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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 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 wealth-decreasing consequences for certain investors.

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1. Introduction

"Round number trading," the tendency for asset market participants to cluster transactions at specific, round number prices (e.g., $5.00 vs. $5.01) may increase stock market volatility [1], reduce wealth for those who engage in such trading [2], [3], and violate classical financial theories and market efficiency [4]. These consequences have led to significant interest in round number trading. Scholarship started with Osborne [5], who demonstrated disproportionate bids at integer prices in over-the-counter quotes; from there, researchers expanded their investigations of round number trading to additional stock market orders and trades [6][11], stock market futures [3], municipal bonds [12], cryptocurrency [13] [15], and foreign currency spot exchange markets [16], [17].

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. Specifically, we ask four primary research questions: (1) Are trading data from known individuals and institutions consistent with round number trading? (2) If so, how does the prevalence of round number trading vary across transaction prices? (3) What evidence is there for investor heterogeneity in round number trading? (4) And finally, which trade-level factors vary with round number trading?

1.1 Theories on the Causes of Round Number Trading

There are two broad sets of theories for why traders might select round prices: strategic maneuvering and psychological accessibility. In the former camp, Harris [6] 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 [9] and Ohta [10] similarly argue that price clustering can reduce effort. Strategic maneuvering can also occur for reasons other than effort reduction; Christie and Schultz [7], for instance, argue that collusion among market makers could lead to 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" [11], [16], or have mental constraints on information processing that would lead them to favor round numbers, in what is known as the "constraint hypothesis" [3], [18], [19].

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. [8] and Sopranzetti and Datar [17], 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 capacities or incentives to engage in strategic maneuvering, such as institutional versus individual investors. Chiao and Wang [19] and Kuo et al. [3] examine limit order data by investor type, finding increased round number trading among individual investors versus institutions. However, both papers are limited to broad classifications of individual investors versus institutions, and do not directly examine characteristics of individual investors.

While these two empirical methods provide evidence on the potential causes of round number trading, they are also limited. 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). Our paper addresses that gap.

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	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	Not attempted
Harris (1991)	Trade, bid, and ask prices on NYSE, AMEX, and NASD during week of 9/28/1987	Integers are 14.2-19.3% of prices on average (with pricing on eighths)	1.14-1.61	Not attempted
Booth et al. (2000)	Helsinki SE trades from 1993 to 1995	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 (vs. expected 10%)	2.1	Not attempted
Sopranzetti & Datar (2002)	Foreign exchange spot market indicative quotes	Integer quotes are 31.99% to 59.74% of sample (vs. expected 10%)	3.2-6.0	Not attempted
Ahn, Cai & Cheung (2005)	Limit order quote and stock trade prices on SE of Hong Kong	"Abnormal" integer price frequency of 4.85-12.21%	Varies, as tick size varies with price	Not attempted

Ohta (2006)	Stock prices on Tokyo SE, a limit order market	Prices ending in 0* are 16.6% of volume	Varies, as tick size varies with price	Not attempted
Aşçıoğlu, Comerton-Forde & McInish (2007)	Stock price bids and asks on Tokyo SE, four quotes per day	Prices ending in 0* are 15% of bids and 17% of asks (each vs. expected 10%)	1.5-1.7	Not attempted
Ikenberry & Weston (2008)	Prices for NYSE and Nasdaq stocks from 7/2002 to 12/2002	NASDAQ = 27.4% NYSE = 21.5% (each vs. expected 10%)	2.15 or 2.74	Not attempted
Chiao & Wang (2009)	Limit orders on Taiwan SE from 9/2005 to 5/2006	"Abnormal" even-price frequency of 3.6% to 6.2%	Varies, as tick size varies with price	Traders are classified as: foreign investors, mutual funds, securities dealers, corporate institutions, or individual investors
Bhattacharya et al. (2012)	Order imbalance in NYSE Trade and Quote Data	Order Imb. for .99 prices is 1.493; Imb. For .01 prices is 1.086. Traders are 27% more likely to buy just below round numbers (e.g., $4.99) and 7.6% likely to buy just above them (e.g., $5.01), compared to typical price points.	Unclear from order imb. data.	Not attempted
Kuo, Lin & Zhao (2015)	Limit orders on Taiwan Futures Exchange from 1/2003 to 9/2008	Orders ending in multiples of 100† are 3.1% of volume	3.1	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	Rounding to $.25 is 46% of prices (vs. expected 37% pre-	1.24 or 1.6	Not attempted

