Blockchain Currency Markets

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Abstract

We conduct the first comprehensive study of blockchain currencies, stablecoins pegged to traditional currencies and traded on decentralized exchanges. Our findings reveal that the blockchain market generally operates efficiently, with blockchain prices and trading volumes closely aligned with those of their traditional counterparts. However, blockchain-specific factors, such as gas fees and Ether volatility, act as frictions. Blockchain prices are determined by macroeconomic fundamentals and order flow. We use a rich transaction-level database of trades and link it to the characteristics of market participants. Traders with significant market share and access to the primary market have a greater impact on pricing, likely due to informational advantages.

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 for both individuals and enterprises through blockchain technology. The sector is characterized by innovative protocols and platforms, including decentralized exchanges (DEXs) and lending protocols. By reducing inefficiencies in traditional financial systems and eliminating the need for intermediaries, DeFi improves both cost-effectiveness and transaction speed.

This paper provides the first comprehensive study of blockchain currencies, specifically stablecoins pegged to traditional currencies and traded on decentralized exchanges. These markets are critical to understanding the broader financial system, as the currency market is the largest financial market globally. Moreover, central banks are increasingly exploring Central Bank Digital Currencies (CBDCs) on blockchain platforms. For example, the BIS Innovation Hub's Project Mariana aims to enhance foreign exchange (FX) trading and settlement through decentralized blockchain markets, striving for greater efficiency, security, transparency, and cross-border interoperability.[1]

An important question in understanding the feasibility of this market is how trading in blockchain markets connects to traditional markets. Specifically, do trades in blockchain markets convey information about fundamentals? This question is particularly relevant in the context of the asymmetric information paradigm, which suggests that different market participants convey varying levels of information in the traditional FX market (Ranaldo and Somogyi, 2021).

The primary contribution of our paper is to analyze the informational role of blockchain transactions in the traditional EUR/USD currency market. Using a rich dataset of transaction-level blockchain data, we identify different market participants and their contributions to price discovery and the processing of fundamental information. We classify these participants into three categories: *sophisticated traders*, who dominate trading volumes and actively engage in the market; *primary dealers*, who have access to fiat currency deposits and withdrawals with the stablecoin issuer; and *liquidity providers (LPs)*, who supply liquidity to the market but lack direct access to primary markets. A key advantage of blockchain data

[1] The BIS Innovation Hub's first cross-center initiative involves collaboration with central banks and monetary authorities, including the Bank of France, the Monetary Authority of Singapore, and the Swiss National Bank.

is its transparency and granularity, which allow for a clear distinction between primary dealers and liquidity providers—groups that are often difficult to separate in traditional financial markets (Hortaçsu and Sareen, 2005; Hagströmer and Menkveld, 2019).[2]

We begin by documenting three stylized facts about market efficiency in blockchain currency markets, providing context for our analysis. First, EURC/USDC prices on DEXs deviate from CLS Benchmark EUR/USD rates by an average of 24 basis points, primarily due to blockchain-specific factors like gas fees and Ether (ETH) volatility (see Figure 1). Second, only 10% of EURC/USDC transactions exceed arbitrage limits due to costs such as gas fees, with these violations nearly disappearing when slippage costs are accounted for. Third, EURC/USDC prices respond promptly to macroeconomic announcements, such as Federal Reserve monetary policy decisions, indicating that blockchain markets efficiently incorporate fundamental information.

[INSERT FIGURE 1 ABOUT HERE]

Building on these facts, we examine how blockchain trading connects to traditional FX markets. Using CLS data, which captures global FX trading volumes categorized by participant type, such as interbank transactions, dealer-fund trades, and dealer-corporate interactions, 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 involves feedback trading, where blockchain activity corrects price discrepancies between EURC/USDC and EUR/USD through arbitrage. The second reflects the processing of fundamental news 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

[2]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.

(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.

We also assess whether blockchain order flow predicts traditional FX rates and reveals asymmetric information among participants. While price impact on DEX returns shows minimal differences, sophisticated traders and primary dealers have more significant price impact when using the CLS benchmark EUR/USD returns. This suggests that participants with greater resources or access to fiat markets possess informational advantages. In contrast, LPs exhibit an insignificant price impact, consistent with their role as hedgers rather than informed traders.

To analyze feedback dynamics, we use a structural vector autoregression (VAR) framework, which reveals that sophisticated traders and primary dealers contribute to persistent price impact. LPs, however, exhibit weaker or negligible impacts. These results remain robust to controls for liquidity provision and traditional CLS order flow, confirming that the observed impacts reflect the processing of information on the fundamentals of the traditional market, rather than changes in market liquidity.

Finally, we investigate whether our price impact results arise from feedback trading or arbitrage rather than fundamental information. By decomposing DEX order flow into feedback-driven and residual components based on lagged price differences between DEX and traditional markets, we find that only the residual component exhibits lasting price impacts. The feedback-driven component does not significantly influence traditional market returns, affirming that the observed price impacts are driven by informational order flow rather than feedback trading.

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

First, we contribute to the growing body of research on stablecoins, which examines their connections to traditional markets, arbitrage mechanisms, price dynamics, and risks of speculative attacks (Barthelemy et al., 2021; Oefele et al., 2023; Eichengreen et al., 2023; Gorton et al., 2022; Lyons and Viswanath-Natraj, 2023; Kozhan and Viswanath-Natraj, 2021; Ma et al., 2023; Liu et al., 2023; Routledge and Zetlin-Jones, 2021; Li and Mayer, 2021; d'Avernas et al., 2022; Bertsch, 2022; Aldasoro et al., 2023; Adams et al., 2023). While Liu et al. (2023) investigates the TerraLuna de-pegging and how sophisticated investors capitalized on it, our study identifies a novel link between stablecoin markets and traditional FX markets. By focusing on market efficiency and price discovery, we demonstrate how decentralized market participants incorporate macroeconomic news into exchange rates. Furthermore, building on Adams et al. (2023), which evaluates the costs of trading on decentralized exchanges compared to traditional remittance and payment systems, we highlight stablecoins' potential as viable alternatives to traditional market infrastructure.

Second, we add to the literature on decentralized exchanges, including research on market efficiency, liquidity provision, and their potential to replace traditional financial market infrastructure (Capponi and Jia, 2021; Aoyagi and Ito, 2021; Hasbrouck et al., 2022; Lehar and Parlour, 2021; Barbon and Ranaldo, 2021; Foley et al., 2023; Malinova and Park, 2023; Fang, 2022; LI et al., 2023; Caparros et al., 2023; Lehar et al., 2023; Hansson, 2023; Klein et al., 2023; Capponi et al., 2023). Our work is closely related to Barbon and Ranaldo (2021), which examines the efficiency of cryptocurrency pairs like ETH/USDC on DEXs and compares them to centralized exchanges. While prior studies focus primarily on blockchain fundamentals such as gas fees, we extend this by exploring the connection between trading on DEXs and traditional FX markets. In particular, we identify two mechanisms through which blockchain markets align with traditional markets: feedback trading and the processing of fundamental information.

Lastly, we bridge the stablecoin literature with the FX and traditional market microstructure literature (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., 2021; Krohn et al., 2022; Hagströmer and Menkveld, 2019). Specifically, we highlight the role of algorithmic bonding curves on Uniswap V3 as an alternative pricing mechanism to traditional models based on portfolio shifts and inventory management (Evans and Lyons, 2002). Our findings reveal that blockchain order flow significantly impacts EUR/USD returns, suggesting that sophisticated traders and primary dealers incorporate fundamental information into prices. Conversely, LPs primarily engage in inventory management, analogous to the role of market makers in limit-order book markets (Hortaçsu and Sareen, 2005). Furthermore, we find evidence of informational advantages among specific market participants in blockchain currency markets, aligning with the presence of asymmetric information documented in traditional markets (Ranaldo and Somogyi, 2021).

The remainder of the paper is structured as follows. Section 2 describes the institutional setting and data. Section 3 examines the connections between blockchain trading and traditional markets, focusing on the information content of different market participants. Section 4 concludes.

2 Definitions and Data

2.1 DEX Market and AMM Functions

Figure 2 provides an overview of both traditional and blockchain market structures, highlighting the differences in how liquidity is provided and price stability is maintained. In traditional markets, an inter-dealer market serves as the core. Dealer banks play a dual role, providing liquidity to the dealer-customer market while also participating in the inter-dealer market to facilitate price discovery. Corporates, funds, and non-bank financial companies typically access liquidity through dealer banks. Since the early 1990s, electronic trading platforms such as Refinitiv and EBS have supported this structure, enabling dealer banks to post bid and ask quotes on electronic limit order books (see King et al., 2012; Chaboud et al., 2023). Dealer banks remain critical to the price discovery process, as evidenced by their impact on order flows and exchange rate dynamics (Evans and Lyons, 2002; Bjønnes and Rime, 2005).

In contrast, blockchain markets operate under a fundamentally different structure, involving both primary and secondary markets. In the primary market, the stablecoin Treasury—managed and operated by Circle—mints EURC and USDC tokens and distributes them to investors, which we denote as 'primary dealers' in our framework. These dealers are responsible for arbitrage between the primary and secondary markets, supplying tokens to the secondary market where trading occurs on centralized exchanges using limit order books (LOBs) or on decentralized exchanges such as Uniswap. Decentralized exchanges facilitate trading of EURC/USDC pairs, involving various participants such as liquidity providers and sophisticated traders, who take on distinct market roles.

[INSERT FIGURE 2 ABOUT HERE]

A key feature of stablecoin markets is the relationship between primary and secondary market rates. The EURC and USDC Treasuries commit to maintaining redemptions at par

(1 EURC = 1 EUR and 1 USDC = 1 USD). Arbitrage mechanisms, executed by primary dealers, play a central role in stabilizing prices in the secondary market. For example, if USDC trades above 1 USD in the secondary market, primary dealers can deposit 1 USD with the issuer in the primary market to receive 1 USDC. This USDC can then be sold at a premium in the secondary market, increasing the circulating supply and exerting downward pressure on the secondary market price to restore parity. Conversely, if USDC trades below 1 USD, primary dealers can purchase the stablecoin at a discount in the secondary market and redeem it in the primary market for 1 USD. This reduces supply and pushes the price upward toward parity.

Additional details on the stablecoin issuance process and arbitrage mechanisms are provided in Appendix C.

2.1.1 Uniswap V2 Bonding Curves

Uniswap is a decentralized AMM protocol built on the Ethereum blockchain. Introduced in November 2018, Uniswap enables users to trade cryptocurrencies and other digital assets directly without the need for traditional intermediaries like exchanges. It has emerged as a key component of the DeFi ecosystem, offering a seamless and permissionless way to swap tokens and provide liquidity to various trading pairs.

The core functionality of Uniswap is based on liquidity pools and smart contracts. LPs deposit pairs of tokens into these pools, establishing reserves for trading. Uniswap relies on a constant product AMM formula, $k = xy$, where x and y are the quantities of two tokens in the pool. This formula ensures that the product of the token quantities remains constant, preserving a mathematically balanced liquidity pool regardless of trade size. This mechanism also reduces uncertainty in price determination, as the algorithm governing price formation is known in advance.

The constant product formula dynamically adjusts token swap rates based on supply and demand within the pool. For instance, if a pool contains 100 EURC and 110 USDC, the constant k is $100 \times 110 = 11,000$, and the exchange rate is 1.10 USDC per EURC. The combinations of token quantities that satisfy the AMM function define a bonding curve, which represents the pool's price discovery process.

We illustrate the dynamics of Uniswap V2 pricing in Panel (a) of Figure 3. The initial equilibrium supply of liquidity is represented by point $E_0 = [L_{USDC}, L_{EURC}]$, which corresponds to the quantities of EURC and USDC in the pool.

[INSERT FIGURE 3 ABOUT HERE]

The left side of Panel (a) demonstrates the dynamics of a "swap" on decentralized exchanges. In this example, a trader swaps EURC for USDC, moving along the bonding curve to the new equilibrium at E_1. The liquidity pool now contains a higher supply of USDC and a lower supply of EURC. The price is determined using the constant product formula $k = xy$, and the updated price is:

$$p_{EURC/USDC} = \frac{L_{USDC}}{L_{EURC} - \Delta L_{EURC}} \tag{1}$$

Since $\Delta L_{EURC} > 0$, there is an appreciation of EURC. For example, if $\Delta L_{EURC} = 5$, the new price is:

$$p_{EURC/USDC} = \frac{110}{100 - 5} = 1.158 \tag{2}$$

The exchange rate appreciates from 1.10 USDC per EURC to 1.158 USDC per EURC. At this price, the constant product rule holds, as the new quantities of EURC and USDC are 95 and 115.8, respectively, with $k = 95 \times 115.8 = 11,000$.

The right side of Panel (a) illustrates liquidity provision. A LP must add both tokens in proportion to the current price. For instance, if the pool holds 100 EURC and 110 USDC, the LP must add liquidity at a ratio of 1.10 USDC per EURC. For example, adding 10 EURC requires adding 11 USDC to maintain the price ratio. This corresponds to a shift of the bonding curve from E_0 to E_2.

2.1.2 Uniswap V3: Liquidity Provision at specified price ranges

Compared to Uniswap V2, the main advancement in Uniswap V3 is the ability for LPs to pre-select a price range.[3] This led to the introduction of Uniswap V3 in July 2021. The EURC/USDC pool only trades on V3 and offers fees of 0.05% to LPs who provide

[3] Another advancement discussed in Barbon and Ranaldo (2021) and Lehar et al. (2023) is the multi-fee tier (MFT) system which introduces multiple pools for each token pair, each with a different swapping fee. LPs can create pools at three fee levels: 0.05%, 0.30%, and 1%. In our study, the Uniswap V3 EURC/USDC pair is traded only in the 0.05% pool.

liquidity in their specified price range, $[p_a, p_b]$, where p_a is the minimum price and p_b is the maximum price. The price curve for Uniswap V3 is a modified AMM function: $\left(x + \frac{L}{\sqrt{p_b}}\right)\left(y + L\sqrt{p_a}\right) = L^2$ where L is the (virtual) liquidity within the price range $[p_a, p_b]$; x and y are the quantities of tokens EURC and USDC deposited within this price range.[4] By offering LPs flexibility with a specified price range, Uniswap V3 simulates a limit order book in traditional markets in which traders can post liquidity to buy or sell at a specified price.

In Uniswap V3, prices are divided into discrete segments termed ticks, represented by i. Each tick corresponds to a price p that is an integer power of 1.0001, described by the relationship $p_i = 1.0001^i$. Adjacent ticks are approximately 1 basis point apart. Every pool has a specific tick spacing. For instance, the EURC-USDC 0.05% pool has a spacing of 10, meaning only ticks divisible by 10 can be initialized for this pool. An LP's liquidity position can span one or multiple tick intervals, enhancing Uniswap V3's "capital efficiency". This design allows LPs to concentrate their liquidity and gives them the flexibility to strategically shift liquidity across different price ranges based on future price predictions.

Panel (b) of Figure 3 illustrates a schematic of liquidity provision.[5] The online fee calculator allows a LP to post a specified price range, deposit, and calculates the amounts of EURC and USDC they need to deposit, as well as gas fees they are required to post. In contrast to the bonding curve of the Uniswap V2 AMM, individual LPs do not necessarily provide both currencies in the pool, and can only post liquidity of one currency based on their specified price range. For example, if LPs provide a price range greater than the current price (e.g. 1.10 EURC/USDC), they are equivalent to posting EURC sell limit orders. Alternatively, if LPs provide a price range less than the current price, they are equivalent to posting EURC buy limit orders.

In our analysis, we construct a measure of net liquidity provided by LPs using liquidity event data, following the methodology outlined in Klein et al. (2023). Net liquidity is defined through "mint" and "burn" events, which represent the addition and removal of liquidity, respectively. A "mint" event occurs when LPs deposit EURC or USDC into the pool, increasing liquidity. In contrast, a "burn" event occurs when LPs withdraw funds,

[4]Source: Uniswap V3 whitepaper available at https://uniswap.org/whitepaper-v3.pdf
[5]For more details we refer readers to the Uniswap interface available at https://uniswap.fish/

reducing liquidity.

To calculate net liquidity, we first compute the net mint and net burn imbalances, which reflect the difference between the total amounts of EURC and USDC deposited and withdrawn by LPs over a given period. The variables $mint^{ask}$ and $burn^{ask}$ refer to mints and burns of liquidity at prices above the current market price, while $mint^{bid}$ and $burn^{bid}$ refer to mints and burns of liquidity at prices below the current price.

$$mint^{net} = mint^{ask} - mint^{bid}, \tag{3}$$

$$burn^{net} = burn^{ask} - burn^{bid}. \tag{4}$$

Net liquidity is calculated as the difference between net mint and net burn. A positive net liquidity value indicates that LPs have contributed more EURC liquidity to the pool than they have withdrawn.

$$Liquidity^{net} = mint^{net} - burn^{net}. \tag{5}$$

We further classify net liquidity based on its proximity to the current market price at the time of the LP's transaction. Liquidity provided within 100 basis points of the current price is classified as "best," reflecting liquidity positioned close to immediate market conditions. Liquidity placed more than 100 basis points from the current price is classified as "away," indicating its positioning farther from the prevailing market price.[6]

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 intra-day bid and ask quotes at 5 minute intervals, that we consolidate to an hourly and daily level 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.[7].

[6] In the context of a traditional limit order book (LOB), positive net liquidity corresponds to a greater volume of sell limit orders placed on the ask side, signifying a buildup of liquidity willing to sell near the current market price.

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

Our CLS benchmark rate provides an effective benchmark for the EURC/USDC rate from the Uniswap V3 pool. Figure 1 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 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, we start our analysis on August 15 2022 in Section 3. 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.

