# Market Fragmentation and Price Efficiency: Evidence from Cryptocurrencies*

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Does market fragmentation improve price efficiency? Predictions from theoretical models and empirical evidence remain mixed. We use a major cryptocurrency trading venue's sudden collapse and coin delistings to assess fragmentation's impact on efficiency. Reduced fragmentation lowers efficiency: efficiency declines by over 43% of its pre-collapse standard deviation after the collapse and by about 40% after delistings. Aggregate price impact rises after both shocks, consistent with traders losing the ability to split orders across venues.

**Key words:** Market Fragmentation, Price Efficiency, Cryptocurrencies

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# 1. Introduction

The trading of a single security across multiple platforms, known as market fragmentation, is a defining feature of modern financial markets. Before 2000, the New York Stock Exchange and NASDAQ handled 95% of U.S. equity trading volume (Haslag and Ringgenberg, 2023). Today, their combined volume share is less than 35%.[1] The same phenomenon is evident in Europe, where the listing exchange only accounts for 40% of volume.[2] Despite this persistent and widespread trend, it is unclear what effect fragmentation has on price efficiency. The challenge lies in isolating the causal impact of fragmentation, which remains difficult in equities. Under regulatory frameworks such as Regulation National Market System (Reg NMS) and the Markets in Financial Instruments Directive (MiFID II) trading venues are highly integrated. Alternative natural experiments are also often contaminated; venue closures are rare, and stock delistings typically coincide with mergers or financial distress. In this paper, we exploit two natural experiments in cryptocurrency markets to provide causal evidence on how fragmentation affects price efficiency.

Theory does not give a clear answer on the link between fragmentation and price efficiency. Fragmentation can harm price efficiency by reducing market depth as the same amount of volume is divided across more venues, increasing adverse selection (Chowdhry and Nanda, 1991, Babus and Parlatore, 2022). It can also lead to inefficiencies and lower liquidity when traders use fragmented markets to reduce competition among themselves (Babus and Parlatore, 2022). In contrast, Chen and Duffie (2021) argue that as market fragmentation increases, efficiency can improve. By splitting orders across a greater number of venues, strategic traders can reduce the overall price impact of their orders. This encourages more aggressive trading and leads to more informative prices across all trading venues, despite the fact that market depth on any single venue

[1] See https://www.cboe.com/us/equities/market_share/.
[2] See ESMA (2023)

is lower.

Empirical findings are likewise mixed. In U.S. equities, market fragmentation has been linked to lower transaction costs, faster execution, and improved price efficiency (O'Hara and Ye, 2011). At the same time, other studies associate fragmentation with wider spreads, slower execution, and reduced depth, all of which impair price efficiency (Chung and Chuwonganant, 2012, Hendershott and Jones, 2005). More recently, Haslag and Ringgenberg (2023) show that fragmentation lowers bid–ask spreads and enhances liquidity for large-cap stocks, but has the opposite effect for small-cap stocks. These conflicting results underscore the difficulty of isolating the causal impact of fragmentation in highly integrated markets, particularly when regulatory changes are introduced gradually over several years.

We address these empirical challenges by turning to cryptocurrency markets and make two main contributions. First, we identify a causal link between fragmentation and price efficiency by exploiting exogenous shocks to fragmentation. Second, we deliver one of the first empirical tests of the order-splitting channel proposed by Chen and Duffie (2021).

The cryptocurrency market provides a valuable natural laboratory for three reasons. First, cryptocurrencies trade across multiple venues[3] that operate independently and without centralized regulation. In the absence of best-execution requirements, trade-through, or order-routing rules, the same asset can be traded simultaneously on distinct venues. Second, the market experiences exogenous shocks to fragmentation through venue closures and coin delistings. Because traders cannot anticipate or prevent these events, our research design circumvents the endogeneity concerns raised by Babus and Parlatore (2022), allowing us to isolate the causal effect of fragmentation on price efficiency rather than the strategic choices that may have formed it. Third,

[3]These venues are known as centralized cryptocurrency exchanges as opposed to decentralized exchanges or automated market makers that operate directly on the blockchain. The centralization refers to the venue being the custodian of the market participant's funds, not the centralization of the market.

cryptocurrencies offer transparent and granular data. Collectively, these features allow us to provide a direct empirical test of the order-splitting channel proposed by Chen and Duffie (2021), in a way that is not feasible in traditional financial markets.

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

In our first 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 U.S. 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. We use a synthetic difference-in-difference (SDID) design to compare coins reliant on FTX with those that were not, 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, measured by variance ratios and return autocorrelation, declines for the affected coins. The first principal component of efficiency decreases by 86% of its pre-period standard deviation. Furthermore, we find that the average trade size for these coins increases and our measure of aggregate price impact rises, consistent with traders being less able to split large orders to mitigate price impact. This is consistent with Chen and Duffie (2021)'s predictions, demonstrating that significant reductions in market

fragmentation adversely affect price efficiency across trading venues.

To test whether the loss of fragmentation is the primary driver of our results, we examine if the treatment effect scales with the intensity of the shock. We categorize coins based on their pre-collapse reliance on FTX, using volume-share cutoffs of 10%, 20%, 30%, and 40%. If our hypothesis is correct, the effects should be stronger for coins that experience a larger shock to their market structure. We find a clear monotonic relationship that supports this prediction: the decline in price efficiency and the increase in aggregate price impact are more pronounced for coins with a greater reliance on FTX. This gradient provides compelling evidence for our proposed mechanism and is consistent with Chen and Duffie (2021), as the adverse effects of consolidation are greatest when traders lose a significant venue for splitting orders and mitigating price impact.

In our second 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 on the remaining venues, thus reducing fragmentation. Following a delisting, we find corroborating evidence: the first principal component of price efficiency decreases by 41% of its pre-delisting standard deviation, aggregate price impact increases, and the average trade size increases.

The remainder of the paper is structured as follows. We introduce our empirical setting, data, sample, and measures of efficiency, price impact, and fragmentation in Section 2. We analyze the effect of the collapse of FTX in Section 3 and the coin delistings on Binance in Section 4. Section 5 concludes.

## 2. Setting, Data, and Sample

There are over 250 cryptocurrency trading venues worldwide.[4] These markets run 24 hours a day, seven days a week, and welcome customers from many regions.[5] They run limit order books and enable high-frequency trading, as opposed to decentralized exchanges and automated market makers, which facilitate trading on the blockchain and occur in block-time.

Cryptocurrency trading venues operate independently, which has two implications for market participants. First, unlike traditional equity markets, they are not integrated through a national best bid and offer system. Traders therefore have to gather price information directly from each venue instead of a centralized data feed. Second, market participants must choose specific trading venues on which to trade and deposit funds directly into each trading venue. There is no centralized routing or best execution mandate. 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).

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 1,768 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

[4] According to data from https://www.coingecko.com/en/exchanges as of October 2023.
[5] Venues may block users in specific jurisdictions for legal reasons.

and quote data through several steps to remove outliers and standardize naming conventions across trading venues. For more detail on this process, see Appendix A.

Although many cryptocurrency trading venues exist, trading volume is highly concentrated among a small number of large platforms. Table 1 reports trading volume (in USD), market share, the number of symbols listed on each venue and the median trade size (in USD). All volumes are converted to USD using Binance's daily average midpoint price. For coins not listed on Binance, we instead use the venue with the longest history and highest trading volume. Market share is defined as a venue's median daily volume relative to the total median daily volume across all venues. Binance alone accounts for 66% of total volume, while the three largest venues—Binance, Coinbase, and FTX—together capture 83%.[6] Trading activity is also concentrated across coins. The ten largest coins represent 47% of total daily volume, and four of these coins are only traded on Binance.

Venues compete not only on volume but also on the breadth of coins offered. Table 1 shows that Binance, despite being the largest venue by volume, does not list the most coins. Gate-io, with only 3.4% market share, lists 1,071 spot coins during the sample period. This pattern suggests differentiation strategies: some venues emphasize a small set of highly liquid coins, while others compete by offering access to a wide variety of smaller, less liquid coins. The clientele differences are further reflected in trade size. Venues with relatively few listed coins, such as Bitstamp (168) and FTX US (49), exhibit the largest median trade sizes ($2,224 and $2,893, respectively). By contrast, venues with extensive listings, such as Gate-io, record much smaller trades (median size $259). In sum, venues appear to specialize either in facilitating large trades in a few liquid assets or in catering to smaller trades across many less liquid assets.

[**Table 1** here]

[6] Prior to its collapse, FTX's market share was approximately 14%.

## 2.1 Efficiency Measures

We measure 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:

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

where $\text{Ret}_t$ is the return at time $t$. In an efficient market, $\rho_k$ 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. To make sure that we include both short term and longer term variations we computed different horizons: 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.

## 2.2 Price Impact Measures

We compute the daily volume-weighted price impact at different future horizons ($h$) in basis points:

$$\text{Price Impact}_t(h) = \sum_{i \in \text{trades on day } t} \frac{2 \times D_{it} \times (M_{t+h} - M_t)}{M_t} \times 10,000 \tag{3}$$

where for each trade $i$, $D_{it}$ is the trade direction (+1 for buys, -1 for sells), $M_t$ is the mid-quote before the trade, and $M_{t+h}$ is the mid-quote at $h$ minutes (or seconds) after the trade at time $t$. Since our sample consists of both highly liquid and less liquid coins, we include a variety of time horizons. We compute price-impacts at: 30-seconds, 1-minute, 5-minutes, and 30-minutes. We volume-weight across trades and then take the first principal component of the four price impact measures (Price Impact PC).

Table 2 shows the average efficiency and price impact measures for each of the venues in our sample. The largest venues generally have more efficient prices. For the 1-minute autocorrelation, mean values range from -0.07 on Binance and FTX U.S. to -0.21 on Upbit, with a sample-wide mean of -0.10. The pattern of larger venues showing higher efficiency holds for the variance ratio measures as well, suggesting their prices more closely follow a random walk.

The price impacts vary significantly across venues. Upbit (73.46 bps at 1-minute) and Kucoin (54.48 bps at 1-minute) have the highest price impacts, while FTX U.S. (19.13 bps at 1-minute) and Ascendex (17.17 bps at 1-minute) have among the lowest. While price impacts are frequently used in the literature as a measure of informed trading, we caution against drawing such conclusions based on these univariate statistics. For example, Coinflex has low price impacts across all horizons, but with very few coins on Coinflex, this exchange is dominated by highly liquid ETH, BTC, and USDT coin pairs where relatively small trades, as described in Table 1, will likely not move prices significantly.

