Uninformed yet Consequential: Liquidity Shocks in FX Markets

August 9, 2024

Abstract

We study how retail liquidity shocks impact prices and volumes in the foreign exchange (FX) spot market. We model risk-averse dealers' accumulation of inventory under asymmetric information and incomplete offset across retail clients. Our model predicts that retail liquidity shocks result in inventory imbalances that are transmitted to the inter-dealer segment, increasing price volatility and trading volumes. Using month-end settlement breaks to instrument for uninformed order flow, we empirically validate these predictions: a one-standard-deviation rise in retail net volume increases volatility by 12-22% and inter-dealer volume by 10%, indicating that liquidity-driven demand interacts with intermediary constraints to determine asset prices.

Keywords: price volatility, liquidity shocks, dealer constraints, market segmentation, financial frictions, risk-bearing capacity

JEL classification: F31, G12, G15, G23

The foreign exchange market, with its daily trading volume of $7.5 trillion, is the world's largest over-the-counter market. Understanding the drivers of price dynamics in this market is crucial given its central role in facilitating international trade and investment. The impact of retail liquidity shocks, i.e., demand shocks unrelated to information signals, on this market remains poorly understood. Our study bridges this gap, providing empirical micro-foundations for how these shocks influence currency prices and dealer behavior.

We extend the understanding of FX markets by documenting how retail uninformed liquidity shocks affect FX market dynamics.[1] First, we isolate these shocks using 'settlement breaks" before month-ends that affect liquidity-driven corporate order flow. Second, we quantify their impact on FX volatility and trading volumes, an area not explored in previous work. Third, we illustrate how corporate liquidity shocks propagate through the inter-dealer market, demonstrating a concrete mechanism for how non-informational trading influences market-wide prices. Finally, we show that even small retail segments can cause significant price volatility, especially when dealer risk-bearing capacity is limited, underscoring the importance of market structure in shock transmission.

Studying liquidity demand shocks provides valuable insights into the microstructure of FX markets. It helps reveal how information and trading frictions affect price formation, trading volumes and bid-ask spreads in a decentralized, over-the-counter market setting. Analyzing these shocks sheds light on how dealers manage inventory risk and how their risk-bearing capacity affects market outcomes. This is especially relevant given the evolving structure of FX markets and changes in regulation affecting dealers' ability to warehouse risk.

We extend Liu and Wang (2016) to study the impact of liquidity shocks on FX asset prices and trading volumes. The model explicitly includes inter-dealer trading as a mechanism for risk sharing

[1]Prior work on FX markets has focused on macroeconomic fundamentals (Colacito, Croce, Liu, and Shaliastovich, 2021, Itskhoki and Mukhin, 2021, Mark, 1995), informed trading (Ranaldo and Somogyi, 2020), and inventory management (Reitz and Umlandt, 2021).

and price discovery, which more accurately reflects the actual organization of OTC FX markets than the original setup of Liu and Wang (2016). The model includes both informed and uninformed retail traders, as well as market makers, capturing the diverse participant base in FX markets. We introduce non-information-based liquidity shocks that align with empirical observations of corporate trading patterns. Our model accounts for dealer inventory risk and its impact on pricing and trading decisions, which is crucial in OTC markets. The model yields several testable implications: (1) net retail trading volume increases with uninformed liquidity shocks, (2) bid-ask spreads widen with such shocks, (3) corporate liquidity shocks boost currency return volatility, and (4) the impact of liquidity shocks is greater with more risk-averse dealers or higher asset volatility.

To validate these model predictions, we introduce "settlement breaks" that isolate liquidity-driven corporate order flow. The proposed "settlement breaks" affect traded volumes and price volatility only because of uninformed liquidity shocks that originate in the retail segment. Such shocks influence the FX markets independently of innovations in currency fundamentals that are unlikely to regularly arrive two days before a month-end. Our instrument leverages the standard two-day settlement period for FX spot transactions and the need of corporate clients for cash flow to arrive before month-ends.

We find that a one-standard-deviation rise in liquidity-driven demand leads to a 12-22% increase in unconditional return volatility. Crucially, we identify the inter-dealer market as the primary channel through which these shocks propagate. Dealers, constrained by inventory risk and balance sheet limitations, respond to end-user liquidity shocks by adjusting their positions in the inter-dealer market. This leads to a significant increase in inter-dealer trading volume; a one-standard-deviation rise in corporate net volume adds 10.4% to inter-dealer volume. Dealers trade in the inter-dealer market because, as we estimate, about 80% of liquidity-driven corporate shocks is not immediately offset by fund order flow. Liquidity shocks impact less liquid and riskier currency markets more

because risk-averse dealers seek compensation for higher volatility.

We use a rich dataset with agent-specific signed order flow in the FX spot market, which allows us to compute the inventory risk faced by dealers at an hourly frequency. We source this dataset from CLS Group, the largest settlement agency in FX markets, across currencies that altogether represent 90% of the spot traded volume over a sample period of 2015 to 2022. Several features of this data set make it ideal for examining the impact of liquidity shocks on FX markets. First, it includes buy and sell volumes contracted between dealers and two sets of end-users, non-financial corporations and investment funds, as well as total traded volumes in the inter-dealer segment. This allows us to extract liquidity shocks originating in the retail segment and link them with inter-dealer volumes and equilibrium prices. Second, the hourly frequency of our data enables us to compute the short-term inventory risk faced by dealers in a highly liquid market, which is harder to glean from data aggregated at a daily frequency or lower. Third, we analyze 31 currency pairs that allows for heterogeneity analysis across currency markets. Based on the triennial turnover survey of the Bank for International Settlements (BIS, 2022), we estimate that our data covers about a quarter of the overall FX spot market turnover.

Importantly, while our focus is on non-financial corporations, the main results are generalizable to liquidity shocks from other uninformed agents as well. We focus on corporations because we can identify pure liquidity-driven shocks in their order flow using settlement breaks, which has not been explored previously. Other market participants, such as investment funds or banks, may also face significant liquidity shocks in FX markets that are difficult to differentiate from information-driven demand shifts. By limiting our focus on non-financial corporations, our results may underestimate the overall importance of liquidity demand shocks on FX market dynamics.

Our findings highlight the pivotal role of dealers' financial constraints in transmitting the effects of uninformed retail trading to asset prices. Our findings reveal that, liquidity shocks originating

in a relatively small retail segment, with less than 6% share in FX trading, can have significant effects on FX volatility and trading volumes, highlighting the critical role of dealer constraints in transmitting these shocks. We show that even these often ignored non-fundamental sources of demand shocks interact with intermediary constraints to induce significant price volatility when dealer risk-bearing capacity is limited. By tracing how liquidity shocks propagate through inter-dealer trading, we shed new light on the microstructure of the FX market and the origins of exchange rate volatility.

Related Literature

Our paper bridges literatures on exchange rate determination, intermediary constraints, and market microstructure.

Exchange Rate Determination: Recent theoretical work on exchange rate determination in segmented markets emphasizes financial shocks and intermediaries' limited risk bearing capacity as drivers of exchange rates (Gabaix and Maggiori, 2015, Itskhoki and Mukhin, 2021, Greenwood, Hanson, Stein, and Sunderam, 2023). Our work contributes to understanding the source of these financial shocks by studying liquidity demand originating from uninformed end-investors. Building on the model in Liu and Wang (2016), we provide a new perspective on exchange rate movement when certain end-users behave like noise traders, and dealers are unable to fully offset these shocks within the retail segment. Empirically, we show that financial shocks can originate from sectors that are otherwise smaller players in the FX market, and still have an economically sizeable impact on prices and traded volume.

Demand imbalances and intermediary constraints: We also contribute to the growing literature on the impact of dealers' inventory holding cost on asset markets: Colliard, Foucault,

and Hoffmann (2021) model the impact of aggregate dealer inventory on prices, Muravyev (2016) empirically shows that inventory holding costs have a greater impact on option prices relative to information asymmetry, and Khetan, Li, Neamtu, and Sen (2023) show that dealers absorb large imbalances in the interest rate swaps market, affecting swap spreads. Our unique contribution to this line of inquiry is to explicitly consider shifts in end-user demand that interacts with intermediary constraints to affect asset prices.

Within the FX market context, Bianchi, Bigio, and Engel (2021) focus on financial institutions' demand for dollar liquid assets, Fang and Liu (2021) study dealers' Value-at-Risk (VaR) constraints, Gallien, Kassibrakis, Klimenko, Malamud, and Teguia (2022) highlights the role of dealer heterogeneity, and Krohn, Mueller, and Whelan (2024) argue that intra-day inventory management by dealers affects exchange rates. Our paper complements these studies by focusing on the diverse nature of end-user demand, and identifying specific scenarios where uninformed order flow significantly influences currency return volatility. Relatedly, Malamud and Schrimpf (2018) and Barbiero, Bräuning, Joaquim, and Stein (2024) argue that the risk-bearing capacity of country-specific financial intermediaries is crucial in determining currency risk. Our model shows that higher risk aversion among market-makers amplifies the impact of liquidity shocks on volatility and traded volume, suggesting potentially pronounced effects during periods of financial turmoil.

Market microstructure: Our paper adds to the studies on microstructure of FX markets by analyzing the behavior of uninformed noise traders. Several studies document heterogeneity in the information content of different end-users' trades (Menkhoff, Sarno, Schmeling, and Schrimpf, 2016, Ranaldo and Somogyi, 2020). On the other hand, Ramadorai (2008) and Holden, Lu, Lugovskyy, and Puzzello (2020) show that dealer spreads decline with order size even for the more likely informed agents, suggesting that private information plays a smaller role than inventory costs in

this market. Our work takes a different approach and shows that uninformed order flow can *jointly* affect prices and volumes when dealers face inventory risk. By doing so, we add to earlier models of "hot-potato" trading (Lyons, 1997) and portfolio shifts (Evans and Lyons, 2002), and speak to more recent work on the disconnect between factors driving volatility in economic fundamentals and those affecting exchange rate volatility (Colacito, Croce, Liu, and Shaliastovich, 2021). Our focus on uninformed agents complements work in other markets as in Foucault, Sraer, and Thesmar (2011) and Glebkin, Malamud, and Teguia (2023).

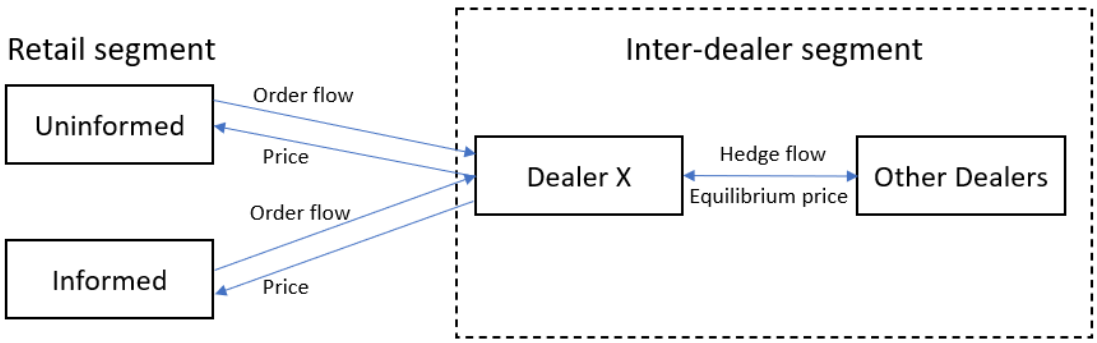
More closely related to our work are studies that link end-user demand shifts to currency returns: Zheng (2023) considers cross-border dividend flows, Aldunate, Da, Larrain, and Sialm (2022) examine Chilean pension plans, Camanho, Hau, and Rey (2022) analyze investment funds' international equity allocations, and Beltran and He (2023) use index rebalancing to shocks fund flows. Non-financial corporations conduct significant cross-border transactions but remain understudied in the FX literature, with Bjønnes and Rime (2005) being a notable exception. Our work uses month-end settlement breaks to provide a systematic study of non-financial corporations' demand for FX spot, and extends the microstructure literature by showing that corporations, despite their overall relatively small size, can significantly impact currency markets by increasing inter-dealer trading and return volatility.

This paper proceeds as follows. Section 1 describes the institutional framework of the FX spot market. Section 2 presents the theoretical model highlighting the role of corporate liquidity shocks in a two-tier segmented market. Section 3 describes our order flow data, Section 4 shows that settlement breaks instrument for uninformed liquidity shocks, and Section 5 tests the model predictions regarding the impact of corporate liquidity shocks on FX price dynamics and trading volumes. Section 6 concludes.

1. Institutional framework

Overview of the OTC FX Market: We briefly review the key aspects of the OTC FX market and its major constituents. Figure 1 depicts a simple framework and Evans and Rime (2019) provide further details on the market microstructure.

Figure 1: OTC FX Market Structure



In this market, currencies trade in a two-tier structure. Dealers quote prices to the retail segment, consisting of agents trading for liquidity needs or to leverage information. Liquidity needs include, among other motives, the clients' need to change the currency composition of cross-border trade and investment flows. Speculative traders capitalize on information about future exchange rates, engage in triangular arbitrage, or exploit carry trade opportunities. Ranaldo and Somogyi (2020) suggest that the order flow from non-financial corporations is less informative about future returns, while that from funds carries more information.

After a retail trade, risk-averse dealers either internalize inventory or hedge it in the inter-dealer market. A liquid inter-dealer market reduces the need to hold inventory, enabling risk-sharing among dealers. The inter-dealer market volume reflects order imbalances and dealers' capacity to absorb inventory (Lyons, 1997). When end-user order flows are negatively correlated, dealers only

need to hedge net imbalances in the inter-dealer market, reducing the price impact of the original order flow. Internalization is more common for less volatile currencies, as risk-averse dealers are willing to hold inventories longer.

The inter-dealer market also serves as a channel for integrating information contained in the end-user order flow into equilibrium prices. The inter-dealer market plays a crucial role in absorbing inventory imbalances across the system. According to Gabaix and Maggiori (2015), dealers operate within constraints, including limits on their balance sheet capacity and overnight position holdings. With a growing emphasis on electronic trading and centralized limit order books, the inter-dealer segment facilitates risk transfer within segmented markets.

Market Trends and Players: The composition of the FX spot market has evolved over time. The share of FX spot trades among reporting dealers has decreased from 56% in 2001 to 46% in 2022, according to the triennial survey of the Bank for International Settlements (BIS, 2022). This decline is attributed to the rise of electronic trading, enabling internalization. The survey also indicates that inter-dealer activity increases when dealers find it challenging to manage inventory risk stemming from end-user demand, particularly during periods of high volatility. Non-bank financial institutions now constitute 26% of traded volume, with institutional investors at 11% and hedge funds/proprietary trading firms at 7%. The proportion of non-financial customers in the market has decreased from 15% in 2001 to 7% in 2022.[2] Daily average FX spot trading across agents has grown from $386 billion in 2001 to over $2.1 trillion in 2022.

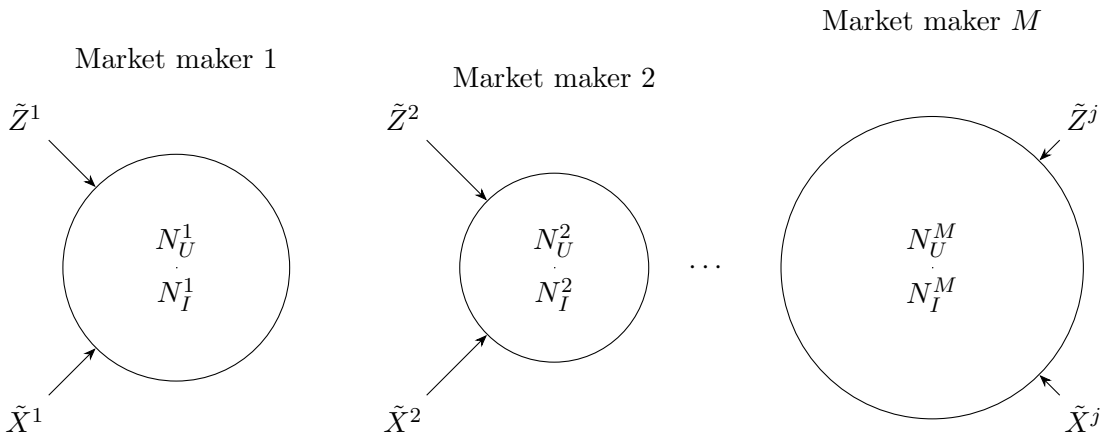
[2]Additionally, 8% of FX spot trading is "non-market facing," i.e., occurring between desks of the same dealer. Excluding these trades slightly increases the share of other participants.

2. Model

Our model mirrors the two-tier trading structure in OTC FX markets (Figure 1), comprising of the retail and inter-dealer segments. We adapt the framework by Liu and Wang (2016). Our paper adds liquidity shocks experienced by uninformed investors and an inter-dealer market segment to this existing setup. These additions allow us to generate new predictions specifically related to the impact of liquidity shocks on FX return volatility and inter-dealer trading volumes. These features also allow us to study the effect of liquidity shocks on retail trading imbalances, retail bid-ask spreads and heterogeneity across currencies and time.

The extended model maintains the core structure of Liu and Wang (2016) but allows for a more comprehensive analysis of how non-informational liquidity demand affects various aspects of the FX market, focusing on the transmission of these shocks through the inter-dealer market.

Figure 2: Trading in the Retail Segment



Notes: M market makers interact with informed and uninformed investors. A market maker j trades with N_I^j informed and N_U^j uninformed investors. $\tilde{X}^j$ and $\tilde{Z}^j$ represent aggregate shocks from informed and uninformed investors, respectively, aggregated across all investors of the same type trading with market maker j: $\tilde{X}^j = \sum_{i=1}^{N_I^j} \tilde{X}i^j/N_I^j$ and $\tilde{Z}^j = \sum i = 1^{N_U^j} \tilde{Z}_i^j/N_U^j$. These aggregates, $\tilde{X}^j$, and $\tilde{Z}^j$, as well as N_U^j and N_I^j, vary across market makers.

2.1. Retail Segment

Figure 2 illustrates the market structure of the retail segment. There are M market makers that trade assets with investors. Each market maker j, trading with N_U^j uninformed and N_I^j informed agents, sets bid and ask prices B^j and A^j, to maximize profits. Investors observe B^j and A^j and determine their optimal demand schedules. All market makers post bid and ask price schedules first, as in a Stackelberg game, considering the impact on investors' demand schedules. Market makers infer how investors trade based on the posted prices.

