Market Fragmentation and Price Efficiency: Evidence from Cryptocurrencies

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Abstract

Does market fragmentation enhance price efficiency? Predictions from theoretical models and empirical evidence remain mixed. We use cryptocurrency delistings and a major trading venue's sudden collapse to assess fragmentation's impact on efficiency. We find evidence that reduced fragmentation harms efficiency: after the venue's closure, efficiency declines by 86% of its pre-collapse standard deviation, and following a coin delisting, it drops by 57%. These findings support the view that fragmented markets enhance price efficiency.

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1. Introduction

Market fragmentation—trading a single security across multiple platforms—has significantly increased in modern financial markets. Before the year 2000, the New York Stock Exchange and NASDAQ collectively handled 95% of U.S. equity trading volume (Haslag and Ringgenberg, 2023). Today their combined volume share is less than 35%.[1] However, isolating the causal impact of fragmentation on price efficiency in equities has proven difficult, especially under regulatory frameworks such as Regulation National Market System (Reg NMS) that integrate trading venues. In this paper, we exploit two natural experiments in cryptocurrency markets to provide causal evidence on how fragmentation affects price efficiency.

Theoretical models offer contrasting predictions on how fragmentation affects price efficiency. Some studies argue that fragmentation can harm price efficiency by increasing adverse selection and reducing market depth (Chowdhry and Nanda, 1991, Babus and Parlatore, 2022). Babus and Parlatore (2022) show that when investors share similar valuations and act strategically, they may prefer fragmented markets to reduce competition among themselves. This can lead to inefficiencies and lower liquidity. In contrast, Chen and Duffie (2021) develop a theoretical model demonstrating that market fragmentation can enhance allocative efficiency and overall price informativeness across trading venues for a single asset. They argue that fragmentation reduces the inhibiting effect of price-impact avoidance on order submission. Allowing traders to split orders across multiple trading venues leads to more aggressive trading and better rebalancing of unwanted positions, thereby improving the asset's price efficiency across all trading venues.

Empirical evidence on fragmentation's effects remains mixed. Some studies find that fragmentation improves liquidity and price efficiency. For example, O'Hara and Ye (2011) show that market fragmentation in U.S. equities is associated with lower transaction costs, faster execution

[1] See https://www.cboe.com/us/equities/market_share/.

speeds, and improved price efficiency. Haslag and Ringgenberg (2023) find that fragmentation reduces bid-ask spreads and enhances liquidity for large-cap stocks but has the opposite effect on small-cap stocks. Other studies report negative effects, especially for less liquid assets. Hendershott and Jones (2005) and Bennett and Wei (2006) find that increased fragmentation is associated with worse liquidity and reduced price efficiency. Similarly, Chung and Chuwonganant (2012) report that fragmentation leads to increased spreads, slower execution, and reduced depth, which can harm price efficiency. This contradiction highlights the challenge of isolating fragmentation's true impact in equity markets, where regulations like Reg NMS were introduced piecemeal and enforced best execution across multiple venues.

In this paper, we make two main contributions. First, we establish a causal link between fragmentation and price efficiency by exploiting shocks in cryptocurrency markets. Although a small number of trading venues account for most trading volume, fragmentation varies substantially across coins and over time, which we exploit in our identification. Second, since these venues are not subject to the venue-integration rules of Reg NMS like traditional equities, we have a clearer identification of how fragmentation affects price efficiency.

Isolating fragmentation's effects in traditional equity markets is challenging when using Reg NMS as the event since the policy —though fully implemented in October 2007—had been proposed earlier and rolled out in phases. As O'Hara and Ye (2011) note, Reg NMS and especially the trade-through rule (Rule 611) were designed to foster competition across multiple trading venues, including newly emerging Electronic Communication Networks and alternative trading systems. Thus, the proliferation of new trading venues and off-exchange platforms did not occur in one clean shock, but rather gradually over several years. At the same time, best-execution and order-routing rules under Reg NMS integrated trading venues, ensuring that prices and trades were closely linked across platforms. This staggered entry of new players and simultaneous push toward integration complicate attempts to isolate fragmentation's impact on price efficiency.

A further challenge arises from traders' strategic choices. Investors may choose fragmented markets to reduce competition among themselves, leading to endogenous fragmentation (Babus and Parlatore, 2022). This strategic behavior makes it difficult to determine whether changes in price efficiency are caused by fragmentation itself or by traders' choices.

Equity trading venue closures can be used as alternative events, but they are rare due to regulatory oversight. Another option is to use stock delistings; however, stock delistings usually result from mergers or financial distress, which contaminates the shock to fragmentation. These factors make it difficult to find natural experiments in traditional markets to study fragmentation's effect on price efficiency.

We address these challenges by using cryptocurrency markets as a natural laboratory for three key reasons. First, cryptocurrencies are traded across multiple venues that are not centrally regulated, creating independent variation in how trading volume is split across coins and over time. Unlike traditional equity markets, cryptocurrency markets lack an overarching framework like Reg NMS, allowing for a more direct measurement of fragmentation's impact on price efficiency. Second, they experience shocks to fragmentation from trading venue closures and coin delistings. Because traders cannot prevent these closures and delistings, we reduce endogeneity from their strategic choices and can better isolate the impact on price efficiency. Third, cryptocurrencies offer transparent, granular data that let us measure both price efficiency and fragmentation. Taken together, these features enable us to test the predictions of Chen and Duffie (2021) in a way not feasible in traditional markets.

We measure price efficiency using variance ratios, which compare the variability of returns over different time intervals, and return autocorrelations, which assess return predictability based on past performance. Our measures are signed so that higher values indicate greater price efficiency. We combine these measures into a single efficiency metric by computing their first

principal component.

To examine the relationship between market fragmentation and price efficiency, we use two identification strategies: an event study on coin delistings and an analysis of the unexpected collapse of a large cryptocurrency trading venue as a natural experiment. Our dataset consists of high-frequency trade and quote data for 5,246 coin pairs traded on 16 major centralized trading venues, including Binance, Coinbase, and FTX, during the period from March 2021 to May 2023. We capture a substantial share of global cryptocurrency trading and assemble a robust sample for studying the relationship between fragmentation and price efficiency.

In our first strategy, we examine how coin delistings from Binance, a major cryptocurrency trading venue, affect price efficiency. When Binance delists a coin, traders who wish to continue trading that coin must move their activity to other venues. This forced redistribution of trading volume increases market concentration and reduces fragmentation, providing variation in fragmentation levels. Following a delisting, the first principal component of price efficiency decreases by 57% of its pre-delisting standard deviation. This result supports Chen and Duffie (2021)'s prediction that trading across multiple venues enhances price efficiency.

For our second strategy, we exploit the unexpected collapse of FTX in November 2022 as a natural experiment to identify the causal impact of reduced market fragmentation on price efficiency. Prior to its collapse, FTX was the second-largest cryptocurrency trading venue in the world by trading volume (FTX representing 14% and FTX US 8%), handling a substantial share of global cryptocurrency transactions across a wide range of coins. Its sudden shutdown eliminated a major trading venue almost overnight, causing an immediate and significant decrease in market fragmentation for many cryptocurrencies.

To isolate the effect of this rare event on price efficiency, we compare coins reliant on FTX and those that were not. We achieve this using a Synthetic Difference-in-Differences (SDID)

design, which builds a control group that mirrors the treated coins' pre-collapse patterns. This allows us to pin down any post-collapse changes in efficiency due to the sudden loss of a major trading venue.

We find that following the collapse of FTX, price efficiency for the affected coins declined. Notably, the first principal component of efficiency decreases by about 86% of its pre-period standard deviation. This further validates Chen and Duffie (2021)'s predictions, demonstrating that significant reductions in market fragmentation adversely affect a single asset's price efficiency across trading venues.

To understand how the magnitude of the fragmentation shock affects price efficiency, we categorize coins based on their reliance on FTX before its collapse. We use volume cutoffs to define treated groups: coins for which FTX accounted for at least 10%, 20%, 30%, or 40% of their total trading volume in the month prior to the collapse. As the reliance on FTX increases—that is, as the shock to fragmentation increases—the decline in price efficiency becomes more pronounced. This gradient effect aligns with Chen and Duffie (2021)'s model, which suggests that the benefits of fragmentation on price efficiency across trading venues are more substantial when traders have greater opportunities to split orders across multiple venues for a single asset.

2. Institutional Details

There are over 250 centralized cryptocurrency trading venues worldwide.[2] Unlike traditional equity markets, they are not integrated through a national best bid and offer system. There is no centralized order routing or trade reporting mechanism that consolidates quotes and trades across trading venues. Market participants must choose specific trading venues on which to trade and

[2] According to data from https://www.coingecko.com/en/exchanges as of October 2023.

deposit funds directly into each trading venue.

These markets run 24 hours a day, seven days a week, and welcome customers from many regions.[3] Although this global reach lets many platforms operate, it does not stitch them together into a single integrated market.

In contrast to U.S. equity markets, where regulations like the Unlisted Trading Privileges (UTP) and Reg NMS promote market integration and price consistency across trading venues, cryptocurrency markets lack such regulatory oversight. Cryptocurrency trading venues operate independently, and there is no mandate for best execution or price consolidation. This leads to price discrepancies and arbitrage opportunities across trading venues. While some high-frequency traders and arbitrageurs actively monitor these discrepancies, the lack of regulatory enforcement means that prices are not always aligned across venues (Makarov and Schoar, 2020).

