# From CeFi to DeFi: What Do Investors (Mis)Trust?


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**Abstract**

A prevailing narrative of the rise of Bitcoin and decentralized finance (DeFi) is that they provide a "self-custody" solution to mitigate the misappropriation problem in the "institution-custody" model of centralized financial services (CeFi). The bankruptcy of the leading cryptocurrency exchange FTX severely impacted the trust of global cryptocurrency investors in centralized exchanges. Countering the prevailing narrative, our research on this trust failure reveals that users did not subsequently adopt decentralized alternatives. Instead, they chose seemingly more reliable centralized exchanges based on their size and level of disclosure. The lack of migration is due to a limited understanding of DeFi. When users are informed about DeFi's features, 30 percent more users will migrate to DeFi. This study reveals the importance of popularizing knowledge about decentralization and strengthening the regulation of centralized financial institutions.



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## 1. Introduction

Centralized finance (CeFi) institutions, such as banks, insurance companies, and mutual funds, often inadvertently grant excessive power to a small group of individuals. Therefore, the underlying requirement for using a CeFi service is to trust some unknown individuals to have both good faith and the necessary capability. In contrast, decentralized finance (DeFi) systems, such as Bitcoin, operate on transparent code, so they instead require users' trust in the software and the underlying distributed system (Harvey et al. 2021; Capponi, Kaplan, and Sarkar 2022; Ding, Lin, and You 2023). The 2008 Global Financial Crisis (GFC) highlighted the vulnerability of trust in CeFi and created a prevalent narrative that the rise of Bitcoin and DeFi was significantly fueled by a growing awareness of the value of "trustless"[1] systems in the wake of the 2008 financial collapse.

DeFi, such as Bitcoin and decentralized exchanges, has experienced rapid growth in recent years. The NYSE stock trading volume was approximately US$6 trillion in September 2025, while the decentralized exchange had a volume of US$390 billion, equivalent to 6.5% of the NYSE's volume. A key debate has emerged: **will DeFi eventually replace CeFi**, such as commercial banks, insurance companies, and stock exchanges? To address this question, it is crucial to understand the motivations behind users adopting DeFi.

In this paper, we examine a narrative widely promoted by blockchain practitioners, which suggests that users are shifting to "self-custody" DeFi due to distrust in CeFi's capabilities in safeguarding customers' assets. We provide a causal interpretation by studying a scenario involving comparable CeFi and DeFi substitutes (i.e., centralized vs decentralized cryptocurrency exchanges) under an exogenous trust shock specifically targeting centralized cryptocurrency exchanges. By analyzing blockchain

[1] "Trustless" in this sentence refers to a common promotional term for DeFi, rather than the author's claim. DeFi is not trustless because it relies on trust in the code, the economic design, the blockchain ecosystem, and the investors themselves.

activity, we examine whether affected users migrate from CeFi to DeFi and gain insights into the motivations of users who stay, switch platforms, or exit the market.

Counterintuitively, the most well-known cryptocurrency exchanges, such as Binance, Coinbase, and Kraken, are centralized financial institutions (hereafter referred to as "centralized exchanges" or "CEXs"). A CEX has centralized control over its operations. Users must transfer their assets to the CEX before trading (so that they lose control of their assets), and in trading, the exchange determines trade outcomes. Several scandals and controversies have been documented due to this centralized control, including wash trading (Cong, Li, et al. 2023; Amiram, Lyandres, and Rabetti 2025) and market manipulation (Griffin and Shams 2020). In contrast, decentralized exchanges (hereafter, "DEXs") operate through immutable programs and distributed ledgers (John, Kogan, and Saleh 2023; Lehar and Parlour 2025). Users always retain control of their assets on a DEX, and trade outcomes are governed by transparent, immutable code. CEXs require users to trust the institution's human beings to securely custody assets and process orders fairly, whereas DEXs require users to trust in code and algorithms.

Today, the functionality of CEXs and DEXs is largely comparable, including features such as leverage and derivatives, and the transaction fees for the most popular trading pairs are similar and low. However, most traders prefer to trade on CEXs, as they are similar to stock brokerage platforms. In contrast, trading on a DEX requires traders to learn how to manage a blockchain wallet first. That partially explains why the most famous cryptocurrency exchanges are CEXs. Even after several recent risk incidents, such as Bitget's assets being hacked in February 2025 and Binance's exchange outage, which caused the USDe stablecoin depeg in October 2025, the dominance of CEXs remains remarkably stable. As of the end of June 2025, the top three CEXs process approximately $8 billion per day, while the top three DEXs process around $0.6 billion per day.

In this study, we study the collapse of the FTX cryptocurrency exchange in November 2022. FTX once ranked among the top three CEXs globally. However, it faced a sudden downfall after its founding team misappropriated $9 billion in customer assets for risky investments and failed to recover the losses. This triggered a banking-style run in November 2022, delivering a significant trust shock to the cryptocurrency industry. The collapse revealed a startling lack of internal controls and a reliance on trust in specific individuals at such a major CEX, catching the industry off guard. Even professional investors, such as Singapore's Temasek, incurred substantial losses, with $275 million wiped out from their investment in FTX (Dugar, Ngui, and Ngui 2023). The DeFi industry predicts that users will become aware of CeFi's problems and DeFi's value, leading to an increase in DeFi service adoption, as evidenced by the positive market reaction to DEX tokens and negative reaction to CEX tokens following the FTX collapse.

Our empirical questions are: Do CEX users actually shift to DEX if they become aware of the severe trust defects in the CeFi model? If they do not migrate to DEX, what is the reason? We manually collect 1,114 CEX wallet addresses and identify 32 million wallet addresses from the Ethereum blockchain that have interacted with CEXs.[2] Since each user may possess multiple wallets, we utilize a unique feature of the CEX business model to cluster the 32 million wallets into 8 million unique users. We then further identify whether a user interacts with CEX or DEX each month, and the intensity of such interaction, to proxy for the usage of CeFi and DeFi. Among these 8 million users, we classify those with more than 50% of their assets allocated in CEX at the time of the FTX collapse as the treatment group, while others form the control group. The rationale is to use portfolio exposure in CEX as a proxy for exposure to trust

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[2] We focus our analysis on Ethereum because, at the time of the FTX collapse, Ethereum was the main blockchain for DEX trading. For example, on November 10, 2022, Ethereum had a US$9 billion DEX trading volume, while BSC and Polygon, in second and third place, had US$0.7 and US$0.6 billion, respectively. Therefore, we consider that capturing activities on Ethereum should be enough to understand users' migration shortly after the FTX collapse.

shocks in CeFi. We exclude FTX users to isolate the impact of wealth loss from the effect of awareness of trust defects. We match treatment and control group users one-to-one to enhance comparability between the two groups.

Our findings highlight several key patterns in user responses. Through a difference-in-differences (DiD) analysis, we find that while CEX users initially reduced their transaction activity by 22.6% immediately after the collapse, most returned to CEXs within three months. However, their engagement with DEX declined by approximately 20% compared with the control group, suggesting a persistent reluctance to view decentralized alternatives as viable substitutes. This finding contradicts practitioners' belief in migrating to DEX after the CEX trust crisis. Instead, users either reallocate within the centralized ecosystem or exit the market entirely.

A potential explanation for the missing migration is information friction, i.e., users may not be aware of DEX as a viable alternative. To verify this conjecture, we further explore the role of prior DeFi experience in adjusting FTX's treatment effect. CEX users who are ex ante familiar with DeFi were more likely to increase their DEX activity by 0.05 transactions per month and increase their self-custody asset share by 1.32 percentage points following the collapse, reflecting a greater appreciation for decentralized systems. By contrast, users without prior DeFi exposure demonstrated behavioral inertia, sticking to CEX even when faced with governance failures in CEX.

To further confirm the causality of this information friction explanation, we conduct a survey experiment to explicitly solicit users' responses and rationales under a controlled environment. Our survey confirms the above conjecture. We provide two alternative information to treatment groups: (1) the reason for the FTX collapse and (2) DEX features (both good and bad). Results show that learning about the reason for the FTX collapse does not significantly change users' choices, whereas understanding the features of DEX substantially increases its adoption by 31.7 percentage points. We also find that a one-standard-deviation increase in perceived switching costs weakens the effect of DEX information provision by 10 percentage points, indicating switching costs could be another important factor limiting DeFi adoption. These findings suggest that the key barrier to decentralization lies in limited DeFi literacy.

We also investigate how CEX users reallocate their assets within CEXs. The FTX collapse did not trigger a wholesale rejection of the centralized model, as the DeFi narrative might have predicted. Instead, it prompted a reallocation of trust within the CeFi ecosystem. Our on-chain analysis reveals that investors demonstrated a clear mistrust of smaller platforms; users of small CEXs reduced their probability of transacting on them by 4.91 percentage points. However, they misplaced their trust in fragile and potentially misleading signals of security. For instance, they shifted activity toward larger platforms, with top-ranked exchanges gaining 0.89 percentage points in market share after the collapse. Similarly, they rewarded partial transparency, as transaction volume on CEXs that published proof-of-reserves increased by 0.33 transactions per user, while it fell by 0.59 transactions on non-disclosing platforms. This is a critical form of mistrust: investors correctly identified a risk but rely on problematic signals, as (1) size does not guarantee good governance—FTX used to be the second-largest—and (2) disclosure of assets alone does not guarantee positive equity.

Together, our results provide a nuanced understanding of what investors trust (or mistrust) in the wake of institutional failure. This behavior reveals the core issue: most cryptocurrency investors are not yet at the stage of consciously choosing between CeFi and DeFi. Rather, due to a limited DeFi literacy, they are confined to evaluating CeFi on its own flawed terms, mistaking superficial traits for genuine trustworthiness. Our findings show that once this information gap is closed and individuals are educated about the structural guarantees of DeFi, a future CeFi trust crisis is likely to trigger a more substantial and meaningful migration toward truly decentralized alternatives, shifting the basis of trust from institutions to code.

This study contributes to the literature by trying to understand the adoption of DeFi (e.g., Harvey and Rabetti 2024). While prior work emphasizes roles of blockchain's

***economic design*** (Budish 2025; Hinzen, John, and Saleh 2022; Cong, Hui, et al. 2023), or users' ***trust*** (Harvey et al. 2021; Saengchote, Putniņš, and Samphantharak 2023; Okat, Paaso, and Pursiainen 2025), we provide empirical evidence that ***information friction*** is the primary impediment. We are among the first to empirically demonstrate the failure to adopt DeFi, even among seasoned cryptocurrency investors. Our on-chain analyses and survey experiment underscore that a lack of understanding of DeFi—not a lack of trust—is the critical and first-order barrier.

This study also contributes to the literature on investor trust in financial intermediaries (Thakor and Merton 2024; Hayes, Jiang, and Pan 2021). Trust is a cornerstone of incumbent financial systems, and its erosion can lead to severe disruptions, from bank runs to broader market collapses (Bottazzi, Da Rin, and Hellmann 2016; Hagendorff, Lim, and Nguyen 2023; Bhagwat and Liu 2020; Pursiainen 2022). Much of the existing literature documents how major shocks can lead to a general decline in trust and alter investors' choices of financial services (Gurun, Stoffman, and Yonker 2018; Yang 2025) ***within*** the CeFi system, or ***within*** the DeFi system (Liu, Makarov, and Schoar 2023; Appel et al. 2025). The substitution between CeFi and DeFi presents a new challenge that remains to be fully understood. If a major CeFi shock indeed triggers a huge outflow to the DeFi system, then the systemic risk of the financial system should be re-evaluated. Our study is among the earliest few studies (e.g., Kogan et al. 2024) to evaluate connection and migration dynamics between CeFi and DeFi systems.

More broadly, this study contributes to the literature on governance. Existing governance literature examines how centralized governance (e.g., companies, CEXs) and external governance (e.g., regulation, mergers and acquisitions, media) operate. Decentralized governance as a new model has been theoretically studied (Yermack 2017; Goldstein, Gupta, and Sverchkov 2024; Abadi and Brunnermeier 2024; Amoussou-Guenou et al. 2024; Appel and Grennan 2023; Cao, Cong, and Yang 2025). This paper empirically demonstrates that certain concepts of decentralized internal governance, such as self-custody and smart contracts, are emerging and gaining popularity, and may potentially become a valid challenger to existing governance models in the future. It contributes to the rising literature on empirical understanding towards decentralized governance (Cong et al. 2025; Fan, Shu, and Xie 2025).

The rest of the paper is organized as follows: Section 2 provides the necessary institutional background to understand the empirical setting of this study. Section 3 introduces the research methodology and data we used. Sections 4 and 5 are user-level on-chain and survey experiment analyses, respectively. We supplement exchange-level analyses in Section 6. In Section 7, we yield our conclusions and policy implications.

## 2. Institutional Background

### 2.1. Centralized and decentralized exchanges

Centralized Exchanges (CEXs) and Decentralized Exchanges (DEXs) represent two fundamentally different institutional arrangements for trading digital assets, distinguished primarily by their approach to custody, governance, and trade execution. The core distinction lies in the locus of trust. CEXs, such as Binance and Coinbase, operate as traditional financial intermediaries. They are custodial platforms that require users to deposit funds into exchange-controlled wallets, thereby demanding trust in the institution to act as a faithful and competent custodian. In contrast, DEXs, such as Uniswap and Curve, are non-custodial protocols built on public blockchains. Users trade directly from their personal wallets, retaining full control of their private keys and replacing trust in an intermediary with trust in verifiable, open-source code.

These foundational differences in trust models manifest in their operational architecture. CEXs typically utilize a private, off-chain order book system, whereas DEXs operate transparently on-chain, most often using an Automated Market Maker (AMM) model (Adams et al. 2021; Lehar and Parlour 2025). This architectural choice reflects their core philosophies: CEXs are private corporations with opaque internal decision-making, while DEXs are often governed by transparent protocols where transactions and governance decisions are recorded on a public, immutable ledger.

For the ordinary trader, the once-significant gaps in market quality and asset availability between these two models have substantially converged. In terms of market quality, leading DEXs now offer liquidity, slippage, and transaction costs that are highly comparable to CEXs for the most commonly traded assets, especially with the widespread adoption of Layer-2 scaling solutions that mitigate high network fees. CEXs typically charge a percentage-based trading fee (e.g., 0.1%–0.2%), which can be reduced for high-volume traders. DEX trading fees are often comparable (e.g., 0.05%–0.3% on Uniswap). The high-volume, reputable tokens that constitute the majority of trading activity are now readily available on both types of platforms.

