Buy-Sell Imbalances On and Around Round Numbers and High-Frequency Trading

Albert J. Lee[*]

College of Economics and Finance, Hanyang University

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[*] Email address: ajlee@hanyang.ac.kr. Mailing address: 602 College of Economics and Finance, 222 Wangsimni-ro, Seongdong-gu, Seoul, Republic of Korea, 04763. For helpful comments and suggestions, the author thanks Kee H. Chung, Antonio Fasano, Veljko Fotak, Svetlana Gavrilova, Todd Griffith, Sahn-Wook Huh, Kentaro Iwatsubo, Feng (Jack) Jiang, Daejin Kim, Hugh Hoikwang Kim, Dominik Rösch, Andriy Shkilko, Cristian Tiu, and Brian Wolfe, seminar participants at Sungkyunkwan University and the University at Buffalo, and conference participants at the Eastern Finance Association, the Academy of Behavioral Finance & Economics, the Financial Management Association, the Southern Finance Association, the Hanyang-Kobe-Nanyang Conference in Economics, KAFA Brown Bag Seminar, and the Joint Conference with the Allied Korea Finance Associations. I also thank Frank Hatheway for providing the NASDAQ high-frequency trading data. All remaining errors are my own. This work was supported by Hanyang University (Project Number: 202200000003125).

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Abstract

The growth of high-frequency trading, due to its heavy reliance on computer algorithms, can be associated with a reduction of human errors and financial anomalies in the market. Transactions in which a non-high-frequency trader is the liquidity demander exhibit abnormally high buy (sell) pressure when prices are immediately below (above) a round number due to psychological effects, while the pattern is completely reversed when a high-frequency trader is the liquidity demander. As a result, the overall sample does not exhibit such imbalances. Furthermore, high-frequency traders earn higher returns when trading on and around round number prices.

JEL Classification: G14, G23, G41

Keywords: high-frequency traders; algorithmic trading; behavioral finance; order imbalance; financial anomaly

1. Introduction

High-frequency trading has become a major topic of interest to investors, regulators, and academic alike in recent years. High-frequency traders (HFTs) are a type of algorithmic traders equipped with superior machines and means of communication that allow them to trade more frequently and faster at a rate that has never been witnessed before. In 2009, more than 70% of U.S. equity trading volume and 50% in futures markets have been associated with HFTs, although only about 2% of 20,000 trading firms can be categorized as an HFT (Easley, López de Prado, and O'Hara, 2012), and the market share of high-frequency trading in the U.S. equity market has been constantly at around 50% ever since.[1] Latencies of HFTs' orders are measured in micro- and nanoseconds, or respectively one-millionth and one-billionth of a second, and high-frequency trading firms spend huge sums of money to gain even just one microsecond advantage over other traders.[2]

Naturally, understanding the market-wide impact of traders with such exceptional and sophisticated capabilities has been of great interest to many market microstructure researchers. So far, there is mixed evidence relating to the societal cost and benefits of HFTs.[3] Many studies including Bershova and Rakhlin (2013), Stoll (2014), Jovanovic and Menkveld (2016), and Malinova, Park, and Riordan (2016) have documented that high-frequency trading benefits liquidity, which is not surprising as HFTs do not possess human constraints such as limited attention span and making mistakes or emotional judgment (Harris, 2013). Moreover, HFTs contribute to the price efficiency (Brogaard, Hendershott, and Riordan, 2014) and their activities are associated with a drop in short-term volatility (Hasbrouck and Saar, 2013).

On the other hand, some studies including Gai, Yao, and Ye (2013), Lee (2015), and Brogaard, Hendershott, and Riordan (2017) find deterioration of or no change in liquidity in association with high-frequency trading. Moreover, HFTs have been linked to activities that may be considered harmful to other investors. For example, Harris (2013) points out that, because of their superior speed, HFTs can pick any outdated quotes and take advantage of them as soon as news of a material event hits the market, without giving any chance for the investors to adjust their quotes.[4] HFTs can also front-run other investors' orders by inferring incoming orders (order anticipation) or marginally improving a large standing order (quote

[1] In contrast, the U.S. equity market share of high-frequency trading was less than 25% in 2005. Source: http://www.businessinsider.com/how-high-frequency-trading-has-changed-the-stock-market-2017-3.

[2] See Harris (2013) and https://www.wired.com/2012/08/ff_wallstreet_trading.

[3] See Chung and Lee (2016) for a more detailed review of high-frequency trading literature.

[4] By impounding new information into prices faster than others, HFTs are essentially enhancing price efficiency by engaging in such activities. However, as Harris (2013) and Brogaard, Hendershott, and Riordan (2014) suggest, the net economic benefit of improving price efficiency by a few seconds may not be positive considering the adverse selection costs HFTs incur on other types of investors.

matching) and reap profits from them, making trades more costly in general for other types of investors.[5] Hirschey (2018) finds that HFTs' orders are followed by those of other traders and that the phenomenon cannot be fully explained by new information arrival or other plausible explanations.[6]

Other concerns include systemic failures triggered or exacerbated by HFTs, such as the Knight Capital case in 2012, the "fat finger" glitch by China Everbright Securities in 2013, and the Flash Crash of 2010 (see CFTC and SEC, 2010), during all of which the market has suffered extreme volatility in a very short time period at least partially due to some issues or mistakes with the way HFTs' algorithms are written. However, attempts from regulatory agencies to control high-frequency trading, including financial transaction tax and fees on excessive number of orders, have generally been unsuccessful, as many resulted in reduction in market quality (see Chung and Lee, 2016).

In this paper, I provide evidence of another channel through which HFTs are beneficial to the market by showing that HFTs do not trade in a way that is driven by cognitive biases. In particular, I investigate the trading behavior of HFTs in relation to the buy-sell imbalance on and around round numbers as documented by Bhattacharya, Holden, and Jacobsen (2012; BHJ), who show that there exist buy-sell imbalances on and around round number prices (e.g., around \$6.00 as opposed to \$6.07) due to three psychological effects: 1) left-digit effect, under which investors perceive a change in the leftmost digit to be more dramatic than a change in other digits of same magnitude; 2) threshold trigger effect, in which investors' preference on roundness (from most to least preferred: whole dollars, half-dollars, quarters, dimes, nickels, and pennies) induces them to peg their private valuation of a stock to a round number; and 3) cluster undercutting effect, which is a combination of limit order prices being more frequently placed on round numbers and investors' submitting a new limit sell (buy) order that is a penny lower (higher) than the current best ask (bid) price. As a result, there is an excess buy (sell) pressure from liquidity demanders when prices are at or just below (above) a round number or when prices fall (rise) to a round number.[7]

I hypothesize that HFTs are not subject to these effects and are even able to take advantage of them, since HFTs use computer algorithms to trade instead of relying on certain psychological reference points that give rise to the above three effects. Using a dataset provided by NASDAQ that identifies liquidity demander and supplier of a trade as a high-frequency trader or not and whether a trade is buyer- or seller-initiated, I show that when a non-high-frequency trader (nHFT) is a liquidity demander, there is an abnormally high proportion of buyer-initiated (seller-initiated) trades just below (above) round number

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[5] Because HFTs are taking them away before anyone else can, best quotes will not be available to the investor who first had an intention to trade at the best quotes, forcing the investor to trade on inferior quotes. Consequently, investors have less incentives to acquire costly information in the presence of front-running. Therefore, if HFTs front-run informed investors, prices will become less informative in the long run (Harris, 2003).

[6] Lewis (2015) also provides anecdotal evidence consistent with the existence of HFTs' order anticipation strategies that raise the transaction costs of brokers and dealers.

[7] The cluster undercutting effect is primarily driven by liquidity suppliers. I discuss its implications in Section 5.

prices, consistent with previous findings that investors are influenced by psychological urges when trading around round numbers. In contrast, I find that HFTs do the exact opposite. That is, for trades that a high-frequency trader demands liquidity, there is an abnormally high proportion of seller-initiated (buyer-initiated) trades immediately below (above) round number prices. Because HFTs' liquidity-demanding trades comprise about 39% of my sample, I do not observe any clear pattern with respect to the psychological effects when I analyze the whole sample.[8] The result also holds when I conduct transaction-level tests to examine trading activities conditional on the national best bid and offer (NBBO), such as when the best ask price falls below an integer threshold (e.g., \$5.00).

Next, I examine stock return patterns from trading under the psychological effects. I find that HFTs' liquidity-demanding trades typically enjoy higher or similar stock returns compared to those of nHFTs. I conclude that, because of their superior trading abilities largely based on sophisticated machines, HFTs are not susceptible to the psychological effects and can better determine whether a price around a round number is likely going to yield higher returns than nHFTs can.

In addition to the liquidity-demanding trades, I also examine the liquidity supply side of trades and what types of trades drive the buy-sell imbalances. When an HFT trades against another HFT, the imbalance is minimal. Rather, the buy-sell imbalance in the opposite direction of the psychological effects is driven by the trades where an HFT takes liquidity from an nHFT. The pattern documented by BHJ is still present among trades where an nHFT is a liquidity demander regardless of whether the liquidity supplier is an HFT, suggesting that HFTs also submit liquidity-supplying orders to take advantage of the psychological effects and that there are some nHFTs who do not appear to be under the influence of the effects.

While their extensive use of algorithms is likely the key reason why HFTs exhibit different trading patterns on and around round numbers, there may still exist reasons that separate HFTs from algorithmic traders in general, who also use algorithms to generate and execute orders. I propose and discuss two additional possible explanations. First, before anyone else can detect and submit orders in response to bias-driven orders in the market, HFTs' superior speed may be essential in taking advantages of the psychological effects. Second, algorithms written by unsophisticated traders may still contain human errors. To the extent that algorithmic trading in general has lower barriers to entry, HFTs are likely to be more sophisticated in writing algorithms on average, thus less prone to initiate bias-driven orders.

While many studies have focused on the effects of HFTs' speed on the market, little attention has been given to what it means for a large part of orders in the market to be generated by machines and computer algorithms as opposed to orders submitted by human traders. To the best of my knowledge, there

[8] The sample period of BHJ is from 2001 to 2006, when the market share of HFTs was relatively low, whereas the proportion of HFTs' dollar trading volume in my sample is 39% of the liquidity-demanding trades, from 2008 to 2009 (see Table 1). Therefore, the psychological pattern shown in the overall sample of BHJ is driven by the lack of high-frequency trading or other non-psychologically-motivated trading activities.

are two other papers that tackle this issue. Chakrabarty, Moulton, and Wang (2022) find that, because machines have perfect attention span while human traders do not, price efficiency improves during times when human traders are likely paying less attention to the market, such as Fridays, when HFTs participate in trading. In their paper, HFTs are described as traders with unlimited attention, whereas HFTs are thought of as unbiased traders in my paper. Davis, Van Ness, and Van Ness (2014) report that prices cluster less when HFTs participate on either side of the trade (and much less when they do on both side), suggesting that price clustering is at least partly explained by human errors. In this paper, in addition to investigating how HFTs trade differently from nHFTs (including human traders), I also show that such discrepancies in trading strategy may result in statistically significantly different wealth transfer.

I contribute to this growing literature of the role of HFTs as traders with no human errors by showing that HFTs' trading pattern is the exact opposite of that of nHFTs under situations that normally induce human bias. Therefore, while it appears that the biases have been eliminated in the overall sample, such an observation is true only for one group of traders but not for the other. In sum, I identify another channel, other than their speed, through which HFTs affect the market quality. The findings also have implications on regulation of high-frequency trading, as regulators and exchanges tend to focus only on how HFTs' speed and ensuing numerous order generations affect market quality.[9]

The rest of this paper is organized as follows. Section 2 provides more background and develops hypotheses. In Section 3, I explain the datasets used for analyses. I show the existence of buy-sell imbalances on and around round numbers and how HFTs' and nHFTs' trading patterns differ in Section 4. Section 5 analyzes stock return consequences of such imbalances. I explore liquidity suppling side of trades and examine which types of trades drive the imbalances in Section 6. The role of algorithms in the results are discussed in Section 7. Finally, Section 8 concludes.

2. Background and hypotheses development

BHJ observe buy-sell imbalances on and around round numbers, in such a way that there is an abnormally high number of buyer-initiated trades below round number thresholds such as integers and seller-initiated trades above round number thresholds. In addition, there is a wealth transfer between investors who demand liquidity in the direction of these imbalances (e.g., submitting a marketable buy order at $4.99) and liquidity suppliers. The authors show that three psychological effects explain why such phenomenon exists. The first is the left-digit effect, where investors perceive changes in price to be much larger when it involves changes in the leftmost digit. For example, when a price drops from $5.00 to $4.99,

[9] For example, regulators and exchanges around the world have introduced financial transaction taxes, penalties on high order-to-trade ratio investors, minimum order resting times, and structural delays in order processing to curb high-frequency trading activities out of concern that their speed is harming the market quality (Chung and Lee, 2016).

investors mentally process the decrease in the leftmost digit from 5 to 4 before fully accounting for other digits into the price change. As a result, a drop in price from $5.00 to $4.99 is perceived to be a greater reduction in price than a drop from, say, $4.33 to $4.32. Thomas and Morwitz (2005) explain that, since human beings generally read from left to right, the effect causes people to subconsciously evaluate the magnitude of a number based on its leftmost digit. This effect is also popular among retailers (Schindler and Kirby, 1997) which is indeed found to be a profitable strategy (Anderson and Simester, 2003).

