Blockchain Currency Markets

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Abstract

We conduct the first comprehensive study of blockchain currencies—stablecoins pegged to fiat currencies and traded on decentralized exchanges. Using transaction-level data linked to wallet characteristics, we show that prices in these markets are generally efficient, though constrained by blockchain-specific frictions such as gas fees and Ether volatility. Decentralized exchange rates closely track traditional currency markets through arbitrage and informed trading. Traders with significant market share and access to primary markets have greater price impact, reflecting informational advantages. While blockchain markets may improve access for customers excluded from traditional venues, their scalability depends on addressing frictions inherent to decentralized trading.

Keywords: Stablecoins, foreign exchange, blockchain, price efficiency, market resilience, microstructure.

JEL Classifications: D53, E44, F31,G18, G20, G28

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1 Introduction

Decentralized finance (DeFi) represents a paradigm shift in the financial landscape, offering global access to financial services through blockchain-based protocols. By replacing traditional intermediaries with smart contracts, DeFi promises improvements in access, transparency, and automation. A central application is in currency markets—the largest and most liquid financial markets globally, with average daily turnover exceeding $7.5 trillion as of 2022.[1] Decentralized exchanges (DEXs) enable the trading of stablecoins pegged to fiat currencies and are increasingly being explored as infrastructure for future cross-border payment systems. For example, the BIS Innovation Hub's Project Mariana investigates how decentralized platforms could facilitate foreign exchange (FX) trading and settlement through greater efficiency, transparency, and interoperability.[2]

This paper provides the first comprehensive study of blockchain currency markets, focusing on the EURC/USDC pair traded on Uniswap V3, a leading DEX. EURC and USDC are fiat-backed stablecoins, pegged to the EUR and USD respectively, and both issued by Circle. We examine the efficiency of price formation, the sources of trading frictions, and the linkages between decentralized and traditional FX markets. An important question in evaluating the feasibility of blockchain-based FX markets is whether alternative trading structures can deliver improvements in pricing, access, and welfare. Assessing whether these markets operate efficiently, and how they connect to their traditional FX counterparts, is crucial for understanding their broader viability. A further consideration is transaction costs. For blockchain markets to scale and compete with existing FX infrastructure, they must offer a cost advantage, particularly for participants excluded from institutional pricing in traditional venues.

The primary contribution of our paper is to analyze how blockchain trading connects to traditional FX markets, highlighting the role of both information and arbitrage in linking these venues. Using a rich dataset of transaction-level blockchain data, we identify different market participants and analyze their trading activity and how it reflects the processing of fundamental information in the traditional EUR/USD currency market. We

[1] See Bank for International Settlements (2022), *Triennial Central Bank Survey of Foreign Exchange and Over-the-Counter (OTC) Derivatives Markets in 2022*. Available at: https://www.bis.org/statistics/rpfx22.htm

[2] See BIS Innovation Hub (2023), "Project Mariana: Cross-border trading and settlement using wholesale CBDC and DeFi infrastructure." Available at: https://www.bis.org/about/bisih/topics/cbdc/mariana.htm

classify these participants into three categories: *sophisticated traders*, who dominate trading volumes and actively engage in both informational trading and arbitrage; *primary dealers*, who have access to fiat currency deposits and withdrawals with the stablecoin issuer; and *liquidity providers (LPs)*, who supply liquidity but lack direct access to primary markets. A key advantage of blockchain data is its transparency and granularity, which allow us to clearly separate primary dealers and liquidity providers—groups that are often difficult to distinguish in traditional financial markets (Hortaçsu and Sareen, 2005; Hagströmer and Menkveld, 2019).[3] Our analysis shows how blockchain markets both correct price discrepancies with traditional FX markets through arbitrage, and reflect the processing of fundamental information, with evidence that sophisticated traders and primary dealers possess informational advantages consistent with the asymmetric information paradigm (Ranaldo and Somogyi, 2021).

We begin our analysis by documenting stylized facts on market efficiency and trading costs in blockchain-based currency markets. First, EURC/USDC prices on DEXs exhibit persistent but modest deviations from the CLS benchmark EUR/USD rate, averaging 24 basis points. These deviations largely remain within arbitrage bounds: only 3–5% of transactions exceed bounds once gas fees, slippage, LP fees, and exchange fees are accounted for. Second, variation in peg efficiency is primarily driven by blockchain-specific frictions, such as gas fees and Ether volatility. In contrast, proxies for traditional intermediary constraints have no explanatory power, suggesting that balance sheet frictions do not spill over into blockchain currency markets. Third, EURC/USDC prices respond promptly to macroeconomic news, including FOMC announcements, consistent with informational efficiency.

We next examine transaction costs at the wallet level, decomposing total costs into gas fees, LP fees, and slippage. These costs vary significantly across trader types. Gas fees dominate for smaller accounts, while slippage becomes more pronounced for larger traders. Median total costs range from 20 to 50 basis points. While these costs are much larger than that faced by inter-dealer markets, they are comparable to those faced by less privileged OTC clients, who may pay spreads of up to 50 basis points (Hau et al., 2021). While blockchain markets are less scalable than traditional platforms, they may

[3] LPs are analogous to market makers in traditional limit order books, providing liquidity and earning fees based on their stake in the pool and trading volume.

offer improved access and pricing transparency for users excluded from institutional FX trading.

Building on these facts, we examine how blockchain trading connects to traditional FX markets. Continuous Linked Settlement (CLS) data, which captures global FX trading volumes categorized by sectors such as interbank, bank-fund, bank-non-financial, and bank-corporate trading volume, provides a benchmark for traditional market activity. We find a significant relationship between blockchain trading volumes and interbank activity.

Blockchain trading typically aligns closely with traditional market hours, reflecting two mechanisms. The first channel, which we label as *feedback trading*, occurs when blockchain activity corrects price discrepancies between EURC/USDC and EUR/USD through arbitrage. The second channel, which we label as the *asymmetric information* channel, reflects the processing of fundamental news, as traders incorporate macroeconomic information during traditional market openings.

Evidence supports both mechanisms. Blockchain order flow frequently corrects price deviations between EURC/USDC and EUR/USD, suggesting active arbitrage trading dominated by sophisticated traders. These traders, characterized by high trading frequency and substantial capital, are better positioned to exploit arbitrage opportunities compared to LPs or primary dealers, whose smaller transaction sizes and higher proportional costs limit their arbitrage activity.

Blockchain markets also process fundamental information. During the USDC depegging event on March 11, 2023—when scrutiny of USDC reserves at Silicon Valley Bank (SVB) caused USDC to drop to 87 cents—sophisticated traders predominantly bought EURC while selling USDC, leveraging their knowledge of USDC's backing. In contrast, LPs exhibited no significant changes in order flow, consistent with their role as uninformed liquidity providers focused on inventory management rather than reacting to price signals.

To assess whether blockchain order flow predicts traditional FX rates and reveals asymmetric information among participants, we use a structural vector autoregression (SVAR) framework that accounts for the persistent and endogenous interactions between blockchain order flow and price movements. Our baseline specification assumes that blockchain order flow impacts prices contemporaneously, while price shocks affect subsequent trading behavior with a lag, following the identification approach of Hasbrouck (1991). By disaggregating order flow into distinct trader categories, we differentiate the price impact of sophisticated traders, primary dealers, and LPs. Our findings indicate that sophisticated traders and primary dealers exhibit significant and persistent price impacts, reinforcing their role in incorporating fundamental information into prices. In contrast, LPs display an insignificant or weakly negative price impact for DEX returns, confirming their primary function as liquidity providers rather than informed traders.

To distinguish informational order flow from arbitrage-based behavior across markets, we decompose blockchain order flow into a predicted component driven by lagged price differences between DEX and traditional FX markets and a residual component. The predicted component captures feedback trading that arises from arbitrage incentives between venues, while the residual serves as a proxy for information-motivated trading. We find that only the residual component yields a significant and persistent price impact on CLS benchmark returns. In contrast, the feedback component is statistically insignificant, particularly for primary dealers where standard error bands are wide. This suggests that arbitrage activity between venues does not drive the permanent price effects observed, which are instead consistent with the processing of fundamental information.

Finally, we conduct several robustness tests to ensure our results are not driven by alternative explanations. First, intra-day analysis shows that price impacts for sophisticated traders and primary dealers are concentrated between 13:00–15:00 UTC, aligning with traditional trading hours when news on exchange rate fundamentals is more prevalent. In contrast, liquidity providers show no impact during this window. Second, controlling for net liquidity provision in our SVAR estimation confirms that shifts in liquidity do not drive our results. Third, we show that while one wallet engages in sophisticated strategies such as just-in-time (JIT) liquidity provision, such behavior is infrequent in the EURC/USDC market over our sample period. Overall, these tests confirm that the observed price impacts reflect informed trading on fundamentals rather than being driven by changes in strategic liquidity provision.

Related Literature. This paper contributes to several strands of literature on stablecoins, decentralized exchanges, and FX market microstructure.

First, we contribute to the growing research on stablecoins, particularly work that examines their interactions with traditional financial markets, the operation of arbitrage mechanisms, price dynamics, and the conditions under which stablecoins are vulnerable to speculative attacks. This literature includes studies of run risk and speculative pressure that threaten stablecoin pegs, as well as analyses of de-pegging episodes and price dynamics under stress (Barthelemy et al., 2023; Oefele et al., 2024; Eichengreen et al., 2023; Gorton et al., 2022; Lyons and Viswanath-Natraj, 2023; Kozhan and Viswanath-Natraj, 2021; Ma et al., 2025; Liu et al., 2023; Routledge and Zetlin-Jones, 2021; Li and Mayer, 2022; d'Avernas et al., 2022; Bertsch, 2023; Aldasoro et al., 2023; Adams et al., 2023; Gorton et al., 2025). Our work is closest to Liu et al. (2023), who examine the TerraLuna de-pegging and how sophisticated investors capitalized on it, and to Adams et al. (2023), who assess trading costs on decentralized exchanges relative to remittance and payment systems. We show that blockchain currency markets are constrained price efficient: prices generally stay within arbitrage bounds despite frictions, and connections to traditional FX markets arise through both arbitrage and informed trading.

Second, we contribute to the literature on DEX market quality by examining market efficiency, liquidity provision, transaction costs, and connections between decentralized and centralized markets (Capponi and Jia, 2021; Hasbrouck et al., 2022; Lehar and Parlour, 2025; Barbon and Ranaldo, 2024; Foley et al., 2023; Malinova and Park, 2024; Fang, 2022; LI et al., 2023; Caparros et al., 2025; Lehar et al., 2025; Hansson, 2024; Klein et al., 2024; Capponi et al., 2024a). Building on Barbon and Ranaldo (2024), which focuses on internal DEX price efficiency, we use the transparency and granularity of blockchain data to identify informational advantages across trader types and to show how these participants connect decentralized and traditional FX markets through both feedback trading and the incorporation of fundamental information. We further assess transaction costs across trader types and test the viability of decentralized trading structures as potential alternatives to traditional OTC markets.

Finally, we highlight informational asymmetries among blockchain market participants, showing that sophisticated traders and primary dealers possess informational advantages, while liquidity providers act as passive participants focused on inventory rebalancing—akin to market makers in limit-order book markets (Hortaçsu and Sareen, 2005). We bridge the stablecoin literature with research on FX market microstructure and price formation in traditional financial markets (Evans and Lyons, 2002; Andersen et al., 2003; Berger et al., 2008; Rime et al., 2010; Kozhan and Salmon, 2012; Ranaldo and Somogyi, 2021; Huang et al., 2025; Krohn et al., 2024; Hagströmer and Menkveld, 2019). Specifically, we contrast algorithmic bonding curves on Uniswap V3 with traditional FX pricing models based on portfolio shifts and inventory management (Evans and Lyons, 2002). Our findings show that blockchain order flow predicts EUR/USD returns, suggesting that sophisticated traders and primary dealers actively incorporate fundamental information into their trading decisions, consistent with the asymmetric information paradigm in FX markets (Ranaldo and Somogyi, 2021).

The remainder of the paper is structured as follows. Section 2 describes the institutional setting and data. Section 3 analyzes market efficiency and transaction costs in decentralized currency markets, focusing on arbitrage bounds and trader-level frictions. Section 4 examines the connections between blockchain trading and traditional markets, focusing on the information content of different market participants. Section 5 concludes.

2 Data and Institutional Background

2.1 DEX Market and AMM Functions

Figure 1 illustrates the structural differences between traditional and blockchain-based currency markets, with a particular focus on liquidity provision and price stabilization. In traditional FX markets, the inter-dealer market is central to price discovery, with dealer banks conducting market making and providing liquidity to customers while trading among themselves to manage inventories and facilitate price formation. Corporates, investment funds, and non-bank financial institutions typically access FX liquidity through these dealer banks. Since the early 1990s, electronic trading platforms such as Refinitiv and EBS have supported this structure by enabling dealers to post bid and ask quotes on centralized limit order books (LOBs) (see King et al., 2012; Chaboud et al., 2023). Dealer banks contribute to FX price formation through the information embedded in customer and inter-dealer order flow, consistent with the inventory and portfolio-shift models of Evans and Lyons (2002) and related work (Bjønnes and Rime, 2005; Huang et al., 2023).

By contrast, blockchain-based markets operate under a decentralized structure in which primary issuance and secondary market trading are disintermediated. In the primary market, the stablecoin treasury—managed by Circle—mints EURC and USDC and distributes tokens to users who interact directly with the issuer, referred to here as *primary dealers*. In the secondary market, tokens can be used in multiple applications, including trading on DEXs or CEXs, depositing in lending and liquidity protocols, or facilitating cross-border payments and remittances (Adams et al., 2023). On DEXs, trades are executed via AMM smart contracts, and market participants include LPs, arbitrageurs, and algorithmic traders, each playing distinct economic roles.

[INSERT FIGURE 1 ABOUT HERE]

Primary dealers play a central role in arbitraging price deviations between primary and secondary markets. A defining feature of EURC and USDC is the issuer's redemption commitment at par—1 EURC = 1 EUR and 1 USDC = 1 USD. This peg is enforced by arbitrage. When USDC trades above 1 USD in the secondary market, primary dealers can deposit 1 USD with Circle to mint 1 USDC, then sell it at a premium. This increases circulating supply and exerts downward price pressure, restoring parity. Conversely, if USDC trades below 1 USD, dealers can buy the token at a discount and redeem it for 1 USD, reducing supply and pushing the price back toward par.

Further details on the mechanics of stablecoin issuance and arbitrage are provided in Appendix C.

2.1.1 Uniswap V2 Bonding Curves

Uniswap is a decentralized AMM protocol implemented as a suite of non-custodial smart contracts on the Ethereum blockchain. The original version (V1) launched in November 2018, and the upgraded V2 contracts were deployed in May 2020.[4] By replacing centralized order books with automated market making, Uniswap has become a core component of the DeFi ecosystem, enabling token swaps and permissionless liquidity provision.

Uniswap V2 operates according to a constant-product pricing rule. Let L_{EURC} and L_{USDC} denote the on-chain reserves of EURC and USDC in a liquidity pool. The smart contract enforces the invariant:

$$k = L_{EURC} \cdot L_{USDC}, \tag{1}$$

which must hold before and after each trade. A swap that removes $\Delta L_{EURC} > 0$ units of EURC and adds USDC updates the reserves to maintain (1). The marginal price of EURC

[4] See Adams et al. (2023) and the Uniswap V2 whitepaper (https://uniswap.org/whitepaper-v2.pdf).

in terms of USDC is:

$$p_{EURC/USDC} = \frac{L_{USDC}}{L_{EURC}}. \tag{2}$$

Because (1) is deterministic and publicly observable, price discovery is algorithmic, and liquidity is continuously available provided both token reserves remain strictly positive.

We illustrate the mechanics of price formation and liquidity provision under the Uniswap V2 constant product formula. For example, a pool with 100 EURC and 110 USDC implies $k = 11{,}000$ and an initial exchange rate of 1.10 USDC per EURC.

[INSERT FIGURE 2 ABOUT HERE]

Panel (a) of Figure 2 illustrates two key dynamics. The left side shows a token swap that moves the pool along the bonding curve. Initially, the system is at equilibrium point $E_0 = [L_{USDC}, L_{EURC}]$. Suppose a trader contributes $\Delta L_{EURC} > 0$ units of EURC in exchange for USDC. The updated EURC reserve is $L'_{EURC} = L_{EURC} - \Delta L_{EURC}$, and the USDC reserve adjusts according to the constant product rule:

$$L'_{USDC} = \frac{k}{L'_{EURC}} = \frac{L_{USDC} \cdot L_{EURC}}{L_{EURC} - \Delta L_{EURC}}. \tag{3}$$

The new spot price—interpreted as the marginal rate of substitution—is:

$$p_{EURC/USDC} = \frac{L'_{USDC}}{L'_{EURC}} = \frac{k}{(L_{EURC} - \Delta L_{EURC})^2}. \tag{4}$$

Since $\Delta L_{EURC} > 0$, the EURC reserve decreases, and the price $p_{EURC/USDC}$ rises, reflecting an appreciation of EURC.

Numerical Example. Let $L_{EURC} = 100$, $L_{USDC} = 110$, and hence $k = 11{,}000$. A trader swaps $\Delta L_{EURC} = 5$ EURC, reducing the EURC reserve to 95. Then:

$$L'_{USDC} = \frac{11{,}000}{95} \approx 115.789, \quad p_{EURC/USDC} = \frac{11{,}000}{95^2} \approx 1.219.$$

The price increases from 1.10 to approximately 1.219 USDC per EURC. The constant product condition holds as $95 \times 115.789 \approx 11{,}000$, up to numerical rounding.

The right side of Panel (a) illustrates the logic of liquidity provision. LPs must contribute both assets in proportion to the current exchange rate to avoid shifting the relative price. Given a price of 1.10 USDC per EURC and reserves of 100 EURC and 110 USDC, an LP must supply 10 EURC and 11 USDC to maintain the pool's price ratio. This results in a parallel outward shift of the bonding curve to a new point E_2, increasing total liquidity while preserving the pricing function.

2.1.2 Uniswap V3: Concentrated Liquidity and Tick-Based Pricing

Uniswap V3 introduces two major innovations relative to V2: (i) the ability for LPs to allocate capital within a user-defined price range, and (ii) a multi-fee tier (MFT) structure that segments liquidity across pools with different trading fees.[5]

Launched in July 2021, Uniswap V3 allows LPs to specify a price interval $[p_a, p_b]$ over which their liquidity is active. Within this range, the reserves of EURC and USDC are denoted by L_{EURC} and L_{USDC}, respectively. The AMM pricing function is given by a bonding curve:

$$\left(L_{EURC} + \frac{L}{\sqrt{p_b}}\right)\left(L_{USDC} + L\sqrt{p_a}\right) = L^2, \tag{5}$$

where L denotes the virtual liquidity. This framework generalizes the constant-product rule by enabling LPs to concentrate liquidity at specific prices, thereby replicating the functionality of a limit order book.

In Uniswap V3, prices are discretized into ticks, indexed by i, where the price at tick i is given by:

$$p_i = 1.0001^i.$$

The spacing between ticks is set at the pool level. For example, the EURC/USDC 0.05% fee pool uses a tick spacing of 10, meaning liquidity positions can only be initialized at price levels separated by approximately 10 basis points.[6] Liquidity providers allocate liquidity over chosen tick intervals, concentrating their capital within specific price ranges to improve capital efficiency and increase the fees earned when trading occurs within these ranges.

Panel (b) of Figure 2 depicts this mechanism. Using the Uniswap interface, LPs define a price range and the interface computes the token amounts and gas fees required. Unlike

[5] Barbon and Ranaldo (2024); Lehar et al. (2025) discuss the MFT system, which allows multiple pools per token pair, each with a distinct fee. Uniswap V3 supports four fee levels: 0.01%, 0.05%, 0.30%, and 1%. In our analysis, the EURC/USDC pair is traded in the 0.05% pool.

[6] Each tick represents a price change of approximately 1 basis point, since $1.0001 \approx 1 + 0.01\%$. A tick spacing of 10 means that initialized price levels must be at indices divisible by 10, corresponding to about 10 basis point increments. This is an approximation; the exact price difference depends on compounding of the 1.0001^i formula.

V2, LPs in V3 are not required to deposit both assets. If the specified range lies above the current market price (e.g., $p_a > p_{current}$), only EURC is deposited—effectively placing a sell limit order. Conversely, if the range lies below the market price, only USDC is deposited, akin to a buy limit order.

Liquidity Measurement. Following Klein et al. (2024), we define net liquidity based on "mint" and "burn" events recorded on-chain. Mints represent liquidity provision; burns represent withdrawal. Let $mint^{ask}$ and $burn^{ask}$ denote actions above the current price, and $mint^{bid}$ and $burn^{bid}$ those below. Then:

$$\begin{aligned} mint^{net} &= mint^{ask} - mint^{bid}, \\ burn^{net} &= burn^{ask} - burn^{bid}, \\ Liquidity^{net} &= mint^{net} - burn^{net}. \end{aligned}$$

A positive $Liquidity^{net}$ indicates net liquidity provision on the ask side—that is, more sell-side EURC liquidity has been added than removed.

We further partition liquidity by its proximity to the current market price. Positions within 100 basis points are labeled *best*, while those farther away are labeled *away*.[7]

2.2 Data

2.2.1 CLS EUR/USD Benchmark and Uniswap EURC/USDC Price

We source a benchmark EUR/USD rate from CLS. This provides a volume-weighted average price at five-minute intervals, which we aggregate to hourly and daily frequencies for our analysis. The data on EURC/USDC is constructed as the last price (both hourly and daily UTC time) using the history of DEX transactions collected from the Uniswap V3 EURC/USDC pool, which is obtained from the Subgraph API.[8]

Our CLS benchmark rate provides an effective benchmark for the EURC/USDC rate from the Uniswap V3 pool. Panel (a) of Figure 3 plots EURC/USDC and EUR/USD prices, as well as the price difference between the EURC/USDC and EUR/USD price. Consistent with Adams et al. (2023), the EURC/USDC market tracks the traditional market and the

[7] This classification parallels traditional LOB usage: "best" orders reflect active trading intent, whereas "away" orders represent more passive positioning.

[8] API available at https://thegraph.com/hosted-service/subgraph/uniswap/uniswap-v3

average (absolute) deviation is 24 basis points. There is more volatility during the early period, which corresponds to low liquidity in the EURC/USDC pool. For this reason, our empirical analysis in Sections 3 and 4 begins on August 15, 2022. Another significant event is the de-pegging of USDC which occurred in March 2023. This event led to USDC trading at a discount due to concerns on the backing of USDC reserves that were held with Silicon Valley Bank. EURC/USDC traded at a relative premium compared to EUR/USD rates during the days of March 11-12 2023.

[INSERT FIGURE 3 ABOUT HERE]

2.2.2 DEX Trading Volume and Liquidity Provision

The Uniswap V3 dataset contains the complete history of "swap" transactions, which represent all trades involving the purchase of EURC (USDC) against the sale of USDC (EURC). These transactions are recorded at the wallet level, where each wallet corresponds to an Ethereum address that securely holds and manages tokens associated with that address.[9]

We complement this with a second dataset from Kaiko, a cryptocurrency market data provider offering regulatory-compliant, institutional-grade data. This dataset records all liquidity transactions executed by LPs, including the amounts of EURC and USDC added to or removed from the pool, along with the specified price range over which liquidity is allocated.[10]

A key feature of our analysis is the use of blockchain-level granularity to examine the heterogeneity of market participants. Specifically, we classify addresses into three categories: (i) traders with significant market share based on cumulative trading volume, (ii) traders who also act as LPs, and (iii) addresses that transact directly with the stablecoin Treasury.

Sophisticated Traders. In each month, we aggregate trading volume by wallets and select wallets that feature in the top 10. The share of top 10 addresses, including any

[9] Technically, a wallet stores the private keys required to access and authorize transactions from a specific Ethereum address.

[10] For example, if the current market price of EURC is 1.10 USDC, an LP may: (i) supply only EURC if the price range lies above 1.10; (ii) supply only USDC if the range lies below 1.10; or (iii) supply both tokens if the range includes the current market price. The precise token amounts are determined by the Uniswap V3 AMM pricing algorithm.

intersection with other categories, averages 52% of aggregate trading volume over our sample from August 15, 2022, to April 30, 2024. Importantly, in our empirical analysis, the category "Top 10" consists only of addresses that do not overlap with primary dealers or LPs, ensuring non-overlapping classifications.

