The Allure of Round Number Prices for Individual Investors

Adam Bloomfield, Alycia Chin, and Adam Craig

Author Note

Adam Bloomfield,☆ U.S. Federal Deposit Insurance Corporation, 550 17th St NW, Washington, DC 20429, abloomfieldclagett@fdic.gov

Alycia Chin,† Office of the Investor Advocate, Securities and Exchange Commission, 100 F Street, NE, Washington, DC 20549, readlinga@sec.gov, ORCID ID: 0000-0002-9570-0549.

Adam W. Craig, Associate Professor, Gatton College of Business and Economics, University of Kentucky, Lexington, KY 40526, adam.craig@uky.edu. ORCID ID: 0000-0002-9021-1981.

Disclaimers

☆The views expressed herein are those of the authors and do not necessarily reflect the views of the FDIC or the U.S. Government.

†This manuscript is provided in the author's official capacity as a Senior Financial Economist of the Office of the Investor Advocate but does not necessarily reflect the views of the Commission, the Commissioners, or other members of the staff.

Acknowledgements

We thank Wändi Bruine de Bruin, Joshua White, Russell Jame, and members of the 2023 RAND Behavioral Finance Forum for their comments on earlier versions of this work.

Declaration of Interest

Nothing to declare.

Abstract

We report novel evidence on the demographic and trade-level correlates of round number price trading in securities markets (e.g., $5.00 instead of $5.01) from a rich, account-level administrative data set capturing over 20 million accounts and 134 million transactions. We find that trades at integer prices are over three times more likely than expected and round number trades (i.e., those ending in 0 or 5 cents) are 6.7% more likely than expected. Round number trades are more prevalent among men and the young, the first time such demographic patterns have been documented. Trade-level factors also predict round number trades, as they are more likely when individual investors are buying, and less likely in retirement accounts and when making trades valued at smaller amounts. Overall, our findings are consistent with psychological accounts that suggest rounding is driven by facility with round numbers, but inconsistent with accounts that strictly attribute round number trades to limited cognitive resources. The findings suggest the need for additional research to explain previously undocumented patterns and potential welfare consequences for certain investors.

Keywords: financial decision-making, investment behavior, round numbers, price clustering

Introduction

Scholarship in "round number trading," the tendency for asset market participants to cluster transactions at specific, round number prices (e.g., \$5.00 vs. \$5.01) spans multiple decades and settings. This literature started with Osborne (1962), who demonstrated disproportionate bids at integer prices in over-the-counter quotes; from there, researchers expanded to additional stock market orders and trades (Harris, 1991; Christie & Schultz, 1994; Kandel, Sarig & Wohl, 2001; Ahn, Cai & Cheung, 2005; Ohta, 2006; Aşçıoğlu, Comerton-Forde & McInish, 2007), stock market futures (Kuo, Lin, & Zhao, 2015), municipal bonds (Griffin et al. 2023), cryptocurrency (Urquhart, 2017; Mbanga, 2018; Baig, Blau & Sabah, 2019), and foreign currency spot exchange markets (Goodhart & Curcio, 1991; Sopranzetti & Datar, 2002). Interest in round number trading stems from concerns that these trades may increase volatility (Blau & Griffith, 2016), reduce welfare for those who engage in such trading (Bhattacharya, Holden, and Jacobsen, 2012; Kuo, Lin, and Zhao, 2015), and violate classical financial theories and market efficiency (Niederhoffer, 1966).

This deep literature has led two broad sets of theories for why traders might select round prices: strategic maneuvering and psychological accessibility. In the former camp, Harris (1991) argues that narrowing the set of numbers for a possible transaction price can minimize the negotiation process and ensure more rapid convergence; Ahn, Cai, and Cheung (2005) and Ohta (2006) similarly argue that price clustering can reduce effort. Strategic maneuvering can also occur for reasons other than effort reduction; Christie and Schultz (1994), for instance, argue that collusion among market makers could lead to the use of round prices. In contrast to these strategic considerations, psychological explanations tend to argue that investors are naturally attracted to certain numbers, in what is known as the "attraction hypothesis" (Goodhart and Curcio 1991; Aşçıoğlu, Comerton-Forde, & McInish, 2007), or have mental constraints on information processing that would lead them to favor round numbers, in what is known as the "constraint hypothesis" (Ikenberry & Weston, 2008; Chiao & Wang, 2009; Kuo, Lin, & Zhao, 2015).

There are two main empirical methods used to distinguish between strategic maneuvering and psychological explanations. First, if strategic maneuvering is irrelevant in a given context, psychological factors (that affect any human actor) become the default explanation. Both Kandel et al. (2001) and Sopranzetti and Datar (2002), for example, examine markets where negotiation is implausible, making strategic considerations less pertinent. A second method for distinguishing between the two sets of theories is to examine investors with varying capacity or incentive to engage in strategic maneuvering, such as institutional versus individual investors. Chiao and Wang (2009) and Kuo et al. (2015) examine limit order data by investor type, finding increased price clustering among individual investors versus institutions. However, both of these papers are limited to broad classifications of individual investors versus institutions, and do not directly access additional characteristics of individual investors.

While both of these methods provide evidence on the potential causes of round number trading, they also have limitations. In particular, they leave open questions about the causes of round number trading in broad sets of markets (versus markets where strategic maneuvering is irrelevant) and about individual investor heterogeneity (in cases where authors concentrate on individuals versus institutions). Ultimately, relatively little is known about round number trading among individual traders, including basic questions about *who* is more likely to engage in such behavior, and *when* they are more likely to do so. Indeed, much of the prior literature on round number trading does not attempt to identify individual traders separately from institutions (see Table 1).

The primary purpose of this article is to contribute to theoretical and descriptive understanding of round number trading by providing a comprehensive empirical account of round number trading in the U.S. equity market and how it varies among both institutional and individual traders. Past research has estimated that buying and selling at or very near round number prices yields an aggregate wealth transfer of over $850 million per year in the U.S. stock market, with stock market participants that exhibit rounding transferring wealth to other participants (Bhattacharya et al., 2012). As such, our analyses also point to potential welfare implications for investors.

Prevalence of Round Number Trading in the US

When making investment decisions, investors decide when to buy and sell investments and for what price. The central theoretical proposition of financial economics, the Efficient Market Hypothesis (EMH), argues that asset prices rationally, instantaneously, and fully reflect all relevant information and thus the fundamental (i.e., true) value of the asset (Samuelson, 1965a; 1965b; 1973; Fama, 1965; LeRoy, 1982; 1989). Under this theory, which is based on rational expectations and a competitive equilibrium framework, transactions should not cluster at particular prices (i.e., trading at $5.00 should not be more likely than $5.01), as prices reflect fundamental value and fluctuate randomly and thus exhibit "random walks."