At $t = 0$, investors trade a risk-free and a risky asset that pays a random payoff $\tilde{V}$ at $t = 1$, allocating initial wealth to optimize expected utility. Investors buy the asset when their reservation price exceeds A^j and sell when it is below B^j. If the reservation price is between B^j and A^j, no trade occurs.

The reservation price for investor i trading with market maker j is given by

$$PR_i^j = \mathbb{E}(\tilde{V}|\mathcal{F}_i) - \delta \text{var}(\tilde{V}|\mathcal{F}_i)(\bar{\theta} - \tilde{Z^j}) - \delta \text{cov}(\tilde{V}, \tilde{L}^j|\mathcal{F}_i)\tilde{X}^j, \tag{1}$$

where $\tilde{X}^j$ are the aggregated demand shocks experienced by all informed agents trading with market marker j. $\tilde{X}^j$ manifest as a random endowment of a non-tradable asset with a payoff $\tilde{L}^j$, following a normal distribution with mean 0 and variance σ_L^2. Notably, this non-tradable asset exhibits a covariance σ_{VL} with the payoff of the risky asset. This setup ensures that equilibrium prices are not fully disclosed. $\bar{\theta}$ is the agent initial endowment in the risky asset of each agent and δ is the degree of agent risk aversion, assumed to be constant across agents. Extending Liu and Wang (2016), we introduce the uninformed liquidity shock $\tilde{Z}^j$, representing additional demand from uninformed agents to offset initial inventory Z_0^j. Uninformed agents seek to offset Z_0^j, resulting in an opposite

trade (with an opposite sign): i.e., the liquidity-driven demand is given by $\tilde{Z}^j = -\tilde{Z}_0^j$. These shocks are also aggregated across all uninformed agents trading with the same market maker j. We discuss the uninformed liquidity shocks in more detail later in this section.

In our framework, both informed and uninformed investors' demand schedules comprise two distinct components: (i) discretionary (price-elastic) demand, and (ii) pure liquidity-driven (price-inelastic) demand. This approach allows us to capture a more comprehensive view of trading motivations in the retail segment of currency markets.

As in Liu and Wang (2016), Δ^j is the difference between the reservation price of informed (I) and informed (U) agents trading with market maker j: $\Delta^j = PR_I^j - PR_U^j$.

$$\Delta^j = \overbrace{\left(\mathbb{E}(\tilde{V}|\mathcal{F}_I) - \mathbb{E}(\tilde{V}|\mathcal{F}_U^j)\right)}^{\text{estimation error effect}} + \underbrace{\delta\bar{\theta}\left(\text{var}(\tilde{V}|\mathcal{F}_I) - \text{var}(\tilde{V}|\mathcal{F}_U^j)\right)}_{\text{estimation risk effect}} + \underbrace{h\tilde{X}^j}_{\text{hedging effect}} + \overbrace{l\tilde{Z}^j}^{\text{liquidity shock effect}}, \quad (2)$$

where $\mathcal{F}_i^j$ represents the information set of agent i trading with market maker j. The information set of informed agents does not depend on which market maker they trade with. The assignment of market maker does affect the information set of uninformed agents, as $\mathcal{F}_U^j = \{\hat{S}^j, \hat{S}_s\}$. The constants h and l represent the hedging premia per unit of the informed and uninformed liquidity shocks, respectively, experienced by agents trading with the same market maker j.

The absolute value of Δ^j can serve as a measure of disagreement about the value of the risky asset between investors of different types. The disagreement between informed and uninformed agents, $|\Delta^j| > 0$, arises due to (i) the estimation error effect, which results from asymmetric information; (ii) the estimation risk effect, which stems from the fact that the level of risk is perceived differently by the two investors; (iii) the hedging effect that exists due to the demand of informed investors to hedge the random endowment shock they experience, $\tilde{X}^j$; and lastly, (iv) the liquidity

shock effect, which is the result of uninformed agents' liquidity shocks to offset in the form $\tilde{Z}^j$.[3]

2.2. Uninformed Liquidity Shocks

We add to Liu and Wang (2016) a non-information-based liquidity shock, denoted as $\tilde{Z}^j$. This shock represents the need for uninformed investors to rebalance their existing portfolios, an addition supported by our empirical findings. Our empirical analysis strongly indicates that uninformed agents, represented by non-financial corporations in our dataset, are subject to liquidity demand shocks unrelated to information signals. We describe these liquidity shocks as follows.

1. The liquidity demand shock $\tilde{Z}^j$ experienced by uninformed investors trading with market maker j is independent of future payoffs and market maker prices.
2. Due to liquidity shocks, uninformed agents trade the fixed quantity $\tilde{Z}^j$ regardless of price, resembling noise trading.
3. The liquidity shock $\tilde{Z}^j$ is observable by market maker j and all investors trading with market maker j.

This extension allows us to capture a more realistic representation of trading dynamics in OTC FX markets, accounting for both information-based and liquidity-driven trading motives. For a detailed exposition of the model setup, including a thorough discussion of the uninformed liquidity shocks $\tilde{Z}^j$, refer to Appendix A.

We assume the initial endowment of uninformed agents consists of two components: $\bar{\theta}$, which is common across all agents, and $\tilde{Z}_0^j$, which is averages across all uninformed investors trading with market maker j. $\tilde{Z}_0^j$ is the initial endowment that uninformed clients wish to offset. The total initial endowment of an uninformed agent trading with market maker j is, thus, determined by

[3] Appendix A details the derivations of conditional expectations of informed and uninformed agents.

$\bar{\theta} + \tilde{Z}_0^j$. Only uninformed agents are endowed with $\tilde{Z}_0^j$ and need to offset this existing inventory by trading in the opposite direction: $\tilde{Z}^j = -\tilde{Z}_0^j$.

In our model, when a liquidity shock, in any direction: buy or sell, occurs ($\uparrow |\tilde{Z}^j|$), the disagreement between agents increases ($\uparrow |\Delta^j|$). This differs from the effect of asymmetric information on reservation prices. Even without asymmetric information, liquidity shocks affecting only one retail segment would make agents to disagree about the reservation price of the risky asset.

2.3. Market Making in the Retail Segment

The vector $\alpha = (\alpha^1, \alpha^2, ..., \alpha^M)'$ describes the volume of assets individual market makers sell at the ask prices $A = (A^1, A^2, ..., A^M)$, and the vector $\beta = (\beta^1, \beta^2, ..., \beta^M)'$ refers to the volume of assets market makers buy from investors at bid prices $B = (B^1, B^2, ..., B^M)$. The market clears when the total volumes traded by all market makers match the demand to trade received from all investors.

$$\sum_{j=1}^{M} \alpha^j = \sum_{j=1}^{M} \sum_{i=I,U} N_i^j \theta_i^*(A^j, B^j)^+ = \sum_{j=1}^{M} \sum_{i=I,U} N_i^j \left[\frac{(PR_i^j - A^j)^+}{\delta \text{var}(\tilde{V}|\mathcal{F}_i^j)} + \tilde{Z}^{j+} \right] \tag{3}$$

and

$$\sum_{j=1}^{M} \beta^j = -\sum_{j=1}^{M} \sum_{i=I,U} N_i^j \theta_i^*(A^j, B^j)^- = -\sum_{j=1}^{M} \sum_{i=I,U} N_i^j \left[\frac{(PR_i^j - B^j)^-}{\delta \text{var}(\tilde{V}|\mathcal{F}_i^j)} + \tilde{Z}^{j-} \right], \tag{4}$$

where $\theta_i^*(A^j, B^j)$ is the optimal demand schedule submitted by investor i trading with market maker j.

The market maker j sets the bid B^j and ask prices A^j to maximize profits from trading with informed and uninformed agents. All market makers are uninformed, $\mathcal{F}_M^j = \mathcal{F}_U^j$.

$$\max_{A^j, B^j} \left[\alpha^j A^j - \beta^j B^j + (\bar{\theta} + \beta^j - \alpha^j) \mathbb{E}(\tilde{V}|\mathcal{F}_U^j) - \frac{1}{2} \delta \text{var}(\tilde{V}|\mathcal{F}_U^j)(\bar{\theta} + \beta^j - \alpha^j)^2 \right], \tag{5}$$

where

$$\alpha^j = N_U^j \left(\frac{PR_U^j - A^j}{\delta \text{var}(\tilde{V}|\mathcal{F}_U^j)} + \tilde{Z}^j \right)$$

and

$$\beta^j = N_I^j \left(\frac{B^j - PR_I^j}{\delta \text{var}(\tilde{V}|\mathcal{F}_I)} \right).$$

Theorem 1. *There is a unique symmetric piecewise linear equilibrium:*

1. *The equilibrium bid and ask prices are set by the market maker to be*

$$A_j^* = PR_U^j + \frac{\nu N_I^j}{2(\bar{N}^j + 1)} \Delta^j + \frac{\Delta^{j+}}{2} + \frac{N_U^j - 2}{2(\bar{N}^j + 1)} \delta \text{var}(\tilde{V}|\mathcal{F}_U^j) \tilde{Z}^j + \frac{1}{2} \delta \text{var}(\tilde{V}|\mathcal{F}_U^j) \tilde{Z}^{j+} \quad (6)$$

$$B_j^* = PR_U^j + \frac{\nu N_I^j}{2(\bar{N}^j + 1)} \Delta^j + \frac{\Delta^{j-}}{2} + \frac{N_U^j - 2}{2(\bar{N}^j + 1)} \delta \text{var}(\tilde{V}|\mathcal{F}_U) \tilde{Z}^j + \frac{1}{2} \delta \text{var}(\tilde{V}|\mathcal{F}_U^j) \tilde{Z}^{j-}, \quad (7)$$

where $\bar{N}^j = \nu N_I^j + N_U^j + 1$ *and* $\nu = \frac{\text{var}(\tilde{V}|\mathcal{F}_U^j)}{\text{var}(\tilde{V}|\mathcal{F}_I)}$.

The equilibrium bid-ask spread is

$$A^{j*} - B^{j*} = \frac{|\Delta^j|}{2} + \delta \text{var}(\tilde{V}|\mathcal{F}_U^j) \frac{|\tilde{Z}^j|}{2}. \quad (8)$$

2. *The equilibrium net trading volume is*

$$\alpha^{j*} - \beta^{j*} = \frac{N_I^j}{(\bar{N}^j + 1) \delta \text{var}(\tilde{V}|\mathcal{F}_I)} \Delta^j + \frac{2N_U^j + \nu N_I^j}{\bar{N}^j + 1} \tilde{Z}^j. \quad (9)$$

We present propositions examined in our empirical analysis, focusing on how liquidity shocks affect bid-ask spreads and trading volumes. Appendix A.2 details the proofs.

Proposition 1 (Liquidity shocks and retail net trading volume)**.** *The equilibrium retail net trading volume,* $\alpha^{j*} - \beta^{j*}$*, increases with the uninformed liquidity shock* $\tilde{Z}^j$ *when* $N_U^j > 0$ *or* $\nu N_I^j > 0$*.*

$$\frac{\partial(\alpha^{j*} - \beta^{j*})}{\partial \tilde{Z}^j} \geq 0 \tag{10}$$

The total net trading volume traded in the retail segment rises with uninformed liquidity shocks, providing a basis for our empirical instrument measuring these shocks. When the liquidity shock is positive (suggesting a buy order), it increases the net trading volume, and vice versa for negative liquidity shocks.[4]

The key distinction between our model and Evans and Lyons (2002)'s portfolio shift model is how dealers handle inventory imbalances. In Evans and Lyons (2002), dealers adjust prices to attract offsetting orders from clients, absorbing shocks within the retail segment, setting inventory imbalances to zero and minimally impacting the inter-dealer market. In our model, uninformed liquidity shocks are not always fully offset, with retail net volumes that can significantly affect inter-dealer trading. This occurs because market makers, aiming to maximize profits, set prices that do not always attract sufficient client demand to offset the inventory. Additionally, clients may have limited capacity or willingness to take on large inventory positions. The effect of retail order imbalance on the inter-dealer market is particularly large when retail clients are exposed to large liquidity demand shocks.

Proposition 2 (Liquidity shocks and the equilibrium bid-ask spread)**.** *The equilibrium bid-ask spread,* $A^{j*} - B^{j*}$*, increases with the absolute value of the uninformed liquidity shock* $|\tilde{Z}^j|$ *when* $\delta > 0$ *and* $\text{var}(\tilde{V}|\mathcal{F}_U^j) > 0$*.*

$$\frac{\partial(A^{j*} - B^{j*})}{\partial|\tilde{Z}^j|} \geq 0 \tag{11}$$

[4]In our data, the instrument that shifts demand is agnostic of the direction of trade. Therefore, we test the impact of the *absolute* size of the liquidity shock on *absolute* net trading volumes.

Widening bid-ask spreads occur when the absolute value of uninformed liquidity shocks amplifies, irrespective of whether these shocks are due to liquidity-driven asset purchases or sales by uninformed agents.

2.4. Inter-dealer Segment

When market makers conclude their trading with informed and uninformed agents, they can turn to the inter-dealer market to hedge and offset their existing order imbalances. In this second segment, market makers engage in trading among themselves at the equilibrium price P^*. Here, market makers are considered price takers, all trading takes place at the exogenously set equilibrium price P^*, assuming perfect competition among them. We assume that each risk-averse market maker j selects the optimal demand θ^{j*} to maximize their expected utility from wealth.

$$\max_{\theta^j} \left[-\theta^j P^* + \mathbb{E}(\tilde{V}|\mathcal{F}_U^j) \left(\bar{\theta} + \beta^{j*} - \alpha^{j*} + \theta^j \right) - \frac{1}{2} \delta \text{var}(\tilde{V}|\mathcal{F}_U^j) \left(\bar{\theta} + \beta^{j*} - \alpha^{j*} + \theta^j \right)^2 \right] \tag{12}$$

The inter-dealer market clears when the equilibrium total volumes traded match the demand to trade received from all market makers.

$$\sum_{j=1}^{M} \theta^{j*} = 0 \tag{13}$$

The optimal quantity to hedge in the inter-dealer market θ_j^* will vary across market makers due to the heterogeneity in investor-specific shocks, $\tilde{X}^j$ and $\tilde{Z}^j$. The variation in these shocks that their clients are exposed to (aggregated on the market maker level) creates motives to trade among market makers.

Theorem 2. *There is a unique symmetric piecewise linear equilibrium describing trading among market dealers.*

1. *The equilibrium inter-dealer price (a perfect competition price) is*

$$P^* = \frac{\nu}{\bar{N}} \sum_{j=1}^{M} N_I^j PR_I^j + \frac{1}{\bar{N}} \sum_{j=1}^{M} N_U^j PR_U^j + \frac{1}{\bar{N}} \sum_{j=1}^{M} PR_M^j, \tag{14}$$

where $\bar{N} = \nu N_I + N_U + M$.

The expected value of P^**, conditional on* $\tilde{Z}^j$*, is*

$$\mathbb{E}(P^*|\tilde{Z}^j) = \bar{V} - \delta \text{var}(\tilde{V}|\mathcal{F}_U) \frac{N_I + N_U + M}{\bar{N}} + \frac{N_U^j}{\bar{N}} \delta \text{var}(\tilde{V}|\mathcal{F}_U^j) \tilde{Z}^j. \tag{15}$$

The unconditional variance of P^* *is*

$$\text{var}(P^*) = a_1^2(\sigma_V^2 + \sigma_\epsilon^2) + a_2^2 \sigma_X^2 + a_3^2, \sigma_\eta^2 + a_4^2 \sigma_Z^2, \tag{16}$$

where $a_1 = \frac{N_I \nu}{\bar{N}} \rho_I + \frac{N_I + M}{\bar{N}} \rho_U$, $a_2 = \frac{N_I^j \nu}{\bar{N}} \delta \text{cov}(\tilde{V}, \tilde{L})$, $a_3 = \left(\frac{N_U + M}{\bar{N}} \right) \rho_U (1 - \rho_X)$ *and* $a_4 = \frac{N_U^j}{\bar{N}} \delta \text{var}(\tilde{V}|\mathcal{F}_U^j)$.

and the absolute change in the equilibrium price is

$$\Delta P^* = a_1 \hat{s} + a_2 \tilde{X} + a_3 \tilde{\eta} + a_4 \tilde{Z}^j. \tag{17}$$

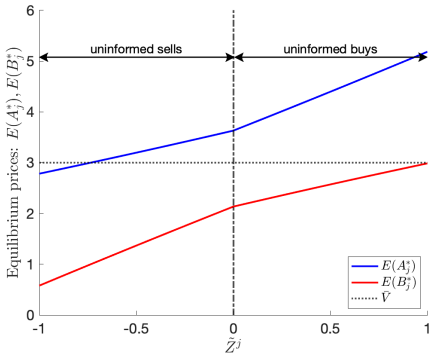
2. *The equilibrium inter-dealer trading volume is*

$$\theta_j^* = \frac{\mathbb{E}(\tilde{V}|\mathcal{F}_U^j) - P^*}{\delta \text{var}(\tilde{V}|\mathcal{F}_U^j)} - \bar{\theta} + (\alpha^{j*} - \beta^{j*}). \tag{18}$$

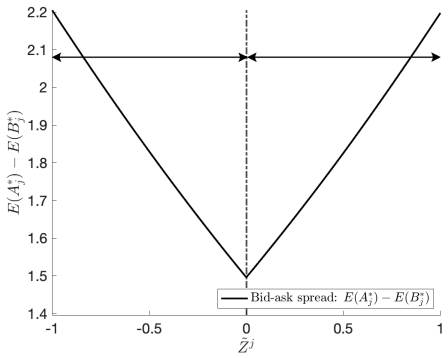
The unconditional variance of equilibrium price P^* rises with the variability of corporate liquidity shocks σ_Z^2. Without $\tilde{Z}^j$ shocks, the overall variance would reduce by $a_4^2 \sigma_Z^2$. This result suggests that liquidity shocks are a crucial driver of price variability, driving the total level of re-

turn volatility. We empirically assess the impact of $\tilde{Z}^j$ on price changes and short-term FX return volatility.