Primary Dealers. Primary dealers are classified as wallets that have transacted with either the EURC or USDC Treasury in our sample.[11] To identify primary dealers, we cross-reference all wallets participating in the EURC/USDC DEX market with the complete set of addresses that have traded with either the USDC or EURC Treasury. These wallets interact with the Treasury by sending fiat currency—USD or EUR—and receiving the corresponding stablecoin (USDC or EURC) at the pegged rate of 1:1. Conversely, they may redeem stablecoins for fiat currency by returning tokens to the Treasury. Primary dealers, including any intersection with other categories, account for 7% of aggregate trading volume. In our regression specifications, the "Primary Dealers" category is non-overlapping, ensuring that primary dealers do not also belong to the "Top 10" or LP groups.

Liquidity Providers (LPs). Traders that provide liquidity are the subset of wallets that swap currencies and deposit or withdraw both currencies from the liquidity pool. LPs, including any intersection with other categories, account for 7% of aggregate trading volume. Similar to the other categories, LPs in our analysis are defined in a mutually exclusive manner.

Table 1 presents summary statistics on the number of transactions and volume per transaction for seven trader groups. The three main groups consist of sophisticated traders, primary dealers, and liquidity providers, with 76, 68, and 90 unique addresses identified for each group, respectively. To ensure clarity in our methodology, these categories are defined to be mutually exclusive: "Top 10" includes only traders ranked among the top 10 by trading volume who are not classified as primary dealers or LPs, while "Primary Dealers" and "LPs" are likewise defined as separate groups without overlap.

Beyond these three primary groups, we also examine sub-categories of traders who

[11] For example, the USDC Treasury address we use to retrieve the transaction history is "0xa0b86991c6218b36c1d19d4a2e9eb0ce3606eb48", and the EURC Treasury address is "0x1abaea1f7c830bd89acc67ec4af516284b1bc33c".

belong to multiple groups to further explore trading patterns. Specifically, six traders are both sophisticated traders and primary dealers, seven are both sophisticated traders and liquidity providers, and three are both primary dealers and liquidity providers.[12] The majority of addresses—2,342 in total—fall into a residual category not classified as sophisticated traders, primary dealers, or liquidity providers.

Transaction frequency varies considerably across groups. Sophisticated traders average 58 transactions per address, while those classified as both sophisticated traders and primary dealers exhibit a higher frequency, averaging 89 transactions per address.

[INSERT TABLE 1 ABOUT HERE]

In Appendix A, we provide detailed summary statistics on the distribution of trading volume, liquidity provision, and wallet characteristics. The first section presents the number of addresses involved, the trading volume, and the percentage of trading volume attributed to sophisticated traders. The second section includes the number of addresses, the aggregate liquidity provision, and the percentage of liquidity provided by the top 5 liquidity providers. The third section reports intra-day patterns in the number of transactions and trading volume of liquidity providers. Finally, the fourth section provides summary statistics on blockchain-level wallet characteristics—such as age, transaction frequency, and token transfer activity—across trader types. These metrics provide insight into the behavioral and activity profiles of different market participants.

Over the sample period, we observe that, on average, 200 addresses engage in trading each month, while approximately 5 to 10 LPs participate in minting or burning tokens monthly. Monthly trading volume reached a peak of 39 EURC million in November 2022, while peak liquidity provision reached 13 EURC million in October 2022. In terms of concentration, sophisticated traders contributed an average of 50–60% of the aggregate trading volume over our full sample from July 2022 to April 2024. By comparison, the top 5 LPs consistently accounted for over 90% of liquidity provision throughout most months within the sample period. Turning to intra-day patterns, we observe that liquidity deposits and withdrawals occur at all hours, with no systematic patterns in net liquidity during the trading day.[13] Sophisticated traders tend to be older and more active, with

[12]This latter group, with only six transactions, is excluded from the analysis of heterogeneous trading behavior.

[13]That LPs are not strategically adding net liquidity is important when we conduct our robustness test of asymmetric information in the FX market in Section 4.5.

higher transaction frequency and token transfers, while LPs and residual wallets exhibit more passive trading patterns. These differences suggest that trading behavior observed on-chain is broadly consistent with our trader classification.

2.2.3 Blockchain Order Flow

In addition to a measure of trading volume, we can also sign trades to construct a measure of blockchain order flow. Each swap trade in the EURC/USDC pool records the amounts in the base currency (a column labeled "amount0" in the dataset) and quoting currency (column labeled "amount1" in the dataset), extracted from the Ethereum blockchain API. The amounts of the base and quoting currency of a swap trade allows us to construct a measure of blockchain order flow. Amounts are signed based on whether they are adding or subtracting liquidity from the pool. For example, in the dataset EURC is the base currency and USDC is the quoting currency. Therefore if the base currency amount is negative, it means a trader is adding USDC and subtracting EURC from the pool. This is a "buyer initiated trade" for EURC. In contrast, if the base currency amount is positive, the trader is removing USDC and adding EURC to the pool. We classify this as a "seller initiated" trade for EURC.

The measure of blockchain order flow is defined as the net buyer-initiated transaction volume over each trading interval (e.g., hour or day), where buyer-initiated transactions are assigned +1, seller-initiated transactions are assigned −1, and the transaction volume is denoted V_{t_K}.

$$OF_t = \sum_{K=i}^{N} \left(\mathbb{1}[T_k = B] - \mathbb{1}[T_k = S]\right) \times V_{t_K} \tag{6}$$

Panel (b) of Figure 3 plots cumulative blockchain order flows and prices. We find there is positive co-movement between the cumulative blockchain order flow and the EURC/USDC price. Subdividing blockchain order flow into two groups: LPs and non LP traders, we find that the cumulative blockchain order flow of LPs follows a very different pattern to non-LP traders. While LPs have on net been buying EURC over the sample period, non-LP traders have been on net selling EURC. That LPs can have net build up of inventory in EURC suggests that they are not dealers in traditional FX markets that aim to balance inventories (Lyons, 1995; Rime et al., 2010). The role LPs play in information, their motives for hedging and their response to de-pegging events will be explored in Section 4.

2.2.4 CLS Volume

To study the transaction volumes in the traditional currency market, we utilize the CLS FX dataset. CLS Group handles around 40% of global FX transaction volume, including spot, swap, and forward transactions, for up to 18 currencies.[14] CLS data provides aggregated spot FX volume at an hourly frequency, and has been used in a number of papers analyzing the microstructure of the FX spot and swap markets (Ranaldo and Somogyi, 2021; Hasbrouck and Levich, 2021; Kloks et al., 2023; Ranaldo, 2023; Huang et al., 2023). We focus on the CLS FX Spot Flow dataset to construct sector-level volumes and order flows. This dataset records transaction buy and sell volumes between price-takers and market-makers (banks), with price-takers further divided into three categories: funds, non-bank financials, and corporates.

Consequently, we use the Flow dataset to construct sector-level volumes, which include: (i) interbank, (ii) bank-funds, (iii) bank-non-bank financials, and (iv) bank-corporates. To measure interbank volume, we take the aggregate volume from the Flow dataset and subtract the bilateral volume involving banks and other participants, such as funds, non-bank financial institutions, and corporates.

Figure 4 plots hourly trading volume. In Panel (a), we report trading on Uniswap V3 in the EURC/USDC market in EURC. In Panel (b), we report trading volume on CLS for the EUR/USD market, disaggregated by the four sector flows.

In general, the bulk of trading in the traditional market occurs between 13:00 and 16:00 UTC, particularly in interbank volume and fund-bank volume, the two main sector groups. This period aligns with the opening hours of major financial markets (London, Frankfurt, and New York). The major WMR fix occurs at 16:00 UTC (4:00 PM London time) and serves as a key benchmark for institutional investors setting the spot price for trades executed shortly beforehand (Krohn et al., 2024).

Comparing the two markets, we observe that blockchain trading on DEXs follows a more dispersed intraday pattern. While there are peaks in trading during afternoon UTC hours, there are also local peaks around 09:00 UTC. A more balanced intraday volume

[14] The 18 currencies are AUD, CAD, DKK, EUR, HKD, HUF, ILS, JPY, MXN, NZD, NOK, SGD, ZAR, KRW, SEK, CHF, GBP, and USD. In total, 33 currency pairs are settled by CLS.

distribution in blockchain markets suggests a more inclusive trading environment, less reliant on traditional FX global dealers (Adams et al., 2023; Marsh et al., 2017; Evans et al., 2018).[15]

A notable observation is that the intraday patterns of blockchain trading closely resemble those observed in the inter-dealer spot FX market. Given that the inter-dealer segment accounts for the majority of trading activity in traditional FX markets, this similarity reinforces the idea that blockchain-based currency markets are well-connected to traditional markets. The synchronization in trading volume patterns supports the notion that market participants actively incorporate price signals and liquidity conditions across both venues.

Turning to the scale of trading volume, the average daily volume in CLS EUR/USD is 28.42 billion EUR, while the average daily volume in Uniswap EURC/USDC is 0.423 million EURC. Expressed as a percentage, the blockchain market accounts for approximately 0.0015% (or 0.15 basis points) of total EUR/USD trading volume, as per CLS data.[16]

[INSERT FIGURE 4 ABOUT HERE]

2.2.5 Additional Data and Variables

In regression-based analyses, we use additional variables with the following interpretations: First, we calculate three variables to account for blockchain-specific factors that can affect pricing efficiency:

Gas Fees. Gas fees are payments made to Ethereum validators (formerly miners) for processing and confirming transactions on the blockchain. We obtain two levels of gas fee data. First, we retrieve the actual gas fee paid in ETH (converted to USDC) for each swap transaction directly from Etherscan. This information is used to construct arbitrage bounds and to compute trader-specific transaction costs. Second, we use an index of average gas fees per transaction (in USD), provided by CoinMetrics (`https://coinmetrics.io`), to examine the determinants of price efficiency at the daily frequency.

[15] In Appendix A.3, we document intra-day patterns in liquidity provision. We find a reduction in both the frequency of mints and burns of liquidity during peak trading hours. However, the volume of mints and burns does not exhibit a systematic pattern over the trading day.

[16] For further details, see the summary statistics of trading volume on blockchain and CLS markets presented in Table 2.

Market Volatility. We use the EthVol financial index as a measure of expected 30-day implied volatility for Ether.[17] This index provides a model-free estimate of expected volatility, derived from the full range of Ether option strikes. It is constructed using a methodology that interpolates between the two nearest option expirations to produce a forward-looking, market-based measure of volatility based on investor expectations.

Intermediary Constraints. We use two complementary measures to capture intermediary frictions. The first is the *intermediary capital risk factor* proposed by He et al. (2017), defined as AR(1) innovations to the market-based capital ratio of U.S. primary dealer holding companies. The capital ratio is measured as the ratio of total market equity to total market assets (book debt plus market equity), and innovations are scaled by the lagged capital ratio to capture shifts in dealer financial constraints.

The second measure follows Huang et al. (2025) and captures violations of the law of one price (VLOOP) in FX inter-dealer markets. VLOOP quantifies deviations from triangular arbitrage conditions among currency triplets. Specifically, for each G10 currency X[18], we compute deviations implied by the no-arbitrage condition involving EUR/USD, USD/X, and EUR/X exchange rates. To construct VLOOP, we obtain minute-level quote data from LSEG Tick History and use the mid-price.[19] Our baseline measure of VLOOP is the first principal component (PC1) of the standardized VLOOP series across currencies. PC1 explains approximately 46% of the total variation and has uniformly positive loadings across all individual currency series.

Summary statistics of volume, prices and blockchain variables in the analysis is provided in Table 2.

[INSERT TABLE 2 ABOUT HERE]

[17]Volatility indexes are available at `https://t3index.com/`.

[18]These currencies include AUD, CAD, CHF, DKK, GBP, JPY, NOK, NZD, and SEK.

[19]For each currency, we calculate absolute VLOOP values from minute-level price quotes, aggregate them to hourly values, trim the top and bottom 1.5 percentiles, and sum these hourly values into daily frequencies. The resulting panel covers nine VLOOP series. All series are standardized before performing PCA.

3 Market Efficiency, Arbitrage Bounds, and Transaction Costs

Market efficiency in FX markets is often evaluated through the lens of arbitrage: prices should reflect fundamental values, and persistent deviations suggest frictions. We investigate efficiency in decentralized currency markets through three dimensions. First, we assess whether price deviations remain within arbitrage bounds. Second, we examine how blockchain-specific frictions and stablecoin dynamics explain inefficiencies. Finally, we test whether prices incorporate macroeconomic news in real time.

Fact #1: *Peg Deviations are within Arbitrage Bounds*

Our baseline measure of efficiency is the absolute price deviation between EURC/USDC and the EUR/USD benchmark, defined as Δ_0 in Equation (7):

$$\Delta_0 = |p_{\text{EURC/USDC}} - p_{\text{EUR/USD}}| \tag{7}$$

Finite liquidity and transaction fees create frictions that limit arbitrage, allowing deviations from efficient prices to persist and reducing the informativeness of transaction prices (Barbon and Ranaldo, 2024). One approach to quantifying these inefficiencies is through triangular arbitrage, which identifies violations of the law of one price in a closed triplet of currency pairs $X \leftrightarrow Y$, $Y \leftrightarrow Z$, and $Z \leftrightarrow X$:

$$\Delta = |1 - P_{XY}P_{YZ}P_{ZX}|\,, \tag{8}$$

where P_{AB} represents the quoted price of currency A in units of currency B. A triangular trade is profitable only if the magnitude of Δ is sufficiently large to exceed transaction costs, including liquidity fees and slippage. Under efficient arbitrage, such deviations should not persist and should align with these frictions.

Extending this framework, we construct alternative efficiency measures that apply triangular arbitrage bounds to combinations of EURC/USDC DEX prices and centralized exchange rates, as defined in Equation (9).[20] We define three measures corresponding to different trading paths. The first, Δ_1, follows a cycle converting 1 EURC to USDC on DEX,

[20]Centralized exchanges are the only platforms with access to USD- or EUR-denominated pairs. EURC/USD and EURC/EUR are listed on Coinbase, while USDC/USD is listed on Kraken, which offers the most liquid pair for USDC/USD.

to USD on Kraken, and back to EURC via the EURC/USD pair on Coinbase. The second, Δ_2, converts 1 EURC to USDC on DEX, to EUR on Coinbase via USDC/EUR, and back to EURC via EURC/EUR. The third, Δ_3, traces a four-currency path: 1 EURC to USDC on DEX, to USD on Kraken, to EUR on Coinbase, and finally to EURC via EURC/EUR.

$$\begin{aligned}
\Delta_1 &= \left|1 - \frac{p_{\text{EURC/USDC}} \cdot p_{\text{USDC/USD}}}{p_{\text{EURC/USD}}}\right| \\
\Delta_2 &= \left|1 - \frac{p_{\text{EURC/USDC}} \cdot p_{\text{USDC/EUR}}}{p_{\text{EURC/EUR}}}\right| \\
\Delta_3 &= \left|1 - \frac{p_{\text{EURC/USDC}} \cdot p_{\text{USDC/USD}}}{p_{\text{EUR/USD}} \cdot p_{\text{EURC/EUR}}}\right|
\end{aligned} \tag{9}$$

These metrics quantify inefficiencies between decentralized and centralized markets and capture frictions arising from liquidity, gas fees, and execution costs.

We begin by comparing our triangular arbitrage metrics with a benchmark measure of market efficiency in Panel (a) of Figure 5. These series are available from March 2023, when centralized exchange pricing became accessible. The alternative arbitrage-based measures are moderately correlated with the benchmark, with coefficients ranging from 0.29 to 0.44.

Panel (a) of Table 3 reports the distribution of these triangular arbitrage deviations across three pricing paths. Median deviations are in the range of 0.2–0.3%, with Δ_1 and Δ_2 slightly lower on average than Δ_3. The maximum deviation reaches 8% in extreme cases, highlighting significant transient inefficiencies across markets.

Panels (b) and (c) of Table 3 evaluate the incidence of arbitrage bound violations under different cost assumptions. In Panel (b), we account for core DeFi trading costs: on-chain gas fees (converted from ETH to USD at the transaction level), a fixed 5 basis point LP fee on the EURC/USDC pool, and slippage. Slippage is measured at the trade level as the difference between the price implied by pre-trade pool balances and the actual execution price.[21] When incorporating these frictions, the share of violations is 16.1% for Δ_1, 18.6% for Δ_2, and 19.1% for Δ_3, indicating persistent inefficiencies despite accounting for key DeFi costs.

Panel (c) extends the arbitrage bounds to include off-chain intermediation costs. These

[21] For the execution price, we use the relative amounts of EURC and USDC exchanged. For example, if a swap increases the pool's EURC by 10 and decreases USDC by 11, the execution price is 1.10 EURC/USDC. The initial price is taken from the most recent completed trade prior to the current one.

consist of tiered taker fees charged on centralized exchanges such as Coinbase and Kraken, which vary with trade size.[22] In addition, we apply an average bid-ask spread of 0.55 basis points for EUR/USD trades in traditional markets, following Filippou et al. (2024). Including these additional costs substantially reduces the share of violations: to 3.7% for Δ_1, 3.2% for Δ_2, and 4.9% for Δ_3. This suggests that many seemingly exploitable arbitrage opportunities disappear once full intermediation costs are considered.

Panel (b) of Figure 5 illustrates how these arbitrage metrics evolve over time relative to the computed transaction cost bounds.

[INSERT FIGURE 5 and TABLE 3 ABOUT HERE]

While most deviations fall within estimated transaction cost bounds, the magnitude of arbitrage spreads remains large in comparison to traditional OTC markets. For comparison, the average hourly VLOOP across EUR–USD–X triplets (where X is a G10 currency) is just 1.59 basis points over our sample period, far below the 20–30 basis point median deviations of triangular arbitrage in cryptocurrency markets observed in our setting. This suggests that, in absolute terms, the EURC/USDC market is not efficient when benchmarked against traditional FX markets.

Nonetheless, we interpret the observed arbitrage bounds as *constrained efficient*, reflecting inherent costs of decentralized and centralized markets and the frictions introduced by blockchain-based trading and settlement mechanisms. This interpretation aligns with theoretical frameworks that highlight how financial and liquidity constraints inherently limit arbitrage, rationalizing persistent deviations from ideal efficiency (Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009; Duffie, 2010).

Fact #2: *Peg Efficiency is Driven by Blockchain-Specific Limits to Arbitrage*

While the previous section established that price deviations remain largely within arbitrage bounds, the next question is: what drives variations in efficiency? A key test of market efficiency is whether blockchain prices systematically reflect underlying currency values.

To explore this, we regress a baseline measure of price efficiency, defined as $\Delta_t = |p_{\mathrm{EURC/USDC},t} - p_{\mathrm{EUR/USD},t}|$, on blockchain-specific frictions, stablecoin peg deviations,

[22] For reference, Coinbase imposes taker fees of 60 basis points for trades under \$10,000, declining to 5 basis points for institutional volumes above \$400 million. Kraken uses a similar schedule. See: Coinbase fee schedule and Kraken fee schedule for more information.

and cryptocurrency market risk factors. This deviation captures how far DEX prices depart from the benchmark EUR/USD rate. Our regression specification is given by:

$$\Delta_t = \beta_0 + \beta_1 \text{gasfee}_t + \beta_2 \sigma^{IV}_{ETH,t} + \beta_3 R_{ETH,t} + \beta_4 \left| p_{\text{USDC/USD},t} - 1 \right| + \beta_5 \left| p_{\text{EURC/EUR},t} - 1 \right| + \beta_6 \text{VLOOP}_t + \beta_7 \text{ICRF}_t + \varepsilon_t \quad (10)$$

The results, presented in Table 4, indicate that blockchain-native frictions are the main drivers of price inefficiencies. Gas fees and Ether volatility have the most consistent explanatory power. A 1 USD increase in gas fees is associated with a 1.3 basis point increase in peg deviations (column 1), while a one basis point increase in σ^{IV}_{ETH} is associated with a 0.13–0.16 basis point increase (columns 2 and 5). These results align with the view that execution costs and on-chain congestion limit arbitrage efficiency (Barbon and Ranaldo, 2024; Foley et al., 2023).

Volatility matters not because of dealer balance sheet constraints, but because it raises uncertainty for traders holding portfolios denominated in cryptoassets. Higher volatility increases perceived risk, reducing willingness to deploy capital for arbitrage and allowing deviations from parity to persist.[23]

We also include peg deviations of the underlying stablecoins—USDC and EURC—from their fiat benchmarks. These capture frictions in primary issuance or redemption markets. The USDC/USD peg deviation is highly significant and robust, with a one basis point increase associated with a 0.75 basis point rise in FX peg deviations (column 3). In contrast, the EURC/EUR peg deviation is positive but statistically insignificant.

We find no evidence that traditional intermediary constraints influence peg deviations. Neither the VLOOP measure of triangular arbitrage violations nor the intermediary capital risk factor (ICRF) are statistically significant across specifications. This suggests that frictions binding intermediaries in dealer-based FX markets do not spill over to DEXs. Instead, inefficiencies reflect blockchain-specific limits to arbitrage.

Overall, the evidence shows that blockchain-based FX efficiency is shaped not by dealer intermediation, but by on-chain frictions and crypto-market risk. These limits constrain arbitrage capacity and allow temporary price dislocations to emerge.

[23] Appendix A shows that sophisticated traders typically transfer a large number of tokens—median of 54 and mean of 101—indicating diversified on-chain positions. Elevated volatility across cryptoassets can therefore erode trader wealth and increase risk exposure, increasing limits to arbitrage.

[INSERT TABLE 4 ABOUT HERE]

Fact #3: *Peg Prices React to Macro News Intra-Day*

An efficient market should incorporate fundamental information into prices. We test this by examining how FX returns respond to macroeconomic news announcements. Using high-frequency timestamps of FOMC announcements in Appendix B, we document the response of EURC/USDC and EUR/USD prices intra-day during scheduled Federal Open Market Committee (FOMC) meetings from July 2022 to April 2024. Our findings show that EURC/USDC closely tracks movements in the EUR/USD pair. Despite the limited number of observations, this suggests that the EURC/USDC pair efficiently reflects macroeconomic information when conditioned on news arrivals.

Fact #4: *Transaction Costs Vary Widely by Trader Type; Gas Fees Dominate for Most, while Slippage Rises for Large Traders*

We now examine the transaction costs faced by individual traders in the EURC/USDC market, extending our earlier analysis of arbitrage bounds. These costs are constructed at the transaction level using three components: gas fees, LP fees, and slippage—each measured relative to trade size and expressed in basis points. Across trader types, median total costs range between 20–50 basis points.

Total transaction cost is calculated as the sum of: (i) gas fees paid in ETH and converted to USD at execution time; (ii) a fixed LP fee of 5 basis points specific to the Uniswap V3 EURC/USDC pool; and (iii) slippage, which reflects the difference between actual execution and expected mid-pricing.

Figure 6 presents a disaggregated breakdown of these costs by trader group. Panel (a) shows the inter-quartile range (IQR) of total costs across seven account types, including Top 10 wallets, primary dealers, LPs, and a residual group of less active or retail-like traders. The distribution reveals considerable heterogeneity. Sophisticated wallets such as Top 10 and PMs tend to incur lower and more compressed transaction costs, while others face greater dispersion.

Panel (b) decomposes the median transaction cost by component. While LP fees are constant across trades, gas fees constitute the largest share of total costs for most participants—particularly smaller or retail traders, for whom fixed gas costs account for a larger proportion of each transaction. By contrast, for larger and more sophisticated accounts, slippage becomes relatively more important. This reflects the inherent mechanics of AMMs: larger orders incur greater price impact due to the convexity of the bonding curve, even as such traders benefit from infrastructure that minimizes gas costs.

[INSERT FIGURE 6 ABOUT HERE]

Fact #5: *Decentralized FX Markets Remain Less Scalable but Improve Access for Marginalized Users*

Building on the trader-level cost analysis, we assess whether DEXs offer a viable alternative to traditional FX OTC markets. The answer depends on the benchmark. Compared to inter-dealer markets, the contrast is clear: EUR/USD spreads averaged just 0.55 basis points in 2023 (Filippou et al., 2024), far below typical on-chain costs. However, not all OTC participants access such favorable pricing. Hau et al. (2021) document that clients at the 90th percentile of FX derivatives trading face spreads up to 50 basis points—comparable to median DEX costs.