[**Table 2** here]

## 2.3 Fragmentation Measures

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:

$$\text{HHI}_{it} = \sum_{e=1}^{E} \left( \frac{\text{Volume}_{ite}}{\sum_{e=1}^{E} \text{Volume}_{ite}} \right)^2 \tag{4}$$

where $\text{Volume}_{ite}$ 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 $t$.

Following Haslag and Ringgenberg (2023), we define fragmentation as one minus the HHI:

$$\text{Fragmentation}_{it} = 1 - \text{HHI}_{it} \tag{5}$$

A higher fragmentation value means trading volume is more evenly distributed across trading platforms, while a lower value indicates concentration on fewer trading venues. Across all coins the average level of fragmentation is 0.17 and the average number of venues is 2.4 as shown in Panel A of Table 3. Since interpreting the numerical value of fragmentation can be difficult, consider this example. Suppose ETH-USDT is traded on two exchanges: 90% on Binance and 10% on Kraken. This results in a Herfindahl-Hirschman Index (HHI) and fragmentation level of:

$$\text{HHI} = 0.9^2 + 0.1^2 = 0.82, \quad \text{Fragmentation} = 1 - 0.82 = 0.18.$$

[**Table 3** here]

This scenario reflects the average coin in our sample and underscores that trading volume is relatively concentrated. More importantly, the standard deviation of 0.2 implies that a one-standard-deviation move from the mean corresponds to an 80/20 volume split between Binance and Kraken in our example. When we look at the extremes, we observe coins with very high fragmentation. For instance, ETH–BTC trades on all but one venue, while BTC–USD exhibits the highest average fragmentation across days in our sample at 0.69. The maximum observed fragmentation is 0.82 for DAI–USD. If we more broadly compare the most (Panel B) and least (Panel C) liquid coin terciles, based on USD trading volume, we see that the most liquid coins are traded across the highest number of venues (3.3 on average) and exhibit the greatest fragmentation. By contrast, the least liquid coins trade on only 1.6 venues on average, with a median of just one venue. To ensure variation in fragmentation, we restrict our sample to coins that are traded on at least two venues at some point during the sample period. Notably, even the least liquid coins have highly fragmented volume with maximum values close to that of the most liquid. This broad distribution of fragmentation provides the backdrop for our analysis in the sections that follow.

We summarize the definitions of all the variables used in our analysis in Table 10 in Appendix A. The pairwise correlations in Table 4 highlight the relationships between our primary variables. Both the number of venues and fragmentation are positively correlated with our efficiency measures and negatively correlated with price impact. The number of venues, for instance, has a correlation of 0.27 with Efficiency PC and -0.23 with Price Impact PC. Fragmentation shows a similar but weaker pattern, with a correlation of 0.06 with Efficiency PC and -0.11 with Price Impact PC. This suggests that as trading activity spreads across more platforms, prices tend to be more efficient and the aggregate price impact across venues is lower.

[**Table 4** here]

# 3. The Collapse of FTX

We begin by examining the collapse of FTX in November 2022 as a market-wide shock to fragmentation. The event is particularly useful for three reasons. First, FTX (including FTX U.S.) was the second-largest exchange globally and, in our sample, listed more than 170 coin pairs. Its sudden removal from the market sharply reduced the number of venues available and the size of the market for even the most liquid coins. This abrupt disruption provides a clear distinction between pre- and post-collapse trading 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 expect its failure.[7] This lack of anticipation lowers the likelihood that traders significantly adjusted their behavior beforehand, reducing concerns about endogeneity.

Third, the collapse affected a broad cross-section of coins simultaneously, generating a fragmentation shock for both the most and least liquid assets. Although many of these coins were also listed on other platforms, FTX often accounted for a significant share of their trading volume. This allows us to classify coins into subsets that were either heavily dependent on FTX or less exposed, thereby introducing variation in the magnitude of the shock.

The events that lead to the collapse of FTX are multifaceted. The trading venue was founded in 2019 by Gary Wang and Sam Bankman-Fried, who had started a proprietary-trading and market making firm years before called Alameda Research. The two entities were supposed to be independent, but in reality they were heavily integrated. Alameda was able to borrow unlimited funds from FTX without the risk of margin calls or liquidations. Most of the debt was collateralized by FTX's native and illiquid token FTT making Alameda vulnerable to volatility in the price

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

of FTT.

In the span of 10 days, FTX went from the third largest cryptocurrency trading venue to bankruptcy. On November 2nd, 2022, a leaked Alameda balance sheet[8] revealed this reliance on FTT. Market participants started to withdraw funds from the exchange and Binance announced a large sell off of FTT resulting in a sharp decline of the price. On November 7th, they announced that they faced a liquidity shortage and sought a bailout from venture funds and Binance. Binance propose to purchase the non-US part of FTX but walked away from the deal on November 9th. On November 11, 2022, FTX filed for bankruptcy. Sam Bankman-Fried and the CEO of Alameda Research Caroline Ellison were arrested in December and have since been sentenced to 25 and 2 years for fraud and money laundering.

Figure 1 shows the average daily trading volume (in USD) for coins on FTX and FTX-US near the collapse date. Despite the news stories, volume remained steady before November 8, 2022, then spiked as traders ran on the trading venue. Trading volume decreases sharply when the shutdown becomes imminent, reaching zero on November 11. The shock to fragmentation also occurred on November 8, as is evident in Figure 2). Given this clear reaction in the market, we use November 8 as our event day in the subsequent analysis. We also use an event window instead, where we block out the days from November 2 to November 10 and compare 30 days before and after. The results, reported in Table 11 in the Internet Appendix are similar in significance, sign, and magnitude. As FTX and FTX-US follow similar patterns we combine the two venues and will refer to both of them as FTX in the remainder of the analysis.

[**Figure 1** here]

[8] CoinDesk published the original story which has since been updated as the events have unfolded see: https://www.coindesk.com/business/2022/11/02/divisions-in-sam-bankman-frieds-crypto-empire-blur-on-his-trading-titan-alamedas-balance-sheet

When investigating the effects of fragmentation we must be clear about how we deal with endogeneity in our identification strategy. Babus and Parlatore (2022) show in their model that when traders have similar beliefs about the value of an asset a centralized market will be disadvantageous as they all try to take the same side of the trade. As such, they have a strategic incentive to fragment the market. Valuations of cryptocurrencies are heavily debated making them incredibly volatile. Investors may therefore be less inclined to strategically fragment the market, but this will vary depending on the asset. Traders in more well-known and liquid coin like bitcoin may have more correlated valuations and benefit more from fragmentation than investors in more obscure coins that have a more ambiguous fundamental value. The collapse of FTX provides a clear exogenous shock to a wide cross-section of coins addressing this endogenous fragmentation issue.

Another challenge we face is defining a control group. The coins traded on FTX were not a random selection of coins available. FTX, like other venues, traded a mix of both highly liquid and illiquid coins but traded a smaller selection of 175 coins. To find a suitable control group we therefore need to match the characteristics of the coins traded on FTX. To do that 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).

Table 5 shows the importance of defining an appropriate control group. The table compares coins traded on FTX with those that were not, 30 days before and after the collapse. Panel A shows that in the pre-period (2022-10-10 to 2022-11-08), coins traded on FTX have higher fragmentation (0.39 vs. 0.26), higher efficiency (0.91 vs. 0.12), and traded on more venues (5.63 vs. 2.72) compared to coins not on FTX shown in Panel B. To contextualize fragmentation levels, consider a simple two-venue market: a fragmentation of 0.39 corresponds to a market share split

where one venue handles approximately 73% of the volume and the other handles 27%. Following the collapse, treated coins experience sharp declines in fragmentation (from 0.39 to 0.26) and trading venues (from 5.63 to 4.82), while coins not traded on FTX show minimal change. This fragmentation decline implies that the dominant trading venue's market share increased from approximately 73% to 85% of volume in our two-venue example.

Table 5 also shows that the coins on FTX experience decreases in efficiency after the collapse and increases in price impact. The efficiency PC falls from 0.91 to 0.66, variance ratios decrease from .85 to .59, and 1-minute autocorrelation decreases slightly by -.01. The price impact principal component for treated coins increases from -.61 to -.02 following the event. Meanwhile, coins not traded on FTX also show reductions in efficiency and an increase in price impact, reflecting the broader market stress during this period of cryptocurrency panic. However, the key insight is that FTX-traded coins experienced a significant reduction in fragmentation (from 0.39 to 0.26) when they lose a major trading venue, while coins not traded on FTX maintain similar fragmentation levels (0.26 to 0.25). This cross-sectional variation is important: all coins face macro conditions during the November 2022 crypto turmoil, yet only FTX-traded coins experience large fragmentation declines, isolating the fragmentation channel from market-wide factors. Thus, to estimate the causal effect of fragmentation on efficiency and test the mechanisms proposed by Chen and Duffie (2021), we employ a difference-in-differences specification that isolates the additional deterioration in efficiency attributable to the fragmentation shock, beyond the market-wide effects experienced by all coins during this period.

[**Table 5** here]

Figure 2 illustrates the dynamics of fragmentation shown in Table 5. It plots the 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 an immediate decline in fragmentation

for the treated coins precisely as the trading venue began to fail. In contrast, no significant change is observed for the group of non-FTX coins. This precise timing demonstrates that the collapse of FTX acted as a concentrated shock to the fragmentation of its listed assets, while the broader market represented by non-FTX coins did not experience a meaningful change to fragmentation.

[**Figure 2** here]

However, what Figure 2 and Table 5 highlight is that the coins not traded on FTX are not following the same trend as those traded on FTX. This is important in a simple Difference-in-Difference strategy as the parallel trends assumption posits that the outcome variable for the treated group would have followed the same trend as the control group in the absence of the treatment. To address this, we employ a synthetic difference-in-differences method creating a more credible counterfactual. The method assigns weights to a combination of coins from the non-FTX group to construct a synthetic control for the treated group that closely matches it on observable characteristics and pre-treatment trends. To examine efficiency (price impact) outcomes, we create a counterfactual treated group by matching on volatility, the number of trading venues, trading volume, and pre-treatment efficiency (price impact) measures.