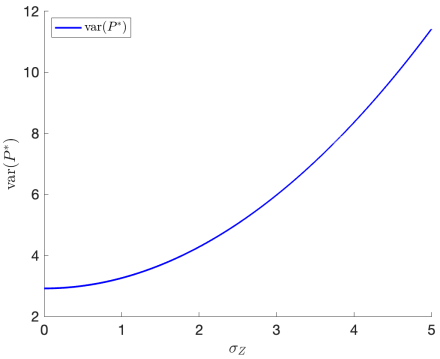
Figure 3: Impact of Liquidity Shocks on the Retail and Inter-dealer Segments



(a) Equilibrium prices



(b) Bid-ask spread



(c) Price volatility

Notes: This figure illustrates how uninformed liquidity shocks ($\tilde{Z}^j$) affect equilibrium prices, quoted by the market maker j, the equilibrium bid-ask spread, and the volatility of the equilibrium (perfect competition) price P^*. The parameters used to produce this figure are $N_I^j = 100, N_U^j = 100, M = 20, \bar{\theta} = 0.3, \bar{V} = 3, \sigma_V = 0.4, \sigma_\epsilon = 0.9, \sigma_\eta = 0.5, \sigma_X = 1, \sigma_L = 0.5, \sigma_Z = 0.5, \text{cov}_{VL} = 0.8, \delta = 4$.

Figure 3 illustrates Theorems 1 and 2, showing the impact of uninformed liquidity shocks on equilibrium bid-ask spreads, net retail volumes, and the equilibrium price volatility. Our model indicates that retail bid-ask spreads widen with an absolute $\tilde{Z}^j$ shock (see Figure 3, panels (a) and (b)). Net retail volumes also increase with an absolute $\tilde{Z}^j$ shock, implying the corporate liquidity shock is not fully offset by order flow from informed agents. These shocks also increase dealer

volumes, increasing market activity, and volatility of the equilibrium price.

We formulate several testable propositions that guide the empirical analysis of the impact of liquidity shocks on the equilibrium price dynamics and the inter-dealer volume.

Proposition 3 (Liquidity shocks and equilibrium price volatility)**.** *The equilibrium price volatility increases when the variation in liquidity shocks (measured by σ_Z^2) increases.*

$$\frac{\partial \text{var}(P^*)}{\partial \sigma_Z^2} > 0 \tag{19}$$

The change in the equilbrium price increases with an uninformed liquidity shock $\tilde{Z}^j$.

$$\frac{\partial (\Delta P^*)}{\partial \tilde{Z}^j} > 0 \tag{20}$$

Our model shows that $\tilde{Z}^j$ shocks are an important driver of asset prices in segmented markets. These shocks lead to increased activity in the inter-dealer market and a rise in the equilibrium price volatility. When absolute changes in $\tilde{Z}^j$ are large, the total variance and the absolute change in the equilibrium price will increase.

In Proposition 4, we study when the impact of shocks $\tilde{Z}^j$ on the absolute price change and the variance of the equilibrium price P^* is particularly large. This proposition allows us to examine the heterogeneity in how corporate liquidity shocks drive return volatility across multiple asset markets with different characteristics.

Proposition 4 (Liquidity shocks, equilibrium price volatility and heterogeneity)**.** *The impact of liquidity shocks on the variance of the equilibrium price and the absolute change in the equilibrium price increases when the dealer risk aversion δ is higher or when the fundamental asset volatility*

σ_V^2 is high.

$$\frac{\partial \text{var}(P^*)^2}{\partial \sigma_Z^2 \partial \delta} \geq 0 \tag{21}$$

$$\frac{\partial (\Delta P^*)^2}{\partial \tilde{Z}^j \partial \delta} \geq 0 \tag{22}$$

$$\frac{\partial \text{var}(P^*)^2}{\partial \sigma_Z^2 \partial \sigma_V^2} \geq 0 \tag{23}$$

$$\frac{\partial (\Delta P^*)^2}{\partial \tilde{Z}^j \partial \sigma_V^2} \geq 0 \tag{24}$$

Distinguishing dealer risk aversion from fundamental asset volatility is challenging, as agents may be more risk averse when trading in volatile currency markets. Empirical measures of returns are influenced by both fundamental asset volatility and risk aversion. Hence, we pool these characteristics and study cross-currency variations in the impact of uninformed liquidity shocks on asset prices, influenced by δ and σ_V^2, jointly. Generally, we expect that risk aversion correlates positively with fundamental volatility.

The first-order condition from the dealer's optimization problem shows that market makers trading in the inter-dealer market have two motives: hedging existing inventory, $\bar{\theta} - (\alpha^{j*} - \beta^{j*})$, and maximizing their wealth through the mean-variance solution that depends on the reservation value, the equilibrium price and the total cost of risk aversion, $\frac{\mathbb{E}(\tilde{V}\mathcal{F}_U^j) - P^*}{\delta \text{var}(\tilde{V}\mathcal{F}_U^j)}$. Liquidity shocks affect both motives in the opposite direction.

Specifically, a positive liquidity shock ($\tilde{Z}^j > 0$) raises the equilibrium price P^*, which reduces the market maker's demand to buy and increases their demand to sell the risky asset. At the same time, this positive liquidity shock boosts the retail net trading volume ($\alpha^{j*} - \beta^{j*}$), see Proposition 1, which decreases the market maker's net volume. This leaves the market maker with more negative inventory they need to offset by buying the risky asset in the inter-dealer market. Their demand

to buy, thus, strengthens with $\tilde{Z}^j > 0$. Proposition 5 shows that the inventory effect dominates the impact of a higher P^*.

Proposition 5 (Liquidity shocks and inter-dealer volume)**.** *The inter-dealer trading volume, θ^{j*}, is a non-decreasing function of the uninformed liquidity shock $\tilde{Z}^j$.*

$$\frac{\partial \theta^{j*}}{\partial \tilde{Z}^j} > 0 \tag{25}$$

Proposition 5 shows that the impact of corporate liquidity shocks on inter-dealer volumes is positive. This holds due to the fact that the effect of $\tilde{Z}^j$ on dealer j's order imbalance outweighs its effect on the equilibrium price P^*, which is the price shared among all dealers, not just dealer j. Other traders may not be trading with uninformed agents to the same extent as dealer j or their uninformed retail clients might be exposed to different levels of liquidity shocks, making the impact of dealer-specific shock $\tilde{Z}^j$ on price P^* less pronounced. Appendix A.2 contains proofs for all theorems and propositions.

3. Data

We analyze liquidity shocks in foreign exchange markets using hourly order flow data for 31 currency pairs from January 2015 to June 2022, totaling over 1.4 million observations. Our data, sourced from CLS Group's global settlement system, covers both retail and inter-dealer segments. Table A1 lists the currencies, and Appendix B details CLS data collection.[5]

Our sample covers 22% of global FX spot turnover (Table A2). BIS (2022) estimates April 2022 daily turnover at $2.1 trillion: we observe 22% overall, 28% in EUR pairs, and 30% in GBP pairs. This extensive coverage is due to the growing use of risk mitigation in over-the-counter FX

[5]Of 40 CLS currency pairs, we focus on 31 with significant volumes across all sectors.

trades. As Glowka and Nilsson (2022) report, over half of FX trades now use these risk-mitigation channels, with CLS holding a 72% share. Currencies eligible for CLS settlement account for 90% of global turnover, excluding Chinese renminbi and Russian rouble. CLS's settlement of both retail and inter-dealer trades offers a comprehensive market view, particularly in inter-dealer trading, with 33% coverage.

3.1. Order Flow and Volume

We observe currency-level buy and sell FX spot trades ("order flow") for retail clients: dealer-to-corporate and dealer-to-fund, and total trading volume among market-making banks in the inter-dealer segment. Corporations in our sample include large multinationals such as Mitsui & Co. and Sumitomo Electric Industries. Funds include hedge funds, mutual funds, and investment managers. Banks include settlement members such as dealers and other non-settlement member banks.[6] Order flow is reported from one counterparty per sector to avoid double counting.

We calculate sector-level "order imbalance" as the absolute difference between buy and sell trades for each currency pair and hour. This variable represents the inventory not netted within a sector, which must be internalized by dealers using other sectors' order flow or offloaded in the inter-dealer market.[7] Following Cespa, Gargano, Riddiough, and Sarno (2022), we de-trend the order imbalance by subtracting the past one month's rolling average, resulting in "absolute net volume." Similarly, we de-trend the total trading volume among market-making banks in the inter-dealer segment. Appendix B shows time-series properties of the de-trended variables. Panel A of Table 1 summarizes hourly volumes from CLS data for all currency pairs, while Table A3 does so

[6] Case studies referencing specific corporations that use CLS to settle their FX trades can be found in CLS Group (2018) and CLS Group (2020). A general reference to the types of funds that use CLS is available here, and the list of banks that constitute settlement members of the CLS is available here.

[7] We also count buy and sell trades by corporations and funds to get an alternate measure of signed order flow.

for individual pairs. Volumes are expressed in US dollars.

Consistent with BIS (2022), Table 1 shows that total volumes are largest in the inter-dealer segment, followed by dealer-to-fund and dealer-to-corporate segments. In the retail segment, corporations trade less frequently than funds (87,208 vs. 668,375 hours of trading activity), but their average trade size ($7.4 vs. $2.6 million) is almost three times larger. This indicates that corporations in the CLS sample are large entities with "lumpy" trades. The net order imbalance relative to total volume is 0.51 for funds and 0.65 for corporations, suggesting greater homogeneity in corporate trades and potentially large inventories for dealers to manage. Table A3 shows that direct pairs like EURUSD and USDJPY have the largest volumes across sectors. Retail clients also have large volumes in indirect pairs like EURJPY, despite the cost advantage of trading via USD (Somogyi, 2021).

3.2. Price and Volatility

We source FX spot market prices from Bloomberg. We snapshot intra-hour price for each currency-pair at 10-minute intervals. We measure the volatility of FX returns using three metrics: the standard deviation of intra-hour returns, absolute hourly returns, and the price range within an hour scaled by the starting price. We measure noise in prices using the auto-covariance of six intra-hour returns. Auto-covariance indicates mean reversion in short-term currency returns, which is likely to increase with non-fundamental price changes caused by transient demand. Appendix C provides further details on our measures of price dynamics and volatility.

Panel B of Table 1 summarizes volatility and noise measures for all 31 currency pairs; Table A4 details individual pairs. While average hourly returns are near zero, intra-hour volatility is significant. The standard deviation of intra-hour returns is about 4 bps, and the price range is about 10 bps. The negative average auto-covariance of intra-hour returns indicates frequent price

reversals, as also seen in equity markets Foucault et al. (2011). Table A4 reports higher volatility for emerging market pairs like USDZAR and USDMXN. We use a GARCH(1,1) model to extract excess volatility for empirical tests (Høidal et al., 2019).

4. Settlement breaks as an instrument for liquidity shocks

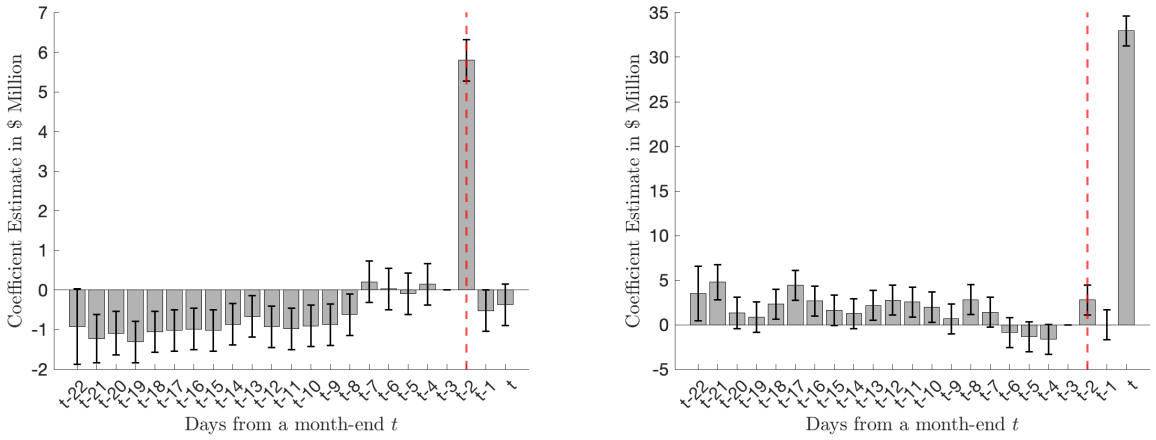
We establish a causal link between liquidity-driven retail trading and FX market outcomes using plausibly exogenous shocks to corporate net volume. Our instrument isolates the end-users' retail demand that is not driven by information shocks or expectations of future returns, i.e., it identifies the timing of the variable $\tilde{Z}^j$ from the model. The proposed instrument serves as a demand shifter that affects traded volumes and price volatility only due to liquidity shocks that originate in the retail segment. Such shocks affect the FX markets independently of innovations in currency fundamentals. The instrument leverages the "T+2" settlement cycle in FX spot market and clients' need for cash flow on specific days of a calendar month, i.e., on *settlement breaks*.

FX spot trades typically settle two business days after the trade date for most currency pairs, except for some like USDCAD. Thus, since money transfer occurs two business days post-trade, trades executed on the last two days of a month ("month-end dates") settle in the next month. Non-financial firms, following monthly cross-border receipts and payments, prefer cash flows within the same calendar month to settle obligations. Hence, they may advance trades from month-end dates so cash flow settles before monthly book closures. These trades are re-allocated to two business days before month-end, termed as the settlement break date.

Settlement breaks provide us with an instrument for demand shifts that are orthogonal to realized or expected returns, and to other informative signals that may affect discretionary or informed trading behavior. Our instrument is similar to calendar effects that are used in other studies to shock trading activity: Lee, Ready, and Seguin (1994) use trading halts on New York

Stock Exchange to shock equity trading volume, and Muravyev (2016) uses option expiration date as an exogenous shock to order imbalance. Our instrument applies this setting to corporate net volume in the FX spot market, where non-financial firms adjust trade timing merely to settle cash flow within the month, not based on fundamental payoff information.

Figure 4: Net Volume and Settlement Breaks



(a) Corporate net volume

(b) Fund net volume

Notes: This figure shows average hourly corporate net volume in panel (a) and fund net volume in panel (b) for each trading day in a month, with t as the last day. Net volume is the difference between buy and sell trades, de-trended using a 30-day rolling average, and shown in $ million. Gray bars represent average net volumes across all months and currencies; black bars show 95% confidence intervals with date $t-3$ as the reference. A settlement break on $t-2$ is marked with red dashed lines. The sample period is January 2015 to June 2022.

4.1. Relevance and Exclusion

Corporate net volumes increase significantly during settlement breaks, i.e., two business days before month-end.[8] Panel (a) of Figure 4 shows that trade dates two business days before month-end (highlighted in vertical dashed line) are relevant for changes in corporate trading behavior.[9] The spike in net volume on date $t-2$ is due to corporations advancing month-end trades by two days

[8]For December, we construct the instrument as the trade date that is three days before Christmas.

[9]The difference in means is statistically significant with a t-statistic exceeding 20.

so that cash flow still settles in the same month, creating an exogenous order imbalance dealers need to absorb. These non-discretionary trades are likely driven by fixed liquidity, accounting, or cash-flow needs.

Panel (b) shows that fund net volumes are unaffected by these settlement breaks, with a spike only on the last day of the month. This increase on last day aligns with Etula, Rinne, Suominen, and Vaittinen (2020), indicating that non-bank institutional investors seek liquidity at month-ends unrelated to FX cash flow settlements. This spike does not coincide with our instrument, supporting its exclusion from these confounding factors driving other agents' order flow.

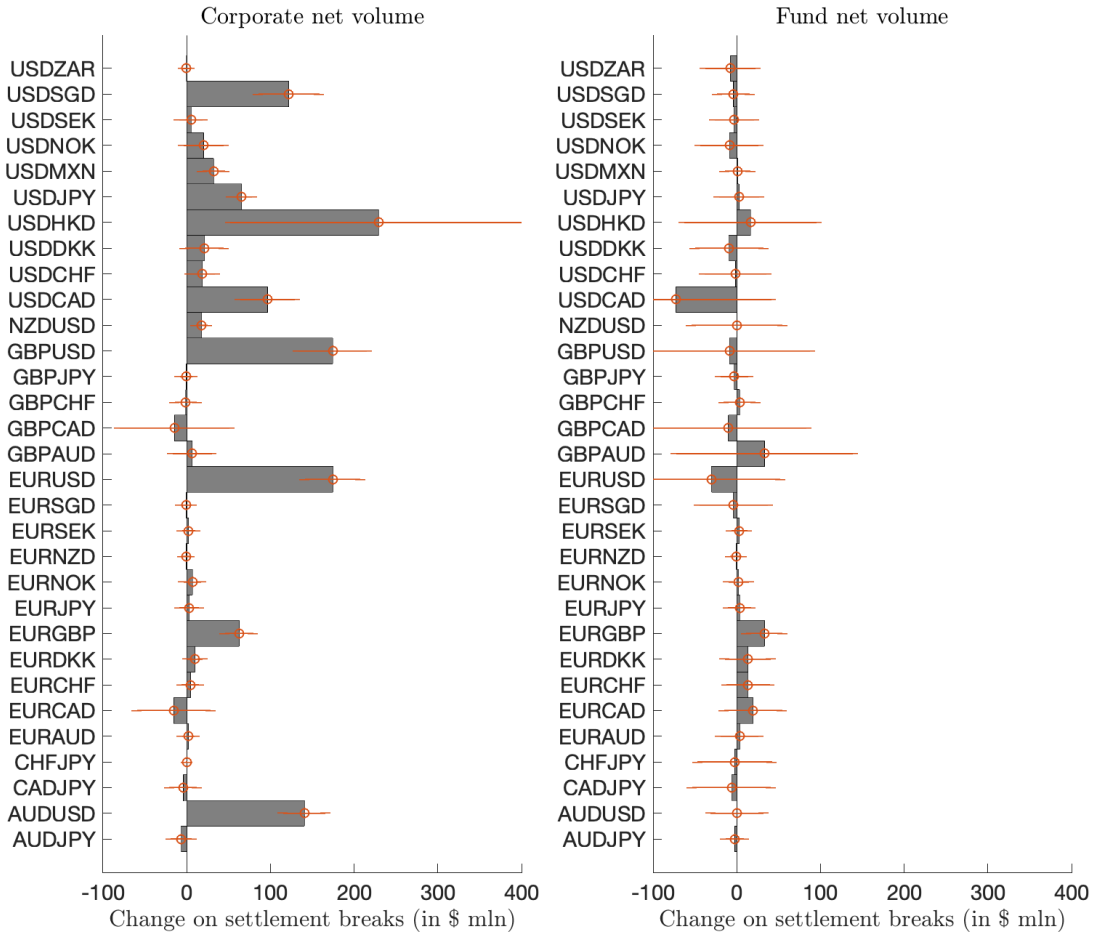
Figure 5 shows that corporate trading shifts on settlement breaks, especially in the most liquid pairs like EURUSD, GBPUSD, and AUDUSD. In less liquid markets, the null hypothesis that traded volume during settlement breaks is the same cannot be rejected, possibly due to a smaller sample size. For fund net volumes, we cannot reject the null hypothesis that trading activity differs significantly during settlement breaks compared to other days. Thus, month-end settlement breaks seem to only affect the corporate segment of the FX retail market.