This suggests that decentralized platforms may provide value to participants excluded from preferred dealer pricing tiers. That said, limited liquidity and depth pose scalability challenges, with slippage particularly high for large trades.

In sum, while scalability remains a limitation, DEXs may offer improved access and fairness for marginalized users, serving as an alternative trading venue to traditional OTC FX markets.

4 Empirical Analysis: Trader Information

4.1 Blockchain Volume Connection

H 1. *DEX trading volume has a systematic connection with traditional market volume, particularly with the interbank segment that incorporates both private and public information.*

We hypothesize a connection between trading activity on the blockchain and the traditional EUR/USD market. Specifically, we posit that DEX and CLS trading volumes exhibit similar intra-day patterns, peaking during the afternoon UTC hours, which correspond to active trading periods in Frankfurt, London, and New York. Using CLS data categorized by sector—interbank activity, volumes handled by market-making banks, non-bank financial institutions, and corporates—we aim to identify relationships between DEX trading volumes by participant type (sophisticated traders, primary dealers, and liquidity providers) and traditional market volume.

This connection is motivated by the literature showing that interbank market volume is responsive to fundamental news through the incorporation of both private and public information (Ranaldo and Somogyi, 2021; Huang et al., 2023). If confirmed, such a link would point to a degree of alignment between DEX trading patterns and those observed in traditional market segments.

To test Hypothesis 1, we use the specification given in equation (11), where the outcome variable represents DEX trading volumes for sophisticated traders, primary dealers, liquidity providers, and wallets that intersect across these categories, as defined in Section 2.

The explanatory variables capture trading volumes in the traditional EUR/USD market, using disaggregated CLS data by sector. This includes interbank volume, volume intermediated by market-making banks and price-taking funds, and activity by non-bank financial institutions and corporates.

$$V_{N_{DEX},t} = \alpha + \sum_{i \in N_{CLS}} \beta_j V_{N_{CLS},t} + \epsilon_t \tag{11}$$

Table 5 presents the results, highlighting a significant correlation between blockchain and traditional market volumes, particularly with interbank activity. Column (1) shows that the coefficient on interbank trading volume is 4.35, indicating a strong, positive relationship with sophisticated traders' activity on the DEX. Specifically, a 1 EUR million increase in interbank trading volume corresponds to a 4.35 EURC increase in DEX activity for sophisticated traders, holding other factors constant. This positive relationship is robust across different trading groups. Column (7) further shows that trading volumes outside of sophisticated traders, primary dealers, and liquidity providers also exhibit a significant correlation with interbank volume, with a coefficient of 3.25. These results are consistent with the view that interbank activity, as the more informed segment of the OTC FX market, may influence patterns of DEX trading activity.

[INSERT TABLE 5 ABOUT HERE]

Building on this correlation, we explore systematic patterns in trading volumes across participant types. Panel (a) of Figure 7 depicts average trading volumes for each participant group during weekdays, segmented into primary market hours (13 to 16 UTC) and other hours. Trading volumes are significantly higher during primary opening hours across all groups. However, the relative decline in trading volume outside these hours is most pronounced for sophisticated traders and primary dealers, with declines of 50% and 37%, respectively. For traders classified as both sophisticated and primary dealers, the volume decreases by 74%.

Panel (b) of Figure 7 performs a similar analysis, comparing average trading volumes on weekdays versus weekends. Again, we observe a sharp decline in trading volume during weekends for all groups, with the largest drop (87%) among sophisticated traders who are also primary dealers. This pattern reflects the close alignment of these traders' activities with traditional market hours.

Two potential channels may explain this heightened activity during traditional market hours: the *feedback trading* channel and the *asymmetric information* channel. First, increased price and trading activity in traditional markets could create more profitable arbitrage opportunities, supporting price alignment across markets through feedback trading. Second, traders may be responding to fundamental news released during these periods, incorporating new information into their trading. This behavior is consistent with asymmetric information (Ranaldo and Somogyi, 2021). In the following sections, we formally analyze these mechanisms: the role of feedback trading through arbitrage in Section 4.2, and the processing of fundamental information in Section 4.3.

[INSERT FIGURE 7 ABOUT HERE]

4.2 Blockchain Order Flow and Feedback Trading

H 2. *Blockchain order flow on DEX is responsive to deviations between DEX and traditional market prices, indicating feedback trading behavior.*

We hypothesize that DEX participants engage in feedback trading, reacting to discrepancies between the DEX reference rate (EURC/USDC) and the CLS benchmark EUR/USD rate. For instance, if the DEX rate trades at a premium to the traditional market rate, traders might sell EURC and buy USDC, bringing the DEX rate closer to the benchmark.

This behavior implies that blockchain order flow is a function of price differences across markets, with the lagged price discrepancy between the DEX and traditional markets driving order flow. Sophisticated traders, due to their greater resources, are more likely to exploit these arbitrage opportunities, while primary dealers and LPs are expected to be less responsive to such price deviations.

To test Hypothesis 2, we examine whether DEX traders adjust their strategies in response to price differences between the DEX reference rate and the CLS benchmark rate. Specifically, we estimate equation (12), regressing blockchain order flow on the lagged price difference between DEX and traditional markets, with controls that include the lagged EURC/USDC return.

$$OF_{i,t} = \alpha + \beta_1(p_{EURC/USDC,t-1} - p_{EUR/USD,t-1}) + controls_t + \epsilon_t \tag{12}$$

[INSERT TABLE 6 ABOUT HERE]

The results, presented in Table 6, provide evidence of feedback trading behavior among sophisticated traders. In column (1), a one-unit increase in the lagged hourly price deviation between Uniswap and CLS rates is associated with a reduction in aggregate blockchain order flow of 0.15 million EURC. Column (4) shows a similar magnitude for traders who are both sophisticated and primary dealers, with order flow decreasing by 0.14 million EURC. In contrast, the effects for standalone primary dealers and LPs, reported in columns (2) and (3), are statistically insignificant.

These findings suggest that sophisticated traders—and those with dual roles as primary dealers—are more likely to engage in arbitrage between decentralized and traditional FX markets. This behavior is likely facilitated by their lower effective trading costs, such as gas fees, which represent a smaller share of transaction size. By contrast, primary dealers and LPs, who typically execute smaller trades, are less responsive to short-term price discrepancies due to higher relative transaction costs.

Primary dealers exhibit limited sensitivity to EURC/USDC price deviations because their smaller transaction sizes make arbitrage economically unattractive once gas fees and slippage are considered. As a result, they are less able to engage in feedback trading compared to sophisticated traders. Instead, their trading activity is more likely motivated by the processing of fundamental information, such as macroeconomic news. We now turn to testing for the informational content of blockchain trading in the following section.

4.3 Blockchain Order Flow and Fundamental Information

H 3. *Market participants exhibit heterogeneous access to information about EUR/USD fundamentals, resulting in differing levels of informational efficiency:*

(a) Sophisticated traders, with high wealth and trading activity, and primary dealers, with access to EUR and USD deposits, possess informational advantages that allow them to incorporate fundamental news into blockchain prices.

(b) LPs are uninformed and primarily engage in inventory management, leading to greater exposure to adverse selection risk.

Market efficiency depends on the extent to which prices reflect available information. A key distinction exists between public and private information. Public information, such as macroeconomic announcements, is widely accessible and should be incorporated into prices with minimal delay. In contrast, private information, reflected in order flow imbalances or arising from asymmetric information, may only gradually be incorporated into prices through informed trading.

The standard model of inter-dealer order flow, as in Evans and Lyons (2002), is based on an OTC structure where the inter-dealer market is used to manage inventory and share inventory risk following customer trading. Dealers absorb public demand and mitigate inventory risk by the end of the day, with portfolio adjustments and exchange rate expectations driving shifts in currency allocations as prices adjust during rebalancing. This two-tiered structure, with a separation between customer and inter-dealer markets, contrasts with how blockchain markets operate.

In blockchain markets, there is no two-tiered structure. In this setting, information refers to the processing of fundamental information about currency value, analogous to an informed trader in the spirit of Kyle (1985). Asymmetric information plays different roles across market structures. In dealer-driven OTC markets, it can shape price formation and trading dynamics (Ranaldo and Somogyi, 2021). Some blockchain participants may possess informational advantages and act on private signals about fundamentals, even if their trades do not themselves move the exchange rate in traditional markets.

We investigate informational efficiency using two approaches. First, in Section 3, we examine how blockchain markets incorporate public information by analyzing price reactions to FOMC announcements. Our results indicate that blockchain prices adjust quickly to macroeconomic news, closely tracking EUR/USD movements.

Second, we assess private information by analyzing trader-specific behavior, particularly during de-pegging events where market stress may reveal informational advantages. We also examine the permanent price impact of order flow to determine whether certain traders systematically predict long-term price movements in the EUR/USD rate, suggesting they process fundamental information.

How traders incorporate fundamental information depends on their market role. Primary dealers, connected to the interbank FX market via fiat deposits, primarily trade on macroeconomic fundamentals rather than short-term arbitrage. In contrast, sophisticated traders, with greater arbitrage capital, exploit price discrepancies across blockchain and traditional markets, efficiently integrating fundamental news. Their ability to manage transaction costs, such as gas fees, allows them to realign blockchain prices with traditional market values.

In contrast, LPs act as passive participants focused on inventory management rather than leveraging informational advantages. They face adverse selection risk (Milionis et al., 2022; Foley et al., 2023), particularly when arbitrageurs exploit price discrepancies between markets. For instance, when EUR/USD fundamentals indicate a higher price than EURC/USDC, arbitrageurs buy EURC and sell USDC, creating imbalances in LP portfolios. LPs then adjust holdings to restore balance, prioritizing liquidity hedging over informed trading based on signals from the traditional FX market.

4.3.1 USDC De-Pegging Event

The USDC de-pegging event on March 11, 2023, provides a unique setting to analyze how blockchain market participants respond to market stress under asymmetric information. This event occurred when SVB, which held $3.3 billion of USDC reserves, declared bankruptcy, raising concerns about the backing of USDC and causing its price to drop to 87 cents. Confidence was restored on March 13 after the Federal Deposit Insurance Corporation (FDIC) guaranteed all SVB deposits.[24]

[INSERT FIGURE 8 ABOUT HERE]

[24] Further details on USDC's reserve composition and Circle's response to the de-pegging event are available at https://www.circle.com/blog/an-update-on-usdc-and-silicon-valley-bank.

We use this event to study resilience in the EURC/USDC market and analyze behavior across trader types. Figure 8 illustrates EURC/USDC price deviations from the EUR/USD market and blockchain order flow by trader groups. Sophisticated traders showed positive order flow leading up to the event, suggesting informational advantages consistent with Hypothesis 3. This behavior mirrors findings from Liu et al. (2023), where informed investors responded similarly during the Terra Luna collapse.

Appendix D provides transaction-level evidence on the behavior of sophisticated traders and liquidity providers during the USDC de-pegging event. For instance, wallet '1c37' exhibited significant USDC selling pressure during the event, executing large and frequent trades across pairs such as EURC/USDC, USDC-GYEN, and USDC-PRIME on Uniswap and SushiSwap. The transaction patterns suggest cross-exchange arbitrage, likely involving the purchase of discounted USDC on centralized exchanges and its sale on decentralized venues.[25]

In contrast, LPs showed minimal strategic repositioning during this period, supporting the view that they act as passive participants.[26]

While this behavior is consistent with an informational advantage interpretation, an alternative explanation is that sophisticated traders were better positioned to act during the crisis due to lower transaction costs. Appendix D.3 shows that during the de-pegging period, Top 10 wallets paid a median of only 12.4 USDC in gas fees per 10,000 EURC transacted—less than half the corresponding figure for non-Top10 wallets (32.8 USDC). This difference reflects the fact that gas fees are largely fixed per transaction and disproportionately affect smaller trades. In this sense, larger and more efficient traders benefit from a lower effective cost of execution, giving them a structural advantage in conducting real-time arbitrage across markets.

This cost asymmetry may have discouraged smaller or retail wallets, including primary dealers, from participating in the EURC/USDC market during the event, effectively pricing

[25]Wallet '1c37' (full address: 0xd64137f743432392538a8f84e8e571fa09f21c37) frequently conducted high-volume transactions during the de-pegging event, including major trades in USDC-PRIME, SYN-USDC, EURC-USDC, and USDC-GYEN pairs. Transaction logs indicate repeated inflows of USDC from Coinbase followed by USDC sales on Uniswap and SushiSwap pools. Detailed transaction logs are provided in Appendix D.

[26]For example, the only LP withdrawal observed during the event occurred at 05:59 UTC on March 11, involving the removal of EURC and USDC at a mid-range price. This inactivity aligns with the behavior of LPs focusing on inventory maintenance rather than market signaling, as discussed in Fang (2022); Foley et al. (2023).

them out of profitable arbitrage. Combined with the evidence on timing and order flow, this suggests that the dominance of sophisticated traders during the crisis likely reflects a combination of informational advantages and lower marginal transaction costs. This complements the analysis of wallet '1c37' and supports the interpretation that access to scale, speed, and low-cost execution are central to understanding who arbitrages during de-pegging events.

4.3.2 Permanent Price Impact

To assess whether blockchain-based trades convey private information about exchange rate fundamentals, we examine the permanent price impact of order flow. Permanent impact refers to the component of order flow that results in lasting changes in prices, distinguishing it from transitory fluctuations due to liquidity provision or noise trading. In the microstructure literature, order flow is often viewed as a proxy for the gradual incorporation of private information into prices, though this has typically been studied in the context of dealer-based OTC markets (Evans and Lyons, 2002).

This mechanism is particularly relevant in blockchain-based FX markets, where low liquidity and participant heterogeneity may amplify the informational role of trades. The availability of wallet-level data enables a more granular analysis of how different trader types, such as sophisticated investors, primary dealers, and liquidity providers, influence prices over time.

We estimate a SVAR to capture the dynamic relationship between order flow and exchange rate changes. To isolate the informational content of blockchain order flow beyond what is already impounded through institutional trading activity, we control for traditional FX order flow obtained from CLS data. This results in a block SVAR specification where variables are grouped into three components: traditional OTC order flow ($\mathbf{OF}_t^{OTC}$), blockchain order flow ($\mathbf{OF}_t^{DEX}$), and exchange rate changes (Δp_t):

$$\begin{bmatrix} \mathbf{OF}_t^{OTC} \\ \mathbf{OF}_t^{DEX} \\ \Delta p_t \end{bmatrix} = \alpha + \sum_{k=1}^{L} \mathbf{A}_k \begin{bmatrix} \mathbf{OF}_{t-k}^{OTC} \\ \mathbf{OF}_{t-k}^{DEX} \\ \Delta p_{t-k} \end{bmatrix} + \epsilon_t. \tag{13}$$

The traditional OTC order flow vector $\mathbf{OF}_t^{OTC}$ consists of hourly buy-minus-sell imbalances disaggregated into non-bank financials, corporates, funds, and interbank dealers using CLS data. The blockchain order flow vector $\mathbf{OF}_t^{DEX}$ includes EURC/USDC transaction flows on Uniswap, grouped by wallet type: LPs, residual wallets ($\notin$ {Top10, PM, LP}), Top10∩LP, PM, Top10, and Top10∩PM, as defined in Section 2. The dependent variable Δp_t denotes the log change in the EUR/USD exchange rate, either from the DEX mid-price or the CLS benchmark rate.

We identify the system using a recursive Cholesky decomposition, assuming the ordering $\mathbf{OF}_t^{OTC} \rightarrow \mathbf{OF}_t^{DEX} \rightarrow \Delta p_t$. This implies that traditional OTC order flow can contemporaneously influence blockchain order flow and prices, while DEX flows do not contemporaneously affect OTC flows. Prices respond immediately to all order flows. This identification scheme reflects the hierarchical structure of FX trading venues and is consistent with information transmission patterns documented in the microstructure literature. Full details of the identification assumptions and block matrix decomposition are provided in Appendix E.

Impulse response functions (IRFs) derived from this SVAR are shown in Figure 9, with Panel (a) reporting responses of EURC/USDC (DEX) returns and Panel (b) showing CLS benchmark EUR/USD returns. The IRFs trace the effect of shocks to DEX order flow components—including sophisticated traders, primary dealers, liquidity providers, and intersecting groups—on returns over a 24-hour horizon.

The results indicate that order flows from sophisticated traders and primary dealers have the most persistent and substantial permanent impact on CLS benchmark returns. Specifically, a 1 million EURC shock to primary dealer order flow generates a permanent return impact of approximately 4.0 percent over 24 hours, while a 1 million EURC shock to sophisticated trader order flow generates a permanent impact of about 2.2 percent. The combined group of Top 10 wallets that are also primary dealers generates a permanent impact of 3.1 percent. In contrast, flows from LPs and residual wallets have negligible permanent effects, with estimates of approximately −0.1 and 0.2 percent respectively, consistent with uninformed trading or liquidity provision.

These findings support Hypothesis 3, revealing informational heterogeneity across blockchain market participants. When scaled to a one-standard-deviation shock in daily order flow, the implied permanent impact on CLS benchmark returns is approximately 1.6 basis points for sophisticated trader flows and 2.9 basis points for primary dealer flows,[27] consistent with earlier studies. Importantly, the informational effects we identify do not arise from inter-dealer price discovery mechanisms, as in Evans and Lyons (2002), but instead reflect private information about exchange rate fundamentals, in the spirit of informed trading models such as Kyle (1985).

[INSERT FIGURE 9 ABOUT HERE]

4.4 Feedback Trading vs Informational Order Flow

We assess whether the observed price impacts stem from feedback trading and arbitrage between decentralized and traditional FX markets, or from genuine informational content. To do so, we decompose blockchain order flow into two components: a feedback-driven component—predicted by the lagged price difference between the EURC/USDC price on DEX and the EUR/USD benchmark rate—and a residual component, which we interpret as a proxy for informational order flow.

Specifically, we estimate equation (12), regressing net EURC buyer flow on the lagged price difference between decentralized and traditional FX markets. The fitted values represent the predicted (feedback) component, while the residual captures order flow orthogonal to these price differences.

[INSERT FIGURE 10 ABOUT HERE]

Figure 10 presents the impulse responses of EUR/USD CLS benchmark returns to a 1 million EURC shock in blockchain order flow, decomposed into these two components. Panel (a) shows that the residual (informational) component generates persistent and statistically significant price impacts, particularly for primary dealers and sophisticated traders, consistent with their role as informed traders. By contrast, Panel (b) shows that the predicted feedback component has no significant impact on traditional FX prices. For primary dealers in particular, the feedback-based predicted component explains little of the variation, with wide confidence bands reinforcing the insignificance of this channel. This supports the interpretation that the permanent price effects we document reflect the incorporation of fundamental information rather than mechanical arbitrage.

[27] The permanent price impact estimates reflect IRF responses expressed in percent returns per 1 million EURC order flow shock. Given that a one-standard-deviation shock in daily order flow is approximately 7,230 EURC, the implied return impact scales proportionally. These estimates align with earlier studies of the price impact of traditional FX order flow, including the 50 basis points per USD 1 billion reported by Evans and Lyons (2002) and Berger et al. (2008). The sample average daily trading volume is EURC 0.423 million (standard deviation EURC 0.674 million).

4.5 Robustness Tests

To validate the robustness of our findings, we conduct several additional tests, which are detailed in Appendix F. Key results are summarized below.

Intra-day Price Impact. We examine intra-day impacts of DEX order flow for each trading group in Appendix F.1. This analysis reveals that price impacts for sophisticated traders and primary dealers are highest during 13-15 UTC, coinciding with the active trading hours of major financial centers. This pattern suggests that informed traders have a stronger impact when traditional markets are open and macroeconomic information is abundant. In contrast, LPs exhibit insignificant impacts during these hours, indicating their trading is less sensitive to macroeconomic conditions and driven more by inventory management.

Price Impact: Controlling for Liquidity Provision. A potential concern is that price impact estimates may be influenced by variations in liquidity provision. For instance, informed liquidity providers might adjust the relative supply of currencies based on return expectations. To address this, we re-estimate our baseline model (Equation (13)) while incorporating controls for net liquidity provision at both the best level (within 1% of the current price) and away (more than ±1% of the current price). Details on the construction of these metrics are provided in Section 2. Results are provided in Appendix F.2. After accounting for liquidity provision, our price impact estimates remain consistent, suggesting that liquidity adjustments do not drive our results.

Just-in-time Liquidity. A related concern is that LPs may be pursuing sophisticated strategies such as JIT liquidity, where providers strategically add and remove liquidity to capture transaction fees while minimizing exposure to adverse selection (Capponi et al., 2024a). Our analysis reveals that while some DEX pools on Uniswap exhibit high-frequency liquidity movements, only one wallet (address ending in 'ae13') in the EURC-USDC pool consistently engages in JIT liquidity behavior. In Appendix F.3, we provide a detailed transaction logs for this wallet.[28] This behavior demonstrates a strategic approach

[28]For example, on 2023-08-23, wallet 'ae13' deposited 50,249 EURC and 311,077 USDC into the liquidity pool within a price range of 1.0898 to 1.0909. Shortly thereafter, a large trade by another user (wallet ending in '2cc4') occurred with a volume of -18,957 EURC. Following this trade, wallet 'ae13' promptly removed its

to minimize adverse selection, though it remains an exception rather than the norm in the EURC-USDC pool.

5 Conclusion

DeFi platforms are reshaping financial markets by enabling global access to financial services without intermediaries. By introducing new trading structures based on smart contracts and automated liquidity provision, these platforms offer a fundamentally different market design from traditional dealer-intermediated markets. This study assesses the efficiency of blockchain-based currency markets and their interaction with traditional FX markets, focusing on the EURC/USDC pair traded on the Uniswap V3 decentralized exchange.

Our findings establish several key facts about market efficiency in blockchain currency markets. First, EURC/USDC prices exhibit small but persistent deviations from the CLS benchmark EUR/USD rate, averaging 24 basis points. These deviations mostly stay within arbitrage bounds, with only 3–5% of transactions exceeding limits once gas fees, slippage, LP fees, and exchange fees are considered. Second, price deviations are mainly driven by blockchain-specific frictions, such as gas fees and ETH volatility. Third, EURC/USDC prices respond efficiently to macroeconomic news, including Federal Reserve announcements.

Fourth, trading costs vary substantially across wallet types. Gas fees dominate for smaller traders, making up the largest share of transaction costs at low volumes. In contrast, slippage rises sharply for larger trades, reflecting liquidity constraints in automated market maker pools. Although overall costs remain higher than those in inter-dealer markets, they are comparable to the costs faced by OTC clients subject to price discrimination, pointing to potential welfare gains for users excluded from institutional FX pricing.

Beyond these stylized facts, we examine how blockchain market activity connects to traditional FX markets. The primary contribution of our paper is to analyze these linkages through the *feedback trading* and *asymmetric information* channels, highlighting the role of information processing and arbitrage. Our analysis shows that blockchain markets help correct price discrepancies through arbitrage and reflect the processing of fundamental information. Sophisticated traders and primary dealers play a key role, exerting greater

liquidity, burning 32,048 EURC and 330,931 USDC.

price impact consistent with asymmetric information, while liquidity providers primarily manage inventory with limited price impact.

The ongoing evolution of blockchain markets offers important avenues for future research. Current infrastructure is not yet scalable for high-volume institutional trading, but may improve execution quality for clients excluded from institutional pricing. As these markets mature, liquidity providers could adopt more strategic behavior, and future work should explore how improvements to DeFi trading structures might lower costs and enhance scalability.

