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Fractional and around the clock: Trading activity in tokenized financial assets☆

Stefan Scharnowski

University of Mannheim, L9, 1-2, 68161 Mannheim, Germany

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A B S T R A C T

In this paper, I empirically analyze trading patterns and investor behavior in a market for tokenized financial assets. Although investors can trade the tokenized assets around the clock, trading activity is substantially higher when the primary listing exchange is open, in particular during the regular trading session. Likewise, price differences between tokenized and underlying assets are wider during the extended trading hours than during the regular trading session. The majority of trades result from fractional order sizes but orders still cluster at round sizes, values, and prices, indicating that investors use relatively simple heuristics when setting quantities and prices. Additionally, a disproportionate number of trades, especially buy trades, use the minimum permissible order size, suggesting the presence of retail traders interested in owning an asset for purposes other than financial gain.

1. Introduction

Tokenized securities, digital representations of existing financial assets recorded on a blockchain, are attracting increasing attention from both market participants and regulators. Robinhood, a retail broker, recently launched tokenized US securities trading for European investors, and Nasdaq has received SEC approval for a rule change enabling exchange-based trading of tokenized securities in the United States. Despite this momentum, the empirical evidence regarding how investors actually trade in tokenized financial securities is scarce. This paper attempts to fill that gap. Using detailed trade-level data from a market for tokenized stocks and funds, I document how around-the-clock access, fractional trading, and the resulting market structure influence investor behavior and token pricing.

Tokenization promises several benefits for financial intermediation, including decentralization, democratization of access, lower costs, faster settlement, around-the-clock trading, fractional ownership, and automation via smart contracts (see, e.g., Benedetti and

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E-mail address: scharnowski@uni-mannheim.de.

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Rodríguez-Garnica, 2023; Lavayssière, 2025). In isolation, some of these features also exist in traditional markets. For instance, some brokers have introduced fractional trading and extended trading hours. However, the simultaneous availability of these features, particularly for international retail investors seeking access to US securities, has historically been limited. The tokenized market studied in this paper offered non-US investors around-the-clock access to fractional shares of US-listed securities at a time when such combined access was largely unavailable through conventional channels. This setting thus provides a first empirical view on how investors behave when some of these market design features are simultaneously present, and serves as early evidence on the characteristics of tokenized securities markets that are now being deployed at larger scale.

Importantly, the tokenized setting also provides a uniquely transparent view of fractional trading. In conventional markets, fractional trades are typically reported to the consolidated tape by rounding up the trade size, making them difficult to observe directly (Bartlett et al., 2025). Researchers have therefore had to rely on proxies such as latency or one-share trade reports to identify fractional activity (Bartlett et al., 2024; Da et al., 2025). In contrast, I directly observe all executed trades, fractional and non-fractional, including precise transaction volumes. This level of observability enables analyses that are not feasible with conventional market data, such as quantifying the mass of trades at the minimum permissible order size, distinguishing share-count clustering from dollar-value clustering, and analyzing how the use of fractional and minimum-size trades varies across regular hours, extended hours, and non-trading days of the underlying asset's primary market.

I examine three key aspects of tokenized trading: around-the-clock market access, fractional order sizes, and pricing dynamics between tokenized assets and their underlying assets. Understanding how these features materialize in practice is important for evaluating the impact of tokenization on market quality, and is becoming increasingly relevant for conventional financial markets as well. For example, the debate regarding optimal trading hours has intensified following announcements by major US exchanges to extend trading hours. In February 2025, the Securities and Exchange Commission (SEC) approved a filing by ICE (Intercontinental Exchange, 2025) to increase trading hours at NYSE Arca to 22 hours a day.

While several of the patterns documented here have analogues in conventional markets, my setting yields testable predictions about how these should appear in tokenized markets. In a market that trades continuously but is itself a thinner secondary venue, off-hours demand should be limited, and trading activity likely remains concentrated during regular US hours. Fractional trading should make higher-priced assets more accessible. Minimum-size trades and sub-one-share orders should be especially common on the buy side and outside the core session if these are frequently used by small retail investors. Finally, arbitrage between the tokens and their underlying assets must pass through an additional layer of intermediation, so price gaps should remain meaningful and are expected to widen when primary markets are closed and arbitrage activity is low. My setting allows me to test these predictions directly.

Exploiting a rich dataset on trades in tokenized stocks and funds, I document several findings, consistent with the predictions above. First, despite around-the-clock availability, trading activity in tokenized assets is substantially concentrated during the hours when the primary listing exchange of the underlying asset is open, suggesting that demand for off-hours trading is largely limited relative to regular-session activity. Second, traders frequently submit fractional orders, but order sizes still cluster at relatively round quantities and values, indicating that investors use simple heuristics when setting trade sizes. Trades smaller than one full share are more frequent for high-priced assets and when the primary market is closed, consistent with the notion that fractional trading particularly appeals to smaller retail investors. A disproportionate share of trades occurs at the minimum permissible order size, resulting in economically trivial transactions. For instance, the 5th percentile of trade values is just USD 0.35, consistent with the presence of traders who appear to hold tokenized assets for reasons beyond financial gain. Third, price differences between tokenized assets and their underlying assets are generally small but non-trivial. Absolute percentage price differences typically exceed transaction costs such as bid–ask spreads in the underlying markets. These differences are driven in part by the sluggish adjustment of token prices to price changes in the underlying asset. Price differences are substantially wider during the extended trading hours, consistent with limits-to-arbitrage explanations.

My study relates to several streams within the literature. Most directly, I contribute to the literature on tokenization. Malinova and Park (2023) provide an overview of tokenization, especially in the context of trading existing assets using blockchain technology. Closely related to my paper, Aspris et al. (2022) investigate the transaction costs of tokenized financial assets, concluding that costs such as bid–ask spreads and exchange fees are much larger than in conventional financial markets. However, they also remark that the gap is decreasing. In a Federal Reserve discussion paper on the financial stability implications of digital assets, Azar et al. (2022) highlight regulatory challenges concerning tokenized assets, explicitly mentioning the same assets studied in this paper.

Swinkels (2023) considers the market for real estate tokens, finding that tokenization increases liquidity and allows for constructing diversified portfolios even for smaller investors. Swinkels (2024) examines investor activity in a tokenized market for voluntary carbon credit trading. Lee et al. (2021) provide a model of markets for tokenized assets with endogenous trade to investigate settlement uncertainty. They show that via programmability, tokenization alleviates the settlement uncertainty problem, but potentially has adverse consequences because it requires traders to reveal more information. More generally, stablecoins can be considered a form of tokenized deposits (Oefele et al., 2024), although aspects such as fractional trading and around-the-clock access are less relevant in that market. However, to the best of my knowledge there is no empirical study investigating investor behavior and trading patterns in tokenized financial assets.

While I focus on the tokenization of existing financial assets, related studies have considered the issuance of security tokens via security token offerings (STOs) and initial coin offerings (ICOs).[1] Gan et al. (2021) provide a model to compare equity token offerings

[1] In practice, the terms ICO and STO are sometimes used interchangeably. In a narrower definition, security tokens refer to blockchain representations of equity that confer rights to a company's future profits, while the utility tokens offered in an ICO usually grant access to the company's goods or services (Gan et al., 2021; Sockin and Xiong, 2023).

to utility tokens. The model predicts that equity tokens may help align incentives of owners and investors, even in unregulated environments. Sockin and Xiong (2023) theoretically analyze the use of tokens by decentralized digital platforms, concluding that utility tokens are preferred over equity as a funding source for platforms with weak fundamentals because utility tokens foster commitment by the platform not to exploit its users. However, regarding the actual implementation of token financing, Momtaz (2021) highlights that there are still open questions concerning securities law and regulation around security tokens.

I also contribute to the emerging literature on fractional trading. Bartlett et al. (2025) demonstrate that the practice of rounding up fractional trade sizes when reporting to the consolidated tape leads to substantially inflated reported trading volume in the shares of Berkshire Hathaway. After developing a method to identify fractional trades from the consolidated tape, Bartlett et al. (2024) show that fractional trades are important as they are informative and predictive of future liquidity and volatility. Looking at the sequential introduction of fractional trading by four brokerage firms, Da et al. (2025) also find that fractional trading matters, as small retail investors use fractional trades to collectively generate price pressure in high-priced stocks. Gempesaw et al. (2022) likewise study the introduction of fractional trading by a retail broker, finding that it makes high-priced stocks accessible to smaller investors. Angerer et al. (2025) provide experimental evidence for a fractionalized asset market and find that it increases financial inclusion by allowing less-wealthy investors to participate. However, trading activity and liquidity in the market for the original asset decrease. Unlike these studies, which must infer fractional trading activity from off-exchange one-share trade reports or changes in retail ownership, my setting allows direct observation and analysis of all fractional trades, including their precise sizes and values.

Unlike regular exchanges, the market for tokenized assets investigated in this study is open around the clock. Generally, several studies have concluded that liquidity and trading volume are lower while volatility is higher outside the core trading session, i.e., during the pre-market and the after-hours market (McInish et al., 2002; Barclay and Hendershott, 2004). The composition of traders may also differ between trading sessions. For example, Cole et al. (2015) find that high-frequency traders are predominantly active during the regular trading sessions and contribute relatively little to price discovery during the extended trading hours. Similar to tokenized assets, other types of derivatives often have different trading hours than the spot market. For instance, Dungey et al. (2009) consider the futures market and find that it is especially relevant for price discovery when other markets are closed. Looking at markets for similar assets with partially overlapping trading hours, as is often the case for cross-listed securities, many studies have documented higher levels of trading activity in the foreign market when the home market is open (Werner and Kleidon, 1996; Grammig et al., 2005; Moulton and Wei, 2009). By analyzing how market activity differs across the overlap of trading hours between the tokenized and underlying markets, I also contribute to this literature on overlapping exchange trading hours and differences between the various trading sessions.

Finally, I relate to the literature on trading and quoting behavior, particularly regarding size clustering and odd-lot trading. Investors may have different reasons to trade at relatively round sizes: They may exhibit the behavioral bias to prefer round numbers, for example in order to minimize the cognitive effort spent when submitting orders (Wyckoff, 1963; Niederhoffer and Osborne, 1966; Kuo et al., 2015). However, there may also be rational reasons to cluster at round trade sizes, for example to disguise trading intentions. Looking at the foreign exchange market, Moulton (2005) and ap Gwilym and Meng (2009) demonstrate that trade size clustering varies over time and is less common at quarter-ends when investors want to construct more precise portfolios, for example because of window dressing or to align their portfolios more closely with stated objectives or benchmarks. Moreover, ap Gwilym and Meng (2009) show that there is a trade-off between trading at exact prices and trading exact quantities. Garvey and Wu (2014) find similar results but for the intraday variation in trade size clustering, showing that round sizes are relatively less frequent towards the end of the trading day. Alexander and Peterson (2007) conclude that clustering is used by stealth traders to disguise their activity, in particular by using medium-sized trades at round lots as these have relatively high price impacts. Lien et al. (2019) investigate both price and size clustering and find that institutional investors are less likely to submit round order sizes than individual investors. Bartlett et al. (2023) show that odd-lot trades are informative even though they are not reported in the National Best Bid or Offer (NBBO). Since I document substantial clustering behavior in trade sizes, values, and prices in the market for tokenized assets, I also contribute to this stream of the literature.

The rest of the paper is organized as follows. Section 2 provides the institutional background of tokenization and introduces the data. Section 3 documents the trading activity in tokenized assets throughout the day. Fractional trading is investigated in Section 4. Section 5 analyzes price differences between tokenized assets and their underlying assets before Section 6 concludes.

2. Institutional background and data

2.1. Institutional setting

The tokenized assets studied in this paper were traded at FTX, which is now defunct but was at the time one of the largest cryptocurrency exchanges (Jalan and Matkovskyy, 2023). Importantly, it operated one of the largest tokenized asset markets to date. Other markets that in the past have offered tokenized financial assets include the cryptocurrency exchanges Binance and Bittrex. More recently, in June 2025 the neobroker Robinhood launched tokenized assets that allow customers in the European Union to invest in hundreds of US stocks and funds.

In essence, the tokenized assets are derivatives that are pegged to the underlying asset by collateralization.[2] Besides the exchange itself, two further entities are part of the tokenization process. Firstly, an asset tokenization platform trades the underlying assets in

[2] Other than the asset-backed tokens described here, some platforms offer synthetic tokenized stocks. These tokens replicate a stock's price through smart contracts or collateral-based mechanisms, without actually owning the underlying asset. Early examples include Mirror Protocol on Terra and Synthetix on Ethereum.

their respective markets and issues corresponding tokens. Both the tokens and the underlying assets are then transferred to the next entity, the custodian, which holds the underlying asset and forwards the tokens to the exchange, where they can be bought by other market participants while the proceeds are used to cover the costs of buying the underlying assets. In principle, the holders of the tokenized assets can redeem their tokens with the custodian, thus aligning the value of the token with that of the underlying asset. However, prices may still diverge due to counterparty risk and liquidity differences between the two markets. Economically, the process is generally similar to depositary receipts such as (unsponsored) American depositary receipts (ADRs, see, e.g., Iliev et al., 2014).[3]

Trading on the platform is subject to onboarding and jurisdictional restrictions. Potential investors in tokenized assets first have to go through a know-your-customer (KYC) process at FTX and at the custodian and would legally also become a customer of the custodian. Due to regulatory concerns, US customers were not allowed to trade in the tokenized assets. The active investor base thus consisted of non-US, predominantly retail traders accessing US-listed assets through this venue.

According to the terms of service of the tokenized assets at FTX, they can be bought and sold with other crypto assets or US dollars. Furthermore, dividend payments and other receivables are paid out in cash or crypto assets. Holders of tokenized stocks do not have any shareholder rights such as voting rights. They also have no claim to delivery of the underlying asset itself, only to a cash or crypto-asset payout of an equivalent amount.

The tokenization process grants a global investor base access to the North American equity markets at costs that are likely substantially lower than those of trading these assets through local-market alternatives such as cross-listed securities or other derivatives. While (Aspris et al., 2022) document relatively high trading costs for these tokenized assets in the form of spreads and other indirect trading costs compared to the primary listing exchanges, the differences in exchange fees and commissions are usually smaller. For example, Aspris et al. (2022) provide a range of 2–7 basis points for explicit exchange costs for trading tokenized equities. While these may be large compared to explicit costs at the underlying assets' primary listing exchanges (usually less than 1 basis point for larger trades), they are substantially smaller than the explicit costs an international retail trader would incur. In particular, fixed fees can be disproportionately large for small and especially fractional retail trades.