Most centralized venues use fee structures that reward liquidity providers. They commonly charge flat fees or adopt a maker-taker model, where makers post limit orders at quoted prices and takers trade against those quotes. Some venues lower fees for high-volume traders or those who hold the venue's native token.

Cryptocurrency trading venues have broad discretion over listing and delisting practices. Listings often depend on factors like the project's viability, compliance with regulatory standards, and expected trading volume. Delistings can occur due to low liquidity, regulatory concerns, or failure to meet the specific trading venues' criteria. Unlike traditional equity markets, there is no standardized regulatory process governing these actions across trading venues. For example, the New York State Department of Financial Services (NYDFS) has issued guidelines on virtual currency listings and delistings for entities under its jurisdiction.[4] However, these guidelines apply only

[3] Venues may block users in specific jurisdictions for legal reasons.

[4] See NYDFS guidelines at https://www.dfs.ny.gov/industry_guidance/industry_letters/il20230605_guidance_virtual_currency.

to trading venues operating in New York State, and many cryptocurrency trading venues operate outside U.S. regulatory reach. Because no single regulatory framework oversees these trading venues, they operate independently. This allows for sudden delistings or collapses, as happened with FTX.

The current legislative landscape is evolving, with proposals for more comprehensive regulation of cryptocurrency markets being considered in various jurisdictions. For instance, in the United States, the "Digital Commodities Consumer Protection Act of 2022" was introduced to establish a regulatory framework for digital assets.[5] However, until these regulations are enacted and enforced globally, cryptocurrency markets will likely continue to operate with minimal integration.

3. Data and Sample

We use high-frequency trade and quote data from Tardis.dev. Tardis.dev provides millisecond-level timestamps for each trading venue–coin–date combination. For each trade we have data on the price, volume, and an indicator of whether trades are buyer- or seller-initiated. We also collect the best bid and ask quotes from these markets, updated every time there is a quote update. Our dataset spans from March 2021 to May 2023 and includes 5,246 unique coin pairs across 16 trading venues: Binance, Coinbase, FTX, Gate-io, Kraken, KuCoin, Binance US, Bybit, Crypto.com, Bitstamp, FTX US, Gemini, AscendEX, Upbit, Bitflyer, and Coinflex. We focus exclusively on spot trading pairs to ensure comparability across trading platforms.

We pre-process the raw trade and quote data through several steps to remove outliers and

[5] See U.S. Senate Bill S.4760, 117th Congress (2021–2022), available at https://www.congress.gov/bill/117th-congress/senate-bill/4760.

standardize naming conventions across trading venues. For more detail on this process see Appendix A.

Although many cryptocurrency trading venues exist, trading volume is concentrated among a few large platforms, resulting in a high average Herfindahl–Hirschman Index (HHI). Table 1 shows volume in USD, market share, and the number of symbols traded by each venue. We convert all volumes to USD using the daily average midpoint price on Binance. If Binance does not trade a certain coin we use the venue with the longest time series and highest volume. The market share is computed as the ratio of a trading venue's median daily volume to the total median daily volume across all venues. The largest venue Binance captures a market share of 66.8% and the three largest - Binance, Coinbase, and FTX[6] - hold a combined market share of 83.2%. Although Binance also offers the largest number of coins (1,696) and executes the highest number of trades (14,984,783) the other venues are much more competitive on those parameters.

[**Table 1**: Cryptocurrency Trading Venues Market Share]

3.1 Efficiency Measures and Fragmentation

We assess price efficiency using variance ratios and autocorrelation coefficients, based on the random walk hypothesis proposed by Lo and MacKinlay (1988). In an efficient market, price changes follow a random walk and returns are uncorrelated over time. We calculate the autocorrelation of returns for each coin at the one-minute interval. The autocorrelation coefficient at lag k is:

$$\rho_k = \left| \frac{\mathrm{Cov}(\mathrm{Ret}_t, \mathrm{Ret}_{t-k})}{\mathrm{Var}(\mathrm{Ret}_t)} \right| \tag{1}$$

[6]Prior to the collapse, FTX had a market share of around 14%.

where Ret_t is the return at time t. In an efficient market, ρ_k should be close to zero for $k > 0$.

The variance ratio compares the variance of returns over different time horizons. We compute it as:

$$\text{Variance Ratio} = \left| \frac{\text{Var}(\text{Ret}_{c\text{-minute}})}{b \times \text{Var}(\text{Ret}_{a\text{-minute}})} - 1 \right| \tag{2}$$

where $c = a \times b$, and a and c represent different time intervals (e.g., 1-minute and 5-minute). A variance ratio close to zero indicates returns follow a random walk. We include variance ratios computed at: 15-second to 1-minute returns, 1-minute to 5-minute returns, 5-minute to 15-minute returns, and 15-minute to 30-minute returns. We take the absolute value and multiply the variance ratio and autocorrelation measures by -1 so that higher values correspond to higher efficiency. Finally, we compute the first principal component of all the efficiency measures and the first principal component of the variance ratios. See Table 11 in Appendix A for all variable definitions.

Table 2 shows the average efficiency and volatility levels across venues-coin-dates as well as the average across all venues. For the autocorrelation measure Auto Corr (1min), mean values range from -0.07 on Binance, Binance US, and FTX US to -0.21 on Upbit, with an overall mean of -0.12. The variance ratio measures likewise show less negative means for the largest trading venues as well as Kraken and Bitstamp. This suggests that the largest trading venues Binance, Coinbase, and FTX broadly have more efficient prices as they follow a random walk more closely and have less correlated returns.

Volatility is measured as $\frac{\max(\text{midquote}) - \min(\text{midquote})}{\text{avg(midquote)}}$, where $\max(\text{midquote})$, $\min(\text{midquote})$, and avg(midquote) are the maximum, minimum, and average midquotes. Table 2 shows that the mean volatility across all trading venues is close to zero at 0.1 and that volatility is fairly similar across most of the trading venues.

[**Table 2**: Summary Statistics by Trading Venue]

Our main analysis compares coins across trading venues. We calculate market concentration for each coin using the Herfindahl–Hirschman Index (HHI). This measure captures how concentrated the trading volume of a given coin is across multiple trading venues on a specific date. The HHI for each coin-day is computed as follows:

$$\text{HHI}_{it} = \sum_{e=1}^{E} \left(\frac{\text{Volume}_{ite}}{\sum_{e=1}^{E} \text{Volume}_{ite}} \right)^2 \tag{3}$$

where Volume_{ite} is the trading volume of coin i on trading venues e at time t, and E is the total number of trading venues trading coin i at time t.

We define fragmentation as one minus the HHI:

$$\text{Fragmentation}_{it} = 1 - \text{HHI}_{it} \tag{4}$$

A higher fragmentation value means trading volume is more evenly distributed across trading platforms, while a lower value indicates concentration on fewer trading venues. This measure of fragmentation follows that of Haslag and Ringgenberg (2023).

We create a panel of coin-date observations by volume-weighting across trading venues. In Table 3, we calculate the average trading volume for each coin across all dates and then group the coins into terciles based on this average. [7]

We construct two separate principal components to capture different aspects of price effi-

[7] This leads to unevenly distributed groups, as the grouping is driven by the natural distribution of trading volume rather than equal-sized bins.

ciency. First, we derive the first principal component from our set of efficiency measures (auto-correlation and variance ratios) and label it as Efficiency PC. Next, we extract the first principal component solely from the variance ratio measures, which we refer to as Var Ratio PC. Both Efficiency PC and Var Ratio PC are computed at the coin-date level (using the volume-weighted mean across trading venues), rather than the coin-date-trading venue level, ensuring that any cross-venue differences are averaged out for each coin on each day.

Focusing on the full sample in Table 3, we see that the average fragmentation is 0.08 and the mean number of trading venues is roughly 1.65. In the highest volume tercile, the average fragmentation increases to 0.12, and the mean number of trading venues is just over 2. To explain what these fragmentation levels mean, we provide the following example. Suppose these two trading venues for a particular coin-day are Binance and Gate-io, and together they account for 100% of that coin's trading volume. A fragmentation level of 0.08 implies that one trading venue holds a substantial majority of the market, while the other has a small share. Specifically, if Binance has X fraction of the market, then the Herfindahl-Hirschman Index (HHI) is $X^2 + (1 - X)^2$, and a fragmentation of 0.12 means

$$1 - (X^2 + (1-X)^2) = 0.12,$$

which occurs if $X \approx 0.94$ (and $1 - X \approx 0.06$), or vice versa. This example illustrates that even in the highest volume tercile where trading is most fragmented trading can be considered relatively concentrated. However, what is more important for our analysis is the variation in fragmentation. In the full sample fragmentation has a mean of 0.08 and a standard deviation of 0.16 so in an example similar to the above, fragmentation varies from $X \approx 0.86$ (and $1 - X \approx 0.14$) to $X \approx 0.96$ (and $1 - X \approx 0.04$) one standard deviation below and above the mean.

Coins in the highest volume tercile are generally more efficient, with an average Efficiency

PC of 0.87 (median 1.13, standard deviation 1.05), compared to -1.50 (median -1.53, standard deviation 1.53) for coins in the lowest volume tercile. This gap points to a strong correlation between trading volume and price efficiency. A similar pattern appears in the variance ratio principal component (Var Ratio PC): coins in the highest volume tercile average 0.76 (median 0.98, standard deviation 1.00), whereas those in the lowest volume tercile average -1.26 (median -1.27, standard deviation 1.31). At the aggregate level, Var Ratio PC is 0.00 on average (median 0.26, standard deviation 1.42), while Efficiency PC is also 0.00 on average (median 0.37, standard deviation 1.60). Volatility is slightly higher among the lowest volume coins (mean 0.14) compared to the highest volume coins (mean 0.09). Finally, coins in the highest volume tercile trade on more trading venues on average (2.16) than the full sample (1.65).