With these functional aspects becoming increasingly similar, the primary distinction for users is now starkly focused on the trust model, rather than fees or liquidity. CEXs offer a curated, user-friendly environment but introduce custodial and institutional risks, such as the potential for mismanagement, censorship, or internal corruption. DEXs, conversely, significantly reduce this institutional risk but place the full responsibility for security and due diligence on the user, as well as requiring trust in the blockchain ecosystem and DEX smart contract codes. Therefore, the decision hinges on a fundamental question: whether to place trust in an opaque institution or in transparent, verifiable code and one's own vigilance. This evolving dynamic is central to understanding user behavior in response to crises of trust within the digital asset ecosystem.

### 2.2. FTX collapse

The structural difference between CeFi and DeFi extends beyond institutional design—it directly shapes how users perceive and manage trust. In centralized finance, particularly in CEX-based ecosystems, users must transfer their assets to the platform before engaging in any trading activity. This separation of ownership and control creates a fundamental vulnerability: the platform gains unrestricted access to customer funds, often without real-time public oversight.

The collapse of FTX in late 2022 served as a defining moment that brought this risk into full view. Once the second- or third-largest centralized cryptocurrency exchange in the world, FTX fell apart when it was revealed that the founding team had misappropriated over $9 billion in customer deposits for speculative investments. This incident echoed the failures of traditional financial institutions such as Lehman Brothers and Silicon Valley Bank, in which centralized control, opacity, and moral hazard played central roles. In all such cases, the failure was not technological but institutional: intermediaries acted without adequate accountability, resulting in irreversible losses for customers who had entrusted them with the custody of their assets.

DeFi emerged precisely as a response to this problem. By removing intermediaries and replacing them with code, DeFi protocols offer a structural guarantee that users retain control over their assets at all times. In the case of decentralized exchanges, trading occurs through smart contracts that ensure atomic execution: users send a fixed amount of token A and immediately receive a corresponding amount of token B, based on a pre-defined pricing rule. There is no period during which the platform holds custody of funds, and transactions are either fully completed or not executed at all. This design removes the need to trust an institution and instead shifts reliance to open-source, verifiable logic embedded in the protocol itself.

The core mechanism enabling this is the Automated Market Maker (AMM), most notably implemented in protocols such as Uniswap (Lehar and Parlour 2025). Unlike traditional order books, where prices are determined by matching buy and sell orders, AMMs use a mathematical pricing function—typically the constant product formula $A \times B = K$, where $A$ and $B$ are the quantities of two tokens in a liquidity pool, and $K$ is a constant. When a user trades, the relative proportions of the tokens in the pool change, thereby adjusting the price of the tokens. This approach requires only two balance variables to be stored and updated, significantly reducing the infrastructure and storage demands compared to CeFi order books, which must continuously update thousands of limit orders even when no trades occur.

Following the collapse of FTX, the cryptocurrency industry grew optimistic about the growth prospects for DeFi. This optimism was rooted in the appeal of self-custody, a core tenet of DeFi that stood in stark contrast to the failures of centralized custodianship. Initial market reactions seemed to validate this sentiment, as evidenced by the strong positive returns of tokens related to DEXs, as shown in Figure 1. Concurrently, the market also correctly predicted that top CEXs, such as Binance and Kraken, would absorb a significant portion of FTX's user base. However, the anticipated boom in DEX adoption failed to materialize. Despite the token price rally, the market share of DEXs, measured by daily trading volume, remained stable at approximately 10%. This stagnation persisted until an external catalyst emerged in 2025, when President Trump's strong promotion of cryptocurrency gained traction.

This paper, therefore, investigates the underlying reasons why the predicted mass migration of users from CEXs to DEXs did not occur in the immediate aftermath of the FTX event.

## 3. Methodology and Data

### 3.1. Research design

Our core research question is whether the collapse of FTX—a major centralized exchange—led to a loss of trust in centralized governance mechanisms among cryptocurrency users, and whether a decentralized governance model emerged as a preferred alternative in its aftermath. To comprehensively address this question, we combine both user-level and exchange-level analyses. We primarily rely on an event study of on-chain data to empirically test changes in users' behavior, and supplement this with a survey experiment to pinpoint the underlying economic mechanisms.

For the event study, since FTX users are directly shocked, they are exposed to many confounding factors, including collective actions and litigation. Additionally, FTX's users may be endogenously selected by FTX. Therefore, we focus on the comparison between users in other CEXs and their control group to examine the effects of CEX trust shock cleanly.

We categorize Ethereum users based on their exposure to centralized exchanges as of October 2022. Specifically, users with a balance of more than US$100 at CEX and who have allocated over 50% of their overall token assets to CEX are classified as CEX Users. We exclude those users with 50% of their assets in FTX for the reasons stated above. In contrast, *Non CEX Users* are those who do not meet either condition above, i.e., they either have less than US$100 of their assets on CEX or less than 50% of their assets on CEX. The idea is that *Non CEX Users* should have less trust shock exposure to the collapse of FTX than CEX Users due to their less skin in the game.

However, it is intuitive that these two groups differ in their trust in CEX fundamentally because they make different choices when allocating their assets. To obtain a more comparable treatment and control group, we match users based on several pre-event characteristics. These include the combined value of each user's on-chain and exchange balances as of October 2022, $Ln(Total\ Balance)$, to control for the investor's wealth level; the number of days since the user's first on-chain transaction ($Tenure$) and the cumulative number of on-chain transactions up to October 2022, $Ln(Num\ Transactions)$, to account for the investor's experience, and the average monthly on-chain balance before November 2022, $Ln(Onchain\ Balance)$, to control for investors' awareness of self-custodian. To control for their experiences of using DeFi and CEX, we also include two dummy indicators for whether the user had interacted with DeFi protocols, $DeFi\ (dummy)$, or centralized exchanges, $CEX\ (dummy)$, prior to the FTX collapse. All continuous variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers. To enhance coefficient readability, dummy indicators are rescaled by multiplying by 100.[3]

[3] This scaling is consistently applied to all continuous and dummy variables throughout the remainder of the analysis.

As shown in Appendix B, although the propensity scores of *CEX User* and *Non CEX User* are indeed clustered at different ranges, they still share a certain overlap. These users have similar trading patterns and asset holdings, but differ in their CEX exposure at the time of the FTX collapse. We focus on the comparison between these matched *CEX Users* and *Non CEX Users* using a difference-in-differences (DID) framework:

$$Y_{it} = \alpha_i + \beta_1 Treat_i * Post_t + \beta_2 Controls_{it} + \mu_i + \gamma_t + \varepsilon_{it}$$

In this specification, the dependent variable captures the user's interaction with DeFi or CEX protocols in month t, measured alternatively by the number of transactions or a dummy variable indicating whether the user conducted at least one transaction. $Treat_i$ indicates whether the user $i$ belongs to the treatment group (i.e., CEX User), and $Post_t$ is a post-event indicator equal to 1 for months after October 2022. Control variables include user-level time-varying controls, specifically monthly on-chain balances, exchange balances, and total transaction counts. We also include user and month fixed effects. This control structure is consistently applied across all subsequent analyses.

The design of survey experiments and exchange-level analyses will be introduced in the following sections.

### 3.2. Data sources

Our analysis relies primarily on two layers of data: user-level transaction data and exchange-level volume data. This dual-layered data architecture enables us to systematically link aggregate-level exchange outcomes with micro-level user behaviors, allowing for a comprehensive empirical investigation of our research questions on the dynamics of centralized and decentralized trading activity.

For user-level transaction data, we rely on comprehensive records from Etherscan. We begin by manually compiling a list of CEX wallet addresses based on information from Etherscan, CoinMarketCap, and CoinCarp. This process yields 1,114 CEX wallet addresses. We then collect all transactions from these CEX addresses and their users, yielding more than 2.5 billion transaction records and over 32 million unique wallet addresses in total. Throughout this process, we extract complete transaction-level information, including token type, transferred amount, transaction parties, and wallet balances. This granular dataset allows us to construct a detailed view of user activity on the Ethereum blockchain.

For exchange-level data, we collect monthly information for the top 30 CEXs as ranked in October 2022 from CoinMarketCap. The dataset includes metrics such as total trading volume, market share, monthly rankings, number of listed assets, and whether this exchange discloses its asset reserve. To further capture visibility and credibility of each exchange, we complement this with monthly measures of their popularity and development activity (i.e., Cointelegraph Top 100 mentions, GitHub star counts, and Twitter follower statistics).

### 3.3. Aggregate accounts to users

Since a blockchain user can create as many addresses as they want, if analyzed at the address level, the user's behaviors are segmented into different addresses. To identify and aggregate multiple blockchain addresses into users, we follow the heuristic-based approach introduced by Victor (2020) and implement a recursive clustering algorithm that maps wallet addresses to inferred users. Furthermore, implement a recursive clustering algorithm that maps wallet addresses to inferred users. The institutional background is visualized in Figure 2.

There are four types of addresses related to our research:

(1) Exchange addresses refer to the publicly known wallets controlled by centralized exchanges. CEXs typically use these addresses for internal fund management, liquidity provisioning, and withdrawals.

(2) Deposit addresses are intermediary wallets that receive inflows from user accounts and forward those funds to CEX addresses. In almost all CEX architectures, each deposit address is uniquely assigned to an individual user. The rationale for having this architecture is that there is difficulty in associating blockchain transactions with CEX user accounts. When a blockchain user transfers some funds to a CEX address, everyone can claim this transfer belongs to them. CEXs invented a so-called deposit address, which every CEX user has. All funds transferred to this deposit address will be treated as this CEX user's funds, which enables CEX to keep track of each user's endowment. Therefore, deposit addresses serve as a crucial link between blockchain users and CEX users.

(3) Individual end users typically control user addresses. These addresses can initiate transactions to deposit addresses when transferring funds into exchanges. Still, they may also receive withdrawals directly from exchange addresses or interact with other user addresses or smart contract addresses.

(4) Smart contract addresses are those addresses that host and operate smart contract codes. When a user attempts to execute a trade with a DEX, they will invoke a "swap" function in the corresponding smart contract to complete the trade. This trade appears as a single blockchain transaction record, typically associated with an inflow of one token and an outflow of another token. Multiple types of smart contracts serve different purposes. We introduce how we identify which transaction records are DeFi activities in subsection 3.4.

We then conduct a three-round crawling procedure to obtain a comprehensive list of transactions related to our research. The first round gathers all addresses that have transactions with known exchange wallets to get deposit addresses. The second round identifies addresses interacting with those deposit addresses to get user addresses. The third round collects transaction partners of the previously identified user addresses. This iterative approach enables us to capture a comprehensive and interconnected map of wallet activity, ultimately covering over 32 million unique wallet addresses.

Then, we use a union-find algorithm to cluster accounts into users. The idea is visualized in Figure 2, while the technical details are explained in Appendix C. Following this process, we can identify a total of over 8 million users. This implies that most users hold only a limited number of on-chain wallets, which is consistent with our subsequent survey experiment findings and supports the validity of our identification approach. Due to computational constraints associated with processing large-scale on-chain data, we are unable to include the entire user set in our downstream analysis. To address this, we conduct a series of robustness checks and confirm that randomly sampling a subset of users does not meaningfully affect the distribution of key outcome variables or the validity of our identification strategy. Accordingly, for tractability, we select a representative sample of 400,000 users for the main empirical analysis.

### 3.4. Identify DeFi activities

To accurately classify on-chain user behaviors, we develop a systematic pipeline to identify DeFi-related activities based on the design of smart contracts. The key challenge is that most on-chain activities lack explicit labels, especially for less prominent contracts. However, blockchain applications that serve similar functions—such as decentralized exchanges or lending protocols—often share standardized architectures. In particular, their smart contracts tend to expose a common set of functions through their application binary interfaces (ABIs), which define how external applications interact with them. This structural similarity allows us to classify unknown contracts by comparing their ABIs to those of well-known DeFi protocols.

To utilize this feature, we first collect a comprehensive set of verified contract addresses deployed on the Ethereum network. For each address, we retrieve its ABI schema using the Etherscan API. We then define three canonical categories of DeFi protocols: DEXs, on-chain lending protocols, and staking services. For each category, we select representative contracts that capture the most widely adopted technical standards. Specifically, we use the ABIs of (1) Uniswap V2 and V3, Curve, and

Balancer to represent DEXs; (2) Compound V2 and Aave V2/V3 for lending; and (3) Lido for staking. These templates serve as structural fingerprints for each category.

We then apply a similarity-matching algorithm to identify the categories of unknown contracts. The similarity score is defined as the percentage of overlapping function names between a given contract and each category's reference templates. If the score exceeds 80%, the contract is classified into the corresponding category. This procedure allows us to identify swap contracts, lending contracts, and staking contracts across the full Ethereum contract universe. After this process, we identify around 300,000 DeFi contracts.

## 4. User-level Analysis

In this section, we examine how individual users adjusted their trading behavior in response to the collapse of FTX. We begin by presenting event study results based on on-chain transaction data to capture changes in user activity before and after the shock. To further support the interpretation of these behavioral patterns, we complement our analysis with a randomized survey experiment that explores user motivations and responsiveness to DeFi-related information, as presented in Section 5. Together, these approaches provide a comprehensive view of user-level responses to institutional trust erosion.

### 4.1. Descriptive statistics for on-chain data

Table 1 reports summary statistics for the user-level sample used throughout the analysis. The dataset comprises over 446,227 observations, including 37,459 active users, and captures a wide range of behaviors in asset allocation, protocol usage, and transaction intensity.

On average, DeFi and CEX transaction counts are 0.65 and 1.89 per month, with standard deviations of 2.67 and 4.04, respectively. Exchange balances average US$58,000, with a standard deviation of US$269,400; the 90th percentile is US$63,900.

On—chain balances average 17,460 (standard deviation: 53,030), with a corresponding percentile of 10,460. The monthly transaction count averages 13.59, with a standard deviation of 30.49, and the 90th percentile is 35, respectively.

Figure 3 further explores user behavior around the FTX collapse, focusing on the transition of CEX users in terms of DeFi experience. We define DeFi experience as a user who has ever interacted with DeFi contracts before the FTX event. Panel A presents a Sankey diagram that visualizes user flows, while Panel B provides a summary of the numeric breakdown. The results reveal an asymmetric pattern: among users with no prior DeFi experience, only 8% began using DeFi after FTX, while 44% became inactive or exited the market entirely. In contrast, among users with prior DeFi experience, 52% continued to use DeFi and only 22% exited.

This simple comparison suggests two preliminary insights regarding user trust. First, for users who had not previously engaged with DeFi, decentralized protocols did not appear to serve as an immediate substitute for centralized platforms during the crisis. Second, users already exposed to DeFi are more loyal to DeFi, with lower exit rates and higher retention rates. While these descriptive patterns do not imply causal relationships, they underscore meaningful heterogeneity in user responses and provide suggestive evidence that knowing DeFi creates significant heterogeneity in users' post-crisis responses. We explore these dynamics more formally in the subsequent DiD analysis and survey experiment.