Figure 3 displays the trends from the efficiency principal component from the SDID analysis, comparing coins with at least 20% of their trading volume on FTX in the month before the collapse to the synthetic control group of non-FTX-listed coins. In the pre-collapse period, the trend line for the FTX-listed coins and their synthetic control follow comparable trends. Immediately after the collapse on November 08, 2022, the two lines sharply diverge, with coins affected by the FTX collapse experiencing a substantial decrease in price efficiency while coins in the synthetic control group do not show a major change in efficiency. A similar pattern emerges when comparing coins that were more or less reliant on FTX. The parallel pre-trends demonstrate successful matching, creating a valid counterfactual that addresses systematic differences between

coin groups.

[**Figure 3** here]

Figure 4 displays the trends of the price impact principal component from the SDID analysis, comparing coins with at least 20% of their trading volume on FTX in the month before the collapse to the synthetic control coins. In the pre-collapse period, the trend line for the FTX-listed coins and their synthetic control follow similar trends. Around FTX's collapse on November 8, 2022, coins on FTX experience a sharp aggregate increase in price impacts, with the principal component rising from near 0 to over 6. The price impact then decreases to a new steady state at a higher level than the pre period. Meanwhile, control coins display a very minor increase in price impacts. A similar pattern emerges when we look at coins that have at least 10% or at least 40% of volume on FTX.

[**Figure 4**: here]

Having established an appropriate control group we turn to testing the effect of fragmentation and the proposed channel by Chen and Duffie (2021). To reiterate, the authors' model suggests that as traders have fewer venues to trade on, they are less able to strategically manage the overall price impact of their order since they are limited to splitting their orders onto fewer markets or not split their orders at all in the extreme case. The price impact should therefore increase. This discourages aggressive trading leading to less informative prices across the entire market.

To quantify the effect of fragmentation on price impacts and efficiency, we estimate the following regression:

$$\text{Outcome}_{it} = \beta(\text{Post}_t \times \text{Treat}_i) + \gamma X_{it} + \alpha_i + \Theta_t + \varepsilon_{it}, \tag{6}$$

where $\text{Outcome}_{it}$ is either the principal component of efficiency or price impact measure for coin $i$ on date $t$. $\text{Post}_t$ is a dummy variable equal to 1 after November 08, 2022. $\text{Treat}_i$ is a dummy variable equal to 1 if coin $i$ was traded on FTX, defined by having a certain percentage of its trading volume on the venue before the collapse. $X_{it}$ includes control variables, $\alpha_i$ is a coin fixed effect, and $\Theta_t$ is a date fixed effect. Control variables include volume in USD, number of trading venues, and Volatility.

Table 6 presents the results for coins that had at least 10%, 20%, 30%, or 40% of their trading volume on FTX in the month before the collapse. The coefficient on the interaction term Treat $\times$ Post captures the average treatment effect.

Panel A reveals a worsening of price impact after the collapse of FTX when fragmentation decreases. Relative to a pre-collapse standard deviation of 1.05, the Price Impact PC increases by 0.78, or 74% of a standard deviation for coins where FTX represents at least 10% of volume. The impact grows dramatically for more exposed coins, increasing by 1.51 (144% of a standard deviation) for both the 20% and 30% cutoffs, and rising further to 1.56 (149% of a standard deviation) for coins with at least 40% of their volume on FTX. The results suggest a causal positive link between centralization and price impact supporting the theory of Chen and Duffie (2021).

If the larger price impact is a reflection of the difficulty with which traders are managing their orders in a less fragmented market and indicates less aggressive trading, price efficiency should decline. Table 6 confirms such a relationship. First, in Panel B all coefficients on efficiency are negative indicating that as fragmentation decreases price efficiency declines. Second, the table shows that as a coin's reliance on FTX increases from 10% to 40% of volume, the negative effect on price efficiency becomes more pronounced. Using the pre-collapse standard deviation of 1.32 for FTX-listed coins as a benchmark, the magnitude of this effect grows with exposure.

For coins with at least 10% of their volume on FTX, the efficiency component decreases by -0.57, equivalent to 43% of a standard deviation. The effect intensifies to -0.95 (72% of a standard deviation) for the 20% cutoff, -0.97 (73% of a standard deviation) for the 30% cutoff, and -1.34 (a substantial 102% of a standard deviation) for the 40% cutoff.

Taken together, the results in Table 6 show a causal positive relationship between centralization and price impact, a negative relationship between centralization and price efficiency, and a clear monotonic pattern as centralization increases. Given our SDID model we are able to rule out alternative explanations. If our results reflected correlated shocks, selection bias, or general market panic, we would not observe this systematic relationship where greater dependence on FTX leads to larger increases in price impact and more severe efficiency losses.

[**Table 6** here]

While the preceding cutoff analysis provides strong evidence of a treatment-response relationship, the thresholds themselves (10%, 20%, etc.) are inherently arbitrary. A coin with 39% exposure to FTX is grouped with one at 31%, yet treated differently from one at 29%. To address this limitation and provide a granular test, our second analysis of the FTX collapse models the treatment effect as a continuous variable. This approach allows us to quantify the marginal impact for each percentage point of exposure, confirming that the observed decline in market quality scales linearly with the intensity of the fragmentation shock. We use the share of each coin's trading volume on FTX in the month prior to the collapse in an event study framework:

$$\text{Outcome}_{it} = \beta\ \text{FTX Volume Share}_{it} + \gamma X_{it} + \alpha_i + \Theta_t + \varepsilon_{it} \tag{7}$$

where $\text{FTX Volume Share}_{it}$ is zero in the pre-period and the coin's historical volume share on

FTX in the post-period. The controls and fixed effects are as previously defined.

Table 7 shows the results of our continuous treatment analysis. The coefficient on FTX Volume Share$_{it}$ is statistically significant across all specifications, indicating that the adverse effects scale directly with the intensity of the fragmentation shock. The Price Impact PC (Column 1) has a large, positive coefficient of 3.38, indicating a dramatic worsening of price impact for coins with greater FTX exposure. This effect is not only statistically significant but also economically large; its magnitude is over three times the pre-collapse standard deviation (1.05). For a coin that had, for example, 30% of its trading volume on FTX, this implies a post-collapse increase in its price impact component of over one full standard deviation ($3.38 \times 0.30 \approx 1.01$). Following Chen and Duffie (2021) this implies a substantial worsening in the ability of traders to strategically manage their price impacts when fragmentation quickly deteriorates.

This increase in price impact is matched by a corresponding decline in price efficiency in Table 7. For the overall Efficiency PC (Column 4), the coefficient is -1.73. This effect is economically large, representing approximately 1.3 times the pre-collapse standard deviation (1.32) of this measure for FTX-listed coins. For a coin with 30% of its volume on FTX this implies a decrease of -0.519, which is approximately 39% of its pre-period standard deviation (1.32). This general decline is consistent with the other efficiency measures. The Var Ratio PC (Column 3) shows a significant decrease (coefficient of -1.54), and the one-minute Auto Corr (Column 2) becomes significantly more negative, with a coefficient of -0.071. A more negative autocorrelation points to increased price reversals, a classic sign of market inefficiency where prices temporarily overreact to trades. This effect is also economically meaningful; for a coin with 100% of its volume on FTX, the '-0.071' coefficient is nearly 89% of the pre-period standard deviation (0.08) for autocorrelation.

To dig into the order splitting channel proposed by Chen and Duffie (2021) we estimate

the effect of fragmentation on the average trade size in (Column 5). Their model predicts that when venues are removed, the ability to conceal large trading intentions through order splitting is diminished. Our finding of a positive coefficient of 1,751 aligns with this view, indicating that a greater reliance on FTX was associated with a larger average trade size on other venues after the collapse. With a key venue for executing trades gone, traders likely submit larger, more concentrated orders on the remaining exchanges. For a coin with 40% of its volume on FTX, the average trade size is predicted to increase by approximately $700 (1{,}751 \times 0.40)$, a substantial 30% increase relative to the pre-collapse mean of $2{,}366$ for FTX-listed coins. Important for this conclusion, we control for the depth on the venues. After FTX collapses, the volume likely redistributes onto the remaining venues, increasing the depth. The larger trade size may therefore be a reflection of more orderbook depth than the ability to split orders. Controlling for depth is therefore important. Interestingly, while the coefficient is small it is negative, suggesting that as the depth increases trades become slightly smaller.

[**Table 7** here]

Taken together, these results offer strong empirical support for the theoretical framework of Chen and Duffie (2021). The loss of a major venue crippled traders' ability to strategically split orders, leading to larger average trade sizes, which in turn generate higher price impact and cause a severe, broad-based decline in price efficiency.

The continuous treatment analysis confirms that efficiency losses scale linearly with fragmentation shocks, ruling out threshold effects or other non-linear confounds. These results reinforce our earlier conclusions, highlighting that the greater the shock to fragmentation from the loss of a major trading venue, the greater the increase in price impact and the more severe the negative impact on price efficiency.

To ensure our main findings are not solely driven by the principal component (PC) analysis, we replicate this event study using the individual measures of efficiency and price impact as dependent variables. The results are presented in the Internet Appendix Table 12. The disaggregated results follow the same sign and significance from the principal component analysis. The FTX collapse led to a significant increase in price impacts across all horizons and a decline in all measures of price efficiency.

# 4. Coin Delistings on Binance

Having analyzed the market-wide collapse of FTX, we next turn to the impact of coin delistings on Binance as an alternative shock to fragmentation. Binance is the largest trading venue in the cryptocurrency market, with a 66.8% market share. Binance delistings, therefore, represent substantial and recurring shocks to market fragmentation.

Binance conducts periodic reviews of the coins traded on their platform based on their legal and compliance risk, the user adoption, liquidity, project development, and ethical concerns.[9] Delistings are announced prior to the event, giving market participants time to divest from the coins or withdraw their funds from the venue. As such, these shocks to fragmentation are not as exogenous as the collapse of FTX.

We focus on coins traded on more than one trading venue prior to the delisting announcement, excluding coins that, after delisting, are no longer traded on any venue in our sample. 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. Following these criteria, our sample includes 33 delisting events from Binance. We verify all delisting notices on Binance's official website to

[9] See: https://www.binance.com/en-KZ/support/faq/detail/e5a9718ccb794acda1c48db5c71753e4

ensure accuracy.

Figure 5 shows how trading volume shifts from Binance to other venues around a delisting announcement. We observe a sharp spike in Binance's trading volume on the day following the announcement. Figure 6 shows that fragmentation drops sharply after the announcement date, and this decline persists for at least 40 days after the announcement.

