Constrained Liquidity Provision in Currency Markets*

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This version: August 10, 2022

Working paper and subject to change.

Abstract
We study dealers' liquidity provision in currency markets. We use a decomposition based on the triangular no-arbitrage condition to measure the cost of liquidity provision along two dimensions: i) shadow costs of intermediary constraints and ii) additional costs arising from enduring inventory imbalances. In normal times, as customers' demand for liquidity increases, dealers cater for it earning a higher compensation. However, when intermediation constraints tighten – for instance, due to high leverage, Value-at-Risk, and funding costs – the liquidity provision costs increase and the elasticity of dealers' liquidity provision weakens by at least 80%. We rationalise our novel empirical findings with a tractable model that sheds light on the key mechanisms of how liquidity provision by dealers can deteriorate when intermediary constraints are tightening.

J.E.L. classification: F31, G12, G15

Keywords: Market liquidity, Dealer constraints, Foreign exchange, Liquidity provision.

*We welcome comments, including references to related papers we have inadvertently overlooked. We are grateful to Briana Chang (discussant), Stijn Claessens, Semyon Malamud, Paul Söderlind, Dagfinn Rime (discussant), and Jonathan Wallen for helpful comments. We also thank seminar and conference participants at the Bank for International Settlements, 11^{th} Workshop on Exchange Rates (SNB), King's College London, 11^{th} Annual 2022 Stern/Salomon Center Microstructure Conference, 2022 SFI Research Days in Gerzensee, CLS Group, Credit Suisse, and the University of St.Gallen. Angelo Ranaldo acknowledges financial support from the Swiss National Science Foundation (SNSF grant 182303). All errors are our own.

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1. Introduction

Financial intermediaries play a crucial role in supporting the functioning of financial markets. This is especially true for over-the-counter (OTC) markets, which are not organised based on centralised exchanges but rely on the intermediation by dealers who provide immediacy to their clients.[1] However, dealers' ability to provide liquidity depends on their willingness to make balance sheet space available. Therefore, constraints on dealers' intermediation capacity can lead to a reduction in dealers' incentives to intermediate trades, an increase in the cost of liquidity provision, as well as widespread asset mispricing (i.e., no-arbitrage violations).[2]

Against this backdrop, the key question that we address in this paper is whether dealer constraints can have a bearing on liquidity provision, in particular, by increasing the cost of market liquidity and by leading dealers to curtail their market-making activity. To analyse this question, we study prices and quantities in the foreign exchange (FX) market based on a globally representative trade data set from CLS Group. The FX market is the largest financial market in the world and often regarded as one of the most liquid and efficient ones. Given that many FX dealer banks provide intermediation services across a host of financial markets, we expect that our findings about the key mechanisms also apply to other OTC markets.

The contribution of this paper is threefold. First, we provide a simple, yet effective, analytical framework to tease out the costs of providing spot FX market liquidity from a no-arbitrage condition. The framework builds on the well-known triangular relation among FX rates (e.g., Chaboud, Chiquoine, Hjalmarsson, and Vega, 2014; Foucault, Kozhan, and Tham, 2016) and outlines two liquidity cost components that both depend on FX dealers' intermediation capacity. First, $VLOOP$, which captures the shadow cost of intermediary constraints and arises when dealers' marginal valuation of a currency pair diverges from its fundamental value. Second, $TCOST$, which is the round-trip transaction cost of performing a triangular arbitrage trade and represents the dealer's compensation to endure inventory imbalances. Our second contribution is to study VLOOP and TCOST through the lenses of constrained financial intermediaries. In particular, we document a novel non-linear relation between the cost of liquidity provision and dealer intermediated trading volume. We show that in *unconstrained* states dealers cater to their clients' trading demand and, as expected, require a higher compensation for doing so. But, in states when dealers' intermediation capacity is *constrained*, their liquidity provision deteriorates along two dimensions: First, market liquidity becomes increasingly more costly. Second, dealers are less prone to provide immediacy to clients and raise the liquidity cost per unit of intermediated volume. Lastly, we provide a tractable model that formalises the intuition on the increasing liquidity costs stemming from constraints on intermediation capacity and the inelastic liquidity provision by dealers.

[1] To be clear, we focus on the role of dealers 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.

How intermediation constraints impact market liquidity is an important issue for both policy makers and academics. In fact, it has been much debated whether the policies put in place since the Global Financial Crisis in 2008/09 have had any consequence on the functioning of OTC markets by disincentivising liquidity provision (e.g., Dudley, 2018). On top of the regulatory costs, the academic literature seeks to understand the increased reluctance of dealers to use their balance sheets for intermediation. Moreover, the monitoring of how liquidity costs fluctuate and are affected by dealer behavior is also beneficial for practitioners as well as central banks operating in such markets.

Our paper consists of three parts. Specifically, we start by proposing a novel analytical approach for measuring the cost of liquidity provision. The conceptual underpinning is a no-arbitrage relation that ties together triplets of spot FX rates. We show that deviations from this no-arbitrage condition represent an amalgam of two liquidity cost components. The first part (i.e., VLOOP) captures the violations from the law of one price. In line with the literature on intermediary asset pricing (e.g., Adrian, Etula, and Muir, 2014; Duffie, 2018; Fleckenstein and Longstaff, 2018; Du, Hébert, and Huber, forthcoming 2022), a natural interpretation of these no-arbitrage violations is that they capture the shadow cost of intermediary constraints.[3] The second part (i.e., TCOST) captures the round-trip trading cost that traders would incur in such a triangular arbitrage trade. Effectively, TCOST represents the dealer's compensation to endure inventory imbalances due to the clients' demand for immediacy.

Based on our spot FX transaction data from CLS Group, we document three new empirical results. First, both liquidity cost components are economically significant but, as expected, VLOOP is an order of magnitude smaller than TCOST. Second, the two cost components move in tandem over time, albeit their correlation is less than 30% on average. This is consistent with the idea that both are affected by dealers' intermediation capacity, but in different ways. While VLOOP reflects the shadow cost of intermediary constraints, TCOST captures dealer's compensation for enduring inventory imbalances. Third, both components, but especially TCOST, tend to rise as intermediated volumes increase. This pattern is in line with the idea that dealers require compensation for their market-making activity the more it requires management of possible inventory imbalances.

In the second part of the paper, we link the cost of liquidity provision to dealers' constraints. The key mechanism is that constrained dealers are less inclined to make balance sheet space available to clients who wish to trade currency positions that create persistent inventory positions. Hence, leveraged and risk-averse dealers have limited intermediation capacity. This mechanism stems from two dealer behaviours that we test empirically: First, dealers pass on their intermediation costs on the prices offered to clients. As such, this will be reflected in our two trading cost measures, which increase as intermediated volumes rise. Second, dealers are less inclined to maintain large and unbalanced inventories for mar-

[3]In line with this strand of literature, one may also refer to these shadow costs as "balance sheet costs" associated with spot FX liquidity provision.

ket making purposes when their intermediation capacity is lower. The higher trading costs charged by dealers will in turn also curb some potential liquidity traders from trading. In other words, dealer constraints can have a bearing not only on the *cost*, but also the *quantity* of FX liquidity provision. The former increases the cost of providing liquidity, while the latter renders dealers' liquidity provision less elastic.

In principle, the underlying mechanism we are interested in could be studied based on any no-arbitrage condition (e.g., put-call parity, treasury cash bonds vs futures, etc.). However, the triangular no-arbitrage condition offers at least two main advantages: First, it provides us with a clean laboratory to measure the cost of liquidity provision in the FX *spot* market. This is because unlike other arbitrage conditions that embed various frictions[4] (e.g., counterparty risk, funding roll-over risk, etc.) the triangular no-arbitrage condition captures the shadow cost of constraints on intermediation activities that are nearly risk-free (i.e., spot FX) and which can be financed by deploying existing balance sheet cash or short-term funding (Andersen, Duffie, and Song, 2019). Second, it allows us to attribute a meaningful economic interpretation to both VLOOP and TCOST liquidity cost components: while the former captures the shadow cost of intermediation constraints arising from differences in the dealer's marginal valuation across a currency pair triplet, the latter reflects the dealer's realised compensation for incurring inventory risk when dealing with clients.

For our empirical analysis, we construct a composite measure of dealers' constraints that increases with higher leverage, Value-at-Risk (VaR), and funding costs. Specifically, we define our time-varying "dealer constraint measure" DCM as the first principal component of the top 10 FX dealer banks' i) FX portfolio VaR, ii) He, Kelly, and Manela (2017) leverage ratio, iii) credit default swap (CDS) premia, and iv) funding costs that are particularly relevant for debt-financed positions and market-making functions (see, e.g. Andersen et al., 2019). To rule out reverse causality, DCM enters all our regression with a lag of 1 day and our results are robust to using more lags. From an institutional perceptive, the relation between the cost of liquidity provision (i.e., VLOOP and TCOST) and dealer-intermediated volume is unlikely to have any effect on DCM. This is because spot FX trading itself does not affect dealer leverage or trading book VaRs, not least given substantial internalisation of trades and netting.[5]

Equipped with a consistent measure of dealers' constraints, we are in an ideal position to analyse the relation between our two liquidity cost components and dealer-provided volumes. Two main results emerge concerning liquidity costs and volumes. First, although well expected, the *cost* of liquidity provision increases significantly with dealers' constraints. Second, to gauge how the *quantity* of supplied liquidity evolves depending in dealer constraints, we regress liquidity provision costs on dealer-intermediated volume conditional on dealers'

[4]For instance, Siriwardane, Sunderam, and Wallen (2021) show that the low correlation in the violation of seven no-arbitrage conditions (excluding the FX triangular no-arbitrage condition) is attributable to various frictions driving both the segmentation of balance sheets and also the funding abilities of financial firms.

[5]Moore, Schrimpf, and Sushko (2016) document that some of the major FX dealer banks have internalisation ratios of up to 90%. Moreover, CLS claims that multilateral netting shrinks funding needs by over 96%.

constrainedness. This analysis highlights how the "elasticity of liquidity provision" – that is, the correlation between liquidity costs and trading volumes – decreases as dealers become more constrained. To do so, we rely on so-called logistic smooth transition regression (LSTAR) methods (e.g., Christiansen, Ranaldo, and Söderlind, 2011) that are particularly well-suited to capture correlations across different regimes. The main goal of the regime-dependent analysis is to investigate how the relation between dealer-intermediated volume and liquidity costs changes across two regimes: i) normal times when dealers are mostly unconstrained, and ii) stressed periods when dealers face more tightening economic conditions. Two novel findings arise: First, changes in dealer-provided volume and our liquidity cost measures co-move with an average correlation of 12%–31%. Second, we find that the correlation between liquidity costs and intermediated volume falls off sharply when dealers' inventory absorption capacity is strained.[6] Despite both liquidity costs (i.e., VLOOP and TCOST) and intermediated volume being on average at least 20–29% higher in the constrained state compared to normal times, the correlation between the two measures decreases by 14–15 percentage points in constrained periods. We interpret this result as a drop in dealers' elasticity to provide liquidity. All findings remain qualitatively unchanged when considering each determinant of the dealer constraint measure as a single regime variable.

In the third part of the paper, we rationalise our empirical findings with a simple partial equilibrium model. Building on standard microstructure theory (see, e.g., Grossman and Miller, 1988; Hendershott and Menkveld, 2014), the model features two periods, three currency pairs, and two types of agents: i) a risk-averse and debt-financed dealer supplying liquidity and ii) liquidity traders with exogenous trading demands. The two liquidity cost components discussed above arise naturally arise from our model. Regarding VLOOP, heterogeneity in private values among liquidity traders results in demand imbalances across the three currency pairs (Gabaix and Maggiori, 2015), which in turn generates imbalanced customer demand. Such imbalances in turn weighs on the dealer's marginal valuation of the three currency pairs due to the implied balance sheet costs. More specifically, this incentivises the dealer to set mid-quotes away from their fundamental value resulting in a violation of the law of a price (VLOOP). VLOOP thus emerges as a key variable to measure the shadow cost of dealer constraints in FX spot trading. It is important to note, however, that for most market participants it is not feasible to benefit from such deviations due to high transaction costs as well as FX quantity conventions on major trading platforms. In particular, the dealer sets bid and ask quotes to be compensated for its customers' demand for immediacy, which consumes economic capital due to debt funding costs, volatility, and risk aversion. Against this backdrop, TCOST represents the total round-trip cost for performing such a triangular no-arbitrage trade in equilibrium.

[6]The key focus of our analysis lies on the supply side of liquidity provision that we capture via our dealer constraint measure DCM. In the robustness section of the paper, we also use a structural vector autoregression with sign restrictions to disentangle liquidity demand and supply dynamics. The setup here closely follows Goldberg (2020) and Goldberg and Nozawa (2020).

Related literature. Our paper contributes to three strands of literature. First, our work is related to the broader literature that emphasises the role of intermediary frictions in affecting asset prices and, in particular, risk premia (e.g., Gârleanu and Pedersen, 2011; He and Krishnamurthy, 2011, 2013; Adrian and Boyarchenko, 2012; Adrian et al., 2014; He et al., 2017). Our main contribution is to show in depth how constrained dealers curtail their liquidity provision and charge higher liquidity costs in times of markets stress. This finding is consistent with the evidence in Nagel (2012) showing 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 intermediaries' balance sheet capacity (Adrian and Shin, 2010) and that intermediary leverage and banks' risk management practices (e.g., following VaR methodologies) tend to be pro-cyclical (Adrian and Shin, 2013). Lastly, our findings suggesting that the cost of dealers' balance sheet space affects both the cost and quantity of liquidity provision are consistent with slow-moving intermediated capital causing distortions in pricing relations (Duffie, 2010).

Second, we add to the literature on limits to arbitrage. Our work differs from previous research along two important 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. (forthcoming 2022) and Siriwardane et al. (2021), we study the role of constrained *dealers* and how their ability to provide immediacy contributes to market liquidity. Second, we use a well-known no-arbitrage identity to derive two liquidity cost components with an economically meaningful interpretation. Thus, our key contribution is to analyse arbitrage conditions to shed light on the relation between liquidity costs and trading volume 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 equity markets (see Gromb and Vayanos, 2010). However, many of the frictions, such as short sale constraints which are considered a major explanation in equities (e.g., Chu, Hirshleifer, and Ma, 2020), do not apply to FX. Related to the stock market literature, recent studies document widespread mispricings in stressful conditions (Pasquariello, 2014), commonality in arbitrage deviations (Rösch, Subrahmanyam, and van Dijk, 2016), and limits to arbitrage impacting market liquidity (Rösch, 2021). We add to this branch of the literature by identifying constrained intermediaries as the main driving force behind such commonalities and by showing how their liquidity provision impacts aggregate trading volume.

Lastly, we contribute to the literature on FX microstructure on understanding the role of trading volume. Our key angle here is to study the relation of both quantities (i.e., volumes from CLS Group) and prices. In contrast to the order flow literature (e.g., Evans, 2002; Evans and Lyons, 2002, 2005), the literature on trading volume is relatively scarce due to the lack of comprehensive data sets. Earlier research has focused largely on 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, Ranaldo, and Wrampelmeyer, 2013; Chaboud et al., 2014). Alternative sources of spot FX volume are proprietary data sets from specific dealer banks (e.g., Bjønnes and Rime, 2005; Menkhoff, Sarno, Schmeling, and Schrimpf, 2016). The recent public access to CLS data has enabled researchers to study customer-dealer volume at a global scale (Hasbrouck and Levich, 2018, 2021; Ranaldo and Santucci de Magistris, 2018; Cespa, Gargano, Riddiough, and Sarno, 2021; Ranaldo and Somogyi, 2021). We contribute to this strand of literature by investigating the impact of FX dealer constraints on both the cost and quantity dimension of global FX market liquidity.

2. Measuring the cost of liquidity provision in FX markets

2.1. Data sources

The empirical analysis employs high-frequency trade and quote data from two main sources. The spot FX volume data come directly from CLS Group (CLS) and is sampled hourly. Note that the dataset excludes any trades between two market makers or two price takers and hence only includes trading activity that is *intermediated* by FX dealer banks. This data set is publicly available from CLS or via Quandl.com, a financial and economic data provider.[7] CLS data have been used in prior research, among others, by Hasbrouck and Levich (2018, 2021), Ranaldo and Santucci de Magistris (2018), Cespa et al. (2021), and Ranaldo and Somogyi (2021). These authors have comprehensively described the CLS volume data.

The full sample period spans from November 2011 to September 2020 and includes data for 18 major currencies and 33 currency pairs. Our goal is to construct measures capturing the cost of liquidity provision. We derive these measures from triangular no-arbitrage trades 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.[8]

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. The indicative bid and ask quotes are directly available for all 25 currency pairs but do not correspond to actually executable transaction prices. This is not an issue for

[7]CLS operates the world's largest payment-vs-payment settlement system handling up to 50% of global FX volumes. At settlement, CLS mitigates principal and operational risk by settling both sides of the trade at once.

[8]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.

our purposes for two reasons: First, we are interested in measuring the cost of liquidity provision rather than identifying actual triangular arbitrage opportunities. Second, on average, the correlation of Olsen indicative quotes with tradeable EBS best bid and offer prices is around 99% and the mean absolute error is roughly 3.3%.[9]

2.2. *Key variables*

We measure the cost of liquidity provision in the spot FX market along two dimensions: i) violations of the law of one price (VLOOP), and ii) round-trip transaction costs (TCOST). In a first step, we explain how we derive the two components and, in a second step, elaborate how they relate to the costs that dealers face when providing spot FX liquidity.

Conceptually, VLOOP captures the price dislocations for two assets or trading positions with the same intrinsic value, while TCOST refers to the round-trip trading costs to take advantage of the violations. We derive both measures from the well-known triangular arbitrage trade that takes advantage of three exchange rates (e.g., Chaboud et al., 2014; Foucault et al., 2016). The VLOOP component of the triangular arbitrage trade can be computed with midquote prices reflecting the intrinsic values of the direct and indirect positions. TCOST in turn is computed from the bid and ask quotes (depending on the base and quote currency).

Deriving VLOOP and TCOST from the triangular no-arbitrage relation. 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 euro is given as:

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

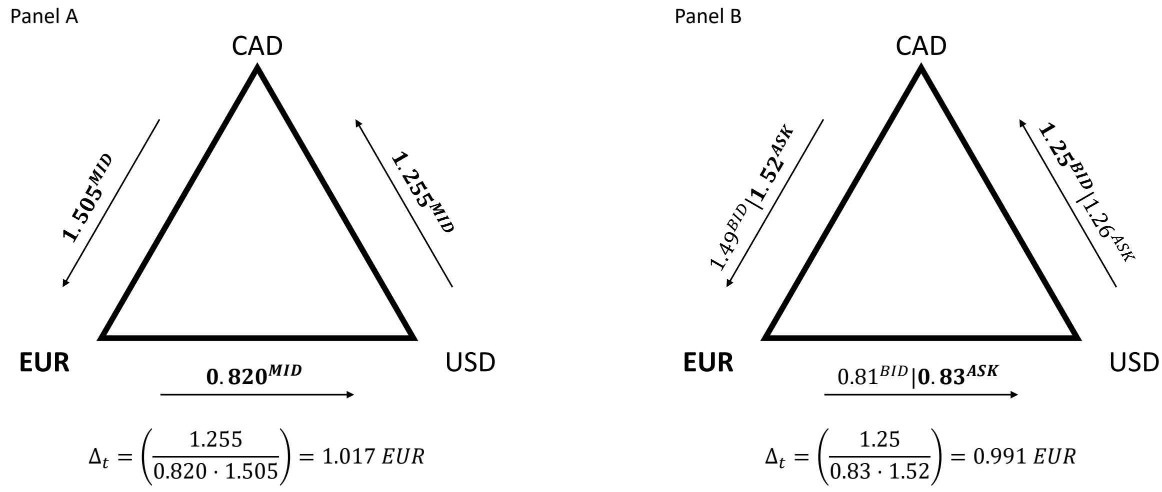
where $P_{1,t} = \frac{1}{USDEUR_t^{mid}}$, $P_{2,t} = USDCAD_t^{mid}$, and $P_{3,t} = \frac{1}{EURCAD_t^{mid}}$ denote midquote exchange rates expressed as the amount of quote currency per unit of base currency, for instance, 1.255 Canadian dollar per US dollar (i.e., indirect quotation).

The trader has identified a violation of the law of one price if Δ_t is different from unity. Note that Δ_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 conditional on Δ_t being positive. Panel A in Figure 1 provides a schematic overview of how to measure such deviations from triangular no-arbitrage conditions based on midquote prices.

[9]To be precise, we estimate correlations and mean absolute errors individually for 25 currency pairs over the full-year of 2016. For brevity, we relegate these results to the Online Appendix.

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, she pays the midquote price plus the half-spread. To reflect this, we replace the midquote prices in Eq. (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 currency. Panel B in Figure 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 1: Triangular arbitrage trade



Note: This figure provides a schematic overview of a triangular arbitrage trade prior (Panel A) and after transaction costs (Panel B). 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 equivalent a negative return of -0.9%.

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

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

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

The first part of Eq. (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. In our context, these costs stem from constraints that are related to spot FX liquidity provision. The second part (i.e., $TCOST_t$) reflects the cumulative round-trip transaction cost of performing such a triangular arbitrage trade. Hence, these transaction costs also represent the dealer's compensation to endure an inventory imbalance due to the clients' demand for immediacy.

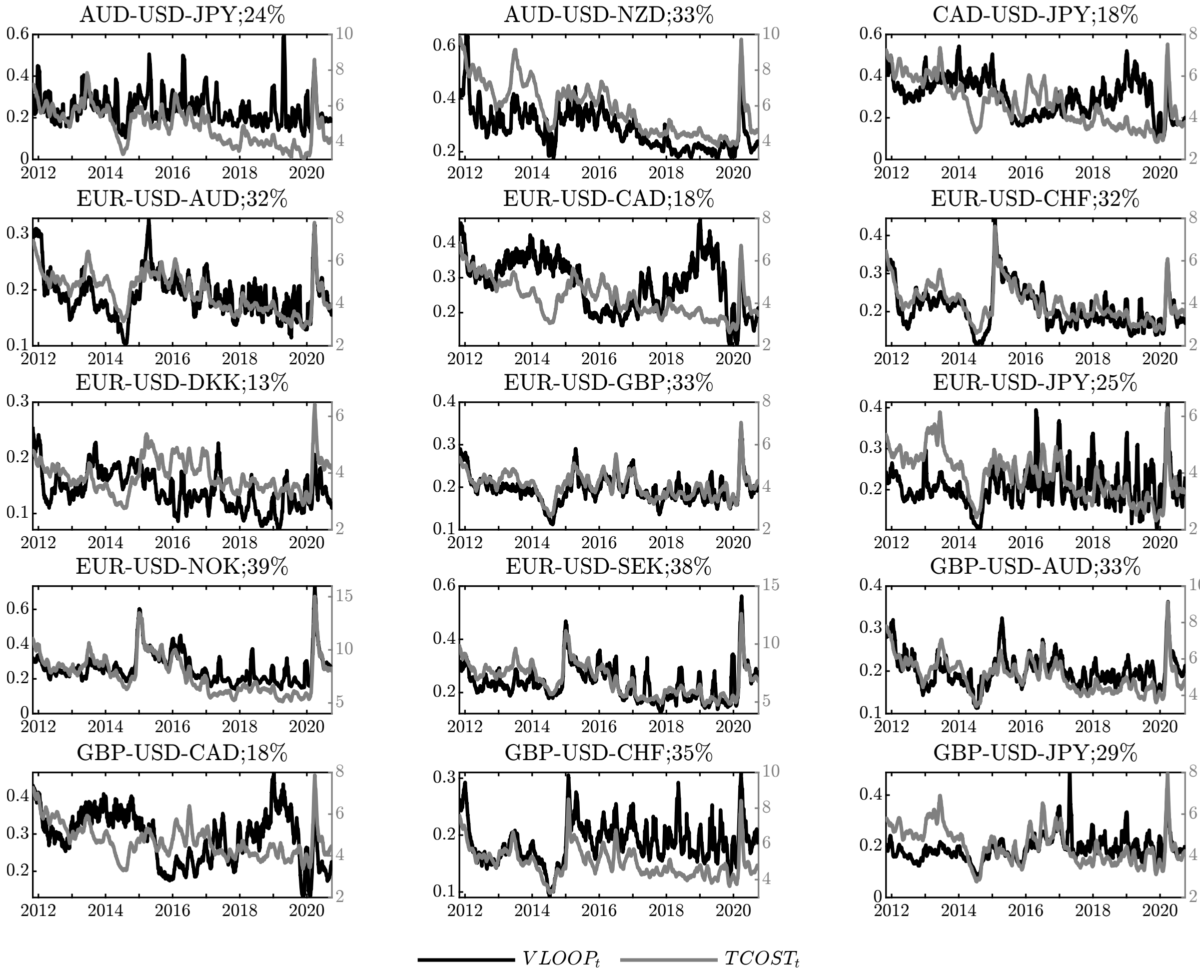
Following our methodology, we compute $VLOOP_t$ and $TCOST_t$ for $k = 1, 2, ..., 15$ triplets of currency pairs. A triplet of currency pairs is defined as one non-dollar currency pair (e.g., EURCAD) plus the two USD legs (e.g., USDEUR and USDCAD).[10] In particular, at every point in time we take the perspective of the arbitrageur above by first, identifying the seemingly profitable direction of the trade by conditioning on $VLOOP_t$ being positive and second, by extracting the associated transaction cost $TCOST_t$. Moreover, we prune the hourly time-series of $VLOOP_t$ and $TCOST_t$, respectively, for heavy outliers, which we define as observations in the top and bottom 1.5 percentiles of the data. Eventually, we can also compute daily measures of $VLOOP_t$ and $TCOST_t$ by summing up hourly observations for each day.

