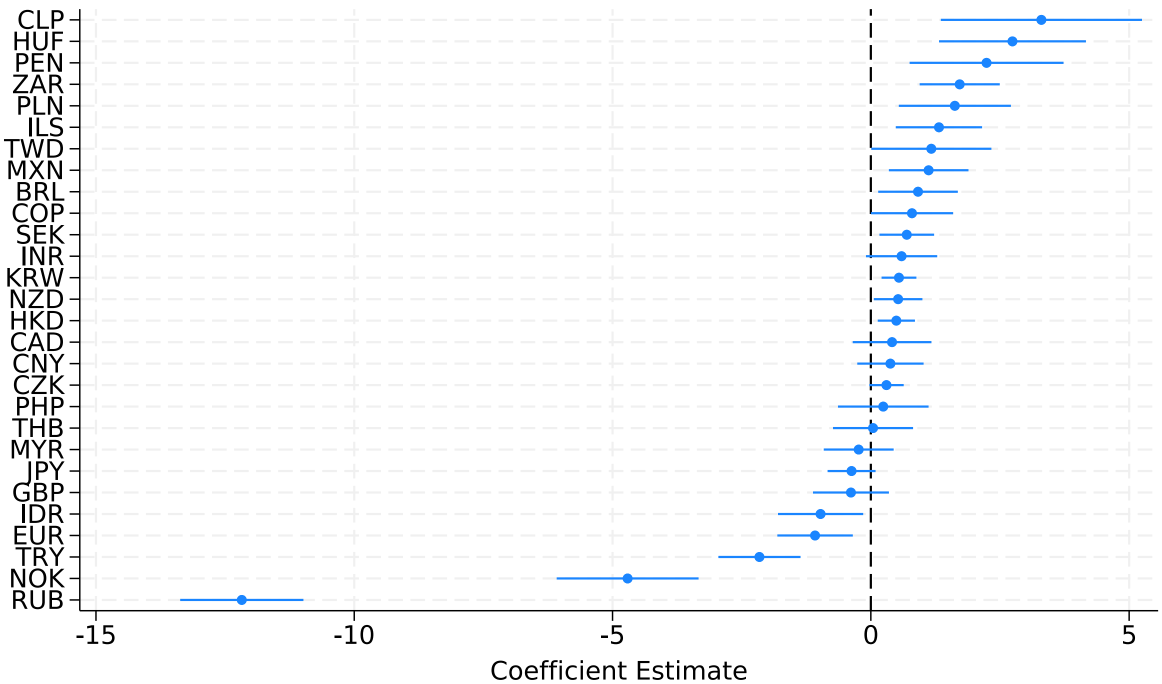
Notes: Baseline currency-level risk limit shocks over time identified from idiosyncratic dealer-level limit changes. *Sources*: FR VV-1, FR Y-14F, authors' calculations.

Figure A.8: Relationship between Limit Shocks over Demand Shifter



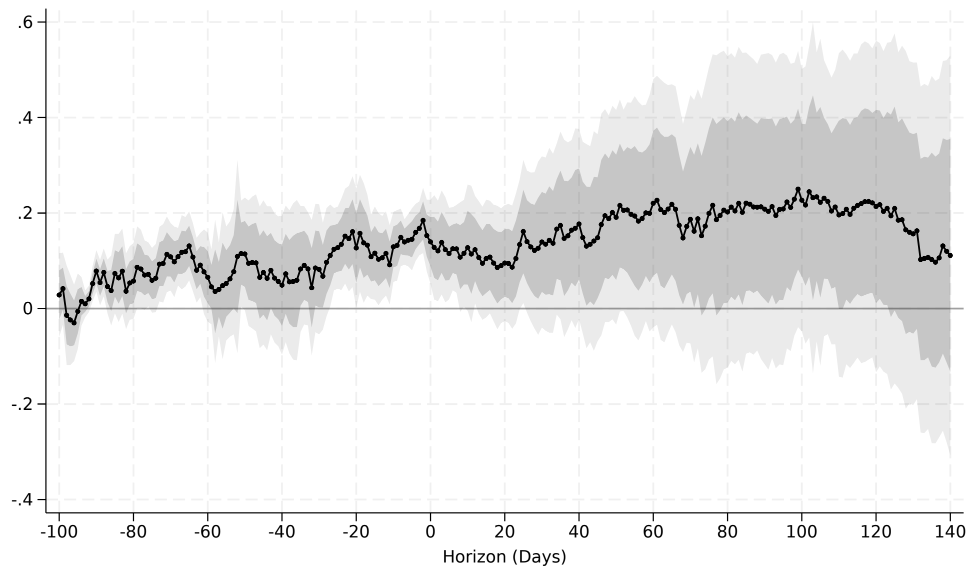
Notes: The binned scatter plot between limit shocks and CDS innovation demand shifter shows that the two variables are uncorrelated. *Sources*: FR VV-1, FR Y-14F, Bloomberg, authors' calculations.