[**Figure 5** here]

[**Figure 6** here]

Based on Binance's historical patterns, delisting announcements are typically issued about one week before the effective delisting date.[10] Given that the market impact begins at the announcement rather than the mechanical delisting, we center our analysis on the announcement date. Where possible we verify the announcement date for all delistings, but when no annoucement is identified we approximate the announcement timing by using the week before the actual delisting date. This aligns with the majority of observed changes in fragmentation shown in Figure 6. Our regression analysis compares market efficiency in the 40 days before and after the announcement date. This approach captures the full market response to the delisting decision from announcement through execution. In the analysis that follows we use the announcement date as the event date, but our results remain robust when we exclude the four days prior to and the eight days following the announcement window, where these volume spikes occur (see Internet Appendix Table 13).

Table 8 presents summary statistics for coins before and after delisting events from Binance. Before delisting, the price impact PC has a mean of -0.35. Efficiency measures are higher, with

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

the Efficiency PC averaging 0.41, and one-minute autocorrelation averaging -0.10. The post-delisting period shows a decrease in efficiency and an increase in price impact measures. The Price Impact PC increases to a mean of 0.39, and all efficiency measures decline substantially: the Efficiency PC falls to -0.44, and autocorrelation becomes more negative at -0.15, suggesting a rise in return predictability and a drop in efficiency. Trading volume (Log(Volume)) falls from a mean of 12.30 to 10.72. The number of venues falls from a mean of 2.77 to 1.84. Overall, these statistics suggest that delisting events are associated with less fragmented, less liquid, more volatile, and less efficient coins.

[**Table 8** here]

To estimate the impact of delisting on efficiency and price impact, we use the following event study specification:

$$\text{Outcome}_{it} = \beta \text{ Post-Delisting}_{it} + \gamma X_{it} + \Theta_t + \alpha_i + \varepsilon_{it} \tag{8}$$

where $\text{Outcome}_{it}$ is a daily measure of price impact, efficiency, or trade size for coin $i$ on date $t$. The key independent variable, $\text{Post-Delisting}_{it}$, is a dummy equal to 1 for the 40 days after delisting and 0 for the 40 days before. We include coin ($\alpha_i$) and date ($\Theta_t$) fixed effects and control for time-varying characteristics $X_{it}$ (volatility, number of venues, trading volume, and market depth). Standard errors are clustered by coin and event date.

Table 9 reports the regression results. The Post-Delisting coefficient captures the impact of delisting events, holding other factors constant. In Column (1), the coefficient on Price Impact PC is positive but insignificant. For the efficiency measures, the effects are large and significant. The coefficient for Auto Corr (1 min) in Column (2) is -0.029, corresponding to a decline of about 36% relative to its pre-delisting standard deviation (0.08). The Var Ratio PC in Column (3) decreases

by -0.47, about 37% of its pre-delisting standard deviation (1.27). The overall Efficiency PC in Column (4) drops by -0.56, or roughly 41% of its pre-delisting standard deviation (1.37). The effect on Avg Trade Size in Column (5) is positive but insignificant. To make sure that our conclusions are not driven by taking the principal component, we use the individual measures as outcome varibles in Internet Appendix table 14. The conclusions remain unchanged.

The results align with those of our earlier analysis of FTX as price efficiency declines when fragmentation declines. However, the regression results cannot speak to the ability of traders to split their orders and manage their price impact as the coefficients are the correct sign but insignificant. This is perhaps unsurprising since delistings are more endogenous shocks to fragmentation than our earlier analysis. Coins that are delisted likely have liquidity, ethical, or governance issues which makes them special relative to the rest of the market.

[**Table 9** here]

# 5. Conclusion

Financial markets in the U.S. and Europe have grown increasingly fragmented over the past 25 years. The NYSE and Nasdaq handled almost all trade volume prior to the year 2000 but are now reduced to executing closer to 35% of volume combined. The same is true in Europe where the listing exchange only handles 40% of volume. Despite this widespread trend we do not have clear theoretical guidance or empirical support for how fragmentation affects price efficiency. One of the major challenges is the integration of stock exchanges following regulation such as Reg NMS and MiFID II.

We overcome these challenges by using high-frequency data from 1,768 coin pairs across 16

cryptocurrency trading venues. The cryptocurrency setting provides unique advantages for studying fragmentation. Unlike traditional exchanges, cryptocurrency venues operate independently without best-execution rules or centralized routing. This allows us observe true fragmentation effects without regulatory interference. We exploit two natural experiments in this market, the sudden collapse of the venue FTX and coin delistings on Binance, to provide causal evidence of fragmentation's effect on price efficiency. We find that reductions in fragmentation lead to decreased price efficiency and that the effect grows as the shock increases.

Our analysis provides the first empirical support of Chen and Duffie (2021)'s theory that market fragmentation improves price efficiency by letting traders split orders across multiple venues reducing their overall price impact. When FTX collapses, coins with at least 10% of their volume on the exchange see their price efficiency drop by 43% of a standard deviation. This effect increases to 149% for coins with at least 40% of volume on FTX. We find that the average trade size increases and the price impact rises by 74% of a standard deviation. Furthermore, when coins are delisted from Binance and lose access to the world's largest exchange, their price efficiency falls by 41% of a standard deviation.

Our findings matter for market design and regulation. Regulators often view market fragmentation as harmful and seek to consolidate trading. Our evidence suggests the opposite: fragmentation can improve efficiency by giving traders more tools to manage their orders and reduce price impact. This challenges the conventional wisdom that centralized markets are always better. As financial markets continue to evolve, policymakers should consider the benefits of fragmentation alongside its costs. The ability of traders to split orders across venues appears to be a key channel through which fragmentation improves the efficiency of prices.

Future research could examine whether these effects vary across different types of assets or market conditions. The optimal level of fragmentation may depend on factors such as asset liq-

uidity, trader sophistication, and market structure. Understanding these nuances will help design better markets that balance efficiency with other concerns such as market integrity and investor protection.

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## Table 1
## Venue Market Share and Trading Statistics

This table presents the daily median and mean trading *Volume* in USD by cryptocurrency trading venue, alongside the number of listed *Coins*, the median *Number of Trades* per day, the median *Trade Size* in USD, and the trading venues' *Market Share* as a percentage of total trading volume. Market share is calculated as the trading venue's median daily volume relative to the total median volume across all trading venues.

| | Median Volume | Mean Volume | Coins | Number of Trades | Trade Size | Market Share (%) |
|---|---|---|---|---|---|---|
| Binance | 14,904,648,755 | 17,368,709,014 | 839 | 24,446,453 | 610 | 65.71 |
| Coinbase | 2,376,713,923 | 2,981,112,092 | 468 | 3,447,094 | 689 | 10.48 |
| FTX | 1,514,433,454 | 1,646,886,025 | 175 | 1,120,991 | 1,351 | 6.68 |
| Gate-io | 779,719,089 | 865,689,668 | 1071 | 3,009,900 | 259 | 3.44 |
| Kraken | 776,043,323 | 936,348,202 | 417 | 482,924 | 1,607 | 3.42 |
| Kucoin | 667,610,514 | 739,812,649 | 883 | 5,668,588 | 118 | 2.94 |
| Binance US | 431,111,758 | 563,448,850 | 330 | 612,033 | 704 | 1.90 |
| Bybit-spot | 328,511,275 | 435,078,666 | 285 | 661,491 | 497 | 1.45 |
| Crypto.com | 312,570,675 | 343,720,526 | 536 | 4,621,070 | 68 | 1.38 |
| Bitstamp | 200,537,072 | 293,483,067 | 168 | 90,184 | 2,224 | 0.88 |
| FTX US | 157,383,104 | 176,145,432 | 49 | 56,149 | 2,803 | 0.69 |
| Gemini | 111,053,701 | 142,391,490 | 124 | 149,522 | 743 | 0.49 |
| Ascendex | 91,670,034 | 110,344,617 | 319 | 329,231 | 278 | 0.40 |
| Upbit | 21,757,634 | 40,580,877 | 139 | 38,469 | 566 | 0.10 |
| Bitflyer | 7,044,453 | 10,307,355 | 6 | 3,621 | 1,945 | 0.03 |
| Coinflex | 339,334 | 610,429 | 13 | 865 | 392 | 0.00 |

## Table 2
## Efficiency and Price Impact by Venue

This table reports mean values for venue–coin–date observations across 16 cryptocurrency trading venues. We present the first-order autocorrelation (*Auto Corr*) of coin returns at the 1-minute frequency, calculated as:

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

The *Variance Ratio* for 1-minute intervals, calculated as:

$$\text{Variance Ratio} = \left| \frac{\text{Var}(\text{Ret}_{\text{1-minute}})}{4 \times \text{Var}(\text{Ret}_{\text{15-second}})} - 1 \right|$$

We also present other time combinations for the variance ratios (5 and 1), (15 and 5), (30 and 15). The volume weighted *Price Impact* in basis points over a horizon $k$ (e.g., 30s, 1m, 5m, 30m) following a trade is calculated as

$$\text{PI}_{i,k} = 2 \times \text{direction}_i \times \left( \frac{\text{Midquote}_{t_i+k} - \text{Midquote}_{t_i}}{\text{Midquote}_{t_i}} \right) \times 10000$$

| | Auto Corr | Variance Ratio | | | | Price Impact | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 1 min | 5 min | 15 min | 30 min | 30 sec | 1 min | 5 min | 30 min |
| Binance | -0.07 | -0.23 | -0.18 | -0.17 | -0.17 | 24.51 | 24.98 | 24.53 | 21.70 |
| Coinbase | -0.08 | -0.23 | -0.20 | -0.18 | -0.17 | 31.83 | 32.93 | 33.25 | 31.23 |
| FTX | -0.09 | -0.27 | -0.22 | -0.18 | -0.17 | 30.87 | 32.29 | 33.94 | 33.46 |
| Gate-io | -0.12 | -0.37 | -0.30 | -0.21 | -0.18 | 23.13 | 24.60 | 27.03 | 27.72 |
| Kraken | -0.09 | -0.24 | -0.21 | -0.18 | -0.17 | 35.11 | 36.65 | 38.05 | 36.67 |
| Kucoin | -0.11 | -0.41 | -0.30 | -0.23 | -0.19 | 53.06 | 54.48 | 54.72 | 52.11 |
| Binance US | -0.07 | -0.27 | -0.20 | -0.17 | -0.16 | 25.56 | 26.48 | 26.84 | 25.91 |
| Bybit | -0.11 | -0.32 | -0.26 | -0.20 | -0.18 | 33.65 | 35.03 | 36.76 | 36.77 |
| Crypto.com | -0.16 | -0.36 | -0.30 | -0.22 | -0.19 | 26.66 | 27.65 | 28.78 | 29.00 |
| Bitstamp | -0.10 | -0.25 | -0.23 | -0.19 | -0.17 | 26.24 | 27.44 | 28.29 | 28.42 |
| FTX US | -0.07 | -0.19 | -0.17 | -0.16 | -0.16 | 18.71 | 19.13 | 18.86 | 17.99 |
| Gemini | -0.10 | -0.34 | -0.27 | -0.22 | -0.19 | 38.53 | 40.80 | 42.42 | 39.71 |
| Ascendex | -0.13 | -0.40 | -0.34 | -0.25 | -0.21 | 16.14 | 17.17 | 19.43 | 21.29 |
| Upbit | -0.21 | -0.56 | -0.55 | -0.35 | -0.25 | 69.48 | 73.46 | 81.51 | 89.30 |
| Bitflyer | -0.10 | -0.34 | -0.23 | -0.18 | -0.16 | 20.68 | 22.44 | 24.73 | 25.00 |
| Coinflex | -0.09 | -0.25 | -0.29 | -0.20 | -0.16 | 8.70 | 10.11 | 13.51 | 16.90 |
| Total | -0.10 | -0.31 | -0.25 | -0.20 | -0.18 | 30.07 | 31.27 | 32.40 | 31.55 |