Despite this theoretical prediction, empirical work has routinely documented round number trading across a variety of countries, market types, and assets (reflected in Table 1). These analyses have found inflated levels of rounding when compared to theoretical levels under a uniform distribution of prices. In the current research, we add to this literature by reporting a more recent estimate of the share of U.S. equity trades that are rounded, both among individual and institutional investors, using a large and diverse data set. This is our first contribution.

Table 1. Selected literature examining round number prices in financial asset markets.

Paper	Context	Type and prevalence of round number prices	Ratio of Actual to Expected Incidence	Identification of Individual Investors Investor Heterogeneity
Osborne (1962)	High, low, and closing prices for stocks traded on NYSE from 1/1959 to 1/1960	Integers (vs. expected 1/8th of prices); specific estimate not given as volumes are displayed graphically	Not clear	Not attempted
Goodhart & Curcio (1991)	Forex market bid/ask prices from Reuters, data from 4/9/1989 to 7/3/1989	Bids 0-end price: 25.83 Ask 0-end price: 23.62 (each vs. 10%)	Bids: 2.5 Asks: 2.4	
Harris (1991)	Trade, bid, and ask prices on NYSE, AMEX, and NASD	Integers are 14.2-19.3% of prices on	1.14-1.61	Not attempted

	during week of 9/28/1987	average (with pricing on eighths)		
Booth et al. (2000)	Helsinki SE	Integer prices are 41-74% of sample (vs. expected 10%)	4.1-7.4	Not attempted
Kandel, Sarig, & Wohl (2001)	Israeli IPO market limit order price submissions	Integers are 20.8% of prices		
Sopranzetti & Datar (2002)	Foreign exchange spot market indicative quotes	Integer quotes are 31.99% to 59.74% of sample		Not attempted
Ahn, Cai & Cheung (2005)	Limit order quote and stock trade prices on SE of Hong Kong			
Ohta (2006)	Stock prices on Tokyo SE, a limit order market	Integers ending in 0* are 16.6% of prices		Not attempted
Ascioglu, Comerton-Forde & McInish (2007)	Stock price bids and asks on Tokyo SE, four quotes per day	Integer prices are 15% of bids and 17% of asks		Not attempted
Ikenberry & Weston (2008)	Prices for NYSE and Nasdaq stocks from 7/2002 to 12/2002	0/8's (Integers?): NASDAQ = 27.4% NYSE = 21.5%		Not attempted
Chiao & Wang (2009)	Limit orders ("true intentions") on Taiwan SE	Even ending prices 0.59 vs. 0.5 expected. Integers XX		Traders are classified into one of five groups: foreign investors, mutual funds, securities dealers, corporate institutions, and individual investors
Bhattacharya et al. (2012)	NYSE Trade and Quote Data			Not attempted
Kuo, Lin & Zhao (2015)	Limit orders on Taiwan Futures Exchange	Integer prices ending in 00 are 3.1% of orders		Traders are classified as individual or institutional investors. Investors' cognitive ability is inferred through the proportion of limit orders submitted at multiples of 10
Blau & Griffith (2016)	Closing stock prices on NYSE	Round number prices ending with 0 or 5 are 32.1% of sample		Not attempted

Chen (2018)	Order imbalance closing prices across 41 stock markets	Order Imb. for Integer prices is 0.969; Order Imb. for 9-ending prices is 1.138.		Informed trade: Given negative (positive) unexpected return, a buy (sell). Uninformed trade: Given negative (positive) unexpected returns, a sell (buy).
Baig et al. (2019)	Closing prices on 88 bitcoin exchanges	Integer prices are 18% of trades (vs. expected 1%)	18	Not attempted
Gao, Lu, & Ni (2019)	Chinese IPO bids			
Lien, Hung, & Hung (2019)	Taiwan SE limit orders	Round number prices are 8.93% higher than expected		Traders classified as mutual funds, foreign investors (experts), individuals
Griffin et al. (2023)				
Current Research	FINRA/SEC Bluesheets for US Equities	Integers are 3.73% of trades	3.73	Accounts linked to institutional or individual investors; for individuals, demographic characteristics (age, gender, etc.) are available and inferred

Note. When a paper gives multiple prevalence estimates, we report the estimate for integer trades. If there are multiple integer trade estimates, we select the estimate we believe reflects the largest sample of the analyzed data. Deviations are authors' calculations based on expected probability of prices.
*On the Tokyo Stock Exchange, all prices are integers.
SE = Stock Exchange.

In documenting the prevalence of round number trading, we also examine variation across transaction prices. Existing research has examined the relationship between rounding and price level, generally finding a positive relationship. Specifically, there is evidence of increased rounding with price level for stock prices (Harris, 1991), Bitcoin (Urquhart, 2017), IPO limit order price submissions (Kandel, Sarig, & Wohl, 2001). Blau and Griffith (2016) also report a positive correlation between clustering and prices, although this is not the central focus of their research.

One notable exception to this literature is Baig, Blau & Sabah (2019), who show *decreased* rounding by price for Bitcoin. Finally, there is some evidence for a more nuanced relationship; for example, in univariate analysis, Ikenberry & Weston (2008) show decreased round number trading for NYSE and Nasdaq stocks with higher prices, but this pattern reverses after controlling for firm size and other factors.

We find as prices increase, so does the prevalence of round number trading, consistent with much of this literature. We add to these findings by documenting the prevalence of round number trading at different levels of granularity. Notably, it is the coarsest levels of rounding (at integers and 50-cent prices) that show the most extreme positive relationships with prices. The relationship between rounding and price is much more muted when examining riding to 5- or 10-cent increments.

Demographic Variation and Heterogeneity

Our second contribution is to describe the demographic correlates of round number trading among individual investors. A number of prior studies have described relationships between round number trading and institution type, showing that institutions are much less likely to trade at integer prices than individual investors, presumably because institutions have greater capacity to process financial information and therefore submit transactions at more precise prices (Chiao and Wang, 2009; Kuo et al., 2015). However, as reflected in Table 1, attempts to identify individual investors have been limited to binary comparisons between institutions and individual investors, likely because personal characteristics are seldom available in financial market data.

Given the limitations of past work, the closest research may be that which examines the characteristics of individuals across other types of financial market transactions. For instance, literature has explored how financial decisions vary across the life cycle. Broadly, this work examines decreased decision quality among the elderly, possibly due to cognitive decline (Korniotis and Kumar 2011), as well as increased speculative trading patterns (e.g., turnover and volatility) among the young (Barber and Odean 2001). When combined, these two patterns mean that some investment mistakes are lowest among the middle aged (Bateman, et al. 2016, citing Agarwal et al. 2009). If round number trading stems from limited cognitive resources, we would expect increased rounding among the elderly; in contrast, if it reflects rapid decision-making or speculative trading, it could be inflated among the young. In fact, our research shows a strong decrease in round number trading with age, with rounding being approximately twice as likely among those aged 18-23 versus those aged 66 or older.