	from 1995 to 2012	decimalization); rounding to \$0.05 is 32% of prices (vs. expected 20% post-decimalization)		
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.	Unclear from order imb. data	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 from 5/2010-10/2018	Integer prices are 18% of trades (vs. expected 1%)	18	Not attempted
Gao, Lu, & Ni (2019)	Chinese IPO bids from 2010-2012	62.07% of bid prices at integers (vs. expected 1%)	62.07	Not attempted
Lien, Hung, & Hung (2019)	Taiwan SE limit orders from 7/2009 to 5/2015	"Abnormal" price rounding of 36.48% to 62.79%	Varies, as tick size varies with price	Traders classified as mutual funds, foreign investors (experts), individuals
Griffin et al. (2023)	Municipal bond markups, using Municipal Securities Rulemaking Board data from 7/2011-12/2017	Transactions at coarse integer prices are 8.7% to 32.4% of prices (vs. expected 12.5%)	0.70 to 2.59	Newly issued bonds are frequently issued to individual investors.
Current Research	FINRA/SEC Bluesheets for U.S. Equities	Integers are 3.73% of trades	3.73	Accounts linked to institutional or individual investors; for individuals, demographic characteristics (age, sex, 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. Aşçıoğlu et al. [11] divide prices before examining ending digits and classifying them as round.
† On the Taiwan Futures Exchange, all prices are integers. Kuo et al. [3] therefore examine rounding to multiples of 10 or 100.
SE = Stock Exchange.

1.2 Prevalence of Round Number Trading in the U.S.

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 [24][29]. 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. They therefore should 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 almost always found inflated levels of rounding when compared to theoretical levels under a uniform distribution of prices, with such rounding being 1.14 to 62 times more likely than expected. In the current research, we add to this literature by reporting a 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. We find round number trading for both entity types, and an overall prevalence estimate of approximately 3.73% for integer prices and 21.34% for round number prices in general. This is our first contribution.

1.3 Prevalence of Round Number Trading Across Transaction Price

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 [6], Bitcoin [13], and IPO limit order price submissions [8]. Blau and Griffith [1] 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 [15], 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 [18] 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 price 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 rounding to 5- or 10-cent increments.

1.4 Investor Heterogeneity

Our third contribution is to describe investor heterogeneity in round number trading. Several prior studies have described relationships between round number trading and trader category, 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 [3], [19]. However, as reflected in Table 1, attempts to identify individual investors have been limited to categorical comparisons between institutions and individual investors, likely because personal and corporate characteristics are seldom available for traders in financial market data.

Given the limitations of past work, the closest research may be that which examines the characteristics of individuals involved in financial market behaviors (i.e., other than round number trading). 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 [30], as well as increased speculative trading patterns (e.g., turnover and volatility) among the young [31]. When combined, these two patterns mean that some investment mistakes are lowest among the middle aged [32] citing [33]. 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 differences between men and women in financial decision-making, concentrating primarily on knowledge and confidence gaps in investing [31], [34] and stock market participation. Barber and Odean [31], for instance, show that men are more likely to trade -- although these trades do not earn them superior returns. Those authors discuss men's higher expectations 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 [35], [36]. If rounding reflects rapid decision-making or overconfidence, it is possible that men would round more. Consistent with this thinking, we find that round number trading is slightly more prevalent for male investors.

1.5 Trade-Level Correlates of Round Number Trading

Our fourth 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 the fact that we and prior researchers find these characteristics affect trading decisions. Early empirical work examined trading in the context of gains or losses, 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 [37]. More recent work has shown variables external to the security itself can impact behavior. In particular, Barber et al. [38] 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 direction (buy, sell, or short). Related to retirement accounts, Barber and Odean [39] 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. [40] observe lower investment turnover tendencies in retirement accounts versus other general accounts, also reflecting a decreased speculative trading likelihood. To our knowledge, no past research has examined investment 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., 401(k) accounts).

