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Abstract

Trading stocks disproportionately at round number prices (e.g., $5.00 instead of $5.01, "round number bias" [RNB]) violates classical assumptions about investor rationality. However, it is unknown which individual investors engage in this bias. We examine the prevalence of RNB and how it relates to individuals' demographic and trading characteristics by analyzing novel, account-level administrative data covering over 20 million accounts and 134 million transactions. We find that integer trades are nearly four times more likely than expected and round number trades are 6.7% more likely than expected. Younger, male, and non-professional investors are much more likely to engage in RNB, particularly when buying relative to selling or shorting securities, the first time such heterogeneity has been documented. Given past findings showing large wealth transfers away from those that exhibit RNB, our results suggest potential welfare consequences for vulnerable investors.

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Introduction

Individual, non-professional investors are increasingly making trades and participating in the stock market (Barber et al., 2022; Eaton et al., 2022; Ozik et al., 2021) to finance their education, retirement, and other life goals. Indeed, more than half of US households engage directly with financial markets through their retirement accounts due to structural changes in the retirement savings ecosystem, including shifts from defined benefit to defined contribution plans for workers and automatic enrollment into retirement plans (Barber et al., 2022; Holden and Bogdan, 2021; Sullivan et al., 2023; Survey of Consumer Finances, 2023). This increasing participation, the so-called "democratization of finance," implies that a larger and more diverse group of people are actively involved in financial markets than ever before. Consequently, their collective behavior exerts a substantial impact on market dynamics (Barber et al. 2021) and carries magnified implications—both positive and negative—for individual investors with greater market exposure and more frequent engagement (Barber and Odean 2013).

In this paper, we examine a particular aspect of individual investors' trading: the tendency to cluster trades at specific, round number prices (e.g., \$5.00 vs. \$5.01), known as "round number bias." 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 this bias transferring wealth to other participants (Bhattacharya et al., 2012). Similar adverse financial outcomes have been measured for individuals in other asset markets. For example, investors who submit a higher proportion of trade orders at round number prices suffer worse investment performance in the Taiwan futures market (Kuo et al., 2015). Furthermore, Griffin et al. (2023) estimate that round number bias among investors enables excess price markups within the U.S. municipal bond market, on the order of \$870 million over the 6.5 year study period, or 21% of total markup revenue.

Our primary contributions are to measure the overall prevalence of RNB in the U.S. equities market, document its higher frequency among individual (vs. institutional) investors, and explore how it varies across traits such as age, gender, account type, and trading strategy. Exploring individual characteristics allows us to expose the likely heterogeneous welfare outcomes of RNB. Our results may thereby help financial regulators and consumer advocates devise strategies to mitigate adverse effects of this tendency for vulnerable investors. We discuss some policy implications of these findings on heterogeneity in investor behavior.

Round Number Bias: Theory and Research

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, argues that asset prices instantaneously and fully reflect all relevant information and thus the asset's fundamental (i.e., true) value of the asset (Samuelson, 1965a; 1965b; 1973; Fama, 1965; LeRoy, 1982; 1989). Under this theory, transaction prices should not have numerical focal points (i.e., trading at $5.00 should not be more likely than $5.01), as prices reflect fundamental value and random fluctuations known as "random walks."

Despite this theoretical prediction, empirical work routinely observes RNB, with trades disproportionately at integer prices and prices ending in 0 or 5. The bias has been documented for multiple financial products including stocks (Bhattacharya, Holden, and Jacobsen, 2012), stock options (Ap Gwilym et al., 1998; Kuo et al., 2015), municipal bonds (Griffin et al., 2023), and cryptocurrency (Baig et al., 2019).

Notably, prior attempts to understand heterogeneity in round number bias have been limited to binary comparisons between institutions and individual investors. This research shows 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; see Supplementary Table 2 where we replicate this pattern). This difference between institutions and individuals is consistent with evidence suggesting heuristic decision making plays a substantial role in individual financial decisions (Alter and Oppenheimer, 2006; Green and Jame, 2013).

Current Research

We examine RNB in the U.S. stock market by analyzing Electronic Blue Sheets (EBS) account-level trading data collected by financial market regulators (FINRA and the SEC) to examine market activity. EBS data contain individual and account-level identifiers, allowing us to identify trades performed by a given person, institution, and/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 ask: Are trading data from known individuals consistent with a bias toward round-number trading? Further, which types of individual investors are most likely to exhibit that behavior, and for which investment types? These questions are important for understanding investor vulnerability, given that an increasing proportion of the population is investing (Barber et al., 2022).