## Table 3
## Fragmentation and Venue Count by Coin Tercile

This table presents the average, median, standard deviation, and maximum statistics of *Fragmentation* and the number of *Venues* for coin terciles. *Fragmentation* is 1 - Herfindahl–Hirschman Index. We group the coins into three terciles based on logged average trading volume (USD) for the coin across our sample.

| | Mean | Median | St.Dev. | Max |
|---|---|---|---|---|
| Panel B: Highest Tercile | | | | |
| Fragmentation | 0.20 | 0.13 | 0.21 | 0.81 |
| Venues | 3.34 | 3.00 | 2.18 | 15.00 |
| Panel C: Middle Tercile | | | | |
| Fragmentation | 0.16 | 0.05 | 0.20 | 0.82 |
| Venues | 1.91 | 2.00 | 0.95 | 7.00 |
| Panel D: Lowest Tercile | | | | |
| Fragmentation | 0.15 | 0.00 | 0.19 | 0.75 |
| Venues | 1.55 | 1.00 | 0.63 | 5.00 |

## Table 4
## Correlation Matrix

This table reports pairwise correlations among the main market variables. *Auto Corr* is defined previously, *Var Ratio PC*, *Efficiency PC*, and *Price Impact PC* are first principal components of our variance ratios, efficiency measures (autocorrelation and variance ratios), and price impact measures. *Fragmentation* is as previously defined. *Venues* is the number of venues a coin is traded on, *Log(Volume)* is the natural log of the volume in USD, and *Volatility* is measured as the difference between the maximum and minimum midquote, divided by the average midquote.

| | Auto Corr | Var Ratio PC | Efficiency PC | Price Impact PC | Fragmentation | Venues | Log(Volume) | Volatility |
|---|---|---|---|---|---|---|---|---|
| Auto Corr | 1.00 | | | | | | | |
| Var Ratio PC | 0.63 | 1.00 | | | | | | |
| Efficiency PC | 0.80 | 0.97 | 1.00 | | | | | |
| Price Impact PC | -0.13 | -0.23 | -0.22 | 1.00 | | | | |
| Fragmentation | 0.03 | 0.06 | 0.06 | -0.11 | 1.00 | | | |
| Venues | 0.19 | 0.28 | 0.27 | -0.23 | 0.58 | 1.00 | | |
| Log(Volume) | 0.40 | 0.58 | 0.57 | -0.26 | 0.13 | 0.46 | 1.00 | |
| Volatility | 0.04 | 0.06 | 0.06 | 0.37 | -0.07 | -0.09 | 0.20 | 1.00 |

## Table 5
## 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). Variables are as previously defined.

| | N | Mean (Pre) | Mean (Post) | St. Dev. (Pre) | St. Dev. (Post) |
|---|---|---|---|---|---|
| Panel A: Coins on FTX | | | | | |
| Fragmentation | 4,170 | 0.39 | 0.26 | 0.20 | 0.20 |
| Auto Corr (1min) | 4,170 | -0.08 | -0.09 | 0.08 | 0.08 |
| Var Ratio PC | 4,170 | 0.85 | 0.59 | 1.18 | 1.33 |
| Efficiency PC | 4,170 | 0.91 | 0.66 | 1.32 | 1.47 |
| Price Impact PC | 4,170 | -0.61 | -0.02 | 1.05 | 2.18 |
| Avg Trade Size | 4,170 | 2365.97 | 1170.54 | 8625.14 | 2265.88 |
| Log(Volume) | 4,170 | 14.41 | 13.79 | 2.54 | 2.91 |
| Volatility | 4,170 | 0.04 | 0.07 | 0.04 | 0.08 |
| Venues | 4,170 | 5.63 | 4.82 | 2.85 | 2.67 |
| Panel B: Coins Not Traded on FTX | | | | | |
| Fragmentation | 42,180 | 0.26 | 0.25 | 0.20 | 0.20 |
| Auto Corr (1min) | 42,180 | -0.11 | -0.12 | 0.09 | 0.10 |
| Var Ratio PC | 42,180 | 0.11 | -0.05 | 1.30 | 1.33 |
| Efficiency PC | 42,180 | 0.12 | -0.05 | 1.47 | 1.51 |
| Price Impact PC | 42,180 | -0.16 | 0.10 | 1.53 | 1.92 |
| Avg Trade Size | 42,180 | 367.88 | 331.65 | 869.18 | 821.32 |
| Log(Volume) | 42,180 | 12.48 | 12.33 | 2.08 | 2.15 |
| Volatility | 42,180 | 0.06 | 0.07 | 0.06 | 0.07 |
| Venues | 42,180 | 2.72 | 2.72 | 1.49 | 1.47 |

## Table 6
## Efficiency and Price Impact Principal Components by the Share of Volume on FTX

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

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

where $\text{Outcome}_{it}$ is either the principal component of efficiency or price impact measure for coin $i$ on date $t$. $\text{Post}_t$ is a dummy variable equal to 1 after November 08, 2022. $\text{Treat}_i$ is a dummy variable equal to 1 if coin $i$ was traded on FTX, defined by having a certain percentage of its trading volume on the venue before the collapse. $X_{it}$ includes control variables, $\alpha_i$ is a coin fixed effect, and $\Theta_t$ is a date fixed effect. Control variables 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. We present significance at 1%, 5% and 10% as ***, **, and * respectively.

| | 10% cutoff | 20% cutoff | 30% cutoff | 40% cutoff |
|---|---|---|---|---|
| Panel A: Price Impact Principal Component | | | | |
| Treat×Post | 0.78** | 1.51** | 1.51** | 1.56* |
| | (0.31) | (0.60) | (0.60) | (0.86) |
| Panel B: Efficiency Principal Component | | | | |
| Treat×Post | -0.57*** | -0.95*** | -0.97*** | -1.34*** |
| | (0.17) | (0.25) | (0.33) | (0.26) |
| Observations | 86,160 | 85,260 | 85,020 | 84,780 |

## Table 7
## Weighted FTX Collapse Event Study

This table includes coins traded on FTX 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.

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

where, $X_{it}$ includes control variables: volatility, number of trading venues, and trading volume in USD. $\alpha_i$ represents coin fixed effects controlling for time-invariant characteristics, and $\Theta_t$ represents date fixed effects capturing common shocks. In column (5), we control for Average Depth Value, defined as the time-weighted ask price times ask amount plus the bid price times the bid amount. The remaining variables are as previously defined. Robust standard errors are clustered by coin and date to account for serial correlation. *** p<0.01, ** p<0.05, * p<0.1.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dep. Var. | Price Impact PC | Auto Corr (1min) | Var Ratio PC | Efficiency PC | Avg Trade Size |
| FTX Volume Share$_{it}$ | 3.38*** | -0.071*** | -1.54*** | -1.73*** | 1,751*** |
| | (1.00) | (0.027) | (0.41) | (0.46) | (443) |
| Log(Volume) | 0.11* | 0.0055* | 0.16*** | 0.17*** | 98.9** |
| | (0.058) | (0.0028) | (0.038) | (0.046) | (42.1) |
| Volatility | 8.21*** | 0.12** | 0.32 | 1.00 | 1,770 |
| | (1.20) | (0.059) | (0.75) | (0.94) | (1,220) |
| Venues | -0.021 | -0.0072*** | -0.11*** | -0.14*** | 279*** |
| | (0.037) | (0.0018) | (0.022) | (0.027) | (85.4) |
| Avg Depth Value | | | | | -0.0023*** |
| | | | | | (0.00058) |
| Observations | 9,595 | 9,595 | 9,595 | 9,595 | 9,595 |
| $R^2$ | 0.572 | 0.426 | 0.670 | 0.664 | 0.620 |

## Table 8
## 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 announcement date. The post-delisting period includes data for 40 days after the announcement (where available). Variables are as previously defined.

| | N | Mean | Median | St. Dev. |
|---|---|---|---|---|
| Panel A: Pre-Delisting | | | | |
| Price Impact PC | 1,427 | -0.35 | -0.67 | 1.33 |
| Auto Corr (1min) | 1,427 | -0.10 | -0.09 | 0.08 |
| Var Ratio PC | 1,427 | 0.34 | 0.52 | 1.27 |
| Efficiency PC | 1,427 | 0.41 | 0.61 | 1.37 |
| Avg Trade Size | 1,427 | 165.71 | 0.06 | 344.62 |
| Log(Volume) | 1,427 | 12.30 | 12.04 | 1.97 |
| Volatility | 1,427 | 0.08 | 0.06 | 0.07 |
| Venues | 1,427 | 2.77 | 2.00 | 1.33 |
| Panel B: Post-Delisting | | | | |
| Price Impact PC | 1,307 | 0.39 | -0.34 | 2.33 |
| Auto Corr (1min) | 1,307 | -0.15 | -0.13 | 0.11 |
| Var Ratio PC | 1,307 | -0.38 | -0.28 | 1.44 |
| Efficiency PC | 1,307 | -0.44 | -0.30 | 1.65 |
| Avg Trade Size | 1,307 | 83.50 | 0.02 | 190.68 |
| Log(Volume) | 1,307 | 10.72 | 10.36 | 2.62 |
| Volatility | 1,307 | 0.11 | 0.08 | 0.09 |
| Venues | 1,307 | 1.84 | 1.00 | 1.23 |

## Table 9
## Delisting on Efficiency and Price Impact Measures

This table presents regressions of coin-level efficiency and market structure measures (volume-weighted by coin) on a post-delisting dummy in a 40-day event window around the announcement of the coin being delisted from Binance.