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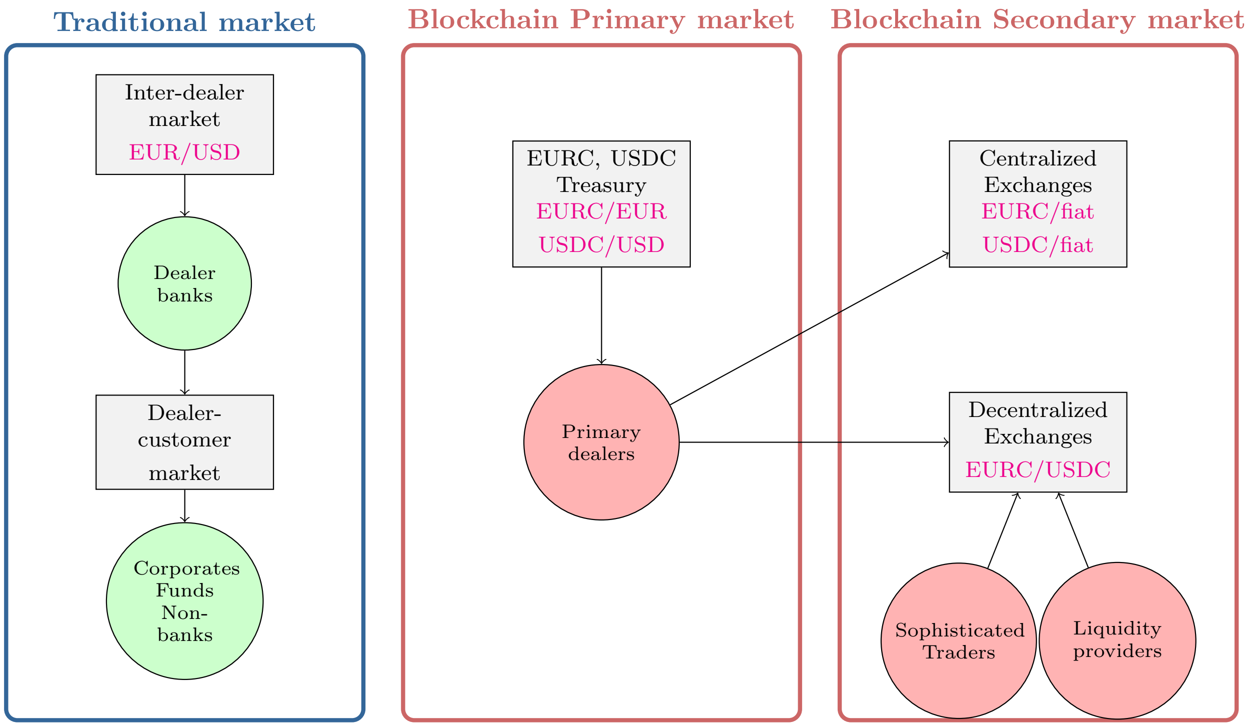
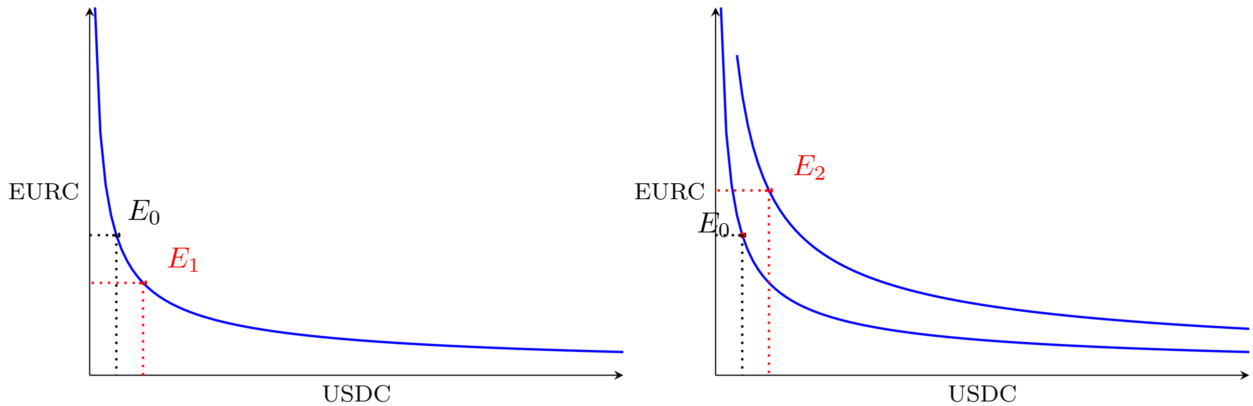
Figure 1: Structure of Traditional and Blockchain Market



Note: This figure presents a schematic of both traditional and blockchain markets. Traditional markets have an inter-dealer market intermediated by dealer banks, that provide liquidity in the dealer-customer market, trading with corporates, funds and non-bank financial companies. The blockchain market has both a primary and secondary market. In the primary market, the Treasury, managed and operated by Circle, mint EURC tokens and USDC tokens, which are then distributed to "primary dealers", that distribute EURC and USDC tokens in the secondary market. Secondary market trading consists of trading in centralized exchanges that deal in limit order books, or alternatively on decentralized exchanges like Uniswap that trade on EURC/USDC. Other trading types on decentralized exchanges include liquidity providers and sophisticated traders.

Figure 2: EURC/USDC Bonding Curves

Panel (a): EURC/USDC Bonding Curves: Swap and Liquidity Trades

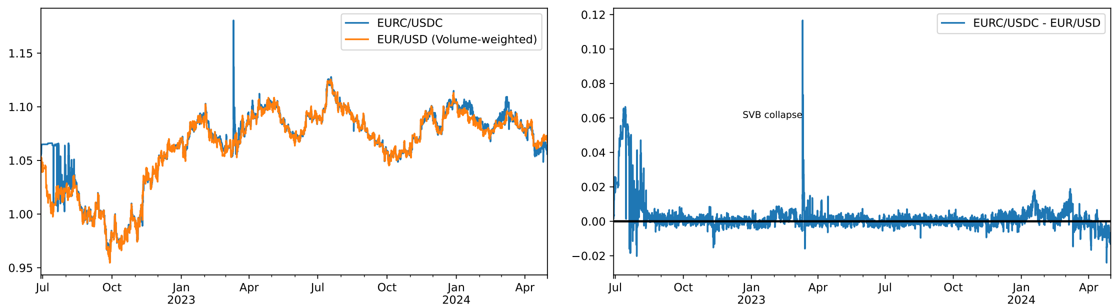


Panel (b): Snapshot of Uniswap Liquidity GUI

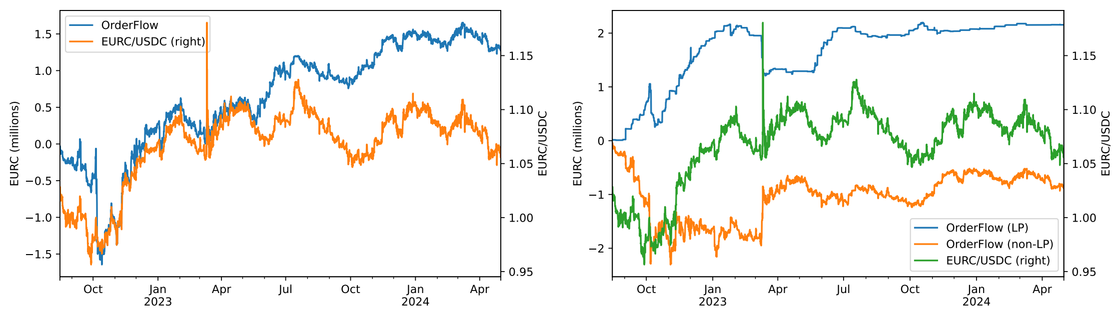
Note: This figure provides a snapshot of liquidity in the EURC/USDC pair. Panel (a) illustrates the principles of a bonding curve and liquidity provision in Uniswap. The aggregate supply of liquidity at point E_0, with a swap trade of purchasing EURC moving the equilibrium from E_0 to E_1, and a LP adding liquidity at the current price from E_0 to E_2. Panel (b) displays the Uniswap user interface for providing liquidity, where users can post liquidity (denoted by "Deposit amount") at specified price ranges. Source: https://uniswap.fish/.

Figure 3: EURC/USDC Prices

Panel (a): EURC/USDC Price (Uniswap) and EUR/USD Price (CLS)



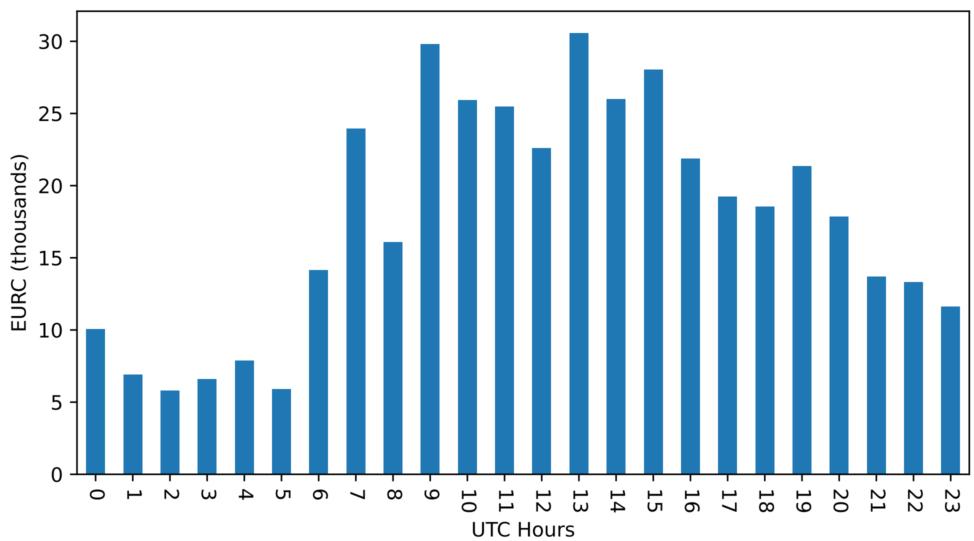
Panel (b): EURC/USDC Price and Cumulative Blockchain Order Flow



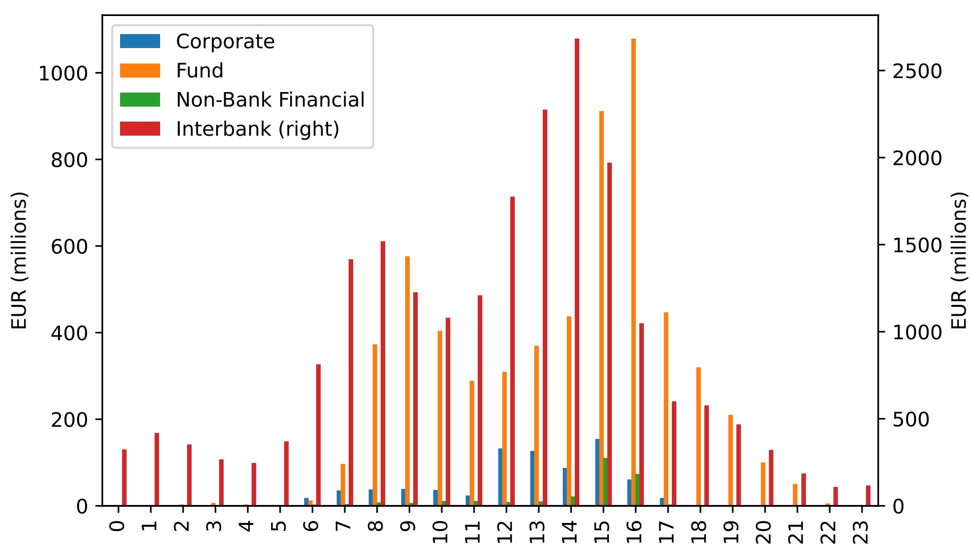
Note: This figure plots EURC/USDC and EUR/USD prices. EURC/USDC prices are sourced from Uniswap V3, and EUR/USD prices are sourced from CLS. Panel (a) shows EURC/USDC price and traditional (CLS) EUR/USD price, and the price difference across markets. Panel (b) presents cumulative order flow and the price in the EURC/USDC market, and order flow disaggregated by LPs and non-LPs. The total sample period for Panel (a) is from 28 June 2022 to 30 April 2024, and for Panel (b) from 15 August 2022 to 30 April 2024.

Figure 4: Hourly FX Trading Volume

Panel (a): DEX Trading Volume



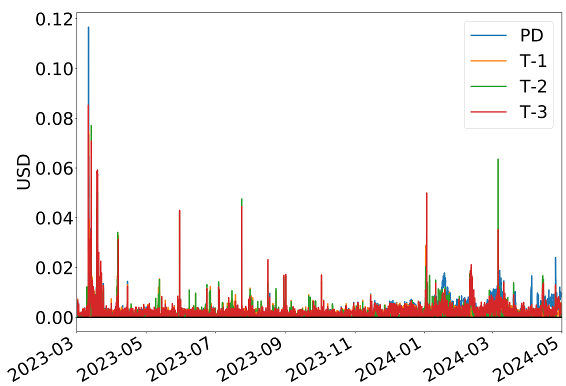
Panel (b): CLS Trading Volume

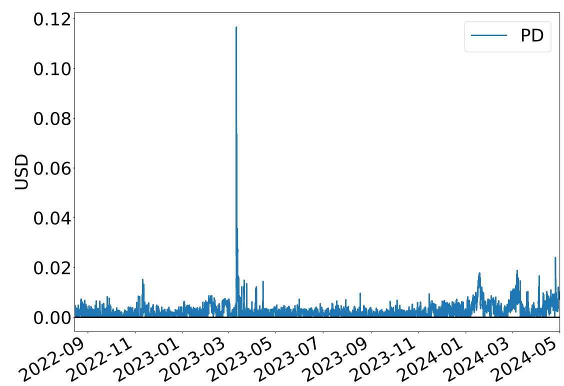


Note: This figure plots hourly trading volume. In Panel (a), we report trading on Uniswap V3 in the EURC/USDC Market in EURC Millions. In Panel (b), we report trading volume on CLS for the EUR/USD market, disaggregated by sectors: Bank-Bank, Bank-Fund, Bank-Corporate, and Non-Bank Financial-Bank. CLS Volume is in EUR Million. The total sample period starts on 15 August 2022, and ends on 30 April 2024.

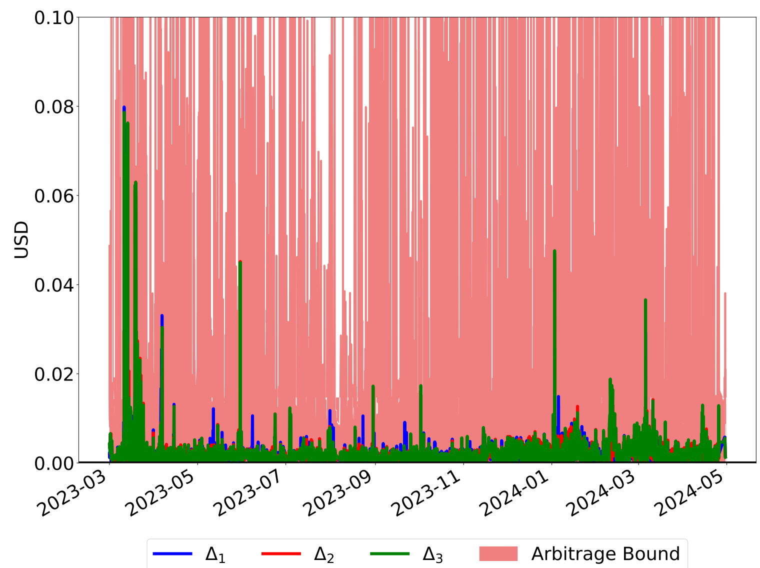
Figure 5: EURC/USDC Measures of Price Efficiency and Arbitrage Bounds

Panel (a): Price Efficiency





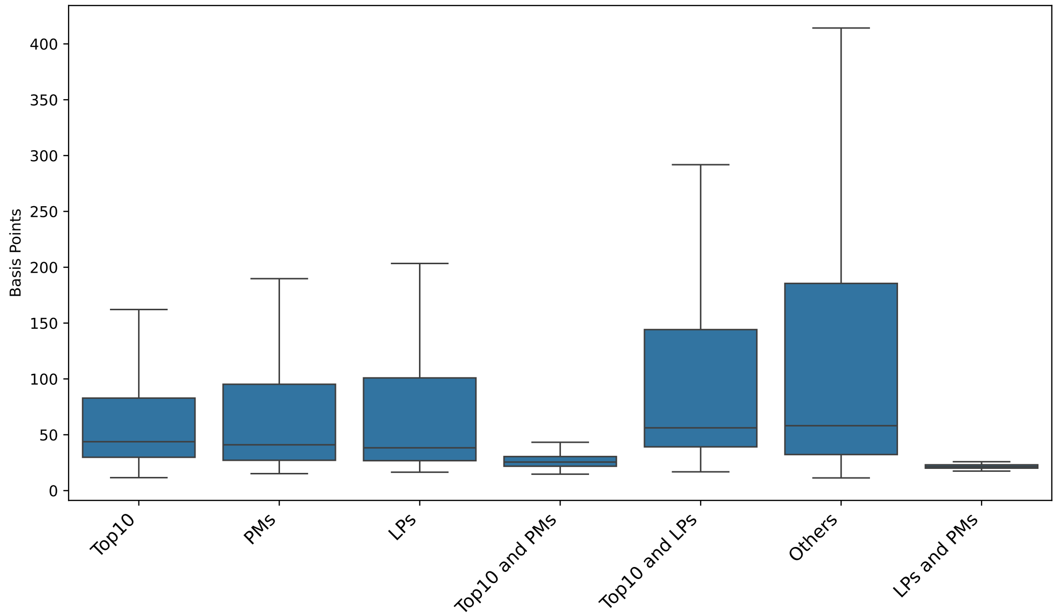
Panel (b): Arbitrage Bounds



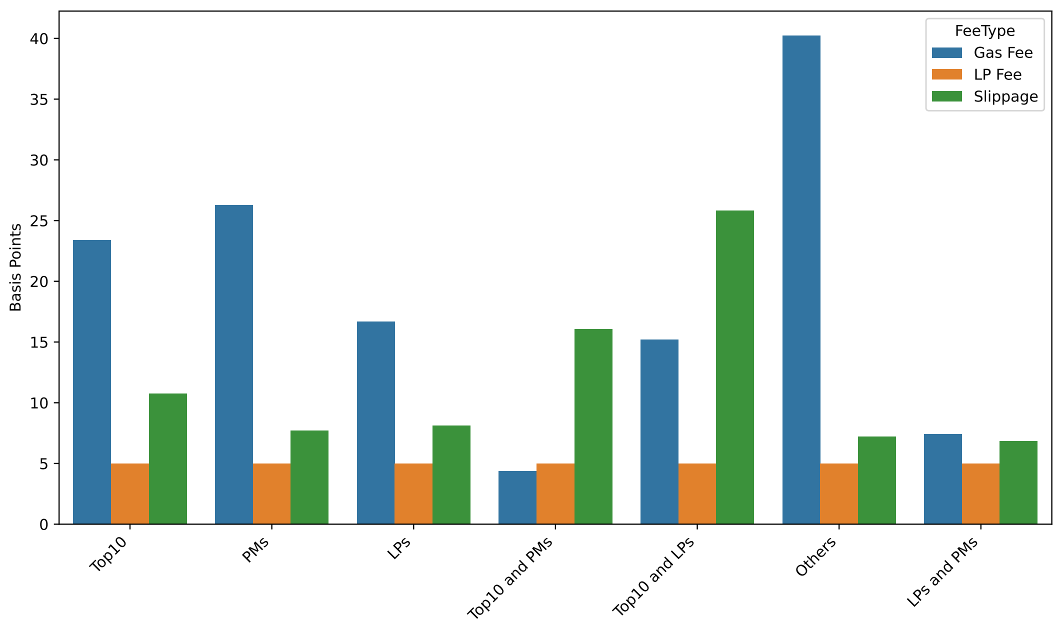
Note: This figure plots market efficiency metrics based on how the EURC/USDC market tracks EUR/USD CLS benchmark rates. Panel (a) plots the triangular arbitrage conditions as alternative measures of market efficiency to the price difference (PD). Panel (b) plots the triangular arbitrage measures and transaction costs for the EURC/USDC pair. Gas fees are based on actual payments in ETH at the transaction level. Additional costs include slippage, which is a measure of the average price impact of trades on the exchanges required to conduct a triangular arbitrage. Sample period is from 1 March 2023 to 30 April 2024.

Figure 6: Trading Costs

Panel (a): Trading Costs: Inter-Quartile Range



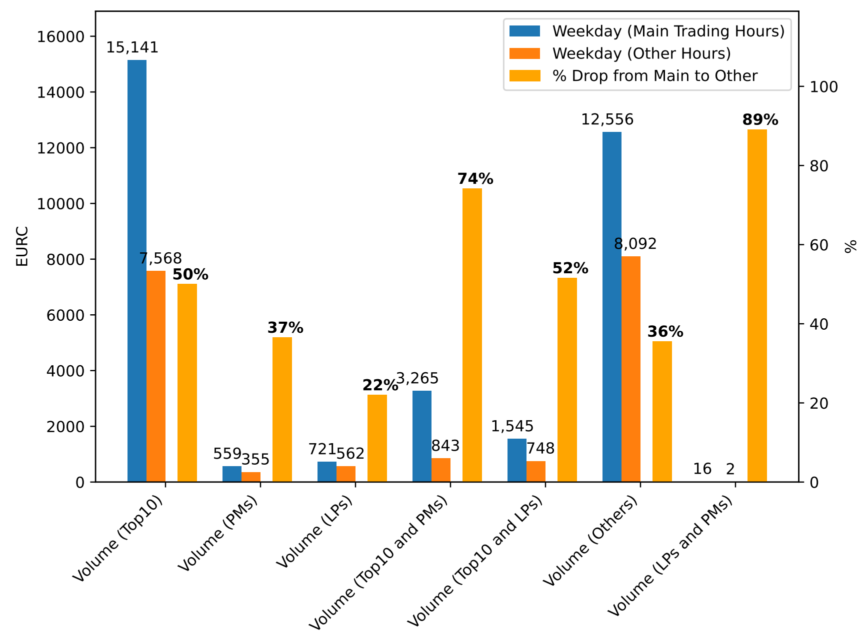
Panel (b): Trading Costs: Median Decomposition



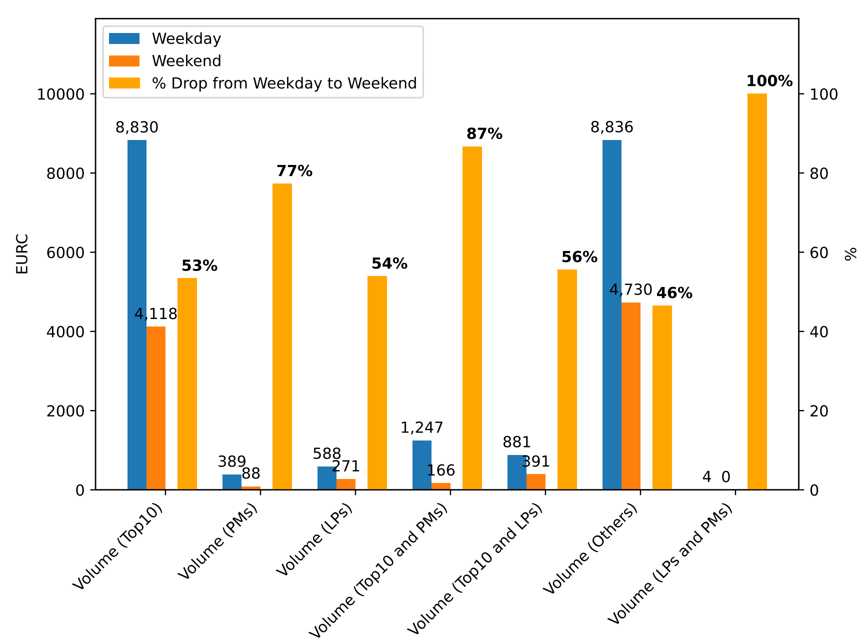
Note: This figure presents trading cost metrics for the EURC/USDC market. Panel (a) plots the inter-quartile range of total transaction costs across account types. The measure combines gas fees (based on ETH transaction fees converted to USD), LP fees (5 basis points for the EURC-USDC pool), and slippage, all measured in basis points. Panel (b) decomposes the median transaction cost into its component parts: gas fees, LP fees, and slippage. Fee components are expressed in basis points and grouped by account type, with medians shown. Account types are categorized into seven sub-groups: sophisticated traders (top 10 wallets), primary dealers, LPs, and combinations of these groups. Sample period is from 1 March 2023 to 30 April 2024.