Turning to transaction size and direction, we hypothesize that both variables could proxy for investors' level of cognitive processing, consistent with psychological explanations for round number trading. Specifically, investors may spend more time considering transactions with a higher dollar volume, as the results of these transactions may have larger wealth implications. If this is the case, then we would expect a negative relationship between dollar volume and round number trading; however, we are not aware of literature examining this relationship. Transaction direction may also signal processing. Ahn, Cai, and Cheung [9] examine 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. Both transaction and limit order quote prices exhibit clustering, but limit order quote prices exhibit greater clustering, particularly those further away from the best price. The authors speculate such investors placing orders further from the best price are less certain about the underlying value of the stock, leading to rounder number submissions. Chiao & Wang [19] and Kuo et al. [3] also observe limit order clustering, particularly for individual investors. If limit order quotes reflect an investor's purposeful number selection, we might expect to see higher levels of round number trades for other types of trades where price is prespecified (e.g., shorting a stock).

1.6 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. 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 [2]. As such, our analyses also point to potential wealth-decreasing implications for many investors.

2. Data and Methods

2.1 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 [41], [42]. Recently, both Wells-Fargo and LPL Financial also paid fines, for self-reported deficient trading data [43]. More information about EBS data is available at FINRA [44][45].

2.2 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.

2.3 Variable Construction for Analysis

2.3.1 Round Number Trades

Consistent with prior literature [2], [46], 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)[47], [48], which are a subset of round number prices commonly examined in literature on round number trades (see Table 1).

2.3.2 Account Type Determination: Individual vs. Institution

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 "Institution" respectively.[2] When this data field is missing, the value "NA" is assigned.

2.3.3 Age from Social Security Numbers

Social Security Numbers (SSNs) can be used to estimate account owner age [49], [50]. 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

[1] We do not believe that such truncation would meaningly 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] The "Institution" category is coded as "Entity," but we change the nomenclature for clarification. For more information, see https://www.finra.org/rules-guidance/notices/20-19

[BDs]), we implement a similar method of estimating the age of individuals represented in EBS data.

2.3.4 Sex

Utilizing long-established inference techniques, we probabilistically inferred male/female classification based on the predicted first name from the "account name" fields in conjunction with first name-sex frequencies over time that are established by U.S. Census Bureau records [51], [52].

2.3.5 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.

3. Results

Table 2 shows descriptive statistics across transaction and account levels for the EBS data. As shown in the table, the age breakdown is 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.

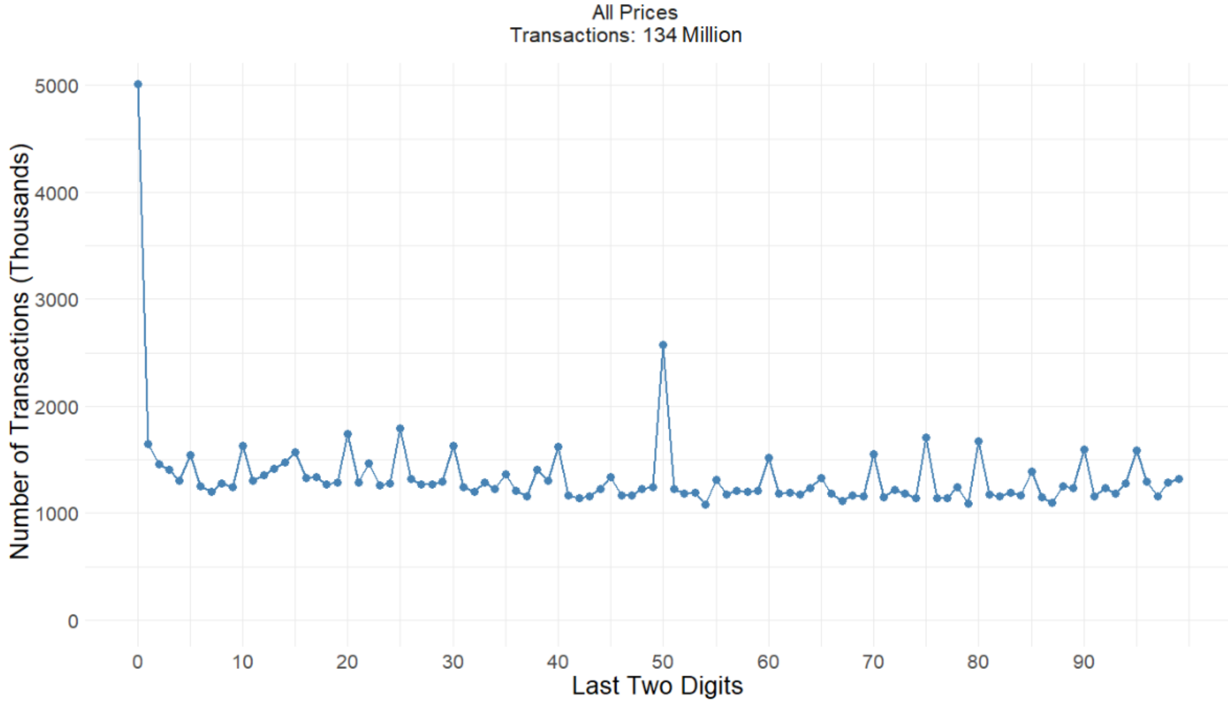
Table 2. Sample descriptive statistics at the transaction and accounts levels, for accounts held by individuals.