Empirical illustrations. Figure 2 shows the time-series and cross-sectional variation of hourly no-arbitrage violations $VLOOP_t$ (left y-axis) and round-trip transaction costs $TCOST_t$ (right y-axis), respectively. Economically, a higher reading of $VLOOP_t$ coincides with a larger shadow cost of intermediary constraints, whereas $TCOST_t$ captures the realised compensations for providing immediacy. Both measures of dealers' liquidity costs exhibit intuitive properties in the sense that they surge during periods of 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 $VLOOP_t$ and $TCOST_t$ is positive for the entire cross-section and ranges from 12–39%. We interpret this as evidence of commonality in no-arbitrage violations and market liquidity in the broader sense (Rösch, 2021).

Table 1 reports the time-series average of hourly triangular no-arbitrage deviations VLOOP and round-trip transaction costs TCOST. In addition, it also tabulates hourly averages of direct trading volume in non-dollar currency pairs (e.g., AUDJPY) and synthetic trading volume in

[10]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 for these additional findings.

Figure 2: No-arbitrage violations and round-trip transaction costs



Note: This figure plots the absolute value of 22-day moving averages of hourly triangular no-arbitrage deviations $VLOOP_t$ (left y-axis) and round-trip trading costs $TCOST_t$ (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 $VLOOP_t$ and $TCOST_t$. The sample covers the period from 1 November 2011 to 30 September 2020.

dollar pairs (e.g., USDAUD and USDJPY). By "synthetic" we refer to the total sum of trading volume in two dollar currency pairs within a currency pair triplet, for instance, AUDJPY, USDAUD, and USDJPY, that we abbreviate as AUD-USD-JPY. Each row corresponds to one triplet of currency pairs.

This simple summary statistics table conveys two main insights: First, deviations from fundamentals VLOOP are an order of magnitude smaller than round-trip transaction costs 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 most of the time will not be 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 currency pairs.[11] 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. Consequently, the average relative bid-ask spread and realised volatility are somewhat smaller in the more heavily traded dollar than in 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	Synthetic
AUD-USD-JPY	0.24	4.88	0.18	5.11	4.15	5.87	14.38	15.86
AUD-USD-NZD	0.29	5.85	0.09	2.01	4.44	7.43	9.32	17.95
CAD-USD-JPY	0.30	4.67	0.03	5.32	4.29	5.21	12.66	13.39
EUR-USD-AUD	0.19	4.52	0.14	7.72	3.54	5.64	11.54	15.51
EUR-USD-CAD	0.28	4.25	0.08	7.94	3.55	4.99	10.15	12.89
EUR-USD-CHF	0.21	3.98	0.37	6.76	2.62	5.41	6.38	13.44
EUR-USD-DKK	0.14	3.89	0.09	6.17	2.54	5.30	1.82	13.03
EUR-USD-GBP	0.19	4.07	0.61	8.16	3.19	4.95	9.52	13.60
EUR-USD-JPY	0.21	3.90	0.65	9.67	3.14	4.83	11.43	13.71
EUR-USD-NOK	0.26	7.69	0.24	6.25	6.25	9.40	11.01	16.90
EUR-USD-SEK	0.23	6.86	0.27	6.27	5.41	8.42	9.18	15.95
GBP-USD-AUD	0.20	5.08	0.04	3.60	4.22	5.99	12.53	15.93
GBP-USD-CAD	0.29	4.69	0.03	3.81	4.00	5.34	10.85	13.31
GBP-USD-CHF	0.19	4.94	0.03	2.64	4.09	5.76	10.69	13.99
GBP-USD-JPY	0.19	4.47	0.20	5.55	3.85	5.18	12.78	14.13

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 currency pairs (e.g., AUDJPY) in $bn, synthetic volume in dollar pairs (e.g., the sum across USDAUD and USDJPY) in $bn, as well as direct and synthetic relative bid-ask spreads and realised volatility in non-dollar and dollar pairs in bps, respectively. 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 2020.

3. Elasticity of liquidity provision and dealer constraints

This section presents evidence consistent with our hypothesis that dealers accommodate their customers' trading demands in normal times, whereas their liquidity provision becomes increasingly inelastic at times of heightened intermediation constraints. The analysis is split into two parts. We first start with some simple motivating evidence showing that the relationship between dealer-intermediated volumes and the cost of liquidity provision depends on dealers' intermediation constraints. We then draw on smooth transition regressions to study the state-dependent nature of this relation more formally.

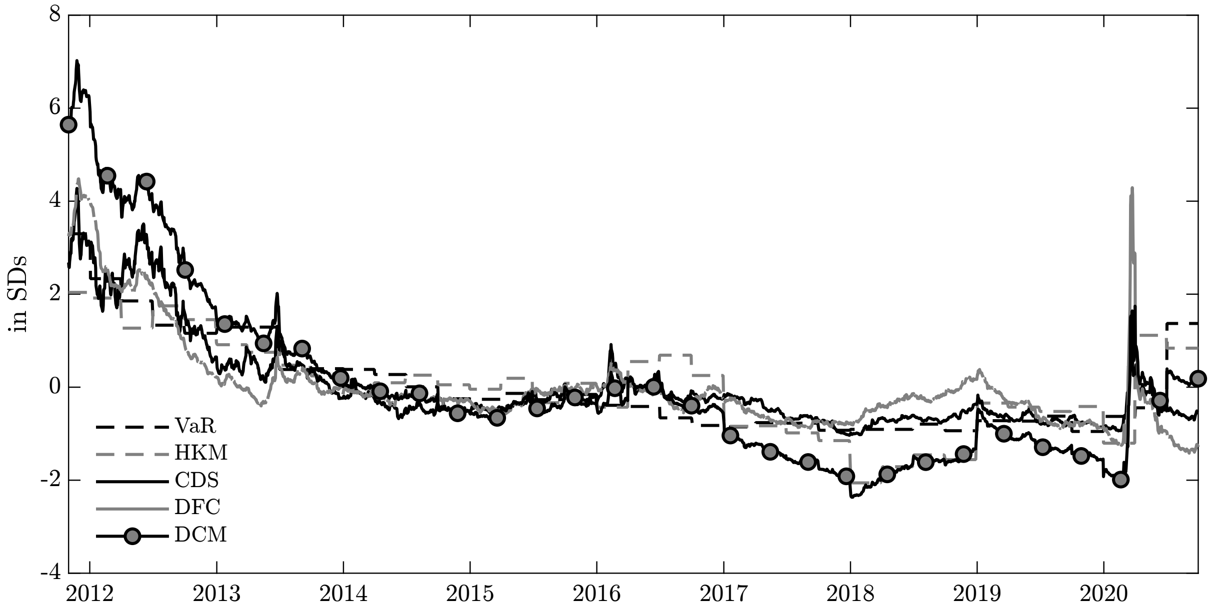
[11] Somogyi (2021) provides both theoretical and empirical evidence in favour of the idea that strategic complementarity in price impact can explain these cross-sectional differences between dollar and non-dollar pairs.

3.1. *Motivating evidence*

For motivational purposes, we first present some descriptive evidence of how trading volume and the costs of liquidity provision (i.e., VLOOP and TCOST) co-move over time. In a second step, we then compute conditional correlations to show how the relation weakens as intermediaries become more constrained.

To measure dealer banks' intermediation constraints we derive a composite dealer constraint measure (DCM) that we compute in two steps. As a first step, we create four time-series based on cross-sectional averages of the top 10 FX dealer banks' (see Euromoney FX surveys) i) Value-at-Risk (VaR) of the FX trading book (quarterly), ii) He et al. (2017) leverage ratio (quarterly), iii) credit default swap (CDS) premia (daily) and iv) debt funding costs (daily). Figure 3 shows the time-series variation of these four measures that exhibit correlations ranging from 58% to 91% percent. See the Online Appendix for details on how we retrieve and compute each of these variables.

Figure 3: State variables: Dealer constraint measure and its components



Note: This figure plots different state variables that we observe at the daily and quarterly frequency. Observations have been standardised by subtracting the sample mean and dividing by the sample standard deviation of every variable. The four state variables are the 1-day lagged value of primary FX dealer banks' i) quarterly Value-at-Risk measure (VaR, dashed black line), ii) quarterly He et al. (2017) leverage ratio (HKM, dashed grey line), iii) daily credit default spread (CDS, solid black line), and iv) daily funding cost yield (DFC, solid 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 2020.

All of these factors can have a bearing on financial intermediaries' capacity to absorb customer order flow imbalances on their balance sheet. For example, self-imposed or regulatory-driven VaR-limits force dealers to scale back their market making or proprietary trading.

Similarly, dealers' willingness to engage in market making activity and liquidity provision is linked to their risk profile, as reflected, for instance, in higher leverage and CDS premia. In addition, elevated risk exposure can lead to an immediate increase in funding costs and valuation adjustments (XVA), including debt and funding value adjustments (Andersen et al., 2019). These factors in turn will affect dealers' assessment of the financing costs for its franchise, and as such will have a bearing on its intermediation activities.

Since large FX dealer banks (e.g., Citi Bank or UBS) typically operate on a global scale and provide liquidity in many currencies and other asset classes at once, they are even more exposed to these issues. As such, intermediaries might be forced to reduce liquidity provision in *all* currency pairs when they endure trading losses in particular positions and/ or experience funding constraints affecting the whole dealer franchise.

As a second step, we extract the first principal component that explains around 83% of the total variance and serves as our composite measure of dealer constraints. Hence, the key advantage of our dealer constraint measure DCM is that it encompasses a range of different factors that can all impact dealers' risk appetite and willingness to warehouse risk.[12] By doing so, we are able to extract common information of all these factors and obtain a *daily* measure of economic constraints on global dealers' intermediation activity.[13]

A valid question is whether our dealer constraint measure may be also affected by the amount of intermediated volume itself. There are at least two reasons why this is unlikely to be the case: First, we use lagged DCM in all our state-dependent regression analyses to rule out any contemporaneous relation or reverse causality issues. Second, spot FX intermediation activity only minimally affects dealer leverage since it is a direct exchange of two currencies (i.e., an accounting exchange on the asset side). And similarly, FX trading volume is unlikely to affect the dealers' credit spread and overall costs of funding.

Figure 4 plots 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.[14] 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

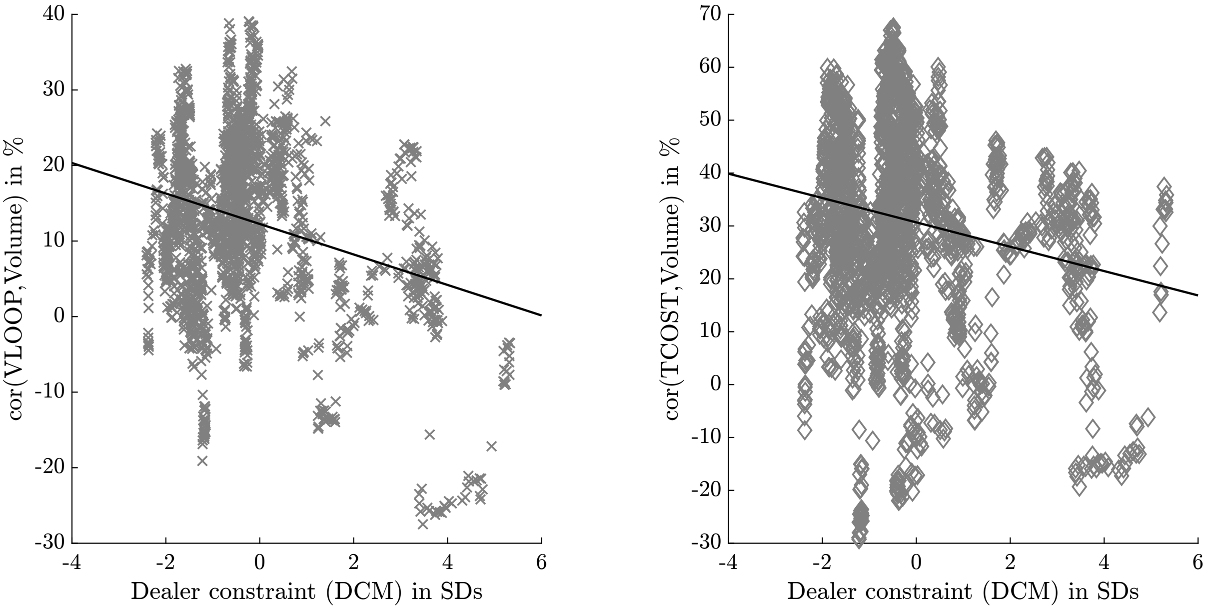
[12]One might wonder how much our results are driven by market-wide state factors that are not dealer specific. To prove robustness, we use the VIX index, TED spread, gold price, and the LIBOR-OIS spread. We find that these state variables do not appropriately capture the state-dependent relation between liquidity costs and trading volume. See the Online Appendix for output tables.

[13]Ideally, we would be able to measure dealer constraints intraday. Unfortunately, this is not feasible due to the low frequency availability of VaRs, leverage ratios, CDS spreads, and debt funding costs at the bank level.

[14]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. Moreover, the decline in DCM since 2012 is also consistent with the rise of electronic and algorithmic trading activity in the FX market.

TCOST) and trading volume weakens substantially as DCM increases.

Figure 4: 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 dealers' (based on the Euromoney FX survey) quarterly Value-at-Risk measure (VaR), quarterly He et al. (2017) leverage ratio (HKM), daily credit default spread (CDS), and daily debt funding cost (DFC). The bold black lines are linear regression lines. The sample covers the period from 1 November 2011 to 30 September 2020.

Table 2 takes the descriptive analysis one step further by computing conditional correlation coefficients of (log) changes in VLOOP, TCOST, and dealer-intermediated trading volume (i.e., VLM) across the quantiles of our dealer constraint measure DCM. Consistent with our intuition, we find that the correlation with each of the two liquidity cost measures (i.e., VLOOP and TCOST) weakens substantially as our dealer constraint measure DCM increases. For instance, the conditional correlation based on the highest DCM decile (i.e., when dealers are most constrained) is a mere 17% for TCOST, and hence economically and statistically significantly lower than the full-sample correlation of 31%. Moreover, we also observe a monotonic increase in both liquidity cost measures and also a stronger commonality of VLOOP and TCOST (i.e., $cor(VLOOP, TCOST)$) across the DCM quantiles.

These initial results suggest that market liquidity tends to deteriorate when dealers are more constrained. Our preliminary explanation (which we formalise based on a simple model in Section 4) for these empirical findings is that there are two main forces at play when dealers are constrained: On the one hand, violations of no-arbitrage conditions (i.e., VLOOP) increase as dealers charge a higher mark-up (or mark-down) across currency pairs reflecting the increase in the shadow cost of intermediary constraints. On the other hand, dealers will also post more conservative bid and ask quotes and thus increasing transaction costs (i.e., TCOST) due to the surge in the cost of economic capital. Consequently, a higher spread will discourage clients' trading activity, which in turn makes dealers' incoming customer flows less imbalanced dampening VLOOP. As we show in the model, the first effect dominates if dealer constraints are sufficiently small resulting in a higher VLOOP. A potential interpretation, which we develop in much more depth below both empirically and theoretically, for this finding is that during constrained periods dealers' liquidity provision is not elastic enough to dampen the deterioration in market liquidity conditions.

Table 2: Liquidity provision cost characteristics across top DCM quantiles

Top DCM quantile		$cor(VLOOP, VLM)$	$cor(TCOST, VLM)$	$cor(VLOOP, TCOST)$	$\overline{VLOOP}$ in %	$\overline{TCOST}$ in %	$\overline{VLM}$ in \$bn	#Obs
least constrained	1.0	0.12	0.31	0.22	0.05	1.12	148.66	2,182
	0.9	0.12	0.31	0.22	0.05	1.14	150.21	1,954
	0.8	0.11	**0.30	0.22	0.05	1.18	153.27	1,726
	0.7	0.13	*0.30	0.22	0.05	1.21	157.93	1,500
	0.6	0.13	**0.30	0.22	0.05	1.23	159.24	1,271
	0.5	0.12	***0.28	0.21	0.05	1.23	158.99	1,042
	0.4	0.12	***0.22	0.21	0.06	1.28	161.65	815
	0.3	0.10	***0.16	*0.20	0.06	1.32	169.36	586
	0.2	***0.06	***0.18	0.22	0.06	1.35	176.74	358
most constrained	0.1	***−0.03	***0.17	***0.28	0.06	1.44	180.52	129

Note: This table shows the conditional correlation of our two liquidity cost measures (i.e., $VLOOP$ and $TCOST$) and total trading volume VLM across the top quantiles of the dealer constraint measure (DCM, columns 1 and 2). Column 3 reports the conditional correlation between $VLOOP$ and $TCOST$. The underlying data are based on a panel of 15 currency pair triplets. The asterisks *, **, and *** indicate that the correlation is significantly different from the full sample (in the first line) estimate at the 90%, 95%, and 99% levels. The corresponding test statistic for the conditional correlation cor^{τ} being equal to the full sample correlation $cor^{\tau=1.00}$, where $\tau \in 0.1, 0.2, ..., 0.9$ refers to top DCM_t deciles, are based on the Fisher z-transformation. Columns 4 to 6 report the average $VLOOP_{k,t}$ ($\overline{VLOOP}$) in %, $TCOST_{k,t}$ ($\overline{TCOST}$) in %, and the average $VLM_{k,t}$ ($\overline{VLM}$) in \$bn across 15 currency pair triplets. The last column contains the average number of observations (#Obs). The full sample covers the period from 1 November 2011 to 30 September 2020.

3.2. *Smooth transition regressions*

We next briefly describe our preferred econometric approach that is based on a simple smooth transition regression (LSTAR) model (e.g., van Dijk, Teräsvirta, and Franses, 2002; Christiansen et al., 2011). The LSTAR model is particularly well-suited for our analysis as constrained and unconstrained regimes are determined endogenously and are allowed to vary smoothly over time.[15]

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

$$G(z_{t-1}) = (1 + \exp(-\gamma'(z_{t-1} - c)))^{-1}, \tag{3}$$

[15] As robustness check, we have also experimented with Markov chain switching models using DCM as an exogenous state variable and found consistent results. These additional findings are available upon request.

where the parameter c is the central location and the vector γ determines the steepness of $G(z_{t-1})$. Hence, the LSTAR model is of the form

$$y_{k,t} = \lambda_t + \alpha_k + [1 - G(z_{t-1})]\beta_1' f_{k,t} + G(z_{t-1})\beta_2' f_{k,t} + \beta_3' w_{k,t} + \varepsilon_{k,t}, \tag{4}$$

where the dependent variable is one of our two liquidity cost measures (i.e., VLOOP or TCOST) and $f_{k,t}$ ($w_{k,t}$) are state-dependent (*state-independent*) regressors. We include both cross-sectional α_k and time-series λ_t fixed effects to control for any unobservable heterogeneity that is constant across triplets of currency pairs k and time t, respectively. For estimation, we use the generalised method of moments (GMM) and determine the optimal parameters γ and c by nonlinear least squares minimising the concentrated sum of squared errors.[16] Note that the slope coefficients in Eq. (4) vary smoothly with the regime variable z_{t-1} from β_1 at low values of $\gamma' z_{t-1}$ to β_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 variable.

The state-dependent explanatory variable $f_{k,t}$ is the total dealer-provided trading volume (i.e., $VLM_{k,t}$) that is defined as the sum of all trading volume in one non-dollar as well as two dollar currency pairs within a particular currency pair triplet k. The state-independent variable is the realised variance (i.e., $RV_{k,t}$) in the direct non-dollar currency pair (e.g., AUDJPY) that we estimate following Barndorff-Nielsen and Shephard (2002) as the sum of squared intraday midquote returns. Note that across all regression specifications both LHS and RHS variables are taken in logs and first differences. The obvious advantage of this is twofold: First, regression coefficients are straightforward to be interpreted as elasticities. Second, FX volume in levels is non-stationary and persistent (see Ranaldo and Santucci de Magistris, 2018), hence taking first-differences is an effective remedy to render the series stationary.

Table 3 shows the passage from a linear model with a dummy to a non-linear smooth transition regression (LSTAR). To be specific, the first two columns in this table report the results from estimating a linear model (OLS) of the form

$$y_{k,t} = \lambda_t + \alpha_k + \beta_1' f_{k,t} + \delta' f_{k,t} \cdot D_{t-1} + \beta_3' w_{k,t} + \epsilon_{k,t}, \tag{5}$$

where $f_{k,t}$ and $w_{k,t}$ collect all regressors and D_{t-1} is a 1-day lagged interaction variable capturing periods of heightened dealer constraints. Note that the estimate of δ corresponds to the difference between the constrained and unconstrained regime coefficient (i.e., $\beta_2 - \beta_1$) of the LSTAR model in Eq. (4). In column 'Dummy', D_t is equal to one if DCM_t is above its 75% quantile in period t. Note that the specifications in 'Dummy' is a simple, yet intuitive, approximation of non-linear regression model. In column 'Logistic', D_t is a logistic transformation of DCM_t based on $1/[1 + exp(-\gamma DCM_t)]$, where γ determines the steepness of the function.

[16]Our inference is based on a Driscoll and Kraay (1998) covariance matrix that allows for random clustering and serial correlation up to 8 lags. We choose the optimal bandwidth using the plug-in procedure for automatic lag selection by Andrews and Monahan (1992) and Newey and West (1994), respectively.

For simplicity, we set $\gamma = 1$ but the results in column 'Logistic' are robust for values of γ ranging from 1 to 12. Lastly, in column 'LSTAR' the table shows results from a smooth transition regression (LSTAR) as in Eq. (4), which constitutes our preferred econometric approach. Again, the logistic function $G(z_{t-1})$ depends on 1-day lagged values of our dealer constraint measure DCM_t.[17] Note that across each of the three specifications we control for the realised variance in the direct non-dollar currency pair (e.g., AUDJPY). Moreover, in the Online Appendix we show that our findings are robust to including the cross-currency (CIP) basis (e.g., Akram, Rime, and Sarno, 2008; Du, Tepper, and Verdelhan, 2018) and the Amihud (2002) price impact as a control for FX funding (Andersen et al., 2019; Rime, Schrimpf, and Syrstad, 2021) and market (e.g., Ranaldo and Santucci de Magistris, 2018) liquidity, respectively.