Three design features of this market are central to the analyses that follow. First, trading is open around the clock, without scheduled session boundaries. Second, fractional order sizes are permitted, so investors can buy or sell portions of a single share. Third, exchange-set minimum order sizes are very low, often well below one share. Together, these features made the venue accessible to international retail investors at the time, and they motivate the empirical analyses in the rest of the paper.

While low absolute trading costs for small orders as well as (almost) global and around-the-clock access reflect some of the advantages of tokenization, not all potential benefits of tokenization materialize in the tokenized assets from FTX. For example, the market is hardly decentralized or disintermediated. On the contrary, the tokens can be traded on one exchange only and require an additional layer of intermediation in their creation, introducing additional counterparty risk.

Even though the market for tokenized assets at FTX has since ceased to exist, the trading environment it created remains highly relevant. FTX offered one of the most active tokenized asset platforms to date, and its structure – featuring around-the-clock access, fractional trading, and low minimum order sizes – mirrors elements now being adopted by other financial platforms, such as Robinhood's recent tokenization offering in the EU. The behaviors documented in this study, such as trade size clustering, small fractional orders, and around-the-clock trading, are likely not idiosyncratic to FTX, but reflect general investor behavior in such a market setting. This paper thus provides a first look at investor behavior in tokenized markets before their broader adoption under more regulated frameworks.

2.2. Data

The data used in this study contains trades in tokenized assets from FTX and was collected using FTX's public API. The data contains prices in US dollars,[4] the size of each trade, timestamps with millisecond precision, and an indicator for buys and sells. Furthermore, liquidating trades are indicated by a binary variable. These trades result from automatic and algorithmic liquidations of investor positions due to margin calls. The dataset is supplemented by trading data from the respective primary listing exchange of the underlying assets. This data was obtained from LSEG Workspace and contains open, high, low, and close prices as well as trading volume and the number of trades for each one-minute interval during the sample. Prices of Canadian stocks are converted to US dollars using the exchange rate of the same one-minute interval. I additionally collect data on earnings announcements from LSEG.

The collected data comprises trades in 49 tokenized assets. After excluding one low-priced token without fractional trading, two tokens with obvious data errors,[5] and tokens with a primary listing exchange outside of North America, the final sample contains 44 tokens. The sample period ranges from December 2021 to the collapse of FTX in November 2022, though some tokens only enter the sample during 2022. Unless otherwise mentioned, the sample is restricted to end in October 2022, shortly before the news spread that FTX and Alameda Research heavily depended on the FTT token for financing, eventually leading to the collapse of the exchange. The price differences between the tokenized assets and those traded at the primary market suggest that the market was not anticipating the collapse of the exchange until after October 2022 (see for example Fig. A.2 in the appendix).

[3] See Appendix B for further details on the institutional background including the specific entities involved in the tokenization process at FTX.

[4] This also holds for the Canadian stocks. One token, TSLA, is quoted not only in US dollars, but also in the cryptocurrencies Bitcoin and Dogecoin. Trading activity in the two pairs quoted in cryptocurrency is omitted in this study.

[5] In these cases, absolute price differences to the underlying asset at the primary market are consistently above 10%.

Table 1
Trading activity by asset.

Ticker	Category	Trade size				Trade value				Daily trades				# Trades
		Mean	P5	P50	P95	Mean	P5	P50	P95	Mean	P5	P50	P95	
ACB	Canada	19.16	0.10	5.60	78.90	40.29	0.55	7.50	135.85	29	1	6	54	9,028
BB	Canada	6.03	0.10	0.10	19.30	43.27	0.47	0.47	149.01	11	1	2	20	1,433
CGC	Canada	16.95	0.10	0.80	65.40	98.69	0.55	3.98	312.99	29	1	6	123	8,676
CRON	Canada	40.92	0.10	11.10	213.50	163.71	0.38	36.44	776.52	8	1	4	26	2,005
GLXY	Canada	11.28	0.10	1.00	41.20	123.84	0.43	8.65	534.92	45	1	9	165	13,217
TLRY	Canada	27.97	0.10	1.30	105.20	128.46	0.61	6.44	438.17	46	1	12	196	14,356
GDX	Commodity	35.90	0.01	0.25	68.00	1,180.17	0.35	6.04	2,068.76	15	1	4	28	3,788
GDXJ	Commodity	23.47	0.01	0.50	156.25	961.56	0.40	20.34	6,887.87	6	1	3	23	1,671
GLD	Commodity	12.12	0.01	0.13	65.74	2,115.76	1.74	20.11	11,166.04	29	1	8	54	9,236
SLV	Commodity	68.36	0.10	1.00	534.90	1,431.04	2.25	22.02	10,690.02	86	3	46	300	28,368
USO	Commodity	11.64	0.01	0.66	30.00	783.52	0.73	49.72	2,219.85	131	3	53	433	42,684
BITO	Crypto	3.91	0.01	0.13	10.82	99.77	0.27	3.31	275.33	22	1	6	78	4,310
BITW	Crypto	5.37	0.01	0.02	12.65	116.59	0.12	0.28	354.11	35	1	4	37	8,738
ETHE	Crypto	74.71	0.20	33.90	217.50	2,456.60	1.68	792.53	8,084.80	178	2	24	612	56,982
GBTC	Crypto	60.93	0.01	23.56	234.72	1,676.60	0.13	361.31	8,667.98	332	9	127	1287	111,287
BYND	Meme/Other	4.03	0.01	0.77	8.42	167.46	0.66	12.72	269.70	63	1	16	216	19,523
DKNG	Meme/Other	2.60	0.01	0.02	9.86	49.22	0.15	0.31	186.82	28	1	5	50	6,906
GME	Meme/Other	1.73	0.02	0.39	5.04	52.20	0.52	10.45	156.62	178	2	48	653	17,484
HOOD	Meme/Other	31.10	0.03	6.39	134.74	466.03	0.31	72.08	1,920.62	33	1	17	122	10,526
PENN	Meme/Other	5.83	0.01	0.02	17.75	253.92	0.32	0.90	858.57	11	1	3	54	2,107
BNTX	Pharma	9.46	0.01	0.20	30.05	1,550.18	1.35	27.72	5,167.84	29	1	9	104	8,766
MRNA	Pharma	17.06	0.01	0.10	138.43	2,553.90	0.75	20.28	20,055.00	11	1	6	35	3,107
PFE	Pharma	27.45	0.01	0.06	33.00	1,435.55	0.44	3.01	1,764.18	15	1	8	43	4,644
SPY	SP500	1.67	0.00	0.01	10.45	673.81	0.37	2.52	4,388.50	259	17	157	715	87,028
AAPL	Tech	3.94	0.01	0.05	6.00	629.41	1.45	8.15	998.42	130	24	101	318	43,737
ABNB	Tech	5.76	0.03	0.10	35.42	824.64	2.97	12.66	4,873.27	10	1	4	29	2,919
AMD	Tech	3.16	0.01	0.05	5.00	291.22	0.94	5.78	499.88	77	2	50	224	25,185
AMZN	Tech	2.69	0.00	0.05	8.26	309.78	0.12	6.29	963.73	150	11	86	432	22,445
ARKK	Tech	9.89	0.01	0.30	48.83	525.67	0.38	15.33	2,332.80	120	4	87	382	40,197
BABA	Tech	10.63	0.01	5.62	35.10	1,092.99	0.99	576.71	3,598.18	152	5	58	548	50,781
COIN	Tech	5.81	0.01	0.11	18.95	488.94	0.81	12.51	1,915.20	110	6	64	376	37,071
FB	Tech	7.60	0.01	0.06	31.17	1,319.09	0.99	6.67	5,149.98	129	6	38	246	43,117
GOOGL	Tech	1.33	0.00	0.00	4.00	149.06	0.10	0.21	412.54	355	15	114	1600	38,314
MSTR	Tech	5.54	0.01	0.10	16.80	1,469.89	1.53	42.58	5,312.50	42	2	18	134	13,921
NFLX	Tech	7.72	0.01	0.10	37.50	1,780.54	2.75	30.10	8,278.65	55	3	27	144	18,384
NIO	Tech	32.54	0.03	1.13	103.49	661.02	0.50	21.10	2,233.09	111	3	38	414	37,012
NVDA	Tech	2.92	0.00	0.10	8.42	502.69	0.63	20.98	1,428.00	92	6	74	231	31,001
PYPL	Tech	22.46	0.01	0.17	125.00	2,093.03	1.05	15.22	11,750.00	37	2	20	104	12,063
SQ	Tech	9.29	0.01	0.10	63.43	843.72	0.52	10.10	5,268.14	29	1	17	95	9,268
TSLA	Tech	1.45	0.01	0.24	3.87	362.46	2.22	56.44	906.44	1022	125	1024	2,161	70,498
TWTR	Tech	47.69	0.05	0.40	248.10	2,167.61	2.20	17.81	10,498.95	49	2	16	198	16,004
UBER	Tech	32.03	0.05	1.05	100.00	1,037.32	1.60	35.16	3,320.00	8	1	4	24	2,433
ZM	Tech	7.86	0.01	0.10	45.94	828.64	0.80	10.48	4,102.23	16	1	7	67	5,042
Total		20.47	0.00	0.29	108.60	928.78	0.35	18.82	4,718.67	2,962	361	2,306	8,060	995,262

This table shows summary statistics for the trading activity in each tokenized asset. *Trade Size* and *Trade Value* are at the trade level and give the distribution of the size of the trades in the number of tokens and in USD, respectively. *Daily Trades* is the number of trades at the token-day level. *# Trades* gives the total number of trades in the sample.

All assets are manually sorted into one of seven categories. Canadian stocks form one category, primarily because trading hours differ at the primary exchange and the stocks are quoted in another currency in their primary market. The remaining categories are commodities, cryptocurrency funds, so-called "meme" stocks and other small stocks that attract a similar retail investor base (see, e.g., Welch, 2022), pharmaceutical companies, and technology companies. Finally, the SPDR S&P 500 ETF forms its own category. The names of the sample assets, the corresponding categories, and the first trading date of the tokenized asset at FTX can be found in Table A.1 in the appendix.

2.3. Empirical approach

The empirical analysis is divided into three parts. First, I provide a detailed analysis of trading activity in the tokenized assets, focusing on how it compares to activity at the primary listing exchanges and how trading activity develops throughout the day. Second, I investigate fractional trading by descriptively showing the prevalence of the phenomenon, documenting investor preferences regarding relatively round trade sizes and prices, and then estimating the determinants of various types of fractional trades in a fixed-effects regression framework. Third, I analyze price differences between tokenized assets and their respective underlying assets, how these differences develop throughout the trading day, and which factors help explain their variability.

Table 2
Trading activity by category.

Category	Trade size				Trade value				Daily trades				# Trades
	Mean	P5	P50	P95	Mean	P5	P50	P95	Mean	P5	P50	P95	
Canada	19.73	0.10	1.70	72.90	104.51	0.47	8.10	371.97	148	4	58	472	48,715
Commodity	31.76	0.01	1.00	115.91	1,162.23	0.77	22.07	4,833.39	255	10	138	659	85,747
Crypto	61.23	0.01	25.00	231.72	1,809.06	0.14	410.82	8,246.94	540	19	204	2,000	181,317
Meme/Other	8.25	0.01	0.45	20.88	176.18	0.30	10.94	412.70	169	3	64	564	56,546
Pharma	15.95	0.01	0.14	34.52	1,706.76	0.50	20.97	5,321.64	50	2	30	145	16,517
SP500	1.67	0.00	0.01	10.45	673.81	0.37	2.52	4,388.50	259	17	157	715	87,028
Tech	9.08	0.00	0.13	31.57	760.17	0.31	17.50	2,520.29	1,546	155	1,148	4,260	519,392
Total	20.47	0.00	0.29	108.60	928.78	0.35	18.82	4,718.67	2,962	361	2,306	8,060	995,262

This table shows summary statistics for the trading activity in the tokenized assets per category. *Trade Size* and *Trade Value* are at the trade level and give the distribution of the size of the trades in the number of tokens and in USD, respectively. *Daily Trades* is the number of trades at the token-day level. *# Trades* gives the total number of trades in the sample.

3. Trading activity

3.1. Trading activity in tokenized assets

Descriptive statistics on the trading activity in the individual tokens and across the seven categories can be found in Tables 1 and 2, respectively. Overall, the sample contains 995,262 trades or 2962 trades per asset-day. The average trade size is 20.47 shares, or USD 928.78. However, there is substantial variation in the distribution of the number of trades and trade sizes both within individual tokens and in the cross-section. For example, the overall median trade size and value are only 0.29 shares and USD 18.82, respectively, indicating that the distributions are highly skewed. Looking at the individual tokens, the token with the highest overall trading activity is the Grayscale Bitcoin Trust, an exchange-listed cryptocurrency fund, with 111,287 total trades. The S&P 500 ETF and the electric vehicle manufacturer Tesla are also among the most frequently traded tokens. At the other end of the trading activity spectrum are the tokens of companies such as the Cronos Group or Uber with fewer than 10 trades per day on average.

Due to the large number of tokens from the technology sector, most trades in the sample are in tokens of companies from that industry, followed by trades in cryptocurrency funds. Average trade sizes and values likewise differ across categories. While tokens of Canadian or Meme stocks have average trade values of less than USD 200, trades in commodities and especially pharmaceutical companies and cryptocurrency funds are much larger on average.

These results already indicate the presence of fractional trading. For many tokens, median trade sizes in shares are smaller than 1, and the 5th percentile of the distribution of trade sizes is less than 0.2 shares in all cases. Across the entire sample, the 5th percentile of trade sizes is less than 0.01 and the corresponding percentile of trade values is just USD 0.35. These smallest trades do not appear economically motivated. Instead, it seems as if traders have other motives when trading tiny amounts, for example because they simply want to own a part of a company that has sentimental value. These types of trades are made possible not only by fractional trading, but also by the relatively low exchange fees. I investigate the determinants of fractional trading and the traders' motives in more detail in Section 4.

Table 3 shows how the total trading activity in tokenized assets compares to trading at the respective primary listing exchanges. The first set of columns shows the activity in tokenized assets as before. The middle set of columns gives the total number of trades and the traded value at the primary market. The rightmost columns provide the trading activity in the tokens relative to that in the underlying assets. Overall, the trading activity is orders of magnitude larger at the primary markets than in the tokens. While there are about 995,000 trades in the tokens with a total value of USD 924 million, in the underlying assets there are about 1.5 billion trades amounting to USD 27 trillion. In relative terms, the number of trades in the tokens is only 0.067% of that in the underlying assets. Since trades in the tokens are also smaller on average, they only reflect 0.003% of the traded value compared to the underlying assets.