The second is the threshold trigger effect, in which investors prefer to peg their private valuation of a stock to a round number such as integers and half-dollars as opposed to pennies. Under this effect, investors prefer whole dollars the most, which is the most round threshold. Other thresholds are, in the order of decreasing preference, half-dollars, quarters, dimes, nickels, and pennies (least round). Finally, the third effect is called the cluster undercutting effect, which occurs due to the frequent placement of limit orders on round numbers (Chiao and Wang, 2009) and a new order being submitted with a price just one penny better than the existing orders. Therefore, a new buy (sell) order will likely to be placed just below (above) a round number.

As a result of the three effects, there is an excess buy (sell) pressure from liquidity demanders when prices are at or just below (above) a round number or when prices fall (rise) to a round number. It is important to note that all of the three effects exist due to cognitive reference points set by investors. Persistence of such reference points has been documented in the psychology literature (Rosch, 1975) as well as in the finance literature. For example, Chung, Van Ness, and Van Ness (2004) and Ikenberry and Weston (2007) find that price clustering at round numbers occurs far more often than what is predicted under rational hypotheses, suggesting that human bias plays a significant role in clustering.[10]

In this study, I hypothesize that HFTs exhibit different trading behaviors in relation to the buy-sell imbalances on and around round numbers. While there is no clear definition of who exactly HFTs are, SEC (2014) highlights five characteristics that are frequently associated with them, one of which is that HFTs use "extraordinarily … sophisticated programs for generating, routing, and executing orders" (p. 4). Definitions and characterizations of HFTs from other regulatory agencies also generally describe HFTs as traders with highly sophisticated algorithms and extremely low latency in trading (Chung and Lee, 2016).

HFTs' heavy reliance on advanced technology and machines implies less human involvement for each trade. Therefore, I expect to observe less human errors from their trading behaviors. To my knowledge, there are a couple of papers that jointly investigate HFTs and human trading behaviors. Davis, Van Ness, and Van Ness (2014) find that price clusters less frequently at five-cent increments (e.g., $5.00, $5.05,

[10] There are two hypotheses in relation to rational explanations of price clustering. The negotiation hypothesis by Harris (1991) argues that orders cluster on round numbers to minimize the costs of negotiating by limiting the number of "frivolous offers and counteroffers." Ball, Torous, and Tschoegl's (1985) price resolution hypothesis contend that the amount of information in the market determines the level of clustering.

$5.10, and so on) when HFTs provide liquidity and conclude that price clustering can be attributed to human bias. On the other hand, Chakrabarty, Moulton, and Wang (2022) show that price inefficiencies during low investor attention periods such as Fridays are significantly lower if HFTs participate in trading. Both studies assume HFTs lack certain human characteristics and therefore are immune from human errors, and indeed find that HFTs trade more often in the direction that is expected for rational investors.

Therefore, it is reasonable to expect a trading pattern from HFTs that is different from the one documented in BHJ.[11] This would indicate that HFTs' buy-sell ratio should be a constant number across different prices, or even be on the opposite direction of the psychological effects in order to take advantage of any potential deviations from efficient prices driven by the effects. That is, HFTs may submit more liquidity-demanding buy orders immediately above round numbers and vice versa. These considerations lead to two competing hypotheses.

Hypothesis 1a: *Trades that HFTs demand liquidity exhibit a constant buy-sell ratio around round number thresholds.*

Hypothesis 1b: *For trades that HFTs demand liquidity, there are more buyer-initiated trades at prices immediately above a round number threshold, and more seller-initiated trades at prices immediately below a round number threshold.*

I expect nHFTs to continue be under the influence of the psychological effects and to send more liquidity-demanding buy orders below round numbers and vice versa. Given that HFTs' liquidity-demanding trades constitute approximately 39% of all dollar trading volume in my sample (see Table 1), I expect the overall sample including both trades where HFTs are the liquidity demander (HFTD) and where nHFTs are the liquidity demander (nHFTD) to exhibit less buy-sell imbalances around round numbers.

Hypothesis 2: *For trades that nHFTs demand liquidity, there are more buyer-initiated trades at prices immediately below a round number, and more seller-initiated trades at prices immediately above a round number.*

Hypothesis 3: *The overall sample including both HFTD and nHFTD trades exhibits less buy-sell imbalances around round numbers.*

Next, I test stock returns from trading in the direction of the effects. Since HFTs generally close each day with a flat position (SEC, 2014), I assume they hold the established position from each trade until the end of the day, at which point their net positions for all stocks become zero.[12] Because HFTs are not

[11] It is possible that at least some of HFTs also trade in the direction of the psychological effects, potentially because human investors are still involved in devising trading strategies. In Section 7, I discuss the possibility of algorithms that follow patterns that are associated with human errors.

[12] While it is reasonable to assume HFTs will close out their positions by the end of each day, it is likely not a reasonable assumption for all nHFTs. However, I make the identical assumption for nHFTs as well to make the stock return results comparable to each other, following Brogaard, Hendershott, and Riordan (2014).

prone to human bias (Hypotheses 1a and 1b) and their liquidity-demanding trades on average are more likely to increase price efficiency (Brogaard, Hendershott, and Riordan, 2014), their stock return is expected be higher than that of nHFTs when they trade at the direction of the psychological effects.

Hypothesis 4: *HFTs' stock return is higher than that of nHFTs when trading at the direction of the psychological effects.*

When both nHFTs and HFTs trade against the direction of the psychological effects, it is unclear whether there would be any difference in stock returns between them. For example, if there exists a subset of nHFTs that is not under the influence of the effects and makes the "right" decision to trade against the effects, then its stock return does not have any particular reason to be different from that of HFTs.

Hypothesis 5: *HFTs and nHFTs do not exhibit significant difference in stock returns when they trade against the psychological effects.*

Finally, provided that HFTD trades are less likely to be in the direction of the psychological effects (Hypotheses 1a and 1b) and that their stock return is higher than or equal to that of nHFTD trades (Hypotheses 4 and 5), HFTs should be the net gainer for trades that occur under the influence of the effects.

Hypothesis 6: *HFTs' profit is higher than that of nHFTs for trades that occur under the influence of the psychological effects.*

3. Data

I obtain stock transactions data from NASDAQ, which contain information on whether each of liquidity demander and supplier of a trade is a high-frequency trader or not.[13] Specifically, each trade is classified into one of four types: HH, HN, NH, and NN. The first letter identifies whether an HFT demands liquidity (H if so, N if not), and the second letter specifies whether an HFT supplies liquidity. For example, HN trades are those that an HFT demands liquidity and an nHFT supplies liquidity. The dataset also contains information regarding stock symbol, transaction date, time (in milliseconds), number of shares, price of transaction, and whether the trade is buyer- or seller-initiated. There are 120 firms included in the sample taken from Russell 3000, 40 representing large firms, another 40 medium firms, and the rest small firms. For each size group, half are listed on NASDAQ and the other half on the New York Stock Exchange (NYSE). The sample contains all stock transactions (including odd lots) during 2008-2009 on NASDAQ.

Lack of a clear consensus on the definition of high-frequency trading naturally implies there is no perfect dataset to conduct research on high-frequency trading (see Chung and Lee, 2016, and SEC, 2014). The NASDAQ dataset I use identifies 26 high-frequency trading firms that are "best thought of as independent proprietary trading [high-frequency trading] firms" based on NASDAQ's "knowledge of their

[13] The dataset is available to academics under a non-disclosure agreement.

customers and analysis of firms' trading, such as how often a firm's net trading in a day crosses zero, its order duration, and its order-to-trade ratio" (Brogaard, Hendershott, and Riordan, 2014, p. 2271-2272).

I use trades from 9:30 AM to 4:00 PM (excluding trades in the opening, closing, and intraday crosses) and with prices \$2 or greater or less than \$100. The latter filter removes all observations of Alphabet Inc. (GOOG), all of whose prices are above \$100 for the entire sample period, which leaves me with a total of 119 firms in the sample.

I also obtain quotes data from the Trade and Quote (TAQ) database to compute the NBBO across all U.S. equity exchanges to analyze trading pattern under certain conditions when the NBBO changes. Lastly, I use closing ask and bid data from the Center for Research in Security Prices (CRSP) to compute stock returns.

[Insert Table 1 Here]

Table 1 presents descriptive statistics of the high-frequency trading sample I use. Most of the trade samples come from the large firm size and small trade size groups. Consistent with Brogaard, Hendershott, and Riordan (2014), HFTD trades account for 38% to 43% of all trades, while they are more active in large firms (39% of all trades in dollar volume, compared to 25% in small firms) relative to nHFTD trades. Relatively high percentage of HFTD trades are executed in small trade size (where they account for 43% of dollar volume, compared to 24% in large trade size), which is consistent with HFTs' trading less than 100 shares of stock (or odd lots) per transaction to conceal their intentions and minimize price impact (O'Hara, Yao, and Ye, 2014).

4. Buy-sell imbalances on and around round numbers

I first explore whether there is any visual difference in the buy-sell ratio (*BSR*) around round numbers. *BSR* is defined as (*buys* – *sells*) / (*buys* + *sells*), where *buys* (*sells*) is defined as one of number of buyer-initiated (seller-initiated) trades, number of shares bought (sold), or dollar volume of buyer-initiated (seller-initiated) trades, over a one-year period for each firm. Note that positive (negative) *BSR* is associated with more buy (sell) imbalance, with a value of 0 indicating no imbalance. I define price point (*pp*) as the decimal part of transaction prices. For example, *pp* of \$5.21 is .21. I compute the annual median *BSR* for each firm at each *pp*.

[Insert Figures 1 and 2 Here]

I present the median of the firm-year median *BSR*s for each *pp* in Figure 1, with all trades included in the sample. All three definitions of *BSR* follow similar trends, and none of them exhibit abnormally high *BSR* below round numbers, which is in contrast with BHJ. Therefore, it appears that there is no evidence of the kind of imbalance documented in the literature in my sample, most likely due to the rise of high-frequency trading activities.

Next, I repeat the procedure but separate the sample into HFTD and nHFTD trades, and present the results in Figure 2. In Panel A, I use the number trades to compute *BSR*. The gray line indicates that the buy-sell imbalance as shown in BHJ exists among nHFTD trades. There is a clear drop in *BSR* from .99 to .01 pp, .49 to .51 *pp*, and so on, suggesting that there are abnormally many buyer-initiated (seller-initiated) trades immediately below (above) round numbers from nHFTD trades. The black line shows that, for HFTD trades, there is a completely reverse trend compared to that of nHFTD trades, as *BSR* rises from .99 to .01 pp, .49 to .51 *pp*, and so on. Using different definitions of *BSR* yields qualitatively similar results in Panels B and C. The findings support Hypothesis 2 that nHFTD trades follow the buy-sell imbalance pattern driven by the psychological effects, and Hypothesis 1b that HFTD trades show the opposite pattern and exhibit higher buyer-initiated (seller-initiated) trades immediately above (below) round numbers.

[Insert Table 2 Here]

I estimate regression models for each of the categories (all sample, only HFTD trades, and only nHFTD trades), where dependent variable is $BSR_{i,y}$ for firm *i* in year *y* and independent variables are dummy variables of *pp*:

$$\begin{aligned} BSR_{i,y} = {} & \beta_1 Below\ Integers_{i,y} + \beta_2 Above\ Integers_{i,y} + \beta_3 Below\ Half\text{-}Dollars_{i,y} \\ & + \beta_4 Above\ Half\text{-}Dollars_{i,y} + \beta_5 Below\ Quarters_{i,y} + \beta_6 Above\ Quarters_{i,y} \\ & + \beta_7 Below\ Dimes_{i,y} + \beta_8 Above\ Dimes_{i,y} + \beta_9 Below\ Nickels_{i,y} \\ & + \beta_{10} Above\ Nickels_{i,y} + \varepsilon_{i,y}, \end{aligned} \tag{1}$$

where *Below Integers* equals to 1 if *pp* = .99 and 0 otherwise, *Above Integers* equals to 1 if *pp* = .01 and 0 otherwise, *Below Half-Dollars* equals to 1 if *pp* = .49 and 0 otherwise, *Above Half-Dollars* equals to 1 if *pp* = .51 and 0 otherwise, *Below Quarters* equals to 1 if *pp* ϵ {.24, .74} and 0 otherwise, *Above Quarters* equals to 1 if *pp* ϵ {.26, .76} and 0 otherwise, *Below Dimes* equals to 1 if *pp* ϵ {.09, .19, .29, .39, .59, .69, .79, .89} and 0 otherwise, *Above Dimes* equals to 1 if *pp* ϵ {.11, .21, .31, .41, .61, .71, .81, .91} and 0 otherwise, *Below Nickels* equals to 1 if *pp* ϵ {.04, .14, .34, .44, .54, .64, .84, .94} and 0 otherwise, and *Above Nickels* equals to 1 if *pp* ϵ {.06, .16, .36, .46, .56, .66, .86, .96} and 0 otherwise. The regression results are presented in Table 2.