To the extent that the arrival of information is not sensitive to month-end settlement breaks, our instrument is unlikely to capture informed trading in FX markets. Trading based on cash-flow expectations, discount-rate shocks, or portfolio shifts is plausibly unrelated to the two-day settlement period of FX cash flows. Consequently, we consider settlement breaks to be a relevant measure of liquidity shocks experienced by corporations, that do not affect our dependent variables of interest, FX return volatility and trading volumes, in ways other than through their impact on liquidity-driven corporate demand.[10]

Our identification relies on the condition that, as a result of settlement breaks, dealers do not

[10]We also confirm that macroeconomic fundamental information such as FOMC meeting outcomes are not released systematically two days before month-end (Hillenbrand, 2021).

Figure 5: Change in Trading Activity During Settlement Breaks



Notes: This figure highlights the impact of settlement breaks on corporate net volume (figure on left) and fund net volume (figure on right) at a currency level. Gray bars represent the average change in the hourly absolute net volume observed during settlement breaks, relative to the average hourly net volume on non-settlement days. Horizontal bars in orange represent 95% confidence intervals.

increase their trading activity two days before a month-end for any reason other than to intermediate end-users' liquidity demand. This is likely true for three reasons. First, intermediary dealers are not subject to accounting and cash-flow constraints like non-financial corporations. Second, dealers, unlike corporations, dominate the FX swap market, holding 56% of its volume compared to corporations' 3% (BIS, 2022). Swaps enable re-balancing of positions without incurring spot

price risk. Third, dealers, mainly large banks, have trading patterns that align more with other financial institutions, showing spikes only at month-ends as panel (b) of Figure 4 illustrates.

Additionally, the focus on non-financial corporations as the source of liquidity shocks may seem narrow. We acknowledge that other market participants, such as hedge funds or central banks, can also be exposed to significant liquidity demand shocks in FX markets. Given our identification strategy, we choose to focus solely on corporate flows, which may miss the full extent of the impact of other types of liquidity shocks. We, therefore, expect that our final results are potentially underestimating the overall relevance of liquidity demand shocks on FX market dynamics.

4.2. IV Strategy

Using settlement breaks, we estimate the effect of corporate liquidity shocks on FX markets in an IV framework. Specifically, we estimate first- and second-stage equations of the form

$$Q^C_{i,t} = \beta \textit{Settlement break}_t + \gamma \mathbf{Z}_{i,t} + \alpha_i + \alpha_t + \epsilon_{i,t}, \tag{26}$$

$$\mathbf{Y}_{i,t} = \beta \widehat{Q^C_{i,t}} + \gamma \mathbf{Z}_{i,t} + \alpha_i + \alpha_t + \varepsilon_{i,t}, \tag{27}$$

where $Q^C_{i,t}$ is the absolute corporate net volume in currency i at time t, and *Settlement break*$_t$ is 1 if the trade date is two business days before a month-end, and 0 otherwise. The set of controls, $\mathbf{Z}_{i,t}$, includes the absolute fund net volume at time t, the realized volatility of returns over the preceding 1 day and 1 week, and spot returns. We also include five lags of absolute corporate net volumes to control for persistence. We control for currency fixed effects, α_i, time fixed effects, α_t, and cluster standard errors by currency-time.

Table 2 reports the results for the first-stage regression. We find that during settlement breaks, the hourly corporate absolute net volume increases by at least \$5 million, more than twice the

unconditional average of $2.2 million reported in Table 1, significant at the 99% confidence level across all specifications. The instrument F-statistic exceeds 10 under all specifications, confirming the relevance of settlement breaks in identifying changes in corporate liquidity-driven demand.

The variable $\mathbf{Y}_{i,t}$ describes the outcome variables examined that include various measures of FX return volatility, retail and inter-dealer trading volumes, and bid-ask spreads. Section 5 presents the results of these second-stage regressions.

5. The Impact of Liquidity Shocks on Return Volatility and Trading Volumes

Our model suggests that currency trading between investors and dealers arises from disagreement on asset valuations, amplified by liquidity-driven demand shocks from non-financial corporations. We measure corporate net volume hourly and use settlement breaks to instrument for these shocks, denoted as $\tilde{Z}^j$ in our model.

Our model predicts that an increase in the absolute corporate liquidity shock $|\tilde{Z}^j|$ leads to

1. a rise in FX return volatility (see Proposition 3),
2. an increase in absolute inter-dealer trading volumes (see Proposition 5),
3. a greater retail trading imbalance (see Proposition 1),
4. and wider retail bid-ask spreads (see Proposition 2).

The impact of liquidity-driven shocks on price dynamics and traded volumes is stronger in markets with higher fundamental volatility or higher dealer risk aversion (see Proposition 4).

We empirically test these predictions using settlement breaks as instruments for shocks to net corporate volume. In the following sections, we document results that confirm these model predictions. We find that return volatility and absolute retail trading volumes increase with liquidity shocks. We also explore variations across currency markets, showing these liquidity shocks to affect

We also explore heterogeneity in these results based on the variation in cross-sectional and time-series properties of currency markets.

5.1. Return Volatility

Corporate liquidity shocks cause a substantial increase in all four measures of return volatility; see Table 3. A one-standard-deviation rise in absolute corporate net volume (due to liquidity shocks) results in about 12-22% increases in return volatility, varying based on the measure of volatility considered and the inclusion of fixed effects.[11] The influence of corporate liquidity shocks on FX return volatility is positive and significant at the 99% confidence level. This outcome is robust to the use of different combinations of fixed effects, including lagged volatility and volumes.

Moreover, we show that liquidity shocks raise noise in returns. The bottom panel of Table 3 indicates negative auto-covariance becoming more pronounced with the arrival of liquidity-driven corporate net volume, a result significant at the 95% level across all specifications.

We find both qualitatively and quantitatively consistent results across all volatility measures considered, indicating a steady impact of corporate liquidity shocks on FX price dynamics. Results from Table 3 corroborate the model Proposition 3, predicting that corporate liquidity shocks, $\tilde{Z}^j$ increase both absolute price changes and return volatility.

We discuss whether alternative explanations can drive our empirical findings. For example, the observed increase in volatility could be due to increased information asymmetry or changes in risk aversion among dealers, rather than liquidity shocks per se. We argue that it is unlikely that dealer risk aversion, the degree of information asymmetric or fundamental asset volatility would systematically spike on settlement breaks, two days before a month end. We include various control

[11] The percentage is computed relative to the mean return volatility shown in Table 1. The standard deviation of absolute corporate net volume is \$38.4 million, while the average standard deviation of returns is 3.8 bps. Therefore, using the coefficient estimated from, for instance, column (3) of Table 3, the effect of a one-standard-deviation rise in corporate net volume on return volatility is: $0.019 \times 38.4 \,/\, 3.8 = 0.19$.

variables and report results that are unaffected by these controls.

Our findings have significant implications for market participants and currency stability. Corporate liquidity events can trigger substantial FX volatility, which FX traders need to monitor. Our results can help in risk assessment and predictive models for market turbulence. Understanding the link between liquidity shocks and FX volatility can benefit institutional investors and multinational corporations in managing currency risks. The impact of corporate liquidity shocks on FX volatility underscores the importance of monitoring corporate financial activities in currency markets, advocating an asset-pricing approach that considers both liquidity-driven flows and fundamental shocks.

5.2. Inter-dealer Volume

Next, we test how liquidity-driven corporate shocks affect inter-dealer market trading volumes. If dealers absorb higher net retail volume and cannot offset it internally, they will do so in the inter-dealer market at price P^*. Our model predicts that the amount of inventory dealers choose to hedge in the inter-dealer market, θ_j^*, increases with the uninformed liquidity shocks, $\tilde{Z}^j$, because the impact these shocks have on dealer inventory risk from net retail volume dominate the impact on the equilibrium price, see Proposition 5.

We validate this model prediction and show that liquidity shocks significantly increase inter-dealer volume in the hour they occur. The positive and significant coefficient for instrumented corporate net volume in Table 4 suggests inter-dealer trading responds strongly to retail liquidity shocks. A one-standard-deviation rise in corporate net volume adds 10.4% to inter-dealer trading relative to the $592.4 million average volume ($1.6 \times 38.4/592.4=0.104$, computed using the coefficient from column (3) in Table 4).

The large impact of corporate liquidity shocks on inter-dealer volume is consistent with a "hot-

potato trading" framework proposed in Lyons (1997), where dealers pass the end-user inventory they cannot internalize among themselves until fully absorbed. According to the Lyons (1997)'s "hot-potato trading" theory, the impact of each additional dollar from a liquidity shock gets amplified when dealers pass these quantities around from one to another until fully absorbed against other client flow. This mechanism might be able to justify the large volumes traded in FX markets (Cespa et al., 2022). Our results in this section complement existing studies in this area by highlighting the contribution of *non-information* based demand shocks to the FX market volume traded between dealers. The key friction that leads to inter-dealer trading activity is that the other clients of the same dealer, such as funds, do not supply enough of offsetting order flow in response to corporate liquidity shocks, requiring the constrained market-maker to hedge in the inter-dealer market.

These findings link corporate liquidity events to inter-dealer trading volumes in foreign exchange markets. Our results may explain why risk-averse dealers trade large volumes in the inter-dealer market. Table 4 shows that, across all four model specifications, the estimated coefficient for corporate net volume is greater than 1. Thus, each additional corporate dollar likely changes hands multiple times, increasing trading volume by \$1.4 to \$5.97, depending on the model estimation. This result can be seen as a sign of hot-potato trading originating from corporate liquidity demand shocks.

5.3. Heterogeneity across Currencies and Time

Our model predicts a lower impact of liquidity shocks when dealers perceive retail trades as less risky, due to either fundamental currency attributes or predictable flows. We test the heterogeneity of the impact of liquidity shocks on volatility and volume in two dimensions: cross-sectionally for G10 currencies with lower fundamental volatility, and in the time-series during the 4PM WMR fixing hour when order flow is largely predictable because it is set in advance.

We find that among G10 currencies, corporate liquidity shocks have a lower impact on return volatility compared to emerging market currencies.[12] Panel A of Table 5 shows that the coefficient on instrumented corporate net volume, β_2, is positive and significant, while the coefficient on the interacted term, β_1, is negative, indicating a lower effect of liquidity shocks in G10 currency markets. The net impact among G10 currency pairs (0.0551 - 0.0460 = 0.0091) is about half compared to the overall sample at 0.0190 as reported in Table 3. This translates to a 25% lower impact on G10 currencies for the same size of corporate liquidity shocks. We find similar estimates for other volatility measures in Table A5.

Liquidity shocks affect returns volatility differently across three types of currency pairs. First, pairs involving the US dollar are more liquid and have lower volatility. Panel A of Table A6 shows weaker impact of liquidity shocks on USD-facing currencies, supporting Somogyi (2021) who notes that investors use USD as a vehicle currency to avoid large price impacts. Second, we consider the three *most liquid* FX pairs: EURUSD, GBPUSD, and USDJPY. Panel B of Table A6 shows that corporate liquidity shocks have less impact on more liquid currencies. Finally, we study two *pegged* currencies: USDHKD and EURDKK, controlled by monetary authorities. Panel C of Table A6 shows a near-complete reversal of the coefficient on corporate net volume, consistent with minimal fundamental risk in these currencies. All of these additional tests help us corroborate Proposition 4 related to currency heterogeneity.

Next, we consider the heterogeneity in the time-series variation in the fundamental risk faced by dealers using the 4 PM GMT WMR fixing time. At 4 PM GMT, dealers simultaneously execute client orders at the Reuters weighted-mean rate (WMR). These client orders represent anticipated demand shocks and are aggregated over the course of the day. Each dealer knows the exact quantity

[12] Greenwood-Nimmo et al. (2016) document the risk properties in G10 currency markets. In Table A1, we list all examined currency pairs, and in Table A4, we show that the average return volatility levels are lower among G10 currencies relative to the entire sample.

that she can internalize with clients, and the residual that would need to be hedged in the inter-dealer market.[13] Consequently, given the high degree of predictability of these these flows being executed at 4PM GMT, we expect that retail demand will impact equilibrium prices to a much lesser extent for trades executed at the 4 PM GMT hour.

We confirm that liquidity shocks lead to a substantially lower rise in return volatility since dealers intermediate largely anticipated demand flows from end-clients. The fundamental risk faced by dealers in these hours is significantly lower, translating into a smaller impact of retail trading on asset prices. Panel B of Table 5 reports that the coefficient associated with the interaction term between corporate net volume and the 4 PM GMT fixing hour is significantly negative, suggesting a diminished impact on return volatility for orders executed at this time of the day. The economic magnitude of the reversal β_1 leaves the net impact on volatility at 0.0025 (0.0408 – 0.0383), which is only a small fraction of about 13% of the average impact of liquidity shocks on return volatility, documented in Table 3.

When we turn our attention back to inter-dealer volumes, we find that the corporate liquidity shocks affect inter-dealer volumes similarly across G10 and non-G10 currencies, and during WMR and non-WMR hours. The coefficient associated with the interaction terms in both panels of Table 6 is negative but statistically insignificant. Furthermore, the net effect of β_1 and β_2 is only slightly below the overall effect reported in Table 3. This implies that dealers' financial constraints may be related to their total positions, not to specific currencies or times. Thus, corporate liquidity shocks can have a similar impact on inter-dealer volumes, due to the need to hedge total currency net flows.

Our results indicate that variations in fundamental risk faced by dealers affect how much retail demand affects asset prices and return volatility. These results align with Maggiori (2017), indi-

[13] Evans (2018) provides more background on the volumes executed at the 4 PM GMT WMR fixing hour.

cating that dealers' capacity to absorb order imbalances varies over time and markets. Our model shows that dealers trading currencies face two constraints: balance sheet limitations and currency volatility. Risk-averse dealers seek compensation for higher volatility which has a direct impact on returns. We find empirical support that these factors affect volatility and traded volume after dealers experience liquidity-drive demand shocks from the retail segment.

These insights into foreign exchange markets focus on liquidity shocks and dealer behavior. Our results indicating reduced impact of liquidity shocks on return volatility during fixing hours, notably at 4 PM GMT, suggest that dealers handle anticipated demand flows better, reducing risk and impact on asset prices. This is useful for executing large orders with minimal market impact. Consistent corporate liquidity shocks on inter-dealer volumes across currencies and periods show that dealers' constraints relate to overall positions, not specific currencies or hours. This helps market makers and risk managers develop strategies for larger liquidity events. Our research also reveals dealers' varying capacity to absorb order imbalances, highlighting balance sheet limitations and the role of intermediary frictions in driving currency volatility. This is crucial for assessing market liquidity and predicting stress points, influencing dealers' risk management and pricing models.

5.4. Trading in the Retail Segment

We study the impact of liquidity shocks on retail trading by non-financial corporations and funds. Without such shocks, their order flow could react in the opposite direction to aggregate factors from past returns. This opposite reaction indicates dealers often use offsetting flows to balance inventory risk. Corporate liquidity shocks, unrelated to information signals, make dealers absorb net retail volume. Figure 4 shows these shocks are not offset by fund flows on settlement breaks, leading to higher bid-ask spreads for retail clients due to increased inventory risk.

Opposite reaction of retail order flow: Table 7 shows that corporations and funds react in opposite ways to realized price changes. Corporations tend to buy the base currency while funds sell it when its price falls in the previous hour. We find this to be true in the hours when the respective agent trades (columns (1) and (2)), and also in the hours when both trade (columns (3) and (4)). The negative correlation in end-user order flow can enable dealers to internalize orders to the extent that these quantities offset each other, ultimately allowing them to hedge only the residual flow in the inter-dealer market.

Internalization with liquidity shocks: In our model, the net volume traded in the retail segment increases with liquidity shocks. To test this proposition in the data, we define the retail net absolute volume in currency i and time t as:

$$\text{Retail absolute net volume} = |Q_B^C + Q_B^F - Q_S^C - Q_S^F|, \tag{28}$$

where Q_B^C and Q_B^F are orders to buy the base currency by corporate and fund clients, respectively, and Q_S^C and Q_S^F are orders to sell. An absolute liquidity shock $|\tilde{Z}^j| > 0$ increases the absolute value of the corporate net volume: $Q_B^C - Q_S^C$. If funds simultaneously absorb this imbalance with the opposite direction of order flow, then the net retail volume should not increase in absolute terms. However, if liquidity shocks to corporations are large in magnitude, then dealers may have to absorb a larger quantity of the net imbalance.

We find that a large portion of the corporate liquidity shocks is not offset by funds and translates into dealer inventory, suggesting limited dealer internalization. Panel A of Table 8 shows that the β coefficient attached to the corporate net volume is around 0.8, which suggests that nearly 80% of these corporate liquidity shocks is not offset by fund net volume within the same hour. The table also reports a near-complete pass-through of fund net volume, with limited offset from corporate

trades (a coefficient attached to fund net volume of 1). We conclude that since liquidity shocks to corporations are not fully absorbed by the opposite reaction of funds, dealers have to absorb this new inventory risk originating in the retail segment.

Bid-ask spreads: Our model predicts that dealers set wider bid-ask spreads in response to liquidity shocks. We test this prediction using an estimated measure of bid-ask spreads that correlates with order handling costs faced by dealers, as proposed by Roll (1984). This measure captures bid-ask spreads using a bounce in actual traded prices (Foucault, Sraer, and Thesmar, 2011, Koudijs, 2016) and is calculated using the intra-hour 10-minute price snapshots to measure the covariance of returns.

$$\text{Spread} = 2 \times \sqrt{-cov(r_t, r_{t-1})} \tag{29}$$

We find that spreads increase significantly in response to liquidity shocks, across all combinations of controls and fixed effects, see Panel B of Table 8. Relative to the mean spread of 3 basis points, a one-standard-deviation rise in corporate net volume leads to a 20% increase in this measure of bid-ask spreads.

