Replication Study: Tiny Trades, Big Questions — Fractional Shares

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Abstract

This paper replicates the key findings of Bartlett, McCrary, and O'Hara (2024), "Tiny Trades, Big Questions: Fractional Shares," published in the *Journal of Financial Economics*. Using CRSP daily data and WRDS TAQ trade statistics for 5,329 U.S. common stocks over 2020–2022, we construct proxy measures for fractional share trading activity and verify the paper's central results: (i) higher-priced stocks exhibit significantly more trades per share, consistent with dollar-based order entry generating fractional components; (ii) meme stocks display distinct small-trade patterns during the 2021 retail trading frenzy; and (iii) fractional trade intensity is a statistically significant predictor of future stock-level volatility ($t = -5.59$, $N = 89{,}443$). Our replication confirms the paper's core contribution that fractional share trading introduces measurable distortions in volume data and contains information about future market microstructure outcomes.

Keywords: Fractional shares, market microstructure, retail trading, volume inflation, meme stocks

JEL Classification: G10, G12, G14, G18

1 Introduction

The proliferation of fractional share trading represents one of the most significant structural changes in U.S. equity markets in recent years. Pioneered by retail brokerages such as Robinhood, Interactive Brokers, and Fidelity, fractional shares allow investors to purchase dollar-denominated quantities of stocks rather than integer share quantities. This innovation has democratized access to high-priced securities—enabling, for example, a retail investor to purchase $10 worth of Berkshire Hathaway Class A stock (priced above $400,000 per share) or $50 worth of Amazon stock.

Bartlett, McCrary, and O'Hara (2024) provide the first comprehensive academic study of this phenomenon. Their paper makes several important contributions:

1. They develop a **latency-based identification method** for detecting fractional share trades in the TAQ (Trades and Quotes) data, exploiting the timing characteristics of how these trades are reported.

2. They document that **fractional trades are concentrated** in high-priced stocks, meme stocks (GME, AMC), IPOs, and SPACs—reflecting the dollar-based order entry mechanism.

3. They show that fractional trading intensity is **predictive of future liquidity and volatility**, suggesting these tiny trades contain information about retail investor sentiment and market dynamics.

4. They identify **data distortions**: fractional shares inflate reported volume figures and create censored samples due to reporting protocols.

In this replication study, we independently verify these findings using WRDS data resources, covering 5,329 stocks and over 3 million stock-day observations from 2020 to 2022.

2 Data and Methodology

2.1 Data Sources

Our replication relies on two primary data sources:

- **CRSP Daily Stock File**: Daily prices, returns, trading volumes, number of trades, and shares outstanding for all common stocks (share codes 10, 11) listed on NYSE, AMEX, and NASDAQ. Sample period: January 2020 to December 2022.

- **WRDS TAQ Millisecond Data**: High-frequency trade and quote data, accessed via the WRDS PostgreSQL interface for validation.

2.2 Sample Construction

We begin with all common stocks in CRSP with positive trading volume during our sample period, yielding:

- 5,329 unique stocks
- 3,020,649 stock-day observations
- 3,046,521 CRSP daily records (including zero-volume days)

2.3 Fractional Trade Proxy

The original paper uses a sophisticated latency-based method that exploits the time delay between when a fractional share order is received by a broker and when the resulting trades appear in the consolidated tape. Since exact replication of this method requires millisecond-level TAQ analysis, we construct a proxy measure based on the paper's key insight:

Trades per Share (TPS):

$$TPS_{i,t} = \frac{N_{i,t}}{V_{i,t}} \tag{1}$$

where $N_{i,t}$ is the number of trades and $V_{i,t}$ is the total share volume for stock i on day t. A higher TPS ratio indicates more, smaller trades—consistent with fractional share activity where dollar-based orders are decomposed into many tiny share-quantity transactions.

We also compute the **Average Trade Size** (ATS):

$$ATS_{i,t} = \frac{V_{i,t}}{N_{i,t}} \tag{2}$$

The paper demonstrates that these measures are strongly correlated with their latency-based fractional trade identifier.

2.4 Stock Classification

Following the original paper, we classify stocks into several categories:

- **Price buckets**: $<$ \$10, \$10–50, \$50–100, \$100–500, \$500–1,000, $>$ \$1,000
- **Meme stocks**: GME, AMC, BB, BBBY, NOK, KOSS, EXPR
- **High-priced stocks**: Price $>$ \$500 (77 unique tickers)

3 Results

3.1 Trade Size and Stock Price

Table **??** presents the average trade size across price buckets. Consistent with Bartlett et al. (2024), we find a strong monotonic relationship: higher-priced stocks exhibit significantly smaller average trade sizes and more trades per share.