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

where $\text{Outcome}_{it}$ is a daily measure of price impact, efficiency, or trade size for coin $i$ on date $t$. The key independent variable, $\text{Post-Delisting}_{it}$, is a dummy equal to 1 for the 40 days after delisting and 0 for the 40 days before. We include coin ($\alpha_i$) and date ($\Theta_t$) fixed effects and control for time-varying characteristics $X_{it}$ (volatility, number of venues, trading volume, and market depth). Standard errors are clustered by coin and event date. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The data spans from March 2021 to May 2023. Variables are as previously defined.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dep. Var. | Price Impact PC | Auto Corr (1min) | Var Ratio PC | Efficiency PC | Avg Trade Size |
| Post-Delisting | 0.053 | -0.029*** | -0.47*** | -0.56*** | 26.5 |
| | (0.21) | (0.0070) | (0.099) | (0.10) | (30.4) |
| Venues | 0.17 | 0.0046 | 0.078 | 0.094 | 110 |
| | (0.13) | (0.0062) | (0.097) | (0.099) | (65.4) |
| Log(Volume) | -0.33*** | 0.0027 | 0.14*** | 0.14** | -8.25 |
| | (0.093) | (0.0042) | (0.040) | (0.052) | (12.7) |
| Volatility | 11.9*** | 0.11* | 2.11*** | 2.45*** | 85.2 |
| | (1.48) | (0.060) | (0.68) | (0.81) | (133) |
| Avg Depth Value | | | | | 0.015** |
| | | | | | (0.0056) |
| Observations | 2,695 | 2,695 | 2,695 | 2,695 | 2,695 |
| $R^2$ | 0.457 | 0.412 | 0.645 | 0.629 | 0.843 |

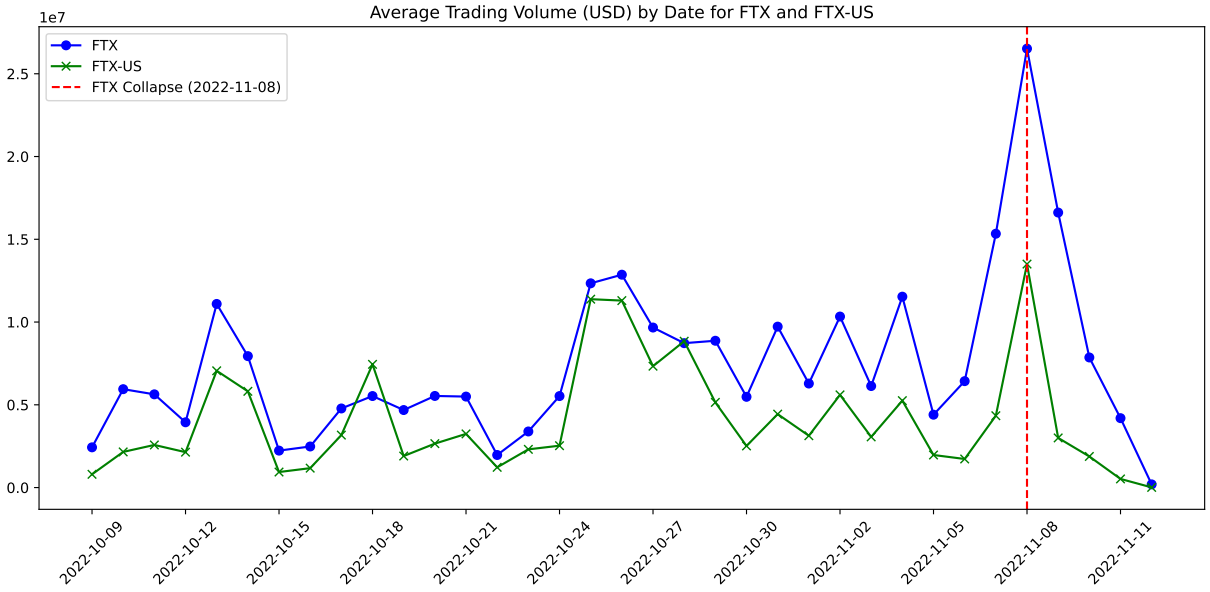



**Figure 1. Trading Volume on FTX**

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.

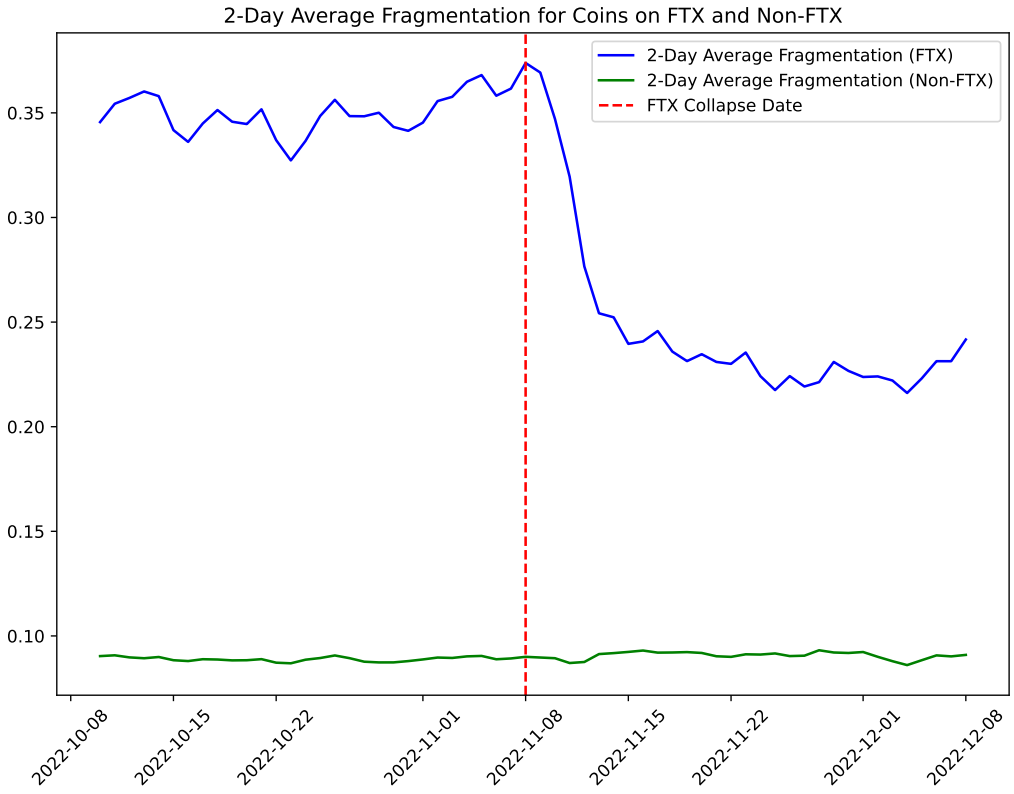



**Figure 2. Fragmentation on FTX and Other Venues**

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.

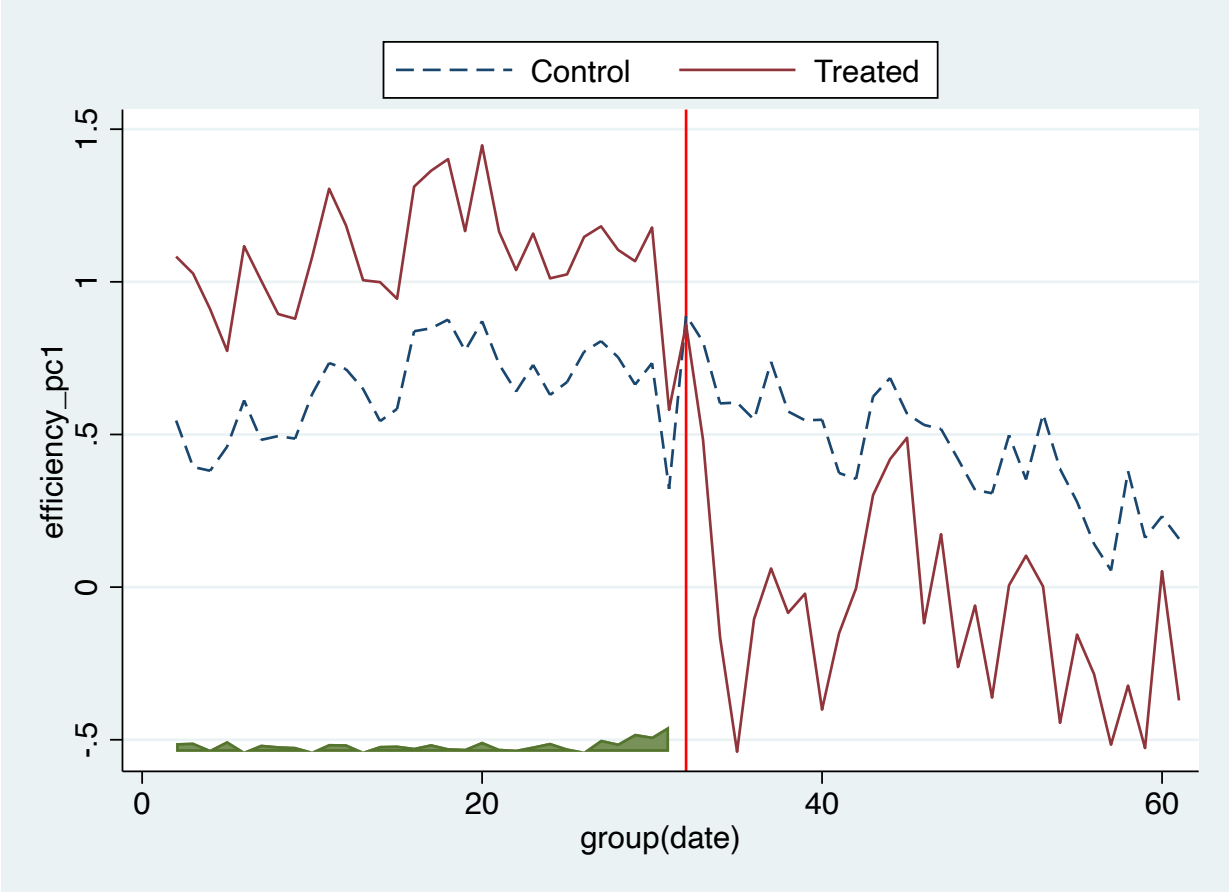



**Figure 3. Efficiency Parallel Trends**

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.