2.2.2 DEX trading volume and liquidity provision

The dataset of Uniswap V3 transactions includes the complete history of "swap" transactions, which represent all trades involving the buying of EURC (USDC) and the selling of USDC (EURC). These transactions are recorded at the wallet level, where a wallet refers to an Ethereum blockchain address that securely stores and manages Ether and other tokens linked to that address.[8] The second dataset records all liquidity transactions made by LPs from Kaiko, a cryptocurrency market data provider that delivers industrial-grade, regulatory-compliant data to businesses. For each address, this records amounts of USDC or EURC are added to the pool, as well as a specified price range in which liquidity is added.[9]

A key aspect of our analysis is exploiting the granularity of blockchain data to understand the heterogeneity of different market participants. Specifically, we can disaggregate trades into those traders with a significant market share based on trading volume, traders who act as LPs, and those who transact with the stablecoin Treasury.

Sophisticated traders. In each month, we aggregate trading volume by wallets and select

[8]Technically, a wallet holds the private keys required to access and control the funds associated with a specific Ethereum address on the blockchain.

[9]For example, if the current market price of EURC is 1.10 USDC, then the LP can either (i) supply EURC at a price greater than 1.10 USDC, (ii) supply USDC at a price less than 1.10 USDC, or (iii) supply EURC and USDC at a price range that contains the current market price of 1.10 USDC. The exact amounts are determined by the Uniswap V3 AMM pricing algorithm.

wallets that feature in the top 10. The share of top 10 addresses, including any intersection with other categories, averages 52% of aggregate trading volume over our sample from August 15, 2022, to April 30, 2024.

Primary dealers. Primary dealers are classified as wallets that have transacted with either the EURC or USDC Treasury in our sample.[10] Etherscan allows us to retrieve the entire history of transactions of the Treasury wallets. We cross-reference the list of wallets that trade in the EURC/USDC DEX market with all wallets that have traded with the USDC (EURC) Treasury. These wallets send USD (EUR) and receive USDC (EURC) from the Treasury at the primary market rate of 1 stablecoin per unit of fiat currency. Alternatively, these wallets can redeem their stablecoin tokens and withdraw their fiat currency deposits. Primary dealers, including any intersection with other categories, account for 7% of aggregate trading volume.

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.

Table 1 presents summary statistics on the number of transactions and volume per transaction for seven trader groups, including sophisticated traders, primary dealers, and liquidity providers, with 76, 68, and 90 unique addresses identified for each group, respectively.

We also consider sub-categories of traders belonging to multiple groups. 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.[11] The majority of addresses, 2,342 in total, belong to a residual group not classified as sophisticated traders, primary dealers, or liquidity providers.

Transaction frequency varies significantly across groups. Sophisticated traders average 58 transactions per address, while those classified as both sophisticated traders and

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

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

primary dealers average 89 transactions per address.

[INSERT TABLE 1 ABOUT HERE]

In Appendix A, we provide detailed summary statistics on the distribution of trading volume and liquidity provision. 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. Sophisticated traders and the top 5 LPs are identified on a monthly basis, allowing these categories to vary over time. The third section includes the intra-day patterns of the number of transactions and trading volume of liquidity providers.

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 in liquidity provision, we observe that liquidity, in terms of deposits and withdrawals, occur at all hours, and there are no systematic patterns in net liquidity during the trading day.[12]

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

[12]That LPs are not strategically adding net liquidity is important when we conduct our tests of asymmetric information in the FX market in Section 3.

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 then given as the net of buyer-initiated transaction volume over intervals of a trading hour and trading day, where buyer-initiated transactions are signed +1 and seller-initiated transactions are signed -1, and the volume of the transaction is denoted V_{t_K}.

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

Panel (b) of Figure 1 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 3.

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.[13] 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). We focus on the spot market and use two CLS datasets. First, we obtain the aggregate trading volume from

[13]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.

the CLS FX Spot Volume dataset. Second, we obtain sector-level volume from the CLS FX Spot Flow dataset. The Flow dataset records transaction volumes between price-takers and market-makers (banks), with the price-takers further divided into three categories: funds, non-bank financials, and corporates.

Consequently, we utilize these two datasets to construct sector-level volume, which includes: (i) interbank, (ii) bank-funds, (iii) bank-non-bank financials, and (iv) bank-corporates. To establish our measure of interbank volume, we use the aggregate data from the CLS FX Spot Volume dataset and subtract the bilateral volume involving banks and other participants, such as funds, non-bank financial institutions, and corporates, as found in the CLS FX Spot Flow dataset.[14]

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 is done during the hours of 13 to 16 UTC time, specifically for the interbank volume and the fund-bank volume which are the two main sector groups. This period of trading corresponds to when major financial markets are open (London, Frankfurt and New York). The major WMR fix is at 4pm London time (typically 16 UTC time), and is used as a benchmark by investors to fix the spot price for trades shortly prior to that time (Krohn et al., 2022).

Comparing the two markets, we note that trading on DEX is much more dispersed during the trading day. While there are peaks of trading during the afternoon UTC hours, there are also local peaks during 9am UTC time. A more balanced intra-day blockchain trading volume suggests a more inclusive market that is less reliant on traditional FX global dealers (Adams et al., 2023; Marsh et al., 2017; Evans et al., 2018).[15] Turning to the scale of trading volume, the average daily volume in CLS EUR/USD is 28.42 EUR billion, while the average daily volume in Uniswap EURC/USDC is 0.423 EURC million. Expressed as a percentage, the blockchain market trading accounts for approximately 0.0015% or 0.15

[14]The Volume dataset lists trading volume in USD, which we convert based on CLS Benchmark EUR/USD Return price, while the Flow dataset records trading volume in EUR. CLS records data in the London time zone, which we convert to the UTC time zone, consistent with DEX data sources.

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

basis points of the aggregate trading in the EUR/USD market, 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 represent the Ether paid to miners for authenticating transactions on the Ethereum network. We use an index of average gas fees per transaction from Coinmetrics (coinmetrics.io).

Market volatility. We use the BitVol and EthVol financial indexes as measures of expected 30-day implied volatility for Bitcoin and Ether, respectively.[17] These indexes provide model-free estimates derived from the full range of option strikes, capturing the market's outlook on expected volatility. The indexes are calculated using Bitcoin and Ether option prices with a methodology that interpolates between the two nearest option expirations to obtain a 30-day forecast, providing a market-based measure of volatility based on investor expectations.

Macroeconomic controls. We compute interest rate differentials using one-month OIS rates on EUR and USD as a fundamental macro determinant. In addition, to capture financial frictions, we utilize innovations to the US dealer capital ratio (He et al., 2017) as a proxy for dealers' financial constraints.

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

[INSERT TABLE 2 ABOUT HERE]

[16] For more details see summary statistics of trading volume on blockchain and CLS market presented in Table 2.

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

2.3 Facts on Market Efficiency

Fact #1: Peg efficiency is driven by blockchain factors

A meaningful way to assess price efficiency is to analyze whether blockchain *prices* systematically reflect underlying currency values. We measure efficiency using the absolute deviation of EURC/USDC prices from the CLS benchmark rate, denoted as Δ_0 in equation (7):

$$\Delta_0 = |\mathrm{p}_{\mathrm{EUR/USD}} - \mathrm{p}_{\mathrm{EURC/USDC}}| \tag{7}$$

We test the determinants of market efficiency using Equation (8). These determinants include Ethereum blockchain characteristics—such as implied volatility of Ether and Bitcoin ($\sigma^{IV}_{ETH,BTC}$), Ether returns (R_{ETH}), and gas fees ($gasfee_t$)—and frictions like market volatility, investor sentiment, and dealer constraints. Due to the shorter sample of triangular arbitrage measures, we use Δ_0 as the outcome variable for our efficiency analysis.

$$Y = \beta_0 + \beta_1 \sigma^{IV}_{ETH,BTC} + \beta_2 gasfee_t + \beta_3 R_{ETH} \tag{8}$$

The results, presented in Table 3, reveal a strong connection between blockchain prices and their underlying values, with relatively small spreads. Among all specifications, blockchain-based characteristics—market volatility and gas fees—have a robust impact on efficiency. A 1 per cent increase in gas fees increases absolute peg deviations by 0.4 per cent, while a 1 per cent rise in Ether and Bitcoin volatility raises deviations by 0.13 and 0.36 per cent, respectively.

Market volatility and gas fees limit arbitrage in DEX markets (Barbon and Ranaldo, 2021; Foley et al., 2023). Higher gas fees hinder informed traders from efficiently tracking traditional market prices, increasing inefficiency. Market volatility, especially in Bitcoin, affects traders whose wealth is typically denominated in risky cryptocurrencies and ERC-20 tokens. Increased volatility heightens market risk, causing traders to reduce arbitrage activity and allowing price discrepancies to emerge.[18]

[18] ERC-20 is a standard enabling token transfers, balance tracking, and total supply measurements via smart contracts on the Ethereum blockchain. Traders in the EURC/USDC market often trade multiple tokens, as shown in Appendix E, where statistics indicate ETH/USDC traders handle an average of 48 tokens.

[INSERT TABLE 3 ABOUT HERE]

Fact # 2: Peg deviations are within arbitrage bounds

Our measure of efficiency highly correlates with alternative triangular arbitrage metrics, which capture deviations from the law of one price. These metrics involve other bilateral pairs traded on centralized exchanges, as shown in equation (9).[19]

Δ_1 measures triangular arbitrage deviations among USDC, EURC, and USD. For example, an investor can start with 1 USDC, buy EURC in the EURC/USDC market, convert EURC to USD in the EURC/USD market, and re-convert to USDC in the USDC/USD market. Δ_2 measures deviations among USDC, EURC, and EUR. Δ_3 captures arbitrage opportunities across four currencies: USDC, EURC, USD, and EUR.

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

Panel (a) of Figure 5 compares our triangular arbitrage measures with the benchmark efficiency measure, starting from March 2023 when centralized exchange data became available. Correlations between the benchmark and alternative measures range from 0.4 to 0.55.

[INSERT FIGURE 5 ABOUT HERE]

Table 4 summarizes triangular arbitrage conditions and transaction costs. The first panel shows percentiles of arbitrage metrics and gas fees per $1 USD$ transaction. We compare these metrics with arbitrage bounds, which include gas fees, liquidity fees (0.05% on the Uniswap V3 EURC/USDC pool), and slippage, representing price changes between trade initiation and execution.[20] The second panel reports arbitrage bound violations

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

[20] We assume slippage of 0.5% based on Uniswap's default setting (https://app.uniswap.org/swap). Slippage settings between 0.1% and 5% are generally recommended. Transactions fail if slippage is set below 0.1%.

accounting for gas and liquidity fees, and the third incorporates slippage costs. Without slippage, up to 5-11% of transactions violate the arbitrage bound. After including slippage, violations drop to approximately 1% of transactions. Additional costs from intermediation fees on centralized exchanges are excluded.

Panel (b) of Figure 5 jointly plots the arbitrage bounds and triangular arbitrage metrics.

[INSERT TABLE 4 ABOUT HERE]

Fact #3: Peg prices react to macro news intra-day

In an efficient market, the price of a financial security should evolve according to its fundamental value. We formally test market efficiency through the systematic relation of FX returns to macroeconomic news announcements. Exploiting the 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. During each meeting, we note EURC/USDC track closely the movements in the EUR/USD pair. Despite the limited number of observations, it appears that the EURC/USDC pair can track movements in the EUR/USD intra-day when conditioned on the arrival of macroeconomic news.

3 Empirical Analysis: Trader Information

3.1 Blockchain Volume Connection

H1: *DEX trading volume has a systematic connection with traditional market volume, particularly with the interbank segment that drives the price discovery process.*

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. If confirmed, this connection would emphasize the critical role of the interbank segment in price discovery, which may influence DEX prices.

To test Hypothesis H1, we use the specification given in equation (10), 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.

$$V_{N_{DEX},t} = \alpha + \sum_{i \in N_{CLS}} V_{N_{CLS},t} + \epsilon_t \tag{10}$$

Table 5 presents the results, highlighting a significant correlation between blockchain and traditional market volumes, particularly with interbank activity. As the more informed segment in the market, interbank activity plays a critical role in price discovery within OTC FX markets (Ranaldo and Somogyi, 2021). In column (1), the coefficient of 4.35 on interbank trading volume indicates 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. Furthermore, in column (6), 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.

[INSERT TABLE 5 ABOUT HERE]

Building on this correlation, we explore systematic patterns in trading volumes across participant types. Panel (a) of Figure 6 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 6 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 factors may explain this heightened activity during traditional market hours. First, increased price and trading activity in traditional markets could provide more profitable arbitrage opportunities, enabling alignment of prices across markets. Second, these traders may be processing fundamental news released during these periods. Second,

[INSERT FIGURE 6 ABOUT HERE]

3.2 Blockchain Order Flow and Feedback Trading

H2: *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 influenced by 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 this hypothesis, 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 (11), regressing blockchain order flow on the lagged price difference between DEX and traditional markets, with controls that include the lagged EURC/USDC return.

$$OF_{i,t} = \alpha + \beta_1(p_{EURC/USDC,t-1} - p_{EUR/USD,t-1}) + controls_t + \epsilon_t \tag{11}$$

[INSERT TABLE 6 ABOUT HERE]

The results, presented in Table 6, provide evidence of feedback trading behavior among sophisticated traders. In column (1), a unit increase in the lagged (hourly) price difference between Uniswap and CLS rates decreases aggregate hourly blockchain order flow by 0.15 EURC million. Similarly, for traders who are both sophisticated traders and primary dealers, as shown in column (4), the order flow decreases by 0.14 EURC million. In contrast, the order flow for primary dealers and LPs, presented in columns (2) and (3), is not statistically significant.

These findings suggest that wealthier traders, such as sophisticated traders and those with dual roles as primary dealers, are more likely to engage in arbitrage between DEX and traditional markets. This is likely due to their lower transaction costs for arbitrage activities, such as gas fees, which constitute a smaller percentage of their trade volume. In comparison, primary dealers and LPs, who typically trade smaller volumes, are less inclined to arbitrage price discrepancies across markets.

3.3 Blockchain Order Flow and Fundamental Information

H3: *Market participants have varying levels of information about the EUR/USD market. Informational advantages exist for sophisticated traders with high wealth and trading activity, primary dealers with access to EUR and USD deposits, whereas liquidity providers (LPs) focus primarily on inventory management and are uninformed with respect to the EUR/USD market.*

The standard model of blockchain order flow, based on the portfolio shifts framework in Evans and Lyons (2002), suggests that dealers absorb public demand for a currency and mitigate inventory risk by the end of the day. Changes in portfolio preferences and expectations about future exchange rates drive shifts in currency allocations, with exchange rates adjusting as dealers offload their risk.

In blockchain markets, traders process common information about fundamentals in distinct ways. Primary dealers, with access to fiat currency deposits, are linked to the interbank FX market, which is typically better informed (Ranaldo and Somogyi, 2021). Sophisticated traders, equipped with significant arbitrage capital, are better positioned to execute profitable trades across blockchain and traditional markets, efficiently incorporating the effects of fundamental news. Their resources allow them to manage transaction costs, such as gas fees, enabling them to align blockchain prices with traditional market values.

In contrast, LPs act as passive participants, primarily focused on inventory management rather than leveraging informational advantages. LPs are often exposed to adverse selection risk (Milionis et al., 2022; Foley et al., 2023), particularly when arbitrageurs exploit price discrepancies between markets. For instance, if the fundamental EUR/USD price rises relative to the EURC/USDC price, arbitrageurs buy EURC and sell USDC to align prices, creating imbalances in LP portfolios. LPs then adjust their holdings to restore balance, focusing on hedging liquidity rather than informed trading based on signals from the traditional EUR/USD market.

3.3.1 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.[21]

We use this event to study resilience in the EURC/USDC market and analyze behavior across trader types. Figure 7 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 H3. This behavior mirrors findings from Liu et al. (2023), where informed investors responded similarly during the Terra Luna collapse.

For instance, wallet '1c37' exhibited significant USDC selling pressure during the event, engaging in high-frequency and large-scale liquidity transactions on Uniswap and SushiSwap. This activity involved substantial liquidity provisions and withdrawals across multiple currency pairs, indicating the exploitation of arbitrage opportunities.[22]

In contrast, LPs showed minimal strategic repositioning during this period, supporting the view that they act as passive participants.[23]

[21] 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.

[22] Wallet '1c37' (full address: 0xd64137f743432392538a8f84e8e571fa09f21c37) frequently conducted high-volume transactions during the de-pegging event, including major trades in USDC-PRIME, SYN-USDC, and EURC-USDC pairs. Its activity primarily involved adding and removing liquidity around large trades. Detailed transaction logs are provided in Appendix D.

[23] For example, the only LP withdrawal observed during the event occurred at 05:59 UTC on March 11,

3.3.2 Contemporaneous Price Impact: Aggregate Order Flow

Building on the case study, we examine the price impact of aggregate order flow to assess how it incorporates private information about market fundamentals. The intuition is that blockchain order flow, beyond reflecting public information, may also contain private signals related to FX rates, as outlined in Evans and Lyons (2002).

$$p_t - p_{t-1} = \alpha + \beta_1 \mathrm{OF}_t + \beta_j x_{j,t} + \epsilon_t \tag{12}$$

In equation (12), p_t is the log spot exchange rate for either the EURC/USDC or EUR/USD pair, and $x_{j,t}$ represents macroeconomic control variables, including interest rate differentials and FX dealer balance sheet constraints.

Table 8 presents the results based on daily aggregate order flow. Columns (1)-(4) use DEX returns as the outcome variable, while columns (5)-(8) use CLS benchmark returns. The findings indicate a significant impact of blockchain order flow on both DEX and CLS returns. A 1 million EURC shock in blockchain order flow results in a 4.79% increase in DEX daily returns and a 3.86% increase in CLS benchmark daily returns. These effects are moderated when considering spillovers to traditional markets.