While overall low, the relative importance of the market for tokenized assets varies substantially in the cross-section. For example, in cryptocurrency funds and in Canadian stocks, the number of trades (the traded value) in the tokenized assets is 1.409% (0.406%) and 0.827% (0.040%), respectively. In US large-cap equities on the other hand, these fractions are substantially lower. For example, the number of trades in tokenized assets of pharmaceutical companies is only 0.024% compared to the primary listing exchange.

In summary, the market for tokenized assets covered in this study is economically relevant with a traded value of almost USD 1 billion and close to 1 million trades, especially because it caters mostly to small retail investors. However, its size is small compared to established equity markets. For this reason, it appears unlikely that trading activity in the tokenized assets affects trading at the primary markets to a measurable extent.

3.2. Intraday trading patterns

Tokenized assets facilitate around-the-clock trading and make the North American equity market more accessible to foreign investors, who may be located in other time zones. A natural question is then how trading activity varies throughout the day.

Table 3
Trading activity in tokenized vs. primary market by category.

Category	Tokenized asset		Primary market		Relative (%)	
	Trades	Volume	Trades	Volume	Trades	Volume
Canada	49	5	5,892	12,651	0.827	0.040
Commodity	86	100	59,804	796,874	0.143	0.013
Crypto	181	328	12,864	80,783	1.409	0.406
Meme/Other	57	10	76,956	229,787	0.073	0.004
Pharma	17	28	69,588	673,619	0.024	0.004
SP500	87	59	142,316	9,217,867	0.061	0.001
Tech	519	395	1,118,173	15,515,356	0.046	0.003
Total	995	924	1,485,594	26,526,937	0.067	0.003

This table shows the number of trades in 1000 trades and the traded value in USD 1 million for the tokenized assets and for the underlying asset as traded at their primary market. The last two columns give the number of trades and the traded volume in tokenized assets relative to that of their underlying assets, respectively, in percentage points.

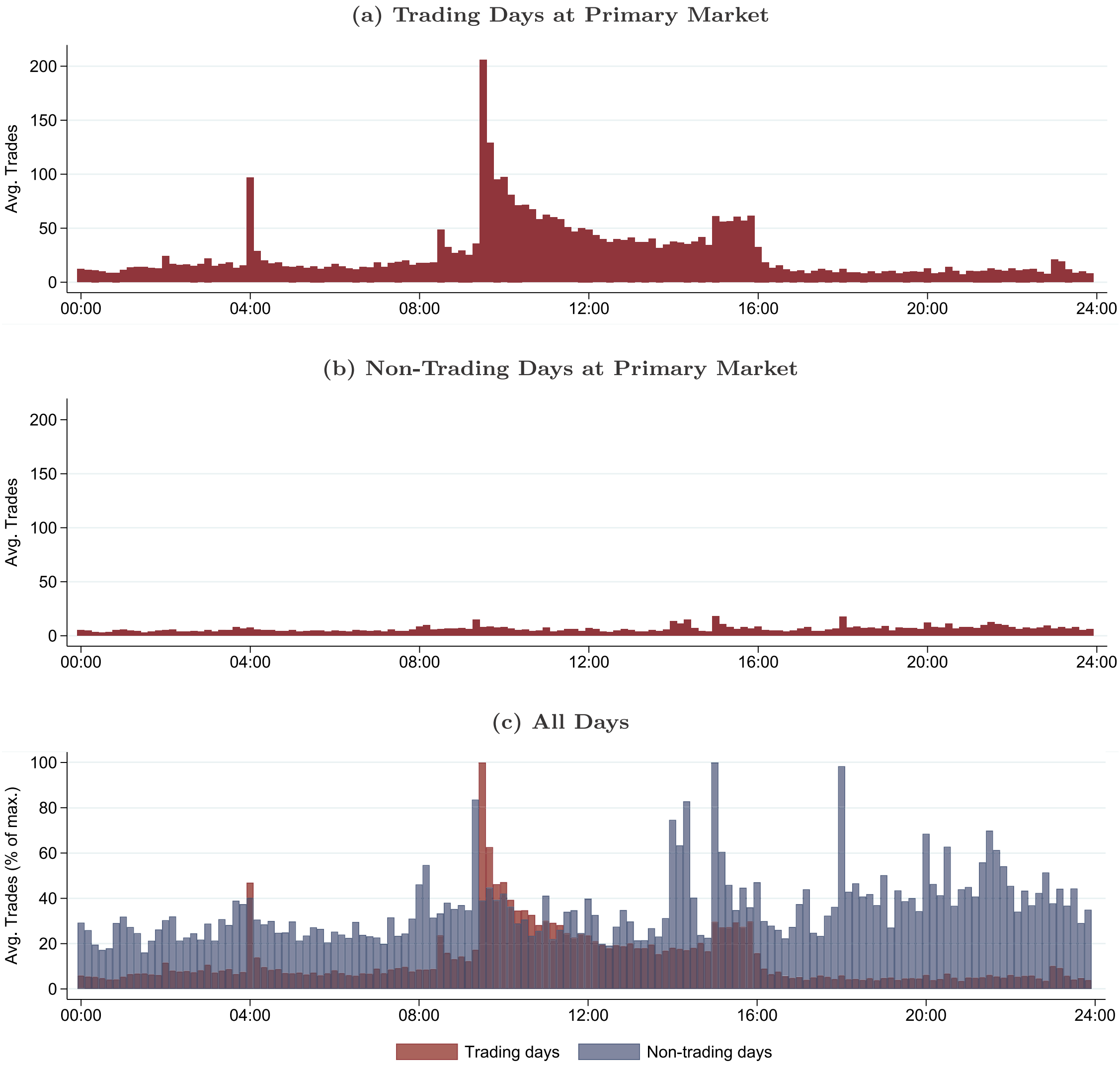

Fig. 1. Intraday # Trades. (These graphs show the distribution of the average daily number of trades in tokenized assets for each 10-minute interval of the day. Panel A shows days where the primary listing exchange is open while panel B shows days where it is closed, both in the number of trades. Panel C overlays both series after scaling each to its own daily maximum where the values are given in percentage points.)

Fig. 1 shows the average number of trades in all tokenized assets throughout the day. Each bar represents a 10-minute interval. In Panel A, only days on which the primary listing exchange is open are included whereas Panel B includes only days when the exchange is closed.[6] On regular trading days, trading activity is concentrated during times when the primary market is open. There are spikes around the opening times at the primary markets. At 4:00 a.m. (Eastern Time throughout), the pre-market at NYSE and NASDAQ opens. While liquidity and trading activity are generally low during this phase, this phase allows traders to trade based on overnight information. Traders in tokenized assets appear to act on information from the pre-market session at the regular exchanges, resulting in the early morning spike. Over-the-counter (OTC) trading generally starts at 8:30 a.m., which is again associated with a higher level of activity. The main trading session at NYSE, NASDAQ, and the Toronto Stock Exchange starts at 9:30 a.m., coinciding with the highest level of trading activity. Activity gradually decreases over the trading day, but increases again towards the end of the main trading session at 4:00 p.m. In the after-hours market at NYSE and NASDAQ between 4:00 p.m. and 8:00 p.m., trading activity is generally low, comparable to levels when the exchange is closed.

The results for regular trading days contrast starkly with the patterns seen on non-trading days. Overall, trading activity is much lower. Furthermore, while there is a slight increase in activity during the hours from 8:00 a.m. to 10:00 a.m. and 2:00 p.m. to 4:00 p.m., the remaining hours that would normally be trading hours see relatively low levels of activity. Instead, there is relatively more activity during the late evening hours from about 6:00 p.m. to midnight. These patterns are consistent with trading by retail investors.

Panel C rescales each series to its own maximum to abstract from the large difference in absolute trade counts and focus on the intraday shape of activity. As seen before, on trading days, activity is heavily concentrated around the opening hours of the primary market, while on non-trading days it is more evenly spread throughout the day, with a relative shift toward the evening hours. This confirms that the intraday pattern of tokenized trading is heavily influenced by the opening hours of the underlying asset's exchange, even if some trading occurs around the clock regardless.

To summarize, even though tokenized assets can be traded around the clock, trading activity still closely follows the schedule of the primary listing exchange. I find that 52% of trades (66% of dollar volume) occur during the regular trading session, with the remainder split across the pre-market session (15% of trades, 14% of volume), after-hours session (6% of trades, 3% of volume), and when the primary market is closed (27% of trades, 17% of volume). The spike in activity at the start of the pre-market session suggests that some traders incorporate overnight information from the primary exchange, while the sharp concentration of volume around the open and close mirrors the well-known intraday U-shape of conventional equity markets. These patterns are consistent with evidence from other settings where two similar assets trade across different markets, such as depositary receipts and cross-listed securities (Werner and Kleidon, 1996; Moulton and Wei, 2009; Grammig et al., 2005).

4. Fractional trading and retail behavior

4.1. Descriptive statistics of fractional trading

Another advantage of tokenized financial assets is that they facilitate fractional trading, which is not a widespread feature in conventional financial markets. In the case of financial assets, this is due more to institutional and historical reasons than to technological limitations. Still, fractional trading is relatively uncommon in many financial markets and – importantly – where it is encountered, observing the actual fractional trades has proved difficult for researchers (Da et al., 2025; Bartlett et al., 2024). In this part, I therefore investigate patterns in investors' fractional trading activity, which I can directly observe in my setting.

The tokens considered in my study differ in their minimum order sizes, which are set by the exchange and remain constant throughout the sample period. Fractional trading is potentially more valuable to investors for high-priced assets than for lower-priced assets. Consistent with this notion, Fig. 2 shows a negative relationship between the average price of the asset and the minimum order size. I provide a more formal analysis of this below.

I investigate three dimensions of fractional trading. In the broadest definition, fractional trading refers to any non-integer order size. Furthermore, I look at below-one trades, i.e., trades with order sizes smaller than one full share, which is the most commonly encountered definition of fractional trading. While non-integer fractional order sizes larger than one full share may for example be used to precisely set the (USD) value of trades according to some preferences, below-one fractional order sizes may be used to invest in high-priced assets. Finally, I consider trades at the absolute minimum order size. The motivation for investing the smallest amount possible may in some cases be non-monetary. For example, some retail investors may simply want to claim ownership of an asset they are interested in, consistent with evidence that retail investors trade for reasons beyond pure profit maximization (Dorn and Sengmueller, 2009; Grinblatt and Keloharju, 2009). While other explanations such as arbitrage or high-frequency trading motives are plausible for fractional trading more broadly, they are more difficult to reconcile with trades at the absolute minimum permissible size, as I discuss further below.

Table 4 shows the relative frequencies of fractional trades across the different categories while Table A.2 in the appendix shows fractional trading at the token level. Overall, fractional trading is prevalent in all categories. 89.88% of all trades result from non-integer order sizes and 59.62% from below-one order sizes. A substantial number of trades (14.20%) are at the minimum order size. When considering the USD volume traded in fractional trades, 86.12% of all volume results from non-integer trading. However, the trading volume of below-one trades is economically small at 1.12% of all volume and trivial for trades at the minimum order

[6] While these graphs include all tokens, category- or listing-exchange-specific graphs are available upon request.

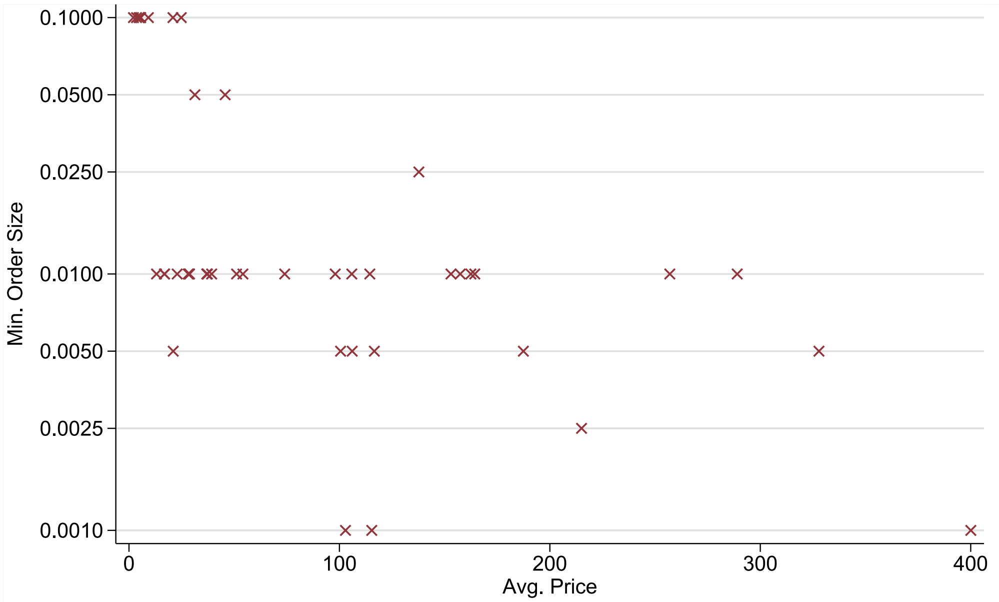

Fig. 2. Minimum Order Sizes. (This graph shows the minimum order size in number of shares against the average price of a single share across the entire sample period, in USD.)

Table 4
Fractional trading by category.