### 4.2. Baseline results

Building on the descriptive evidence of heterogeneous responses to the FTX collapse, we next conduct a formal difference-in-differences (DID) analysis to test whether CEX users exhibited systematically different behavioral changes compared to non-CEX users. We begin our user-level analysis by estimating dynamic treatment effects to assess whether CEX users exhibited systematically different behaviors compared to non-CEX users following the FTX collapse. Figure 4 presents dynamic difference-in-differences estimates relative to October 2022 (the benchmark month), illustrating how user trading intensity and participation probabilities evolved in the months before and after the FTX collapse.

Panel A of Figure 4 shows the intensive margin. Before the event, CEX users and non-CEX users exhibited parallel trends in both DeFi and CEX usage, supporting the validity of the DID design. In the immediate aftermath of the collapse (November 2022), we observe that CEX transaction intensity bottomed out in the first month and rebounded to its pre-crisis level within approximately three months. However, DeFi activity among CEX users not only declined in the aftermath of the shock but also continued on a downward trajectory compared with non-CEX users. This divergence suggests a persistent reluctance to engage with decentralized protocols among users previously reliant on centralized platforms, even after experiencing a direct shock from the collapse of a major CEX like FTX. Panel B examines the extensive margin by evaluating user exit behavior. While immediate exits were limited, the likelihood of attrition spiked one month after the collapse. This delayed reaction may reflect the time required to clear positions and withdraw funds. Still, it nonetheless signals a significant erosion of users' trust in the crypto assets market among CEX users. Note that we do not test for parallel trends on the extensive margin, as our treatment and control assignment implicitly requires users to be active as of October 2022.

We further show the average treatment effects of these baseline DID estimates in Table 2. Regression decomposes the treatment effect into two components: the impact in the shock month (November 2022) and the average effect in subsequent months. Four outcome variables are considered: whether a user transacts with DeFi, the number of DeFi transactions, whether a user transacts with CEX, and the number of CEX transactions.

Across all four outcomes, CEX users exhibit a pronounced behavioral shift in the shock month (November 2022). The probability of interacting with CEXs dropped by 1.67 percentage points, and the average number of CEX transactions decreased by

0.428, from 1.89 to approximately 1.46, representing a substantial decline in user engagement with centralized platforms during the collapse. This corresponds to a 22.6% decline in transaction activity relative to the pre-collapse mean.

In the months following the shock, CEX users gradually returned to centralized exchanges but continued to reduce their DeFi usage relative to non-CEX users. For CEX usage, the probability of participation increased by 2.05 percentage points, more than offsetting the initial decline and surpassing the recovery observed among non-CEX users. Moreover, the number of CEX transactions also recovered to pre-crisis levels. In contrast, the DeFi activity of CEX users continued to deteriorate over the post-shock period. The probability of interacting with DeFi protocols declined by 1.88 percentage points, from 12.02% to approximately 10.14%, and the average number of DeFi transactions dropped by 0.128, falling from 0.65 to 0.52, roughly a 20% decline. These findings highlight a persistent decline in both the likelihood and intensity of DeFi usage among CEX users.

Taken together, these results yield two key insights. First, the sharp decline in CEX usage during the first month validates the empirical design. It aligns with real-world developments, reflecting that early CEX users did recognize the risks posed by centralized exchanges in the immediate aftermath of the FTX collapse. Meanwhile, the divergent responses in the months that followed—where CEX usage rebounds while DeFi activity continues to fall—suggest that decentralized alternatives failed to serve as effective substitutes for disillusioned CEX users. Second, the elevated attrition rate among CEX users highlights that many opted to exit the market entirely rather than transition toward DeFi. This behavioral pattern may reflect two possible explanations. One possibility is that users did not fully understand the true causes of the FTX collapse. Another is that users lacked sufficient knowledge or familiarity with decentralized exchanges. Either of these factors, or both, could have contributed to the limited substitution between CEX and DEX. We further explore these conjectures in the next subsection and in the subsequent survey experiment.

### 4.3. DeFi experience for CEX users

Building on the above findings, we further explore why CEX users did not turn to DeFi following the FTX collapse, a pattern that highlights notable behavioral inertia. This subsection examines potential mechanisms behind this lack of substitution. Several possibilities are (1) users do not consider DEX comparable with CEX; (2) users do not know the reason for FTX's collapse is a CEX-specific problem; or (3) users do not know the difference between CEX and DEX.

To further examine the mechanisms behind users' post-shock behavior, we investigate how prior familiarity with DeFi influences CEX users' responses to the FTX collapse. Specifically, we test whether users with DeFi-related experience were more likely to reallocate their activity toward decentralized alternatives or increase their reliance on self-custody. The latter serves as a useful proxy for users' decentralization awareness, as self-custody reflects an intentional choice to avoid relying on intermediaries for controlling assets. This analysis is motivated by our earlier findings in both the descriptive user flow (Figure 3) and baseline regression results (Table 2).

We construct two treatment definitions to proxy for a user's familiarity with DeFi, as shown in Table 3. In Panel A, we classify treatment users as CEX users who transacted with DeFi before the FTX collapse, while the control group includes CEX users without such activity. In Panel B, treatment is based on whether the user held any DeFi-related tokens before the event. In both cases, we reasonably assume that greater prior engagement with DeFi—either through usage or asset holdings—implies higher levels of familiarity with the concept of DeFi. Across both panels, we examine three outcome measures: monthly transaction counts with DeFi and CEX protocols, and the share of assets held in self-custody (i.e., on-chain wallets), which reflects users' lack of trust in centralized custodians.

The results offer several important insights. First, CEX users with prior DeFi experience exhibit a statistically significant increase in DeFi activity after the FTX collapse. Specifically, the number of monthly DeFi transactions rises by 0.050 relative to users without such experience, suggesting that users familiar with decentralized platforms are more likely to adopt them as substitutes in the wake of centralized failure. This behavioral pattern is further supported in Panel B, where users who previously held DeFi tokens—another proxy for familiarity with DeFi—also increase their DeFi transaction count by 0.194. Although this estimate is not statistically significant at conventional levels, it is close to significance and directionally consistent. Second, both types of experienced users demonstrate a notable shift toward self-custody. For users with prior DeFi usage, the share of assets held in self-custodied wallets increases by 1.318 percentage points, while those who only held DeFi tokens exhibit a rise of 1.033 points. At the same time, these users also remain more active on centralized platforms, with CEX transaction counts increasing by 0.420 and 0.262, respectively, for users with prior DeFi usage and DeFi token holdings. This enhanced engagement with CEXs may reflect the fact that users familiar with DeFi tend to have stronger overall confidence in the crypto ecosystem. Rather than exiting or scaling back their investment entirely, they diversify across platforms while adjusting custody practices in response to perceived risk. These changes indicate a clear reallocation of asset storage away from centralized exchanges toward personal wallets, reflecting a decline in trust among informed users in custodial platforms. These findings remain robust when the analysis is expanded to the full user sample, rather than focusing solely on CEX users, as documented in Appendix D.

These results are consistent with the information-based channel: the absence of migration to DeFi among the average CEX user may be interpreted as reflecting not a lack of demand, but rather a lack of awareness or perceived substitutability. However, this interpretation is still indirect and based on observational on-chain behavior rather than explicitly elicited motives. In the next section, we therefore design a randomized survey experiment that directly manipulates information about CeFi failures and DeFi features to test this conjecture causally. At the same time, the increase in self-custody among experienced users reinforces the interpretation that knowledgeable users, shaped by prior DeFi exposure, have a clearer understanding of the value of decentralized systems.

Before moving to the survey experiment, we first introduce other findings for individual-level on-chain analysis to explore what "trust" signals investors rely on when migrating between CEXs.

### 4.4. Size and reserve disclosure as trust signals

While previous analyses show that most CEX users did not turn to DeFi and many exited the market entirely, the remaining group continued to stay engaged. The behavior of these users remains less understood: to what extent did the trust shock influence their choice of exchange? Moreover, if they changed their platform usage, what factors guided their decision? To address these questions, we distinguish CEX users by their pre-crisis engagement with small versus large exchanges. Table 4 presents the estimates for each user type. By measuring the monthly likelihood of engaging with small CEXs, large CEXs, or DeFi protocols, we assess whether users adjusted their trading behavior in response to the collapse and, more importantly, what forms of trust these DeFi-unfamiliar users relied upon when centralized trust was shaken.

We find that Small CEX Users exhibit a marked negative adjustment following the collapse. Their probability of trading with DeFi protocols declines by 2.415 percentage points, and their usage of small CEXs drops by 4.910 percentage points. At the same time, their likelihood of transacting with large CEX platforms rises by 0.671 percentage points. This pattern suggests an intra-CEX substitution response, where users retreat from smaller, possibly less transparent exchanges and reallocate activity toward larger platforms perceived as more stable.

In contrast, Large CEX Users increase their overall CEX engagement, with their probability of using any centralized exchange rising by 2.815 percentage points. This increase is roughly split between continued usage of large platforms (1.415 percentage points) and additional use of small platforms (1.474 percentage points). The results suggest that platform size serves as a perceived indicator of institutional credibility, influencing user reallocation during periods of uncertainty. It is possible that users already embedded in large platforms had a higher sense of security and thus remained confident in the broader CEX ecosystem. Alternatively, the relative increase could be partly driven by a sharper decline among non-CEX users (the control group).

However, platform size is not the only signal users rely on. In the aftermath of FTX's collapse, many exchanges began to publish proof-of-reserve statements to restore users' trust. Figure 5 examines whether such disclosures influenced user behavior. The dynamic event study reveals a clear divergence beginning in the second month post-collapse: users gradually re-engaged with platforms that disclosed reserves, while disengagement from non-disclosing platforms continued. This rebound suggests that users may interpret reserve disclosure as a reassuring sign of solvency or institutional transparency.

Regression results in Table 5 confirm this view. In the collapse month, both disclosing and non-disclosing exchanges experienced transaction drops (−0.384 and −0.187, respectively). However, in the months that followed, users engaging with disclosing platforms exhibited a significant increase in transaction volume (+0.330), while those using non-disclosing platforms saw a further reduction (−0.594). These results highlight the powerful signaling role of reserve disclosure, even if such disclosures offer only partial information.

These results suggest that most CEX users tend to interpret visible platform features—such as exchange size and reserve disclosure—as proxies for institutional credibility. When confronted with uncertainty, users reallocate activity toward larger platforms and those that disclose asset reserves, reflecting an intuitive but potentially misguided search for safety.

Both of these signals warrant caution. The shift from small to large exchanges appears to reflect a belief that size equates to stability. However, this belief may be misplaced. FTX, one of the world's largest exchanges, failed catastrophically despite its size. Size, in itself, offers no guarantee of sound governance, risk control, or transparency. Similarly, reserve disclosure, while seemingly reassuring, typically reveals only the asset side of the balance sheet and omits critical information about liabilities. CEX platforms can hide the true liabilities to customers, or they can even make collateral loans from some financial institutions using customers' assets, which further expands their liability size. Without visibility into obligations or internal risk structures, such disclosures can foster a false sense of security rather than provide meaningful transparency. These findings underscore a key limitation in users' adaptive behavior. In the absence of robust institutional safeguards, the heuristics users rely on to restore trust, such as platform size and selective disclosures, may not reflect the true underlying risk. This could be a type of mistrust, and could cause these users to suffer loss from centralized governance failure again in the future.

## 5. Survey Experiment

The core empirical patterns documented in the previous sections suggest that informational frictions may limit users' migration from CEXs to DEXs. Users may be unfamiliar with DeFi, i.e., unaware of the underlying causes of CeFi failures, or with decentralized exchanges, or both. However, these interpretations are conjectures based on observational evidence rather than established causal findings. It is almost impossible to solicit users' motivation using only on-chain data. To establish a causal link between users' lack of "DeFi literacy" and their limited migration from CEX to DEX, we conducted a randomized controlled survey experiment on the CloudResearch platform to examine the mechanisms through which such information shapes user behavior. In the following sections, we describe the experimental design and present the main results.

### 5.1. Experiment design

The CloudResearch platform allows researchers to pre-screen participants based on demographic and behavioral criteria. So before starting the survey, we restricted eligibility to investors in the United States who reported having traded cryptocurrencies in the past. The experiment design is depicted in Figure 6. This experiment was designed to disentangle the effects of two distinct sources of informational friction: a lack of understanding about centralized exchange failures and a lack of familiarity with decentralized exchanges.

To do so, participants were randomly assigned to four groups. For all groups, we first inform the participants that they are users of Binance, a top-ranked cryptocurrency exchange, as large CEX users comprise the largest portion of our on-chain analysis sample. The control group received only a neutral description of the FTX collapse. The first treatment group was additionally provided with the reason for the collapse of FTX, i.e., misappropriation of customer assets. Parallelly, the second treatment group received an introduction to decentralized exchanges, highlighting their non-custodial nature, transparency through smart contracts, and the protection they offer against centralized governance failures. To provide an unbiased introduction, we also noted a key disadvantage of DEXs: they can be more difficult to learn and set up initially. The third treatment group received both pieces of information: the reason for the FTX collapse and the introduction of the DEX. The exact wording and details of the information are reported in Appendices E and F, and the treatment arms are illustrated in Figure 6.

After receiving their assigned information, respondents were asked to make a hypothetical choice of which venue they would prefer to trade at. The four mutually exclusive options were: (1) to exit the market, (2) to continue trading on a large CEX, (3) to transfer to a small CEX, or (4) to switch to a DEX. The experimental treatments are therefore designed to identify how different types of information frictions shape platform choices. Information about the reason for the FTX collapse examines whether learning from the weakness of CeFi influences users' trading venue choices.

Information about DEXs tests whether improving understanding of DeFi affects adoption decisions. The combined information treatment is to capture the interaction effect between these two information channels.

Immediately after reporting their platform choice, respondents are asked to explain the direct motivation for their decision. They select from predefined options that describe, for example, whether they still trust their current exchange, whether they believe other exchanges remain acceptable, whether they consider all exchanges problematic but still want to trade, or whether they do not want to trade cryptocurrency in the short term.

In addition to these direct questions, we also collected information on several individual attributes that may influence our treatment effects, including perceived switching cost, sense of security, and risk aversion. Each of these dimensions was measured through multiple items designed to capture different aspects of the underlying construct. These measures reflect behavioral and institutional frictions that could jointly explain users' behavior. We will discuss these factors and their measurement in greater detail in later relevant subsections.

This design enables us to causally identify how different forms of information provision affect users' platform choices and to differentiate between the economic channels through which information frictions contribute to users' persistent stickiness to centralized exchanges.