There is a consistent picture that arises across all three specifications in Table 3: the difference between the slope coefficient on total trading volume in constrained and unconstrained periods is negative and highly statistically significant for both VLOOP and TCOST. Moreover, the estimated slope coefficients are almost identical for the linear model with dummy (column 'Dummy') and the LSTAR model (column 'LSTAR'). In both cases, the difference in the slope coefficients (i.e., $\beta_2 - \beta_1$) is at least 80% lower when dealer banks are constrained and hence less willing or able to cater their customers' trading demands. In sum, two findings stand out from this analysis: First, dealer-provided volume covaries significantly less with VLOOP and TCOST during times when dealers are more constrained. Second, it is above all the relation between VLOOP and trading volume that strongly diverges and even exhibits negative (albeit insignificant) coefficients in the constrained regime.

Taken together, these results highlight the state-dependent nature of the relation between our two liquidity cost measures (i.e., VLOOP and TCOST) and dealer-intermediated trading volume.[18] Moreover, the estimated coefficient linking VLOOP and TCOST to DCM can be interpreted as an elasticity due the log and first-difference transformation of all variables. From this perspective, our results suggest that dealers' liquidity provision is generally elastic in normal times, supporting market liquidity. However, when dealers face constraints their liquidity supply becomes more inelastic, which adversely affects both the noise in exchange rates (i.e., VLOOP) and also the level of transaction costs (i.e., TCOST).

To hone some further intuition for the LSTAR model, we plot the resulting time path of the fitted regime function $G(DCM_t)$ for VLOOP and TCOST in Panels A and B of Figure 5. Except for the first two years of the sample, the fitted $G(DCM_t)$ is mostly close to 0 (it is less than 0.25 on 57% and 72% of the days in the sample for VLOOP and TCOST, respectively) and occasionally increases above 0.75 (36% and 22% of the days for VLOOP and TCOST, respectively). These upward spikes are particularly pronounced during the European sovereign debt crisis through 2014/15, uncertainty around Brexit and US elections in 2016, and also the

[17] In the Online Appendix we show that our findings are robust to using up to 22 lags (see Figures B.4 and B.5).

[18] Note that our estimates for the difference in the slope coefficients across constrained and unconstrained regimes are very similar when using either VLOOP or TCOST as a regressor and VLM as the dependent variable.

Table 3: From linear model with dummies to smooth transition regression

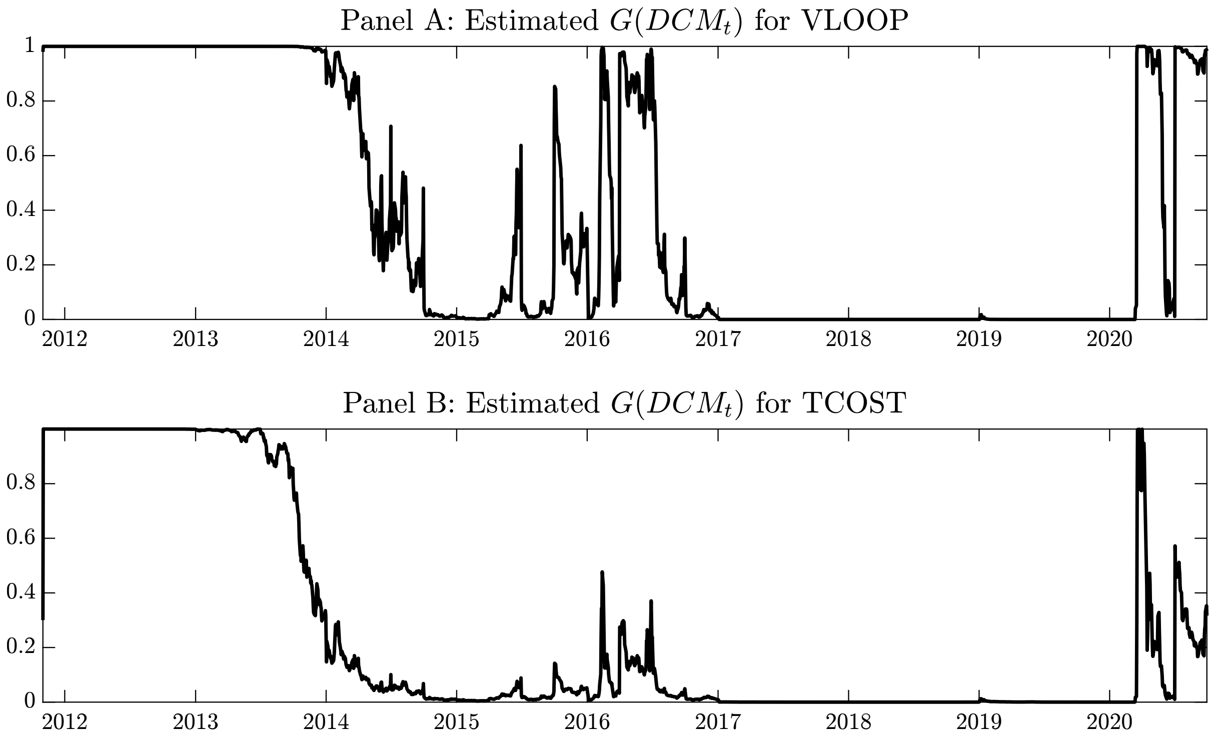
	VLOOP			TCOST		
	Dummy	Logistic	LSTAR	Dummy	Logistic	LSTAR
γ		1.00	***12.05		1.00	***5.94
c			***−0.14			***0.39
Unconstrained volume	***0.08	***0.16	***0.11	***0.09	***0.12	***0.09
	[2.94]	[3.47]	[3.50]	[11.07]	[8.55]	[10.85]
Constrained volume	−0.07	*−0.09	−0.05	0.01	0.02	0.01
	[1.37]	[1.72]	[1.40]	[0.85]	[1.14]	[0.96]
Realised variance	**0.02	**0.02	**0.02	***0.03	***0.03	***0.03
	[2.05]	[2.01]	[2.02]	[7.98]	[7.95]	[7.95]
Constrained-Unconstrained	***−0.14	***−0.25	***−0.16	***−0.08	***−0.10	***−0.08
	[2.66]	[2.90]	[3.25]	[4.88]	[4.19]	[4.78]
R^2 in %	0.13	0.14	0.15	3.78	3.73	3.78
Avg. #Time periods	2,182	2,182	2,182	2,185	2,185	2,185
#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: In columns labelled 'Dummy' and 'Logistic' this table reports results from estimating a linear model (OLS) of the form $y_{k,t} = \lambda_t + \alpha_k + \beta_1' f_{k,t} + \delta' f_{k,t} \cdot D_{t-1} + \beta_3' w_{k,t} + \epsilon_{k,t}$, 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 δ 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% quantile in period t. In column 'Logistic', D_t is a logistic transformation of DCM_t based on $1/[1 + exp(-\gamma DCM_t)]$, where γ determines the steepness of the function. In column 'LSTAR' the table shows results from a smooth transition regression (LSTAR) of the form $y_{k,t} = \lambda_t + \alpha_k + [1 - G(z_{t-1})]\beta_1' f_{k,t} + G(z_{t-1})\beta_2' f_{k,t} + \beta_3' w_{k,t} + \varepsilon_{k,t}$, 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 γ 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 2020. 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; Newey and West, 1994) are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% levels.

Covid-19 period in 2020. Hence, the unconstrained regime (when β_1 is the effective slope coefficient) corresponds to a normal market situation, while the constrained regime (when the effective slope coefficient is close to β_2) represents stressed periods when dealers face constraints on their risk-bearing capacity.

Besides the LSTAR approach, we also rely on an alternative methodology in the robustness section of the paper. Specifically, we estimate the correlation between each of our two liquidity cost measures (i.e., VLOOP and TCOST) and dealer-intermediated volume in a rolling window and regress it on DCM. Consistent with our baseline results, we find that the rolling correlation between VLOOP or TCOST and volume decreases as DCM increases. Moreover, we extract exogenous liquidity demand and supply shocks from a structural vector autoregression inspired by Goldberg (2020). We use the demand shocks as instrument for DCM and the supply shocks as an alternative measure of tightening dealer constraints arising outside of the FX market (see Section 5 for further details).

Figure 5: Time-series of fitted regime function $G(\text{CDS})$



Note: Panel A of this figure shows the fitted regime function $G(DCM_t)$ for VLOOP using the point estimates in column 3 of Table 3, whereas Panel B shows the fitted regime function $G(DCM_t)$ for TCOST using the point estimates in column 6 of Table 3. The sample covers the period from 1 November 2011 to 30 September 2020.

4. A simple model of constrained liquidity supply

This section presents a static partial equilibrium model that rationalises the two main empirical findings from the previous section:

1. The cost of liquidity provision (i.e., VLOOP and also TCOST) is higher when volatility is higher and FX dealer banks are more constrained (see Table 2).
2. Liquidity provision costs and dealer-provided volume co-move when the dealers are unconstrained but the positive correlation decreases when dealer constraints tighten (see Table 3).

The model features two periods ($t = 0, 1$), three currency pairs (e.g., EURCAD, USDEUR, USDCAD) and two types of agents: liquidity traders and one representative dealer. At $t = 0$, liquidity traders arrive and trade with the dealer. At $t = 1$, the uncertainty is resolved.

4.1. *Trading environment*

FX spot contracts. Let us denote the three currency pairs as x, y, and z. Let $\mathbf{p}$ denote the exchange rates of the three currency pairs $[p^x, p^y, p^z]^T$ at $t = 0$ whereby the base currency for the first currency pair is the EUR, whereas for the other two it is the USD. For instance, for currency pair x, 1 EUR = p^x CAD. More specifically, let a^j and b^j denote the ask and bid price of currency pair j, and m^j and s^j denote the mid-quote and the spread of currency pair j.

The agents trading these three currency pairs at $t = 1$ get the fundamental value, in which there is no difference between the direct FX rate (i.e., EURCAD) and the correspondent synthetic rate computed with two indirect rates (i.e., first USDEUR and then USDCAD). We denote the fundamental value of the three currency pairs as $\tilde{\mathbf{e}} = [\tilde{e}^x, \tilde{e}^y, \tilde{e}^z]^T$. The mean and variance of the fundamental value are $\mathbf{e} = [e^x, e^y, e^z]^T$ and $\boldsymbol{\sigma} = [\sigma, \sigma, \sigma]^T$, respectively. Note that the three fundamental values are intimately linked via $e^x = e^y e^z$.

Liquidity 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). At $t = 0$, there is L unit mass of liquidity traders in each currency pair where L is increasing in σ. In addition, L is a decreasing function of the transaction cost, that is, the (absolute) spread s quoted by the dealer. Let λ denote the trading demand parameter and hence $L = \lambda\sigma(1 - s)$. A π fraction of the liquidity traders in currency pair x are buyers and the rest are sellers. For currency pair y, a π fraction of liquidity traders are sellers and the rest are buyers. For currency pair z, half of them are buyers, whereas the other half are sellers.

The demand is imbalanced across the three currency pairs due to diverging private values among market participants (i.e., disagreement), following the spirit of Gabaix and Maggiori (2015).[19] For simplicity, suppose that π is larger than $1/2$. Thus, the liquidity traders impose net buying pressure $(2\pi - 1)$ in currency pair x and net selling pressure $(1 - 2\pi)$ in currency pair y. As a result, the liquidity traders' demand imbalance (i.e., the net buying pressure)[20] in each of the three currencies is given as

$$\mathbf{d} = \lambda\sigma(1 - s) \times [2\pi - 1, 1 - 2\pi, 0]^T. \tag{6}$$

Dealer. There is a representative and competitive dealer, à la Foucault, Pagano, and Roell (2013, Sec. 3.5). The dealer is risk-averse and is endowed with equity capital that is worth

[19] To account for the effect of disagreement, we have explored regression specifications including alternative high-frequency measures of disagreement. For instance, we consider the dispersion of order flows of corporates, funds, non-bank financials, and banks (Cespa et al., 2021) as well as the volume-volatility ratio (Liu and Tsyvinski, 2020) as control variables and have found that our key empirical results remain qualitatively unchanged. These additional findings are available upon request.

[20] As the empirical results suggest in the previous section, the violation of the law of one price does 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.

$\mathbf{E}$ and makes the market at $t = 0$. Being competitive and starting with zero inventory, she decides on her positions $\mathbf{q}$ in the three currency pairs, where $q^j > 0$ means the dealer sells the currency pair j, taking the market-clearing prices $\mathbf{p}$ as given.

The dealer is assumed to be debt-financed and incurs funding costs when managing inventory positions associated with market making (e.g., Scott, 1976; van Binsbergen, Graham, and Yang, 2010). The funding cost has two components: a financing cost and an economic capital cost. The financing cost is proportional to the net positions in the three currency pairs: $\mathbf{1^T}|\mathbf{q}|$, where $\mathbf{1} = [1, 1, 1]^T$. The economic capital increases in the Value-at-Risk of the currency positions: $\mathbf{q^T \Sigma q}$, where $\mathbf{\Sigma}$ is the covariance matrix across the triplet of currency pairs.[21] For simplicity, suppose the per-unit funding cost across the three currency pairs is the identical and is denoted by η which increases in the dealer's leverage and her debt financing costs. Hence, η can be interpreted as a measure of the dealer's constrainedness. The utility of the dealer is given as

$$U^D = E\Big(\mathbf{p^T q} - \mathbf{e^T q}\Big) - \eta\Big(\underbrace{\mathbf{1^T}|\mathbf{q}|}_{\text{Outstanding position}} + \underbrace{\mathbf{q^T \Sigma q}}_{\text{Economic capital}} \Big). \tag{7}$$

Thus, the empirical constraints examined in Section 3 (i.e., leverage ratio in He et al. (2017), CDS spreads, dealers' bond financing cost, and Value-at-Risk constraint) are captured via the financing and economic capital components of the debt funding cost η.[22]

Market clearing. The market clearing condition is the following: At $t = 0$, the liquidity traders' demand is equal to the dealer's position $\mathbf{q}$. In other words,

$$\mathbf{d} = \mathbf{q}. \tag{8}$$

4.2. *Equilibrium outcomes*

At $t = 0$, the supply function of the dealer is pinned down by her first order condition:

$$\frac{\partial U^D}{\partial q^j} = \begin{cases} \underbrace{a^j - \eta - e^j}_{\text{marginal value of selling}} - \underbrace{2\eta\sigma^2 q^j}_{\text{price impact}} & \text{if } q^j > 0, \\ \underbrace{b^j + \eta - e^j}_{\text{marginal value of buying}} - \underbrace{2\eta\sigma^2 q^j}_{\text{price impact}} & \text{if } q^j < 0. \end{cases} \tag{9}$$

The first order condition suggests that there are two components in the dealer's supply function. The first one is related to the marginal valuation of buying and selling and arises from

[21] We assume the three currencies are i.i.d. and hence the correlations among currencies are zero. Relaxing this assumption will not change our results quantitatively.

[22] "Constrained" in our context refers to impaired risk-bearing capacity, which does not necessarily imply binding restrictions. Hence, in the model, the dealer is not subject to any additional (regulatory) binding constraints.

the debt financing cost. The second component is the price impact, which depends on the dealer's cost of economic capital. Thus, the supply function is

$$q^j = \begin{cases} \frac{a^j - \eta - e^j}{2\eta\sigma^2} & \text{if } q^j > 0, \\ \frac{b^j + \eta - e^j}{2\eta\sigma^2} & \text{if } q^j < 0. \end{cases} \tag{10}$$

Facing the liquidity traders' demand, the bid and ask prices for the three currency pairs are pinned down by the following six market clearing conditions (see Eqs (11) to (13)). There are two equations for each currency pair: one is when the dealer is buying (i.e., bid price) and the other is when the dealer is selling (i.e., ask price). Taking the first condition as an example, the left-hand side is the amount sold by the liquidity traders and the right-hand side is the amount bought from the dealer in currency pair x. Eventually, in equilibrium, the bid price of currency pair x is determined by market clearing:

$$-\lambda\sigma(1-s^x)(1-\pi) = \frac{b^x + \eta - e^x}{2\eta\sigma^2}, \qquad \lambda\sigma(1-s^x)\pi = \frac{a^x - \eta - e^x}{2\eta\sigma^2}; \tag{11}$$

$$-\lambda\sigma(1-s^y)\pi = \frac{b^y + \eta - e^y}{2\eta\sigma^2}, \qquad \lambda\sigma(1-s^y)(1-\pi) = \frac{a^y - \eta - e^y}{2\eta\sigma^2}; \tag{12}$$

$$-\frac{1}{2}\lambda\sigma(1-s^z) = \frac{b^z + \eta - e^z}{2\eta\sigma^2}, \qquad \frac{1}{2}\lambda\sigma(1-s^z) = \frac{a^z - \eta - e^z}{2\eta\sigma^2}. \tag{13}$$

Solving the system of equations, the bid-ask spreads for the three currency pairs turn out to be the same. The intuition for this hinges on the simplifying assumption that the dealers' debt financing cost and leverage as well as the volatility of fundamental values are the same across the three currency pairs.[23] Therefore, in this setup, the half bid-ask spread is given by the following expression:

$$\text{s} = \frac{\eta(1+\lambda\sigma^3)}{1+2\eta\lambda\sigma^3}. \tag{14}$$

Thus, we can express TCOST, which is equal to three times the half bid-ask spread (since financing cost, leverage, and volatility are symmetric across currency pairs) as follows:

$$TCOST = \frac{3s}{2} = \frac{3\eta(1+\lambda\sigma^3)}{1+2\eta\lambda\sigma^3}. \tag{15}$$

As a result, both the bid-ask spread and TCOST are increasing in η. Put differently, when the dealer is more constrained, either because leverage is high, or due to high debt financing cost, the bid-ask spread is also higher. Moreover, as the dealer-intermediated volume is proportional to $(1-s)$, the model implicitly assumes that $s < 1$, since volume cannot be

[23] Relaxing the assumption of homogeneous volatility across currency pairs (i.e., having currency pair specific volatility) does not change the results qualitatively because the market clearing conditions Eqs (11) to (13) are also currency pair specific.

negative. Thus, Eq. (14) implies that $\eta < 1/2$. In this case, one finds that the bid-ask spread increases in σ. Substituting $2s$ into the market clearing conditions, the mid-quotes are

$$m^x = e^x + \frac{\eta\lambda\sigma^3\,(2\pi-1)\,(1-2\eta)}{1+2\eta\lambda\sigma^3}, \quad m^y = e^y + \frac{\eta\lambda\sigma^3\,(1-2\pi)\,(1-2\eta)}{1+2\eta\lambda\sigma^3}, \quad m^z = e^z. \tag{16}$$

The mid-quotes of currency pair x and y in Eq. (16) deviate from their fundamental values e^x and e^y, if $\pi \neq \frac{1}{2}$ and $\eta \neq \frac{1}{2}$, respectively. On the contrary, the midquote for currency pair z is equal to its fundamental value (i.e., $m^z = e^z$).[24] The effect of volatility and the dealer constraints on the mid-quotes are directional and depend on the (net) order imbalance across the three currency pairs. Take currency pair x as an example. The buying pressure from the liquidity traders dominates their selling pressure, which subsequently pushes up the mid-quote price above its fundamental value. In other words, due to the buying pressure, the dealer charges a mark-up on currency pair x. This mark-up increases in the order flow imbalance (i.e., $\lambda\sigma(2\pi-1)(1-s)$) and the dealer's economic cost due to the Value-at-Risk constraint (i.e., $\eta\sigma^2$). The deviation of the mid-quotes set by the dealer from the fundamental values represents a violation of the law of one price:

$$\text{VLOOP} = m^x - m^y m^z = \lambda\sigma^3(2\pi-1)(1+e^z)\frac{\eta(1-2\eta)}{1+2\eta\lambda\sigma^3}. \tag{17}$$

Note that such deviations from the law of one price are not necessarily profitable arbitrage opportunities due to non-zero transaction costs (TCOST), that is, bid-ask spreads, which define the arbitrage bounds (Shleifer and Vishny, 1997).[25]

4.3. *The links between the model and the empirical results*

Taking the first order derivatives of TCOST with respect to σ and η, from Eq. (14) we have

$$\frac{\partial \text{TCOST}}{\partial \sigma} = \frac{9\eta\lambda\sigma^2\overbrace{(1-2\eta)}^{>0 \text{ as } \eta<1/2}}{(1+2\eta\lambda\sigma^3)^2} > 0, \tag{18}$$

$$\frac{\partial \text{TCOST}}{\partial \eta} = \frac{3(1+\lambda\sigma^3+2\eta\lambda\sigma^3)}{(1+2\eta\lambda\sigma^3)^2} > 0. \tag{19}$$

In other words, TCOST increases in both volatility (i.e., σ) and the dealer's constraint (i.e., η). The left panel in Figure 6 visualises these effects. The intuition behind the effect of volatility

[24]Note that this choice is for simplicity in the sense that with a slightly different setup on demand imbalances we could also have that $m^z \neq e^z$. More generally, as long as the demand imbalance across the three currency pairs is not exactly the same, the size of the deviations of the mid-quotes from the fundamental values is different across the three currency pairs, generating violations of the law of one price. For brevity, our modeling focuses on one illustrative example.

[25]As indicated in footnote 20, the model focuses on the cases when there are no actually profitable arbitrage opportunities and is hence consistent with the empirical evidence in Section 3.

comes from two channels. First, when volatility is higher, then the order flow imbalance is larger, pushing up TCOST. Second, a higher volatility also leads to a higher economic capital cost for the dealer. Hence, she will ask for a higher spread as compensation for larger risk. Similarly, when the dealer is more constrained (i.e., higher η), she will also charge a higher bid-ask spread as a compensation for higher debt funding costs.

Taking the first order derivative of VLOOP in Eq. (17) with respect to σ and η we get that

$$\frac{\partial \text{VLOOP}}{\partial \sigma} = (2\pi - 1)(1 + e^z)\frac{3\eta\lambda\sigma^2(1-2\eta)}{(1+2\eta\lambda\sigma^3)^2} > 0, \tag{20}$$

$$\frac{\partial \text{VLOOP}}{\partial \eta} = \frac{\lambda\sigma^3(2\pi - 1)(1+e^z)}{(1+2\eta\lambda\sigma^3)}\left(1 - s - 2\eta\right). \tag{21}$$

Hence, VLOOP increases in volatility (i.e., σ) unconditionally, but it increases in the dealer's constraint (i.e., η) only if $\eta < (1-s)/2$. The intuition behind volatility is similar to the case of TCOST. However, the impact of η on VLOOP has two offsetting effects. On the one hand, when the dealer is more constrained (e.g., higher leverage), she charges a higher mark-up (or mark-down) for currency x (or y) since her marginal valuation is higher (or lower) for currency x (or y), which increases VLOOP. On the other hand, a higher η also leads to a higher TCOST, suppressing the order flow imbalance, which dampens VLOOP. With a small η, i.e., when $\eta < (1-s)/2$, the first effect dominates the latter. In this case, VLOOP increases in η. As shown in Table 2, VLOOP is larger when FX dealers are more constrained, suggesting that the first channel indeed dominates the second one. Hence, the analysis below focuses on the case where $\eta < (1-s)/2$. The right panel in Figure 6 visualises these effects.

Proposition 1 summarises these results and formalises the intuition behind the empirical findings in Table 2 showing that more severe dealer constraints (i.e., higher η and empirically higher DCM) are associated with both higher VLOOP and TCOST. In addition, across different parameter specifications, it turns out that the VLOOP is much smaller than TCOST, which is also one of the stylized facts in the empirical analysis (see Table 1). Proposition 1 summarises these results, which are consistent with the empirical findings in Table 3.