Figure 7: Weekend and Weekday Volume by Trader type

Panel (a): Weekday trading: traditional hours versus close

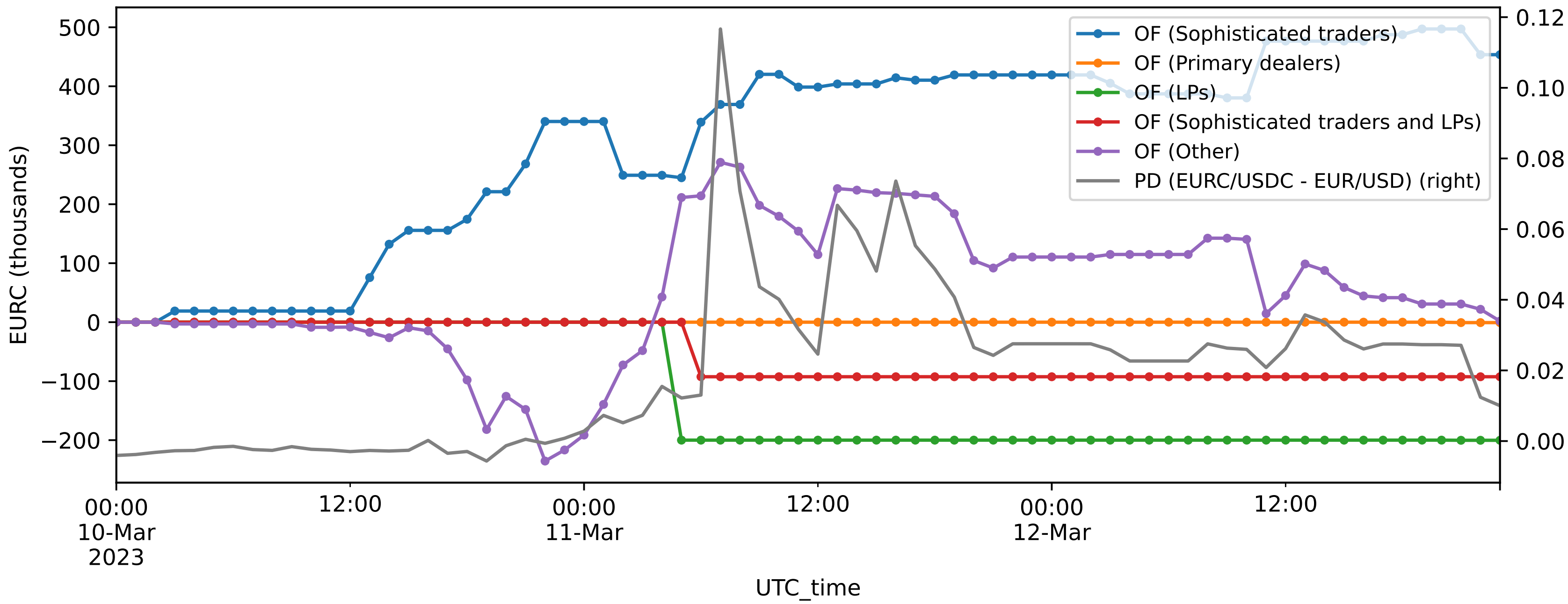


Panel (b): Weekday vs Weekend trading



Note: The figure plots average hourly trading volume, distinguishing between weekday and weekend trading for each group. In Panel (a), we compare trading volume for each group during traditional primary opening hours (13–16 UTC) versus other hours on weekdays. Panel (b) presents average trading volume for each group over weekdays and weekends. All volumes are expressed in EURC. Blockchain volume is categorized into seven sub-groups: sophisticated traders (top 10 wallets), primary dealers, LPs, and combinations of these groups. The sample period spans from 15 August 2022 to 30 April 2024.

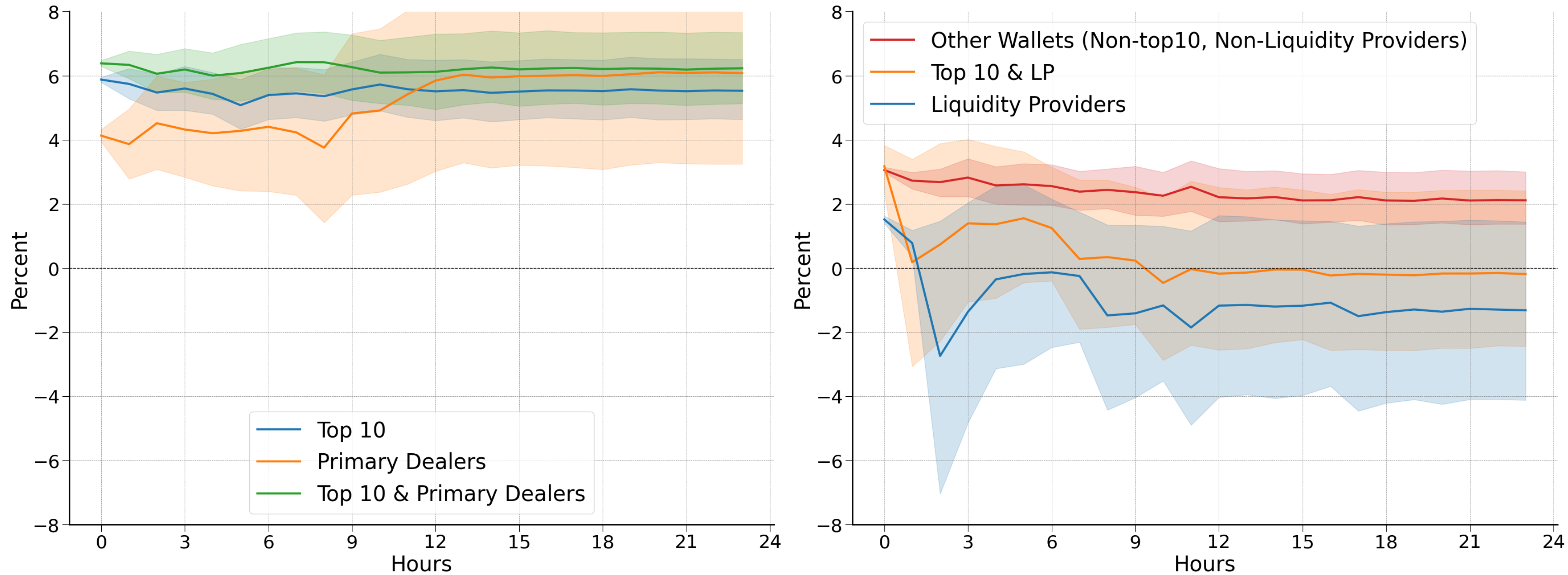
Figure 8: USDC De-Pegging event: blockchain order flow of different trading groups



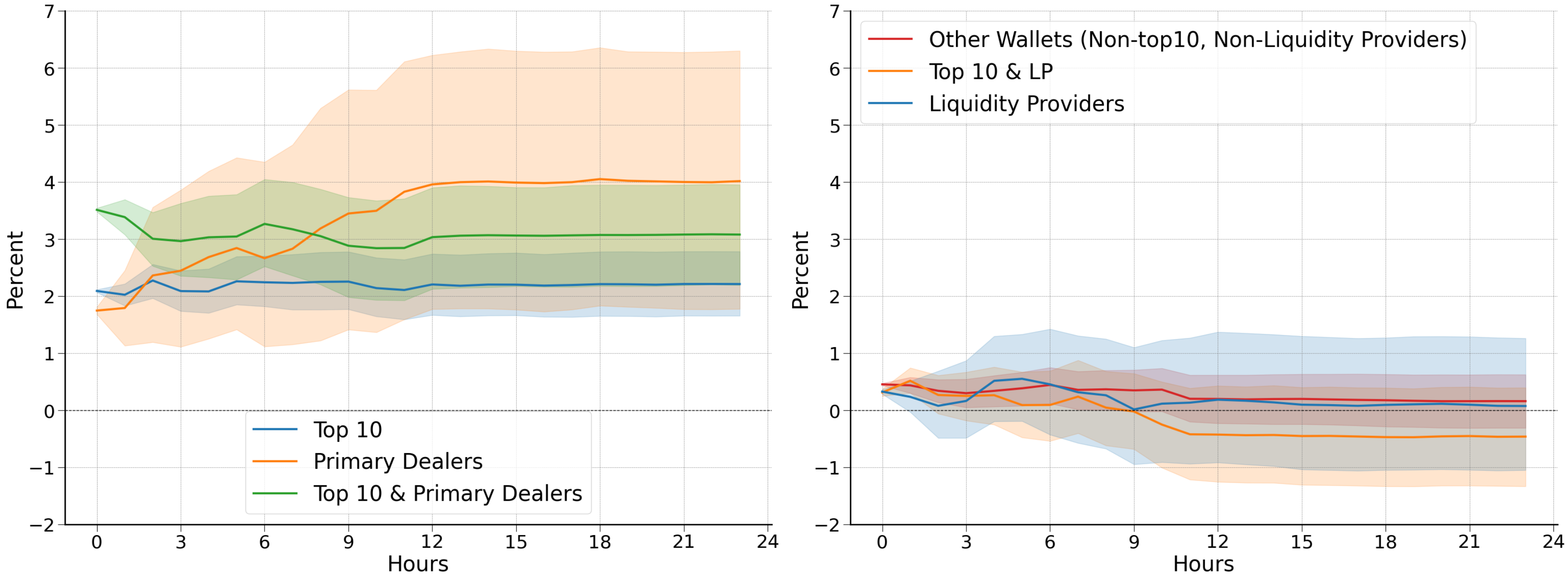
Note: This figure plots the response of blockchain order flow to the de-pegging event of USDC. PD is the difference between EURC/USDC and EUR/USD prices, sourced from Uniswap V3 and CLS respectively. OF is measuring the net buyer transactions of purchasing EURC, and is sourced from Uniswap V3 trade data. Cumulative blockchain order flow is divided into the following sub-categories: sophisticated traders (top 10 wallets), primary dealers, and LPs, denoted by OF_{top10}, OF_{PM} and OF_{LP} respectively. Additionally, we include blockchain order flow of the intersection of sophisticated traders and primary dealers, $OF_{top10 \cap PM}$, and the intersection of sophisticated traders and LPs, $OF_{top10 \cap LP}$, and blockchain order flow of traders that do not belong to the three groups, $OF_{\notin top10, PM, LP}$. Total sample period is from 10 March 2023 to 12 March 2023.

Figure 9: Price impact of blockchain order flow: dynamic effects

Panel (a): EURC/USDC Return



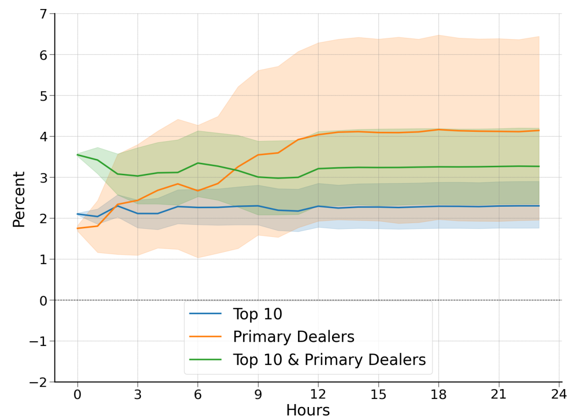
Panel (b): EUR/USD Return (CLS)



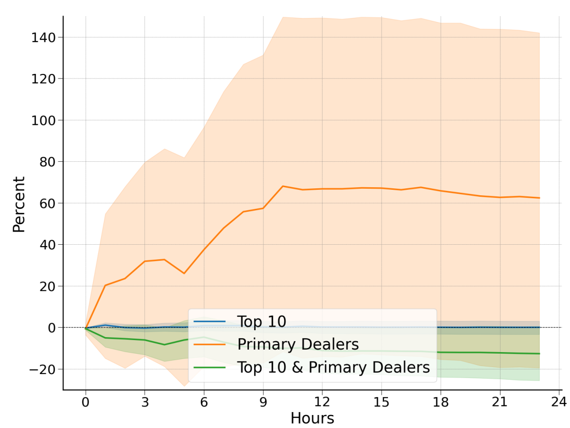
Note: This figure plots the impulse response of changes in spot returns to a 1 million EURC shock in blockchain order flow using a structural VAR framework, estimated with 1,000 bootstrap replications. Blockchain order flow measures the net buyer transactions of EURC and is sourced from Uniswap V3 trade data. EURC/USDC returns are calculated using Uniswap V3 prices, while EUR/USD prices are sourced from CLS. Panel (a) shows the response of EURC/USDC returns, and Panel (b) shows the response of EUR/USD returns. Blockchain order flow is categorized into six sub-groups: sophisticated traders (top 10 wallets), primary dealers, LPs, and combinations of these. The sample period spans from 15 August 2022 to 30 April 2024.

Figure 10: Price impact of blockchain order flow: information versus feedback trading (EUR/USD CLS Return)

Panel (a): Residual component (information proxy)



Panel (b): Predicted component (feedback/arbitrage proxy)



Note: This figure plots the impulse response of spot returns to a 1 million EURC shock in blockchain order flow using a structural VAR framework, estimated with 1,000 bootstrap replications. Blockchain order flow measures net EURC buyer transactions from Uniswap V3 trade data, while EUR/USD prices are sourced from CLS. To isolate informational content from feedback trading and arbitrage effects between DEX and traditional markets, we decompose order flow by regressing it on the lagged price difference between markets, separating it into a feedback component and a residual component. Panel (a) shows the response of EUR/USD returns to the residual component, and Panel (b) shows the response of EUR/USD returns to the feedback/arbitrage component. Results are presented for blockchain order flow sub-categories: sophisticated traders (top 10 wallets), primary dealers, and their intersecting group. The sample period spans from 15 August 2022 to 30 April 2024.

Table 1: Trader classification

Panel (a): Number of transactions

Group	top10	PrimaryDealer	LP	$N_{addresses}$	Tx	Tx/$N_{addresses}$
Top10	✓	×	×	76	4439	58.41
PM	×	✓	×	68	363	5.34
LP	×	×	✓	90	446	4.96
Top10 ∩ PM	✓	✓	×	6	534	89.00
Top10 ∩ LP	✓	×	✓	7	249	35.57
PM ∩ LP	×	✓	✓	3	6	2.00
$\notin Top10, PM, LP$	×	×	×	2342	9118	3.89

Panel (b): Volume per transaction (EURC)

Group	mean	std	min	25%	50%	75%	max
Top10	25,301	48,886	1	7,845	13,715	27,545	1,040,295
PM	12,528	18,558	3	991	8,000	18,596	183,500
LP	16,752	25,887	1	1,149	8,079	24,260	289,800
Top10 ∩ PM	26,373	10,664	100	20,000	25,000	30,000	95,990
Top10 ∩ LP	44,665	62,339	100	4,290	31,212	50,000	343,333
PM ∩ LP	7,537	9,931	352	2,394	4,556	6,262	27,256
$\notin Top10, PM, LP$	12,611	21,334	0	1,061	5,069	15,169	557,076

Note: Panel (a) presents summary statistics for the number of transactions (Tx) of different trading groups, and the transactions per unique address (Tx/$N_{address}$). Panel (b) presents summary statistics for the volume per transaction in EURC for different trading groups. We characterize wallets in the following trading groups: sophisticated traders (top 10 wallets), primary dealers, and are LPs, denoted by Top10, PM and LP respectively. Additionally, we include sub-categories of traders that are the intersection of sophisticated traders and have primary dealers, Top10 ∩ PM, the intersection of sophisticated traders and LPs, Top10 ∩ LP, and traders that do not belong to the three groups, $\notin \{Top10, PM, LP\}$. Sample period is from 15 August 2022 to 30 April 2024.

Table 2: Summary statistics: Prices, Volume and Blockchain Variables

	count	mean	std	min	25%	50%	75%	max
Panel (a): Trading Volume (CLS) - EUR Billion								
Volume-Corporate-Bank	625	0.777	1.255	0.000	0.000	0.450	0.924	11.018
Volume-Fund-Bank	625	6.003	6.062	0.000	0.000	6.111	8.552	44.678
Volume-Non-Bank Financial-Bank	625	0.275	1.106	0.000	0.000	0.030	0.106	10.331
Volume-Interbank	625	21.366	15.671	0.000	0.354	25.560	31.197	82.861
Volume-Aggregate	625	28.421	20.657	0.000	0.354	34.114	42.077	94.397
Panel (b): Trading Volume (Uniswap)- EURC Million								
Volume (Aggregate)	625	0.423	0.674	0.0001	0.103	0.232	0.490	8.545
Volume (top10)	625	0.180	0.341	0.0	0.015	0.067	0.199	3.453
Volume (PM)	625	0.007	0.020	0.0	0.000	0.000	0.002	0.184
Volume (LP)	625	0.012	0.036	0.0	0.000	0.000	0.002	0.464
Volume (top10 ∩ PM)	625	0.023	0.047	0.0	0.000	0.000	0.030	0.343
Volume (top10 ∩ LP)	625	0.018	0.084	0.0	0.000	0.000	0.000	1.381
Volume ($\notin \{Top10, PM, LP\}$)	625	0.184	0.360	0.0	0.042	0.097	0.193	5.259
Volume (PM ∩ LP)	625	0.0001	0.0013	0.0	0.000	0.000	0.000	0.027
Panel (c): Additional Variables								
$p_{\mathrm{EURC/USDC}}$	625	1.067	0.035	0.962	1.058	1.078	1.091	1.128
$p_{\mathrm{EUR/USD}}$	625	1.066	0.035	0.960	1.058	1.077	1.089	1.124
$\lvert p_{\mathrm{EUR/USD}} - p_{\mathrm{EURC/USDC}} \rvert$	625	0.002	0.003	0.000	0.001	0.002	0.003	0.028
σ_{ETH}	625	0.007	0.002	0.003	0.005	0.006	0.008	0.013
GasFee	625	0.006	0.001	0.004	0.005	0.006	0.007	0.009
R_{ETH}	624	0.001	0.031	-0.189	-0.012	0.000	0.015	0.160

Note: Panel (a) presents summary statistics of trading volume for EUR/USD pair from CLS. CLS volume is measured in EUR Billions, and is aggregated as well as in the following sub-categories: BuySide Bank-SellSide, Corporate-Bank, Fund-Bank and Non-Bank Financial-Bank volume. Panel (b) presents summary statistics of trading volume for the EURC/USDC pair from Uniswap. DEX volume is divided into different trading groups based on whether they are sophisticated traders (top10), primary dealers (PM), or are LPs. See classification in Table 1 for more details. Panel (c) presents summary statistics of a series of price, blockchain and traditional FX market statistics. Blockchain characteristics include the returns and volatility of Coinbase ETH/USD, and an index of gas fees. Sample period is from 15 August 2022 to 30 April 2024.

Table 3: Triangular arbitrage conditions and transaction costs: violations of the upper bound

	count	mean	std	min	25%	50%	75%	max
Panel (a): Triangular arbitrage metrics								
Δ_1	9049	0.003	0.006	0.000	0.001	0.002	0.003	0.080
Δ_2	9049	0.004	0.007	0.000	0.001	0.002	0.004	0.071
Δ_3	9049	0.004	0.008	0.000	0.001	0.002	0.004	0.079
Panel (b): Transaction costs: gas fees + liquidity fees + slippage								
Δ_1 Arbitrage Bound Violation	9049	0.161	0.368	0.000	0.000	0.000	0.000	1.000
Δ_2 Arbitrage Bound Violation	9049	0.186	0.389	0.000	0.000	0.000	0.000	1.000
Δ_3 Arbitrage Bound Violation	9049	0.191	0.393	0.000	0.000	0.000	0.000	1.000
Panel (c): Transaction costs: gas fees + liquidity fees + slippage + CEX fees								
Δ_1 Arbitrage Bound Violation	9049	0.037	0.188	0.000	0.000	0.000	0.000	1.000
Δ_2 Arbitrage Bound Violation	9049	0.032	0.177	0.000	0.000	0.000	0.000	1.000
Δ_3 Arbitrage Bound Violation	9049	0.049	0.216	0.000	0.000	0.000	0.000	1.000

Note: This table reports summary statistics on violations of no-arbitrage conditions based on triangular arbitrage metrics (Δ_1, Δ_2, Δ_3) constructed from EUR/USD and EURC/USDC price quotes. Panel (a) shows absolute percentage deviations implied by different arbitrage paths. Panel (b) reports the share of instances where the arbitrage metrics exceed estimated transaction costs, incorporating on-chain gas fees (in ETH converted to USD), a constant liquidity provider fee of 0.05%, and slippage. Slippage reflects the average execution price impact and is captured at the transaction level. Panel (c) augments the bounds further by including estimated taker fees from centralized exchanges (Coinbase and Kraken) based on transaction size, as well as bid-ask spread proxies. CEX fees follow tiered schedules, with fee rates decreasing in transaction size. Binary indicators flag violations when arbitrage metrics exceed these bounds. Gas fees and transaction costs are winsorized at the top 1% level. Sample period is 1 March 2023 to 30 April 2024.

Table 4: Determinants of EURC-USDC Peg Deviations

	| EURC/USDC – EUR/USD | Peg Deviations				
	(1)	(2)	(3)	(4)	(5)
gasfee	1.3283***				1.1787**
	(0.5036)				(0.4718)
σ_{ETH}^{IV}		0.1349*			0.1582**
		(0.0803)			(0.0723)
R_{ETH}		0.0050			0.0011
		(0.0042)			(0.0031)
$\lvert p_{\text{USDC/USD}} - 1\rvert$			0.6438***		0.7532***
			(0.0931)		(0.0272)
$\lvert p_{\text{EURC/EUR}} - 1\rvert$			0.1797		
			(0.1137)		
VLOOP				-1.0602	-0.3698
				(0.8011)	(0.7163)
ICRF				32.9633	49.2961
				(111.2642)	(98.4555)
constant	15.9478***	15.0894***	20.6290***	23.9748***	5.1853
	(2.9195)	(5.3608)	(2.1497)	(1.8659)	(5.9025)
R-squared	0.0552	0.0139	0.2805	0.0019	0.2294
No. observations	625	624	429	625	624

Note: This table reports OLS regressions of daily absolute peg deviations $\lvert p_{\text{EURC/USDC}} - p_{\text{EUR/USD}}\rvert$. Gas fees measure average transaction costs on the Ethereum network, expressed in USD per transaction. σ_{ETH}^{IV} denotes the 30-day implied volatility for Ether from the EthVol index. R_{ETH} is the daily return on ETH-USDC based on closing prices. VLOOP is the standardized first principal component of FX arbitrage violations (triangular no-arbitrage deviations) across nine G10 currency pairs. ICRF is the intermediary capital risk factor, from He et al. (2017), reflects shocks to U.S. dealer capital constraints based on equity-to-asset ratios. $\lvert p_{\text{USDC/USD}} - 1\rvert$ and $\lvert p_{\text{EURC/EUR}} - 1\rvert$ are peg deviations of the USDC and EURC stablecoins from their respective fiat reference values. All data is measured at the daily frequency, and peg-price deviations, returns, and volatility measures are expressed in basis points. Standard errors are Newey-West (HAC) and reported in parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 5: DEX and CLS Volume correlations

	V_{top10}	V_{PM}	V_{LP}	$V_{top10 \cap PM}$	$V_{top10 \cap LP}$	$V_{LP \cap PM}$	$V_{\notin top10,PM,LP}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Interbank	4.3478***	0.1984***	0.3286**	0.8337***	0.4106*	-0.0001	3.2545***
	(0.7699)	(0.0413)	(0.1309)	(0.1027)	(0.2480)	(0.0006)	(0.7452)
Corporate-Bank	1.5545	-0.0026	0.3532	0.5860*	-0.4185**	-0.0018	2.2923
	(1.5778)	(0.1899)	(0.3098)	(0.3324)	(0.1945)	(0.0013)	(1.9787)
Fund-Bank	1.1120***	0.0353	0.0166	0.2303***	0.0369	0.0017	0.9016***
	(0.3931)	(0.0308)	(0.0419)	(0.0651)	(0.0844)	(0.0017)	(0.3087)
Non-Bank Financial-Bank	2.3239	0.3554	-0.0312	0.7064	0.0518	-0.0002	6.8670
	(3.7332)	(0.3012)	(0.1768)	(0.6986)	(0.1026)	(0.0002)	(7.7577)
constant	3261.9288***	113.7215***	190.3928**	111.9940	379.6192***	2.7742	4390.3679***
	(529.2313)	(35.7043)	(92.8885)	(68.7749)	(136.5073)	(2.3496)	(600.3514)
R-squared	0.017	0.005	0.005	0.028	0.001	0.000	0.018
No. observations	14,999	14,999	14,999	14,999	14,999	14,999	14,999

Note: This table presents the results of regressing CLS volume on DEX volume. DEX volume is measuring the aggregate buy and sell transactions in EURC, and is sourced from Uniswap V3 trade data. DEX volume is divided into sub-categories: sophisticated traders (top 10 wallets), primary dealers, and LPs, denoted by V_{top10}, V_{PM} and V_{LP} respectively. Additionally, we include DEX trading volume of the intersection of sophisticated traders and primary dealers, $V_{top10 \cap PM}$, and the intersection of sophisticated traders and LPs, $V_{top10 \cap LP}$, and traders that do not belong to the three groups, $V_{\notin top10,PM,LP}$. CLS volume is measured in EUR Millions, and is aggregated as well as in the following sub-categories: BuySide Bank-SellSide, Corporate-Bank, Fund-Bank and Non-Bank Financial-Bank volume. Total sample period is from 15 August 2022 to 30 April 2024. Standard errors are Newey-West (HAC) and reported in parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 6: Determinants of EURC/USDC Order Flow

	$OF_{top10,t}$	$OF_{PM,t}$	$OF_{LP,t}$	$OF_{top10\cap PM,t}$	$OF_{top10\cap LP,t}$	$OF_{LP\cap PM,t}$	$OF_{\notin top10,PM,LP,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$P_{DEX,t-1} - P_{CLS,t-1}$	-0.1454**	-0.0097	-0.0207*	-0.1374***	-0.0032	-0.0003	-0.2247***
	(0.0609)	(0.0072)	(0.0121)	(0.0297)	(0.0085)	(0.0002)	(0.0354)
DEXReturn$_{t-1}$	-0.0077**	-0.0002	0.0003	-0.0012	0.0002	-0.0000	-0.0008
	(0.0035)	(0.0002)	(0.0006)	(0.0010)	(0.0002)	(0.0000)	(0.0026)
$OF_{top10,t-1}$	0.1995***						
	(0.0687)						
$OF_{PM,t-1}$		0.0257**					
		(0.0128)					
$OF_{LP,t-1}$			0.0153				
			(0.0138)				
$OF_{top10\cap PM,t-1}$				0.0654**			
				(0.0261)			
$OF_{top10\cap LP,t-1}$					-0.0888		
					(0.1617)		
$OF_{LP\cap PM,t-1}$						0.0000	
						(0.0001)	
$OF_{\notin top10,PM,LP,t-1}$							0.1332
							(0.0863)
constant	0.0001	0.0000	0.0001**	-0.0000	0.0000	-0.0000	0.0003*
	(0.0002)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0002)
R-squared	0.042	0.001	0.000	0.012	0.008	0.000	0.020
No. observations	14,998	14,998	14,998	14,998	14,998	14,998	14,998

Note: This table presents the results of regressing order flow on the price difference between the DEX and CLS exchange rates. OF measures net buyer transactions of EURC, sourced from Uniswap V3 data. $P_{DEX} - P_{CLS}$ measures the price difference between DEX and CLS exchange rates. Order flow is divided into sub-categories such as top 10 wallets, access to primary markets, and liquidity providers. The sample period is from 15 August 2022 to 30 April 2024. Standard errors are Newey-West (HAC) and reported in parentheses. *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.

