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## Constrained Liquidity Provision in Currency Markets


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**Abstract**

We devise a simple model of liquidity demand and supply to deepen the understanding of dealers' liquidity provision in currency markets. Drawing on a globally representative data set on currency trading volumes, we show that at times when dealers' intermediation capacity is constrained the cost of liquidity provision increases disproportionately relative to dealer-intermediated volume. Thus, the otherwise strong and positive relation between liquidity costs and trading volume effectively shrinks to zero when dealers are more constrained. Using various econometric approaches, we show that this result primarily stems from a reduction in the elasticity of liquidity supply, rather than changes in liquidity demand.

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# 1. Introduction

Financial intermediaries play a crucial role in maintaining the functioning of modern financial markets. This is especially true for the foreign exchange market (FX), where dealer banks are the primary providers of market liquidity.[1] However, dealer banks' ability to provide liquidity in over-the-counter (OTC) markets is contingent upon their balance sheet capacity to absorb and fund trading positions. Constraints on dealers' intermediation capacity can in turn reduce their incentives to intermediate trades, increase liquidity costs, and generate violations of no-arbitrage conditions.[2]

Against this backdrop, the key question that we address in this paper is how dealers' intermediation constraints affect both the *cost* and *quantity* of liquidity provision in currency markets. To study this question, we build a simple model of liquidity demand and supply and test its predictions drawing on a globally representative data set on FX spot trading volumes. We find that the cost of providing FX liquidity increases disproportionately more relative to trading volume, when dealers face tighter constraints on their intermediation capacity. More specifically, when the dealer sector is more constrained due to higher funding costs and more restrictive Value-at-Risk (VaR) constraints the otherwise strong and positive correlation between the cost and the quantity of FX liquidity provision weakens substantially. Guided by our theoretical framework and by employing various econometric techniques, we show that this result primarily stems from a reduction in the elasticity of liquidity supply, rather than changes in liquidity demand.

In the context of the FX spot market, we first identify two liquidity cost measures based on the well-known triangular no-arbitrage condition that ties together triplets of exchange rates.[3] The first measure captures **v**iolations in the **l**aw **o**f **o**ne **p**rice, which we label as VLOOP. Conceptually, VLOOP quantifies the divergence of the mid-quote prices from the triangular no-arbitrage relation. In line with the literature on intermediary asset pricing, VLOOP can be interpreted as the shadow cost of intermediary constraints.[4] The second component captures the round-trip **t**ransaction **cost** of performing a triangular arbitrage trade, which we label as TCOST. It reflects the dealer's realised compensation to endure inventory risks stemming from customers' order flows.

Our model builds on the premise that tighter constraints reduce dealers' short-run flexibility to intermediate and provide liquidity to customers (see, e.g., Duffie, 2010, 2023). The dealer

[1]To be clear, we focus on the role of FX dealer banks as liquidity providers rather than cross-market arbitrageurs. This is consistent with the role that these institutions have played after the clampdown on proprietary trading in the aftermath of the Global Financial Crisis.

[2]See "Holistic Review of the March Market Turmoil," Financial Stability Board, November 2020.

[3]For instance, the triangular no-arbitrage condition has been studied in Chaboud, Chiquoine, Hjalmarsson, and Vega (2014) and Foucault, Kozhan, and Tham (2016).

[4]In accord with this strand of literature (e.g., Adrian, Etula, and Muir, 2014; Kisin and Manela, 2016; Duffie, 2018; Fleckenstein and Longstaff, 2018; Du, Hébert, and Huber, 2022), one may also refer to these shadow costs as "balance sheet costs" associated with FX spot liquidity provision.

sector faces two types of constraints when intermediating customers' order flows: i) debt funding costs to finance inventory positions that stem from absorbing directional customer order flows; and ii) VaR limits that arise from both regulatory and internal risk management practices (Adrian and Shin, 2010). The first one represents a cost factor in the "production" of market liquidity by dealers (Foucault, Pagano, and Roell, 2013), while the second one is a hard constraint that can directly restrict dealers' intermediation capacity. In particular, VaR limits can become binding for a fraction of dealers. Taken together, dealers are less willing to intermediate in FX spot markets when their debt funding costs are higher and/ or VaR limits are stricter. Thus, when dealers face tighter constraints, the liquidity supply curve becomes steeper, reflecting a decrease in the elasticity of their liquidity supply. This leads to the first empirical implication: the shadow cost of intermediary constraints (i.e., VLOOP) and transaction costs (i.e., TCOST) are positively related to measures of dealer constraints.

Our model sheds light on how dealer constraints affect the relation between the price and the quantity of currency market liquidity. When price-sensitive customers demand more liquidity (as in Gabaix and Maggiori (2015)), both the equilibrium price (i.e., VLOOP and TCOST) and the equilibrium quantity (i.e., dealer-intermediated volume) of liquidity increase. When dealer constraints remain unchanged, the price and quantity increase proportionately. In contrast, when dealer constraints tighten, the price of liquidity increases disproportionately more relative to the quantity. This nonlinear effect stems from two factors. On the one hand, the more binding VaR constraints imply that the unconstrained dealers need to accommodate a larger share of customers' order imbalances. Within our framework, the VaR constraint can become more binding either due to a larger share of dealers being restricted by the constraint (higher extensive margin captured by $\omega$) and/ or because of each binding constraint allowing for lower intermediated quantity (higher intensive margin captured by $\sigma \times q$). On the other hand, the unconstrained dealers are left to absorb the order imbalance at higher debt funding costs (captured by $\eta$). As a result, an increase in customers' demand for liquidity leads to a more pronounced increase in the equilibrium price compared to volume. This underpins our second empirical implication: while liquidity costs and dealer-intermediated volumes exhibit a positive correlation, this connection noticeably weakens during times when dealer constraints are more stringent.

We test these two theoretical predictions using a unique data set on global FX spot trading activity from CLS Group. To measure dealer constraints in line with our model, we construct an empirical counterpart of each model-based measure of dealer constraints: dealers' VaR $\sigma \times q$, their debt funding costs $\eta$, and the share of dealers facing binding VaR limits $\omega$. We study these measures separately and, for conciseness, combined as a single metric of intermediary constraints that we dub "DCM" (referring to **D**ealer **C**onstraint **M**easure). To construct DCM, we first create (cross-sectionally averaged) time-series of dealer portfolio VaR, debt funding costs, and VaR breaches of the 10 leading FX dealer banks. We then define the first principal component of these time-series as our DCM measure of dealer constraints. For robustness, we also consider other measures previously proposed in the related literature to capture the balance sheet capacity of financial intermediaries. Specifically, we consider the He, Kelly, and Manela (2017) leverage ratio, credit default swap (CDS) premia (Andersen, Duffie, and Song, 2019), and deviations from the covered interest rate parity (CIP) condition (Du, Tepper, and Verdelhan, 2018; Rime, Schrimpf, and Syrstad, 2022).

The following three empirical findings arise: First, the two liquidity cost measures VLOOP and TCOST co-move over time, albeit their correlation is less than 54% on average. Second, when the dealer sector is largely unconstrained, the correlation between liquidity costs and dealer-intermediated volume is overall positive and ranges from 9 to 25%. This result is consistent with the idea that dealers require a higher compensation when providing more immediacy to clients. These first two findings are fully in line with the previous literature on commonality in FX liquidity (Mancini, Ranaldo, and Wrampelmeyer, 2013; Karnaukh, Ranaldo, and Söderlind, 2015). Third, and most strikingly, when dealer constraints tighten, both liquidity cost measures increase disproportionately more relative to dealer-intermediated volumes. In times when the dealer sector is constrained, the conditional correlation between liquidity costs and the intermediated quantities drops by at least 50%. To establish this result, we estimate smooth transition regression (LSTAR) models,[5] which are especially well-suited for our analysis because constrained and unconstrained regimes are determined endogenously and may vary over time. Overall, our findings highlight the vulnerability of market liquidity arising from limitations on dealers' intermediation capacity.

Through the prism of our model, the drop in the correlation between liquidity costs and volume stems from a more inelastic (i.e., steeper) supply curve. However, when it comes to the empirical estimation, one might be concerned that our dealer constraint measure is correlated with factors affecting liquidity demand. Put differently, we can only attribute the weakening of the correlation between liquidity cost and intermediated volume in constrained periods to a drop in the elasticity of liquidity supply once we are appropriately controlling for shifts in liquidity demand. To account for changes in liquidity demand, we rely on two approaches: First, we use a rich set of fixed effects (both time-series and cross-sectional) and control variables such as FX volatility and measures of price impact to account for observable and unobservable factors related to liquidity demand. Second, we employ a structural vector autoregression (SVAR) with sign restrictions to more explicitly disentangle liquidity demand and supply dynamics. Our setup to estimate liquidity demand and supply shocks closely follows Goldberg (2020) and Goldberg and Nozawa (2020), respectively, and employs the same set of sign restrictions. In a next step, we use both liquidity supply and demand shocks as alternative measures of tightening dealer constraints. In line with our model, it turns out that only liquidity supply (rather than demand) shocks are economically and statistically significant determinants of the variation in the correlation between liquidity costs (i.e., VLOOP and TCOST) and dealer-intermediated trading volume.

[5]Studies using alternative forms of smooth transition regressions to perform exchange rate or carry trade predictability include, for instance, Kilian and Taylor (2003), Christiansen, Ranaldo, and Söderlind (2011), Tenreyro and Thwaites (2016), Jeanneret and Sokolovski (2019).

## 2. Related literature

Our paper contributes to three strands of literature. First, we contribute to the literature on currency market liquidity. Prior research in this field provides empirical evidence on the correlation between funding liquidity and market liquidity (Mancini et al., 2013; Karnaukh et al., 2015). Our work goes significantly beyond these empirically focused papers by elucidating (both theoretically and empirically) the economic mechanism through which this connection arises. In particular, we add to the microstructure literature by deepening the understanding of how the co-movement of traded quantities and market liquidity depends on dealers' constraints. To do so, we leverage data on dealer-intermediated FX trading volumes from CLS group. The literature on trading volume is relatively scarce due to the lack of comprehensive data. Earlier research has instead focused on order flows (e.g., Evans, 2002; Evans and Lyons, 2002, 2005) primarily analysing the inter-dealer segment, which is dominated by two platforms: Reuters (e.g., Evans, 2002; Payne, 2003; Foucault et al., 2016) and EBS (e.g., Chaboud, Chernenko, and Wright, 2008; Mancini et al., 2013; Chaboud et al., 2014). Other sources of FX spot volume are proprietary data sets from specific dealer banks.[6] The recent public access to CLS data has enabled researchers to study customer-dealer volume at a global scale (Hasbrouck and Levich, 2018, 2021; Cespa, Gargano, Riddiough, and Sarno, 2021; Ranaldo and Somogyi, 2021; Ranaldo and Santucci de Magistris, 2022). We contribute to this strand of literature by investigating the impact of dealer constraints on both the cost and quantity dimensions of FX liquidity. While the main focus is on currency markets, we believe that our theoretical and empirical results can also provide some insights into liquidity provision in other key OTC markets, in particular, fixed income (Duffie, 2023; Duffie, Fleming, Keane, Nelson, Shachar, and Van Tassel, 2023)

Second, our work is related to the broad literature that emphasises the role of intermediary frictions in affecting asset prices and financial market conditions.[7] Our main contribution is to show in depth how constrained dealers charge higher liquidity costs and decrease their elasticity of liquidity provision in the FX spot market. This finding is in accord with the evidence documented for other markets, in particular, stocks (Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes, 2010; Çötelioğlu, Franzoni, and Plazzi, 2020) and corporate bonds (Bao, O'Hara, and Zhou, 2018). Our research expands the related literature by conceptualising and empirically examining how constraints on dealers, like debt financing costs and VaR limits, affect liquidity costs and trading volume in the FX spot market. Our results remain consistent across a suite of measures that are coherently tied to our theoretical framework, as well as when utilising broader proxies for dealers' balance sheet capacity such as the

[6] See, for instance, Bjønnes and Rime (2005), Menkhoff, Sarno, Schmeling, and Schrimpf (2016), Gallien, Kassibrakis, Klimenko, Malamud, and Teguia (2018).

[7] See, for example, Gârleanu and Pedersen (2011), He and Krishnamurthy (2011), He and Krishnamurthy (2013), Adrian and Boyarchenko (2012), Adrian et al. (2014), He et al. (2017), Chen, Joslin, and Ni (2018), Gospodinov and Robotti (2021), Baron and Muir (2021), Haddad and Muir (2021), Kargar (2021), and He, Nagel, and Song (2022).

equity capital ratio of financial intermediaries (He et al., 2017), credit default swap spreads (Andersen et al., 2019), and deviations from CIP (Du et al., 2018, 2022; Du, Hébert, and Li, 2023; Rime et al., 2022), respectively. Our findings are also in line with Nagel (2012) who shows that market makers' liquidity supply is increasing in their intermediation capacity and decreasing in the level of risk. Moreover, our paper corroborates the idea that market-wide liquidity conditions depend on intermediary constraints (e.g., Adrian and Shin, 2010) and that intermediary leverage and banks' risk management practices (e.g., following Value-at-Risk methodologies) tend to be pro-cyclical (Adrian and Shin, 2013). Lastly, our findings suggesting that dealers' balance sheet space affects both the cost and quantity of liquidity provision are consistent with slow-moving intermediary capital being a key factor behind distortions in asset pricing relations (Duffie, 2010).

Finally, we add to the literature on limits to arbitrage along two dimensions. First, while prior research has mostly focused on constrained *arbitrageurs* (e.g., Shleifer and Vishny (1997), Gromb and Vayanos (2002), Hombert and Thesmar (2014) and more recently Du et al. (2022) and Siriwardane, Sunderam, and Wallen (2021)), our main angle is to study constrained *dealers*. Second, we propose to draw on the classical no-arbitrage identity to derive two liquidity cost components with an economically meaningful interpretation. Thus, our key contribution is to elucidate the relation between liquidity costs and volumes using arbitrage conditions and to show how this relation critically depends on the intermediation capacity of dealers. In addition, a large body of prior research has studied limits to arbitrage in equities (see Gromb and Vayanos, 2010). However, many of the frictions considered in that literature, such as short sale constraints (e.g., Chu, Hirshleifer, and Ma, 2020), do not apply to FX. Related to the stock market literature, recent studies document widespread mispricings in stressed times (Pasquariello, 2014), commonality in arbitrage deviations (e.g., Rösch, Subrahmanyam, and van Dijk, 2016; Du et al., 2022), and limits to arbitrage impacting market liquidity (Rösch, 2021). We add to this branch of the literature by identifying constrained dealers as the main driving force behind such commonalities and by showing how their liquidity provision impacts global FX trading volumes.

## 3. A simple model of constrained liquidity supply

The central idea underpinning our work is that tighter dealer constraints affect both the *cost* and *quantity* of liquidity provision. To formalise this intuition, we develop a simple model characterising the supply and demand of liquidity in the FX spot market. The main building block is a set of risk-averse dealers, facing Value-at-Risk (VaR) constraints as well as debt funding costs when catering to the demand from price-sensitive liquidity traders. In particular, dealers are price takers and choose their net positions $q$ (i.e., the quantity they are willing to intermediate) subject to the following VaR constraint:

$$\sigma \times q \leq T,$$

where $\sigma$ denotes exchange rate volatility and $T$ denotes the VaR limit. In a first step, we use this framework to derive two liquidity cost measures from a triangular no-arbitrage condition that ties together a triplet of exchange rates. In a second step, we use the model to show how dealer constraints affect liquidity provision in terms of both the price and quantity of currency liquidity. The main insights that come from our model can be summarised in two main propositions:

1. Both liquidity cost measures (i.e., VLOOP and TCOST) increase when FX dealers are more constrained in their intermediation capacity (see Proposition 1 below).

2. When dealer constraints tighten, the liquidity supply curve shifts inward and thereby increases the cost of liquidity provision and decreases dealer-intermediated volume (relative to the counterfactual). Thus, the correlation between liquidity costs and dealer-intermediated volume drops with tighter dealer constraints (see Proposition 2 below).

**Liquidity cost measures.** Consider a trader who wants to exchange euros for Canadian dollars. The trader can do this either directly (via currency pair $x = EURCAD$) or indirectly via a vehicle currency, that is, by first exchanging euros to US dollars (via currency pair $y = USDEUR$) and then by subsequently swapping US dollars to Canadian dollars (via currency pair $z = USDCAD$). We denote the midquotes of the three pairs as $m^j$, where $j \in \{x, y, z\}$. Hence, the difference between the two approaches is given by $m^x - m^y m^z$. When such a difference deviates from zero, there is a violation of the law of one price (VLOOP):

$$\text{VLOOP} = m^x - m^y m^z. \tag{1}$$

Clearly, such law of one price deviations are not necessarily profitable arbitrage opportunities due to the presence of transaction costs. In particular, we denote the bid-ask spread as $s^j = a^j - b^j$, where $a^j$ and $b^j$ are the ask and the bid price of currency $j$. Thus, the total round-trip transaction cost (TCOST) is:

$$\text{TCOST} = \frac{s^x + s^y + s^z}{2}. \tag{2}$$

In equilibrium, VLOOP and TCOST are determined by the demand for and supply of liquidity. To fix ideas, consider a unit mass of dealers catering to the demand of liquidity traders (henceforth *traders*). At $t = 0$, agents trade with the dealers at price $p^j$, which could be either $a^j$ or $b^j$ depending on the direction of their trade. The fundamental value of currency pair $j$ is stochastic, and denoted as $\tilde{e}^j$, with mean $e^j$. The three fundamental values are intimately linked via $e^x = e^y e^z$. We assume that the three currency pairs are i.i.d. and have the same volatility denoted as $\sigma$. At $t = 1$, the uncertainty is resolved and traders receive the fundamental value of each currency pair. Figure 1 summarises the timeline of the model.

Figure 1: Timeline

| $t = 0$ | $t = 1$ |
|---|---|
| • Liquidity traders arrive with demand imbalance $d^j$ for each currency pair $j$.<br>• Dealer $i$ decides on their positions $q_i^j$ subject to their constraints.<br>• Equilibrium bid and ask prices $b^j$ and $a^j$ clear the currency market. | • The fundamental value $\tilde{e}^j$ is realized.<br>• The profit/ loss of each agent is final. |

**Traders.** We model liquidity demand in reduced form, following the classic market microstructure literature (see, e.g., Grossman and Miller, 1988; Hendershott and Menkveld, 2014). Liquidity traders are price sensitive and arrive at $t = 0$. Their aggregate liquidity demand decreases in the bid-ask spread quoted by the dealers. Furthermore, the demand is higher when the currency pairs are more volatile reflecting higher disagreement about the fundamental value. Specifically, the demand for currency pair $j$ is given by $\sigma(1 - s^j)$, which is increasing in volatility $\sigma$ and decreasing in the bid-ask spread $s^j$.

Trading demand is imbalanced across the three currency pairs due to diverging private values among traders following the spirit of Gabaix and Maggiori (2015). For simplicity, we assume that a $\pi > 1/2$ fraction of traders in currency pair $x$ are buyers and the rest are sellers. Conversely, for currency pair $y$, a $1 - \pi$ fraction of traders are sellers and the rest are buyers. For currency pair $z$, half of the traders are buyers, whereas the other half are sellers. Thus, traders impose net buying pressure $2\pi - 1$ in currency pair $x$ and net selling pressure $1 - 2\pi$ in pair $y$.[8] As a result, the traders' demand imbalance that needs to be absorbed by dealers in pair $j$ is given as[9]

$$d^x = \sigma(1 - s^x)(2\pi - 1), \tag{3}$$

$$d^y = \sigma(1 - s^y)(1 - 2\pi), \tag{4}$$

$$d^z = 0. \tag{5}$$

**Dealers.** There is a unit mass of competitive dealers that intermediate buy and sell orders in the currency market (see Foucault et al., 2013, Sec. 3.5). The dealers are subject to Value-at-Risk (VaR) constraints due to both regulatory and internal risk management practices. A proportion $\omega$ of the dealers have tight VaR constraints with low thresholds $T_L$ and the rest (i.e., $1 - \omega$) have loose VaR constraints with high thresholds $T_H$. These differences between

[8]The net buying pressure is simply the buy orders minus the sell orders. Hence, for currency pair $x$, the net buying pressure is $\pi - (1 - \pi) = 2\pi - 1 > 0$, and it is $(1 - \pi) - \pi = 1 - 2\pi < 0$ for currency pair $y$. Thus, the aggregate (net) demand of the traders is to swap EUR for CAD (i.e., being long currency pair $x$) and to swap EUR for USD (i.e., being short currency pair $y$).

[9] As the empirical results suggest in Section 5, violations of the law of one price do not directly imply that there are profitable triangular arbitrage opportunities if transaction costs in the form of bid-ask spreads are sufficiently large. Hence, for simplicity, in the model we abstract away from any cross-market arbitrageurs.

the VaR constraints reflect the differences in dealers' balance sheet capacity. The VaR of a dealer $i \in \{L, H\}$ is $VaR_i^j \equiv \sigma \times q_i^j$, where $q_i^j$ denotes the the dealer's net position in a given currency pair $j$.[10] Specifically, $q_i^j > 0$ indicates that the dealer is selling the quote currency to and purchasing the base currency from the customer. Hence, the VaR constraint is given by $\sigma \times q_i^j \leq T_i$ (see, e.g., Duffie and Pan, 1997; Adrian and Shin, 2013).

Dealer $i$ finances their net position $q_i^j$ in each of the three currency pairs by issuing debt (e.g., Scott, 1976; van Binsbergen, Graham, and Yang, 2010). Specifically, the dealer trades-off their convex debt funding cost $\eta$ against the spread between the prices they quote and the fundamental value of each currency.[11] Thus, the utility of dealer $i$ is given as follows:

$$U_i^D = \underbrace{E\Big((p^x - \tilde{e}^x)q_i^x + (p^y - \tilde{e}^y)q_i^y + (p^z - \tilde{e}^z)q_i^z\Big)}_{\text{Gain from trade}} - \underbrace{\frac{\eta}{2}\Big(q_i^{x,2} + q_i^{y,2} + q_i^{z,2}\Big)}_{\text{Debt funding cost}} \tag{6}$$

$$\text{subject to:} \qquad \underbrace{\sigma \times q_i^x \leq T_i, \quad \sigma \times q_i^y \leq T_i, \quad \sigma \times q_i^z \leq T_i,}_{\text{VaR constraints}} \text{ where } k \in \{L, H\}. \tag{7}$$

All dealers are competitive and start with zero inventory. At $t = 0$, they take prices $p^j$ as given and choose their net positions $q_i^j$ (i.e., the quantity they are willing to intermediate) subject to their VaR constraints. Note that the sign of $q_i^j$ is determined by the direction of the incoming customer flow. Therefore, the supply function of a dealer with a nonbinding VaR limit is simply pinned down by the first order conditions:

$$\frac{\partial U_i^D}{\partial q_i^j} = 0 = \begin{cases} a_i^j - e^j - \underbrace{\eta|q_i^j|}_{\text{marginal funding cost}} & \text{, if } q_i^j > 0, \\ b_i^j - e^j + \underbrace{\eta|q_i^j|}_{\text{marginal funding cost}} & \text{, if } q_i^j < 0. \end{cases} \tag{8}$$

The first order conditions in Eq. (8) suggest that there are two components in the dealer's supply function. The first one is related to the marginal value of buying and selling and reflects the spread between the quoted prices and the fundamental value (i.e., $a_i^j - e^j$ and $b_i^j - e^j$). The second component $\eta|q_i^j|$ is the debt funding cost, which depends on both the size and the direction of the incoming customer order flow. If the VaR constraint is binding, dealer $i$'s net position is equal to $T_i/\sigma$. Thus, the dealer's net position (induced by customers'

[10]Note that because the aggregate demand from traders is to swap EUR for CAD and to swap EUR for USD (see Footnote 8), dealers do not benefit from netting across multiple currency pairs in our setup. For simplicity, we do not separately model dealers' positions as well as the associated funding costs and VaR constraints in each currency. This is because the same analysis carries through at both the currency-level and the currency-pair-level.

[11]To simplify the notation, we assume that both the VaR threshold $T_i$ and debt funding cost $\eta$ are the same across the three currency pairs. Relaxing this constraint will not change our main results qualitatively.

order flows) for currency pair $j$ is bounded as follows:

$$q_i^j = \min\left\{\frac{p_i^j - e^j}{\eta}, \frac{T_i}{\sigma}\right\}. \tag{9}$$

**Market clearing.** At $t = 0$, traders' demand must be equal to dealers' liquidity supply:

$$d^j = \int_i q_i^j. \tag{10}$$

**Equilibrium outcomes.** In our context, the parameter space of interest is the situation where the dealer sector is only partially constrained, that is, when a nonzero proportion $\omega$ of dealers (with $T_L$) face binding constraints while the rest (i.e., $1 - \omega$) are not constrained by the VaR thresholds. In the following analysis, we suppress the subscript of $H$ and $L$ when discussing the VaR thresholds and use $T$ to denote $T_L$. In this case, for currency pair $z$, which is assumed to have balanced order flows, Eq. (10) implies that all dealers are unconstrained since $q_i^z = 0$. However, for currency pairs $x$ and $y$ with unbalanced order flows the constrained dealers' *total* net positions are bounded by the following VaR constraints:

$$q_L^x = \frac{\omega T}{\sigma}, \qquad q_L^y = -\frac{\omega T}{\sigma}.$$

Thus, in equilibrium, the unconstrained dealers need to absorb the remaining order flows:

$$q_H^x = \underbrace{\sigma(1 - s^x)(2\pi - 1)}_{d^x} - \frac{\omega T}{\sigma}, \qquad q_H^y = \underbrace{\sigma(1 - s^x)(1 - 2\pi)}_{d^y} + \frac{\omega T}{\sigma},$$

and the market clearing prices for currency pairs $x$ and $y$ are determined by the unconstrained dealers' supply functions that arise from Eq. (8). We assume that dealers have equal probabilities in meeting the traders and hence take their orders "pro rata." Thus, the selling and buying amounts of the unconstrained dealers are[12]

$$q_{H,S}^x = q_H^x \frac{\pi}{2\pi - 1}, \quad q_{H,B}^x = q_H^x \frac{\pi - 1}{2\pi - 1}, \quad q_{H,S}^y = q_H^y \frac{1 - \pi}{1 - 2\pi}, \quad q_{H,B}^y = q_H^y \frac{-\pi}{1 - 2\pi}.$$

There are two market clearing conditions for each currency pair: one for the case when the unconstrained dealers are buying (i.e., bid price) and another reflecting the situation when they are selling (i.e., ask price). Taking currency pair $x$ as an example (first equation in Eq. (11)), the left-hand side is the amount that needs to be bought by the unconstrained dealers (to clear the market), and the right-hand side is their supply function from Eq. (8):

$$q_{H,B}^x = (1 - \omega)\frac{b^x - e^x}{\eta}, \qquad q_{H,S}^x = (1 - \omega)\frac{a^x - e^x}{\eta}; \tag{11}$$

[12]As $q_H^x > 0$ and $q_H^y < 0$, the buying and selling amounts match the general rule that $q_i^j > 0$ means the dealer sells the quote currency and buys the base currency (i.e., $q_{H,S}^x > 0$ and $q_{H,S}^y > 0$) from the client.

$$q^y_{H,B} = (1-\omega)\frac{b^y - e^y}{\eta}, \qquad q^y_{H,S} = (1-\omega)\frac{a^y - e^y}{\eta}. \tag{12}$$

Solving this system of equations (i.e., subtracting both sides of the equations on the left from those on the right in both Eqs (11) and (12)), the bid-ask spread for currency pairs $x$ and $y$ turns out to be the same (due to the simplifying assumptions of symmetric directional order flows, as well as due to having the same $\sigma$, $\eta$, and $T$ across currencies):

$$s^x = s^y = \frac{\eta((2\pi-1)\sigma^2 - \omega T)}{\sigma(2\pi-1)(\eta\sigma + 1 - \omega)}. \tag{13}$$

Similarly, the market clearing conditions for the balanced currency pair $z$ are:

$$-\frac{1}{2}\sigma^z(1-s^z) = \frac{b^z - e^z}{\eta}, \qquad \frac{1}{2}\sigma^z(1-s^z) = \frac{a^z - e^z}{\eta}, \tag{14}$$

which leads to the following bid-ask spread:

$$s^z = \frac{\eta\sigma}{1+\eta\sigma}. \tag{15}$$

Eventually, we can express TCOST (see Eq. (2)), which is equal to the sum of the half bid-ask spreads across three currency pairs, as follows:

$$\text{TCOST} = \frac{s^x + s^y + s^z}{2} = \frac{\eta((2\pi-1)\sigma^2 - \omega T)}{\sigma((2\pi-1)\eta\sigma + 1 - \omega)} + \frac{\eta\sigma}{2(1+\eta\sigma)}. \tag{16}$$

Substituting $s^j$ into the market clearing conditions yields the following expression for the mid prices in currency pairs $x$, $y$, and $z$:

$$m^x = e^x + \left(\pi - \tfrac{1}{2}\right)\underbrace{\tfrac{\eta((2\pi-1)\sigma^2-\omega T)}{\sigma(2\pi-1)(\eta\sigma+1-\omega)}}_{s^x}, \quad m^y = e^y + \left(\tfrac{1}{2} - \pi\right)\underbrace{\tfrac{\eta((2\pi-1)\sigma^2-\omega T)}{\sigma(2\pi-1)(\eta\sigma+1-\omega)}}_{s^y}, \quad m^z = e^z. \tag{17}$$

The midquotes of currency pairs $x$ and $y$ in Eq. (17) deviate from their fundamental values $e^x$ and $e^y$, respectively, if $\pi \neq \frac{1}{2}$ or $\eta \neq 0$. Contrarily, the midquote for currency pair $z$ is equal to its fundamental value (i.e., $m^z = e^z$) because order flows are balanced. Thus, deviations of the midquotes (set by the market clearing conditions and unconstrained dealers' supply function) from the fundamental values represent violations of the law of one price (see Eq. (1)):

$$\text{VLOOP} = m^x - m^y m^z = \left(\pi - \frac{1}{2}\right)(1 - e^z)s^x. \tag{18}$$

Proposition 1: *Both VLOOP and TCOST are higher when*

*i) the VaR is higher due to a surge in currency volatility (i.e., higher $\sigma \times q$);*

*ii) the dealer's debt funding cost is higher (i.e., higher $\eta$);*

*iii) the proportion of the constrained dealers is higher (i.e., higher $\omega$);*

We delegate the proofs of the model to the Online Appendix Section A and instead focus on the economic intuition here. Both VLOOP and TCOST increase in the bid-ask spread. It is evident from Eq. (8) that a higher $\eta$ represents a higher funding cost and leads to a larger balance sheet cost for a given order size. Thus, all else equal, the spread increases in $\eta$, and so do VLOOP and TCOST.

A surge in volatility $\sigma$ affects VLOOP and TCOST along two channels. On the one hand, the liquidity demand and hence, the order imbalance both increase in volatility and thereby push up the spread. On the other hand, when the VaR limit becomes more binding for the constrained dealers, the unconstrained dealers are only willing to absorb a larger amount of order imbalance if they are sufficiently compensated by a larger spread. Thus, both channels push up the spread and hence increase VLOOP as well as TCOST.

A higher $\omega$ indicates that a larger proportion of dealers is constrained by the VaR limit, reducing the pool of unconstrained dealers available to balance the order flow. As a consequence, this smaller group of dealers is left to absorb the order imbalance, which intuitively leads to an increase in spreads and, as a result, higher VLOOP and TCOST.