Category	$Size_{Min}$	$Price_{Mean}$	% of Trades			% of Volume		
			Frac	< 1	Min	Frac	< 1	Min
Canada	0.100	5.69	86.00	41.36	11.38	73.24	0.88	0.06
Commodity	0.040	63.42	81.41	48.25	13.47	86.72	0.44	0.01
Crypto	0.038	23.36	87.72	30.42	10.09	92.45	0.05	0.00
Meme/Other	0.010	27.61	95.31	65.12	7.87	95.09	2.67	0.02
Pharma	0.009	135.85	95.97	71.93	20.54	92.96	0.76	0.01
SP500	0.001	400.06	97.56	87.47	22.52	91.41	2.98	0.01
Tech	0.009	141.14	90.32	67.74	15.12	79.38	1.90	0.03
Total	0.021	122.46	89.88	59.62	14.20	86.12	1.12	0.01

This table shows summary statistics for fractional trading activity across the different categories. $Size_{Min}$ is the average minimum order size of the tokens in a given category while $Price_{Mean}$ is their average price. *Frac*, < 1 and *Min* indicate non-integer trades, below-one trades, and trades at the minimum order size, respectively. These measures are provided both as a percentage of all trades and as a percentage of the contained USD trading value in percentage points.

size. There are some cross-sectional differences in the frequency of fractional trading. In particular, fractional trading, especially below-one trading, is relatively more common in the higher-priced assets such as the S&P 500 ETF or pharmaceutical and technology stocks. The Spearman rank correlation between the average price of a token and the fraction of below-one trades is 47.90% and highly statistically significant with a p-value of 0.0012. Fractional trading thus allows investors to set the size of their trades more accurately, even for larger trades, while also making higher-priced assets more accessible to smaller investors as in Angerer et al. (2025).

My findings thus agree with (Gempesaw et al., 2022) who document that below-one fractional trading is used for assets with relatively high prices. Also, as in their study, below-one trade sizes only represent a small share of overall market activity. However, my setting also allows me to consider all non-integer fractional trades, which in my sample constitute the vast majority of trades. This previously undocumented behavior suggests that fractional trading is not solely used to access high-priced assets, but also to trade more precise quantities even for large trades.

4.2. Size, value, and price clustering

Clustering and round-number preferences are well-documented phenomena in many financial markets (Moulton, 2005; Alexander and Peterson, 2007; ap Gwilym and Meng, 2009; Garvey and Wu, 2014; Kupfer and Schmidt, 2021). I observe the same clustering behavior in trade sizes of tokenized assets, not only for non-fractional trades but also for fractional trades that tend to cluster at relatively round numbers. In Fig. 3 I show the distribution of trade sizes for tokenized assets with a minimum order size of 0.01 shares, which is the most commonly encountered minimum size. The three panels show different ranges of order sizes where the

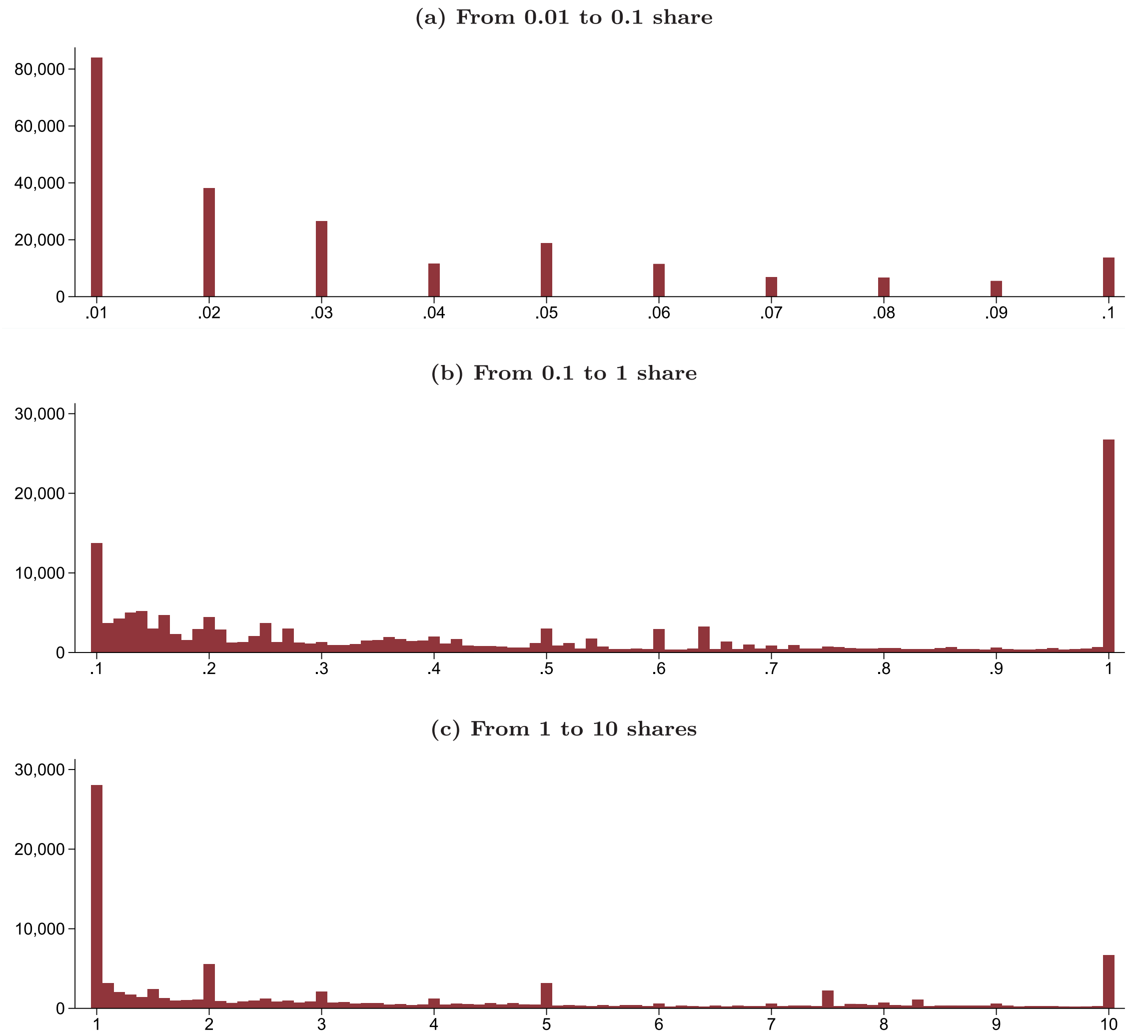

Fig. 3. Distribution of Order Sizes. (These graphs show the absolute frequency of trade sizes in units of shares of all tokenized assets with a minimum order size of 0.01 shares. Panel A shows trade sizes up to 0.1 shares, panel B from 0.1 up to 1 share, and panel C from 1 to 10 shares. For reference, the last bar of a panel is equal to the first bar of the next panel.)

last bucket corresponds to the first bucket of the next panel for reference. I make several observations: Trade sizes at the minimum order size are the single most frequently encountered trade size. However, there is substantial clustering at relatively round trade sizes. In particular, trading one full share is the second most frequently observed trade size. Furthermore, trades tend to cluster at other round sizes such as 0.05, 0.1, 0.5, 2, 5, and 10. These observations are consistent with the round-number preferences of investors documented in other markets, though I show that these preferences also extend to fractional trading.

Fractional order sizes also facilitate another type of clustering: order-value clustering, in particular for low-value trades. Fig. 4 shows the distribution of the value of all trades with a volume smaller than USD 100 in tokenized assets with a current price larger than USD 100.[7] All of these trades are hence below-one fractional trades and would not be possible without fractional trading. While most trades are relatively small, there is trade value clustering at round order values. In particular, there are spikes in the distribution at multiples of USD 10 up until USD 60. It therefore appears as though investors not only exhibit preferences for relatively round order sizes, but also for relatively round order values.[8]

Finally, investors tend to have preferences for relatively round prices. Fig. 5 shows the distribution of decimal places of trade prices in the sample. Although the minimum tick size is at least USD 0.01 for all assets and sometimes lower, investors frequently

[7] Similar figures for lower-priced assets can be found in Fig. A.1 in the appendix.

[8] When placing orders on FTX (as with most cryptocurrency exchanges), the size of the order could either be entered in the number of shares or in the quote currency. For the latter, the size is automatically converted so that no explicit calculation by the trader is necessary. The tokenized Canadian stocks are also quoted in USD.

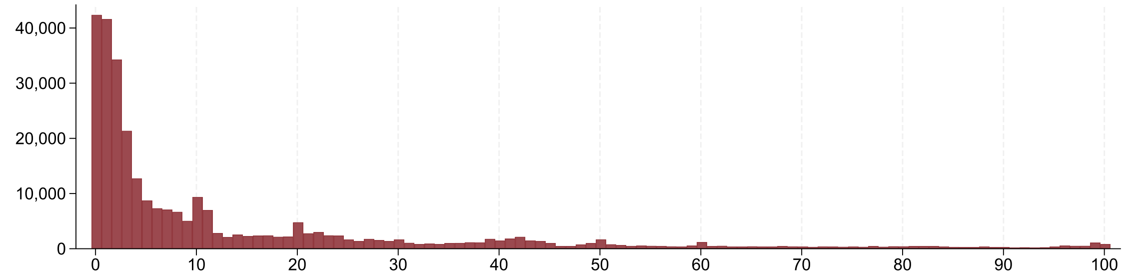

Fig. 4. Distribution of Order Value (USD). (This graph shows the absolute frequency of trade values in US dollars in all tokenized assets with a current price larger than USD 100.)

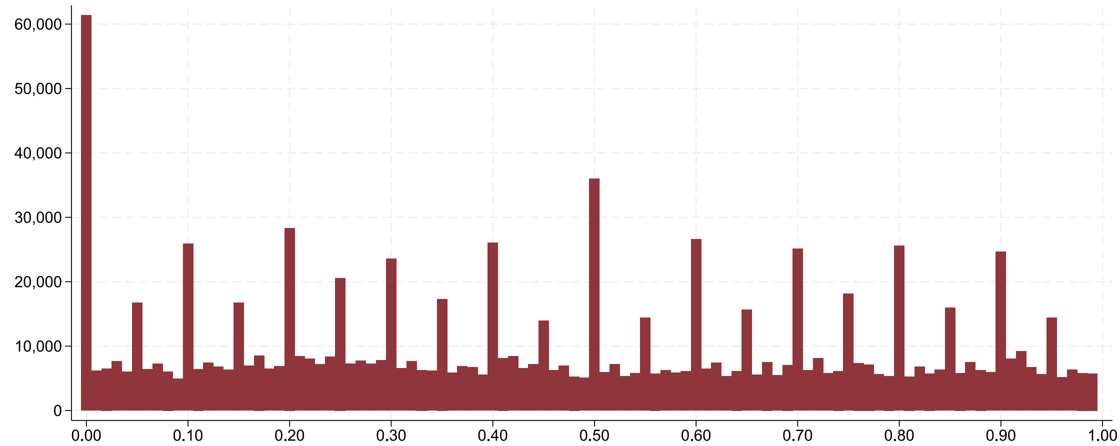

Fig. 5. Distribution of Trade Prices. (This graph shows the absolute frequency of the decimals of trade prices.)

trade at prices where the decimal is a multiple of USD 0.10 or, to a lesser extent, other multiples of USD 0.05. Integer prices and those ending in USD 0.50 are especially popular. I hence observe clustering not only in order size and value, but also in prices, in the market for tokenized financial assets.

Prior research has proposed several potential explanations for these round-number preferences. One explanation can be found in cognitive limitations, as using relatively round numbers may limit the cognitive effort required when submitting orders (Wyckoff, 1963; Niederhoffer and Osborne, 1966; Kuo et al., 2015). Alternatively, trading in round numbers may make coordination and negotiations among market participants easier (Harris, 1991). Finally, round numbers may be used by informed traders to conceal their trading intentions (Alexander and Peterson, 2007). While I cannot formally rule out the latter two explanations, they appear less likely to apply to the market for tokenized assets considered in this study, because it is mainly targeted at retail investors. These are unlikely to engage in direct negotiations, to collude (as in Christie and Schultz, 1994), to use order-splitting algorithms, or to be particularly informed. I hence conclude that the round-number preferences observed in trade sizes, values, and prices likely result from behavioral biases related to cognitive limitations as investors rely on simple heuristics when submitting their orders.

4.3. Intraday patterns in fractional trading

In Section 3, I document that trading activity in tokenized assets generally aligns with the trading hours at the primary listing exchange. I have also just documented that a substantial fraction of trades occur at the absolute minimum order size, and these are more likely to originate from small retail traders. Building on these two observations, Fig. 6 shows the relative frequency of trades at the minimum order size throughout the day, again split by trading days and non-trading days at the primary listing exchange. On trading days, the frequency of trades at the minimum order size appears to be negatively correlated with overall trading activity. During the regular trading session, these small trades constitute only about 10% of all trades. They are relatively more frequent when the primary listing exchange is closed. This is consistent with the notion that larger, professional investors predominantly trade when the primary market is open while retail trading activity is less dependent on exchange opening hours. These smallest trades are particularly frequent in the afternoon on non-trading days at the primary market, reaching almost 80% of all trades during some intervals. This pattern again suggests that trades at the minimum order size are driven by retail traders.

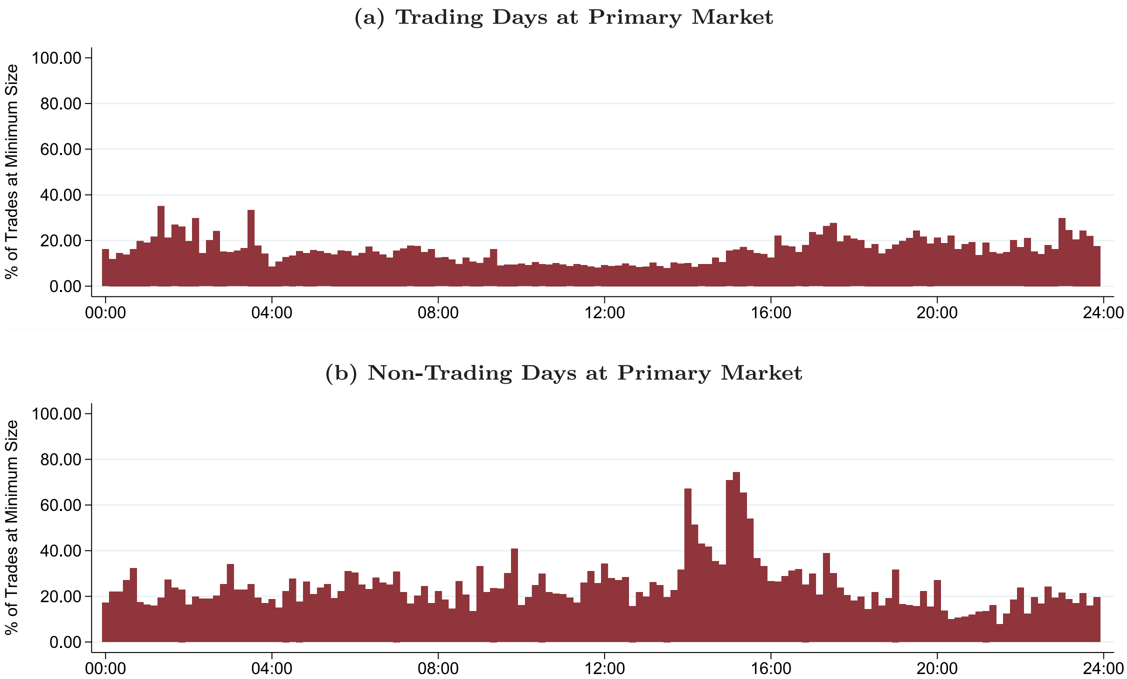

Fig. 6. Intraday % of Trades at Minimum Size. (These graphs show the fraction of trades in tokenized assets where the size equals the minimum trade size relative to all trades for each 10-minute interval of the day in percentage points. Panel A shows days where the primary listing exchange is open while panel B shows days where it is closed.)