	Transaction Level	**Account Level**
Age Range (Median)	48-53	48-53
Sex	Male 67.5% Female 22.7% N/A 9.8%	Male 64.1% Female 27.7% N/A 8.3%
Retirement Account	22.6%	29.1%
Transaction Type	Buy 57.7% Sell 41.7% Short .6%	--
Transaction Dollar Volume - Average (Median)	$4,419 ($462)	--
Transaction Price - Average (Median)	$68.74 ($23.77)	--

3.1 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.

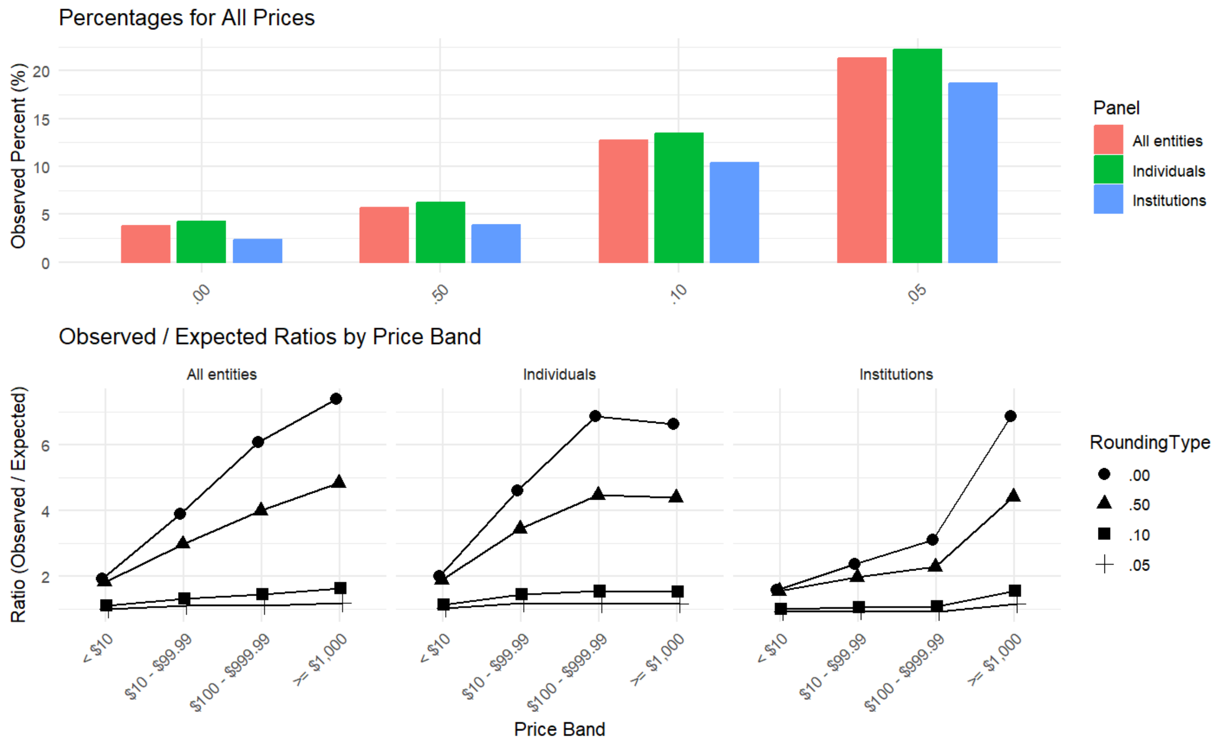
Figure 1. Volume of Transactions Occurring at Each Price by Last Two Digits.