**Liquidity supply and demand.** Next, we examine the supply and demand curves of liquidity in the spot FX market. We use currency pair $x$ with unbalanced order flows as an example. For simplicity, we suppress the superscript $x$ for the rest of this section. First, we rewrite Eq. (3) such that the price of liquidity $p^D$ (i.e., the bid-ask spread $s$) is a function of the demanded quantity $q^D$ (i.e., net buying pressure $d$ that needs to be warehoused by dealers):

$$p^D = 1 - \frac{q^D}{\sigma(2\pi - 1)}. \tag{19}$$

The demand curve is downward-sloping because liquidity traders are price sensitive. Moreover, the slope of the demand curve steepens with volatility $\sigma$ since liquidity demand increases in volatility. The demand slope is also steeper when customer order flows are more unbalanced (i.e., when $\pi$ is higher).

On the supply side, constrained dealers can only provide a fixed quantity (i.e., $\omega \times T/\sigma$) as dictated by the binding VaR constraint. Therefore, market clearing requires that the remaining trading demand is intermediated by dealers that are unconstrained. Thus, in equilibrium, the supply curve is determined by the first order condition Eq. (8) of the unconstrained dealers' maximisation problem. The price of liquidity $p^S$ (i.e., the bid-ask spread $s$) is a function of the total supplied quantity $q^S$ (i.e., the net buying quantity from the traders' perspective) minus the net position taken by the constrained dealers (i.e., $\omega \times T/\sigma$), that is,

$$p^S = \frac{\eta}{1-\omega}\left(q^S - \frac{\omega T}{\sigma}\right). \tag{20}$$

The supply curve is upward-sloping and its slope increases with debt financing cost $\eta$ because the unconstrained dealers require a higher compensation for each additional marginal unit of currency that they intermediate. As volatility $\sigma$ increases, the VaR limit faced by the constrained dealers becomes more binding and the net positions taken by them are smaller, increasing the slope of the supply curve. Furthermore, the slope is steeper when $\omega$ is higher, because a smaller amount of unconstrained dealers need to absorb the entire customer order imbalance. Overall, the dealer sector is more constrained when $\eta$, $\sigma \times q$, and $\omega$ are large. Collectively, these variables can be interpreted as a measure of the (shadow) costs of providing immediacy in the currency market.

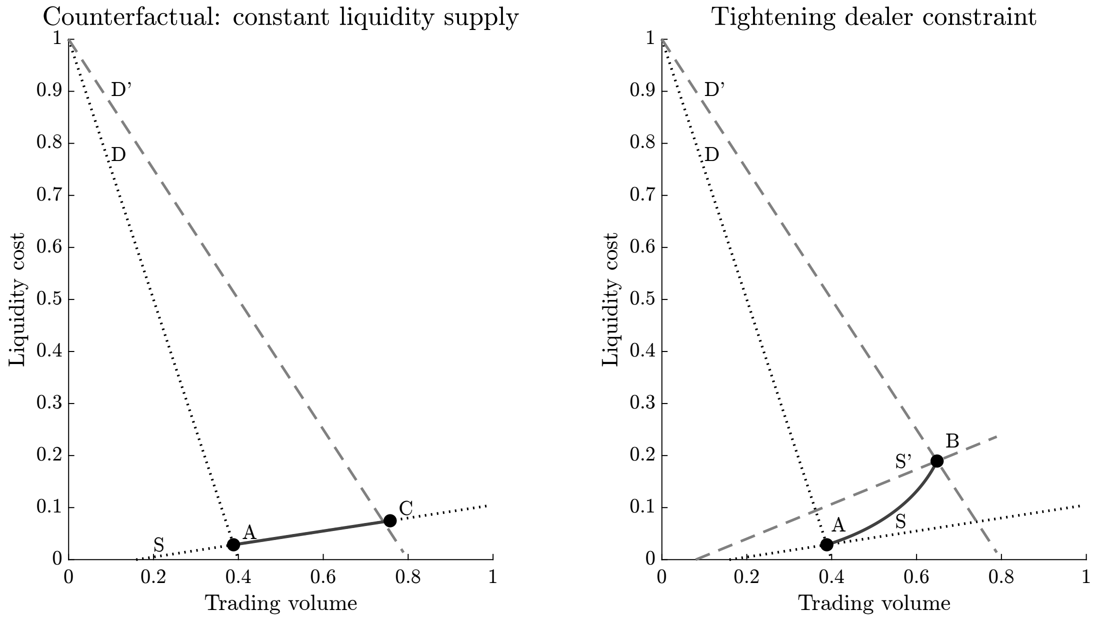
Figure 2 illustrates how a more constrained dealer sector affects liquidity costs and (equilibrium) trading volume. The left panel in Figure 2 illustrates the counterfactual in which liquidity supply is kept constant while liquidity demand shifts outwards (due to an increase in volatility $\sigma$). As a result, liquidity costs and trading volume increase at the same rate (equal to the slope of the supply curve) from point A to C. The right panel in Figure 2 in turn illustrates supply and demand in the constrained dealer sector. Specifically, it shows how the outward shift in liquidity demand is counterbalanced by the inward shift in liquidity supply due to a higher $\eta$, $\sigma \times q$, and $\omega$, respectively. Importantly, the inward shift in liquidity supply leads to an increase in liquidity cost but *lower* volume compared to the counterfactual shown in the left panel. Consequently, the co-movement between liquidity cost and volume *weakens* as the dealer sector becomes more constrained. Proposition 2 summarises these results.

Proposition 2: *A more constrained dealer sector – stemming from higher $\eta$, $\sigma \times q$, and $\omega$ – causes an inward shift of liquidity supply. Specifically, it increases the cost of liquidity provision and decreases dealer-intermediated volume (relative to the counterfactual). Consequently, the co-movement between liquidity cost and dealer-intermediated volume declines with tighter dealer constraints.*

Following Proposition 2, the correlation between liquidity costs and the volume intermediated by dealers falls with the degree of dealer constrainedness. The economic intuition is that the increase in liquidity costs outpaces the increase in trading volume for three reasons: i) a surge in the share of dealers that faces binding VaR risk limits (i.e., larger $\omega$), ii) an increase in dealers' debt funding costs (i.e., higher $\eta$), or iii) a rise in overall market risk (i.e., higher $\sigma$) that directly affects the VaR of dealers' FX positions.

Equipped with these theoretical propositions, the goal of our empirical analysis in the subsequent sections of the paper is threefold: First, to provide a thorough empirical examination of these theoretical predictions. Second, to document how the correlation between liquidity cost and volume changes conditional on dealer constraints tightening. Third, to use various econometric techniques (i.e., panel regressions with fixed effects and structural VaRs) to tease out to what extent this result is driven by changes in the elasticity of liquidity supply.

Figure 2: Liquidity supply and demand




*Note*: This figure plots liquidity costs against dealer-intermediated volumes. The baseline parameters are $\pi = 0.7$, $e^x = 1.32$, $e^y = 1.1$, $e^z = 1.2$, where $\pi$ denotes the fraction of traders that are buyers (sellers) in currency pair $x$ ($y$), $e^x$, $e^y$, and $e^z$ denote the fundamental values of currency pairs $x$, $y$, and $z$, respectively. When the dealer is unconstrained (i.e., S and D), $\eta = 0.05, \omega = 0.2, VaR = 0.8$, whereas $\eta = 0.1, \omega = 0.4, VaR = 0.4$ when the dealer is constrained (i.e., S′ and D′). The solid lines indicate the equilibrium outcomes when varying the volatility of the exchange rates $\sigma$ from 0.5 to 0.7. The parameter space for the left and right panel are identical. The only difference is the assumption that the liquidity supply curve does not shift in the counterfactual (left panel). Both liquidity costs and dealer-intermediated volume are normalised to unity.

# 4. Measuring the cost of FX spot liquidity provision

## *4.1. Data sources*

Our empirical analysis employs trade and quote data from two main sources. The FX spot volume data come directly from CLS Group (CLS), which is the world's largest payment-vs-payment settlement system.[13] Since all-to-all trading is non-existent in FX, the data set does not include trades between two customers (e.g., corporates, funds, and non-bank financials). As such, it only features trading activity that passes through the main intermediaries (i.e., FX dealer banks) that are either trading with each other or with their customers. This data set is publicly available and has been used in prior research, among others, by Cespa et al. (2021), Ranaldo and Somogyi (2021), and Ranaldo and Santucci de Magistris (2022).[14] These authors

[13]At settlement, CLS mitigates principal and operational risk by settling both sides of the trade at once. The comprehensiveness of CLS' coverage of global FX transactions is unmatched, as it handles more than half of global FX trading volumes. Cespa et al. (2021) show that there is an almost perfect overlap between the share of volume across currency pairs in the BIS Triennial Surveys and the CLS data.

[14]Hasbrouck and Levich (2018, 2021) also analyse CLS data but using proprietary and transaction-level data.

have also comprehensively described the data. The CLS volume data is available to us at the hourly frequency. The full sample period spans from November 2011 to September 2022 and includes data for 18 major currencies and 33 currency pairs.

For testing the predictions of the model, we also need to construct empirical measures capturing the cost of dealers' liquidity provision. We derive these measures from the triangular no-arbitrage relation involving one non-dollar currency pair (e.g., AUDJPY) and two dollar legs (i.e., USDAUD and USDJPY). Hence, we exclude the USDHKD, USDILS, USDKRW, USDMXP, USDSGD, and USDZAR from our sample because there are no further non-dollar currency pairs involving the respective quote currencies (i.e., HKD, ILS, KRW, MXP, SGD, and ZAR). Furthermore, to maintain a balanced panel, we also remove all currency pairs involving the Hungarian forint (HUF), which enters the data set later, on 7 November 2015.[15] The remaining 25 currency pairs cover at least 75% of global FX spot trading volume according to the Bank for International Settlements (see "Triennial central bank survey — global foreign exchange market turnover in 2022," September 2022).

Next, we pair the hourly FX volume data with intraday spot bid and ask quotes from Olsen, a well-known provider of high-frequency data. Olsen compiles historical tick-by-tick data from various electronic trading platforms, both from the inter-dealer and dealer-customer segments. A key advantage of the Olsen data is that it accurately matches both the cross-sectional and also the time-series dimension of the CLS volume data. A possible downside is that the bid and ask quotes are indicative and hence, do not correspond to actually executable prices. This means that choosing between Olsen data and inter-dealer prices (e.g., from EBS or Reuters) requires balancing the trade-off between comprehensive coverage (across currency pairs and time periods) and the tradeability of the quotes. We are convinced that for our empirical analysis, the advantage of having a sufficiently large sample across both the time-series and cross-sectional dimension compensates for the indicative nature of the quotes. This is because our primary goal is not to pinpoint any specific arbitrage opportunities on a particular trading platform, but to develop a measure of trading costs that accurately represents the global currency market.[16]

### 4.2. *Key variables*

**Liquidity cost measures.** Our model implies two measures of liquidity costs in the FX spot market: i) violations of the law of one price (VLOOP), and ii) round-trip transaction costs (TCOST). VLOOP captures the price dislocations for two assets or trading positions with the

[15] This filtering leaves us 15 non-dollar currency pairs (i.e., AUDJPY, AUDNZD, CADJPY, EURAUD, EURCAD, EURCHF, EURDKK, EURGBP, EURJPY, EURNOK, EURSEK, GBPAUD, GBPCAD, GBPCHF, and GBPJPY) and 10 dollar pairs (i.e., USDAUD, USDCAD, USDCHF, USDDKK, USDEUR, USDGBP, USDJPY, USDNOK, USDNZD, and USDSEK) that are used to synthetically replicate each of the non-dollar pairs.

[16] In the Online Appendix Section G we conduct a comprehensive comparison of Olsen and EBS data for the full-year of 2016. The key takeaway is that EBS and Olsen quotes (and also VLOOP and TCOST) are positively correlated and the mean absolute difference is especially low for currency pairs that are mainly traded on EBS.

same intrinsic value, while TCOST refers to the round-trip trading cost to take advantage of such dislocations. The VLOOP component of the triangular arbitrage trade is computed with midquote prices and reflects the difference between exchanging a currency pair directly or indirectly, that is, by using another currency (e.g., the US dollar) as a vehicle. The TCOST part is computed from the bid and ask quotes (depending on the base and quote currency) involved in the currency pair triplet.

We compute VLOOP and TCOST for $k = 1, 2, ..., 15$ triplets of currency pairs (see the Online Appendix for further details). A triplet is defined as one non-dollar pair (e.g., EURCAD) plus the two USD legs (e.g., USDEUR and USDCAD).[17] At every point in time we take the perspective of an arbitrageur by, first, identifying the seemingly profitable direction of the trade (i.e., by conditioning on VLOOP being positive), and second, by computing the associated trading cost TCOST.[18] For our main analysis we rely on daily measures of VLOOP and TCOST that we obtain by summing up hourly observations for each day.

Figure 3 shows the time-series and cross-sectional variation of hourly no-arbitrage violations VLOOP (left y-axis) and round-trip transaction costs TCOST (right y-axis), respectively. Economically, a higher reading of VLOOP coincides with a larger shadow cost of intermediary constraints, whereas TCOST captures the realised compensations for providing immediacy. Both measures of dealers' liquidity costs exhibit intuitive properties in the sense that they surge during market stress and mean-revert during calm periods. The large spike during the Covid-19 market turmoil in March and April 2020 is particularly well pronounced across all 15 triplets of currency pairs and is indicative of the global nature of the stress. The correlation of VLOOP and TCOST is positive for the entire cross-section and ranges from 15–40%. We interpret this as evidence of commonality in no-arbitrage violations (e.g., Rösch et al., 2016; Du et al., 2022) and market liquidity in the broader sense (Rösch, 2021).

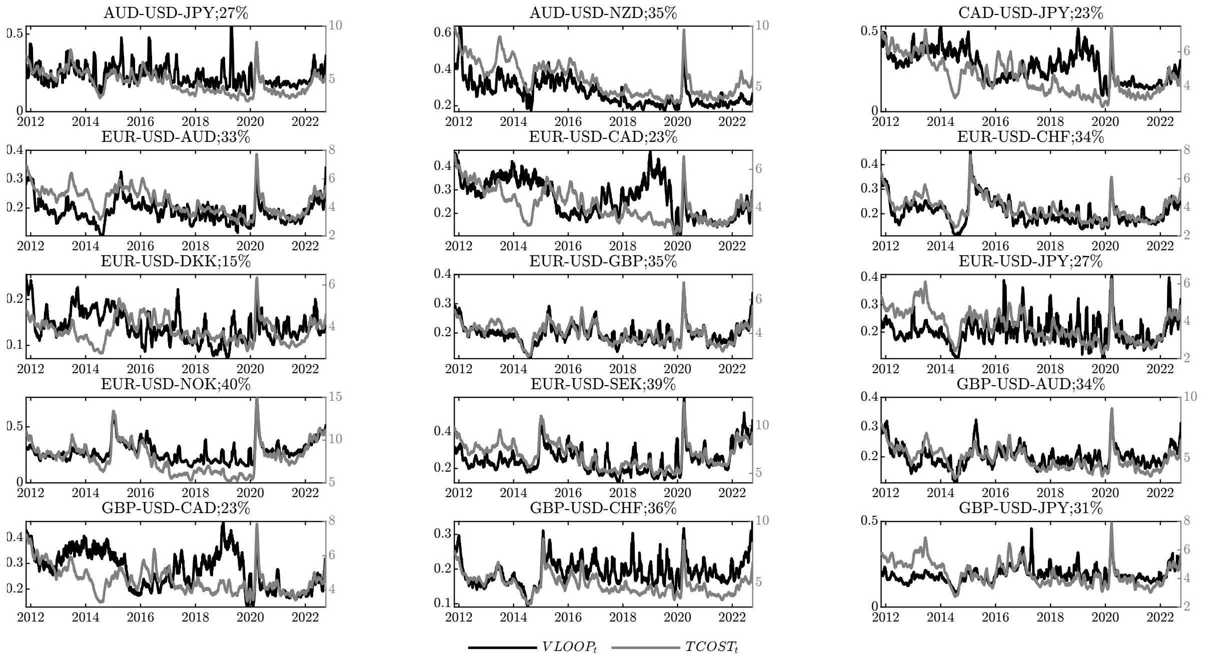
**Summary statistics.** Table 1 reports the time-series average of hourly no-arbitrage deviations (VLOOP) and round-trip trading costs (TCOST). In addition, it tabulates hourly averages of direct trading volume in non-dollar currency pairs (e.g., AUDJPY) and synthetic trading volume in dollar currency pairs. By "synthetic" we refer to the sum of trading volume in two dollar pairs (e.g., USDAUD and USDJPY) within a triplet of currency pairs. Each row corresponds to one currency pair triplet, which we abbreviate as, for instance, AUD-USD-JPY.

This simple summary table conveys three main insights: First, deviations from fundamentals (as measured by VLOOP) are an order of magnitude smaller than round-trip transaction

[17] As a robustness check, we have also constructed triplets of euro-based currency pairs that do not involve any dollar currency pairs (e.g., AUD-EUR-JPY). This leaves us with 6 currency pair triplets: AUD-EUR-JPY, CAD-EUR-JPY, GBP-EUR-AUD, GBP-EUR-CAD, GBP-EUR-CHF, and GBP-EUR-JPY, respectively. All our key empirical results remain qualitatively unchanged when estimated based on this alternative cross-section of currency pair triplets. See the Online Appendix Section G for these findings.

[18] To mitigate the effect of outliers, we remove observations at the top and bottom 1.5 percentiles of the hourly VLOOP and TCOST series.

Figure 3: No-arbitrage violations and round-trip transaction costs




*Note*: This figure plots the 22-day moving averages of hourly triangular no-arbitrage deviations VLOOP (left y-axis) and round-trip trading costs TCOST (right y-axis), respectively, for 15 triplets of currency pairs. Both variables are measured in basis points. The numbers in the titles refer to the correlation coefficient of VLOOP and TCOST. The sample covers the period from 1 November 2011 to 30 September 2022.

costs (as measured by TCOST). We interpret this result as suggestive evidence that dealers recharge their intermediation costs on the bid and ask prices offered to their customers. Another implication is that seemingly profitable violations of triangular no-arbitrage are most of the time not exploitable by the average trader as transactions costs are prohibitively high (i.e., there is no free lunch). Second, trading volume in non-dollar currency pairs is considerably smaller relative to the synthetic volume in dollar pairs. This is essentially the case for all 15 currency pair triplets but the effect is less pronounced for those involving the NOK and SEK, where the euro crosses play a bigger role. Finally, the synthetic relative bid-ask spread is somewhat larger than the direct spread in non-dollar currency pairs.[19]

**Measures of dealer constraints.** Our model suggests three main sources of dealer constraints that have a bearing on liquidity provision: dealers' VaR ($\sigma \times q$), their funding costs ($\eta$), and the portion of dealers facing binding VaR limits ($\omega$). In our empirical implementation we seek to capture these intermediary constraints in a single metric that we dub "DCM," which stands for dealer constraint measure. We construct this measure in two steps.

As a first step, we create three time-series based on cross-sectional averages of the top 10

[19] This finding is fully consistent with Somogyi (2021) who shows that strategic complementarity in price impact rather than traditional trading costs (e.g., bid-ask spreads) is the key determinant of the cross-sectional differences in trading volume between dollar and non-dollar currency pairs.

Table 1: Summary statistics

| | Liquidity cost in bps | | Volume in $bn | | Bid-ask spread in bps | | Volatility in bps |
|---|---|---|---|---|---|---|---|
| | VLOOP | TCOST | Direct | Synthetic | Direct | Synthetic | Direct |
| AUD-USD-JPY | 0.23 | 4.73 | 0.18 | 4.93 | 4.00 | 5.71 | 14.13 |
| AUD-USD-NZD | 0.27 | 5.61 | 0.09 | 1.93 | 4.17 | 7.25 | 8.96 |
| CAD-USD-JPY | 0.28 | 4.50 | 0.03 | 5.27 | 4.10 | 5.06 | 12.36 |
| EUR-USD-AUD | 0.19 | 4.40 | 0.13 | 7.47 | 3.40 | 5.52 | 11.30 |
| EUR-USD-CAD | 0.27 | 4.10 | 0.08 | 7.81 | 3.37 | 4.88 | 9.88 |
| EUR-USD-CHF | 0.21 | 3.91 | 0.36 | 6.56 | 2.60 | 5.27 | 6.49 |
| EUR-USD-DKK | 0.14 | 3.84 | 0.09 | 5.98 | 2.45 | 5.27 | 1.79 |
| EUR-USD-GBP | 0.20 | 4.01 | 0.59 | 7.94 | 3.11 | 4.89 | 9.33 |
| EUR-USD-JPY | 0.20 | 3.78 | 0.61 | 9.35 | 3.03 | 4.69 | 11.06 |
| EUR-USD-NOK | 0.27 | 7.92 | 0.24 | 6.06 | 6.43 | 9.55 | 11.66 |
| EUR-USD-SEK | 0.25 | 6.91 | 0.27 | 6.08 | 5.41 | 8.45 | 9.39 |
| GBP-USD-AUD | 0.20 | 4.95 | 0.04 | 3.51 | 4.03 | 5.91 | 12.14 |
| GBP-USD-CAD | 0.27 | 4.58 | 0.03 | 3.85 | 3.84 | 5.27 | 10.59 |
| GBP-USD-CHF | 0.19 | 4.84 | 0.03 | 2.60 | 3.99 | 5.66 | 10.55 |
| GBP-USD-JPY | 0.19 | 4.35 | 0.20 | 5.39 | 3.71 | 5.08 | 12.47 |

*Note*: This table reports the time-series average of hourly triangular no-arbitrage deviations $VLOOP$ in basis points (bps), round-trip trading costs $TCOST$ in bps, direct trading volume in non-dollar pairs (e.g., AUDJPY) in $bn, synthetic volume in dollar pairs in $bn, direct and synthetic relative bid-ask spreads, and realised volatility in non-dollar pairs in bps. By "synthetic" we refer to the sum of trading volumes and relative bid-ask spreads in two dollar pairs (e.g., USDAUD and USDJPY) within a currency pair triplet. Each row corresponds to a triplet of currency pairs, for example, AUDJPY, USDAUD, and USDJPY that we abbreviate as AUD-USD-JPY. The sample covers the period from 1 November 2011 to 30 September 2022.

FX dealer banks' i) VaR measure of their overall trading book (quarterly), ii) debt funding costs (daily), and iii) VaR breaches (each quarter).[20] To determine the top FX dealers we rely on the well-known Euromoney FX surveys. In every given year we assign an equal weight to each of the top FX dealers. Note that for certain variables (i.e., Value-at-Risk and number of VaR breaches) we were only able to collect data for a subset of banks. In such situations, we compute equally weighted averages based on the available set of dealer bank observations (see the Online Appendix Section C for further details). For the VaR breaches in turn we exploit the fact that US banks as well as foreign banks with US subsidiaries that are subject to the "Market Risk Capital Rule FFIEC 102" are required to report the number of VaR breaches in any given quarter since January 2015.

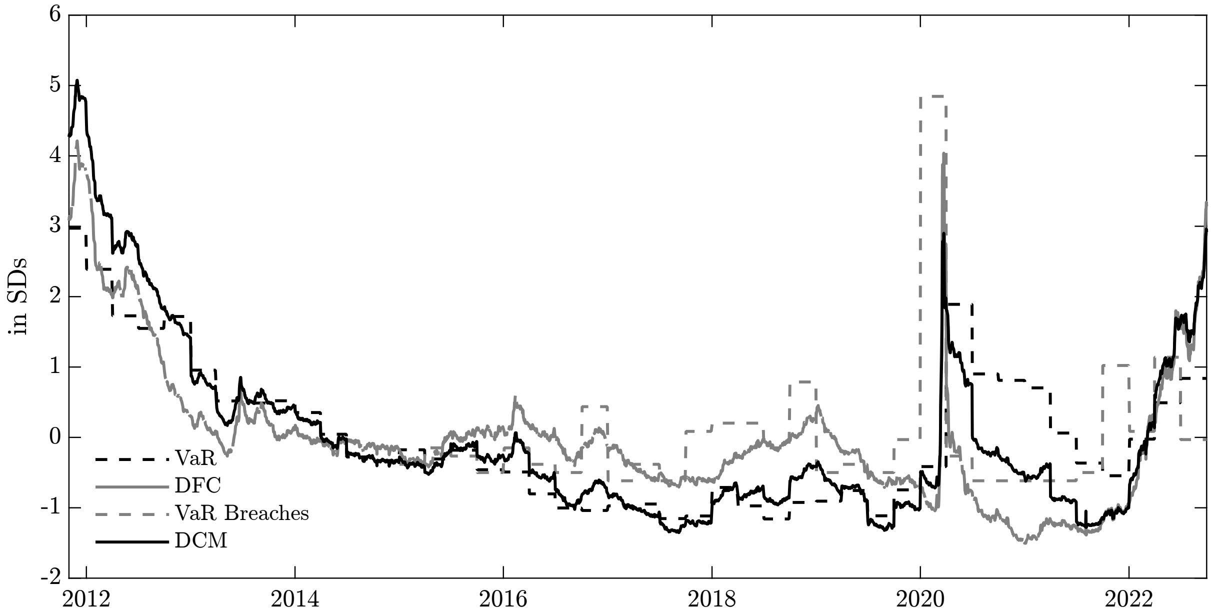
As a second step, we distil the information in the individual measures of dealer constraints to derive the composite dealer constraint measure DCM. The key advantage of DCM is that it encompasses all the model-based factors that can impact dealers' short-run flexibility to intermediate in currency markets. It is simply constructed by extracting the first principal component of the three individual dealer constraint series.[21] The first principal component explains around 53% of the total variance of the individual dealer constraint time-series.

[20]We compute cross-sectional averages because the CLS volume data does not contain any information about traders' identities. See the Online Appendix for details on how we retrieve and compute each of these variables.

[21]All our findings are robust to computing an unweighted average across the three state variables, that is, dealers' FX Value-at-Risk (VaR), debt funding costs, and the number of VaR breaches per quarter.

Figure 4 depicts how the three model-derived dealer constraint measures and the composite measure vary over time. The three series exhibit a notable co-movement (cf. Table 2). Hence, the common component is well reflected by the composite dealer constraint measure. The decline in DCM from 2012 up to the Covid-19 pandemic is consistent with the drop in bank credit spreads after the European sovereign debt crisis (Berndt, Duffie, and Zhu, 2023).

Figure 4: State variables: Dealer constraint measure (DCM) and its components




*Note*: This figure plots different state variables that we observe at the daily and quarterly frequencies. Observations have been standardised by subtracting the sample mean and dividing by the sample standard deviation of every variable. The three state variables are primary FX dealer banks' i) quarterly Value-at-Risk measure (VaR, dashed black line), ii) daily debt funding cost yield (DFC, solid grey line), and iii) the number of VaR breached in a given quarter (NVB, dashed grey line). We define our dealer constraint measure (DCM, black solid line with grey markers) as the first principal component across these four variables. The sample covers the period from 1 November 2011 to 30 September 2022.

Besides the factors analysed explicitly in our theoretical framework, we also consider four additional dealer constraint measures proposed in the related literature. First, He et al. (2017) show that negative shocks to intermediary capital (i.e., dealers' quarterly leverage ratio) reduce their risk bearing capacity across many asset classes including FX. Second, an increase in dealers' credit default swap (CDS) premia and valuation adjustments (XVA) (Andersen et al., 2019) can hamper their willingness to make balance sheet space available when facing customer order flow imbalances. Third, CIP deviations can be interpreted as a proxy for dealer funding costs (Rime et al., 2022) and balance sheet capacity in a broader sense (Du et al., 2018). In particular, we compute the average CIP deviations across our set of ten US dollar currency pairs. Fourth, we follow Andersen et al. (2019) to devise an alternative measure for $\omega$. Specifically, we compute the fraction of dealers that have 5-year CDS spreads above the 5-year USDJPY covered interest rate parity (CIP) basis. The intuition is that dealers can only arbitrage CIP violations if the deviations are larger than their credit spreads. We discuss robustness results based on these additional four measures in Section 6.

## 5. Liquidity provision and dealer constraints

In this section, we test the two main implications of our model. We start by exploring whether our liquidity cost measures (i.e., VLOOP and TCOST) are indeed positively related to various measures of dealer constraints (see Proposition 1). We then assess whether liquidity costs increase disproportionately more relative to dealer-intermediated volumes when dealer constraints tighten, in turn leading to a falling correlation between liquidity costs and trading volumes (see Proposition 2).

The analysis is split into three main parts. The first part presents motivating evidence using two simple correlation tables to support the empirical implications of the model. The first table relates our empirical liquidity cost measures to our model-derived measures of dealer constraints and provides evidence in favour of a positive association between the two. The second table shows that the correlation between the cost and the quantity of liquidity provision (i.e., dealer-intermediated volumes) depends on dealers' intermediation constraints. In the second part of the empirical analysis, we assess Proposition 2 of the model more formally. Specifically we rely on state-dependent regression analysis to quantify the change in the correlation between liquidity costs and trading volume, while controlling for factors influencing liquidity demand. Eventually, in the third part, we investigate the validity of Proposition 2 using structural vector autoregressions with sign restrictions that allow us to disentangle liquidity demand and supply shocks.

### *5.1. Motivating evidence*

Table 2 provides motivating evidence in favour of the first prediction of our model. It illustrates how the two liquidity cost measures are contemporaneously positively related to dealers' portfolio VaR $\sigma \times q$, measures of debt funding costs $\eta$, and the proportion of constrained dealers in the economy $\omega$. The economic magnitude of the correlations is comparable across both VLOOP and TCOST, albeit TCOST seems to be more correlated with VaR as well as the constrained dealer share. In addition, VLOOP and TCOST are positively correlated with exchange rate volatility $\sigma$, which is in line with our model. Hence, we will control for realized volatility in all regression-based analyses.

Table 3 presents empirical support for the second prediction of our model, namely that changes in dealer capacity have a nonlinear effect on market liquidity. The first three columns show how the average liquidity cost and dealer-intermediated volume (i.e., VLM) increase across the percentiles of our dealer constraint measure DCM. The monotonic increase in both liquidity cost measures and trading volume across the DCM percentiles suggests that the

Table 2: Correlations of key variables

| | VLOOP | TCOST | $\sigma$ | $\sigma \times q$ | $\eta$ |
|---|---|---|---|---|---|
| TCOST | ***59.28 | | | | |
| $\sigma$ | ***45.98 | ***42.31 | | | |
| $\sigma \times q$ | ***26.86 | ***49.43 | −5.43 | | |
| $\eta$ | ***30.90 | ***41.35 | ***18.93 | ***41.07 | |
| $\omega$ | ***23.30 | ***8.92 | ***26.27 | 0.90 | ***28.05 |

*Note*: This table reports the pairwise Pearson correlation coefficient (in percent, %) of (log) changes in quarterly triangular no-arbitrage deviations $VLOOP$, round-trip trading costs $TCOST$, realised variance $\sigma$, dealers' VaR measure $\sigma \times q$, debt funding costs $\eta$, and the share of constrained dealers $\omega$. Significant correlations at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The sample covers the period from 1 November 2011 to 30 September 2022 with the exception of $\omega$ due to the fact that US as well as foreign dealer banks with US subsidiaries were not required to report VaR breaches prior to 2015.

dealer sector as a whole accommodates the rise in trading demands even at times when intermediation constraints tighten. That said, dealers pass on the rise in liquidity costs to their customers more than what would be commensurate based on the rise in trading demands. This finding is fully in line with our model where currency demand is increasing in constrained periods due to volatility being higher than in normal times.[22] Eventually, columns 4 and 5 show the conditional correlation of (log) changes in each of our two liquidity cost measures and total trading volume.[23] Consistent with the model's predictions, we find that the correlation of volume with each of the two liquidity cost measures weakens substantially as DCM increases. For instance, the conditional correlation based on the highest DCM decile (i.e., when dealers are most constrained) is a mere 9% for TCOST, and hence economically and statistically significantly lower than the full-sample correlation of 25%.

