Blockchain Currency Markets

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This version: May 1, 2024

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 Ethereum 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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[§]For comments, we would like to thank Andrea Barbon, Dirk Baur, Mathieu Bouvard, Kim-Sau Chung, Barry Eichengreen, Rich Lyons, Andreas Park, Olav Syrstad and seminar participants at the Digital Economy Seminar (HK Baptist, Monash, NTU, and RUC), the Swiss National Bank, University of Reading, University of Toulouse Sustainable Finance conference, and the University of Western Australia. Angelo Ranaldo acknowledges financial support from the Swiss National Science Foundation (SNSF grant 204721). We would like to thank Edouard Mattille for assistance with the CLS Market Data.

1 Introduction and Motivation

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 marked by innovative protocols and platforms such as decentralized exchanges (DEX) and lending protocols. DeFi promises to reduce inefficiencies in traditional financial systems and eliminate the need for intermediaries, thereby improving both cost-effectiveness and transaction speed.

This paper provides the first comprehensive study of blockchain currencies, stablecoins pegged to traditional currencies and traded on decentralized exchanges. This is an important question to study because the currency market is the largest financial market in the world, and central banks are actively exploring the feasibility of Central Bank Digital Currencies (CBDCs) on blockchain platforms. For example, the BIS Innovation Hub's Project Mariana seeks to improve FX trading and settlement through decentralized blockchain markets, aiming for increased efficiency, security, transparency, and cross-border interoperability.[1]

Our key contribution is to understand the information content of blockchain transactions for the traditional EUR/USD currency market. Using a rich transaction-level data from the blockchain allows us to identify different market participants and their contributions to price discovery and the processing of fundamental news. We identify three categories of traders: First, those with a significant market share based on trading volume, which we label as *sophisticated traders*. Second, the second group includes traders that have access to the primary market, which we define as having deposits and withdrawals of fiat currency with the stablecoin issuer. We refer to them as *primary dealers*, as this access grants them private information in traditional markets. Third, we isolate pure market makers who provide liquidity (*LPs*) to customers without accessing the primary market. Importantly, we can make a clear distinction between primary dealers and LPs, which is not possible in traditional financial markets (Hortaçsu and Sareen, 2005; Hagströmer and Menkveld, 2019).[2]

By utilizing trader-level information available on the blockchain, we find that sophisticated traders and primary dealers have more permanent price impact, likely due to informational advantages. The source of information is reduced limits to arbitrage in

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

[2]LPs are analogous to a market maker on a limit order book in traditional markets. Similar to how market makers can provide liquidity and earn bid-ask spreads, LPs earn fees that is a function of their stake in the pool and the amount of trades.

trading across the DEX and traditional EUR/USD market, and access to the traditional banking system by having access to EUR and USD deposits with the stablecoin issuer. In contrast, LPs exhibit insignificant price impact and act as uninformed hedgers.

Our analysis leverages a comprehensive dataset of trading and pricing information for the EURC/USDC pair, sourced from the Uniswap V3 exchange. Trading in this pair began in June 2022 and it is based on Automated Market Maker (AMM) technology for pricing. As a point of comparison, we benchmark the performance of these blockchain-based currency markets against their traditional FX counterparts, specifically using Reuters EUR/USD rates, which are widely considered indicative of the FX interdealer market where price discovery primarily occurs (Figure 1).

[INSERT FIGURE 1 ABOUT HERE]

We motivate our study by documenting four facts on market efficiency of blockchain currency markets. First, we find an average deviation of 20 basis points between blockchain-based EURC/USDC rates and traditional Reuters EUR/USD rates, mainly due to blockchain-specific factors like gas fees and Ethereum's volatility. Second, only a relatively small fraction (10-15%) of EURC/USDC transactions exceed arbitrage limits due to costs such as gas, liquidity fees, and slippage on Uniswap V3. Third, EURC/USDC prices respond quickly to Federal Open Market Committee (FOMC) announcements, demonstrating blockchain markets are adept at quickly assimilating fundamental macroeconomic information into currency valuations. Fourth, LPs are resilient during de-pegging events with minimal withdrawal activity.

We then test the information content of blockchain trades using transaction-level data of market participants. First, we analyze whether the blockchain market is connected with the underlying market in terms of trading volumes. To proxy traditional market trading activity, we make use of the CLS data that are representative for the global currency market and can be disaggregated into categories of market participants, including interdealer transactions, and dealer transactions with funds, corporates and non-bank financial firms. Our findings indicate a close link between blockchain volume and the interdealer segment, highlighting the segment's pivotal role in the OTC FX market's price discovery process, including for blockchain-based pegged prices.

Second, we extend the analysis of price determination by using order flow as a key determinant of FX rates (Evans and Lyons, 2002). We compute blockchain order flow, which is a measure of the net demand for a currency based on transaction-level data of the EURC/USDC pair. We find it significantly predicts FX traditional rates. A 1 EURC Million change in blockchain order flow is associated with a 3.96 per cent increase in the

Reuters EUR/USD return, and is robust to controlling for macroeconomic fundamentals, such as changes in interest rate differentials, measures of global risk and dealer capital constraints.

We then examine variations in the price impact of blockchain order flow across the three distinct trader categories. In our analysis of DEX returns, we observe minimal variation in the price impact among these trader groups, indicating a level of fairness in this emerging market landscape. However, we also find that sophisticated traders and primary dealers exhibit a greater price impact when evaluated using Reuters EUR/USD returns. This suggests that traders with more wealth and systematic access to the USD and EUR markets are likely to have some informational advantage in traditional markets. In contrast, LPs acting as traders have an insignificant price impact, implying that they mainly trade to hedge their positions and are comparatively less informed.

We conclude with a set of further tests to detect heterogeneous trading. To test for dynamic effects, we conduct a structural vector autoregression (VAR) framework to show permanent cumulative price impacts among different trader types. Sophisticated traders and primary dealers exhibit more persistent price impact than LPs. Intra-day patterns of price impact show that more informed participants have higher impact during periods coinciding with the trading hours of major financial centers.

Additionally, we find evidence of arbitrage trading, which is when blockchain order flow is correcting price differences between the EURC/USDC and traditional EUR/USD market rate. We find sophisticated traders are the most active engaging in arbitrage, as these traders have more abundant capital and can scale trades to be profitable. In contrast, LPs and primary dealers are less likely to conduct arbitrage trading, as their transactions are typically smaller, and in the presence of fixed transaction costs, are not sufficiently scale-able to make arbitrage profits.

Finally, we exploit a de-pegging event of EURC/USDC on March 11, 2023 as a laboratory to test the informational advantages of different market participants.[3] We find that during the run on USDC, more sophisticated traders with higher blockchain volume predominantly bought EURC while selling USDC, and LPs remained passive with no significant change in blockchain order flow.

Related Literature. We contribute to a growing literature on stablecoins. This includes connections between stablecoins and traditional markets, arbitrage design mechanisms,

[3]Circle, the US-based issuer of the stablecoin USDC held 3.3 USD billion (around 9%) of its backing assets as deposits with SVB. Uncertainty in the market as to whether Circle could access these deposits from SVB led to an immediate loss of confidence in the stablecoin, and resulted in USDC trading at 87 cents on March 11, 2023. After US authorities confirmed that SVB deposits would be secure, confidence in the stablecoin was restored and USDC recovered its value against the dollar on March 13, 2023 (Bank of England, 2023)

and theoretical studies on the price dynamics of stablecoins and the role 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, 2018; Li and Mayer, 2021; d'Avernas et al., 2022; Bertsch, 2022; Aldasoro et al., 2023). Examining the potential risks of stablecoins de-pegging, Liu et al. (2023) focus on how more sophisticated investors are able to run first during the TerraLuna de-pegging. Our contribution is to identify a novel link between stablecoin markets and traditional FX. By studying the market efficiency and price discovery, we show how participants in these markets can actually trade on information, and how macroeconomic news can become impounded in exchange rates set in a decentralized setting. Our study contributes to the viability of stablecoins and blockchain-based currencies as an alternative to traditional market infrastructure.

We contribute to a literature on decentralized exchanges, covering topics in market efficiency, the determinants of liquidity provision and its potential in replacing 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). Our work relates to Barbon and Ranaldo (2021), which discusses the efficiency of major cryptocurrency pairs like ETH/USDC, and compare these markets to their centralized exchange counterparts. While these studies focus primarily on blockchain fundamentals like gas fees as drivers of information content and liquidity provision, we highlight potential connections between trading on DEX to traditional FX markets.

Finally, our study bridges stablecoins with the market microstructure literature in FX and traditional markets (Evans and Lyons, 2002; Andersen et al., 2003; Berger et al., 2008; Rime et al., 2010; Kozhan and Salmon, 2012; Ranaldo and Somogyi, 2021; Huang et al., 2021; Krohn et al., 2022; Hagströmer and Menkveld, 2019). Our contribution is to highlight the role of algorithmic bonding curves on Uniswap V3, which is an alternative to traditional pricing mechanisms based on portfolio shifts and inventory management (Evans and Lyons, 2002). We discover that DEX trades significantly influence Reuters EUR/USD returns, with sophisticated traders and primary dealers exerting more substantial impact on prices. Conversely, LPs appear less informed, primarily trading to manage liquidity, which is consistent with the role of dealers in limit-order book markets providing liquidity (Hortaçsu and Sareen, 2005). We also show how macroeconomic announcements (e.g., Andersen et al. (2003)) and private information (e.g., Ranaldo and Somogyi (2021)) is incorporated into exchange rates of blockchain-based currencies.

The remainder of the paper is structured as follows. In section 2 we introduce the institutional setting and data. In section 3 we present key facts on the market efficiency of blockchain currency markets. In section 4 we present empirical evidence on the information content of different market participants. Section 5 concludes.

2 Definitions and Data

2.1 DEX Market and AMM Functions

2.1.1 Primary and Secondary EURC/USDC Markets

Figure 2 presents a schematic of the distribution of EURC and USDC. Each Treasury, managed and operated by Circle, mint EURC tokens and USDC tokens when investors deposit EUR and USD respectively. These tokens can then be used by investors to trade directly in the EURC/USDC AMM market, as indicated by the black solid arrows. Alternatively, these investors may use these currencies in alternative markets, for example in ETH/USDC or ETH/EURC markets. Subsequent trading can feed into the EURC/USDC market indirectly, which we indicate by the dotted lines.

It is important to make a distinction between primary and secondary market rates. The EURC and USDC Treasuries are committed to meet redemptions at par (1 EURC=1 EUR and 1 USDC=1 USD). Arbitrage is necessary to stabilize the secondary market. To illustrate, let us consider a case when the USDC stablecoin price trades above 1 USD in the secondary market. Investors can make a profit by depositing 1 USD with the issuer in the primary market, receive 1 USDC, and subsequently sell the stablecoin in the secondary market. The arbitrage increases circulating supply, putting downward pressure on stablecoin market price toward parity. Conversely, consider the USDC stablecoin trading at a discount. An investor can make a profit by purchasing the stablecoin cheaply in the secondary market and redeeming the stablecoin in the primary market to obtain 1 USD. We provide additional details on stablecoin issuance and the arbitrage mechanism in Appendix A.

[INSERT FIGURE 2 ABOUT HERE]

2.1.2 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 revolves around liquidity pools and smart contracts. LPs deposit pairs of tokens into these pools, establishing reserves for trading. Uniswap relies on a constant product formula to maintain a constant ratio between the quantities of the two tokens in each pool. This means that the product of the token quantities remains constant, regardless of the trade size, resulting in a mathematically balanced liquidity pool. Hence, economic agents are aware in advance of the algorithm governing the price formation process, thereby reducing uncertainty surrounding price determination by design.

Trading on Uniswap V2 is determined based on the constant product Automated Market Maker (AMM) function k=xy, (where x and y are the quantities of USDC and EURC in the pool) which preserves the product of the quantities of each currency in the pool. This automated price discovery mechanism ensures that the token swap rates adjust dynamically according to the demand and supply in the pool. If, for example, there are 100 EURC and 110 USDC in the pool, the constant product function is $k = 100 \times 110 = 11000$ and the exchange rate will be 1.10 USDC per EURC. The combinations of EURC and USDC that satisfy the AMM function is known as a bonding curve.

We illustrate the dynamics of Uniswap V2 pricing in Figure 3. In the top panel, the aggregate supply of liquidity is given by point $E_0 = [L_{USDC}, L_{EURC}]$, which is the level of EURC and USDC supplied in the pool.

[INSERT FIGURE 3 ABOUT HERE]

The second panel shows an example of a trade, which is commonly referred to as a "swap" on decentralized exchanges. Here, the trader swaps EURC for USDC, and we move along the bonding curve to the point E_1. The liquidity pool now has an increase in the supply of USDC and a decrease in the supply of EURC. The price is determined by simple comparative statics: assuming a constant product function of $k = xy$, the new price is given by the following formula:

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

By definition, as there is a decrease in the supply of EURC, denoted by $\Delta L_{EURC} > 0$, it follows that there is an appreciation of EURC.[4]

[4] For example, suppose $\Delta L_{EURC} = 5$, the new price is given by $\frac{110}{100-5} = 1.158$. Therefore the exchange rate has appreciated from 1.10 USDC per EURC to 1.158 USDC per EURC. The constant product rule is satisfied at this price: the new quantities of EURC and USDC are 95 and 115.8, and the product is $k = 95 \times 115.8 = 11000$.

The third panel shows an example of liquidity provision. A LP needs to add liquidity of both tokens based on the current price. For example, if there are 100 EURC and 110 USDC, the provider needs to add tokens at the ratio of 1.10 USDC to 1 EURC to the pool.[5] Therefore LPs are analogous to shifts of the bonding curve from equilibrium E_0 to E_2.

2.1.3 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.[6] 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 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.[7] 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.

Figure 4 illustrates a schematic of liquidity provision.[8] 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 illustrated in Figure 3, 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

[5] If they add 10 EURC, they are required to add 11 USDC to keep the ratio of USDC to EURC constant at 1.10.
[6] 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.
[7] Source: Uniswap V3 whitepaper available at https://uniswap.org/whitepaper-v3.pdf
[8] For more details we refer readers to the Uniswap interface available at https://uniswap.fish/

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.

[INSERT FIGURE 4 ABOUT HERE]

2.2 Data

2.2.1 Reuters FX Benchmark and Uniswap EURC/USDC Price

We source a benchmark EUR/USD rate from Reuters Tick History. 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.[9].

Our Reuters 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 20 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 4. 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 contains the entire history of "swap" transactions, which are all trades of buying EURC (USDC) and selling USDC (EURC). These transactions also provide details at the wallet level, which is a Ethereum blockchain address refers to a digital container that securely stores and manages Ethereum cryptocurrency (ETH) and other tokens associated with that address.[10] 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,

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

[10] In technical terms, it holds the private keys necessary to access and control the funds associated with a specific Ethereum address on the blockchain.

this records amounts of USDC or EURC are added to the pool, as well as a specified price range in which liquidity is added.[11]

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 with direct primary dealers.

Sophisticated traders. In each month, we aggregate trading volume by wallets, and select wallets that feature in the top 10. The share of top 10 addresses trading volume averages 49.8% of aggregate trading volume over our sample from August 15 2022 to July 31 2023.

Primary dealers. Primary dealers are classified as wallets that have transacted with either the EURC or USDC Treasury in our sample.[12] 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 are typically a small subset of traders, and account for 6.2% of aggregate trading volume.