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 (see https://www.sec.gov/news/press-release/2015-214 and https://www.sec.gov/news/press-release/2016-138). More information about EBS data is available at: https://www.finra.org/filing-reporting/electronic-blue-sheets-ebs.

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 numbers 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).

Account Type Determination: Individual vs. Entity

[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.

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 SSNs

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 easily 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 method of estimating the age of individuals represented in EBS data. The development and testing of this estimation method over the years suggests that the inferred ages have minimal and unbiased variance, typically differing by just a few years from the actual age of the account holder.

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.

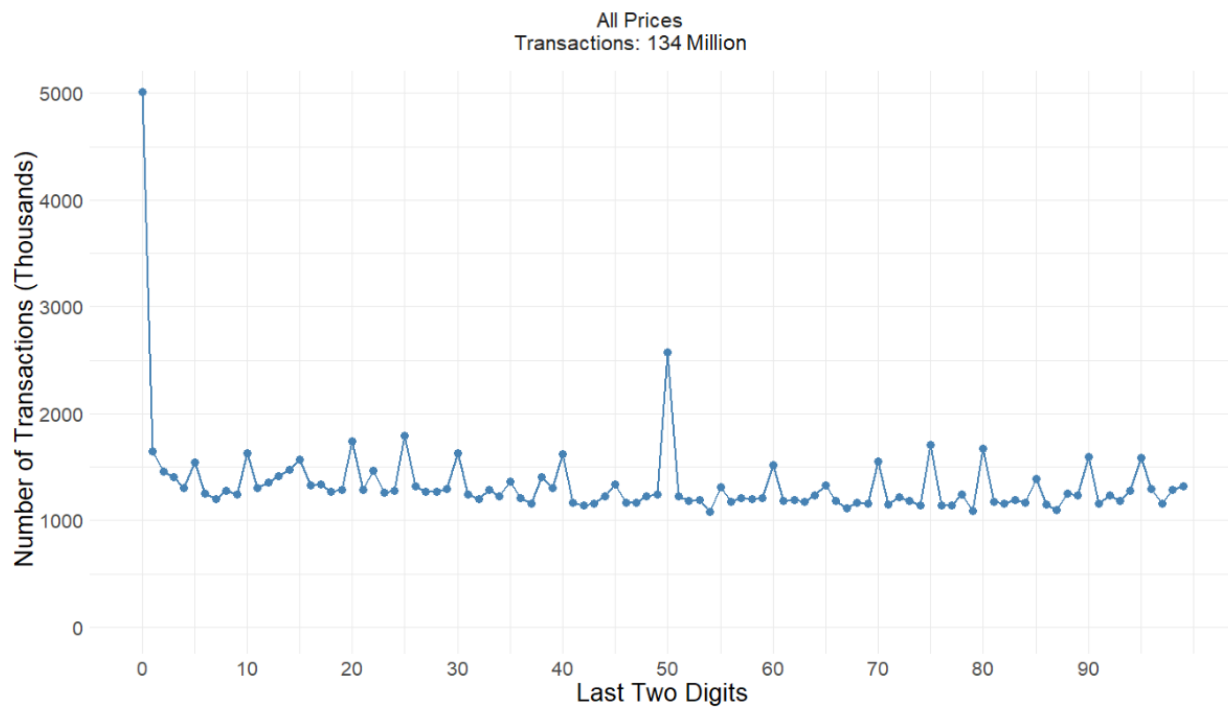
[2] See https://www.finra.org/rules-guidance/notices/20-19

Results

Prevalence of Round Number Bias and Moderation by Price

Before examining factors predicting RNB in individuals, we first examine the volume of trades at one-cent price increments to confirm our data reflect RNB trends at aggregate market level previously identified in prior work (Bhattacharya et al. 2012). As shown, the number of trades at each one-cent value is not the same, with obvious spikes in volume at certain values (Figure 1). Transaction volume is particularly strong 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 1). Additionally, 5.64% 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 (Table 1). Simple proportion tests show that all of these deviations are statistically significant (all *p*s < .001).