An alternative and perhaps more direct approach to compute bid-ask spreads would be to use the traded prices observed in our data set. However, we only observe prices for the hours when clients trade, resulting in mostly missing observations. In addition, the spreads in our data are likely to be impacted by factors beyond order-handling costs, such as client relationship with the dealer (Hendershott et al., 2017). Since our model abstracts away from client-specific attributes in the setting of bid-ask spreads, we focus on the measure that most closely captures dealers' overall intermediation costs.

These findings on the impact of liquidity shocks on the Roll (1984)'s measure of bid-ask spreads

provide valuable insights into how dealers respond to liquidity shocks. Our results may suggest that during periods of corporate liquidity shocks, transaction costs are likely to rise, which could impact trading strategies and execution costs. This information is particularly relevant for algorithmic traders and institutional investors who need to factor in these potential cost increases.

The consistency of these results across different control variables and fixed effects lends credibility to the findings and suggests a robust relationship between liquidity shocks and market microstructure. Importantly, these results tie together the effects of corporate liquidity shocks on return volatility, inter-dealer volume, and bid-ask spreads, providing a comprehensive picture of how liquidity shocks propagate through different aspects of FX market structure.

6. Conclusion

This paper investigates the impact of liquidity shocks from uninformed retail traders on foreign exchange (FX) prices and dealer behavior. We extend the Liu and Wang (2016) model to include liquidity shocks experienced by uninformed investors, predicting positive relationships between these shocks, trading volumes, bid-ask spreads and volatility.

Using settlement breaks around month-ends as an instrument for uninformed liquidity shocks, we analyze signed order flow data from CLS Group covering 31 currency pairs. Our findings reveal that a one-standard-deviation increase in the demand for retail liquidity leads to a 12- 22% increase in the volatility of the FX and a 10% increase in the volume between dealers. A large amount, about 80%, of these corporate liquidity shocks is not immediately offset by flow from other retail agents.

We identify the inter-dealer market as the primary channel for transmitting liquidity shocks to asset prices. Dealers respond to these shocks by adjusting positions in the inter-dealer market,

consistent with the "hot-potato trading" framework. While liquidity shocks generally widen bid-ask spreads, their impact is diminished during fixing hours, particularly at 4 PM GMT.

Our research provides empirical micro-foundations for understanding how corporate liquidity shocks affect global currency markets. It highlights the role of non-information based demand shocks in driving market activity and emphasizes the importance of the inter-dealer market as a transmission channel.

Our paper has several important policy implications. First, the significant impact of uninformed liquidity shocks on FX volatility (12-22% increase) suggests that these events could potentially destabilize markets. This highlights the need for policymakers and regulators to closely monitor and potentially develop mechanisms to manage large corporate currency transactions. Furthermore, our results have implications for corporate hedging strategies and market microstructure. Companies may need to reassess their FX hedging practices to minimize market impact, potentially by spreading large transactions over time. The finding that liquidity shocks have less impact during certain fixing hours, particularly at 4 PM GMT, suggests that some market structures may be more resilient to these shocks. This could inform future market design considerations. Lastly, the significant short-term volatility caused by corporate liquidity events may need to be factored into monetary policy decisions, especially in countries where exchange rate stability is a key objective.

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Table 1: Descriptive Statistics

Panel A. Volume	Mean	SD	p25	p50	p75	N
Corporate buy trades (count)	0.4	4.3	0.0	0.0	0.0	1,445,592
Corporate sell trades (count)	0.4	5.2	0.0	0.0	0.0	1,445,592
Signed corporate order flow (count)	0.0	3.4	0.0	0.0	0.0	1,445,592
Corporate total trades (count)	0.8	9.0	0.0	0.0	0.0	1,445,592
Fund buy trades (count)	7.9	24.4	0.0	0.0	5.0	1,445,592
Fund sell trades (count)	8.1	25.1	0.0	0.0	5.0	1,445,592
Signed fund order flow (count)	-0.2	16.0	0.0	0.0	0.0	1,445,592
Fund total trades (count)	16.0	46.9	0.0	0.0	10.0	1,445,592
Corporate total volume ($, million)	3.4	50.4	0.0	0.0	0.0	1,444,998
Fund total volume ($, million)	39.7	225.4	0.0	0.0	11.5	1,444,998
Corporate avg. trade size ($, million)	7.4	27.5	1.1	2.3	6.0	87,208
Fund avg. trade size ($, million)	2.6	8.1	0.5	1.0	2.2	668,375
Inter-dealer total volume ($, million)	592.4	1681.2	17.2	100.4	437.9	1,445,592
Absolute corporate net volume ($, million)	2.2	38.4	0.0	0.0	0.0	1,445,592
Absolute fund net volume ($, million)	20.6	130.8	0.0	0.0	5.9	1,445,592
Panel B. Price and volatility (in basis points)						
Return	0.0	12.3	-4.4	0.0	4.4	1,443,909
Standard Deviation (intra-hour returns)	3.8	4.2	1.7	3.0	4.9	1,443,909
Return (absolute)	7.3	9.9	1.6	4.4	9.5	1,443,909
Range (intra-hour)	9.6	11.1	3.9	7.1	12.2	1,443,909
Autocovariance (intra-hour returns)	-6.3	212.0	-5.7	-1.1	0.1	1,443,909
Realized Amihud	2.8	1325.6	0.0	0.0	0.2	1,400,344

Notes: This table describes hourly volume and price variables for all 31 currency pairs in our sample. (Table A1 provides the list of currency pairs.) Panel A describes the hourly volume variables in CLS data for corporate, fund, and inter-dealer segments of the FX spot market. These variables are expressed in terms of count of trades and volume (in $ million). We define order imbalance as the absolute of buy minus sell volume in a given hour for the respective segment. Panel B describes the market price variables in terms of hourly returns, four measures of volatility, and realized Amihud ratio that measures illiquidity. All variables in Panel B are expressed in basis points. Our sample period runs from January 2015 through June 2022.

Table 2: Settlement Breaks and Corporate Net Volume: IV First-stage

	Corporate net volume			
	(1)	(2)	(3)	(4)
Settlement break$_t$	6.443***	5.302***	5.327***	5.487***
	(1.820)	(1.609)	(1.613)	(1.621)
Fund net volume$_t$	0.012***	0.009***	0.008***	0.001
	(0.002)	(0.002)	(0.001)	(0.001)
$\sigma(r)_{t,t-24}$	0.017***	-0.026	-0.003	0.009
	(0.006)	(0.017)	(0.008)	(0.008)
$\sigma(r)_{t,t-120}$	-0.016	-0.015	-0.015**	-0.013
	(0.010)	(0.010)	(0.008)	(0.008)
$\Delta Spot_{t,t-1}(ln)$	-33.784	-5.969	-15.559	-1.297
	(30.532)	(34.261)	(26.748)	(20.917)
Observations	1,443,049	1,439,584	1,439,584	1,439,584
Instrument F-statistic	12.54	10.86	10.91	11.46
Volume Lags	N	Y	Y	Y
Currency FE	N	N	Y	N
Time FE	N	N	Y	N
Currency X Time FE	N	N	N	Y

Notes: This table shows that corporate net volume significantly increases during settlement break days, defined as two business days before a month-end (or before Christmas in the case of December months). We estimate the following model to measure the impact of settlement breaks on corporate net volume.

$$Q^C_{i,t} = \beta \textit{Settlement break}_t + \gamma \mathbf{Z} + \alpha_i + \alpha_t + \epsilon_{i,t}, \tag{30}$$

where $Q^C_{i,t}$ is the corporate net volume in currency i at time t, and *Settlement break*$_t$ is 1 if the trade date is two business days before a month-end, and 0 otherwise. $\mathbf{Z}$ includes fund net volume at time t, the realized volatility of returns over the preceding 1 day and 1 week, and spot returns. We include five lags of net volumes to control for persistence. This analysis uses a panel of 31 currency pairs, with currency and time fixed effects, and standard errors clustered by currency-time. $^*p < 0.1$;$^{**}p < 0.05$;$^{***}p < 0.01$.

Table 3: Liquidity Shocks and Return Volatility

	Standard deviation			
	(1)	(2)	(3)	(4)
$\widehat{\text{Corporate net}}$ volume$_t$	0.0158***	0.0126***	0.0190***	0.0193***
	(0.005)	(0.005)	(0.006)	(0.006)
Fund net volume$_t$	0.0010***	0.0004***	0.0001*	0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)
	Absolute returns			
$\widehat{\text{Corporate net}}$ volume$_t$	0.0320***	0.0257***	0.0438***	0.0445***
	(0.010)	(0.010)	(0.015)	(0.014)
	Range			
$\widehat{\text{Corporate net}}$ volume$_t$	0.0473***	0.0355***	0.0565***	0.0581***
	(0.014)	(0.013)	(0.019)	(0.019)
	Auto-covariance			
$\widehat{\text{Corporate net}}$ volume$_t$	-0.2283**	-0.2705**	-0.3345**	-0.3275**
	(0.104)	(0.130)	(0.156)	(0.151)
Observations	1,443,049	1,439,584	1,439,584	1,439,584
Volatility and volume Lags	N	Y	Y	Y
Controls	Y	Y	Y	Y
Currency FE	N	N	Y	N
Time FE	N	N	Y	N
Currency X Time FE	N	N	N	Y

Notes: This table shows that liquidity shocks increase return volatility. Estimates are from a two-stage least squares procedure for four dependent variables: intra-hour return standard deviation, hourly absolute returns, price range, and autocovariance. The estimated model is:

$$\text{Volatility}_{i,t} = \beta \widehat{Q^C_{i,t}} + \gamma \mathbf{Z} + \alpha_i + \alpha_t + \varepsilon_{i,t}, \tag{31}$$

where $\text{Volatility}_{i,t}$ represents one of four FX return volatility measures: (i) standard deviation, (ii) absolute return, (iii) intra-hour range, and (iv) autocovariance. $\widehat{Q^C_{i,t}}$ is the instrumented corporate net volume, and β measures its impact. Dependent variables are GARCH(1,1) model residuals capturing "excess volatility." The vector $\mathbf{Z}$ includes controls: fund net volume in currency i at time t, realized volatility of returns from the previous 1 day and 1 week, and spot returns. Five lags each for corporate and fund net volumes and the dependent variable are included to account for trading activity persistence. Standard errors are clustered by currency-time. $^{*}p < 0.1;^{**}p < 0.05;^{***}p < 0.01$.

Table 4: Liquidity Shocks and Inter-dealer Trading

	Inter-dealer volume			
	(1)	(2)	(3)	(4)
$\widehat{\text{Corporate net}}$ volume$_t$	5.9647***	1.3657*	1.6067**	2.3246***
	(1.300)	(0.712)	(0.710)	(0.737)
Fund net volume$_t$	2.4661***	0.9113***	0.8674***	0.6451***
	(0.289)	(0.124)	(0.125)	(0.142)
Observations	1,443,049	1,442,894	1,442,894	1,442,894
Volume Lags	N	Y	Y	Y
Controls	Y	Y	Y	Y
Currency FE	N	N	Y	N
Time FE	N	N	Y	N
Currency X Time FE	N	N	N	Y

Notes: This table shows that liquidity shocks increase inter-dealer traded volumes. We estimate the impact of liquidity shocks on inter-dealer volume using a two-stage least squares procedure,

$$Q^D_{i,t} = \beta \widehat{Q^C_{i,t}} + \gamma \mathbf{Z} + \alpha_i + \alpha_t + \varepsilon_{i,t}, \tag{32}$$

where $Q^D_{i,t}$ is the gross volume traded between banks in currency i at time t, $\widehat{Q^C_{i,t}}$ is the instrumented corporate net volume, and $\mathbf{Z}$ is a vector of controls from Equation 31. We de-trend all volume variables by subtracting the past one-month rolling average from the volume traded at time t. This table shows that liquidity shocks increase inter-dealer traded volumes. All columns include controls for fund net volume, standard deviation of returns over the past one day and one week, and log changes in spot rate. Standard errors clustered by currency-time are reported in parentheses. $^{*}p < 0.1$;$^{**}p < 0.05$;$^{***}p < 0.01$.

Table 5: Heterogeneity in Returns Volatility from Fundamental Risk

	Standard deviation			
Panel A: G10 currency pairs	(1)	(2)	(3)	(4)
$\widehat{\text{Corporate net}}$ volume$_t$	0.0508***	0.0387***	0.0551***	0.0571***
	(0.018)	(0.015)	(0.020)	(0.020)
Corporate $\widehat{\text{net volume}}_t \times$ G10	-0.0433**	-0.0333**	-0.0460**	-0.0480**
	(0.018)	(0.015)	(0.020)	(0.020)
Panel B: 4PM WMR fixing hour				
$\widehat{\text{Corporate net}}$ volume$_t$	0.0320***	0.0268**	0.0408**	0.0403**
	(0.012)	(0.013)	(0.018)	(0.017)
Corporate $\widehat{\text{net volume}}_t \times$ WMR	-0.0297**	-0.0250**	-0.0383**	-0.0379**
	(0.012)	(0.013)	(0.018)	(0.017)
Observations	1,443,049	1,439,584	1,439,584	1,439,584
Volatility and volume Lags	N	Y	Y	Y
Controls	Y	Y	Y	Y
Currency FE	N	N	Y	N
Time FE	N	N	Y	N
Currency X Time FE	N	N	N	Y

Notes: This table shows how liquidity shocks impact return volatility in different currency groups and times of day. It reports estimates from a two-stage least squares procedure testing if corporate liquidity shocks affect G10 currencies less.

$$\text{Volatility}_{i,t} = \beta_1 \widehat{Q}^C_{i,t} \times \mathbf{X} + \beta_2 \widehat{Q}^C_{i,t} + G10 + \gamma \mathbf{Z} + \alpha_i + \alpha_t + \varepsilon_{i,t}. \tag{33}$$

To estimate $\widehat{Q}^C_{i,t}$, we instrument corporate net volume using month-end settlement breaks as documented in our baseline specification in Equation 30. The dependent variable is one of four return volatility measures. Vector $\mathbf{Z}$ includes control variables. In Panel A, we interact the instrumented corporate net volume with a binary variable $G10$, which is 1 for G10 currency pairs and 0 otherwise. In Panel B, we interact the instrumented corporate net volume with a 4PM GMT WMR/Fixing hour indicator. We control for fund net volume, past one-day and one-week return standard deviations, and log changes in spot rate. Standard errors are clustered by currency-time (in parentheses). $^{*}p < 0.1;^{**}p < 0.05;^{***}p < 0.01$.

Table 6: Heterogeneity in Traded Volume from Fundamental Risk

	Inter-dealer volume			
Panel A: G10 currency pairs	(1)	(2)	(3)	(4)
$\widehat{\text{Corporate net}}$ volume$_t$	10.5983***	2.9096*	3.2495**	4.2434***
	(3.231)	(1.616)	(1.633)	(1.513)
$\widehat{\text{Corporate net volume}}_t \times$ G10	-5.7214	-1.9599	-2.0885	-2.4397
	(3.495)	(1.641)	(1.673)	(1.717)
Panel B: 4PM WMR fixing hour				
$\widehat{\text{Corporate net}}$ volume$_t$	10.1773***	1.9388	2.4429	3.7346*
	(3.257)	(1.624)	(1.671)	(1.930)
$\widehat{\text{Corporate net volume}}_t \times$ WMR	-7.7249**	-1.0261	-1.4877	-2.5333
	(3.298)	(1.573)	(1.626)	(1.908)
Observations	1,443,049	1,439,584	1,439,584	1,439,584
Volume Lags	N	Y	Y	Y
Controls	Y	Y	Y	Y
Currency FE	N	N	Y	N
Time FE	N	N	Y	N
Currency X Time FE	N	N	N	Y

Notes: This table shows heterogeneity in the impact of liquidity shocks on inter-dealer traded volume with variation in risk faced by dealers. The table reports estimates of Equation 31 using a two-stage least squares procedure for the dependent variable of inter-dealer volume. Panel A interacts corporate net volume with an indicator variable for G10 currency pairs (Table A1 provides the list of currency pairs and their type), and Panel B interacts corporate net volume with an indicator variable for 4PM GMT WMR/Fixing hour. All columns include controls for fund net volume, standard deviation of returns over the past one day and one week, and log changes in spot rate. Standard errors clustered by currency-time are reported in parentheses. $^{*}p < 0.1;^{**}p < 0.05;^{***}p < 0.01$.

Table 7: Order Flow Determinants

	Respective agent trades		Both trade	
	Corporate net order flow	Fund net order flow	Corporate net order flow	Fund net order flow
	(1)	(2)	(3)	(4)
Return_t	-0.0352***	0.0566***	-0.0368***	0.0986***
	(0.006)	(0.006)	(0.006)	(0.017)
Return_{t-1}	-0.0093***	0.0321***	-0.0090**	0.0345***
	(0.003)	(0.004)	(0.004)	(0.011)
Order flow_{t-1}	0.3823***	0.1661***	0.3805***	0.2467***
	(0.031)	(0.015)	(0.032)	(0.021)
Order flow_{t-2}	0.0528***	0.0832***	0.0448**	0.1442***
	(0.020)	(0.009)	(0.020)	(0.016)
Order flow_{t-3}	0.0457**	0.0518***	0.0441**	0.1289***
	(0.019)	(0.009)	(0.019)	(0.027)
Order flow_{t-4}	0.0483**	0.0345***	0.0450**	0.0791**
	(0.021)	(0.007)	(0.021)	(0.032)
Order flow_{t-5}	0.0653***	0.0333***	0.0645***	0.1017**
	(0.022)	(0.009)	(0.022)	(0.042)
Observations	87,061	667,888	75,331	75,331
Adj. R^2	0.18	0.06	0.18	0.12
Currency X Time FE	Y	Y	Y	Y

Notes: This table reports the estimated coefficients from the fixed-effects panel regression where each agent's signed order flow is a function of realized returns as an aggregate demand factor.

$$q^I_{i,t} = \sum_{j=0}^{1} \gamma_j r_{i,t-j} + \sum_{k=1}^{5} \delta_k q^I_{i,t-k} + \alpha_{i,t} + \epsilon^I_{i,t}. \tag{34}$$

Columns (1) and (2) restrict to hours when corporations or funds, respectively, trade. Columns (3) and (4) include hours when both agents trade. All columns include currency-time ($\alpha_{i,t}$) fixed effects. Standard errors are clustered at the currency-time level and reported in parentheses. $^{*}p < 0.1$;$^{**}p < 0.05$;$^{***}p < 0.01$.