### 5.2. Descriptive statistics for survey

Table 6 reports descriptive statistics for the demographic variables and other variables used in our analysis. The sample consists of 823 respondents, the majority of whom are male (approximately 69 percent). The average age is around 38 years, with most participants falling in the 30–45 age range. The respondents' education level is relatively high. Most participants have received higher education, with a large share holding at least an undergraduate degree. The detailed distribution of education levels is reported in Appendix G. Household income is also skewed toward the higher end, with an average of nearly US$70,000 and a median of US$75,000, which is notably above the U.S. national median income. Consistent with prior evidence on the demographic profiles of cryptocurrency investors (e.g., Kogan et al. 2024; Pursiainen and Toczynski 2022), our sample represents a relatively young, male-dominated, and well-educated group with above-average income levels, closely mirroring the demographic composition of U.S. cryptocurrency investors.[4]

Regarding cryptocurrency-specific characteristics, we first asked respondents how they primarily store their cryptocurrency assets, before examining their on-chain wallet holdings. More than half of them (458 out of 823) reported using on-chain wallets (see Appendix G for the detailed distribution). Among those who use on-chain wallets, respondents typically maintain a small number of them: the mean is around 1.76, and the 75th percentile is at two wallets, suggesting that most investors hold only a single wallet or at most two to three. In terms of investing experience, the average duration of cryptocurrency investment is approximately 3.42 years, with an interquartile range between 2 and 4 years, indicating that most respondents have been engaged in crypto trading for a moderate period rather than being recent entrants. In Appendix G, we also demonstrate that most respondents have invested in major cryptocurrencies, including Bitcoin, Ethereum, Solana, and Polygon. At the same time, only a small fraction have ever held decentralized exchange tokens, indicating limited direct engagement with DeFi assets.

Turning to the heterogeneous indices, all three measures of sense of security, switching cost, and risk aversion have been standardized for comparability. The distributions of these indices are well spread, with values transitioning smoothly from

[4] Surveys by the JPMorgan Chase Institute (https://www.jpmorganchase.com/institute/all-topics/financial-health-wealth-creation/dynamics-demographics-us-household-crypto-asset-cryptocurrency-use) also indicate that cryptocurrency ownership is concentrated among younger, higher-income, and better-educated individuals, with men accounting for roughly 70% of all crypto users.

the 10th to the 90th percentile. This pattern suggests that the survey questions provide sufficient variation across respondents and effectively capture heterogeneity in perceived security, perceived frictions, and individual risk attitudes.

In general, our sample is representative of ordinary cryptocurrency investors in the United States, and our questions have reasonable and sufficient variation for statistical analyses.

### 5.3. Main results for survey

Table 7 presents the main results of the survey experiment. The coefficients capture the effect of information treatments on participants' platform choice relative to the control group. The results show that providing a reason for the FTX collapse alone does not significantly affect respondents' choices. The estimated coefficients are close to zero across all outcomes, suggesting that learning about the fundamental weakness of CeFi, namely the cause of the FTX collapse, does not alter investors' trading venue decisions.

By contrast, treatments that introduce features of DeFi have substantial effects. Respondents who received information about the features of DEXs were significantly more likely to choose a DEX and less likely to remain with a CEX. Specifically, the probability of switching to a DEX increased by 31.7 percentage points, while the probability of staying with a CEX decreased by 18.8 percentage points. These effects are statistically significant at the 1% level. Providing both FTX and DEX information produced very similar results: the probability of adopting a DEX rose by 27.1 percentage points, and the likelihood of staying with a CEX declined by 20.1 percentage points, indicating that there might not exist an interaction effect between the FTX collapse cause and DEX ignorance. Instead, not knowing DEX itself explains almost all treatment effects.

Additionally, the results suggest that reducing information friction enables participants to make fewer hesitations. All treatments that alleviate informational uncertainty lowered the probability of reporting "Not Sure" about future trading choices. This finding supports the existence of information friction.

No treatment had a significant effect on the probability of quitting the market. This finding differs from what we find in on-chain data analysis and is likely because, at the time of the survey (August 2025), U.S. investors were overall more optimistic about cryptocurrency investment than in November 2022, due to President Trump's promotion.

Overall, the findings highlight that the information about DeFi's features plays a central role in shaping user preferences. The results also falsify the alternative statement that users do not think DEX comparable with CEX since as long as they know the differences between CEX and DEX, a significant portion of investors will shift to DEX.

### 5.4. Reason for the choice

Table 8 examines the direct reasons respondents reported for their platform choices. Compared with the control group, the FTX information treatment alone had limited overall effects, but it significantly reduced the share of respondents choosing the "all exchanges problematic" option by 7.7%. Results in column 3 convey two important insights. First, even among U.S. cryptocurrency investors, not all respondents appear to fully understand the true causes of the FTX collapse, as evidenced by the statistically significant difference between the control and FTX information groups. Second, merely informing investors about the reason for the FTX collapse does not lead them to consider the trade-off between CEX and DEX; instead, it prompts them to re-evaluate only among centralized exchanges. This finding is consistent with our on-chain data analysis that users mainly migrate within CEXs instead of between CEXs and DEXs.

By contrast, DEX information significantly reshapes respondents' decision rationales, as shown in column 5. The share of respondents who consider their current exchange acceptable falls by 19.2%, while the share reporting that other exchanges will still be acceptable rises by 12.4%. In addition, the fraction who believe that all exchanges are problematic increases by 9.5%. This suggests that exposure to DEX information encourages respondents to reinterpret risks in terms of broader governance differences between CeFi and DeFi.

When both types of information are provided, the effects are similar to those observed in the DEX-only treatment but somewhat weaker in magnitude. The share who view their current exchange as acceptable falls by 13.5%, while the share accepting other exchanges rises by 11.1%. The share selecting "all exchanges problematic" is not statistically significant. This attenuation may reflect the dilution of the DEX-related treatment effect when multiple messages are presented simultaneously. A plausible explanation is that exposure to both pieces of information prompts investors to engage in a trade-off between the two messages, a behavior commonly observed in real-world decision-making contexts.

Taken together, investors reveal that motivation aligns with our main results: Only after investors have a complete set of information do they begin to consider the tradeoffs between CeFi and DeFi. Before that, the tradeoff in their minds was weighing the "seemingly good" CeFi against the "seemingly bad" CeFi.

### 5.5. Heterogeneous effects

To gain a deeper understanding of the factors that may limit DeFi adoption, we further examine three potential factors: switching costs, sense of security, and risk aversion. These three indices are designed to capture distinct behavioral frictions that may jointly explain users' stickiness to centralized exchanges. The detailed survey questions and construction of each index are described in Appendix H.

A first possibility is that even when users have a full set of information, they may perceive the cost of switching to decentralized alternatives as prohibitively high. In this interpretation, the problem is not a lack of understanding of CeFi's weaknesses, but rather the perceived burden of transferring assets, learning new interfaces, and adapting to a new trading environment. Prior literature suggests that switching costs can be a significant deterrent in many relationship adjustment decisions, such as those between customers and suppliers (Klemperer 1987), making it a natural dimension to consider in this context as well. To examine this mechanism, we designed follow-up survey questions that measure respondents' perceived difficulty in changing trading venues. These items capture both logistical challenges, such as moving assets across platforms, and cognitive challenges, such as adjusting to new trading interfaces. Responses were standardized and aggregated into a switching cost index.

The results in column 1 of Table 9 indicate that switching costs indeed play a meaningful role. The interaction term between the combined information treatment and switching cost is negative and statistically significant for DEX adoption, suggesting that information about DEXs is more effective among respondents who perceive lower switching frictions. Consistent with intuition, switching cost itself is also negatively correlated with the probability of choosing a DEX. However, the results also show that switching costs may not be the primary reason for limited DeFi adoption. To mute the treatment effect requires 2.72 (= 0.272/0.100) standard deviations higher perceived switching costs, equivalent to the top 1 percentile level. For the vast majority of investors, information about DEX has statistically positive effects on migration to DEX.

Some additional explanations include investors' lack of confidence in DeFi or their being too risk-averse to try new solutions. We also solicit investors' perceptions on these two dimensions, but we find no significant effects of these perceptions alone and no interaction effects with our treatment.

Taken together, these results provide supporting evidence that information friction, rather than other explanations, might be the primary reason investors stick with the CeFi platform.

Overall, the survey experiment provides direct causal evidence that investors' limited migration from centralized to decentralized platforms is primarily driven by informational frictions rather than by inertia, fear, or structural constraints. Learning about the reason for the FTX collapse alone does not meaningfully alter investors' choices, as most users either remain within the centralized ecosystem or exit the market altogether. In contrast, when users are informed about the fundamental features and benefits of DEXs, their willingness to adopt decentralized platforms increases substantially. Together with the analyses of switching costs, sense of security, and risk aversion, these findings highlight that the key constraint in the post-FTX environment is not the absence of motivation, but rather the absence of understanding: only when users comprehend what decentralization entails do they begin to treat DeFi as a viable alternative to CeFi.

## 6. Exchange-level Analysis

At the exchange level, we analyze how the FTX collapse reshaped the market share dynamics of CEXs. This institutional-level perspective complements the user-level evidence by assessing whether the aggregate redistribution of trading activity reflects systematic differences in perceived credibility across platforms. It also provides a broader view of how trust signals influence competition within the centralized exchange ecosystem. We describe top CEXs and DEXs for this analysis in Appendix I. We estimate the following DiD specification at the exchange-day level:

$$MarketShare_{it} = \alpha_i + \delta_t + \beta Post_t * Traits_i + \varepsilon_{it}$$

where $MarketShare_{it}$ denotes the market share (in percentage terms) of exchange $i$ in month $t$. The key explanatory variable is the interaction between $Post_t$, a post-event indicator equal to one for months after November 2, 2022, and $Traits_i$, a vector of pre-determined, time-invariant exchange characteristics that proxy for institutional trustworthiness. Specifically, $Traits_i$ includes the number of listed trading pairs (for market comprehensiveness), These characteristics include whether the exchange was among the top three on CoinMarketCap as of October 31 2022 (Ranking), whether it disclosed proof-of-reserve information before December 2022, the number of listed trading pairs (market comprehensiveness), whether its executives appeared in Cointelegraph's "Top 100" list (media reputation), the number of Twitter followers (social visibility), and the exchange's age (operating history). We also include exchange and month fixed effects.

Table 10 reports the results. The estimates show that top-ranked exchanges gained significant market share after the FTX collapse, suggesting that users reallocated activity toward larger and more established platforms. The market share of a top-ranked CEX increases by 0.891 percentage points, equivalent to 27% of the sample average. Moreover, the positive and statistically significant triple interaction between Post, Ranking, and Disclose Reserve implies that reserve disclosure was particularly valuable for top-tier exchanges, whose reputational stakes and visibility were already high. These exchanges increase market share by 1.44 percentage points, equivalent to 44% of the sample average. Other traits, such as the number of listed assets, social media presence, or prior media recognition, show no consistent explanatory power.

Overall, these results provide validity to our on-chain data analysis and demonstrate that users' choice of trading venue in the aftermath of the FTX collapse was not indiscriminate. Instead, investors systematically favored platforms that signaled greater transparency and institutional strength. The findings highlight that, within the centralized exchange sector, credibility signals such as reserve disclosure and pre-established reputation played a central role in preserving trust during a period of systemic uncertainty.

## 7. Conclusion and Implications

This study investigates a fundamental question for the future of finance: Does a crisis of trust in CeFi accelerate the adoption of DeFi? Our analysis of the FTX collapse reveals the answer: no. Contrary to the narrative that CeFi's failures would fuel a flight to DeFi systems, we find limited evidence of CEX users migrating to DeFi. Instead, the majority either exited the market or sought refuge in other CEXs, reallocating trust based on fragile signals, such as institutional size and partial proof-of-reserve disclosures. This behavioral inertia stems from a critical information gap; only users understand the features of DeFi shifted toward decentralized platforms and self-custody.

Our findings offer clear, actionable implications for key stakeholders in the digital asset ecosystem: (1) For the DeFi industry, growth depends on education. To move beyond a niche user base, practitioners must clearly articulate the value of "self-custody" architecture, making it accessible and understandable to the average user. (2) For the CeFi industry, trust is fragile and must be earned through verifiable safeguards, not just marketing. Relying on size or selective disclosures is a temporary strategy; robust internal controls and transparent risk management are essential for long-term survival. (3) For regulators, our results underscore the urgent need for oversight. The market did not self-correct toward safer, decentralized models. The continued dominance of opaque CEXs, combined with powerful user information frictions, creates significant investor risk, making robust external governance indispensable, i.e., prompt legislation and strong enforcement.

Ultimately, our research demonstrates that decentralization is not a self-executing solution. Its promise of a "self-custody" financial system can only be realized if users are aware of it as a viable choice. Until then, even as centralized systems falter, their decentralized counterparts may remain on the sidelines, waiting for a crisis of trust to become a crisis of awareness.