[**Table 3**: Summary Statistics by Coin Volume Tercile]

4. Identifying the Impact of Fragmentation

We start our analysis of how market fragmentation in cryptocurrency coin pairs impacts efficiency by estimating the following simple OLS regression:

$$Efficiency_{it} = \text{Fragmentation}_{it} + \Theta_t + \gamma_i + X_{it} \tag{5}$$

where $Efficiency_{it}$ is the volume-weighted daily efficiency measure (*variance ratio* or *autocorrelation*) for coin i on date t, *Fragmentation* is $1 - \text{HHI}$, X_{it} includes control variables, Θ_t is a date fixed effect, and γ_i is a coin fixed effect. We control for volatility, the number of trading venues, and the logarithm of trading volume in USD. Standard errors are clustered by coin and date.

[**Table 4**: Daily Fragmentation and Efficiency Measures]

Our results in Table 4 highlight how fragmentation influences various efficiency measures. Column (1) examines the autocorrelation of returns (Auto Corr (1min)), and shows that higher fragmentation is associated with a reduction in autocorrelation, with a coefficient of -0.014. The total sample standard deviation of Auto Corr (1min) from Table 3 is 0.12. A one standard deviation increase in fragmentation (0.16 from Table 3) would decrease Auto Corr (1min) by approximately $0.16 \times (-0.014) = -0.002$ a small impact relative to the observed variation.

Column (2) focuses on the variance ratio principal component (Var Ratio PC), where the coefficient of -0.25 suggests that fragmentation reduces the extent to which prices follow a random walk, reducing price efficiency. With a standard deviation of 1.42 for Var Ratio PC, a one standard deviation increase in fragmentation reduces Var Ratio PC by approximately $0.16 \times (-0.25) = -0.040$ representing 2.8% of the standard deviation.

We examine the effect on overall efficiency using the principal component (Efficiency PC) in Column (3), which combines metrics of autocorrelation and variance ratios. The coefficient of -0.28 indicates that fragmentation broadly reduces efficiency. Given a standard deviation of 1.60 for Efficiency PC, a one standard deviation increase in fragmentation decreases Efficiency PC by approximately $0.16 \times (-0.28) = -0.045$, representing 2.8% of its standard deviation. These results collectively indicate that while fragmentation reduces efficiency, the magnitude of the effect is modest relative to the variability observed in the sample.

The opposite signs of the coefficients for number of *Venues* and *Fragmentation* in Table 4 may result from differences in how these variables capture market structure and from potential endogeneity in fragmentation. The number of trading venues measures the availability of a coin across trading venues. A higher number of trading venues listing a coin generally enhances liquidity, broadens the investor base, and facilitates information flow, all of which contribute to improved price efficiency. In contrast, fragmentation measures how trading volume is distributed

across the trading venues listing a coin. Higher fragmentation indicates that trading activity is more evenly spread among multiple trading platforms. The results in Table 4 therefore suggest that a coin being traded on more venues improves efficiency, but if the volume is more equally distributed across these venues the efficiency gains disappear and efficiency decreases.

A possible explanation for this result is the endogeneity of the fragmentation variable in the OLS regression. Although we control for volatility and volume, fragmentation may still be influenced by unobserved factors that affect both fragmentation and efficiency. For example, fragmentation can be affected by strategic trader behavior, market microstructure differences, and other unobserved variables that influence the distribution of trading volume. These factors may introduce measurement errors or omitted variable bias, distorting the estimated relationship. We therefore use exogenous events in the next sections to overcome this limitation of the OLS analysis.

4.1 The Impact of Coin Delistings on Market Fragmentation

We examine the impact of Binance delistings as shocks to fragmentation and study how this affects efficiency. We focus on Binance delistings since Binance is the largest trading venue in the cryptocurrency market, with a 66.8% market share of global trading volume. Its delistings, therefore, represent substantial exogenous shocks to market fragmentation.

We focus on coins traded on more than one trading venue prior to the delisting announcement, excluding coins that go from being listed on Binance to none. This ensures that the delisting event leads to a redistribution of trading volume among remaining venues rather than a complete cessation of trading for that coin, resulting in 33 delisting events from Binance. We verify all delisting notices on Binance's official website to ensure the accuracy and reliability of our events.

When a coin is delisted, the trading volume previously handled by Binance is redistributed to other trading venues, increasing market concentration and reducing fragmentation. This setup allows us to observe fragmentation's effects more directly, similar to the approach of Chen and Duffie (2021), who demonstrate that fragmentation enhances price efficiency by allowing traders to split orders across multiple venues. For example, before a delisting, suppose the trading volume of BETH-USDT is 40% on Binance, 30% on Kraken, and 30% on Coinbase. After Binance delists the coin, its 40% share is reallocated equally to Kraken and Coinbase, resulting in 50% on Kraken and 50% on Coinbase. Before delisting, the Herfindahl-Hirschman Index (HHI) is:

$$\text{HHI} = 0.4^2 + 0.3^2 + 0.3^2 = 0.34, \quad \text{Fragmentation} = 1 - 0.34 = 0.66.$$

After delisting, the HHI increases to:

$$\text{HHI} = 0.5^2 + 0.5^2 = 0.50, \quad \text{Fragmentation} = 1 - 0.50 = 0.50.$$

As such we use these significant shocks to fragmentation to test how price efficiency is affected by fragmentation. Figure 6 illustrates the volume reshuffling from Binance to other trading venues in our example. Notably, trading volume on Binance begins to spike approximately 8-9 days before the delisting date. This likely reflects traders reacting to Binance's announcements of the delisting, which frequently happens around a week before the delisting date[8] Figure 7 shows that around the delisting date, fragmentation drops sharply, and this decline persists for at least 40 days. To account for the potential anticipatory behavior during the announcement window, we exclude days -9 to the event date in the regression analysis.

[**Figure 6**: Volumes Surrounding Delisting Events]

[8] See Binance's delisting announcements at https://www.binance.com/en/support/announcement/delisting?c=161&navId=161.

[**Figure** 7: Fragmentation Surrounding Delisting Events]

Table 5 presents summary statistics for coins before and after delisting events from Binance. Before the delisting, fragmentation has a mean of 0.26, a median of 0.24, and a standard deviation of 0.19. After delisting, fragmentation decreases to a mean of 0.11, with a median of 0.00 and a standard deviation of 0.19, reflecting increased market concentration as trading activity consolidates on fewer venues.

Price efficiency measures show a noticeable decline post-delisting. The autocorrelation at the one-minute interval (Auto Corr (1min)) has a mean of -0.10 (median -0.09, standard deviation 0.08) before the delisting, and -0.16 (median -0.14, standard deviation 0.11) after, suggesting a rise in return predictability and a decrease in efficiency. The first principal component of efficiency measures (Efficiency PC) moves from a mean of 0.47 (median 0.68, standard deviation 1.37) to -0.54 (median -0.47, standard deviation 1.59), indicating a more pronounced drop in overall price efficiency when the market becomes more concentrated.

Trading volume (Log(Volume)) also declines, with a mean of 12.26 (median 12.01, standard deviation 1.99) before the delisting and 10.16 (median 9.65, standard deviation 2.44) afterwards. This indicates that after the coin is delisted from Binance, the volume is not just redistributed, volume decreases, highlighting the importance of Binance to market participants. Volatility, meanwhile, increases from 0.09 (median 0.06, standard deviation 0.11) to 0.13 (median 0.08, standard deviation 0.17), highlighting that prices become more volatile in a less fragmented market. The number of trading venues (venues) falls from a mean of 2.62 (median 2.00, standard deviation 1.12) to 1.49 (median 1.00, standard deviation 0.87) which is a mechanical effect of the delisting.[9]

Overall, these statistics demonstrate that Binance's delisting events lead to decreased market

[9]The sample size for the pre-delisting period is 1,347 observations, whereas the post-delisting period includes 1,191. Some coins do not have a full 40 days of post-delisting data, and others cease trading on remaining venues, reducing the sample available after the event.

fragmentation, reduced trading volume, increased volatility, and a decline in price efficiency. Next, we test these effects in a formal regression setup.

[**Table 5**: Summary Statistics for Coins Around Delisting Events]

To estimate the impact of a coin delisting (which decreases fragmentation) on efficiency measures, we use the following specification:

$$\text{Efficiency}_{it} = \beta \text{ Post-Delisting}_{it} + \gamma X_{it} + \Theta_t + \alpha_i + \varepsilon_{it} \tag{6}$$

where Efficiency_{it} is the volume-weighted daily efficiency measure (Var Ratio PC, Efficiency PC, Auto Corr (1min)) for coin i on date t, $\text{Post-Delisting}_{it}$ is a dummy variable that equals 1 during the 40 days following the delisting and 0 during the 40 days before, X_{it} includes control variables, Θ_t is a date fixed effect, and α_i is a coin fixed effect. We control for volatility, the number of trading venues, and trading volume in USD. Controlling for trading volume is important, as Haslag and Ringgenberg (2023) find that firm-specific characteristics like size and volume can influence fragmentation's effects on price efficiency. We cluster standard errors by coin and event date.