Research has also examined gender differences in financial decision-making, concentrating primarily on knowledge and confidence gaps in investing (Lewellen et al. 1977; Barber & Odean, 2001), and stock market participation (XXX). Barber and Odean (2001), for instance, show that men are more likely to trade -- although these trades do not earn them superior returns. Those authors discuss mens' higher expectation for market overperformance, citing data from Gallup surveys (p. 265). In nationally representative surveys, men also report more optimistic expectations for future stock market performance than women (Chin, et al., 2025; Dominitz & Manski, 2011). If rounding reflects rapid decision-making or overconfidence, it is possible that it would also show inflated levels in men. Consistent with this thinking, we find that round number trading is slightly more prevalent for male investors.

Finally, we examine race and ethnicity differences in round number trading. There are large racial and ethnic differences in stock market participation in the U.S., in terms of account ownership and wealth levels (XXX). There are also racial and ethnic differences in subjective factors like trust, which correlates with use of financial advisors and account ownership (Carman & Cook, 2025). It is unclear how these demographic differences would affect round number trading; thus, we provide descriptive evidence across race and ethnicity.

Trade-Level Correlates of Round Number Trading

Our third major contribution is to document trade-level correlates of round number trading, a topic which has received relatively less attention in the scholarly literature, despite these characteristics affecting a number of trading decisions. Early work on context effects examined gain or loss trading contexts, identifying a tendency to sell stock winners too soon and hold losing stocks too long--in other words, the gain or loss frame under which a retail investor finds themselves affects their disposition likelihood (Barber and Odean 1999). More recent work has shown variables external to the security itself can impact behavior. In particular, Barber et al. (2022) observe that trading app features may increase speculative trading goals.

Our analysis is driven by characteristics that could change for a given investor from one trade to another: account type (retirement and non-retirement accounts), transaction size (measured in terms of dollars), and transaction type (buy, sell, or short). Related to retirement accounts, Barber and Odean (2000) observe that taxable (vs. tax deferred) accounts have a stronger tilt toward small growth firms and higher turnover. The authors conclude that investors associate their retirement accounts "with future safety and therefore trade less speculatively in these accounts" (p. 23). Linnainmaa et al. (2021) observe lower turnover tendencies in retirement accounts versus other general accounts, also reflecting a decreased speculative trading likelihood. To our knowledge, no past research has examined account type and round number trading. Given that omission, we suggest that if account goals encourage long term planning rather than impulsive, short term speculative trading, then we might see less round number trading in accounts explicitly designated for retirement (e.g., 401k's).

Ahn, Cai, and Cheung (2005) examine the transaction prices and quote prices on the Stock Exchange of Hong Kong; in this market, short sales are prohibited for a subset of the market. They compare price clustering among these stocks, versus others, finding… Both transaction and limit order quote prices exhibit clustering. Limit order quote prices exhibit greater clustering, particularly those further away from the best price--the authors speculate that such investors are less certain about the underlying value of the stock, leading to rounder number submissions. [The limit order/market order nature of some of the patterns in Table 1 might also suggest that rounding would be more common when people are setting prices(?)] Chiao & Wang (2009) and Kuo et al. (2015) also observe limit order clustering, particularly for individual investors (Chiao and Wang). If limit order quotes reflect an investor's purposeful number selection, we might expect to see higher levels of round number trades for other quote trades [is that the right term, eg.., shorts and limits?] such as selecting a price when shorting a stock.

Research Overview

We examine round number trading in the U.S. stock market by analyzing Electronic Blue Sheets (EBS) account-level trading data collected by financial market regulators, the Financial Industry Regulatory Authority (FINRA) and the Securities and Exchange Commission (SEC), to examine market activity. EBS data contain individual and account-level identifiers, allowing us to identify trades performed by a given person, institution, or account over time. For accounts held by individuals, demographic characteristics are observable or derived via probabilistic bayesian inference. We analyze transactions occurring between July 2019 to June 2020, yielding about 134 million transactions in 20 million accounts.

We have four primary research questions: Are trading data from known individuals and institutions consistent with increased round-number trading? If so, how does round number trading vary across transaction price? Which types of individual investors are most likely to exhibit that behavior? And finally, which trade-level factors vary with round number trading?

Data and Methods

Electronic Blue Sheets Data

Firms, such as broker-dealers and clearinghouses, provide EBS data in response to regulatory requests from FINRA or the SEC. The data typically contain information including the identity of the security that was traded, customer-level and account identifiers, the number of shares that were traded, the time that the transaction occurred, the direction of trade, and the price. Dollar prices greater than four digits are truncated, so prices of $10,000 and more are not routinely recorded.[1]

The data captured in EBS are monitored for accuracy, and firms can face consequences for failing to respond to EBS requests or if the data they provide is found to be incomplete or insufficient. For example, both Citigroup and Credit Suisse paid multi-million dollar fines for submitting insufficient EBS information (SEC 2015, 2016). Recently, both Wells-Fargo and LPL Financial paid a lesser fine, since the errors were discovered and self-reported deficient trading data (SEC, 2024). More information about EBS data is available at FINRA (2024a; 2024b).

Trade Aggregation

For computational feasibility, EBS data are stored at an account-security-date-direction transaction level. Transaction prices are averaged when a single account transacts multiple times in a particular security, on the same day, in the same direction (i.e., “buy,” “sell,” and “short” are each a unique direction). We omit averaged transactions to ensure we are analyzing disaggregated prices.

Variable Construction for Analysis

Round Number Trades

Consistent with prior literature (e.g., Ap Gwilym et al., 1998; Bhattacharya et al., 2012), we define “round number prices” as those ending in a “0” or “5”; for example, a transaction occurring at $1.25 is considered round. We also examine transactions occurring at “rounder,” more fluently processed “integer prices” (e.g., $1.00; Loschelder et al., 2014; Loschelder et al., 2016), which are a subset of round number prices commonly examined in literature on round number trades (see Table 1).

Account Type Determination: Individual vs. Entity

In EBS data, clearing broker-dealer (BD) firms are required to categorize reported trade records by the account type of customers. Specifically, BDs must indicate if the tax-identification number (TIN) of the account holder is a Social Security Number or Taxpayer ID, which are interpreted as the categories “Individual” or “Entity” respectively.[2] When this data field is missing, the value “NA” is assigned.

Age from Social Security Numbers

---

[1] We do not believe that such truncation would meaningfully affect the pattern of our results, as the transaction volume declines at higher values (e.g., only 5 million trades occurring at $1,000 or more, versus over 800 million occurring between $10 and $100; see Figure 2). Any additional examination above the $10,000 threshold would likely represent a small trade volume.