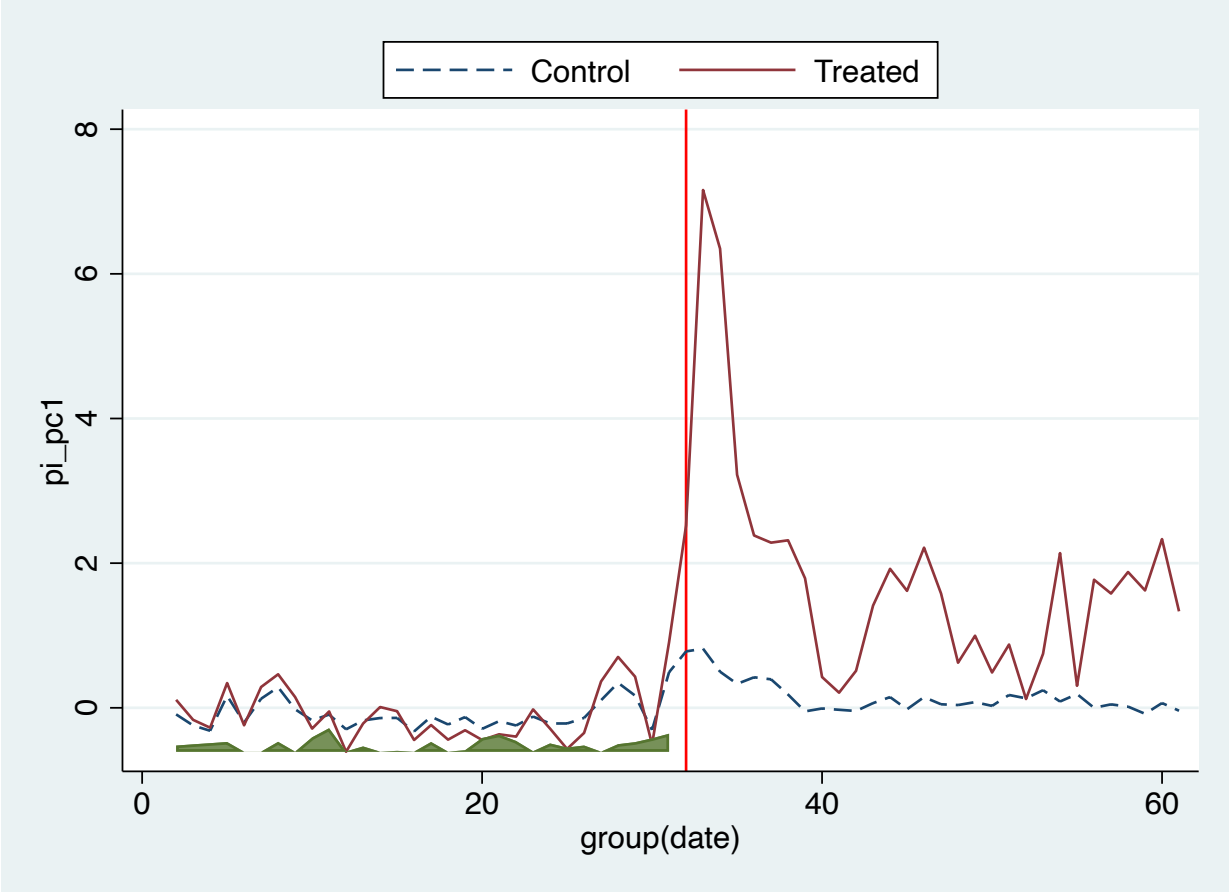



**Figure 4. Price Impact Parallel Trends**

This figure shows parallel trends from a synthetic difference-in-differences (SDID) analysis comparing price impact 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.

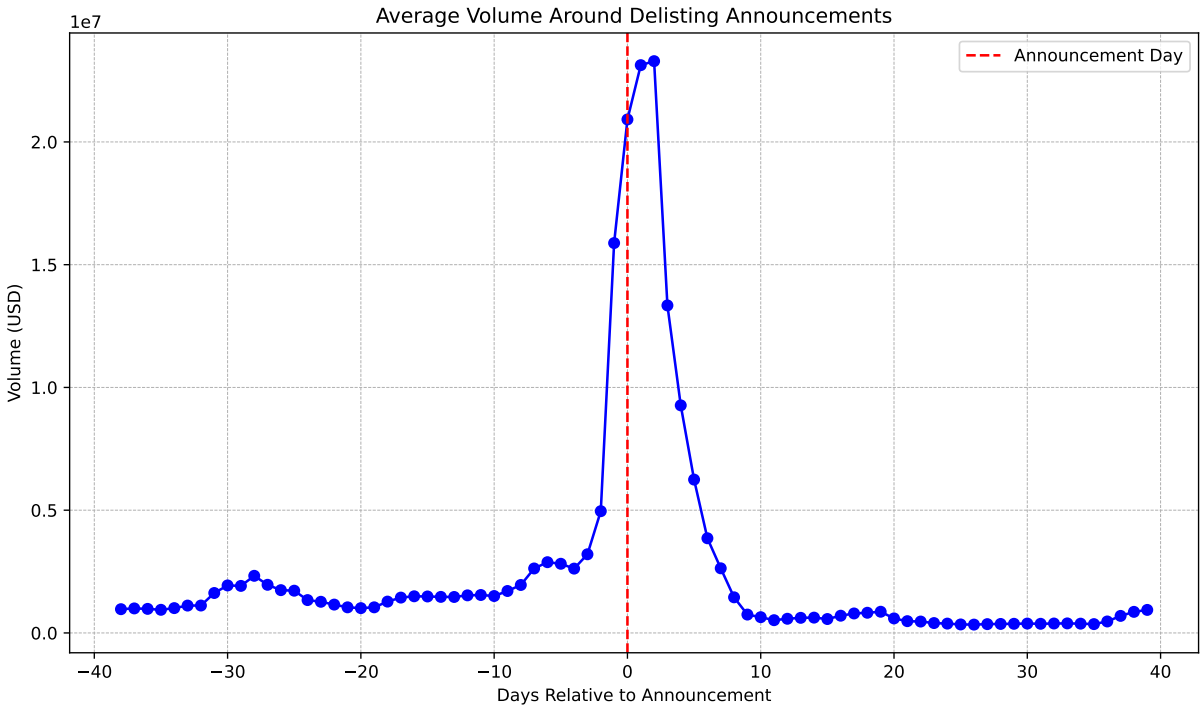



**Figure 5. Volumes Surrounding Delisting Events**

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.

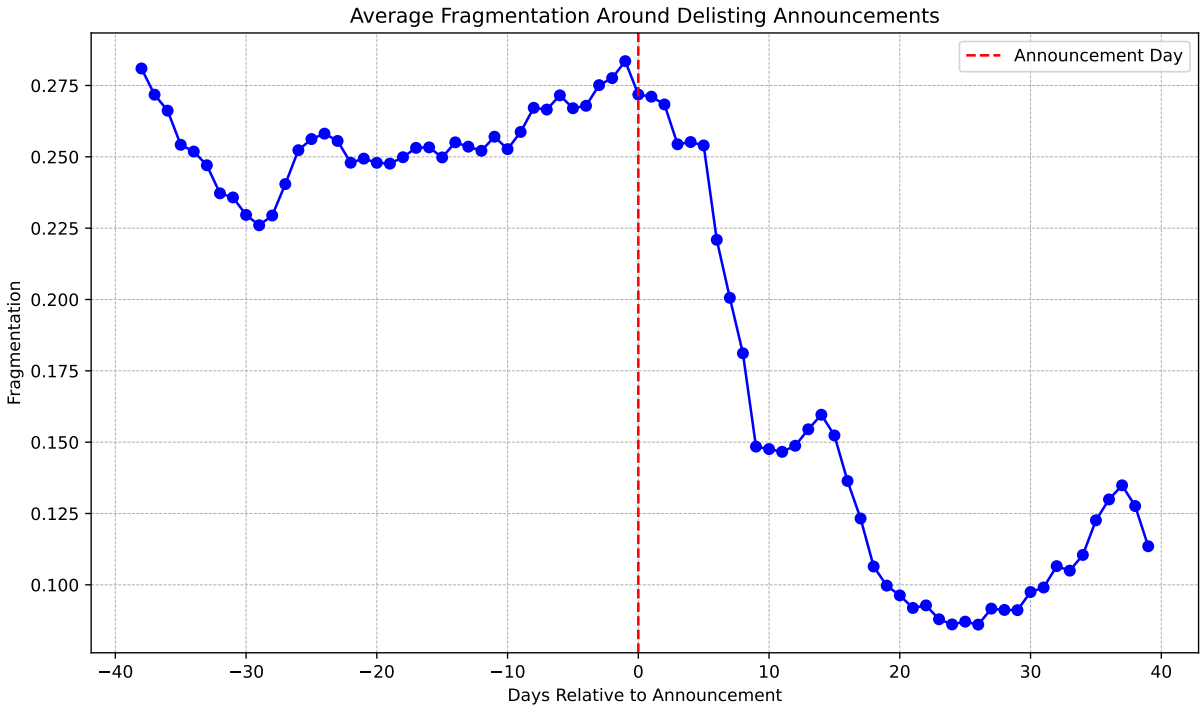



**Figure 6. Fragmentation Surrounding Delisting Events**

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.

# 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 10.

# B. Individual Efficiency and Price Impact Measures

To ensure our main findings are not solely driven by the principal component (PC) analysis, we replicate both event studies using the individual measures of efficiency and price impact as dependent variables. The results are presented in Table 12 for the FTX collapse and Table 14 for exchange delistings.