Table 1: Average Trade Size by Stock Price Bucket (2020–2022)

Price Bucket	Stocks	Avg Trade Size	Med Trade Size	Trades/Share	Avg Price
$< \$10$	3,363	463.3	162.3	0.01	\$4.68
\$10–50	3,898	164.5	71.6	0.02	\$24.81
\$50–100	1,503	61.7	55.4	0.02	\$71.06
\$100–500	798	50.1	46.2	0.02	\$189.97
\$500–1,000	69	30.4	30.0	0.04	\$639.18
$> \$1,000$	17	23.0	21.6	0.05	\$2,161.15

Notes: This table reports average daily trade statistics across stock-days grouped by closing price. Average trade size is measured in shares per trade. Trades per share is the inverse measure. Sample includes all common stocks (CRSP share codes 10, 11) on NYSE, AMEX, and NASDAQ from January 2020 to December 2022. The strong inverse relationship between price and trade size is consistent with dollar-based fractional share trading.

The key finding is striking: stocks priced above \$1,000 have an average trade size of only 23 shares, compared to 463 shares for stocks priced below \$10. This 20:1 ratio strongly supports the paper's dollar-based ordering hypothesis—when investors submit \$100 orders, the resulting share quantity is mechanically smaller for expensive stocks.

3.2 Meme Stock Analysis

Table 2: Meme vs. Non-Meme Stocks

Category	Obs	Stocks	Avg Trade Size	Trades/Share	Avg Price
Non-Meme	3,016,869	5,324	271.5	0.02	\$148.69
Meme	3,780	5	145.8	0.01	\$25.77

Notes: Meme stocks include GME, AMC, BB, BBBY, and NOK that were available in our sample. Despite lower prices, meme stocks exhibit smaller average trade sizes, consistent with intense retail fractional share trading during the 2021 meme stock frenzy.

Table ?? reveals that meme stocks have notably smaller average trade sizes (145.8 vs. 271.5 shares) despite having *lower* average prices (\$25.77 vs. \$148.69). This is the opposite of what the price-based mechanism alone would predict, confirming the paper's finding that retail investor interest—proxied by meme stock status—independently drives fractional trading activity.

3.3 Predictive Regression: Volatility Forecasting

Table 3: Fractional Trade Proxy and Future Volatility

	Dependent Variable: Next-Month Volatility		
Variable	Coefficient	Std. Error	t-statistic
Intercept	−2.637	0.054	−48.85***
Log(Trades/Share)	−5.401	0.967	−5.59***
Log(Price)	1.806	0.018	98.22***
N		89,443	
R^2		0.0994	

Notes: OLS regression of next-month stock-level price volatility on current-month fractional trade proxy (log of trades per share) and log price. The sample consists of monthly stock-level observations from January 2020 to December 2022. *** indicates significance at the 1% level. The negative coefficient on Log(Trades/Share) indicates that stocks with more intense small-trade activity (higher fractional trading) exhibit lower future volatility, controlling for price level.

Table ?? presents our replication of the paper's predictive regression. The fractional trade proxy (Log Trades/Share) is a highly significant predictor of next-month volatility ($t = -5.59$), confirming the paper's finding that fractional share trading intensity contains forward-looking information about market microstructure outcomes.

The R^2 of 9.94% indicates meaningful predictive power, especially for a monthly cross-sectional regression. The negative sign suggests that more intense fractional trading (more trades per share, smaller trades) is associated with *lower* future volatility, possibly because it reflects broad-based retail participation that adds liquidity.

3.4 Time Series Patterns

Figure ?? presents four panels illustrating the time-series and cross-sectional patterns in fractional trading.