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

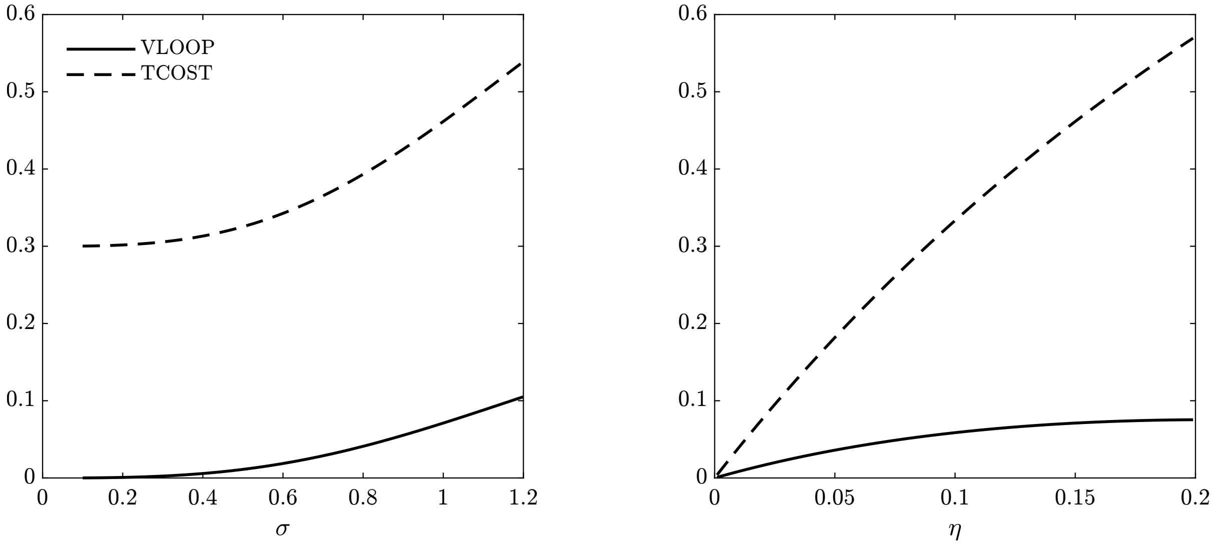
i) the volatility of the currency pairs is higher (i.e., higher σ);

ii) the (representative) dealer is more levered or has a higher debt financing cost (i.e., higher η).

Proof. See the discussion preceding this Proposition. □

Next, we investigate the dealer's elasticity of liquidity provision, which corresponds to the regression coefficients on dealer-intermediated volume in the previous section. Note that

Figure 6: The effects of volatility and the dealer's constraint on VLOOP and TCOST



Note: This figure shows how volatility and the dealer's constraint affect VLOOP and TCOST. The baseline parameters are $\pi = 0.7$, $\lambda = 1$, $\sigma = 1$, $\eta = 0.15$, $e^x = 1.32$, $e^y = 1.1$, $e^z = 1.2$, where π denotes the fraction of liquidity traders that are buyers (sellers) in currency pair x (y), λ is the trading demand parameter, σ is the fundamental volatility of exchange rates, η is a measure of dealer constrainedness, whereas e^x, e^y, and e^z denote the fundamental values of currency pairs x, y, and z, respectively.

volume, VLOOP, and TCOST are equilibrium outcomes. The dealer-provided volume is[26]

$$VLM = 3\lambda\sigma(1-s) = \frac{3\lambda\sigma(1-2\eta)}{1+2\eta\lambda\sigma^3}. \tag{22}$$

Taking the first order derivative with respect to σ, we have that

$$\frac{\partial VLM}{\partial \sigma} = 3\lambda(1-2\eta)\frac{(1-4\eta\lambda\sigma^3)}{(1+2\eta\lambda\sigma^3)^2}. \tag{23}$$

As $\eta < 1/2$, $(1-2\eta)$ is positive. Thus, when $\lambda < 1/(4\eta\sigma^3)$, the dealer-intermediated volume increases in volatility. Intuitively, as discussed above, an increase in volatility affects volume via two channels: First, it induces a higher trading demand due to a larger dispersion in fundamentals. Second, it lowers trading volume due to the concurrent rise in the bid-ask spread. When the trading demand parameter λ is small, the former dominates the latter. As shown in Table 2, dealer-intermediated volume increases in volatility, indicating that the parameter space of interest is indeed $\lambda < 1/(4\eta\sigma^3)$. Thus, for the rest of this section, we only focus on this particular case.

From Eq. (23), it is clear that when η is larger, the first order derivative is smaller (yet still positive). Put differently, dealer-intermediated volume (i.e., VLM) increases in volatility (i.e., σ) at a slower pace as the dealer becomes more constrained. Lemma 1 summarises this result.

[26]Note that the scalar 3 comes from the fact that each triplet comprises three currency pairs.

Lemma 1: *When the dealer is more constrained, volume increases in volatility at a slower pace.*

Proof. See the discussions preceding this Lemma. □

Both TCOST and VLOOP increase in volatility for a given η (see Eqs (18) and (20)):

$$\frac{\partial VLM}{\partial \sigma} / \frac{\partial TCOST}{\partial \sigma} = \frac{(1 - 4\eta\lambda\sigma^3)}{3\eta\sigma^2}, \qquad \frac{\partial VLM}{\partial \sigma} / \frac{\partial VLOOP}{\partial \sigma} = \frac{(1 - 4\eta\lambda\sigma^3)}{\eta\sigma^2(2\pi - 1)(1 + e^z)}. \tag{24}$$

Hence, as volatility increases, the dealer-provided volume (i.e., VLM) positively correlates with both TCOST and VLOOP. This positive correlations capture the elasticity of liquidity provision and correspond to the regression coefficient with respect to trading volume in the regression analysis (see Section 3). In essence, the positive correlations between dealer-intermediated volume and the two liquidity cost components represent how the market depth reacts to price dislocations. If both market depth and pricing distortions are large, then liquidity provision is more elastic and hence more resilient to demand and supply shocks.

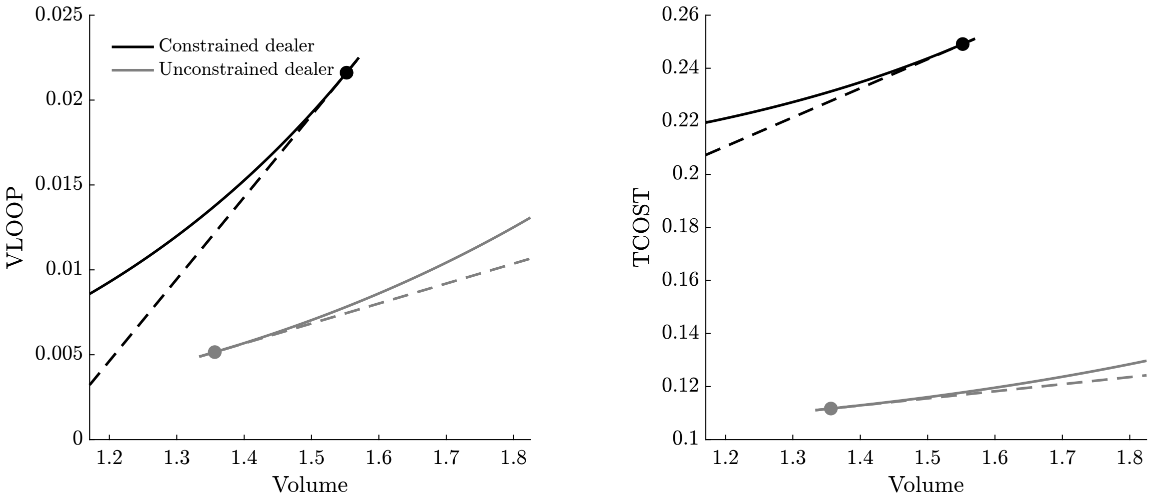
Figure 7 visualises the elasticity of liquidity provision across constrained and unconstrained regimes. When the dealer is unconstrained, that is, η is small, both the dealer-intermediated volume and each of the two liquidity cost components are small as well (see grey line). Hence, in unconstrained periods liquidity provision is elastic since both variables correlate positively conditional on different realisations of volatility. However, when the dealer is more constrained, the line shifts towards the upper right (see black line), with a modest increase of volume but a significant increase in both liquidity cost components, suggesting that liquidity provision is more inelastic. To see why, compare the slope of the two tangent dotted lines, which capture the elasticity of liquidity provision across the two market states: i) unconstrained dealers and low volatility and ii) constrained dealers and high volatility. Beyond doubt, the slope of the latter is much steeper, implying that liquidity provision is much more inelastic when dealers are more constrained. This numerical result squares well with the fact that both derivatives in Eq. (24) are decreasing in η. The intuition for this finding is that in constrained periods the dealer charges a higher spread that subsequently leads to a slower increase in equilibrium trading volume. Proposition 2 summarises these results.

Proposition 2: *Dealer-intermediated volume correlates positively with both VLOOP and TCOST. However, this positive correlation, capturing the elasticity of liquidity provision, weakens when the dealer is more constrained due to higher funding costs (i.e., higher η).*

Proof. See the discussion preceding this Proposition. □

Proposition 2 finds compelling support in our empirical analyses. Specifically, Table 2 shows that dealer-provided volume increases even when dealers are more constrained. However, the state-dependent correlation between intermediated volume and the cost of liquidity provision weakens when dealer constraints intensify. This result holds for both liquidity cost

Figure 7: The elasticity of liquidity provision



Note: This figure plots the dealer-intermediated volume against VLOOP and TCOST, respectively. The baseline parameters are $\pi = 0.7$, $\lambda = 1$, $e^x = 1.32$, $e^y = 1.1$, $e^z = 1.2$, where π denotes the fraction of liquidity traders that are buyers (sellers) in currency pair x (y), λ is the trading demand parameter, whereas e^x, e^y, and e^z denote the fundamental values of currency pairs x, y, and z, respectively. The unconstrained dealer faces $\eta = 0.05$, whereas the constrained one is exposed to $\eta = 0.1$. The solid lines indicate the equilibrium outcomes when varying the fundamental volatility exchange rates σ from 0.5 to 0.7. The grey dashed line indicates the derivative of volume with respect to VLOOP and TCOST when the dealer is unconstrained and fundamental volatility is low. The black dashed line is the derivative of volume with respect to VLOOP and TCOST when the dealer is constrained and fundamental volatility is high.

measures (VLOOP and TCOST) no matter which econometric model is applied (Table 3) and after controlling for volatility and other confounding factors (see Online Appendix).

5. Additional analyses and robustness tests

The key goal of our empirical analysis is to show how the elasticity of dealer banks' liquidity provision (i.e., the correlation between the cost of liquidity provision and dealer-intermediated volume) weakens as dealer constraints tighten. To demonstrate this we have relied on logistic smooth transition regressions (LSTAR) that are particularly well-suited to capture non-linear relations. However, one might wonder whether our results are robust to using alternative methods and measures of dealer constraints. To address this issue, we employ rolling window correlations and structural vector autoregressions to infer exogenous liquidity demand and supply shocks directly from price and quantity data.

5.1. *Disentangling liquidity demand and supply*

The empirical analysis based on LSTAR has employed our dealers constraint measure (i.e., DCM) as an exogenous proxy for liquidity supply shocks. 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 Nicoló, 2002; Rubio-Ramírez, Waggoner, and Zha, 2010), which has become widely used in economics and finance to estimate models with sign restrictions. Eventually, we are using the supply shocks as an alternative measure for tightening dealer constraints, whereas we employ demand shocks as an instrument for our dealer constraint measure. Our 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-provided volume VLM. To identify 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 C for a detailed explanation of the setup and the estimation procedure). In particular, the sign restrictions assume that supply shifts lead to opposite-sign changes in liquidity costs and trading volume, whereas demand shifts are assumed to lead to same-sign changes in liquidity costs and volume. As a result, the structural shocks have a natural interpretation as inward and outward shifts of liquidity supply and demand, respectively.

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[27] rolling window fashion (cf. Figure 4) and estimate the following panel regression model:

$$\rho_{k,t} = \alpha_k + \eta_1 DCM_t + \eta_2 RV_{k,t} + \eta_3 Amihud_{k,t} + \epsilon_{k,t}, \tag{25}$$

where the dependent variable is the 30-day rolling window correlation of a liquidity cost measure (i.e., VLOOP or TCOST) and trading volume, α_k denotes currency triplet 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. Throughout this paper, we estimate Amihud as the ratio between daily realised volatility and aggregate daily trading volume following Ranaldo and Santucci de Magistris (2018).

Table 4 documents the results of estimating Eq. (25) by OLS and 2SLS, respectively. In particular, Panel A shows the OLS estimates of Eq. (25), whereas Panel B uses liquidity demand shocks $\delta^d_{k,t}$ from the SVAR as an instrument for DCM.[28] The economic intuition following our theoretical framework in Section 4 is that a positive liquidity demand shock causes more imbalanced customer order flows to which dealers respond by increasing the bid-ask spread to dampen volumes. However, concurrently, no-arbitrage deviations (i.e., VLOOP) increase due to the customer order flows being more imbalanced. Panel C reports the results of us-

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

[28] We estimate demand and supply shocks individually for every currency pair triplet and then stack them together. Our findings are robust to extracting the shocks from a panel SVAR with currency triplet fixed effects.

ing liquidity supply shocks $\delta^s_{k,t}$ as an alternative measure of tightening dealer constraints.[29] The key takeaway from Table 4 is fully consistent with the LSTAR analysis (see Table 3) and corroborates the idea that soaring dealer constraints are associated with a significantly lower elasticity of liquidity provision (i.e., smaller $\rho_{k,t}$).

5.2. *Robustness tests*

To investigate the robustness of our main findings we run five additional robustness tests: i) decompose the dealer constraint measure into its constituents, ii) split volume into inter-bank and customer-bank trades, iii) perform a subsampling analysis, iv) estimate the LSTAR currency pair triplet by triplet, and v) account for potential bias in the bid-ask spread.

Different components of dealer constraints. We consider the same LSTAR specification as in Eq. (4) but instead of our dealer constraint measure DCM we use its four constituents. In particular, we use the 1-day lagged value of primary FX dealer banks' quarterly Value-at-Risk measure (VaR), quarterly He et al. (2017) leverage ratio (HKM), daily credit default spread (CDS), and daily funding cost yield (DFC) as regime variables. Table 5 reports the estimates of using each of the four aforementioned measures as a state variable. The difference between the constrained and unconstrained coefficients is negative and significant across all four specifications for both VLOOP and TCOST. These estimates are fully in line with our baseline specification based on DCM in terms of economic magnitudes. The robustness of our results is not surprising given the strong co-movement across these four different regime variables.

Inter-bank vs customer-bank volumes. We decompose trading volume into to 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 customers, that is, corporates, funds, and non-bank financials.[30] Note that bilateral trades between two such customer groups are quasi non-existent given the two-tier structure of the FX market (Rime and Schrimpf, 2013) 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).

[29]In the Online Appendix we also exploit the unexpected removal of the Swiss franc cap on 15 January 2015 by the Swiss National Bank as a quasi-natural experiment. We find that the elasticity of dealer banks' liquidity provision drops significantly in currency pair triplets involving the Swiss franc (i.e., EUR-USD-CHF and GBP-USD-CHF) but not in other triplets. These findings support the idea that dealers face currency (pair) specific risk limits. See the Online Appendix Section D for additional information.

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

Table 4: Elasticity of liquidity provision and dealer constraints

	cor(VLOOP,Volume)			cor(TCOST,Volume)		
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
DCM	***−0.03	***−0.03	***−0.03	***−0.04	***−0.04	***−0.03
	[3.50]	[3.51]	[3.57]	[2.92]	[2.92]	[2.77]
Realised variance		*0.00	0.00		−0.01	−0.01
		[1.70]	[1.17]		[1.47]	[0.93]
Amihud (2002)			***0.03			***−0.08
			[3.31]			[5.14]
Adj. R^2 in %	1.65	1.70	1.87	1.76	1.93	2.80
Avg. #Time periods	2,159	2,159	2,159	2,159	2,159	2,159
Panel B						
Instrumented DCM	***−0.07	***−0.08	***−0.07	*−0.06	*−0.06	**−0.07
	[3.62]	[3.75]	[3.60]	[1.76]	[1.77]	[2.14]
Realised variance		0.01	0.00		−0.01	−0.01
		[1.57]	[1.26]		[1.47]	[0.89]
Amihud (2002)			**0.02			***−0.09
			[2.39]			[5.54]
Avg. #Time periods	2,159	2,159	2,159	2,159	2,159	2,159
Panel C						
δ^s	***−0.01	***−0.01	***−0.01	***−0.02	***−0.02	***−0.02
	[3.64]	[3.61]	[3.76]	[4.28]	[4.75]	[4.10]
Realised variance		*0.00	*0.00		−0.01	−0.01
		[1.89]	[1.89]		[1.51]	[1.45]
Amihud (2002)			0.00			−0.01
			[0.02]			[1.46]
Adj. R^2 in %	0.10	0.13	0.13	0.38	0.62	0.77
Avg. #Time periods	2,256	2,256	2,256	2,256	2,256	2,256
#Exchange rates	15	15	15	15	15	15
Currency FE	yes	yes	yes	yes	yes	yes
Time series FE	no	no	no	no	no	no

Note: This table reports results from daily fixed effects panel regressions of the form $\rho_{k,t} = \alpha_k + \eta_1 DCM_t + \eta_2 RV_{k,t} + \eta_3 Amihud_{k,t} + \epsilon_{k,t}$, 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), α_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. (25), whereas Panel B uses liquidity demand shocks δ^d as an instrument for DCM. Panel C reports the results of using liquidity supply shocks δ^s as an alternative measure of tightening dealer constraints. All regressors have been normalised to have unit standard deviation. Hence, the regression coefficients measure the increase in ρ associated with a one standard deviation increase in DCM and δ^s, respectively. The sample covers the period from 1 September 2012 to 30 September 2020. 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.

Table 6 reports the results of estimating the LSTAR model in Eq. (4) 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

Table 5: Smooth transition regression with different state variables

	VLOOP				TCOST			
	VaR	HKM	CDS	DFC	VaR	HKM	CDS	DFC
γ	***11.15	***4.97	***9.20	***12.10	***12.08	***4.93	***12.03	***3.92
c	***0.25	***0.59	***−0.10	***−0.35	***0.39	***0.60	***−0.16	***−0.10
Unconstr. volume	***0.09	**0.06	***0.08	***0.16	***0.09	***0.09	***0.10	***0.10
	[3.16]	[2.23]	[2.89]	[3.59]	[11.35]	[10.61]	[11.26]	[7.83]
Constr. volume	**−0.08	−0.03	*−0.06	−0.01	*0.02	**0.03	**0.03	***0.04
	[2.12]	[0.73]	[1.66]	[0.42]	[1.65]	[2.45]	[2.31]	[2.99]
Realised variance	**0.02	**0.02	**0.02	**0.02	***0.03	***0.03	***0.03	***0.03
	[2.07]	[2.13]	[2.11]	[2.09]	[8.35]	[8.39]	[8.37]	[8.00]
Constr.-Unconstr.	***−0.17	*−0.10	***−0.15	***−0.18	***−0.07	***−0.05	***−0.07	***−0.06
	[3.50]	[1.68]	[3.00]	[3.04]	[4.28]	[3.28]	[4.83]	[2.82]
R^2 in %	0.13	0.08	0.11	0.15	3.72	3.65	3.77	3.66
BIC	91.61	91.62	91.61	91.06	49.24	49.25	49.23	48.55
Avg. #Time periods	2,280	2,280	2,280	2,182	2,284	2,284	2,284	2,185
#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 primary FX dealer banks': quarterly Value-at-Risk measure (VaR, columns 1 and 6), quarterly He et al. (2017) leverage ratio (HKM, columns 2 and 7), daily credit default spread (CDS, columns 3 and 8), and daily funding cost yield (DFC, columns 4 and 9). 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 γ 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 2020. 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.

more elastic liquidity provision in the former. On the other hand, the elasticity of liquidity provision 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 facing similar constraints. Of course, this does not rule out the possibility that dealers charge higher spreads to their customers 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 May 2016, whereas the second half runs from June 2016 to September 2020. 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 7 documents the same regression specifications as in our baseline (see Table 3) except for

Table 6: Smooth transition regression with different counterparty groups

	VLOOP				TCOST			
	Non-bank	Non-bank	Bank	Bank	Non-bank	Non-bank	Bank	Bank
γ	20.01	20.02	***20.03	***20.06	20.04	20.08	***14.96	**20.03
c	***1.10	***0.37	***−0.15	***−0.15	0.03	0.03	***0.57	***0.58
Unconstr. volume	**0.03	*0.03	***0.12	***0.11	***0.03	***0.02	***0.12	***0.09
	[2.11]	[1.87]	[3.68]	[3.14]	[6.77]	[5.40]	[13.70]	[9.53]
Constr. volume	−0.03	−0.02	−0.05	−0.06	0.01	0.00	0.02	−0.01
	[1.16]	[0.81]	[1.07]	[1.38]	[1.51]	[0.33]	[1.07]	[0.23]
Realised variance		**0.02		*0.02		***0.04		***0.03
		[2.27]		[1.68]		[9.02]		[7.14]
Constr.-Unconstr.	**−0.06	−0.05	***−0.17	***−0.17	***−0.02	***−0.02	***−0.09	***−0.09
	[2.06]	[1.62]	[2.98]	[2.96]	[2.62]	[2.86]	[3.84]	[3.74]
R^2 in %	0.05	0.10	0.14	0.16	0.54	2.99	2.49	3.90
Avg. #Time periods	1,979	1,979	1,979	1,979	1,983	1,982	1,983	1,982
#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 γ 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 September 2012 to 30 September 2020. 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.

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.

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 of currency pairs. We further contrast the result with a simple linear model that does not distinguish between constrained and unconstrained regimes. We report these analyses in Online Appendix (see Tables B.1 and B.2).

The currency pair triplet by triplet estimates strongly support the idea that intermediary constraints non-linearly impact the relation between dealer-provided volume and the cost of liquidity provision. In particular, the difference between the parameter estimates of con-

Table 7: Sample split: Smooth transition panel regression with DCM as state variable

	11/2011 – 05/2016				06/2016 – 09/2020			
	VLOOP		TCOST		VLOOP		TCOST	
γ	***4.98	***4.96	***6.51	***7.48	12.03	12.06	12.02	12.10
c	***−0.40	***−0.41	***−0.41	***−0.40	*0.47	*0.46	***0.89	***0.90
Unconstr. volume	0.06	0.05	***0.13	***0.11	***0.13	**0.10	***0.13	***0.10
	[1.42]	[1.07]	[10.72]	[8.62]	[3.10]	[2.38]	[10.89]	[7.36]
Constr. volume	*−0.09	**−0.10	*0.03	0.01	0.10	0.08	***0.08	**0.05
	[1.82]	[2.00]	[1.92]	[0.51]	[1.44]	[1.08]	[3.36]	[2.03]
Realised variance		0.01		***0.02		**0.03		***0.03
		[1.20]		[4.44]		[2.27]		[6.39]
Constr.-Unconstr.	**−0.15	**−0.15	***−0.10	***−0.10	−0.03	−0.03	**−0.05	*−0.05
	[2.26]	[2.24]	[5.35]	[5.18]	[0.36]	[0.32]	[2.04]	[1.85]
R^2 in %	0.06	0.08	2.77	3.77	0.17	0.24	2.41	3.82
Avg. #Time periods	1121	1121	1122	1122	1061	1060	1063	1062
#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 γ 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 2020. 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.

strained and unconstrained regimes (i.e., $\beta_2 - \beta_1$) is significantly negative for 10 and 9 out of 15 triplets of currency pairs for VLOOP and TCOST, respectively. In line with this finding, the R^2s 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.

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

$$m^{wp} = \frac{b \times q^{buys} + a \times q^{sells}}{q^{buys} + q^{sells}}, \tag{26}$$

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 8 shows the results of estimating the same regression specifications as in our baseline in Eq. (4), 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 most specifications. Thus, we conclude that our findings are not materially affected by any potential bias in the quoted bid-ask spread in the Olsen data.