These patterns are in line with the mechanism illustrated in Figure 2. Specifically, they show that liquidity costs increase disproportionately more relative to intermediated volumes given the inward shift in liquidity supply. Note that this is *not* a mechanical effect as the unconditional correlation between changes in VLOOP or TCOST and DCM is less than 1%.

These initial results are in line with prior research relating FX market liquidity and funding liquidity (Mancini et al., 2013; Karnaukh et al., 2015) and hence, deepen the understanding of the main mechanisms leading to a deterioration of FX market liquidity by highlighting the role of dealer constraints. Based on the theoretical framework in Section 3 the explanation for these empirical results hinges on two economic forces: For one, the price of market liquidity (i.e., VLOOP and TCOST) increases as dealers pass-through higher marginal funding costs (reflected by the surge of DCM) to their customers. For another, higher liquidity costs discour-

[22]Following, Clark (1973) and Tauchen and Pitts (1983), this result is consistent with the idea that volatility carries information about dispersion in fundamental trading demands (i.e., investor disagreement), which induce trading volume in the spirit of Gabaix and Maggiori (2015).

[23]Note that the CLS volume data include the FX trading activity of all top dealer banks listed in the Euromoney FX surveys. In particular, the banks that show up in the Euromoney FX surveys are also the most dominant players on the CLS settlement system.

age customers' trading activity (given they are price-sensitive and have a downward-sloping demand function) and suppresses trading demands. Consequently, when dealer constraints tighten, there is a marked imbalance: the equilibrium volume expands less compared to the surge in the equilibrium price of liquidity. This disparity underscores the intricate interplay between dealer constraints and market dynamics that are shaping FX liquidity conditions.

Table 3: Liquidity provision cost characteristics across DCM percentiles

| DCM percentile | | $\overline{VLOOP}$ in % | $\overline{TCOST}$ in % | $\overline{VLM}$ in \$bn | $cor(VLOOP, VLM)$ | $cor(TCOST, VLM)$ | #Obs |
|---|---|---|---|---|---|---|---|
| full sample | 0.0 | 0.05 | 1.10 | 141.81 | 0.09 | 0.25 | 2,796 |
| **least constrained** | 0.1 | 0.05 | 1.12 | 144.41 | 0.10 | 0.25 | 2,516 |
| | 0.2 | 0.05 | 1.15 | 147.85 | 0.10 | 0.24 | 2,238 |
| | 0.3 | 0.05 | 1.17 | 150.57 | 0.10 | *0.26 | 1,958 |
| | 0.4 | 0.05 | 1.20 | 154.19 | 0.10 | ***0.28 | 1,679 |
| | 0.5 | 0.05 | 1.22 | 156.56 | 0.10 | ***0.29 | 1,399 |
| | 0.6 | 0.06 | 1.25 | 154.66 | 0.09 | **0.27 | 1,119 |
| | 0.7 | 0.06 | 1.30 | 159.25 | ***0.07 | ***0.21 | 839 |
| | 0.8 | 0.06 | 1.31 | 156.50 | ***0.05 | ***0.17 | 559 |
| **most constrained** | 0.9 | 0.06 | 1.36 | 166.17 | ***−0.01 | ***0.08 | 280 |

*Note*: The first three columns in this table report the within-decile average of $VLOOP_{k,t}$ ($\overline{VLOOP}$) in %, $TCOST_{k,t}$ ($\overline{TCOST}$) in %, and the average $VLM_{k,t}$ ($\overline{VLM}$) in \$bn across percentiles of the dealer constraint measure $DCM$. The underlying data are based on a panel of 15 currency pair triplets. Columns 4 and 5 tabulate the conditional Pearson correlation of (log) changes in the two liquidity cost measures (i.e., $VLOOP$ and $TCOST$) and total trading volume $VLM$ across the percentiles of the dealer constraint measure. The last column shows the average number of observations for each $DCM$ percentile. The asterisks *, **, and *** indicate that the correlation is significantly different from the full sample estimate (in the first row) at the 90%, 95%, and 99% levels. The corresponding test statistic for the conditional correlation $cor^{\tau}$ being equal to the full sample correlation $cor^{\tau=1.00}$, where $\tau \in 0.1, 0.2, ..., 0.9$ refers to $DCM_t$ deciles, are based on the Fisher $z$-transformation. The sample covers the period from 1 November 2011 to 30 September 2022.

### 5.2. *Regression analysis*

To formally underpin the above reasoning that dealer constraints have a nonlinear effect on market liquidity, we employ smooth transition regression (LSTAR) models (e.g., van Dijk, Teräsvirta, and Franses, 2002; Christiansen et al., 2011). These nonlinear LSTAR models are particularly well-suited for our analysis as constrained and unconstrained regimes are determined endogenously (i.e., the econometrician is not choosing a particular cutoff value) and may vary smoothly over time. In particular, the constrained and unconstrained periods (governed by $\gamma$ and $c$) are determined by estimating a nonlinear regression model based on the generalised method of moments (GMM).[24]

For the LSTAR model, let $G(z_{t-1})$ be a logistic function depending on the 1-day lagged

[24]Following Granger and Terasvirta (1997), $\gamma$ and $c$ are free parameters that are bounded to avoid any corner solution (e.g., where all dealers are constrained at all times). Specifically, we allow $\gamma$ to vary from 1 to 12, whereas $c$ is bounded between $-0.5$ and $+0.5$. Our results are robust to varying these bounds.

regime variable $z_{t-1}$:

$$G(z_{t-1}) = (1 + \exp(-\gamma'(z_{t-1} - c)))^{-1}, \tag{21}$$

where the parameter $c$ is the central location and the vector $\gamma$ determines the steepness of $G(z_{t-1})$. We use the 1-day lagged value of DCM in all our state-dependent regression analyses to rule out any contemporaneous relation between our dealer constraint measure and the amount of intermediated volume.[25] Hence, the LSTAR model is of the form

$$y_{k,t} = \lambda_t + \alpha_k + [1 - G(z_{t-1})]\beta_1' f_{k,t} + G(z_{t-1})\beta_2' f_{k,t} + \beta_3' \mathbf{w}_{k,t} + \varepsilon_{k,t}, \tag{22}$$

where the dependent variable $y_{k,t}$ is one of our two liquidity cost measures (i.e., VLOOP or TCOST), $f_{k,t}$ is the total aggregate trading volume (i.e., $VLM_{k,t}$) that is defined as the sum of trading volume in one non-dollar as well as two dollar pairs within a particular currency pair triplet $k$. The state-independent control variable $\mathbf{w}_{k,t}$ includes either the realised variance $RV_{k,t}$ or the Amihud (2002) price impact $Amihud_{k,t}$ in the non-dollar currency pair within each triplet $k$.[26] The slope coefficients in Eq. (22) vary smoothly with the regime variable $z_{t-1}$ from $\beta_1$ at low values of $\gamma' z_{t-1}$ to $\beta_2$ at high values of $\gamma' z_{t-1}$. There are two interesting boundary cases: First, if $\beta_1 = \beta_2$ we effectively have a linear regression. Second, the limit case where $\gamma \to \infty$ is equivalent to a linear regression with a dummy.

Across all regression specifications, both the dependent and independent variables are taken in logs and first differences. The obvious advantage of this is twofold: First, regression coefficients can be interpreted as elasticities. Second, FX volume in levels is non-stationary and persistent (see Ranaldo and Santucci de Magistris, 2022), hence taking first-differences is an effective way to render the time-series stationary.

The key coefficient of interest in Eq. (22) is the difference between $\beta_2$ and $\beta_1$ capturing the change in the correlation between liquidity costs and dealer-intermediated volume across unconstrained and constrained regimes. To estimate all parameters (including $\gamma$ and $c$) in Eq. (22), we use GMM and conduct inference based on Driscoll and Kraay's (1998) covariance matrix which allows for random clustering and serial correlation up to 8 lags.[27]

Note that we include both cross-sectional $\alpha_k$ and time-series $\lambda_t$ fixed effects to control for any unobservable heterogeneity that is constant across triplets of currency pairs $k$ and days $t$, respectively.[28] The inclusion of time-series fixed effects implicitly assumes that (lagged)

[25] In the Online Appendix we show that our findings are robust to using up to 90 lags (see Figures D.4 and D.5) and are hence not driven by the fact that some of the DCM constituents are measured at the quarterly frequency (i.e., Value-at-Risk and number of VaR breaches). This exercise also provides evidence in favour of the idea that dealer constraints have a lasting (i.e., persistent) adverse effect on FX liquidity provision.

[26] We estimate $RV_{k,t}$ following Barndorff-Nielsen and Shephard (2002) as the sum of squared intraday midquote returns. Following Ranaldo and Santucci de Magistris (2022), we estimate the Amihud measure as the ratio between daily realised volatility and aggregate daily trading volume. To limit the detrimental effect of outliers, we winsorize $Amihud_{k,t}$ at the 0.5% level.

[27] We choose the optimal number of lags (i.e., "bandwidth") using the plug-in procedure for automatic lag selection by Andrews and Monahan (1992) and Newey and West (1994), respectively.

[28] As a result, all reported $R^2$ are "within" rather than "overall" coefficients of determination.

dealer constraints have no direct bearing on liquidity costs. In the Online Appendix, we show that this assumption is reasonable given that the lagged dealer constraint measure is statistically insignificant in a regression without time-series fixed effects.

Table 4 presents our baseline results. We observe a consistent picture across all three specifications: the difference between the slope coefficient on total trading volume in constrained and unconstrained periods (i.e., $\beta_2 - \beta_1$) is negative and statistically significant for both VLOOP and TCOST. Moreover, the estimated slope coefficients are at least 50% (e.g., $-0.07/0.12 = 58\%$) lower when dealer banks are constrained. Note that we control for several factors affecting the demand for liquidity. In particular, the day fixed effects $\lambda_t$ control for any global market factors such as global volatility (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012) or global illiquidity (Karnaukh et al., 2015). In addition, realised variance $RV_{k,t}$ is a state-independent control variable that plays a dual role in our empirical analysis. On the one hand, it controls for any differences in currency demand related to volatility. On the other hand, it can also account for differences in dealer competition across currency triplets.[29]

Related to our efforts to control for currency demand, one might wonder how much our results are driven by market-wide state factors that are not dealer specific and which are also more related to liquidity demand rather than supply. To address this question, we conduct a placebo exercise where we explore a set of non-dealer specific regime variables that are presumably more exposed to liquidity demand as well as broad market conditions. In particular, we consider the VIX, the TED spread, the price of gold, and the LIBOR-OIS spread as alternative regime variables. We find that these state variables do not appropriately capture dealer constraints because the relation between liquidity costs and volume is not state-dependent. We document these additional results in the Online Appendix Section D.

In sum, the empirical results in this section provide two key takeaways that lend support to our model. First, the correlation between liquidity cost measures and dealer-intermediated volume is significantly smaller during times when dealers are more constrained (i.e., the difference between the slope coefficients with respect to trading volume across unconstrained and constrained states is negative). Second, it is above all the relation between VLOOP and dealer-intermediated trading volume that strongly diverges and even exhibits negative (albeit insignificant) coefficients in the constrained regime.

Our theoretical framework in Section 3 suggests that the drop in the correlation between liquidity cost and volume stems from a more inelastic (i.e., steeper) supply curve. However, empirically, one might be concerned that our dealer constraint measure (DCM) is correlated with factors simultaneously affecting both liquidity supply and demand. To address this issue more conclusively, we employ a structural vector autoregression setup with sign restrictions in the next section. This econometric approach allows us to explicitly disentangle liquidity

[29] The intuition for this is based on Huang and Masulis (1999) showing that currency volatility is highly correlated with the number of dealers active in the market. The latter is both theoretically and empirically a sensible proxy for dealer competition.

Table 4: Smooth transition regression with DCM as state variable

| | VLOOP | | | TCOST | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\gamma$ | ***12.00 | ***12.00 | ***12.00 | ***12.00 | ***12.00 | ***12.00 |
| c | −0.03 | −0.03 | −0.03 | ***0.14 | ***0.14 | ***0.14 |
| Unconstr. volume | ***0.10 | ***0.10 | ***0.08 | ***0.12 | ***0.12 | ***0.10 |
| | [4.13] | [4.02] | [3.18] | [16.90] | [16.84] | [12.90] |
| Constr. volume | −0.03 | −0.03 | −0.05 | ***0.05 | ***0.06 | **0.03 |
| | [0.90] | [0.96] | [1.42] | [4.11] | [4.17] | [2.54] |
| Amihud (2002) | | 0.00 | | | **0.00 | |
| | | [0.73] | | | [2.07] | |
| Realised variance | | | ***0.02 | | | ***0.02 |
| | | | [3.17] | | | [8.83] |
| Constr.-Unconstr. | ***−0.13 | ***−0.13 | ***−0.12 | ***−0.07 | ***−0.07 | ***−0.06 |
| | [3.12] | [3.12] | [3.03] | [4.45] | [4.46] | [3.95] |
| $R^2$ in % | 0.09 | 0.09 | 0.14 | 2.38 | 2.40 | 3.44 |
| Avg. #Time periods | 2,796 | 2,796 | 2,796 | 2,801 | 2,801 | 2,800 |
| #Currency triplets | 15 | 15 | 15 | 15 | 15 | 15 |
| Currency triplet FE | yes | yes | yes | yes | yes | yes |
| Time-series FE | yes | yes | yes | yes | yes | yes |

*Note*: This table reports results from daily fixed effects LSTAR panel regressions of the form $y_{k,t} = \lambda_t + \alpha_k + [1 - G(z_{t-1})]\beta_1' f_{k,t} + G(z_{t-1})\beta_2' f_{k,t} + \beta_3' w_{k,t} + \varepsilon_{k,t}$, where the dependent variable $y_{k,t}$ is a liquidity cost measure (i.e., *VLOOP* or *TCOST*), $f_{k,t}$ ($w_{k,t}$) are state-dependent (*state-independent*) regressors, and $G(z_{t-1})$ is a logistic function depending on state variable $z_{t-1}$. The regime variable is the 1-day lagged value of the dealer constraint measure $DCM_t$. The optimal parameters $\gamma$ and $c$ are determined by nonlinear least squares minimising the concentrated sum of squared errors. Both dependent and independent variables are taken in logs and changes. The sample covers the period from 1 November 2011 to 30 September 2022. The test statistics based on Driscoll and Kraay (1998) robust standard errors allowing for random clustering and serial correlation (using the plug-in procedure for automatic lag selection by Andrews and Monahan (1992) and Newey and West (1994)) are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% levels.

demand and supply dynamics.

### 5.3. *Disentangling liquidity demand and supply*

The empirical analysis based on LSTAR models has interpreted our dealer constraint measure (i.e., DCM) as a quasi-exogenous proxy for shifts in liquidity supply. Here, we take the analysis one step further by explicitly disentangling liquidity demand and supply shocks using a structural vector autoregression with sign restrictions. Specifically, we build on the approach by Uhlig (2005) and others (e.g., Canova and De Nicoló, 2002; Rubio-Ramírez, Waggoner, and Zha, 2010), which has become widely used in economics and finance to estimate models with sign restrictions. Our empirical analysis proceeds in two steps.

In a first step, we estimate a structural (bivariate) vector autoregression (SVAR) model of liquidity cost measures (i.e., VLOOP or TCOST) and dealer-intermediated volume (VLM). To identify liquidity supply and demand shifts, we estimate the SVAR imposing sign restrictions in the spirit of Cohen, Diether, and Malloy (2007), Goldberg (2020), and Goldberg and Nozawa (2020), respectively, using Bayesian methods (see the Online Appendix Section E for further details). Let $Y_{k,t} = [X_{k,t} \; VLM_{k,t}]^T$ be a $2 \times 1$ vector containing $X \in \{VLOOP, TCOST\}$ and $VLM$ in currency pair triplet $k$ and day $t$. The bivariate panel SVAR for $Y_{k,t}$ is:

$$Y_{k,t} = \alpha_k + \sum_{i=1}^{l} B_{k,i} Y_{k,t-i} + \xi_{k,t}, \tag{23}$$

where $B_{k,i}$ is a $2 \times 2$ matrix of coefficients, $l$ the lag length, $\xi_{k,t} = [\xi_{X;k,t} \; \xi_{VLM;k,t}]^T$ the reduced form error, and $\alpha_k$ is a $2 \times 1$ vector of currency triplet fixed effects. The vector of residuals $\xi_{k,t}$ can be mapped to the structural liquidity supply $\delta^s_{k,t}$ and demand $\delta^d_{k,t}$ shocks using the following relation:

$$\begin{bmatrix} \xi_{X;k,t} \\ \xi_{VLM;k,t} \end{bmatrix} = A_k \begin{bmatrix} \delta^s_{k,t} \\ \delta^d_{k,t} \end{bmatrix}, \tag{24}$$

where $A_k$ is a $2 \times 2$ matrix and $\delta_{k,t} = [\delta^s_{k,t} \; \delta^d_{k,t}]^T$ is a $2 \times 1$ vector. Based on Eqs (23) and (24), the first column of $A_k$ corresponds to changes in liquidity provision costs (i.e., VLOOP or TCOST) and dealer-intermediated volume associated with an increase in $\delta^s_{k,t}$. The second column in turn corresponds to changes in liquidity costs and intermediated volumes associated with an increase in $\delta^d_{k,t}$. Following Goldberg (2020), if $A_k$ satisfies the following sign restrictions:

$$sign(A_k) = \begin{pmatrix} + & + \\ - & + \end{pmatrix}, \tag{25}$$

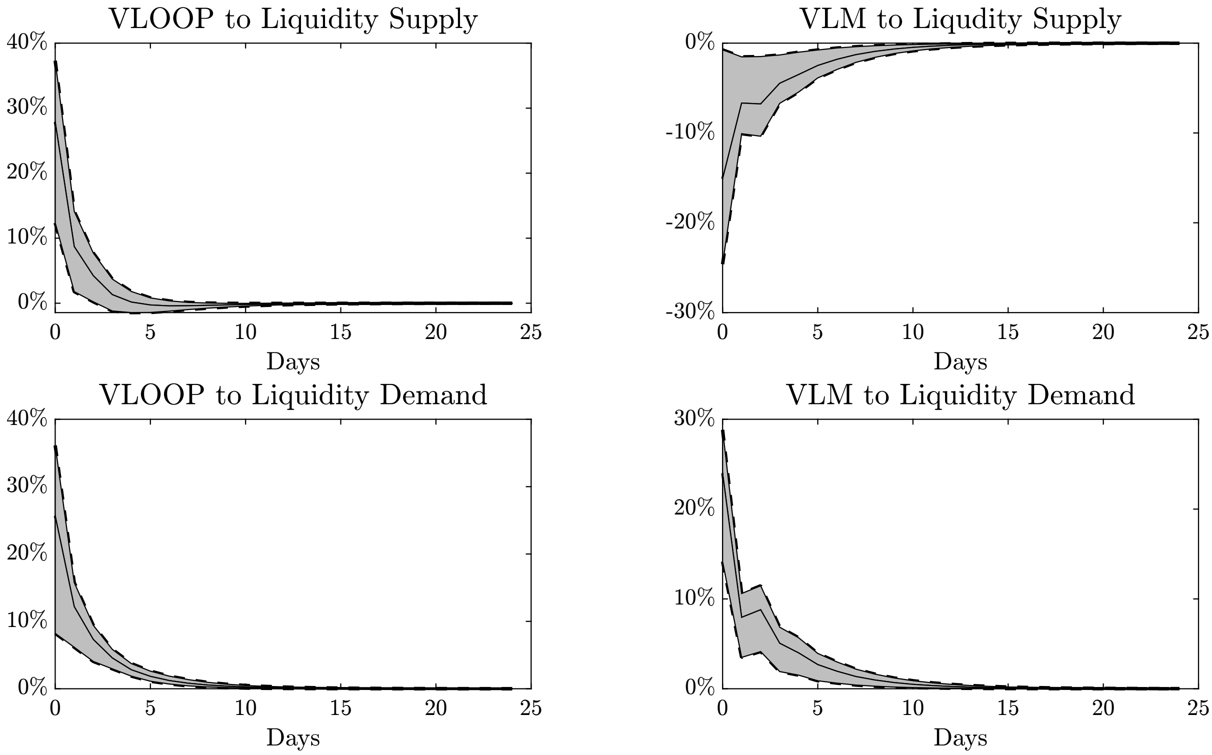
then $\delta^s_{k,t}$ can be interpreted as an inward shift in liquidity supply reflecting a tightening of dealer constraints, whereas $\delta^d_{k,t}$ corresponds to an outward shift in liquidity demand.

The sign restrictions in Eq. (25) assume that supply shifts lead to changes in liquidity costs and trading volume that have opposite signs. In other words, a shock to liquidity supply will lead to a rise in liquidity costs but at the same time a fall in intermediated volume. Demand shocks, by contrast, are assumed to lead to changes in liquidity costs and volume in the same direction. That is, in the case of demand shocks, the increase in liquidity costs goes in hand with a rise in dealer-intermediated volume.

These sign restrictions are fully consistent with our model (see Section 3), which rationalises how dealer constraints (i.e., $\sigma \times q$, $\eta$, and $\omega$) affect both the level and the slope of the liquidity supply curve. In particular, the SVAR model embraces the basic economic intuition that an inward (*outward*) shift of the supply (*demand*) curve corresponds to a higher equilibrium price (i.e., cost of liquidity) when holding demand (*supply*) constant. Moreover, the model features a feedback effect between supply and demand in the following sense: A rise in dealer constraints increases bid-ask spreads which in turn suppresses additional trading demands, thereby rendering order flows less imbalanced. Consequently, the shadow cost of intermediary constraints decreases, dampening the increase in the cost of liquidity provision.

For illustrative purposes, Figure 5 (Figure 6) shows estimates of the impulse responses of $VLOOP$ ($TCOST$) and $VLM$ to liquidity supply and demand shifts for the EUR-USD-JPY currency pair triplet.[30] In line with the above reasoning, concurrently with a supply shift, VLOOP (TCOST) rises and VLM positions decline. As shown in Figure 5, contemporaneous with a supply shift, VLOOP (TCOST) rises 32% (5%) and VLM positions decline 16% (18%), according to the posterior mean. Contrarily, a demand shock is associated with an increase in VLOOP (TCOST) as well as an increase in VLM by 26% and 25% (12% and 20%), respectively.

Figure 5: Dynamic impulse response function for EUR-USD-JPY; VLOOP




*Note*: This figure plots the estimated dynamic impulse response of the shadow cost of intermediary constraints (VLOOP) and dealer-intermediated volume (VLM) associated with liquidity supply and demand shifts. The median response is shown by the black solid line. The grey shaded area marks a pointwise 95% confidence interval around the median. The sample covers the period from 1 November 2011 to 30 September 2022.

In a second step, we estimate the correlation between the cost of liquidity provision (i.e., VLOOP or TCOST) and dealer-intermediated trading volume (i.e., VLM) in a 30-day rolling window[31] fashion and estimate the following panel regression model:

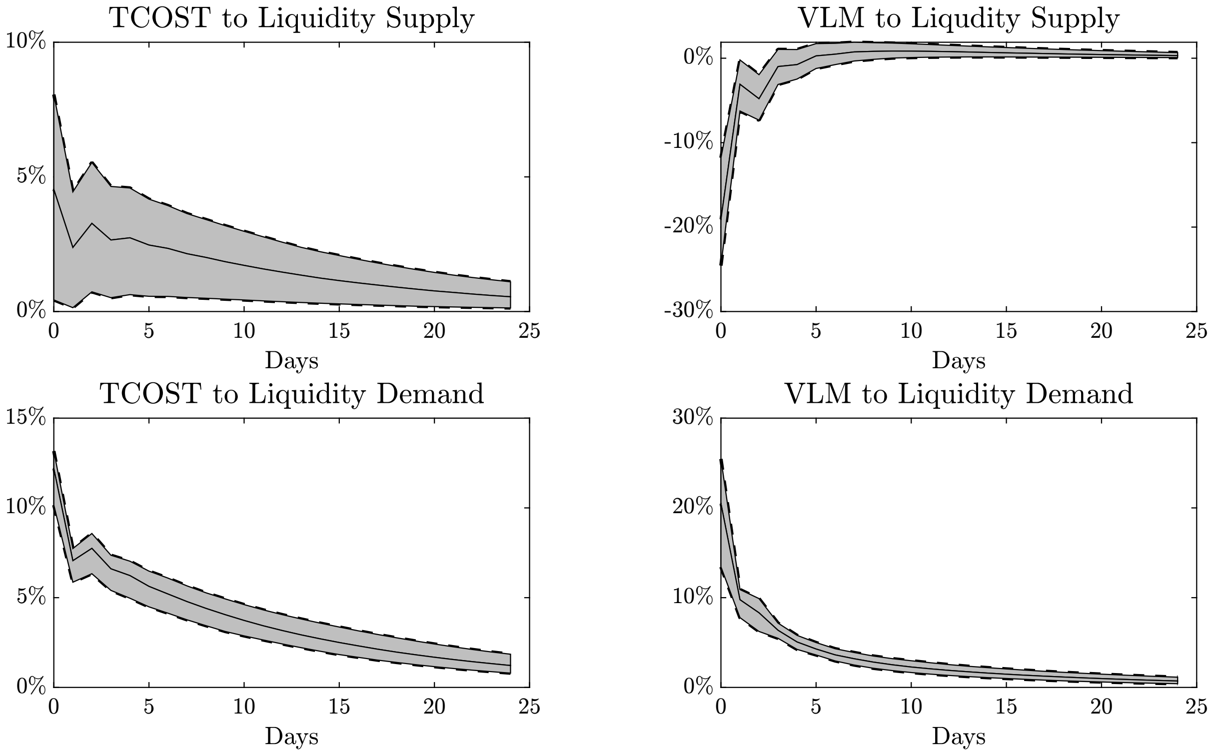
$$\rho_{k,t} = \alpha_k + \phi_1 DCM_t + \phi_2 RV_{k,t} + \phi_3 Amihud_{k,t} + \epsilon_{k,t}, \tag{26}$$

where the dependent variable is the 30-day rolling window correlation of a liquidity cost measure (i.e., VLOOP or TCOST) and trading volume, $\alpha_k$ denotes currency triplet fixed ef-

[30]The impulse response functions for the other 14 currency pair triplets exhibit qualitatively similar patters.

[31]All our results are qualitatively unchanged when using longer or shorter estimation windows.

Figure 6: Dynamic impulse response function for EUR-USD-JPY; TCOST




*Note*: This figure plots the estimated dynamic impulse response of dealers' compensation for enduring inventory imbalances (TCOST) and dealer-intermediated volume (VLM) associated with liquidity supply and demand shifts. The median response is shown by the black solid line. The grey shaded area marks a pointwise 95% confidence interval around the median. The sample covers the period from 1 November 2011 to 30 September 2022.

fects, $RV_{k,t}$ the realised variance, $Amihud_{k,t}$ the Amihud (2002) price impact in the non-dollar currency pair within each triplet $k$, and $DCM_t$ is our dealer constraint measure.

The regression in Eq. (26) may suffer from endogeneity of $DCM_t$ due to a missing factor simultaneously affecting the correlation between liquidity costs and volumes $\rho_{k,t}$. In other words, $DCM_t$ may not (fully) capture the dealer constraints $\sigma \times q$, $\eta$ and $\omega$ in our model. To address this issue, we use the supply shocks that we extract from the SVAR as an alternative measure for tightening dealer constraints. Additionally, to account for potential shifts in liquidity demand, we include demand shocks as an additional control variable in Eq. (26).

Table 5 documents the results of estimating Eq. (26) by OLS and 2SLS, respectively. In particular, Panel A shows the OLS estimates of Eq. (26), whereas Panel B uses both liquidity supply and demand shocks as alternative measures of tightening dealer constraints. We estimate demand and supply shocks from a panel SVAR with currency triplet fixed effects. The key takeaway from Table 5 is consistent with the LSTAR analysis (see Table 4) and corroborates the idea that more binding dealer constraints are associated with dealers' liquidity provision becoming less elastic (i.e., smaller $\rho_{k,t}$). It turns out that, in line with the model, liquidity supply (rather than demand) shocks are the pivotal determinant of the variation in the correlation between liquidity costs and trading volume.

Table 5: Disentangling liquidity demand and supply

| | cor(VLOOP,VLM) | | | cor(TCOST,VLM) | | |
|---|---|---|---|---|---|---|
| *Panel A* | (1) | (2) | (3) | (4) | (5) | (6) |
| DCM | ***−0.09 | ***−0.09 | ***−0.10 | *−0.08 | *−0.08 | *−0.07 |
| | [2.58] | [2.60] | [2.69] | [1.89] | [1.87] | [1.73] |
| Realised variance | | *0.02 | | | −0.03 | |
| | | [1.70] | | | [1.54] | |
| Amihud (2002) | | | ***0.07 | | | ***−0.14 |
| | | | [3.89] | | | [5.33] |
| Adj. $R^2$ in % | 0.80 | 0.85 | 1.01 | 0.59 | 0.69 | 1.36 |
| Avg. #Time periods | 2,772 | 2,772 | 2,772 | 2,772 | 2,772 | 2,772 |
| #Currency triplets | 15 | 15 | 15 | 15 | 15 | 15 |
| Currency triplet FE | yes | yes | yes | yes | yes | yes |
| Time series FE | yes | yes | yes | yes | yes | yes |
| *Panel B* | | | | | | |
| $\delta^s$ | ***−0.05 | ***−0.05 | ***−0.06 | ***−0.06 | ***−0.07 | ***−0.06 |
| | [5.41] | [5.39] | [5.60] | [5.55] | [5.75] | [4.90] |
| $\delta^d$ | 0.00 | 0.00 | 0.00 | 0.01 | 0.01 | 0.01 |
| | [0.15] | [0.18] | [0.14] | [1.56] | [1.57] | [0.99] |
| Realised variance | | **0.00 | | | **−0.02 | |
| | | [2.17] | | | [2.05] | |
| Amihud (2002) | | | **0.04 | | | ***−0.06 |
| | | | [2.57] | | | [4.59] |
| Adj. $R^2$ in % | 0.20 | 0.20 | 0.25 | 0.20 | 0.24 | 0.47 |
| Avg. #Time periods | 2,772 | 2,772 | 2,772 | 2,772 | 2,772 | 2,772 |
| #Currency triplets | 15 | 15 | 15 | 15 | 15 | 15 |
| Currency triplet FE | yes | yes | yes | yes | yes | yes |
| Time series FE | yes | yes | yes | yes | yes | yes |

*Note*: This table reports results from daily fixed effects panel regressions of the form $\rho_{k,t} = \alpha_k + \phi_1 DCM_t + \phi_2 RV_{k,t} + \phi_3 Amihud_{k,t} + \epsilon_{k,t}$, where the dependent variable is the 30-day rolling window correlation of a liquidity cost measure (i.e., $VLOOP$, or $TCOST$) and trading volume (i.e., $VLM$), $\alpha_k$ denotes cross-sectional fixed effects, $RV_{k,t}$ ($Amihud_{k,t}$) the realised variance (Amihud (2002) price impact) in the non-dollar currency pair within each triplet $k$, and $DCM_t$ is our dealer constraint measure. Panel A shows the OLS estimates of Eq. (26), whereas Panel B uses both liquidity supply $\delta^s_{k,t}$ and demand shocks $\delta^d_{k,t}$ from the SVAR as alternative measures of tightening dealer constraints. All regressors have been normalised to have unit standard deviation. Hence, the regression coefficients measure the increase in $\rho$ associated with a one standard deviation increase in $DCM$, $\delta^s$, and $\delta^d$, respectively. The sample covers the period from 1 September 2012 to 30 September 2022. The test statistics based on Driscoll and Kraay (1998) robust standard errors allowing for random clustering and serial correlation (using the plug-in procedure for automatic lag selection by Newey and West, 1994) are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% levels.