Using the number of trades to compute *BSR*, Column (1) of Table 2 Panel A shows that, for the sample including all trades, there is not much discernible pattern with respect to *pp* dummies, let alone statistical significance for most of the coefficients. For example, the coefficients indicate that there are more seller-initiated trades for both above and below round numbers. This lack of a clear pattern with respect to the psychological effect is consistent with Hypothesis 3. I find empirical support for Hypotheses 1b and 2 in Columns (2) and (3), and the result is consistent with Figures 2 and 3. HFTD trades are more likely to be buyer-initiated above round numbers (integers, half-dollars, quarters, dimes, and nickels) and seller-initiated below them. nHFTD trades are the exact opposite and follow the trading pattern consistent with the psychological effects, with more buyer-initiated (seller-initiated) trades below (above) round numbers. Computing *BSR* by using the number of shares or the dollar volume of shares yields similar results, as presented in Panels B and C. In sum, I find that while nHFTs still follow the psychologically-influenced trading pattern, HFTs do the exact opposite, resulting in the overall sample that does not exhibit any clear pattern in relation to the psychological effects.

While the results in Table 2 using Equation (1) clearly suggest a pattern around round numbers, they are unconditional with respect to the changes in quotes. In addition, they only show patterns *around* round numbers, while two of the three psychological effects also occur *on* round numbers. Therefore, I conduct a conditional test to more formally examine the three psychological effects that cause the buy-sell imbalances on and around round numbers. I run the following three transaction-level regression models: logit (where a buyer-initiated trade is coded as 1 and a seller-initiated trade as 0); OLS with number of shares for buyer-initiated trades or negative number of shares for seller-initiated trades as a dependent variable; and OLS with dollar volume of shares for buyer-initiated trades or negative dollar volume for seller-initiated trades as a dependent variable.

I compute the prevailing NBBO at the time of each transaction and identify transactions that meet the following four conditions: when the best ask price falls below a round number ("*Ask Falls Below*"), the best ask price falls to a round number ("*Ask Falls to*"), the best bid price rises to a round number ("*Bid Rises to*"), and the best bid price rises above a round number ("*Bid Rises Above*").[14] The left-digit effect predicts that there will be an excess buy pressure under *Ask Falls Below* condition, and excess sell pressure under *Bid Rises to* condition. The threshold trigger effect predicts an excess buy pressure under *Ask Falls Below* and *Ask Falls to* conditions, and excess sell pressure under *Bid Rises to* and *Bid Rises Above* conditions. The cluster undercutting effect predicts excess buy pressure under *Ask Falls Below* condition, and excess sell pressure under *Bid Rises Above* condition.

[14] In this paper, I may use the term "reach cases" to indicate *Ask Falls to* and *Bid Rises to*, and "cross cases" to indicate *Ask Falls Below* and *Bid Rises Above*.

Two round number thresholds are used in the conditional tests: integer (*pp* = .00) to observe the order imbalance; and nickel (*pp* ϵ *K* = {.15, .25, .35, .45, .55, .65, .75, .85}) to control for any unobservable factor that may have caused the order imbalance across all price changes. I create dummy variables for each condition that indicate whether each transaction satisfies the condition:

- *Ask Falls Below Integer*: 1 if a trade is executed after the best ask price falls from *pp* ϵ [.00, .10] to below the integer threshold before the best ask price leaves *pp* ϵ [.90, .99], 0 otherwise.
- *Ask Falls Below Nickel*: 1 if a trade is executed after the best ask price falls from *pp* ϵ [*K*, *K* + .10] to below the nickel threshold before the best ask price leaves *pp* ϵ [*K* - .10, *K* - .01], 0 otherwise.
- *Ask Falls to Integer*: 1 if a trade is executed after the best ask price falls from *pp* ϵ [.01, .10] to *pp* = .00 before best ask price ask leaves *pp* = .00, 0 otherwise.
- *Ask Falls to Nickel*: 1 if a trade is executed after the best ask price falls from *pp* ϵ [*K* + .01, *K* + .10] to *pp* = *K* before the best ask price leaves *pp* = *K*, 0 otherwise.
- *Bid Rises to Integer*: 1 if a trade is executed after the best bid price increases from *pp* ϵ [.90, .99] to *pp* = .00 before the best bid price leaves *pp* = .00, 0 otherwise.
- *Bid Rises to Nickel*: 1 if a trade is executed after the best bid price increases from *pp* ϵ [*K* - .10, *K* - .01] to *pp* = *K* before the best bid price leaves *pp* = *K*, 0 otherwise.
- *Bid Rises Above Integer*: 1 if a trade is executed after the best bid price increases from *pp* ϵ [.90, .99] to above the integer threshold before the best bid price leaves *pp* ϵ [.01, .10], 0 otherwise.
- *Bid Rises Above Nickel*: 1 if a trade is executed after the best bid price increases from *pp* ϵ [*K* - .10, *K* - .01] to above the nickel threshold before the best bid price leaves *pp* ϵ [*K* + .01, *K* + .10].

To understand how HFTs and nHFTs behave differently under these conditions, I create a dummy variable *HFTD*, which equals to 1 if the liquidity demander of a trade is an HFT and 0 if not. Then, I create interaction terms of *HFTD* and each of the conditional dummy variables listed above. In addition, I add fixed effects for firm, month, transaction price level, and trade size in the regression model. Price level groups are: price < \$20; \$20 ≤ price < \$40; \$40 ≤ price < \$60; \$60 ≤ price < \$80; and \$80 < price. Trade size groups are: less than 500 shares; between 500 and 2,000 shares; and more than 2,000 shares. I run the following regression model:

$$
\begin{aligned}
DEPVAR_{i,j} = {} & \beta_1 Ask\ Falls\ Below\ Integer_{i,j} + \beta_2 Ask\ Falls\ Below\ Integer_{i,j} \times HFTD_{i,j} \\
& + \beta_3 Ask\ Falls\ Below\ Nickel_{i,j} + \beta_4 Ask\ Falls\ Below\ Nickel_{i,j} \times HFTD_{i,j} \\
& + \beta_5 Ask\ Falls\ to\ Integer_{i,j} + \beta_6 Ask\ Falls\ to\ Integer_{i,j} \times HFTD_{i,j} \\
& + \beta_7 Ask\ Falls\ to\ Nickel_{i,j} + \beta_8 Ask\ Falls\ to\ Nickel_{i,j} \times HFTD_{i,j} \\
& + \beta_9 Bid\ Rises\ to\ Integer_{i,j} + \beta_{10} Bid\ Rises\ to\ Integer_{i,j} \times HFTD_{i,j} \\
& + \beta_{11} Bid\ Rises\ to\ Nickel_{i,j} + \beta_{12} Bid\ Rises\ to\ Nickel_{i,j} \times HFTD_{i,j} \\
& + \beta_{13} Bid\ Rises\ Above\ Integer_{i,j} + \beta_{14} Bid\ Rises\ Above\ Integer_{i,j} \times HFTD_{i,j} \\
& + \beta_{15} Bid\ Rises\ Above\ Nickel_{i,j} + \beta_{16} Bid\ Rises\ Above\ Nickel_{i,j} \times HFTD_{i,j} \\
& + HFTD_{i,j} + \text{Fixed Effects} + \varepsilon_{i,j}, \qquad (2)
\end{aligned}
$$

where $DEPVAR_{i,j}$ is one of the dependent variables from the three types of regression models: 1) logit; 2) OLS with number of shares; and 3) OLS with dollar volume. I only report the abnormal amount at each integer threshold for following tables, where the abnormal amount indicates the difference between integer and nickel threshold coefficients. For example, the abnormal coefficient estimate for *Ask Falls Below Integer* is the difference in the coefficient estimates between *Ask Falls Below Integer* and *Ask Falls Below Nickel* [i.e., β_1 minus β_3 in Equation (2)]. In this example, *Ask Falls Below Nickel* accounts for any factors that may have not been controlled for when the ask price normally falls, not just around integer thresholds. Therefore, the abnormal coefficient estimate shows the incremental effect of *Ask Falls Below Integer* after controlling the effect of the ask price moving down in general. I report the regression results in Table 3.

[Insert Table 3 Here]

Column (1) of Table 3 uses a logit model where buyer-initiated trades are coded as 1 and seller-initiated trades as 0, Column (2) uses OLS, with dependent variable equal to the number of shares for buyer-initiated trades or negative number of shares for seller-initiated trades, and Column (3) also uses OLS, but with the dollar volume of shares for buyer-initiated trades or negative dollar volume for seller-initiated trades. For all regression models, positive coefficient indicates more buying pressure, while negative coefficient indicates more selling pressure. All three columns support Hypotheses 1b and 2. That is, nHFTD trades are abnormally buyer-initiated when price falls to or below the integer thresholds (i.e., positive estimates for *Ask Falls Below Integer – Ask Falls Below Nickel* and *Ask Falls to Integer – Ask Falls to Nickel*) and are abnormally seller-initiated when prices rise to or above the integer thresholds (i.e., negative estimates for *Bid Rises to Integer – Bid Rises to Nickel* and *Bid Rises Above Integer – Bid Rises Above Nickel*), while HFTD trades exhibit the exact opposite sign or are weaker in magnitude in the direction of the psychological effects. For example, in Column (3), the difference in coefficient estimates for *Ask Falls*

Below Integer and *Ask Falls Below Nickel* is 353.36, indicating that nHFTD trades exhibit abnormal buy pressure in the amount of $353.36 per trade on average. On the other hand, the difference in coefficient estimates for *Ask Falls Below Integer* × *HFTD* and *Ask Falls Below Nickel* × *HFTD* is -380.58, which suggests that relative to nHFTD trades, HFTD trades exhibit abnormal sell pressure in the amount of $380.58 per trade on average relative to nHFTD trades. This implies that HFTD trades exhibit abnormal sell pressure of $27.72 (which is equal to the absolute value of $353.36 – $380.58). Coefficients of reach cases (i.e., *Ask Falls to Integer* and *Bid Rises to Integer*) are much bigger than those of cross cases (i.e., *Ask Falls Below Integer* and *Bid Rises Above Integer*) in magnitude, suggesting that the impact of the left-digit and the threshold trigger effects is more dominant compared to that of the cluster undercutting effect.

The sample analyzed in Table 3 largely consists of transactions from the small trade volume and the large market cap groups and HFTD trade activities are predominantly concentrated on those groups as well (see Table 1). Therefore, I run Equation (2) by subsamples of trade volume and firm size to test if the results in Table 3 are only found in certain groups. Trade volume is divided into three categories of small (less than 500 shares), medium (500 to 2,000 shares), and large (more than 2,000 shares), and firm size also into three categories of small, medium, and large.[15] Table 4 presents the subsample results.

[Insert Table 4 Here]

Results from all subsample groups in Table 4 including those with relatively small sample size such as the small firm size and large trade volume groups are consistent with those from Table 3, with all 144 p-values of interest being statistically significant at the 1% level and all coefficients of interest being in the direction that supports Hypotheses 1b and 2.

Results thus far strongly suggest that, while nHFTs continue to follow the psychological trend as documented in BHJ and demand more buy orders when prices fall below/to a round number threshold and more sell order when prices rise above/to such a threshold, HFTs generally behave in the opposite way, resulting in the aggregate sample that does not exhibit any pattern relating to the psychological effects as shown in Figure 1.[16]

[15] The sample firms included in the NASDAQ dataset are already selected from a stratified sample of three firm size groups. The largest 40 stocks of the Russell 3000 are classified as the large market cap group, another 40 around the 1,000th largest stock as the medium market cap, and the remaining 40 around the 2,000th largest as the small size group.
[16] Not all of the three psychological effects dictate that the liquidity demander is biased. Specifically, under the cluster undercutting effect, it is the liquidity supplier who submits an order that may deviate from the fundamental value of a stock. I discuss the implications of this later in the paper when investigating stock returns. For now, it is clear that the trades that nHFTs demand liquidity (nHFTD) follow patterns consistent with the psychological effects, while those that HFTs demand liquidity (HFTD) exhibit the opposite pattern.