Table 8: Liquidity Shocks and Trading in the Retail Segment

	Retail net volume			
	(1)	(2)	(3)	(4)
$\widehat{\text{Corporate net}}$ volume$_t$	0.7825***	0.8010***	0.8004***	0.7902***
	(0.022)	(0.025)	(0.025)	(0.026)
Fund net volume$_t$	0.9901***	0.9906***	0.9907***	0.9920***
	(0.002)	(0.002)	(0.002)	(0.001)
	Bid-ask spread estimates using Roll (1984)			
$\widehat{\text{Corporate net}}$ volume$_t$	0.0156***	0.0140***	0.0156***	0.0155***
	(0.005)	(0.005)	(0.006)	(0.006)
Fund net volume$_t$	0.0008***	0.0005***	0.0001**	0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,443,049	1,439,584	1,439,584	1,439,584
Dependent variable Lags	N	Y	Y	Y
Fund volume Lags	N	Y	Y	Y
Corp volume Lags	N	Y	Y	Y
Currency FE	N	N	Y	N
Time FE	N	N	Y	N
Currency X Time FE	N	N	N	Y

Notes: This table shows that liquidity shocks increase retail net trading volume and bid-ask spreads. We estimate the fraction of liquidity shocks that translates into dealers' inventory using the following model:

$$\text{Retail net volume}_{i,t} = \beta \widehat{Q^C_{i,t}} + \gamma \mathbf{Z} + \alpha_i + \alpha_t + \varepsilon_{i,t}. \tag{35}$$

We de-trend the retail net volume using the rolling average of the past one-month, and instrument for the corporate net volume using settlement breaks. Panel A reports the estimation results. Panel B shows estimates of the model for bid-ask spreads.

$$\text{Spread}_{i,t} = \beta \widehat{Q^C_{i,t}} + \gamma \mathbf{Z} + \alpha_i + \alpha_t + \varepsilon_{i,t}. \tag{36}$$

All columns include controls for fund net volume, standard deviation of returns over the past one day and one week, and log changes in spot rate. Standard errors clustered by currency-time are reported in parentheses. $^{*}p < 0.1;^{**}p < 0.05;^{***}p < 0.01$.

Internet Appendix

"Uninformed yet Consequential: Liquidity Shocks in FX Markets"

August 2024

A. Model Setup

There are N_U uninformed and N_I informed investors trading with M market makers. Each market maker j serves subsets of uninformed clients, N_U^j, and informed clients, N_I^j, leading to varying informed-to-uninformed ratios across market makers. Each investor i is matched with one market maker j. We describe trading in the retail segment first, then the inter-dealer segment.

A.1. Trading in the retail segment

At $t = 0$, investor i trades a risk-free and a risky asset with market maker j, allocating initial wealth to optimize expected utility. At $t = 1$, the risky asset's random payoff, $\tilde{V}$, is normally distributed with mean $\bar{V}$ and variance σ_V^2.

At $t = 0$, all informed investors receive a private signal $\tilde{s}$, defined as $\tilde{s} = \tilde{V} - \bar{V} + \tilde{\epsilon}$, where $\tilde{\epsilon}$ follows a normal distribution with mean 0 and variance σ_ϵ^2. Additionally, all investors receive a public signal $\hat{S}_s$, which is a noisier version of the private signal: $\hat{S}_s = \hat{s} + \tilde{\eta}$, with $\tilde{\eta}$ following a normal distribution with mean 0 and variance σ_η^2. The parameter σ_η quantifies the degree of information asymmetry between investors.

Following Liu and Wang (2016), informed investors face a random shock $\tilde{X}_j \sim N(0, \sigma_X^2)$. This

shock is a random endowment of a non-tradable asset with payoff $\tilde{L} \sim N(0, \sigma_L^2)$, and covariance σ_{VL} with the risky asset's payoff. We integrate uninformed liquidity shocks $\tilde{Z}_j$ into Liu and Wang (2016). Uninformed investors face a liquidity shock $\tilde{Z}_j \sim N(0, \sigma_Z^2)$ due to portfolio rebalancing needs. We allow these two types of shock to vary between market makers (i.e. between j). [14]

Investors determine their equilibrium demand quantities for the risky asset based on their information. Investor i can sell to market maker j at bid B^j or buy at ask A^j. Given A^j, B^j, risk aversion δ, and information set $\mathcal{F}_i$, investor i chooses demand θ_i to maximize expected utility from wealth $\tilde{W}_i$.

$$\max_{\theta_i} \mathbb{E}(-e^{-\delta \tilde{W}_i} | \mathcal{F}_i), \tag{A.1}$$

subject to the agent's budget constraint

$$\tilde{W}_i = (\theta_i^- + \tilde{Z}^{j-})B^j - (\theta_i^+ + \tilde{Z}^{j+})A^j + (\bar{\theta} + \theta_i + \tilde{Z}^j)\tilde{V} + \tilde{X}^j \tilde{L}, \tag{A.2}$$

where $x^- = \max(0, -x)$ represents the sell quantity and $x^+ = \max(x, 0)$ refers to a buy order quantity.

Conditional expectations of informed agents: The conditional expected value assigned by an informed agent i depends on the common information set $\mathcal{F}_I$ available to all informed agents. This set $\mathcal{F}_I$ does not vary across different market makers. The information available does not depend on which market maker they are trading with, i.e. on j, since informed agents are not learning from

[14] For simplicity, we assume that the liquidity shocks $\tilde{Z}^j$ are normally distributed. This assumption, however, is not critical for our main results. It is possible that real-world liquidity shocks in FX markets may exhibit fat tails or other non-Gaussian properties. We assume that agents can fully observe the level of $\tilde{Z}_j$ shocks. Our model predictions are, thus, ties to the observed levels of $\tilde{Z}_j$.

$\tilde{X}^j$ or $\tilde{Z}^j$.

$$\mathbb{E}(\tilde{V}|\mathcal{F}_I) = \bar{V} + \frac{\text{cov}(\hat{s}, \tilde{V})}{\text{var}(\hat{s})}\hat{s} = \bar{V} + \underbrace{\frac{\sigma_V^2}{\sigma_V^2 + \sigma_\epsilon^2}}_{\rho_I}\hat{s} \tag{A.3}$$

The term ρ_I measures the precision of the private signal and it is negatively associated with noise in the private signal σ_ϵ^2. The variance of $\tilde{V}$, conditional on $\mathcal{F}_I$ is given by

$$\text{var}(\tilde{V}|\mathcal{F}_I) = \text{var}(\tilde{V}) - \frac{\text{cov}(\tilde{V}, \hat{s})^2}{\text{var}(\hat{s})} = \frac{\sigma_V^2\sigma_\epsilon^2}{\sigma_V^2 + \sigma_\epsilon^2} = (1 - \rho_I)\sigma_V^2 = \sigma_\epsilon^2\rho_I. \tag{A.4}$$

Lastly, the covariance of $\tilde{V}$ and $\tilde{L}$, conditional on $\mathcal{F}_I$ is

$$\text{cov}(\tilde{V}, \tilde{L}|\mathcal{F}_I) = (1 - \rho_I)\sigma_{VL}. \tag{A.5}$$

Conditional expectations of uninformed agents: The uninformed agent i trading with market maker j cannot observe the private signal $\hat{s}$ or the non-information-based demand shock $\tilde{X}^j$. The agent conjectures that equilibrium prices A^{j*} and B^{j*} depend on $\hat{s}$ and $\tilde{X}^j$ through their impact on informed demand for the risky asset. As in Liu and Wang (2016), we assume uninformed agents infer the composite signal $\hat{S}$, measuring the joint impact of the private signal and demand shock on market prices.

$$\hat{S}^j = \hat{s} - \frac{\delta(1 - \rho_I)\sigma_{VL}}{\rho_I}\hat{X}^j = \hat{s} - \frac{h}{\rho_I}\hat{X}^j, \tag{A.6}$$

where h is the hedging premium per unit of the informed liquidity shock.

$$h = -\delta(1 - \rho_I)\sigma_{VL} \tag{A.7}$$

The conditional expected payoff for uninformed agents U matched with market maker j is

$$\mathbb{E}(\tilde{V}|\mathcal{F}_U^j) = \mathbb{E}(\tilde{V}|\hat{S}^j, \hat{S}_s) = \bar{V} + \rho_U \left[(1-\rho_X)\hat{S}^j + \rho_X \hat{S}_s\right], \tag{A.8}$$

where

$$\rho_X = \frac{h^2\sigma_X^2}{h^2\sigma_X^2 + \sigma_I^2\sigma_\eta^2} \tag{A.9}$$

and

$$\rho_U = \frac{\sigma_V^2}{\sigma_V^2 + \rho_X\rho_I\sigma_\eta^2}\rho_I < \rho_I. \tag{A.10}$$

The conditional variance of $\tilde{V}$ given $\{\hat{S}^j, \hat{S}\}$ is the same for all uninformed agents.

$$\text{var}(\tilde{V}|\mathcal{F}_U) = \text{var}(\tilde{V}|\hat{S}^j, \hat{S}) = (1-\rho_U)\sigma_V^2 \tag{A.11}$$

The ratio of the conditional variance for uninformed to informed agents, denoted as ν, is the same across all market makers.

$$\nu = \frac{\text{var}(\tilde{V}|\mathcal{F}_U)}{\text{var}(\tilde{V}|\mathcal{F}_I)} = \frac{1-\rho_U}{1-\rho_I} \geq 1 \tag{A.12}$$

A.2. Proofs

Theorem 1: Retail segment

Proof. We prove the case when $\Delta^j < 0$, distinguishing our retail model with uninformed liquidity shocks $\tilde{Z}_U$ from Liu and Wang (2016). When $\Delta^j < 0$, informed investors I sell, and uninformed investors U buy. We assume the non-discretionary component $\tilde{Z}^j$ of uninformed demand is positive to ensure that the total uninformed demand positive. The agents' optimal demand is the solution to the mean-variance optimization problem from (A.1). The optimal demand of all informed agents trading with the maker market j is

$$\theta^*_{Ij} = \frac{PR^j_I - B^j}{\delta \text{var}(\tilde{V}|\mathcal{F}_I)} \tag{A.13}$$

The demand from all uninformed agents trading with market maker j also includes the non-discretionary component $\tilde{Z}^j$, a result of the liquidity demand shock.

$$\theta^*_{Ij} = \frac{PR^j_U - A^j}{\delta \text{var}(\tilde{V}|\mathcal{F}^j_U)} + \tilde{Z}^j \tag{A.14}$$

The Market Maker's Optimization Problem: The market maker sets bid and ask prices to maximize profits from trading with informed and uninformed agents. The market maker j and their uninformed clients share the same information set: $\mathcal{F}^j_U = \mathcal{F}^j_M$.

$$\max_{A^j, B^j} \left[\alpha^j A^j - \beta^j B^j + (\bar{\theta} + \beta^j - \alpha^j)\mathbb{E}(\tilde{V}|\mathcal{F}^j_U) - \frac{1}{2}\delta \text{var}(\tilde{V}|\mathcal{F}^j_U)(\bar{\theta} + \beta^j - \alpha^j)^2 \right], \tag{A.15}$$

where

$$\alpha^j = N^j_U \left(\frac{PR^j_U - A^j}{\delta \text{var}(\tilde{V}|\mathcal{F}^j_U)} + \tilde{Z}^j \right)$$

and

$$\beta^j = N_I^j \left(\frac{B^j - PR_I^j}{\delta \text{var}(\tilde{V}|\mathcal{F}_I)} \right).$$

The first order conditions, re-arranged in terms of α^{j*} and β^{j*}, yield the following set of equations.

$$\alpha^{j*}(2 + N_U^j) - 2N_U^j \tilde{Z}^j - N_U^j \beta^{j*} = 0$$

$$\beta^{j*}(2 + N_I^j \nu) - \alpha^{j*} N_I^j \nu = -\Delta^j \frac{N_I^j}{\delta \text{var}(\tilde{V}|\mathcal{F}_I)} - \tilde{Z}^j N_I^j \nu$$

We define $\bar{N}_j = \nu N_I^j + N_U^j + 1$ and solve for α^{j*} and β^{j*}.

$$\alpha^{j*} = -\Delta^j \frac{N_I^j N_U^j}{2(\bar{N}_j + 1)} \frac{1}{\delta \text{var}(\tilde{V}|\mathcal{F}_I)} + \tilde{Z}^j \frac{N_U^j (N_I^j \nu + 4)}{2(\bar{N}_j + 1)} \tag{A.16}$$

$$\beta^{j*} = -\Delta^j \frac{N_I^j (N_U^j + 2)}{2(\bar{N}_j + 1)} \frac{1}{\delta \text{var}(\tilde{V}|\mathcal{F}_I)} + \tilde{Z}^j \frac{N_I^j \nu (N_U^j - 2)}{2(\bar{N}_j + 1)} \tag{A.17}$$

Substituting α^{j*} and β^{j*} into A.16 and A.17, we derive the equilibrium ask and bid prices A^{j*} and B^{j*}, assigned by the market maker j.

$$A^{j*} = PR_U^j + \Delta^j \frac{N_I^j \nu}{2(\bar{N}_j + 1)} + \tilde{Z}^j \delta \text{var}(\tilde{V}|\mathcal{F}_U) \frac{N_I^j \nu + 2N_U^j}{2(\bar{N}_j + 1)} \tag{A.18}$$

$$B^{j*} = PR_U^j + \Delta^j \frac{2N_I^j \nu + N_U^j + 2}{2(\bar{N}_j + 1)} + \tilde{Z}^j \delta \text{var}(\tilde{V}|\mathcal{F}_U) \frac{N_U^j - 2}{2(\bar{N}_j + 1)} \tag{A.19}$$

In a similar fashion, we can prove the case of Theorem 1 for the other case where informed investors buy and uninformed investors sell from the market maker j.

□

Theorem 2: Inter-dealer segment

Proof. As in Liu and Wang (2016), we assume that the equilibrium price at which price-taking market makers trade among themselves is the weighted average of the asset's reservation price. This is a result of the market-clearing condition that determines the market clearing price. We assume that each market maker's demand is linear in the difference between their reservation price and the market price. The market clearing condition sums these linear demands across all agents. Solving this equation leads to a price that is a weighted average of reservation prices, with weights determined by the number of each type of agent and their relative risk perception (captured by the ν term).

$$P^* = \frac{\nu}{\bar{N}} \sum_{j=1}^{M} N_I^j PR_I^j + \frac{1}{\bar{N}} \sum_{j=1}^{M} N_U^j PR_U^j + \frac{1}{\bar{N}} \sum_{j=1}^{M} PR_M^j, \tag{A.20}$$

where $\bar{N} = \sum_{j=1}^{M} \bar{N}^j$. The equilibrium price P^* is a function of the uninformed liquidity shock $\tilde{Z}^j$ because it directly affects the reservation price PR_U^j. For the sake of simplicty, we assume that other liquidity shocks that affect uninformed agents of other dealers are independent of $\tilde{Z}^j$. Next, we substitute all agent-specific reservation prices defined in (2) into the equilibrium price, as solve for the expected equilibrium price, given $\tilde{Z}^j$,

$$\mathbb{E}(P^*|\tilde{Z}^j) = \bar{V} - \delta \text{var}(\tilde{V}|\mathcal{F}_U) \frac{N_I + N_U + M}{\bar{N}} + \delta \text{var}(\tilde{V}|\mathcal{F}_U^j) \frac{N_U^j}{\bar{N}} \tilde{Z}^j. \tag{A.21}$$

The unconditional variance of the equilibrium price P^* is a function of the variances of five orthogonal shocks, one of them being the variance of the uninformed liquidity shocks σ_Z^2.