LPs. Traders that provide liquidity are the subset of wallets that swap currencies (EURC/USDC) and deposit or withdraw both currencies from the liquidity pool. LPs are typically a small subset of traders, and account for 4.6% of aggregate trading volume.

We present summary statistics of the number of transactions and volume per transaction for each trading group in Table 1. We characterize trading into 7 groups. This includes sophisticated traders, primary dealers and LPs. We identify 62, 40 and 88 unique addresses for each category respectively. Additionally, we include sub-categories of traders that are in the intersection of different trading groups. For example, this includes 4 traders that belong to the intersection of sophisticated traders and primary dealers (Top10 $\cap$ PM), and 6 traders in the intersection of sophisticated traders and LPs, (Top10 $\cap$ LP). There is only 1 trader that is a primary dealer and a LP (PM $\cap$ LP).[13] Finally, we have a residual

[11]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.

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

[13]As this wallet only has 1 transaction over the whole sample, we exclude this trading group from our

group of 1859 traders, $\notin \{Top10, PM, LP\}$, which includes the majority of addresses in our sample. Wallets with high market share trade more frequently, 44 transactions per address for sophisticated traders, and 84 transactions per address for wallets belonging to the intersection of sophisticated traders with primary dealers.

[INSERT TABLE 1 ABOUT HERE]

We provide summary statistics of the distribution of trading volume and liquidity provision in Figure 5. Panel (a) shows the number of addresses, the trading volume and the percentage of trading volume from sophisticated traders. Panel (b) shows the number of addresses, the aggregate liquidity provision and the percentage of liquidity provided by the top 5 LPs. We identify sophisticated traders and top 5 LPs each month; thus, they vary over time every month. Over the sample, there are typically 200 to 300 addresses trading each month, with a much smaller number of LPs minting or burning new tokens at 10 per month. Average monthly trading volume reached a peak of 39 EURC Million in November 2022, and peak new liquidity reached 13 EURC Million in October 2022. Turning to a time series of concentration, sophisticated traders have an average of 50-60% of aggregate trading volume over the sample period of July 1st 2022 to July 31st 2023. An analogous measure of liquidity concentration using the top 5 addresses is typically over 90% over most months of our sample.

[INSERT FIGURE 5 ABOUT HERE]

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 ETH blockchain API. The amounts of the base and quoting currency of a swap trade allows us to construct a measure of blockchain order flow. Amounts are signed based on whether they are adding or subtracting liquidity from the pool. For example, in the dataset EURC is the base currency and USDC is the quoting currency. Therefore if the base currency amount is negative, it means a trader is adding USDC and subtracting EURC from the pool. This is a "buyer initiated trade" for EURC. In contrast, if the base currency amount is positive, the trader is removing USDC and adding EURC to the pool. We classify this as a "seller initiated" trade for EURC.

analysis on the heterogeneous trading of different market participants.

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}.

$$OF_t = \sum_{k=t}^{k=t+1} (\mathbb{1}[T_k = B] - \mathbb{1}[T_k = S]) \times V_{T_K} \tag{2}$$

Figure 6 plots cumulative blockchain order flows and prices. Panel (a) plots the price and cumulative blockchain order flow for the EURC/USDC pair. We find there is positive co-movement between the cumulative blockchain order flow and the EURC/USDC price. Panel (b) divides blockchain order flow into two groups: LPs and non LP traders. We find that the cumulative blockchain order flow of LPs follows a very different pattern to non-LP traders. While LPs have on net been buying EURC over the sample period, non-LP traders have been on net selling EURC. That LPs can have net build up of inventory in EURC suggests that they are not dealers in traditional FX markets that aim to balance inventories (Lyons, 1995; Rime et al., 2010). The role LPs play in information, their motives for hedging and their response to de-pegging events will be explored in Section 4.

[INSERT FIGURE 6 ABOUT HERE]

2.2.4 CLS Volume

To study the transaction volumes in the traditional currency market, we utilize the CLS FX dataset. CLS Group handles around 40% of global FX transaction volume, including spot, swap, and forward transactions, for up to 18 currencies.[14] CLS data provides aggregated spot FX volume at an hourly frequency, and has been used in a number of papers analyzing the microstructure of the FX spot and swap markets (Ranaldo and Somogyi, 2021; Hasbrouck and Levich, 2021; Kloks et al., 2023; Ranaldo, 2023). We focus on the spot market and use two CLS datasets. First, we obtain the aggregate trading volume from 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-

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

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.[15]

Figure 7 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).[16] Turning to the scale of trading volume, the average daily volume in CLS EUR/USD is 95.78 EUR Billion, while the average daily volume in Uniswap EURC/USDC is 0.568 EURC Million. Expressed as a percentage, the blockchain market trading accounts for 0.0006% or 0.06 basis points of the aggregate trading in the EUR/USD market, as per CLS data.[17]

[INSERT FIGURE 7 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. Transaction gas fees a measure of the amount of Ethereum (ETH) a user pays to perform a given activity, or batch of activities, on the Ethereum network. These costs

[15]The Volume dataset lists trading volume in USD, which we convert based on Reuters EUR/USD 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.

[16]In Appendix B, 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.

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

are paid to the miners who authenticate the transactions on the Ethereum blockchain. We use an index of gas fees obtained from Coinmetrics, `coinmetrics.io` that computes the average fee per transaction authenticated on the Ethereum blockchain.

Market volatility. Intra-day volatility of ETH is calculated as the square root of the daily average sum of squared returns over hourly intervals.

Amihud ratio. We compute the Amihud measure (Amihud, 2002) for blockchain currencies as the ratio between daily absolute returns and trading volume on the DEX EURC/USDC market. We also calculate the Amihud measure for traditional currencies, using the ratio of daily absolute Reuters Return to CLS trading volume.

Macroeconomic controls. We compute interest rate differentials using one-month OIS rates on EUR and USD as a fundamental macro determinant. In addition, we utilize two variables related to possible frictions in financial markets: (i) innovations to US dealer capital ratio (He et al., 2017) as a proxy of dealers' financial constraints, and (ii) fluctuations in the VIX index commonly as a global fear index (e.g., Mancini et al. (2013)).

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

[INSERT TABLE 2 ABOUT HERE]

3 Empirical Analysis: Market Efficiency

Fact #1: Peg efficiency is driven by blockchain factors

One meaningful way to assess price efficiency is to analyze whether the blockchain *prices* are systematically connected with the underlying currency values. The main measure of efficiency we use is the absolute deviations of the EURC/USDC from the Reuters benchmark rate, which we denote as Δ_0 in equation (3).

$$\Delta_0 = |\mathrm{p}_{\mathrm{EUR/USD}} - \mathrm{p}_{\mathrm{EURC/USDC}}| \tag{3}$$

We test the main determinants of market efficiency in Equation (4). We divide these determinants into characteristics related to the ETH blockchain and "frictions" related to dealer constraints, market liquidity, and investors' sentiment. Blockchain characteristics include a measure of intra-day volatility in Ethereum (σ_{ETH}), ETH returns (R_{ETH}), gas fees ($gasfee_t$) and our Amihud measure of daily illiquidity ($Amihud_{EURC/USDC}$). The other variables account for investors' global fear (ΔVIX), interest rate differentials ($i_{EUR} - i_{USD}$), and dealer's financial constraints (HKM). Due to the shorter sample of our triangular arbitrage measures, we will use the benchmark measure in equation (3) as the outcome variable in our analysis of market efficiency.

$$Y = \beta_0 + \beta_1 \sigma_{ETH} + \beta_2 R_{ETH} + \beta_3 gasfee_t + \beta_4 Amihud_{EURC/USDC} + \beta_5 \Delta VIX + \beta_6 (i_{EUR} - i_{USD}) + \beta_7 HKM \quad (4)$$

We present the results of the specification in Table 3. The picture that emerges is a generally strong connection of blockchain prices to their underlying with a relatively small spread. Across all of our specifications, the only variables that have a robust effect on our market efficiency measure are blockchain-based characteristics such as market volatility of ETH and gas fees. Quantitatively, a 1 per cent increase in gas fees leads to a 0.1 per cent increase in absolute peg deviations, and a 1 per cent increase in market volatility of ETH leads to a 0.03 per cent increase in absolute peg deviations. Both of these variables are important in determining limits to arbitrage for trading in the DEX market (Barbon and Ranaldo, 2021; Foley et al., 2023). Higher gas fees, all else equal, reduce market inefficiency as it makes it more difficult for informed traders to track the price in traditional markets. Periods of increased market volatility in ETH tighten the constraints of traders, that typically have their wealth denominated in ERC-20 tokens.[18] Therefore increased market risk can cause traders to reduce their arbitrage trading and price discrepancies between markets can emerge.

[INSERT TABLE 3 ABOUT HERE]

Fact # 2: Peg deviations are within arbitrage bounds

Our measure of efficiency highly correlates with alternatives that are based on triangular arbitrage, which measures dislocations based on deviations from the law of one price. These measures of triangular arbitrage involve other bilateral pairs that are on centralized exchanges, and are listed in equation (5).[19] Δ_1 measures the triangular arbitrage deviation associated with the currencies of USDC, EURC and USD. For example, an investor can start off with 1 USDC, or alternatively buy EURC in the EURC/USDC market, convert EURC

[18]ERC20 is a standard which provides features including the transfer of tokens from one account to another, measuring the current token balance of an account, and measuring the total supply of the token available on the network. It deploys smart contracts, auto-executing code on the blockchain, to perform these various functions. Traders in the EURC-USDC market typically trade multiple tokens. Summary statistics are provided in the Appendix C. For example, traders in the ETH-USDC market typically trade an average of 48 tokens.

[19]Centralized exchanges are by definition the only exchanges that have access to USD or EUR denominated pairs. EURC/USD and EURC/EUR is listed on Coinbase. USDC/USDC is listed on Kraken (which is the most liquid pair for USDC/USD).

to USD in the EURC/USD market, and finally re-convert to USDC using the USDC/USD market. Δ_2 measures the triangular arbitrage deviation associated with the currencies of USDC, EURC and EUR respectively. Finally, we can conduct an arbitrage using a round trip across 4 currencies, USDC, EURC, USD and EUR.

$$\begin{aligned}\Delta_1 &= \left|1 - \frac{p_{\mathrm{EURC/USDC}} \times p_{\mathrm{USDC/USD}}}{p_{\mathrm{EURC/USD}}}\right| \\ \Delta_2 &= \left|1 - \frac{p_{\mathrm{EUR/USD}} \times p_{\mathrm{EURC/EUR}}}{p_{\mathrm{EURC/USD}}}\right| \\ \Delta_3 &= \left|1 - \frac{p_{\mathrm{EUR/USD}} \times p_{\mathrm{EURC/EUR}}}{p_{\mathrm{EURC/USDC}} \times p_{\mathrm{USDC/USD}}}\right|\end{aligned} \tag{5}$$

Panel (a) of Figure 8 shows the results of our triangular arbitrage measures and compares them to our benchmark measure. Our analysis starts in March 2023 as centralized exchange data on EURC/EUR, EURC/USD needed for our calculations only start trading in March 2023. In general, there is a high correlation between our benchmark measure and alternative measures using mis-pricing from triangular arbitrage, which ranges from 0.5 to 0.6 over our sample period.

[INSERT FIGURE 8 ABOUT HERE]

Table 4 provides summary statistics on triangular arbitrage conditions and transaction costs. The first panel presents percentiles of triangular arbitrage metrics and gas fees per 1 USD volume transaction. We compare the metrics of triangular arbitrage with the arbitrage bound, which is governed by the gas fees of the transaction, the payment to LPs (which is 0.05% on the Uniswap V3 EURC/USDC pool), and slippage on exchanges, which represents the impact of market price changes between trade initiation and execution.[20] The second panel of Table 4 reports arbitrage bound violations considering gas fees and liquidity fees, and the third panel extends the analysis by incorporating slippage costs. If we only account for gas and liquidity fees, there are up to 40-50 % of exploitable arbitrage opportunities based on the violations of the upper bound in panel (b). Once we account for slippage costs on the Uniswap V3 exchange, violations of the arbitrage bound drop to 10-15% of transactions. The analysis excludes additional costs due to slippage and intermediation fees on centralized exchanges. The arbitrage bound and triangular arbitrage metrics are jointly plotted in panel (b) of Figure 8.

[20]For slippage we assume a value of 0.5% based on the default slippage protection provided on Uniswap https://app.uniswap.org/swap. In general a slippage protection anywhere between 0.1% to 5% is recommended on the exchange. Transactions may fail to execute if the slippage parameter is set less than 0.1%.

[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 Figure 9, we document the response of EURC/USDC and EUR/USD prices intra-day during scheduled Federal Open Market Committee (FOMC) meetings from August 2022 to July 2023. 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.

[INSERT FIGURE 9 ABOUT HERE]

Fact #4: resilience of liquidity during de-pegging events

We exploit the USDC de-pegging event that took place on March 11 2023 as a test of the resilience of the EURC/USDC market. We study liquidity provision during this event, and report the activities of LPs in Table 5. In panel (a), we record LP transactions related to the amounts of EURC and USDC added or removed from the liquidity pool, as well as the price ranges within which liquidity was supplied. Interestingly, we find little evidence of strategic liquidity re-positioning by LPs during the de-pegging event. Only one LP actually withdrew both EURC and USDC from the pool at 05:59 UTC on March 11, 2023. The inactivity of LPs is important for the resilience of the protocol. This could reflect in part that LPs are passive and do not necessarily re-balance their portfolios on new information (Fang, 2022; Foley et al., 2023; LI et al., 2023).

We can also test if LPs intervened through trading in the EURC/USDC pair. In panel (b), we present swap transactions carried out by LPs. Interestingly, we record only two swap transactions by LPs during the de-pegging event. This includes a LP that sold 92,509 EURC at 06:57 UTC on March 11 2023, and another LP sold a negligible amount of 253 EURC at 21:32 UTC on March 12. In general, while the aggregate activity of LPs is limited, the buying pressure on USDC helped support the peg and counter the general sell-off of USDC.

[INSERT TABLE 5 ABOUT HERE]

4 Empirical Analysis: Trader Information

4.1 Research hypotheses

H1: *Blockchain trading is systematically linked to the underlying market, with a stronger connection with the interbank segment leading the price discovery process.*

DEX and CLS trading volume have similar trading patterns intra-day (Figure 7), with peaks occurring during afternoon hours UTC time, when major financial markets in Frankfurt, London and New York are open. Blockchain trading can correlate with different segments of the underlying market represented by CLS trading groups. We hypothesize a systematic connection between trading activity on the blockchain and the underlying market. Should blockchain trading convey fundamental information, this connection is expected to be stronger with the interbank segment, which leads the price discovery process. This result would be consistent with the heterogeneous and superior information of some groups of market participants, with the interbank being most informed and corporates being least informed in the FX spot market (Ranaldo and Somogyi, 2021). Therefore we hypothesize that the information content of blockchain trades is through volume connection to the EUR/USD market, with stronger connections to interbank trading volume.

H2a: *Market participants have information on the EUR/USD Market. Informational advantages exist for (i) sophisticated traders with high wealth and trading activity and (ii) primary dealers with access to EUR and USD deposits.*

The standard model of blockchain order flow in Evans and Lyons (2002) assumes a portfolio shifts model, in which dealers absorb public demand for the currency, and share their inventory risk with the public at the end of day. This framework posits that changes in investors' portfolio preferences and expectations about future exchange rates lead to shifts in currency allocations. If the public's demand for assets is not perfectly elastic, the exchange rate adjustment in equilibrium is required for dealers to successfully offload their inventory risk and for the public to absorb the order imbalance. Therefore, a positive blockchain order flow for a currency–more buy orders than sell orders, causes the relative price of the currency to rise in the FX market.