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). Similarly, 5.64% of trades occur at 50-cent increments (including integers) and in total, 21.34% of trades are round (see red bars in Figure 2). Simple proportion tests show that these deviations are statistically significant (all ps < .001).

Figure 2. Rounded transactions relative to expected rounded transactions, by price band.



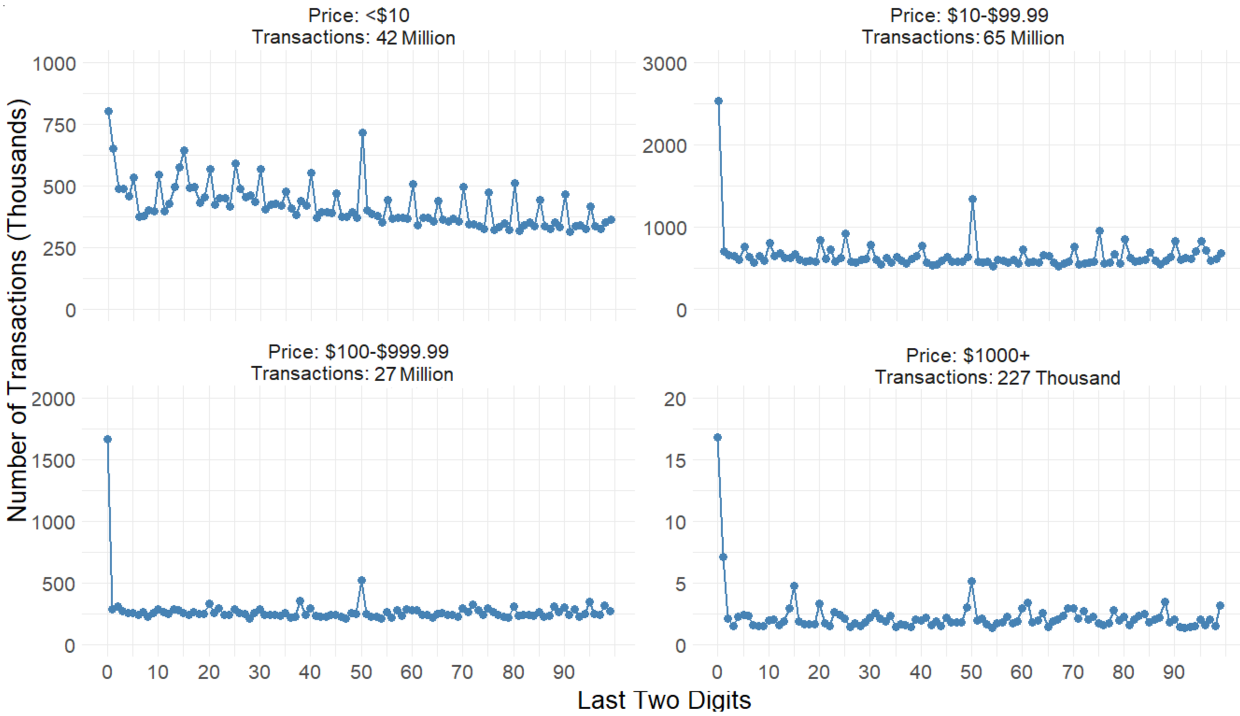
Note. The top panel shows the observed percent of prices occurring at each degree of rounding. ".00" denotes trades at integer prices, ".50" to each 50-cent increment (i.e., integers or values ending in 50 cents), ".10" to each 10-cent increment, and ".05" to each 5-cent increment. The bottom panel shows the ratio of observed to expected trades (under a uniform distribution), across different price bands. For example, the upper right point in the "All entities" panel shows that integer trades made up over 7% of expected volume (i.e., 7% observed / 1% expected under a null hypothesis) for transactions that occurred at prices ≥ $1000.