Table 8: Smooth transition panel regression with DCM as state variable

	VLOOP				TCOST			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
γ	**4.97	***4.99	***4.91	12.09	***4.98	***5.00	***5.49	***4.96
c	***1.10	***−0.41	***−0.41	***0.26	***0.53	***0.54	***0.58	***0.36
Unconstr. volume	*0.03	**0.06	**0.06	0.03	***0.12	***0.12	***0.11	***0.12
	[1.69]	[2.19]	[2.28]	[1.52]	[11.65]	[11.32]	[9.24]	[9.47]
Constr. volume	−0.06	−0.01	−0.01	−0.04	***0.07	**0.06	**0.05	*0.05
	[0.85]	[0.50]	[0.32]	[0.81]	[2.70]	[2.53]	[1.97]	[1.77]
Amihud (2002)		0.00				−0.01		
		[0.05]				[1.33]		
Realised variance			−0.01				***0.02	
			[0.80]				[3.36]	
1M CIP basis				0.00				0.00
				[0.72]				[0.21]
Constr.-Unconstr.	−0.09	*−0.07	*−0.07	−0.07	**−0.06	**−0.06	**−0.06	**−0.07
	[1.27]	[1.67]	[1.69]	[1.35]	[2.07]	[2.07]	[2.02]	[2.05]
R^2 in %	0.02	0.03	0.04	0.03	1.36	1.38	1.56	1.21
Avg. #Time periods	1,981	1,981	1,981	1,786	1,983	1,982	1,982	1,788
#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 $TCOST$) 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 γ 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 September 2012 to 30 September 2020. 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.

To summarise, the first robustness check has delved into the determinants of our composite dealer constraint measure, whereas the second robustness test has sought to better understand how dealer constraints affect customer-dealer and inter-dealer relations. The third one has aimed to shed some light on the role of non-bank liquidity providers for FX liquidity. The fourth one has estimated the LSTAR model currency pair triplet by triplet, while the last one has accounted for bias in the bid-ask spread. Overall, these tests corroborate our previous results and support the main mechanisms of our model. Dealers promote market liquidity in normal times through elastic liquidity provision. As such, dealer intermediation contributes to better market liquidity, that is, narrow spreads and more informative prices (i.e., lower transactions costs and tight no-arbitrage conditions). However, during periods of market stress FX dealer banks are more constrained and as a result their intermediation activities cannot keep up with the deterioration of market liquidity.

6. Conclusion

In this paper, we have studied whether dealer constraints have adverse implications on market liquidity. Using a unique data set of prices and volumes in the FX market, we provide a novel analytical method to identify and measure the cost of liquidity provision, and its main components: the shadow cost of intermediary constraints and dealers' realised compensation for enduring inventory imbalances. Second, we uncover the following novel empirical findings: On the one hand, when dealers are unconstrained they support market liquidity by providing immediacy to their clients. On the other hand, when dealers are constrained, for instance, when they face Value-at-Risk, leverage, or funding constraints, their liquidity provision is impaired and consequently the positive correlation between intermediated volume and the cost of liquidity provision breaks down. We rationalise our findings with a theoretical model outlining how market liquidity deteriorates when markets are more volatile and when financial intermediaries are more constrained.

We obtain our results for the FX spot market, which is commonly regarded as one of the most liquid financial markets in the world. However, we believe that our findings also have implications for other over-the-counter (OTC) markets. For instance, broadly similar mechanisms could be at play when pricing distortions emerge between similar government bonds (Hu, Pan, and Wang, 2013) with pronounced deviations from a smooth yield curve (as observed during the Covid-19 crisis). We leave the study of the role of dealer constraints on the liquidity provision in other important OTC markets (e.g., government and corporate bonds, OTC derivatives) to future research.

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Appendix A. 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 spot FX 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).

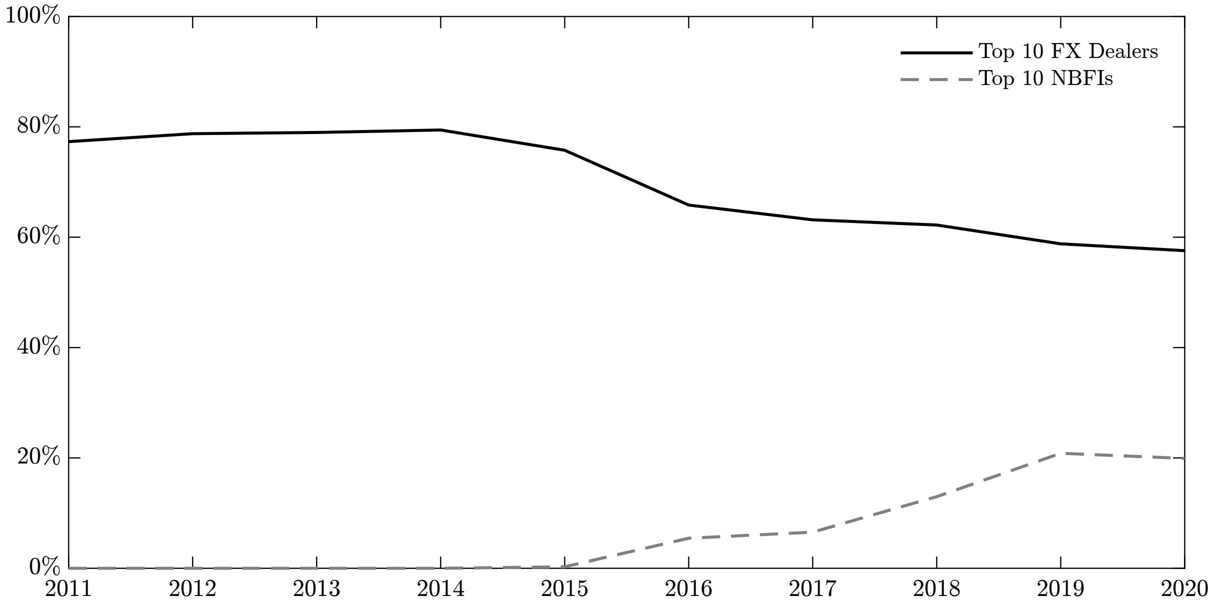
Customers can be categorised into four groups: corporates, funds, non-bank financial firms, and non-dealer banks. "Funds" may also include principal trading firms (PTFs) such as high-frequency trading firms and electronic non-bank liquidity providers (e.g., XTX or Jump Trading). The majority of these 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 2020, we retrieve the ranking of the top 10 FX dealer banks from the Euromoney FX surveys, which are publicly available. See Table A.1 for an overview of the top 10 FX dealer banks over the sample period from 2011 to 2020. 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. What follows lists the data source for each of the four subcomponents of our composite dealer constraint measure (DCM).

- **Value-at-Risk (VaR)** is retrieved directly from the financial statements for each of the top 10 dealer banks and is based on banks' FX trading books. The frequency is quarterly.
- **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. The frequency is quarterly.
- **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.

- **Debt Funding cost (DFC)** is retrieved from iBoxx for each dealer bank corresponding to the average bond issuance cost across different maturities and major currencies (i.e., USD, EUR, and GBP). The frequency is daily.

Figure 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 2020 from the Euromoney FX surveys.

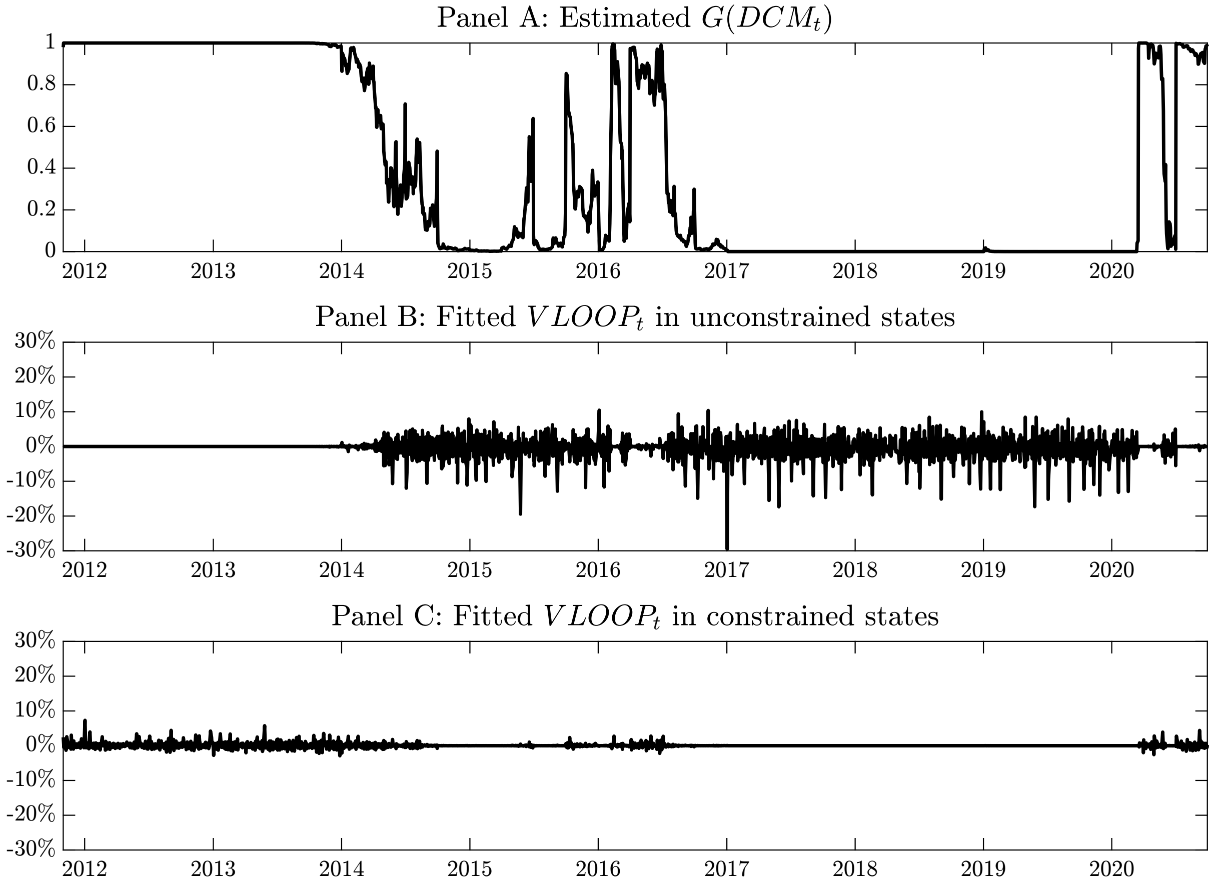
Table A.1: Top 10 FX dealer banks

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

Note: This table reports the ranking of the top 10 FX dealer banks for the years 2011 to 2020 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.

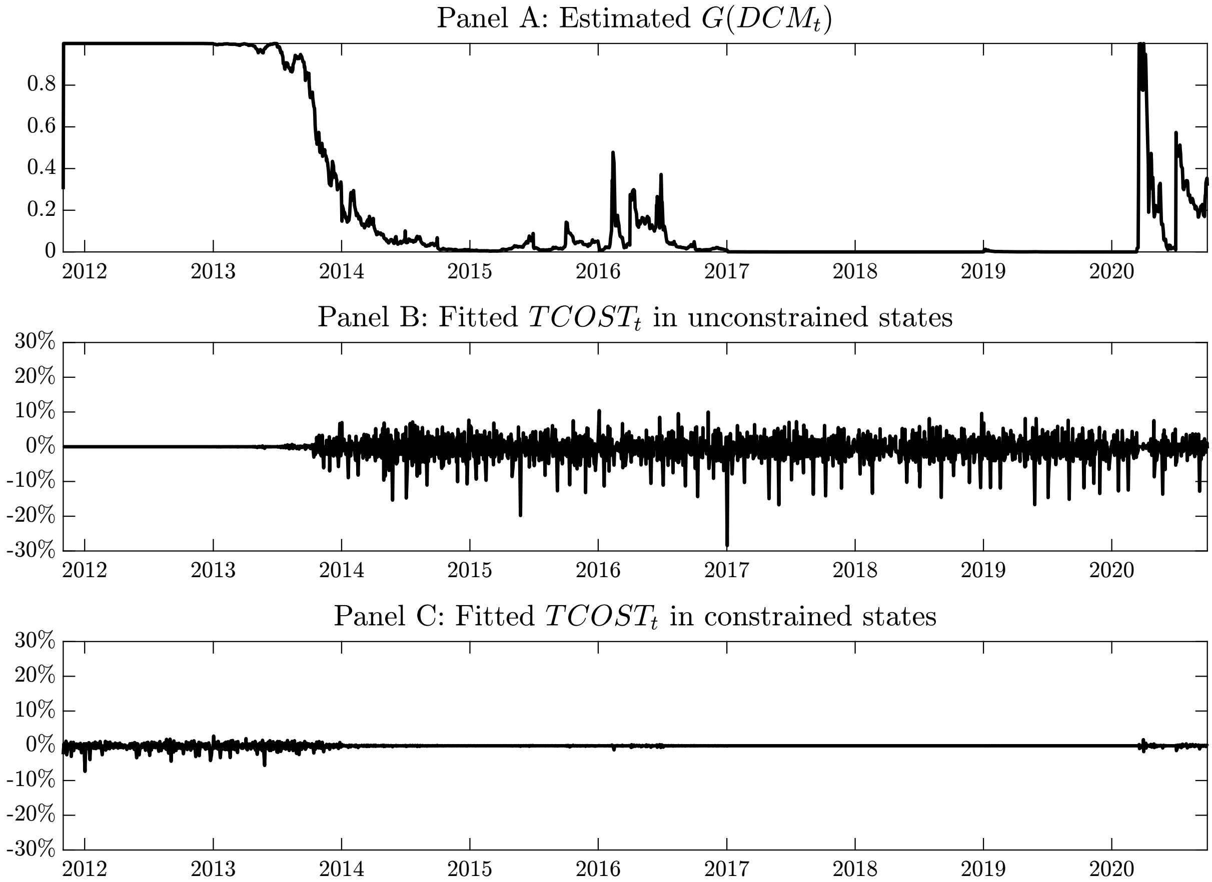
Appendix B. Estimating a panel LSTAR model

Figure B.1: Time-series of fitted $G(\text{CDS})$ and VLOOP



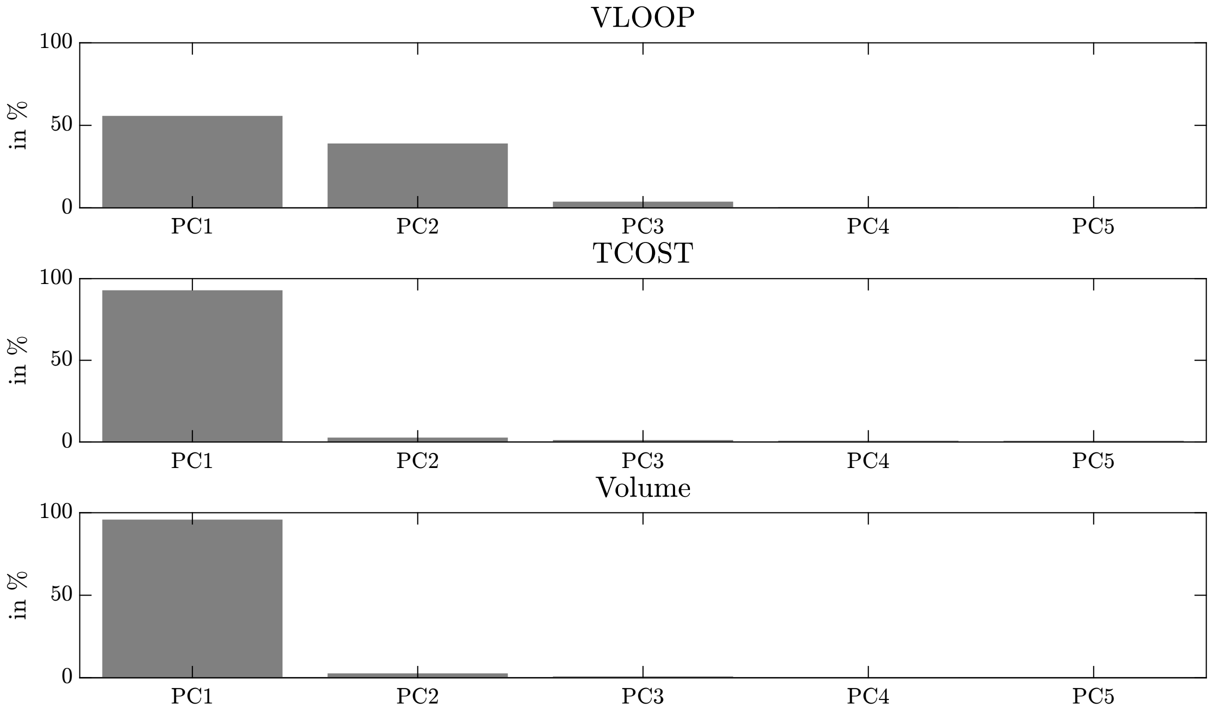
Note: Panel A of this figure shows the fitted regime function $G(DCM_t)$, using the point estimates in column 3 of Table 3. Panel B shows the cross-sectional average of the part of the fitted log changes in $VLOOP_t$ that is driven by unconstrained state coefficients ($[1 - G(z_{t-1})]\beta_1' f_t$). 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 2020.

Figure B.2: Time-series of fitted G(CDS) 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 3. 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 2020.

Figure B.3: 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 2020.

Table B.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 (α)	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
	[0.13]	[0.01]	[0.45]	[0.12]	[0.02]	[0.14]	[0.17]	[0.06]	[0.78]	[0.09]	[0.26]	[0.02]	[0.02]	[0.07]	[0.54]
Volume	***0.22	***0.08	0.02	***0.14	0.00	0.00	0.02	***0.07	***0.18	**0.05	0.04	***0.12	***−0.11	***0.08	***0.17
	[4.10]	[2.78]	[0.43]	[4.31]	[0.03]	[0.07]	[0.65]	[2.66]	[2.97]	[2.06]	[1.38]	[3.24]	[3.12]	[2.63]	[3.84]
Realised variance	***0.08	***0.09	**0.07	*0.06	0.02	**0.05	***0.09	***0.06	**0.07	***0.09	***0.11	*0.05	***0.06	***0.10	***0.10
	[2.84]	[5.90]	[2.42]	[1.96]	[0.76]	[2.50]	[3.97]	[3.32]	[2.12]	[4.99]	[6.15]	[1.65]	[2.75]	[5.03]	[4.01]
Panel B: LSTAR	AUDJPY	AUDNZD	CADJPY	EURAUD	EURCAD	EURCHF	EURDKK	EURGBP	EURJPY	EURNOK	EURSEK	GBPAUD	GBPCAD	GBPCHF	GBPJPY
γ	12.00	12.00	12.00	12.00	12.00	12.00	12.00	3.46	1.00	12.00	1.00	12.00	12.00	12.00	1.29
c	1.56	1.47	1.89	−1.38	−0.64	−1.56	0.78	−0.44	2.00	1.44	−0.23	1.69	−1.70	−0.97	−0.94
Unconstrained volume	***0.32	***0.13	*0.09	***0.26	−0.16	0.06	*0.05	***0.20	**0.31	***0.10	0.20	***0.19	0.19	**0.14	**0.60
	[5.70]	[3.95]	[1.69]	[3.91]	[0.18]	[0.91]	[1.78]	[3.86]	[2.13]	[3.41]	[0.25]	[4.76]	[1.18]	[2.52]	[2.20]
Constrained volume	0.17	−0.02	−0.07	**0.10	0.08	0.00	−0.08	0.00	−0.10	**−0.13	−0.11	0.04	***−0.18	***0.10	0.06
	[1.04]	[0.21]	[1.04]	[2.46]	[0.09]	[0.13]	[1.49]	[0.06]	[0.38]	[2.06]	[0.24]	[0.58]	[3.73]	[2.75]	[0.93]
Intercept (α)	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	*0.01	0.00	0.00	0.00	0.00	0.00	0.00
	[1.02]	[1.09]	[1.01]	[0.21]	[0.00]	[0.12]	[0.00]	[0.93]	[1.72]	[0.74]	[0.11]	[1.15]	[0.86]	[1.00]	[0.78]
Realised variance	*0.05	***0.08	0.04	*0.05	0.02	**0.05	***0.09	***0.05	*0.06	***0.09	***0.10	0.03	***0.07	***0.09	***0.08
	[1.82]	[4.93]	[1.47]	[1.85]	[0.30]	[2.34]	[4.06]	[2.98]	[1.93]	[5.25]	[5.72]	[1.03]	[2.61]	[4.79]	[2.95]
Constrained-Unconstrained	−0.15	−0.15	*−0.17	**−0.16	*0.24	−0.06	**−0.12	**−0.20	***−0.41	***−0.23	−0.31	*−0.15	**−0.36	−0.04	*−0.53
	[0.93]	[1.38]	[1.89]	[1.99]	[1.72]	[0.86]	[2.13]	[2.22]	[2.66]	[3.27]	[0.25]	[1.78]	[2.24]	[0.69]	[1.77]
Adj. R^2 in % - OLS	4.26	2.79	0.33	3.40	−0.04	0.77	3.27	2.82	3.79	2.02	2.81	2.89	0.48	4.15	6.29
Adj. R^2 in % - LSTAR	4.84	3.24	0.43	3.12	0.30	0.68	3.67	3.85	5.03	2.77	3.26	3.65	0.78	4.36	8.49
#Obs	2,273	2,285	2,271	2,285	2,285	2,283	2,283	2,285	2,265	2,285	2,283	2,285	2,285	2,285	2,266

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 γ 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 2020. The test statistics based on robust standard errors (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 B.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 (α)	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
	[0.19]	[0.22]	[0.10]	[0.23]	[0.28]	[0.29]	[0.07]	[0.09]	[0.15]	[0.13]	[0.14]	[0.18]	[0.23]	[0.21]	[0.09]
Volume	***0.10	***0.09	***0.07	***0.08	***0.07	***0.07	***0.09	***0.06	***0.11	*0.02	***0.03	***0.06	**0.03	**0.03	***0.08
	[3.99]	[7.77]	[4.24]	[5.78]	[6.23]	[6.44]	[8.35]	[4.30]	[5.39]	[1.74]	[2.63]	[2.93]	[2.23]	[2.10]	[2.98]
Realised variance	***0.07	***0.05	***0.06	***0.07	***0.04	**0.04	***0.03	***0.05	***0.06	***0.08	***0.06	***0.07	*0.03	***0.06	**0.05
	[4.06]	[6.19]	[4.64]	[6.08]	[3.33]	[2.50]	[5.87]	[3.35]	[3.57]	[6.71]	[8.32]	[3.89]	[1.82]	[2.85]	[2.01]
Panel B: LSTAR	AUDJPY	AUDNZD	CADJPY	EURAUD	EURCAD	EURCHF	EURDKK	EURGBP	EURJPY	EURNOK	EURSEK	GBPAUD	GBPCAD	GBPCHF	GBPJPY
γ	1.20	12.00	12.00	12.00	1.68	12.00	12.00	12.00	1.00	3.72	12.00	12.00	12.00	12.00	12.00
c	−0.56	1.35	0.91	−1.22	0.35	0.90	−0.10	−1.39	−0.66	0.70	1.41	−1.28	1.57	−2.00	−0.05
Unconstrained volume	***0.24	***0.13	***0.10	***0.15	0.10	***0.08	***0.10	**0.10	0.26	**0.04	***0.04	***0.13	***0.05	−0.07	***0.14
	[3.09]	[9.03]	[5.79]	[6.25]	[1.04]	[5.93]	[8.78]	[2.14]	[0.93]	[2.13]	[3.14]	[4.65]	[2.63]	[0.79]	[3.39]
Constrained volume	0.02	0.02	−0.01	***0.06	0.01	**0.04	*0.05	***0.06	0.01	−0.03	−0.03	**0.05	−0.02	**0.04	**0.05
	[0.52]	[0.64]	[0.63]	[4.14]	[0.42]	[1.99]	[1.88]	[3.38]	[0.10]	[1.07]	[1.09]	[2.34]	[0.51]	[2.36]	[2.30]
Intercept (α)	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
	[0.50]	[1.52]	[0.29]	[0.33]	[0.27]	[0.11]	[0.79]	[0.34]	[0.38]	[0.48]	[0.10]	[0.61]	[0.11]	[0.18]	[0.88]
Realised variance	***0.06	***0.05	***0.06	***0.07	***0.04	**0.04	***0.03	***0.05	***0.06	***0.08	***0.06	***0.07	0.03	***0.06	0.04
	[3.76]	[5.49]	[3.98]	[5.91]	[3.28]	[2.39]	[5.99]	[3.17]	[3.35]	[6.41]	[7.91]	[3.60]	[1.38]	[2.69]	[1.64]
Constrained-Unconstrained	**−0.22	***−0.12	***−0.12	***−0.08	−0.09	−0.04	−0.05	−0.05	−0.25	**−0.08	**−0.07	***−0.08	*−0.06	0.11	**−0.09
	[2.13]	[4.19]	[4.78]	[3.15]	[1.03]	[1.59]	[1.43]	[1.05]	[0.72]	[2.49]	[2.17]	[2.62]	[1.82]	[1.22]	[2.27]
Adj. R^2 in % - OLS	19.18	13.44	14.04	16.31	9.48	10.45	10.18	10.97	19.84	8.75	7.20	11.97	3.09	8.84	11.89
Adj. R^2 in % - LSTAR	20.75	15.07	14.27	16.19	8.69	9.92	8.45	10.30	19.62	9.15	7.30	12.23	2.89	8.30	12.58
#Obs	2,285	2,285	2,278	2,285	2,285	2,285	2,285	2,285	2,285	2,285	2,285	2,285	2,285	2,285	2,277