In our blockchain-based AMM, the market adjusts to the portfolio shift through an algorithm. The elasticity of the public demand is governed by the relative quantities of the currencies in the liquidity pool. If there is relatively more liquidity of one currency than the other (for example, if most of the liquidity distribution is one-sided and LPs are only willing to sell EURC), then the price adjustment required is greater than if the LPs distribution is symmetric. We can test the portfolio shifts model within this framework.

We hypothesize an increase in investor expectations of EUR/USD valuation, a decrease in transaction costs and market volatility of ETH, and an increase in wealth of the trader lead to an increase in the price impact of blockchain order flow. We can proxy for wealth by the amount of trading activity. Traders with more wealth are more likely to arbitrage price differences between the traditional and blockchain market, and are able to overcome limits to arbitrage such as gas fees.

We also hypothesize that primary dealers have more information on traditional markets. As they have dollar or euro deposits with the USDC or EURC treasury, they must pay attention to developments in Euro and USD Money markets more than the average investor. It is easier for primary dealers to conduct arbitrage between the EUR/USD and EURC/USDC market. For example, suppose EURC/USDC trades at a premium relative to the EUR/USD. To increase the relative supply of EURC, an investor can deposit EUR with the EURC Treasury and sell EURC in the EURC/USDC DEX market. Therefore primary dealers facilitates arbitrage trading between the DEX and traditional market.[21]

H2b: *LPs trade to maintain their inventory, and are therefore uninformed with respect to the EUR/USD market.*

LPs are often passive and face losses to liquidity provision such as adverse selection risk (Milionis et al., 2022; Foley et al., 2023). These losses can occur when the trade price moves away from the price at which you deposit the tokens in the liquidity pool. For example, consider the fundamental EUR/USD price increases relative to the EURC/USDC price. Arbitrageurs have an incentive to equate prices across markets, and increase the relative price of EURC, by removing EURC and adding USDC to the pool, a LP will now face a relative decline in their portfolio holdings of EURC and a relative increase in their holdings of USDC. If they want to maintain their portfolio as a LP, they have an incentive to add EURC to the pool and decrease their holdings of USDC. While this swap hedges their liquidity position, however this trade can have negative price impact and is disconnected from information in traditional markets.

4.2 Volume connection

In this section we test hypothesis H1 for links between trading volume in the DEX and the traditional market. We run the specification in equation (6). The outcome variable is

[21] In principle, arbitrage can be primarily undertaken in the EURC/EUR and USDC/USD markets, for example, by depositing EUR with the Treasury, obtaining EURC tokens and selling EURC in the EURC/EUR market when EURC trades at a premium. However, the arbitrageur has an incentive to sell EURC in any market where it is trading at a relative premium.

DEX volume for sophisticated traders, primary dealers and LPs. We also include wallets in the intersection of these trading types, as defined in Section 2.

The explanatory variables are measures of trading volume in the traditional EUR/USD market using CLS data. This data disaggregates trading volume by sector type, which includes interbank volume, and volume intermediated by marker maker banks and price taker funds, non-bank financial institutions and corporates.

$$V_{N_{DEX},t} = \alpha + \sum_{i \in N_{CLS}} V_{N_{CLS},t} + \epsilon_t \tag{6}$$

We present the results of the regression specification in Table 6. The main result is that blockchain volume is tied to that in the underlying market, especially to the interdealer volume. In column (1), the coefficient of 2.7812 on interbank suggests a strong and positive relationship with the market activity of sophisticated traders and interbank trading volume. All else equal, a 1 EUR Million increase in interbank trading volume increases the trading activity of sophisticated traders by 2.78 EURC. These effects are robust across different trading groups. Lastly, in column (6), for activities outside sophisticated traders, primary dealers, and LPs, $V_{\notin top10,PM,LP}$, the coefficient is 2.02, suggesting other market participants also correlate significantly with interbank trading activity.

[INSERT TABLE 6 ABOUT HERE]

This result accords well with the fact that the interdealer segment is at the heart of the entire OTC FX market. Supported by a few centralized and relatively transparent trading platforms, the interdealer segment leads the price discovery process, which is essential for determining the value of blockchain prices.

In addition to volume correlations, we can examine the effect of illiquidity measures, such as the Amihud ratio measured in Amihud (2002). We define illiquidity as the daily absolute return per unit volume.[22] We regress DEX illiquidity based on aggregating trading volume, against measures of CLS trading volume in equation (7).

$$Illiq_{DEX,t} = \alpha + \sum_{i \in N_{CLS}} V_{N_{CLS},t} + \epsilon_t \tag{7}$$

Table 7 presents the results of regressing the Amihud ratio on measures of CLS volume. Columns (1) and (2) in Panel (a) calculates the Amihud ratio of the EURC/USDC pair based on the DEX return, and columns (3) and (4) in Panel (b) uses the Reuters return. For both

[22]For readability of our regression estimates, we amplify Amihud (DEX Return) by 10^6 and amplify Amihud (Reuters Return) by 10^9.

the DEX and Reuters return, we observe negative correlation between DEX illiquidity and CLS trading volume. For example, an increase in CLS trading volume (of 1 EUR Billion) generates a decline in the Amihud illiquidity measure of 0.004, and 0.0009 when using Reuters returns. When we disaggregate by sectors, we find that individual sector volume does not affect illiquidity using DEX returns, however interbank volume is significant in predicting a decline in illiquidity on the DEX market when using Reuters return in column (4). This supports our hypothesis that interbank trading volume is the most correlated to blockchain activity, and can predict periods of illiquidity in DEX markets.

[INSERT TABLE 7 ABOUT HERE]

4.3 Price determination and blockchain order flow

4.3.1 Baseline specification: Aggregate blockchain order flow

In this section, we want to extend the analysis of price determination by examining blockchain order flow of traders. In addition to public information, FX rates are determined by blockchain order flow, which may contain private information (Evans and Lyons, 2002).

$$p_t - p_{t-1} = \alpha + \beta_1 OF_t + \beta_j x_{j,t} + \epsilon_t \tag{8}$$

Our baseline specification for testing the price impact of blockchain order flow is outlined in equation (8). p_t is the spot exchange rate (in logs) of either the EURC/USDC exchange rate in units of USDC, or the EUR/USD exchange rate in units of USD. We introduce a set of controls $x_{j,t}$ to capture macroeconomic variables such as interest rate differentials, changes in the VIX index and balance sheet constraints. F

We present the results of the specification in Table 8. Columns (1) to (4) use DEX returns as the outcome variable, and columns (5) to (8) use Reuters returns. All returns are winsorized at 1%. The sample uses daily data on all macroeconomic variables and aggregates blockchain order flow over the trading day. We find that blockchain order flow has significant price impact using both DEX and Reuters returns. A 1 EURC Million shock in blockchain order flow leads to a 4.52 per cent increase in the DEX return and a 3.96 per cent increase in the Reuters return, respectively. The price impact estimates are attenuated when examining spillovers to traditional markets.

[INSERT TABLE 8 ABOUT HERE]

Consistent with the literature (eg. Evans and Lyons (2002)), interest rate differentials, changes in the VIX index and balance sheet constraints are a robust predictor of exchange rate returns. An increase in the EUR interest rate relative to USD interest rate leads to an appreciation of the EUR/USD. Periods of increased market volatility (when the VIX index increases), and negative shocks to dealer capital (A negative change in HKM) causes an appreciation of the USD. This is consistent with theories of the USD as being a gauge of risk appetite, with periods of tightening balance sheet constraints leading to a flight to safety and an appreciation of the USD (Avdjiev et al., 2019; Jiang et al., 2021; Hu et al., n.d.). Comparing DEX and Reuters returns, we find the effects of macroeconomic variables on exchange rate returns are quantitatively similar. For example, a 1 per cent shock to the dealer capital ratio leads to an exchange rate return of 0.245 per cent using DEX returns, and 0.242 per cent when using Reuters returns.

4.3.2 Heterogeneous blockchain order flow

Market participants can have a heterogeneous impact on price (Ranaldo and Somogyi, 2021). Consequently, after analyzing aggregate blockchain order flow, we investigate hypotheses H2a and H2b in section 4.1 on whether distinct categories of market participants exert differential effects on both blockchain-based and traditional FX rates. We run the regression specification outlined in equation (9). We disaggregate our measure of blockchain order flow into sub-groups based on sophisticated traders, primary dealers, and traders that are also LPs. We also include wallets in the intersection of these trading types, as defined in Section 2.

$$p_t - p_{t-1} = \alpha + \sum_{i \in N_k} \beta_i OF_{i,t} + + \epsilon_t \tag{9}$$

We present the results of the baseline specification in Table 9. The sample aggregates blockchain order flow for each sub-grouping at an hourly frequency. The dependent variable in column (1) use DEX returns (log price change of the EURC/USDC), and column (2) use Reuters returns (log price change of EUR/USD).

We examine the price impact of DEX returns for each trading group in column (1). A 1 EURC Million blockchain order flow of the sophisticated traders leads to a 4.49 per cent increase in the DEX return, compared to a 5.13 per cent increase for primary dealers, and 4.60 per cent for LPs. The set of traders that do not belong to these groups have a price impact of 4.91 per cent. Therefore there no significant differences in price impact across trading types with respect to DEX returns.

Turning to Reuters returns in column (2), we find informational advantages for sophisticated traders and primary dealers. A 1 EURC Million blockchain order flow of sophisticated traders leads to a 1.19 per cent increase in the Reuters return, compared to a 0.96 per cent increase for primary dealers, and a 0.75 per cent increase for traders that also provide liquidity. The pecking order of information is additionally tested through the intersections of the different groups of traders. The group of traders with the highest price impact, of 1.92 per cent, is the intersection of sophisticated traders with primary dealers. In contrast, LPs have the lowest price impact on the Reuters return across trading groups. The lower price impact may be due to trading in the blockchain market to hedge their positions and not necessarily trading on information in traditional markets.

In summary, our findings are consistent with our research hypotheses H2a and H2b on the information heterogeneity across market participants on the blockchain. While LPs are uninformed, we find traders with a dominant market share and primary dealers are likely sophisticated traders with informational advantages.[23]

[INSERT TABLE 9 ABOUT HERE]

4.4 Trader heterogeneity: robustness tests

4.4.1 Dynamic effects

So far, we have studied the contemporaneous blockchain order flow and its impact on currency values. However, prices and flows can follow persistent and endogenous processes. A sensitive way to take such aspects into consideration is to test for dynamic effects using a structural VAR framework (Hasbrouck, 1991; Ranaldo and Somogyi, 2021). We estimate the following bivariate VAR of blockchain order flow OF and spot returns (measured as the price difference in logs) Δp, illustrated in equations (10) and (11). In equation (10), a contemporaneous shock to hourly blockchain order flow is impounded in the price the same hour. In contrast, we allow for shocks to prices to affect blockchain order flow with a lag. The identification assumption is consistent with causality running from blockchain order flow to exchange rate returns (Evans and Lyons, 2002). Our baseline specification contains $L = 24$ lags.

$$\Delta p_t = \alpha_1 + \sum_{k=1}^{L} \gamma_{1,k} \Delta p_{t-k} + \sum_{k=0}^{L} \beta_{1,k} OF_{t-k} + \epsilon_{1,t} \tag{10}$$

$$OF_t = \alpha_2 + \sum_{k=1}^{L} \gamma_{2,k} \Delta p_{t-k} + \sum_{k=1}^{L} \beta_{2,k} OF_{t-k} + \epsilon_{2,t} \tag{11}$$

[23]In Appendix C, we test whether alternative characteristics, such as the number of tokens traded by a wallet, the frequency of transactions, and the age of a wallet are measures of informed trading. We find no evidence of a systematic relationship between these blockchain characteristics and the price impact of blockchain order flow.

We compare the cumulative price impact of different trader types in Figure 10. Panel (a) reports the coefficients using DEX EURC/USDC returns, panel (b) reports the coefficients using Reuters EUR/USD returns. In both panels, we find a clearly stronger permanent price impact for sophisticated traders and those with primary dealers. In contrast, LPs have insignificant price impact, and is even weakly negative with respect to DEX returns. Therefore, consistent with our contemporaneous effects presented in Table 9, traders with greater market share and primary dealers are more informed, whereas LPs are primarily trading in the markets to hedge their positions and are relatively uninformed.

[INSERT FIGURE 10 ABOUT HERE]

4.4.2 Intra-day insights

Our analysis has shown price impact of the DEX market, and heterogeneity across trader types. If particular trading groups are more connected to the traditional financial market, we hypothesize these traders will have higher price impact during periods when major financial markets are open and there is more trading activity in traditional markets. These hours typically correspond to afternoon UTC time, which corresponds to the opening of trading in New York. For example, in describing the CLS data in Section 2, we note traditional financial markets based on CLS volume have a peak hourly volume in the hours of 13-16 UTC.

To test this formally, we run a regression specification in equation (12), which estimates the intra-day hourly price impact by trader type N_k, where D_i is a dummy for each hour of the day (measured in UTC time). The coefficient $\beta_{i,k}$ estimates the price impact of blockchain order flow of each trading type during each hour of day.

$$p_t - p_{t-1} = \alpha + \sum_{i=1}^{24} \sum_{k \in N_k} \beta_{i,k} OF_{k,t} \times D_i + \beta_j x_{j,t} + \epsilon_t \tag{12}$$

Figure 11 estimates the coefficients for different trader types. Panel (a) reports the coefficients using DEX EURC/USDC returns, panel (b) reports the coefficients using Reuters EUR/USD returns. For all trader types, the time-varying price impact is similar to the aggregate estimates when using DEX returns. However, examining price impact estimates using Reuters returns in panel (b), we observe a higher price impact of blockchain order flow for sophisticated traders and primary dealers. The effects are more pronounced during the hours of 13-15 UTC time, which is when traditional markets of London, New York and Frankfurt are open. This supports our hypothesis that the price impact of these traders are typically higher when there is more information in traditional financial markets. In contrast, traders that are LPs have insignificant price impact during the same period. This suggests they are relatively inattentive to any macroeconomic information and are trading due to their hedging demands.

[INSERT FIGURE 11 ABOUT HERE]

4.4.3 Arbitrage trading

If traders on DEX are connected to traditional markets, a related question we can ask is whether they are responding to deviations between the DEX reference rate and the Reuters rate. For example, if the DEX exchange rate EURC/USDC trades at a premium relative to EUR/USD, a trader can in principle sell EURC and buy USDC to get closer to the benchmark rate. Therefore, we hypothesize a key determinant of blockchain order flow is the deviation between the DEX and benchmark Reuters rate. We test this assertion in equation (13), where we regress blockchain order flow on the lagged price difference between the DEX and Reuters market. Controls include the lagged EURC/USDC return.

$$OF_{i,t} = \alpha + \beta_1(p_{EURC/USDC,t-1} - p_{EUR/USD,t-1}) + controls_t + \epsilon_t \tag{13}$$

[INSERT TABLE 10 ABOUT HERE]

We present the results of the baseline specification in Table 10. For sophisticated traders in column (1), a unit increase in the lagged (hourly) price difference between the Uniswap and Reuters exchange rates decreases aggregate hourly blockchain order flow by 0.33 EURC Million. The intersection of sophisticated traders and primary dealers decrease blockchain order flow by 0.15 EURC Million. In contrast, we find blockchain order flow of primary dealers and LPs are insignificant in columns (2) and (3). Our results suggest wealthier traders are more likely to conduct arbitrage between DEX and the traditional market. This is intuitive as these traders find it more profitable as they incur lower transaction costs of arbitrage (eg. gas fees as a percentage of trade). In contrast, LPs and primary dealers, who typically trader lower volume, do not necessarily trade to arbitrage price differences across markets.