Internet Appendix to

"Blockchain Currency Markets"

(Not for publication)

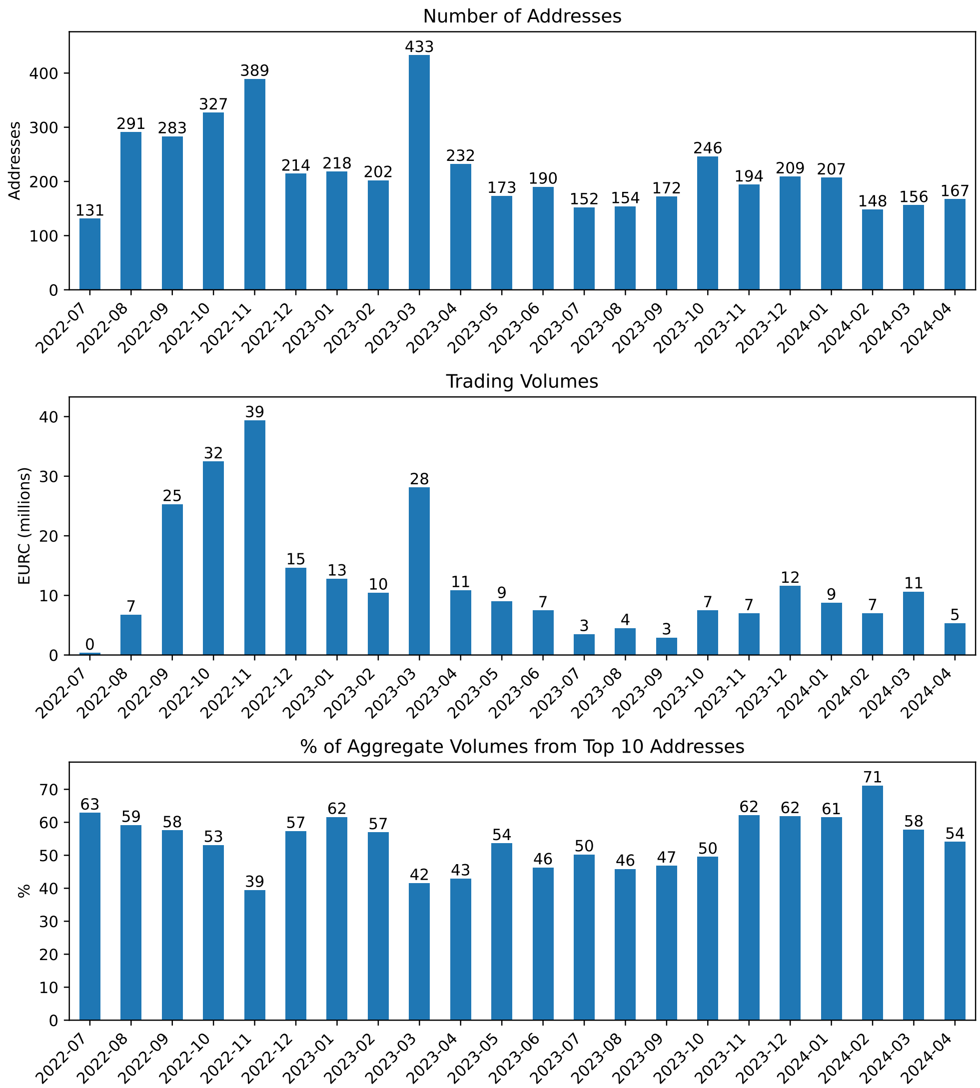
We provide a roadmap of each section of our Appendix.

1. Appendix A presents additional statistics, including trading volume, liquidity provision, and intra-day liquidity provider patterns.
2. Appendix B analyzes the reaction of EURC/USDC and EUR/USD rates to monetary announcements from the Federal Reserve, using event study methodology.
3. Appendix C examines primary market issuance of USDC and EURC, describing Treasury transactions and their impact on stablecoin supply and circulation.
4. Appendix D provides transaction details for sophisticated investors and liquidity providers during the USDC de-pegging event (March 10–12, 2023).
5. Appendix E details the SVAR identification strategy, including recursive Cholesky assumptions and matrix construction for traditional OTC and blockchain order flows.
6. Appendix F presents robustness tests, including a study of intra-day price impact, controls for liquidity provision, and investigates just-in-time (JIT) liquidity provision in the EURC/USDC pool, documenting transaction details of sophisticated liquidity providers.

Appendix A: Additional Statistics

A.1 Trading Volume

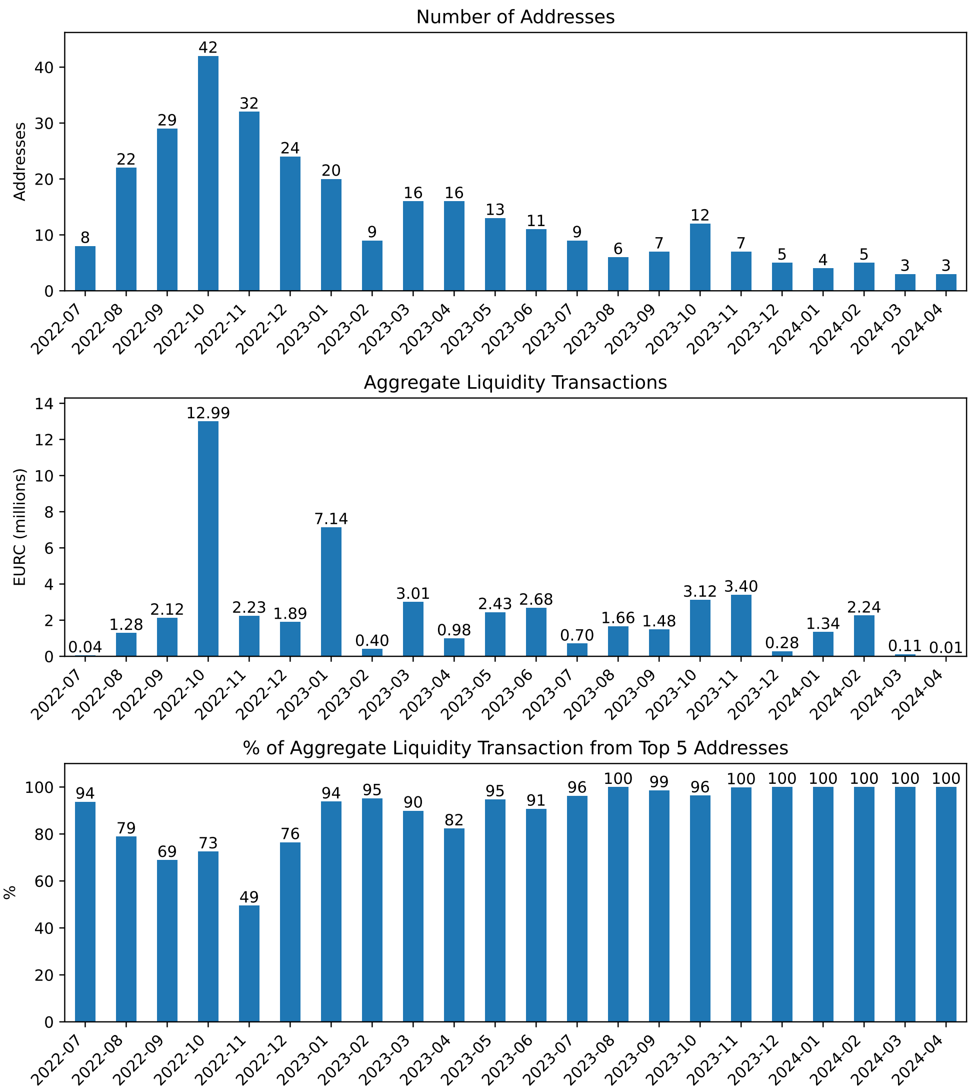
Figure A1: Summary statistics of trading volume



Note: This figure plots monthly summary statistics of the distribution of trading volume. It shows the number of addresses, the trading volume, and the percentage of trading volume from sophisticated traders (top 10 wallets). The total sample period is from 1 July 2022 to 30 April 2024.

A.2 Liquidity Provision

Figure A2: Summary statistics of liquidity provision

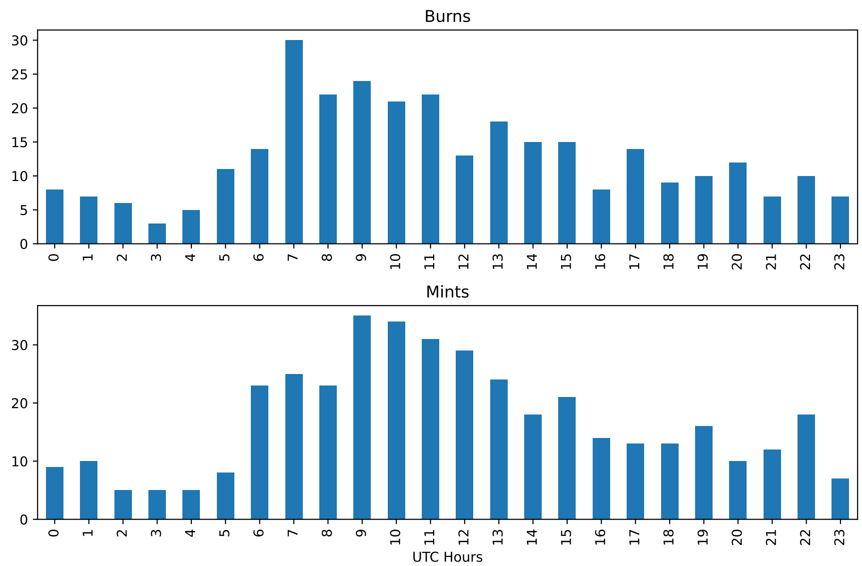


Note: This figure plots monthly summary statistics of the distribution of liquidity provision. It shows the number of addresses, the aggregate liquidity provision, and the percentage of liquidity provided by the top 5 LPs. The total sample period is from 1 July 2022 to 30 April 2024.

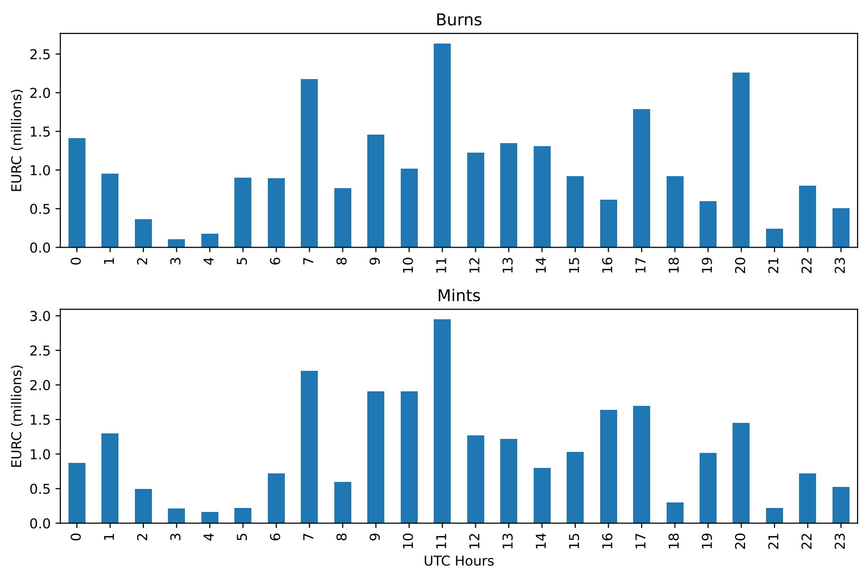
A.3 Liquidity Providers- intra-day patterns

Figure A3: Intra-day LP Mints and Burns

Panel (a): Number of transactions



Panel (b): Volume



Note: Figure plots hourly liquidity provision, classified into mints (addition of liquidity) and burns (withdrawal of liquidity). In Panel (a), we report LPs transaction count of mints and burns. In Panel (b), we report LPs volume of mints and burns. The total sample period starts on 15 August 2022, and ends on 30 April 2024.

A.4 Blockchain characteristics

In this section, we provide supplementary information on blockchain-level characteristics of trader wallets, specifically wallet age, the number of tokens transferred, and the average frequency of transactions per day. We examine these characteristics across different trader types: sophisticated traders, primary dealers (PMs), and liquidity providers (LPs). Table A1 presents summary statistics across seven mutually exclusive groups.

Panel (a) reports statistics for sophisticated traders. These wallets are relatively older, with a median age of 742 days, and show the highest transaction frequency, with a median of 0.68 transactions per day. They also tend to transfer a larger number of tokens, with a median of 54.

Panel (b) shows that primary dealers have somewhat younger wallets (median age 613 days) and lower token transfer activity (median of 20), but still transact relatively frequently, with a median frequency of 0.58 transactions per day.

Panel (c) presents LPs, who have the oldest median wallet age (813 days), moderate token transfer activity (median of 30), and a lower transaction frequency (median of 0.32 per day), suggesting more infrequent but potentially larger or passive transactions.

Panels (d) to (f) report statistics for wallets belonging to multiple categories. These subgroups show a range of behaviors, but generally have higher transaction frequency and token transfers than their single-category counterparts. For instance, sophisticated traders who are also LPs exhibit a notably high median number of tokens transferred (88) and higher transaction frequency (1.13 per day).

Finally, Panel (g) covers wallets that do not fall into any of the above categories. These wallets have the lowest medians across most metrics, including a transaction frequency of 0.24 per day and only 14 tokens transferred, highlighting the less active behavior of the residual group.

Overall, the summary statistics show differences in activity patterns across trader types. Sophisticated traders and PMs tend to be more active and older, while LPs operate with lower frequency. However, the correlation between wallet-level blockchain activity and trader classification remains moderate, suggesting blockchain activity alone does not fully explain observed trading roles or strategies.

Table A1: Blockchain characteristics by address type

	count	mean	std	min	0.25	0.50	0.75	max
Panel (a): Sophisticated traders								
Age (days)	75	805.01	465.37	154.00	535.50	742.00	990.00	2624.00
Number of Tokens Transferred	75	100.83	105.77	5.00	15.50	54.00	184.00	383.00
Frequency (transactions per day)	75	10.29	47.62	0.01	0.07	0.68	2.20	384.94
Panel (b): Primary dealers								
Age (days)	68	750.31	495.65	15.00	412.50	612.50	942.25	2389.00
Number of Tokens Transferred	68	57.16	108.64	1.00	5.00	19.50	49.50	643.00
Frequency (transactions per day)	68	1.75	3.46	0.02	0.13	0.58	1.82	23.99
Panel (c): LPs								
Age (days)	90	911.97	428.14	194.00	601.25	813.00	1101.25	2301.00
Number of Tokens Transferred	90	44.28	46.04	2.00	14.25	29.50	55.00	258.00
Frequency (transactions per day)	90	0.56	0.96	0.02	0.16	0.32	0.56	8.00
Panel (d): Sophisticated traders and primary dealers								
Age (days)	6	507.50	152.10	376.00	394.50	475.00	546.50	781.00
Number of Tokens Transferred	6	21.00	7.92	11.00	15.25	21.00	26.00	32.00
Frequency (transactions per day)	6	3.94	3.40	0.63	1.80	2.38	6.90	8.23
Panel (e): Sophisticated traders and LPs								
Age (days)	7	630.86	370.45	341.00	373.00	421.00	781.50	1345.00
Number of Tokens Transferred	7	357.00	527.28	11.00	53.50	88.00	449.00	1395.00
Frequency (transactions per day)	7	4.51	7.67	0.12	0.36	1.13	4.16	21.32
Panel (f): LPs and primary dealers								
Age (days)	3	1337.00	1005.61	696.00	757.50	819.00	1657.50	2496.00
Number of Tokens Transferred	3	105.67	78.68	36.00	63.00	90.00	140.50	191.00
Frequency (transactions per day)	3	1.21	0.47	0.79	0.96	1.13	1.42	1.71
Panel (g): Not sophisticated traders, primary dealers and LPs								
Age (days)	2316	707.10	492.28	1.00	406.75	585.50	944.50	2834.00

Number of Tokens Transferred	2316	64.64	251.83	1.00	4.00	14.00	46.00	7631.00
Frequency (transactions per day)	2316	2.28	16.88	0.00	0.07	0.24	0.92	558.01

Note: This table presents summary statistics of blockchain characteristics, based on age (days since wallet started trading), number of tokens transferred by the wallet, and frequency (measured in transactions per day). We compute summary statistics for 7 trading groups, including sophisticated traders, primary dealers, LPs, the intersection of sophisticated traders and primary dealers, the intersection of sophisticated traders and LPs, LPs and primary dealers, and traders that do not belong to the three groups. Total sample period is from 15 August 2022 to 30 April 2024.

Appendix B: Monetary Announcements

Figure B1: Federal Reserve Monetary Announcements (Part 1)

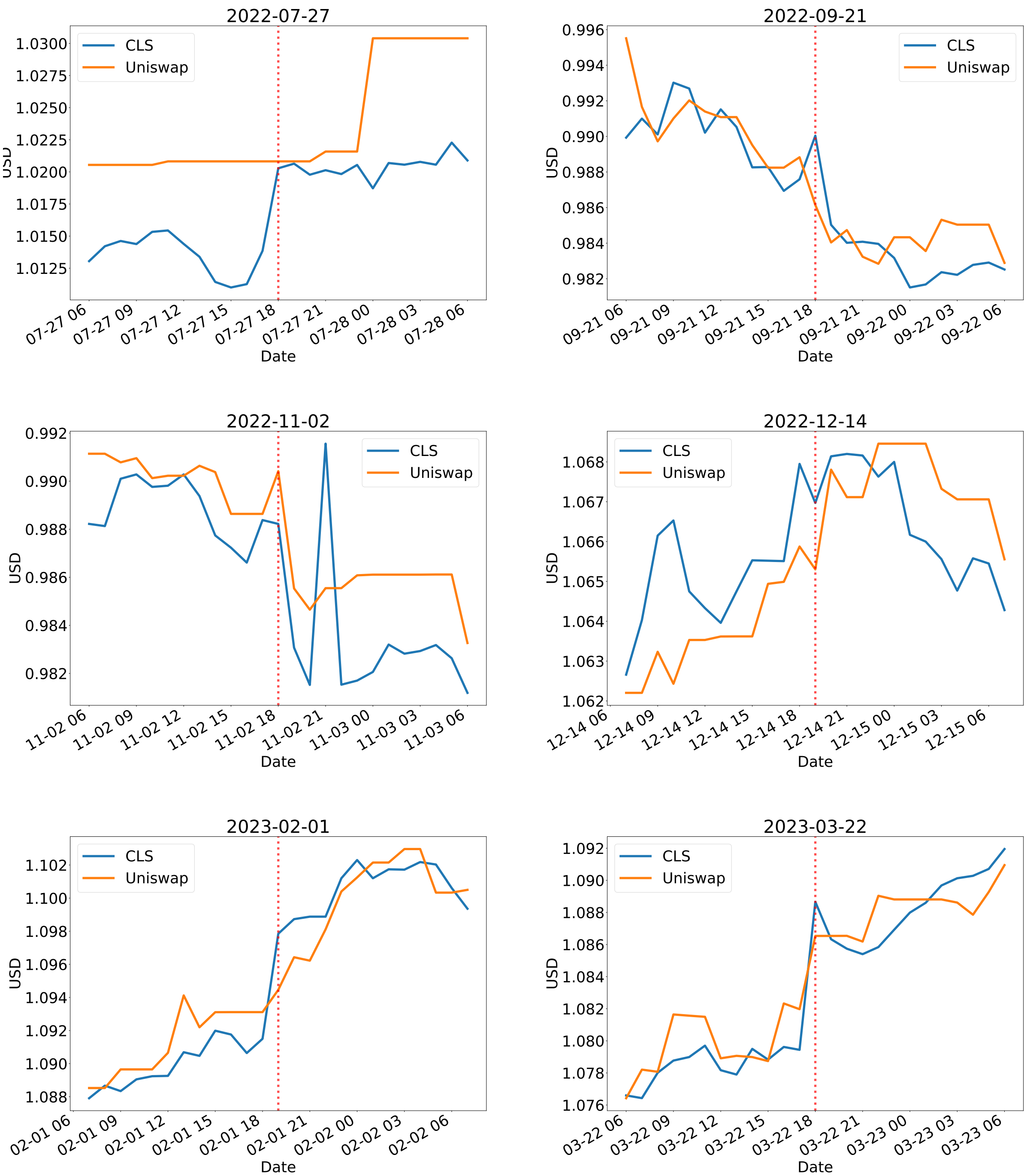


Figure B2: Federal Reserve Monetary Announcements (Part 2)