5. Stock returns and wealth transfer

In this section, I examine the returns to trading in the direction of and against the psychological effects. HFTs typically "[end] the trading day in as close to a flat position as possible (that is, not carrying significant, unhedged positions overnight)" (SEC, 2014, p. 4). Accordingly, I assume that HFTs close their position by the end of each trading day and thus buy (sell) at the closing price for a stock on the day they sold (bought) it. To make a direct comparison, I make an identical assumption for nHFTs as well, following Brogaard, Hendershott, and Riordan (2014).

I use two dependent variables as proxies of stock returns. The trade price return is computed using the daily closing bid or ask, depending on whether the trade is a purchase or sale. If a trade is buyer-initiated (seller-initiated), its trade price return is the closing bid minus the trade price (the trade price minus the closing ask), scaled by the trade price. Similarly, the midpoint price return is derived using the closing quote midpoint (average of bid and ask) as the price to close out any established position during the day.

The same conditions from the previous section are used again, in addition to further specifying whether each trade is buyer-initiated ("*Buys*") or seller-initiated ("*Sells*"). For example, *Ask Falls Below Integer Buys* equals to 1 if a trade is buyer-initiated and is executed under the condition *Ask Falls Below Integer*, 0 otherwise. Again, each of the integer threshold dummy variable is controlled by its corresponding nickel threshold variable and I only report the difference in coefficients (or, the "abnormal" amount). As in Equation (2), I include the fixed effect controls for firm, month, price level, and trade size in the regression analyses:

$$
\begin{aligned}
DEPVAR_{i,j} = {} & \beta_1 Ask\ Falls\ Below\ Integer\ Buys_{i,j} + \beta_2 Ask\ Falls\ Below\ Integer\ Buys_{i,j} \\
& \times HFTD_{i,j} + \beta_3 Ask\ Falls\ Below\ Nickel\ Buys_{i,j} \\
& + \beta_4 Ask\ Falls\ Below\ Nickel\ Buys_{i,j} \times HFTD_{i,j} + \beta_5 Ask\ Falls\ to\ Integer\ Buys_{i,j} \\
& + \beta_6 Ask\ Falls\ to\ Integer\ Buys_{i,j} \times HFTD_{i,j} + \beta_7 Ask\ Falls\ to\ Nickel\ Buys_{i,j} \\
& + \beta_8 Ask\ Falls\ to\ Nickel\ Buys_{i,j} \times HFTD_{i,j} + \beta_9 Bid\ Rises\ to\ Integer\ Sells_{i,j} \\
& + \beta_{10} Bid\ Rises\ to\ Integer\ Sells_{i,j} \times HFTD_{i,j} + \beta_{11} Bid\ Rises\ to\ Nickel\ Sells_{i,j} \\
& + \beta_{12} Bid\ Rises\ to\ Nickel\ Sells_{i,j} \times HFTD_{i,j} \\
& + \beta_{13} Bid\ Rises\ Above\ Integer\ Sells_{i,j} + \beta_{14} Bid\ Rises\ Above\ Integer\ Sells_{i,j} \\
& \times HFTD_{i,j} + \beta_{15} Bid\ Rises\ Above\ Nickel\ Sells_{i,j} \\
& + \beta_{16} Bid\ Rises\ Above\ Nickel\ Sells_{i,j} \times HFTD_{i,j} + HFTD_{i,j} + \text{Fixed Effects} + \varepsilon_{i,j}. \quad (3)
\end{aligned}
$$

[Insert Table 5 Here]

Table 5 shows the regression results for stock returns when investors trade in the direction of the psychological effects. I present both the result with and without HFTD dummy variable (*HFTD*) and the interaction terms. Column (1) shows that there is a mixed signal as to whether those who trade in the direction of the psychological effects gain or lose, when using trade price as a return proxy. The stock returns for the cross cases (*Ask Falls Below Integer Buys* and *Bid Rises Above Integer Sells*) are negatively significant, indicating that traders lose on average, but those for the reach cases (*Ask Falls to Integer Buys* and *Bid Rises to Integer Sells*) are either positively significant or negatively insignificant, suggesting that trading in the direction of the psychological effects does not necessarily mean investors will lose.[17] Column (2) includes the HFTD dummy variable and shows that nHFTs may still gain when prices reach integer thresholds but lose when prices cross the thresholds. On the other hand, the HFTD interaction terms indicate that HFTs' returns are more than or equal to those of nHFTs under all conditions. In three cases, the coefficients of HFTD interaction terms are positively significant at the 5% level, and in one case the coefficient is negative, but not statistically significant. I find consistent results when the midpoint price is used as a return proxy in Columns (3) and (4).

[Insert Table 6 Here]

Table 6 presents the stock return results by different groups of firm size and trade volume. While HFTs in the small market cap group (Panel A) exhibit statistically significantly lower return than nHFTs for *Ask Falls to Integer Buys*, in all other cases throughout the table the HFT return is significantly higher than or not significantly different from the nHFT return at the 5% level. In the medium market cap group (Panel B), HFTs exhibit significantly higher return in two cases, while their return is not statistically significantly different from that of nHFT in the other two cases. For the large market cap and small trade volume groups (Panels C and D), the results are mostly consistent with the overall sample (Table 5) except one case in Panel C. HFTs exhibit weaker dominance in the medium trade volume group (Panel E) with two cases of positive statistical significance, and no significant dominance in the large trade volume group (Panel F), where no coefficients are statistically significant at the 5% level.

Weaker results from the small and medium firm size groups are not surprising. Brogaard, Hendershott, and Riordan (2014) show that HFTs' revenue is lower than that of nHFTs in the small and

[17] The negative coefficients in the cross cases do not necessarily support the notion that trades that follow the direction of the psychological effects result in lower returns. As pointed out earlier, the cluster undercutting effect is driven by the liquidity supplying activities, not the liquidity demanding side. In addition, Hypotheses 4 through 6 specifically contrast the difference between HFTs and nHFTs, not simply between liquidity demander and supplier. I also discuss this issue in more detail later.

medium firm size categories, when trading fees are not considered. In their results, HFTs' profit comes from both the liquidity-demanding and -supplying trades and is mainly supported by trades from the large firm size group. Weaker results from the medium and large trade volume groups are consistent with O'Hara, Yao, and Ye (2014), who show that much of price discovery comes from trades with less than 100 shares (or odd lots) and that they are more likely to be used by HFTs than nHFTs.[18] In sum, the results support Hypothesis 4 that HFTs' stock return is generally higher than that of nHFTs when trading at the direction of the psychological effects, with some noteworthy exceptions.

As noted earlier, one might argue that the results from Tables 5 and 6 do not necessarily support Hypothesis 4, given that not all of the psychological effects indicate traders are making a mistake when they buy (sell) at a price immediately below (above) round numbers. To elaborate, the left-digit and threshold trigger effects predict excess buy orders at, say, \$6.99, while the cluster undercutting effect predicts that more limit sell orders will be submitted at \$6.99, which in turn leads to more buyer-initiated trades. Therefore, to the extent that those under the psychological effects are paying too much or receiving too little from transactions, the return of purchasing a stock at \$6.99 should be negative under the left-digit and threshold trigger effects, while it should be positive under the cluster undercutting effects since the liquidity provider received too little when selling the stock. While it is not possible to examine each effect separately, I offer four explanations in support of Hypothesis 4.

First, note that the coefficients of HFTD interaction terms in Table 5 for the reach cases (where the cluster undercutting effect does not play a role) are either positively significant or insignificant, indicating that HFTs' stock returns are at least as high as those of nHFTs. This suggests that at least for the left-digit and threshold trigger effects, Hypothesis 4 holds. Second, if the cluster undercutting effect is the dominant effect at, say, \$6.99, we should expect the coefficients of HFTD interaction terms in Table 5 for the cross cases to be insignificant according to Hypothesis 6, since both nHFTs and HFTs are trading against the direction of the psychological effect. However, this is not the case as all coefficients are positively significant. Third, the coefficients of the reach cases in Table 3 are much larger in magnitude than those of the cross cases, suggesting that the magnitude of the left-digit and threshold trigger effects combined is likely to be higher than that of the cluster undercutting effect. Lastly, I compute the returns to initiating trades in the opposite directions of the psychological effects (the "opportunistic" trades) later in this section, which is reported in Table 7, and report the aggregate wealth transfer in Table 9. I show that HFTs are the overall winners, consistent with Hypothesis 4.

Next, I examine the stock returns when investors trade in the opposite direction of the psychological effects (i.e., the "opportunistic" trades that are potentially taking advantage of the psychological effects).

[18] When HFTs intend to trade a large number of shares, they typically split their trading interest into many smaller orders to "hide" their intention and minimize price impact.

To do so, I create conditional dummy variables for trades doing the opposite of what we have studied in Equation (3) and Table 5 – buying a stock when the psychologically affected traders are likely to sell and vice versa. For example, I test whether selling a stock when ask falls below an integer threshold (i.e., *Ask Falls Below Integer Sells* equals to 1) results in a statistically significant profit. Formally, the regression model is:

$$
\begin{aligned}
DEPVAR_{i,j} = {} & \beta_1 Ask\ Falls\ Below\ Integer\ Sells_{i,j} + \beta_2 Ask\ Falls\ Below\ Integer\ Sells_{i,j} \\
& \times HFTD_{i,j} + \beta_3 Ask\ Falls\ Below\ Nickel\ Sells_{i,j} \\
& + \beta_4 Ask\ Falls\ Below\ Nickel\ Sells_{i,j} \times HFTD_{i,j} + \beta_5 Ask\ Falls\ to\ Integer\ Sells_{i,j} \\
& + \beta_6 Ask\ Falls\ to\ Integer\ Sells_{i,j} \times HFTD_{i,j} + \beta_7 Ask\ Falls\ to\ Nickel\ Sells_{i,j} \\
& + \beta_8 Ask\ Falls\ to\ Nickel\ Sells_{i,j} \times HFTD_{i,j} + \beta_9 Bid\ Rises\ to\ Integer\ Buys_{i,j} \\
& + \beta_{10} Bid\ Rises\ to\ Integer\ Buys_{i,j} \times HFTD_{i,j} + \beta_{11} Bid\ Rises\ to\ Nickel\ Buys_{i,j} \\
& + \beta_{12} Bid\ Rises\ to\ Nickel\ Buys_{i,j} \times HFTD_{i,j} \\
& + \beta_{13} Bid\ Rises\ Above\ Integer\ Buys_{i,j} + \beta_{14} Bid\ Rises\ Above\ Integer\ Buys_{i,j} \\
& \times HFTD_{i,j} + \beta_{15} Bid\ Rises\ Above\ Nickel\ Buys_{i,j} \\
& + \beta_{16} Bid\ Rises\ Above\ Nickel\ Buys_{i,j} \times HFTD_{i,j} + HFTD_{i,j} + \text{EQ3 Variables} \\
& + \text{Fixed Effects} + \varepsilon_{i,j}, \qquad (4)
\end{aligned}
$$

where EQ3 Variables include the conditional variables used in Equation (3).

[Insert Table 7 Here]

The regression results for Equation (4) are presented in Table 7. Note that the first eight results (from *Ask Falls Below Integer Sells* to *Bid Rises Above Integer Buys*) pertain to the abnormal opportunistic stock returns, whereas the next eight rows (from *Ask Falls Below Integer Buys* to *Bid Rises Above Integer Sells*) present the abnormal coefficient estimates for EQ3 Variables, the stock return variables taken from Equation (3). As in previous regression models, I include the fixed effect controls for firm, month, trade size, and price levels and only report the abnormal amount (i.e., the coefficient differences between the integer conditions and their nickel counterparts). Whether the dependent variable is the trade price return (Column 1) or the midpoint return (Column 2), nHFTs earn positively significant return in three (*Ask Falls Below Integer Sells*, *Bid Rises Above Integer Buys*, and *Bid Rises to Integer Buys*) out of four opportunistic stock return cases, and negatively significant return in the remaining case (*Ask Falls to Integer Sells*). On the other hand, HFTD trades have significantly higher returns than those of nHFTD in two cases (*Ask Falls to Integer Sells* and *Bid Rises Above Integer Buys*), significantly lower returns in one case (*Ask Falls Below Integer Sells*), and no significant difference in return in one case (*Bid Rises to Integer Buys*). The result is consistent with Hypothesis 5 that there is no clear winner when both HFTD and nHFTD trades are executed against the psychological effects. The coefficient estimates and statistical significance for EQ3 Variables are qualitatively similar to the results in Table 5, with an exception of *Ask Falls to Integer Buys* for HFTD, which is no longer statistically significant.