## 6. Robustness tests

To investigate the robustness of our findings we run two additional empirical tests: i) decompose the dealer constraint measure into its constituents and use alternative measures of dealer constraints (leverage ratio, CIP basis, CDS spreads) and ii) capture the share of constrained dealers based on differences in CDS spreads and the CIP basis. We relegate all additional robustness checks pertaining to the LSTAR model to the Online Appendix Section D. In total, we perform nine additional analyses supporting our base line results in Table 4. For instance, we perform a subsample analysis, split trading volume into inter-bank and customer-bank trades, and account for potential bias in the bid-ask spread.

**Different components of dealer constraints.** We consider the same LSTAR specification as in Eq. (22) but instead of our dealer constraint measure DCM we use its three constituents. In particular, we use the lagged value of primary FX dealer banks' quarterly Value-at-Risk measure (VaR), daily funding cost yield (DFC), and the number of VaR breaches (NVB) in a given quarter as regime variables. In addition, we follow the related literature and use three broad measures of dealer balance sheet capacity: i) He et al. (2017) leverage ratio (i.e., $1-$*capital ratio*) (quarterly), ii) credit default swap (CDS) premia (daily), and iii) the average CIP deviation (daily) across our set of ten US dollar currency pairs.

Table 6 reports the estimates of using each of the six aforementioned measures as a state variable. The difference between the constrained and unconstrained coefficient is negative and significant across all specifications for both VLOOP and TCOST. The only exception is column 9 (NVB for TCOST) where the difference is statistically insignificant. These estimates are in line with our baseline specification based on DCM in terms of economic magnitudes.

**Share of constrained dealers.** Here we propose an alternative measure for the share of constrained dealers that is based on the related literature on funding liquidity and, in particular, Andersen et al. (2019). The key intuition is that arbitraging CIP violations is only beneficial to a dealer if the deviations exceed the dealer's credit spread. Put differently, dealers that have credit spreads above the CIP basis are "constrained" in the sense that they are unable to perform the arbitrage trade. Specifically, we compare the 5-year basis in the USDJPY to the 5-year CDS spread of each top dealer bank and then compute the fraction of banks that have long-term CDS spreads below the long-term CIP basis.[32] Next, we use this fraction as an alternative measure for $\omega$. Table 7 provides quantitative support in favour of this funding liquidity-based measure for the share of constrained dealers. The difference between the constrained and unconstrained coefficient is negative and significant across all specifications except for TCOST when controlling for the Amihud (2002) price impact.

**Additional analyses.** In the Online Appendix Section D we document nine additional robustness checks for our baseline result (see Table 4). First, we estimate the LSTAR currency pair triplet by triplet (see Tables D.1 and D.2) to shed light on the cross-sectional differences across currency pair triplets. In line with the panel regression, we find that the difference between the slope coefficient on trading volume in constrained and unconstrained periods

[32] We focus on the USDJPY basis because it is the largest and most persistent for our sample period.

Table 6: Smooth transition regression with different state variables

| | VLOOP | | | | | | TCOST | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | VaR | DFC | NVB | HKM | CDS | CIP | VaR | DFC | NVB | HKM | CDS | CIP |
| $\gamma$ | *12.00 | ***12.00 | ***12.00 | ***8.63 | ***12.00 | ***1.21 | ***12.00 | ***1.00 | 12.00 | ***12.00 | ***4.89 | ***2.58 |
| c | 0.06 | ***−0.25 | ***0.10 | −0.01 | ***0.24 | ***0.50 | ***0.26 | ***−0.37 | ***0.50 | −0.03 | ***0.03 | ***0.50 |
| Unconstr. volume | ***0.08 | ***0.12 | ***0.12 | ***0.10 | ***0.07 | ***0.14 | ***0.10 | ***0.17 | ***0.09 | ***0.11 | ***0.11 | ***0.09 |
| | [3.03] | [3.78] | [3.15] | [3.58] | [3.03] | [2.90] | [12.50] | [6.50] | [7.57] | [11.64] | [12.80] | [10.30] |
| Constr. volume | −0.03 | −0.02 | −0.03 | −0.02 | *−0.07 | *−0.14 | ***0.04 | 0.01 | ***0.12 | ***0.05 | 0.02 | **0.04 |
| | [1.00] | [0.68] | [0.55] | [0.76] | [1.86] | [1.82] | [3.61] | [0.52] | [4.03] | [5.67] | [1.05] | [2.05] |
| Realised variance | ***0.02 | ***0.02 | **0.02 | ***0.02 | ***0.02 | ***0.02 | ***0.02 | ***0.03 | ***0.03 | ***0.03 | ***0.03 | ***0.03 |
| | [3.14] | [3.29] | [2.15] | [3.22] | [3.20] | [3.20] | [8.83] | [8.95] | [5.25] | [8.97] | [8.90] | [8.91] |
| Constr.-Unconstr. | ***−0.11 | ***−0.14 | **−0.16 | ***−0.12 | ***−0.14 | **−0.28 | ***−0.05 | ***−0.16 | 0.03 | ***−0.06 | ***−0.10 | **−0.06 |
| | [2.70] | [3.29] | [2.13] | [2.95] | [3.14] | [2.34] | [3.57] | [3.44] | [1.00] | [4.44] | [5.17] | [2.35] |
| $R^2$ in % | 0.13 | 0.15 | 0.28 | 0.14 | 0.14 | 0.12 | 3.41 | 3.42 | 3.57 | 3.45 | 3.52 | 3.33 |
| BIC | 94.08 | 94.08 | 88.67 | 94.08 | 94.08 | 94.08 | 52.57 | 52.57 | 49.43 | 52.57 | 52.55 | 52.58 |
| Avg. #Time periods | 2,796 | 2,796 | 1,985 | 2,796 | 2,796 | 2,796 | 2,800 | 2,800 | 1,988 | 2,800 | 2,800 | 2,800 |
| #Currency triplets | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 |
| Currency triplet FE | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes |
| Time-series FE | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes |

*Note*: This table reports results from daily fixed effects LSTAR panel regressions of the form $y_{k,t} = \lambda_t + \alpha_k + [1 - G(z_{t-1})]\beta_1' f_{k,t} + G(z_{t-1})\beta_2' f_{k,t} + \beta_3' w_{k,t} + \varepsilon_{k,t}$, where the dependent variable $y_{k,t}$ is a liquidity cost measure (i.e., $VLOOP$ or $TCOST$), $f_{k,t}$ ($w_{k,t}$) are state-dependent (*state-independent*) regressors and $G(z_{t-1})$ is a logistic function depending on the regime variable $z_{t-1}$. The regime variables are the 1-day lagged values of primary FX dealer banks': quarterly Value-at-Risk measure (VaR, columns 1 and 7), daily funding cost yield (DFC, columns 2 and 8), number of VaR breaches per quarter (NVB, columns 3 and 9), quarterly He et al. (2017) leverage ratio (HKM, columns 4 and 10), daily credit default spread (CDS, columns 5 and 11), and daily average CIP basis in US dollar currency pairs (CIP, columns 6 and 12). Note that we assign an equal weight to each top 10 FX dealer bank (based on the Euromoney FX survey) when computing a cross-sectional average. The optimal parameters $\gamma$ and $c$ are determined by nonlinear least squares minimising the concentrated sum of squared errors. The row 'Constr. - Unconstr.' reports the difference between the slope coefficient on constrained and unconstrained volume, respectively. Both dependent and independent variables are taken in logs and changes. The sample covers the period from 1 November 2011 to 30 September 2022. The test statistics based on Driscoll and Kraay (1998) robust standard errors allowing for random clustering and serial correlation (using the plug-in procedure for automatic lag selection by Andrews and Monahan, 1992; Newey and West, 1994) are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% levels.

Table 7: Smooth transition regression with constrained dealer share as state variable

| | VLOOP | | | TCOST | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\gamma$ | ***1.45 | ***1.43 | ***1.35 | 12.00 | 12.00 | 12.00 |
| c | ***0.50 | ***0.50 | ***0.50 | ***0.50 | ***0.50 | ***0.50 |
| Unconstr. volume | ***0.15 | ***0.15 | ***0.14 | ***0.11 | ***0.12 | ***0.09 |
| | [3.85] | [3.73] | [3.35] | [13.75] | [13.83] | [10.29] |
| Constr. volume | *−0.10 | **−0.11 | **−0.12 | ***0.08 | ***0.09 | ***0.06 |
| | [1.95] | [2.05] | [2.21] | [7.35] | [7.36] | [5.44] |
| Amihud (2002) | | −0.01 | | | **0.00 | |
| | | [1.47] | | | [2.11] | |
| Realised variance | | | **0.02 | | | ***0.03 |
| | | | [2.28] | | | [8.53] |
| Constr.-Unconstr. | ***−0.25 | ***−0.26 | ***−0.26 | **−0.03 | **−0.03 | −0.02 |
| | [3.11] | [3.11] | [3.04] | [2.08] | [2.09] | [1.61] |
| $R^2$ in % | 0.11 | 0.12 | 0.14 | 2.21 | 2.25 | 3.39 |
| Avg. #Time periods | 2,604 | 2,604 | 2,604 | 2,609 | 2,609 | 2,608 |
| #Currency triplets | 15 | 15 | 15 | 15 | 15 | 15 |
| Currency triplet FE | yes | yes | yes | yes | yes | yes |
| Time-series FE | yes | yes | yes | yes | yes | yes |

*Note*: This table reports results from daily fixed effects LSTAR panel regressions of the form $y_{k,t} = \lambda_t + \alpha_k + [1 - G(z_{t-1})]\beta_1' f_{k,t} + G(z_{t-1})\beta_2' f_{k,t} + \beta_3' w_{k,t} + \varepsilon_{k,t}$, where the dependent variable $y_{k,t}$ is a liquidity cost measure (i.e., $VLOOP$ or $TCOST$), $f_{k,t}$ ($w_{k,t}$) are state-dependent (*state-independent*) regressors, and $G(z_{t-1})$ is a logistic function depending on the state variable $z_{t-1}$. The regime variable is the 1-day lagged value of the share of constrained dealers (i.e., $\omega$) that is captured by the fraction of top 10 dealer banks with 5-year CDS spreads exceeding the 5-year USDJPY CIP basis. The optimal parameters $\gamma$ and $c$ are determined by nonlinear least squares minimising the concentrated sum of squared errors. The row 'Constr. - Unconstr.' reports the difference between the slope coefficient on constrained and unconstrained volume, respectively. Both dependent and independent variables are taken in logs and changes. The sample covers the period from 1 September 2012 to 30 September 2022. The test statistics based on Driscoll and Kraay (1998) robust standard errors allowing for random clustering and serial correlation (using the plug-in procedure for automatic lag selection by Andrews and Monahan, 1992; Newey and West, 1994) are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% levels.

is negative and significant for several currency pair triplets. Second, we split volume into inter-bank and customer-bank trades (see Table D.3) and find that large dealer banks mainly curtail their liquidity provision in trades with other banks (rather than customers). Third, we perform a subsample analysis (see Table D.4) to account for the rise of non-bank liquidity providers since 2016. In line with the hypothesis that non-bank liquidity providers are more flexible in their liquidity provision than traditional dealer banks, we find that the constrained minus unconstrained coefficient with respect to trading volume is almost twice as large in terms of economic magnitude for the first half than for the second half. Fourth, to account for potential bias in the bid-ask spread (see Table D.5) we follow Hagströmer (2021) and compute both no-arbitrage violations VLOOP and round-trip transaction costs TCOST using the "weighted midpoint" method. Fifth, we relax time-series fixed effects (see Table D.6) and find that the lagged dealer constraint measure is insignificant in such a regression. Sixth, in a placebo exercise, we explore a different set of regime variables that are not dealer specific (see Table D.8) and which are thus more directly exposed to liquidity demand and general market conditions (e.g., the VIX index or the TED spread). We find no significant drop in the correlation between liquidity costs and trading volume for any of these alternative state variables. Seventh, we vary the number of lags in the LSTAR model (see Figures D.3 and D.4) and find that dealer constraints have a lasting adverse effect on FX liquidity provision. Eights, we focus on the main London stock market trading hours (see Table D.9) to rule out that our results are driven by more illiquid trading hours. Lastly, we employ euro-based currency triplets (see Table D.10) to show that our results are not driven by the dominant role of the US dollar in FX trading.

To summarise, these additional robustness tests corroborate our previous results and support the main mechanisms of our theoretical framework. Dealers promote FX market liquidity in normal times through elastic liquidity provision. As such, dealer intermediation contributes to better market liquidity, that is, narrower spreads and more informative prices (i.e., lower transactions costs and tighter no-arbitrage conditions). However, when FX dealers are constrained they increase liquidity costs disproportionately more relative to their market-making activities (i.e., dealer-intermediated trading volumes).

## 7. Conclusion

In this paper, we have studied how constraints on dealers' intermediation capacity affect currency market liquidity. Using a simple model and a unique data set on global FX spot trading activity, we provide a novel analytical method to identify and measure how dealer constraints affect not only the price of market liquidity, but also its relation to the quantity of liquidity. We show that during times when the dealer sector is more constrained, for instance, due to higher funding costs and/ or stricter Value-at-Risk limits, liquidity cost measures increase disproportionately more relative to equilibrium trading volumes. As a result, the otherwise strong and positive relation between liquidity costs and trading volume weakens by at least 50% relative to times when dealers are largely unconstrained. To account for changes in both liquidity demand and supply we employ a structural vector autoregression with sign restrictions and show that this result is mainly driven by a drop in the elasticity of liquidity supply rather than an increase in demand.

Our paper has implications for policymakers and academics alike. After the Global Financial Crisis erupted in 2008, policymakers have largely focused on making (FX) derivatives more stable. Regarding the FX spot market, policymakers have merely observed the ongoing changes such as the proliferation of multiple trading venues that have led to a surge in fragmentation of market liquidity.[33] Our study shows that this type of fragmentation becomes

[33]See "FX execution algorithms and market functioning," Bank for International Settlements, Report submitted by a Study Group established by the Markets Committee, October 2020.

amplified with dealer constraints, that is, exactly when high market resilience would be desirable. With respect to the academic literature, our study covers the FX spot market, which is commonly regarded as one of the most liquid financial markets in the world. We leave the study of the role of dealer constraints on the liquidity provision in other OTC markets (e.g., government bonds and OTC derivatives) to future research.

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**Online Appendix**

to accompany the paper

# "Constrained Liquidity Provision in Currency Markets"

# Appendix A. Proofs for the model

**Proposition 1.**

*Proof.* Taking the first order derivatives of $s^z$ with respect to $\eta$ and $\sigma$ we have that $s^z$ increases in both $\eta$ and $\sigma$ as follows:

$$\frac{ds^z}{d\eta} = \frac{\sigma}{(1+\eta\sigma)^2} > 0, \qquad \frac{ds^z}{d\sigma} = \frac{\eta}{(1+\eta\sigma)^2} > 0. \tag{A.1}$$

For currency pairs $x$ and $y$ we have that their bid-ask spreads $s^j$ for $j \in \{x, y\}$ increase in $\eta$, $\sigma$, and $\omega$ as follows:

$$\frac{ds^j}{d\eta} = \frac{(1-\omega)((2\pi-1)\sigma^2 - \omega T)}{\sigma(2\pi-1)(1-\omega+\eta\sigma)^2} > 0; \tag{A.2}$$

$$\frac{ds^j}{d\sigma} = \frac{\eta((1-\omega)(\sigma^2(2\pi-1)+\omega T) + 2\eta\sigma\omega T)}{\sigma^2(2\pi-1)(1-\omega+\eta\sigma)^2} > 0; \tag{A.3}$$

$$\frac{ds^j}{d\omega} = \frac{\eta((2\pi-1)\sigma^2 - (1+\eta\sigma))T)}{\sigma(2\pi-1)(1-\omega+\eta\sigma)^2} > 0, \tag{A.4}$$

where the first and third inequality come from the condition that the VaR thresholds are binding for the constrained dealers: $T/\sigma < \sigma(2\pi-1)(1-s^j) < \sigma(2\pi-1)$.

□

**Proposition 2.**

*Proof.* Dealer-intermediated volume is given by

$$VLM = \sigma(1-s^x) + \sigma(1-s^y) + \sigma(1-s^z), \tag{A.5}$$

Taking the first order derivative with respect to volatility $\sigma$ and plugging in for $s^j$, we have that

$$\frac{dVLM}{d\sigma} = 2\frac{(2\pi-1)(1-\omega)^2 - \omega\eta^2 T}{(2\pi-1)(1-\omega+\eta\sigma)^2} + \frac{1}{(1+\eta\sigma)^2}. \tag{A.6}$$

Thus, dealer-intermediated volume increases in volatility if $\omega\eta^2 T \leq (2\pi-1)(1-\omega)^2$ (since $\pi > 1/2$). Intuitively, an increase in volatility affects volume via two channels: First, trading demand increases due to a larger dispersion in fundamentals. Second, trading demand is suppressed due to the concurrent rise in the bid-ask spread. When the overall constraint of the dealer sector is less binding (i.e., $\omega\eta^2 T$ is smaller) the first channel dominates the second one. As shown in Table 3, dealer-intermediated volume increases in volatility, indicating that the parameter space of interest is indeed $\omega\eta^2 T \leq (2\pi-1)(1-\omega)^2$. Thus, for the rest of the proof, we only focus on the latter case.

Both TCOST and VLOOP increase in volatility $\sigma$ for a given level of the dealer's constraint $\eta$ and $\omega$, respectively. Specifically, an increase in volatility is associated with a rise in equilibrium volume (i.e., VLM) as well as an increase in both TCOST and VLOOP:

$$\frac{dVLM}{d\sigma} / \frac{dTCOST}{d\sigma} = \frac{2\sigma^2((2\pi-1)(1-\omega)^2 - \omega\eta^2 T)}{\eta((1-\omega)(\sigma^2(2\pi-1)+\omega T)+2\eta\sigma\omega T)}, \tag{A.7}$$

$$\frac{dVLM}{d\sigma} / \frac{dVLOOP}{d\sigma} = \frac{\sigma^2((2\pi-1)(1-\omega)^2 - \omega\eta^2 T)}{\eta(\pi-\frac{1}{2})(1-e^z)((1-\omega)(\sigma^2(2\pi-1)+\omega T)+2\eta\sigma\omega T)}. \tag{A.8}$$

where the two partial derivatives above are capturing changes in volume together with TCOST (see Eq. (A.7)) as well as changes in volume and VLOOP (see Eq. (A.8)), respectively. In essence, Eq. (A.7) and Eq. (A.8) capture how the co-movement between dealer-intermediated volume and the two liquidity cost measures changes conditional on the level of the dealer's constraint $\eta$, $\omega$, and $\sigma$, respectively.

Both ratios in Eqs (A.7) and (A.8) decrease in $\eta$, $\omega$, and $\sigma$, respectively. In other words, when the dealer sector is more constrained due to dealers facing higher debt-financing costs $\eta$, a larger share of constrained dealers $\omega$, or dealers experiencing higher VaRs because of a higher $\sigma$ dealer-intermediated volume increases less relative to liquidity costs. □

# Appendix B. Liquidity cost measures

To derive VLOOP, consider a trader exchanging one euro (EUR) to some amount of US dollar (USD), exchanging the amount of US dollar to some amount of Canadian dollar (CAD) and exchanging back the amount of Canadian dollar to euro instantaneously at time $t$. The final amount of such a round-trip transaction measured in euros is given as:

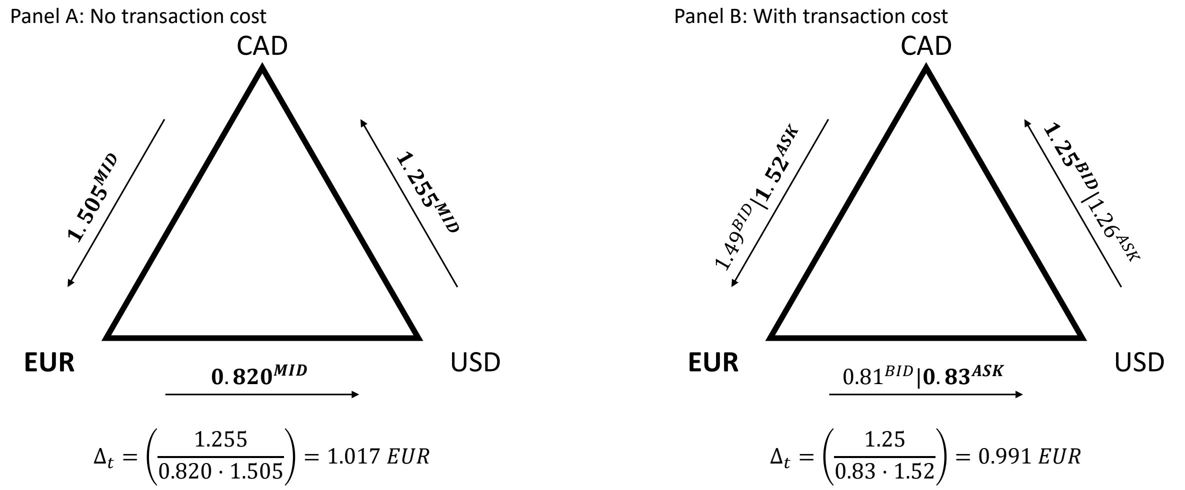
$$\Delta_t \equiv \prod_{i=1}^{3} P_{i,t}, \tag{B.1}$$

The trader has identified a violation of the law of one price if $\Delta_t$ is different from unity. Note that $\Delta_t$ may be positive or negative depending on the direction of the trade but will be identical in absolute terms (if measured in logs) irrespective of the initial endowment of the trader (i.e., CAD, EUR or USD). Clearly, an arbitrageur would take this into account by choosing the direction of the triangular no-arbitrage trade, provided that corresponding arbitrage profits can be reaped. Panel A in Figure B.1 illustrates how to measure such deviations from triangular no-arbitrage conditions based on midquote prices.

To derive TCOST, we consider the same trader as before but now incorporate transaction costs by accounting for bid-ask spreads. Specifically, for every transaction that a trader makes, they pay the midquote price plus the half-spread. To reflect this, we replace the midquote prices in Eq. (B.1) by bid and ask prices, that is, $P_{1,t} = \frac{1}{USDEUR_t^{ask}}$, $P_{2,t} = USDCAD_t^{bid}$, and

$P_{3,t} = \frac{1}{EURCAD_t^{ask}}$, respectively. The superscripts 'bid' and 'ask' refer to the price at which someone sells and buys one currency for another. Panel B in Figure B.1 provides an overview of such a triangular arbitrage trade including transactions costs. Note that the bid and ask prices in this example are illustrative and do not correspond to actual data.

Figure B.1: Triangular arbitrage trade




*Note*: This figure provides a schematic overview of a triangular arbitrage trade before and after transaction costs. The arrows denote the direction of the trade. Panel A shows the prior transaction cost return of a trader starting with one euro, first exchanging it to $\frac{1}{0.820} = 1.220$ US dollars, then exchanging 1.220 US dollars to Canadian dollars at the midquote price of 1.255 Canadian dollars per US dollar. This yields 1.531 Canadian dollars that are exchanged back to euros at the CADEUR midquote that is equivalent to $\frac{1}{EURCAD^{MID}} = \frac{1}{1.505}$. Such a round-trip yields 1.017 euros or equivalent a positive return of 1.7% in this example. Panel B shows the return of first exchanging one euro to $\frac{1}{0.83} = 1.21$ US dollars at the ask price, then exchanging 1.21 US dollars to Canadian dollars at the bid price of 1.25 Canadian dollars per US dollar. This yields 1.51 Canadian dollars that are exchanged back to euros at the CADEUR bid price that is equivalent to $\frac{1}{EURCAD^{ASK}} = \frac{1}{1.52}$. Such a round-trip yields 0.991 euros or equivalently a negative return of $-0.9\%$.

The last step in the derivation of the two liquidity cost metrics consists of taking the log on both sides of Eq. (B.1), and leveraging the fact that bid and ask prices are the midquote minus and plus half the bid-ask spread. This yields the following expression:

$$log(\Delta_t) \equiv \underbrace{log\left(\frac{USDCAD_t^{mid}}{USDEUR_t^{mid} \cdot EURCAD_t^{mid}}\right)}_{VLOOP_t} - \underbrace{log\left(\frac{\left(1 + \frac{USDEUR_t^{bas}}{2}\right) \cdot \left(1 + \frac{EURCAD_t^{bas}}{2}\right)}{1 - \frac{USDCAD_t^{bas}}{2}}\right)}_{TCOST_t}, \tag{B.2}$$

where the superscripts 'mid' and 'bas' denote the midquote price (i.e., the average of the bid and ask price) and the relative bid-ask spread (i.e., the difference between ask and bid price relative to the midquote). Note that in this expression $TCOST_t$ is by definition *positive*.

The first part of Eq. (B.2) (i.e., $VLOOP_t$) captures the violations from the law of one price.

Following the literature on intermediary asset pricing (e.g., Adrian et al., 2014; Duffie, 2018), we interpret these no-arbitrage violations as a measure of the lower bound of the shadow cost of intermediary constraints. The second part (i.e., $TCOST_t$) reflects the cumulative round-trip transaction cost of performing such a triangular arbitrage trade. These transaction costs represent the dealer's compensation to endure an inventory imbalance due to the customers' demand for immediacy. If no arbitrage holds, then $TCOST_t$ constitutes the theoretical upper bound for the shadow cost of intermediary constraints (see Eq. (B.2)).

# Appendix C. Data sources

**CLS data.** The CLS system is owned by its 72 settlement members, which include all the dealer banks listed in the Euromoney FX surveys. To protect member anonymity, CLS does not disclose any transaction-level information about settlement activity. Therefore, the CLS data set only contains hourly aggregates of the trading activity in each currency pair and provides no information about traders' identities or executed transaction prices.

The CLS FX spot volume and order flow data sets are interrelated. Volume data include the sum of all inter-dealer and dealer-to-customer trades. Order flow data contain separate entries for buying and selling activity but only for dealer-to-customer transactions. Moreover, the buy and sell volume in a given hour and currency pair refers to how much of the base currency was bought and sold by customers from dealer banks (see Somogyi, 2021).

Customers can be categorised into four groups: corporates, funds, non-bank financial firms, and non-dealer banks. "Funds" may also include principal trading firms (PTFs) such as high-frequency trading firms and electronic non-bank liquidity providers (e.g., XTX or Jump Trading). The majority of these PTFs relies on prime brokers to gain access to the FX market (Schrimpf and Sushko, 2019). Hence, if PTFs trade via a prime broker who is a CLS member, then this trade would appear as a bank-to-bank trade. Inter-bank trades are excluded from the flow (but not from the volume) data set unless one of the counterparties is classified as a non-dealer bank. See Ranaldo and Somogyi (2021) for further details on how CLS categorises market participants into customers and dealer/non-dealer banks, respectively.

**Euromoney FX survey.** Major FX dealer banks are at the heart of our composite dealer constraint measure. For each year from 2011 to 2022, we retrieve the ranking of the top 10 FX dealer banks from the Euromoney FX surveys, which are publicly available. See Table C.1 for an overview of the top 10 FX dealer banks over the sample period from 2011 to 2022. Note that this implies that we do not include any non-bank financial liquidity providers (i.e., XTX or Jump Trading), which are privately held companies. For certain variables (i.e., Value-at-Risk and number of VaR breaches) we were only able to collect data for a subset of banks. In such situations, we compute averages based on the available set of dealer bank observations listed below. What follows lists the data source for each of our dealer constraint measures used in Table 6.

- **Value-at-Risk (VaR)** is retrieved directly from the financial statements for each of the top 10 dealer banks and is based on the porfolio risk in banks' overall trading book. Hence the VaR measure captures, among others, risks related to fixed income, equities, commodities, derivatives, and foreign exchange trading positions. Note that these VaR measures are only available to us for the following 13 entities: Bank of America, Barclays, BNP Paribas, Citi Bank, Credit Suisse, Deutsche Bank, Goldman Sachs, HSBC, JP Morgan Chase, Morgan Stanley, Royal Bank of Scotland, Societe Generale, UBS. Note that these are also the banks that show up regularly in the top 10 of the Euromoney FX surveys. The frequency is quarterly.

- **Debt funding cost (DFC)** is retrieved from iBoxx for each dealer bank and corresponds to the average bond issuance cost across different maturities and major currencies (i.e., USD, EUR, and GBP). Note that conceptually our measure of debt funding costs is similar to the across-the-curve credit spread index (AXI) proposed by Berndt et al. (2023). The main difference is that our key measure of bond issuance cost is the annual yield, whereas Berndt et al. (2023) utilise credit spreads. The frequency is daily.

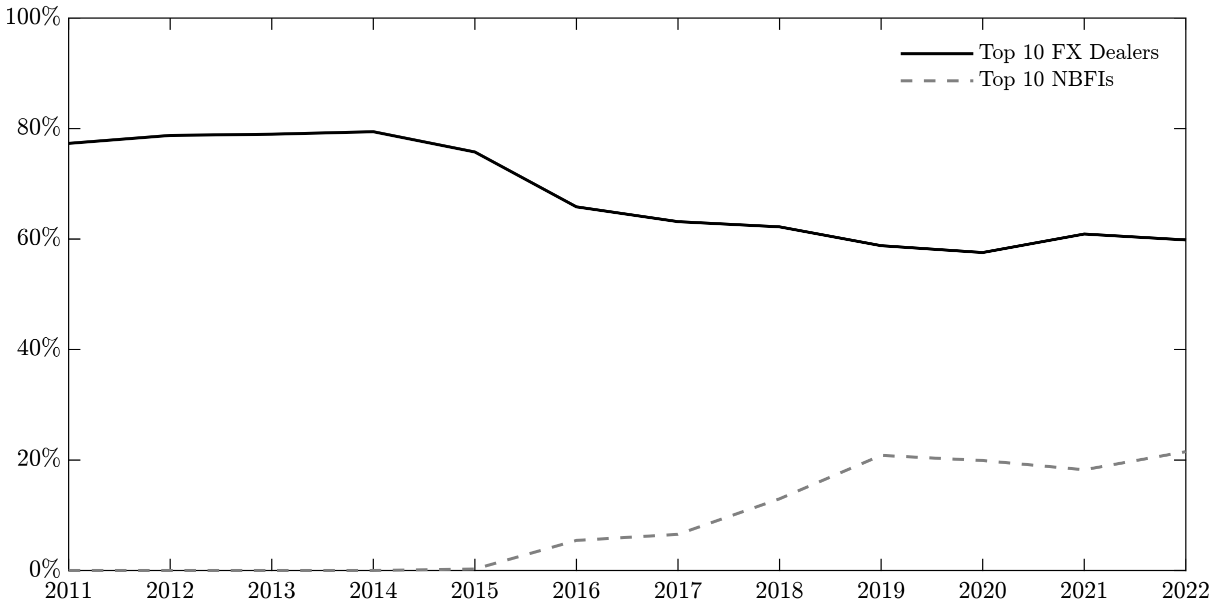
- **Number of VaR Breaches (NVB)** is calculated based on the regulatory reporting of banks that are subject to the "Market Risk Capital Rule FFIEC 102." Leveraging this regulatory reporting requirement we collect the number of breaches in any given quarter (starting from the first quarter in 2015, which is the inception of the regulation) for the following 12 entities: Bank of America, Barclays, BNP Paribas, Citi Bank, Credit Suisse, Deutsche Bank, Goldman Sachs, HSBC, JP Morgan Chase, Morgan Stanley, State Street, and UBS. Note that these are also the banks that show up regularly in the top 10 of the Euromoney FX surveys. NVB is simply computed as the average number of breaches across the twelve aforementioned banks in any given quarter. We winsorise the time series at the 3% level to taper the effect of the large spike in VaR breaches during the Covid-19 turmoil in March 2020.