The market maker j chooses how much of their total net imbalance to hedge in the inter-dealer

market. They choose the optimal level of θ^j to maximize expected wealth.

$$\max_{\theta^j}\left[-\theta^j P^* + (\bar{\theta} + \beta^{j*} - \alpha^{j*} + \theta^j)\mathbb{E}(\tilde{V}|\mathcal{F}_U^j) - \frac{1}{2}\delta \text{var}(\tilde{V}|\mathcal{F}_U)(\bar{\theta} + \beta^{j*} - \alpha^{j*} + \theta^j)^2\right], \tag{A.22}$$

The optimal volume traded by the market maker j is driven by the size of the net order imbalance and the expected value of the risky asset relative to the equilibrium price P^*.

$$\theta^{j*} = \frac{\mathbb{E}(\tilde{V}|\mathcal{F}_U^j) - P^*}{\delta \text{var}(\tilde{V}|\mathcal{F}_U)} - (\bar{\theta} + \beta^{j*} - \alpha^{j*}) \tag{A.23}$$

Substituting α^{j*}, β^{j*} and P^* into A.23 yields the equilibrium demand of market maker j to trade with other dealers.

$$\frac{\partial \theta^{j*}}{\partial \tilde{Z}^j} = \underbrace{\frac{N_I^j \nu + 2N_U^j}{\bar{N}_j + 1}}_{\frac{\partial(\alpha^{j*} - \beta^{j*})}{\partial \tilde{Z}^j}} \overbrace{-\frac{N_U^j}{\bar{N}}}^{\frac{\partial P^*}{\partial \tilde{Z}^j}/(\delta \text{var}(\tilde{V}|\mathcal{F}_U))} \tag{A.24}$$

□

Proposition 1: Liquidity shocks and retail net trading volume

Proof. The equilibrium (retail) net trading volume, $\alpha^{j*} - \beta^{j*}$, increases with the uninformed liquidity shock $\tilde{Z}^j$ because the partial derivative is strictly positive when $N_U^j > 0$ or $\nu N_I^j > 0$.

$$\frac{\partial(\alpha^{j*} - \beta^{j*})}{\partial \tilde{Z}^j} = \frac{2N_U^j + \nu N_I^j}{\bar{N}^j + 1} > 0 \tag{A.25}$$

□

Proposition 2: Liquidity shocks and the equilibrium bid-ask spread

Proof. The equilibrium bid-ask spread, $A^{j*} - B^{j*}$, increases with the absolute value of the uninformed liquidity shock $|\tilde{Z}^j|$ because the partial derivative is strictly positive when $\delta > 0$ and $\text{var}(\tilde{V}|\mathcal{F}_U^j) > 0$.

$$\frac{\partial(A^{j*} - B^{j*})}{\partial|\tilde{Z}^j|} = \delta \text{var}(\tilde{V}|\mathcal{F}_U^j) > 0 \tag{A.26}$$

□

Propositions 3 & 4: Liquidity shocks and price volatility

Proof. The equilibrium price volatility $\text{var}(P^*)$ increases when the variation in liquidity shocks (measured by σ_Z^2) increases when $N_U^j > 0$ and $\delta > 0$.

$$\frac{\partial \text{var}(P^*)}{\partial \sigma_Z^2} = a_4^2 = \left(\frac{N_U^j}{\bar{N}} \delta \text{var}(\tilde{V}|\mathcal{F}_U^j)\right)^2 > 0 \tag{A.27}$$

The price change ΔP^* increases with an uninformed liquidity shock $\tilde{Z}_U$ when $N_U^j > 0$ and $\delta > 0$.

$$\frac{\partial \Delta P^*}{\partial \tilde{Z}_U} = a_4 = \delta \text{var}(\tilde{V}|\mathcal{F}_U^j) \frac{N_U^j}{\bar{N}} > 0 \tag{A.28}$$

Taking the second partial derivative with respect to δ and σ_V^2 yields Proposition 4 because $\text{var}(\tilde{V}|\mathcal{F}_U^j) = (1 - \rho_U)\sigma_V^2$. □

Proposition 5: Liquidity shocks and inter-dealer volume

Proof. The inter-dealer trading volume, θ^{j*}, is a non-decreasing function of the uninformed liquidity shock $\tilde{Z}^j$ when the positive effect of $\tilde{Z}^j$ on the net trading volume $(\alpha^{j*} - \beta^{j*})$ dominates the negative

impact $\tilde{Z}^j$ has on the equilibrium price P^*, i.e., when $\frac{N_I^j \nu + 2N_U^j}{\bar{N}_j + 1} > \frac{N_U^j}{\bar{N}}$.

$$\frac{\partial \theta^{j*}}{\partial \tilde{Z}^j} > 0 \iff \frac{N_I^j \nu + 2N_U^j}{\bar{N}_j + 1} > \frac{N_U^j}{\bar{N}} \tag{A.29}$$

This always holds because $\bar{N} = \sum_{j=1}^{M} \bar{N}_j$. And thus

$$\frac{N_I^j \nu}{\bar{N}_j + 1} + \frac{N_U^j(\bar{N} - \bar{N}_j) + N_U^j(\bar{N} - 1)}{(\bar{N}_j + 1)\bar{N}} > 0. \tag{A.30}$$

□

B. CLS Data

This appendix describes the CLS trade-recording process, data coverage, and time-series properties of volume variables.

B.1. CLS Data Collection

The dataset consists of hourly FX spot signed volumes settled by the CLS Group ("CLS"), aggregated and anonymized at the sector level. CLS operates the world's largest multi-currency cash settlement system, settling FX transactions on a payment-versus-payment (PvP) basis for 18 currencies. Acting as a third-party facility, CLS reduces counterparty credit risk by settling both sides of FX transactions without being a principal. Glowka and Nilsson (2022) estimate about half of global FX turnover in 2022 was settled through risk-mitigation mechanisms like PvP. CLS settlements form the largest component of these mechanisms with a volume share of 72%.

CLS settles trades for direct settlement members (76 large financial institutions) and third-party members (over 25,000 banks, non-bank financial firms, and non-financial corporations).[15] Direct members send trade instructions directly to CLS, while third-party members use one of the settlement members. This ensures CLS data reflect trades among direct members and between members and other clients. Our sample of inter-dealer trades represents direct members, and retail trades represent third-party members.

CLS creates a sector-level dataset of signed order flow by aggregating trades into hourly observations. It records buy and sell volumes and counts executed between Sunday 9 pm and Friday 9 pm (GMT) to match the FX trading week. Trades are grouped into sectors based on participant type: dealers/banks, funds, non-bank financial firms, and non-financial corporations. Funds

[15] The list of direct settlement members is provided on CLS website.

include pension, hedge, and sovereign wealth funds. Non-bank financial firms include insurance companies, brokers, and clearing houses. Non-bank financial firms, funds, and corporations are price takers; banks act as market makers. Both parties to a trade submit transaction details to CLS, which identifies the product type (spot, forward, or swap) and constructs hourly sector-level datasets after removing duplicates. Data are reported separately for buy and sell trades in the base currency from the price-takers' perspective. Inter-dealer trades are reported as gross volume since both sides are in the same sector.

CLS confirms most trades within 2 minutes of execution (Hasbrouck and Levich, 2017), using the earliest of two reports for the timestamp. To publish data, CLS requires at least two trades per currency-time combination. The final dataset includes all matched trades in eligible currencies between CLS members with at least two trades during the reporting period.[16]

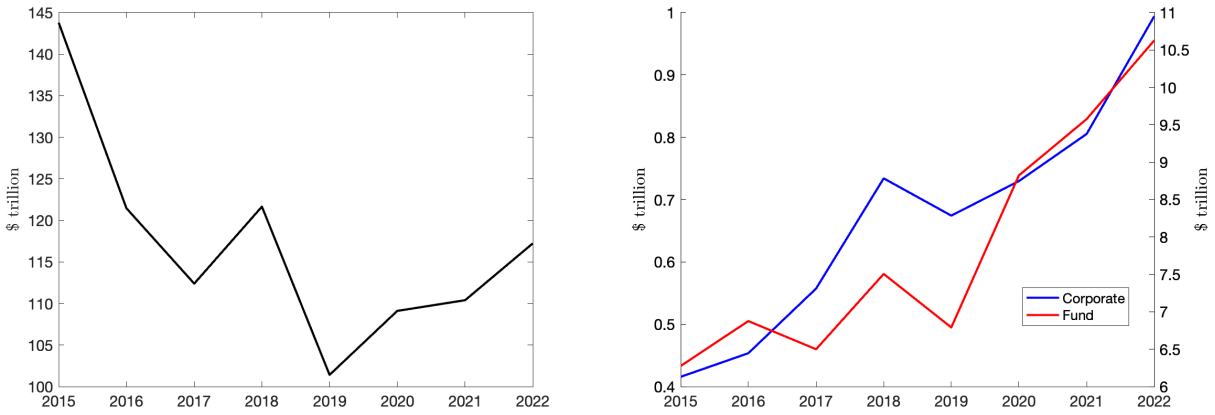
B.2. Coverage and Representativeness

Using the April 2022 BIS triennial survey as a benchmark (BIS, 2022), we estimate our CLS FX spot data covers 22% of the market. Table A2 shows our data's market coverage and representativeness in terms of currencies and sectors. Coverage is consistent across major currencies, with the highest being the inter-dealer market at 33%, followed by funds and corporate. Hasbrouck and Levich (2017) estimate CLS data cover 37.2% of global spot FX turnover, 14.4% of forwards, and 35.1% of FX swaps, corroborating representation by currency. These comparisons are likely lower bounds, as Hasbrouck and Levich (2017) and Cespa, Gargano, Riddiough, and Sarno (2022) note a significant fraction of BIS-reported volume is interbank trading across desks and double-counts prime-brokered trades. Our sample omits 9 currency pairs with trivial end-user volumes and excludes the non-bank financial sector to focus on model predictions.

[16] More details are available on CLSMarketData.

Our sample period spans from January 1, 2015 to June 30, 2022, covering hourly FX trading volume for 18 currencies and 31 currency pairs. Figure A1 shows yearly total volume for the inter-dealer segment in panel (a) and the price-taker segment in panel (b). During this time, the BIS conducted three triennial FX market volume surveys. These surveys support the representativeness of CLS data. First, the inter-dealer segment is much larger than the client segments. Second, BIS (2022) indicates that FX spot turnover declined between 2016 and 2019 and recovered in 2022, as shown in panel (a) of Figure A1.

Figure A1: Annual Traded Volume



(a) Inter-dealer segment

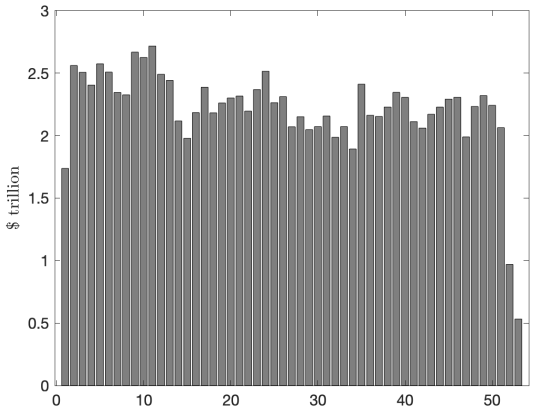
(b) Retail segment

Notes: This figure plots the annual $-equivalent FX spot volume settled among dealers in panel (a) and between dealers and price-takers in panel (b) in the CLS data for January 2015 through June 2022. Volume for 2022 is scaled for visual comparison. In panel (b), total volume (buy plus sell) for non-financial corporations is shown in blue and for funds in red.

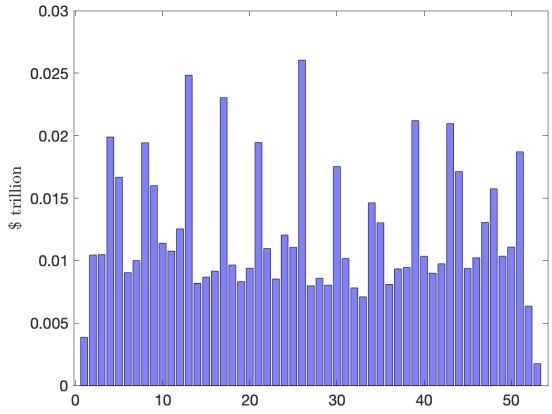
B.3. Time-series Properties

FX trading volume varies by week and time of day. Figure A2 shows weekly spot volume traded by the three agents, with a higher volume at the end of the month and a lower volume during the holidays. year. The corporate retail segment has noticeable month-end spikes (see Panel (b)).

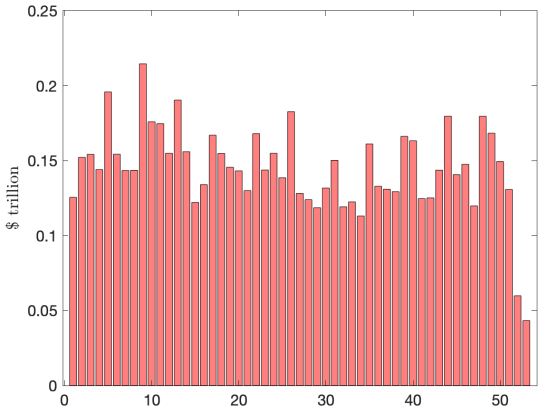
Figure A2: Weekly Average Trading Volume



(a) Inter-dealer market



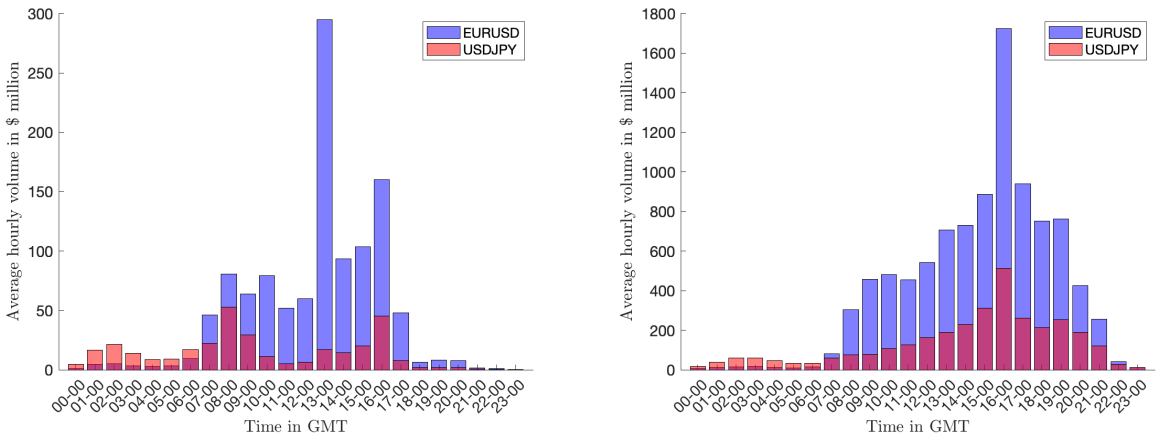
(b) Corporate retail segment



(c) Fund retail segment

Notes: This figure shows the average total weekly absolute net volumes traded in the inter-dealer segment (panel (a)), the corporate retail segment (panel (b)) and the fund retail segment (panel (c)). The sample data is from January 2015 to June 2022.

Figure A3: Intra-day Net Volume



(a) Corporate net volume

(b) Fund net volume

Notes: This figure shows the average hourly absolute net volumes traded in the corporate retail segment (panel (a)) and the fund retail segment (panel (b)) for two currencies: EURUSD (in blue) and USDJPY (in red). The sample data is from January 2015 to June 2022.

C. Variable construction

We measure the 10-minute intra-hour returns' standard deviation to assess two-way price movements when end-user order flow occurs. Converting the 10-minute prices into returns r, we use these six observations per hour to compute the standard deviation (Std. Dev.$_t$) as:

$$\text{Std. Dev.}_t = \sqrt{\frac{1}{5}\sum_{i=1}^{6}(r_i - \bar{r})^2}, \tag{A.31}$$

where r_i represents returns observed in i-th interval within the observation hour t.

Our second volatility measure is the absolute return, defined as the absolute change in spot price within the hour of order flow, scaled by the starting price.

$$\text{Return}_t \text{ (abs.)} = \frac{|Price_{t+1} - Price_t|}{Price_t} \tag{A.32}$$

The range in returns measures the maximum absolute deviation from the starting price, scaled by the starting price:

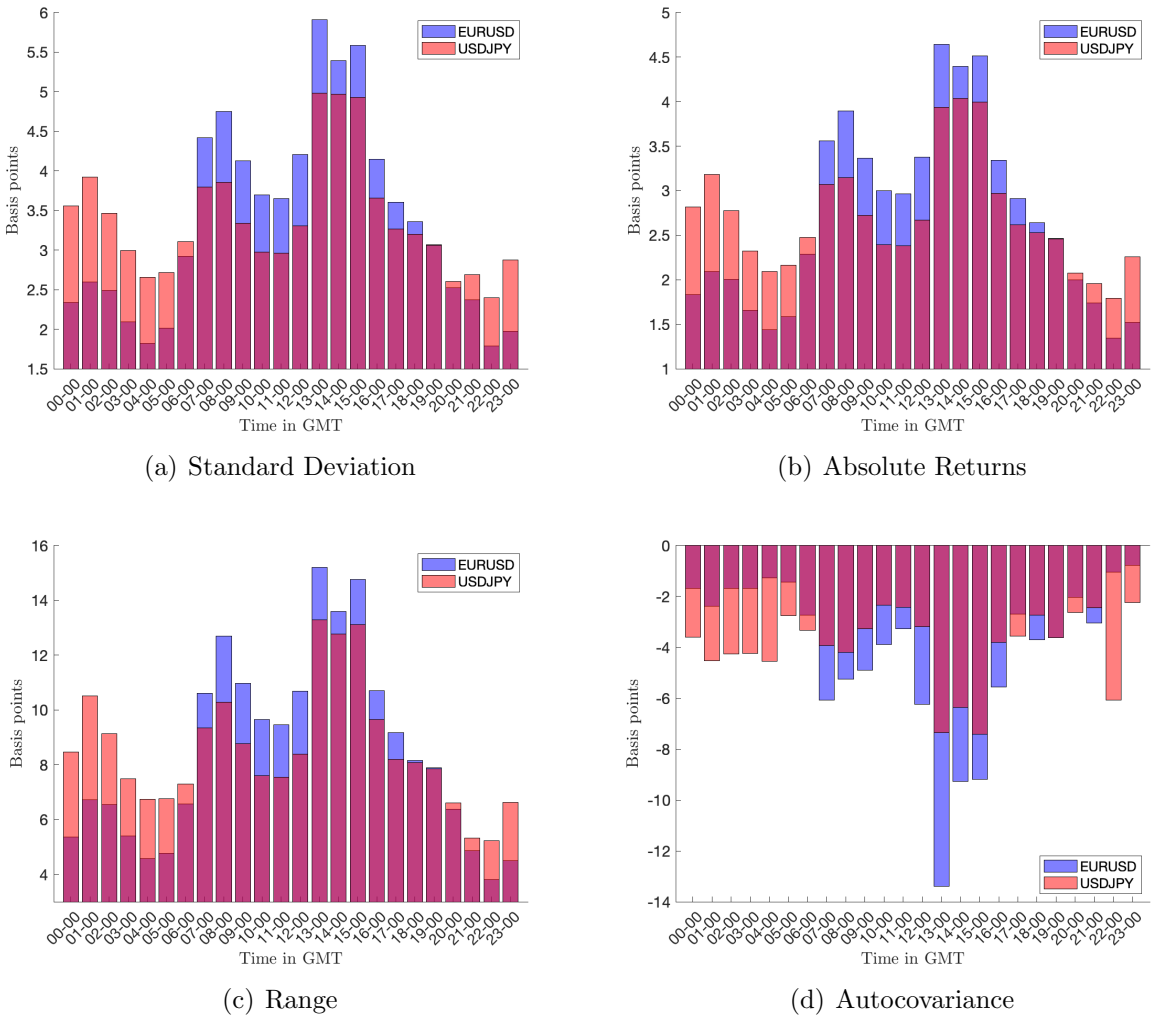
$$\text{Range}_t = \frac{|Price_{max} - Price_{min}|}{Price_t}. \tag{A.33}$$

Measuring noise in returns

We compute the intra-hour return auto-covariance using six observations per hour. This measure captures mean reversion in currency returns and is more negative with greater price noise. The measure is defined as

$$\text{Autocov.}_t = \frac{1}{5}\sum_{i=1}^{5}(r_i - \bar{r})(r_{i+1} - \bar{r}). \tag{A.34}$$

Figure A4: Intra-day Volatility Patterns for EURUSD and USDJPY



(a) Standard Deviation

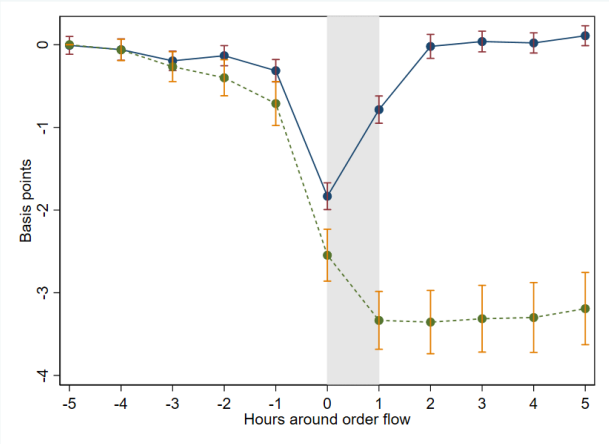
(b) Absolute Returns

(c) Range

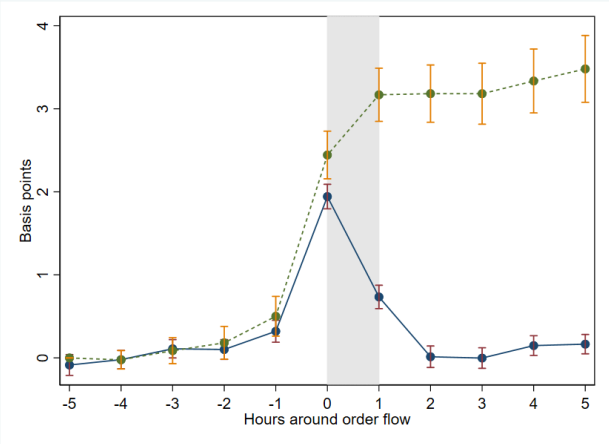
(d) Autocovariance

Notes: This figure shows the average levels of the standard deviation of 10-minute intra-hour return in panel (a), the hourly absolute returns in panel (b), the hourly return range in panel (c), and the auto-covariance of intra-hour returns in panel (d); measured using the six 10-minute observations in each hour for two currencies: EURUSD (in blue) and USDJPY (in red). The sample data is from January 2015 to June 2022.