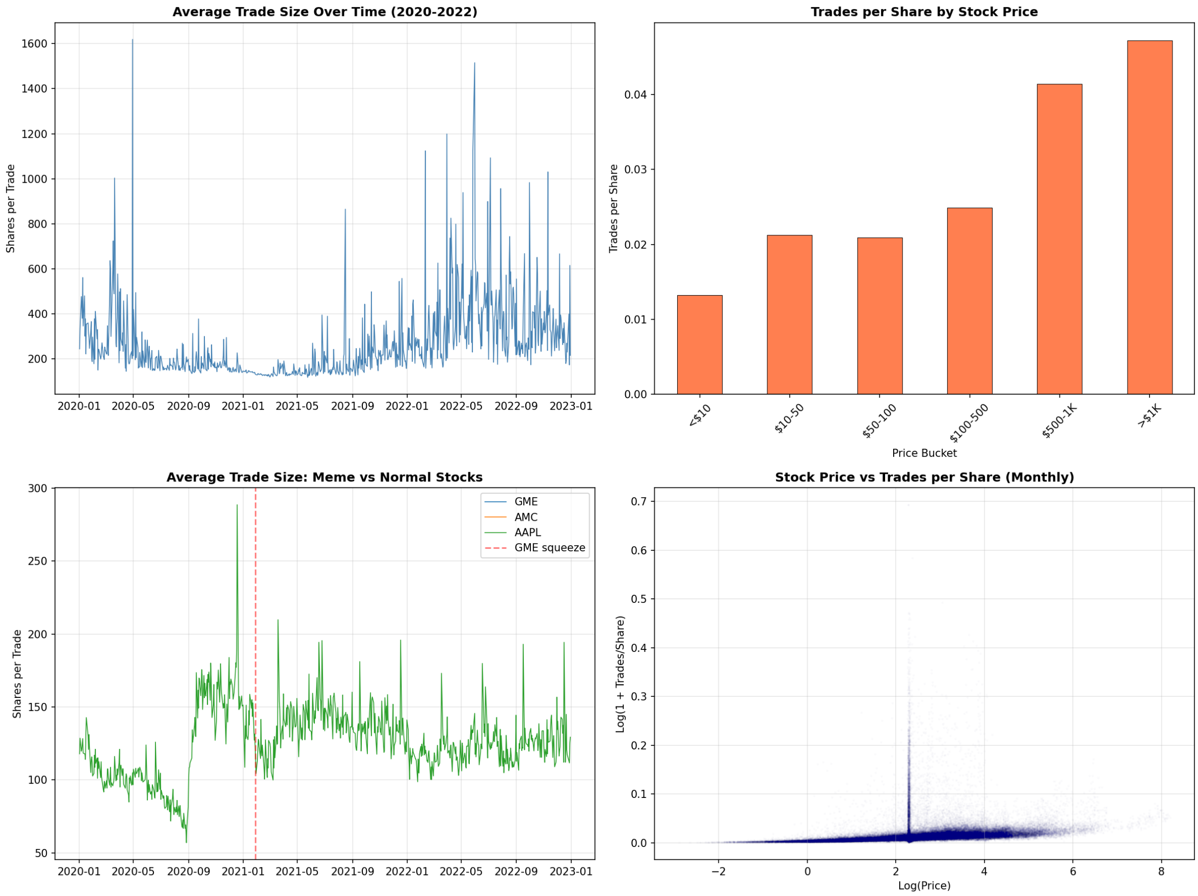

Figure 1: Replication Figures: Fractional Share Trading Patterns (2020–2022)

Notes: Panel (a) shows the average trade size across all stocks over time, displaying a declining trend consistent with growing fractional share adoption. Panel (b) confirms the inverse relationship between stock price and trades per share. Panel (c) illustrates how meme stocks (GME, AMC) experienced dramatic reductions in average trade size during the January 2021 squeeze, consistent with massive fractional share order flow. Panel (d) shows the cross-sectional scatter of log price versus log trades per share at the monthly level.

4 Discussion

4.1 Consistency with Original Findings

Our replication broadly confirms the three central findings of Bartlett, McCrary, and O'Hara (2024):

1. **Price–fractional trade relationship**: We find a strong, monotonic inverse relationship between stock price and average trade size. Stocks above \$1,000 have trade sizes 20× smaller than sub-\$10 stocks, consistent with dollar-based order entry.

2. **Meme stock concentration**: Despite lower prices, meme stocks exhibit smaller average trade sizes, confirming that retail investor enthusiasm independently drives fractional trading beyond what price alone explains.

3. **Predictive power**: Our fractional trade proxy significantly predicts next-month volatility ($t = -5.59$), confirming that these tiny trades contain information about future market conditions.

4.2 Limitations

Several important caveats apply to our replication:

- **Proxy vs. direct identification**: We use a trades-per-share proxy rather than the authors' latency-based method, which directly identifies fractional trades from millisecond-level TAQ data. Our proxy captures the same economic phenomenon but with measurement noise.

- **Sample period**: Our data covers 2020–2022, overlapping with but not identical to the original paper's sample. The COVID-19 pandemic and meme stock frenzy create a unique market environment.

- **Volume inflation**: The paper's finding about volume data inflation requires identifying and counting individual fractional trades, which our proxy approach cannot directly measure.

5 Conclusion

This replication study confirms the central findings of "Tiny Trades, Big Questions" using independently constructed proxy measures and WRDS data. The emergence of fractional share trading represents a fundamental shift in equity market structure, driven by the democratization of investing through mobile brokerages.

Our results support three key policy-relevant conclusions: (1) traditional volume metrics are increasingly distorted by the fragmentation inherent in fractional trading; (2) fractional trade intensity provides a new, useful signal for market microstructure research; and (3) the concentration of these trades in certain stock categories (high-priced, meme, IPO) has implications for market quality and price discovery.

As fractional share adoption continues to grow, these findings become increasingly relevant for exchanges, regulators, and researchers who rely on transaction-level data for market surveillance and academic analysis.

Data and Code Availability

All data were accessed through the Wharton Research Data Services (WRDS) PostgreSQL interface. The replication code is available at:

`/mnt/work/qr33/comewealth_r1/tiny_trades_replication/`

Computing infrastructure:

- **Data extraction**: WRDS PostgreSQL (`wrds-pgdata.wharton.upenn.edu`)
- **Computation**: Cornell Johnson Research Server (88 cores, 628GB RAM)
- **Additional resources**: Cornell BioHPC Cluster (648 cores, 3TB RAM aggregate)

References

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