4.4.4 Trading behavior during a de-pegging event

To understand the behavior of traders during the de-pegging event, Figure 12 plots the response of EURC/USDC prices and blockchain order flow of different trading types to the de-pegging event of USDC. The Figure plots the price difference between the EURC/USDC and EUR/USD markets, and includes blockchain order flow for the different trader groups.

blockchain order flow for sophisticated traders was positive during the lead-up to the de-pegging event on March 10 and 11, which suggests informational advantages in the run on USDC. This is consistent with Liu et al. (2023) which finds similar behavior by sophisticated investors in the Terra Luna run. Interestingly LPs and smaller traders had a negative blockchain order flow in the lead-up to the run on USDC, consistent with having less access to information on USDC and Circle Treasury reserves in the lead-up to the de-pegging event on March 11.

[INSERT FIGURE 12 ABOUT HERE]

5 Conclusion

DeFi platforms are increasingly offering accessibility and financial inclusion on a global scale, transcending geographical and temporal limitations. This study sets out to evaluate the efficiency and resilience of blockchain-based currency markets.

Using a rich dataset of trade and price data on EURC/USDC from the Uniswap V3 exchange, we assess pricing efficiency. We find that blockchain currencies are generally efficient but not immune to frictions, such as gas fees and Ethereum's volatility. Blockchain currency prices are systematically related to macroeconomic fundamentals like interest rate differentials are highly responsive to macroeconomic announcements, indicating that blockchain-based currency markets are adept at swiftly assimilating new fundamental information. We also show the market's resilience during periods when the stablecoin breaks parity.

Our main contribution is to understand the information content of blockchain trades and how the behavior of market participants is connected to the traditional EUR/USD market. Blockchain order flow impacts prices in the traditional market venue, and furthermore, we observe heterogeneity in the price impact of blockchain order flow across different trading groups. We find sophisticated traders and primary dealers are more informed. These informational advantages are likely due to reduced limits to arbitrage in trading across the DEX and traditional EUR/USD market, and through connections with the traditional banking system by having access to EUR and USD deposits with the stablecoin issuer. In contrast, LPs exhibit insignificant price impact and act as uninformed hedgers.

Several avenues for future research remain. As these markets expand, LPs, currently passive in their response to de-pegging events, should become more active in liquidity provision by withdrawing liquidity and scaling back their capital, evolving into entities that mirror FX dealers. While blockchain-specific limitations like gas fees are currently significant, traditional market constraints, such as dealer balance sheet limitations, could become more relevant as these decentralized platforms grow.

In summary, our findings offer valuable insights into the operational efficiencies, information assimilation, and robustness of blockchain currency markets with respect to their traditional counterparts. The increasing relevance of blockchain markets in the financial ecosystem makes understanding their efficiency and resilience not just an academic exercise but a pressing policy concern.

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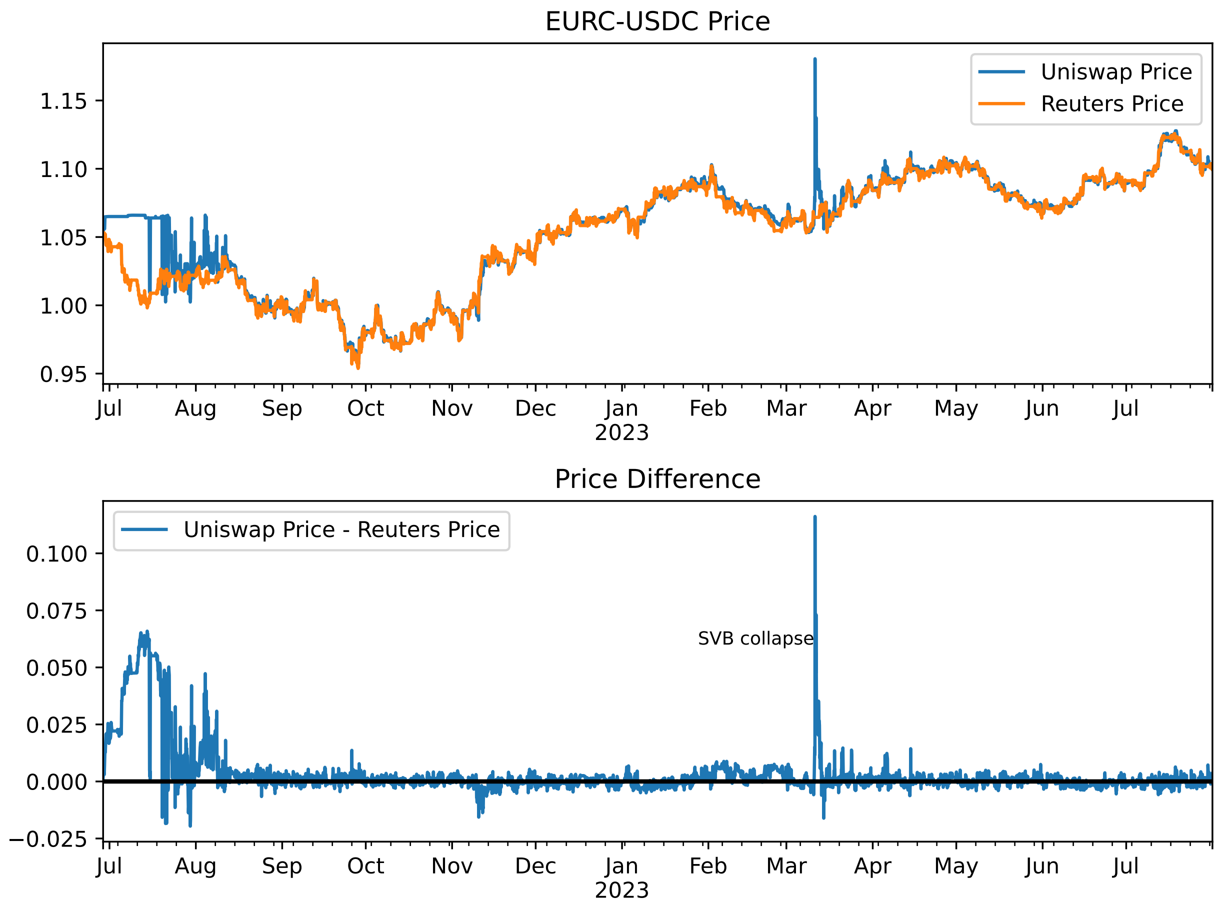
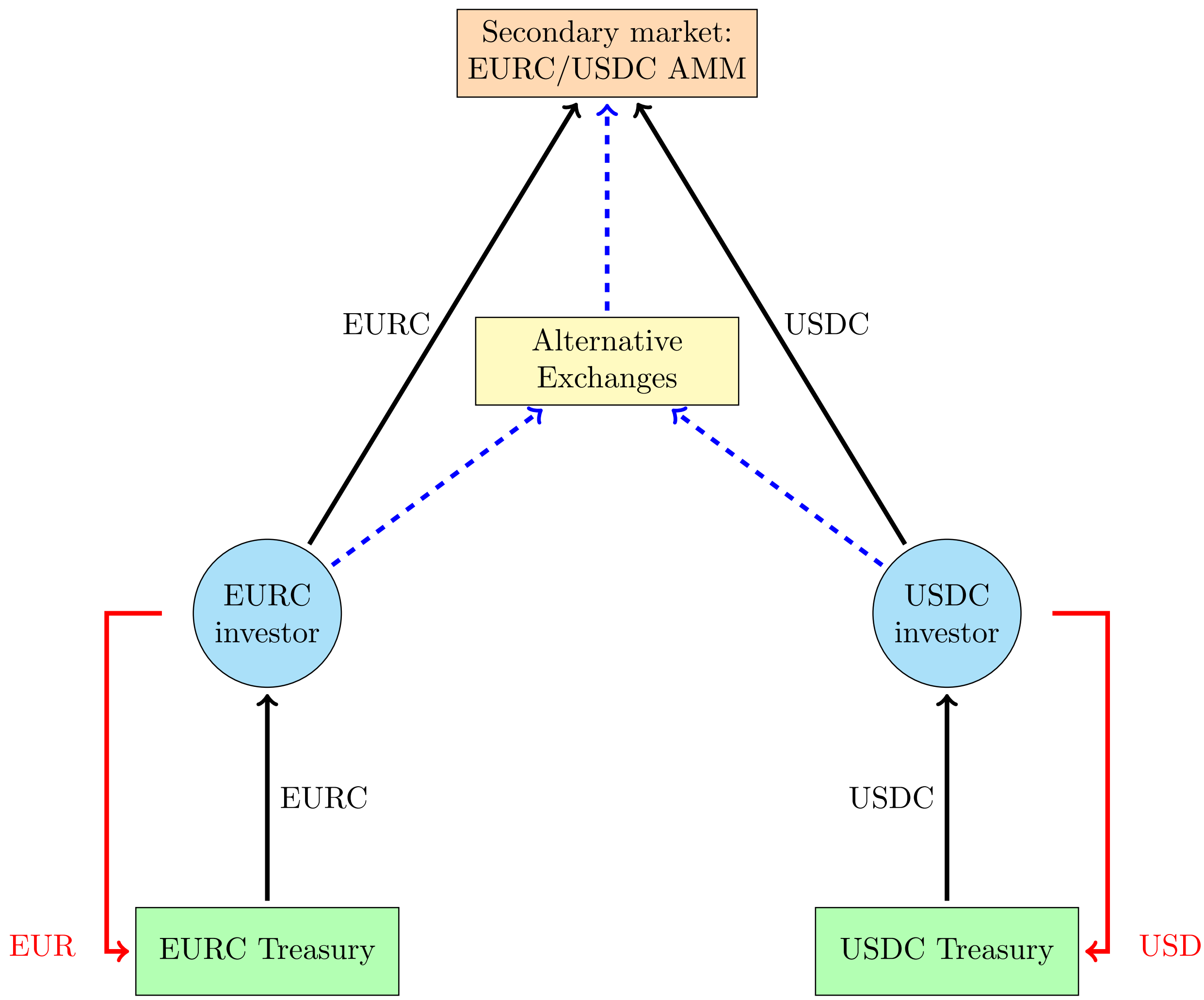
Figures

Figure 1: EURC/USDC Prices



Note: This figure plots EURC/USDC and EUR/USD prices. EURC/USDC prices are sourced from Uniswap V3. EUR/USD prices are sourced from Thomson Reuters tick history. The top panel reports prices, and the bottom panel reports the price difference between the EURC/USDC and EUR/USD price. The total sample period for the top two figures is from 28 June 2022, to 31 July 2023.

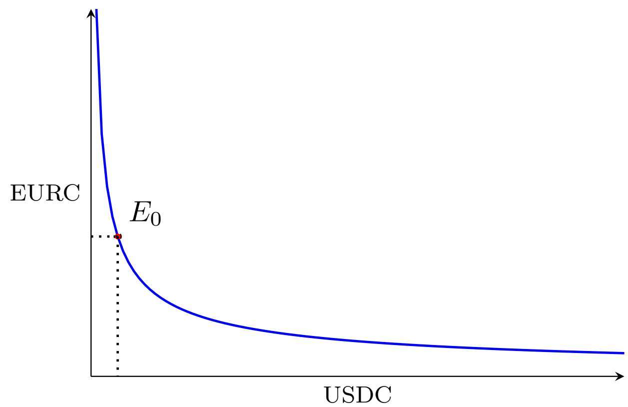
Figure 2: EURC/USDC Primary and Secondary Markets



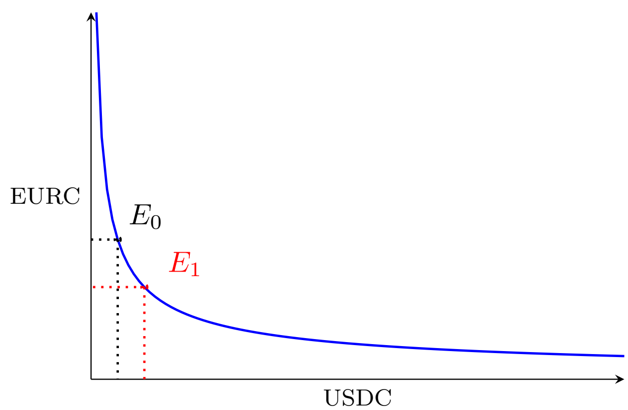
Note: This Figure presents a schematic of the distribution of EURC and USDC. Each Treasury, managed and operated by Circle, mint EURC tokens and USDC tokens when investors deposit EUR and USD respectively. These tokens can then be used by investors to trade directly in the EURC/USDC AMM market, as indicated by the black solid arrows. Alternatively, these investors may use these currencies in alternative markets, for example in ETH/USDC or ETH/EURC markets. Subsequent trading can feed into the EURC/USDC market indirectly, which we indicate by the dotted lines.

Figure 3: EURC/USDC bonding curves

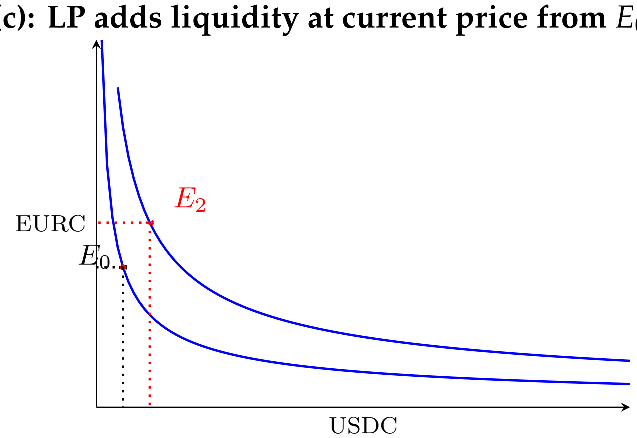
Panel (a): Aggregate supply of liquidity at point E_0



Panel (b): Swap trade from E_0 to E_1.



Panel (c): LP adds liquidity at current price from E_0 to E_2.