4.4. Determinants of fractional trading

While the previous analyses have mostly been descriptive, I now more formally investigate fractional trading. In particular, I investigate the determinants of fractional trades to better understand the motives for trading fractional quantities. I repeat the analysis for below-one trades and minimum-size trades.[9] Table 5 shows the results of trade-level regressions where the dependent variable is a binary variable indicating below-one fractional trades. In the first column, I employ a logit model and show marginal effects, though the results do not differ materially from the linear model presented in column 2. I then use the linear model and include various specifications of fixed effects in columns 3 through 5.

Consistent with economic intuition, I find strong evidence that traders use below-one fractional trades to trade assets with relatively high prices. Notably, this result prevails when including asset-date fixed effects, suggesting that it also holds when the same asset is traded at different prices on the same day.[10] To illustrate the economic magnitude, in the specification with asset-date fixed effects, a 10% price increase is associated with an approximately 5.3 percentage point higher probability of observing a below-one trade, corresponding to a relative increase of about 9% over the baseline mean of 59.6%. Likewise, below-one trades are less likely for assets with larger minimum order sizes, consistent with the notion that higher minimum sizes mechanically reduce the scope for below-one trading. The interaction between price and minimum order size is negative and significant when controlling for asset or asset-date fixed effects, indicating that the positive effect of price on below-one trading is attenuated for assets with larger minimum order sizes.

There is a negative relationship between trading at relatively round prices and trading in below-one quantities. This suggests that traders using relatively small, fractional trade sizes are not particularly prone to using simple heuristics when setting trade prices.

Below-one trades are more likely for buy than for sell orders, though this result only holds when controlling for category or asset-fixed effects. The effect is economically modest in absolute terms: Buy orders are 3.3 percentage points more likely to be below-one trades than sell orders, a relative increase of roughly 6% over the baseline. Conversely, automatically triggered liquidation trades are less likely to be below-one fractional trades, though this effect disappears when controlling for asset fixed effects. Since the results in the appendix show that non-integer trades are more likely for liquidating trades, I conclude that the negative coefficient found for below-one trades reflects that such orders liquidate the entire position of the trader, which oftentimes will be larger than one full share.

[9] The results for all non-integer trades are available upon request.
[10] The results are qualitatively very similar when using prices in levels instead of logs.

Table 5
Determinants of fractional trades with size below 1.

	(1)	(2)	(3)	(4)	(5)
log Price	0.094***	0.095***	0.104***	0.132*	0.551***
	(4.06)	(3.43)	(4.16)	(1.90)	(3.89)
log Min. Size	−0.079**	−0.070**	−0.082***		
	(−2.47)	(−2.08)	(−3.48)		
log Min. Size × *log* Price	−0.017	−0.006	−0.002	−0.070**	−0.192**
	(−1.20)	(−0.47)	(−0.11)	(−2.27)	(−2.54)
Round Price	−0.092**	−0.080*	−0.118***	−0.054**	−0.044**
	(−2.35)	(−1.89)	(−3.69)	(−2.68)	(−2.59)
Buy	0.044	0.042	0.057**	0.065***	0.033***
	(1.27)	(1.18)	(2.09)	(4.34)	(4.43)
Liquidation	−0.075**	−0.078**	−0.080**	−0.023	−0.018
	(−2.13)	(−2.11)	(−2.68)	(−0.71)	(−0.78)
Pre-Market	−0.029	−0.030	−0.023	0.009	0.010
	(−0.82)	(−0.82)	(−0.68)	(0.41)	(0.74)
After Hours	0.086**	0.087**	0.087**	0.063***	0.051**
	(2.29)	(2.20)	(2.24)	(2.71)	(2.38)
Market Closed	0.074	0.076	0.084	0.057**	0.045**
	(1.41)	(1.42)	(1.66)	(2.09)	(2.33)
Canada			0.356***		
			(2.73)		
Commodity			0.094		
			(0.81)		
Crypto			−0.022		
			(−0.20)		
Meme			0.292**		
			(2.17)		
Pharma			0.191		
			(1.60)		
Tech			0.128		
			(1.25)		
Baseline Mean	0.596	0.596	0.596	0.596	0.596
Model	Logit	Linear	Linear	Linear	Linear
Asset FE	–	–	–	✓	–
Date FE	–	–	–	✓	–
Asset × Date FE	–	–	–	–	✓
Adj./Pseudo R^2	0.11	0.14	0.18	0.34	0.51
Observations	995,262	995,262	995,262	995,262	995,262

This table shows trade-level regression results where the dependent variable is a binary variable indicating trades with a trade size below one share. *Price* is the price of the trade in USD 1000. *Min. Size* is the minimum order size in number of shares. All continuous variables have been demeaned prior to forming the interaction terms. *Round Price* is a binary variable indicating if the decimals of the trade price are multiples of USD 0.1. *Buy* indicates buy trades. *Liquidation* indicates automatically triggered liquidating trades. *Pre-Market*, *After Hours*, and *Market Closed* indicate if the trade occurred in the respective trading phase at the primary listing exchange. The remaining independent variables indicate the respective asset's category. An unreported constant is included in all models. The column for the logit model shows marginal effects. Standard errors are double-clustered with respect to both asset and date while t-statistics are given in parentheses.

*** Significance at the 1% level.

** Significance at the 5% level.

* Significance at the 10% level.

Generally, below-one trades are more frequent in the after-hours market or when the exchange is closed, consistent with retail trader activity. In economic terms, trading during the after-hours session increases the probability of a below-one trade by 5.1 percentage points, and trading when the market is closed raises it by 4.5 percentage points, representing relative increases of approximately 9% and 8% over the baseline probability, respectively. I do not find evidence that below-one trading is more common during the pre-market session.[11] I do not find strong systematic differences across the various categories.

Table 6 shows similar regression results, but for the determinants of observing a trade at the minimum order size. Trades in higher-priced assets are more likely to occur at the minimum size, but the effect is driven mostly by cross-sectional differences and

[11] I also examine whether the trading-session effect varies with price and minimum order size by interacting a binary variable indicating hours outside the main trading session with log(Price), log(SizeMin), and their product. None of these terms are statistically significant. The after-hours level effect thus appears uniform across assets, which may reflect that after-hours activity on this platform is largely driven by retail traders with similar behavioral patterns regardless of asset price or minimum order size. The results are available upon request.

Table 6
Determinants of trades at minimum size.

	(1)	(2)	(3)	(4)	(5)
log Price	0.026**	0.027**	0.020	0.004	0.132
	(2.19)	(2.40)	(0.88)	(0.09)	(1.52)
log Min. Size	−0.008	−0.009	−0.008		
	(−0.57)	(−0.72)	(−0.45)		
log Min. Size × *log* Price	−0.002	−0.003	0.004	−0.010	−0.055
	(−0.39)	(−0.89)	(0.33)	(−0.80)	(−1.10)
Round Price	−0.034	−0.035	−0.035*	−0.007	−0.014***
	(−1.45)	(−1.54)	(−1.96)	(−0.70)	(−2.88)
Buy	0.037**	0.036**	0.038**	0.044***	0.024***
	(2.30)	(2.23)	(2.51)	(4.06)	(4.14)
Liquidation	−0.129***	−0.093***	−0.091***	−0.087***	−0.083***
	(−6.62)	(−7.53)	(−6.89)	(−4.05)	(−5.09)
Pre-Market	0.017	0.013	0.012	0.025***	0.015**
	(1.18)	(1.09)	(1.03)	(2.94)	(2.47)
After Hours	0.086***	0.090***	0.091***	0.083***	0.049***
	(5.34)	(4.91)	(5.19)	(5.62)	(4.70)
Market Closed	0.106***	0.114***	0.114***	0.082***	0.061***
	(5.63)	(5.37)	(5.62)	(5.63)	(5.41)
Canada			0.012		
			(0.11)		
Commodity			−0.026		
			(−0.24)		
Crypto			−0.059		
			(−0.51)		
Meme			−0.063		
			(−0.54)		
Pharma			0.030		
			(0.26)		
Tech			−0.037		
			(−0.41)		
Baseline Mean	0.142	0.142	0.142	0.142	0.142
Model	Logit	Linear	Linear	Linear	Linear
Asset FE	–	–	–	✓	–
Date FE	–	–	–	✓	–
Asset × Date FE	–	–	–	–	✓
Adj./Pseudo R^2	0.04	0.04	0.04	0.15	0.35
Observations	995,262	995,262	995,262	995,262	995,262

This table shows trade-level regression results where the dependent variable is a binary variable indicating trades at the minimum order size. *Price* is the price of the trade in USD 1000. *Min. Size* is the minimum order size in number of shares. All continuous variables have been demeaned prior to forming the interaction terms. *Round Price* is a binary variable indicating if the decimals of the trade price are multiples of USD 0.1. *Buy* indicates buy trades. *Liquidation* indicates automatically triggered liquidating trades. *Pre-Market*, *After Hours*, and *Market Closed* indicate if the trade occurred in the respective trading phase at the primary listing exchange. The remaining independent variables indicate the respective asset's category. An unreported constant is included in all models. The column for the logit model shows marginal effects. Standard errors are double-clustered with respect to both asset and date while t-statistics are given in parentheses.
*** Significance at the 1% level.
** Significance at the 5% level.
* Significance at the 10% level.

disappears when controlling for category or asset fixed effects. In contrast to below-one trades, neither the minimum order size nor its interaction with price is a significant determinant of trading at the minimum size, suggesting that the minimum order size itself does not systematically shape this behavior once other factors are accounted for.

There is a negative relationship between trading at relatively round prices and trading at the minimum order size, though this is only significant when controlling for category or asset-date fixed effects.

As for below-one trades, trades at the minimum order size are significantly more likely to be initiated by buyers than sellers. This effect is economically substantial relative to the baseline: Buy orders are 2.4 percentage points more likely to occur at the minimum size than sell orders, representing an increase of approximately 17% relative to the unconditional mean of 14.2%. Assuming retail traders are more likely to use market orders than limit orders, this is consistent with the notion suggested above that some investors may merely want to claim ownership of an asset or have other non-monetary motives for engaging in this sort of trading behavior (similar to Dorn and Sengmueller, 2009, and Grinblatt and Keloharju, 2009). These traders would simply buy the tokenized asset to hold it, thus not selling it. While I cannot rule out that some of these traders are exploiting price differences

Table 7
Price differences by category.

Category	Absolute difference (%)				Signed difference (%)			
	Mean	P5	P50	P95	Mean	P5	P50	P95
Canada	0.62	0.03	0.31	2.26	0.03	−1.22	0.00	1.33
Commodity	0.25	0.01	0.09	1.10	0.06	−0.43	0.03	0.67
Crypto	2.33	0.14	1.47	6.18	1.64	−1.32	1.31	5.73
Meme/Other	1.23	0.05	0.73	3.50	−0.14	−2.93	−0.05	2.56
Pharma	0.53	0.01	0.15	1.82	0.34	−0.37	0.08	1.72
SP500	0.14	0.01	0.10	0.35	0.12	−0.05	0.10	0.33
Tech	0.43	0.02	0.22	1.27	0.19	−0.52	0.15	0.98
Total	0.78	0.02	0.25	3.63	0.40	−0.97	0.14	3.38

This table shows summary statistics of price differences between the tokens and the underlying assets as traded on their respective primary listing exchange across the different categories. All values are given in percentage points. The left columns provide statistics on the absolute percentage differences while the right columns show those for the signed relative differences.

between the token and its underlying, such a strategy would be economically implausible at these trade sizes.[12] Typically, arbitrage trading is a low-margin, high-volume business, making minimum-size trades an unlikely vehicle for such strategies. As expected, liquidating trades are significantly less likely to be at the minimum order size.

Confirming the visual evidence in Section 4.3, trades at the minimum order size are substantially more likely during the extended trading hours and especially when the primary listing exchange is closed, again indicative of retail trading. The magnitudes are economically large. In column 5, trading during the after-hours session and when the market is closed increases the probability of a minimum-size trade by 4.9 and 6.1 percentage points, respectively, corresponding to relative increases of roughly 35% and 43%. These are among the strongest effects in the model and suggest that off-hours trading on this platform is disproportionately driven by the smallest retail participants. Unlike for below-one trades, I also find a significantly higher frequency of minimum-size trades during the pre-market session, at least when controlling for asset or asset-date fixed effects.

5. Price differences

5.1. Descriptive statistics and intraday patterns in price differences

Since tokenized assets are derivatives, their relative pricing is an important aspect of market quality. I therefore investigate price differences between the tokens and their respective underlying assets as traded at their primary listing exchanges. I define trade-level price differences as

$$\text{Signed Price Difference} = \frac{P_{\text{Token}} - P_{\text{Underlying Asset}}}{P_{\text{Underlying Asset}}}$$

where P_{Token} is the price of a trade in a tokenized asset and $P_{\text{Underlying Asset}}$ is the average of the opening and closing prices of the underlying asset from the primary listing exchange of the one-minute interval during which the trade occurred. In my analysis, I consider these signed price differences but also their absolute values, though both measures are expressed in relative terms:

$$\text{Abs. Price Difference} = |\text{Signed Price Difference}|$$

Table 7 shows absolute and signed percentage price differences across the different categories.[13] On average, the absolute price difference across all assets is 0.78%, which is much larger than the trading costs in the underlying assets. It is on average smallest for the S&P 500 ETF and largest for the cryptocurrency funds and meme stocks, but there is substantial variation in absolute price differences both across time and in the cross-section. For example, across the entire sample, the 5th percentile is 2 basis points while the 95th percentile is 363 basis points.