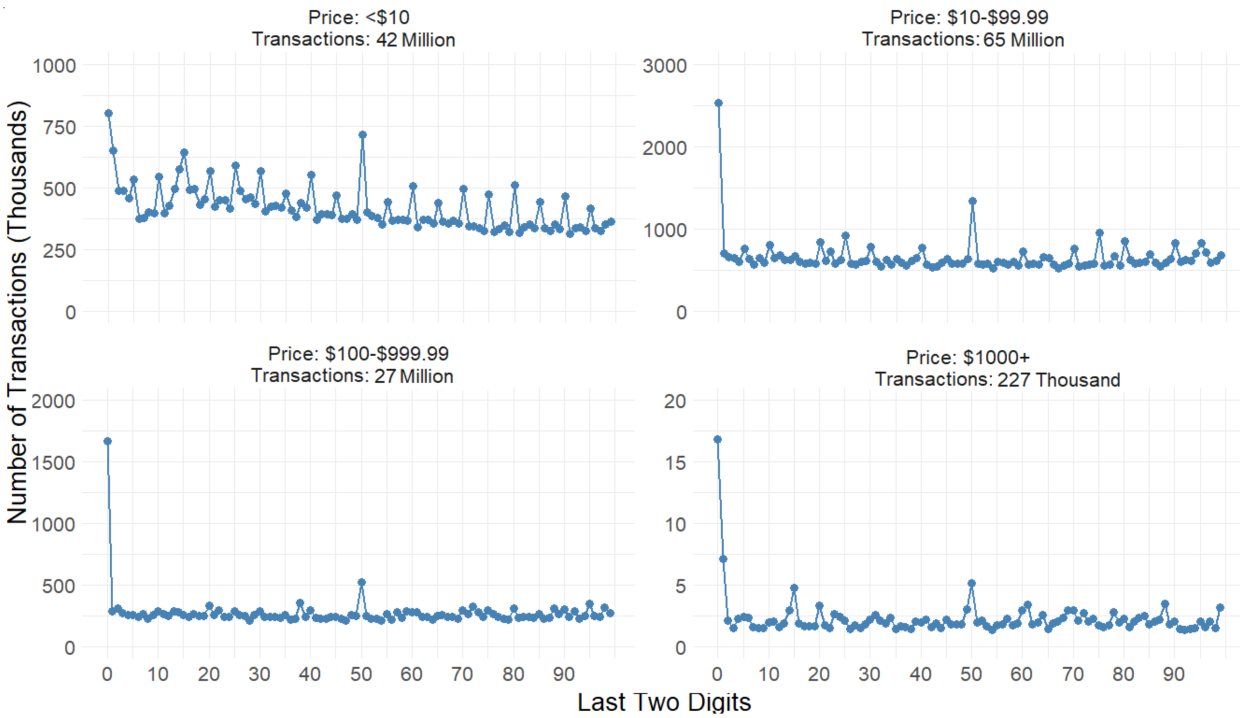
Table 1. Round number trades are more likely than predicted under financial market theory.

	Percent of trades occurring at this price	Predicted percent of trades occurring with no round number bias	Deviation in percentage points	Percent deviation between predicted and actual
Ending in $.00 exactly (integers)	3.73	1.00	2.73	273%***
Ending in $.50 exactly	5.64	1.00	4.64	464%***
All 10 cent increments	12.67	10.00	2.67	26.70%***
All 5 cent increments	21.34	20.00	1.34	6.70%***

Note: Table 1 provides statistics across individuals and entities, including one-sample proportion tests of transaction volume versus predicted percent of trades. *** $p < .001$

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 a spike at 50-cent values, and the integer price rounding is particularly prevalent at values above $10. Kolmogorov-Smirnov tests confirm that each of these distributions is significantly greater than expected (*p*s < .001; see Supplementary Information Table S1). Table S1 provides an additional breakdown of the transaction volume between individuals and entities. 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.



Heterogeneity in Round Number Bias across Investor Types and Trading Behavior

Our data allow us to separately identify individual and institutional investors. Consistent with past literature, we find that integer price trades for equities are more prevalent among individual investors (vs. institutional investors; *B* = .018, *SE* < .001; see Supplementary Information Table S2). Among individuals, the demographic characteristics that predict integer and round number trades are largely consistent across the two trade types (Table 2). Integer price trades are nearly twice as likely for young investors as older ones (i.e., approximately 5.4% for those aged 18-23, vs. less than 3.3% for those aged 66+). Integer price trades are also more likely among men (vs. women; *B* = .001, *SE* = .001; Table 2, Model 1) and white investors (vs. Black and Hispanic investors). They are more likely in retirement accounts (*B* = .002; *SE* = .001) and less likely when selling stocks (vs. buying; *B* = -.002; *SE* = .000). They are more likely when shorting (vs buying; *B* = .031; *SE* = .001; all *p*s < .001; see Table 2).

The same patterns occur for all round number price trades (Model 2); 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+). Round number price trading is more likely in retirement accounts (*B* = .002; *SE* = .001) and less when selling stocks (vs. buying; *B* = -.008, *SE* < .001). They are more likely when shorting (vs. buying; *B* = .045; *SE* = .002; all *p*s < .001; see Table 2). As such, investors of different types and demographic profiles exhibit clear differences in their propensity to trade at round number prices.