Table 6 shows the regressions of daily efficiency measures on the post-delisting indicator. The autocorrelation at 1 minute decreases by -0.057 which is a 71% decline relative to the pre-delisting standard deviation. This implies that returns become more predictable and less efficient after a coin loses access to Binance.

The principal component of the variance ratios decrease by -0.57, but the decline is only marginally significant at the 10% level. Since *Var Ratio PC* has a standard deviation of 1.37 before the delisting, -0.57 is approximately 42% of that standard deviation. The overall efficiency

principal component (*Efficiency PC*) decreases by -0.78, which is a 57% reduction of the pre-delisting standard deviation of 1.37. Together, these results indicate that delisting from Binance, which reduces market fragmentation, substantially lowers short-term return efficiency, variance ratio efficiency, and overall price efficiency.

Our combined delisting results align with the theoretical model of Chen and Duffie (2021), which posits that market fragmentation enhances allocative price efficiency across trading venues. In our context, the delisting of coins reduces fragmentation, leading to a significant decline in efficiency measures. This supports the notion that multiple trading venues facilitate more efficient price discovery in cryptocurrency markets.

[**Table 6**: Delisting on Efficiency Measures]

4.2 The Collapse of FTX and Its Impact on Market Fragmentation

Building on our delisting analysis, we examine the collapse of FTX in November 2022 as a market wide shock to market fragmentation. FTX's collapse serves as an excellent shock to market fragmentation for several reasons. First, FTX (including FTX US) held a 22% market share of global cryptocurrency spot trading volume. The sudden removal of FTX from the market caused an immediate and substantial reduction in the number of venues where even the most popular and liquid coins could be traded. This abrupt change contrasts with gradual market shifts or predictable delistings, offering a clear distinction between pre- and post-collapse market conditions.

Second, although there were warning signs in the days leading up to the collapse, the speed and severity of FTX's downfall were not fully anticipated by most market participants. Even sophisticated investors did not anticipate its collapse.[10] The lack of widespread anticipation reduces

[10] See https://www.fnlondon.com/articles/ftx-crypto-hedge-funds-exposures-sell-20221114.

the likelihood that traders significantly adjusted their behavior in advance, which might otherwise confound the analysis. This suddenness also minimizes concerns about endogeneity that might arise if changes in fragmentation were driven by factors related to the coins themselves.

Third, the collapse affected a wide range of coins simultaneously. Many coins listed on FTX were also available on other trading platforms, but FTX often accounted for a substantial portion of their trading volume. By examining coins that traded on FTX and at least one other trading venue before the collapse, we can assess whether the relationship between fragmentation and efficiency observed in the delisting analysis holds in a broader context.

On November 11, 2022, FTX filed for bankruptcy after a rapid decline in liquidity and failed acquisition attempts. The trading venue halted withdrawals and ceased trading operations, leaving users unable to access their funds. The collapse was precipitated by concerns over the company's solvency and allegations of mismanagement, including the misuse of customer funds and lack of proper risk controls. This led to a loss of confidence among users and investors, triggering a run on the trading venue.

Figure 8 shows the average daily trading volume (in USD) for coins on FTX and FTX-US near the collapse date. Volume remains steady before November 8, 2022, then spikes as traders run on the trading venue and then drops sharply when the shutdown becomes imminent, reaching zero on November 11. Because the shock to fragmentation occurs on November 8, 2022 (see Figure 9), this is the date that we use in subsequent analysis.

[**Figure 8**: Trading Volume on FTX]

To analyze the impact of the FTX collapse on price efficiency, we employ a Synthetic Difference-in-Differences (SDID) approach. This method combines elements of Difference-in-Differences

and Synthetic Control to estimate causal effects when a treatment affects multiple units simultaneously and there is no clear single control group (Arkhangelsky, Athey, Hirshberg, Imbens, and Wager, 2021). The SDID approach is appropriate in our context because the collapse is an aggregate shock affecting many coins at once.

By constructing a synthetic control group that closely matches the treated group in terms of pre-collapse characteristics and trends, we address the endogeneity concerns raised by Babus and Parlatore (2022), who highlight that investors' strategic choices can lead to endogenous market fragmentation. The exogenous nature of the FTX collapse allows us to isolate the effect of fragmentation on price efficiency without the confounding influence of strategic trader behavior.

Table 7 compares coins traded on FTX with coins not traded on FTX before and after the collapse. In the pre-period (2022-10-10 to 2022-11-08), coins traded on FTX have a mean fragmentation of 0.38. Their average efficiency principal component is 1.33, and they trade on 5.57 venues on average.

Coins not traded on FTX have a mean fragmentation of 0.11 (median 0.00, standard deviation 0.18), a mean efficiency principal component of 0.20 (median 0.42, standard deviation 1.49), and 1.72 venues on average (median 1.00, standard deviation 1.30). These numbers show that coins traded on FTX are listed on more venues, have higher fragmentation, and display higher efficiency before the collapse.

After the collapse, coins traded on FTX experience decreases in fragmentation and the number of venues. Their mean fragmentation moves to 0.26, their efficiency principal component to 1.10 , and their average number of venues to 4.75. Coins not traded on FTX remain steady, with a mean fragmentation of 0.11, an efficiency principal component of 0.08, and an average of 1.72 venues. This contrast suggests that coins that depended on FTX face more disruptions, while coins outside FTX see few changes.

[**Table 7**: Summary Statistics for Coins by FTX Status]

Figure 9 illustrates the dynamics of fragmentation as shown in Table 7. It plots the two-day average fragmentation for coins traded on FTX compared to those not traded on FTX, centered around the collapse date of November 08, 2022. The figure reveals a sharp decline in fragmentation for the treated coins, dropping from approximately 0.35 to 0.22 on the collapse date. In contrast, no change is observed for the group of non-FTX coins. It's important to note that the levels of fragmentation were different between the two groups even before the collapse.

[**Figure 9**: Fragmentation on FTX and Other Venues]

The notable differences in trends between the groups imply that a simple Difference-in-Differences (DiD) approach may not be suitable, as it relies on the parallel trends assumption that both groups would have followed similar paths in the absence of the treatment.

To address this issue, we employ the Synthetic Difference-in-Differences (SDID) method. This approach constructs a synthetic control group that closely matches the treated group in observable characteristics and pre-treatment trends, enhancing comparability and strengthening the validity of our causal inference. We match on volatility, the number of trading venues, trading volume in USD, and pre-treatment trends in efficiency measures during October 2022. This ensures that, in the absence of the FTX collapse, the treated coins and the synthetic control group would have followed similar paths in terms of price efficiency.

Figure 10 shows the parallel trends for the first principal component of efficiency for coins that had at least 20% of their trading volume on FTX. This figure displays the trends from the SDID analysis 30 days before and after the FTX collapse comparing coins listed on FTX with those that were not. The red line indicates the FTX collapse date, November 08, 2022. The figure

shows that coins affected by the FTX collapse experienced substantial and sudden decreases in price efficiency measures compared to the synthetic control group.

[**Figure 10**: Efficiency Parallel Trends]

To test this reduction in price efficiency, we estimate the following regression:

$$\text{Efficiency}_{it} = \beta(\text{Post}_t \times \text{Treat}_i) + \gamma X_{it} + \alpha_i + \Theta_t + \varepsilon_{it}, \tag{7}$$

where: Efficiency_{it} is the efficiency measure for coin i on date t (Var Ratio PC, Efficiency PC, Auto Corr (1min)). Post_t is a dummy variable equal to 1 after November 08, 2022, and 0 before. Treat_i is a dummy variable equal to 1 if coin i was traded on FTX before the collapse and 0 otherwise. X_{it} includes control variables (volatility, number of trading venues, trading volume in USD). α_i is a coin fixed effect controlling for time-invariant coin characteristics. Θ_t is a date fixed effect capturing common shocks. ε_{it} is the error term. We cluster standard errors by coin and date to account for serial correlation within coins over time.

Table 8 shows the results for coins that had at least 20% or 30% of their trading volume on FTX prior to the collapse. The coefficient on the interaction term $treat \times post$ captures the average treatment effect of the FTX collapse on price efficiency measures. In Table 8 Panel A, the coefficient on Auto Corr (1min) is -0.045, which amounts to about 56% of its 0.08 standard deviation. The coefficient on Var Ratio PC is -0.89, approximately 86% of its 1.04 standard deviation. The coefficient on Efficiency PC is -0.91, around 82% of its 1.11 standard deviation. These findings show that losing FTX leads to a notable drop in short-term autocorrelation efficiency, variance ratio efficiency, and overall efficiency.

The negative effects grow larger in Panel B with a 30% volume cutoff. The coefficient on Var

Ratio PC is -1.13, roughly 109% of its 1.04 standard deviation. The coefficient on Efficiency PC is -0.96, near 86% of its 1.11 standard deviation. These stronger impacts suggest that coins more dependent on FTX experience more pronounced declines in efficiency once they lose a major trading platform.

[**Table 8**: Synthetic Difference-in-Differences: FTX Collapse with 20% and 30% Volume Cutoffs]

As indicated in Table 8 we expect an increasing effect on price efficiency the more FTX represented of total volume. To test the monotonicity we run regressions where FTX represented 10%, 20%, 30%, and 40% of trading volume. Table 9 indicate that as the shock to fragmentation grows, the effect on price efficiency becomes more pronounced. For instance, at a 10% volume cutoff, the efficiency principal component decreases by -0.53, whereas at 40% the drop intensifies to -1.17. Since the standard deviation of the efficiency principal component is about 1.60, this -1.17 shift amounts to nearly 73% of a standard deviation. In other words, coins that depend more on FTX before the collapse experience larger declines in efficiency. This gradient pattern is consistent with the idea that bigger disruptions to fragmentation cause greater harm to the price discovery process.