[INSERT TABLE 8 ABOUT HERE]

Our estimates remain robust after accounting for interest rate differentials and balance sheet constraints. However, they are considerably larger than prior estimates, such as the 50 basis points per USD 1 billion reported by Evans and Lyons (2002) and Berger et al. (2008). This difference likely reflects the lower liquidity of the EURC/USDC market, where the average daily trading volume is approximately EURC 0.423 million, with a standard deviation of EURC 0.674 million. The average daily order flow is similarly low, around 2.1k EURC, with a standard deviation of 7.23k EURC. When normalized to a 1-standard-deviation shock in order flow, the price impact on CLS benchmark returns reduces to approximately 3 basis points, aligning with the lower liquidity observed in blockchain markets.

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).

3.3.3 Contemporaneous Price Impact: Asymmetric Information

Market participants exhibit heterogeneous impacts on price (Ranaldo and Somogyi, 2021). We now test whether distinct participant categories differentially affect blockchain-based and traditional FX rates. The regression model in equation (13) disaggregates blockchain order flow by participant type, including sophisticated traders, primary dealers, LPs, and wallets at the intersection of these groups (defined in Section 2).

$$p_t - p_{t-1} = \alpha + \sum_{i \in N_k} \beta_i \mathrm{OF}_{i,t} + \epsilon_t \tag{13}$$

Table 9 aggregates order flow for each subgroup at an hourly frequency. In column (1), the dependent variable is the log price change of EURC/USDC (DEX returns), while column (2) uses the log price change of EUR/USD (CLS benchmark returns).

For DEX returns in column (1), a 1 million EURC order flow by sophisticated traders leads to a 6.61% increase in DEX hourly returns, compared to a 7.54% increase for primary dealers and a 6.56% increase for LPs. Non-group traders show a 7.27% price impact, with no significant differences across trading types.

In column (2), focusing on CLS benchmark returns, sophisticated traders and primary dealers exhibit informational advantages. A 1 million EURC order flow by sophisticated traders results in a 2.30% increase in CLS hourly returns, compared to 3.00% for primary dealers and 1.82% for LPs. The combined group of sophisticated traders and primary dealers has the highest price impact at 3.25%, while LPs show the lowest impact at 0.89%. These findings suggest that LPs primarily hedge positions rather than trade on information relevant to traditional markets.

In summary, these results support Hypothesis H3, highlighting informational heterogeneity among blockchain participants. Sophisticated traders and primary dealers, especially those with significant market share, likely hold informational advantages, while LPs appear less informed.

Additionally, we examine intra-day price impact patterns in Appendix E, estimating hourly impacts of DEX order flow for each trading group. 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.

Further, in the same Appendix, we assess whether blockchain characteristics such as the number of tokens traded, transaction frequency, and wallet age predict informed trading. Our results show no systematic relationship between these characteristics and the price impact of blockchain order flow, indicating that these metrics do not reliably capture information-based trading activity in our sample.

[INSERT TABLE 9 ABOUT HERE]

3.4 Price Impact: Dynamic Effects

Thus far, our analysis has focused on contemporaneous blockchain order flow and its immediate impact on currency values. However, prices and flows often exhibit persistent and endogenous dynamics. To account for these effects, we test for dynamic relationships using a structural VAR framework that controls for feedback between prices and order flow (Hasbrouck, 1991; Ranaldo and Somogyi, 2021). The following bivariate VAR model captures blockchain order flow OF and spot returns (measured as the log price difference) Δp, as shown in equations (14) and (15).

In equation (14), a contemporaneous shock to hourly blockchain order flow is reflected in the price within the same hour. Conversely, equation (15) allows for price shocks to influence blockchain order flow with a lag. This identification assumption aligns with the causality direction proposed by Evans and Lyons (2002), where blockchain order flow drives exchange rate returns. Our baseline specification includes $L = 24$ lags.

$$\Delta p_t = \alpha_1 + \sum_{k=1}^{L} \gamma_{1,k} \Delta p_{t-k} + \sum_{k=0}^{L} \beta_{1,k} OF_{t-k} + \epsilon_{1,t} \tag{14}$$

$$OF_t = \alpha_2 + \sum_{k=1}^{L} \gamma_{2,k} \Delta p_{t-k} + \sum_{k=1}^{L} \beta_{2,k} OF_{t-k} + \epsilon_{2,t} \tag{15}$$

Figure 8 compares the cumulative price impact of different trader types. Panel (a) presents coefficients for DEX EURC/USDC returns, while Panel (b) shows coefficients for CLS Benchmark EUR/USD returns. In both panels, trading by sophisticated traders and primary dealers exhibits significantly stronger permanent price impacts compared to LPs. Notably, LPs exhibit an insignificant price impact, which is even weakly negative for DEX returns. These findings are consistent with the contemporaneous effects reported in Table 9, reinforcing the notion that sophisticated traders and primary dealers are more informed, while LPs primarily hedge positions and lack substantial information.

[INSERT FIGURE 8 ABOUT HERE]

3.4.1 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.

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 (15)) 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. After accounting for liquidity provision, our price impact estimates remain consistent, suggesting that liquidity adjustments do not drive our results.

We also investigate the presence of just-in-time (JIT) liquidity, where providers strategically add and remove liquidity to capture transaction fees while minimizing exposure to adverse selection (Capponi et al., 2023). 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. Appendix G provides detailed transaction logs for this wallet.[24] This behavior demonstrates a strategic approach to minimize adverse selection, though it remains an exception rather than the norm in the EURC-USDC pool.

Traditional Order Flow. Another concern is the potential correlation between blockchain

[24]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 liquidity, burning 32,048 EURC and 330,931 USDC.

order flow and traditional CLS order flow, which could confound our price impact estimates. To address this, we include CLS order flow as a control, encompassing both aggregate and sectoral flows (e.g., interbank, bank-corporate, and bank-fund). The stability of our DEX order flow price impact after accounting for CLS flows confirms that our findings are not subsumed by traditional market activity.

Feedback Trading. Finally, we examine whether the observed price impacts arise from feedback trading and arbitrage between DEX and traditional markets rather than informational content. We decompose DEX order flow into a feedback-driven component (based on the lagged price difference between DEX and traditional markets) and a residual component as a proxy for informational order flow. Impulse response analysis shows that only the residual component exhibits lasting price impacts, consistent with our baseline estimates. In contrast, the feedback-driven component does not significantly influence traditional market returns, indicating that the observed price impacts stem from informational order flow rather than mechanical trading dynamics.

4 Conclusion

DeFi platforms are transforming the financial landscape by providing global access to financial services without intermediaries. This study evaluates the efficiency of blockchain-based currency markets and their connections to traditional FX markets, focusing on the EURC/USDC pair traded on decentralized exchanges.

Our findings show that blockchain currency markets are generally efficient, with prices trading within arbitrage bounds and responding promptly to macroeconomic announcements. However, these markets face frictions, such as gas fees and market volatility, which affect price efficiency. Blockchain trading aligns closely with traditional market hours, driven by feedback trading and the processing of fundamental information.

Our main contribution lies in analyzing the informational role of blockchain transactions and the differences in price impact among market participants. Blockchain order flow has a significant influence on prices in traditional markets, with sophisticated traders and primary dealers showing a greater price impact due to their informational advantages and access to fiat currency deposits. In contrast, liquidity providers act as uninformed hedgers, contributing minimally to price impact and primarily focusing on maintaining liquidity rather than leveraging informational advantages.

The evolution of blockchain markets presents several promising directions for future research. As these markets grow, liquidity providers, currently passive during de-pegging events, may adopt behaviors similar to traditional FX dealers, actively adjusting their positions and capital. Additionally, while gas fees and slippage are significant factors in decentralized trading today, traditional market constraints, such as dealer balance sheet limitations, may become more relevant as decentralized platforms expand.

Future research should examine transaction costs across blockchain and traditional FX markets, comparing elements like gas fees and slippage on decentralized platforms with bid-ask spreads in traditional venues. Such analysis would offer insights into the cost-effectiveness and viability of decentralized platforms as alternatives to conventional FX infrastructure.

References

Adams, Austin, Mary-Catherine Lader, Gordon Liao, David Puth, and Xin Wan, "On-Chain Foreign Exchange and Cross-Border Payments," *Available at SSRN 4328948*, 2023.

Aldasoro, Iñaki, Rashad Ahmed, and Chanelle Duley, "Par for the course: Public information and stablecoin runs," *Available at SSRN*, 2023.

Andersen, Torben G., Tim Bollerslev, Francis X. Diebold, and Clara Vega, "Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange," *American Economic Review*, March 2003, *93* (1), 38–62.

Aoyagi, Jun and Yuki Ito, "Liquidity Implication of Constant Product Market Makers," *Available at SSRN 3808755*, 2021.

Barbon, Andrea and Angelo Ranaldo, "On The Quality Of Cryptocurrency Markets: Centralized Versus Decentralized Exchanges," *arXiv preprint arXiv:2112.07386*, 2021.

Barthelemy, Jean, Paul Gardin, and Benoît Nguyen, "Stablecoins and the real economy," *Available at SSRN 3973538*, 2021.

Berger, David W, Alain P Chaboud, Sergey V Chernenko, Edward Howorka, and Jonathan H Wright, "Order flow and exchange rate dynamics in electronic brokerage system data," *Journal of international Economics*, 2008, *75* (1), 93–109.

Bertsch, Christoph, "Stablecoins: Adoption and Fragility," 2022.

Bjønnes, Geir Høidal and Dagfinn Rime, "Dealer behavior and trading systems in foreign exchange markets," *Journal of Financial Economics*, 2005, *75* (3), 571–605.

Caparros, Basile, Amit Chaudhary, and Olga Klein, "Blockchain Scaling and Liquidity Concentration on Decentralized Exchanges," *Available at SSRN 4475460*, 2023.

Capponi, Agostino and Ruizhe Jia, "The Adoption of Blockchain-based Decentralized Exchanges: A Market Microstructure Analysis of the Automated Market Maker," *Available at SSRN 3805095*, 2021.

_, _, and Brian Zhu, "The paradox of just-in-time liquidity in decentralized exchanges: More providers can sometimes mean less liquidity," *Available at SSRN*, 2023.

Chaboud, Alain, Dagfinn Rime, and Vladyslav Sushko, "The foreign exchange market," in "Research Handbook of Financial Markets," Edward Elgar Publishing, 2023, pp. 253–275.

d'Avernas, Adrien, Vincent Maurin, and Quentin Vandeweyer, "Can Stablecoins be Stable?," *University of Chicago, Becker Friedman Institute for Economics Working Paper*, 2022, (2022-131).

Eichengreen, Barry, My T Nguyen, and Ganesh Viswanath-Natraj, "Stablecoin Devaluation Risk," *WBS Finance Group Research Paper*, 2023.

Evans, Martin DD and Richard K Lyons, "Order Flow and Exchange Rate Dynamics," *Journal of Political Economy*, 2002, *110* (1), 170–180.

_ , Peter O'Neill, Dagfinn Rime, and Jo Saakvitne, "Fixing the Fix? Assessing the Effectiveness of the 4pm Fix Benchmark," *FCA Occasional Paper*, 2018.

Fang, Chuck, "Liquidity Misallocation on Decentralized Exchanges," *Available at SSRN 4281293*, 2022.

Foley, Sean, Peter O'Neill, and Tālis J Putniņš, "A Better Market Design? Applying 'Automated Market Makers' to Traditional Financial Markets," *Applying 'Automated Market Makers' to Traditional Financial Markets (May 26, 2023)*, 2023.

Gorton, Gary B, Chase P Ross, and Sharon Y Ross, "Making Money," Technical Report, National Bureau of Economic Research 2022.

Hagströmer, Björn and Albert J Menkveld, "Information revelation in decentralized markets," *The Journal of Finance*, 2019, *74* (6), 2751–2787.

Hansson, Magnus, "Price Discovery in Constant Product Markets," *Available at SSRN 4582649*, 2023.

Hasbrouck, Joel, "Measuring the information content of stock trades," *The Journal of Finance*, 1991, *46* (1), 179–207.

_ and Richard M Levich, "Network structure and pricing in the FX market," *Journal of Financial Economics*, 2021, *141* (2), 705–729.

—, Thomas J Rivera, and Fahad Saleh, "The need for fees at a dex: How increases in fees can increase dex trading volume," *Available at SSRN*, 2022.

He, Zhiguo, Bryan Kelly, and Asaf Manela, "Intermediary asset pricing: New evidence from many asset classes," *Journal of Financial Economics*, 2017, *126* (1), 1–35.

Hortaçsu, Ali and Samita Sareen, "Order flow and the formation of dealer bids: information flows and strategic behavior in the Government of Canada securities auctions," 2005.

Huang, Wenqian, Angelo Ranaldo, Andreas Schrimpf, and Fabricius Somogyi, "Constrained Dealers and Market Efficiency," *Available at SSRN 3956582*, 2021.

King, Michael R, Carol Osler, and Dagfinn Rime, "Foreign exchange market structure, players, and evolution," *Handbook of exchange rates*, 2012, pp. 1–44.

Klein, Olga, Roman Kozhan, Ganesh Viswanath-Natraj, and Junxuan Wang, "Price Discovery in Cryptocurrencies: Trades versus Liquidity Provision," *Available at SSRN 4642411*, 2023.

Kloks, Peteris, Edouard Mattille, and Angelo Ranaldo, "Foreign Exchange Swap Liquidity," *Swiss Finance Institute Research Paper*, 2023, (23-22).

Kozhan, Roman and Ganesh Viswanath-Natraj, "Decentralized Stablecoins and Collateral Risk," *WBS Finance Group Research Paper Forthcoming*, 2021.

— and Mark Salmon, "The information content of a limit order book: The case of an FX market," *Journal of Financial Markets*, 2012, *15* (1), 1–28.

Krohn, Ingomar, Philippe Mueller, and Paul Whelan, "Foreign exchange fixings and returns around the clock," in "Journal of Finance forthcoming, Proceedings of the EUROFIDAI-ESSEC Paris December Finance Meeting" 2022.

Lehar, Alfred and Christine Parlour, "Decentralized Exchanges," *Working Paper*, 2021.

—, —, and Marius Zoican, "Liquidity fragmentation on decentralized exchanges," *arXiv preprint arXiv:2307.13772*, 2023.

LI, Thomas, Siddharth Naik, Andrew Papanicolaou, and Lorenzo Schoenleber, "Maneuvering and Investing in Yield Farms," *Available at SSRN 4422213*, 2023.

Li, Ye and Simon Mayer, "Money Creation in Decentralized Finance: A Dynamic Model of Stablecoin and Crypto Shadow Banking," 2021.

Liu, Jiageng, Igor Makarov, and Antoinette Schoar, "Anatomy of a run: The terra luna crash," Technical Report, National Bureau of Economic Research 2023.

Lyons, Richard K, "Tests of microstructural hypotheses in the foreign exchange market," *Journal of Financial Economics*, 1995, *39* (2-3), 321–351.

_ **and Ganesh Viswanath-Natraj**, "What keeps stablecoins stable?," *Journal of International Money and Finance*, 2023, *131*, 102777.

Ma, Yiming, Yao Zeng, and Anthony Lee Zhang, "Stablecoin Runs and the Centralization of Arbitrage," *Available at SSRN 4398546*, 2023.

Malinova, Katya and Andreas Park, "Learning from DeFi: Would Automated Market Makers Improve Equity Trading?," 2023.

Marsh, Ian W, Panagiotis Panagiotou, and Richard Payne, "The WMR fix and its impact on currency markets," *Unpublished Manuscript*, 2017.

Milionis, Jason, Ciamac C Moallemi, Tim Roughgarden, and Anthony Lee Zhang, "Automated market making and loss-versus-rebalancing," *arXiv preprint arXiv:2208.06046*, 2022.

Oefele, Nico, Dirk G Baur, and Lee A Smales, "Are Stablecoins the Money Market Mutual Funds of the Future?," *Available at SSRN 4550177*, 2023.

Ranaldo, Angelo, "20. Foreign exchange swaps and cross-currency swaps," *Research Handbook of Financial Markets*, 2023, p. 451.

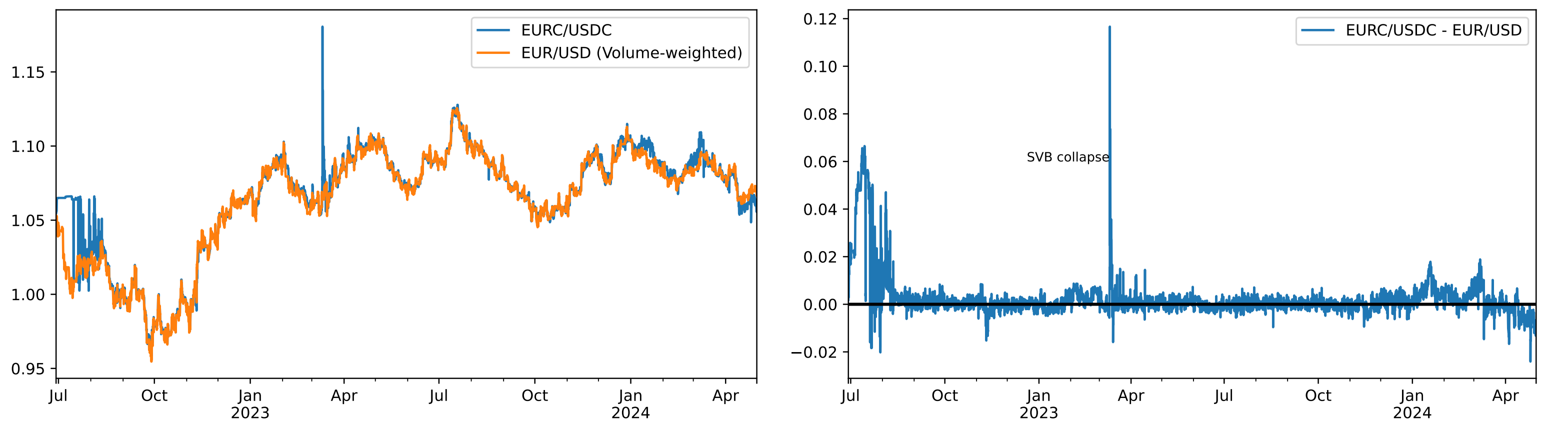
_ **and Fabricius Somogyi**, "Asymmetric information risk in FX markets," *Journal of Financial Economics*, 2021, *140* (2), 391–411.