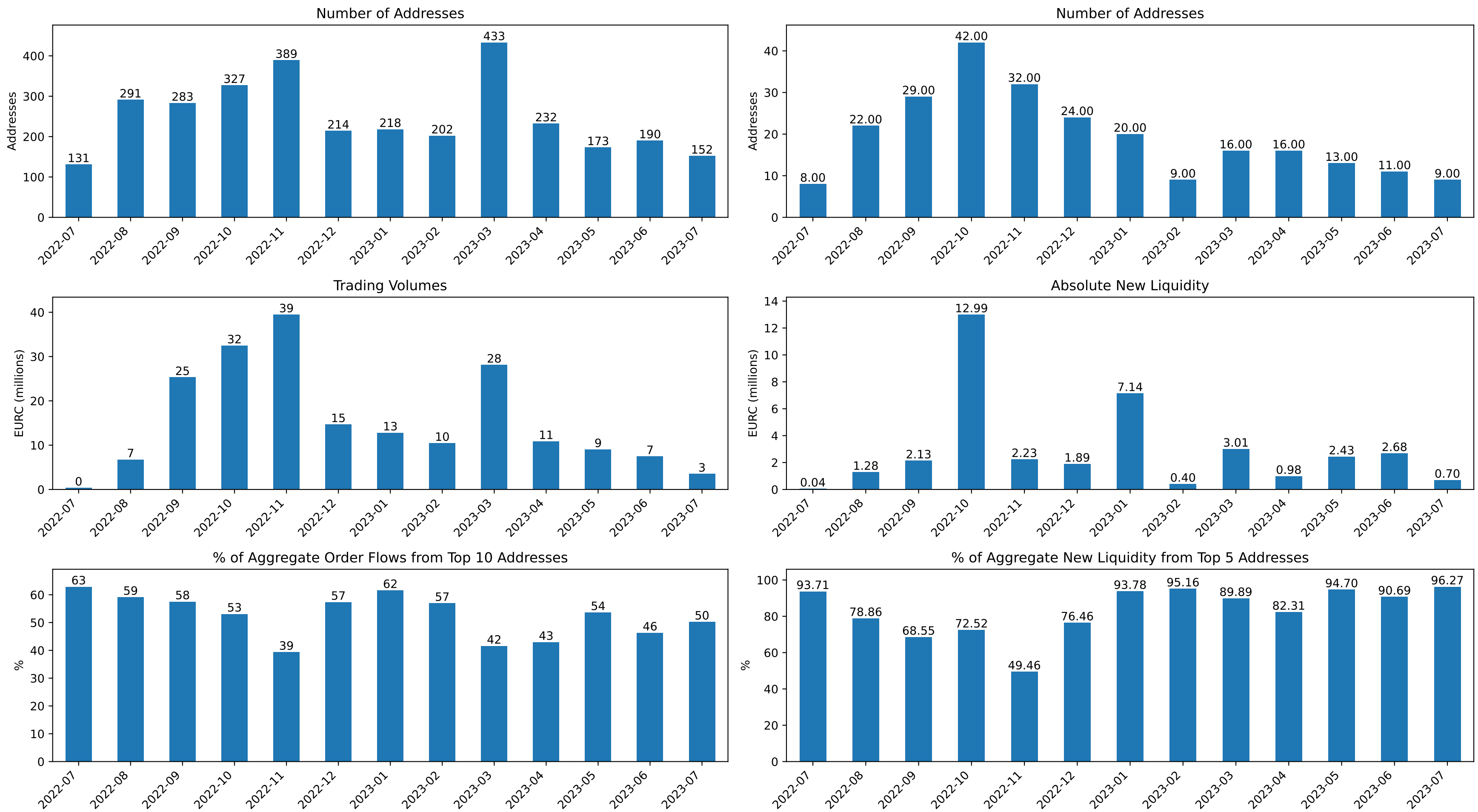
Note: This Figure illustrates the principles of a bonding curve. In panel (a), the aggregate supply of liquidity is given by point E_0, which is the level of EURC and USDC supplied in the pool. Panel (b) shows an example of a trade, which is commonly referred to as a "swap" on decentralized exchanges. Here, the trader swaps EURC for USDC, and we move along the bonding curve to the point E_1. The liquidity pool now has a larger supply of USDC and a decline in the supply of EURC. In panel (c), a LP adds liquidity of both tokens based on the current price.

Figure 4: EURC/USDC Uniswap Liquidity Provision

Note: This figure records a snapshot of liquidity in the EURC/USDC pair. This interface allows users to post liquidity (denoted by "Deposit amount") at specified price ranges. Source: https://uniswap.fish/

Figure 5: Summary statistics of trading volume and liquidity provision

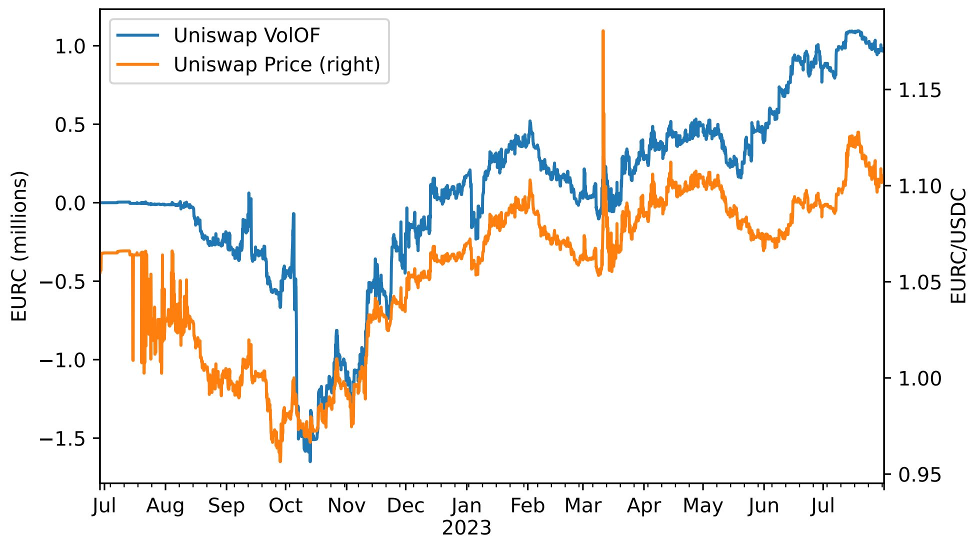
Panel (a): Trading Volume | **Panel (b): Liquidity Provision**



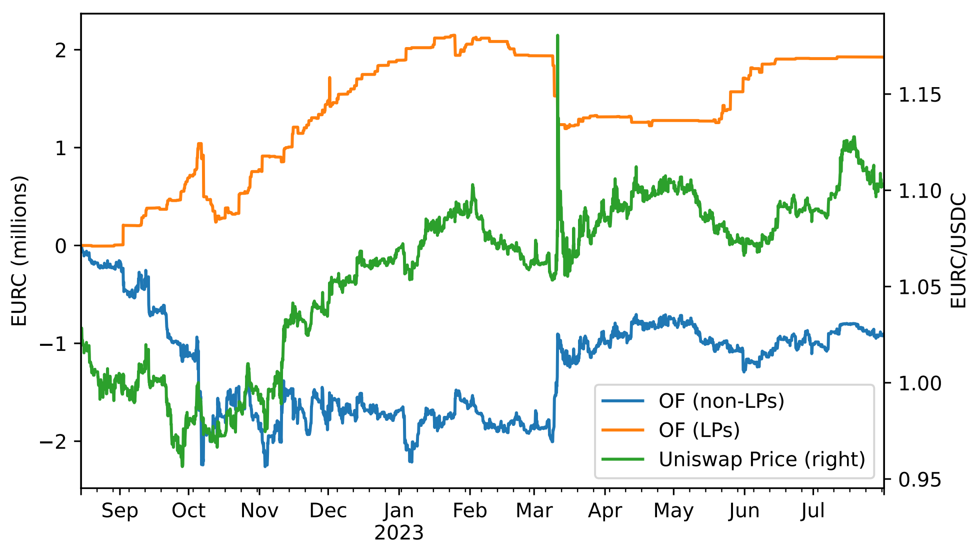
Note: This figure plots monthly summary statistics of the distribution of trading volume and liquidity provision. Panel (a) shows the number of addresses, the trading volume and the percentage of trading volume from sophisticated traders (top 10 wallets). Panel (b) shows the number of addresses, the aggregate liquidity provision and the percentage of liquidity provided by the top 5 LPs. Total sample period is from 1 July 2022 to 31 July 2023.

Figure 6: EURC/USDC Prices and cumulative blockchain order flow

Panel (a): EURC/USDC Price and Cumulative blockchain order flow



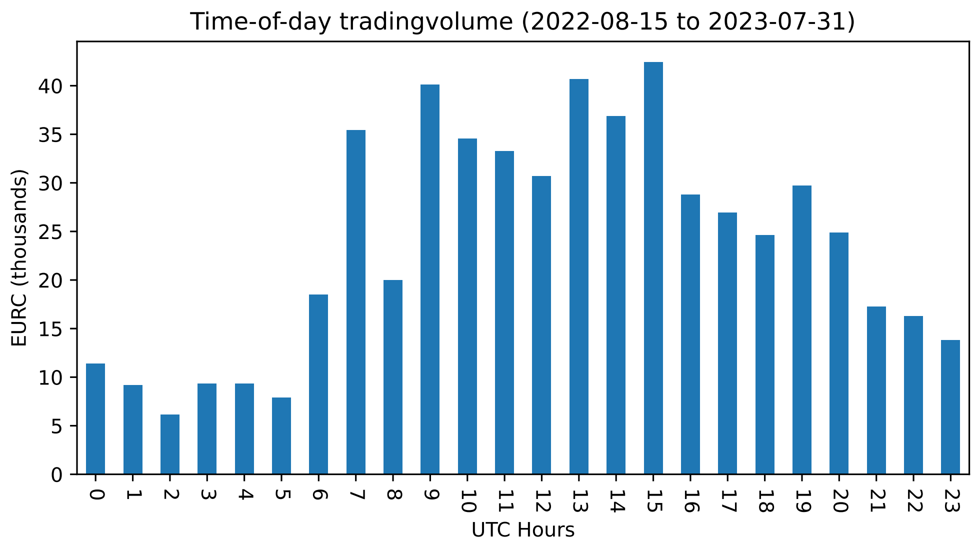
Panel (b): EURC/USD Price and Cumulative blockchain order flow by LPs and Non-LPs



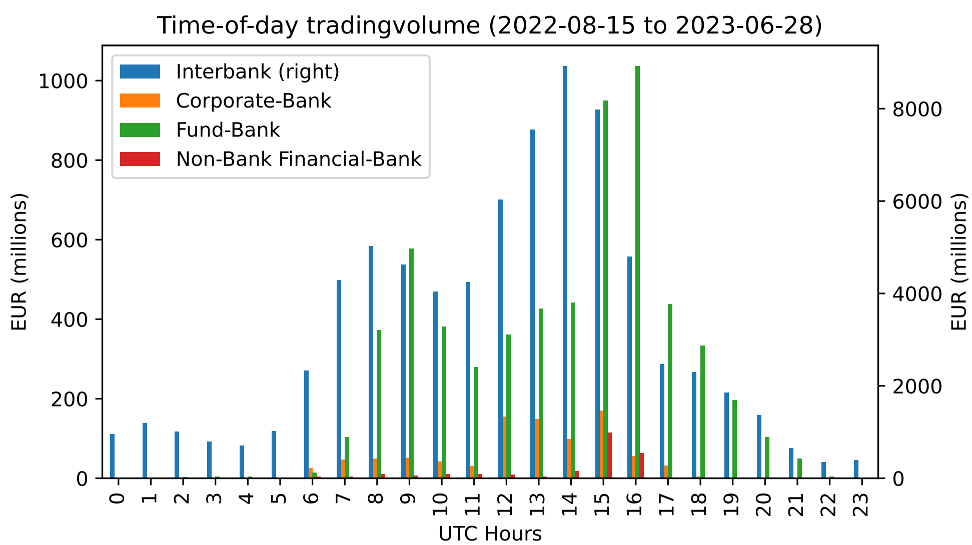
Note: This figure plots cumulative trading volume and prices. Panel (a) plots the price and cumulative blockchain order flow for the EURC/USDC pair. Panel (b) plots the price and cumulative blockchain order flow for the EURC/USDC pair, disaggregated by LPs and non-LPs. Total sample period is from 15 August 2022 to 31 July 2023.

Figure 7: Hourly FX Trading Volume

Panel (a): DEX Trading Volume



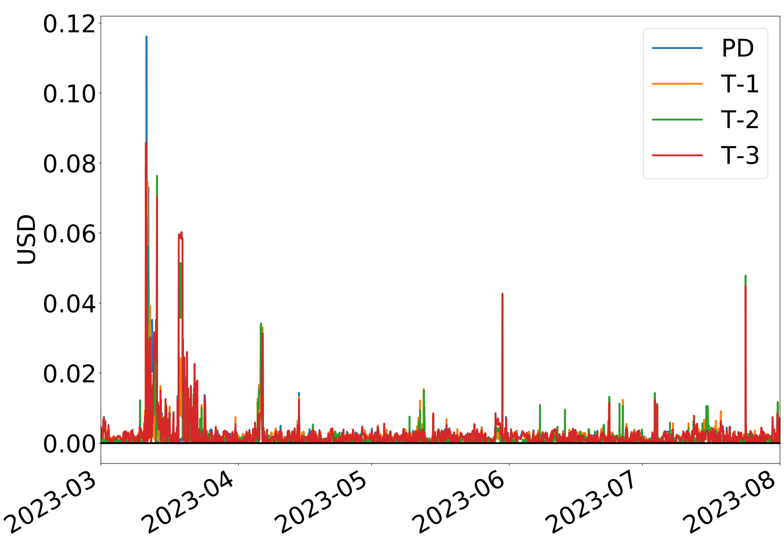
Panel (b): CLS Trading Volume



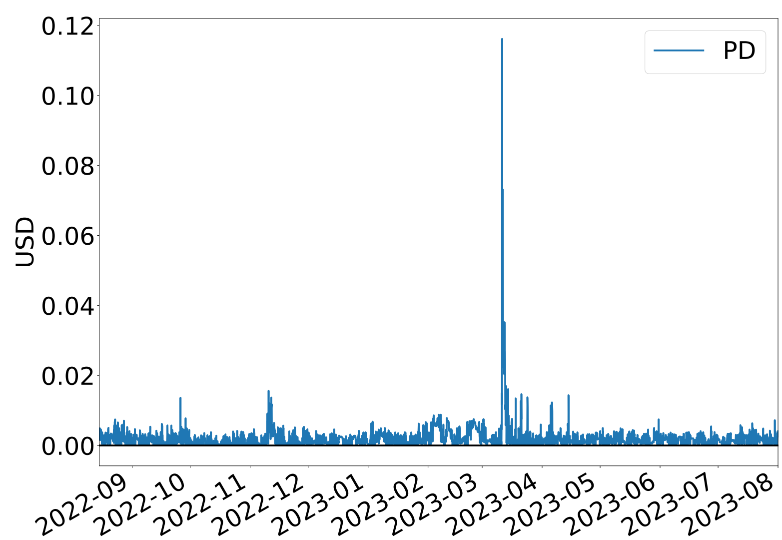
Note: Figure plots hourly trading volume. In panel (a), we report trading on Uniswap V3 in the EURC/USDC Market in EURC Millions. In panel (b), we report trading volume on CLS for the EUR/USD market, disaggregated by sectors: Bank-Bank, Bank-Fund, Bank-Corporate, and Non-Bank Financial-Bank. CLS Volume is in EUR Million. The total sample period starts on 15 August 2022, and ends on 31 July 2023, for Panel (a) and on 28 June 2023, for Panel (b).