Signed price differences show that, on average, the tokens trade at a premium. Several factors could push price differences in either direction. Tokens might trade at a discount because holders bear counterparty risk from the custodian, because the tokens carry no voting rights since they represent a derivative rather than direct equity ownership, or because the token market is less liquid than the underlying market, which would require a liquidity discount. Conversely, tokens could trade at a premium because they offer features the underlying asset does not, such as around-the-clock and fractional trading, and because they provide access to US equity markets for investors who would otherwise face significant regulatory or cost barriers to trading there directly. The observed average premium could also reflect an asymmetry in how mispricing can be exploited: arbitrage is easier when tokens trade at a discount, since investors can then buy the token and redeem it for the higher-priced underlying asset or an equivalent cash amount with the custodian. The reverse requires the custodian or tokenization platform to issue new tokens, which is outside

[12] The 5th percentile of trade values in the sample is just USD 0.35, implying a potential gain of roughly USD 0.01 even at the 95th percentile of observed absolute price differences (3.63%).

[13] Token-level summary statistics on price differences are available upon request.

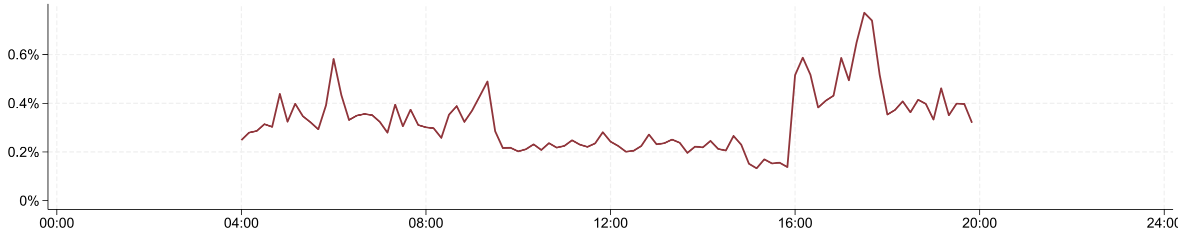

Fig. 7. Intraday Absolute Percentage Price Differences. (This graph shows the median of absolute percentage price differences between the tokenized assets and the underlying assets as traded at their respective primary listing exchanges during each 10-minute window of a trading day.)

the control of ordinary investors. Arbitrage strategies in the market for tokenized assets thus differ from other settings where traders can easily trade in several markets simultaneously to, for example, exploit triangular arbitrage opportunities (Saggese et al., 2023). Although I cannot disentangle these factors empirically beyond the analysis presented in Section 5.2, the fact that tokens trade at a premium on average suggests that the forces pushing prices above the underlying value outweigh those pushing them below.

While I observe cross-sectional variations in price differences, I also find systematic intraday patterns. Fig. 7 shows median absolute price differences throughout the trading day. Strikingly, differences are much narrower during the regular trading session at the primary listing exchange but wider in the extended trading hours, especially during the after-hours market. This could reflect lower liquidity in both markets during these times. It also suggests that institutional investors who exploit any mispricing are relatively less active outside the regular trading session.

5.2. Determinants of price differences and speed of price adjustment

I now investigate the potential determinants of price differences. Table 8 shows the results for absolute price differences while Table A.4 in the appendix shows those for signed differences.

Without fixed effects, price differences are smaller for higher-priced underlying assets, consistent with these assets being better arbitraged. This effect is amplified for assets with larger minimum order sizes, though neither result is robust to including fixed effects. With asset-date fixed effects, however, the effect of the price of the underlying turns positive and significant, suggesting that trades occurring at higher intraday prices are associated with wider price differences, consistent with the slow price adjustment documented in Fig. 8, where a price increase in the underlying asset only gradually propagates to the tokenized market. The minimum order size and its interaction with price do not systematically explain price differences in most specifications.

Earnings announcements are associated with smaller absolute price differences when controlling for asset-date fixed effects, possibly reflecting heightened attention and arbitrage activity around these events. With a coefficient of −0.44 percentage points, the reduction amounts to roughly half the unconditional mean, suggesting that arbitrage activity compresses price differences meaningfully around these high-information events.

The positive and significant coefficient on log volume in the first column suggests that larger trades are more likely to show wider price differences, but once I control for asset-date fixed effects, the coefficient turns negative and significant, indicating that within the same asset and day, price differences are actually smaller for larger trades. There are no clear systematic differences between buy and sell orders. The negative coefficients for liquidating trades indicate that these automatically triggered trades are generally priced closer to the current prices at the primary listing exchanges.[14]

Trades at relatively round prices and fractional trades are not generally priced differently when controlling for asset fixed effects. However, the regression results confirm that price differences are substantially and significantly wider during the extended trading hours, even when controlling for asset-date fixed effects. Relative to the regular trading session, the absolute price difference is 0.39 percentage points wider during the pre-market and 0.45 percentage points wider during the after-hours session, representing an increase of roughly 50% and 57%, respectively.[15] Furthermore, price differences are significantly larger in absolute terms for cryptocurrency funds than for the S&P 500 ETF.

Finally, I study how quickly the prices of the tokenized assets react to changes in prices of the underlying assets. To capture the speed of price adjustment, I take one-minute closing prices of the tokenized assets and calculate logarithmic returns. For each asset

[14] The results for signed differences in the appendix show that this is driven by relatively lower prices in the tokenized assets for liquidating trades. Given that most liquidating trades result from sell orders, this would indicate that traders on average received worse prices than they would usually have received when their positions are automatically liquidated, even though (or rather: because) they are priced closer to the primary listing exchange.

[15] In untabulated analyses, I also test whether the after-hours widening of price differences varies with the minimum order size by interacting a binary variable for hours outside the main trading session with *log(SizeMin)* and with the product of *log(SizeMin)* and *log*($Price_U$). Neither term is statistically significant, suggesting that the role of the minimum order size in shaping price differences does not differ across trading sessions. However, the interaction between irregular hours and *log*($Price_U$) is negative and significant, consistent with the notion that the off-hours increases in price gaps are smaller for higher-priced assets.

Table 8
Determinants of absolute percentage price differences.

	(1)	(2)	(3)	(4)
log Price_{U}	−0.296**	0.031	−0.200	4.213*
	(−2.34)	(0.30)	(−1.09)	(1.73)
log Min. Size	0.066	0.116*		
	(0.49)	(1.70)		
log Min. Size × *log* Price_{U}	0.066	0.108	0.368*	4.940
	(1.36)	(1.16)	(1.98)	(1.48)
Round Price	−0.213*	0.009	−0.016	−0.010
	(−1.85)	(0.18)	(−0.75)	(−1.15)
Buy	0.240**	0.116	0.021	0.013
	(2.04)	(1.59)	(0.55)	(0.56)
Liquidation	−0.181*	−0.076	−0.159***	−0.113*
	(−1.69)	(−1.60)	(−3.25)	(−1.69)
log Volume	0.104**	0.026	−0.013	−0.012*
	(2.44)	(1.57)	(−1.32)	(−1.98)
Earnings Announcement_{1h}	0.002	0.145	−0.136	−0.444**
	(0.01)	(1.39)	(−0.84)	(−2.22)
Pre-Market	0.389**	0.443***	0.484***	0.391***
	(2.17)	(2.90)	(3.21)	(3.31)
After Hours	0.583***	0.565***	0.528***	0.451***
	(4.67)	(5.32)	(6.17)	(4.82)
Fractional	0.417***	0.145**	0.056**	0.008
	(3.24)	(2.46)	(2.25)	(0.43)
Canada		0.546		
		(1.41)		
Commodity		−0.493		
		(−1.30)		
Crypto		1.557***		
		(3.51)		
Meme		0.572		
		(1.14)		
Pharma		−0.221		
		(−0.49)		
Tech		−0.290		
		(−0.70)		
Asset FE	–	–	✓	–
Date FE	–	–	✓	–
Asset × Date FE	–	–	–	✓
Adj. R^2	0.14	0.26	0.44	0.63
Observations	727,308	727,308	727,308	727,308

This table shows trade-level regression results where the dependent variable is the absolute value of the percentage price difference between a trade in a tokenized asset and the average of the opening and closing prices at the underlying asset's primary listing exchange of the one-minute interval during which the trade occurred in percentage points. $Price_U$ is the price of the underlying asset at its primary listing exchange in USD 1000. *Min. Size* is the minimum order size in number of shares. All continuous variables have been demeaned prior to forming the interaction terms. *Volume* is the traded value in USD. $Earnings\ Announcement_{1h}$ is a binary variable indicating if the trade occurred within one hour following an earnings announcement of the underlying asset. *Buy* indicates buy trades. *Liquidation* indicates automatically triggered liquidating trades. *Round Price* is a binary variable indicating if the decimals of the trade price are multiples of USD 0.1. *Fractional* is an indicator variable for non-integer trade sizes. *Pre-Market* and *After Hours* indicate if the trade occurred in the respective trading phase at the primary listing exchange. The remaining independent variables indicate the respective asset's category with the S&P 500 ETF serving as the baseline case. An unreported constant is included in all models. The unconditional mean of the dependent variable is reported in Table 7. Standard errors are double-clustered with respect to both asset and date while t-statistics are given in parentheses.

*** Significance at the 1% level.
** Significance at the 5% level.
* Significance at the 10% level.

i individually, I then regress these returns on a constant and contemporaneous and lagged returns of the underlying assets up to a lag length j of 100 min.

$$r_{i,t}^{\text{Token}} = \alpha_i + \sum_{j=0}^{100} \beta_{i,j} r_{i,t-j}^{\text{Underlying}} + \varepsilon_{i,t}$$

I then compute the cross-sectional average $\bar{\beta}_j = \frac{1}{I}\sum_{i=1}^{I} \beta_{i,j}$ where I is the total number of tokenized assets and obtain confidence intervals based on the cross-sectional t-tests.

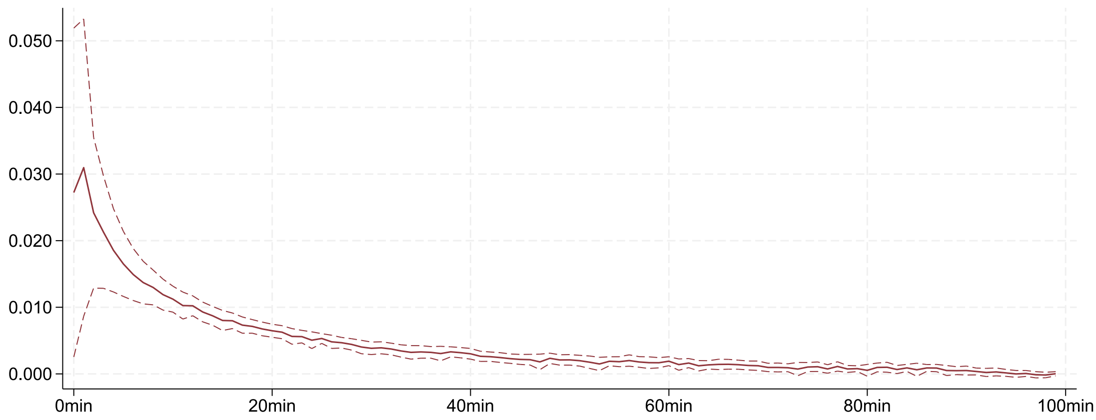

Fig. 8. Reaction of Tokenized Asset Returns to Underlying Asset Returns. (This graph shows the cross-sectional average of estimated coefficients from regressions of tokenized asset returns on contemporaneous and lagged returns of the respective underlying asset as traded on its primary listing exchange. Regressions are estimated separately for each asset, and coefficients are then averaged across assets. Up to 100 min of lagged returns are included in the model. Returns are based on minutely closing prices. The dashed lines show 99% confidence bands based on cross-sectional standard errors.)

The results can be seen in Fig. 8. Overall, the market for tokenized assets only reacts slowly to the underlying market. The coefficient for contemporaneous returns is statistically significant, suggesting that prices in both markets sometimes react simultaneously to the same information. However, the effect is economically small. On average, a 1% return at the primary listing exchange is accompanied by a return of 0.03% in the tokenized assets. The reaction is strongest after 1 min and then gradually diminishes. After about 80 min, it turns statistically insignificant. This means that it takes more than one hour for the price of the tokenized assets to fully react to price changes at the primary listing exchange. However, this does not necessarily imply that the prices diverge by more. As documented previously, average absolute price differences are small, suggesting the presence of arbitrageurs. The slow price adjustment therefore reflects not a sustained divergence in levels, but rather a gradual convergence process in which arbitrage activity operates with a meaningful lag. This is consistent with infrequent trading in the tokenized asset market.[16]

6. Concluding remarks

Tokenized securities markets combine around-the-clock access, fractional trading, and low entry barriers in ways that have historically been difficult for international investors to access simultaneously for US-listed assets. This study provides an early empirical analysis of investor trading behavior in such a market, using trade-level data that allows direct observation of all transactions, including their precise fractional sizes.

I document three main findings. First, trading activity remains heavily concentrated during regular US hours despite continuous market availability, suggesting that demand for off-hours trading is more limited than proponents of 24-hour markets anticipate. Second, fractional trading is pervasive, yet order sizes cluster at round quantities and values, indicating that investors rely on simple heuristics even when continuous order sizes are available. A disproportionate share of trades occurs at the minimum permissible size, consistent with investors seeking symbolic ownership rather than financial returns. Third, tokenized asset prices adjust relatively slowly to changes in the underlying asset's price, producing price gaps that substantially exceed typical transaction costs, particularly during extended hours when trading activity is thin.

Although FTX's tokenized asset market is no longer active, similar design features are now being adopted at a larger scale by other platforms. The trading patterns documented here are likely attributable to general market design features rather than platform-specific effects, making them relevant to other trading venues introducing tokenized assets. For example, the prevalence of economically trivial trade sizes suggests that tokenized markets attract retail participants whose motives differ from those assumed in standard microstructure models. That said, the sample consists of non-US investors trading on a lightly regulated exchange, and future markets will likely differ in regulatory oversight and investor composition; the findings are therefore best read as early evidence on one implementation of tokenized markets.

Tokenization has been proposed to deliver a broader set of benefits than those examined here. Because my dataset captures centralized exchange executions rather than the post-trade process, I do not test settlement speed or whether on-chain settlement

[16] Consistent with the notion that more active trading facilitates price discovery, more actively traded tokens adjust more quickly to the underlying asset than less actively traded ones, as shown in Fig. A.3 in the appendix. It is also worth noting that, as expected given the relatively small size of the market for tokenized assets, the underlying market does not materially react to returns in the tokens. The corresponding results can be found in Fig. A.4 in the appendix.