[**Table 9**: Efficiency Principal Components by the Share of Volume on FTX]

To gauge this effect from a different perspective we use the share of each coin's trading volume on FTX in the month prior to the collapse in an event study.

$$\text{Efficiency}_{it} = \beta\ \text{FTX Volume Share}_{it} + \gamma X_{it} + \alpha_i + \Theta_t + \varepsilon_{it} \tag{8}$$

where FTX Volume Share$_{it}$ is zero in the pre period and the volume share FTX represented prior to the collapse in the post-period. X_{it} includes control variables (volatility, number of trading venues, trading volume in USD). α_i is a coin fixed effect controlling for time-invariant coin characteristics. Θ_t is a date fixed effect capturing common shocks. ε_{it} is the error term. We cluster standard errors by coin and date to account for serial correlation within coins over time.

Table 10 shows the coefficient on Auto Corr (1min) is -0.031, which is about 39% of its pre-collapse standard deviation of 0.08 and 52% of its median value of 0.06 (in absolute terms). The Var Ratio PC declines by -1.17, representing about 112% of its 1.04 standard deviation and 77% of its 1.51 median. Efficiency PC decreases by -1.19, or roughly 107% of its 1.11 standard deviation and 72% of its 1.66 median. These results suggest that coins more reliant on FTX experienced a larger decline in price efficiency, reflecting the greater shock from losing a major trading venue.

This result reinforces our earlier conclusions by highlighting that the greater the shock to fragmentation, the more severe the impact on price efficiency. Coins that relied more heavily on FTX suffered a larger disruption to trading activity, leading to greater inefficiencies in the market.

[**Table 10**: Weighted FTX Collapse Event Study]

5. Conclusion

Financial markets have grown increasingly fragmented over the past 25 years. The NYSE and Nasdaq handled almost all trade volume prior to the year 2000 but is now reduced to executing closer to 35% of volume combined. Despite this change in fragmentation, it is difficult to use traditional financial markets to explore how fragmentation affects price efficiency. Regulation

like Reg NMS and UTP integrate trading venues by enforcing best execution and a national best bid and offer. As a result empirical evidence is mixed.

We overcome these challenges by using high-frequency data from 5,246 coin pairs across 16 cryptocurrency trading venues. We exploit natural experiments — coin delistings from Binance and the sudden collapse of FTX — to provide evidence on how changes in fragmentation affect price efficiency. Overall we find that reductions in fragmentation lead to decreased price efficiency and that the effect intensifies as the shock increases.

These findings support theoretical models suggesting that market fragmentation can improve price efficiency by allowing traders to distribute their orders across multiple venues (Chen and Duffie, 2021). Access to multiple trading venues enables traders to adjust their strategies more effectively and respond to new information, contributing to more efficient pricing mechanisms in the market.

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Table 1
Cryptocurrency Trading Venues Market Share

This table presents the daily median and mean trading volumes (in USD) by cryptocurrency trading venue, alongside the number of listed coins, the median number of trades per day, and the trading venues' market share as a percentage of total trading volume. Market share is calculated as the ratio of the trading venue's median daily volume to the total median volume across all trading venues. For variable definitions, see Table 11 in Appendix A.

	Median Volume (USD)	Mean Volume (USD)	Coins	Number of Trades	Market Share (%)
Binance	$15,954,074,080	$18,47 6,865,370	1696	14,984,783	66.80%
Coinbase	$2,432,896,706	$3,030,535,875	565	2,241,115	10.19%
FTX	$1,479,535,647	$1,630,837,582	256	821,371	6.20%
Gate-io	$813,683,844	$922,387,678	2603	2,829,934	3.41%
Kraken	$803,670,113	$988,044,294	607	400,200	3.37%
Kucoin	$716,296,203	$784,921,645	1287	3,531,754	3.00%
Binance US	$430,388,992	$559,469,178	343	409,286	1.80%
Bybit	$335,469,642	$440,484,192	334	584,614	1.40%
Crypto.com	$315,331,124	$347,982,284	648	4,844,038	1.32%
Bitstamp	$196,055,402	$298,615,189	183	72,065	0.82%
FTX US	$152,900,174	$169,473,231	49	42,004	0.64%
Gemini	$112,296,218	$141,046,870	137	101,839	0.47%
Ascendex	$100,915,166	$119,153,835	383	355,221	0.42%
Upbit	$31,768,535	$59,854,822	189	42,497	0.13%
Bitflyer	$6,821,240	$9,983,189	7	3,245	0.03%
Coinflex	$546,257	$918,751	24	1,843	0.00%

Table 2
Summary Statistics by Trading Venue

This table presents summary statistics for trading venue-coin-date observations across 16 cryptocurrency trading venues. All entries represent mean values only. For variable definitions, see Table 11 in Appendix A.

	Auto Corr (1min)	Var Ratio (1min)	Var Ratio (5min)	Var Ratio (15min)	Volatility
Binance	-0.07	-0.27	-0.20	-0.17	0.09
Coinbase	-0.09	-0.25	-0.22	-0.19	0.09
FTX	-0.11	-0.33	-0.27	-0.21	0.09
Gate-io	-0.18	-0.47	-0.40	-0.27	0.12
Kraken	-0.10	-0.28	-0.24	-0.19	0.09
Kucoin	-0.12	-0.44	-0.33	-0.24	0.09
Binance US	-0.07	-0.28	-0.21	-0.17	0.09
Bybit	-0.12	-0.35	-0.27	-0.21	0.09
Crypto.com	-0.16	-0.37	-0.31	-0.23	0.10
Bitstamp	-0.10	-0.25	-0.23	-0.19	0.11
FTX US	-0.07	-0.19	-0.17	-0.16	0.08
Gemini	-0.10	-0.34	-0.27	-0.22	0.10
Ascendex	-0.14	-0.42	-0.36	-0.27	0.15
Upbit	-0.21	-0.57	-0.56	-0.36	0.11
Bitflyer	-0.11	-0.37	-0.27	-0.20	0.06
Coinflex	-0.11	-0.33	-0.35	-0.27	0.17
Total	-0.12	-0.35	-0.29	-0.21	0.10

Table 3
Summary Statistics by Coin Volume Tercile

This table provides summary statistics across all coins and for coins grouped into three terciles based on logged average trading volume (USD) for the coin across our sample. The terciles are categorized as the highest, middle, and lowest volume terciles. The data spans from March 2021 to May 2023. For variable definitions, see Table 11 in Appendix A.

	N	Mean	Median	St. Dev.
Panel A: Full Sample				
Log(Volume)	2,182,957	12.09	11.98	2.77
Auto Corr (1min)	2,182,957	-0.13	-0.09	0.12
Var Ratio PC	2,182,957	-0.00	0.26	1.42
Efficiency PC	2,182,957	-0.00	0.37	1.60
Fragmentation	2,182,957	0.08	0.00	0.16
Venues	2,182,957	1.65	1.00	1.37
Volatility	2,182,957	0.11	0.07	0.12
Panel B: Highest Volume Tercile				
Log(Volume)	1,055,948	14.12	14.00	2.06
Auto Corr (1min)	1,055,948	-0.08	-0.06	0.07
Var Ratio PC	1,055,948	0.76	0.98	1.00
Efficiency PC	1,055,948	0.87	1.13	1.05
Fragmentation	1,055,948	0.12	0.00	0.19
Venues	1,055,948	2.16	1.00	1.77
Volatility	1,055,948	0.09	0.07	0.08
Panel C: Middle Volume Tercile				
Log(Volume)	679,247	11.06	11.07	1.57
Auto Corr (1min)	679,247	-0.14	-0.11	0.12
Var Ratio PC	679,247	-0.35	-0.22	1.33
Efficiency PC	679,247	-0.37	-0.18	1.49
Fragmentation	679,247	0.07	0.00	0.15
Venues	679,247	1.27	1.00	0.55
Volatility	679,247	0.10	0.07	0.10
Panel D: Lowest Volume Tercile				
Log(Volume)	447,762	8.84	9.13	1.31
Auto Corr (1min)	447,762	-0.22	-0.21	0.15
Var Ratio PC	447,762	-1.26	-1.27	1.31
Efficiency PC	447,762	-1.50	-1.53	1.53
Fragmentation	447,762	0.01	0.00	0.05
Venues	447,762	1.03	1.00	0.16
Volatility	447,762	0.14	0.08	0.18

Table 4
Daily Fragmentation and Efficiency Measures

This table presents regressions of efficiency measures (volume-weighted by coin) on daily Fragmentation (1 - HHI):

$$\text{Efficiency}_{it} = \text{Fragmentation}_{it} + \Theta_t + \gamma_i + X_{it}$$

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered by date and coin. The data spans from March 2021 to May 2023. For variable definitions, see Table 11 in Appendix A.

	(1)	(2)	(3)
Dep. Var.	Auto Corr (1min)	Var Ratio PC	Efficiency PC
Fragmentation	-0.014***	-0.25***	-0.28***
	(0.0029)	(0.037)	(0.041)
Venues	0.0052***	0.059***	0.074***
	(0.00048)	(0.0064)	(0.0073)
Log(Volume)	0.0075***	0.17***	0.18***
	(0.00039)	(0.0047)	(0.0054)
Volatility	0.039***	0.13***	0.32***
	(0.0044)	(0.038)	(0.049)
Observations	2,182,955	2,182,955	2,182,955
R^2	0.465	0.634	0.648

Table 5
Summary Statistics for Coins Around Delisting Events

This table presents summary statistics for coins before and after delisting events from Binance. The pre-delisting period includes data for 40 days before the delisting date, excluding days -9 to 0, and the delisting date. The post-delisting period includes data for 40 days after (where available). For variable definitions, see Table 11 in Appendix A.