3.2 Prevalence of Rounding by Transaction Price

In Figure 3, 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 per share, between $10 and $99.99, between $100 and $999.99, and equal to or greater than $1,000. Each of the four plots shows pronounced and relatively increasing spikes at integer and 50-cent values; Kolmogorov-Smirnov tests confirm that rounding is significantly greater than expected ($ps < .001$).

The bottom panel of Figure 2 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 bands, albeit higher than expectation at all levels. In contrast, rounding to integers and 50-cent price trades are increasing by price band, demonstrating that such rounding is more common as prices increase. Possibly, as transaction prices increase, mental limitations on numeric processing increase rounding to coarser values. This increased rounding across price bands occurs markedly for both individuals and institutions, although rounding among institutions appears to be pronounced especially for transaction prices above $1,000. The fact that at the highest price band, institutions trade at round prices with slightly greater frequency than individuals, may suggest that limitations to cognitive processing may not fully explain these clear patterns.

Figure 3. Round Number Trading, 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.

3.3 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 investor types (Table 1; cf. [3], [19], [23]), and with no such studies on U.S. equity markets, we first explore whether round number trades vary by this classification. The top panel of Figure 2 provides a breakdown of the transaction volume between individuals and institutions, showing that rounding is higher among individuals than institutions. Yet, even among institutions, integer and 50-cent price trades are at least twice as likely as expected.

Table 4, Model 1 shows that integer priced 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 investors that are not identified as individuals or institutions.

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 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+, assuming a female trader). There are also small differences in terms of sex, as integer price trades are 0.01 percentage points more likely among men than women.

The same patterns occur for all round number price trades (Model 3); that is, men 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.

	Integer price trades				Round number price trades			
Indicator	(1)		(2)		(3)		(4)	
Sex (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
Age (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***	.0025
42-47	-.0116***	.0012	-.0113***	.0014	-.0183***	.0021	-.0179***	.0024
48-53	-.0124***	.0012	-.0163***	.0014	-.0202***	.0021	-.0252***	.0025
54-59	-.0151***	.0012	-.0235***	.0014	-.0265***	.0021	-.0371***	.0025
60-65	-.0170***	.0012	-.0282***	.0014	-.0306***	.0022	-.0447***	.0025
66-71	-.0209***	.0012	-.0330***	.0014	-.0380***	.0021	-.0531***	.0025

72-77	-.0230***	.0012	-.0356***	.0014	-.0417***	.0021	-.0573***	.0025
78-83	-.0248***	.0012	-.0379***	.0014	-.0454***	.0022	-.0618***	.0025
84-89	-.0280***	.0012	-.0418***	.0014	-.0520***	.0022	-.0691***	.0025
90+	-.0296***	.0012	-.0436***	.0015	-.0565***	.0023	-.0739***	.0026
Retirement Status (Ref: Not retired)			-.0048***	.0000			-.0067***	.0002
Side (Ref: Buy)								
Sell			-.0043***	.0000			-.0109***	.0001
Short			.0085***	.0010			.0153***	.0016
Log(dollars)			.0086***	.0000			.0112***	.0000
Constant	.0534***	.0012	.0110***	.0014	.2418***	.0021	.1890***	.0024
R2	.0016		.0103		.0012		.0048	

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

3.4 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, outside the context of price clustering, has utilized transaction size as an indicator for investor experience [53], [54] and transaction risk. When including these variables in our regressions (Models 2 and 4), we observe several important changes in our estimated effects. Older investors still exhibit far less integer trading than younger investors, 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 trade-level factors (Model 2), albeit the estimate is of small magnitude.

A model examining all round number trades (as opposed to integer trades), while accounting for individual 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. In contrast to integer trades, Model 4 shows that men are more likely to conduct round number trades, even when controlling for trade-level factors.