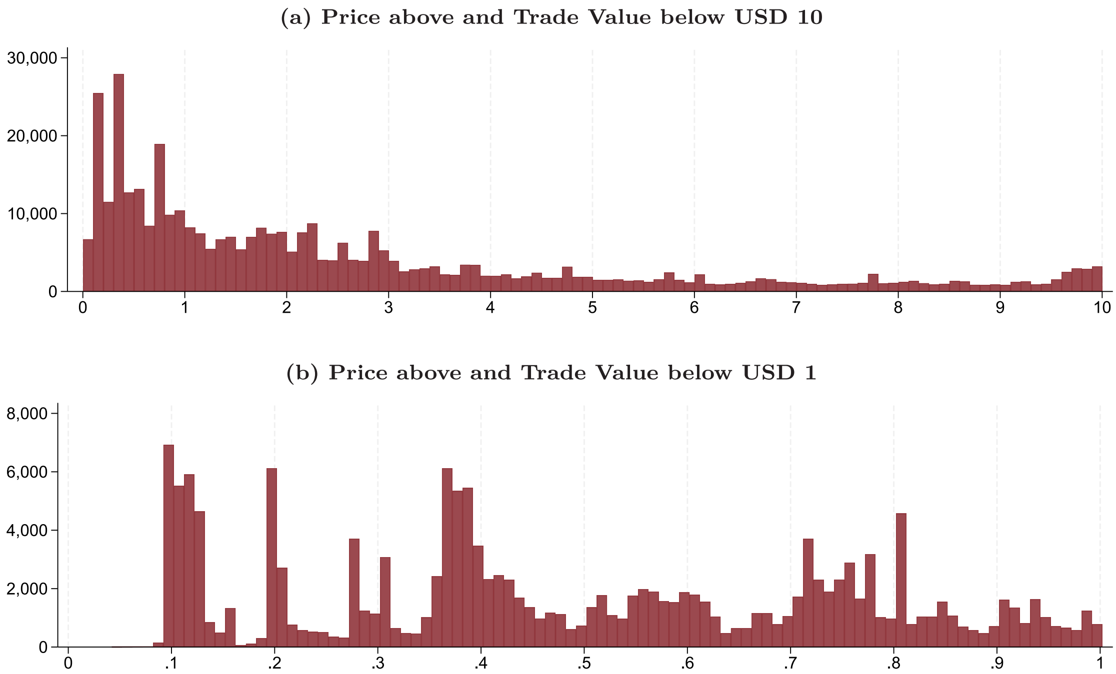

Fig. A.1. Distribution of Order Value for Lower-Priced Assets (USD). (This graph shows the absolute frequency of trade values in US dollars in the tokenized assets. In Panel A, only trades in assets with a trade value smaller than USD 10 and a current price larger than USD 10 are included. In Panel B, that threshold is USD 1.)

potentially reduces counterparty or custody risk. Nor do I examine potential gains from smart contract automation of corporate actions such as dividend payments or voting, greater transparency and auditability of issuance and reserves, or the integration of tokenized securities into decentralized collateral and lending. Whether these benefits materialize, and under what regulatory and market design conditions, are natural directions for future research.

Declaration of generative AI and AI-assisted technologies

During the preparation of this manuscript, I used ChatGPT and Claude as proofreading tools to assist with minor edits and refinements of the text. After using these tools, I reviewed and edited the content and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary figures and tables

In this appendix, I provide supplementary tables and figures referenced in the main text. Table A.1 lists the individual tokenized assets in the sample along with their categories, primary listing exchanges, and first trading dates. Table A.2 complements the category-level analysis in Section 4 by reporting fractional trading statistics at the individual token level.

Fig. A.1 extends the order-value distribution in Section 4 to lower-priced assets (priced below USD 100), with Panel A restricted to prices above USD 10 and trade values below USD 10, and Panel B to prices above USD 1 and trade values below USD 1.

Table A.3 shows regression results for the determinants of all fractional trades while Table A.4 shows regression results for the determinants of signed price differences. Fig. A.2 plots daily average absolute price differences for the tokenized SPDR S&P 500 ETF, including the first days of November 2022 around the collapse of FTX. Fig. A.3 splits the price adjustment analysis from Section 5 by trading activity, showing the reaction of tokenized asset returns to underlying asset returns separately for tokens with below-median and above-median numbers of trades. Finally, Fig. A.4 presents the reverse direction, showing the reaction of underlying asset returns to tokenized asset returns.

Table A.1
Sample assets.

Ticker	Name	Category	Exchange	First date
ACB	Aurora Cannabis Inc	Canada	TSX	2021–12–01
BB	BlackBerry	Canada	TSX	2021–12–01
CGC	Canopy Growth Corp	Canada	TSX	2021–12–01
CRON	Cronos Group Inc	Canada	TSX	2021–12–01
GLXY	Galaxy Digital Holdings	Canada	TSX	2021–12–01
TLRY	Tilray Inc	Canada	TSX	2021–12–01
GDX	VanEck Gold Miners ETF	Commodity	NYSE Arca	2021–12–01
GDXJ	VanEck Jr. Gold Miners ETF	Commodity	NYSE Arca	2021–12–01
GLD	SPDR Gold Shares	Commodity	NYSE Arca	2021–12–01
SLV	iShares Silver Trust	Commodity	NYSE Arca	2021–12–01
USO	United States Oil Fund	Commodity	NYSE Arca	2021–12–01
BITO	ProShares Bitcoin Strat ETF	Crypto	NYSE Arca	2021–12–01
BITW	Bitwise 10 Crypto Index Fund	Crypto	OTCQX	2021–12–01
ETHE	Grayscale Ethereum Trust	Crypto	OTCQX	2021–12–01
GBTC	Grayscale Bitcoin Trust	Crypto	NYSE Arca	2021–12–01
BYND	Beyond Meat Inc	Meme	NASDAQ	2021–12–01
DKNG	DraftKings	Meme	NASDAQ	2021–12–01
GME	GameStop	Meme	NYSE	2022–07–23
HOOD	Robinhood	Meme	NASDAQ	2021–12–01
PENN	Penn National Gaming	Meme	NASDAQ	2021–12–01
BNTX	BioNTech	Pharma	NASDAQ	2021–12–01
MRNA	Moderna	Pharma	NASDAQ	2021–12–01
PFE	Pfizer	Pharma	NYSE	2021–12–01
SPY	SPDR S&P 500 ETF	SP500	NYSE Arca	2021–12–01
AAPL	Apple	Tech	NASDAQ	2021–12–01
ABNB	Airbnb	Tech	NASDAQ	2021–12–01
AMD	Advanced Micro Devices	Tech	NASDAQ	2021–12–01
AMZN	Amazon	Tech	NASDAQ	2022–06–05
ARKK	ARK Innovation ETF	Tech	NYSE Arca	2021–12–01
BABA	Alibaba	Tech	NYSE	2021–12–01
COIN	Coinbase	Tech	NASDAQ	2021–12–01
FB	Facebook	Tech	NASDAQ	2021–12–01
GOOGL	Google	Tech	NASDAQ	2022–07–17
MSTR	MicroStrategy	Tech	NASDAQ	2021–12–01
NFLX	Netflix	Tech	NASDAQ	2021–12–01
NIO	Nio	Tech	NYSE	2021–12–01
NVDA	NVIDIA	Tech	NASDAQ	2021–12–01
PYPL	PayPal	Tech	NASDAQ	2021–12–01
SQ	Block	Tech	NYSE	2021–12–01
TSLA	Tesla	Tech	NASDAQ	2022–08–25
TWTR	Twitter	Tech	NYSE	2021–12–01
UBER	Uber	Tech	NYSE	2021–12–01
ZM	Zoom	Tech	NASDAQ	2021–12–01

This table shows the tokenized assets of the sample. *First Date* gives the date of the first observation of a trade in the tokenized asset.

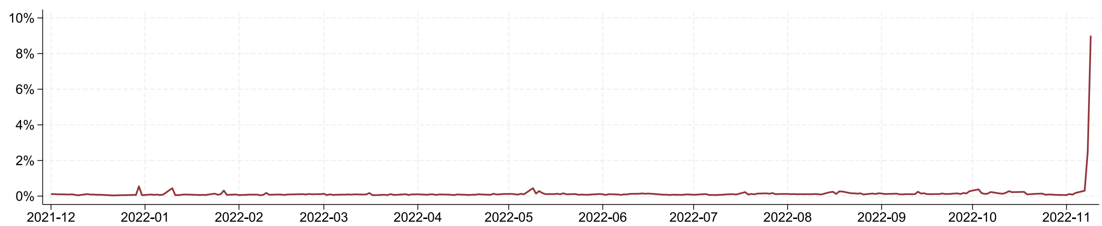

Fig. A.2. Absolute Price Differences for SPDR S&P 500 ETF Including November 2022. (This graph shows daily average absolute percentage price differences between the tokenized SPDR S&P 500 ETF and the same fund as traded at NYSE Arca. The graph includes the first ten days of November 2022, which are excluded in the other analyses.)

Appendix B. Further details on the institutional background

FTX initially partnered with CM-Equity AG, a regulated German brokerage firm, taking on the role of custodian. In January 2022, the partnership with the brokerage firm officially ended while a Swiss-based FTX subsidiary took over the duties of the custodian. The tokenization was provided by Digital Assets DA AG. Both firms appear to be closely linked to each other and to FTX, though the FTX corporate structure was very complex (Elder, 2022). As of January 2022, Digital Assets DA AG owned a roughly 10% stake in

Table A.2
Fractional trading by asset.

Ticker	Category	$Size_{Min}$	$Price_{Mean}$	% of Trades			% of Volume		
				Frac	< 1	Min	Frac	< 1	Min
ACB	Canada	0.100	2.10	83.56	10.53	5.13	84.95	0.20	0.05
BB	Canada	0.100	5.44	94.42	75.30	69.36	92.19	1.28	0.79
CGC	Canada	0.100	4.79	85.12	50.80	9.08	59.36	0.42	0.06
CRON	Canada	0.100	3.60	85.49	14.26	8.68	72.27	0.08	0.02
GLXY	Canada	0.100	9.21	80.23	48.91	7.66	69.77	1.73	0.03
TLRY	Canada	0.100	5.57	92.60	48.50	14.70	79.99	0.61	0.07
GDX	Commodity	0.010	28.17	93.64	75.18	6.39	61.30	0.41	0.00
GDXJ	Commodity	0.010	37.28	95.81	57.15	8.74	95.82	0.43	0.00
GLD	Commodity	0.010	164.33	96.71	72.02	10.70	93.99	0.65	0.01
SLV	Commodity	0.100	20.89	62.18	27.50	7.85	86.19	0.14	0.01
USO	Commodity	0.010	73.99	89.23	54.16	18.62	86.08	0.69	0.02
BITO	Crypto	0.010	28.67	96.38	71.11	30.84	97.04	2.45	0.10
BITW	Crypto	0.010	16.83	98.20	85.73	14.34	96.79	0.80	0.02
ETHE	Crypto	0.100	24.84	75.26	10.41	4.90	88.98	0.02	0.00
GBTC	Crypto	0.010	22.91	92.94	34.75	11.61	95.01	0.07	0.00
BYND	Meme/Other	0.010	36.95	92.69	60.81	10.66	95.69	3.24	0.04
DKNG	Meme/Other	0.010	16.89	98.65	88.02	20.33	91.62	2.60	0.06
GME	Meme/Other	0.010	28.75	98.74	82.98	1.65	94.44	14.57	0.01
HOOD	Meme/Other	0.010	13.08	91.63	24.34	4.57	95.41	0.22	0.00
PENN	Meme/Other	0.010	39.28	98.67	85.43	9.11	91.82	1.36	0.01
BNTX	Pharma	0.010	162.46	97.65	65.21	16.72	97.91	0.95	0.02
MRNA	Pharma	0.005	187.42	96.40	80.05	8.95	90.23	0.86	0.00
PFE	Pharma	0.010	51.12	92.51	79.18	35.51	86.11	0.26	0.01
SPY	SP500	0.001	400.06	97.56	87.47	22.52	91.41	2.98	0.01
AAPL	Tech	0.010	157.41	94.97	87.06	25.58	81.95	2.30	0.07
ABNB	Tech	0.025	137.76	93.94	77.53	14.25	85.83	1.79	0.06
AMD	Tech	0.010	98.02	90.89	83.44	22.15	65.39	2.77	0.08
AMZN	Tech	0.001	115.36	93.42	73.43	8.64	76.12	2.95	0.00
ARKK	Tech	0.010	54.14	69.06	55.40	19.66	72.29	0.76	0.02
BABA	Tech	0.005	100.55	95.11	24.40	3.56	86.99	0.39	0.00
COIN	Tech	0.010	105.88	88.96	62.04	13.31	76.19	1.44	0.04
FB	Tech	0.010	153.02	91.44	79.62	17.67	77.63	1.05	0.02
GOOGL	Tech	0.001	102.88	97.82	91.60	31.19	86.21	2.16	0.02
MSTR	Tech	0.005	327.89	92.67	69.59	15.82	80.90	1.77	0.02
NFLX	Tech	0.010	289.04	90.15	72.00	11.96	82.20	1.34	0.02
NIO	Tech	0.005	21.01	96.54	43.75	0.38	97.31	0.21	0.00
NVDA	Tech	0.002	215.06	92.46	83.19	8.07	68.08	4.66	0.01
PYPL	Tech	0.005	116.58	88.28	69.24	3.49	71.36	0.52	0.00
SQ	Tech	0.005	106.07	90.62	71.70	11.62	67.36	1.04	0.01
TSLA	Tech	0.010	257.00	86.93	74.63	15.86	77.17	12.20	0.11
TWTR	Tech	0.050	45.70	86.25	57.26	27.24	75.51	0.21	0.03
UBER	Tech	0.050	31.31	88.86	46.32	7.32	69.90	0.44	0.01
ZM	Tech	0.010	114.45	96.67	81.55	18.96	82.07	1.78	0.02
Total		0.021	122.46	89.88	59.62	14.20	86.12	1.12	0.01

This table shows summary statistics for fractional trading activity for the individual tokens. $Size_{Min}$ is the average minimum order size of the token while $Price_{Mean}$ is its average price. *Frac*, < 1 and *Min* indicate non-integer trades, below-one trades, and trades at the minimum order size, respectively. These measures are provided both as a percentage of all trades and as a percentage of the contained USD trading value in percentage points.