Rime, Dagfinn, Lucio Sarno, and Elvira Sojli, "Exchange rate forecasting, order flow and macroeconomic information," *Journal of International Economics*, 2010, *80* (1), 72–88.

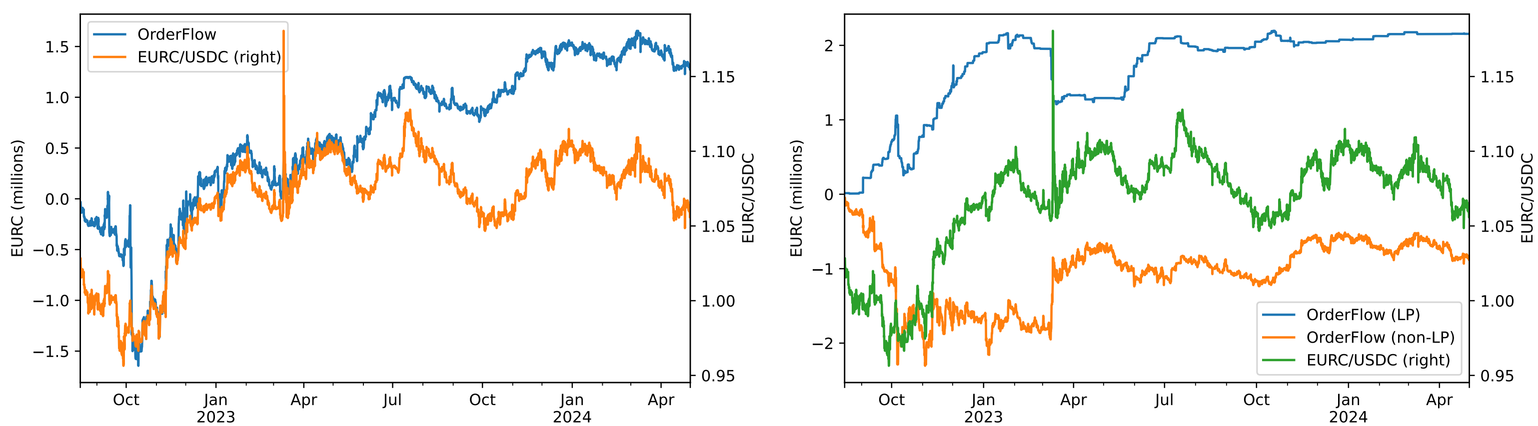
Routledge, Bryan and Ariel Zetlin-Jones, "Currency stability using blockchain technology," *Journal of Economic Dynamics and Control*, 2021, p. 104155.

Figure 1: EURC/USDC Prices

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

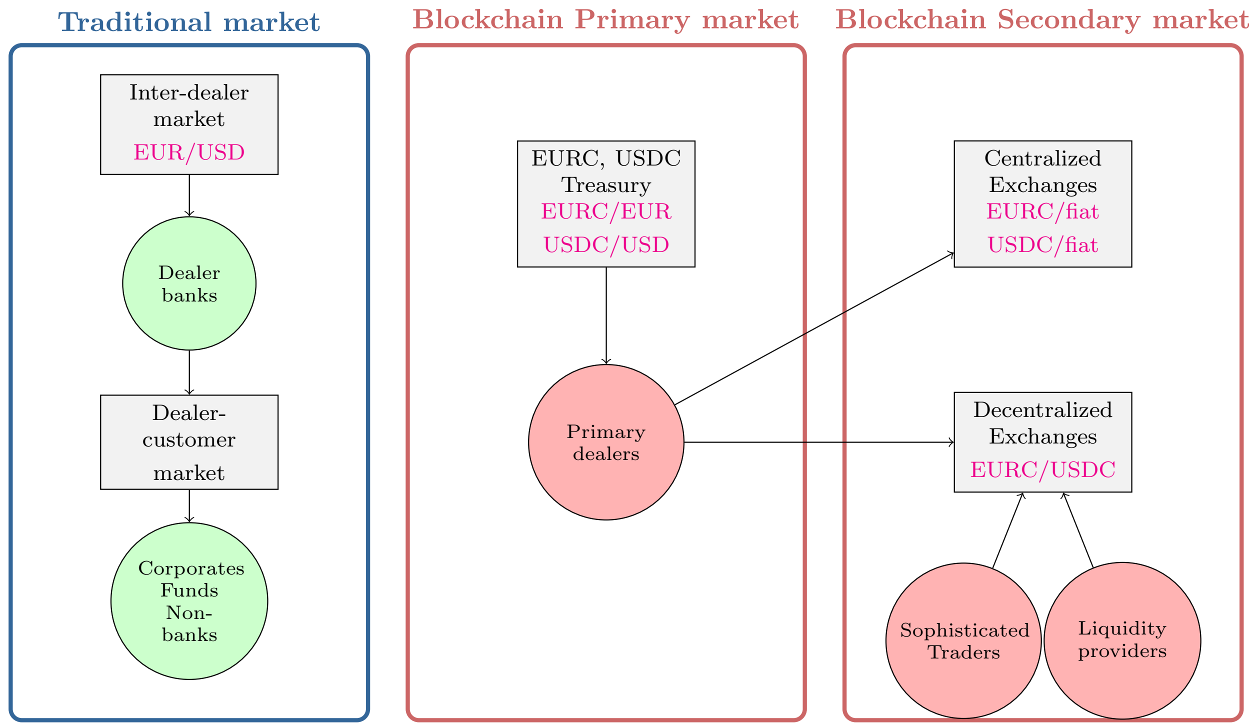


Panel (b): EURC/USDC Price and Cumulative Blockchain Order Flow



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.

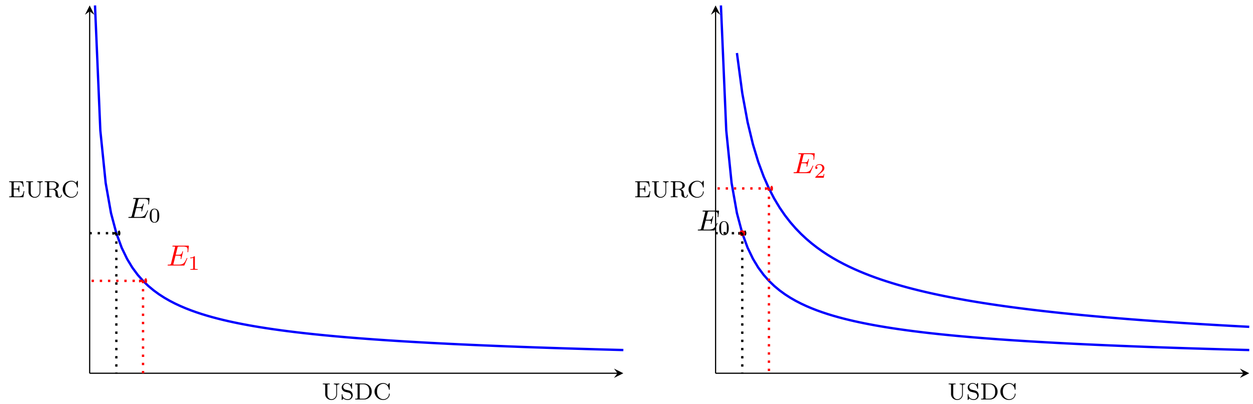
Figure 2: Structure of Traditional and Blockchain Market



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 (LOB), 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 3: EURC/USDC Bonding Curves

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

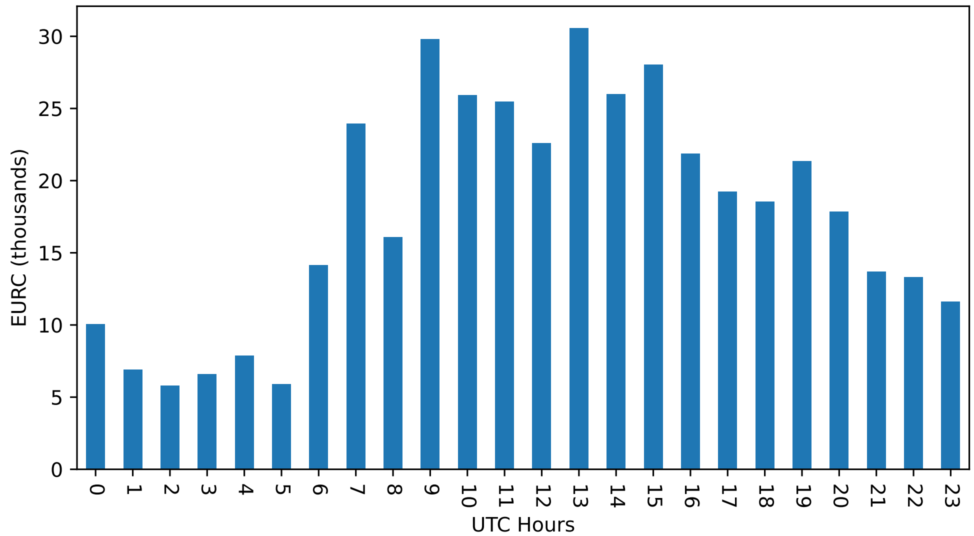


Panel (b): Snapshot of Uniswap Liquidity GUI

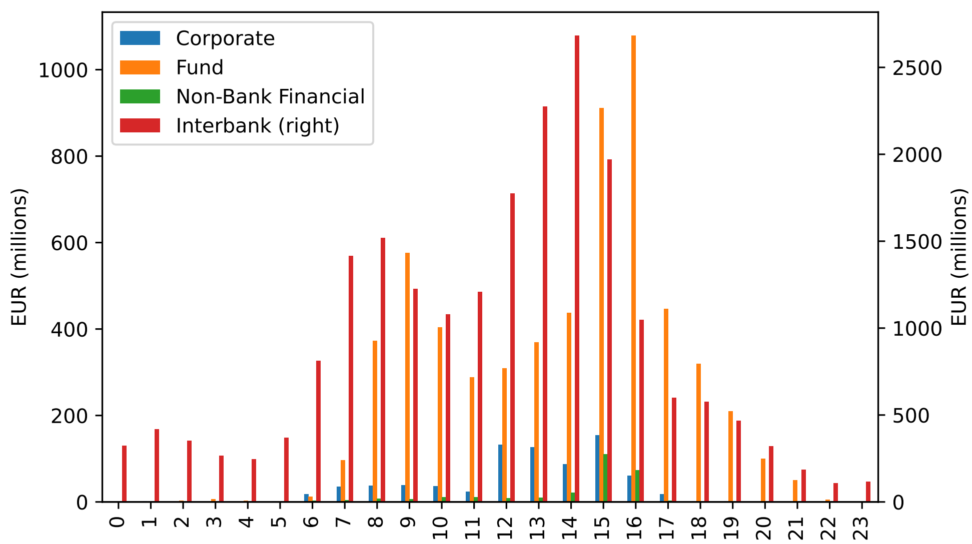
Note: This figure provides a snapshot of liquidity in the EURC/USDC pair. Panel (a) illustrates the principles of a bonding curve and liquidity provision in Uniswap. The aggregate supply of liquidity at point E_0, with a swap trade of purchasing EURC moving the equilibrium from E_0 to E_1, and a LP adding 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 4: Hourly FX Trading Volume

Panel (a): DEX Trading Volume



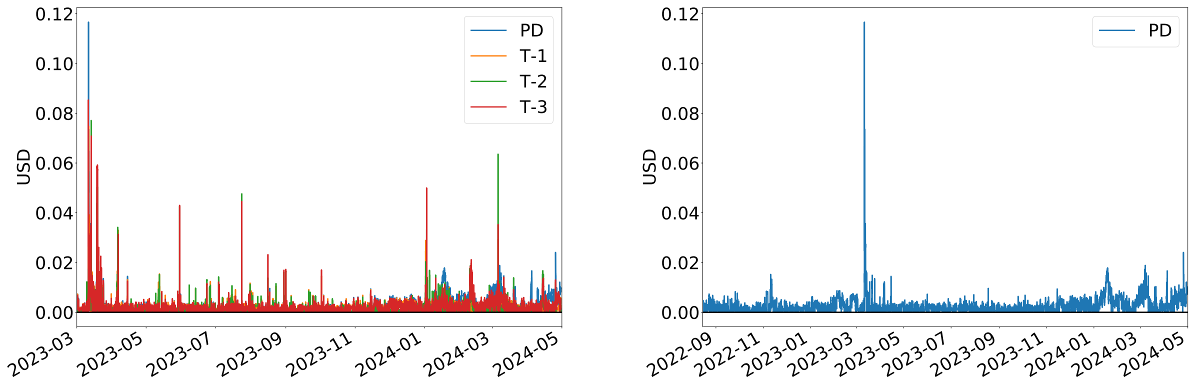
Panel (b): CLS Trading Volume



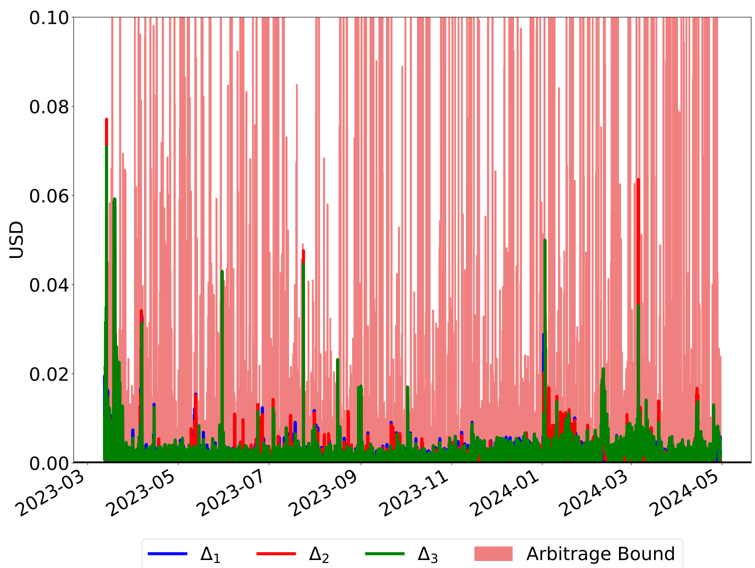
Note: Figure plots hourly trading volume. In Panel (a), we report trading on Uniswap V3 in the EURC/USDC Market in EURC Millions. In Panel (b), we report trading volume on CLS for the EUR/USD market, disaggregated by sectors: Bank-Bank, Bank-Fund, Bank-Corporate, and Non-Bank Financial-Bank. CLS Volume 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



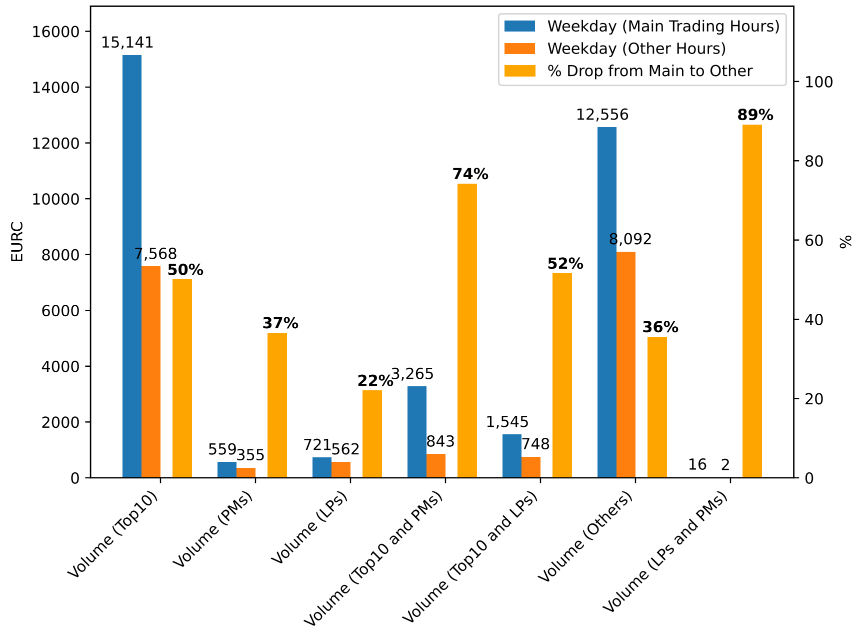
Panel (b): Arbitrage Bounds



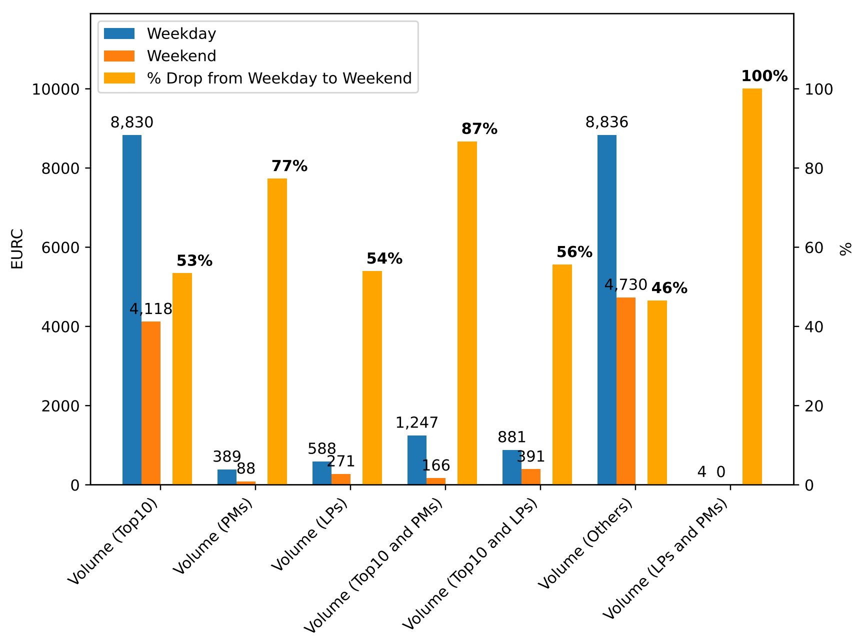
Note: This figure plots market efficiency metrics based on how the EURC/USDC market tracks EUR/USD CLS benchmark rates. Panel (a) plots the triangular arbitrage conditions as alternative measures of market efficiency to the price difference (PD). Panel (b) plots the triangular arbitrage measures and 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: Weekend and Weekday Volume by Trader type