[Insert Table 8 Here]

Table 8 reports the subsample results for Table 7. Again, the first eight results (from *Ask Falls Below Integer Sells* to *Bid Rises Above Integer Buys*) relate to the opportunistic stock returns, whereas the next eight rows (from *Ask Falls Below Integer Buys* to *Bid Rises Above Integer Sells*) present the abnormal coefficient estimates for EQ3 Variables. Results from the large firm size (Panel C) subsample are consistent with Table 7, but HFTD trades perform worse in other groups. For the small firm size (Panel A), medium firm size (Panel B), small trade volume (Panel D), and medium trade volume (Panel E) groups, HFTD trade returns are statistically significantly higher in one case and lower in another case, and not statistically significantly different in the other two cases. This further supports that there is no clear winner between HFTD and nHFTD opportunistic trades. However, for the large trade volume group, HFTD returns are lower than that of nHFTD under *Bid Rises to Integer Buys*, and statistically insignificantly different in the remaining three cases.

[Insert Table 9 Here]

Lastly, I estimate the overall wealth transfer among trades that occur in the directions of and against the psychological effects. I compute the dollar volume of trades at each conditions (e.g., *Ask Falls Below Integer Buys* and *Bid Rises to Integer Buys*) in the sample, separately for the HFTD and nHFTD trades, and multiply each by their corresponding abnormal stock return coefficients in Table 7. These numbers represent the aggregate gain (or loss) for each type of trader under the sample period and firms. Since my sample can be thought of as a stratified random sample of Russell 3000, I scale the numbers by multiplying them by 3,000 and then dividing by 238 (119 firms in my sample for 2 years) to have an estimate of the annual wealth transfer for stocks in the index. Table 9 shows that the total gain of HFTD trades is higher than that of nHFTD trades, regardless of the dependent variable. HFTD trades gain $107.3 ($110.7) million per year, while nHFTD trades gain $77.7 ($79.7) million when trade price (midpoint) return is used. The results suggest that HFTs are the net gainers, supporting Hypothesis 6. I also compute the dollar volume-weighted returns to trading in the direction of and against the psychological effects, using the dollar volume of trades executed under the conditions from Table 7. I obtain trade price (midpoint) return of 0.0072%

(0.0074%) for HFTD trades and 0.0033% (0.0034%) for nHFTD trades, consistent with HFTs gaining higher percentage returns.

In an untabulated analysis, I compute the mean and standard deviation of all transactions in the sample. Assuming the risk-free rate is zero, the Sharpe ratio for HFTD trades is -0.0199 (0.0034) when the trade price (midpoint) return is used, while that of nHFTD trades is -0.0238 (0.0005). The Sharpe ratio for only the transactions that occur under one of the conditions in Table 9 is -0.0172 (0.0061) for HFTD trades when the trade price (midpoint) return is used, while that of nHFTD trades is -0.0226 (0.0018). The negative Sharpe ratios are likely driven by the transaction costs, since the trade price return assumes that a liquidity-demanding order (e.g., market order) is used for both opening and closing the position within the same day. Nonetheless, the result is consistent with Hypothesis 6.[19]

Note that the profits in Table 9 are those in excess of average profits, since the coefficient estimates in Table 7 are controlled by the average stock return of each trader group (namely, HFTD and the intercept) and the corresponding nickel threshold variables. In other words, the profits estimated in Table 9 are abnormal profits at integer thresholds only, and do not include profits from all the round number thresholds discussed in this paper (i.e., profits on and around half-dollars, quarters, dimes, and nickels). In addition, anecdotal evidence suggests that HFTs may earn a very small amount of profit for each strategy, but makes up for it by engaging in numerous different strategies.[20] Therefore, the wealth transfer estimated in this section should be taken as evidence of HFTs' collecting positive revenue from one of many possible strategies that can be formulated to take advantage of human errors, rather than gauging whether their profits from one particular case are disruptively large.

6. Liquidity supply side of trades

This paper has focused thus far on the imbalance on the liquidity-demanding side of transactions and has shown that HFTs gain higher stock returns. Given that HFTs are less susceptible to the psychological effects and the trading strategy that takes advantage of the effects is profitable, as documented in Section 5, I expect to observe a quoting pattern such that HFTs (nHFTs) are supplying liquidity in a manner consistent with Hypothesis 1b (2).[21]

---

[19] It is also worth noting that the Sharpe ratios are higher for both HFTD and nHFTD trades under the opportunistic conditions compared to the original conditions analyzed in Table 5.

[20] An example of how HFTs may earn profits is illustrated in an article by Jerry Adler in 2012, titled "Raging Bulls: How Wall Street Got Addicted to Light-Speed Trading." In the example, an HFT may earn $600 per strategy per day, but given HFTs run many algorithms ("in the high hundreds"), the actual profit is likely much higher. See https://www.wired.com/2012/08/ff_wallstreet_trading.

[21] An advantage of supplying liquidity through limit orders is that the transaction price is guaranteed. On the other hand, limit orders may not be executed in a reasonable timeframe (in contrast to market orders which are executed immediately), or at all, if no trader is interested in that particular price and quantity.

The NASDAQ dataset classifies each trade into one of the following: HH, HN, NH, and NN.[22] The first letter identifies whether an HFT demands liquidity (H if so, N if not), and the second letter specifies whether an HFT supplies liquidity. I group HH and NH as trades that an HFT supplies liquidity ("HFTS trades") and HN and NN as trades that an nHFT supplies liquidity ("nHFTS trades").

[Insert Table 10 Here]

I examine the liquidity supply side with respect to the psychological effects by estimating Equation (1) with the sample separated by HFTS and nHFTS trades and present the results in Table 10. For the HFTS trades in Column (1) of Panel A, there are more buyer-initiated (seller-initiated) trades below (above) the round number thresholds, when the number of trades are used to calculate the buy-sell ratio. This suggests that HFT liquidity suppliers place a limit sell (buy) order below (above) the thresholds, consistent with the HFT liquidity-demanding activities in Table 2 and with the notion that HFTs supply liquidity to take advantage of the psychological effects. For the nHFTS trades, Column (2) of Panel A shows mixed evidence in relation to the psychological effects, with some coefficients that are consistent with Hypothesis 2 and Table 2 but others that are not. Using different definitions of the buy-sell ratio in Panels B and C yields qualitatively similar results.

[Insert Table 11 Here]

To investigate why the results for nHFTS trades are not more in line with Hypothesis 2, I estimate Equation (1) for each of the four trade types (HH, HN, NH, and NN) and report the results in Table 11. For the HH trades in Column (1) of Panel A, there is no clear pattern with regards to the buy-sell imbalance, except two statistically significant coefficients that are consistent with Table 2. This is consistent with the notion that HFTs are not susceptible to the psychological effects, both on the liquidity-demanding and -supplying sides. The regression result for the HN trades in Column (2) is consistent with Hypotheses 1b and 2 that HFTs demand liquidity in the opposite direction of the psychological effects (i.e., selling below and buying above the thresholds) and nHFTs supply liquidity in the direction of the effects. Combining the findings from Columns (1) and (2) suggests that the results in Table 2 Column (2) for the HFTD trades are largely driven by HFTs' submitting (marketable) orders in the opposite direction of the psychological effects in response to the quotes posted by the nHFTs.

[22] Ideally, I would observe every order submitted to the exchange and be able to identify whether an HFT submitted each order. Unfortunately, to my knowledge, such a procedure is not possible with the NASDAQ dataset or any other publicly-available data for the sample used in this paper. As long as the correlation between trades and quote submissions is consistent across *pp*, results using the transaction data from the NASDAQ dataset should be consistent.

The coefficient estimates from Columns (3) and (4) which respectively use the NH trades and NN trades only are consistent with Column (3) of Table 2 in that the nHFTD trades are more buyer-initiated (seller-initiated) below (above) the thresholds, in the direction of the psychological effects. That HH trades do not exhibit psychological patterns but NH trades do, which are the findings from Columns (1) and (3), suggest that the HFTS trades result from Column (1) of Table 10 is primarily driven by HFTs' supplying liquidity to nHFTs, not to other HFTs. On the other hand, the coefficients of Columns (2) and (4) are in the opposite direction of each other, explaining the mixed evidence from Column (2) of Table 10 with regards to nHFTs' liquidity-supplying behavior. In other words, while HFTs pick up any psychologically-driven quotes from nHFTs [shown in Column (2)], there are also nHFTs who quote against the psychological effects that attract other nHFTs who are under the influence of the effects [shown in Column (4)]. Overall, the results are consistent with Hypotheses 1b and 2, while suggesting that some nHFTs may trade against the psychological effects.[23] Findings from Panel A of Table 11 are robust to using different definitions of the buy-sell ratio in Panels B and C.

7. Differences between high-frequency trading and algorithmic trading

The results so far indicate that HFTs and nHFTs trade strikingly differently on and around round numbers. In Section 2, I hypothesized (Hypothesis 1b) that HFTs' trading pattern differs from that of nHFTs because HFTs extensively use sophisticated programs to trade. If the algorithms used by HFTs are the sole drivers of the differences shown in this paper between HFTs and nHFTs, it is reasonable to conjecture that algorithmic traders that are not HFTs also exhibit the same trading patterns as HFTs do. While the algorithms are likely the main reason behind the different trading patterns on and around round numbers and therefore at least some algorithmic traders excluding HFTs may be trading against the psychological effects, I discuss two ways that HFTs may differ from algorithmic traders in general with respect to the buy-sell imbalances on and around round numbers.

One of the most prominent characteristics of high-frequency trading is its superior speed over other investors (SEC, 2014). While speed itself is not likely to affect whether a trade decision is driven by psychological effects, it increases the probability of being able to trade on an opportunity. To elaborate, suppose the best ask price of a stock is currently \$5.00, with the quoted depth of 100 shares. If the algorithms used by both an HFT and an algorithmic trader are triggered because \$5.00 is cheaper than the fundamental value (and because the price was driven by a psychological effect), both traders will submit a marketable

[23] While it is possible that some nHFTs are not driven by the psychological effects, some traders who are classified as an nHFT may actually be an HFT. The classification of HFTs in the NASDAQ dataset was conducted manually and some HFTs are intentionally categorized as an nHFT (e.g., brokers). To that extent, the results documented in this paper for nHFTs can be thought of as conservative estimates of nHFTs' behavior, and in reality the results for nHFTS trades from Column (2) of Table 10 would be more likely to exhibit patterns documented in Column (3) of Table 2.

buy order of 100 shares. However, since the HFT can receive the quote information and react to it more quickly, the HFT's order will be executed, while the algorithmic trader's order will be executed on the next best price or be cancelled. Therefore, while the algorithms used by both types of traders may be triggered by the same signal, only HFTs might be able to trade on it, making speed an important factor that may have influenced the results seen in Table 2.

While algorithms and machines that investors use to trade do not inherently possess psychological limits, human decisions are still involved in the programming process. In an extreme example, if an algorithmic trader writes a trading algorithm that would buy some shares of a stock at around $4.99 because the trader thinks the price is cheaper than what it really is, the resulting trades are still impacted by the psychological effects even though an algorithm submitted the order for the trader. D'Acunto, Prabhala, and Rossi (2019) find that, while investors exhibit significantly less behavioral biases after adopting robo-advisers, which provide financial advice to investors through automated algorithms, biases do not disappear completely. Lambrecht and Tucker (2019) show that algorithm-delivered ads are delivered to fewer women relative to men, even though the algorithms in their sample are designed to be gender-neutral. The authors explain that younger women are generally more expensive to reach, and therefore the algorithms, which take cost into account, ended up showing fewer ads to women. In a similar vein, suppose a trader comes up with an algorithm that analyzes real-time buy-sell imbalances, and trades when there exists a strong trend of buying or selling. Based on my findings, this algorithm would execute more buy trades when the ask falls below integer, and sell trades when the bid rises above integer in the absence of HFTs. Therefore, using an algorithm alone does not guarantee that the trading strategy will not follow the biased patterns.

Therefore, while both HFTs and algorithmic traders use algorithms to trade, potentially different levels of sophistication in regards to both investing and programming expertise could affect the difference in trading behaviors. While there is no definitive evidence on whether HFTs are better educated investors and programmers than algorithmic traders, it may be supported given that HFTs typically spend huge sums of money on their trading equipment and programs while algorithmic traders can involve a diverse group of investors with different levels sophistication.[24]

8. Concluding remarks

High-frequency trading has been of major topic of interest due to its superior speed. Not only HFTs can use their unmatched speed to quickly take advantage of quotes that are yet to be updated to new

[24] Generally, algorithmic trading has lower barriers to entry, as trading platforms have introduced ways for those who are not a professional or full-time trader to engage in algorithmic trading. For example, see an article by Austen Hufford published in 2015, titled "Algorithmic Trading: The Play-at-Home Version," available at https://www.wsj.com/articles/an-algo-and-a-dream-for-day-traders-1439160100.

information, thereby imposing adverse selection costs on slower investors, they can also use it to engage in activities that can potentially harm the market quality and stability by front-running other investors' orders or by generating erroneous orders that drive prices significantly away from the fundamental value.