	N	Mean	Median	St. Dev.
Panel A: Pre-Delisting				
Fragmentation	1,347	0.26	0.24	0.19
Auto Corr (1min)	1,347	-0.10	-0.09	0.08
Var Ratio PC	1,347	0.47	0.68	1.37
Efficiency PC	1,347	0.47	0.68	1.37
Log(Volume)	1,347	12.26	12.01	1.99
Volatility	1,347	0.09	0.06	0.11
Venues	1,347	2.62	2.00	1.12
Panel B: Post-Delisting				
Fragmentation	1,191	0.11	0.00	0.19
Auto Corr (1min)	1,191	-0.16	-0.14	0.11
Var Ratio PC	1,191	-0.54	-0.47	1.59
Efficiency PC	1,191	-0.54	-0.47	1.59
Log(Volume)	1,191	10.16	9.65	2.44
Volatility	1,191	0.13	0.08	0.17
Venues	1,191	1.49	1.00	0.87

Table 6
Delisting on Efficiency Measures

This table presents regressions of coin-level efficiency (volume-weighted by coin) on a post-delisting dummy in a 40-day event window around the coin being delisted from Binance. Days -9 to 0 are excluded to account for announcement effects.

$$\text{Efficiency}_{it} = \beta \text{ Post-Delisting}_{it} + \gamma X_{it} + \Theta_t + \alpha_i + \varepsilon_{it}$$

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The post-delisting window is 1 for 40 days after the delisting and 0 for 40 days before. The data spans from March 2021 to May 2023. Standard errors are clustered by date and coin. All specifications include date and coin fixed effects. For variable definitions, see Table 11 in Appendix A.

	(1)	(2)	(3)
Dep. Var.	Auto Corr (1min)	Var Ratio PC	Efficiency PC
Post-Delisting	-0.057**	-0.57*	-0.78**
	(0.021)	(0.30)	(0.35)
Venues	-0.0075	-0.024	-0.062
	(0.0094)	(0.14)	(0.15)
Log(Volume)	0.0056	0.22***	0.22***
	(0.0043)	(0.041)	(0.053)
Volatility	0.061***	0.68*	0.92**
	(0.019)	(0.39)	(0.39)
Observations	2,173	2,173	2,173
R^2	0.450	0.637	0.625

Table 7
Summary Statistics for Coins by FTX Status

This table presents summary statistics for coins that were traded on FTX and coins that were not traded on FTX, split into pre-period (2022-10-10 to 2022-11-08) and post-period (2022-11-09 to 2022-12-08). For variable definitions, see Table 11 in Appendix A.

	N	Mean (Pre)	Mean (Post)	St. Dev. (Pre)	St. Dev. (Post)
Panel A: Coins Not Traded on FTX					
Fragmentation	101,400	0.11	0.11	0.18	0.18
Auto Corr (1min)	101,400	-0.15	-0.16	0.13	0.13
Var Ratio PC	101,400	0.21	0.08	1.27	1.29
Efficiency PC	101,400	0.20	0.08	1.49	1.50
Log(Volume)	101,400	11.43	11.30	2.19	2.29
Volatility	101,400	0.09	0.11	0.09	0.12
Venues	101,400	1.72	1.72	1.30	1.28
Panel B: Coins on FTX					
Fragmentation	4,290	0.38	0.26	0.21	0.20
Auto Corr (1min)	4,290	-0.09	-0.09	0.08	0.08
Var Ratio PC	4,290	1.22	0.97	1.04	1.18
Efficiency PC	4,290	1.33	1.10	1.11	1.26
Log(Volume)	4,290	14.32	13.68	2.57	2.97
Volatility	4,290	0.07	0.11	0.07	0.12
Venues	4,290	5.57	4.75	2.91	2.72

Table 8
Synthetic Difference-in-Differences: FTX Collapse with 20% and 30% Volume Cutoffs

This table shows synthetic difference-in-difference regressions on the impact of the FTX collapse using 20% and 30% volume cutoffs. Panel A presents results for the 20% volume cutoff, and Panel B presents results for the 30% volume cutoff. The treatment variable is interacted with the post-period dummy. Controls include volume, number of trading venues, and Volatility. Standard errors are bootstrapped with 100 replications. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The collapse date is 2022-11-08, and the dates range from 2022-10-10 to 2022-12-08. For variable definitions, see Table 11 in Appendix A.

$$\text{Efficiency}_{it} = \beta(\text{Post}_t \times \text{Treat}_i) + \gamma X_{it} + \alpha_i + \Theta_t + \varepsilon_{it}$$

	(1)	(2)	(3)
Dep. Var.	Auto Corr (1min)	Var Ratio PC	Efficiency PC
Panel A: 20% Volume Cutoff			
Treat×Post	-0.045***	-0.89***	-0.91***
	(0.012)	(0.11)	(0.13)
Observations	203,820	203,820	203,820
Panel B: 30% Volume Cutoff			
Treat×Post	-0.045***	-1.13***	-0.96***
	(0.013)	(0.23)	(0.20)
Observations	203,580	203,340	203,580

Table 9
Efficiency Principal Components by the Share of Volume on FTX

This table shows the principal components of efficiency measures with different volume cutoffs, ranging from 10% to 40% of volume on FTX in the month prior to the collapse.

$$\text{Efficiency}_{it} = \beta\ \text{Volume_Cutoff}_{it} + \gamma X_{it} + \alpha_i + \Theta_t + \varepsilon_{it}$$

Controls include volume in USD, number of trading venues, and Volatility. The collapse date is 2022-11-08, and the dates range from 2022-10-10 to 2022-12-08. Standard errors are bootstrapped with 100 replications. Controls are optimized. For variable definitions, see Table 11 in Appendix A.

	10% cutoff	20% cutoff	30% cutoff	40% cutoff
Dep. Var.	Efficiency PC	Efficiency PC	Efficiency PC	Efficiency PC
Treat×Post	-0.53***	-0.915***	-0.96***	-1.17***
	(0.13)	(0.174)	(0.20)	(0.24)
Observations	204,780	203,820	203,580	203,340

Table 10
Weighted FTX Collapse Event Study

This table includes coins traded on FTX or FTX-US and at least one other trading venue prior to the collapse. The coin weight on FTX is computed as the average volume weight on FTX in the month before the collapse. We include 30 days before and 30 days after the collapse. The variable FTX Volume Share$_{it}$ is zero in the pre-period and represents the volume share of FTX prior to the collapse in the post-period.

$$\text{Efficiency}_{it} = \beta \text{ FTX Volume Share}_{it} + \gamma X_{it} + \alpha_i + \Theta_t + \varepsilon_{it}$$

Here, X_{it} includes control variables: volatility, number of trading venues, and trading volume in USD. α_i represents coin fixed effects controlling for time-invariant characteristics, and Θ_t represents date fixed effects capturing common shocks. Robust standard errors are clustered by coin and date to account for serial correlation. *** p<0.01, ** p<0.05, * p<0.1. For variable definitions, see Table 11 in Appendix A.

	(1)	(2)	(3)
Dep. Var.	Auto Corr (1min)	Var Ratio PC	Efficiency PC
FTX Volume Share$_{it}$	-0.031	-1.17***	-1.19***
	(0.023)	(0.38)	(0.42)
Log(Volume)	0.0095***	0.19***	0.22***
	(0.0022)	(0.033)	(0.038)
Volatility	-0.028	-0.64*	-0.68*
	(0.021)	(0.33)	(0.37)
Venues	-0.010***	-0.14***	-0.18***
	(0.0024)	(0.026)	(0.034)
Observations	9,687	9,687	9,687
R^2	0.420	0.670	0.663