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

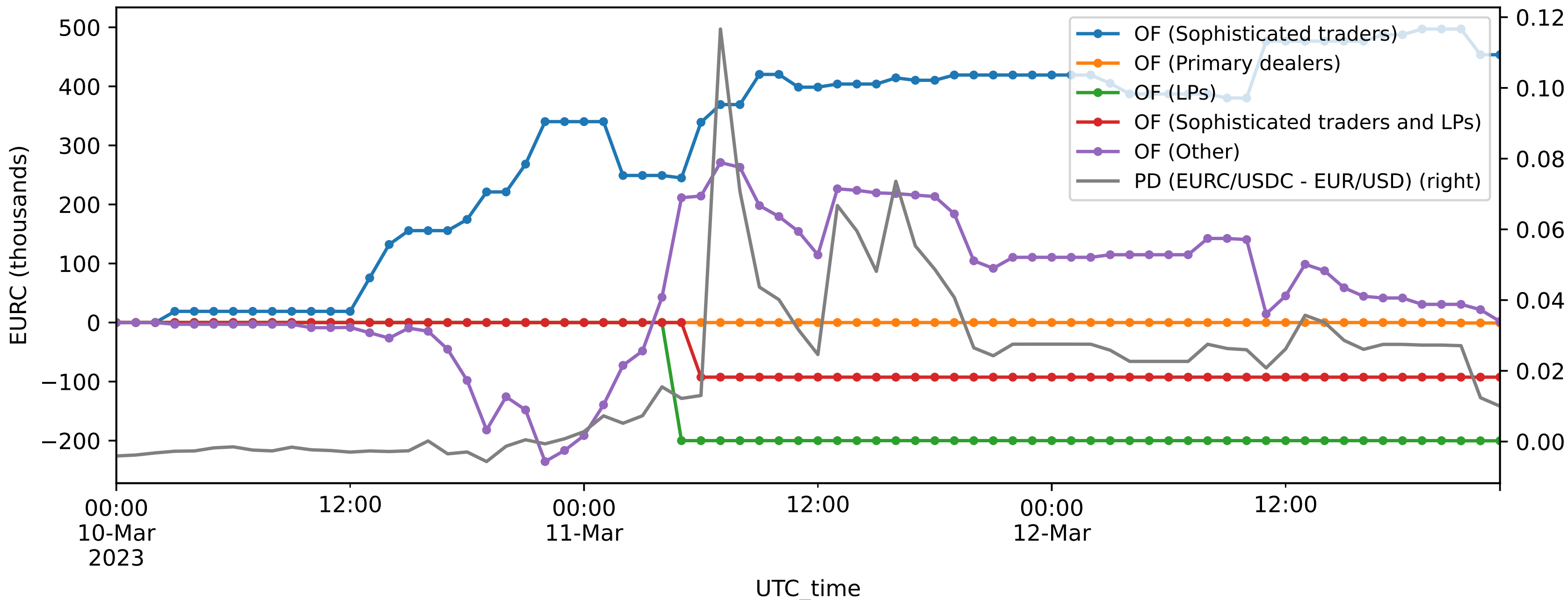


Panel (b): Weekday vs Weekend trading



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.

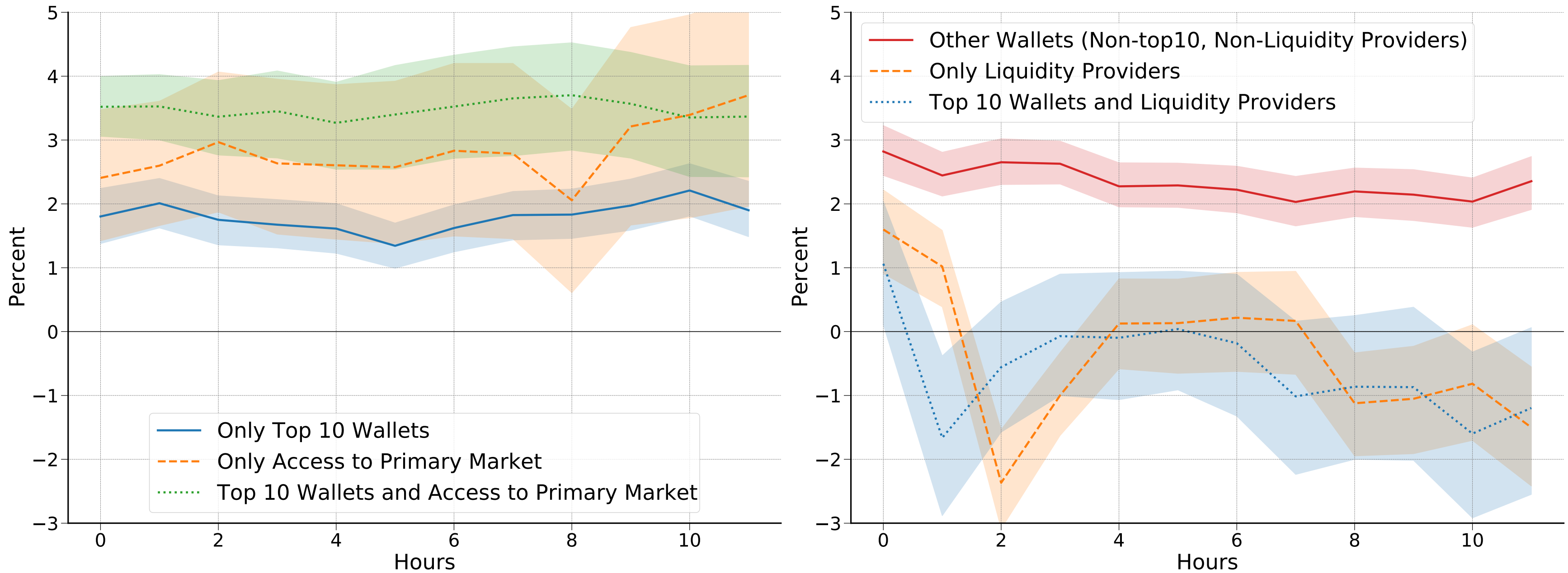
Figure 7: USDC De-Pegging event: blockchain order flow of different trading groups



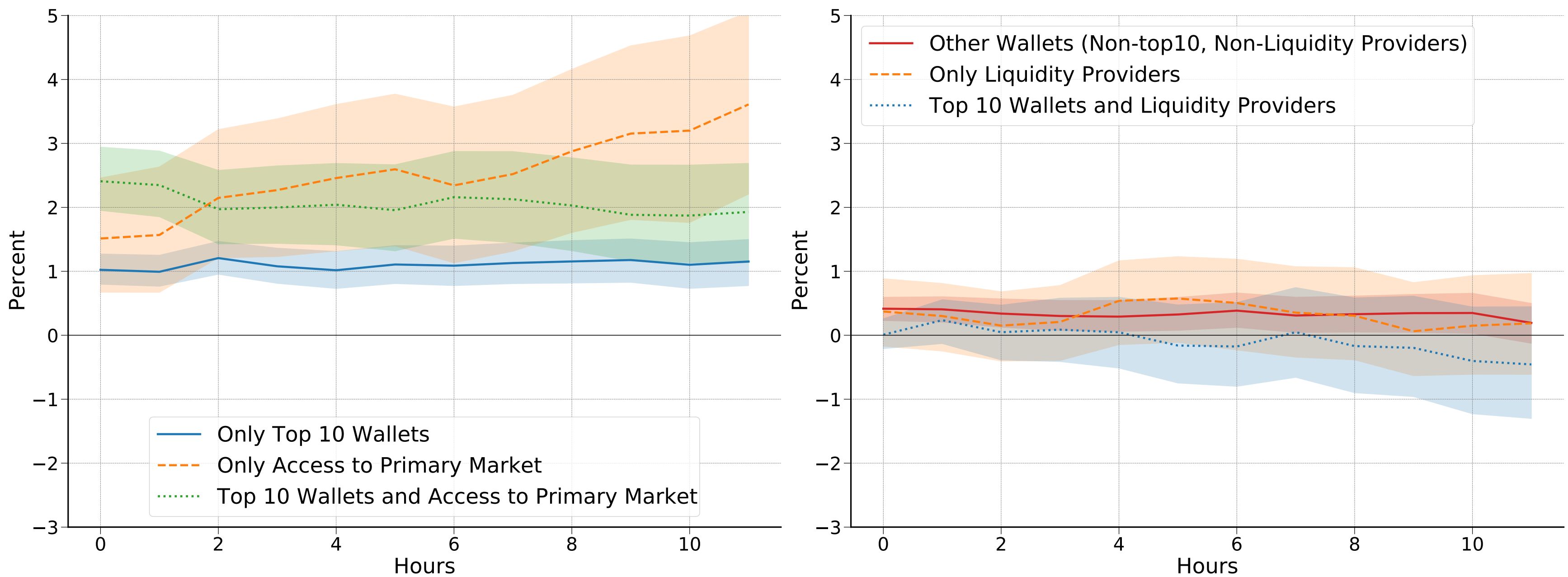
Note: This figure plots the response of blockchain order flow to the de-pegging event of USDC. PD is the difference between EURC/USDC and EUR/USD prices, sourced from Uniswap V3 and CLS respectively. OF is measuring the net buyer transactions of purchasing EURC, and is sourced from Uniswap V3 trade data. 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 2022 to 12 March 2023.

Figure 8: 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 the change in spot returns to a 1 Million EURC shock in blockchain order flowusing a structural VAR framework. 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. 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 combinations of these. The sample period is 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	4447	58.51
PM	×	✓	×	68	363	5.34
LP	×	×	✓	90	446	4.96
Top10 ∩ PM	✓	✓	×	6	534	89.00
Top10 ∩ LP	✓	×	✓	7	254	36.29
PM ∩ LP	×	✓	✓	3	6	2.00
$\notin \{Top10, PM, LP\}$	×	×	×	2342	9137	3.90

Panel (b): Volume per transaction (EURC)

Group	mean	std	min	25%	50%	75%	max
Top10	25,256	48,853	1	7,818	13,693	27,525	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	43,786	62,026	100	4,131	30,754	50,000	343,333
PM ∩ LP	7,537	9,931	352	2,394	4,556	6,262	27,256
$\notin \{Top10, PM, LP\}$	12,585	21,311	0	1,061	5,055	15,126	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, Blockchain and Macroeconomic 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 $\cap$ PM)	625	0.023	0.047	0.0	0.000	0.000	0.030	0.343
Volume (top10 $\cap$ 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 $\cap$ LP)	625	0.0001	0.0013	0.0	0.000	0.000	0.000	0.027
Panel (c): Additional Variables								
$p_{EURC/USDC}$	625	1.067	0.035	0.962	1.058	1.078	1.091	1.128
$p_{EUR/USD}$	625	1.066	0.035	0.960	1.058	1.077	1.089	1.124
$\lvert p_{EUR/USD} - p_{EURC/USDC}\rvert$	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
$i_{EUR} - i_{USD}$	625	-1.822	0.419	-2.563	-2.187	-1.712	-1.440	-0.663
HKM	625	0.001	0.011	-0.041	-0.006	0.001	0.006	0.044

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, traditional FX market and macroeconomic statistics. Blockchain characteristics include the returns and volatility of Coinbase ETH/USD, and an index of gas fees. Macroeconomic characteristics include the interest rate differential between EUR and USD (1 month OIS), and a measure of dealer balance sheet constraints based on He et al. (2017). Sample period is from 15 August 2022 to 30 April 2024.

Table 3: Determinants of EURC-USDC Peg Deviations

	|EURC/USDC-EUR/USD| Peg Deviations					
	(1)	(2)	(3)	(4)	(5)	(6)
σ^{IV}_{ETH}	0.1328***				0.1608***	
	(0.0454)				(0.0479)	
σ^{IV}_{BTC}		0.3605***				0.3568***
		(0.0816)				(0.0801)
gasfee			0.4054**		0.4624**	0.3982**
			(0.1992)		(0.2036)	(0.1923)
R_{ETH}				0.0036	0.0041	0.0039
				(0.0041)	(0.0039)	(0.0038)
constant	0.0015***	0.0002	0.0019***	0.0024***	0.0008*	-0.0002
	(0.0003)	(0.0005)	(0.0002)	(0.0001)	(0.0004)	(0.0005)
R-squared	0.0104	0.0284	0.0160	0.0019	0.0328	0.0457
No. observations	625	625	625	624	624	624

Note: This table presents the results of regressions on absolute EURC-USDC peg deviations using blockchain and traditional macroeconomic variables. Outcome variable is the absolute deviation of EURC/USDC from EUR/USD. Explanatory variables include Ether volatility and Bitcoin implied volatility, gas fees, and returns on ETH. Combined models include multiple explanatory variables to assess joint effects. Standard errors are heteroscedasticity-robust and reported in parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 4: 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	9926	0.002	0.002	0.000	0.001	0.001	0.003	0.033
Δ_2	9926	0.001	0.003	0.000	0.000	0.001	0.001	0.077
Δ_3	9926	0.002	0.004	0.000	0.001	0.002	0.003	0.071
Panel (b): Transaction costs: gas fees+liquidity fees								
Δ_1 Arbitrage Bound Violation	9926	0.105	0.307	0.000	0.000	0.000	0.000	1.000
Δ_2 Arbitrage Bound Violation	9926	0.051	0.220	0.000	0.000	0.000	0.000	1.000
Δ_3 Arbitrage Bound Violation	9926	0.111	0.315	0.000	0.000	0.000	0.000	1.000
Panel (c): Transaction costs: gas fees+liquidity fees+slippage								
Δ_1 Arbitrage Bound Violation	9926	0.008	0.087	0.000	0.000	0.000	0.000	1.000
Δ_2 Arbitrage Bound Violation	9926	0.012	0.111	0.000	0.000	0.000	0.000	1.000
Δ_3 Arbitrage Bound Violation	9926	0.013	0.112	0.000	0.000	0.000	0.000	1.000

Note: This table presents summary statistics of arbitrage bound violations for the triangular arbitrage metrics for the EURC/USDC pair. The first panel documents the different percentiles of the triangular arbitrage metrics, and the gas fee per 1 USD volume transaction. The second panel presents summary statistics of arbitrage bound violations in the presence of gas fees and liquidity fees (when the triangular arbitrage metric exceeds transaction costs). Gas fees are based on actual payments in ETH at the transaction level. Liquidity fees are 0.05% on the Uniswap V3 EURC/USDC pool. The lower panel presents summary statistics of arbitrage bound violations after accounting for slippage, which is the loss because when market prices change after the trade was initiated but before it was executed. It is 0.5% by default on the Uniswap V3 app https://app.uniswap.org/swap. Gas fees (per 1 USD transaction) are winsorized at the 99% level. Sample period is from 1 March 2023 to 30 April 2024.

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***
	(0.6874)	(0.0408)	(0.1295)	(0.0859)	(0.2462)	(0.0006)	(0.5365)
Corporate-Bank	1.5545	-0.0026	0.3532	0.5860	-0.4185**	-0.0018	2.2923
	(1.6186)	(0.1902)	(0.3012)	(0.3777)	(0.1643)	(0.0013)	(1.9664)
Fund-Bank	1.1120***	0.0353	0.0166	0.2303***	0.0369	0.0017	0.9016***
	(0.3915)	(0.0285)	(0.0392)	(0.0613)	(0.0734)	(0.0017)	(0.3031)
Non-Bank Financial-Bank	2.3239	0.3554	-0.0312	0.7064	0.0518	-0.0002	6.8670
	(3.7023)	(0.3001)	(0.1766)	(0.7246)	(0.0985)	(0.0002)	(7.7152)
constant	3261.9288***	113.7215***	190.3928**	111.9940*	379.6192***	2.7742	4390.3679***
	(494.1829)	(35.6057)	(91.4735)	(60.5383)	(135.9636)	(2.3514)	(428.4421)
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. White heteroscedasticity-robust standard errors are 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 EUROC/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***
	(0.0474)	(0.0071)	(0.0126)	(0.0196)	(0.0074)	(0.0002)	(0.0488)
DEXReturn_{t-1}	-0.0077**	-0.0002	0.0003	-0.0012	0.0002	-0.0000	-0.0008
	(0.0032)	(0.0002)	(0.0005)	(0.0010)	(0.0002)	(0.0000)	(0.0019)
$OF_{top10,t-1}$	0.1995***						
	(0.0528)						
$OF_{PM,t-1}$		0.0257*					
		(0.0142)					
$OF_{LP,t-1}$			0.0153				
			(0.0136)				
$OF_{top10 \cap PM,t-1}$				0.0654***			
				(0.0250)			
$OF_{top10 \cap LP,t-1}$					-0.0888		
					(0.1839)		
$OF_{LP \cap PM,t-1}$						0.0000	
						(0.0001)	
$OF_{\notin top10,PM,LP,t-1}$							0.1332**
							(0.0590)
constant	0.0001	0.0000	0.0001***	-0.0000	0.0000	-0.0000	0.0003**
	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0001)
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 EUROC, 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. Heteroscedasticity-robust standard errors are reported in parentheses. *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 7: 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.