Table 2. Linear Probability Regressions Predicting Integer and Round Price Trades.

Indicator	Model 1: Integer price trades		Model 2: Round number price trades	
Gender (Ref: Female)	B	Std. Err.	B	Std. Err.
Male	.0010***	.0001	.0026***	.0002
NA	.0133***	.0002	.0236***	.0004
Ethnicity (Ref: White)				
Black	-.0005***	.0001	-.0004	.0002
Asian	.0002	.0001	-.0002	.0003
Hispanic	-.0002*	.0001	-.0005*	.0002
Other	-.0001	.0002	-.0000	.0004
Age bucket (Ref: 18-23)				
24-29	.0008	.0015	.0012	.0026
30-35	-.0003	.0014	-.0012	.0024
36-41	-.0008***	.0014	-.0134***	.0024
42-47	-.0116***	.0014	-.0182***	.0024
48-53	-.0125***	.0014	-.0203***	.0024
54-59	-.0155***	.0014	-.0267***	.0024
60-65	-.0174***	.0014	-.0307***	.0024
66-71	-.0214***	.0014	-.0380***	.0024
72-77	-.0233***	.0014	-.0415***	.0024
78-83	-.0250***	.0014	-.0451***	.0024
84-89	-.0282***	.0014	-.0514***	.0024
90+	-.0294***	.0014	-.0556***	.0025
Retirement Status (Ref: Not retired)	.0021***	.0001	.0021***	.0002
Side (Ref: Buy)				
Sell	-.0024***	.0000	-.0083***	.0001
Short	.0311***	.0010	.0446***	.0017
Constant	.0540***	.0013	.2445***	.0023
N transactions	95,534,324		95,534,324	
N accounts	18,997,768		18,997,768	

*** $p < .001$, ** $p < .01$, * $p < .05$

Note. Regressions include clustered standard errors at the account level.

Conclusion and Discussion

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. Using a large, regulatory account-level data set, we document strong evidence of round number bias for individual investors: investments are disproportionately traded at integer prices and those ending in "0" or "5" cents. 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). To our knowledge, all previous research on round number trading has used anonymized and/or aggregated transaction-level data rather than account-level data, such as ours, where granular investor characteristics can be observed. Similarly, previous empirical analyses of individual investors using microdata have typically been restricted to one or two broker-dealers, raising external validity concerns. In contrast, our data covers millions of accounts across thousands of broker dealers, and may permit a broader measure of investor behavior.

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 has been shown to be highly correlated with individuals performing worse in their investments (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 RNB, and thus experiencing the associated financial losses, more than others, while overall, most individual investors are transferring wealth to institutions.

Our results also speak to a number of decision-making issues. First, though individual investors commonly exhibit this bias in general, younger investors are much more likely to trade at round prices. Because younger investors are more likely to engage in equity markets through online platforms with limited advisor intermediation, this finding suggests that more work is needed to understand how access to, and the design of, trading technology may affect financial decisions. Disproportionate RNB among younger investors may also highlight the susceptibility of market newcomers, drawn by easy-to-use trading applications and social media influence. This finding also points to emerging perspectives on the relative vulnerability of new investors who may disproportionately attempt to outperform the stock market for short-term gain rather than adopt steady and longer-term savings strategies commonly advocated for by financial professionals. Second, our results speak to the possible benefits of educating investors about strategies to reduce trading that requires 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. Third, our finding that individual brokerage account investors (vs. those trading within retirement accounts) are more likely to trade at round numbers raises important questions about how savings context (e.g., retirement vs. non-retirement) influences individual biases as well as differences between investors who have access to retirement accounts relative to those who do not. Fourth, men frequently engage in more risk taking behavior both in financial (Charness and Gneezy 2012) and non-financial domains (Byrnes et al. 1999). We observe higher RNB among men, suggesting future research should examine whether round number bias is driven by risk seeking or impulsive behavior.

EBS data have some limitations for the purposes of examining round number trading. First, there is inherent selection in trading markets such that 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. Second, 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. Therefore, even though we capture millions of accounts and billions of transactions, some investors, market events, and securities are represented more than others. Nevertheless, we believe these data are valuable for the purposes of studying round number trades as they represent the largest and most diverse set of transactions yet analyzed from U.S. capital markets.

For individual investors, trading at round prices may serve as a warning that one is trading under the influence of an emotional state, rather than based on an asset's fundamental (i.e., "true") value. As such, these trades may offer regulators and financial intermediaries a straightforward indicator to pinpoint investors who need extra guidance or targeted interventions.