Figure 8: EURC/USDC Measures of Price Efficiency and Arbitrage Bounds

Panel (a): Triangular Arbitrage Conditions

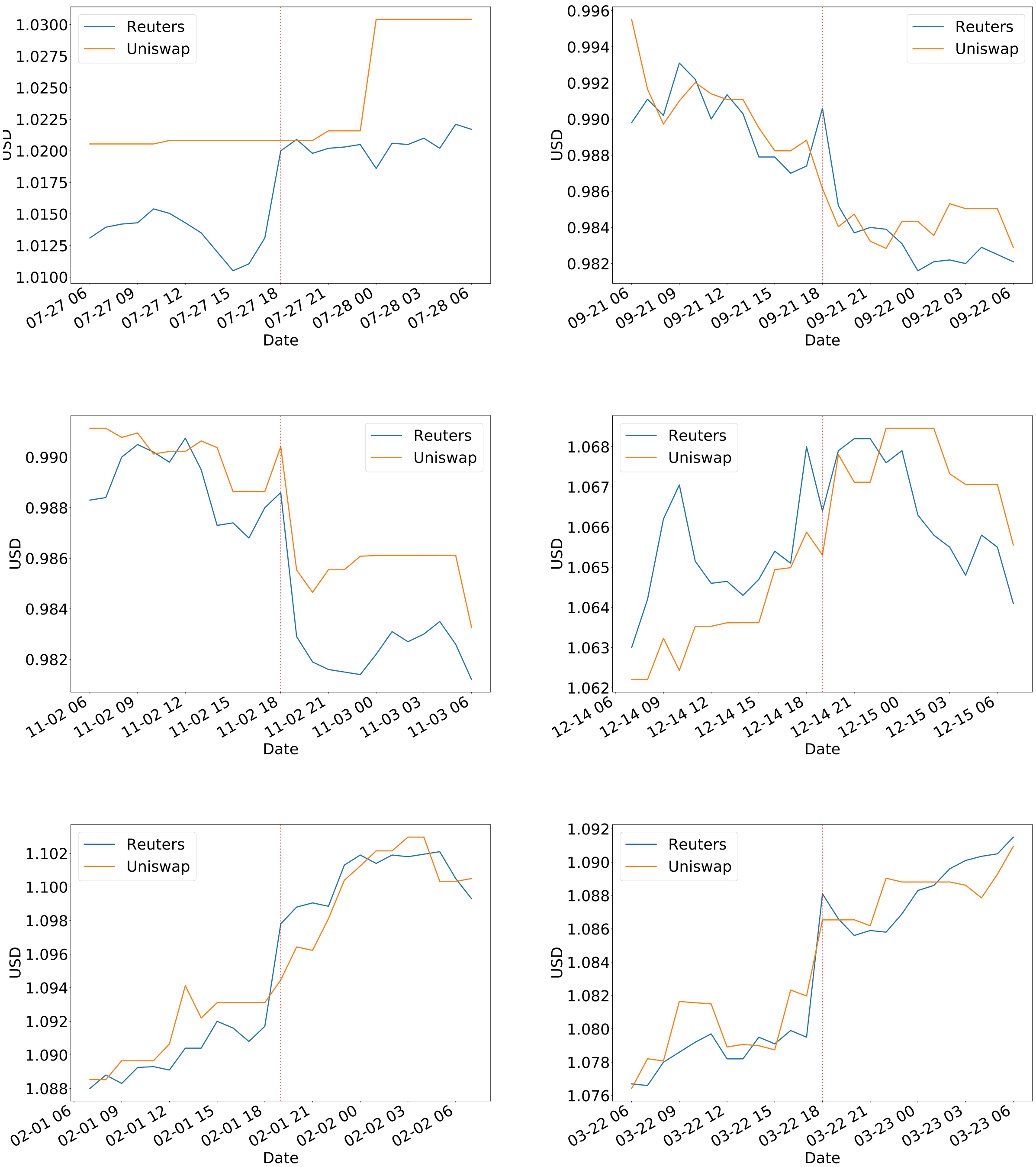


Panel (b): Triangular Arbitrage Measures and Transaction Costs



Note: This figure plots market efficiency metrics based on how the EURC/USDC market tracks EUR/USD Reuters 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 31 July 2023.

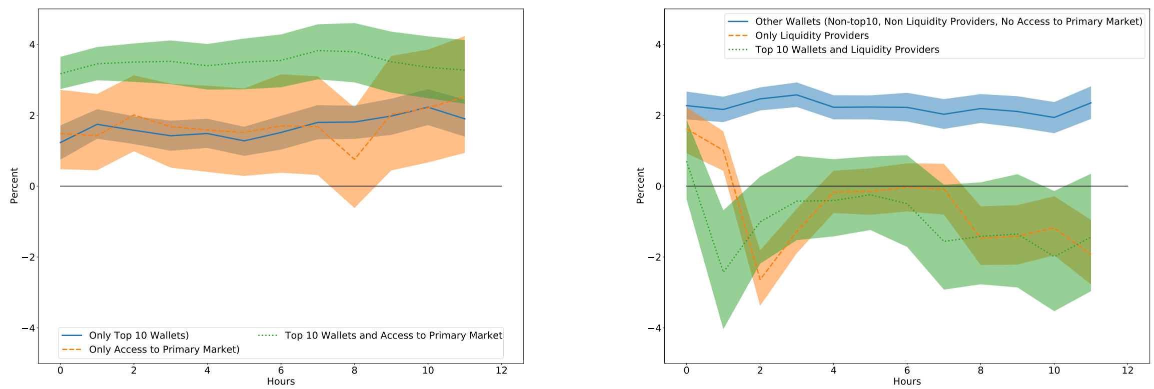
Figure 9: Federal Reserve Monetary Announcements



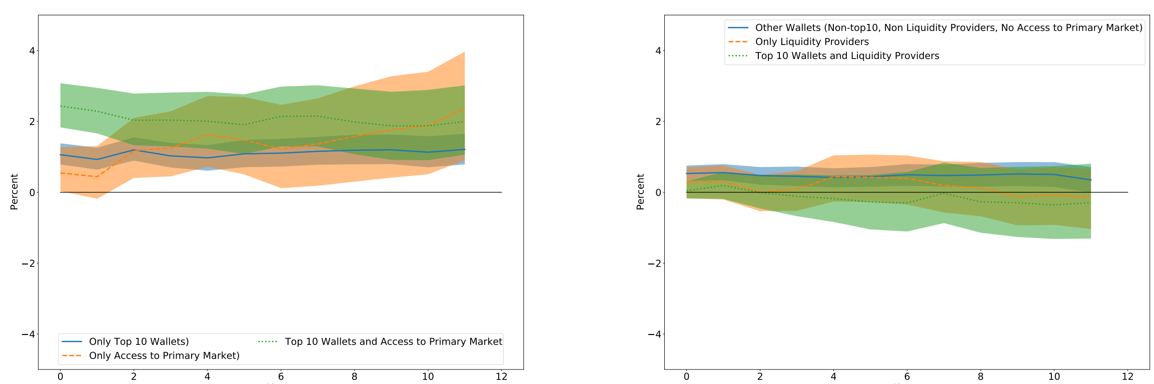
Note: This figure plots event studies of the reaction of EURC/USDC and EUR/USD rates around monetary announcements of the Federal Reserve. EURC/USDC prices are sourced from Uniswap V3. EUR/USD prices are sourced from Thomson Reuters tick history. Total sample period is from 15 August 2022 to 6 April 2023.

Figure 10: Price impact of blockchain order flow: dynamic effects

Panel (a): EURC/USDC Return



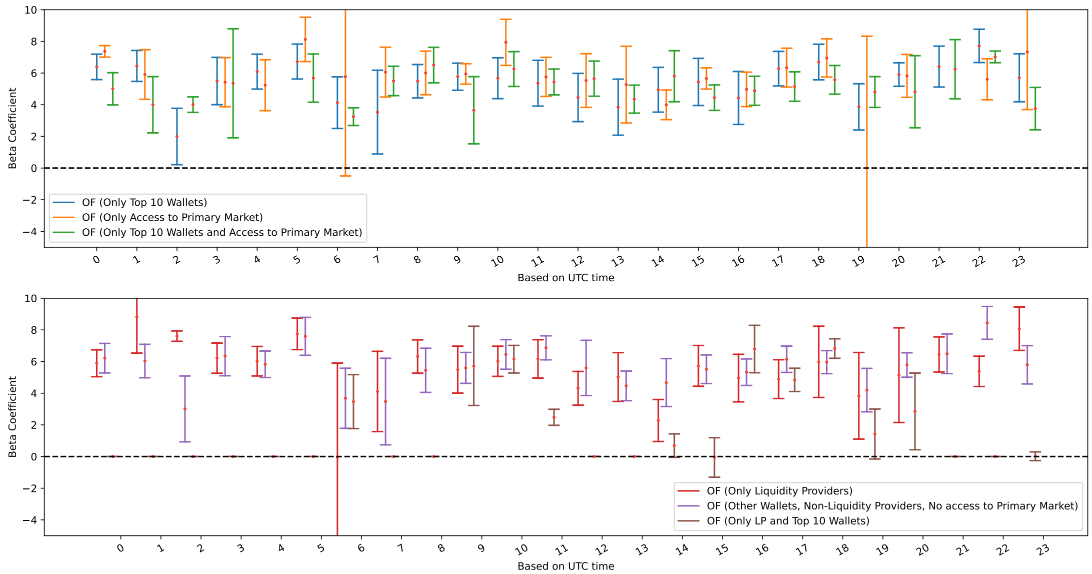
Panel (b): Reuters EUR/USD Return



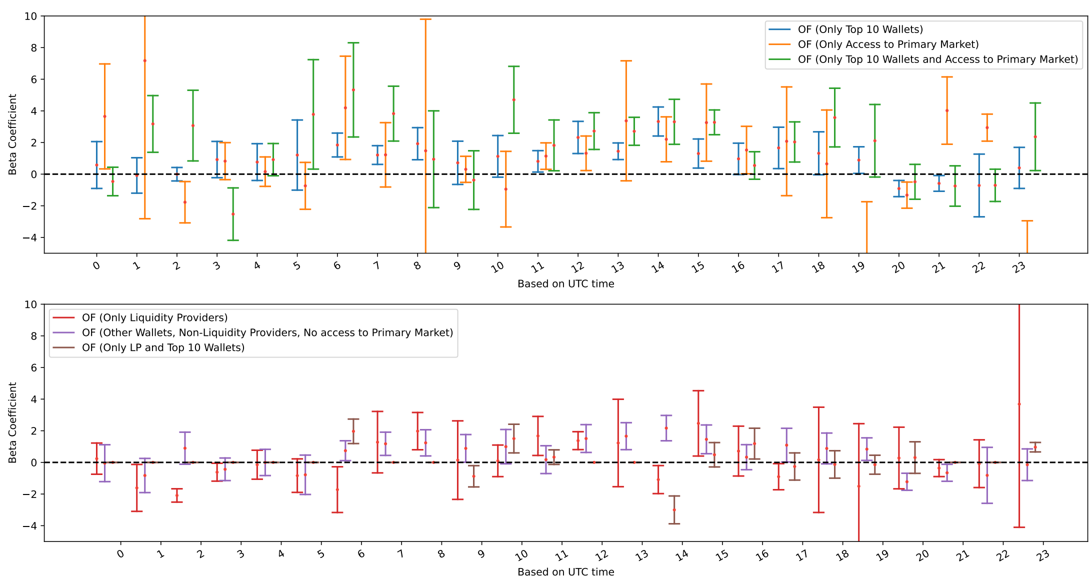
Note: This figure plots the impulse response of the change in spot returns to a 1 Million EURC shock in blockchain order flow, using a structural VAR framework (Hasbrouck, 1991; Ranaldo and Somogyi, 2021). blockchain order flow is measuring the net buyer transactions of purchasing EURC, and is sourced from Uniswap V3 trade data. EURC/USDC returns are calculated using Uniswap V3 prices. EUR/USD prices are sourced from Thomson Reuters Tick History. 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 and the intersection of sophisticated traders, LPs and other wallets, and the intersection of sophisticated traders and LPs. Total sample period is from 15 August 2022 to 31 July 2023.

Figure 11: Price impact of blockchain order flow: intra-day patterns

Panel (a): EURC/USDC Return

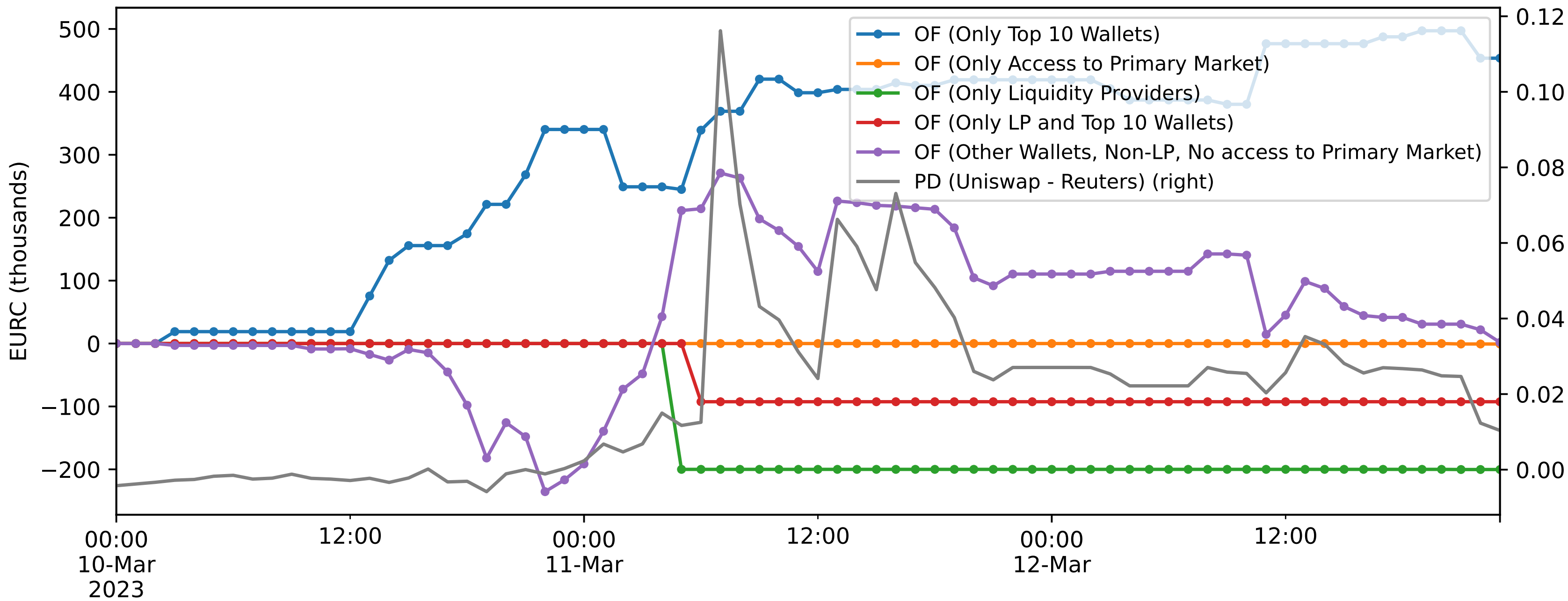


Panel (b): Reuters EUR/USD Return



Note: This figure plots hourly price impact estimates in spot returns to a 1 Million EURC shock in blockchain order flow. blockchain order flow is measuring the net buyer transactions of purchasing EURC, and is sourced from Uniswap V3 trade data. EURC/USDC returns are calculated using Uniswap V3 prices. EUR/USD prices are sourced from Thomson Reuters Tick History. 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 and the intersection of sophisticated traders, LPs and other wallets, and the intersection of sophisticated traders and LPs. Total sample period is from 15 August 2022 to 31 July 2023.