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**Appendix A. Variable Definition**

This table defines the variables used in our analysis.

| Variable | Definition | Source |
|---|---|---|
| **User-level** | | |
| DeFi (count) | Monthly number of transactions with decentralized exchanges. | Etherscan |
| DeFi (dummy) | An indicator variable equal to 1 if the user transacted with a DEX in a given month, and 0 otherwise. | Etherscan |
| CEX (count) | Monthly number of transactions with centralized exchanges. | Etherscan |
| CEX (dummy) | An indicator variable equal to 1 if the user transacted with a CEX in a given month, and 0 otherwise. | Etherscan |
| Exit (dummy) | An indicator variable equal to 1 if the user exited the market during the post-FTX sample period (i.e., no longer active after the collapse), and 0 otherwise. | Etherscan |
| CEX User | An indicator for users with over $100 in assets and more than 50% of their total assets on centralized exchanges before the FTX collapse. | Etherscan |
| DeFi Experience | An indicator for users who had prior interactions with DeFi protocols before the FTX collapse. | Etherscan |
| Self-custodian (percentage) | The share of a user's assets held in on-chain wallets relative to their total crypto holdings. | Etherscan |
| Self-custodian (dummy) | An indicator variable equal to 100 if the user holds any portion of their assets in self-custodial (on-chain) wallets, and 0 otherwise. | Etherscan |
| On-chain balance | The total value (in USD) of assets held in a user's on-chain wallets. | Etherscan |
| Exchange balance | The estimated total value (in USD) of assets held by a user on centralized exchanges. | Etherscan |
| Monthly transaction count | The total number of transactions by a user per month. | Etherscan |
| **Exchange-level** | | |
| Market Share | An exchange's daily trading volume as a percentage of the total CEX market volume. | CoinMarketCap |

| | | |
|---|---|---|
| Ranking | The exchange is ranked on CoinMarketCap as of October 2022. Ranking equals 1 if an exchange was among the top three on CoinMarketCap as of October 31, 2022. | CoinMarketCap |
| Disclose Reserve | An indicator variable equal to 1 if the exchange published a proof-of-reserve statement, and 0 otherwise. | Exchange Announcements, CoinMarketCap |
| Many Tickers | An indicator variable equal to 1 if the exchange lists more than 50 assets. | CoinMarketCap |
| Cointelegraph Top 100 | An indicator variable equal to 1 if any of its executives or founders appeared in Cointelegraph's annual "Top 100" list between 2020 and 2022. | Cointelegraph |
| High Twitter Followers | High Twitter Followers equals 1 if the exchange's official Twitter account had above-median followers before the collapse. | Twitter |
| History | History measures the number of years since the exchange was established. | CoinMarketCap |
| **Survey** | | |
| Female | An indicator variable equal to 1 if the respondent self-identified as female, and 0 otherwise. | Our survey on CloudResearch |
| Age | Respondent's age group based on self-reported age category: under 18, 18 – 24, 25 – 30, 31 – 40, 41 – 50, 51 – 60, or 61 and above. | Our survey on CloudResearch |
| Investing Duration | The number of years (categorical) the respondent has been investing in cryptocurrencies, ranging from "less than 6 months" to "more than 5 years" | Our survey on CloudResearch |
| Number of on-chain Wallets | The number of different on-chain wallets where the respondent stores their assets, categorized into four groups: 1, 2 – 3, 4 – 5, or more than 5. This question was displayed only if the respondent did not select "mainly keep assets in a CEX." | Our survey on CloudResearch |
| Household Income | Self-reported annual household income, categorized as less than \$5,000, \$5,000 – 10,000, \$10,000 – 30,000, \$30,000 – 50,000, \$50,000 – 100,000, or more than \$100,000. | Our survey on CloudResearch |
| Sense of Security | An index capturing respondents' perceived safety and trust toward cryptocurrency exchanges, standardized across the sample. Detailed construction is described in | Our survey on CloudResearch |

| | | |
|---|---|---|
| | Appendix H. | |
| Switching Cost | An index reflecting respondents' perceived effort, cost, and difficulty in switching between exchanges or wallets, standardized across the sample. Detailed construction is described in Appendix H. | Our survey on CloudResearch |
| Risk Aversion | An index measuring respondents' tolerance for financial risk based on sequential gamble choices, standardized across the sample. Detailed construction is described in Appendix H. | Our survey on CloudResearch |
| Platform Choice (DEX, Stay, Exit, and Not Sure) | Respondents stated their exchange preference after reading the treatment scenario (Q12). Responses include four mutually exclusive options: staying on Binance, moving to a smaller centralized exchange, switching to a DEX, exiting the market, or not sure. In the analysis, these outcomes are coded into separate dummy variables for each category (DEX, Stay, Exit, and Not Sure), with the control group serving as the baseline. The detailed question is described in Appendix H. | Our survey on CloudResearch |

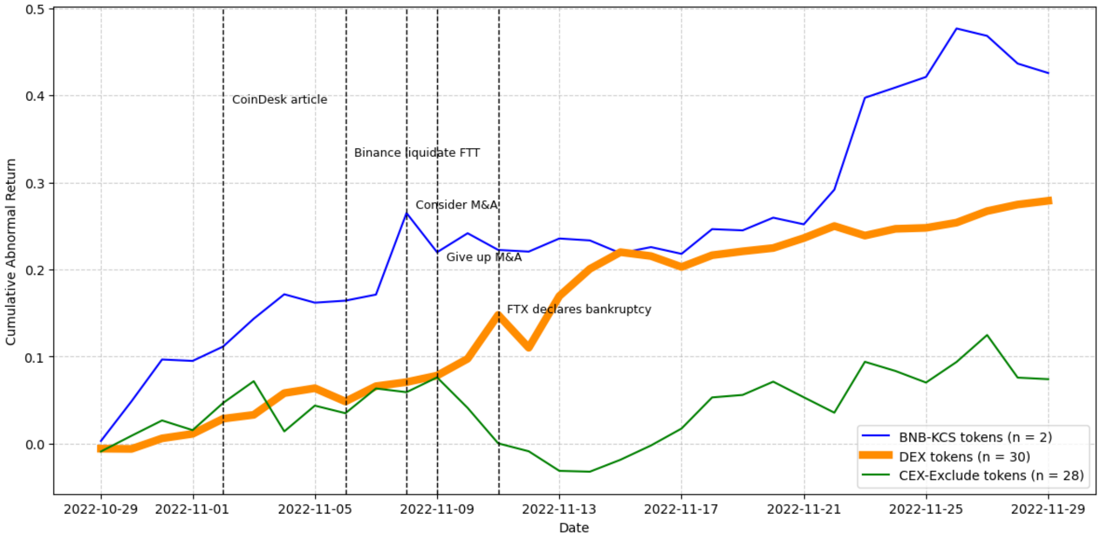



**Figure 1. Market Reaction for CEX and DEX Token**

This figure illustrates the cumulative abnormal returns of CEX and DEX tokens following the FTX collapse. The token's beta is estimated using a 360-day to 30-day cryptocurrency value-weighted market return. Three lines represent the DEX token, the token of FTX's top competitor CEXs, and the token of other CEXs.

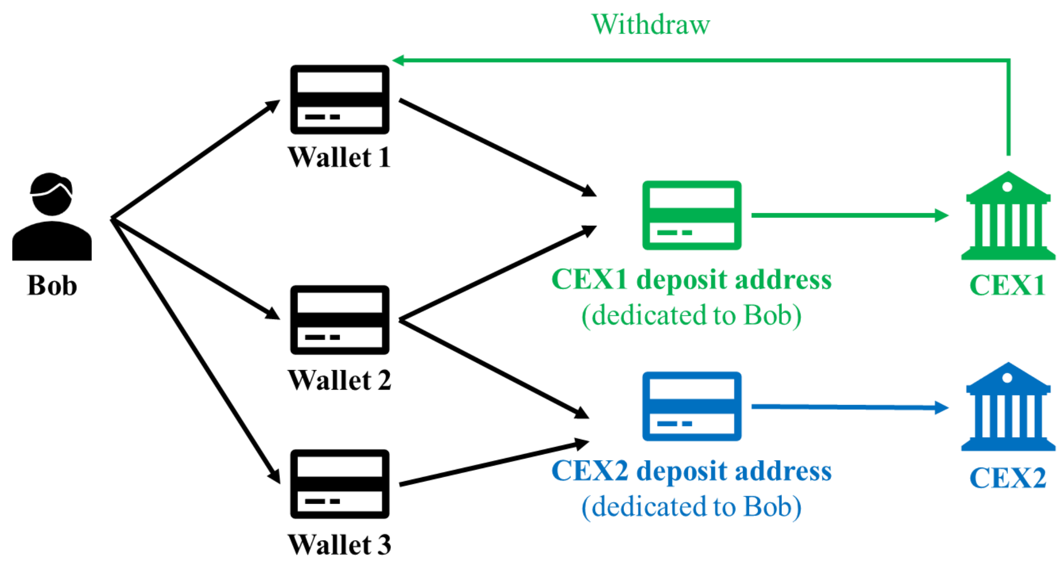
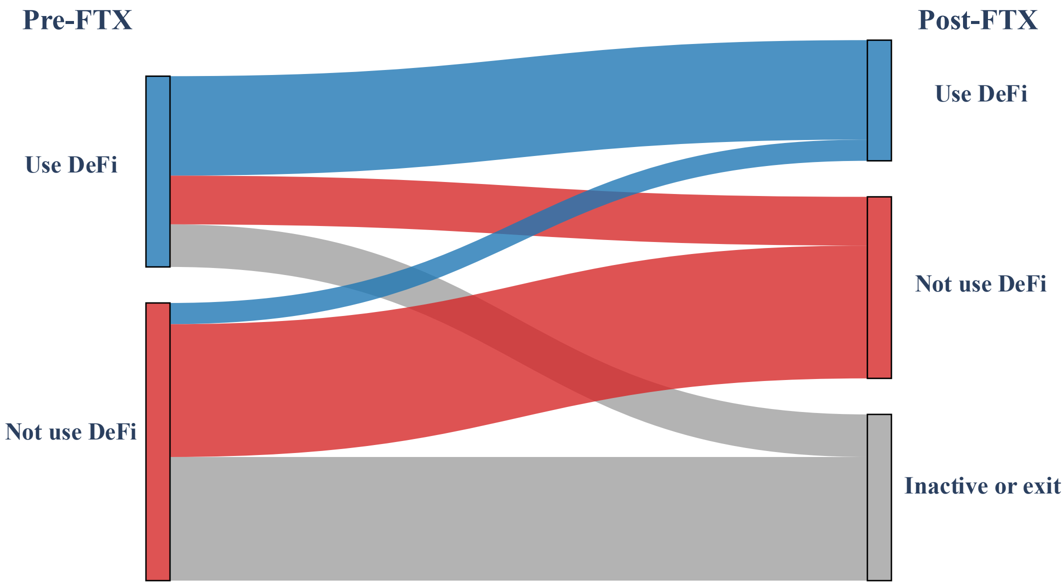



**Figure 2. Accounts Aggregation**

This figure shows how we aggregate multiple accounts held by blockchain users to the user level. We first identify CEX's deposit address dedicated to a user. Wallets 1 and 2 both deposit assets into the CEX1 deposit address, and Wallets 2 and 3 deposit assets to the CEX2 deposit address. Therefore, we label these three wallets controlled by one user.



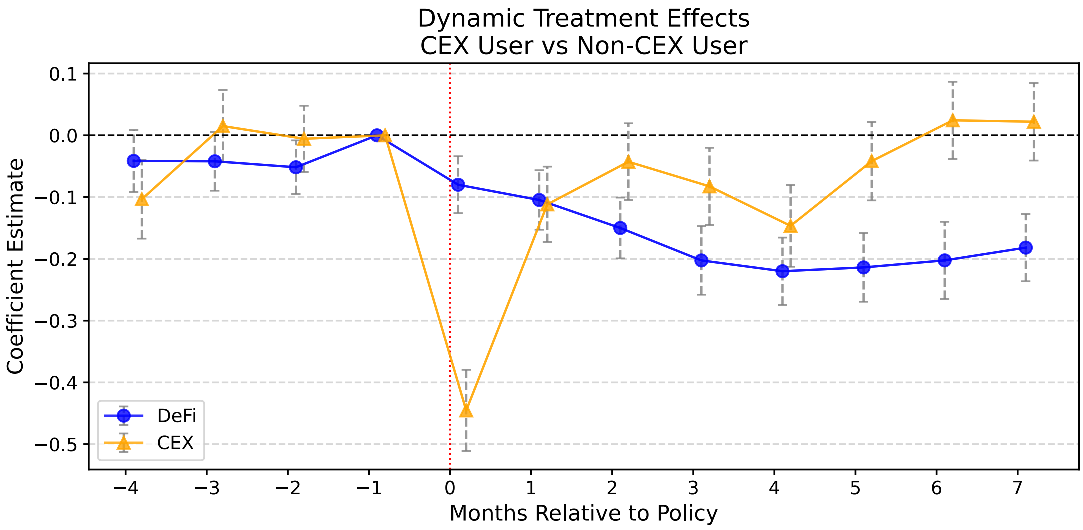

**Panel A. Flow of CEX users**

| | Pre-FTX CEX User | |
|---|---|---|
| | Use DeFi | Not use DeFi |
| **Post-FTX** | | |
| Use DeFi | 25,289<br>(52%) | 5,392<br>(8%) |
| Not use DeFi | 12,394<br>(26%) | 33,771<br>(48%) |
| Inactive or exit | 10,824<br>(22%) | 31,439<br>(44%) |
| Sub Total | 48,507 | 70,602 |
| Total | 119,109 | |

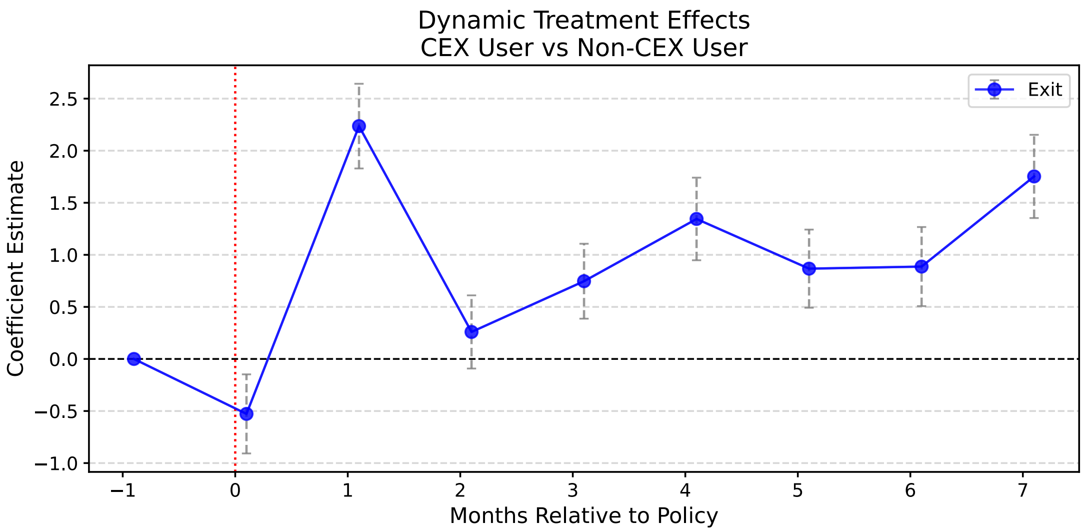
**Panel B. Flow of CEX users (statistics)**

**Figure 3. Flow of Users**

This figure illustrates the shift in DeFi usage among CEX users following the FTX collapse, with Panel A providing a visual representation and Panel B offering a quantitative breakdown. The Sankey diagram in Panel A illustrates the flow of users from their pre-FTX status (whether they use or do not use DeFi) to their post-FTX outcomes (DeFi usage, non-DeFi usage, or inactivity), where the flow widths represent the number of users. Complementing this, the table in Panel B details these transitions, showing the specific number and percentage of users for each path, categorized by their DeFi experience prior to the event.




**Panel A. Intensive margin**




**Panel B. Extensive margin**

**Figure 4. Responses of CEX Users**

This figure presents dynamic treatment effects estimated in a difference-in-differences framework, comparing CEX users (the treatment group) with non-CEX users (the control group). The event time $t = 0$ corresponds to November 2022, the month of the FTX collapse. All coefficient estimates are relative to the reference period $t = -1$ (October 2022). The x-axis indicates months relative to the event, and the y-axis plots the estimated treatment effects with 95% confidence intervals. Panel A shows dynamic changes in trading activity with DeFi and CEX for users who remained active throughout the sample period (intensive margin). Panel B presents the dynamic effects on user exit behavior (extensive margin), capturing the likelihood of exiting the market following the shock.