However, the fact that machines are not prone to human errors implies that HFTs can eliminate much of inefficiency in the prices stemming from psychological biases. In this paper, I empirically show that the buy-sell imbalances on and around round numbers caused by the psychological effects documented in the literature have vanished in a more recent sample due to the rise of HFTs, who trade in the opposite direction of what investors with the psychological bias typically do. Furthermore, when trading under a situation that is typically influenced by the psychological effects, HFTs earn higher or similar stock returns compared to those of nHFTs, suggesting that HFTs can identify when trades are likely driven by the psychological effects. Interestingly, the imbalances are also gone for trades that both liquidity demander and supplier are an HFT, suggesting that HFTs benefit the most from the psychological effects when interacting with an nHFT.

My findings suggest that HFTs' impact on the market is not merely through their speed. Rather, their sophisticated trading capabilities can help correct inefficiencies by trading without psychological constraints that may induce human errors. Moreover, seeming disappearance of behavioral biases in the overall sample cannot necessarily rule out the possibility that human traders as a whole are still making the same bias-driven investment decisions. This result has implications to the vast literature of financial anomalies that relate to human biases and errors, especially those that document diminishing anomalies, and to the regulators and exchanges as they assess the impacts of high-frequency trading in the market.

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Figure 1: Median Buy-Sell Ratio of All Liquidity Demanders at .XX Price Points

This figure presents the median buy-sell ratio (*BSR*), which is defined as (*buys* – *sells*) / (*buys* + *sells*), of all transactions at each price point ranging from .00 to .99. *buys* (*sells*) is defined as one of number of buyer-initiated (seller-initiated) trades, number of shares bought (sold), or dollar volume of buyer-initiated (seller-initiated) trades, over a one-year period for each firm.

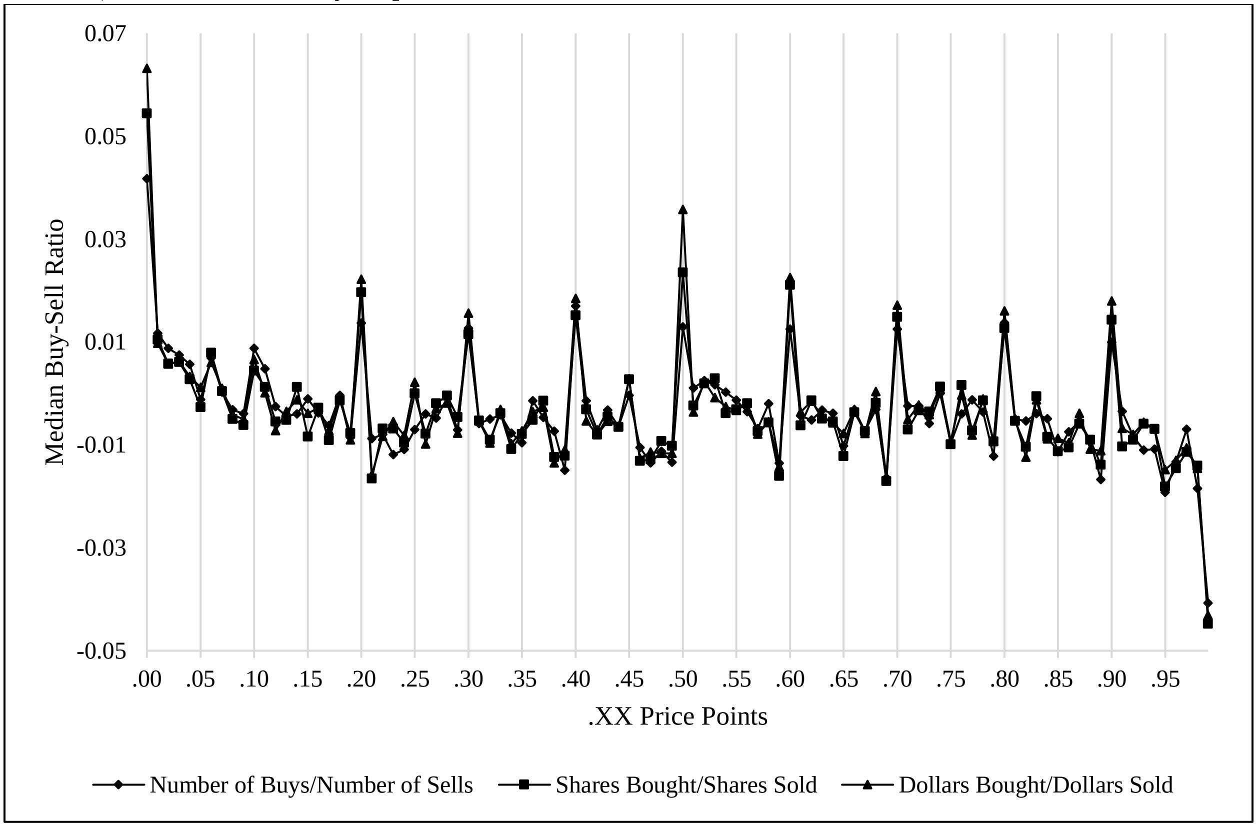
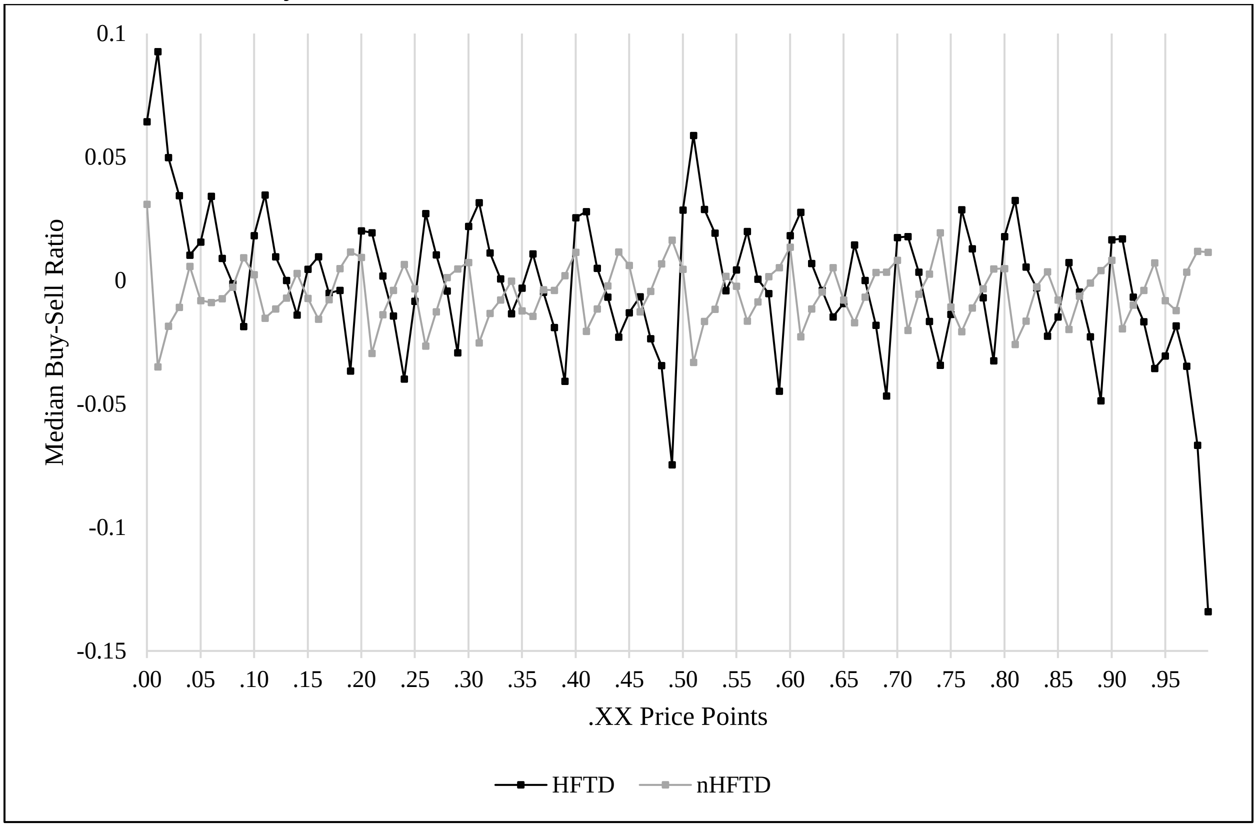


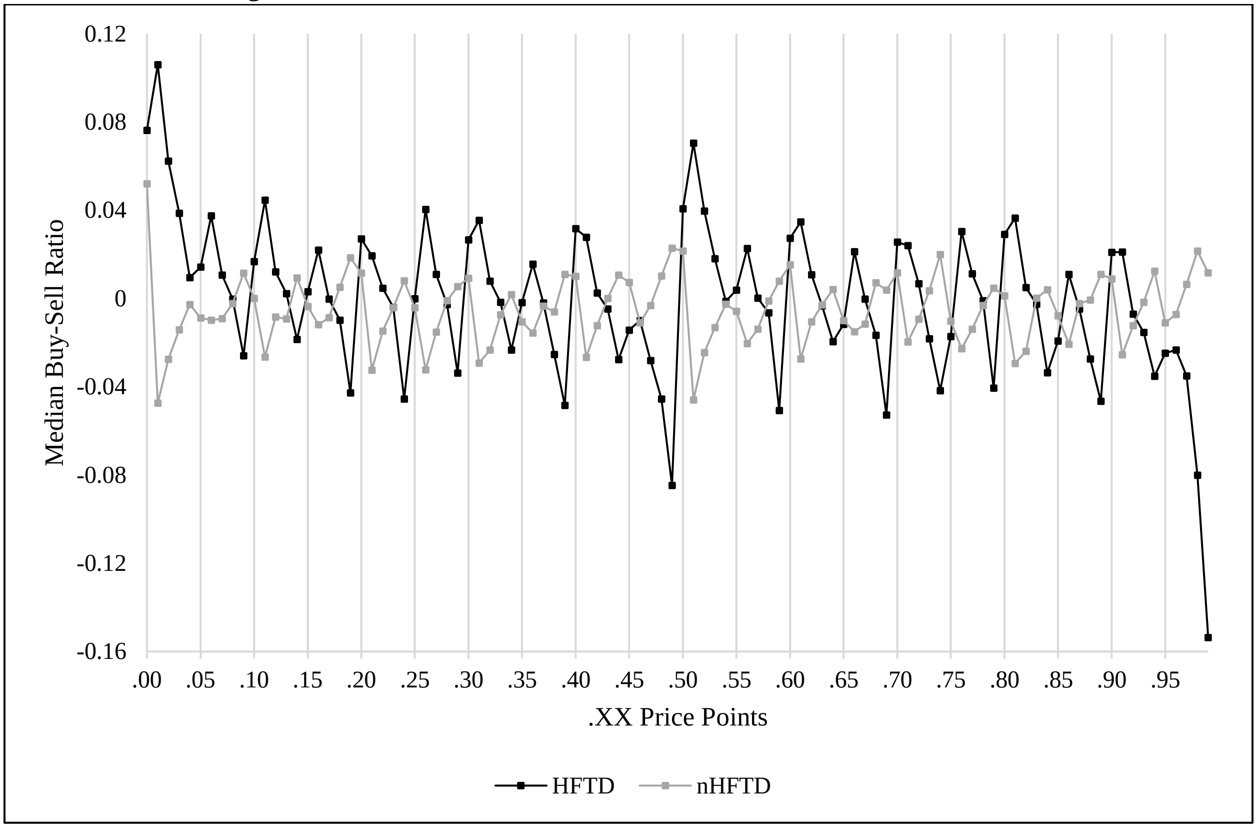
Figure 2: Median Buy-Sell Ratio of HFTD and nHFTD Trades at .XX Price Points

This figure presents the median buy-sell ratio (*BSR*), which is defined as (*buys* – *sells*) / (*buys* + *sells*), of transactions separated by HFTD and nHFTD trades at each price point ranging from .00 to .99. In Panel A, *buys* and *sells* are defined respectively as the number of buyer- and seller-initiated trades, while in Panels B and C they are defined as the number of shares bought and sold and the dollar volume of buyer- and seller-initiated trades.