Table 8: Determinants of EURC-USDC and EUR-USD Returns

	Panel (a): DEX Return		**Panel (b): CLS benchmark return**	
	(1)	(2)	(3)	(4)
OF	4.9558***	4.7939***	4.1538***	3.8618***
	(0.1423)	(0.1492)	(0.1676)	(0.1738)
$i_{EUR} - i_{USD}$		0.0003		0.0001
		(0.0002)		(0.0003)
HKM		3.3564***		5.8713***
		(0.9645)		(1.1233)
constant	-0.0050	0.0501	-0.0015	0.0186
	(0.0103)	(0.0456)	(0.0121)	(0.0531)
R-squared	0.6609	0.6684	0.4970	0.5185
No. observations	624	624	624	624

Note: This table presents the results of regressions on changes in EURC/USDC and EUR/USD returns. VolOF represents the volume of net buyer transactions in EURC (in millions USDC) on Uniswap V3. The interest rate differential and the intermediary capital risk factor (HKM) are included as macroeconomic variables, with the latter capturing balance sheet constraints. Returns are expressed in percentage terms. The sample period spans from August 15, 2022, to April 30, 2024. White heteroscedasticity-robust standard errors are reported in parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 9: Price impact: variation across trading size, liquidity provision and issuance

	DEXReturn	CLSReturn
OF_{top10}	6.6094***	2.2984***
	(0.4929)	(0.1798)
OF_{PM}	7.5372***	2.9974***
	(0.4370)	(0.5617)
OF_{LP}	6.5598***	1.8161***
	(0.4440)	(0.2317)
$\text{OF}_{top10\cap PM}$	6.6047***	3.2516***
	(0.2858)	(0.2998)
$\text{OF}_{top10\cap LP}$	5.2599***	0.8859**
	(0.7113)	(0.3789)
$\text{OF}_{LP\cap PM}$	9.6165***	-0.2970
	(0.7925)	(0.4060)
$\text{OF}_{\notin top10,PM,LP}$	7.2696***	1.9088***
	(0.4741)	(0.1516)
CLSReturn_{t-1}	-0.0021	
	(0.0150)	
DEXReturn_{t-1}		0.0120*
		(0.0062)
constant	-0.0004	0.0003
	(0.0008)	(0.0007)
R-squared	0.472	0.132
No. observations	14,998	14,998

Note: This table presents the results of regressing blockchain order flow on changes in EURC/USDC and EUR/USD prices. OF is measuring the net buyer transactions of purchasing EURC, and is sourced from Uniswap V3 trade data. 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, $OF_{\notin top10,PM,LP}$. EURC/USDC returns are calculated using Uniswap V3 prices. EUR/USD prices are sourced from CLS. Spot returns of DEX EURC/USDC and EUR/USD are measured in per cent. Total sample period is from 15 August 2022 to 30 April 2024. White heteroscedasticity-robust standard errors are reported in parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Internet Appendix to

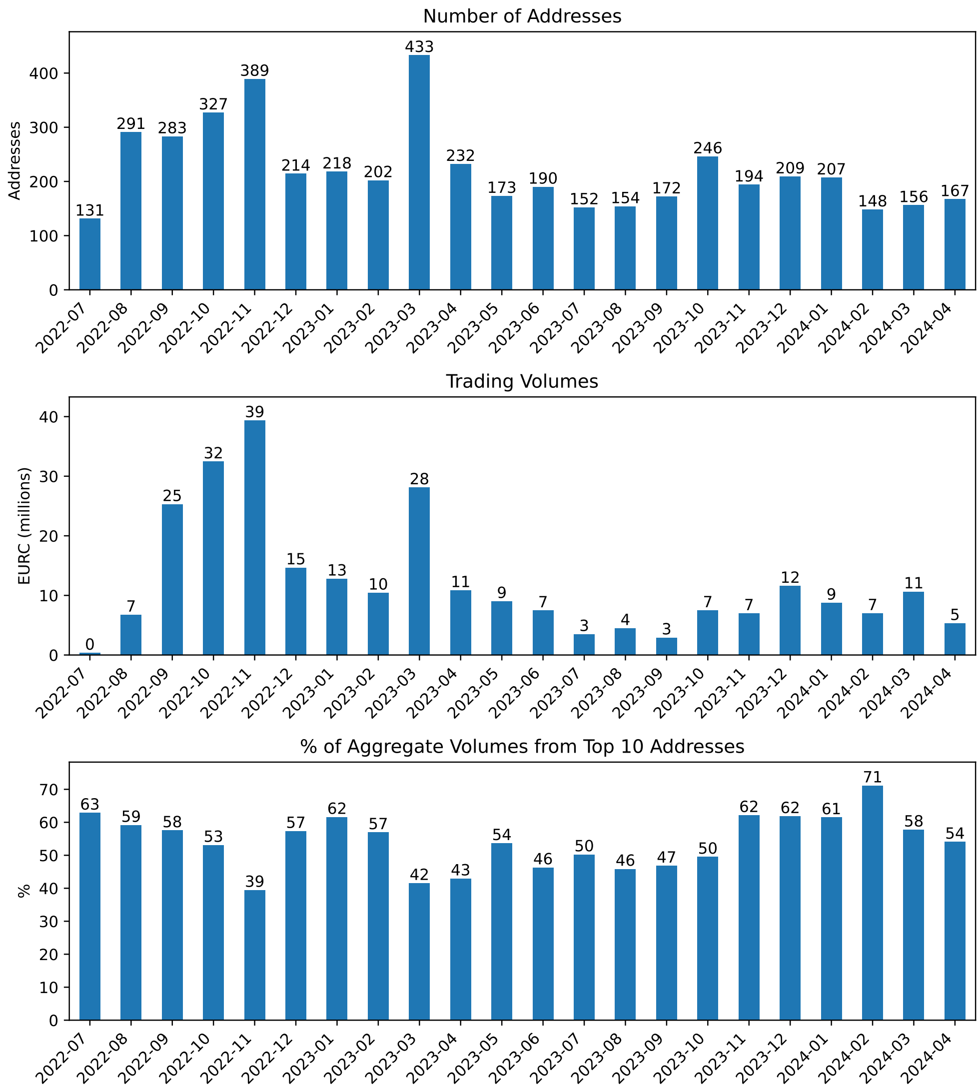
"Blockchain Currency Markets"

(Not for publication)

Appendix A: Additional Statistics

A.1 Trading Volume

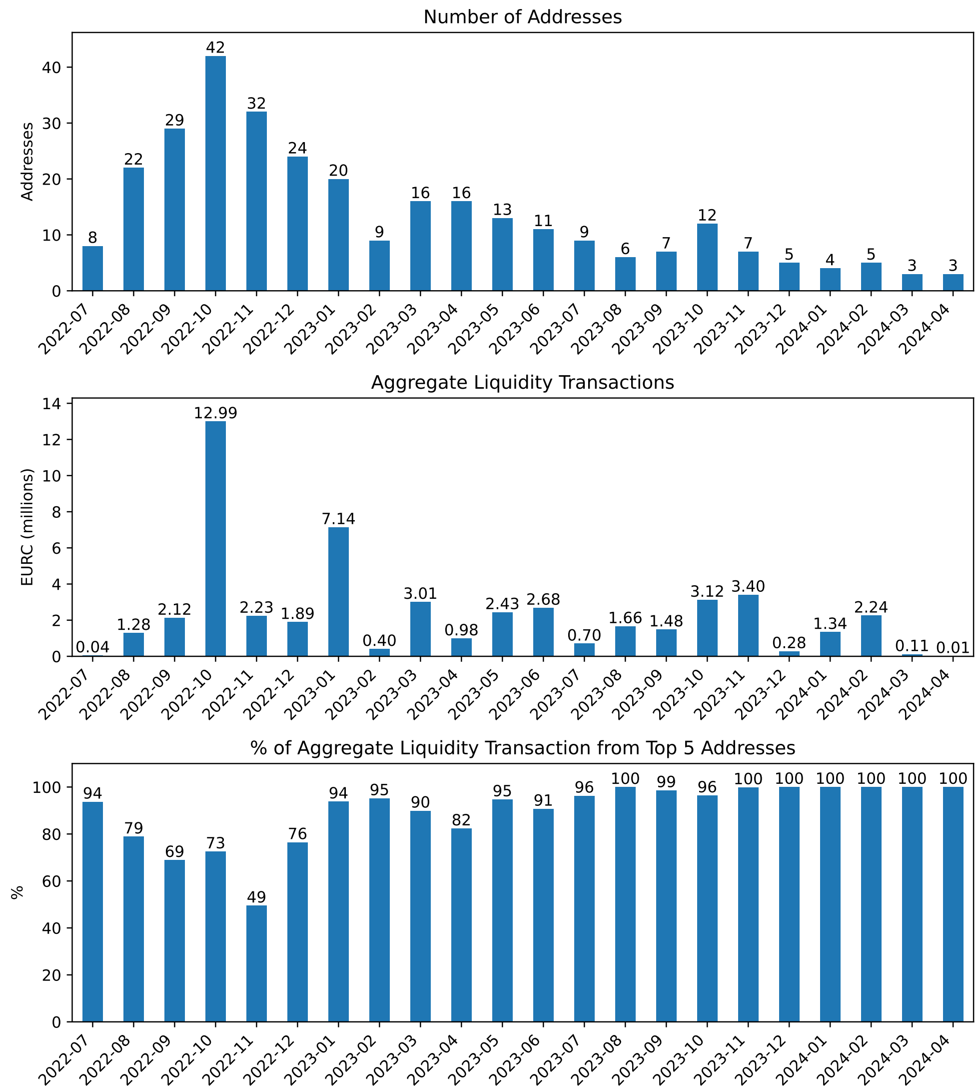
Figure A1: Summary statistics of trading volume



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

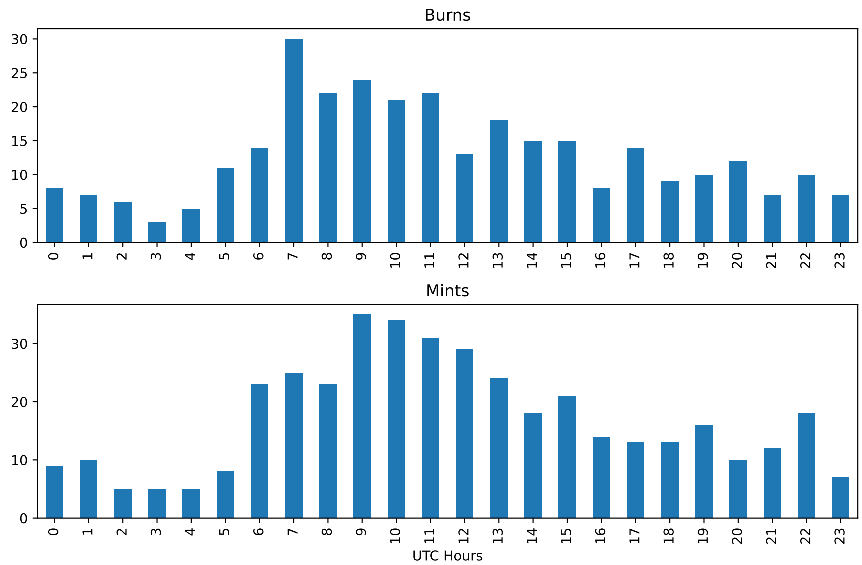


Note: This figure plots monthly summary statistics of the distribution of liquidity provision. It shows the number of addresses, the aggregate liquidity provision, and the percentage of liquidity provided by the top 5 LPs. The total sample period is from 1 July 2022 to 30 April 2024.

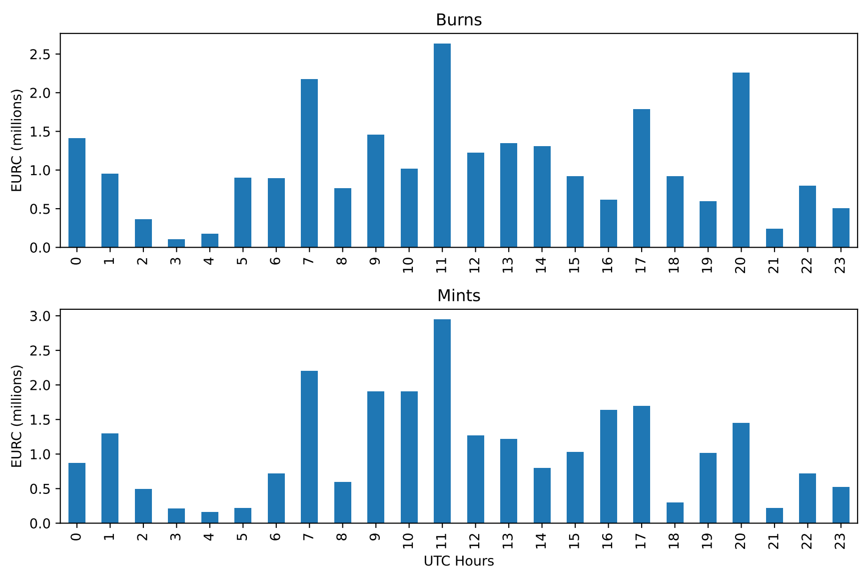
A.3 Liquidity Providers- intra-day patterns

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.

Appendix B: Monetary Announcements

Figure B1: Federal Reserve Monetary Announcements (Part 1)

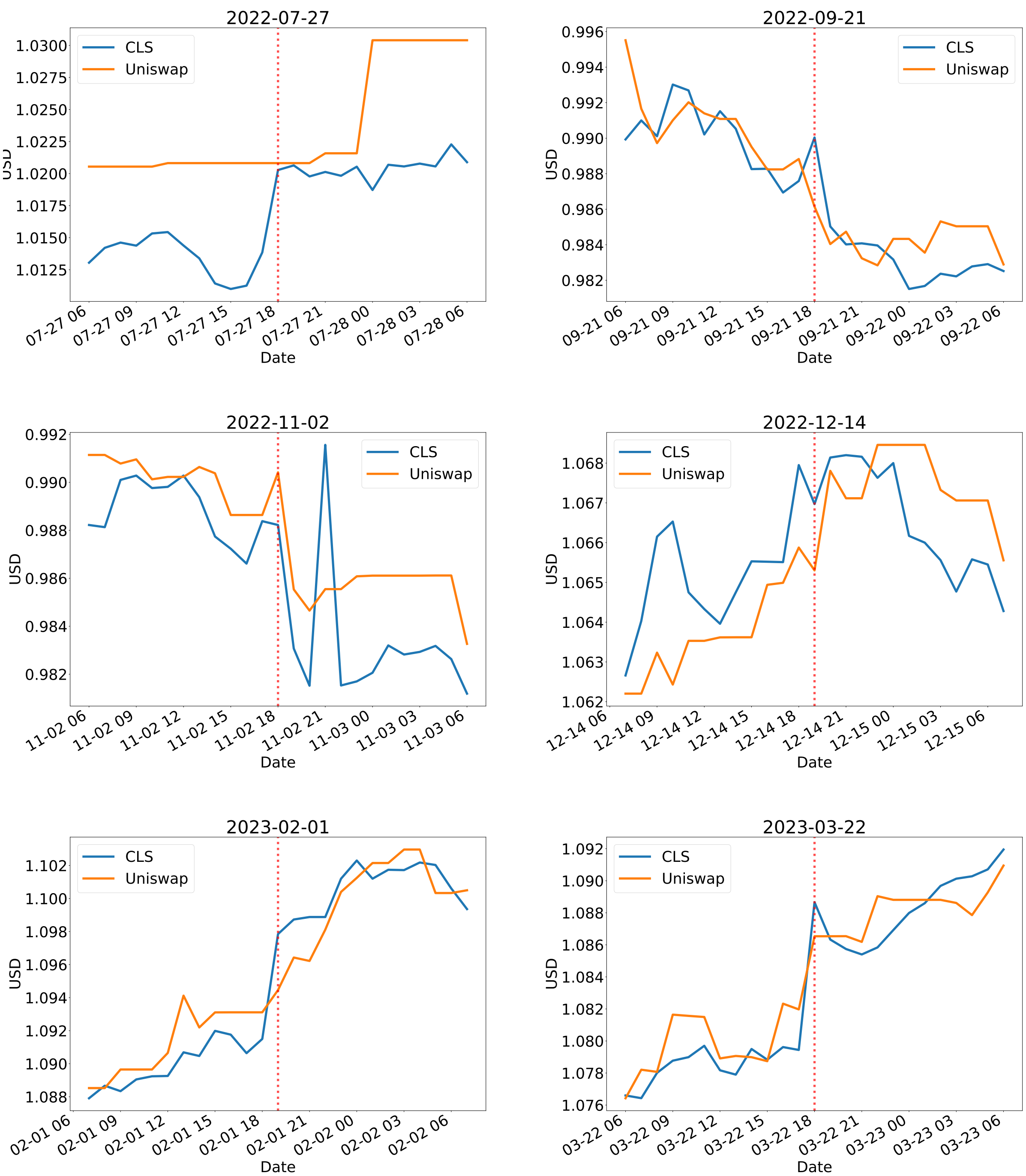


Figure B2: Federal Reserve Monetary Announcements (Part 2)