- **Leverage ratio (HKM)** is computed following the work by He et al. (2017) as book debt (i.e., short plus long term debt) relative to the sum of market equity (i.e., shares outstanding times share price) and book debt that are retrieved from Bloomberg for each dealer bank. Hence, the leverage ratio is equal to one minus the capital ratio in He et al. (2017). Our implied capital ratio exhibits a correlation of 89.9% with the daily "intermediary capital ratio" published on Zhiguo He's website.[34] All our results in Table 6 are qualitatively unchanged. The frequency is quarterly.

[34]https://voices.uchicago.edu/zhiguohe/data-and-empirical-patterns/

- **Credit default spread (CDS)** with 5-year maturity is retrieved from Bloomberg for each dealer bank. The CDS premia are denominated in dollars for US banks and in euros for all Europeans banks, including the UK domiciled ones. The frequency is daily.
- **Covered interest parity deviations (CIP)** are computed using three months inter-bank rates (e.g., country specific "LIBOR" rates) as well as three months forward discounts from Bloomberg. We compute the cross-currency basis for our set of ten US dollar currency pairs by computing the difference between the inter-bank offer rates and the forward discount. To mitigate the effect of the quarter-end movements in the basis (see Du et al., 2018) we orthogonalise the basis against a quarter-end dummy, which is equal to one surrounding three days around the quarter-end. Next, we take the absolute value of the CIP basis (since some of the bases have opposing signs) and transform each basis to have mean zero and standard deviation of one. In a final step, we compute a cross-sectional average across these standardised CIP bases and smooth the time-series over three days to minimise the impact of noise.

Figure C.1: Time-series of top 10 FX dealer share




*Note*: This figure reports the market share of the top 10 FX dealer banks (e.g., Citi Bank or UBS) as well as non-bank financial liquidity providers (i.e., XTX, HC Tech or Jump Trading) for the years 2011 to 2022 from the Euromoney FX surveys.

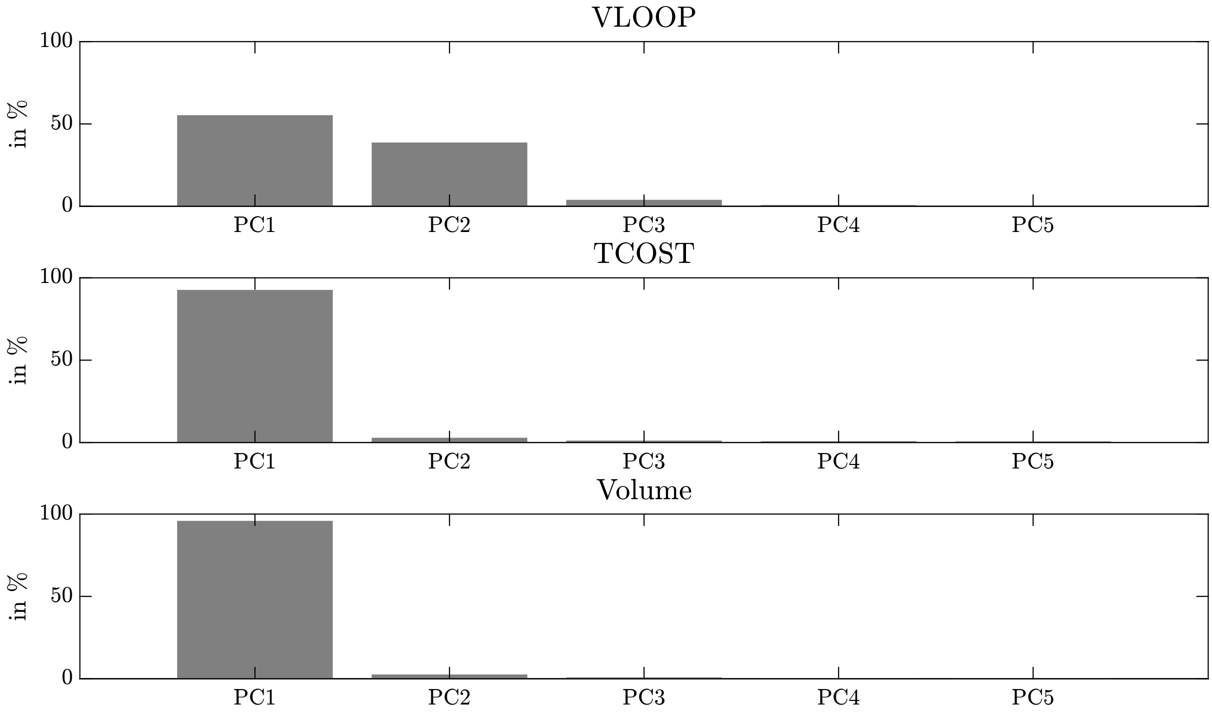
Table C.1: Top 10 FX dealer banks

| Rank | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 |
|---|---|---|---|---|---|---|
| 1 | Deutsche Bank | Deutsche Bank | Deutsche Bank | Citi Bank | Citi Bank | Citi Bank |
| 2 | Barclays | Citi Bank | Citi Bank | Deutsche Bank | Deutsche Bank | JP Morgan Chase |
| 3 | UBS | Barclays | Barclays | Barclays | Barclays | UBS |
| 4 | Citi Bank | UBS | UBS | UBS | JP Morgan Chase | Deutsche Bank |
| 5 | JP Morgan Chase | HSBC | HSBC | HSBC | UBS | Bank of America |
| 6 | HSBC | JP Morgan Chase | JP Morgan Chase | JP Morgan Chase | Bank of America | Barclays |
| 7 | Royal Bank of Scotland | Royal Bank of Scotland | Royal Bank of Scotland | Bank of America | HSBC | Goldman Sachs |
| 8 | Credit Suisse | Credit Suisse | Credit Suisse | Royal Bank of Scotland | BNP Paribas | HSBC |
| 9 | Goldman Sachs | Morgan Stanley | Morgan Stanley | BNP Paribas | Goldman Sachs | Morgan Stanley |
| 10 | Morgan Stanley | Goldman Sachs | Bank of America | Goldman Sachs | Royal Bank of Scotland | BNP Paribas |
| Rank | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 |
| 1 | Citi Bank | JP Morgan Chase | JP Morgan Chase | JP Morgan Chase | JP Morgan Chase | Deutsche Bank |
| 2 | JP Morgan Chase | UBS | Deutsche Bank | UBS | UBS | UBS |
| 3 | UBS | Bank of America | Citi Bank | Deutsche Bank | Deutsche Bank | JP Morgan Chase |
| 4 | Bank of America | Citi Bank | UBS | Citi Bank | Citi | State Street |
| 5 | Deutsche Bank | HSBC | State Street | HSBC | Goldman Sachs | Citi |
| 6 | HSBC | Goldman Sachs | HSBC | Goldman Sachs | Bank of America | BNY Mellon |
| 7 | Barclays | Deutsche Bank | Bank of America | State Street | State Street | Bank of America |
| 8 | Goldman Sachs | Standard Chartered | Goldman Sachs | Bank of America | HSBC | Goldman Sachs |
| 9 | Standard Chartered | State Street | Barclays | BNP Paribas | Morgan Stanley | BNP Paribas |
| 10 | BNP Paribas | Barclays | BNP Paribas | Barclays | BNP Paribas | Morgan Stanley |

*Note*: This table reports the ranking of the top 10 FX dealer banks for the years 2011 to 2022 from the Euromoney FX surveys. Note that this ranking only includes banks and excludes any non-bank financial liquidity providers (i.e., XTX, HC Tech or Jump Trading), which are privately held companies.

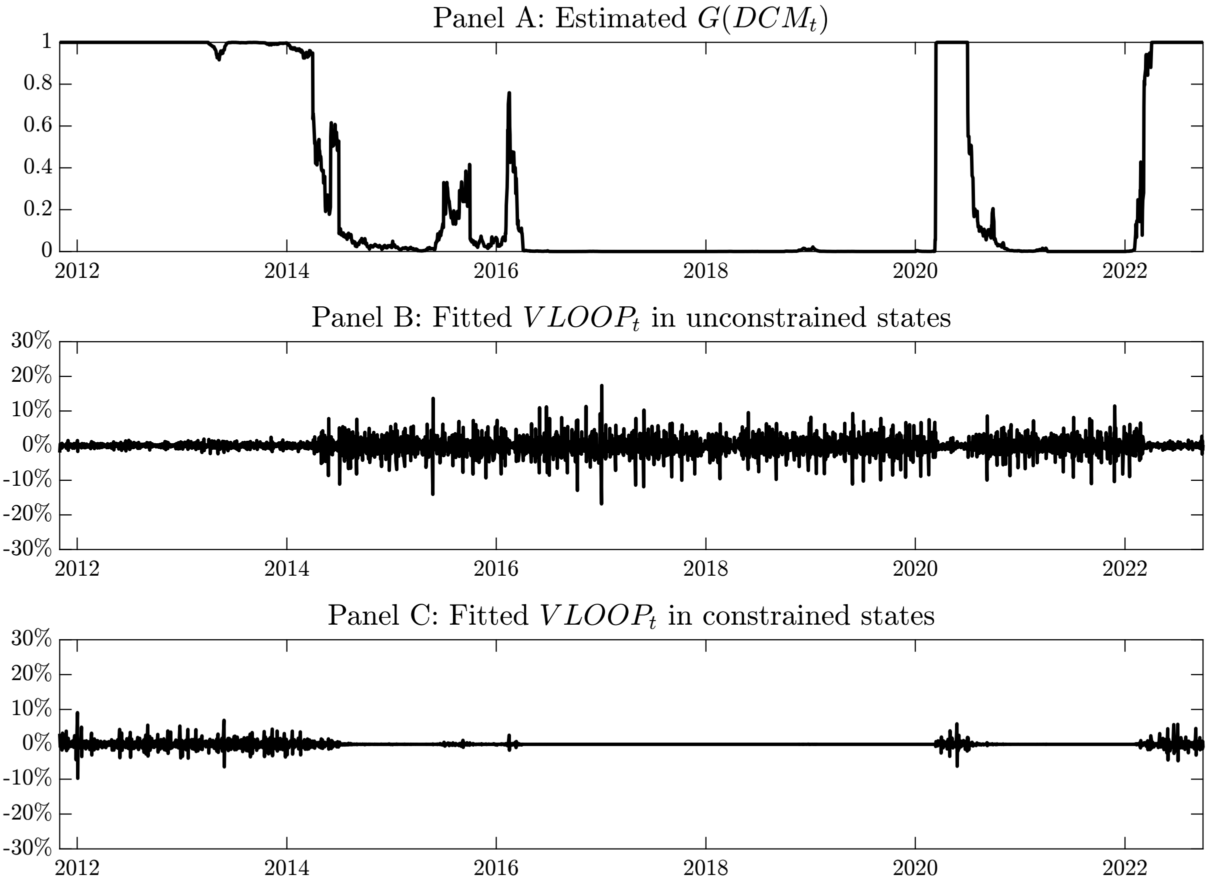
# Appendix D. Estimating a panel LSTAR model

Figure D.1: Principal component analysis



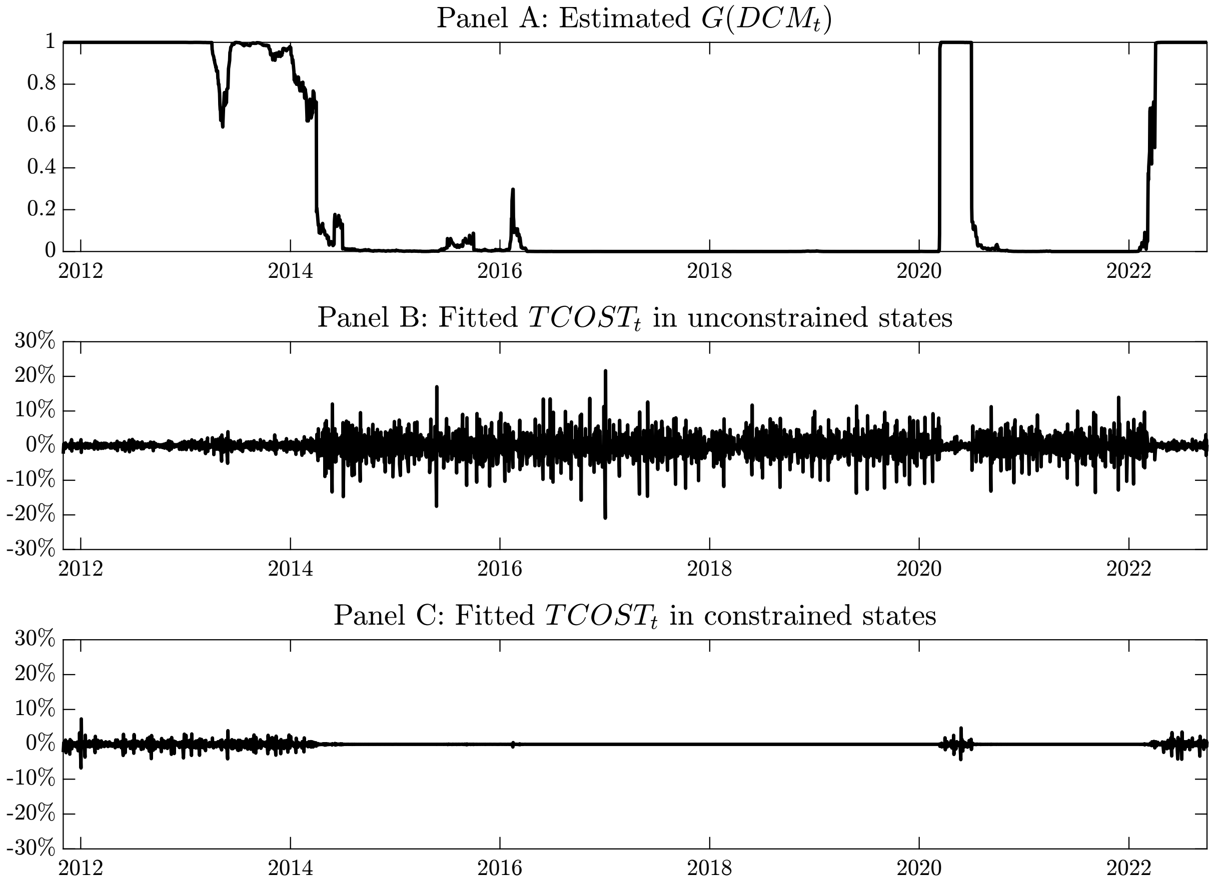

*Note*: This figure plots the share of variation (in %) across currency pair triplets explained by the first 5 principal components (PCs). The top two figures are based on our two liquidity cost measures (i.e., VLOOP or TCOST), whereas the bottom figure is based on total trading volume. The sample covers the period from 1 November 2011 to 30 September 2022.

Figure D.2: Time-series of fitted $G(\text{DCM})$ and VLOOP




*Note*: Panel A of this figure shows the fitted regime function $G(DCM_t)$, using the point estimates in column 3 of Table 4. Panel B shows the cross-sectional average of the part of the fitted log changes in $VLOOP_t$ that is driven by unconstrained state coefficients ($[1 - G(z_{t-1})]\beta_1' f_t$). Panel C shows the cross-sectional average of the part driven by the constrained state coefficients ($G(z_{t-1})\beta_2' f_t$). By construction, the fitted values for log changes in $TCOST_t$ are the sum of Panels B and C. The sample covers the period from 1 November 2011 to 30 September 2022.

Figure D.3: Time-series of fitted $G$(DCM) and TCOST




*Note*: Panel A of this figure shows the fitted regime function $G(DCM_t)$, using the point estimates in column 6 of Table 4. Panel B shows the cross-sectional average of the part of the fitted log changes in $TCOST_t$ that is driven by unconstrained state coefficients ($[1 - G(z_{t-1})]\beta_1' f_t$). Panel C shows the cross-sectional average of the part driven by the constrained state coefficients ($G(z_{t-1})\beta_2' f_t$). By construction, the fitted values for log changes in $TCOST_t$ are the sum of Panels B and C. The sample covers the period from 1 November 2011 to 30 September 2022.

Here we document several additional robustness results: i) estimate the LSTAR currency pair triplet by triplet, ii) split volume into inter-bank and customer-bank trades, iii) perform a subsample analysis, iv) account for potential bias in the bid-ask spread, v) relax time-series fixed effects, vi) use non-dealer specific state variables, vii) vary the number of lags in the LSTAR model, viii) focus on the main London stock market trading hours, and ix) employ euro-based currency pair triplets. Table 4 presents our baseline result.

**LSTAR estimates currency pair triplet by triplet.** Thus far, we have mainly focused on the time-series dimension of the relation between trading volume and the cost of liquidity provision but have not delved deeper into the cross-section of currency pair triplets. To explore the cross-sectional heterogeneity, we estimate the LSTAR model individually for 15 triplets. We further contrast the result with a simple linear model that does not distinguish between constrained and unconstrained regimes (see Tables D.1 and D.2 in the Online Appendix).

In particular, Panel A shows the results from estimating a linear model (OLS) of the form

$$PIM_{k,t} = \alpha_k + \beta_k\, VLM_{k,t} + \eta_k\, RV_{k,t} + \epsilon_{k,t}, \tag{D.1}$$

where $VLM_{k,t}$ is the total trading volume within each currency pair triplet $k$ and $RV_{k,t}$ the realised variance in the non-dollar currency pair. In Panel B the same table shows results based on the LSTAR model in Eq. (22), where the regime variable is again the 1-day lagged value of the dealer constraint measure $DCM_t$. As before, both dependent and independent variables are taken in logs and changes to support the interpretation of the regression coefficients as percentage point changes (or, equivalently, elasticities).

The currency pair triplet by triplet estimates strongly support the idea that intermediary constraints nonlinearly impact the relation between dealer-intermediated volume and the cost of liquidity provision. In particular, the difference between the parameter estimates of constrained and unconstrained regimes (i.e., $\beta_2 - \beta_1$) is significantly negative for 5 and 6 out of 15 triplets of currency pairs for VLOOP and TCOST, respectively. In line with this finding, the $R^2$s of these regressions are rather close to the linear model. This is entirely expected, given that the coefficient with respect to trading volume in constrained regimes is close to zero. In sum, both results are consistent with the idea that in calm periods dealers' liquidity provision is elastic supporting FX market liquidity, however it becomes more inelastic when dealer constraints are tightening.

**Inter-bank vs customer-bank volumes.** We decompose trading volume into inter-bank and customer-bank volume to better understand which market segments suffer the most from reduced liquidity provision when dealer constraints tighten. Specifically, the CLS customer-bank order flow data comprise three groups of non-bank customers, that is, corporates, funds,

## Table D.1: Linear model and smooth transition regression for VLOOP with DCM as state variable

| **Panel A: OLS** | AUDJPY | AUDNZD | CADJPY | EURAUD | EURCAD | EURCHF | EURDKK | EURGBP | EURJPY | EURNOK | EURSEK | GBPAUD | GBPCAD | GBPCHF | GBPJPY |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept ($\alpha$) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | [0.20] | [0.02] | [0.27] | [0.01] | [0.02] | [0.05] | [0.01] | [0.01] | [0.31] | [0.01] | [0.08] | [0.02] | [0.03] | [0.14] | [0.13] |
| Volume | ***0.20 | ***0.08 | 0.02 | ***0.11 | 0.01 | −0.01 | 0.02 | ***0.07 | ***0.17 | ***0.06 | 0.03 | ***0.11 | ***−0.08 | ***0.09 | ***0.17 |
| | [4.87] | [3.54] | [0.59] | [4.82] | [0.18] | [0.67] | [1.22] | [3.57] | [4.10] | [3.27] | [1.31] | [3.98] | [3.14] | [3.89] | [5.05] |
| Realised variance | ***0.08 | ***0.09 | ***0.07 | ***0.06 | 0.03 | ***0.06 | ***0.09 | ***0.06 | ***0.08 | ***0.09 | ***0.11 | ***0.05 | ***0.08 | ***0.09 | ***0.11 |
| | [3.19] | [7.16] | [3.16] | [2.89] | [1.32] | [4.78] | [5.44] | [4.23] | [2.94] | [6.38] | [8.85] | [2.99] | [4.11] | [6.41] | [4.50] |
| **Panel B: LSTAR** | AUDJPY | AUDNZD | CADJPY | EURAUD | EURCAD | EURCHF | EURDKK | EURGBP | EURJPY | EURNOK | EURSEK | GBPAUD | GBPCAD | GBPCHF | GBPJPY |
| $\gamma$ | 2.03 | 12.00 | 12.00 | 12.00 | 2.78 | 12.00 | 12.00 | 2.26 | 1.00 | 12.00 | 1.25 | 2.44 | 12.00 | 12.00 | 1.00 |
| $c$ | 1.75 | −0.29 | −0.44 | 1.45 | −1.75 | −1.16 | −0.86 | −0.15 | 1.75 | 1.27 | 1.75 | 1.75 | 0.16 | −0.62 | 1.75 |
| Unconstrained volume | ***0.23 | 0.05 | −0.06 | ***0.12 | −1.31 | **−0.23 | 0.06 | 0.14 | **0.23 | ***0.09 | 0.07 | ***0.13 | −0.05 | **0.12 | **0.23 |
| | [5.05] | [1.44] | [1.21] | [4.69] | [0.38] | [2.41] | [1.25] | [1.22] | [2.00] | [3.73] | [0.73] | [4.10] | [1.41] | [2.29] | [2.53] |
| Constrained volume | 0.01 | *0.11 | *0.09 | 0.00 | 0.08 | 0.01 | 0.01 | −0.01 | −0.09 | −0.08 | *−0.20 | −0.04 | ***−0.14 | ***0.07 | −0.06 |
| | [0.02] | [1.76] | [1.70] | [0.00] | [1.20] | [0.52] | [0.31] | [0.26] | [0.42] | [1.58] | [1.73] | [0.45] | [2.58] | [2.73] | [0.58] |
| Intercept ($\alpha$) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | [0.22] | [0.02] | [0.37] | [0.01] | [0.02] | [0.07] | [0.01] | [0.01] | [0.38] | [0.01] | [0.11] | [0.03] | [0.04] | [0.17] | [0.16] |
| Realised variance | ***0.08 | ***0.09 | ***0.07 | **0.06 | 0.03 | ***0.06 | ***0.09 | ***0.06 | ***0.08 | ***0.09 | ***0.11 | **0.05 | ***0.07 | ***0.09 | ***0.10 |
| | [2.85] | [6.72] | [3.01] | [2.40] | [1.14] | [4.25] | [5.02] | [3.66] | [2.64] | [5.88] | [7.92] | [2.40] | [3.42] | [5.79] | [4.48] |
| Constrained-Unconstrained | −0.22 | 0.06 | **0.15 | *−0.12 | 1.39 | **0.24 | −0.06 | −0.15 | −0.31 | ***−0.16 | ***−0.27 | **−0.16 | −0.09 | −0.04 | *−0.30 |
| | [0.51] | [0.75] | [2.39] | [1.65] | [0.41] | [2.49] | [0.83] | [1.19] | [1.04] | [3.01] | [2.88] | [1.98] | [1.38] | [0.86] | [1.85] |
| Adj. $R^2$ in % - OLS | 3.69 | 3.04 | 0.43 | 2.26 | 0.03 | 0.99 | 3.69 | 2.50 | 3.60 | 2.29 | 3.07 | 2.72 | 0.46 | 4.08 | 6.21 |
| Adj. $R^2$ in % - LSTAR | 3.83 | 3.08 | 0.59 | 2.37 | 0.35 | 1.29 | 3.71 | 2.81 | 3.84 | 2.54 | 3.39 | 2.93 | 0.50 | 4.09 | 6.54 |
| #Obs | 2,787 | 2,801 | 2,785 | 2,801 | 2,801 | 2,799 | 2,799 | 2,801 | 2,781 | 2,801 | 2,799 | 2,801 | 2,801 | 2,799 | 2,781 |

*Note*: In Panel A this table reports results from estimating a linear model (OLS) of the form $VLOOP_{k,t} = \alpha_k + \beta_1' v_{k,t} + beta_3' w_{k,t} + \epsilon_{k,t}$, where $v_{k,t}$ collects all regressors. In Panel B the table shows results from a smooth transition regression (LSTAR) of the form $VLOOP_{k,t} = \alpha_k + [1 - G(z_{t-1})]\beta_1' f_{k,t} + G(z_{t-1})\beta_2' f_{k,t} + \beta_3' w_{k,t} + \varepsilon_{k,t}$, where $f_{k,t}$ ($w_{k,t}$) are state-dependent (*state-independent*) regressors and $G(z_{t-1})$ is a logistic function depending on the state variable $z_{t-1}$. The regime variable is the 1-day lagged value of the dealer constraint measure $DCM_t$. The optimal parameters $\gamma$ and $c$ are determined by nonlinear least squares minimising the concentrated sum of squared errors. Both dependent and independent variables are taken in logs and changes. The sample covers the period from 1 November 2011 to 30 September 2022. The test statistics based on robust standard errors (using the plug-in procedure for automatic lag selection by Andrews and Monahan (1992) and Newey and West (1994)) are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% levels.

# Table D.2: Linear model and smooth transition regression for TCOST with DCM as state variable

| **Panel A: OLS** | AUDJPY | AUDNZD | CADJPY | EURAUD | EURCAD | EURCHF | EURDKK | EURGBP | EURJPY | EURNOK | EURSEK | GBPAUD | GBPCAD | GBPCHF | GBPJPY |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept ($\alpha$) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | [0.05] | [0.07] | [0.03] | [0.04] | [0.06] | [0.06] | [0.02] | [0.03] | [0.04] | [0.02] | [0.04] | [0.06] | [0.07] | [0.07] | [0.04] |
| Volume | ***0.09 | ***0.09 | ***0.07 | ***0.07 | ***0.05 | ***0.07 | ***0.08 | ***0.05 | ***0.10 | **0.02 | ***0.03 | ***0.05 | ***0.03 | **0.03 | ***0.08 |
| | [5.64] | [10.49] | [5.78] | [6.88] | [5.51] | [6.88] | [10.62] | [5.63] | [7.42] | [2.49] | [4.04] | [3.82] | [2.89] | [2.19] | [4.26] |
| Realised variance | ***0.07 | ***0.06 | ***0.07 | ***0.08 | ***0.05 | ***0.05 | ***0.04 | ***0.06 | ***0.07 | ***0.07 | ***0.06 | ***0.08 | ***0.04 | ***0.08 | ***0.06 |
| | [6.12] | [8.54] | [7.29] | [8.72] | [5.52] | [3.55] | [9.66] | [5.57] | [4.85] | [8.48] | [12.50] | [6.19] | [3.24] | [5.12] | [3.42] |
| **Panel B: LSTAR** | AUDJPY | AUDNZD | CADJPY | EURAUD | EURCAD | EURCHF | EURDKK | EURGBP | EURJPY | EURNOK | EURSEK | GBPAUD | GBPCAD | GBPCHF | GBPJPY |
| $\gamma$ | 1.15 | 12.00 | 12.00 | 2.05 | 12.00 | 12.00 | 12.00 | 12.00 | 1.00 | 12.00 | 12.00 | 12.00 | 12.00 | 12.00 | 4.25 |
| $c$ | 1.75 | 0.79 | 0.16 | 1.75 | −0.49 | −0.92 | −1.75 | −0.49 | 1.75 | 1.75 | 1.75 | −0.47 | −0.48 | −0.36 | 1.75 |
| Unconstrained volume | 0.12 | ***0.11 | ***0.08 | ***0.08 | ***0.04 | ***0.08 | −12.17 | *0.03 | **0.13 | **0.03 | ***0.04 | 0.02 | 0.00 | 0.01 | ***0.09 |
| | [1.35] | [9.15] | [4.51] | [6.50] | [2.58] | [3.33] | [0.36] | [1.75] | [2.28] | [2.52] | [4.00] | [1.06] | [0.10] | [0.51] | [3.62] |
| Constrained volume | −0.02 | **0.04 | **0.03 | −0.02 | ***0.07 | ***0.06 | ***0.09 | ***0.08 | −0.04 | −0.03 | −0.02 | ***0.07 | ***0.06 | ***0.05 | −0.01 |
| | [0.33] | [1.97] | [2.41] | [0.07] | [4.42] | [5.45] | [9.02] | [4.64] | [0.62] | [1.25] | [1.00] | [3.93] | [4.07] | [3.21] | [0.03] |
| Intercept ($\alpha$) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | [0.08] | [0.11] | [0.06] | [0.07] | [0.06] | [0.08] | [0.04] | [0.03] | [0.07] | [0.03] | [0.05] | [0.07] | [0.08] | [0.09] | [0.04] |
| Realised variance | ***0.07 | ***0.06 | ***0.07 | ***0.08 | ***0.05 | ***0.05 | ***0.04 | ***0.06 | ***0.07 | ***0.07 | ***0.06 | ***0.08 | ***0.04 | ***0.08 | ***0.06 |
| | [4.80] | [7.29] | [5.78] | [7.56] | [4.74] | [3.41] | [9.03] | [4.52] | [3.96] | [7.71] | [10.83] | [5.25] | [2.85] | [4.68] | [2.65] |
| Constrained-Unconstrained | *−0.14 | ***−0.06 | **−0.05 | −0.09 | 0.03 | −0.02 | 12.26 | *0.05 | *−0.17 | **−0.06 | **−0.06 | 0.04 | ***0.06 | *0.04 | −0.10 |
| | [1.72] | [2.62] | [2.48] | [0.40] | [1.64] | [0.62] | [0.36] | [1.81] | [1.76] | [2.06] | [2.29] | [1.54] | [2.66] | [1.83] | [0.37] |
| Adj. $R^2$ in % - OLS | 17.75 | 13.35 | 14.50 | 14.02 | 8.34 | 11.38 | 10.21 | 10.08 | 17.90 | 8.06 | 8.05 | 10.89 | 3.41 | 10.32 | 11.82 |
| Adj. $R^2$ in % - LSTAR | 18.41 | 13.64 | 14.82 | 14.40 | 8.47 | 11.38 | 10.31 | 10.34 | 18.64 | 8.20 | 8.22 | 11.08 | 3.85 | 10.51 | 12.26 |
| #Obs | 2,801 | 2,801 | 2,794 | 2,801 | 2,801 | 2,801 | 2,801 | 2801, | 2801, | 280,1 | 280,1 | 2801 | 2801 | 2801 | 2793 |

*Note*: In Panel A this table reports results from estimating a linear model (OLS) of the form $TCOST_{k,t} = \alpha_k + \beta_1' v_{k,t} + beta_3' w_{k,t} + \epsilon_{k,t}$, where $v_{k,t}$ collects all regressors. In Panel B the table shows results from a smooth transition regression (LSTAR) of the form $TCOST_{k,t} = \alpha_k + [1 - G(z_{t-1})]\beta_1' f_{k,t} + G(z_{t-1})\beta_2' f_{k,t} + \beta_3' w_{k,t} + \varepsilon_{k,t}$, where $f_{k,t}$ ($w_{k,t}$) are state-dependent (*state-independent*) regressors and $G(z_{t-1})$ is a logistic function depending on the state variable $z_{t-1}$. The regime variable is the 1-day lagged value of the dealer constraint measure $DCM_t$. The optimal parameters $\gamma$ and $c$ are determined by nonlinear least squares minimising the concentrated sum of squared errors. Both dependent and independent variables are taken in logs and changes. The sample covers the period from 1 November 2011 to 30 September 2022. The test statistics based on robust standard errors (using the plug-in procedure for automatic lag selection by Andrews and Monahan (1992) and Newey and West (1994)) are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% levels.

and non-bank financials.[35] Note that bilateral trades between two such customer groups are quasi non-existent given the two-tier structure of the FX market (Chaboud, Rime, and Sushko, 2023) and hence also do not form part of the data that CLS provides. As a result, the customer-bank data only contains trades that pass through an FX dealer bank (e.g., Citi Bank or UBS). Moreover, the inter-bank data include trades between two banks that are members of the CLS system. Some of these banks are GSIBs, whereas others include lower-tier banks outside of the main dealer community (e.g., Danske Bank or Commerzbank).