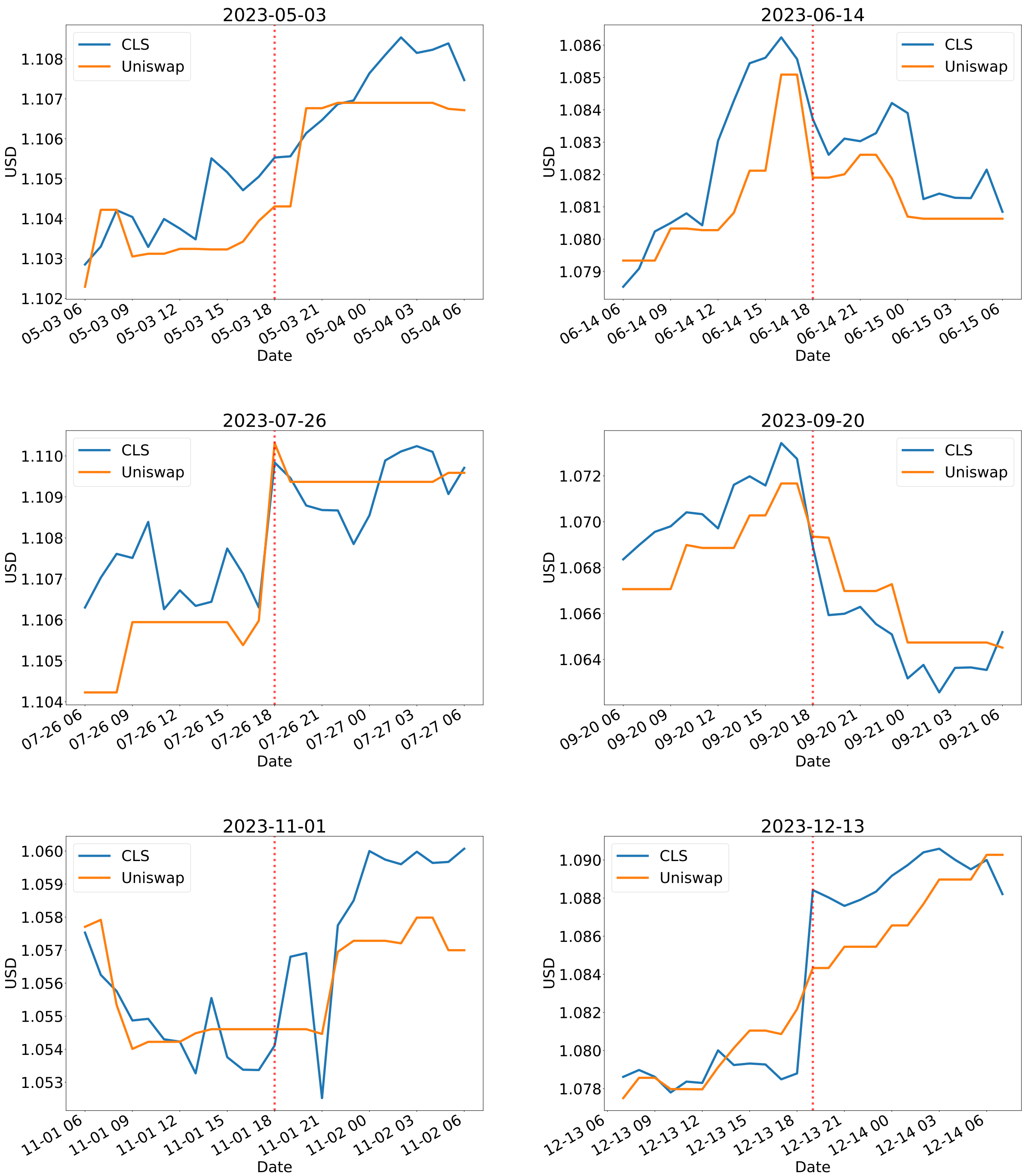
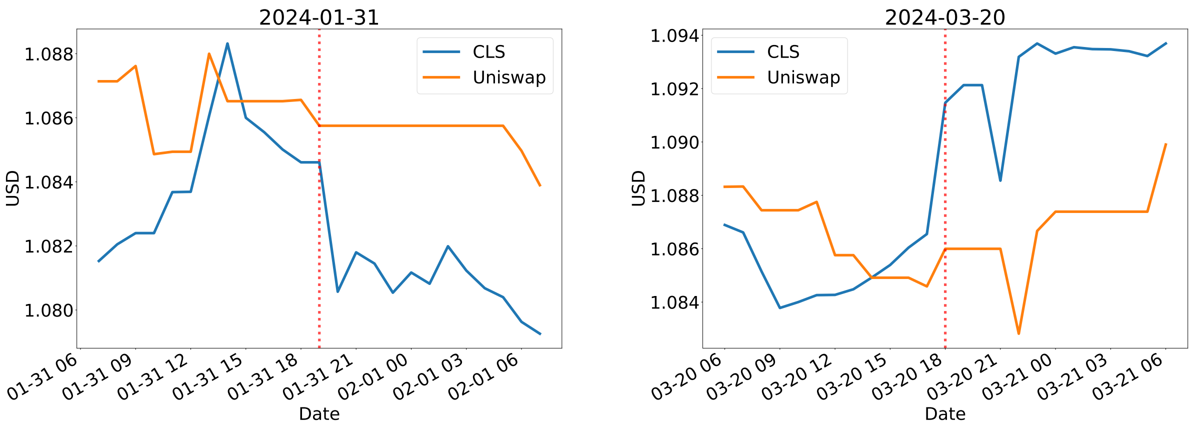


Figure B3: Federal Reserve Monetary Announcements (Part 3)



Note: This figure presents event studies of the reaction of EURC/USDC and EUR/USD rates around monetary announcements of the Federal Reserve. EURC/USDC prices are sourced from Uniswap V3, while EUR/USD prices are sourced from CLS. The total sample period covers announcements from July 2022 to March 2024.

Appendix C: Primary Market Issuance

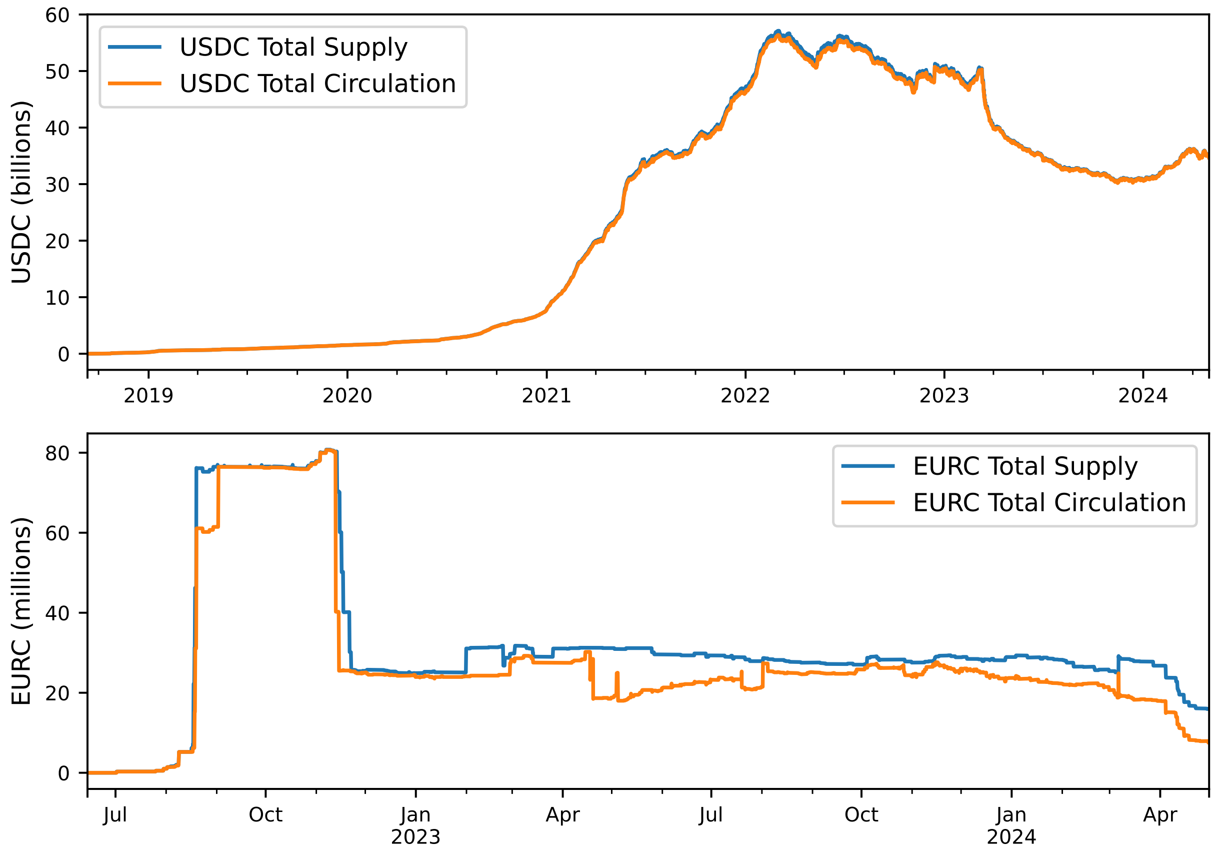
We obtain data on the primary market issuance from the Ethereum blockchain API. The primary market issuance uses a Circle Treasury address of the EURC and USDC Treasury. This dataset provides an entire history of Treasury transactions, with details on the size, timestamp, and the type of transaction. USDC tokens are created through a "grant" when new USDC tokens are minted. USDC tokens are destroyed through a "revoke" when USDC tokens are redeemed. Transactions between the Treasury and secondary market recipients are recorded based on whether counter parties are listed on the "send" and "receive" sides of the transaction.[29] The supply of USDC and EURC is shown in Figure B4. In addition to documenting the aggregate supply of USDC and EURC, we net out the amount of Circle tokens held by the Treasury that is not circulating in private wallets. This is indicated by the labels "USDC Total Circulation" and "EURC Total Circulation". The USDC primary market started issuance in early 2019, and reached a peak of nearly 60 USDC Billion in 2022. In contrast, the EURC Issuance started in June 2022 and reached a peak of 75 EURC Million.[30]

An important function of the USDC and EURC Treasury is guaranteeing a primary market rate, which is the rate at which the Treasury is willing to exchange USDC for dollars. The primary market rate is 1 USDC:USD for the Circle USDC Treasury, and 1 EURC:EUR for the Circle EURC Treasury. Trading of USDC/USD and EURC/EUR are on select centralized exchanges, that we can use to construct measures of market efficiency in the following subsection. Stability of the USDC and EURC pegs are based on a decentralized arbitrage mechanism (Lyons and Viswanath-Natraj, 2023; Ma et al., 2025). If the secondary market price of USDC (EURC) trades above one dollar, an investor can buy USDC (EURC) from the Treasury at a one-for-one rate, and sell USDC (EURC) at the prevailing market rate to profit, resulting in a flow of USDC (EURC) from the Treasury to the secondary market.

[29]The USDC Treasury address we use to retrieve the transaction history is "0xa0b86991c6218b36c1d19d4a2e9eb0ce3606eb48". The EURC Treasury address is "0x1abaea1f7c830bd89acc67ec4af516284b1bc33c"

[30]One caveat regarding the primary market issuance data is that we can only download activities related to the transfer of ERC-20 tokens. As a result, we might miss certain transaction activities, such as internal transactions. However, our data is representative and valid for understanding the overall trend in primary market issuance.

Figure B4: Primary Market Issuance



Note: This figure plots the total supply of USDC and EURC, as well as the total in circulation (net of Treasury). The top panel reports the total supply of USDC, and the bottom panel reports the total supply of EURC. The total sample period for the top two figures is from 28 June 2022, to 30 April 2024. For the bottom two figures, the sample period goes back to the early issuance dates of USDC and EURC. We use data starting from 10 September 2018, for USDC and from 23 June 2020, for EURC.

Appendix D: USDC De-Pegging Event

D.1 USDC De-Pegging Event: Sophisticated Investor Trades

Table D1: Transactions of Sophisticated Investor during USDC De-Pegging Event (2023-03-10 to 2023-03-12)

Date (UTC)	Hash	From	To	USDC	From Name	To Name
2023-03-10 00:14:47	ea98	1c37	02ce	83333333.3333333	trader	Uniswap V3: USDC-PRIME 2
2023-03-10 01:29:47	4daa	1c37	60ae	250000000.0	trader	SushiSwap: SYN-USDC
2023-03-10 02:11:11	36a6	1c37	60ae	333333333.333333	trader	SushiSwap: SYN-USDC
2023-03-10 02:28:23	62e5	1c37	60ae	333333333.333333	trader	SushiSwap: SYN-USDC
2023-03-10 03:25:35	d18f	1c37	60ae	666666666.666666	trader	SushiSwap: SYN-USDC
2023-03-10 03:47:47	c30e	1c37	73d6	3333333333.33333	trader	Uniswap V3: EURC-USDC
2023-03-10 04:06:11	46f0	3e43	1c37	16666666666.6666	Coinbase	trader
2023-03-10 09:49:47	65dc	1c37	1690	166666666.666666	trader	SushiSwap: DDX-USDC
2023-03-10 12:35:47	18de	1c37	1690	250000000.0	trader	SushiSwap: DDX-USDC
2023-03-10 13:30:11	cfa9	1c37	73d6	3333333333.33333	trader	Uniswap V3: EURC-USDC
2023-03-10 13:34:59	3601	1c37	73d6	3333333333.33333	trader	Uniswap V3: EURC-USDC
2023-03-10 13:43:35	5de7	1c37	73d6	3333333333.33333	trader	Uniswap V3: EURC-USDC
2023-03-10 14:11:11	ae67	1c37	73d6	3333333333.33333	trader	Uniswap V3: EURC-USDC
2023-03-10 14:24:47	6aa6	1c37	73d6	3333333333.33333	trader	Uniswap V3: EURC-USDC
2023-03-10 14:29:11	5102	3e43	1c37	16666666666.6666	Coinbase	trader
2023-03-10 14:29:59	b043	1c37	73d6	3333333333.33333	trader	Uniswap V3: EURC-USDC
2023-03-10 14:36:59	ebaf	1c37	73d6	3333333333.33333	trader	Uniswap V3: EURC-USDC

Continued...

Date (UTC)	Hash	From	To	USDC	From Name	To Name
2023-03-10 14:43:35	021d	1c37	73d6	3333333333.33333	trader	Uniswap V3: EURC-USDC
2023-03-10 15:03:47	3c82	1c37	73d6	3333333333.33333	trader	Uniswap V3: EURC-USDC
2023-03-10 15:11:23	103a	1c37	1690	166666666.666666	trader	SushiSwap: DDX-USDC
2023-03-10 15:39:35	2426	1c37	73d6	833333333.333333	trader	Uniswap V3: EURC-USDC
2023-03-10 15:55:11	e414	1c37	02ce	833333333.333333	trader	Uniswap V3: USDC-PRIME 2
2023-03-10 16:00:59	3e42	1c37	02ce	666666666.666666	trader	Uniswap V3: USDC-PRIME 2
2023-03-10 16:05:11	4a84	3e43	1c37	16666666666.6666	Coinbase	trader
2023-03-10 16:05:59	2e85	1c37	02ce	666666666.666666	trader	Uniswap V3: USDC-PRIME 2
2023-03-10 18:31:11	69e9	1c37	73d6	3333333333.33333	trader	Uniswap V3: EURC-USDC
2023-03-10 19:55:47	c9e0	1c37	73d6	1250000000.0	trader	Uniswap V3: EURC-USDC
2023-03-10 21:30:35	5f29	1c37	73d6	1666666666.66666	trader	Uniswap V3: EURC-USDC
2023-03-10 21:34:47	419e	1c37	73d6	3333333333.33333	trader	Uniswap V3: EURC-USDC
2023-03-10 21:40:47	8acd	1c37	73d6	3333333333.33333	trader	Uniswap V3: EURC-USDC
2023-03-10 22:26:11	54a8	1c37	2286	1666666666.66666	trader	Uniswap V3: USDC-GYEN
2023-03-10 22:26:23	f5f5	1c37	2286	1666666666.66666	trader	Uniswap V3: USDC-GYEN
2023-03-10 22:29:35	56e4	1c37	2286	1666666666.66666	trader	Uniswap V3: USDC-GYEN
2023-03-10 22:31:11	2f23	1c37	2286	1666666666.66666	trader	Uniswap V3: USDC-GYEN
2023-03-10 22:31:11	3521	3e43	1c37	16666666666.6666	Coinbase	trader
2023-03-10 22:33:35	0a02	1c37	2286	1666666666.66666	trader	Uniswap V3: USDC-GYEN
2023-03-10 22:38:47	707e	1c37	2286	1666666666.66666	trader	Uniswap V3: USDC-GYEN
2023-03-10 22:42:23	0393	1c37	2286	1666666666.66666	trader	Uniswap V3: USDC-GYEN
2023-03-10 22:43:35	2d24	1c37	2286	1666666666.66666	trader	Uniswap V3: USDC-GYEN
2023-03-10 22:46:23	410c	1c37	2286	1666666666.66666	trader	Uniswap V3: USDC-GYEN
2023-03-10 22:47:23	23ed	1c37	2286	1666666666.66666	trader	Uniswap V3: USDC-GYEN

Continued...

Date (UTC)	Hash	From	To	USDC	From Name	To Name
2023-03-10 22:52:35	7987	1c37	2286	1666666666.66666	trader	Uniswap V3: USDC-GYEN
2023-03-10 22:55:47	e358	1c37	73d6	3333333333.33333	trader	Uniswap V3: EURC-USDC
2023-03-10 22:57:11	f239	3e43	1c37	16666666666.6666	Coinbase	trader
2023-03-10 22:59:11	9bb9	1c37	73d6	3333333333.33333	trader	Uniswap V3: EURC-USDC
2023-03-10 23:09:47	f719	1c37	2286	1666666666.66666	trader	Uniswap V3: USDC-GYEN
2023-03-10 23:19:35	536f	1c37	2286	1666666666.66666	trader	Uniswap V3: USDC-GYEN
2023-03-10 23:19:47	5c76	1c37	2286	1666666666.66666	trader	Uniswap V3: USDC-GYEN
2023-03-10 23:21:35	cd37	1c37	2286	1666666666.66666	trader	Uniswap V3: USDC-GYEN
2023-03-10 23:24:23	a95a	1c37	2286	1666666666.66666	trader	Uniswap V3: USDC-GYEN
2023-03-11 00:13:23	9b13	1c37	2286	1666666666.66666	trader	Uniswap V3: USDC-GYEN
2023-03-11 00:13:35	1421	1c37	2286	1666666666.66666	trader	Uniswap V3: USDC-GYEN
2023-03-11 00:18:35	5a94	1c37	2286	1666666666.66666	trader	Uniswap V3: USDC-GYEN
2023-03-11 00:18:47	4725	1c37	2286	1666666666.66666	trader	Uniswap V3: USDC-GYEN
2023-03-11 00:19:47	ab0c	1c37	2286	500000000.0	trader	Uniswap V3: USDC-GYEN
2023-03-11 00:19:59	41e0	1c37	2286	833333333.333333	trader	Uniswap V3: USDC-GYEN
2023-03-11 00:42:11	5c32	3e43	1c37	16666666666.6666	Coinbase	trader
2023-03-11 01:43:23	8e21	1c37	02ce	833333333.333333	trader	Uniswap V3: USDC-PRIME 2
2023-03-11 02:02:59	b24c	1c37	e180	666666666.666666	trader	Uniswap V3: BTRST-USDC
2023-03-11 02:40:11	aab8	1c37	b3e3	83333333.3333333	trader	Uniswap V3: FORT-USDC
2023-03-11 02:44:59	67b6	1c37	2286	1666666666.66666	trader	Uniswap V3: USDC-GYEN
2023-03-11 02:45:11	9ee4	1c37	2286	1666666666.66666	trader	Uniswap V3: USDC-GYEN
2023-03-11 02:45:23	b6c0	1c37	2286	1666666666.66666	trader	Uniswap V3: USDC-GYEN
2023-03-11 02:52:59	e5a4	1c37	e180	500000000.0	trader	Uniswap V3: BTRST-USDC
2023-03-11 03:08:23	465c	1c37	2286	833333333.333333	trader	Uniswap V3: USDC-GYEN

Continued...

Date (UTC)	Hash	From	To	USDC	From Name	To Name
2023-03-11 03:27:35	b37a	1c37	2286	833333333.333333	trader	Uniswap V3: USDC-GYEN
2023-03-12 19:01:59	b0a1	1c37	1690	333333333.333333	trader	SushiSwap: DDX-USDC
2023-03-12 21:30:11	2d77	1c37	02ce	250000000.0	trader	Uniswap V3: USDC-PRIME 2
2023-03-12 21:35:23	205d	1c37	02ce	250000000.0	trader	Uniswap V3: USDC-PRIME 2
2023-03-12 23:00:35	2fc2	1c37	1690	250000000.0	trader	SushiSwap: DDX-USDC

Note: This table presents swap transactions from the sophisticated investor with wallet ID ’0xd64137f743432392538a8f84e8e571fa09f21c37’, abbreviated to wallet ’1c37’, during the USDC de-pegging event on March 10-12, 2023. Transactions are sourced from Etherscan API. This wallet was the largest single source of USDC selling pressure during the de-pegging event. The ’From’ and ’To’ refer to transfers of USDC. Transactions typically show transfers of USDC from Coinbase to wallet ’1c37’. Wallet ’1c37’ then transfers USDC to decentralized exchange pools in Uniswap V3. The sample period is from 10 March 2023 to 12 March 2023.

D.2 USDC De-Pegging Event: Liquidity Provision

Table B2: Liquidity provision during USDC de-pegging event

Panel (a): Mint/Burn

UTC Time	User Address	EURC	USDC	Price	Lower Price	Upper Price
3/10/23 5:57	0x767f840400070112ead7b6f64603897ce0144f35	48656.685	62725.785	1.057	1.013	1.094
3/11/23 5:59	0x767f840400070112ead7b6f64603897ce0144f35	-92233.623	-355866.065	1.076	1.013	1.094
3/11/23 9:47	0xf550786c496bd9b99d2f91b3db6a01ce32704f8f	0	-312108.039	1.110	1.000	1.080
3/11/23 9:51	0xf550786c496bd9b99d2f91b3db6a01ce32704f8f	0	312665.183	1.108	1.035	1.107
3/12/23 21:34	0x251691e49c2ea15882883c4ed3a4fdcd28abebb3	0	506.468	1.091	1.005	1.075

Panel (b): Swap

UTC Time	Origin	Swap Price	Price After Swap	OF (EURC)
3/11/23 6:57	0x767f840400070112ead7b6f64603897ce0144f35	1.071	1.065	-92509.174
3/12/23 21:32	0x251691e49c2ea15882883c4ed3a4fdcd28abebb3	1.091	1.091	-252.598

Note: This table presents transactions by LPs during the USDC de-pegging event on March 11, 2023. Panel (a) reports mints and burns, and Panel (b) reports swap transactions. For mint and burn transactions, EURC and USDC represent the amounts of EURC and USDC added or subtracted to the liquidity pool. The price represents the market price, and the lower and upper price represent the tick range in which liquidity is provided. For swap, OF measures the net purchases of EURC, and we quote the price of the swap, and the price after the swap. The sample period is from 10 March 2022 to 12 March 2023.

D.3 Gas Fees across Trader Types: Full Sample and USDC De-Pegging Event

Table B3: Gas Fees in USDC per 10,000 EURC Transacted

Panel (a): Full Sample (2022-08-15 to 2024-04-30)

Group	Count	Mean	Std	Min	25%	50%	75%	Max
All	15,155	359,118.47	40,583,248.55	0.045	5.090	17.542	73.478	4,975,681,243.48
Top10	4,439	87.14	2,550.26	0.045	3.775	12.481	43.005	169,622.03
PM	363	325.92	2,056.57	0.300	4.933	19.560	75.545	31,146.34
LP	446	175.82	1,296.89	0.298	2.458	7.667	37.351	25,916.66
Top10 ∩ PM	534	5.10	12.42	0.388	1.594	2.981	5.317	251.50
Top10 ∩ LP	249	168.98	643.03	0.203	3.362	15.831	83.927	8,430.81
PM ∩ LP	6	42.83	66.52	4.321	6.983	11.090	40.961	173.97
$\notin \{Top10, PM, LP\}$	9,118	596,820.78	52,320,660.66	0.045	7.564	25.010	121.569	4,975,681,243.48

Panel (b): USDC De-Pegging Period (2023-03-10 to 2023-03-12)

Group	Count	Mean	Std	Min	25%	50%	75%	Max
All	299	162.47	752.35	0.611	11.119	24.928	78.663	8,665.39
Top10	54	42.87	125.03	1.355	4.826	12.439	24.949	890.29
PM	1	181.20	–	181.20	181.20	181.20	181.20	181.20
LP	3	72.95	119.29	3.948	4.076	4.203	107.45	210.70
Top10 ∩ LP	1	15.97	–	15.97	15.97	15.97	15.97	15.97
$\notin \{Top10, PM, LP\}$	240	191.04	835.42	0.611	12.547	32.820	102.360	8,665.39

Note: This table reports gas fees paid in USDC per 10,000 EURC transacted across trader types. Panel (a) reports full-sample results. Panel (b) isolates the period of the USDC de-pegging crisis from March 10–12, 2023. Groups are defined in line with Table 1, including intersections such as Top10 ∩ PM, and a residual category of traders not belonging to any primary group. Median gas fees were substantially lower for Top10 wallets relative to other groups, particularly during crisis periods.