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 γ 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 2020. The test statistics based on robust standard errors (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 B.3: Smooth transition panel regression with DCM as state variable

	VLOOP				TCOST			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
γ	***12.02	***12.02	***12.05	***12.08	***5.38	***5.38	***5.93	***4.96
c	***−0.14	***−0.14	***−0.14	***−0.20	***0.34	***0.34	***0.39	***0.34
Unconstr. volume	***0.13	***0.12	***0.11	***0.13	***0.12	***0.13	***0.09	***0.13
	[4.09]	[3.96]	[3.50]	[3.33]	[15.01]	[15.04]	[10.85]	[12.17]
Constr. volume	−0.04	−0.04	−0.05	−0.05	***0.04	***0.04	0.01	**0.03
	[1.04]	[1.15]	[1.40]	[1.43]	[2.77]	[2.91]	[0.96]	[2.13]
Amihud (2002)		−0.01				**0.01		
		[1.08]				[2.24]		
Realised variance			**0.02				***0.03	
			[2.02]				[7.95]	
1M CIP basis				0.01				0.00
				[1.07]				[0.65]
Constr.-Unconstr.	***−0.16	***−0.16	***−0.16	***−0.18	***−0.09	***−0.09	***−0.08	***−0.09
	[3.30]	[3.30]	[3.25]	[3.23]	[5.22]	[5.19]	[4.78]	[4.63]
R^2 in %	0.12	0.13	0.15	0.12	2.47	2.51	3.78	2.31
Avg. #Time periods	2,182	2,182	2,182	1,978	2,186	2,185	2,185	1,981
#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 γ 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 2020. 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 B.4: Smooth transition regression with non dealer specific state variables

	VLOOP				TCOST			
	VIX	XAU	TED	LOIS	VIX	XAU	TED	LOIS
γ	***4.16	*12.08	***12.06	12.01	*7.65	12.04	12.02	12.07
c	***−0.50	***−0.17	***−0.39	**−0.48	***0.50	*−0.11	0.50	−0.31
Unconstr. volume	0.10	**0.06	−0.02	0.00	***0.07	***0.08	***0.08	***0.07
	[1.64]	[2.11]	[0.71]	[0.07]	[9.04]	[9.80]	[9.27]	[5.26]
Constr. volume	0.02	0.00	***0.09	0.05	***0.09	***0.06	***0.07	***0.07
	[0.46]	[0.07]	[2.66]	[1.02]	[5.36]	[4.78]	[4.84]	[5.46]
Realised variance	**0.02	**0.02	**0.02	**0.02	***0.03	***0.03	***0.03	***0.03
	[2.10]	[2.15]	[2.30]	[2.14]	[8.39]	[8.43]	[8.45]	[6.54]
Constr.-Unconstr.	−0.09	−0.06	**0.12	0.05	0.02	*−0.03	0.00	0.00
	[1.03]	[1.32]	[2.31]	[0.83]	[0.98]	[1.81]	[0.14]	[0.12]
R^2 in %	0.09	0.08	0.11	0.09	3.64	3.65	3.65	3.93
BIC	91.33	91.61	91.44	87.90	48.78	49.21	48.99	43.20
Avg. #Time periods	2,221	2,279	2,247	1,853	2,225	2,283	2,251	1,855
#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

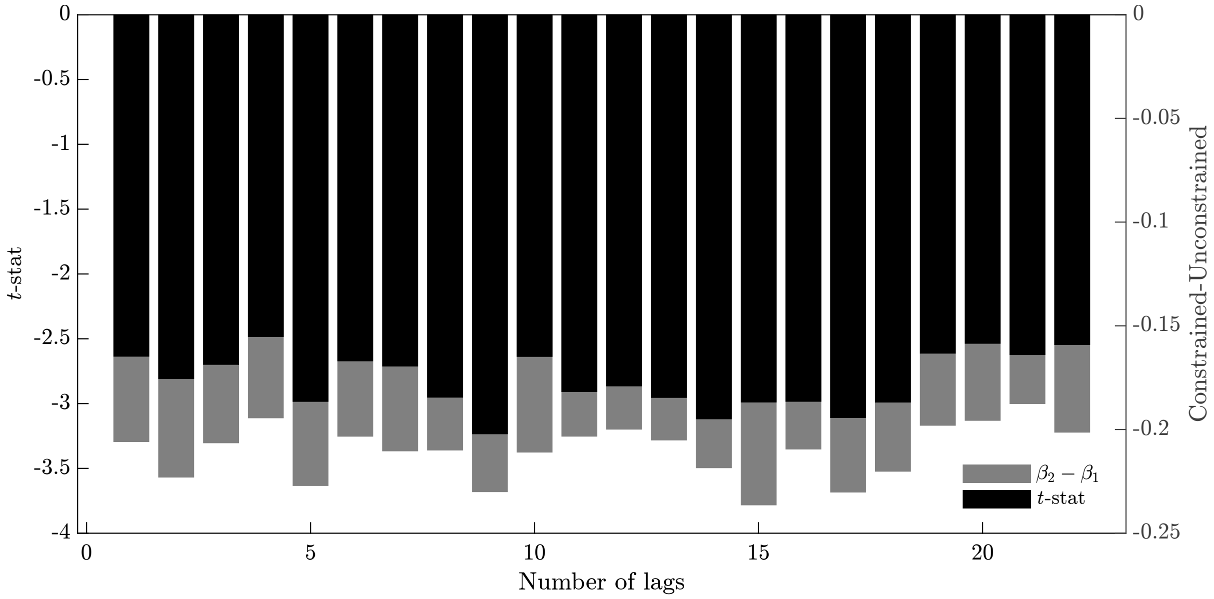
Note: This table reports results from daily fixed effects LSTAR panel regressions of the form $y_{k,t} = \lambda_t + \alpha_k + [1 - G(z_{t-1})]\beta_1' f_{k,t} + G(z_{t-1})\beta_2' f_{k,t} + \beta_3' w_{k,t} + \varepsilon_{k,t}$, where the dependent variable $y_{k,t}$ is a liquidity cost measure (i.e., $VLOOP$ 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 Chicago Board Options Exchange'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 γ 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 2020. 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 B.5: Smooth transition regression with different state variables using market shares

	VLOOP				TCOST			
	VaR	HKM	CDS	DFC	VaR	HKM	CDS	DFC
γ	***12.05	***12.05	***7.85	***12.08	***12.10	***12.04	***6.65	***5.00
c	***0.25	***0.71	***−0.10	***−0.36	***0.39	***0.72	***−0.15	***−0.09
Unconstr. volume	***0.09	***0.07	***0.09	***0.17	***0.09	***0.09	***0.10	***0.10
	[3.15]	[2.66]	[2.88]	[3.77]	[11.35]	[11.56]	[10.83]	[8.74]
Constr. volume	**−0.08	*−0.09	−0.06	−0.02	*0.02	0.01	**0.03	**0.03
	[2.11]	[1.90]	[1.55]	[0.73]	[1.65]	[0.73]	[2.19]	[2.55]
Realised variance	**0.02	**0.02	**0.02	**0.02	***0.03	***0.03	***0.03	***0.03
	[2.07]	[2.10]	[2.11]	[2.07]	[8.35]	[8.34]	[8.37]	[7.98]
Constr.-Unconstr.	***−0.17	***−0.16	***−0.14	***−0.19	***−0.07	***−0.08	***−0.08	***−0.07
	[3.50]	[2.88]	[2.90]	[3.27]	[4.28]	[4.88]	[4.81]	[3.43]
R^2 in %	0.13	0.11	0.11	0.16	3.72	3.74	3.76	3.69
BIC	91.61	91.61	91.61	91.05	49.24	49.23	49.23	48.54
Avg. #Time periods	2,280	2,280	2,280	2,182	2,284	2,284	2,284	2,185
#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

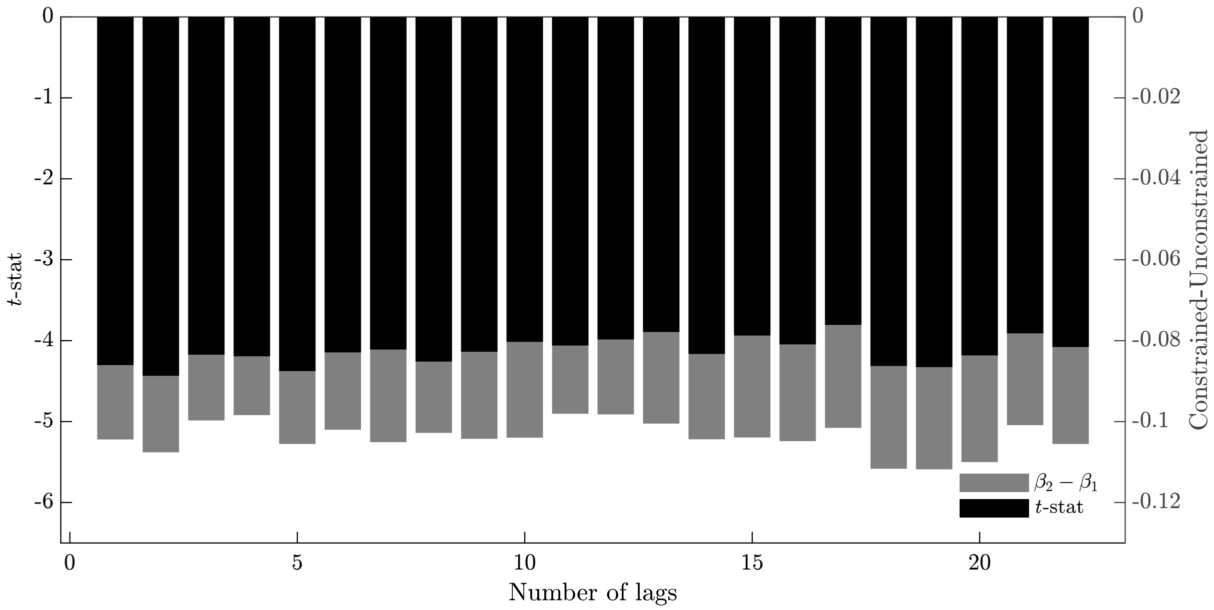
Note: This table reports results from daily fixed effects LSTAR panel regressions of the form $y_{k,t} = \lambda_t + \alpha_k + [1 - G(z_{t-1})]\beta_1' f_{k,t} + G(z_{t-1})\beta_2' f_{k,t} + \beta_3' w_{k,t} + \varepsilon_{k,t}$, where the dependent variable $y_{k,t}$ is a liquidity cost measure (i.e., $VLOOP$ 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 primary FX dealer banks': quarterly Value-at-Risk measure (VaR, columns 1 and 6), quarterly He et al. (2017) leverage ratio (HKM, columns 2 and 7), daily credit default spread (CDS, columns 3 and 8), and daily funding cost yield (DFC, columns 4 and 9). 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 γ 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 2020. 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.

Figure B.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. (4) with VLOOP being the dependent variable and conditional on varying the number of lags in the regime variable DCM_{t-n} for $n = 1, 2, ..., 22$. The sample covers the period from 1 November 2011 to 30 September 2020.

Figure B.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. (4) with TCOST being the dependent variable and conditional on varying the number of lags in the regime variable DCM_{t-n} for $n = 1, 2, ..., 22$. The sample covers the period from 1 November 2011 to 30 September 2020.

Table B.6: LSTAR panel regression 'London hours' with DCM as state variable

	VLOOP				TCOST			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
γ	*12.03	***4.97	***6.04	*12.04	***12.04	***12.06	***12.07	***12.04
c	***0.42	***0.72	***0.75	***0.35	***0.24	***0.24	***0.27	***0.26
Unconstr. volume	***0.11	***0.11	**0.06	***0.10	***0.13	***0.13	***0.10	***0.14
	[3.99]	[4.13]	[2.20]	[3.17]	[11.90]	[11.47]	[7.89]	[10.10]
Constr. volume	−0.07	−0.09	**−0.13	−0.08	*0.03	*0.03	0.00	0.03
	[1.41]	[1.59]	[2.31]	[1.56]	[1.72]	[1.76]	[0.18]	[1.43]
Amihud (2002)		0.01				0.00		
		[1.05]				[0.51]		
Realised variance			***0.05				***0.03	
			[4.13]				[3.80]	
1M CIP basis				0.00				0.00
				[0.97]				[0.46]
Constr.-Unconstr.	***−0.18	***−0.20	***−0.19	***−0.18	***−0.10	***−0.10	***−0.09	***−0.11
	[3.08]	[3.22]	[3.11]	[2.93]	[4.91]	[4.89]	[4.47]	[4.38]
R^2 in %	0.11	0.12	0.24	0.10	1.82	1.82	2.75	1.86
Avg. #Time periods	2,173	2,173	2,173	1,970	2,186	2,185	2,185	1,981
#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 γ 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 5 pm GMT). The sample covers the period from 1 November 2011 to 30 September 2020. 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 B.7: Smooth transition panel regression with DCM as state variable (euro triplets)

	VLOOP				TCOST			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
γ	12.09	12.01	12.06	12.03	***4.94	***12.08	**12.05	***12.08
c	−0.06	−0.06	−0.06	−0.07	***−0.33	***−0.21	***0.53	***−0.23
Unconstr. volume	***0.20	***0.21	***0.19	***0.18	***0.10	***0.10	***0.06	***0.10
	[4.56]	[4.54]	[4.13]	[4.20]	[8.86]	[9.54]	[6.84]	[9.00]
Constr. volume	**0.12	**0.12	**0.11	**0.11	***0.05	***0.05	0.01	***0.05
	[2.28]	[2.41]	[2.04]	[2.01]	[4.26]	[4.37]	[1.00]	[4.22]
Amihud (2002)		0.01				*0.00		
		[0.88]				[1.69]		
Realised variance			0.01				***0.04	
			[0.95]				[9.07]	
1M CIP basis				0.01				0.00
				[1.24]				[0.28]
Constr.-Unconstr.	−0.09	−0.08	−0.08	−0.07	***−0.06	***−0.05	***−0.04	***−0.05
	[1.21]	[1.16]	[1.13]	[0.99]	[3.28]	[3.22]	[2.93]	[3.04]
R^2 in %	0.71	0.70	0.71	0.61	3.33	3.37	5.91	3.55
Avg. #Time periods	2,183	2,182	2,182	2,092	2,186	2,184	2,184	2,095
#Currency triplets	6	6	6	6	6	6	6	6
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 γ 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 2020. 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.

Appendix C. Estimating an SVAR with sign restrictions

We estimate a structural vector autoregression (SVAR) model of liquidity cost measures (i.e., VLOOP or TCOST) and dealer-provided volume VLM. Let $Y_{k,t} = [X_{k,t}\ VLM_{k,t}]^T$ be a 2×1 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:

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

where $B_{k,i}$ is a 2×2 matrix of coefficients, l the lag length, $\xi_{k,t} = [\xi_{X;k,t}\ \xi_{VLM;k,t}]^T$ the reduced form error, and α_k is a 2×1 vector of currency triplet fixed effects. The residual $\xi_{k,t}$ is:

$$\begin{bmatrix} \xi_{X;k,t} \\ \xi_{VLM;k,t} \end{bmatrix} = A_k \begin{bmatrix} \delta^s_{k,t} \\ \delta^d_{k,t} \end{bmatrix}, \tag{C.2}$$

where A_k is a 2×2 matrix and $\delta_{k,t} = [\delta^s_{k,t}\ \delta^d_{k,t}]^T$ is a 2×1 vector. Based on Eqs (C.1) and (C.2), 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 $\delta^s_{k,t}$, whereas the second column corresponds to changes in liquidity costs and VLM associated with an increase in $\delta^d_{k,t}$. Following Goldberg (2020), if A_k satisfies the following sign restrictions:

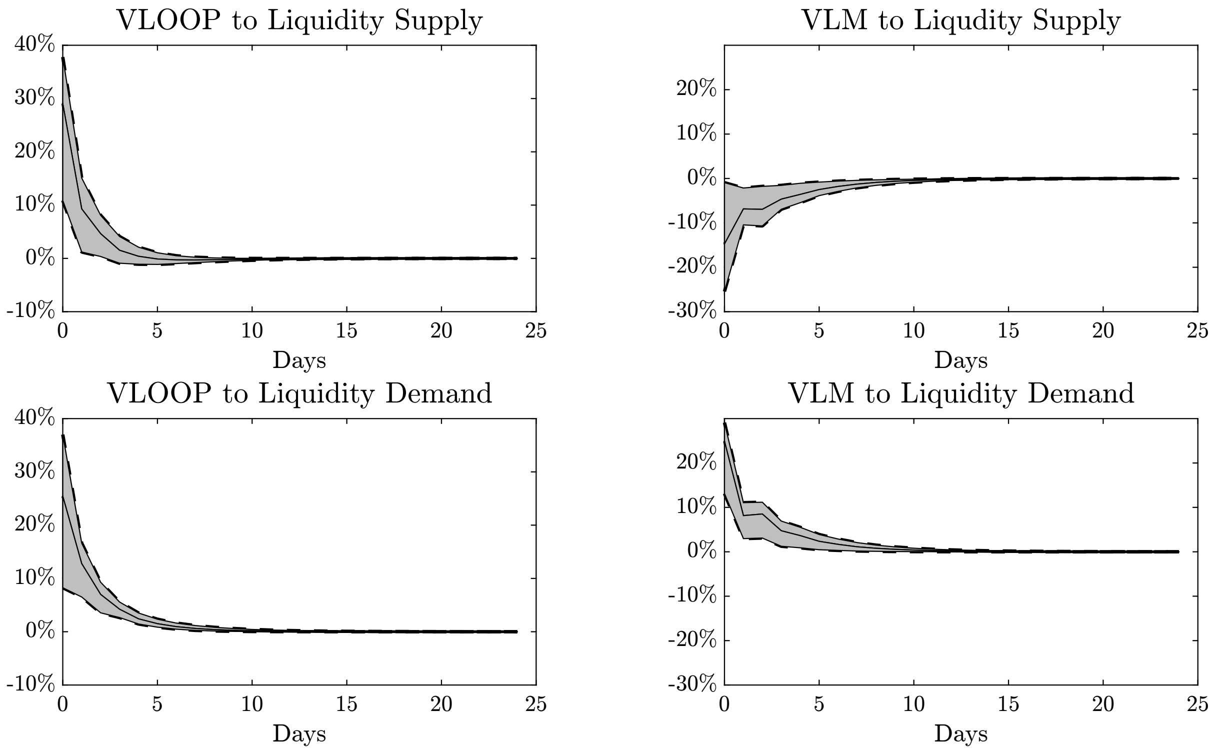
$$sign(A_k) = \begin{pmatrix} + & + \\ - & + \end{pmatrix}, \tag{C.3}$$

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 customers' liquidity demand. In particular, the sign restrictions in Eq. (C.3) assume that supply shifts lead to opposite-sign changes in liquidity costs and trading volumes, whereas demand shifts are assumed to lead to same-sign changes in liquidity costs and volume.

To identify supply and demand shifts, we estimate Eqs (C.1) and (C.2) imposing the sign restrictions in Eq. (C.3) 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. (C.1) with parameters $B_k = [B_{k,1}, ..., B_{k,l}]$ and covariance matrix Σ_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, Σ_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 Σ_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. (C.3) 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 Σ_k and, for each B_k and Σ_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.

For illustrative purposes, Figure C.1 (Figure C.2) shows estimates of the dynamic responses of $VLOOP$ ($TCOST$) and VLM to supply and demand shifts for the EUR-USD-JPY currency pair triplet.[31] By construction, concurrently with a liquidity supply shift, VLOOP (TCOST) rises and VLM positions decline. As shown in Figure C.1, contemporaneous with a liquidity supply shift, VLOOP (TCOST) rises 31% (6%) and VLM positions decline 15% (18%), according to the posterior mean. Contrarily, a liquidity demand shock is associated with an increase in VLOOP (TCOST) and VLM by 25% and 12% (13% and 21%), respectively.

Figure C.1: VLOOP: Dynamic impulse response function for EUR-USD-JPY

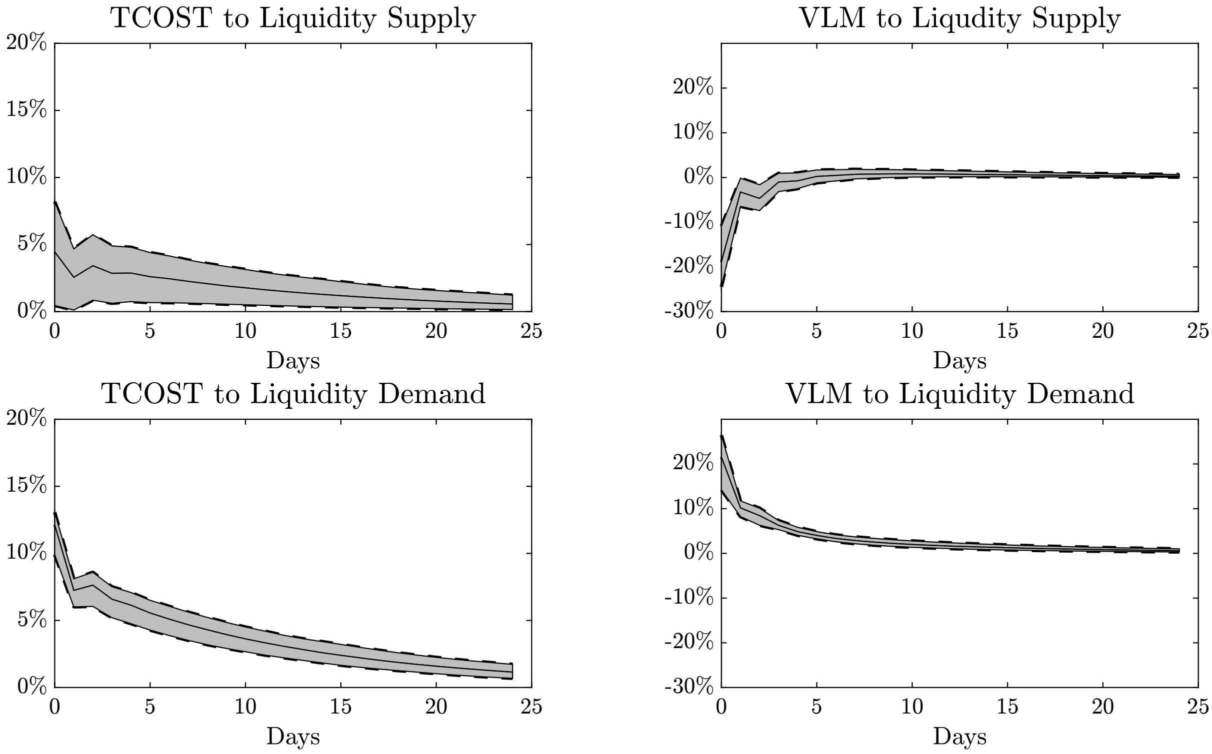


Note: This figure plots the estimated dynamic response of the shadow cost of intermediary constraints (VLOOP) and dealer-intermediated volume (VLM) associated with liquidity supply and demand shifts. The median response is shown by the black solid line. The grey shaded area marks a pointwise 95% confidence interval around the median. The sample covers the period from 1 November 2011 to 30 September 2020.