[2] See https://www.finra.org/rules-guidance/notices/20-19

Social Security Numbers (SSNs) can be used to estimate account owner age (Block et al., 1983; Cabasag et al., 2016). SSNs issued prior to 2014 can be associated with particular Social Security Administration (SSA) offices, and the sequence of digits indicates the order in which the numbers were assigned. This regionally and sequentially encoded structure to pre-2014 SSNs aids researchers in making strong relative inferences about the age of the individuals holding a particular SSN. By leveraging over 40 million SSNs within the EBS data, and in comparing them with more than 5 million "true positive" SSNs (where the exact age of the individual has been confirmed by broker dealers [BDs]), we implement a similar method of estimating the age of individuals represented in EBS data.

Gender and Race/Ethnicity

Utilizing long-established inference techniques, we probabilistically inferred gender based on the predicted first name from the "account name" fields in conjunction with first name-gender frequencies over time that are established by U.S. Census Bureau records (Blevins and Mullen, 2015; Mihaljevic et al., 2019). Similarly, race and ethnicity were probabilistically inferred from the predicted last names from the "account name" fields in conjunction with last name-race/ethnicity frequencies over time that are established by U.S. Census Bureau records (Imai and Khanna, 2016; Xie, 2022).

Determining Retirement Accounts

Keyword-driven Natural Language Processing (NLP) was used to categorize whether an account was retirement-related. By scanning for specific stop words within the account title descriptions, such as '401k', 'IRA', 'Roth', '457', '403b', 'thrift savings', and others, we were able to classify accounts as retirement or non-retirement.

Results

Table 2 shows descriptive statistics across transaction and account levels for the EBS data. As shown in the table, the age and race/ethnicity breakdown are similar across transactions and accounts. Men perform somewhat more (and women somewhat fewer) transactions. Additionally, more transactions are performed outside of retirement accounts than inside.

Table 2. Sample descriptive statistics at the transaction and accounts levels, for accounts held by individuals.

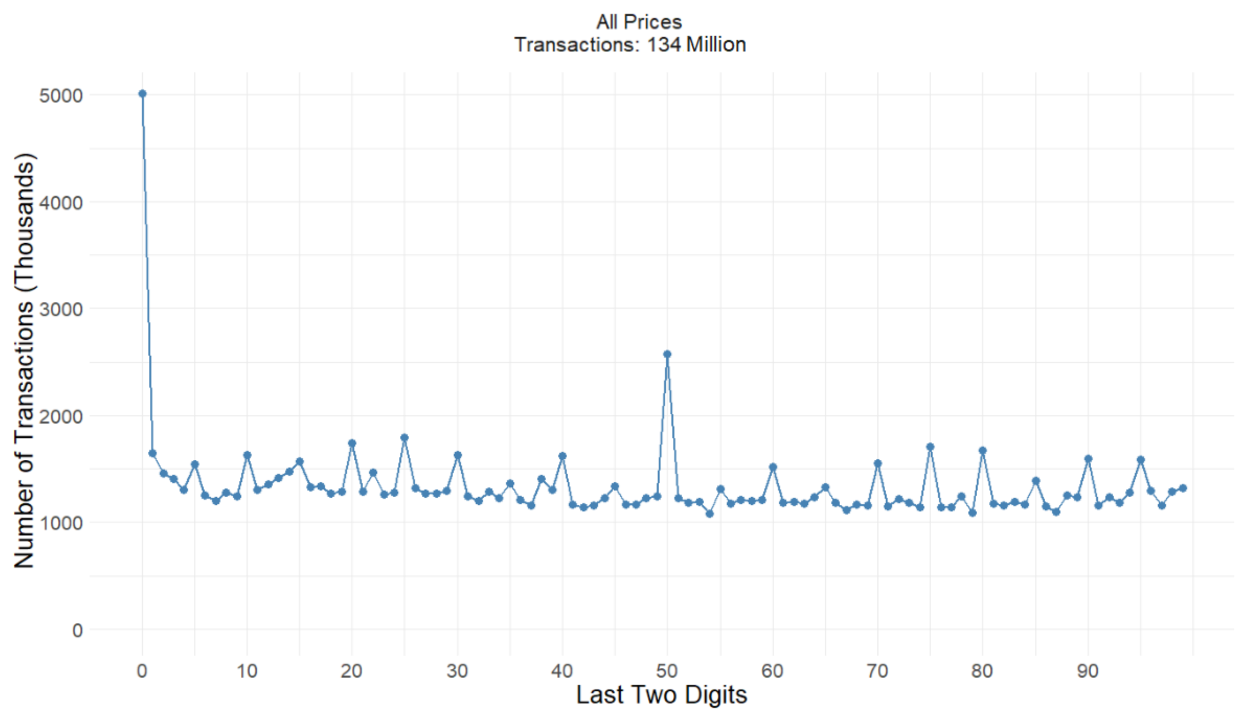
	Transaction Level	Account Level
Age Range (Median)	48-53	48-53
Gender	Male 67.5% Female 22.7% N/A 9.8%	Male 64.1% Female 27.7% N/A 8.3%
Ethnicity	White 64.5% Black 11.1% Asian 11.7% Hispanic 10.1%	White 64.5% Black 11.0% Asian 11.6% Hispanic 10.1%

	Other 2.7%	Other 2.7%
Retirement Account	22.6%	29.1%
Transaction Type	57.7% 41.7% .6%	--
Transaction Dollar Volume - Average (Median)	$4,419 ($462)	--
Transaction Price - Average (Median)	$68.74 ($23.77)	--

Prevalence of Round Number Trades and Moderation by Price

We first examine the volume of trades at one-cent price increments to confirm that statistics from our granular microdata reflect increased rounding at prices ending in 0 or 5 (Figure 1). As shown, the number of trades at each one-cent value shows a non-uniform distribution, with obvious spikes in volume at certain round price values (Figure 1). Transaction volume is particularly large at integers (i.e., values ending in $X.00). There are also more than 2 million transactions occurring at values ending in 50 cents, compared to fewer than 1.5 million occurring at values ending in 49 cents.

Figure 1. Volume of Transactions Occurring at Each Price by Last Two Digits.



Note. This figure displays transaction volume (in thousands) for individuals and institutions at different price points. The x-axis shows price values trailing the decimal place; for instance, "50" includes transactions occurring at prices such as $1.50 or $2.50.

Put another way, 3.73% of transactions occur at integers, versus the 1% that would be consistent with no bias (as, under a null hypothesis, each trade has a 1% chance of ending on an integer price), representing a 273% deviation in expected volume (Table 3). Additionally, 5.64% of trades occur at 50-cent increments (representing a 464% deviation), suggesting that the bias toward round numbers is prevalent across different round number types. In total, 21.34% of trades are round, versus the 20% that would be consistent with no bias, representing a 6.7% deviation in the expected volume. Simple proportion tests show that all of these deviations are statistically significant (all *p*s < .001).