Appendix E: SVAR Identification Assumptions

This appendix provides further detail on the identification strategy for the structural vector autoregression (SVAR) used to estimate the permanent price impact of blockchain order flow. Specifically, we describe the variable blocks, recursive ordering assumptions, and the structure of the Cholesky decomposition.

We estimate a structural VAR to examine the contemporaneous and dynamic relationship between sector-level order flow and exchange rate changes. The structural form is given by:

$$AY_t = A_0 + \sum_{j=1}^{L} A_j Y_{t-j} + \varepsilon_t, \tag{14}$$

where $Y_t = \left[\mathbf{OF}_t^{OTC},\ \mathbf{OF}_t^{DEX},\ \Delta p_t\right]^\top$, and ε_t is a vector of orthogonal structural shocks.

The reduced-form VAR is obtained by applying A^{-1} to both sides:

$$Y_t = C_0 + CY_{t-1} + B\varepsilon_t, \tag{15}$$

where $B = A^{-1}$, $C_0 = A^{-1}A_0$, and $C = A^{-1}A_1$. The matrix A is the Cholesky (impact) matrix and imposes the identifying restrictions in the SVAR.

We define the order flow vectors as:

$$\mathbf{OF}_t^{OTC} = \left[\mathrm{OF}_{\text{non-bank}},\ \mathrm{OF}_{\text{corporate}},\ \mathrm{OF}_{\text{fund}},\ \mathrm{OF}_{\text{bank}}\right]^\top,$$

$$\mathbf{OF}_t^{DEX} = \left[\mathrm{OF}_{\text{LP}},\ \mathrm{OF}_{\notin\{\text{Top10,PM,LP}\}},\ \mathrm{OF}_{\text{Top10}\cap\text{LP}},\ \mathrm{OF}_{\text{PM}},\ \mathrm{OF}_{\text{Top10}},\ \mathrm{OF}_{\text{Top10}\cap\text{PM}}\right]^\top.$$

We impose a recursive causal structure on matrix A, which is lower triangular and decomposed into three blocks:

$$A = \begin{bmatrix} A^{OTC} \\ A^{DEX} \\ A^{\Delta p} \end{bmatrix}, \quad \text{where} \quad A^{OTC} \in \mathbb{R}^{4\times 11},\ A^{DEX} \in \mathbb{R}^{6\times 11},\ A^{\Delta p} \in \mathbb{R}^{1\times 11}.$$

1. OTC Block A^{OTC}:

$$A^{OTC} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

This ordering follows Huang et al. (2023), which assumes that dealer-to-customer (D2C) flows (non-bank, corporate, and fund) affect dealer-to-dealer (D2D) flows (bank) contemporaneously, but not vice versa. This hierarchy generates a lower bound on the price impact and information share of inter-dealer trading, and is consistent with inventory-based models of exchange rates in which inter-dealer markets learn from customer order flow.

2. DEX Block A^{DEX}:

$$A^{DEX} = \begin{bmatrix} a_{51} & a_{52} & a_{53} & a_{54} & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & 1 & 0 & 0 & 0 & 0 & 0 \\ a_{71} & a_{72} & a_{73} & a_{74} & a_{75} & a_{76} & 1 & 0 & 0 & 0 & 0 \\ a_{81} & a_{82} & a_{83} & a_{84} & a_{85} & a_{86} & a_{87} & 1 & 0 & 0 & 0 \\ a_{91} & a_{92} & a_{93} & a_{94} & a_{95} & a_{96} & a_{97} & a_{98} & 1 & 0 & 0 \\ a_{10,1} & a_{10,2} & a_{10,3} & a_{10,4} & a_{10,5} & a_{10,6} & a_{10,7} & a_{10,8} & a_{10,9} & 1 & 0 \end{bmatrix}$$

We assume that DEX order flows can contemporaneously respond to OTC flows. Within the DEX block, wallet types are ordered by size and sophistication: passive LPs appear first, and large sophisticated traders (Top10, PM) appear later. This ordering reflects the idea that informed wallets react to aggregate flows, consistent with models of informed trading in segmented markets. It also generates a lower bound on the information share of sophisticated traders and PMs. This ordering assumption is consistent with concurrent literature studying the informational content of order flows in DEX markets (Capponi et al., 2024b; Klein et al., 2024).

3. Price Equation $A^{\Delta p}$:

$$A^{\Delta p} = \begin{bmatrix} a_{11,1} & a_{11,2} & a_{11,3} & a_{11,4} & a_{11,5} & a_{11,6} & a_{11,7} & a_{11,8} & a_{11,9} & a_{11,10} & 1 \end{bmatrix}$$

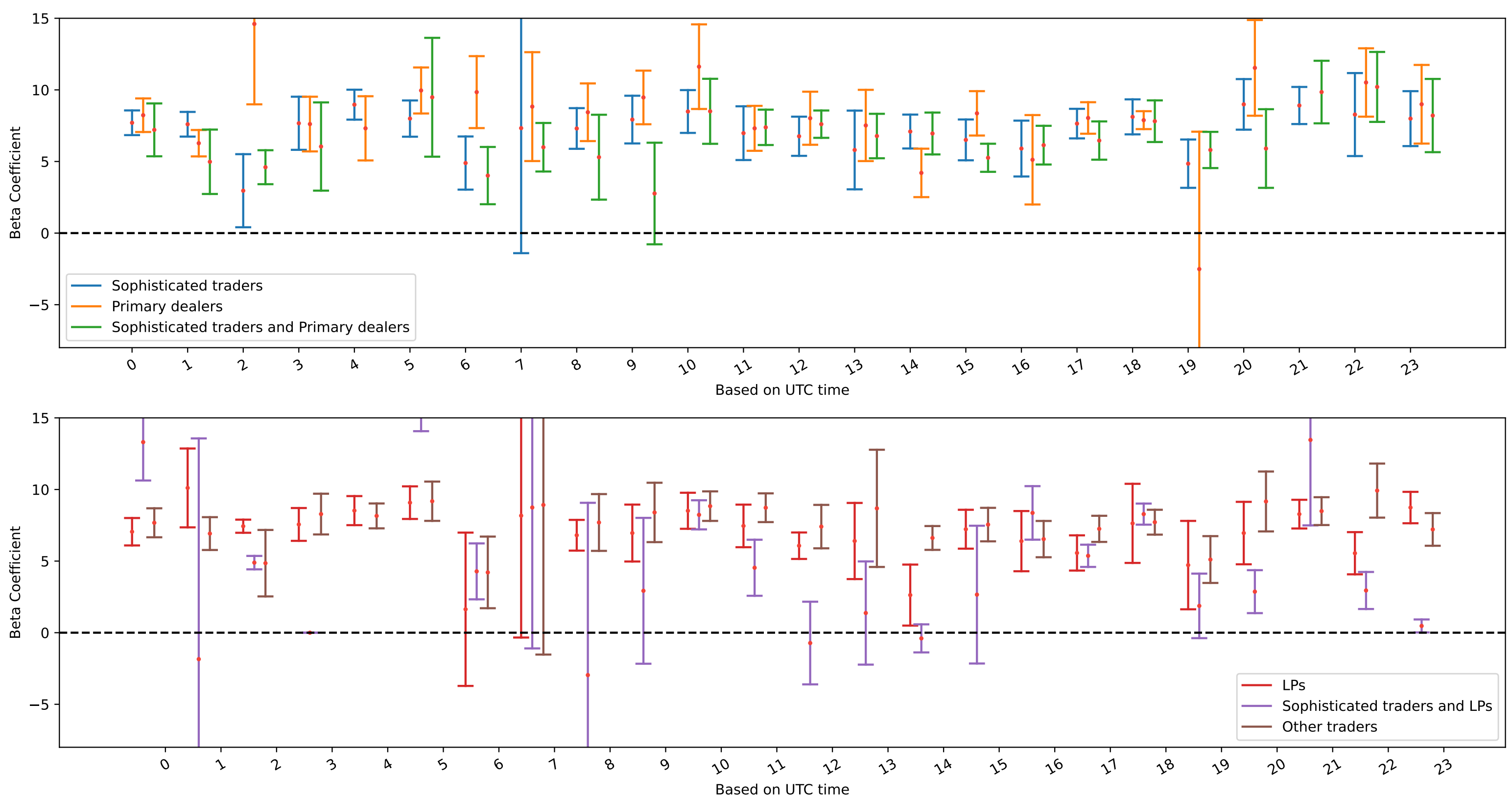
The exchange rate is assumed to respond contemporaneously to all order flows in the system, both OTC and DEX.

Appendix F: Price impact: Additional tests

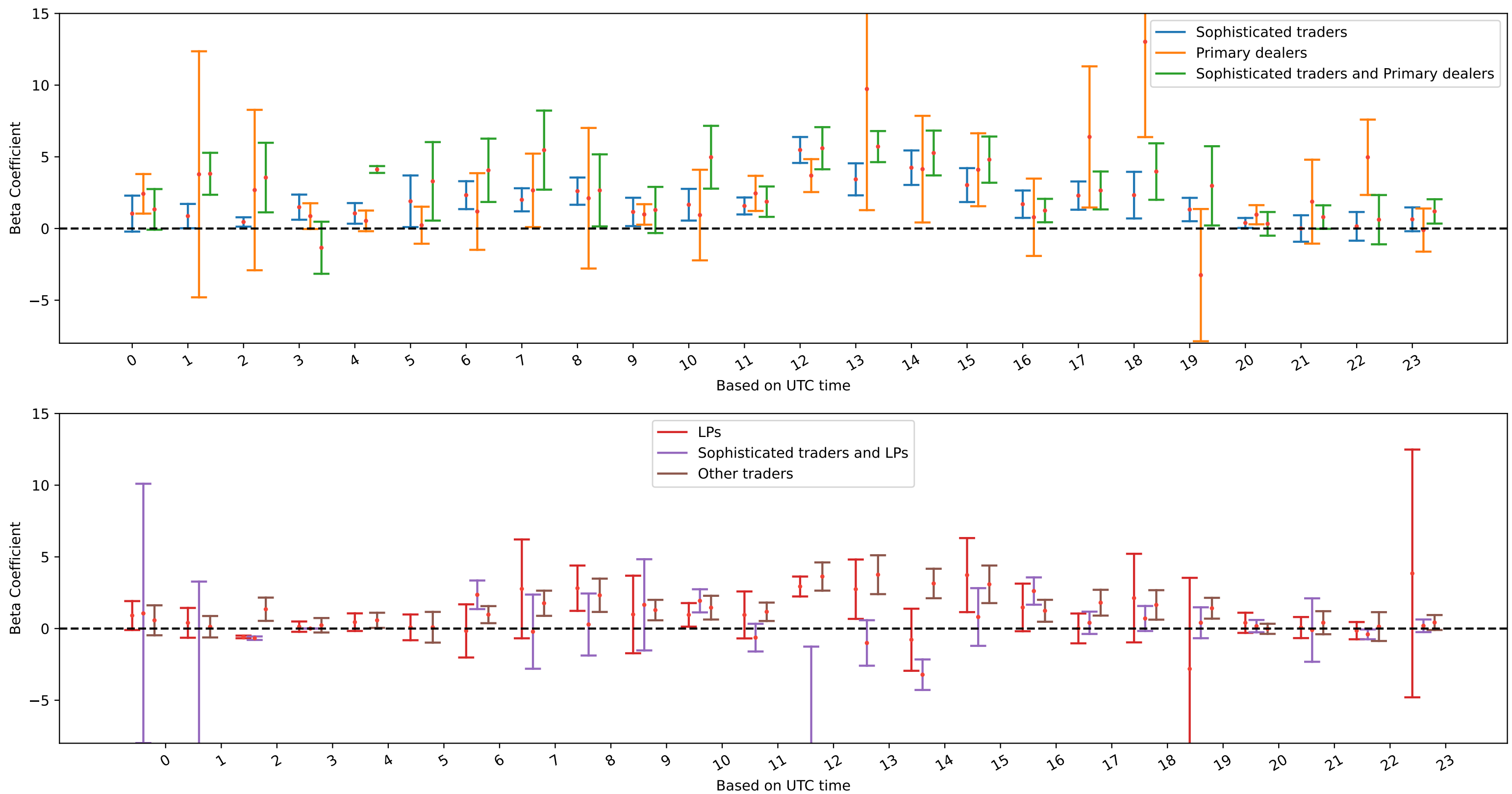
F.1 Intra-day patterns

Figure E1: Price impact of blockchain order flow: intra-day patterns

Panel (a): EURC/USDC Return



Panel (b): CLS Benchmark EUR/USD Return

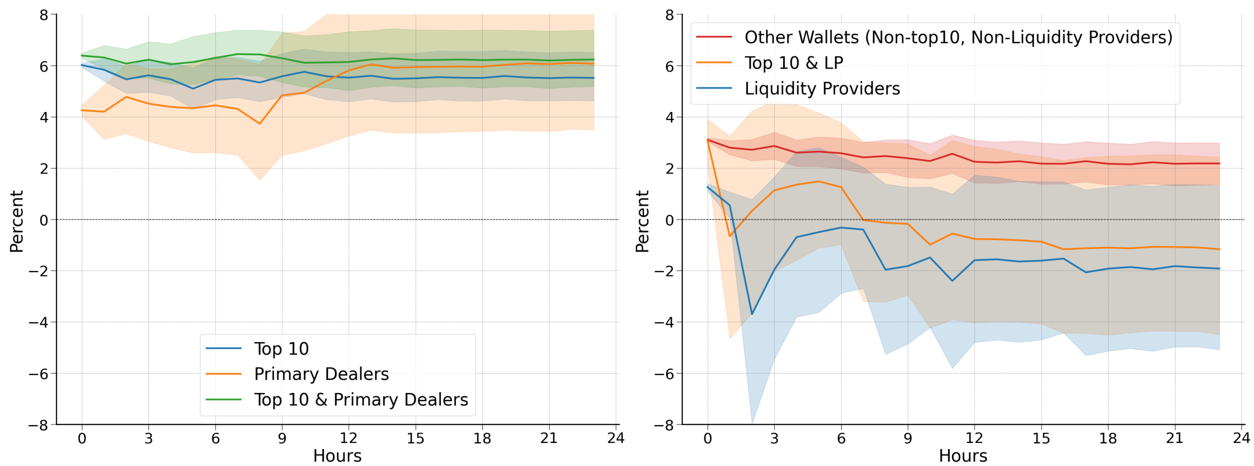


Note: This figure plots hourly price impact estimates in spot returns to a 1 Million EURC shock in blockchain order flow. Blockchain order flow measures net buyer transactions for purchasing EURC and is sourced from Uniswap V3 trade data. EURC/USDC returns are calculated using Uniswap V3 prices, and EUR/USD prices are sourced from CLS. Panel (a) shows the response of EURC/USDC returns, and Panel (b) shows the response of EUR/USD returns. The blockchain order flow is divided into six sub-categories: sophisticated traders (top 10 wallets), primary dealers, LPs, and intersections among these groups. The sample period is from 15 August 2022 to 30 April 2024.

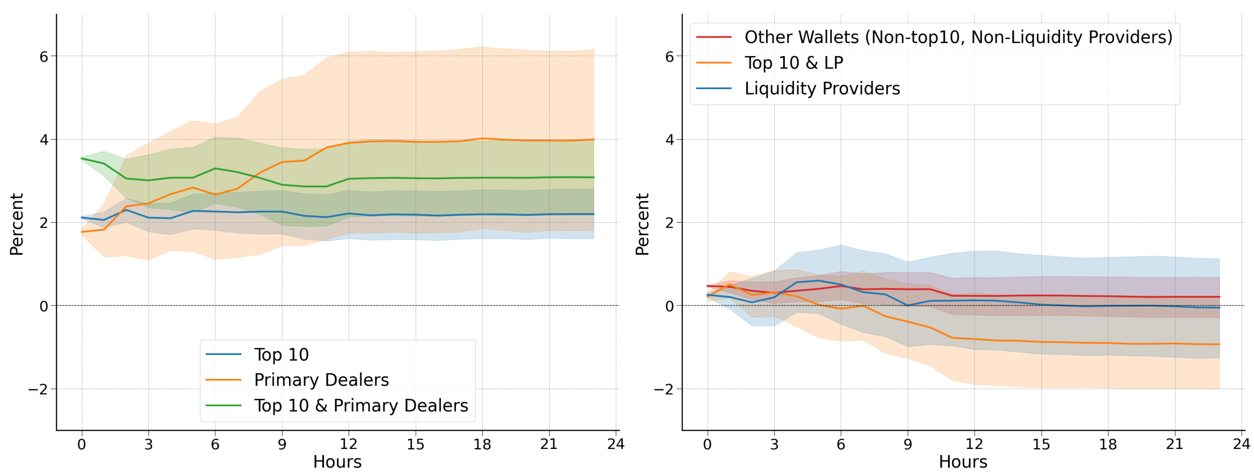
F.2 Controlling for Liquidity Provision

Figure F1: Price impact of blockchain order flow: dynamic effects

Panel (a): EURC/USDC Return



Panel (b): EUR/USD Return (CLS)



Note: This figure plots the impulse response of spot returns to a 1 million EURC shock in blockchain order flow using a structural VAR framework, estimated with 1,000 bootstrap replications. The specification controls for liquidity provision. Blockchain order flow measures net EURC buyer transactions from Uniswap V3 trade data. EURC/USDC returns are computed using Uniswap V3 prices, and EUR/USD prices are sourced from CLS. Liquidity provision by LPs is captured through net liquidity derived from mint and burn imbalances, where positive values indicate additional EURC liquidity in the pool. Panel (a) shows the response of EURC/USDC returns, and Panel (b) shows the response of EUR/USD returns. Blockchain order flow is categorized into six sub-groups: sophisticated traders (top 10 wallets), primary dealers, LPs, and combinations of these. The sample period spans from 15 August 2022 to 30 April 2024.

F.3 Sophisticated Liquidity Providers (Just-in-time Liquidity)

Table G1: Transaction Details

Date (UTC)	Blk Num	Type	User	EURC	USDC	Lower Price	Upper Price	Price
2023-08-23 07:55	17976054	mint	ae13	50249.82	311076.93	1.09	1.09	
2023-08-23 07:55	17976054	swap	2cc4	-18956.61				1.09
2023-08-23 07:55	17976054	burn	ae13	-32048.08	-330930.63	1.09	1.09	
2023-08-30 09:07	18026424	mint	ae13	82322.59	7347.05	1.09	1.10	
2023-08-30 09:07	18026424	swap	6945	-56915.47				1.09
2023-08-30 09:07	18026424	burn	ae13	-28776.74	-65957.32	1.09	1.10	
2023-09-23 22:53	18201622	mint	ae13	64752.18	238260.06	1.07	1.07	
2023-09-23 22:53	18201622	swap	7cd3	-20246.88				1.07
2023-09-23 22:53	18201622	burn	ae13	-45252.44	-259148.72	1.07	1.07	
2023-10-05 18:33	18286118	mint	ae13	45404.15	7821.33	1.06	1.06	
2023-10-05 18:33	18286118	swap	3592	-9950.00				1.06
2023-10-05 18:33	18286118	burn	ae13	-36795.91	-16936.49	1.06	1.06	
2023-10-06 15:04	18292236	mint	ae13	45905.79	144510.45	1.06	1.06	
2023-10-06 15:04	18292236	swap	c128	-10162.90				1.06
2023-10-06 15:04	18292236	burn	ae13	-36178.39	-154826.68	1.06	1.06	
2023-10-08 00:20	18302152	mint	ae13	71135.53	303399.61	1.06	1.06	
2023-10-08 00:20	18302152	swap	10f2	-9865.26				1.06
2023-10-08 00:20	18302152	burn	ae13	-61490.61	-313649.24	1.06	1.06	
2023-10-11 10:23	18326578	mint	ae13	299169.38	12166.39	1.10	1.10	
2023-10-11 10:23	18326578	swap	aa20	-23186.98				1.10
2023-10-11 10:23	18326578	burn	ae13	-276435.77	-37067.49	1.10	1.10	

Continued on next page

Table G1: Transaction Details

Date (UTC)	Blk Num	Type	User	EURC	USDC	Lower Price	Upper Price	Price
2023-10-14 08:03	18347311	mint	ae13	46293.22	12237.06	1.06	1.06	
2023-10-14 08:03	18347311	swap	f7d7	-9964.28				1.06
2023-10-14 08:03	18347311	burn	ae13	-37591.08	-21442.93	1.06	1.06	
2023-10-17 12:33	18370121	mint	ae13	49133.49	6172.49	1.06	1.06	
2023-10-17 12:33	18370121	swap	3592	-19338.40				1.06
2023-10-17 12:33	18370121	burn	ae13	-32279.83	-24072.91	1.06	1.06	
2023-11-03 13:02	18491700	mint	ae13	260626.98	51902.25	1.10	1.10	
2023-11-03 13:02	18491700	swap	9593	-17213.04				1.10
2023-11-03 13:02	18491700	burn	ae13	-243688.26	-70495.13	1.10	1.10	
2023-11-03 13:13	18491757	mint	ae13	243720.52	69561.03	1.10	1.10	
2023-11-03 13:13	18491757	swap	9593	-20386.83				1.10
2023-11-03 13:13	18491757	burn	ae13	-223658.74	-91671.48	1.10	1.10	
2023-11-07 16:49	18521374	mint	ae13	59330.57	256372.22	1.07	1.07	
2023-11-07 16:49	18521374	swap	46f5	-18621.87				1.07
2023-11-07 16:49	18521374	burn	ae13	-41311.27	-275714.07	1.07	1.07	
2023-11-11 23:46	18552054	mint	ae13	147338.11	36400.63	1.08	1.09	
2023-11-11 23:46	18552054	swap	5319	-38379.19				1.08
2023-11-11 23:46	18552054	burn	ae13	-110425.65	-76438.77	1.08	1.09	
2023-11-30 00:25	18680832	mint	ae13	53340.95	424301.65	1.15	1.15	
2023-11-30 00:25	18680832	swap	b299	-3287.17				1.15
2023-11-30 00:25	18680832	burn	ae13	-50053.88	-428078.41	1.15	1.15	
2024-01-25 17:33	19085149	mint	ae13	208855.00	161529.61	1.12	1.13	
2024-01-25 17:33	19085149	swap	9593	-22789.61				1.12

Continued on next page

Table G1: Transaction Details

Date (UTC)	Blk Num	Type	User	EURC	USDC	Lower Price	Upper Price	Price
2024-01-25 17:33	19085149	burn	ae13	-186138.52	-187076.72	1.12	1.13	
2024-01-25 19:18	19085666	mint	ae13	208451.09	66998.77	1.12	1.13	
2024-01-25 19:18	19085666	swap	9593	-18933.66				1.12
2024-01-25 19:18	19085666	burn	ae13	-189597.26	-88198.05	1.12	1.13	
2024-02-09 11:57	19190417	mint	ae13	323979.98	618278.92	1.15	1.15	
2024-02-09 11:57	19190417	swap	54a1	-23745.69				1.15
2024-02-09 11:57	19190417	burn	ae13	-300250.49	-645564.26	1.15	1.15	
2024-02-25 19:05	19306570	mint	ae13	61302.68	16123.49	1.09	1.09	
2024-02-25 19:05	19306570	swap	07d3	-27421.90				1.09
2024-02-25 19:05	19306570	burn	ae13	-36095.84	-43686.38	1.09	1.09	

Note: This table presents Just-in-time Liquidity (JIT) transactions in the EURC-USDC pool. The liquidity provider full address is "0xae2fc483527b8ef99eb5d9b44875f005ba1fae13", with last 4 characters 'ae13'. Each set of JIT transactions involves a 'mint', 'swap' and 'burn', transaction, and happen in the same block. The wallet 'ae13' conducts a mint and burn transaction, sandwiching the swap transaction within the block. Liquidity posted at the specified price range, given by the bounds of lower and upper price, for the mint and burn transactions are provided. The sample period is from 15 August 2022 to April 30 2024.