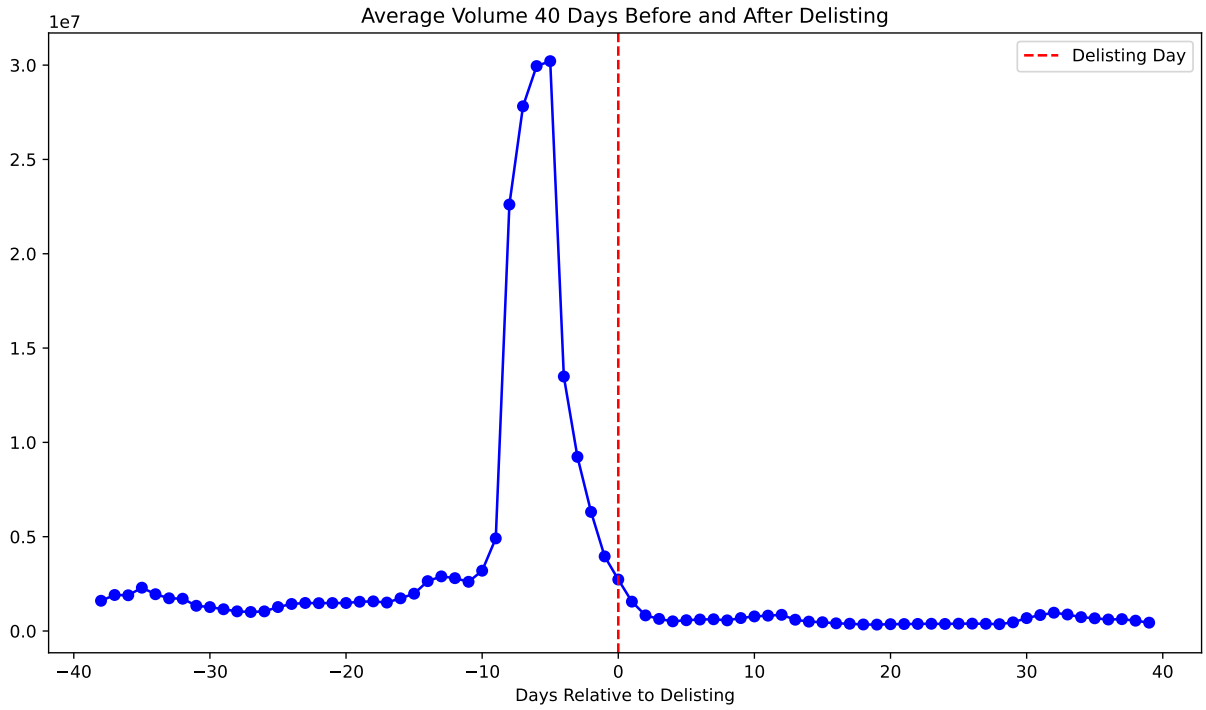


Figure 6. Volumes Surrounding Delisting Events

This figure shows the daily trading volume (in USD) across trading venues for coins that were traded on Binance, delisted from Binance, and continued trading on at least one other trading venue. The y-axis shows the average daily trading volume in USD. The x-axis shows the days relative to the delisting event, with day 0 marking the delisting date. The figure covers a 40-day window, spanning 40 days before and 40 days after the delisting.

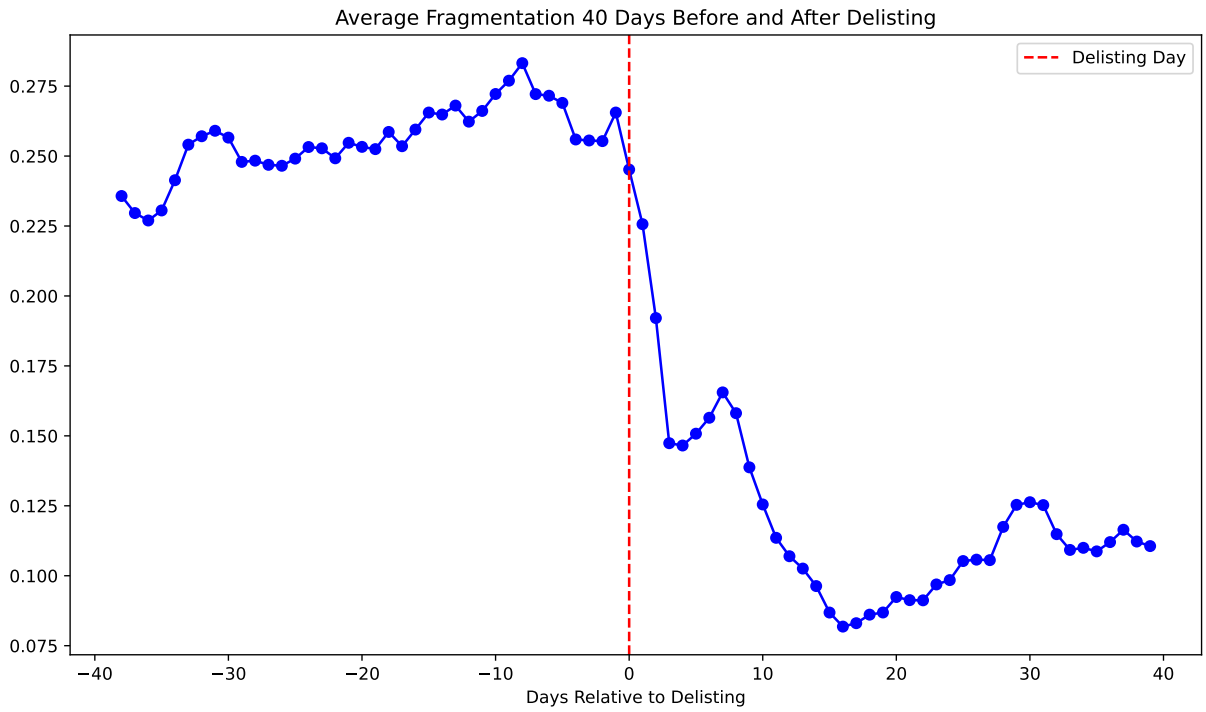


Figure 7. Fragmentation Surrounding Delisting Events

This figure shows daily changes in market fragmentation across trading venues for coins that were traded on Binance, delisted from Binance, and continued trading on at least one other trading venue. The y-axis represents fragmentation (1-Herfindahl-Hirschman Index). The x-axis shows the days relative to the delisting event, with day 0 marking the day the coin was removed from Binance. The figure covers 40 days before and 40 days after the delisting.

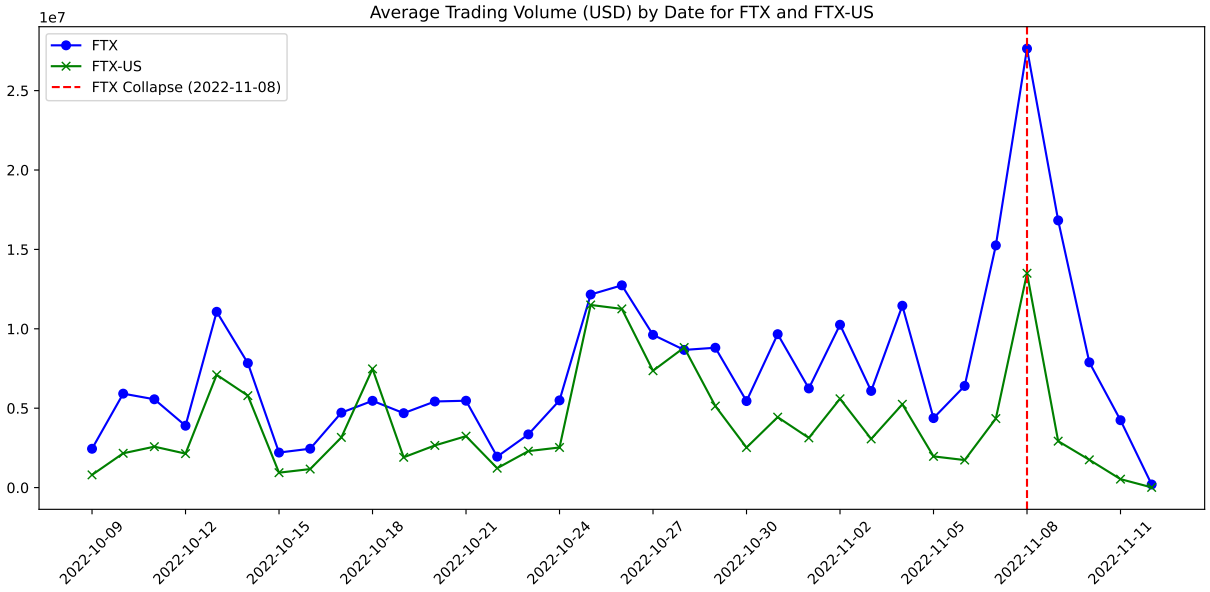


Figure 8. Trading Volume on FTX

This figure shows the average daily trading volume (in USD) for coins traded on FTX and FTX-US during the period around the FTX collapse on November 08, 2022. The y-axis represents the average daily trading volume in USD. The x-axis shows the date. The red vertical line indicates the collapse date.

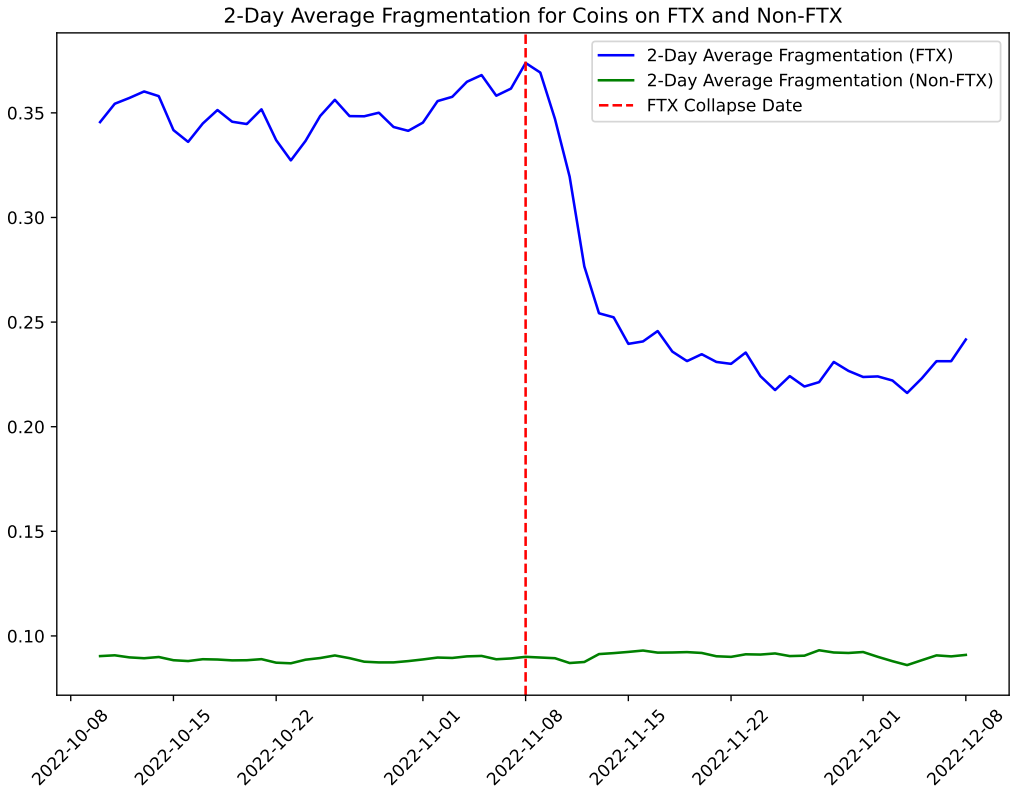


Figure 9. Fragmentation on FTX and Other Venues

This figure compares the two-day average market fragmentation for coins traded on FTX with those not traded on FTX during the period around the FTX collapse on November 08, 2022. The y-axis displays fragmentation, calculated as 1 minus the Herfindahl-Hirschman Index (1-HHI). The x-axis shows the date. The red vertical line indicates the collapse date.