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Supplementary Materials

EBS Data Limitations

Order Type

The order type of transactions is not included in EBS data. This means that we are not able to distinguish among (i.e., control for) transactions executed under market, limit, and other order type designations. Generally, a market order is an instruction to buy/sell a stock at the best available price in the market, and thus it ensures an execution but not at a specified price. In contrast, a limit order provides instructions to buy/sell a stock at a specified price or better. If we expect there to be some degree of round number bias, it is more likely to occur in a transaction executed under limit order (i.e., active choice over price) instructions versus market order instructions. Because we have both market and limit orders within our sample, the market orders should substantially reduce the size of our estimates relative to considering only transactions executed under conditions of active choice over price by investors. Similarly, investors are unlikely to be equal in their propensity to place market and limit orders (Bloomfield et al, 2005; Linnainmaa, 2010). The extent to which there are time-invariant differences in the propensity to place limit/market orders, between institutional and individual investors as well as across different types of individual investors, may weaken the estimates we generate relative to an analysis that is able to condition on active investor choice over price.

Fractional Shares

If fractional shares are traded, firms are instructed by the EBS submission rules to delete the fractional share and round down to the nearest whole number; however, if there is less than one share reported, they are instructed to round up to 1. This fact means that we are not able to segregate fractional share trades from non-fractional share trades. Given that fractional share trades are often required to be executed as market orders[3], there is reason to believe that the presence of fractional share trades in our samples would reduce round number price effects relative to a sample composed exclusively of non-fractional share trades.

Supplementary Results

Table S1 shows the proportion of round number trades occurring in different price ranges, divided by investor type. Among the whole sample, the first column of Table S2 shows that, as prices increase, a higher proportion of transactions occur at integers; 1.91% of transactions under $10 occur at integers, as compared to 7.4% of transactions at prices of $1,000 or more. The relative increase in rounding for higher priced transactions also occurs for all $0.50, $0.10, and $0.05

[3] https://robinhood.com/us/en/support/articles/fractional-shares/ https://www.webull.com.sg/help/faq/1230-How-do-I-trade-Fractional-Shares

increments (columns 2-4). Such a pattern is broadly consistent with psychological literature, as more trailing zeros are considered more round (Converse and Dennis 2018).

Table S1 also shows that the overall prevalence of round number trading is stronger among individuals than institutions (comparing Panel B to Panel C). Individuals tend to show increased rounding, but not at all price ranges, whereas institutions show particularly strong rounding for securities with higher prices.

Table S1. Percent of Transactions Occurring at Different Types of Round Numbers Increases with Higher Price Ranges.

Price	Trades ending in $.00 exactly (1)	All 50 cent increments (2)	All 10 cent increments (3)	All 5 cent increments (4)
Panel A: All entities				
< $10	1.91	3.62	10.90	19.88
$10 - $99.99	3.89	5.94	13.10	21.98
$100 - $999.99	6.09	7.99	14.35	22.03
>= $1,000	7.40	9.65	16.14	23.67
All prices	3.73	5.64	12.67	21.34
Panel B: Individuals				
< $10	2.00	3.76	11.13	20.22
$10 - $99.99	4.60	6.88	14.29	23.44
$100 - $999.99	6.88	8.92	15.32	22.96
>= $1,000	6.62	8.77	15.21	23.06
All prices	4.17	6.22	13.41	22.23

Panel C: Institutions				
< $10	1.57	3.08	9.86	18.42
$10 - $99.99	2.36	3.92	10.49	18.87
$100 - $999.99	3.11	4.56	10.59	18.40
>= $1,000	6.88	8.82	15.46	22.97
All prices	2.35	3.88	10.38	18.69

Note. N = 95,534,324 transactions for individuals, and 26,118,868 transactions for institutions. All values are statistically significantly different from expected based on Kolmogorov-Smirnoff tests, at $p < .001$.

Table S2 shows regression models estimating whether individuals (vs. institutions) conduct more integer price trades and all round number price trades. As shown, both models show that individuals are estimated to be more likely to conduct trades at round numbers. This pattern is consistent with prior research, which has not been able to identify individual characteristics (e.g., Chiao and Wang, 2009; Kuo et al., 2015).

Table S2. Regression model estimating likelihood of integer and round number price trades.

	Model 1: Integer price trades		Model 2: Round number price trades	
Indicator	B	Std. Err.	B	Std. Err.
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 by account.

Additional References in Supplementary Materials

Converse, Benjamin A., and Patrick J. Dennis. "The role of “Prominent Numbers” in open numerical judgment: Strained decision makers choose from a limited set of accessible numbers." *Organizational Behavior and Human Decision Processes* 147, 94-107 (2018). https://doi.org/10.1016/j.obhdp.2018.05.007