Figure A.9: Currency-Specific Limit Shock Effect on Exchange Rate

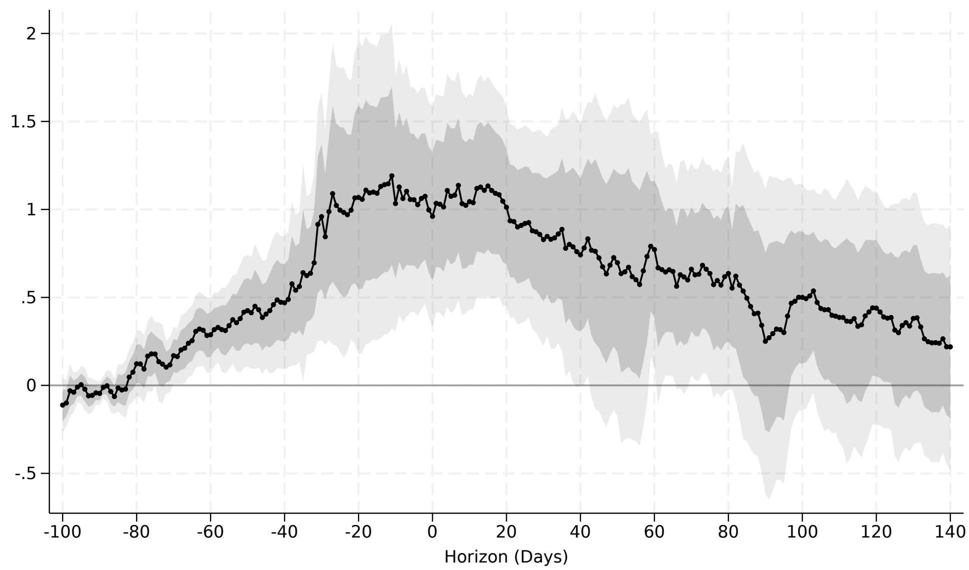


Notes: This figure depicts currency-specific estimates of the coefficient on the interaction term between Limit Shock and Demand Shifter, $\beta_{2,c}$. The regression equation is $\Delta e_{c,t} = \beta_{1,c}\text{Limit Shock}_{c,t} + \beta_{2,c}\text{Limit Shock}_{c,t} \times \text{Demand Shifter}_{c,t} + \beta_{3,c}\text{Demand Shifter}_{c,t} + \alpha_i + \alpha_t + \gamma' X_{c,t} + u_{c,t}$. Note that the coefficients on the uninteracted variables Limit Shock and Demand Shifter are also estimated for each country separately. Limit Shock and Demand Shifter are standardized by currency to have mean 0 and unit variance within each currency. Point estimate shown as the dot, and the bars represent 95% confidence intervals. *Sources*: FR VV-1, FR Y-14F, Bloomberg, authors' calculations.

Figure A.10: 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: Table 3 using Implied Vola as Demand Shifter

	Δ FX Rate		Δ Net Exposure		Δ Bid-Ask Spread	
	(1)	(2)	(3)	(4)	(5)	(6)
Limit Shock	0.038	0.004	-0.065	-0.245	0.062**	0.061**
	(0.057)	(0.067)	(0.320)	(0.354)	(0.026)	(0.028)
Demand Shifter		1.182***		0.081		0.103***
(Vola. Innovation)		(0.350)		(0.377)		(0.037)
Limit Shock × Demand Shifter		0.212***		-0.804***		0.029*
		(0.063)		(0.222)		(0.015)
Controls	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	0.037	0.097	0.329	0.335	0.430	0.442
N	800	800	768	768	758	758

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

Table B.3: Table 3 using Credit Rating as Demand Shifter

	Δ FX Rate		Δ Net Exposure		Δ Bid-Ask Spread	
	(1)	(2)	(3)	(4)	(5)	(6)
Limit Shock	0.038	0.090	-0.065	-0.126	0.062**	0.062*
	(0.057)	(0.087)	(0.320)	(0.331)	(0.026)	(0.030)
Demand Shifter		-0.357		0.093		0.013
(Rating Innovation)		(0.221)		(0.464)		(0.031)
Limit Shock × Demand Shifter		-0.207		0.630		-0.012
		(0.214)		(0.649)		(0.038)
Controls	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	0.037	0.040	0.329	0.345	0.430	0.427
N	800	767	768	736	758	725