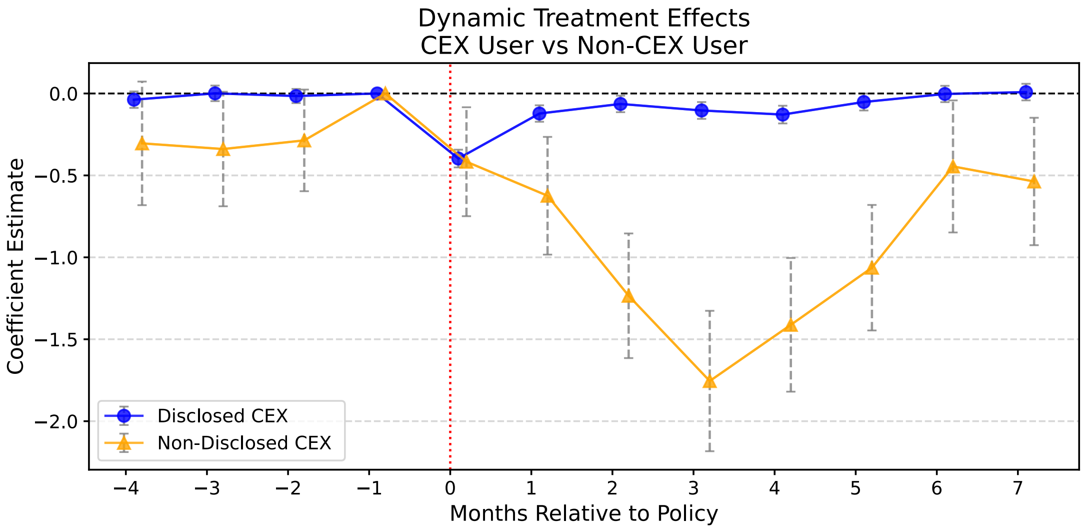



**Figure 5. Reserve Disclosure**

This figure presents dynamic treatment effects by comparing CEX users (the treatment group) with non-CEX users (the control group), focusing on transaction volume across different types of CEX platforms. The x-axis indicates months relative to the FTX collapse, with $t = 0$ denoting November 2022. Coefficient estimates are plotted with 95% confidence intervals.

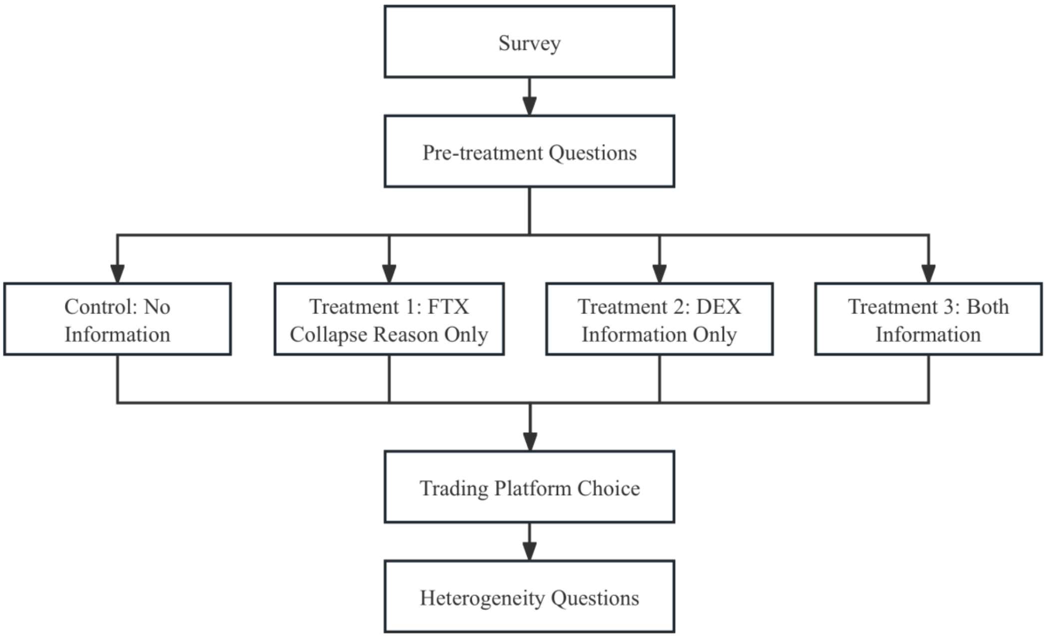



**Figure 6. Survey Experiment Design**

This figure illustrates the structure of our survey experiment. Respondents were randomly assigned to four treatment arms: a control group with no additional information, a treatment group receiving information about the FTX collapse, a treatment group receiving information about DEXs, and a treatment group receiving both types of information. After the treatment, all participants were asked to indicate their future platform choice among large CEX, small CEX, DEX, or market exit. In addition, they completed a post-treatment module designed to capture potential mechanisms and heterogeneities.

**Table 1. Summary Statistics**

This table reports summary statistics for the key user-level variables used in the analysis. Variables labeled "log" are transformed using the function $log(1 + x)$. For all columns except "Exit," the statistics are based on users who remained active throughout the sample period ("survived users"). The "Exit" column includes users who exited the market during the post-FTX sample period, as well as those who remained. All variables are defined in Appendix A.

| Variable | Num. Obs. | Mean | Std. Dev. | 10th | 25th | Median | 75th | 90th |
|---|---|---|---|---|---|---|---|---|
| DeFi (count) | 446,277 | 0.65 | 2.67 | 0 | 0 | 0 | 0 | 1 |
| DeFi (dummy) | 446,277 | 12.02 | 32.58 | 0 | 0 | 0 | 0 | 100 |
| CEX (count) | 446,277 | 1.89 | 4.04 | 0 | 0 | 0 | 2 | 6 |
| CEX (dummy) | 446,277 | 40.0 | 48.99 | 0 | 0 | 0 | 100 | 100 |
| Exit (dummy) | 647,505 | 2.19 | 14.63 | 0 | 0 | 0 | 0 | 0 |
| Self-custodian (percentage) | 446,277 | 56.20 | 33.38 | 0 | 38.33 | 48.71 | 100 | 100 |
| Self-custodian (dummy) | 446,277 | 89.80 | 30.26 | 0 | 100 | 100 | 100 | 100 |
| On-chain balance (th. US$) | 446,277 | 17.46 | 53.03 | 0 | 0.07 | 0.48 | 5.00 | 3.50 |
| On-chain balance (log) | 446,277 | 6.07 | 3.40 | 0 | 4.21 | 6.19 | 8.52 | 10.46 |
| Exchange balance (th. US$) | 446,277 | 58.03 | 269.40 | 0 | 0 | 0.60 | 8.15 | 63.90 |
| Exchange balance (log) | 446,277 | 5.52 | 4.44 | 0 | 0 | 6.40 | 9.01 | 11.07 |
| Monthly transaction count (raw) | 446,277 | 13.59 | 30.49 | 0 | 0 | 2.00 | 11.00 | 35.00 |
| Monthly transaction count (log) | 446,277 | 1.46 | 1.47 | 0 | 0 | 1.10 | 2.49 | 3.58 |

**Table 2. Responses of CEX Users**

This table reports difference-in-differences estimates of the impact of the FTX collapse on user interactions with DeFi and CEX, comparing CEX users (the treatment group) with non-CEX users (the control group). The sample period spans from July 2022 to June 2023. The post-treatment period begins in November 2022, the month of the FTX collapse. The specification separates the effect in the shock month (November 2022) from the effects in the subsequent months. The dependent variables include binary indicators and transaction counts for DeFi (columns 1 and 2) and CEX (columns 3 and 4). All variables are defined in Appendix A. All regressions control for user-level and month fixed effects, along with other covariates. Standard errors are clustered at the user level. Robust standard errors clustered at the user level are reported in parentheses. ∗∗∗, ∗∗, and ∗ denote significance levels at 1%, 5%, and 10%, respectively.

| | DeFi | | CEX | |
|---|---|---|---|---|
| | Dummy | Count | Dummy | Count |
| | (1) | (2) | (3) | (4) |
| Post * CEX User * Shock Month | -0.765*** | -0.020** | -1.674*** | -0.428*** |
| | (0.287) | (0.021) | (0.398) | (0.031) |
| Post * CEX User * Months After | -1.875*** | -0.128*** | 2.052*** | -0.001 |
| | (0.190) | (0.017) | (0.263) | (0.020) |
| Controls | Y | Y | Y | Y |
| User FE | Y | Y | Y | Y |
| Month FE | Y | Y | Y | Y |
| Control group | Non-CEX User | | | |
| # Obs | 446,277 | 446,277 | 446,277 | 446,277 |
| Adjusted R2 | 0.571 | 0.507 | 0.720 | 0.592 |
| # Clusters | 37,459 | 37,459 | 37,459 | 37,459 |

**Table 3. CEX User with DeFi Experience**

This table reports treatment effects among CEX users, focusing on heterogeneous responses based on prior DeFi experience (Panel A) and prior DeFi token holdings (Panel B). In Panel A, the treatment group comprises CEX users who interacted with DeFi before the FTX collapse, and the control group consists of CEX users with no prior DeFi experience. In Panel B, the treatment group includes CEX users who held DeFi tokens prior to the collapse, while the control group did not. The dependent variables are monthly transaction counts with DeFi and CEX platforms (columns 1–2), and the share of self-custodied assets (on-chain wallet balance as a percentage of total crypto holdings; column 3). All variables are defined in Appendix A. All regressions include user and month fixed effects, as well as additional controls. Standard errors are clustered at the user level. Robust standard errors clustered at the user level are reported in parentheses. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

**Panel A. Use DeFi before**

| | DeFi (count) | CEX (count) | Self-custodian (percentage) |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post * CEX User with DeFi Exp. | 0.050* | 0.420*** | 1.318*** |
| | (0.026) | (0.028) | (0.117) |
| Controls | Y | Y | Y |
| User FE | Y | Y | Y |
| Month FE | Y | Y | Y |
| Control group | CEX User without DeFi Exp. | | |
| # Obs | 187,391 | 187,391 | 187,391 |
| Adjusted R2 | 0.570 | 0.691 | 0.921 |
| # Clusters | 15,693 | 15,693 | 15,693 |

**Panel B. Held DeFi token before**

| | DeFi (count) | CEX (count) | Self-custodian (percentage) |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post * CEX User Held DeFi Token | 0.194 | 0.262*** | 1.033*** |
| | (0.121) | (0.095) | (0.211) |
| Controls | Y | Y | Y |
| User FE | Y | Y | Y |
| Month FE | Y | Y | Y |
| Control group | CEX User not Held DeFi Token | | |
| # Obs | 187,391 | 187,391 | 187,391 |
| Adjusted R2 | 0.570 | 0.691 | 0.921 |
| # Clusters | 15,693 | 15,693 | 15,693 |

**Table 4. Size and Exchange Choice**

This table reports treatment effects of the FTX collapse on users of small centralized exchanges (Small CEX Users), using non-CEX users as the control group. The sample period spans from July 2022 to June 2023, with the post-period beginning in November 2022. The outcome variables indicate whether users interacted with DeFi, CEX, large CEX platforms, or small CEX platforms (dummy and transaction count). All variables are defined in Appendix A. All regressions include user and month fixed effects, as well as additional controls. Standard errors are clustered at the user level. Standard errors are clustered at the user level. Robust standard errors clustered at the user level are reported in parentheses. ∗∗∗, ∗∗, and ∗ denote significance levels at 1%, 5%, and 10%, respectively.

| | DeFi (dummy) | CEX (dummy) | Large CEX (dummy) | Small CEX (dummy) |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Post * Small CEX User | -2.415*** | -0.782** | 0.671** | -4.910*** |
| | (0.241) | (0.356) | (0.340) | (0.355) |
| Post * Large CEX User | -1.374*** | 2.815*** | 1.415*** | 1.474*** |
| | （0.214） | (0.291) | (0.288) | (0.236) |
| Controls | Y | Y | Y | Y |
| User FE | Y | Y | Y | Y |
| Month FE | Y | Y | Y | Y |
| Control group | Non-CEX User | | | |
| # Obs | 446,277 | 446,277 | 446,277 | 446,277 |
| Adjusted R2 | 0.507 | 0.597 | 0.581 | 0.419 |
| # Clusters | 37,459 | 37,459 | 37,459 | 37,459 |

**Table 5. Reserve Disclosure and Exchange Choice**

This table reports DiD estimates comparing CEX users to non-CEX users, with transaction volumes separated by whether the CEX disclosed reserve information. The specification separates the effect in the shock month (November 2022) and the post-shock months. All variables are defined in Appendix A. Standard errors are clustered at the user level. Robust standard errors clustered at the user level are reported in parentheses. ∗∗∗, ∗∗, and ∗ denote significance levels at 1%, 5%, and 10%, respectively.

| | CEX (count) | |
|---|---|---|
| Disclose reserve in the first month | Yes | No |
| | (1) | (2) |
| Post * CEX User | -0.384*** | -0.187 |
| | (0.025) | (0.154) |
| Post * CEX User * After first month | 0.330*** | -0.594*** |
| | (0.024) | (0.158) |
| Controls | Y | Y |
| User FE | Y | Y |
| Month FE | Y | Y |
| Control group | Non-CEX User | |
| # Obs | 446,277 | 446,277 |
| Adjusted R2 | 0.695 | 0.790 |
| # Clusters | 37,459 | 37,459 |

**Table 6. Summary Statistics of Survey Experiment**

This table reports descriptive statistics for demographic variables and mediator indices. Gender is coded as 0 for male and 1 for female. Age is coded based on categorical ranges, with midpoints assigned to each group (e.g., 21 for ages 18 – 24, 27 for ages 25 – 30, 35 for ages 31 – 40). Household income is measured in thousands of U.S. dollars, with categorical brackets converted into midpoint values. We measure three mediators—switching cost, sense of security, and risk aversion—based on multi-item survey questions designed to capture each construct. Detailed question wording, coding, and index construction are provided in Section 5.1 and Appendix H.

| Variable | Num. Obs. | Mean | Std. Dev. | $10^{th}$ | $25^{th}$ | Median | $75^{th}$ | $90^{th}$ |
|---|---|---|---|---|---|---|---|---|
| Female | 823 | 0.31 | 0.46 | 0 | 0 | 0 | 1 | 1 |
| Age | 823 | 37.88 | 10.32 | 27 | 35 | 35 | 45 | 55 |
| Investing Duration | 823 | 3.42 | 1.85 | 0.75 | 2 | 4 | 4 | 6 |
| Number of on-chain Wallets | 458 | 1.76 | 1.07 | 1 | 1 | 2 | 2 | 2 |
| Household Income (thousand USD) | 823 | 69.72 | 29.40 | 20 | 40 | 75 | 100 | 100 |
| Sense of Security | 823 | 0.00 | 1.00 | -1.20 | -0.62 | 0.03 | 0.69 | 1.26 |
| Switching Cost | 823 | 0.00 | 1.00 | -1.27 | -0.55 | 0.16 | 0.60 | 1.29 |
| Risk Aversion | 823 | 0.00 | 1.00 | -1.41 | -0.27 | -0.274 | 0..866 | 0.866 |