Panel A: Number of Buys / Number of Sells



Panel B: Shares Bought / Shares Sold



Panel C: Dollars Bought / Dollars Sold

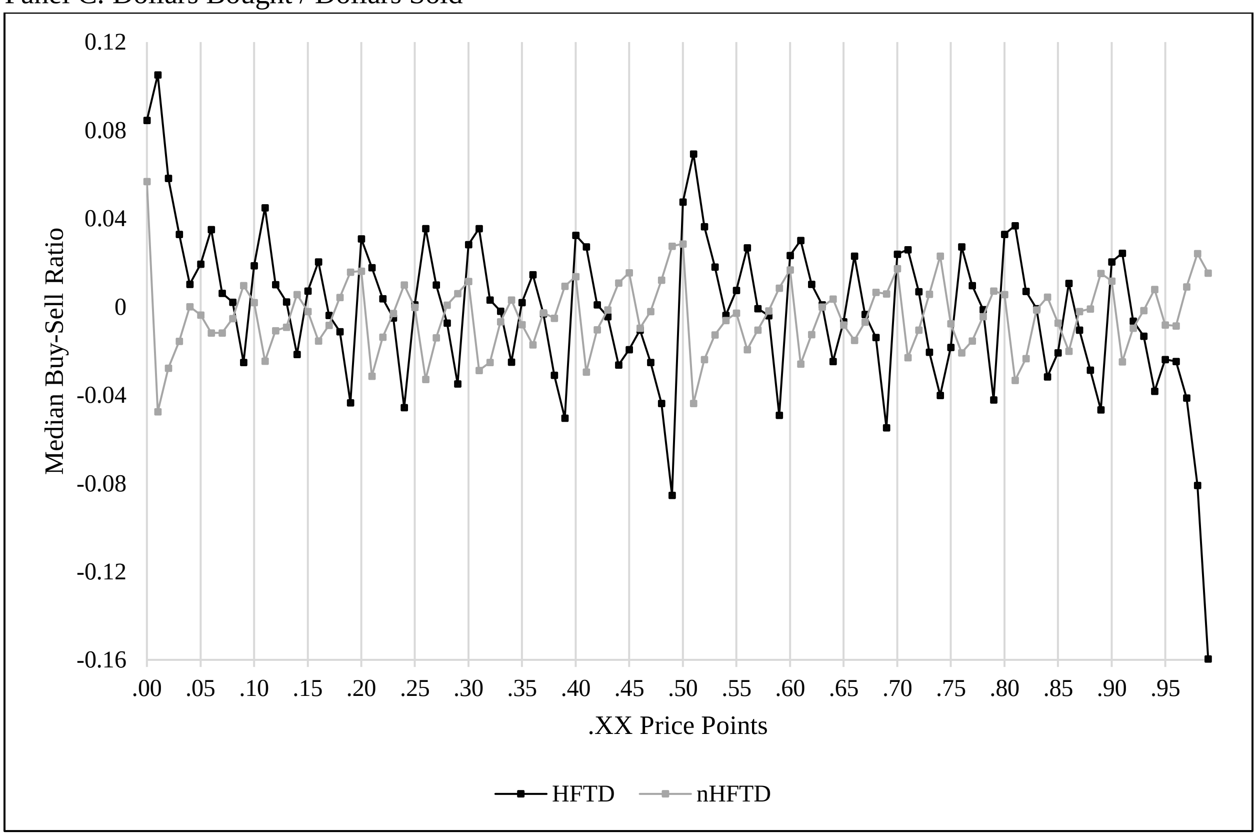


Table 1: Descriptive Statistics

Descriptive statistics of the sample are presented. HFTD (nHFTD) trades are those that a HFT (nHFT) is a liquidity demander. Number in parentheses indicates percentage with respect to the total amount of trades in respective columns. Both overall sample and subsamples divided into firm size and trade size are reported. Large firm size is defined as those at the top of the Russell 3000 index, medium group consists of firms around 1000th place in the index, and small group is taken around 2000th place in the index. Large trade size is defined as trades with more than 2,000 shares traded, medium as trades between 500 and 2,000 shares, and small as less than 500 shares. *N* indicates the sample size.

		Firm Size			Trade Size		
	All Sample	Small	Medium	Large	Small	Medium	Large
Price (mean)	$31.62	$15.11	$23.88	$32.90	$32.46	$22.06	$20.61
Price (median)	$23.85	$13.44	$19.74	$24.63	$24.75	$19.00	$18.80
HFTD Trades	215,799	2,841	18,753	194,205	202,242	12,781	776
(in thousand)	(43%)	(24%)	(40%)	(44%)	(44%)	(35%)	(27%)
nHFTD Trades	282,604	8,932	28,325	245,347	256,553	23,925	2,127
(in thousand)	(57%)	(76%)	(60%)	(56%)	(56%)	(65%)	(73%)
HFTD Shares Traded	37,399	309	2,084	35,005	24,747	9,780	2,872
(in million)	(38%)	(22%)	(34%)	(38%)	(42%)	(34%)	(24%)
nHFTD Shares Traded	61,656	1,091	3,975	56,590	33,928	18,746	8,982
(in million)	(62%)	(78%)	(66%)	(62%)	(58%)	(66%)	(76%)
HFTD Dollar Volume	$1,027,843	$5,072	$48,073	$974,697	$758,433	$210,606	$58,804
(in million)	(39%)	(25%)	(36%)	(39%)	(43%)	(34%)	(24%)
nHFTD Dollar Volume	$1,619,902	$15,374	$84,068	$1,520,460	$1,023,028	$412,884	$183,990
(in million)	(61%)	(75%)	(64%)	(61%)	(57%)	(66%)	(76%)
N	498,403,028	11,772,966	47,078,044	439,552,018	458,794,447	36,705,421	2,903,160

Table 2: Buy-Sell Ratio by Price Point Dummies

This table presents the regression results for Equation (1). The dependent variable is the buy-sell ratio (*BSR*), which is defined as (*buys* – *sells*) / (*buys* + *sells*), of liquidity demanders for each firm-year. In Panel A, *buys* and *sells* are defined respectively as the number of buyer- and seller-initiated trades, while in Panels B and C they are defined as the number of shares bought and sold and the dollar volume of buyer- and seller-initiated trades. The independent variables are dummy variables for price points: *Below Integers* equals to 1 if *pp* = .99 and 0 otherwise, *Above Integers* equals to 1 if *pp* = .01 and 0 otherwise, *Below Half-Dollars* equals to 1 if *pp* = .49 and 0 otherwise, *Above Half-Dollars* equals to 1 if *pp* = .51 and 0 otherwise, *Below Quarters* equals to 1 if *pp* ϵ {.24, .74} and 0 otherwise, *Above Quarters* equals to 1 if *pp* ϵ {.26, .76} and 0 otherwise, *Below Dimes* equals to 1 if *pp* ϵ {.09, .19, .29, .39, .59, .69, .79, .89} and 0 otherwise, *Above Dimes* equals to 1 if *pp* ϵ {.11, .21, .31, .41, .61, .71, .81, .91} and 0 otherwise, *Below Nickels* equals to 1 if *pp* ϵ {.04, .14, .34, .44, .54, .64, .84, .94} and 0 otherwise, and *Above Nickels* equals to 1 if *pp* ϵ {.06, .16, .36, .46, .56, .66, .86, .96} and 0 otherwise. Column (1) includes all trades, Column (2) includes trades initiated by HFTs only (HFTD trades), and Column (3) includes trades initiated by nHFTs only (nHFTD trades). *N* indicates the sample size.

	(1) All Trades	p-value	(2) HFTD Trades	p-value	(3) nHFTD Trades	p-value
Panel A: Number of Buys and Sells						
Intercept	-0.0009	0.1574	-0.0009	0.3997	-0.0018	0.0086
Below Integers	-0.0311	<0.0001	-0.1347	<0.0001	0.0245	<0.0001
Above Integers	-0.0027	0.5711	0.0941	<0.0001	-0.0522	<0.0001
Below Half-Dollars	-0.0099	0.0395	-0.0843	<0.0001	0.0282	<0.0001
Above Half-Dollars	-0.0035	0.4631	0.0642	<0.0001	-0.0389	<0.0001
Below Quarters	-0.0027	0.4260	-0.0439	<0.0001	0.0177	<0.0001
Above Quarters	-0.0080	0.0192	0.0278	<0.0001	-0.0261	<0.0001
Below Dimes	-0.0060	0.0008	-0.0425	<0.0001	0.0116	<0.0001
Above Dimes	-0.0080	<0.0001	0.0258	<0.0001	-0.0242	<0.0001
Below Nickels	-0.0015	0.4145	-0.0238	<0.0001	0.0072	0.0002
Above Nickels	-0.0071	<0.0001	0.0085	0.0041	-0.0140	<0.0001
N	23,700		23,700		23,700	
Panel B: Shares Bought and Sold						
Intercept	-0.0019	0.0099	-0.0005	0.6610	-0.0032	<0.0001
Below Integers	-0.0285	<0.0001	-0.1504	<0.0001	0.0302	<0.0001
Above Integers	-0.0109	0.0600	0.1021	<0.0001	-0.0613	<0.0001
Below Half-Dollars	-0.0034	0.5591	-0.0874	<0.0001	0.0360	<0.0001

Above Half-Dollars	-0.0097	0.0928	0.0746	<0.0001	-0.0483	<0.0001
Below Quarters	-0.0012	0.7806	-0.0510	<0.0001	0.0233	<0.0001
Above Quarters	-0.0090	0.0284	0.0313	<0.0001	-0.0287	<0.0001
Below Dimes	-0.0039	0.0728	-0.0443	<0.0001	0.0142	<0.0001
Above Dimes	-0.0122	<0.0001	0.0269	<0.0001	-0.0296	<0.0001
Below Nickels	-0.0008	0.6946	-0.0277	<0.0001	0.0088	0.0001
Above Nickels	-0.0088	<0.0001	0.0104	0.0025	-0.0169	<0.0001
N	23,700		23,700		23,700	
Panel C: Dollars Bought and Sold						
Intercept	-0.0005	0.5446	-0.0006	0.6220	-0.0013	0.0993
Below Integers	-0.0273	<0.0001	-0.1521	<0.0001	0.0328	<0.0001
Above Integers	-0.0115	0.0485	0.1019	<0.0001	-0.0628	<0.0001
Below Half-Dollars	-0.0027	0.6451	-0.0883	<0.0001	0.0371	<0.0001
Above Half-Dollars	-0.0110	0.0603	0.0743	<0.0001	-0.0497	<0.0001
Below Quarters	0.0000	0.9883	-0.0523	<0.0001	0.0225	<0.0001
Above Quarters	-0.0101	0.0156	0.0301	<0.0001	-0.0298	<0.0001
Below Dimes	-0.0045	0.0413	-0.0455	<0.0001	0.0138	<0.0001
Above Dimes	-0.0134	<0.0001	0.0262	<0.0001	-0.0310	<0.0001
Below Nickels	-0.0021	0.3279	-0.0298	<0.0001	0.0076	0.0012
Above Nickels	-0.0102	<0.0001	0.0092	0.0089	-0.0183	<0.0001
N	23,700		23,700		23,700	

Table 3: Conditional Buy-Sell Ratio by Price Point Dummies

This table presents the regression results for Equation (2). Column (1) uses a logit model where buyer-initiated trades are coded as 1 and seller-initiated trades as 0. Column (2) uses OLS, with dependent variable equal to number of shares for buyer-initiated trades or negative number of shares for seller-initiated trades. Column (3) also uses OLS, but with dollar volume of shares for buyer-initiated trades or negative dollar volume for seller-initiated trades. Independent variables are conditional dummy variables of when the trades have occurred, and their definitions are provided in Section 4. Coefficients reported are difference in coefficients of integer dummy variables and their corresponding nickel variables. *(HFTD)* indicates an interaction of the conditional dummy variables and *HFTD*, which is a dummy variable that equals to 1 if liquidity demander is a HFT and 0 if it is an nHFT. All regression models include fixed effect controls for firm, month, price level, and trade size. *N* indicates the sample size.

	(1)		(2)		(3)	
	Logit: 1 for buy, 0 for sell	p-value	OLS: +shares bought or – shares sold	p-value	OLS: +dollars bought or – dollars sold	p-value
Ask Falls Below Integer – Ask Falls Below Nickel	0.0949	<0.0001	11.70	<0.0001	353.36	<0.0001
Ask Falls Below Integer – Ask Falls Below Nickel (HFTD)	-0.1087	<0.0001	-13.23	<0.0001	-380.58	<0.0001
Ask Falls to Integer – Ask Falls to Nickel	0.2832	<0.0001	29.05	<0.0001	882.74	<0.0001
Ask Falls to Integer – Ask Falls to Nickel (HFTD)	-0.1139	<0.0001	-17.43	<0.0001	-510.04	<0.0001
Bid Rises to Integer – Bid Rises to Nickel	-0.2296	<0.0001	-22.61	<0.0001	-678.90	<0.0001
Bid Rises to Integer – Bid Rises to Nickel (HFTD)	0.1257	<0.0001	16.12	<0.0001	493.96	<0.0001
Bid Rises Above Integer – Bid Rises Above Nickel	-0.0962	<0.0001	-11.59	<0.0001	-368.21	<0.0001
Bid Rises Above Integer – Bid Rises Above Nickel (HFTD)	0.0964	<0.0001	12.71	<0.0001	367.31	<0.0001
HFTD	0.0171	<0.0001	1.40	<0.0001	29.17	<0.0001
Firm fixed effects	Yes		Yes		Yes	
Month fixed effects	Yes		Yes		Yes	
Price level fixed effects	Yes		Yes		Yes	
Trade size fixed effects	Yes		Yes		Yes	
N	498,394,084		498,394,084		498,394,084	

Table 4: Conditional Buy-Sell Ratio by Price Point Dummies, by Trade Volume and Firm Size

This table presents the regression results for Equation (2) by subsamples of three groups of firm size (Panels A through C) and three groups of trade volume (Panels D through F). Column (1) uses a logit model where buyer-initiated trades are coded as 1 and seller-initiated trades as 0. Column (2) uses OLS, with dependent variable equal to number of shares for buyer-initiated trades or negative number of shares for seller-initiated trades. Column (3) also uses OLS, but with dollar volume of shares for buyer-initiated trades or negative dollar volume for seller-initiated trades. Independent variables are conditional dummy variables of when the trades have occurred, and their definitions are provided in Section 4. Coefficients reported are difference in coefficients of integer dummy variables and their corresponding nickel variables. *(HFTD)* indicates an interaction of the conditional dummy variables and *HFTD*, which is a dummy variable that equals to 1 if liquidity demander is a HFT and 0 if it is an nHFT. All regression models include fixed effect controls for firm, month, and price level, while Panels A–C also include trade size fixed effects. *N* indicates the sample size.