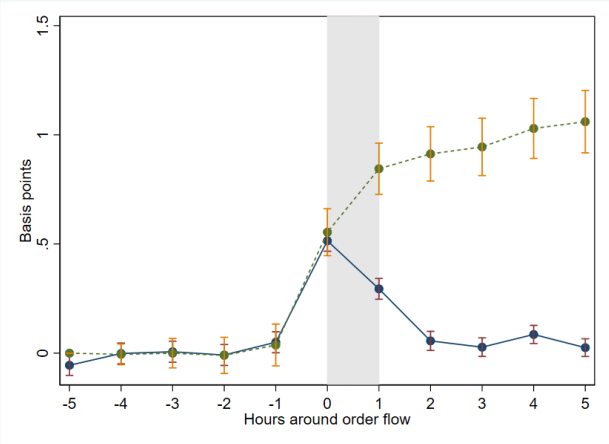
Figure A5: Retail Net Order Flow and Realized Returns



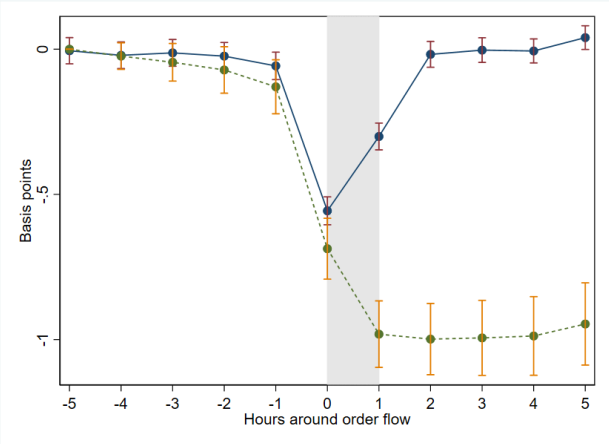
(a) Corporate Net Buy



(b) Corporate Net Sell



(c) Fund Net Buy



(d) Fund Net Sell

Notes: This figure shows end-users reacting in the opposite direction to realized FX spot returns. Blue lines plot hourly returns, orange lines plot cumulative returns starting 5 hours before order flow occurs. Vertical bars indicate 95% confidence intervals; shaded region shows execution hours. Panel (a): corporations buy the base currency when its price falls. Panel (b): corporations sell when price rises. Panel (c): funds buy when price rises. Panel (d): funds sell when price falls. Data: hourly signed order flow in 31 FX spot currency pairs from CLS Group.

Table A1: Currency Pairs in the Sample

Currency pair	Base currency	Terms currency	Group
AUDJPY	AUD : Australian dollar	JPY : Japanese yen	Non-G10
AUDUSD	AUD : Australian dollar	USD : US dollar	G10
CADJPY	CAD : Canadian dollar	JPY : Japanese yen	Non-G10
CHFJPY	CHF : Swiss franc	JPY : Japanese yen	Non-G10
EURAUD	EUR : Euro	AUD : Australian dollar	Non-G10
EURCAD	EUR : Euro	CAD : Canadian dollar	Non-G10
EURCHF	EUR : Euro	CHF : Swiss franc	Non-G10
EURDKK	EUR : Euro	DKK : Danish krone	Pegged
EURGBP	EUR : Euro	GBP : British pound	Non-G10
EURJPY	EUR : Euro	JPY : Japanese yen	Non-G10
EURNOK	EUR : Euro	NOK : Norwegian krone	Non-G10
EURNZD	EUR : Euro	NZD : New Zealand dollar	Non-G10
EURSEK	EUR : Euro	SEK : Swedish krona	Non-G10
EURSGD	EUR : Euro	SGD : Singapore dollar	Non-G10
EURUSD	EUR : Euro	USD : US dollar	G10
GBPAUD	GBP : British pound	AUD : Australian dollar	Non-G10
GBPCAD	GBP : British pound	CAD : Canadian dollar	Non-G10
GBPCHF	GBP : British pound	CHF : Swiss franc	Non-G10
GBPJPY	GBP : British pound	JPY : Japanese yen	Non-G10
GBPUSD	GBP : British pound	USD : US dollar	G10
NZDUSD	NZD : New Zealand dollar	USD : US dollar	G10
USDCAD	USD : US dollar	CAD : Canadian dollar	G10
USDCHF	USD : US dollar	CHF : Swiss franc	G10
USDDKK	USD : US dollar	DKK : Danish krone	G10
USDHKD	USD : US dollar	HKD : Hong Kong dollar	Pegged
USDJPY	USD : US dollar	JPY : Japanese yen	G10
USDMXN	USD : US dollar	MXN : Mexican peso	Non-G10
USDNOK	USD : US dollar	NOK : Norwegian krone	G10
USDSEK	USD : US dollar	SEK : Swedish krona	G10
USDSGD	USD : US dollar	SGD : Singapore dollar	Non-G10
USDZAR	USD : US dollar	ZAR : South African rand	Non-G10

Notes: This table shows the 31 currency pairs in our sample, categorized as G10, Non-G10, or Pegged, based on trading liquidity and exchange-rate regime.

Table A2: CLS Data Coverage and Representativeness

Panel A: Share of volume by currency	BIS ($ billion)	CLS Share (%)
Total	2,104	22
USD	1,807	22
EUR	616	28
JPY	439	24
GBP	231	30
AUD	156	20
CAD	128	45
CHF	88	25
Panel B: Share of volume by sector	**BIS ($ billion)**	**CLS Share (%)**
Reporting dealers + non-reporting banks	1,296	33
Institutional investors + hedge funds	450	8
Non-financial institutions	150	2

Notes: This table compares the FX spot transaction coverage and representativeness of CLS data with the BIS April 2022 FX turnover survey. Panel A shows the share of total and currency-specific volumes reported by the BIS and observed in CLS data. Panel B details the gross transaction volumes between reporting dealers and other sectors as per the BIS, along with the CLS data coverage. Access BIS data here. CLS volumes are averaged across all trading days in April 2022.

Table A3: Summary Statistics of Volume by Currency Pair

	Corporate net volume		Fund net volume		Inter-dealer volume	
	Mean	SD	Mean	SD	Mean	SD
AUDJPY	0.13	2.34	1.72	8.94	125.18	103.00
AUDUSD	0.72	16.49	27.14	67.26	877.03	675.44
CADJPY	0.06	0.91	0.70	5.76	22.53	33.76
CHFJPY	0.01	0.79	0.59	11.11	21.57	38.79
EURAUD	0.19	2.29	4.74	24.05	117.34	118.89
EURCAD	1.00	17.17	4.96	28.13	74.75	103.91
EURCHF	1.80	13.92	12.65	53.04	305.76	411.26
EURDKK	0.43	5.66	5.51	30.57	73.09	116.88
EURGBP	7.41	47.67	22.75	93.85	547.13	660.78
EURJPY	2.82	23.11	12.80	63.17	532.45	529.21
EURNOK	1.08	9.11	7.00	22.39	255.07	318.24
EURNZD	0.01	0.18	0.62	6.52	20.43	34.04
EURSEK	2.81	14.92	10.97	31.12	275.70	351.29
EURSGD	0.05	1.13	0.46	6.57	8.18	16.93
EURUSD	28.36	178.44	163.18	485.55	5,422.53	5,613.19
GBPAUD	0.01	0.51	3.25	22.14	47.36	71.92
GBPCAD	0.24	14.16	2.55	19.77	24.96	48.84
GBPCHF	0.13	2.10	2.41	23.21	25.79	44.62
GBPJPY	0.12	1.75	5.13	32.79	266.71	257.40
GBPUSD	7.23	75.73	92.92	336.71	2,258.38	2,403.43
NZDUSD	0.04	1.14	9.51	39.17	252.38	223.69
USDCAD	1.01	15.54	83.44	254.10	1,674.55	1,746.97
USDCHF	3.23	18.61	23.42	88.11	498.78	569.60
USDDKK	0.15	2.99	5.50	26.00	19.25	60.21
USDHKD	0.27	12.62	19.23	49.91	303.71	317.63
USDJPY	7.78	48.18	63.88	185.10	3,028.05	2,531.03
USDMXN	0.40	5.74	13.57	38.51	418.51	556.04
USDNOK	0.17	3.83	8.37	31.81	101.29	138.60
USDSEK	0.67	7.00	12.46	40.96	114.02	155.10
USDSGD	0.45	8.92	8.28	26.46	390.10	343.07
USDZAR	0.07	1.09	8.71	40.60	262.66	320.71

Notes: This table summarizes hourly FX spot volume ($ million) for 31 currency pairs. Corporate and fund net volumes are the absolute difference between buy and sell volumes per agent. Inter-dealer volume represents the total volume traded between banks.

Table A4: Summary Statistics of Volatility by Currency Pair

	Std. Dev.		Return (abs.)		Range		Autocov.	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
AUDJPY	5.17	4.36	9.97	11.75	13.10	12.03	-9.74	175.47
AUDUSD	4.63	3.45	8.88	9.89	11.67	9.83	-7.28	61.92
CADJPY	4.53	3.60	8.83	10.25	11.56	10.06	-6.68	62.72
CHFJPY	3.75	6.67	7.06	10.25	9.45	17.76	-7.52	366.41
EURAUD	4.17	3.36	7.95	9.39	10.57	9.38	-6.49	67.52
EURCAD	3.66	2.97	6.99	8.47	9.30	8.27	-4.76	33.09
EURCHF	2.55	6.51	4.64	8.22	6.35	15.93	-3.59	164.67
EURDKK	0.17	0.22	0.27	0.45	0.35	0.49	-0.03	0.70
EURGBP	3.53	3.12	6.69	8.65	8.87	8.28	-3.89	158.96
EURJPY	3.83	3.13	7.35	8.80	9.58	8.54	-5.84	92.23
EURNOK	4.01	4.36	7.50	10.05	9.82	10.94	-7.72	152.69
EURNZD	4.39	3.39	8.17	9.29	10.96	8.89	-7.59	89.11
EURSEK	3.01	2.74	5.54	6.84	7.35	7.30	-4.17	28.95
EURSGD	2.97	2.28	5.40	6.32	7.30	6.21	-3.28	20.70
EURUSD	3.37	2.76	6.48	7.83	8.47	7.71	-4.03	31.20
GBPAUD	4.52	3.63	8.51	9.95	11.36	9.63	-7.24	162.48
GBPCAD	4.01	3.37	7.56	9.56	10.10	9.09	-5.37	163.49
GBPCHF	4.06	6.67	7.62	11.27	10.21	16.90	-8.51	611.86
GBPJPY	4.63	4.03	8.98	11.37	11.70	11.09	-7.81	121.86
GBPUSD	3.86	3.35	7.47	9.62	9.73	9.18	-4.62	170.64
NZDUSD	4.86	3.48	9.21	10.03	12.15	9.48	-8.03	62.64
USDCAD	3.34	2.53	6.47	7.47	8.51	7.17	-3.42	28.02
USDCHF	3.51	6.36	6.65	9.79	8.81	16.02	-8.38	759.03
USDDKK	3.35	2.77	6.50	7.85	8.48	7.69	-3.99	32.01
USDHKD	0.26	0.29	0.49	0.74	0.62	0.80	-0.04	0.31
USDJPY	3.39	2.86	6.62	7.94	8.55	7.90	-3.95	46.94
USDMXN	5.52	4.85	10.93	13.91	14.25	14.05	-10.17	81.24
USDNOK	5.34	4.95	10.20	12.43	13.32	12.85	-12.59	181.19
USDSEK	4.52	3.59	8.71	9.99	11.40	10.03	-7.27	42.64
USDSGD	2.23	1.57	4.26	4.56	5.58	4.38	-1.62	9.29
USDZAR	7.15	5.78	13.86	16.01	17.97	16.22	-19.43	152.74

Notes: This table shows the hourly measures of return volatility in basis points for 31 currency pairs. Standard deviation, range, and auto-covariance are computed using price snapshots at 10-minute intervals, and absolute returns are based on prices at the start and end of each hour. See Appendix C for more details.

Table A5: G10 versus non-G10 (Alternative Measures of Volatility)

	Absolute Returns			
	(1)	(2)	(3)	(4)
$\widehat{\text{Corporate net volume}}_t$	0.1114***	0.0872**	0.1346***	0.1396***
	(0.042)	(0.036)	(0.049)	(0.050)
$\widehat{\text{Corporate net volume}}_t \times$ G10	-0.0980**	-0.0783**	-0.1158**	-0.1207**
	(0.042)	(0.036)	(0.049)	(0.050)
	Range			
$\widehat{\text{Corporate net volume}}_t$	0.1702***	0.1191***	0.1758***	0.1849***
	(0.059)	(0.045)	(0.062)	(0.064)
$\widehat{\text{Corporate net volume}}_t \times$ G10	-0.1516**	-0.1065**	-0.1521**	-0.1610**
	(0.059)	(0.045)	(0.062)	(0.064)
	Auto-covariance			
$\widehat{\text{Corporate net volume}}_t$	-0.8964*	-0.9151*	-1.0915**	-1.0879**
	(0.462)	(0.477)	(0.548)	(0.547)
$\widehat{\text{Corporate net volume}}_t \times$ G10	0.8244*	0.8207*	0.9660*	0.9658*
	(0.454)	(0.460)	(0.526)	(0.526)
Observations	1,443,049	1,439,584	1,439,584	1,439,584
Volatility and volume Lags	N	Y	Y	Y
Controls	Y	Y	Y	Y
Currency FE	N	N	Y	N
Time FE	N	N	Y	N
Currency X Time FE	N	N	N	Y

Notes: This table displays the heterogeneous impact of liquidity shocks on return volatility in G10 versus non-G10 currency markets. We interact absolute corporate net volume with a G10 currency pairs indicator variable to assess whether the impact of corporate liquidity shocks differs across currency types (see Table A1 for a list of currencies in G10). We control for absolute fund net volume, standard deviation of returns over the previous day and week, and log changes in spot rate. Standard errors, clustered by currency-time, are in parentheses. $^{*}p < 0.1;^{**}p < 0.05;^{***}p < 0.01$.

Table A6: Currency Heterogeneity Results

Panel A: USD pairs	Standard deviation			
	(1)	(2)	(3)	(4)
$\widehat{\text{Corporate net}}$ volume$_t$	0.0625**	0.0459**	0.0649**	0.0673**
	(0.026)	(0.021)	(0.028)	(0.028)
Corporate $\widehat{\text{net volume}}_t \times$ USD	-0.0544**	-0.0394*	-0.0543**	-0.0567**
	(0.026)	(0.020)	(0.027)	(0.028)
Panel B: Most liquid pairs				
$\widehat{\text{Corporate net}}$ volume$_t$	0.0486***	0.0363***	0.0512***	0.0533***
	(0.015)	(0.012)	(0.016)	(0.016)
Corporate net $\widehat{\text{volume}}_t \times$ Most Liquid	-0.0455***	-0.0347***	-0.0474***	-0.0494***
	(0.015)	(0.012)	(0.016)	(0.016)
Panel C: Pegged pairs				
$\widehat{\text{Corporate net}}$ volume$_t$	0.0178***	0.0141***	0.0194***	0.0198***
	(0.005)	(0.005)	(0.007)	(0.007)
Corporate net $\widehat{\text{volume}}_t \times$ Pegged	-0.0149**	-0.0114**	-0.0145**	-0.0153**
	(0.006)	(0.005)	(0.007)	(0.007)
Observations	1,443,049	1,439,584	1,439,584	1,439,584
Volatility and volume Lags	N	Y	Y	Y
Controls	Y	Y	Y	Y
Currency FE	N	N	Y	N
Time FE	N	N	Y	N
Currency X Time FE	N	N	N	Y

Notes: This table displays the heterogeneous impact of liquidity shocks on return volatility in USD currency pairs (Panel A), the most liquid currencies (Panel B) and among pegged currencies (Panel C). We interact the instrumented absolute corporate net volume with a given currency-characteristic indicator to assess whether the impact of corporate liquidity shocks differs across currency types (see Table A1 for a list of currency characteristics). We control for absolute fund net volume, standard deviation of returns over the previous day and week, and log changes in spot rate. Standard errors, clustered by currency-time, are in parentheses. $^{*}p < 0.1;^{**}p < 0.05;^{***}p < 0.01$.

Disclosure Statement

Petra Sinagl: I have nothing to disclose.

Umang Khetan: I have nothing to disclose.