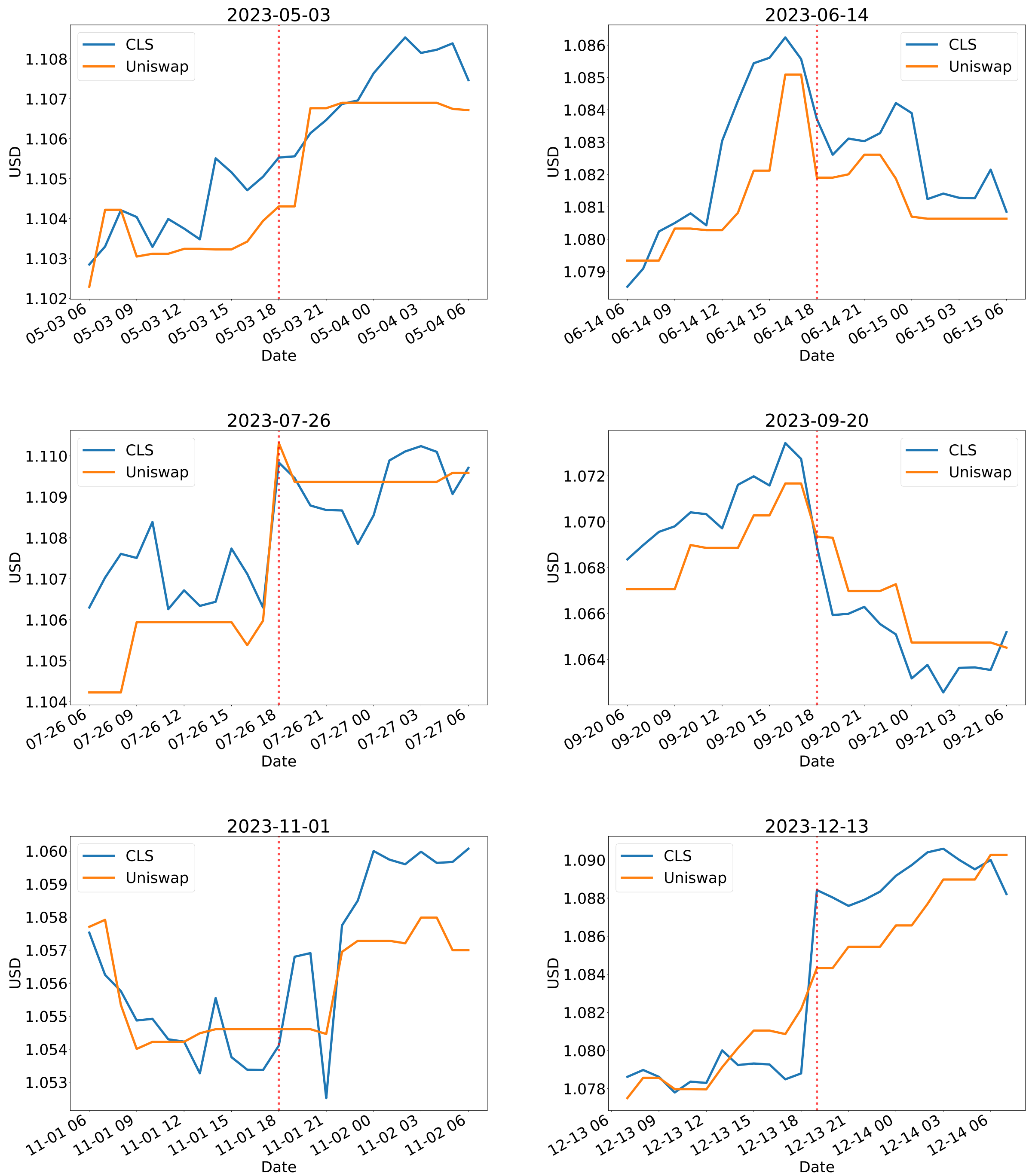
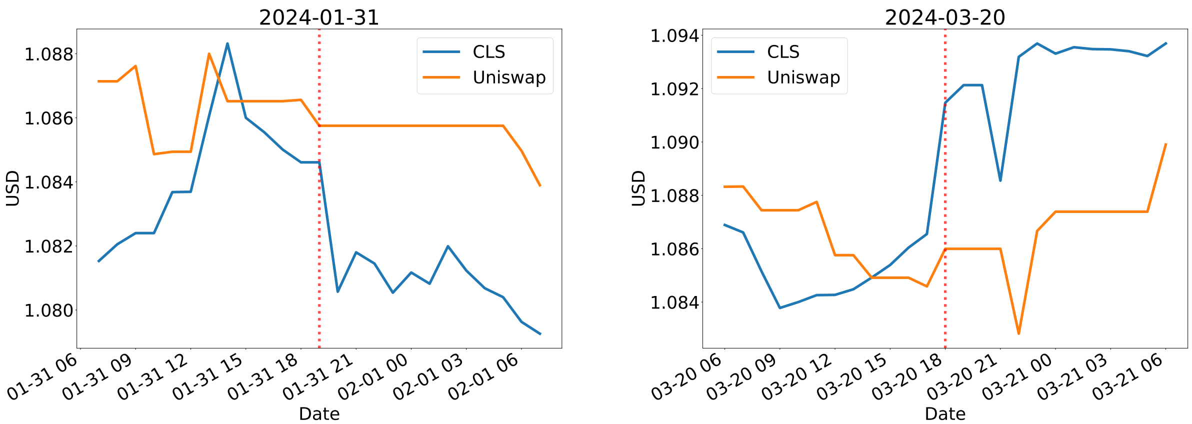


Figure B3: Federal Reserve Monetary Announcements (Part 3)



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.[25] The supply of USDC and EURC is shown in Figure C1. 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.[26]

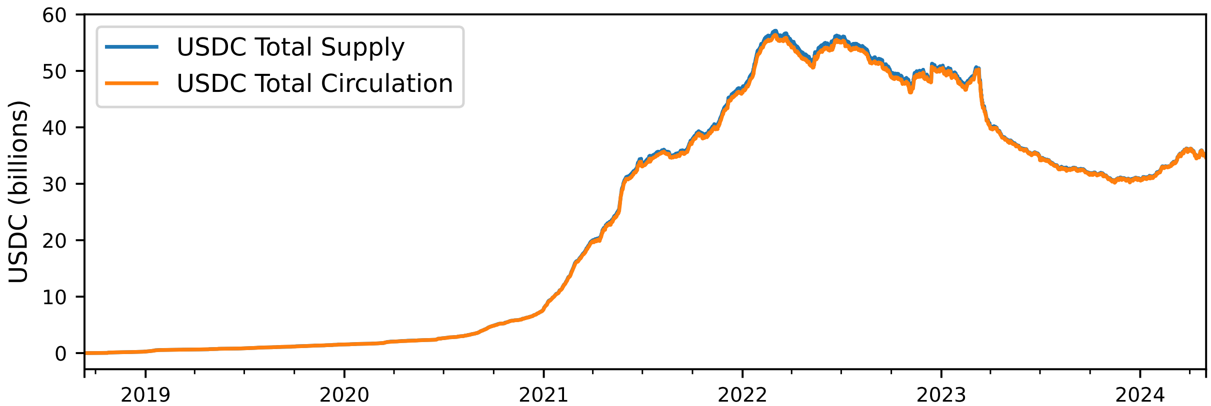
[25] The USDC Treasury address we use to retrieve the transaction history is "0xa0b86991c6218b36c1d19d4a2e9eb0ce3606eb48". The EURC Treasury address is "0x1abaea1f7c830bd89acc67ec4af516284b1bc33c"

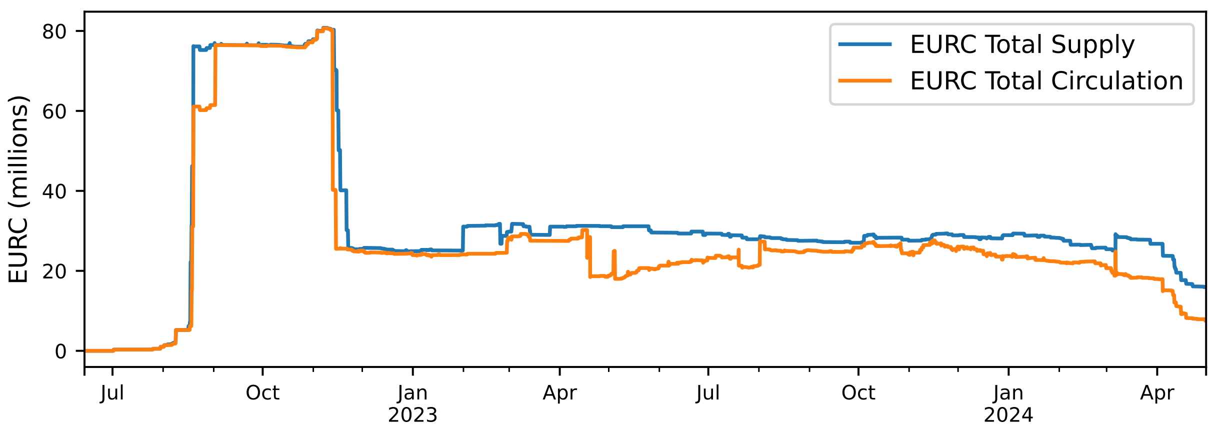
[26] One caveat regarding the primary market issuance data is that we can only download activities related to the transfer of ERC-20 tokens. As a result, we might miss certain transaction activities, such as internal

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., 2023). 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.

transactions. However, our data is representative and valid for understanding the overall trend in primary market issuance.

Figure C1: 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-Sophisticated Investor

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: EUROC-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: EUROC-USDC
2023-03-10 13:34:59	3601	1c37	73d6	3333333333.33333	trader	Uniswap V3: EUROC-USDC
2023-03-10 13:43:35	5de7	1c37	73d6	3333333333.33333	trader	Uniswap V3: EUROC-USDC
2023-03-10 14:11:11	ae67	1c37	73d6	3333333333.33333	trader	Uniswap V3: EUROC-USDC
2023-03-10 14:24:47	6aa6	1c37	73d6	3333333333.33333	trader	Uniswap V3: EUROC-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: EUROC-USDC
2023-03-10 14:36:59	ebaf	1c37	73d6	3333333333.33333	trader	Uniswap V3: EUROC-USDC
2023-03-10 14:43:35	021d	1c37	73d6	3333333333.33333	trader	Uniswap V3: EUROC-USDC

Continued...

Date (UTC)	Hash	From	To	USDC	From Name	To Name
2023-03-10 15:03:47	3c82	1c37	73d6	3333333333.33333	trader	Uniswap V3: EUROC-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: EUROC-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: EUROC-USDC
2023-03-10 19:55:47	c9e0	1c37	73d6	1250000000.0	trader	Uniswap V3: EUROC-USDC
2023-03-10 21:30:35	5f29	1c37	73d6	1666666666.66666	trader	Uniswap V3: EUROC-USDC
2023-03-10 21:34:47	419e	1c37	73d6	3333333333.33333	trader	Uniswap V3: EUROC-USDC
2023-03-10 21:40:47	8acd	1c37	73d6	3333333333.33333	trader	Uniswap V3: EUROC-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
2023-03-10 22:52:35	7987	1c37	2286	1666666666.66666	trader	Uniswap V3: USDC-GYEN

Continued...

Date (UTC)	Hash	From	To	USDC	From Name	To Name
2023-03-10 22:55:47	e358	1c37	73d6	3333333333.33333	trader	Uniswap V3: EUROC-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: EUROC-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
2023-03-11 03:27:35	b37a	1c37	2286	833333333.333333	trader	Uniswap V3: USDC-GYEN

Continued...

Date (UTC)	Hash	From	To	USDC	From Name	To Name
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

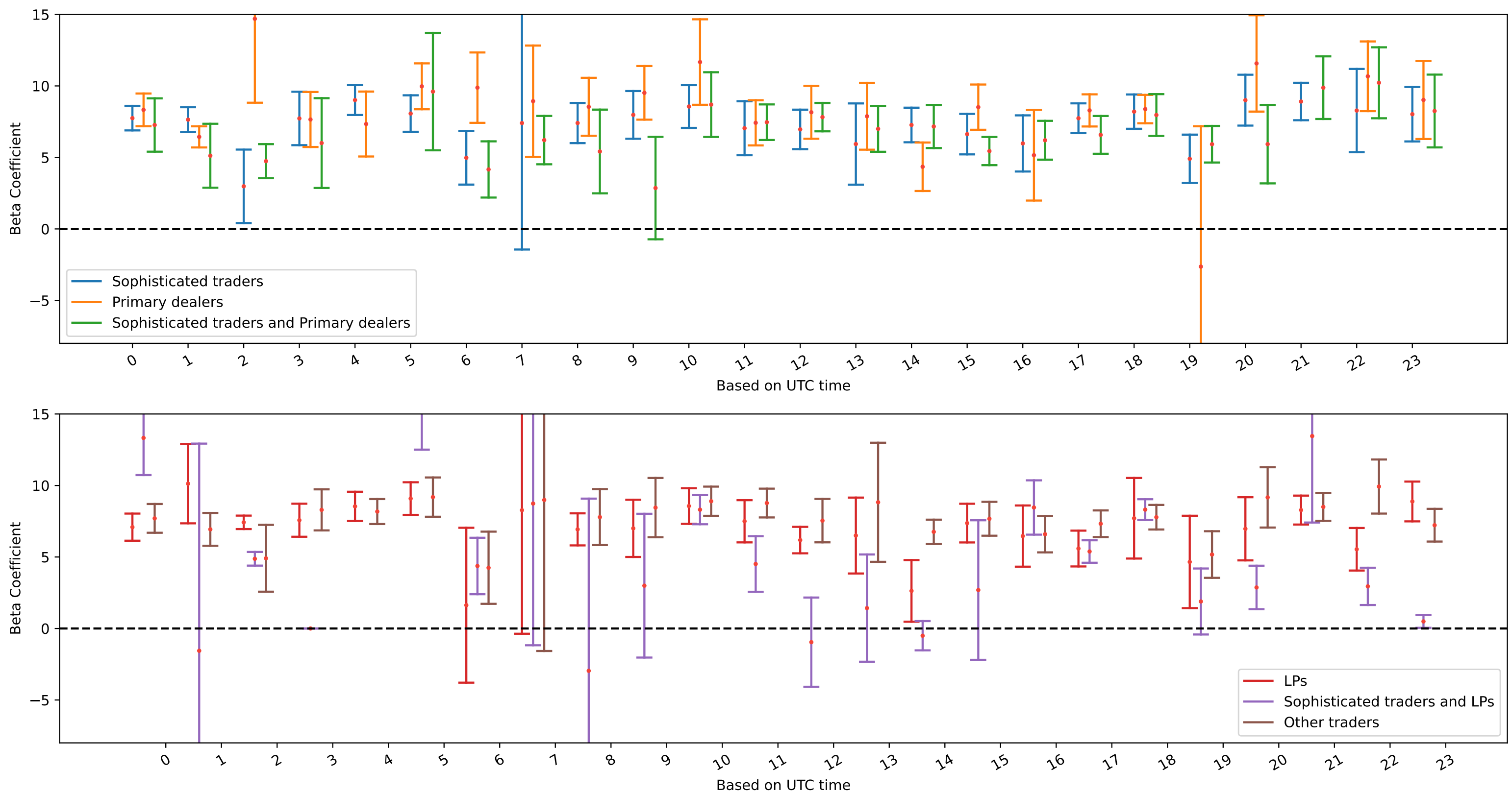
Note: This table presents swap transactions from the sophisticated investor with wallet ID '0xd64137f743432392538a8f84e8e571fa09f21c37', abbreviated to wallet '1c37', during the USDC de-pegging event on March 10-12, 2023. Transactions are sourced from Etherscan API. This wallet was the largest single 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.

Appendix E: Price impact: Additional tests

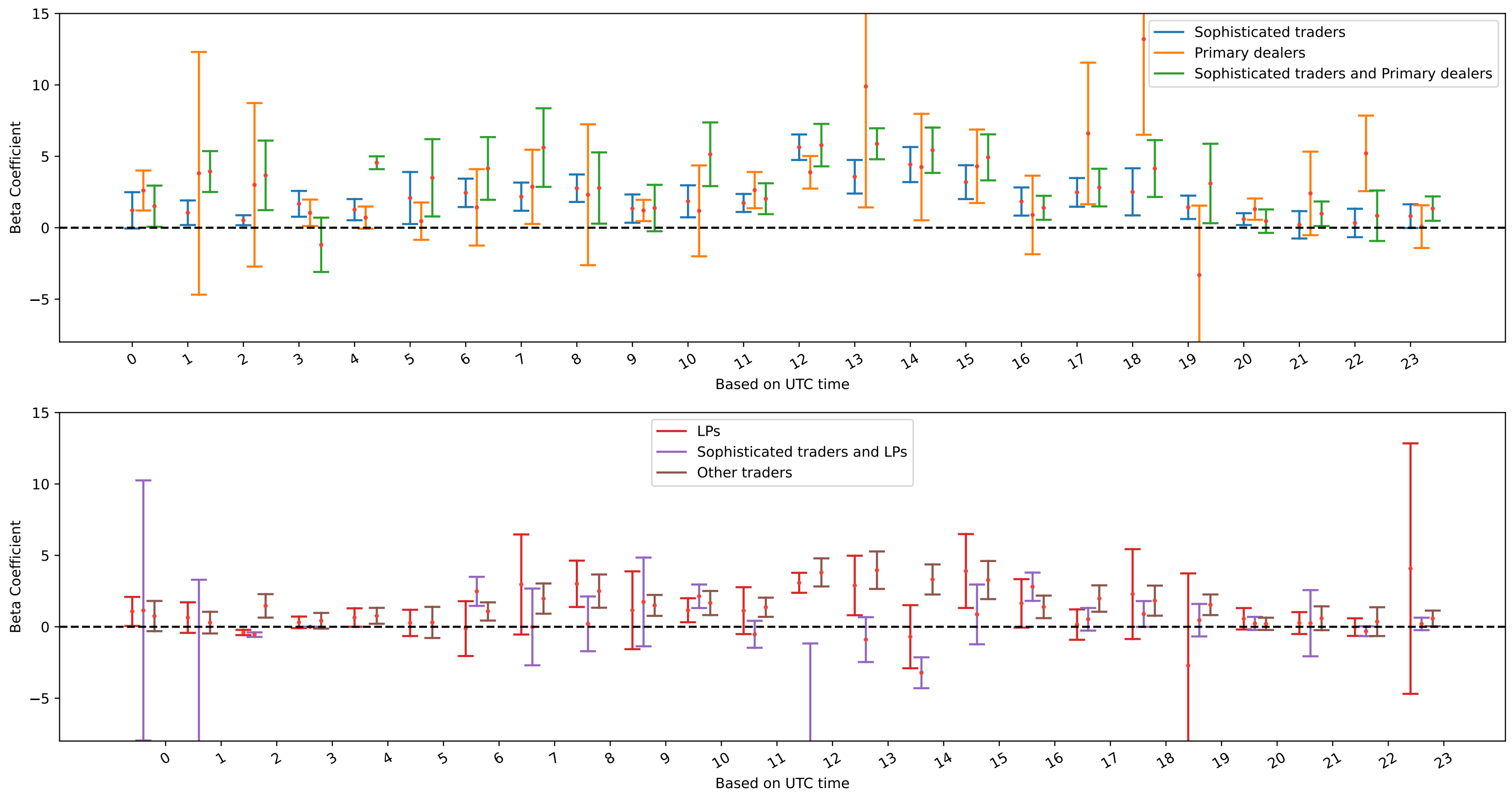
E.1 Intra-day patterns

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

Panel (a): EURC/USDC Return



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

E.2 Blockchain characteristics

In this section, we examine how price impact varies with blockchain characteristics at the wallet level, specifically age, the number of tokens transferred, and the frequency of transactions per day. We estimate the regression model specified in equation (16). For each characteristic $i \in \{\text{Age}, N_{\text{Tokens}}, \text{Transactions/day}\}$, we categorize blockchain order flow into three groups: wallets in the first quartile (0-25th percentile), the interquartile range (25-75th percentile), and the last quartile (75-100th percentile).

$$p_t - p_{t-1} = \alpha + \beta_1 OF_{0-25,i,t} + \beta_2 OF_{25-75,i,t} + \beta_3 OF_{75-100,i,t} + \epsilon_t \tag{16}$$

We present the results of this baseline specification in Table E1. Columns (1) through (3) report results using DEX returns (log price change of the EURC/USDC), while columns (4) to (6) use CLS benchmark returns (log price change of EUR/USD).