4. 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 use a recent, broad sample of reliable data to concentrate on four primary findings. First, we find elevated levels of round number trading relative to what would be predicted under the efficient markets hypothesis. Integer trades are nearly four times as likely as expected, an estimate that is consistent with a breadth of literature of price clustering, and that falls within the range of increased rounding we document (i.e., rounding is 0.7

to 62 times as likely as expected; Table 1). Second, consistent with most past literature [6], [13], but not all (cf., [15]), round number trading is more common when securities have higher overall prices. We newly document that this increase is particularly pronounced for integer and 50-cent rounding, rather than all round numbers and that there is variation between individuals and institutions (Figure 2). Third, we leverage our unique data set to explore investor heterogeneity in round number trading. Both individuals and institutions round at levels that are greater than expected. For individuals, 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 trade direction, transaction size and retirement account status, of which the latter two could proxy for wealth and financial sophistication differences. Fourth, 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.

4.1 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., [8], [17]), we believe that strategic considerations such as reduced negotiation effort are less likely to apply to much of the context that we examine.[3] For retail and individual investors, we believe psychological considerations are the more plausible explanation for rounding. However, the extent to which we observe institutional traders rounding their prices, particularly in higher priced transactions, implies that strategic reasons may apply or many institutions are more prone to psychological factors than prior research has described. Beyond that relatively high-level consideration, however, our results speak to several 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 or young investors would engage in more round number trading, why such trading would differ across trade-level factors such as account type, or why the overall prevalence of round number trades would vary across situations (as shown in Table 1). When taken together, we suggest that our findings are consistent with a 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 and impulsive behavior in both financial [55] and non-financial domains [56]. 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 [31]. The fact that the large age gradient we observe persists, and in fact strengthens after trade-level factors (e.g., transaction dollar volume) are controlled for, suggests that traditional proxies for financial wealth and sophistication do not attenuate this youth-driven propensity to round. Finally, individual brokerage account investors (vs. those trading within retirement accounts) are more likely to trade at round numbers, possibly because the savings context (e.g., retirement vs. non-retirement) affects individuals' investment decision making; indeed

[3] Another interpretation of our results (Figure 2) is that round number trading for institutions arises due to multiple mechanisms at different prices levels. Round number trading increases significantly at higher prices, where reducing negotiation costs might be highly efficient; at low prices, such trading may be less optimal, given the strategic advantage provided by transacting around round numbers [2].

Linnainmaa et al. [40] observe patterns consistent with less speculative trading (e.g., lower turnover) in retirement accounts versus other brokerage accounts. We believe this account-level finding suggests that round number trading is more of a heuristic, consistent with the attraction hypothesis [11], rather than a strict "constraint" account that points to information processing capacity. Better understanding of each of these factors deserves additional targeted research that focuses on a variety of individual investors and trading contexts.

4.2 Implications for Policy

Investigating investors' decision-making can help identify sources of market inefficiency and household wealth losses, which may allow policymakers and other stakeholders to promote appropriate market structures and regulatory interventions. From a market perspective, a tendency toward round number prices may be associated with reductions in trading efficiency and market liquidity that favor some market participants over others; for instance, financial institutions who are aware of round number trading could trade at prices slightly above or below round numbers to take advantage of increased volume (see [2]).

Prior research has documented large wealth transfers from investors who trade at round number prices to other financial market participants [2], [12]. 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 [3]. 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 wealth-reducing financial decisions (e.g., [57], [58]). Our findings further suggest that some types of investors are exhibiting round number trading, and thus experiencing the associated financial losses, much more than others, while overall, individual investors are disproportionately 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 trading. Given that individuals likely transfer wealth to institutions when trading at round numbers [2], [12], adopting long-term perspectives may help individuals reach their long-term goals more efficiently.

4.3 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 all 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 a disproportionate interest in securities and events where they believe various market violations (e.g., insider trading) are likely to occur. Finally, our EBS data do not allow us to distinguish limit vs. market orders, obscuring our ability to draw inferences on how this order type difference might vary with round number trading tendency, as previous literature has attempted [3]; our findings that such trading is less likely when buying than shorting may be due to market orders for purchases.

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.

4.4 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.

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