Figure 12: 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 Thomson Reuters Tick History 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.

Tables

Table 1: Trader classification

Panel (a): Number of transactions

Group	top10	Issuance	LP	$N_{addresses}$	Tx	Tx/$N_{addresses}$
Top10	✓	×	×	62	2711	43.73
PM	×	✓	×	40	197	4.93
LP	×	×	✓	88	407	4.63
Top10 ∩ PM	✓	✓	×	4	336	84.00
Top10 ∩ LP	✓	×	✓	6	29	4.83
$\notin \{Top10, PM, LP\}$	×	×	×	1859	6642	3.57
PM ∩ LP	×	✓	✓	1	1	1.00

Panel (b): Volume per transaction (EURC)

Group	mean	std	min	25%	50%	75%	max
Top10	32569	60221	1	8812	19000	37746	1040295
PM	14884	22235	5	932	7441	20000	183500
LP	16646	26613	1	1162	7109	22937	289800
Top10 ∩ PM	28339	11258	100	20000	30000	30000	95990
Top10 ∩ LP	80882	75742	1032	40540	60524	110278	343333
$\notin \{Top10, PM, LP\}$	13745	23434	0	1052	5376	16438	557076
PM ∩ LP	352	-	352	352	352	352	352

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, $\notin \{Top10, PM, LP\}$.

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	273	1.072	1.437	0.000	0.335	0.778	1.208	11.018
Volume-Fund-Bank	273	7.090	6.195	0.000	4.598	6.789	9.253	44.678
Volume-Non-Bank Financial-Bank	273	0.311	1.157	0.000	0.023	0.065	0.156	10.331
Volume-Interbank	273	87.304	47.577	0.028	75.082	94.800	115.081	229.161
Volume-Aggregate	273	95.778	52.434	0.028	80.640	105.925	127.282	240.698
Panel (b): Trading Volume (Uniswap)- EURC Million								
Volume (Aggregate)	351	0.568	0.850	0.001	0.132	0.303	0.685	8.545
Volume (top10)	351	0.250	0.431	0.0	0.021	0.107	0.273	3.453
Volume (PM)	351	0.008	0.024	0.0	0.000	0.000	0.001	0.184
Volume (LP)	351	0.019	0.045	0.0	0.000	0.000	0.018	0.464
Volume (top10 $\cap$ PM)	351	0.027	0.058	0.0	0.000	0.000	0.030	0.343
Volume (top10 $\cap$ LP)	351	0.007	0.045	0.0	0.000	0.000	0.000	0.532
Volume ($\notin \{Top10, PM, LP\}$)	351	0.257	0.468	0.0	0.053	0.136	0.281	5.309
Volume (PM $\cap$ LP)	351	0.000	0.000	0.0	0.000	0.000	0.000	0.000
Panel (c): Additional Variables								
$\mathrm{P}_{\mathrm{EURC/USDC}}$	351	1.057	0.042	0.961	1.021	1.071	1.089	1.128
$\mathrm{P}_{\mathrm{EUR/USD}}$	351	1.056	0.042	0.960	1.022	1.069	1.089	1.124
$\lvert \mathrm{P}_{\mathrm{EUR/USD}} - \mathrm{P}_{\mathrm{EURC/USDC}} \rvert$	351	0.0020	0.0022	0.0000	0.0008	0.0016	0.0025	0.0271
σ_{ETH}	351	0.026	0.016	0.005	0.016	0.023	0.032	0.124
GasFee	351	0.003	0.002	0.001	0.002	0.003	0.003	0.014
R_{ETH}	351	-0.000	0.033	-0.189	-0.014	-0.001	0.014	0.160
$Amihud_{EURC/USDC}$	351	0.016	0.041	0.000	0.003	0.008	0.018	0.687
$i_{EUR} - i_{USD}$	351	-0.021	0.003	-0.031	-0.024	-0.021	-0.019	-0.016
VIX	346	20.765	5.011	12.910	17.082	20.345	23.782	33.630
HKM	241	0.000	0.013	-0.041	-0.007	-0.000	0.008	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, the Amihud ratio of the EURC/USDC pair, and an index of gas fees. Macroeconomic characteristics include the daily VIX index, 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 2023 to 31 July 2023.

Table 3: Determinants of EURC-USDC peg deviations

	|EURC/USDC-EUR/USD| Peg Deviations						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
σ_{ETH}	0.032***	0.033***	0.034***	0.033***	0.034***	0.034***	
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	
GasFee		0.191***	0.194***	0.194***	0.186***	0.185***	
		(0.060)	(0.060)	(0.060)	(0.066)	(0.067)	
R_{ETH}			0.004	0.004	0.004	0.005	
			(0.004)	(0.004)	(0.004)	(0.004)	
$Amihud_{EURC/USDC}$				-0.001	-0.001	-0.001	
				(0.003)	(0.003)	(0.003)	
$i_{EUR} - i_{USD}$					0.014	0.019	
					(0.047)	(0.048)	
ΔVIX						0.003	
						(0.003)	
Intercept	0.001***	0.001**	0.001*	0.001*	0.001	0.001	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	
R-squared	0.051	0.078	0.081	0.082	0.082	0.083	
No. observations	351	351	351	351	351	343	

Note: This table presents the results of regressing absolute peg-price deviations on blockchain and traditional macroeconomic characteristics. Outcome variable is the absolute measure of deviations of Uniswap EURC/USDC from Reuters EUR/USD. Blockchain characteristics include the returns and volatility of Coinbase ETH/USD, the Amihud ratio of the EURC/USDC pair, and an index of gas fees. Macroeconomic characteristics include the daily VIX index, the interest rate differential between EUR and USD (1 month OIS). Total sample period is from 15 August 2022 to 6 April 2023 for columns (1) to (6). For column (7), sample period is from 15 August 2022 to March 31, 2023. 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 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	3656	0.005	0.010	0.000	0.001	0.002	0.005	0.087
Δ_2	3656	0.004	0.011	0.000	0.000	0.001	0.002	0.076
Δ_3	3656	0.006	0.011	0.000	0.001	0.002	0.006	0.094
gas fee (per 1 USD transaction)	3656	0.015	0.040	0.001	0.001	0.003	0.010	0.314
Panel (b): Transaction costs: gas fees+liquidity fees								
Δ_1 Arbitrage Bound Violation	3656	0.426	0.495	0.000	0.000	0.000	1.000	1.000
Δ_2 Arbitrage Bound Violation	3656	0.280	0.449	0.000	0.000	0.000	1.000	1.000
Δ_3 Arbitrage Bound Violation	3656	0.450	0.498	0.000	0.000	0.000	1.000	1.000
Panel (c): Transaction costs: gas fees+liquidity fees+slippage								
Δ_1 Arbitrage Bound Violation	3656	0.141	0.348	0.000	0.000	0.000	0.000	1.000
Δ_2 Arbitrage Bound Violation	3656	0.116	0.320	0.000	0.000	0.000	0.000	1.000
Δ_3 Arbitrage Bound Violation	3656	0.169	0.375	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 31 July 2023.

Table 5: 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. Total sample period is from 10 March 2022 to 12 March 2023.

Table 6: DEX and CLS Volume correlations

	V_{top10}	V_{PM}	V_{LP}	$V_{top10 \cap PM}$	$V_{top10 \cap LP}$	$V_{\notin top10,PM,LP}$
Interbank	2.7812***	0.0796***	0.1849**	0.3688***	0.0227	2.0239***
	(0.4607)	(0.0214)	(0.0774)	(0.0503)	(0.0220)	(0.3108)
Corporate-Bank	-3.4496	-0.0923	0.2034	0.0383	-0.2188	-2.0914
	(2.1489)	(0.2951)	(0.4337)	(0.5024)	(0.1944)	(3.1769)
Fund-Bank	-2.8586**	-0.0479	-0.2558	-0.1592	0.1135*	-2.4354***
	(1.2293)	(0.0646)	(0.1777)	(0.1405)	(0.0590)	(0.7315)
Non-Bank Financial-Bank	2.9610	0.6244	-0.1983	0.8526	-0.0221	12.5965
	(6.9340)	(0.5267)	(0.3386)	(1.2619)	(0.0537)	(15.4710)
constant	3431.4890***	143.2486**	361.5936**	66.2051	215.1407***	5810.6331***
	(971.4202)	(57.3306)	(160.9152)	(100.6616)	(82.1872)	(775.0637)
R-squared	0.0294	0.0055	0.0073	0.0301	0.0004	0.0305
R-squared Adj.	0.0289	0.0050	0.0068	0.0296	-0.0001	0.0300
No. observations	7629	7629	7629	7629	7629	7629

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 28 June 2023. 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 7: Determinants of EURC/USDC Illiquidity

	Panel (a): Amihud (DEX Return)		**Panel (b): Amihud (Reuters Return)**	
	(1)	(2)	(3)	(4)
CLS Volume All	-0.0040**		-0.0009***	
	(0.0016)		(0.0003)	
Interbank		-0.0048**		-0.0010***
		(0.0022)		(0.0003)
Corporate-Bank		0.1180		0.0003
		(0.0760)		(0.0015)
Fund-Bank		-0.0096		-0.0002
		(0.0095)		(0.0004)
Non-Bank Financial-Bank		-0.0784		0.0005
		(0.0528)		(0.0014)
constant	1.5934***	1.5954***	0.1121***	0.1128***
	(0.1902)	(0.1915)	(0.0320)	(0.0325)
R-squared	0.0207	0.0267	0.1198	0.1208
No. observations	318	318	273	273

Note: This table presents the results of regressing the Amihud ratio on measures of CLS volume. The Amihud ratio is defined as the absolute return per unit volume in the DEX EURC/USDC pool. We amplify Amihud (DEX Return) by 10^6 and amplify Amihud (Reuters Return) by 10^9. Panel (a) uses the DEX return and Panel (b) uses the Reuters return to calculate the Amihud ratio. CLS volume is measured in EUR Billions, and is aggregated as well as in the following sub-categories: Interbank, Corporate-Bank, Fund-Bank and Non-Bank Financial-Bank volume. Total sample period is from 15 August 2022 to 28 June 2023. 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 8: Determinants of EURC-USDC Returns and EUR-USD Returns

	Panel (a): DEX Return				**Panel (b): Reuters Return**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OF	4.516***	4.476***	4.365***	4.036***	3.964***	3.924***	3.709***	3.690***
	(0.171)	(0.171)	(0.182)	(0.213)	(0.193)	(0.194)	(0.204)	(0.256)
$\Delta i_{EUR} - i_{USD}$		0.537**	0.498*	0.538*		0.537*	0.476*	0.463
		(0.253)	(0.254)	(0.277)		(0.287)	(0.285)	(0.332)
ΔVIX			-0.009**	-0.003			-0.015***	-0.007
			(0.004)	(0.005)			(0.004)	(0.006)
HKM				4.885**				5.242*
				(2.267)				(2.724)
Intercept	0.008	0.007	0.007	0.013	0.010	0.009	0.009	0.020
	(0.016)	(0.016)	(0.016)	(0.021)	(0.018)	(0.018)	(0.018)	(0.025)
R-squared	0.668	0.672	0.673	0.704	0.548	0.552	0.561	0.595
No. observations	350	350	342	237	350	350	342	237

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 (millions USDC), and is sourced from Uniswap V3 trade data. EURC/USDC returns are calculated using Uniswap V3 prices. EUR/USD prices are sourced from Thomson Reuters Tick History. Macroeconomic characteristics include the daily (log) change in the VIX index, the interest rate differential between EUR and USD (1 month OIS), and a measure of dealer balance sheet constraints based on the intermediary capital risk factor in He et al. (2017). Spot returns of EURC/USDC and EUR/USD, interest rate and VIX (log) differences are measured in per cent. Total sample period is from 15 August 2022 to 31 July 2023. 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	ReutersReturn
OF_{top10}	4.4933***	1.1930***
	(0.3288)	(0.1651)
OF_{PM}	5.1283***	0.9557***
	(0.2884)	(0.2814)
OF_{LP}	4.6026***	0.7540***
	(0.3655)	(0.2204)
$\text{OF}_{top10\cap PM}$	4.8478***	1.9201***
	(0.2041)	(0.2779)
$\text{OF}_{top10\cap LP}$	3.9388***	0.2903
	(0.5648)	(0.3131)
$\text{OF}_{\notin top10,PM,LP}$	4.9100***	0.8862***
	(0.2692)	(0.1649)
$\text{ReutersReturn}_{t-1}$	0.0599***	
	(0.0136)	
DEXReturn_{t-1}		0.1352***
		(0.0263)
Intercept	-0.0008	0.0009
	(0.0006)	(0.0009)
R-squared	0.6831	0.1275
No. observations	8424	8424

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 Thomson Reuters Tick History. Spot returns of DEX EURC/USDC and EUR/USD are measured in per cent. Total sample period is from 15 August 2022 to 31 July 2023. 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 10: Determinants of EURC/USDC blockchain order flow

	$OF_{top10,t}$	$OF_{PM,t}$	$OF_{LP,t}$	$OF_{top10\cap PM,t}$	$OF_{top10\cap LP,t}$	$OF_{\notin top10,PM,LP,t}$
$P_{DEX,t-1} - P_{Reuters,t-1}$	-0.3328***	-0.0007	-0.0361	-0.1508***	0.0007	-0.2759***
	(0.0841)	(0.0069)	(0.0293)	(0.0328)	(0.0125)	(0.0848)
DEXReturn$_{t-1}$	-0.0150***	0.0003	0.0011	-0.0010	0.0002	-0.0020
	(0.0051)	(0.0006)	(0.0015)	(0.0010)	(0.0008)	(0.0041)
$OF_{top10,t-1}$	0.2336***					
	(0.0612)					
$OF_{PM,t-1}$		0.0075				
		(0.0093)				
$OF_{LP,t-1}$			0.0147			
			(0.0145)			
$OF_{top10\cap PM,t}$				0.0675**		
				(0.0305)		
$OF_{top10\cap LP,t}$					-0.1072	
					(0.2209)	
$OF_{\notin top10,PM,LP,t}$						0.1686**
						(0.0681)
Intercept	-0.0003	0.0000	0.0003***	-0.0000	-0.0000	0.0009***
	(0.0002)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
R-squared	0.0587	0.0001	0.0007	0.0095	0.0115	0.0290
No. observations	8423	8423	8423	8423	8423	8423

Note: This table presents the results of regressing blockchain order flow on the price difference between the DEX and Reuters exchange rates. OF is measuring the net buyer transactions of purchasing EURC, and is sourced from Uniswap V3 trade data. $P_{uniswap} - P_{reuters}$ measures the price difference between the Uniswap and Reuters rate. blockchain order flow is divided into the following sub-categories: sophisticated traders (top 10 wallets), primary dealers, and LPs. EURC/USDC returns are calculated using Uniswap V3 prices. EUR/USD prices are sourced from Thomson Reuters Tick History. Total sample period is from 15 August 2022 to 31 July 2023. 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: Primary Market Issuance