Figures C.3 and C.4 plot the rolling correlation between each of our two liquidity cost

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

Figure C.2: TCOST: Dynamic impulse response function for EUR-USD-JPY



Note: This figure plots the estimated dynamic 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 2020.

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.

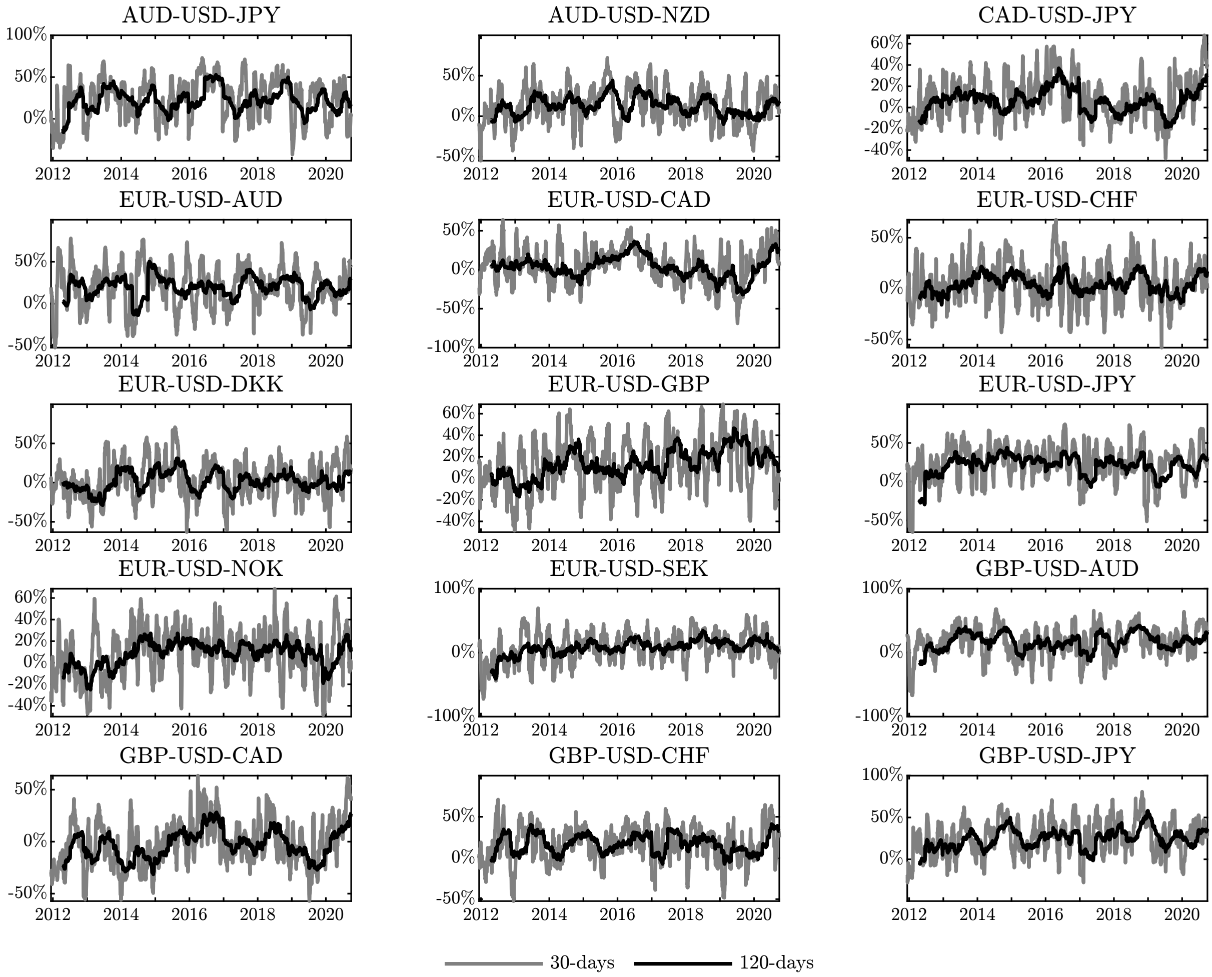
Appendix D. Quasi-natural experiment: Swiss franc decap

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

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

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), α 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 η_3 is the difference-in-differences (DnD) coefficient. $w_{k,t}$ 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 η_3 to be negative and

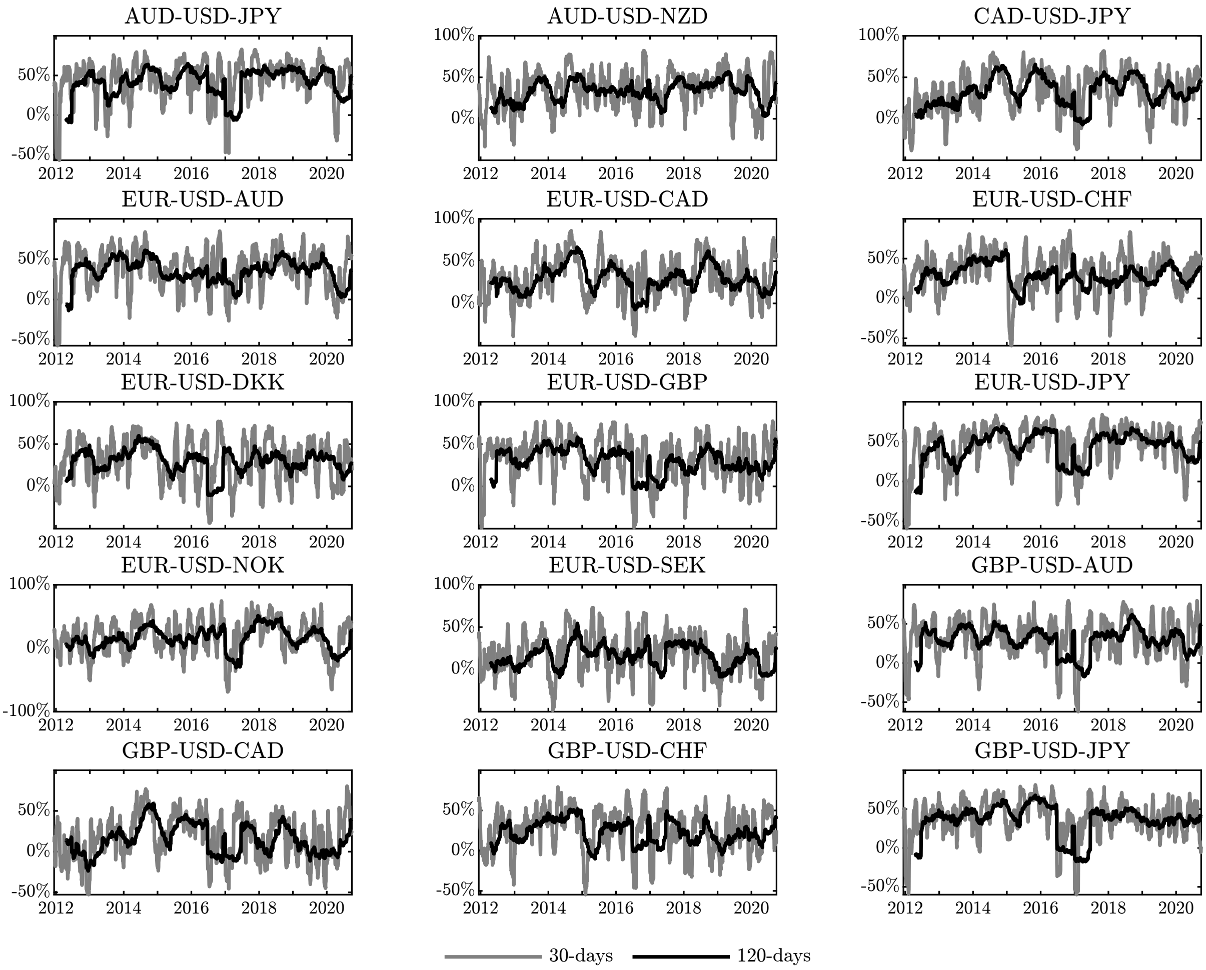
Figure C.3: Rolling window correlation VLOOP and VLM



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 2020.

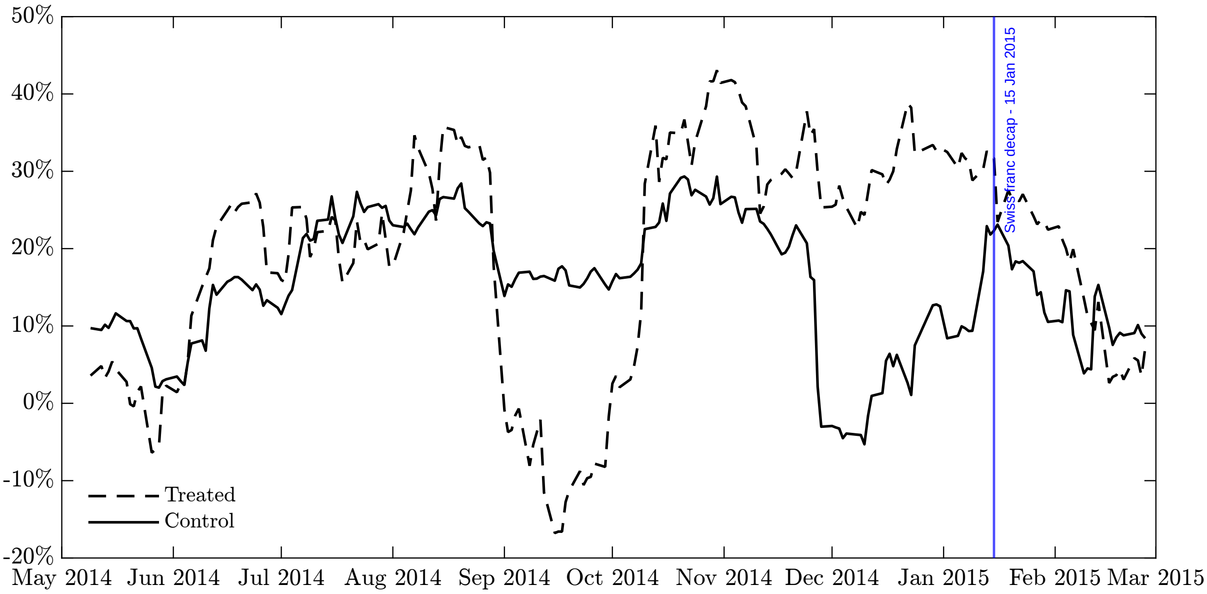
statistically significant. For instance, after the removal of the Swiss franc cap the correlation between TCOST and VLM is 54 percentage points lower for currency pair triplets involving the Swiss franc. Figures D.1 and D.2 illustrate the drop in the rolling window correlation coefficient based on each of our two liquidity cost measures (i.e., VLOOP or TCOST) after the removal of the Swiss franc cap.

Figure C.4: Rolling window correlation TCOST and VLM



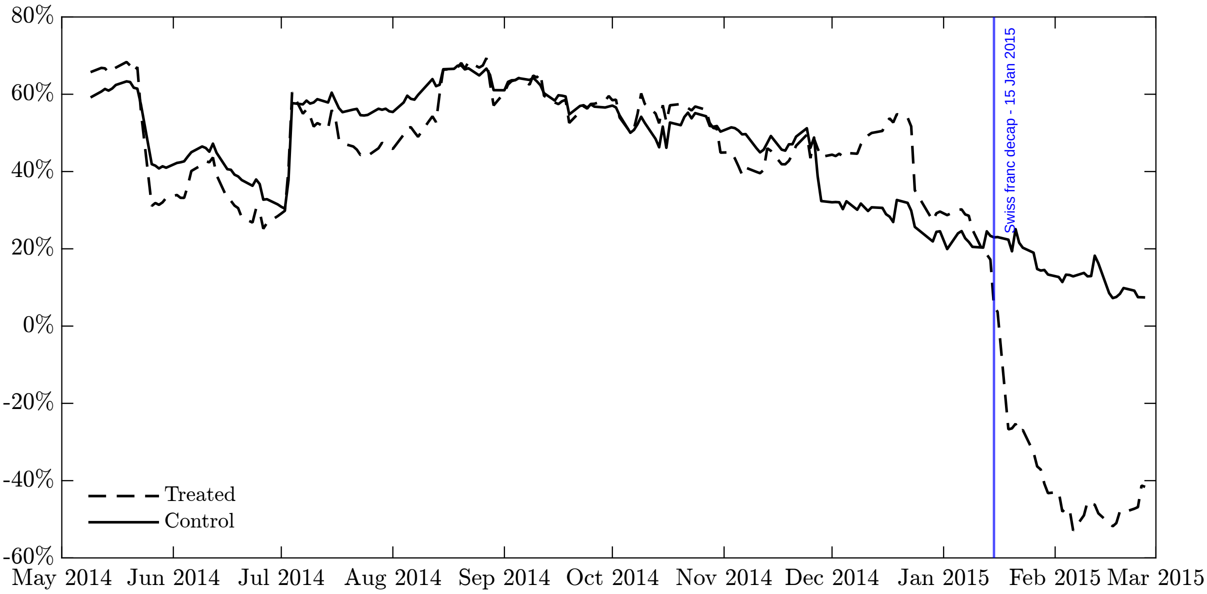
Note: This figure plots the 30- and 252-day rolling window correlation of daily cumulative round-trip transaction cost TCOST (i.e., dealers' compensation for enduring inventory imbalances) and dealer-intermediated trading volume VLM. The sample covers the period from 1 November 2011 to 30 September 2020.

Figure D.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 D.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.

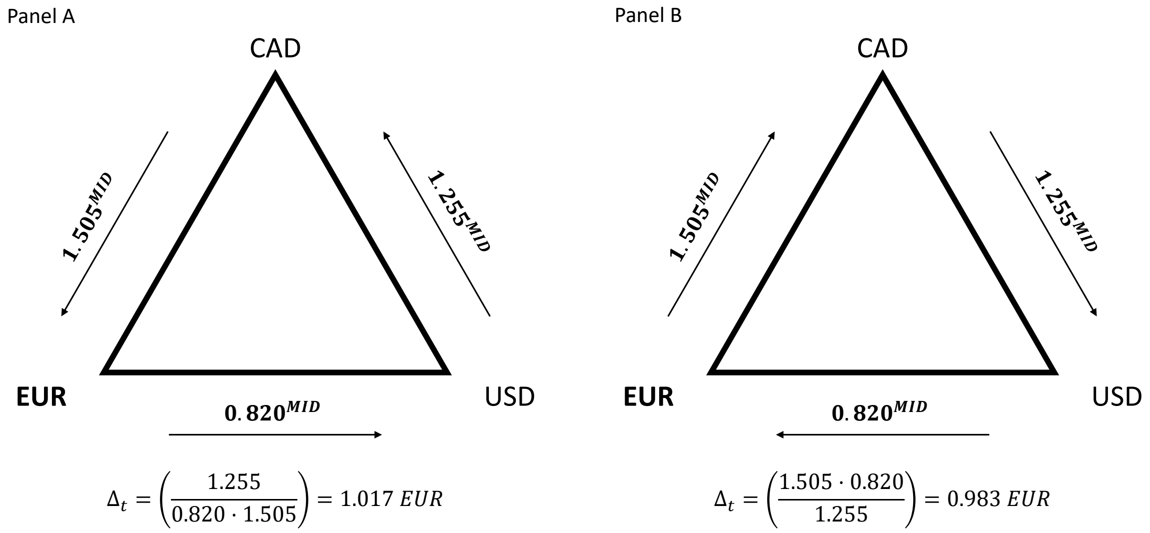
Table D.1: Event study panel regression: Removal of the Swiss franc cap

	cor(VLOOP,Volume)			cor(TCOST,Volume)		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	***0.16	***0.16	***0.19	***0.49	***0.49	***0.49
	[11.42]	[11.40]	[11.55]	[23.15]	[23.21]	[26.74]
$D_{k,t}$	0.04	0.04	0.04	0.00	0.00	0.00
	[1.49]	[1.46]	[1.63]	[0.13]	[0.05]	[0.14]
$Post_t$	*−0.04	*−0.04	−0.03	***−0.35	***−0.35	***−0.34
	[1.93]	[1.94]	[1.23]	[12.36]	[12.33]	[11.48]
$D_{k,t} \times Post_t$	0.00	0.00	0.05	***−0.54	***−0.54	***−0.53
	[0.03]	[0.02]	[1.17]	[18.99]	[19.33]	[19.00]
Realised variance		***0.00	***0.02		***−0.01	**−0.01
		[6.16]	[5.48]		[6.40]	[2.51]
Amihud (2002)			***−0.04			−0.02
			[4.55]			[1.62]
R^2 in %	29.35	29.37	31.19	86.11	86.19	86.27
Adj. R^2 in %	29.28	29.28	31.08	86.09	86.18	86.25
Avg. #Time periods	207	207	207	207	207	207
#Exchange rates	15	15	15	15	15	15

Note: This table reports results from daily panel regressions of the form $\rho_{k,t} = \alpha + \eta_1 D_{k,t} + \eta_2 Post_t + \eta_3(D_{k,t} \times Post_t) + \kappa' w_{k,t} + \epsilon_{k,t}$, 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), α 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 η_3 is the difference-in-differences coefficient. $w_{k,t}$ 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.

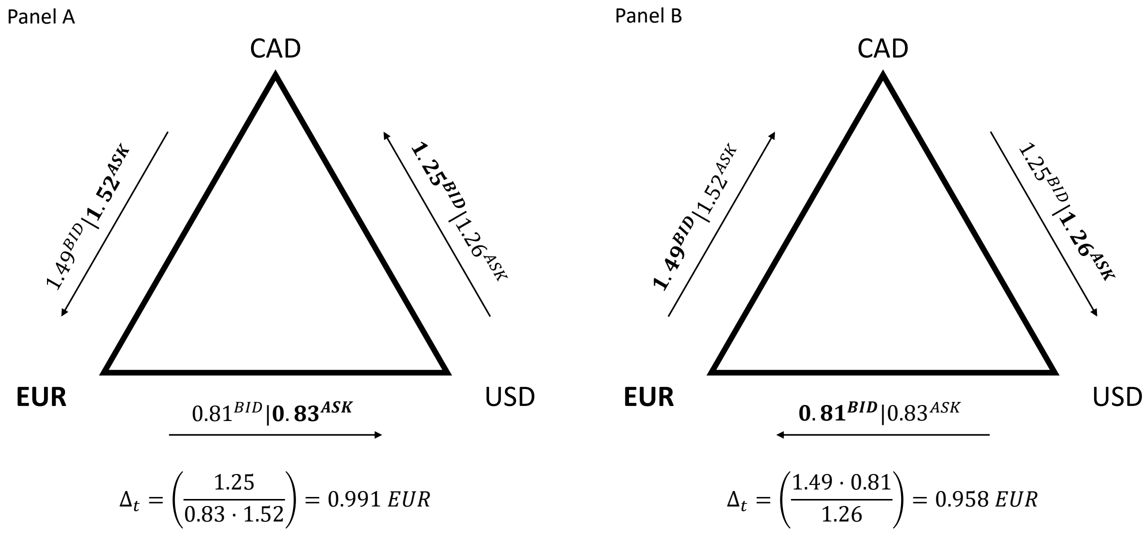
Appendix E. Additional empirical results

Figure 2: Identifying a triangular arbitrage opportunity



Note: This figure provides a schematic overview of two triangular arbitrage strategies, where the arrows denote the direction. Panel A shows the hypothetical profit 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 embraces the same logic but going the opposite direction, that is, first from euro to Canadian dollar, to US dollar and then back to euro yielding a negative return of -1.7%.

Figure 3: Triangular arbitrage trade with transaction costs



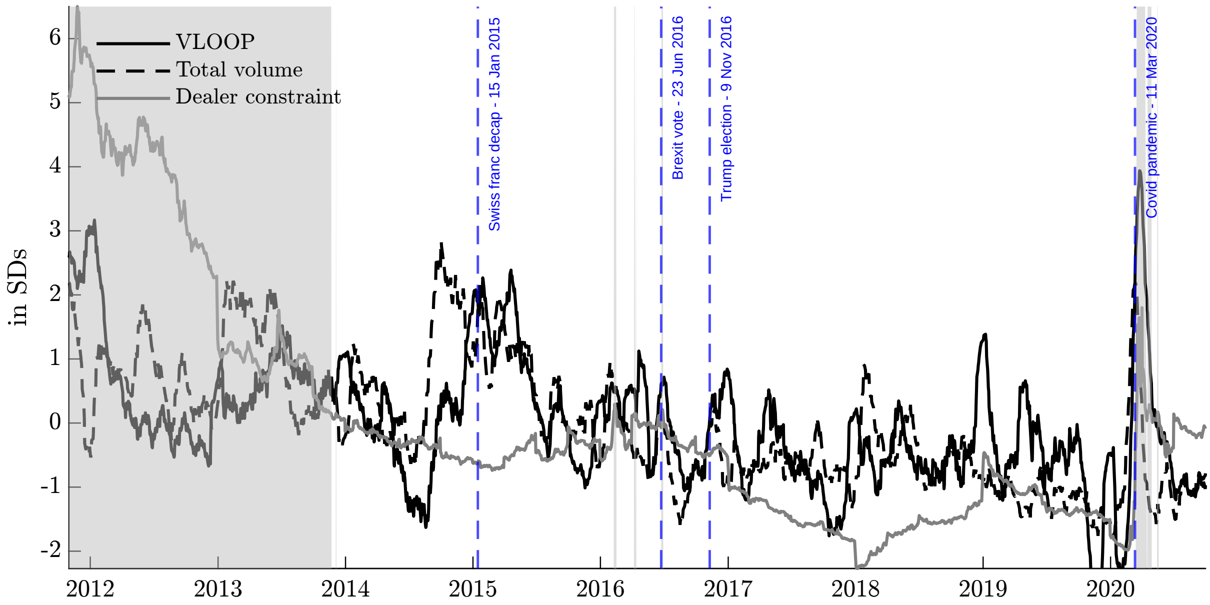
Note: This figure provides a schematic overview of two triangular arbitrage strategies, where the arrows denote the direction. Panel A shows the profit of first exchanging one euro to $\frac{1}{0.83} = 1.21$ US dollars at the ask price, then exchanging 1.21 US dollars to Canadian dollars at the bid price 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 equivalent a negative return of -0.9%. Panel B embraces the same logic but going the opposite direction, that is, first from euro to Canadian dollar, to US dollar and then back to euro.