Table 3. Round number trades are more likely than predicted under financial market theory.

	Percent of trades occurring at this price	Predicted percent of trades occurring with no round number bias	Deviation in percentage points	Ratio of Actual to Expected Incidence
Ending in $.00 exactly (integers)	3.73	1.00	2.73	3.73
Ending in $.50 exactly	5.64	1.00	4.64	
All 10 cent increments	12.67	10.00	2.67	1.27
All 5 cent increments	21.34	20.00	1.34	1.07

Note: Statistics are across individuals and entities. The last column includes one-sample proportion tests of transaction volume versus predicted percent of trades. *** $p < .001$

Prevalence of Rounding by Transaction Price

In Figure 2, we show the same breakdown of transaction volume as in Figure 1, divided over four mutually exclusive price intervals: those for stocks that cost less than $10, between $10 and $99.99, between $100 and $999.99, and more than $1,000. Each of the four plots shows pronounced spikes at integer and 50-cent values; Kolmogorov-Smirnov tests confirm that rounding is significantly greater than expected (*p*s < .001; see Supplementary Information Table S1).

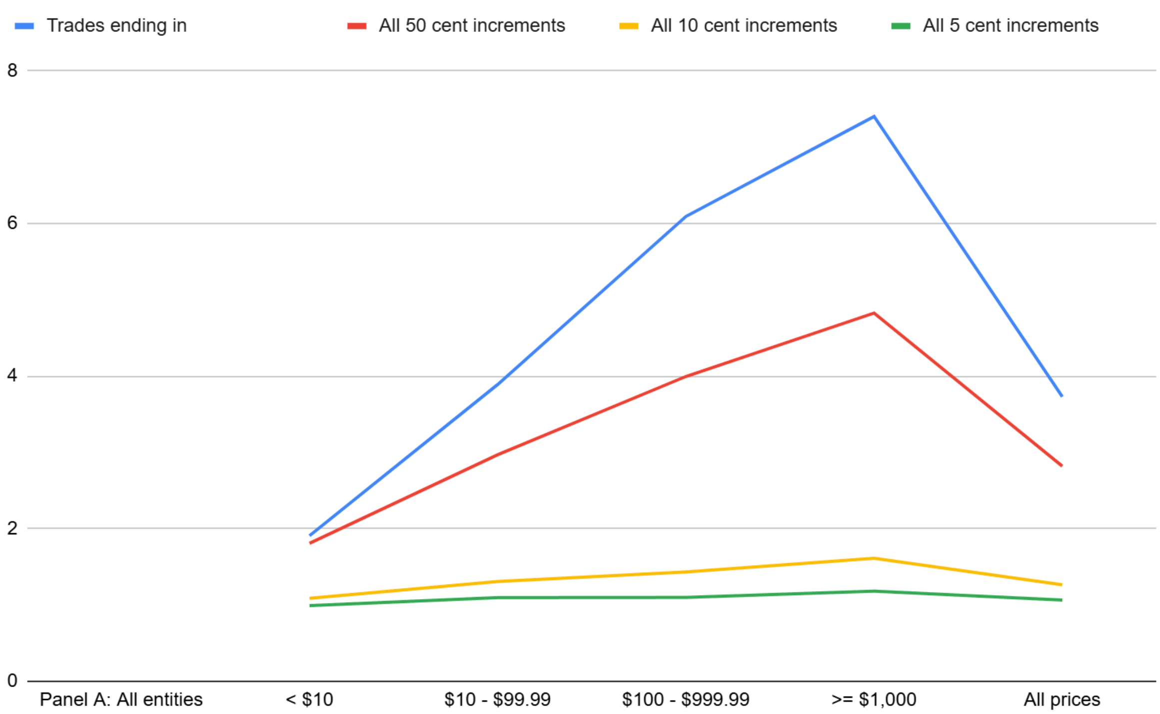
Figure 3 shows the ratios of the proportion of rounded prices, relative to the expected proportion of rounded prices, across these four price bands. As shown, the level of 10-cent and 5-cent rounding is relatively flat across transaction price. In contrast, rounding to integers and 50-cent price trades are strictly increasing by price band, demonstrating that such rounding is more common as prices increase.

Table S1 provides an additional breakdown of the transaction volume between individuals and entities, showing that, even among institutions, integer and 50-cent price trades are approximately twice as likely as expected. In general, for both individuals and entities, the percentage of round number trades increases with higher price intervals.

Figure 2. Round Number Bias, Particularly for Integer Prices, is Greater in Higher Price Ranges.

Note. This figure displays transaction volume (in thousands) for individuals and institutions at different price points and in different price ranges. The x-axis shows price values trailing the decimal place; for instance, "50" includes transactions occurring at prices such as $1.50 or $2.50.

Figure 3. Rounded transactions relative to expected rounded transactions, by price band.



Heterogeneity in Round Number Trades across Investor Types

Our data allow us to directly identify individual and institutional investors. Given the limited past literature showing increased rounding among individual investors (Table 1; cf. Chiao & Wang, 2009; Kuo et al., 2015; Lien et al., 2019), we first explore whether round number trades vary across these entity types. Table 4, Model 1 shows that integer trades are about twice as prevalent among individual investors (vs. institutional investors) and round number trades are about 18% more likely for individuals (Model 2). Both types of round number trading are also more prevalent among those entities that are not identified as individuals or institutions, versus institutional investors.

Table 4. Linear probability model predicting integer and round number price trades among institutions and individuals.

	Model 1: Integer price trades		Model 2: Round number price trades	
Indicator	B	s.e.	B	s.e.
Investor type (Ref: Institutional)				
Individual	.0183***	.0003	.0354***	.0006
NA	.0080***	.0006	.0132***	.0012
Constant	.0235***	.0003	.1869***	.0006
N transactions	134,066,741		134,066,741	
N accounts	20,798,516		20,798,516	

Note. *** $p < .001$. Regressions include clustered standard errors at the account level.

Among individual investors, there is significant heterogeneity in rounding. As shown in Table 5, the demographic characteristics predicting rounding are largely consistent across integer and round number trades (Model 1 and Model 3). The dominant pattern is by age; integer price trades are nearly twice as likely for young investors as older ones (i.e., an estimated increase of approximately 5.4% for those aged 18-23, vs. less than 3.3% for those aged 66+). There are also small differences in terms of gender and race, as integer price trades are 0.01 percentage points more likely among men than women and white investors (vs. Black and Hispanic investors).

The same patterns occur for all round number price trades (Model 3); that is, men (B = .003, SE = .000; Model 2) and younger investors exhibit higher propensity to trade at round number prices (i.e., approximately 24% of transactions are round for those aged 18-23, vs. less than 21% for those aged 66+).

Table 5. Linear Probability Regressions Predicting Integer and Round Price Trades.