CM-Equity AG. During an extraordinary general meeting of CM-Equity AG in January 2022, Digital Assets DA AG was represented by the sole other shareholder of CM-Equity AG, its CEO. In February 2022, Digital Assets DA AG became FTX Europe AG.

The Swiss subsidiary that became the custodian in January 2022, FTX Switzerland GmbH, was previously known as Canco GmbH and Crypto Lawyers GmbH. It shares the same address and has overlapping board members with FTX Europe AG (previously Digital Assets DA AG) and other FTX subsidiaries such as FTX Derivatives GmbH. Both CM-Equity AG and Digital Assets DA AG previously partnered with the cryptocurrency exchange Binance in a similar tokenized assets program, which was eventually closed by the exchange amid regulatory concerns.

Whether and when the custodians actually held the underlying assets in custody in a ratio of 1:1 (or at all) is still unclear. The most recent entry regarding tokenized stocks in the FTX help section states that *"FTX Switzerland custodies the equities at a third party brokerage firm"* but does not specify which firm exactly. There has been speculation in the media regarding the backing of the tokenized assets and their use in price manipulation of smaller stocks.[17] Preliminary evidence found in the bankruptcy proceedings of FTX does not suggest that – at the time of bankruptcy – the assets were actually held in custody, but rather bought in the market

[17] https://www.thestreet.com/memestocks/gme/sam-bankman-fried-gme-and-amc-tokenized-shares

Table A.3
Determinants of fractional trades.

	(1)	(2)	(3)	(4)	(5)
log Price	−0.005 (−0.63)	−0.008 (−1.12)	0.021 (0.99)	0.044 (1.53)	0.135*** (2.75)
log Min. Size	−0.051*** (−5.95)	−0.050*** (−5.77)	−0.052*** (−5.01)		
log Min. Size × *log* Price	−0.002 (−0.33)	0.006 (1.01)	0.027** (2.12)	0.005 (0.14)	−0.106*** (−3.05)
Round Price	−0.030** (−2.42)	−0.030** (−2.61)	−0.024* (−1.87)	−0.020 (−1.30)	−0.026 (−1.67)
Buy	0.017** (2.08)	0.014 (1.63)	0.014* (1.96)	0.012** (2.57)	0.007 (1.38)
Liquidation	0.062*** (3.02)	0.052*** (3.02)	0.055*** (3.08)	0.061*** (4.28)	0.051*** (3.21)
Pre-Market	−0.008 (−0.81)	−0.006 (−0.61)	0.001 (0.13)	0.005 (0.86)	0.004 (0.62)
After Hours	0.021 (1.32)	0.019 (1.34)	0.023 (1.64)	0.022** (2.58)	0.013 (1.61)
Market Closed	0.021 (1.01)	0.022 (1.14)	0.027 (1.46)	0.022 (1.64)	0.017 (1.39)
Canada			0.295** (2.64)		
Commodity			−0.027 (−0.32)		
Crypto			0.049 (0.50)		
Meme			0.070 (0.69)		
Pharma			0.034 (0.43)		
Tech			−0.037 (−0.58)		
Baseline Mean	0.899	0.899	0.899	0.899	0.899
Model	Logit	Linear	Linear	Linear	Linear
Asset FE	–	–	–	✓	–
Date FE	–	–	–	✓	–
Asset × Date FE	–	–	–	–	✓
Adj./Pseudo R^2	0.06	0.04	0.06	0.14	0.30
Observations	995,262	995,262	995,262	995,262	995,262

This table shows regression results where the dependent variable is a binary variable indicating non-integer trade sizes. *Price* is the price of the trade in USD 1000. *Min. Size* is the minimum order size in number of shares. All continuous variables have been demeaned prior to forming the interaction terms. *Round Price* is a binary variable indicating if the decimals of the trade price are multiples of USD 0.1. *Buy* indicates buy trades. *Liquidation* indicates automatically triggered liquidating trades. *Pre-Market*, *After Hours*, and *Market Closed* indicate if the trade occurred in the respective trading phase at the primary listing exchange. The remaining independent variables indicate the respective asset's category. An unreported constant is included in all models. The column for the logit model shows marginal effects. Standard errors are double-clustered with respect to both asset and date while *t*-statistics are given in parentheses.

*** Significance at the 1% level.

** Significance at the 5% level.

* Significance at the 10% level.

Table A.4
Determinants of signed price differences.

	(1)	(2)	(3)	(4)
log Price_U	0.011	0.225	0.335	19.158***
	(0.12)	(1.31)	(0.97)	(2.84)
log Min. Size	0.145	0.165*		
	(1.38)	(2.01)		
log Min. Size × *log* Price_U	0.046	0.139	0.340**	6.600***
	(0.99)	(1.27)	(2.15)	(3.10)
Round Price	−0.181	0.015	0.023	0.007
	(−1.58)	(0.30)	(0.94)	(0.52)
Buy	0.319*	0.212	0.075	0.014
	(1.76)	(1.48)	(1.53)	(0.43)
Liquidation	−0.580***	−0.455***	−0.539***	−0.294***
	(−3.58)	(−4.18)	(−4.46)	(−3.72)
log Volume	0.104**	0.030	−0.010	−0.008**
	(2.29)	(1.33)	(−1.01)	(−2.62)
Earnings Announcement_{1h}	0.176	0.369	−0.049	−0.592*
	(0.74)	(1.36)	(−0.48)	(−1.82)
Pre-Market	−0.054	−0.028	0.030	0.044
	(−0.31)	(−0.16)	(0.26)	(0.98)
After Hours	0.103	0.067	0.023	0.088
	(1.21)	(0.71)	(0.30)	(1.64)
Fractional	0.322*	0.102	0.025	−0.032
	(1.98)	(0.97)	(0.60)	(−1.62)
Canada		0.556		
		(0.91)		
Commodity		−0.455		
		(−0.89)		
Crypto		1.169*		
		(2.00)		
Meme		−0.456		
		(−0.57)		
Pharma		−0.352		
		(−0.66)		
Tech		−0.454		
		(−0.90)		
Asset FE	–	–	✓	–
Date FE	–	–	✓	–
Asset × Date FE	–	–	–	✓
Adj. R^2	0.06	0.14	0.38	0.66
Observations	727,308	727,308	727,308	727,308

This table shows trade-level regression results where the dependent variable is the signed value of the relative price difference between a trade in a tokenized asset and the average of the opening and closing prices at the underlying asset's primary listing exchange of the one-minute interval during which the trade occurred in percentage points. $Price_U$ is the price of the underlying asset at its primary listing exchange in USD 1000. *Min. Size* is the minimum order size in number of shares. All continuous variables have been demeaned prior to forming the interaction terms. *Volume* is the traded value in USD. *Earnings* $Announcement_{1h}$ is a binary variable indicating if the trade occurred within one hour following an earnings announcement of the underlying asset. *Buy* indicates buy trades. *Liquidation* indicates automatically triggered liquidating trades. *Round Price* is a binary variable indicating if the decimals of the trade price are multiples of USD 0.1. *Fractional* is an indicator variable for non-integer trade sizes. *Pre-Market* and *After Hours* indicate if the trade occurred in the respective trading phase at the primary listing exchange. The remaining independent variables indicate the respective asset's category with the S&P 500 ETF serving as the baseline case. An unreported constant is included in all models. The unconditional mean of the dependent variable is reported in Table 7. Standard errors are double-clustered with respect to both asset and date while t-statistics are given in parentheses.

*** Significance at the 1% level.

** Significance at the 5% level.

* Significance at the 10% level.

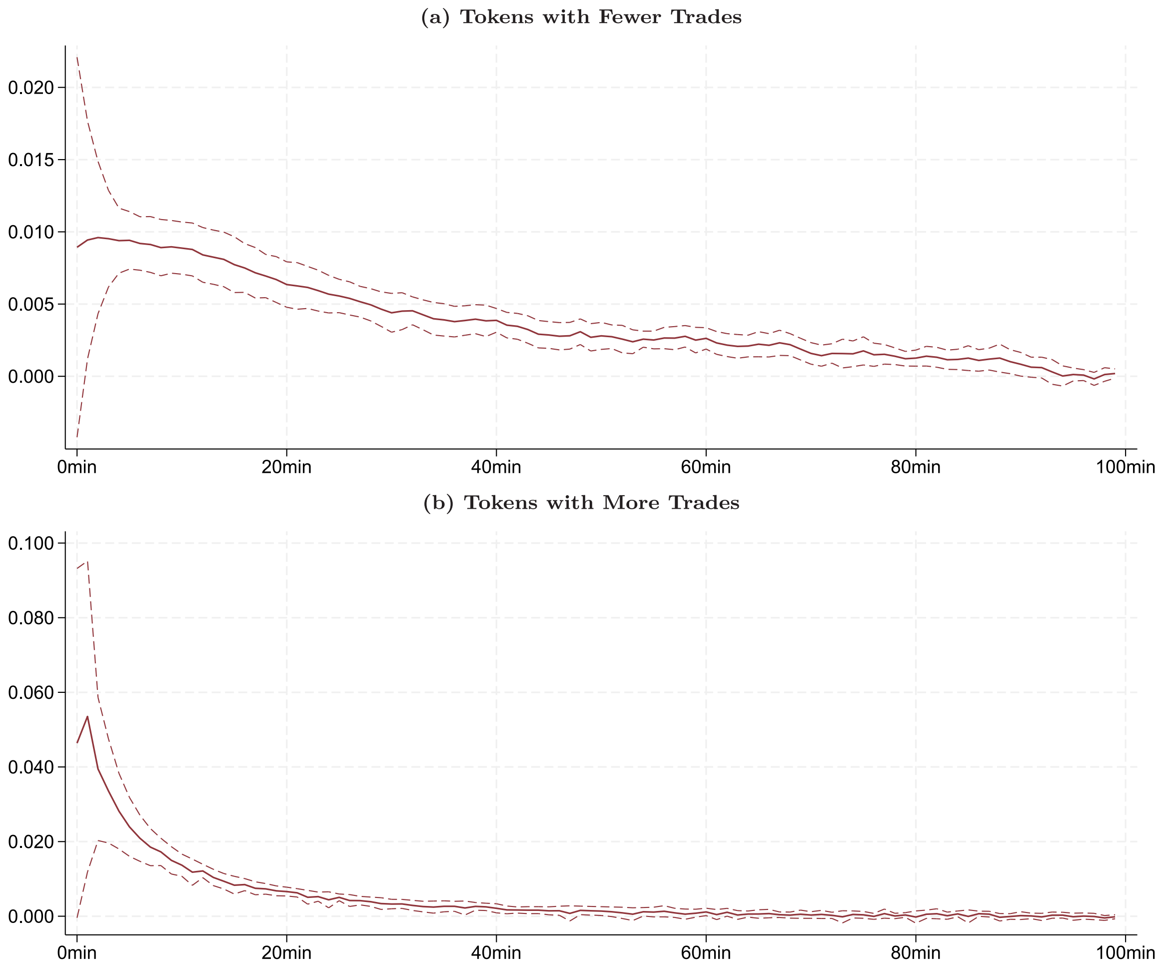

Fig. A.3. Reaction of Tokenized Asset Returns to Underlying Asset Returns by # Trades. (This graph shows the cross-sectional average of estimated coefficients from regressions of tokenized asset returns on contemporaneous and lagged returns of the respective underlying asset as traded on its primary listing exchange. Regressions are estimated separately for each asset, and coefficients are then averaged across assets. Up to 100 min of lagged returns are included in the model. Returns are based on minutely closing prices. The dashed lines show 99% confidence bands based on cross-sectional standard errors. The top and bottom figures show tokens with below-median and above-median number of trades, respectively.)

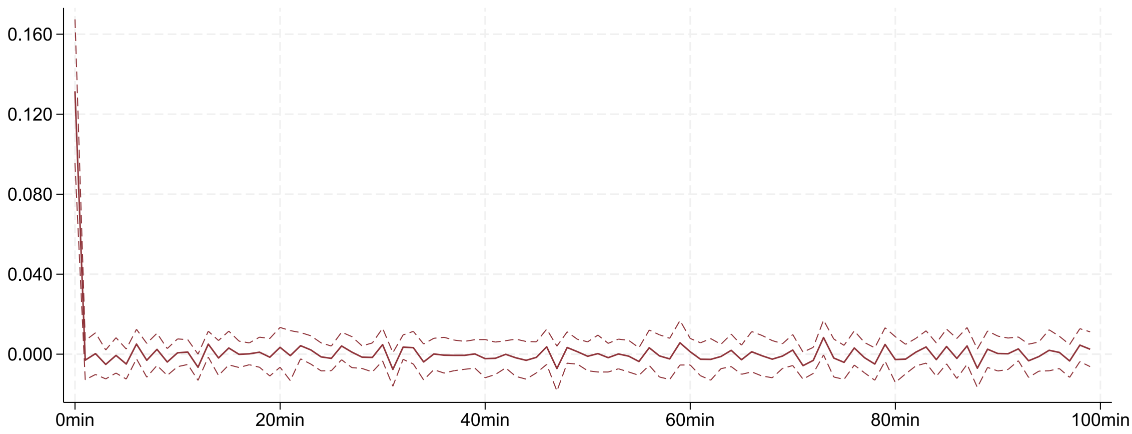

Fig. A.4. Reaction of Underlying Asset Returns to Tokenized Asset Returns. (This graph shows the cross-sectional average of estimated coefficients from regressions of underlying asset returns as traded on its primary listing exchange on contemporaneous and lagged returns of the respective tokenized asset. Regressions are estimated separately for each asset, and coefficients are then averaged across assets. Up to 100 min of lagged returns are included in the model. Returns are based on minutely closing prices. The dashed lines show 99% confidence bands based on cross-sectional standard errors.)

in case a token holder wanted to redeem their tokens. As of March 2023, the proceedings list USD 0.3 billion in liquid securities, of which USD 268 million is found in positions in the Grayscale and Bitwise cryptocurrency funds held in Alameda Research brokerage accounts. These funds are also among the tokenized assets. The bankruptcy case information can be found with the claims agent, the restructuring administration firm (Kroll, 2023).

However, until shortly before the bankruptcy of FTX, it does not appear that traders were concerned about this lack of transparency or possibly missing collateral. As can be seen in the example of the tokenized SPDR ETF in Fig. A.2, price differences between the tokenized asset and the underlying asset were small and relatively constant until November 2022.

Data availability

The authors do not have permission to share data.

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