**Table 7. Treatment Effects of Information Provision**

This table reports the treatment effects of information provision on platform choice. Each column corresponds to a different outcome: choosing a DEX, staying with a CEX, exiting the market, or reporting difficulties in deciding. "Stay" includes both large and small CEXs. Explanatory variables are treatment dummies: FTX, DEX, and Both, which equal one if the respondent was assigned to the corresponding treatment arm and zero otherwise. The control group with no additional information serves as the baseline. Coefficients are estimated from linear probability models, with standard errors reported in parentheses. For a detailed description of the experimental design and the exact wording of the treatments, see Section 5.1 and Appendix E. *** and ** denote statistical significance at the 1% and 5% levels, respectively.

| | Platform Choice | | | |
|---|---|---|---|---|
| | DEX | Stay | Exit | Not Sure |
| | (1) | (2) | (3) | (4) |
| Treatment (FTX) | +0.033 | +0.009 | +0.002 | -0.044 |
| | (0.046) | (0.050) | (0.033) | (0.029) |
| Treatment (DEX) | +0.317*** | -0.188*** | -0.040 | -0.089*** |
| | (0.045) | (0.049) | (0.033) | (0.028) |
| Treatment (Both) | +0.271*** | -0.201*** | -0.009 | -0.061*** |
| | (0.044) | (0.048) | (0.032) | (0.028) |
| Baseline level of Control | 0.159*** | 0.571*** | 0.132*** | 0.138*** |
| | (0.033) | (0.036) | (0.024) | (0.020) |
| # Obs | 823 | 823 | 823 | 823 |
| Adjusted R2 | 0.085 | 0.036 | -0.001 | 0.009 |
| Mean of Dep. Var. | 0.323 | 0.469 | 0.120 | 0.087 |

**Table 8. Reason for the Choice**

This table reports respondents' direct reasons for choosing a platform across treatment arms. The control group receives no additional information. Treatment 1 receives reasons for the collapse of FTX. Treatment 2 receives DEX-related information. Treatment 3 receives both types of information. Reported figures are means by group, with differences from the control group shown in percentage points. We report t-statistics in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| | **Control** | **Treatment 1: FTX Info** | | **Treatment 2: DEX Info** | | **Treatment 3: Both Info** | |
|---|---|---|---|---|---|---|---|
| Know why FTX collapsed | No | ***Yes*** | | No | | ***Yes*** | |
| Know DEX | No | No | | ***Yes*** | | ***Yes*** | |
| | N=189 | N=193 | | N=206 | | N=235 | |
| | Mean | Mean | Diff | Mean | Diff | Mean | Diff |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7)=(6)-(1) |
| Current exchange acceptable | 45.0% | 49.7 | 4.8% | 25.7% | **-19.2%*** ** | 31.5% | **-13.5%*** ** |
| | | % | (0.933) | | **(-4.008)** | | **(-2.851)** |
| Other exchanges acceptable | 19.6% | 25.9 | 6.3% | 32.0% | **12.4%*** ** | 30.6% | **11.1%*** ** |
| | | % | (1.475) | | **(2.818)** | | **(2.591)** |
| All exchanges problematic | 20.1% | 12.4 | **-7.7%** ** | 29.6% | **9.5%** ** | 26.4% | 6.3% |
| | | % | **(-2.033)** | | **(2.178)** | | (1.513) |
| Stop trading | 12.7% | 8.8% | -3.9% | 10.7% | -2.0% | 9.8% | -2.9% |
| | | | (-1.228) | | (-0.625) | | (-0.949) |
| Other | 2.6% | 3.1% | 0.5 | 1.9% | -0.7% | 1.7% | -0.9% |
| | | | (0.271) | | (-0.468) | | (-0.67) |

**Table 9. Heterogeneous Effects**

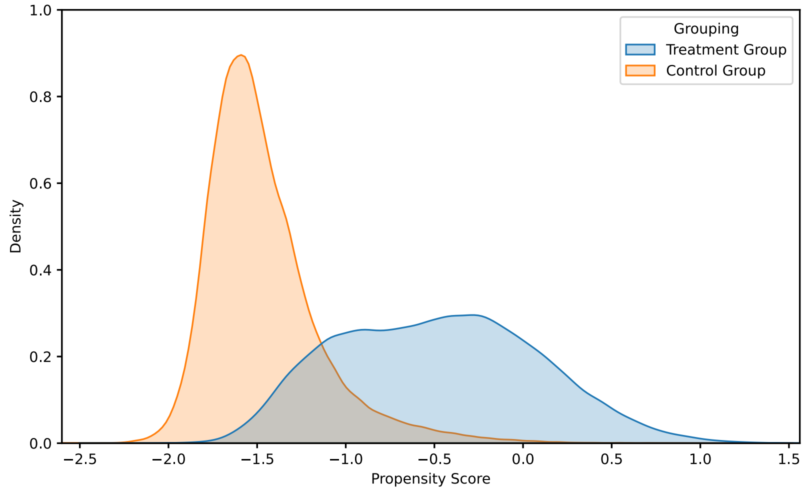
This table reports mediation analyses of the combined information treatment ("Both") on platform choice. The dependent variable is a binary indicator for choosing to switch to a DEX. Each pair of columns introduces one of the three mediators: switching cost, sense of security, and risk aversion. "Treatment (Both)" is a dummy equal to one if the respondent was assigned to the combined treatment arm. "Trait" represents the standardized index (or parameter) capturing the corresponding mechanism. "Treatment (Both) * Trait" is the interaction term testing whether the treatment effect varies by heterogeneous traits. Coefficients are estimated from linear probability models, with standard errors reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| | DEX | | |
|---|---|---|---|
| Trait= | Switching Cost | Sense of Security | Risk Aversion |
| | (1) | (2) | (3) |
| Treatment (Both) * Trait | -0.100** | 0.048 | 0.005 |
| | (0.041) | (0.044) | (0.044) |
| Treatment (Both) | 0.272*** | 0.266*** | 0.271*** |
| | (0.041) | (0.033) | (0.043) |
| Trait | -0.080** | -0.003 | -0.018 |
| | (0.032) | (0.033) | (0.032) |
| # Obs | 424 | 424 | 424 |
| Adjusted R2 | 0.180 | 0.084 | 0.080 |
| Mean of Dep. Var. | 0.309 | 0.309 | 0.309 |

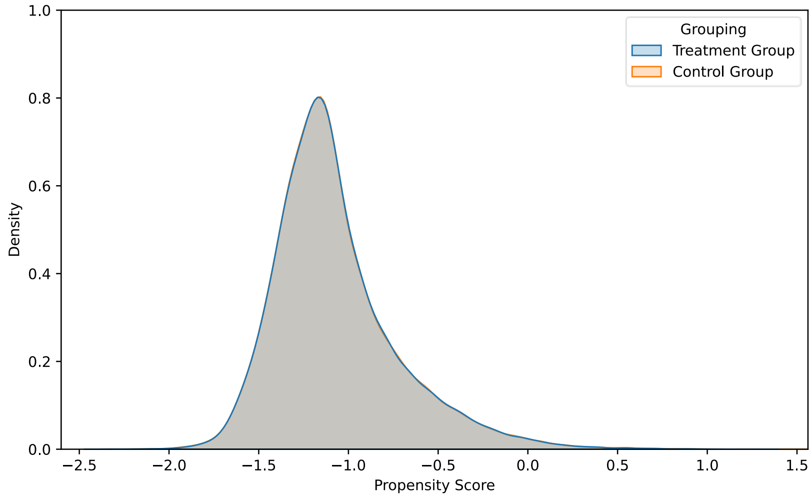
**Table 10. Drivers of Market Share Change**

This table reports how the market shares of CEXs changed after the FTX collapse, conditional on their pre-FTX characteristics. Market Share is calculated as an exchange's trading volume divided by the total CEX trading volume on a given date. Post equals 1 for dates after November 2, 2022. *Ranking* equals one if an exchange was among the top three on CoinMarketCap as of October 31, 2022, and zero otherwise. *Disclose Reserve* indicates whether the exchange disclosed proof-of-reserve information before December 31, 2022. *Many Tickers* equal one if the exchange lists more than 50 assets. *Cointelegraph Top 100* equals one if any of its executives or founders appeared in the Cointelegraph annual "Top 100" list between 2020 and 2022. *High Twitter Followers* equals one if the exchange's official Twitter account had above-median followers before the collapse. *History* measures the number of years since the exchange was established. All regressions include exchange and date fixed effects, and standard errors are clustered at the exchange level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

| | Market Share (%) | |
|---|---|---|
| | CEX | |
| | (1) | (2) |
| Post * Ranking | 0.891*** | 0.566** |
| | (3.029) | (2.326) |
| Post * Disclose Reserve | 0.378 | 0.302 |
| | (0.873) | (0.733) |
| Post * Ranking * Disclose Reserve | | 0.874** |
| | | (2.168) |
| Post * Many Tickers | 0.457 | 0.513 |
| | (1.046) | (1.147) |
| Post * Cointelegraph Top 100 | -0.092 | -0.191 |
| | (-0.380) | (-0.731) |
| Post * High Twitter Followers | -0.769 | -0.759 |
| | (-1.419) | (-1.431) |
| Post * History | 0.028 | 0.059 |
| | (0.299) | (0.573) |
| Exchange FE | Y | Y |
| Date FE | Y | Y |
| # Obs | 5,430 | 5,430 |
| Adjusted R2 | 0.962 | 0.962 |
| # Exchanges | 30 | 30 |
| Mean of Dep. Var. | 3.28 | 3.28 |




**Panel A. Before matching**




**Panel B. After matching**

**Appendix B. Propensity Score Matching**

This figure illustrates the distribution of estimated propensity scores for the treatment (CEX users) and control (non-CEX users) groups before and after matching. The x-axis represents the estimated propensity score, and the y-axis indicates the kernel density of users within each group. Propensity scores are obtained from a Poisson fixed effects regression. The treatment indicator is regressed on log total portfolio value, wallet balance, transaction volume, tenure (in days since first on-chain activity), and monthly activity dummies for DeFi and CEX usage. Panel A shows the distribution before matching, revealing a substantial imbalance between the two groups. Panel B presents the distribution after matching, where users are stratified into 50 bins based on their propensity scores. Within each bin, equal-sized random samples of treatment and control users are drawn to ensure balanced comparability.

## Appendix C. Details of User Aggregation

Our clustering algorithm proceeds iteratively in multiple rounds. Starting from known exchange addresses, we identify deposit addresses that have forwarded tokens exclusively to exchanges. These deposit addresses are then used to trace upstream user addresses that sent funds to them. In subsequent rounds, new counterparties interacting with these user addresses are also incorporated, allowing us to expand the transaction network in breadth and depth.

To map user addresses to actual users, we assume that each deposit address typically serves a unique user. Thus, if multiple addresses send funds to the same deposit address, they are likely controlled by the same entity. Similarly, these deposits are grouped if one address sends funds to multiple deposits. We model this structure as a dynamic graph and apply a union-find (disjoint-set) algorithm to iteratively merge deposit groups, with user addresses attached to each deposit.

To ensure the robustness of the clustering process and mitigate false linkages between unrelated users, we implement a series of strict filtering rules that draw directly from observed behavioral patterns on-chain and are operationalized through our algorithm.

(1) Construction of a dynamic blocklist: We identify and exclude addresses exhibiting abnormal connectivity patterns inconsistent with typical end-user behavior. Specifically, any user address linked to more than 50 distinct deposit addresses is flagged as anomalous and added to a blocklist. This threshold is based on the assumption that normal users rarely interact with such a high number of deposit addresses. High-connectivity addresses are more likely to be associated with automated bots, aggregators, or service providers, such as mixers or arbitrage systems. Once blocklisted, these addresses are not used as linkage nodes and are excluded from deposit-user mappings during the clustering process. The blocklist is augmented with additional labeled addresses from external sources (e.g., known CEX and DeFi project

addresses, smart contracts, liquidity pools) to ensure that system-level accounts and infrastructure wallets are systematically excluded from user-level inference.

(2) Deposit address filtering by transfer latency: We distinguish between two types of deposit address behaviors based on transaction timing: Instant deposit addresses are those for which outbound transfers (i.e., forwarding to an exchange) occur within one day of the inbound user transaction. This rapid fund forwarding is consistent with standard deposit behavior in CEX architectures. Delayed deposit addresses, by contrast, exhibit a median latency of more than 24 hours between receiving and forwarding user funds. Such behavior is atypical and may indicate the use of cold wallets, batched settlements, or manually managed addresses. Our algorithm retains only instant deposit addresses for the clustering procedure. Their timely forwarding behavior implies a higher likelihood of deterministic one-to-one user mapping. Delayed deposit addresses, although still collected and recorded, are excluded from linkage construction to prevent the incorporation of ambiguous or stale relationships that could compromise cluster purity.

(3) Graph cleaning and node consolidation: After filtering, we construct a bipartite user-deposit graph where edges represent fund transfers from user addresses to filtered deposit addresses. We then use a union-find algorithm to merge deposits that share common user addresses iteratively, treating each connected component as an individual user entity. By excluding blocklisted nodes and delay-prone deposits from the graph, we ensure that all links in the clustering network represent high-confidence behavioral associations.

This layered filtration strategy—encompassing address-level outlier detection, behavior-based deposit classification, and temporal transaction analysis—enables us to maximize the fidelity of our inferred user clusters while minimizing overlinking and noise from anomalous blockchain activity.

For the entire transaction information, we extract the sender, recipient, token, value, and timestamp fields, then classify the transactions to build the deposit-user mapping. Finally, we output a user-level dictionary linking users to all associated wallet addresses.

This clustering procedure yields a refined, user-centric view of the Ethereum transaction network. It enables us to trace balance changes and behavioral shifts at the user level, rather than at the address level. This level of granularity is critical for analyzing the interplay between centralized exchanges and DeFi ecosystems.