Indicator	Integer price trades				Round number price trades			
	(1)		(2)		(3)		(4)	
Gender (Ref: Female)	B	s.e.	B	s.e.	B	s.e.	B	s.e.
Male	.0009***	.0001	-.0002*	.0001	.0027***	.0002	.0012***	.0002
NA	.0134***	.0002	.0066***	.0002	.0238***	.0004	.0149***	.0004
Ethnicity (Ref: White)								
Black	-.0005***	.0001	-.0002	.0001	-.0005	.0002	-.0001	.0002
Asian	.0002	.0001	-.0008***	.0002	-.0002	.0003	-.0015***	.0003
Hispanic	-.0002*	.0001	-.0000	.0001	-.0005*	.0002	-.0002	.0002
Other	-.0001	.0002	-.0002	.0002	-.0000	.0004	-.0001	.0004
Age bucket (Ref: 18-23)								
24-29	.0006	.0013	.0003	.0016	.0010	.0023	.0006	.0028
30-35	-.0004	.0012	-.0014	.0014	-.0014	.0022	-.0026	.0025
36-41	-.0085***	.0012	-.0007***	.0014	-.0136***	.0021	-.0119***	.0024
42-47	-.0116***	.0012	-.0113***	.0014	-.0182***	.0021	-.0179***	.0024
48-53	-.0124***	.0012	-.0163***	.0014	-.0202***	.0021	-.0252***	.0024
54-59	-.0151***	.0012	-.0235***	.0014	-.0265***	.0021	-.0371***	.0024
60-65	-.0170***	.0012	-.0282***	.0014	-.0306***	.0022	-.0447***	.0025
66-71	-.0209***	.0012	-.0330***	.0014	-.0380***	.0021	-.0531***	.0024
72-77	-.0230***	.0012	-.0356***	.0014	-.0417***	.0021	-.0573***	.0024
78-83	-.0248***	.0012	-.0379***	.0014	-.0454***	.0022	-.0618***	.0024
84-89	-.0280***	.0012	-.0418***	.0014	-.0520***	.0022	-.0691***	.0025
90+	-.0296***	.0013	-.0436***	.0014	-.0565***	.0023	-.0739***	.0026

Retirement Status (Ref: Not retired)			-.0048***	.0001			-.0067***	.0002
Side (Ref: Buy)								
Sell			-.0043***	.0000			-.0109***	.0001
Short			.0085***	.0010			.0153***	.0016
Log(dollars)			.0086***	.0000			.0112***	.0000
Constant	.0535***	.002	.0112***	.0014	.2418***	.0021	.1890***	.0024
R2	.0016		.0103		.0012		.0048	

*** $p < .001$, ** $p < .01$, * $p < .05$
Note. Regressions include 95,534,324 transactions and 18,997,768 accounts. Regressions include clustered standard errors at the account level.

Heterogeneity in Round Number Bias across Trade-Level Characteristics

In Table 5, we also introduce a set of variables to examine trade-level characteristics: retirement account status, trade side (i.e., buy, sell, or short) and transaction size (log dollars). Prior research has utilized transaction size as an indicator for investor experience and transaction risk. When including these variables in our regressions (Models 2 and 4), we observe many consistencies in our effects. For example, older investors still exhibit less integer trading, and this pattern is exacerbated relative to Model 1. We also find that integer trading is less likely in retirement accounts, less likely when selling stocks (versus buying), and more likely when shorting. Interestingly, we observe a directional flip in the effect of men's trading. Instead of exhibiting more integer trades, men exhibit less, when controlling for transaction size (Model 2).

A model examining all round number trades (as opposed to integer trades), while accounting for demographic and trade-level characteristics, is shown in Model 4. Round number trading is less likely in retirement accounts and less when selling stocks. Such trading is also more likely when investors are shorting. Finally, in contrast to integer trades, Model 4 shows that men conduct more round number trades.

General Discussion

We address gaps in existing research on round number price trades by providing a rich empirical account of such trading in U.S. equity markets. We concentrate on three primary findings. First, we find elevated levels of round number trading relative to what would be predicted under the efficient markets hypothesis, a pattern consistent with a breadth of literature on price clustering (Table 1); integer trades are about three times as likely as expected. Consistent with most past literature (e.g., Harris, 1991; Urquhart, 2017), but not all (cf., Baig, Blau & Sabah, 2019), round number trading is more common when securities have higher overall prices, and this increase is particularly pronounced for integer and 50-cent rounding, rather than all round numbers (Figure XX). Second, we newly document individual demographic heterogeneity in round number trading. While there are small differences by gender and race/ethnicity, the most prominent pattern is by age -- older investors are significantly less likely to trade at round prices, and this pattern only strengthens when adding in variables for transaction size and retirement account status that could proxy for wealth differences. Third, we find differences by trade-level variables, with rounding being more likely for higher dollar transactions, when buying or shorting (vs. selling), and in non-retirement accounts.

Implications for theory and research on rounding

As discussed above, research on price rounding largely conceives of this behavior as due to either strategic or psychological considerations. Consistent with some past research in this domain (e.g., Kandel et al. 2001; Sopranzetti & Datar, 2002) we believe that strategic considerations such as reduced negotiation effort are less likely to apply to the context that we examine. For retail and individual investors, we believe psychological considerations are the more plausible explanation for rounding. Beyond that relatively high-level consideration, however, our results speak to a number of issues that we believe could benefit from additional research and theory development.

To our knowledge, none of the existing theories fully describes or predicts reasons for why men, young investors, and white investors would engage in more round number trading, nor why such trading would differ across trade-level factors such as account type. When taken together, we suggest that our findings are consistent with a more nuanced account of investor psychology where rounding is driven partially by an interaction between speculative, short-term thinking and accessibility of certain numeric values. In particular, we generally observe higher rounding among younger investors and men, both of whom are frequently found to engage in more risk-taking behavior in both financial (Charness and Gneezy 2012) and non-financial domains (Byrnes et al. 1999). Younger investors also tend to be more likely to engage in equity markets through online platforms with limited advisor intermediation, which could drive their trading behavior toward more frequent, speculative decisions (Barber and Odean, 2001). Finally, individual brokerage account investors (vs. those trading within retirement accounts) are more likely to trade at round numbers, possibly because savings context (e.g., retirement vs. non-retirement) affects individuals' investment decision making; indeed Linnainmaa et al. (2021) observe patterns consistent with less speculative trading (e.g., lower turnover) in retirement accounts lower turnover tendencies in retirement accounts versus other general accounts. We believe this account-level finding is they are suggestive that round number trading is more of a heuristic, consistent with the attraction hypothesis (Aşçıoğlu, Comerton-Forde, & McInish, 2007), rather than a strict "constraint" account that points at information processing capacity (XXX). Better understanding each of these factors deserves additional targeted research using a variety of individual investors.