Table D.3 reports the results of estimating the LSTAR model in Eq. (22) based on inter-bank and customer-bank volume rather than total volume. To be precise, we define total volume in each client group as the sum of buy and sell volume in a given currency pair. There is an interesting picture that arises: On the one hand, the coefficients related to unconstrained volume of the inter-bank segment are higher than those of the customer-bank segment suggesting a more elastic liquidity provision in the former. On the other hand, the co-movement between liquidity costs and trading volume weakens significantly with dealer constraints for both inter- and customer-bank trading activity. However, the economic magnitudes of the constrained minus unconstrained coefficients suggest that large dealer banks mainly curtail their liquidity provision in trades with other banks. Of course, this does not rule out the possibility that dealers charge higher spreads to their customers in order to dampen additional trading demands when they are more constrained.

**Non-bank liquidity providers.** To shed some light on the importance of non-bank liquidity providers (e.g., XTX, HC Tech or Jump Trading) we split our sample period into two halves. The first half concerns the time period from November 2011 until December 2016, whereas the second half runs from January 2017 to September 2022. Our sample split is motivated by the fact that XTX enters the top 10 of the Euromoney FX surveys for the first time in 2016. Table D.4 documents the same regression specifications as in our baseline in Eq. (22) except for the time periods being different. The key takeaway from comparing the constrained minus unconstrained coefficients across the first and second half of the sample is that the economic magnitudes of the coefficients are almost twice as large for the first half than for the second half. We interpret this as suggestive evidence in favour of the idea that non-bank liquidity providers are much less affected by our dealer constraint measure and are hence able to provide additional liquidity when dealer banks are more constrained.[36]

**Bias in the bid-ask spread.** Hagströmer (2021) shows that the effective bid-ask spread measured relative to the spread midpoint overstates the true bid-ask spread in markets with discrete prices and elastic liquidity demand (e.g., the currency market). To address this issue,

[35]See Cespa et al. (2021) and Ranaldo and Somogyi (2021) for a detailed description of the CLS flow data set.

[36]Ideally, we would be able to directly identify non-bank liquidity providers in our data set. However, this is not possible because the CLS volume and order flow data do not contain any information about traders' identities.

Table D.3: Smooth transition regression with different counterparty groups

| | VLOOP | | | | TCOST | | | |
|---|---|---|---|---|---|---|---|---|
| | Non-bank | Non-bank | Bank | Bank | Non-bank | Non-bank | Bank | Bank |
| $\gamma$ | *12.00 | *12.00 | ***12.00 | ***12.00 | 12.00 | 12.00 | ***12.00 | ***12.00 |
| c | ***0.50 | ***0.50 | −0.05 | −0.05 | ***0.31 | ***0.27 | ***0.14 | ***0.13 |
| Unconstr. volume | **0.03 | **0.03 | ***0.10 | ***0.08 | ***0.03 | ***0.02 | ***0.12 | ***0.09 |
| | [2.51] | [2.19] | [3.80] | [2.91] | [6.78] | [5.49] | [15.47] | [11.60] |
| Constr. volume | *−0.04 | *−0.04 | −0.03 | −0.05 | 0.01 | 0.00 | ***0.05 | *0.03 |
| | [1.74] | [1.89] | [0.71] | [1.17] | [1.26] | [0.61] | [3.06] | [1.74] |
| Realised variance | | ***0.03 | | ***0.02 | | ***0.03 | | ***0.03 |
| | | [3.39] | | [2.79] | | [10.53] | | [8.24] |
| Constr.-Unconstr. | ***−0.07 | ***−0.07 | ***−0.13 | **−0.12 | **−0.02 | **−0.02 | ***−0.06 | ***−0.06 |
| | [2.63] | [2.63] | [2.59] | [2.53] | [2.12] | [2.18] | [3.22] | [2.93] |
| $R^2$ in % | 0.05 | 0.13 | 0.09 | 0.14 | 0.48 | 2.55 | 2.42 | 3.55 |
| Avg. #Time periods | 2,580 | 2,580 | 2,580 | 2,580 | 2,585 | 2,584 | 2,585 | 2,584 |
| #Currency triplets | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 |
| Currency triplet FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Time-series FE | yes | yes | yes | yes | yes | yes | yes | yes |

*Note*: This table reports results from daily fixed effects LSTAR panel regressions of the form $y_{k,t} = \lambda_t + \alpha_k + [1 - G(z_{t-1})]\beta_1' f_{k,t} + G(z_{t-1})\beta_2' f_{k,t} + \beta_3' w_{k,t} + \varepsilon_{k,t}$, where the dependent variable $y_{k,t}$ is a liquidity cost measure (i.e., *VLOOP* or *TCOST*), $f_{k,t}$ ($w_{k,t}$) are state-dependent (*state-independent*) regressors, and $G(z_{t-1})$ is a logistic function depending on the regime variable $z_{t-1}$. The regime variable is the 1-day lagged value of the dealer constraint measure $DCM_t$. The optimal parameters $\gamma$ and $c$ are determined by nonlinear least squares minimising the concentrated sum of squared errors. The row 'Constr. - Unconstr.' reports the difference between the slope coefficient on constrained and unconstrained volume, respectively. Both dependent and independent variables are taken in logs and changes. The sample covers the period from 1 September 2012 to 30 September 2022. The test statistics based on Driscoll and Kraay (1998) robust standard errors allowing for random clustering and serial correlation (using the plug-in procedure for automatic lag selection by Newey and West, 1994) are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% levels.

we compute both no-arbitrage violations VLOOP and round-trip transaction costs TCOST using the "weighted midpoint" (i.e., $m^{wp}$) as an alternative measure of the midquote price:

$$m^{wp} = \frac{b \times q^{buys} + a \times q^{sells}}{q^{buys} + q^{sells}}, \tag{D.2}$$

where $b$ and $a$ are bid and ask prices, respectively, whereas $q^{buys}$ and $q^{sells}$ are the buy and sell volume in a given currency pair. Table D.10 shows the results of estimating the same regression specifications as in our baseline in Eq. (22), but using $m^{wp}$ instead of the spread midpoint $m$ to compute VLOOP and TCOST. The difference between the constrained and unconstrained coefficient on intermediated-trading volume is negative and economically significant for both VLOOP and TCOST across all specifications. Thus, we conclude that our findings are not affected by any potential bias in the quoted bid-ask spread in the Olsen data.

**Relaxing time-series fixed effects.** Here we provide support in favour of using time-series fixed effects in our main regression specification. This is because the lagged dealer constraint measure in Table D.6 is insignificant in a regression without time-series fixed effects.

Table D.4: Sample split: Smooth transition regression with DCM as state variable

| | 11/2011 – 12/2016 | | | | 01/2017 – 09/2020 | | | |
|---|---|---|---|---|---|---|---|---|
| | VLOOP | | TCOST | | VLOOP | | TCOST | |
| $\gamma$ | ***12.00 | ***12.00 | ***12.00 | ***12.00 | ***12.00 | 12.00 | ***12.00 | ***12.00 |
| c | ***−0.21 | ***−0.21 | ***−0.50 | ***−0.50 | ***−0.37 | 0.50 | ***−0.41 | ***−0.41 |
| Unconstr. volume | ***0.17 | ***0.15 | **0.08 | 0.06 | ***0.10 | ***0.10 | ***0.12 | ***0.10 |
| | [4.08] | [3.58] | [1.99] | [1.47] | [6.23] | [9.56] | [9.76] | [8.05] |
| Constr. volume | *0.06 | 0.03 | **−0.10 | **−0.11 | ***0.13 | ***0.09 | ***0.04 | **0.02 |
| | [1.70] | [0.92] | [2.25] | [2.48] | [10.87] | [3.11] | [3.82] | [2.02] |
| Realised variance | | ***0.03 | | 0.02 | | ***0.03 | | ***0.02 |
| | | [2.85] | | [1.57] | | [7.18] | | [4.67] |
| Constr.-Unconstr. | **−0.11 | **−0.11 | ***−0.18 | ***−0.17 | 0.03 | 0.00 | ***−0.08 | ***−0.07 |
| | [1.98] | [2.12] | [2.88] | [2.81] | [1.45] | [0.11] | [4.78] | [4.41] |
| $R^2$ in % | 0.17 | 0.25 | 0.10 | 0.12 | 2.59 | 3.67 | 2.26 | 3.16 |
| Avg. #Time periods | 1472 | 1472 | 1324 | 1324 | 1475 | 1474 | 1325 | 1325 |
| #Currency triplets | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 |
| Currency triplet FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Time-series FE | yes | yes | yes | yes | yes | yes | yes | yes |

*Note*: This table reports results from daily fixed effects LSTAR panel regressions of the form $y_{k,t} = \lambda_t + \alpha_k + [1 - G(z_{t-1})]\beta_1' f_{k,t} + G(z_{t-1})\beta_2' f_{k,t} + \beta_3' w_{k,t} + \varepsilon_{k,t}$, where the dependent variable $y_{k,t}$ is a liquidity cost measure (i.e., $VLOOP$ or $TCOST$), $f_{k,t}$ ($w_{k,t}$) are state-dependent (*state-independent*) regressors, and $G(z_{t-1})$ is a logistic function depending on the state variable $z_{t-1}$. The regime variable is the 1-day lagged value of the dealer constraint measure $DCM_t$. The optimal parameters $\gamma$ and $c$ are determined by nonlinear least squares minimising the concentrated sum of squared errors. The row 'Constr. - Unconstr.' reports the difference between the slope coefficient on constrained and unconstrained volume, respectively. Both dependent and independent variables are taken in logs and changes. The sample covers the period from 1 November 2011 to 30 September 2022. The test statistics based on Driscoll and Kraay (1998) robust standard errors allowing for random clustering and serial correlation (using the plug-in procedure for automatic lag selection by Andrews and Monahan (1992) and Newey and West (1994)) are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% levels.

**Weight banks by market share.** Table D.7 shows that our findings are robust to weighting each top 10 FX dealer bank (from the Euromoney FX survey) by its relative market share when computing a cross-sectional average for Value-at-Risk (VaR), debt funding costs, and the number of VaR breaches.

**Non-dealer specific state variables.** One might wonder how much our results are driven by market-wide state factors that are not dealer specific and which are potentially also more related to liquidity demand rather than supply. To address this question, we conduct a placebo exercise in Table D.8 where we explore a set of non-dealer specific regime variables that are presumably more exposed to liquidity demand and broad market conditions. In particular, we consider the VIX index, the TED spread, the price of gold, and the LIBOR-OIS spread as alternative regime variables. We find that these state variables do not appropriately capture dealer constraints because the relation between liquidity costs and volume is not state-dependent.

Table D.5: Weighted midpoint: Smooth transition regression with DCM as state variable

| | VLOOP | | | TCOST | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\gamma$ | ***4.79 | ***4.76 | ***4.76 | ***12.00 | ***12.00 | ***12.00 |
| c | ***−0.50 | ***−0.50 | ***−0.50 | ***0.18 | ***0.18 | ***0.17 |
| Unconstr. volume | ***0.07 | ***0.07 | ***0.08 | ***0.13 | ***0.12 | ***0.12 |
| | [2.90] | [2.93] | [2.94] | [14.03] | [13.30] | [11.85] |
| Constr. volume | −0.01 | −0.01 | 0.00 | ***0.07 | ***0.07 | ***0.06 |
| | [0.29] | [0.26] | [0.08] | [3.85] | [3.61] | [3.21] |
| Amihud (2002) | | 0.00 | | | *−0.01 | |
| | | [0.22] | | | [1.70] | |
| Realised variance | | | −0.01 | | | ***0.01 |
| | | | [0.94] | | | [3.13] |
| Constr.-Unconstr. | **−0.08 | **−0.08 | **−0.08 | ***−0.06 | ***−0.06 | ***−0.06 |
| | [2.07] | [2.07] | [2.07] | [2.76] | [2.76] | [2.64] |
| $R^2$ in % | 0.04 | 0.04 | 0.05 | 1.35 | 1.37 | 1.47 |
| Avg. #Time periods | 2,583 | 2583 | 2583 | 2585 | 2585 | 2584 |
| #Currency triplets | 15 | 15 | 15 | 15 | 15 | 15 |
| Currency triplet FE | yes | yes | yes | yes | yes | yes |
| Time-series FE | yes | yes | yes | yes | yes | yes |

*Note*: This table reports results from daily fixed effects LSTAR panel regressions of the form $y_{k,t} = \lambda_t + \alpha_k + [1 - G(z_{t-1})]\beta_1' f_{k,t} + G(z_{t-1})\beta_2' f_{k,t} + \beta_3' w_{k,t} + \varepsilon_{k,t}$, where the dependent variable $y_{k,t}$ is a liquidity cost measure (i.e., $VLOOP$ or $TCOST$) computed based on the weighted midquote price (Hagströmer, 2021), $f_{k,t}$ ($w_{k,t}$) are state-dependent (*state-independent*) regressors, and $G(z_{t-1})$ is a logistic function depending on the state variable $z_{t-1}$. The regime variable is the 1-day lagged value of the dealer constraint measure $DCM_t$. The optimal parameters $\gamma$ and $c$ are determined by nonlinear least squares minimising the concentrated sum of squared errors. The row 'Constr. - Unconstr.' reports the difference between the slope coefficient on constrained and unconstrained volume, respectively. Both dependent and independent variables are taken in logs and changes. The sample covers the period from 1 September 2012 to 30 September 2022. The test statistics based on Driscoll and Kraay (1998) robust standard errors allowing for random clustering and serial correlation (using the plug-in procedure for automatic lag selection by Andrews and Monahan, 1992; Newey and West, 1994) are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% levels.

**Number of lags in state variable.** In Figure D.4 we show that our findings are robust to using up to 90 lags and are hence not driven by the fact that some of the DCM constituents are measured at the quarterly frequency (i.e., Value-at-Risk (VaR) and number of VaR breaches). This exercise also provides evidence in favour of the idea that dealer constraints have a lasting (i.e., persistent) adverse effect on FX liquidity provision.

**Focus on main London trading hours.** Table D.9 shows that our findings are robust to omitting any observations outside of the main London stock market trading hours (i.e., from 8 am to 6 pm GMT) when aggregating hourly to daily data.

**Cross-section of euro triplets.** We have also constructed triplets of euro-based currency pairs that do not involve any dollar currency pairs (e.g., AUD-EUR-JPY). This leaves us with

Table D.6: From linear model with dummies to smooth transition regressions

| | VLOOP | | | TCOST | | |
|---|---|---|---|---|---|---|
| | Dummy | Logistic | LSTAR | Dummy | Logistic | LSTAR |
| $\gamma$ | | 1.00 | 1.00 | | 1.00 | 5.99 |
| c | | | 0.50 | | | 0.50 |
| Unconstr. volume | **0.05 | ***0.14 | ***0.10 | ***0.09 | ***0.13 | ***0.07 |
| | [2.20] | [2.98] | [3.57] | [12.45] | [7.69] | [6.27] |
| Constr. volume | 0.00 | −0.08 | 0.00 | ***0.04 | 0.02 | ***0.04 |
| | [0.10] | [1.59] | [0.10] | [2.63] | [1.02] | [3.35] |
| Realised variance | ***0.02 | ***0.02 | ***0.08 | ***0.02 | ***0.02 | ***0.06 |
| | [3.20] | [3.17] | [10.94] | [8.84] | [8.83] | [7.02] |
| Lagged $DCM_t$ | −0.03 | −0.03 | 0.00 | 0.00 | 0.00 | 0.00 |
| | [0.08] | [0.07] | [0.36] | [0.02] | [0.02] | [0.40] |
| Constr.-Unconstr. | −0.05 | **−0.21 | −0.09 | ***−0.05 | ***−0.11 | −0.02 |
| | [1.31] | [2.49] | [0.45] | [3.18] | [3.25] | [1.21] |
| $R^2$ in % | 0.11 | 0.13 | 1.94 | 3.39 | 3.40 | 10.83 |
| Avg. #Time periods | 2,795 | 2,795 | 2,796 | 2,799 | 2,799 | 2,800 |
| #Currency triplets | 15 | 15 | 15 | 15 | 15 | 15 |
| Currency triplet FE | yes | yes | yes | yes | yes | yes |
| Time-series FE | no | no | no | no | no | no |

*Note*: In columns labelled 'Dummy' and 'Logistic' this table reports results from estimating a linear model (OLS) of the form $y_{k,t} = \alpha_k + \beta_1' f_{k,t} + \delta' f_{k,t} \cdot D_{t-1} + \beta_3' w_{k,t} + \beta_4' D_{t-1} + \epsilon_{k,t}$, where the dependent variable $y_{k,t}$ is a liquidity cost measure (i.e., $VLOOP$ or $TCOST$), $f_{k,t}$ and $w_{k,t}$ collect all regressors and $D_{t-1}$ is a 1-day lagged interaction variable capturing distressed market periods. Note that the estimate of $\delta$ corresponds to the difference between the constrained and unconstrained regime coefficient (i.e., $\beta_2 - \beta_1$) in column 'LSTAR'. In column 'Dummy', $D_t$ is equal to one if $DCM_t$ is above its 75% percentile in period $t$. In column 'Logistic', $D_t$ is a logistic transformation of $DCM_t$ based on $1/[1 + exp(-\gamma DCM_t)]$, where $\gamma$ determines the steepness of the function. In column 'LSTAR' the table shows results from a smooth transition regression (LSTAR) of the form $y_{k,t} = \lambda_t + \alpha_k + [1 - G(z_{t-1})]\beta_1' f_{k,t} + G(z_{t-1})\beta_2' f_{k,t} + \beta_3' w_{k,t} + \beta_4' D_{t-1} + \varepsilon_{k,t}$, where $f_{k,t}$ ($w_{k,t}$) are state-dependent (*state-independent*) regressors and $G(z_{t-1})$ is a logistic function depending on the state variable $z_{t-1}$. The regime variable is the 1-day lagged value of $DCM_t$. The optimal parameters $\gamma$ and $c$ are determined by nonlinear least squares minimising the concentrated sum of squared errors. The row 'Constrained - Unconstrained' reports the difference between the slope coefficient on constrained and unconstrained volume, respectively. Both dependent and independent variables are taken in logs and changes. The sample covers the period from 1 November 2011 to 30 September 2022. The test statistics based on Driscoll and Kraay (1998) robust standard errors (using the plug-in procedure for automatic lag selection by Andrews and Monahan (1992) and Newey and West (1994)) are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% levels.

6 currency pair triplets: AUD-EUR-JPY, CAD-EUR-JPY, GBP-EUR-AUD, GBP-EUR-CAD, GBP-EUR-CHF, and GBP-EUR-JPY, respectively. Table D.10 buttresses that all our key empirical results remain qualitatively unchanged when estimated based on this alternative cross-section of currency pair triplets.

Table D.7: Smooth transition regression with different state variables using market shares

| | VLOOP | | | | | | TCOST | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | VaR | DFC | NVB | HKM | CDS | CIP | VaR | DFC | NVB | HKM | CDS | CIP |
| $\gamma$ | **12.00 | ***12.00 | ***12.00 | ***2.52 | ***6.21 | ***1.21 | ***12.00 | ***1.07 | ***2.19 | ***2.34 | ***4.23 | ***2.58 |
| c | ***0.31 | ***−0.26 | ***0.32 | ***0.50 | ***0.13 | ***0.50 | ***0.50 | ***−0.35 | ***0.50 | ***0.50 | ***0.04 | ***0.50 |
| Unconstr. volume | ***0.08 | ***0.13 | ***0.12 | ***0.10 | ***0.08 | ***0.14 | ***0.10 | ***0.17 | ***0.09 | ***0.11 | ***0.11 | ***0.09 |
| | [3.16] | [4.04] | [3.09] | [3.70] | [3.16] | [2.90] | [12.13] | [6.93] | [5.44] | [11.74] | [12.53] | [10.30] |
| Constr. volume | −0.05 | −0.03 | −0.04 | **−0.09 | *−0.06 | *−0.14 | ***0.04 | 0.01 | ***0.12 | 0.02 | 0.02 | **0.04 |
| | [1.41] | [1.01] | [0.65] | [2.03] | [1.68] | [1.82] | [2.98] | [0.38] | [3.22] | [1.49] | [1.03] | [2.05] |
| Realised variance | ***0.02 | ***0.02 | **0.02 | ***0.02 | ***0.02 | ***0.02 | ***0.02 | ***0.03 | ***0.03 | ***0.02 | ***0.02 | ***0.03 |
| | [3.15] | [3.28] | [2.15] | [3.19] | [3.21] | [3.20] | [8.84] | [8.93] | [5.23] | [8.87] | [8.90] | [8.91] |
| Constr.-Unconstr. | ***−0.12 | ***−0.16 | **−0.16 | ***−0.19 | ***−0.14 | **−0.28 | ***−0.06 | ***−0.16 | 0.03 | ***−0.09 | ***−0.10 | **−0.06 |
| | [2.99] | [3.61] | [2.09] | [3.29] | [3.01] | [2.34] | [4.19] | [3.76] | [0.69] | [5.03] | [5.10] | [2.35] |
| $R^2$ in % | 0.14 | 0.16 | 0.28 | 0.15 | 0.14 | 0.12 | 3.41 | 3.44 | 3.56 | 3.45 | 3.52 | 3.33 |
| BIC | 94.08 | 94.07 | 88.67 | 94.08 | 94.08 | 94.08 | 52.57 | 52.57 | 49.43 | 52.56 | 52.55 | 52.58 |
| Avg. #Time periods | 2,796 | 2,796 | 1,985 | 2,796 | 2,796 | 2,796 | 2,800 | 2,800 | 1,988 | 2,800 | 2,800 | 2,800 |
| #Currency triplets | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 |
| Currency triplet FE | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes |
| Time-series FE | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes |

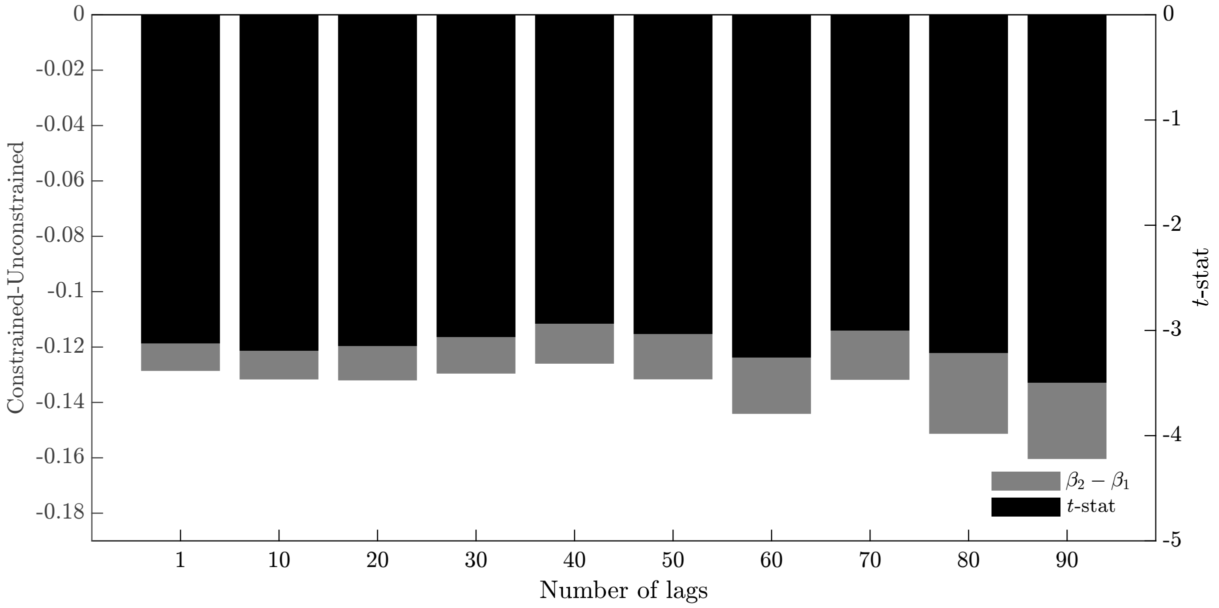
*Note*: This table reports results from daily fixed effects LSTAR panel regressions of the form $y_{k,t} = \lambda_t + \alpha_k + [1 - G(z_{t-1})]\beta_1' f_{k,t} + G(z_{t-1})\beta_2' f_{k,t} + \beta_3' w_{k,t} + \varepsilon_{k,t}$, where the dependent variable $y_{k,t}$ is a liquidity cost measure (i.e., *VLOOP* or *TCOST*), $f_{k,t}$ ($w_{k,t}$) are state-dependent (*state-independent*) regressors and $G(z_{t-1})$ is a logistic function depending on the regime variable $z_{t-1}$. The regime variables are the 1-day lagged values of primary FX dealer banks': quarterly Value-at-Risk measure (VaR, columns 1 and 7), daily funding cost yield (DFC, columns 2 and 8), number of VaR breaches per quarter (NVB, columns 3 and 9), quarterly He et al. (2017) leverage ratio (HKM, columns 4 and 10), daily credit default spread (CDS, columns 5 and 11), and daily average CIP basis in US dollar currency pairs (CIP, columns 6 and 12). Note that we weight each top 10 FX dealer bank (based on the Euromoney FX survey) by its relative market share when computing a cross-sectional average. The optimal parameters $\gamma$ and $c$ are determined by nonlinear least squares minimising the concentrated sum of squared errors. The row 'Constr. - Unconstr.' reports the difference between the slope coefficient on constrained and unconstrained volume, respectively. Both dependent and independent variables are taken in logs and changes. The sample covers the period from 1 November 2011 to 30 September 2022. The test statistics based on Driscoll and Kraay (1998) robust standard errors allowing for random clustering and serial correlation (using the plug-in procedure for automatic lag selection by Andrews and Monahan, 1992; Newey and West, 1994) are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% levels.

Table D.8: Smooth transition regression with non-dealer specific state variables

| | VLOOP | | | | TCOST | | | |
|---|---|---|---|---|---|---|---|---|
| | VIX | XAU | TED | LOIS | VIX | XAU | TED | LOIS |
| $\gamma$ | 12.00 | 12.00 | ***12.00 | 12.00 | **12.00 | 12.00 | *12.00 | 3.80 |
| c | ***−0.37 | ***−0.50 | ***−0.26 | **−0.48 | **−0.12 | −0.43 | ***−0.50 | **−0.50 |
| Unconstr. volume | 0.03 | *0.05 | 0.00 | −0.01 | ***0.07 | ***0.08 | ***0.09 | ***0.07 |
| | [0.82] | [1.74] | [0.05] | [0.17] | [8.82] | [9.40] | [7.22] | [3.35] |
| Constr. volume | **0.05 | 0.02 | **0.08 | 0.05 | ***0.09 | ***0.08 | ***0.07 | ***0.06 |
| | [1.97] | [0.89] | [2.44] | [0.84] | [7.58] | [7.16] | [9.06] | [3.89] |
| Realised variance | ***0.02 | ***0.02 | ***0.02 | *0.02 | ***0.03 | ***0.03 | ***0.03 | ***0.03 |
| | [3.25] | [3.21] | [3.23] | [1.90] | [8.95] | [8.93] | [9.03] | [5.63] |
| Constr.-Unconstr. | 0.02 | −0.03 | *0.08 | 0.06 | 0.02 | 0.00 | −0.02 | −0.01 |
| | [0.54] | [0.70] | [1.87] | [0.77] | [1.23] | [0.15] | [1.08] | [0.41] |
| $R^2$ in % | 0.10 | 0.10 | 0.12 | 0.09 | 3.31 | 3.29 | 3.30 | 3.78 |
| BIC | 94.08 | 94.08 | 94.08 | 87.85 | 52.59 | 52.59 | 52.59 | 43.16 |
| Avg. #Time periods | 2,796 | 2,796 | 2,796 | 1,857 | 2,800 | 2,800 | 2,800 | 1,859 |
| #Currency triplets | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 |
| Currency triplet FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Time-series FE | yes | yes | yes | yes | yes | yes | yes | yes |

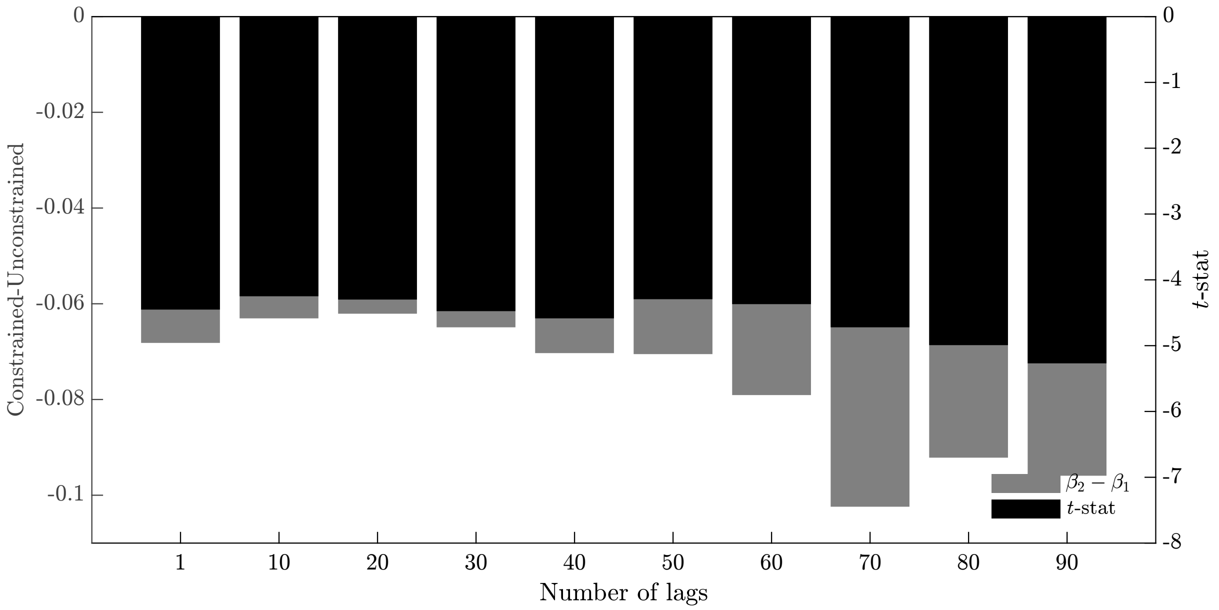
*Note*: This table reports results from daily fixed effects LSTAR panel regressions of the form $y_{k,t} = \lambda_t + \alpha_k + [1 - G(z_{t-1})]\beta_1' f_{k,t} + G(z_{t-1})\beta_2' f_{k,t} + \beta_3' w_{k,t} + \varepsilon_{k,t}$, where the dependent variable $y_{k,t}$ is a liquidity cost measure (i.e., $VLOOP$ or $TCOST$), $f_{k,t}$ ($w_{k,t}$) are state-dependent (*state-independent*) regressors and $G(z_{t-1})$ is a logistic function depending on the regime variable $z_{t-1}$. The regime variables are the 1-day lagged value of the $VIX$ index, which is the CBOE's volatility index measuring the stock market's expectation of volatility based on S&P 500 index options; the gold price (i.e., $XAU$); the $TED$ spread, which is the difference between the interest rates for three-month U.S. Treasuries contracts and the three-month Eurodollars contract; and the LIBOR-OIS spread (i.e., $LOIS$), which is considered to be measuring the health of the banking system. The optimal parameters $\gamma$ and $c$ are determined by nonlinear least squares minimising the concentrated sum of squared errors. The row 'Constr. - Unconstr.' reports the difference between the slope coefficient on constrained and unconstrained volume, respectively. Both dependent and independent variables are taken in logs and changes. The sample covers the period from 1 November 2011 to 30 September 2022. The test statistics based on Driscoll and Kraay (1998) robust standard errors allowing for random clustering and serial correlation (using the plug-in procedure for automatic lag selection by Andrews and Monahan (1992) and Newey and West (1994)) are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% levels.