For both events, the disaggregated results following the same sign and significance from the PC analysis. The FTX collapse led to a significant decline in all measures of price efficiency and a simultaneous increase in price impacts across all horizons. Similarly, an exchange delisting is followed by a significant decrease in price efficiency, as seen in the negative coefficients for autocorrelation and the variance ratios. While the direct effect of delisting on price impact is

not statistically significant, the results show that lower volume post-delisting is associated with significantly higher price impacts.

## Table 10
## Variable Definitions

| Variable | Description |
|---|---|
| Volume | Daily trading volume in USD for a coin. |
| Log(Volume) | Natural logarithm of the daily trading volume (USD) for a coin. |
| Fragmentation | A measure of market fragmentation, calculated as 1 minus the Herfindahl-Hirschman Index (HHI) of market shares. |
| Venues | The number of unique trading venues where the coin is listed. |
| Avg Trade Size | The average USD value of an individual trade over a 24-hour period. |
| Avg Depth Value | The time-weighted average of the total value (in USD) available at the best bid and ask prices. |
| Volatility | The daily price range, measured as the difference between the maximum and minimum midquote, divided by the average midquote. |
| Price Impact ($k$) | The volume-weighted price impact in basis points over a horizon $k$ (e.g., 30s, 1m, 5m, 30m) following a trade, calculated as: $\text{PI}_{i,k} = 2 \times \text{direction}_i \times \left( \frac{\text{Midquote}_{t_i+k} - \text{Midquote}_{t_i}}{\text{Midquote}_{t_i}} \right) \times 10000.$ The daily measure is the sum of all trade-level impacts, weighted by each trade's share of the total daily volume. |
| Price Impact PC | First principal component of the price impact measures at all horizons (30s, 1m, 5m, 30m). |
| Auto Corr (1min) | The 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) | The 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) | The variance ratio for 5-minute intervals, comparing 5-minute return variance to 1-minute return variance. |
| Var Ratio (15min) | The variance ratio for 15-minute intervals, comparing 15-minute return variance to 5-minute return variance. |
| Var Ratio (30min) | The variance ratio for 30-minute intervals, comparing 30-minute return variance to 15-minute return variance. |
| Var Ratio PC | The first principal component of all variance ratios. |
| Efficiency PC | The first principal component of Auto Corr (1min) and all variance ratios, capturing overall price efficiency. |
| FTX Volume Share$_{it}$ | A variable equal to zero in the pre-FTX collapse period and equal to the coin's volume share on FTX prior to the collapse in the post-period. |
| Post Delisting | An indicator variable for the 40-day window following a delisting announcement from Binance. |
| Treat$\times$Post | An interaction term indicating treated coins (e.g., those traded on FTX) in the post-event period. |

## Table 11
## Weighted FTX Collapse Event Study Excluding Immediate Collapse Window

This table includes coins traded on FTX and at least one other trading venue prior to the collapse, excluding the period from November 2 to November 10. 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 (excluding November 2-10). 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.

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

Here, $X_{it}$ includes control variables: volatility, number of trading venues, and trading volume in USD. $\alpha_i$ represents coin fixed effects controlling for time-invariant characteristics, and $\Theta_t$ 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.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dep. Var. | Price Impact PC | Auto Corr (1min) | Var Ratio PC | Efficiency PC | Avg Trade Size |
| FTX Volume Share$_{it}$ | 3.20*** | -0.080*** | -1.57*** | -1.82*** | 1,843*** |
| | (1.03) | (0.030) | (0.48) | (0.54) | (470) |
| Log(Volume) | 0.11* | 0.0050 | 0.16*** | 0.17*** | 114*** |
| | (0.063) | (0.0030) | (0.041) | (0.051) | (42.4) |
| Volatility | 8.30*** | 0.15** | 0.45 | 1.31 | 1,704 |
| | (1.33) | (0.061) | (0.85) | (1.03) | (1,061) |
| Venues | -0.0076 | -0.0077*** | -0.10*** | -0.13*** | 254*** |
| | (0.039) | (0.0020) | (0.025) | (0.030) | (80.7) |
| Avg Depth Value | | | | | -0.0026*** |
| | | | | | (0.00047) |
| Observations | 8,140 | 8,140 | 8,140 | 8,140 | 8,140 |
| $R^2$ | 0.565 | 0.437 | 0.674 | 0.670 | 0.640 |
| Coin FE | Yes | Yes | Yes | Yes | Yes |
| Date FE | Yes | Yes | Yes | Yes | Yes |
| Clustered SE | Coin & Date | Coin & Date | Coin & Date | Coin & Date | Coin & Date |

## Table 12
## FTX Collapse Event Study on Individual Measures

This table presents robustness checks for the FTX collapse event study using individual measures of efficiency and price impact as dependent variables. The variable FTX Volume Share$_{it}$ is zero in the pre-period and represents the coin's volume share on FTX prior to the collapse in the post-period. The sample includes coins traded on FTX or FTX-US and at least one other trading venue for 30 days before and 30 days after the collapse. Control variables include trading volume (USD), volatility, and the number of exchanges. All specifications include coin and date fixed effects. Standard errors, clustered by coin and date, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Dep. Var. | Auto Corr | Var Ratio | Var Ratio | Var Ratio | Var Ratio | Price Impact | Price Impact | Price Impact | Price Impact |
| | (1min) | (1min) | (5min) | (15min) | (30min) | (30s) | (1min) | (5min) | (30min) |
| FTX Volume Share$_{it}$ | -0.071*** | -0.20*** | -0.16** | -0.19*** | -0.062 | 72.7*** | 77.5*** | 87.9*** | 98.3*** |
| | (0.027) | (0.055) | (0.064) | (0.051) | (0.043) | (21.2) | (22.7) | (26.6) | (30.9) |
| Volume (USD) | 0.0055** | 0.025*** | 0.021*** | 0.0093** | 0.0018 | 2.56* | 2.49* | 2.50 | 3.02* |
| | (0.0028) | (0.0050) | (0.0044) | (0.0037) | (0.0038) | (1.46) | (1.48) | (1.56) | (1.55) |
| Volatility | 0.12** | 0.35*** | 0.033 | -0.14 | -0.13* | 181*** | 204*** | 220*** | 201*** |
| | (0.059) | (0.081) | (0.10) | (0.086) | (0.061) | (29.8) | (30.8) | (30.2) | (35.8) |
| Venues | -0.0072*** | -0.017*** | -0.013*** | -0.0066** | -0.0048 | -0.30 | -0.39 | -0.88 | -0.57 |
| | (0.0018) | (0.0043) | (0.0037) | (0.0025) | (0.0037) | (0.89) | (0.89) | (1.01) | (1.12) |
| Observations | 9,595 | 9,595 | 9,595 | 9,595 | 9,595 | 9,595 | 9,595 | 9,595 | 9,595 |
| $R^2$ | 0.426 | 0.693 | 0.518 | 0.279 | 0.135 | 0.556 | 0.559 | 0.521 | 0.403 |

## Table 13
## Delisting on Efficiency and Price Impact Measures Excluding Days Around Event

This table presents regressions of coin-level efficiency and market structure measures (volume-weighted by coin) on a post-delisting dummy in a 40-day event window around the announcement of the coin being delisted from Binance, excluding days -4 to +8 around the delisting announcement to avoid the volume spike period.

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

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 announcement of the delisting and 0 for 40 days before the announcement. 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 10 in Appendix A.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dep. Var. | Price Impact PC | Auto Corr (1min) | Var Ratio PC | Efficiency PC | Avg Trade Size |
| Post-Delisting | 0.083 | -0.043*** | -0.62*** | -0.75*** | 12.0 |
| | (0.25) | (0.011) | (0.14) | (0.16) | (42.6) |
| Venues | 0.16 | 0.0042 | 0.066 | 0.080 | 94.1 |
| | (0.15) | (0.0075) | (0.10) | (0.11) | (56.7) |
| Log(Volume) | -0.31*** | -0.00026 | 0.12*** | 0.11* | -10.1 |
| | (0.081) | (0.0046) | (0.041) | (0.053) | (13.6) |
| Volatility | 12.4*** | 0.17** | 3.08*** | 3.63*** | 27.4 |
| | (1.75) | (0.066) | (0.71) | (0.83) | (124) |
| Avg Depth Value | | | | | 0.019** |
| | | | | | (0.0071) |
| Observations | 2,233 | 2,233 | 2,233 | 2,233 | 2,233 |
| $R^2$ | 0.479 | 0.427 | 0.657 | 0.638 | 0.857 |

## Table 14
## Delisting Event Study on Individual Measures

This table presents a robustness check for the delisting event study, using individual measures of efficiency and price impact as dependent variables. The analysis uses a 40-day event window around the announcement of a coin being delisted from an exchange.

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

All specifications include coin and date fixed effects. Standard errors, clustered by date and coin, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Dep. Var. | Auto Corr | Var Ratio | Var Ratio | Var Ratio | Var Ratio | Price Impact | Price Impact | Price Impact | Price Impact |
| | (1min) | (1min) | (5min) | (15min) | (30min) | (30s) | (1min) | (5min) | (30min) |
| Post-Delisting | -0.029*** | -0.050*** | -0.049*** | -0.046*** | -0.028*** | 0.070 | 0.076 | 1.67 | 3.50 |
| | (0.0070) | (0.017) | (0.017) | (0.015) | (0.0093) | (4.39) | (4.72) | (5.93) | (6.06) |
| Venues | 0.0046 | 0.026 | 0.013 | -0.0052 | -0.0096 | 3.18 | 3.99 | 7.08** | 2.20 |
| | (0.0062) | (0.017) | (0.013) | (0.017) | (0.012) | (3.29) | (3.18) | (3.28) | (3.72) |
| Volume (USD) | 0.0027 | 0.015 | 0.018** | 0.013** | 0.0081 | -6.50*** | -7.15*** | -9.23*** | -8.47*** |
| | (0.0042) | (0.0091) | (0.0068) | (0.0056) | (0.0053) | (2.26) | (2.33) | (2.21) | (2.22) |
| Volatility | 0.11* | 0.44*** | 0.38*** | 0.039 | -0.20** | 245*** | 270*** | 334*** | 292*** |
| | (0.060) | (0.095) | (0.11) | (0.084) | (0.096) | (33.4) | (36.0) | (39.9) | (38.4) |
| Observations | 2,695 | 2,695 | 2,695 | 2,695 | 2,695 | 2,695 | 2,695 | 2,695 | 2,695 |
| $R^2$ | 0.412 | 0.596 | 0.536 | 0.361 | 0.231 | 0.442 | 0.438 | 0.424 | 0.424 |