Implications for policy

Investigating investors' decision biases, and the way they vary across the population, can help identify sources of market inefficiency and household welfare losses, which may allow policymakers and other stakeholders to promote market structures and regulatory interventions that acknowledge and ameliorate these tendencies, where appropriate. From a market perspective, a bias toward round number prices may be associated with reductions in trading efficiency and liquidity that favor some market participants over others; for instance, financial institutions who are aware of this bias could trade at values slightly above or below round numbers to take advantage of increased trading volume at nearby prices (see Bhattacharya et al., 2012).

Prior research has documented large wealth transfers from investors that trade at round number prices to other financial market participants (Bhattacharya et al., 2012; Griffin et al., 2023). Furthermore, the propensity to trade at round numbers is correlated with lower investment performance, measured in terms of the economic loss on a given transaction (Kuo et al., 2015). If trading at round number prices is correlated with investor losses, the patterns that we document are consistent with previous academic findings about other behavioral phenomena, such as excessive trading, where certain demographic factors correlate with welfare-reducing financial decisions (e.g., Grinblatt and Keloharju 2009; Barber et al. 2009). Our findings further suggest that some types of investors are exhibiting round number trading, and thus experiencing the associated financial losses, more than others, while overall, most individual investors are transferring wealth to institutions.

Our results speak to the possible benefits of educating investors about strategies to reduce active decisions over prices. For instance, investors who adopt slow, steady savings strategies such as trading at specific time intervals (e.g., every two weeks) or with fixed dollar amounts (e.g., "dollar cost averaging"), rather than at specific prices, would be unlikely to exhibit round number bias. Given that individuals likely transfer wealth to institutions when trading at round numbers (Bhattacharya et al., 2012; Griffin et al., 2023), adopting long-term perspectives may help the individuals reach their long term goals more efficiently.

Limitations

Despite the advantages of our data for understanding round number trading, there are limitations to our approach. First, although we have a large and diverse set of transactions from U.S. capital markets, the EBS data are not likely to be a representative sample of U.S. investors; indeed, investors who trade more frequently are more likely to appear in the data than those who trade less frequently. If less frequent traders are more likely to trade at round prices, our results would underestimate the propensity of the average individual investor to engage in round number trading. Similarly, EBS data are not randomly collected. Regulators may take disproportionate interest in securities and events where they believe various market violations (e.g., insider trading) are likely to occur.

From a theoretical perspective, we have examined cross-sectional data and have not ascribed causality to the measures we examine, including the trade-level characteristics. It is possible that there is, for instance, a third variable driving the relationship between trading in a retirement account and (less) rounding, such as increased automaticity of trades.

Concluding Thoughts

Ultimately, we see our research as encouraging several future directions, especially concentrating on individual and trade-level factors driving round number trades. Studying these drivers of round number trading can help to inform our understanding of these trades across a variety of markets and contexts, deepening our theoretical understanding of this behavior.

References

Ahn, H. J., Cai, J., & Cheung, Y. L. (2005). Price clustering on the limit-order book: Evidence from the Stock Exchange of Hong Kong. *Journal of Financial Markets*, *8*(4), 421-451.

Alter, A. L. & Oppenheimer, D. M. Predicting short-term stock fluctuations by using processing fluency. *P Natl Acad Sci USA* **103**, 9369-9372 (2006). https://doi.org/DOI 10.1073/pnas.0601071103

Aşçıoğlu, A., Comerton-Forde, C., & McInish, T. H. (2010). An examination of minimum tick sizes on the Tokyo Stock Exchange. *Japan and the World Economy*, *22*(1), 40-48.

Baig, A., Blau, B. M., & Sabah, N. (2019). Price clustering and sentiment in bitcoin. *Finance Research Letters*, *29*, 111-116.

Barber, B. M., Huang, X., Odean, T. & Schwarz, C. Attention-Induced Trading and Returns: Evidence from Robinhood Users. *J Financ* **77**, 3141-3190 (2022). https://doi.org/10.1111/jofi.13183

Barber, B. M., Lee, Y. T., Liu, Y. J. & Odean, T. Just How Much Do Individual Investors Lose by Trading? *Rev Financ Stud* **22**, 609-632 (2009). https://doi.org/10.1093/rfs/hhn046

Barber, Brad M., and Terrance Odean. "Boys will be boys: Gender, overconfidence, and common stock investment." The quarterly journal of economics 116, no. 1 (2001): 261-292.

Barber, B. M. & Odean, T. in *Handbook of the Economics of Finance* Vol. 2, 1533-1570 (Elsevier, 2013).

Bhattacharya, U., Holden, C. W. & Jacobsen, S. Penny Wise, Dollar Foolish: Buy-Sell Imbalances On and Around Round Numbers. *Management Science* **58**, 413-431 (2012). https://doi.org/10.1287/mnsc.1110.1364

Blau, B. M., & Griffith, T. G. (2016). Price clustering and the stability of stock prices. *Journal of Business Research*, *69*(10), 3933-3942.

Blevins, C. & Mullen, L. Jane, John ... Leslie? A Historical Method for Algorithmic Gender Prediction. *Digit Humanities Q* **9** (2015).

Block, G., Matanoski, G. M. & Seltser, R. S. A method for estimating year of birth using social security number. *American journal of epidemiology* **118**, 377-395 (1983).

Bloomfield, R., O'Hara, M. & Saar, G. The "make or take" decision in an electronic market: Evidence on the evolution of liquidity. *Journal of Financial Economics* **75**, 165-199 (2005). https://doi.org/10.1016/j.jfineco.2004.07.001

Byrnes, J. P., Miller, D. C. & Schafer, W. D. Gender differences in risk taking: A meta-analysis. *Psychol Bull* **125**, 367-383 (1999). https://doi.org/Doi 10.1037/0033-2909.125.3.367

Cabasag, C. J., Ziogas, A., Shehata, M. & Anton-Culver, H. A Validation Method to Determine Missing Years of Birth in a Cohort Study of Shipyard Workers Using Social Security Number. *J Occup Environ Med* **58**, 631-635 (2016). https://doi.org/10.1097/Jom.0000000000000740

Carman, K. & Cook, J. A. (2025). Trust in Financial Services. OIAD Working Paper 2025-1.

Charness, G. & Gneezy, U. Strong Evidence for Gender Differences in Risk Taking. *Journal of Economic Behavior & Organization* **83**, 50-58 (2012). https://doi.org/10.1016/j.jebo.2011.06.007

Chiao, C. S. & Wang, Z. M. Price Clustering: Evidence Using Comprehensive Limit-Order Data. *Financ Rev* **44**, 1-29 (2009). https://doi.org/10.1111/j.1540-6288.2008.00208.x

Chin, Alycia, Eric M. VanEpps, Brian Scholl, and Steven Nash. "How should I know? Lack of confidence biases stock market expectations toward zero." *Journal of Economic Behavior & Organization* 229 (2025): 106826.