Figure D.4: VLOOP: Constrained–Unconstrained coefficient and $t$-stat




*Note*: This figure plots the difference between the constrained and unconstrained regime coefficient (i.e., $\beta_2 - \beta_1$) of the LSTAR model in Eq. (22) with VLOOP being the dependent variable and conditional on varying the number of lags in the regime variable $DCM_{t-n}$ for $n = 1, 10, ..., 90$. The sample covers the period from 1 November 2011 to 30 September 2022.

Figure D.5: Constrained–Unconstrained coefficient and $t$-stat




*Note*: This figure plots the difference between the constrained and unconstrained regime coefficient (i.e., $\beta_2 - \beta_1$) of the LSTAR model in Eq. (22) with TCOST being the dependent variable and conditional on varying the number of lags in the regime variable $DCM_{t-n}$ for $n = 1, 10, ..., 90$. The sample covers the period from 1 November 2011 to 30 September 2022.

Table D.9: London hours: Smooth transition regression with DCM as state variable

| | VLOOP | | | TCOST | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\gamma$ | **12.00 | **12.00 | **12.00 | ***12.00 | ***12.00 | ***12.00 |
| c | 0.08 | 0.07 | 0.07 | ***0.16 | ***0.16 | ***0.15 |
| Unconstr. volume | ***0.11 | ***0.12 | **0.07 | ***0.13 | ***0.13 | ***0.09 |
| | [4.61] | [4.77] | [2.52] | [13.74] | [13.61] | [9.40] |
| Constr. volume | 0.02 | 0.02 | −0.02 | ***0.05 | ***0.05 | 0.02 |
| | [0.48] | [0.62] | [0.57] | [3.20] | [3.27] | [1.24] |
| Amihud (2002) | | 0.01 | | | 0.00 | |
| | | [1.40] | | | [1.52] | |
| Realised variance | | | ***0.05 | | | ***0.04 |
| | | | [5.57] | | | [7.71] |
| Constr.-Unconstr. | **−0.10 | **−0.10 | **−0.09 | ***−0.08 | ***−0.08 | ***−0.07 |
| | [2.22] | [2.23] | [1.97] | [4.34] | [4.33] | [3.75] |
| $R^2$ in % | 0.10 | 0.11 | 0.28 | 1.86 | 1.87 | 3.32 |
| Avg. #Time periods | 2,786 | 2,786 | 2,786 | 2,801 | 2,801 | 2,800 |
| #Currency triplets | 15 | 15 | 15 | 15 | 15 | 15 |
| Currency triplet FE | yes | yes | yes | yes | yes | yes |
| Time-series FE | yes | yes | yes | yes | yes | yes |

*Note*: This table reports results from daily fixed effects LSTAR panel regressions of the form $y_{k,t} = \lambda_t + \alpha_k + [1 - G(z_{t-1})]\beta_1' f_{k,t} + G(z_{t-1})\beta_2' f_{k,t} + \beta_3' w_{k,t} + \varepsilon_{k,t}$, where the dependent variable $y_{k,t}$ is a liquidity cost measure (i.e., $VLOOP$ or $TCOST$), $f_{k,t}$ ($w_{k,t}$) are state-dependent (*state-independent*) regressors, and $G(z_{t-1})$ is a logistic function depending on the regime variable $z_{t-1}$. The regime variable is the 1-day lagged value of the dealer constraint measure $DCM_t$. The optimal parameters $\gamma$ and $c$ are determined by nonlinear least squares minimising the concentrated sum of squared errors. Both dependent and independent variables are taken in logs and changes. When aggregating hourly to daily data we omit any observations outside of the main London stock market trading hours (i.e., from 8 am to 6 pm GMT). The sample covers the period from 1 November 2011 to 30 September 2022. The test statistics based on Driscoll and Kraay (1998) robust standard errors allowing for random clustering and serial correlation (using the plug-in procedure for automatic lag selection by Andrews and Monahan (1992) and Newey and West (1994)) are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% levels.

Table D.10: Smooth transition regression with DCM as state variable (euro triplets)

| | VLOOP | | | TCOST | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\gamma$ | ***3.48 | ***3.38 | ***3.40 | ***12.00 | ***12.00 | ***12.00 |
| c | ***0.50 | ***0.48 | ***0.50 | 0.06 | 0.05 | 0.06 |
| Unconstr. volume | ***0.14 | ***0.15 | ***0.12 | ***0.08 | ***0.08 | ***0.07 |
| | [4.29] | [4.52] | [3.59] | [10.01] | [10.07] | [7.27] |
| Constr. volume | 0.04 | 0.06 | 0.03 | ***0.04 | ***0.04 | **0.03 |
| | [0.71] | [0.96] | [0.47] | [3.77] | [3.91] | [2.20] |
| Amihud (2002) | | **0.02 | | | 0.00 | |
| | | [2.12] | | | [1.62] | |
| Realised variance | | | 0.02 | | | ***0.02 |
| | | | [1.32] | | | [3.32] |
| Constr.-Unconstr. | −0.10 | −0.10 | −0.09 | ***−0.04 | ***−0.04 | ***−0.04 |
| | [1.36] | [1.36] | [1.32] | [3.15] | [3.16] | [2.97] |
| $R^2$ in % | 0.33 | 0.38 | 0.37 | 1.92 | 1.96 | 2.47 |
| Avg. #Time periods | 2,792 | 2,792 | 2,792 | 2,801 | 2,801 | 2,798 |
| #Currency triplets | 6 | 6 | 6 | 6 | 6 | 6 |
| Currency triplet FE | yes | yes | yes | yes | yes | yes |
| Time-series FE | yes | yes | yes | yes | yes | yes |

*Note*: This table reports results from daily fixed effects LSTAR panel regressions of the form $y_{k,t} = \lambda_t + \alpha_k + [1 - G(z_{t-1})]\beta_1' f_{k,t} + G(z_{t-1})\beta_2' f_{k,t} + \beta_3' w_{k,t} + \varepsilon_{k,t}$, where the dependent variable $y_{k,t}$ is a liquidity cost measure (i.e., $VLOOP$ or $TCOST$), $f_{k,t}$ ($w_{k,t}$) are state-dependent (*state-independent*) regressors, and $G(z_{t-1})$ is a logistic function depending on the state variable $z_{t-1}$. The regime variable is the 1-day lagged value of the dealer constraint measure $DCM_t$. The optimal parameters $\gamma$ and $c$ are determined by nonlinear least squares minimising the concentrated sum of squared errors. Both dependent and independent variables are taken in logs and changes. The sample consists of 6 euro-based currency pair triplets that do not involve any dollar currency pairs (i.e., AUD-EUR-JPY, CAD-EUR-JPY, GBP-EUR-AUD, GBP-EUR-CAD, GBP-EUR-CHF, and GBP-EUR-JPY) and covers the period from 1 November 2011 to 30 September 2022. The test statistics based on Driscoll and Kraay (1998) robust standard errors allowing for random clustering and serial correlation (using the plug-in procedure for automatic lag selection by Andrews and Monahan (1992) and Newey and West (1994)) are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% levels.

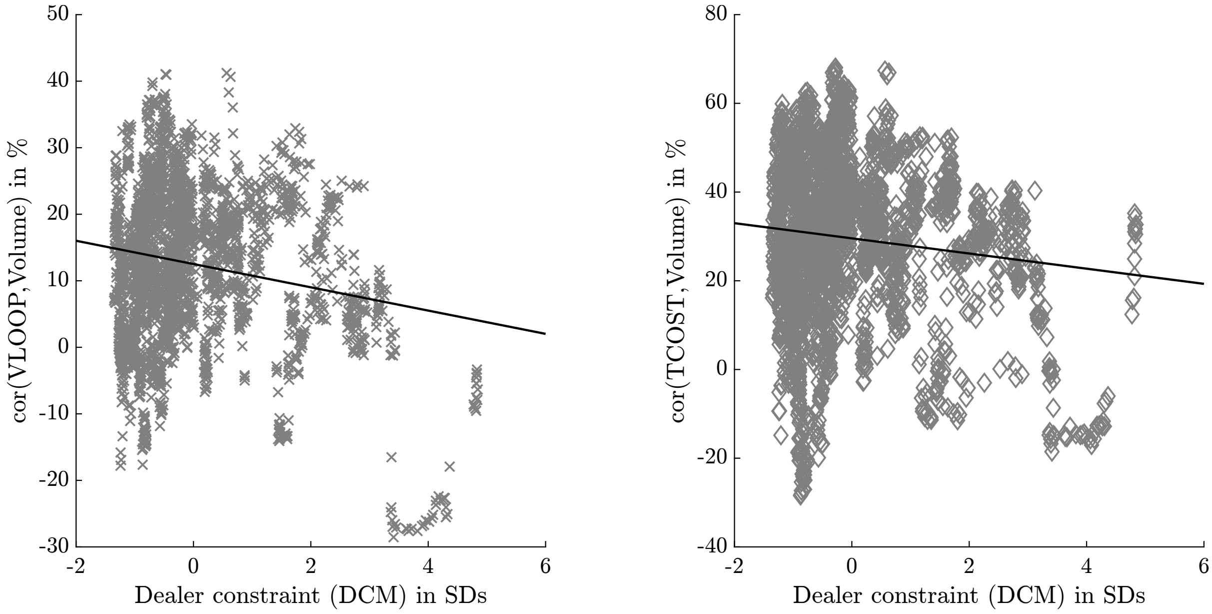
# Appendix E. Estimating an SVAR with sign restrictions

To identify supply and demand shifts, we estimate Eqs (23) and (24) imposing the sign restrictions in Eq. (25) using Bayesian methods. Specifically, we follow the approach of Uhlig (2005) and others, which has become widely used to estimate models with sign restrictions. Both the liquidity cost measure (i.e., VLOOP or TCOST) and dealer-intermediated volume enter in log levels. Consider the reduced-form SVAR in Eq. (23) with parameters $B_k = [B_{k,1}, ..., B_{k,l}]$ and covariance matrix $\Sigma_k$ for currency pair triplet $k$. We use a weak Normal-Wishart prior over these parameters. The lag length $l$ is determined according to the Akaike Information Criterion and is equal to 2 in our baseline estimation. The parameters of the panel SVAR are $B_k$, $\Sigma_k$, and $A_k$, where $A_k$ is the mapping from the liquidity supply and demand shifts $\delta_{k,t}$ to the reduced-form residual $\xi_{k,t}$ given by $\xi_{k,t} = A_k \delta_{k,t}$. The ultimate aim is to draw from the posterior distribution of $\delta_{k,t}$. Hence, we first draw from the posterior distribution over $B_k$ and $\Sigma_k$. By definition, $A_k$ has to satisfy $A_k A_k^T = \Sigma_k$. Specifically, we draw $A_k$ by using Cholesky factorisation: $\Sigma_k = chol(\Sigma_k) chol(\Sigma_k)^T$. Next, we draw orthonormal matrices $Q_k$ uniformly from the unit circle and compute $A_k = chol(\Sigma_k) Q_k$. If the resulting $A_k$ satisfies the sign restrictions in Eq. (25) over 2 periods then we keep the draw and discard it otherwise. When implementing this estimation procedure we make 500 draws over $B_k$ and $\Sigma_k$ and, for each $B_k$ and $\Sigma_k$, 500 draws over $Q_k$. Eventually, the liquidity supply and demand shift proxies are normalised to have mean zero and standard deviation equal to one.

Figure E.1 presents a scatter plot of the average 30-day rolling window correlation between each of our two liquidity cost measures (i.e., VLOOP and TCOST) and total dealer-intermediated trading volume against our dealer constraint measure DCM. For ease of illustration, we show the cross-sectional average of these rolling window correlations across 15 triplets of currency pairs. There are two key takeaways from this figure: First, both dimensions of liquidity costs (i.e., VLOOP and TCOST) covary positively on average with dealer-intermediated trading volume. Second, the correlation between the cost of liquidity provision (i.e., VLOOP and TCOST) and trading volume weakens substantially as DCM increases.

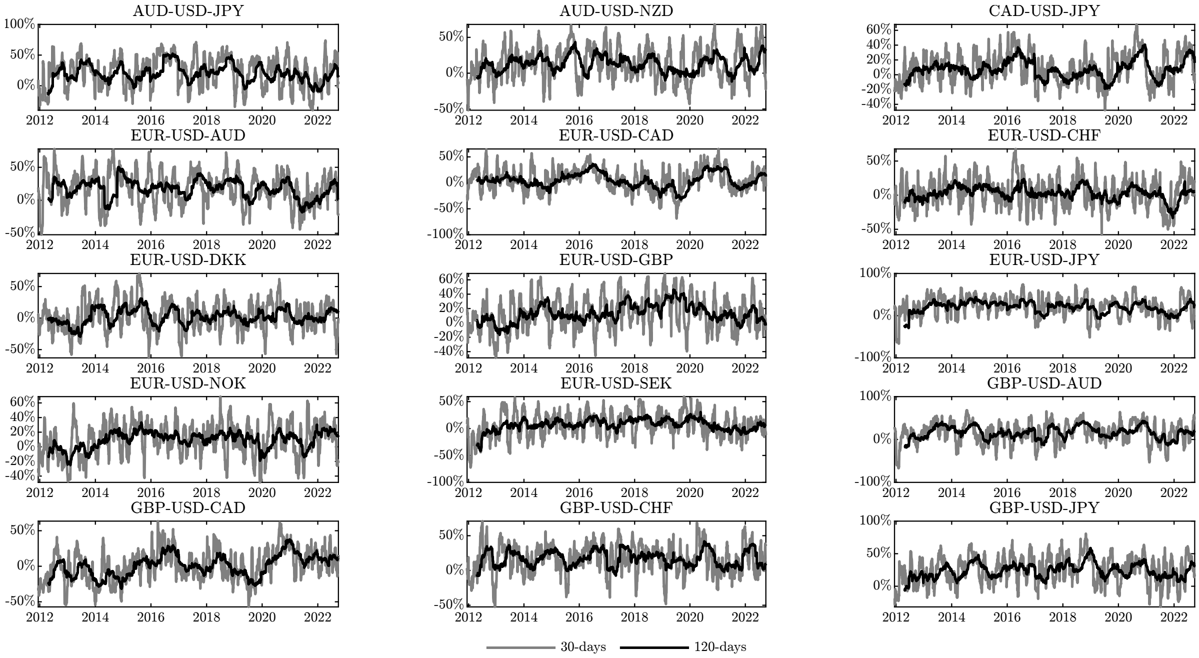
Figures E.2 and E.3 plot the rolling correlation between each of our two liquidity cost measures (i.e., VLOOP or TCOST) and dealer-provided volumes. It is easy to see that the strong positive association between liquidity costs and trading volume breaks down during the Covid-19 market turmoil in March and April 2020 across all 15 currency pair triplets.

Figure E.1: Rolling correlations of liquidity costs and volumes vs dealer constraints



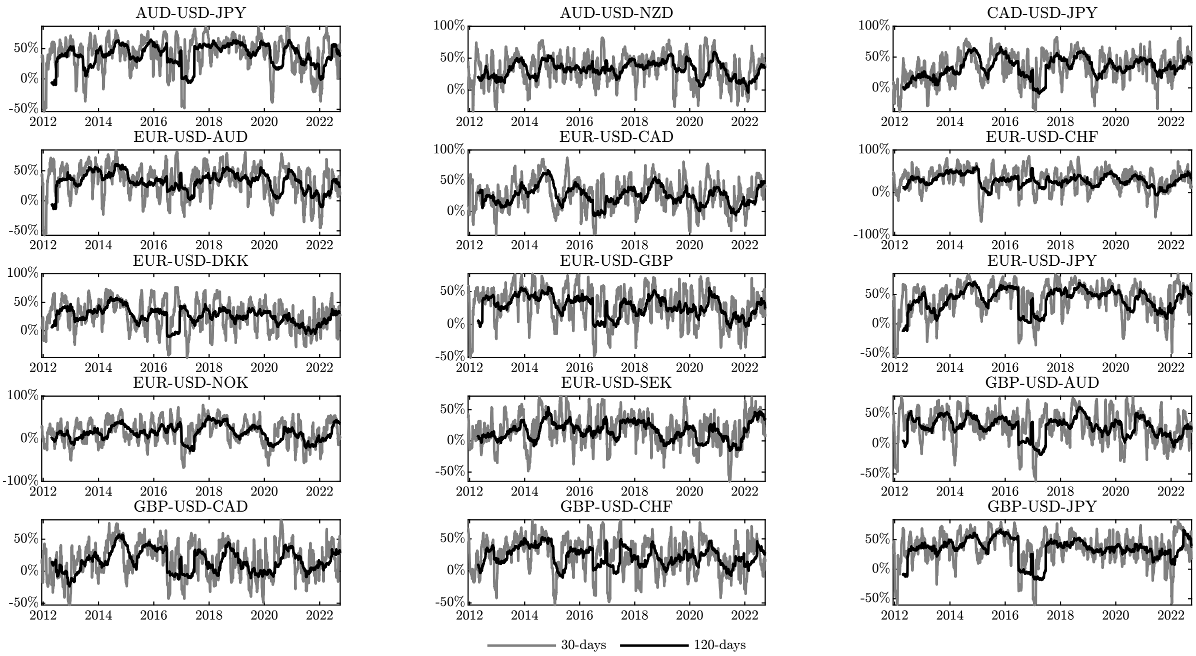

*Note*: This figure plots the cross-sectional average of the 30-day rolling window correlation between the shadow cost of intermediary constraints and total dealer-intermediated trading volume (i.e., $cor(VLOOP, Volume)$, left figure) as well as between dealers' compensation to endure inventory imbalances and total dealer-intermediated trading volume (i.e., $cor(TCOST, Volume)$, right figure) in percent (%). Our dealer constraint measure (DCM) is in units of standard deviations. We define DCM as the first principal component of the top 10 FX dealer banks' (based on the Euromoney FX survey) quarterly Value-at-Risk measure (VaR), daily debt funding cost (DFC), and average number of VaR breaches in a given quarter (NVB). The bold black lines are linear regression lines. The sample covers the period from 1 November 2011 to 30 September 2022.

Figure E.2: Rolling window correlation VLOOP and VLM




*Note*: This figure plots the 30- and 252-day rolling window correlation of daily cumulative no-arbitrage deviations VLOOP (i.e., shadow cost of intermediary constraints) and dealer-intermediated trading volume VLM. The sample covers the period from 1 November 2011 to 30 September 2022.

Figure E.3: Rolling window correlation TCOST and VLM




*Note*: This figure plots the 30- and 252-day rolling window correlation of daily cumulative round-trip transaction cost TCOST (i.e., dealers' compensation for enduring inventory imbalances) and dealer-intermediated trading volume VLM. The sample covers the period from 1 November 2011 to 30 September 2022.

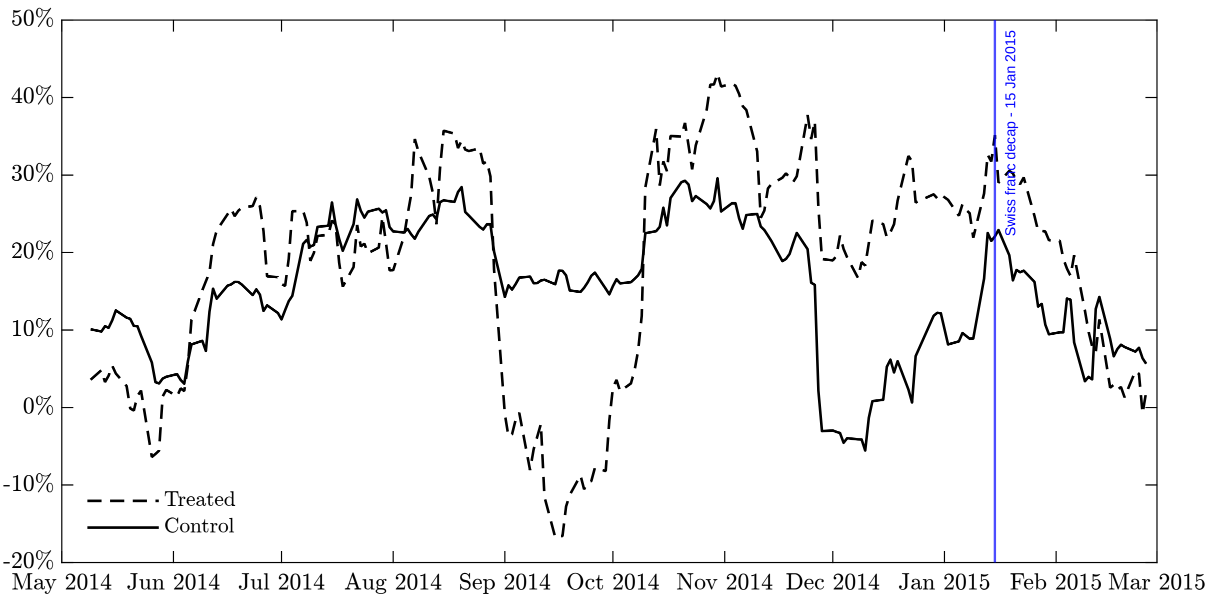
# Appendix F. Quasi-natural experiment: Swiss franc decap

Table F.1 reports the results from daily panel regressions of the form:

$$\rho_{k,t} = \alpha + \eta_1 D_{k,t} + \eta_2 Post_t + \eta_3 (D_{k,t} \times Post_t) + \kappa' \mathbf{w}_{k,t} + \epsilon_{k,t}, \tag{F.1}$$

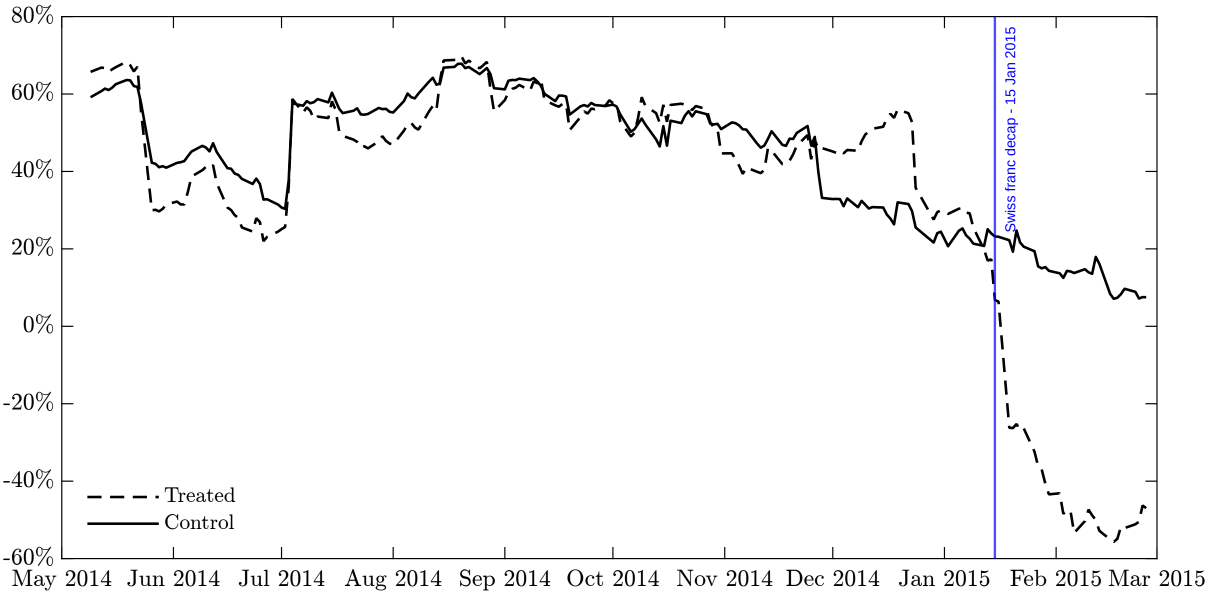
where the dependent variable is the 30-day rolling window correlation of liquidity provision costs (i.e., VLOOP or TCOST) and dealer-provided trading volume (i.e., VLM), $\alpha$ denotes the intercept, $D_{k,t}$ is equal to one if currency pair triplet $k$ contains the Swiss franc, $Post_t$ is one for the time period after the removal of the Swiss franc cap on 15 January 2015, and $\eta_3$ is the difference-in-differences (DnD) coefficient. $\mathbf{w}_{k,t}$ collects additional control variables such as the realised variance or Amihud (2002) price impact measure. Except for the case where $\rho = cor(VLOOP, VLM)$ we find the DnD regression coefficient $\eta_3$ to be negative and statistically significant. For instance, after the removal of the Swiss franc cap the correlation between TCOST and VLM is 54 percentage points lower for currency pair triplets involving the Swiss franc. Figures F.1 and F.2 illustrate the drop in the rolling window correlation coefficient based on each of our two liquidity cost measures (i.e., VLOOP or TCOST) after the removal of the Swiss franc cap.

Figure F.1: Event study: $cor(VLOOP, VLM)$ around the Swiss franc decap




*Note*: This figure plots the cross-sectional average of 30-day rolling window correlations of daily VLOOP (i.e., shadow cost of intermediary constraints) and dealer-intermediated trading volume VLM. The "Treated" group comprises currency pair triplets that involve the Swiss franc (i.e., EUR-USD-CHF and GBP-USD-CHF) and the "Control" group contains the remaining 13 triplets.

Figure F.2: Event study: $cor(TCOST, VLM)$ around the Swiss franc decap




*Note*: This figure plots the cross-sectional average of 30-day rolling window correlations of daily TCOST (i.e., dealers' compensation for enduring inventory imbalances) and dealer-intermediated trading volume VLM. The "Treated" group comprises currency pair triplets that involve the Swiss franc (i.e., EUR-USD-CHF and GBP-USD-CHF) and the "Control" group contains the remaining 13 triplets.

Table F.1: Event study panel regression: Removal of the Swiss franc cap

| | cor(VLOOP,Volume) | | | cor(TCOST,Volume) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Intercept | ***0.16 | ***0.16 | ***0.19 | ***0.49 | ***0.49 | ***0.50 |
| | [11.55] | [11.53] | [11.77] | [23.38] | [23.44] | [27.32] |
| $D_{k,t}$ | 0.03 | 0.03 | 0.03 | −0.01 | 0.00 | 0.00 |
| | [1.22] | [1.18] | [1.38] | [0.46] | [0.29] | [0.18] |
| $Post_t$ | **−0.05 | **−0.05 | −0.03 | ***−0.35 | ***−0.34 | ***−0.34 |
| | [2.36] | [2.37] | [1.60] | [12.32] | [12.29] | [11.31] |
| $D_{k,t} \times Post_t$ | 0.01 | 0.01 | 0.07 | ***−0.56 | ***−0.56 | ***−0.54 |
| | [0.39] | [0.40] | [1.63] | [16.73] | [16.95] | [16.04] |
| Realised variance | | ***0.00 | ***0.01 | | ***−0.01 | ***−0.01 |
| | | [7.04] | [7.37] | | [6.47] | [5.62] |
| Amihud (2002) | | | ***−0.04 | | | −0.02 |
| | | | [5.11] | | | [1.58] |
| $R^2$ in % | 29.15 | 29.18 | 31.19 | 86.29 | 86.37 | 86.46 |
| Avg. #Time periods | 207 | 207 | 207 | 207 | 207 | 207 |
| #Currency triplets | 15 | 15 | 15 | 15 | 15 | 15 |

*Note*: This table reports results from daily panel regressions of the form $\rho_{k,t} = \alpha + \eta_1 D_{k,t} + \eta_2 Post_t + \eta_3 (D_{k,t} \times Post_t) + \kappa' \mathbf{w}_{k,t} + \epsilon_{k,t}$, where the dependent variable is the 30-day rolling window correlation of our liquidity cost measure (i.e., VLOOP or TCOST) and trading volume (i.e., VLM), $\alpha$ denotes the intercept, $D_{k,t}$ is equal to one if currency pair triplet $k$ contains the Swiss franc, $Post_t$ is one for the time period after the removal of the Swiss franc cap on 15 January 2015, and $\eta_3$ is the difference-in-differences coefficient. $\mathbf{w}_{k,t}$ collects additional control variables such as the realised variance or Amihud (2002) price impact measure. The sample covers the period from 9 May 2014 to 26 February 2015. The test statistics based on Driscoll and Kraay (1998) robust standard errors allowing for random clustering and serial correlation (using the plug-in procedure for automatic lag selection by Newey and West, 1994) are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% levels.

# Appendix G. Additional empirical results

Table G.1: Summary statistics

| | Liquidity cost in bps | | Volume in $bn | | Bid-ask spread in bps | | Volatility in bps | VLOOP>TCOST in % |
|---|---|---|---|---|---|---|---|---|
| | VLOOP | TCOST | Direct | Synthetic | Direct | Synthetic | Direct | |
| AUD-USD-JPY | 0.23 | 4.73 | 0.18 | 4.93 | 4.00 | 5.71 | 14.13 | 0.15 |
| AUD-USD-NZD | 0.27 | 5.61 | 0.09 | 1.93 | 4.17 | 7.25 | 8.96 | 0.02 |
| CAD-USD-JPY | 0.28 | 4.50 | 0.03 | 5.27 | 4.10 | 5.06 | 12.36 | 0.36 |
| EUR-USD-AUD | 0.19 | 4.40 | 0.13 | 7.47 | 3.40 | 5.52 | 11.30 | 0.03 |
| EUR-USD-CAD | 0.27 | 4.10 | 0.08 | 7.81 | 3.37 | 4.88 | 9.88 | 0.06 |
| EUR-USD-CHF | 0.21 | 3.91 | 0.36 | 6.56 | 2.60 | 5.27 | 6.49 | 0.09 |
| EUR-USD-DKK | 0.14 | 3.84 | 0.09 | 5.98 | 2.45 | 5.27 | 1.79 | 0.06 |
| EUR-USD-GBP | 0.20 | 4.01 | 0.59 | 7.94 | 3.11 | 4.89 | 9.33 | 0.03 |
| EUR-USD-JPY | 0.20 | 3.78 | 0.61 | 9.35 | 3.03 | 4.69 | 11.06 | 0.59 |
| EUR-USD-NOK | 0.27 | 7.92 | 0.24 | 6.06 | 6.43 | 9.55 | 11.66 | 0.10 |
| EUR-USD-SEK | 0.25 | 6.91 | 0.27 | 6.08 | 5.41 | 8.45 | 9.39 | 0.06 |
| GBP-USD-AUD | 0.20 | 4.95 | 0.04 | 3.51 | 4.03 | 5.91 | 12.14 | 0.02 |
| GBP-USD-CAD | 0.27 | 4.58 | 0.03 | 3.85 | 3.84 | 5.27 | 10.59 | 0.05 |
| GBP-USD-CHF | 0.19 | 4.84 | 0.03 | 2.60 | 3.99 | 5.66 | 10.55 | 0.02 |
| GBP-USD-JPY | 0.19 | 4.35 | 0.20 | 5.39 | 3.71 | 5.08 | 12.47 | 0.52 |

*Note*: This table reports the time-series average of hourly triangular no-arbitrage deviations $VLOOP$ in basis points (bps), round-trip trading costs $TCOST$ in bps, direct trading volume in non-dollar pairs (e.g., AUDJPY) in $bn, synthetic volume in dollar pairs in $bn, direct and synthetic relative bid-ask spreads, and realised volatility in non-dollar pairs in bps. By "synthetic" we refer to the sum of trading volumes and relative bid-ask spreads in two dollar pairs (e.g., USDAUD and USDJPY) within a currency pair triplet. The last column shows the relative share of VLOOP>TCOST in %. Each row corresponds to a triplet of currency pairs, for example, AUDJPY, USDAUD, and USDJPY that we abbreviate as AUD-USD-JPY. The sample covers the period from 1 November 2011 to 30 September 2022.