Table E.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	Synthetic	
AUD-USD-JPY	0.24	4.88	0.18	5.11	4.15	5.87	14.38	15.86	0.18
AUD-USD-NZD	0.29	5.85	0.09	2.01	4.44	7.43	9.32	17.95	0.02
CAD-USD-JPY	0.30	4.67	0.03	5.32	4.29	5.21	12.66	13.39	0.43
EUR-USD-AUD	0.19	4.52	0.14	7.72	3.54	5.64	11.54	15.51	0.04
EUR-USD-CAD	0.28	4.25	0.08	7.94	3.55	4.99	10.15	12.89	0.07
EUR-USD-CHF	0.21	3.98	0.37	6.76	2.62	5.41	6.38	13.44	0.10
EUR-USD-DKK	0.14	3.89	0.09	6.17	2.54	5.30	1.82	13.03	0.05
EUR-USD-GBP	0.19	4.07	0.61	8.16	3.19	4.95	9.52	13.60	0.03
EUR-USD-JPY	0.21	3.90	0.65	9.67	3.14	4.83	11.43	13.71	0.66
EUR-USD-NOK	0.26	7.69	0.24	6.25	6.25	9.40	11.01	16.90	0.05
EUR-USD-SEK	0.23	6.86	0.27	6.27	5.41	8.42	9.18	15.95	0.05
GBP-USD-AUD	0.20	5.08	0.04	3.60	4.22	5.99	12.53	15.93	0.02
GBP-USD-CAD	0.29	4.69	0.03	3.81	4.00	5.34	10.85	13.31	0.05
GBP-USD-CHF	0.19	4.94	0.03	2.64	4.09	5.76	10.69	13.99	0.03
GBP-USD-JPY	0.19	4.47	0.20	5.55	3.85	5.18	12.78	14.13	0.62

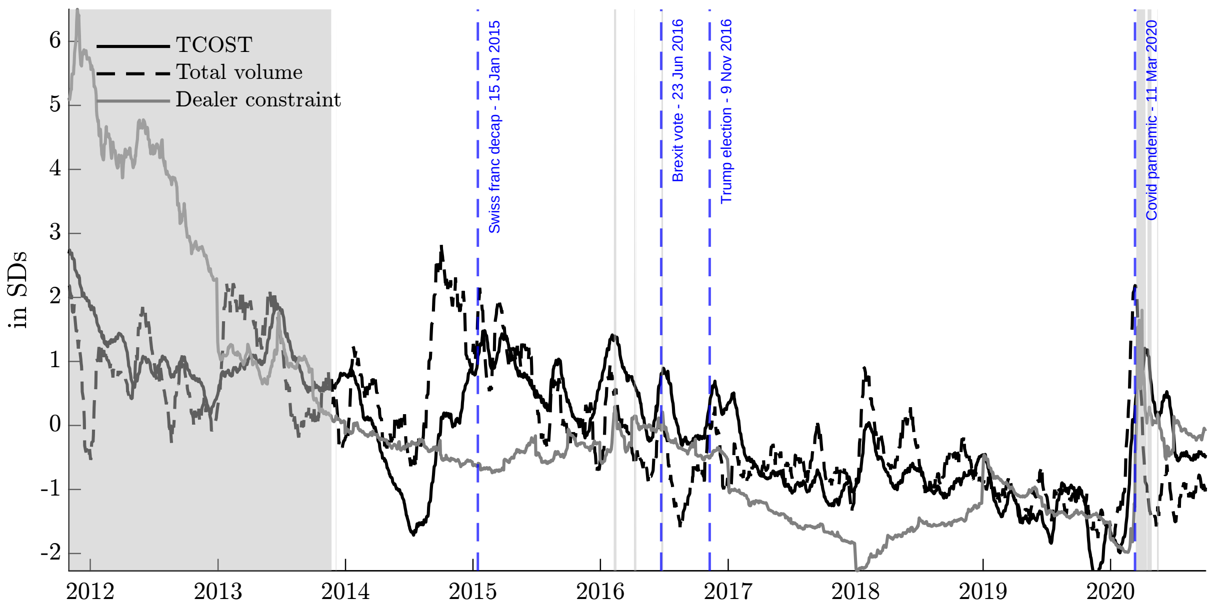
Note: This table reports the time-series average of hourly triangular no-arbitrage deviations $VLOOP$ in basis points (bps), round-trip trading costs $TCOST$ in bps, direct trading volume in non-dollar currency pairs (e.g., AUDJPY) in \$bn, synthetic trading volume in dollar pairs (e.g., the sum across USDAUD and USDJPY) in \$bn, as well as direct and synthetic relative bid-ask spreads and realised volatility in non-dollar and dollar currency pairs in bps, respectively. 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 2020.

Figure 4: Law of one price violations, intermediated volume, dealer constraints



Note: This figure plots the cross-sectional average of the shadow cost of intermediary constraints (VLOOP, black solid line) against total trading volume (Total volume, black dashed line) in units of standard deviations. Both time-series correspond to 22-day moving averages. The grey line plots our dealer constraint measure (DCM). The grey shaded areas correspond to times when DCM exceeds its 75% quantile. The sample covers the period from 1 November 2011 to 30 September 2020.

Figure 5: Round-trip trading costs, intermediated volume, dealer constraints



Note: This figure plots the cross-sectional average of dealers' compensation for enduring inventory imbalances (TCOST, black solid line) against total trading volume (Total volume, black dashed line) in units of standard deviations. Both time-series correspond to 22-day moving averages. The grey line plots our dealer constraint measure (DCM). The grey shaded areas correspond to times when DCM exceeds its 75% quantile. The sample covers the period from 1 November 2011 to 30 September 2020.

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

	RMSE		MAE		CORR	
	BID	ASK	BID	ASK	BID	ASK
AUDJPY	0.286	0.232	0.131	0.126	0.996	0.997
AUDNZD	0.001	0.001	0.001	0.001	0.999	0.999
AUDUSD	0.001	0.002	0.001	0.001	0.998	0.997
CADJPY	0.335	0.315	0.148	0.147	0.995	0.996
EURAUD	0.003	0.002	0.002	0.002	0.998	0.998
EURCAD	0.002	0.002	0.001	0.001	0.998	0.998
EURCHF	0.001	0.001	0.001	0.001	0.993	0.992
EURDKK	0.001	0.001	0.001	0.001	0.991	0.988
EURGBP	0.001	0.001	0.001	0.001	1.000	1.000
EURJPY	0.211	0.201	0.124	0.124	0.999	0.999
EURNOK	0.016	0.012	0.008	0.008	0.996	0.998
EURSEK	0.009	0.009	0.006	0.006	0.999	0.999
EURUSD	0.002	0.002	0.001	0.001	0.997	0.998
GBPAUD	0.004	0.005	0.003	0.003	1.000	0.999
GBPCAD	0.004	0.004	0.003	0.003	0.999	0.999
GBPCHF	0.003	0.003	0.002	0.002	0.999	0.999
GBPJPY	0.523	0.590	0.251	0.257	0.999	0.999
GBPUSD	0.002	0.003	0.001	0.001	1.000	0.999
NZDUSD	0.001	0.001	0.001	0.001	0.999	0.999
USDCAD	0.002	0.002	0.001	0.001	0.999	0.999
USDCHF	0.001	0.001	0.001	0.001	0.998	0.998
USDDKK	0.007	0.007	0.005	0.005	0.999	0.999
USDJPY	0.178	0.194	0.112	0.111	1.000	0.999
USDNOK	0.014	0.016	0.010	0.010	0.998	0.998
USDSEK	0.018	0.013	0.009	0.008	0.999	0.999

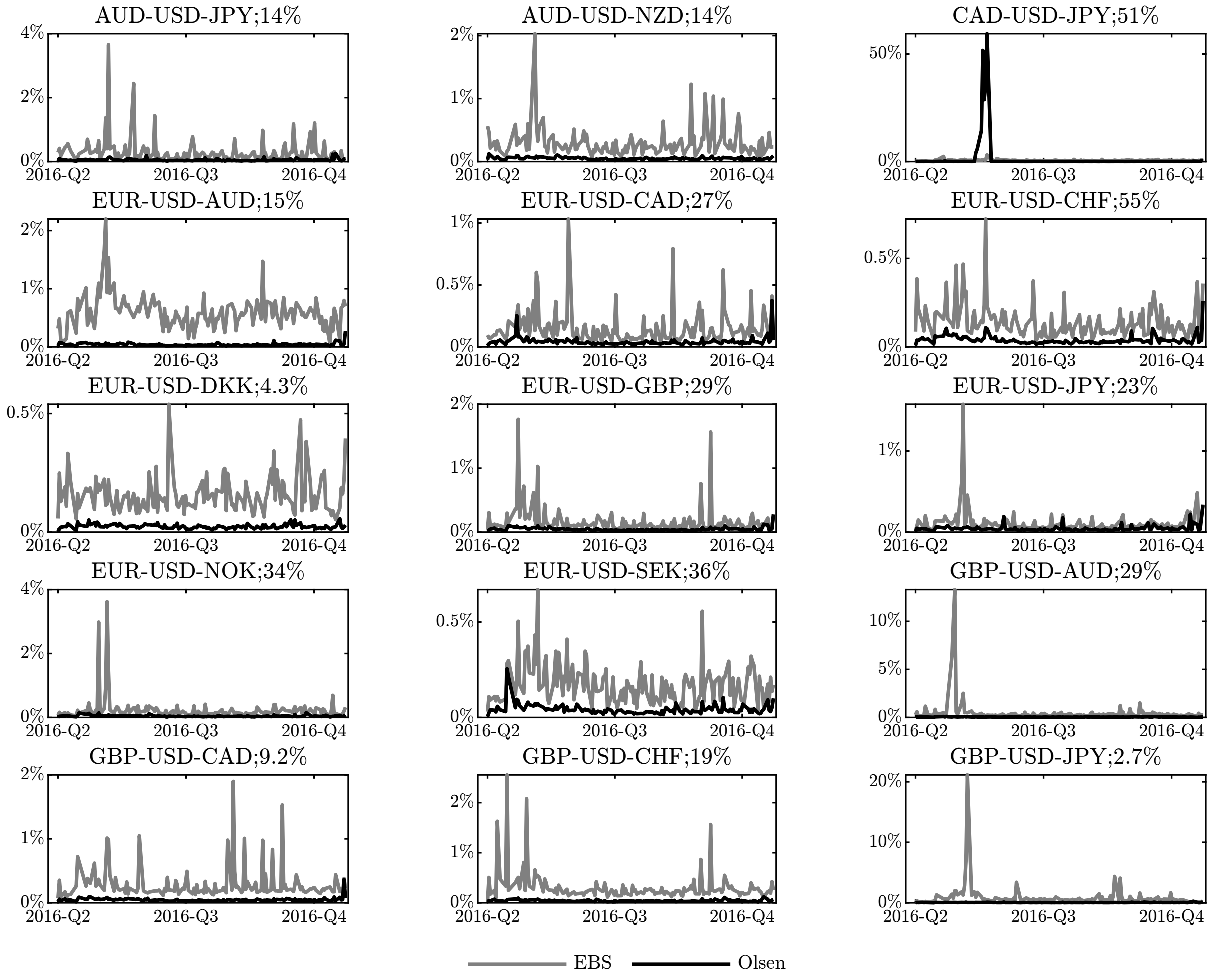
Note: This table reports the root mean squared error ($RMSE$, columns 1 and 2), the mean absolute error (MAE, columns 3 and 4), and the pairwise correlation coefficient ($CORR$, columns 5 and 6) for bid and ask quotes based on EBS and Olsen data, respectively. The sample covers the period from 4 January 2016 to 30 December 2016.

Table E.3: Correlations in percent

	VLOOP	TCOST	VOD	VOS	BAD	BAS	RVD
TCOST	***28.10						
VOD	***−0.48	***6.19					
VOS	***4.93	***16.53	***61.87				
BAD	***23.24	***74.34	***1.85	***9.59			
BAS	***20.68	***75.85	***17.01	***34.91	***83.36		
RVD	***15.52	***37.78	***27.43	***37.57	***54.60	***49.05	
RVS	***13.22	***44.43	***31.47	***55.92	***45.59	***69.84	***74.85

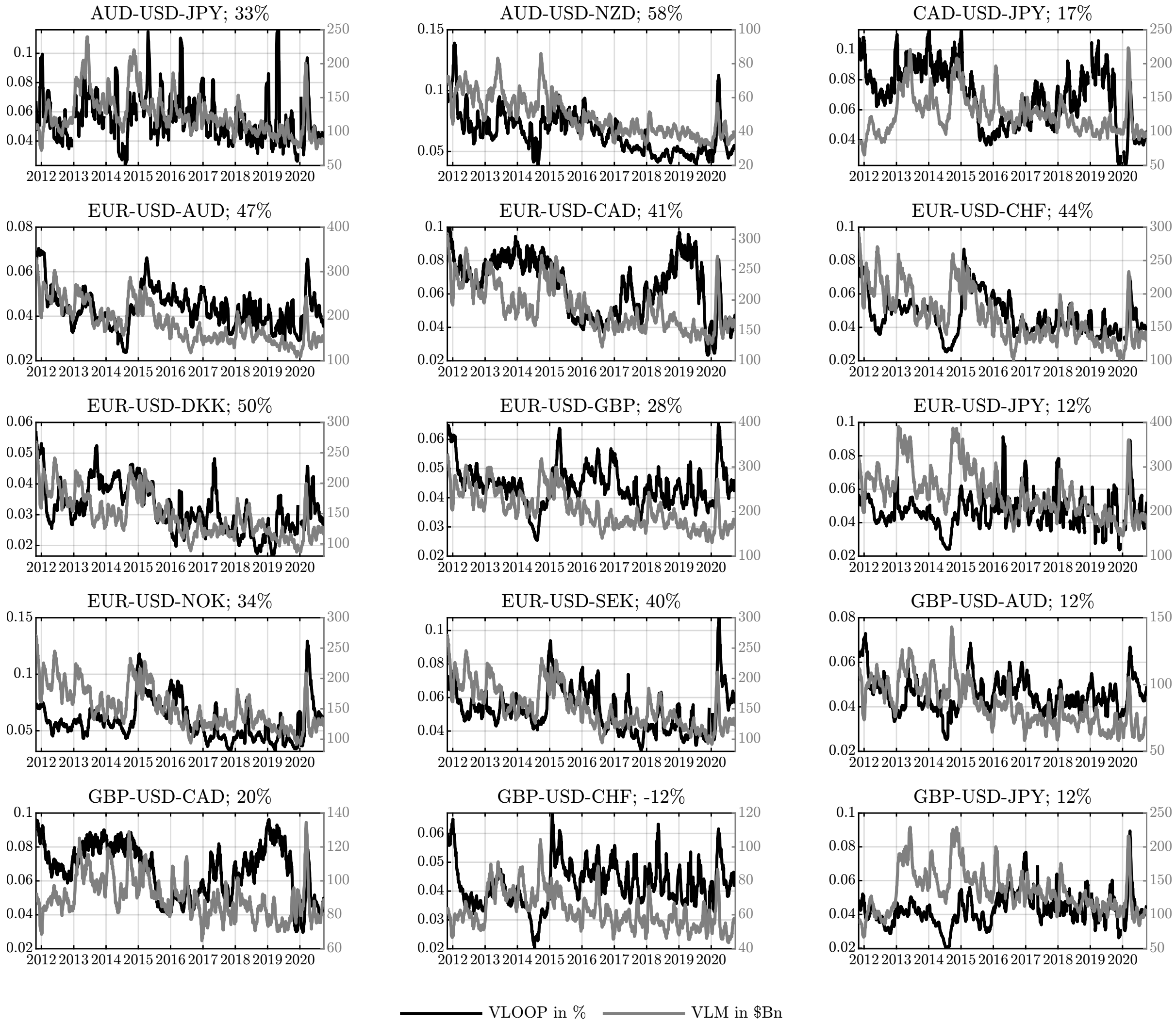
Note: This table reports the pairwise correlation coefficient of hourly triangular no-arbitrage deviations $VLOOP$, trading costs $TCOST$, direct trading volume VOD in non-dollar pairs (e.g., XXXYYY), synthetic trading volume VOS in dollar pairs (e.g., the average across USDXXX and USDYYY), relative 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 2020.

Figure E.1: Comparison of no-arbitrage violation using EBS vs Olsen data



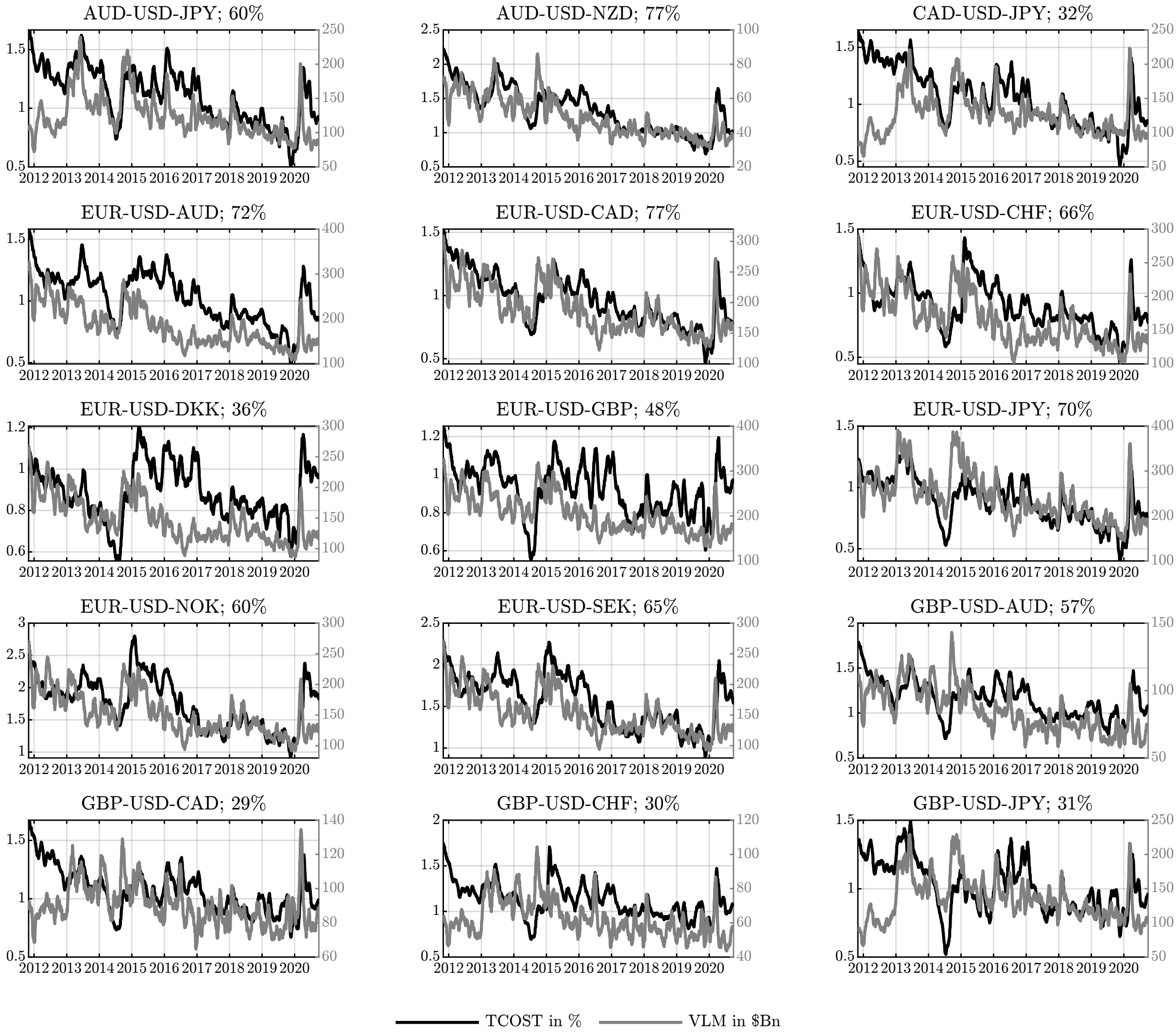
Note: This figure plots the daily cumulative sum of hourly no-arbitrage deviations (VLOOP) computed based on EBS and Olsen data, respectively. The percentages in the titles report the Pearson correlation coefficient between the two time-series. The sample covers the period from 8 June 2016 to 30 December 2016.

Figure E.2: No-arbitrage violations and trading volumes



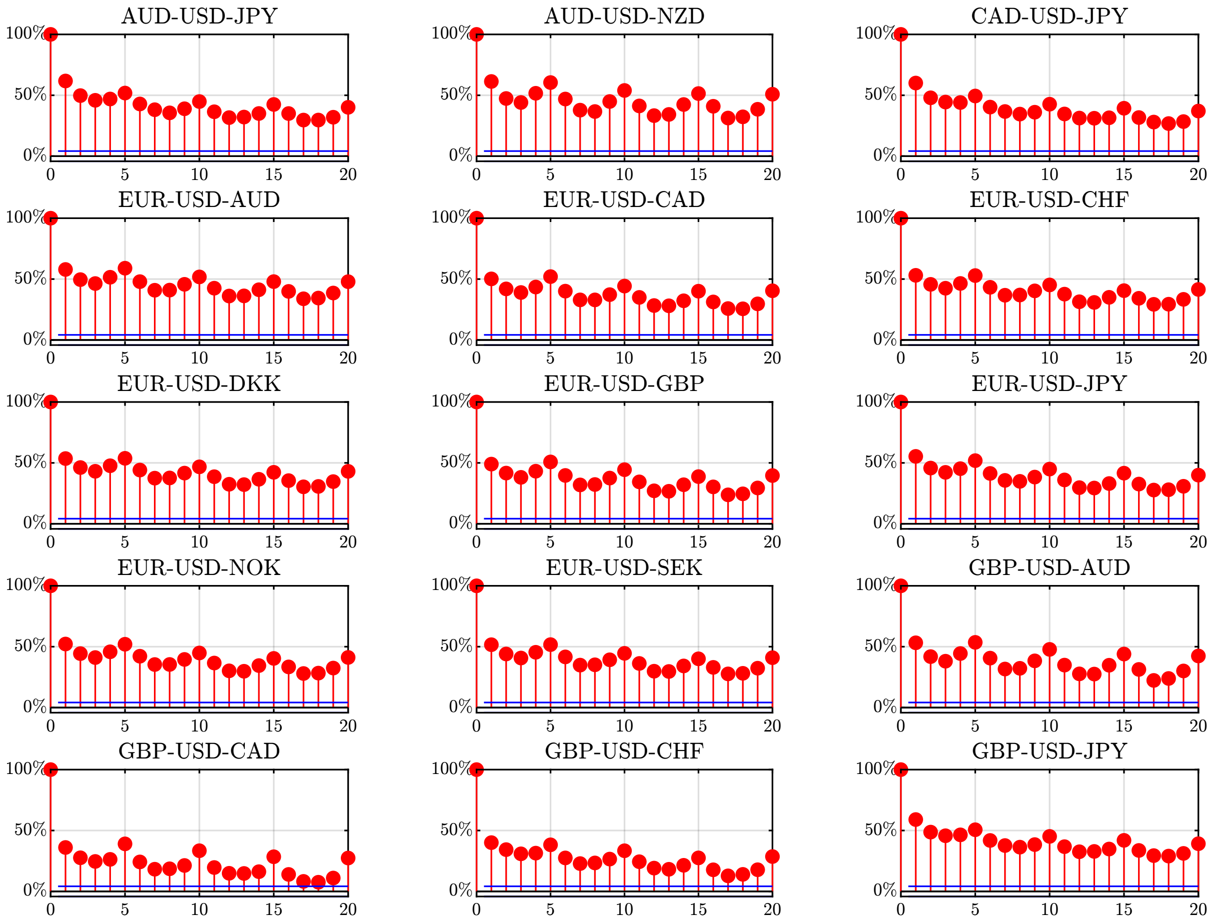
Note: This figure plots total trading volume VLM against no-arbitrage deviations VLOOP (i.e., shadow cost of intermediary constraints) for 15 triplets of currency pairs. Currency pair triplets are denoted as XXX-USD-YYY, consisting of two dollar currency pairs (i.e., USDXXX, and USDYYY) as well as one 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 2020.

Figure E.3: 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 2020.

Figure E.4: 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. Both time-series correspond to 22-day moving averages. The sample covers the period from 1 November 2011 to 30 September 2020.

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