Christie, William G., and Paul H. Schultz. "Why do NASDAQ market makers avoid odd-eighth quotes?." *The Journal of Finance* 49.5 (1994): 1813-1840.

Dominitz, Jeff, and Charles F. Manski. "Measuring and interpreting expectations of equity returns." *Journal of applied econometrics* 26.3 (2011): 352-370.

Eaton, G. W., Green, T. C., Roseman, B. S. & Wu, Y. B. Retail trader sophistication and stock market quality: Evidence from brokerage outages. *Journal of Financial Economics* **146**, 502-528 (2022). https://doi.org/10.1016/j.jfineco.2022.08.002

Fama, E. F. The Behavior of Stock-Market Prices. *J Bus* **38**, 34-105 (1965). https://doi.org/Doi 10.1086/294743

Gao, S., Lu, R., & Ni, C. (2019). Institutional investors' cognitive constraints during initial public offerings. *Journal of Banking & Finance*, *108*, 105627.

Green, T. C. & Jame, R. Company name fluency, investor recognition, and firm value. *Journal of Financial Economics* **109**, 813-834 (2013). https://doi.org/10.1016/j.jfineco.2013.04.007

Griffin, J. M., Hirschey, N. & Kruger, S. Do Municipal Bond Dealers Give Their Customers "Fair and Reasonable" Pricing? *J Financ* **78**, 887-934 (2023). https://doi.org/10.1111/jofi.13214

Grinblatt, M. & Keloharju, M. Sensation Seeking, Overconfidence, and Trading Activity. *J Financ* **64**, 549-578 (2009). https://doi.org/10.1111/j.1540-6261.2009.01443.x

Harris, L. (1991). Stock price clustering and discreteness. *The Review of Financial Studies*, *4*(3), 389-415.

Holden, Sarah and Michael Bogdan. Main Street Owns Wall Street (2021). https://www.ici.org/doc-server/pdf%3A21_view_equityownership_print.pdf

Ikenberry, D. L., & Weston, J. P. (2008). Clustering in US stock prices after decimalisation. *European Financial Management*, *14*(1), 30-54.

Imai, K. & Khanna, K. Improving Ecological Inference by Predicting Individual Ethnicity from Voter Registration Records. *Polit Anal* **24**, 263-272 (2016). https://doi.org/10.1093/pan/mpw001

Kandel, Shmuel, Oded Sarig, and Avi Wohl. "Do investors prefer round stock prices? Evidence from Israeli IPO auctions." *Journal of banking & finance* 25.8 (2001): 1543-1551.

Korniotis, M., and Kumar, Alok. (2011) "Do older investors make better investment decisions?." The Review of Economics and Statistics, 93(1): 244-265.

Kuo, W. Y., Lin, T. C. & Zhao, J. Cognitive Limitation and Investment Performance: Evidence from Limit Order Clustering. *Rev Financ Stud* **28**, 838-875 (2015). https://doi.org/10.1093/rfs/hhu044

Leroy, S. F. Expectations Models of Asset Prices - a Survey of Theory. *J Financ* **37**, 185-217 (1982). https://doi.org/Doi 10.2307/2327125

Leroy, S. F. Efficient Capital-Markets and Martingales. *Journal of Economic Literature* **27**, 1583-1621 (1989).

Li, Y. *et al.* Sound credit scores and financial decisions despite cognitive aging. *P Natl Acad Sci USA* **112**, 65-69 (2015). https://doi.org/10.1073/pnas.1413570112

Lien, D., Hung, P. H., & Hung, I. C. (2019). Order price clustering, size clustering, and stock price movements: Evidence from the Taiwan Stock Exchange. *Journal of Empirical finance*, *52*, 149-177.

Linnainmaa, J. T. Do Limit Orders Alter Inferences about Investor Performance and Behavior? *J Financ* **65**, 1473-1506 (2010). https://doi.org/10.1111/j.1540-6261.2010.01576.x

Loschelder, D. D., Friese, M., Schaerer, M. & Galinsky, A. D. The Too-Much-Precision Effect: When and Why Precise Anchors Backfire With Experts. *Psychol Sci* **27**, 1573-1587 (2016). https://doi.org/10.1177/0956797616666074

Loschelder, D. D., Stuppi, J. & Trötschel, R. "(sic) 14,875?!": Precision Boosts the Anchoring Potency of First Offers. *Soc Psychol Pers Sci* **5**, 491-499 (2014). https://doi.org/10.1177/1948550613499942

Mbanga, C. L. (2019). The day-of-the-week pattern of price clustering in Bitcoin. *Applied Economics Letters*, *26*(10), 807-811.

Mihaljevic, H., Tullney, M., Santamaría, L. & Steinfeldt, C. Reflections on Gender Analyses of Bibliographic Corpora. *Front Big Data* **2** (2019). https://doi.org/ARTN 29 10.3389/fdata.2019.00029

Niederhoffer, Victor. "Clustering of stock prices." *Operations research* 13.2 (1965): 258-265.

Ohta, W. (2006). An analysis of intraday patterns in price clustering on the Tokyo Stock Exchange. *Journal of Banking & Finance*, *30*(3), 1023-1039.

Ozik, G., Sadka, R. & Shen, S. Y. Flattening the Illiquidity Curve: Retail Trading During the COVID-19 Lockdown. *J Financ Quant Anal* **56**, 2356-2388 (2021). https://doi.org/Pii S002210902100038710.1017/S0022109021000387

Samuelson, P. A. Proof That Properly Anticipated Prices Fluctuate Randomly. *Imr-Ind Manag Rev* **6**, 41-49 (1965).

Samuelson, P. A. Rational Theory of Warrant Pricing. *Imr-Ind Manag Rev* **6**, 13-32 (1965).

Samuelson, P. A. Proof That Properly Discounted Present Values of Assets Vibrate Randomly. *Bell J Econ* **4**, 369-374 (1973). https://doi.org/Doi 10.2307/3003046

Sopranzetti, B. J., & Datar, V. (2002). Price clustering in foreign exchange spot markets. *Journal of Financial Markets*, *5*(4), 411-417.

Sullivan, B., Hays, D., and Bennett, N. The Wealth of Households: 2021. *Current Population Reports*, Paper P70BR-183 (2023).

https://www.census.gov/content/dam/Census/library/publications/2023/demo/p70br-183.pdf

Survey of Consumer Finances, (2020). https://www.federalreserve.gov/publications/files/scf20.pdf

Urquhart, A. (2017). Price clustering in Bitcoin. *Economics letters*, *159*, 145-148.

Xie, F. Z. rethnicity: An R package for predicting ethnicity from names. *Softwarex* **17** (2022). https://doi.org/ARTN 10096510.1016/j.softx.2021.100965