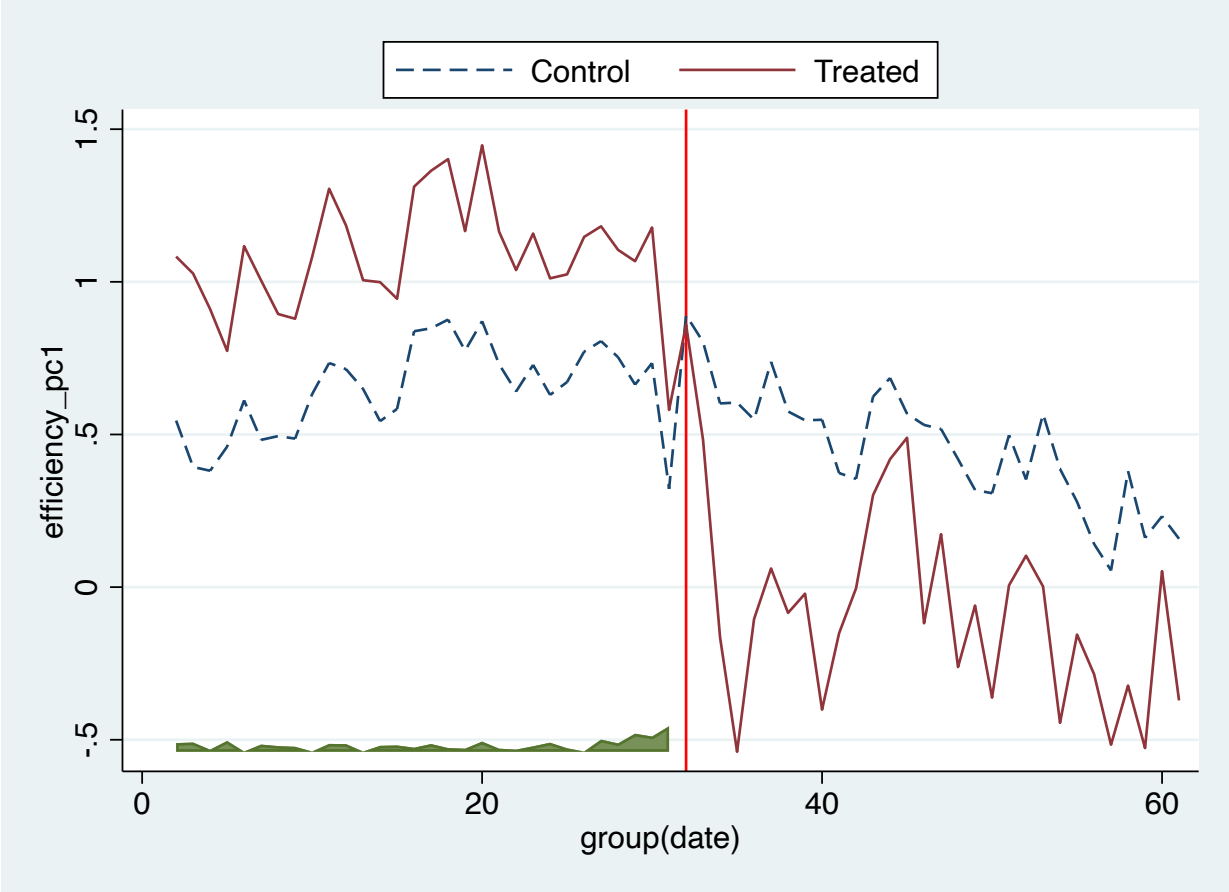


Figure 10. Efficiency Parallel Trends

This figure shows parallel trends from a synthetic difference-in-differences (SDID) analysis comparing price efficiency for coins in the treated group, defined as those with at least 20% of trading volume on FTX, and coins in the control group, which were not traded on FTX. The y-axis represents the first principal component of efficiency, and the x-axis shows days relative to the FTX collapse on November 08, 2022, with day 0 marking the event. The red vertical line indicates the collapse date.

Internet Appendix

A. Data Processing Detail

We pre-process the data from Tardis.dev in several steps. We first drop observations where the bid or ask price is zero, trade volume is negative, the bid price exceeds the ask price, the bid-ask spread exceeds 5%, or returns between consecutive 5-millisecond timestamps exceed 5%. At the daily level, we include only trading venue–coin–day combinations with at least 10 trade observations.

We resample the data to 5-millisecond intervals to capture high-frequency movements while reducing reporting errors. For quotes, we retain the last quote within each 5-millisecond interval. For trades, we aggregate all trades within each interval by summing trade amounts in the same direction (buy or sell) and computing a volume-weighted average price.

After resampling, we remove extreme outliers and data inconsistencies. We correct coin pairs reported in reverse order (e.g., changing *USDT-BTC* to *BTC-USDT*). We exclude coins that experience price changes exceeding 10,000% that remain elevated for at least seven days, and coin-days with prices surging over 1,000% in a single day (e.g., Terra (LUNA) due to its extreme volatility). We remove observations where a coin's price on a trading venue deviates by more than 100% from the median price across other trading venues on the same day; if a coin is flagged as an outlier for more than 30 days on any trading venues, we remove it entirely from the dataset. We also remove coin-day observations where the average midpoint-price exceeds $75,000; for non-Bitcoin (BTC) coins, we exclude prices above $60,000. After applying these filters, we winsorize the efficiency measures and volatility at the 1% and 99% levels monthly to mitigate the impact of remaining outliers.

We then standardize coin naming conventions across trading venues and exclude remaining futures contracts. We rename 'XBT' to 'BTC', reorder coin pairs for uniformity (e.g., changing PAXETH to ETH-PAX, and remove symbols such as underscores and hyphens from coin names. Since Tardis.dev data does not classify security types into futures and spot trading pairs, we remove futures contracts using specific criteria. We exclude coins with names containing terms like "futures," "PERP," or "perpetual"; symbols ending with digits or containing date patterns; and leveraged coins and tokens. We also manually verify each coin's security type on each trading venue's website to ensure accuracy. After identifying the set of spot currencies, we convert all trade volumes into U.S. dollars using daily average trading venues rates.

We calculate a variety of metrics to measure the effect of fragmentation on price efficiency. We also calculate variables to control for the number of venues and volatility. All variables using in summary tables and regressions are defined in Table 11.

Table 11
Variable Definitions

Variable	Description
Volume	Trading volume (USD) for a coin.
Log(Volume)	Natural logarithm of the trading volume (USD) for a coin.
Auto Corr (1min)	First-order autocorrelation of coin returns at the 1-minute frequency, calculated as: $\rho_k = \left\lvert \frac{\text{Cov}(\text{Ret}_t, \text{Ret}_{t-k})}{\text{Var}(\text{Ret}_t)} \right\rvert$.
Var Ratio (1min)	Variance ratio for 1-minute intervals, calculated as: Variance Ratio = $\left\lvert \frac{\text{Var}(\text{Ret}_{\text{1-minute}})}{4 \times \text{Var}(\text{Ret}_{\text{15-second}})} - 1 \right\rvert$.
Var Ratio (5min)	Variance ratio for 5-minute intervals, comparing the variance of returns over 5-minute intervals to 1-minute intervals (5 intervals per 5 minutes).
Var Ratio (15min)	Variance ratio for 15-minute intervals, comparing the variance of returns over 15-minute intervals to 5-minute intervals (3 intervals per 15 minutes).
Var Ratio PC	First principal component of all variance ratios.
Efficiency PC	First principal component of Auto Corr (1min), Var Ratio (1min), Var Ratio (5min), and Var Ratio (15min), capturing overall price efficiency.
Fragmentation	Measure of market fragmentation, calculated as 1 minus the Herfindahl-Hirschman Index (HHI) of market shares.
Venues	Number of unique trading venues where the coin is listed.
Volatility	Measured as the difference between the maximum midquote and the minimum midquote, divided by the average midquote.
FTX Volume Share$_{it}$	A variable equal to zero in the pre-period and the volume share FTX represented prior to the collapse in the post-period.
Post Delisting	Indicates the 40-day window around Binance delistings.
Treat$\times$Post	Interaction term indicating treated coins (e.g., traded on FTX) in the post-event period.