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

Table B.4: Table 3 using Alternative Limit Shocks, Part I

	Limit Shock: 3 Factors			Limit Shock: 1 Factor			Limit Shock: GIV3			Limit Shock: Raw Changes		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Δ FX Rate	Δ Net Exposure	Δ Bid-Ask Spread	Δ FX Rate	Δ Net Exposure	Δ Bid-Ask Spread	Δ FX Rate	Δ Net Exposure	Δ Bid-Ask Spread	Δ FX Rate	Δ Net Exposure	Δ Bid-Ask Spread
Limit Shock	0.060	-0.108	0.059	0.197	-1.490***	0.090**	0.001	-0.556	0.074*	0.167	0.139	-0.042
	(0.087)	(0.304)	(0.042)	(0.201)	(0.526)	(0.043)	(0.228)	(0.435)	(0.041)	(0.166)	(0.431)	(0.028)
Demand Shifter	0.979**	-0.167	0.083**	0.823**	0.202	0.063	0.968**	-0.022	0.087**	1.021***	-0.239	0.080**
(CDS Innovation)	(0.370)	(0.550)	(0.037)	(0.369)	(0.538)	(0.040)	(0.367)	(0.580)	(0.035)	(0.361)	(0.580)	(0.037)
Limit Shock × Demand Shifter	0.242*	-0.635**	-0.009	0.339	-0.736*	0.040	0.076	-0.576**	0.004	0.074	-0.195	-0.020
	(0.126)	(0.305)	(0.032)	(0.207)	(0.390)	(0.031)	(0.123)	(0.213)	(0.032)	(0.179)	(0.544)	(0.016)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Currency FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R-squared	0.077	0.369	0.456	0.079	0.378	0.457	0.075	0.370	0.456	0.076	0.366	0.454
N	702	675	660	702	675	660	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 (3) to (6) show our baseline shock using delta-based limits instead of VaR-based limits. Columns (7) to (9) drops the common factor structure in the shock construction. Columns (10)-(12) use raw changes in log limits to construct the shock.

Table B.5: Table 3 using Alternative Limit Shocks, Part II

	Limit Shock: 3 Factors			Limit Shock: 1 Factor			Limit Shock: GIV3			Limit Shock: Raw Changes		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Δ FX Rate	Δ Net Exposure	Δ Bid-Ask Spread	Δ FX Rate	Δ Net Exposure	Δ Bid-Ask Spread	Δ FX Rate	Δ Net Exposure	Δ Bid-Ask Spread	Δ FX Rate	Δ Net Exposure	Δ Bid-Ask Spread
Limit Shock	-0.042	0.007	0.055	0.203	-1.426**	0.084**	-0.048	-0.515	0.072*	-0.025	0.151	-0.039
	(0.067)	(0.329)	(0.038)	(0.182)	(0.513)	(0.040)	(0.222)	(0.382)	(0.041)	(0.188)	(0.365)	(0.024)
Demand Shifter	1.108**	-0.105	0.075*	0.865**	0.292	0.054	1.022**	0.004	0.079**	1.082**	-0.130	0.074*
(CDS Innovation)	(0.399)	(0.551)	(0.038)	(0.415)	(0.532)	(0.040)	(0.402)	(0.577)	(0.037)	(0.397)	(0.572)	(0.039)
Limit Shock × Demand Shifter	-0.041	-0.338	-0.029	0.473*	-0.773*	0.037	0.239*	-0.465**	-0.000	-0.248	-0.111	-0.010
	(0.249)	(0.244)	(0.030)	(0.238)	(0.427)	(0.029)	(0.116)	(0.225)	(0.019)	(0.150)	(0.352)	(0.013)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Currency FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R-squared	0.081	0.372	0.453	0.087	0.383	0.453	0.083	0.375	0.452	0.084	0.371	0.450
N	731	704	687	731	704	687	731	704	687	731	704	687

Notes: Same as Table but using alternative limit shocks. Currency FE not interacted with COVID dummy.

Table B.6: Table 3 using Next Period's Dependent Variable

	Δ FX Rate$_{t+1}$		Δ Net Exposure$_{t+1}$		Δ Bid-Ask Spread$_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Limit Shock	0.153	0.219	0.176	0.078	0.023	0.025
	(0.133)	(0.182)	(0.381)	(0.492)	(0.028)	(0.029)
Demand Shifter		0.186		-0.603		0.025
(CDS Innovation)		(0.494)		(0.615)		(0.035)
Limit Shock × Demand Shifter		-0.026		-0.016		0.018
		(0.262)		(0.375)		(0.026)
Controls	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	0.770	0.160	0.140	0.042	0.033
N	768	674	736	647	727	633

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