In column (1), the blockchain order flow based on wallet age shows a monotonic increase in price impact for DEX returns, with the highest price impact for wallets in the 0-25th percentile. However, for CLS benchmark returns in column (4), the maximum price impact occurs for wallets in the 25-75th percentile of age.

When disaggregating blockchain order flow by the number of tokens transferred (columns (2) and (5)), the highest price impact occurs for wallets in the 25-75th percentile for both DEX and CLS benchmark returns. For frequency of transactions, the results in columns (3) and (6) show that wallets in the 25-75th percentile have the largest price impact on DEX returns but the smallest on CLS benchmark returns. In both cases, the price impacts of the 0-25th and 75-100th percentiles are relatively similar.

To understand why blockchain characteristics may have limited predictive power, we examine their relationship with different trader types: sophisticated traders, primary dealers, and LPs. Table E2 presents summary statistics of these blockchain characteristics.

In Panel (a), we report statistics for sophisticated traders. While these traders have a slightly younger average age and a higher frequency of transactions, the median transaction frequency is only 0.68 per day, compared to 0.28 transactions per day for other wallets.

Panel (b) shows primary dealers, who have a similar average number of tokens transferred and slightly lower wallet age. Their average transaction frequency is higher, with a median of 0.63 transactions per day, compared to 0.28 for wallets without primary market access.

Panel (c) presents LPs, who tend to have younger wallets, transfer fewer tokens on average, and exhibit a low average transaction frequency per day. However, the median values for tokens transferred and transaction frequency are higher for LPs.

Overall, these results indicate a weak correlation between blockchain characteristics and trader types, which may explain the lack of a clear pattern in price impact when blockchain order flow is disaggregated by these characteristics.

Table E1: Price impact: variation across blockchain characteristics

	Panel (a): DEX Return			Panel (b): CLS Return		
	(1)	(2)	(3)	(4)	(5)	(6)
OF-Bottom25 [Age (days)]	7.5842***			1.8513***		
	(0.3223)			(0.1488)		
OF-Middle50 [Age (days)]	6.4839***			2.3160***		
	(0.4968)			(0.1694)		
OF-Top25 [Age (days)]	6.4733***			2.2243***		
	(0.4742)			(0.2050)		
OF-Bottom25 [Number of Tokens Transferred]		7.0322***			2.4171***	
		(0.5571)			(0.2983)	
OF-Middle50 [Number of Tokens Transferred]		6.7399***			2.3483***	
		(0.4319)			(0.1854)	
OF-Top25 [Number of Tokens Transferred]		6.7336***			2.0362***	
		(0.4610)			(0.1379)	
OF-Bottom25 [Frequency (transactions per day)]			7.0002***			2.2101***
			(0.6336)			(0.1937)
OF-Middle50 [Frequency (transactions per day)]			6.9921***			1.7955***
			(0.4986)			(0.1460)
OF-Top25 [Frequency (transactions per day)]			6.6424***			2.3677***
			(0.4164)			(0.1649)
CLSReturn_{t-1}	0.0055	0.0030	0.0050			
	(0.0152)	(0.0153)	(0.0152)			
DEXReturn_{t-1}				0.0079	0.0084	0.0104*
				(0.0057)	(0.0060)	(0.0062)
constant	-0.0003	-0.0003	-0.0005	0.0001	0.0001	0.0003
	(0.0009)	(0.0009)	(0.0008)	(0.0007)	(0.0007)	(0.0007)
R-squared	0.465	0.461	0.462	0.119	0.120	0.124
No. observations	14,998	14,998	14,998	14,998	14,998	14,998

Note: This table presents the results of regressing blockchain order flow on changes in EURC/USDC and EUR/USD prices. OF measures the net buyer transactions of purchasing EURC, sourced from Uniswap V3 trade data. Blockchain order flow is divided into sub-categories based on blockchain characteristics: age (days since wallet started trading), number of tokens transferred by the wallet, and frequency (measured in transactions per day). Order flow within these characteristics is divided into the top quartile, bottom quartile, and inter-quartile range (25th-75th percentile). EURC/USDC returns are calculated using Uniswap V3 prices. EUR/USD prices are sourced from CLS. The total sample period is from 15 August 2022 to 30 April 2024. White heteroscedasticity-robust standard errors are reported in parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table E2: Blockchain characteristics by address type

Panel (a): Sophisticated traders								
	count	mean	std	min	0.25	0.50	0.75	max
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								
	count	mean	std	min	0.25	0.50	0.75	max
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								
	count	mean	std	min	0.25	0.50	0.75	max
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								
	count	mean	std	min	0.25	0.50	0.75	max
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								
	count	mean	std	min	0.25	0.50	0.75	max
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								
	count	mean	std	min	0.25	0.50	0.75	max
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								
	count	mean	std	min	0.25	0.50	0.75	max
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

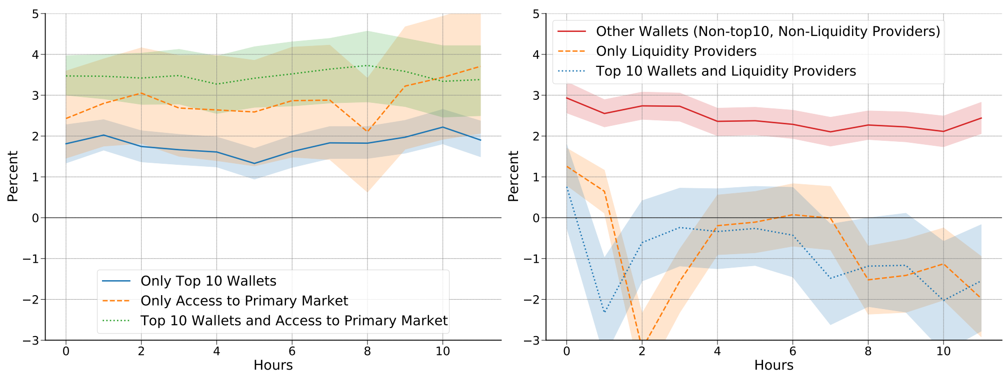
Note: This table presents summary statistics of blockchain characteristics, based on age (days since wallet started trading), number of tokens transferred by the wallet, and frequency (measured in transactions per day). We compute summary statistics for 7 trading groups, including sophisticated traders, 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 F: Robustness tests: permanent price impact

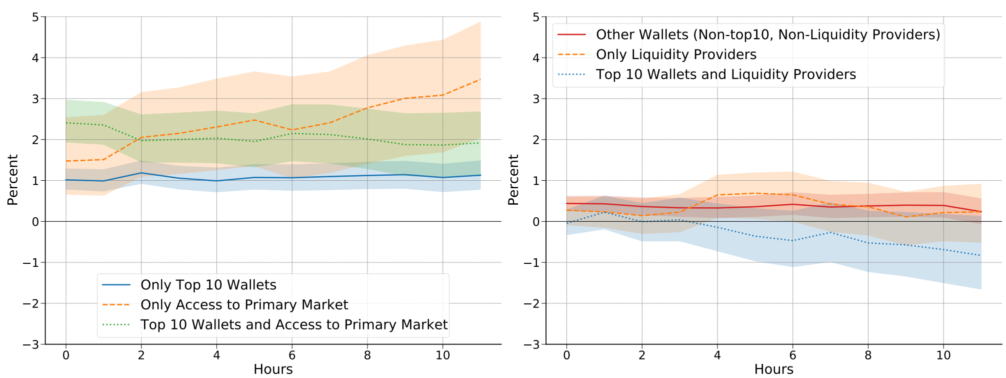
F.1 Liquidity Provision

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

Panel (a): EURC/USDC Return



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



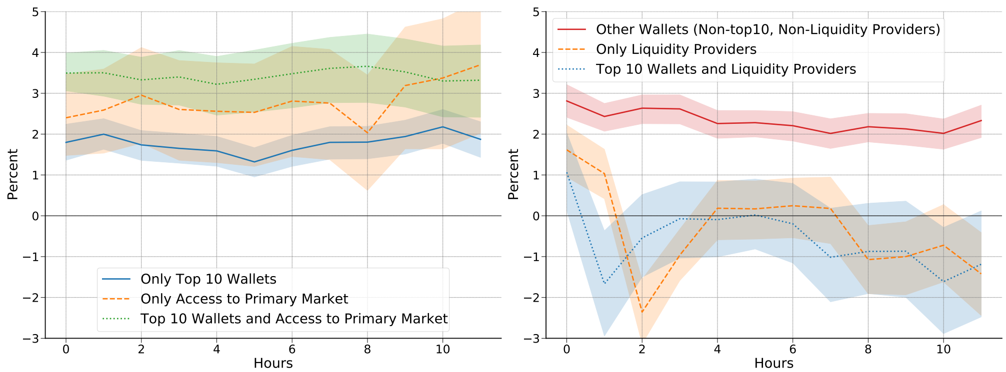
Note: This figure plots the impulse response of the change in spot returns to a 1 Million EURC shock in blockchain order flow using a structural VAR framework, in a specification that controls for liquidity provision. Blockchain order flow measures net buyer transactions of EURC from Uniswap V3 trade data. EURC/USDC returns are calculated using Uniswap V3 prices, and EUR/USD prices are sourced from CLS. Liquidity provision by LPs is measured 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. The blockchain order flow is divided into six sub-categories: sophisticated traders (top 10 wallets), primary dealers, LPs, and combinations of these. The sample period is from 15 August 2022 to 30 April 2024.

F.2 Traditional Order Flow

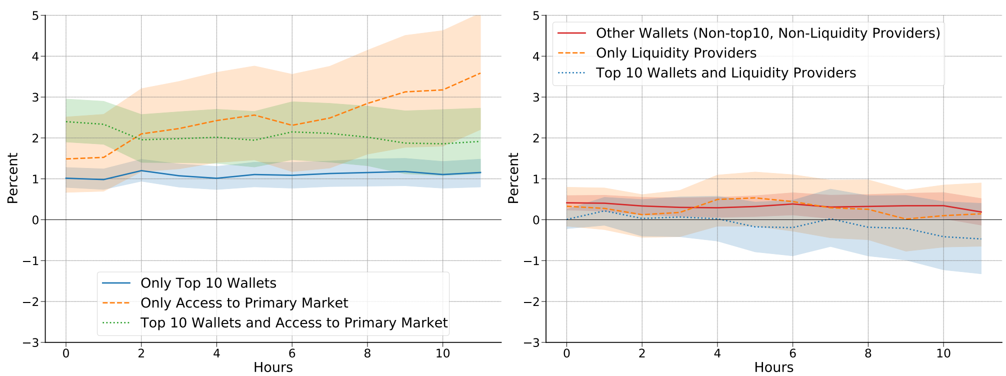
F.2.1 Aggregate CLS Order Flow

Figure F2: Price impact of blockchain order flow: dynamic effects

Panel (a): EURC/USDC Return



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

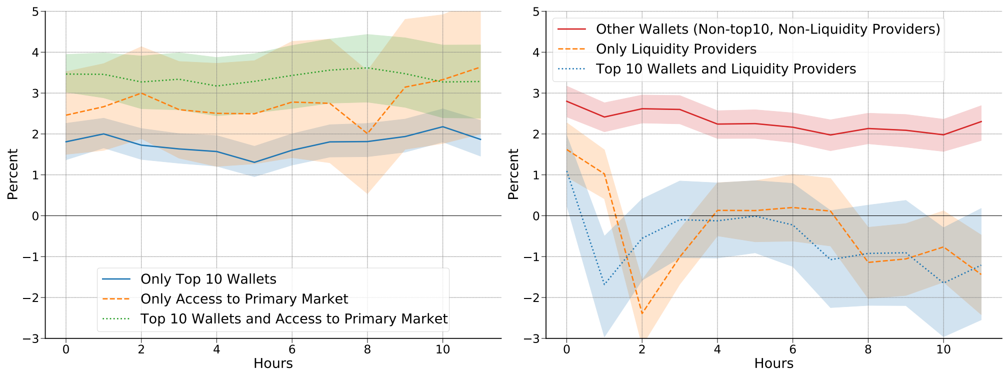


Note: This figure plots the impulse response of the change in spot returns to a 1 Million EURC shock in blockchain order flow using a structural VAR framework, controlling for aggregate CLS order flow. Blockchain order flow measures the net buyer transactions of EURC from Uniswap V3 trade data. EURC/USDC returns are calculated using Uniswap V3 prices, and EUR/USD prices are sourced from CLS. CLS order flow data includes aggregate and sector-level flows between interbank participants, funds, non-bank financials, and corporates. 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 combinations of these. The sample period is from 15 August 2022 to 30 April 2024.

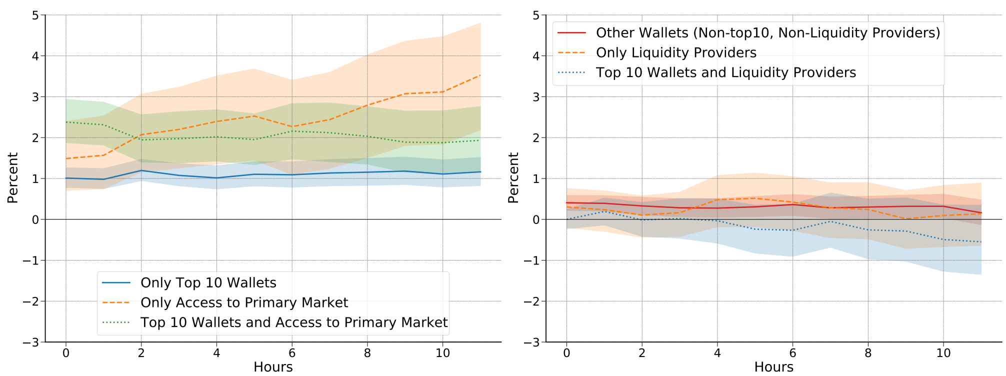
F.2.2 Sector level CLS Order Flow

Figure F3: Price impact of blockchain order flow: dynamic effects

Panel (a): EURC/USDC Return



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

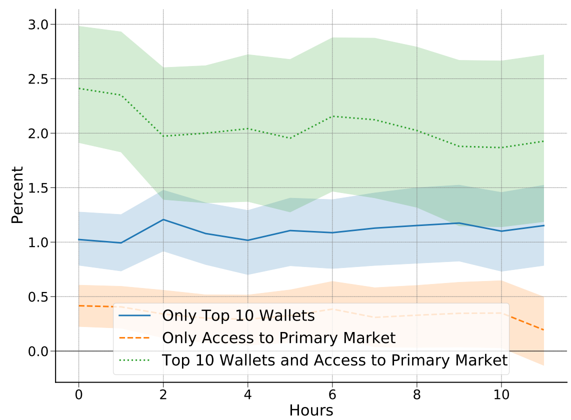


Note: This figure plots the impulse response of the change in spot returns to a 1 Million EURC shock in blockchain order flow using a structural VAR framework, controlling for sector-level CLS order flow. Blockchain order flow measures the net buyer transactions of EURC from Uniswap V3 trade data. EURC/USDC returns are calculated using Uniswap V3 prices, and EUR/USD prices are sourced from CLS. CLS order flow data includes aggregate and sector-level flows between interbank participants, funds, non-bank financials, and corporates. 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 combinations of these. The sample period is from 15 August 2022 to 30 April 2024.

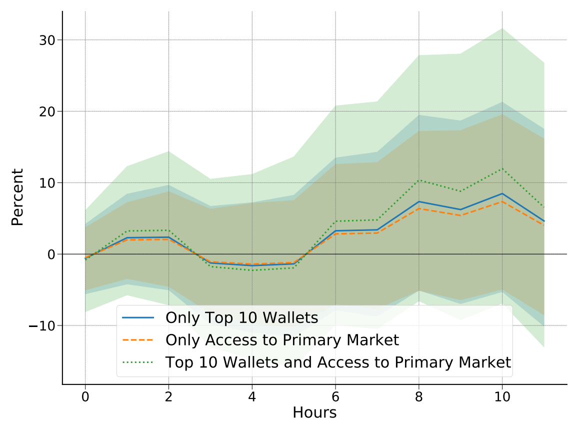
F.3 Feedback Trading

Figure F4: 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 the change in spot returns to a 1 Million EURC shock in blockchain order flow using a structural VAR framework. 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 the 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 is from 15 August 2022 to 30 April 2024.

Appendix G: 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.