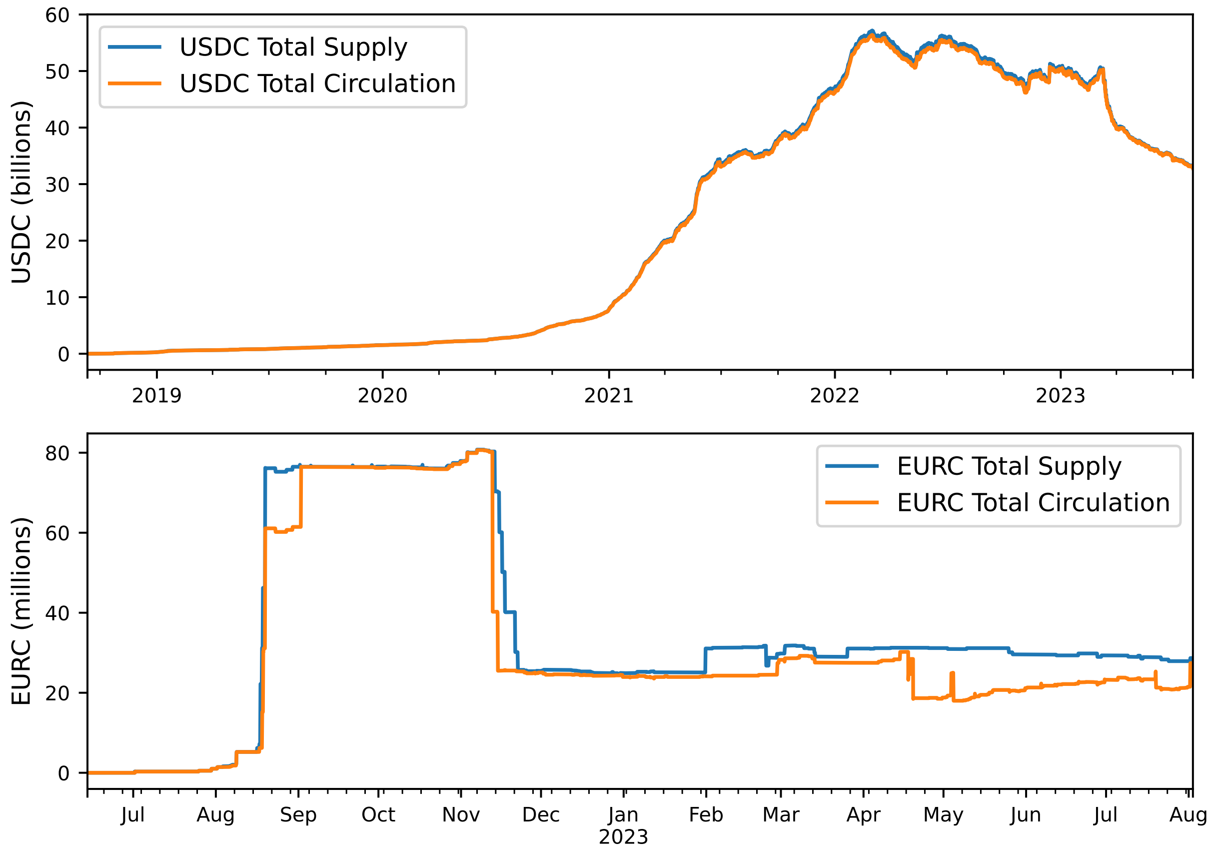
We obtain data on the primary market issuance from the Ethereum blockchain API. The primary market issuance uses a Circle Treasury address of the EURC and USDC Treasury. This dataset provides an entire history of Treasury transactions, with details on the size, timestamp, and the type of transaction. 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.[24] The supply of USDC and EURC is shown in Figure A1. 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.[25]

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.

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

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

Figure A1: Primary Market Issuance

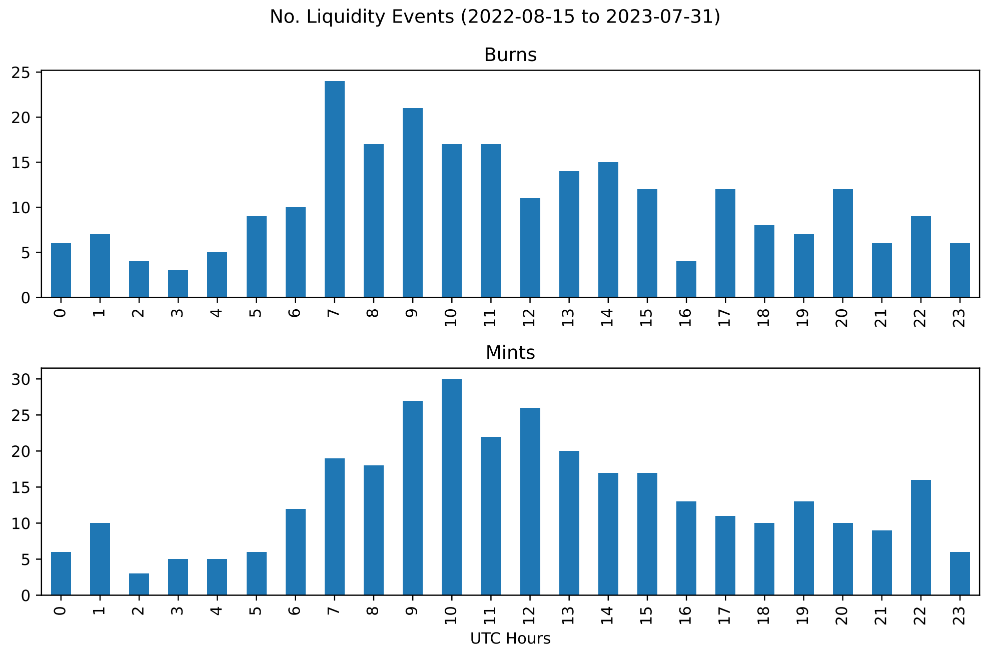


Note: This figure plots the total supply of USDC and EURC, as well as the total in circulation (net of Treasury). The top panel reports the total supply of USDC, and the bottom panel reports the total supply of EURC. The total sample period for the top two figures is from 28 June 2022, to 31 July 2023. 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.

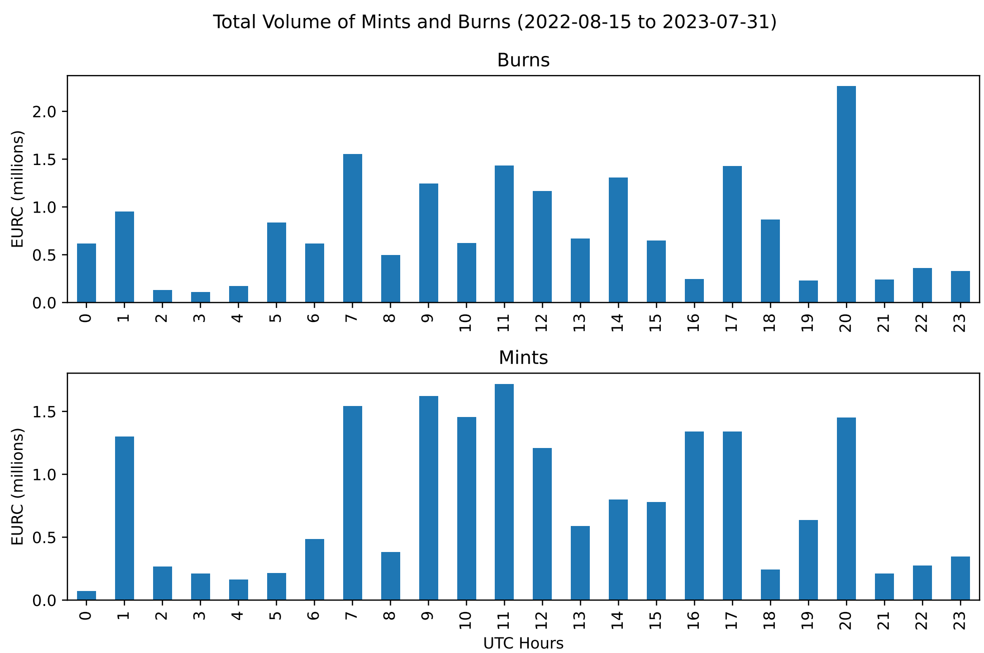
Appendix B: Liquidity Providers- intra-day patterns

Figure A2: 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 31 July 2023.

Appendix C: Heterogeneity in price impact: blockchain characteristics

In this section we examine heterogeneity in price impact based on blockchain characteristics at the wallet level, such as age, the number of tokens transferred and the frequency of transactions per day. We run the regression specification outlined in equation (14). For each blockchain characteristic, $i \in \{Age, N_{Tokens}, Transaction/day\}$ we disaggregate our measure of blockchain order flow into three sub-groupings. blockchain order flow based on wallets in the first quartile (0-25th percentile), the inter-quartile range (25th-75th percentile), and the last quartile (75-100th percentile).

$$p_t - p_{t-1} = \alpha + \beta_1 OF_{0-25,i,t} + \beta_2 OF_{25-75,i,t} + \beta_3 OF_{75-100,i,t} \epsilon_t \tag{14}$$

We present the results of the baseline specification in Table A1. Columns (1) through to (3) use DEX returns (log price change of the EURC/USDC), and columns (4) to (6) use Reuters returns (log price change of EUR/USD). In column (1), the blockchain order flow conditioned on age shows a monotonic change in the price impact for DEX returns with the highest price impact in the 0-25th percentiles. However, for Reuters returns in column (2), the maximum price impact occurs for wallets in the 25th to 75th percentile of age. When we disaggregate blockchain order flow by the number of tokens transferred by the wallet, as shown in columns (2) and (5), the highest price impact of blockchain order flow occurs for wallets in the 25th to 75th percentile. When measuring blockchain order flow based on frequency of transactions: the 25th to 75th percentile of blockchain order flow has the largest price impact for DEX returns, however it has the smallest price impact when using Reuters return. In both cases the price impact of the 0-25th and 75-100th percentiles are quantitatively similar.

To rationalize why blockchain characteristics do not matter, we find they are not a very robust predictor of our trader types: sophisticated traders, primary dealers and LPs. Table A2 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 three different sets of wallets: Panel (a) reports sophisticated traders. We find the age and number of tokens are not substantially different to other wallets. The average age of sophisticated traders is slightly lower, and they have a higher frequency of transactions on average, but the median sophisticated trader is still transacting 0.68 a day, versus 0.28 transactions a day for other wallets. Panel (b) reports wallets that have primary dealers. We find that primary dealers have a very similar number of tokens transferred on average, have a smaller age and have a similar average frequency of transactions, with the median increasing to 0.63 per day as opposed to 0.28 per day for wallets with no primary market access. Panel (c) reports wallets that are LPs. We find that traders who also provide liquidity provision are younger wallets, transfer less tokens and have a very small frequency of transactions per day on average. However, when examining the median tokens transferred and frequency of transactions, we find it is higher for LPs. In sum, there is a weak correlation between our blockchain characteristics and our trader types. This can help explain why we do not observe a clear pattern of price impact when disaggregating blockchain order flow by these blockchain characteristics.

Table A1: Price impact: variation across blockchain characteristics

	Panel (a): DEX Return			Panel (b): Reuters Return		
	(1)	(2)	(3)	(4)	(5)	(6)
OF-Bottom25 [Age (days)]	4.7091***			0.9964***		
	(0.2360)			(0.1648)		
OF-Middle50 [Age (days)]	4.5534***			1.1996***		
	(0.2708)			(0.1545)		
OF-Top25 [Age (days)]	4.5030***			0.9389***		
	(0.3037)			(0.1685)		
OF-Bottom25 [Number of Tokens Transferred]		4.6275***			1.0287***	
		(0.2519)			(0.1680)	
OF-Middle50 [Number of Tokens Transferred]		4.7599***			1.1480***	
		(0.2708)			(0.1762)	
OF-Top25 [Number of Tokens Transferred]		4.4779***			1.0383***	
		(0.2845)			(0.1587)	
OF-Bottom25 [Frequency (transactions per day)]			4.5779***			1.0966***
			(0.2875)			(0.1579)
OF-Middle50 [Frequency (transactions per day)]			4.6814***			0.8054***
			(0.2812)			(0.1568)
OF-Top25 [Frequency (transactions per day)]			4.5290***			1.1565***
			(0.2678)			(0.1522)
Reuters Return	0.0663***	0.0644***	0.0677***			
	(0.0140)	(0.0142)	(0.0140)			
DEX Return				0.1415***	0.1383***	0.1442***
				(0.0254)	(0.0258)	(0.0251)
constant	-0.0005	-0.0008	-0.0008	0.0005	0.0004	0.0009
	(0.0007)	(0.0006)	(0.0006)	(0.0009)	(0.0009)	(0.0009)
R-squared	0.6611	0.6622	0.6610	0.1184	0.1165	0.1203
No. observations	8424	8424	8424	8424	8424	8424

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 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). blockchain 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 Thomson Reuters Tick History. Total sample period is from 15 August 2022 to 31 July 2023. 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 A2: Blockchain characteristics by address type

Panel (a): Sophisticated traders

	count	mean	std	min	0.25	0.50	0.75	max
Age (days)	51	559.96	318.43	28.00	336.50	478.00	716.00	1459.00
Number of Tokens Transferred	51	41.12	59.89	1.00	7.50	13.00	45.00	262.00
Frequency (transactions per day)	51	8.79	32.43	0.01	0.04	0.21	1.93	208.42

Panel (b): Primary dealers

	count	mean	std	min	0.25	0.50	0.75	max
Age (days)	34	492.68	358.48	37.00	239.75	383.50	630.25	1639.00
Number of Tokens Transferred	34	48.21	107.65	2.00	4.50	16.50	37.00	531.00
Frequency (transactions per day)	34	2.29	4.32	0.02	0.18	0.59	2.24	21.25

Panel (c): LPs

	count	mean	std	min	0.25	0.50	0.75	max
Age (days)	83	695.17	445.41	3.00	346.00	552.00	891.50	2222.00
Number of Tokens Transferred	83	38.16	43.28	2.00	13.00	23.00	41.00	241.00
Frequency (transactions per day)	83	0.77	1.34	0.02	0.18	0.33	0.68	8.00

Panel (d): Sophisticated traders and primary dealers

	count	mean	std	min	0.25	0.50	0.75	max
Age (days)	4	281.25	169.17	102.00	197.25	258.00	342.00	507.00
Number of Tokens Transferred	4	17.25	4.65	13.00	13.75	16.50	20.00	23.00
Frequency (transactions per day)	4	4.34	3.11	0.63	3.29	4.24	5.29	8.23

Panel (e): Sophisticated traders and LPs

	count	mean	std	min	0.25	0.50	0.75	max
Age (days)	5	448.80	410.69	67.00	91.00	449.00	566.00	1071.00
Number of Tokens Transferred	5	190.40	326.51	9.00	17.00	23.00	136.00	767.00
Frequency (transactions per day)	5	10.41	21.85	0.23	0.48	0.73	1.13	49.49

Panel (f): Not sophisticated traders, primary dealers and LPs

	count	mean	std	min	0.25	0.50	0.75	max
Age (days)	1548	558.27	466.56	0.00	250.00	387.00	764.25	2560.00
Number of Tokens Transferred	1548	55.76	238.24	1.00	4.00	11.00	36.00	5680.00
Frequency (transactions per day)	1548	1.75	7.41	0.00	0.10	0.27	1.00	146.68

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 6 trading groups, which are sophisticated traders, primary dealers, LPs, the intersection of sophisticated traders and primary dealers, the intersection of sophisticated traders and LPs, and traders that do not belong to the three groups ($\notin top10, PM, LP$). Total sample period is from 15 August 2022 to 31 July 2023.