Table G.2: Comparison EBS vs Olsen bid and ask quotes

| | RMSE | | | MAE | | | CORR | | | Relative Spread in BPS | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | BID | ASK | BID-ASK | BID | ASK | BID-ASK | BID | ASK | BID-ASK | Mean EBS | Mean Olsen |
| AUDJPY | 0.0841 | 0.0832 | 0.0002 | 0.0584 | 0.0581 | 0.0002 | 0.9996 | 0.9996 | 0.4951 | 3.64 | 4.89 |
| AUDNZD | 0.0007 | 0.0007 | 0.0006 | 0.0005 | 0.0005 | 0.0004 | 0.9997 | 0.9997 | 0.7907 | 8.46 | 4.17 |
| AUDUSD | 0.0006 | 0.0006 | 0.0003 | 0.0005 | 0.0005 | 0.0001 | 0.9996 | 0.9996 | 0.4782 | 2.78 | 3.91 |
| CADJPY | 0.3106 | 0.3137 | 0.0005 | 0.1068 | 0.1077 | 0.0002 | 0.9959 | 0.9957 | 0.2005 | 6.95 | 5.22 |
| EURAUD | 0.0018 | 0.0014 | 0.0013 | 0.0010 | 0.0009 | 0.0005 | 0.9990 | 0.9994 | 0.5026 | 8.51 | 4.20 |
| EURCAD | 0.0014 | 0.0014 | 0.0002 | 0.0010 | 0.0010 | 0.0001 | 0.9994 | 0.9994 | 0.5774 | 3.31 | 4.29 |
| EURCHF | 0.0005 | 0.0005 | 0.0001 | 0.0004 | 0.0004 | 0.0001 | 0.9988 | 0.9989 | 0.6383 | 1.71 | 2.64 |
| EURDKK | 0.0010 | 0.0010 | 0.0003 | 0.0009 | 0.0009 | 0.0002 | 0.9960 | 0.9958 | 0.0010 | 1.81 | 3.49 |
| EURGBP | 0.0007 | 0.0007 | 0.0003 | 0.0005 | 0.0005 | 0.0001 | 0.9999 | 0.9999 | 0.3440 | 3.36 | 4.06 |
| EURJPY | 0.0977 | 0.0957 | 0.0002 | 0.0693 | 0.0682 | 0.0002 | 0.9998 | 0.9998 | 0.5209 | 2.08 | 3.64 |
| EURNOK | 0.0076 | 0.0075 | 0.0003 | 0.0054 | 0.0054 | 0.0001 | 0.9992 | 0.9992 | 0.6180 | 6.32 | 5.59 |
| EURSEK | 0.0056 | 0.0057 | 0.0002 | 0.0040 | 0.0041 | 0.0001 | 0.9996 | 0.9996 | 0.7075 | 4.85 | 4.20 |
| EURUSD | 0.0008 | 0.0008 | 0.0002 | 0.0005 | 0.0005 | 0.0002 | 0.9995 | 0.9995 | 0.3831 | 1.01 | 2.86 |
| GBPAUD | 0.0029 | 0.0036 | 0.0031 | 0.0025 | 0.0028 | 0.0028 | 0.9998 | 0.9997 | 0.1396 | 32.64 | 4.90 |
| GBPCAD | 0.0028 | 0.0029 | 0.0027 | 0.0024 | 0.0025 | 0.0026 | 0.9997 | 0.9997 | 0.0749 | 29.96 | 4.90 |
| GBPCHF | 0.0021 | 0.0022 | 0.0028 | 0.0018 | 0.0019 | 0.0027 | 0.9997 | 0.9997 | 0.0698 | 31.51 | 4.92 |
| GBPJPY | 0.2071 | 0.2769 | 0.0021 | 0.1562 | 0.1658 | 0.0012 | 0.9999 | 0.9998 | 0.1793 | 16.42 | 4.98 |
| GBPUSD | 0.0012 | 0.0012 | 0.0003 | 0.0009 | 0.0009 | 0.0001 | 0.9999 | 0.9999 | 0.2774 | 2.94 | 3.71 |
| NZDUSD | 0.0006 | 0.0006 | 0.0004 | 0.0005 | 0.0005 | 0.0001 | 0.9997 | 0.9997 | 0.5816 | 4.54 | 4.40 |
| USDCAD | 0.0011 | 0.0011 | 0.0002 | 0.0008 | 0.0008 | 0.0001 | 0.9997 | 0.9997 | 0.3373 | 2.89 | 3.35 |
| USDCHF | 0.0007 | 0.0007 | 0.0002 | 0.0005 | 0.0005 | 0.0001 | 0.9993 | 0.9993 | 0.4070 | 2.00 | 3.33 |
| USDDKK | 0.0049 | 0.0049 | 0.0004 | 0.0034 | 0.0034 | 0.0003 | 0.9995 | 0.9995 | 0.3739 | 6.41 | 3.38 |
| USDJPY | 0.0839 | 0.0824 | 0.0002 | 0.0600 | 0.0592 | 0.0002 | 0.9999 | 0.9999 | 0.3042 | 1.24 | 3.07 |
| USDNOK | 0.0091 | 0.0091 | 0.0009 | 0.0067 | 0.0067 | 0.0005 | 0.9992 | 0.9992 | 0.5275 | 10.49 | 6.33 |
| USDSEK | 0.0142 | 0.0081 | 0.0017 | 0.0068 | 0.0057 | 0.0003 | 0.9992 | 0.9997 | 0.2824 | 7.49 | 5.45 |

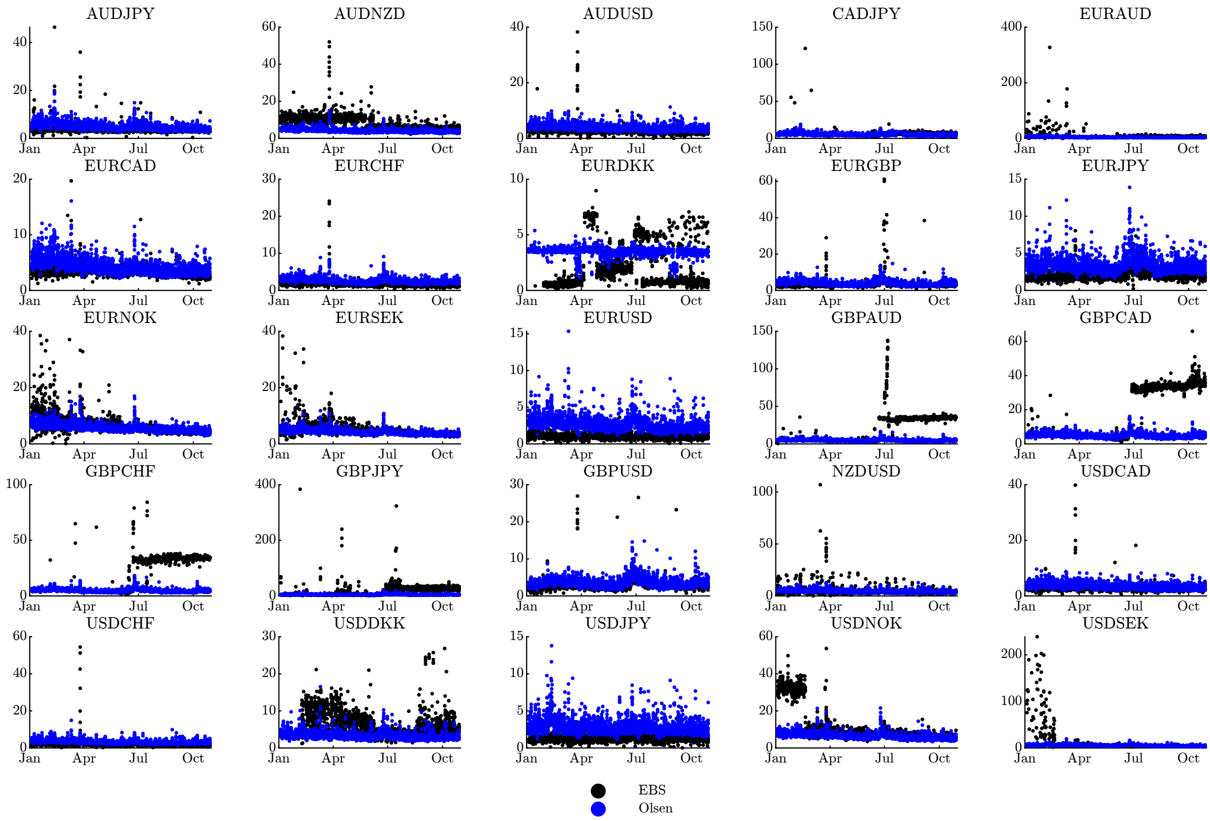
*Note*: This table reports the root mean squared error ($RMSE$, columns $1-3$), the mean absolute error ($MAE$, columns $4-6$), and the pairwise correlation coefficient ($CORR$, columns $7-9$) for hourly bid and ask quotes as well as the hourly average bid-ask spread based on EBS and Olsen data, respectively. The last two columns report the sample averages of the relative bid-ask spread in basis points (BPS). The sample covers the period from 4 January 2016 to 30 December 2016.

Table G.3: Correlations in percent

| | VLOOP | TCOST | VOD | VOS | BAD | BAS | RVD |
|---|---|---|---|---|---|---|---|
| TCOST | ***31.14 | | | | | | |
| VOD | ***0.84 | ***6.21 | | | | | |
| VOS | ***5.83 | ***15.02 | ***61.71 | | | | |
| BAD | ***28.16 | ***75.84 | ***3.23 | ***9.56 | | | |
| BAS | ***26.27 | ***77.01 | ***15.98 | ***31.40 | ***86.08 | | |
| RVD | ***18.45 | ***39.39 | ***24.75 | ***33.79 | ***59.67 | ***55.81 | |
| RVS | ***16.44 | ***44.53 | ***28.75 | ***49.95 | ***50.28 | ***70.40 | ***79.02 |

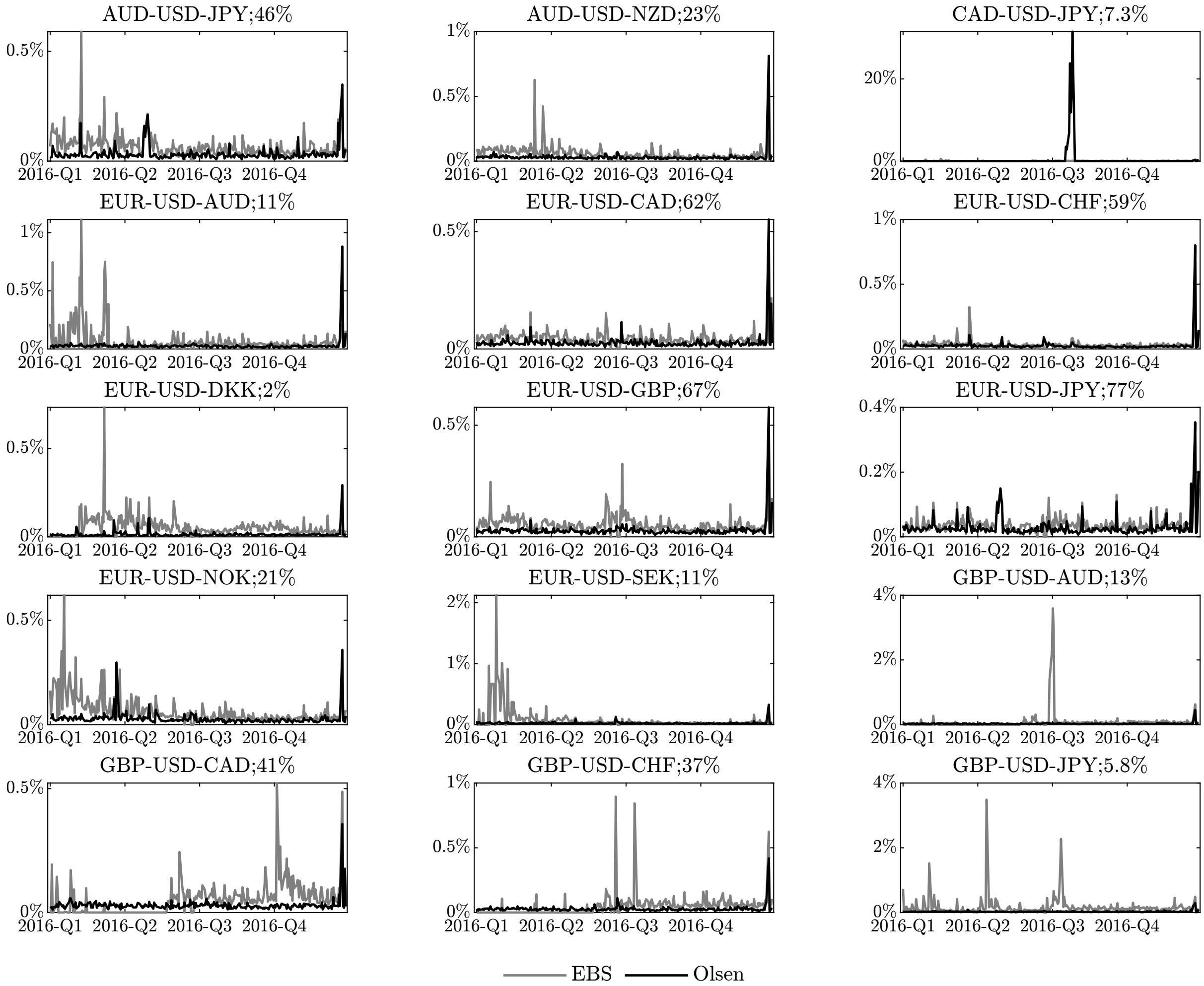
*Note*: This table reports the pairwise Pearson correlation coefficient of hourly triangular no-arbitrage deviations $VLOOP$, trading costs $TCOST$, direct trading volume $VOD$ in non-dollar pairs (e.g., XXXYYY), synthetic trading volume $VOS$ in dollar pairs (e.g., the average across USDXXX and USDYYY), relative bid-ask spread $BAD$ and realised volatility $RVD$ in non-dollar pairs, as well as relative bid-ask spreads $BAS$ and realised volatility $RVS$ in dollar currency pairs in percent (%). Significant correlations at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The sample covers the period from 1 November 2011 to 30 September 2022.

## Figure G.1: Comparison EBS vs Olsen bid-ask spreads



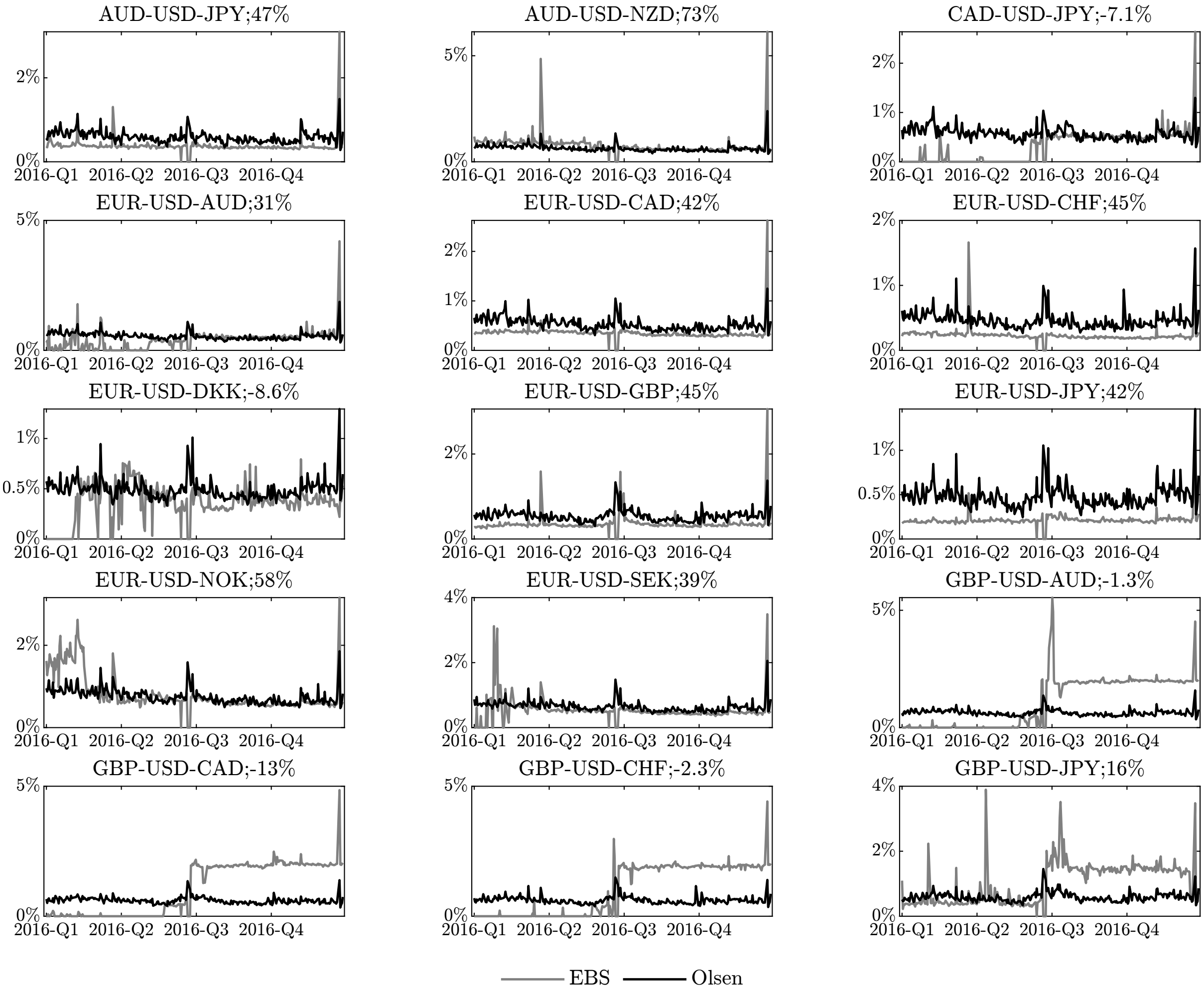

*Note*: This figure plots the time-series variation in EBS and Olsen hourly average relative bid-ask spreads. Each of the dots corresponds to one hourly observation in either EBS (black dots) or Olsen (blue dots). The sample covers the period from 4 January 2016 to 30 December 2016.

Figure G.2: Comparison EBS- vs Olsen- based VLOOP



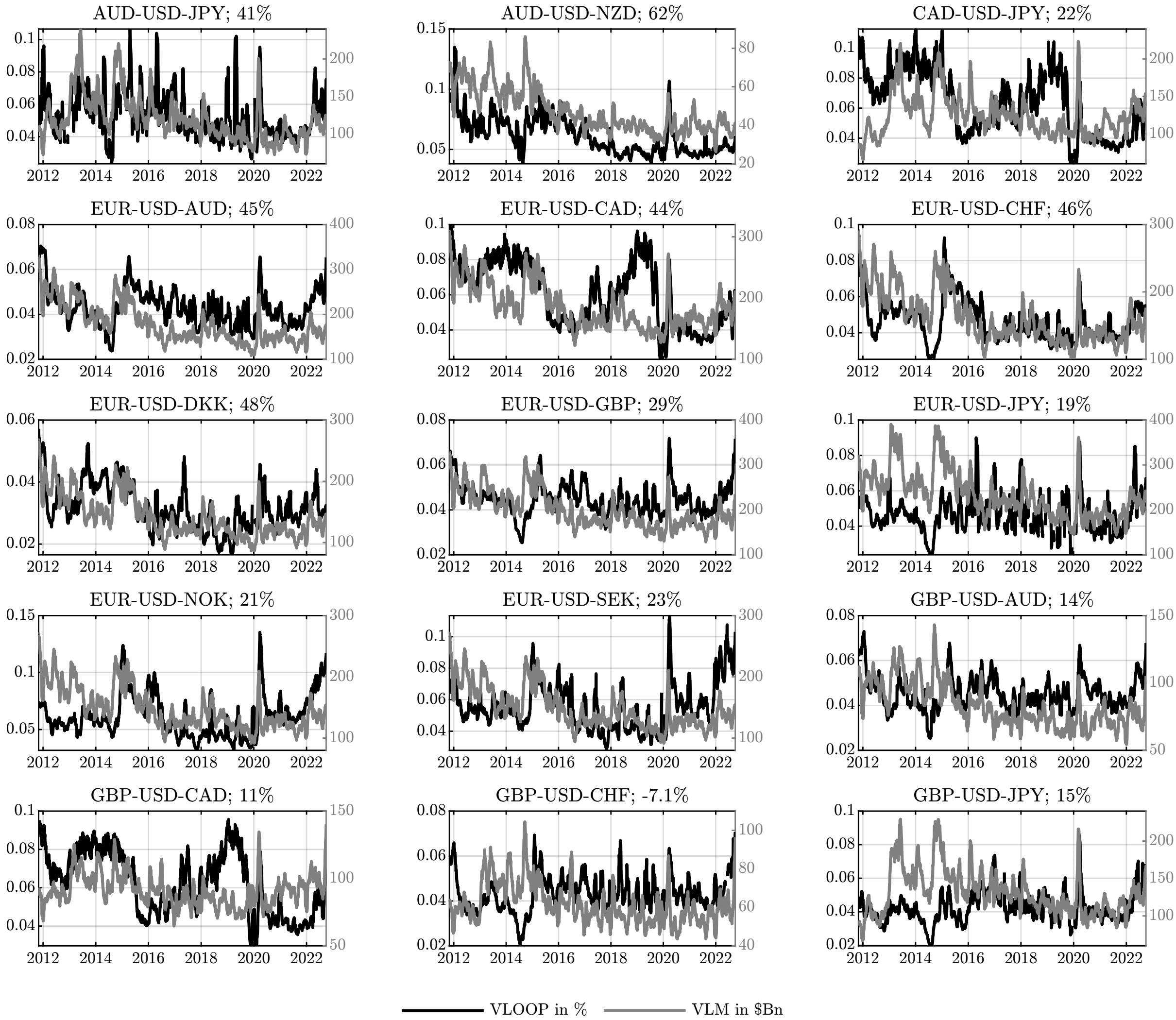

*Note*: This figure plots the daily cumulative sum of hourly no-arbitrage deviations (VLOOP) computed based on EBS and Olsen data, respectively. The percentages in the titles report the Pearson correlation coefficient between the two time-series. The sample covers the period from 4 January 2016 to 30 December 2016.

Figure G.3: Comparison EBS- vs Olsen- based TCOST



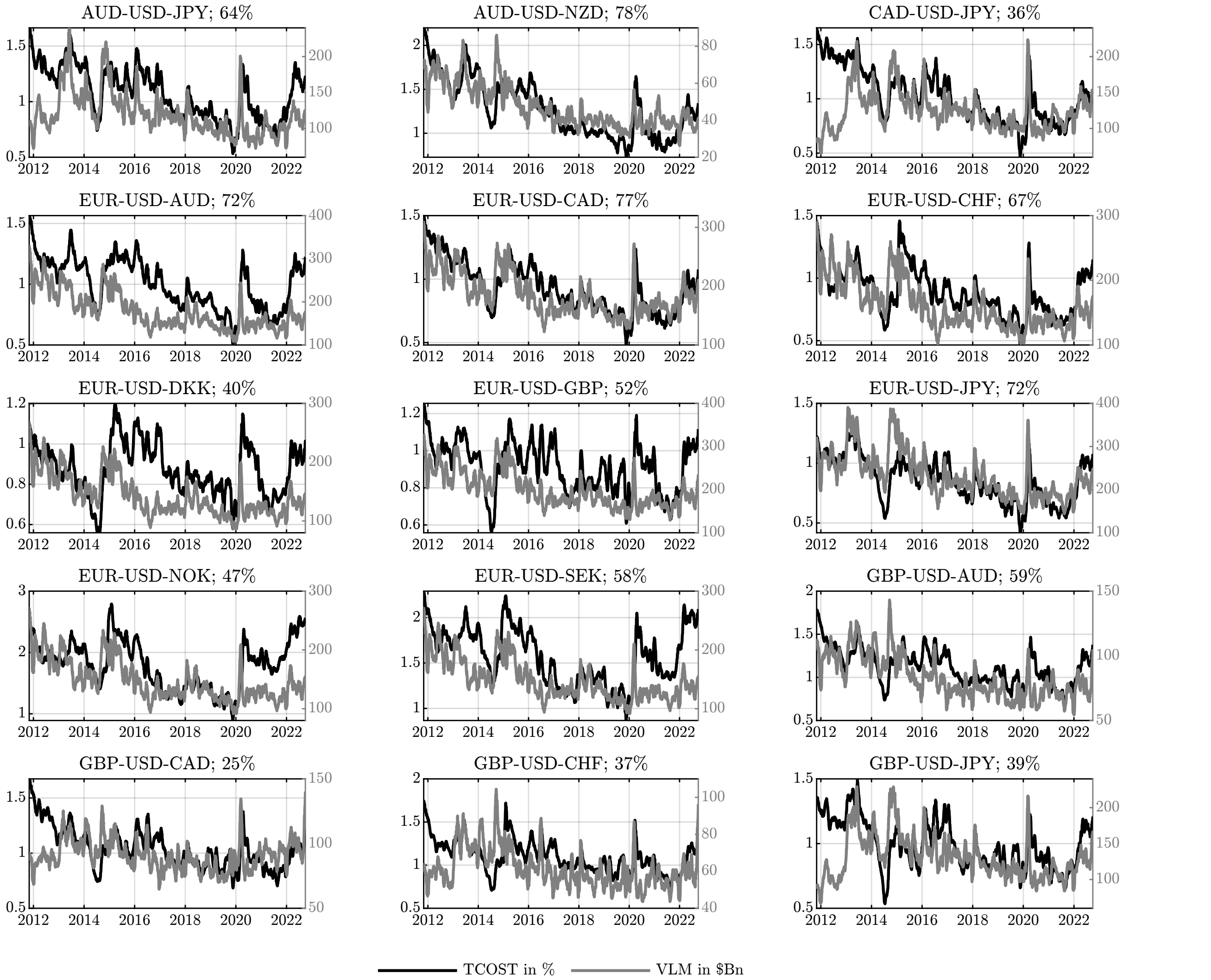

*Note*: This figure plots the daily cumulative sum of hourly round-trip transaction costs (TCOST) computed based on EBS and Olsen data, respectively. The percentages in the titles report the Pearson correlation coefficient between the two time-series. The sample covers the period from 4 January 2016 to 30 December 2016.

Figure G.4: No-arbitrage violations and trading volumes



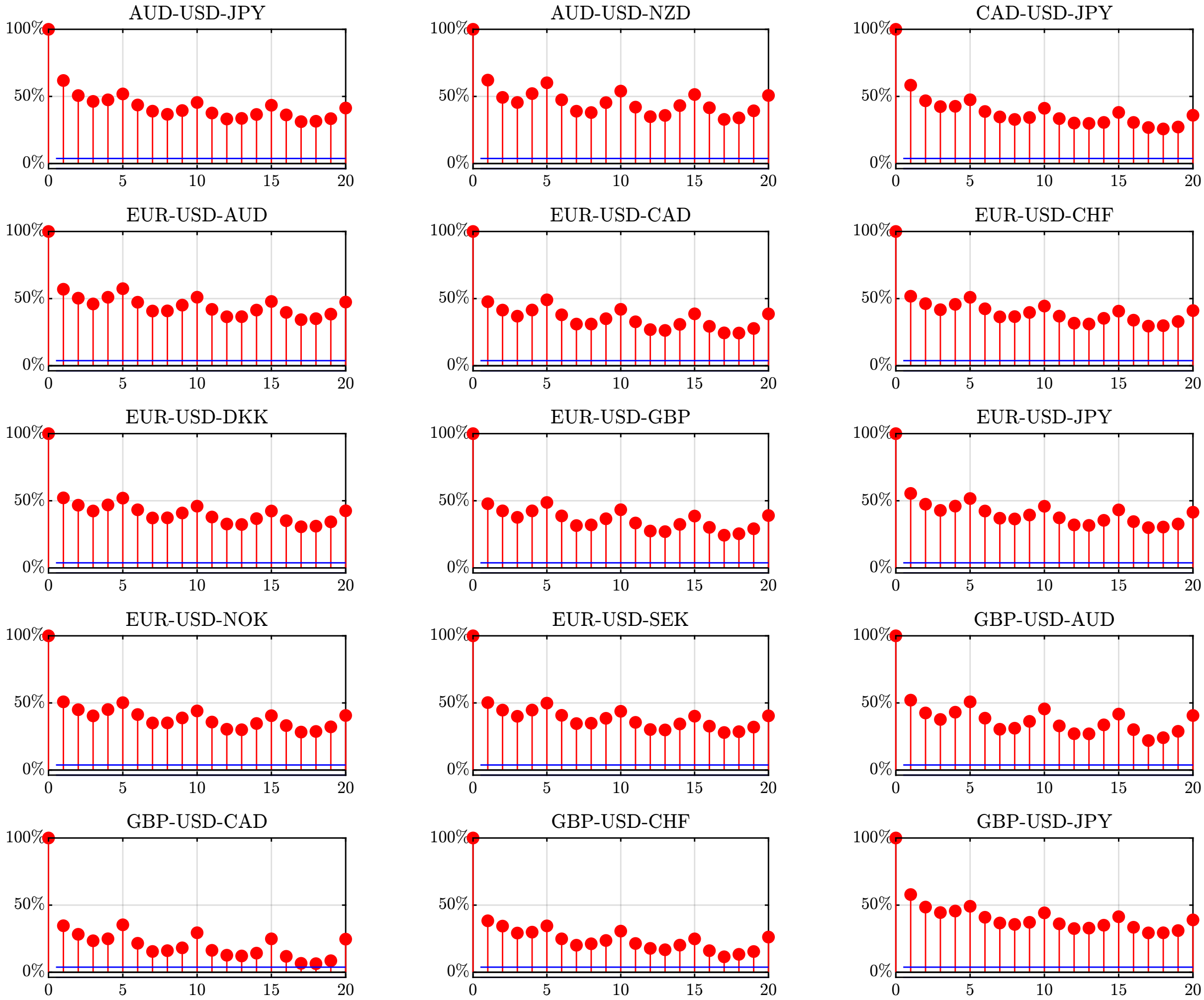

*Note*: This figure plots total trading volume VLM against no-arbitrage deviations VLOOP (i.e., shadow cost of intermediary constraints) for 15 triplets of currency pairs. Currency pair triplets are denoted as XXX-USD-YYY, consisting of two dollar currency pairs (i.e., USDXXX, and USDYYY) as well as one non-dollar currency pair (i.e., XXXYYY). The percentages in the titles report the Pearson correlation coefficient between VLM and VLOOP. Both time-series correspond to 22-day moving averages. The sample covers the period from 1 November 2011 to 30 September 2022.

Figure G.5: Round-trip transaction costs and trading volumes




*Note*: This figure plots total trading volume VLM against round-trip transaction cost TCOST (i.e., dealers' compensation for enduring inventory imbalances) for 15 triplets of currency pairs. Currency pair triplets are denoted as XXX-USD-YYY, consisting of two dollar currency pairs (i.e., USDXXX, and USDYYY) as well as one non-dollar currency pair (i.e., XXXYYY). The percentages in the titles report the Pearson correlation coefficient between VLM and TCOST. Both time-series correspond to 22-day moving averages. The sample covers the period from 1 November 2011 to 30 September 2022.

Figure G.6: Autocorrelated trading volume




*Note*: This figure plots the autocorrelation coefficient of total dealer-provided trading volume VLM for 15 triplets of currency pairs. Currency pair triplets are denoted as XXX-USD-YYY, consisting of two dollar currency pairs (i.e., USDXXX, and USDYYY) as well as one non-dollar currency pair (i.e., XXXYYY). The solid lines are approximate 95% confidence bounds. The sample covers the period from 1 November 2011 to 30 September 2022.

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