**Appendix D. DeFi Users**

This table reports treatment effects using users with prior DeFi experience as the treatment group and those without DeFi transactions as the control group. The dependent variables include monthly transaction count with DeFi (column 1), CEX (column 2), and the share of on-chain (self-custodian) assets relative to total crypto holdings (column 3). "Self-custodian" is the ratio of on-chain wallet balance to the sum of on-chain and exchange balances. All regressions control for user and month fixed effects, as well as additional covariates. Standard errors are clustered at the user level. Robust standard errors clustered at the user level are reported in parentheses. ∗∗∗, ∗∗, and ∗ denote significance levels at 1%, 5%, and 10%, respectively.

| | DeFi (count) | CEX (count) | Self-custodian (percentage) |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post * DeFi User | 0.057*** | 0.525*** | 2.313*** |
| | (0.017) | (0.020) | (0.127) |
| Controls | Y | Y | Y |
| User FE | Y | Y | Y |
| Month FE | Y | Y | Y |
| Control group | User without DeFi Experience | | |
| # Obs | 446,277 | 446,277 | 446,277 |
| Adjusted R2 | 0.572 | 0.724 | 0.919 |
| # Clusters | 37,459 | 37,459 | 37,459 |

## Appendix E. Survey Experiment Design

| Group | Message presented |
|---|---|
| Control | Assume you are a Binance user. Binance is the world's largest cryptocurrency exchange. You have deposited 2,000 USD on this exchange to trade cryptocurrencies.<br>Last month, the world's second-largest exchange, FTX, went bankrupt, causing all of FTX's users' deposits to be completely lost. |
| Treatment<br>(FTX collapse reason) | Assume you are a Binance user. Binance is the world's largest cryptocurrency exchange. You have deposited 2,000 USD on this exchange to trade cryptocurrencies.<br>Last month, the world's second-largest exchange, FTX, went bankrupt. The reason was that FTX's founder misappropriated clients' assets, causing all of FTX's users' deposits to be completely lost. |
| Treatment<br>(DEX information) | Assume you are a Binance user. Binance is the world's largest cryptocurrency exchange. You have deposited 2,000 USD on this exchange to trade cryptocurrencies.<br>Last month, the world's second-largest exchange, FTX, went bankrupt, causing all of FTX's users' deposits to be completely lost.<br>Binance and FTX are both centralized exchanges, which require users to deposit funds into the exchange account before trading. The advantage is that they are easy to learn and use.<br>In contrast, decentralized exchanges allow users to maintain control of their assets from start to finish, without transferring funds to another account first. The disadvantage is that they can be more difficult to learn and set up initially. |
| Treatment<br>(both information) | Assume you are a Binance user. Binance is the world's largest cryptocurrency exchange. You have deposited 2,000 USD on this exchange to trade |

| | |
|---|---|
| | cryptocurrencies.<br>Last month, the world's second-largest exchange, FTX, went bankrupt. The reason was that FTX's founder misappropriated clients' assets, causing all of FTX's users' deposits to be completely lost.<br>Binance and FTX are both centralized exchanges, which require users to deposit funds into the exchange account before trading. The advantage is that they are easy to learn and use.<br>In contrast, decentralized exchanges allow users to maintain control of their assets from start to finish, without transferring funds to another account first. The disadvantage is that they can be more difficult to learn and set up initially. |

**Appendix F. Survey Questions**

**A. Pre-treatment Questions**

1. Your gender:
   Male
   Female

2. What is your age?
   Under 18
   18-24
   25-30
   31-40
   41-50
   51-60
   61 or above

3. What is your highest level of education?
   Below college
   College/undergrad or equivalent
   Master's or above

4. What is your annual household income?
   Less than 5,000 USD
   5,000–10,000 USD
   10,000–30,000 USD
   30,000–50,000 USD
   50,000–100,000 USD
   More than 100,000 USD

5. Have you ever owned any of the following assets? (multiple choice)
   Bitcoin, Ethereum, Solana, Polygon
   USDT, USDC, or other stablecoins
   Uniswap, Maker, Curve, dYdX, or other decentralized exchange tokens
   Dogecoin, Shiba Inu, Pepe, or other meme coins
   Any other cryptocurrencies

6. How do you mainly hold your cryptocurrency assets?
   I mainly keep my assets in a centralized exchange (CEX)
   I mainly keep my assets in my own wallet (e.g., a mobile app wallet or hardware wallet)
   I use both, but most of my assets are in an exchange
   I use both, but most of my assets are in a wallet

7. In how many different on-chain wallets are your assets stored? [Displayed only if Q6 $\neq$ "I mainly keep my assets in a centralized exchange (CEX)"]

Only 1
2–3
4–5
more than 5

8. How long have you been investing in cryptocurrencies?

Less than 6 months
6 months – 1 year
1 – 3 years
3 – 5 years
More than 5 years

9. Suppose you are the only source of income in your family, and you already have a good job that guarantees your current level of income every year. You are offered a new job that is equally good in other aspects. The new job has a 50% chance of doubling your income, but also a 50% chance of reducing your income by 20%. Would you accept this new job?

Yes
No

10. At this point, suppose this new job has a 50% chance of doubling your income, but also a 50% chance of reducing your income by 33%. Would you accept this new job?

Yes
No

11. At this point, suppose this new job has a 50% chance of doubling your income, but also a 50% chance of reducing your income by 50%. Would you accept this new job?

Yes
No

**B. Treatment Questions**

1. Please read the following scenario. After experiencing this event, which type of exchange would you choose to trade on?

**[Treatment or control scenarios described in Appendix E]**

Stay on Binance
Move to another exchange smaller than Binance
Move to a decentralized exchange
I will not trade cryptocurrencies in the short term
Not sure

**C. Post-treatment Questions**

1. Which of the following best explains why you chose your choice in the previous scenario question?

I think the exchange I am currently using is still acceptable.

If I had experienced the previously described situation, I would have lost trust in my current exchange, but I believe there are still other exchanges I could accept.

If I had experienced the previously described situation, I would have felt that all crypto exchanges have problems, but I would still want to trade cryptocurrencies.

If I had experienced the previously described situation, I would have temporarily stopped trading cryptocurrencies.

Other

2. Regarding the choice you made in the scenario question, to what extent do you agree with the following statement: I believe this choice can protect the safety of my digital assets.

Strongly disagree
Disagree
Neutral
Agree
Strongly agree
I do not understand the statement

3. To what extent do you agree with the following statement: If an exchange makes its reserve assets publicly available, I would trust this exchange more.

Strongly disagree
Disagree
Neutral
Agree
Strongly agree
I do not understand the statement

4. To what extent do you agree with the following statement: Even if an exchange is very popular and highly recommended by many people, I may still worry that keeping my assets there is unsafe.

Strongly disagree
Disagree
Neutral
Agree
Strongly agree
I do not understand the statement

5. To what extent do you agree with the following statement: If an exchange offers sufficiently high discounts or incentives, I would be willing to compromise somewhat on security.

Strongly disagree
Disagree
Neutral
Agree
Strongly agree
I do not understand the statement

6. To what extent do you agree with the following statement: Transferring my assets from my current exchange and switching to a new one would cost me too much time and effort.

Strongly disagree
Disagree
Neutral
Agree
Strongly agree
I do not understand the statement

7. To what extent do you agree with the following statement: Considering fees and other financial costs, I am not willing to switch exchanges frequently.

Strongly disagree
Disagree
Neutral
Agree
Strongly agree
I do not understand the statement

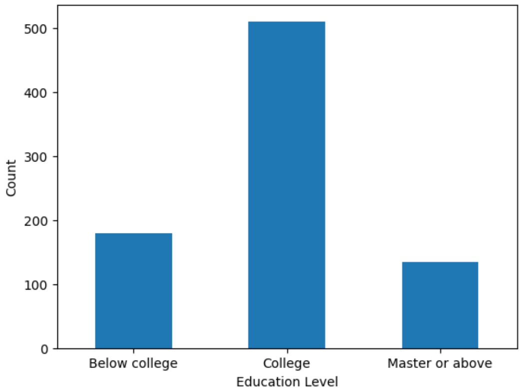
8. To what extent do you agree with the following statement: Learning to use a new exchange or digital wallet feels too hard for me.

Strongly disagree
Disagree
Neutral
Agree
Strongly agree
I do not understand the statement

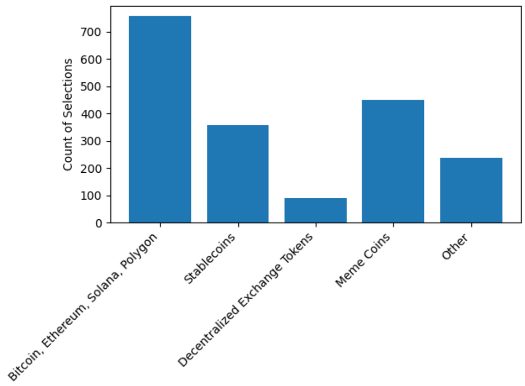
9. To what extent do you agree with the following statement: For convenience, I prefer to stay with the exchange I am familiar with, even if it may be less transparent or less secure than other options.

Strongly disagree

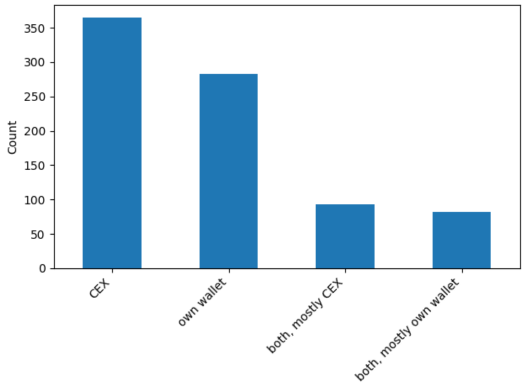
Disagree
Neutral
Agree
Strongly agree
I do not understand the statement




**Panel A. Distribution of Education Level**




**Panel B. Distribution of Cryptocurrency Investment Categories**




**Panel C. Distribution of Cryptocurrency Storage Locations**

**Appendix G. Categorical Variable Histograms**

This figure presents the distribution of key categorical variables from the survey experiment. Panel A reports the respondents' educational distribution, grouped as below college, college, and master's or above. Panel B reports the distribution of respondents' cryptocurrency investments based on a multiple-choice question. Participants were allowed to select all categories of crypto assets they had ever invested in. Panel C reports the distribution of respondents by where they mainly store their cryptocurrency assets, distinguishing between CEX, own wallets, and mixed holdings (both, mostly CEX / both, mostly own wallet).

## Appendix H. Heterogeneous index construction

### Sense of Security Index

The Sense of Security Index is constructed from four Likert-scale questions (C2 – C5) that capture respondents' perceived safety of digital assets, trust in exchanges, concern about exchange security, and willingness to compromise on safety for benefits. Responses are coded from 1 (Strongly disagree) to 5 (Strongly agree), with "I do not understand the statement" coded as -1 and treated as missing. Each item is first standardized within the sample to remove scale differences. Each item is standardized within the sample, and the average of the standardized scores is computed and re-standardized to obtain the composite index. A higher value of the index indicates a stronger perceived sense of security and greater confidence in the safety of one's cryptocurrency holdings and trading platforms.

### Switching Cost Index

The Switching Cost Index measures respondents' perceived frictions or barriers to switching trading platforms or wallets. It is based on four Likert-scale questions (C6 – C9) that assess perceived time and effort required to transfer assets, financial or fee-related costs, difficulty in learning to use new exchanges, and preference for staying with familiar platforms. Responses are coded from 1 (Strongly disagree) to 5 (Strongly agree), with "I do not understand the statement" coded as -1 and treated as missing. Each item is standardized within the sample, and the average of the standardized scores is computed and re-standardized to obtain the composite index. Higher values indicate higher perceived switching costs and stronger behavioral inertia.

### Risk Aversion Index

The Risk Aversion Index is derived from three sequential binary gamble questions (A9 - A11). The three questions are coded to ensure sequential consistency: the second gamble can be accepted only if the first was accepted, and the third can be accepted only if both previous gambles were accepted. The number of accepted gambles (ranging from 0 to 3) is then mapped to an ordered risk-aversion score, where 1 corresponds to the least risk-averse (accepting all gambles) and 4 to the most risk-averse (rejecting all). The resulting scale is standardized across respondents to form the Risk Aversion Index, with higher values reflecting greater risk aversion.

## Appendix I. Exchange Description

This table presents the key information of the top 10 in-sample CEX and DEX exchanges for exchange-level analysis, selected from the top 30 exchanges listed on CoinMarketCap (CMC) as of October 31, 2022. # Symbols is the number of trading pairs available on the exchange. Year Est. indicates the year the exchange was founded. The Volume and Market Share listed are calculated as the 90-day averages prior to November 2, 2022 (before the FTX collapse). Cointelegraph Top 100 indicates whether an exchange was mentioned in the 2020 to 2022 Cointelegraph Top 100 crypto characters. Reserve indicates whether an exchange disclosed its reserve in December 2022. The token is the token issued by this exchange that is more representative of its value.

### Panel A. CEX

| Name | Year Est. | # Symbols | Volume (Bil. US$) | Market Share (%) | Cointelegraph Top 100 | Reserve | Token |
|---|---|---|---|---|---|---|---|
| Binance | 2017 | >100 | 61.12 | 43.84 | Y | Y | BNB |
| Coinbase Exchange | 2012 | >100 | 1.68 | 1.20 | N | N | |
| Kraken | 2011 | >100 | 0.55 | 0.39 | Y | N | |
| KuCoin | 2014 | >100 | 4.17 | 3.00 | N | Y | KCS |
| Binance.US | 2019 | >100 | 0.38 | 0.27 | N | N | |
| HTX(Huobi) | 2013 | >100 | 2.71 | 1.95 | Y | Y | HT |
| Gate.io | 2013 | >100 | 2.69 | 1.95 | N | N | GT |
| Bitstamp | 2013 | >100 | 0.15 | 0.10 | Y | N | |
| Bitfinex | 2014 | >100 | 0.52 | 0.37 | Y | Y | |
| Gemini | 2014 | >100 | 0.06 | 0.04 | Y | N | |
| Others(N=20) | | | | | | | |

### Panel B. DEX

| Name | Year Est. | # Symbols | Volume (Bil. US$) | Market Share (%) | Cointelegraph Top 100 | Token |
|---|---|---|---|---|---|---|
| Uniswap(v3) | 2021 | >100 | 0.74 | 0.53 | 1 | UNI |
| DODO | 2020 | 6 | 0.10 | 0.13 | 0 | DODO |
| Curve | 2020 | 88 | 0.06 | 0.07 | 1 | CRV |
| PancakeSwap(v2) | 2020 | >100 | 0.32 | 0.38 | 1 | CAKE |
| Uniswap(v2) | 2018 | >100 | 0.05 | 0.06 | 1 | UNI |
| SushiSwap | 2020 | >100 | 0.05 | 0.09 | 1 | SUSHI |
| Orca | 2021 | >100 | 0.01 | 0.01 | 0 | ORCA |
| KyberSwap Elastic | 2018 | 27 | 0.01 | 0.01 | 0 | KNC |
| Osmosis | 2021 | 100 | 0.01 | 0.01 | 0 | OSMO |
| SunSwap(v2) | 2021 | 100 | 0.01 | 0.01 | 0 | SUN |
| Others(N=20) | | | | | | |