	(1)		(2)		(3)	
	Logit: 1 for buy, 0 for sell	p-value	OLS: +shares bought or – shares sold	p-value	OLS: +dollars bought or – dollars sold	p-value
Panel A: Small Firm Size						
Ask Falls Below Integer – Ask Falls Below Nickel	0.1316	<0.0001	9.42	<0.0001	125.89	<0.0001
Ask Falls Below Integer – Ask Falls Below Nickel (HFTD)	-0.0704	<0.0001	-5.31	<0.0001	-42.10	0.0002
Ask Falls to Integer – Ask Falls to Nickel	0.4615	<0.0001	34.06	<0.0001	518.91	<0.0001
Ask Falls to Integer – Ask Falls to Nickel (HFTD)	-0.2246	<0.0001	-20.86	<0.0001	-308.89	<0.0001
Bid Rises to Integer – Bid Rises to Nickel	-0.4221	<0.0001	-33.44	<0.0001	-458.15	<0.0001
Bid Rises to Integer – Bid Rises to Nickel (HFTD)	0.2387	<0.0001	24.17	<0.0001	311.30	<0.0001
Bid Rises Above Integer – Bid Rises Above Nickel	-0.1600	<0.0001	-9.59	<0.0001	-156.65	<0.0001
Bid Rises Above Integer – Bid Rises Above Nickel (HFTD)	0.0950	<0.0001	5.42	<0.0001	56.65	<0.0001
HFTD	-0.0009	0.7537	0.39	0.2358	-4.49	0.3798
Firm fixed effects	Yes		Yes		Yes	
Month fixed effects	Yes		Yes		Yes	
Price level fixed effects	Yes		Yes		Yes	
Trade size fixed effects	Yes		Yes		Yes	
N	11,772,657		11,772,657		11,772,657	
Panel B: Medium Firm Size						
Ask Falls Below Integer – Ask Falls Below Nickel	0.0954	<0.0001	8.13	<0.0001	189.43	<0.0001

Ask Falls Below Integer – Ask Falls Below Nickel (HFTD)	-0.1025	<0.0001	-9.07	<0.0001	-197.85	<0.0001
Ask Falls to Integer – Ask Falls to Nickel	0.3915	<0.0001	31.21	<0.0001	782.97	<0.0001
Ask Falls to Integer – Ask Falls to Nickel (HFTD)	-0.2013	<0.0001	-21.61	<0.0001	-520.24	<0.0001
Bid Rises to Integer – Bid Rises to Nickel	-0.3239	<0.0001	-24.62	<0.0001	-647.42	<0.0001
Bid Rises to Integer – Bid Rises to Nickel (HFTD)	0.1985	<0.0001	19.61	<0.0001	510.15	<0.0001
Bid Rises Above Integer – Bid Rises Above Nickel	-0.1066	<0.0001	-8.51	<0.0001	-208.80	<0.0001
Bid Rises Above Integer – Bid Rises Above Nickel (HFTD)	0.0704	<0.0001	7.34	<0.0001	162.71	<0.0001
HFTD	-0.0027	0.0312	0.42	0.0076	5.70	0.0997
Firm fixed effects	Yes		Yes		Yes	
Month fixed effects	Yes		Yes		Yes	
Price level fixed effects	Yes		Yes		Yes	
Trade size fixed effects	Yes		Yes		Yes	
N	47,077,296		47,077,296		47,077,296	
Panel C: Large Firm Size						
Ask Falls Below Integer – Ask Falls Below Nickel	0.0940	<0.0001	12.12	<0.0001	376.50	<0.0001
Ask Falls Below Integer – Ask Falls Below Nickel (HFTD)	-0.1086	<0.0001	-13.77	<0.0001	-407.47	<0.0001
Ask Falls to Integer – Ask Falls to Nickel	0.2543	<0.0001	27.68	<0.0001	890.28	<0.0001
Ask Falls to Integer – Ask Falls to Nickel (HFTD)	-0.0885	<0.0001	-16.09	<0.0001	-515.67	<0.0001
Bid Rises to Integer – Bid Rises to Nickel	-0.2043	<0.0001	-21.18	<0.0001	-674.76	<0.0001
Bid Rises to Integer – Bid Rises to Nickel (HFTD)	0.1045	<0.0001	14.76	<0.0001	493.72	<0.0001
Bid Rises Above Integer – Bid Rises Above Nickel	-0.0936	<0.0001	-11.95	<0.0001	-389.74	<0.0001
Bid Rises Above Integer – Bid Rises Above Nickel (HFTD)	0.0975	<0.0001	13.35	<0.0001	395.20	<0.0001
HFTD	0.0192	<0.0001	1.50	<0.0001	31.43	<0.0001
Firm fixed effects	Yes		Yes		Yes	
Month fixed effects	Yes		Yes		Yes	
Price level fixed effects	Yes		Yes		Yes	
Trade size fixed effects	Yes		Yes		Yes	
N	439,544,131		439,544,131		439,544,131	
Panel D: Small Trade Volume (Less than 500 Shares)						
Ask Falls Below Integer – Ask Falls Below Nickel	0.0939	<0.0001	6.07	<0.0001	221.00	<0.0001
Ask Falls Below Integer – Ask Falls Below Nickel (HFTD)	-0.1076	<0.0001	-7.48	<0.0001	-256.29	<0.0001
Ask Falls to Integer – Ask Falls to Nickel	0.2866	<0.0001	18.05	<0.0001	606.05	<0.0001

Ask Falls to Integer – Ask Falls to Nickel (HFTD)	-0.1144	<0.0001	-8.57	<0.0001	-275.54	<0.0001
Bid Rises to Integer – Bid Rises to Nickel	-0.2308	<0.0001	-14.59	<0.0001	-486.47	<0.0001
Bid Rises to Integer – Bid Rises to Nickel (HFTD)	0.1261	<0.0001	9.06	<0.0001	316.78	<0.0001
Bid Rises Above Integer – Bid Rises Above Nickel	-0.0954	<0.0001	-6.16	<0.0001	-228.74	<0.0001
Bid Rises Above Integer – Bid Rises Above Nickel (HFTD)	0.0943	<0.0001	6.66	<0.0001	230.37	<0.0001
HFTD	0.0167	<0.0001	0.95	<0.0001	20.33	<0.0001
Firm fixed effects	Yes		Yes		Yes	
Month fixed effects	Yes		Yes		Yes	
Price level fixed effects	Yes		Yes		Yes	
Trade size fixed effects	No		No		No	
N	458,786,586		458,786,586		458,786,586	
Panel E: Medium Trade Volume (500 to 2,000 Shares)						
Ask Falls Below Integer – Ask Falls Below Nickel	0.1030	<0.0001	41.49	<0.0001	1,090.98	<0.0001
Ask Falls Below Integer – Ask Falls Below Nickel (HFTD)	-0.1163	<0.0001	-46.04	<0.0001	-1,074.69	<0.0001
Ask Falls to Integer – Ask Falls to Nickel	0.2461	<0.0001	89.71	<0.0001	2,375.58	<0.0001
Ask Falls to Integer – Ask Falls to Nickel (HFTD)	-0.1201	<0.0001	-45.03	<0.0001	-1,262.70	<0.0001
Bid Rises to Integer – Bid Rises to Nickel	-0.2141	<0.0001	-78.72	<0.0001	-2,047.94	<0.0001
Bid Rises to Integer – Bid Rises to Nickel (HFTD)	0.1207	<0.0001	46.34	<0.0001	1,354.04	<0.0001
Bid Rises Above Integer – Bid Rises Above Nickel	-0.1023	<0.0001	-42.21	<0.0001	-1,144.19	<0.0001
Bid Rises Above Integer – Bid Rises Above Nickel (HFTD)	0.1187	<0.0001	48.93	<0.0001	1,114.03	<0.0001
HFTD	0.0255	<0.0001	9.97	<0.0001	224.42	<0.0001
Firm fixed effects	Yes		Yes		Yes	
Month fixed effects	Yes		Yes		Yes	
Price level fixed effects	Yes		Yes		Yes	
Trade size fixed effects	No		No		No	
N	36,704,425		36,704,425		36,704,425	
Panel F: Large Trade Volume (More than 2,000 Shares)						
Ask Falls Below Integer – Ask Falls Below Nickel	0.1329	<0.0001	315.50	<0.0001	7,149.00	<0.0001
Ask Falls Below Integer – Ask Falls Below Nickel (HFTD)	-0.1343	<0.0001	-314.83	<0.0001	-6,192.19	<0.0001
Ask Falls to Integer – Ask Falls to Nickel	0.2862	<0.0001	727.29	<0.0001	17,880.99	<0.0001
Ask Falls to Integer – Ask Falls to Nickel (HFTD)	-0.1932	<0.0001	-576.29	<0.0001	-16,050.71	<0.0001
Bid Rises to Integer – Bid Rises to Nickel	-0.2266	<0.0001	-463.34	<0.0001	-10,558.90	<0.0001

Bid Rises to Integer – Bid Rises to Nickel (HFTD)	0.2541	<0.0001	485.57	<0.0001	11,794.12	<0.0001
Bid Rises Above Integer – Bid Rises Above Nickel	-0.1260	<0.0001	-293.71	<0.0001	-7,800.98	<0.0001
Bid Rises Above Integer – Bid Rises Above Nickel (HFTD)	0.1675	<0.0001	371.54	<0.0001	7,967.13	<0.0001
HFTD	0.0055	0.3521	-3.26	0.8410	-6.55	0.9856
Firm fixed effects	Yes		Yes		Yes	
Month fixed effects	Yes		Yes		Yes	
Price level fixed effects	Yes		Yes		Yes	
Trade size fixed effects	No		No		No	
N	2,903,073		2,903,073		2,903,073	

Table 5: Stock Returns by Price Point Dummies

This table presents the regression results for Equation (3). Dependent variables are the stock returns to closing positions at the daily closing prices. Columns (1) and (2) use the daily closing bid (ask) if the trade was a purchase (sale) to compute returns, while Columns (3) and (4) use the daily closing midpoint. Independent variables are conditional dummy variables of when the trades have occurred, and their definitions are provided in Section 4. Coefficients reported are difference in coefficients of integer dummy variables and their corresponding nickel variables. *(HFTD)* indicates an interaction of the conditional dummy variables and *HFTD*, which is a dummy variable that equals to 1 if liquidity demander is a HFT and 0 if it is an nHFT. All regression models include fixed effect controls for firm, month, trade size, and price level. *N* indicates the sample size.

	(1)		(2)		(3)		(4)	
	Trade Price	p-value	Trade Price	p-value	Midpoint	p-value	Midpoint	p-value
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys	-0.01376%	<0.0001	-0.01953%	<0.0001	-0.01323%	<0.0001	-0.01914%	<0.0001
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys (HFTD)			0.01318%	<0.0001			0.01347%	<0.0001
Ask Falls to Integer Buys – Ask Falls to Nickel Buys	0.02785%	<0.0001	0.02467%	<0.0001	0.02862%	<0.0001	0.02529%	<0.0001
Ask Falls to Integer Buys – Ask Falls to Nickel Buys (HFTD)			0.00840%	0.0318			0.00881%	0.0241
Bid Rises to Integer Sells – Bid Rises to Nickel Sells	-0.00283%	0.1504	-0.00090%	0.7173	-0.00334%	0.0885	-0.00148%	0.5531
Bid Rises to Integer Sells – Bid Rises to Nickel Sells (HFTD)			-0.00482%	0.2347			-0.00469%	0.2468
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells	-0.01770%	<0.0001	-0.02088%	<0.0001	-0.01794%	<0.0001	-0.02115%	<0.0001
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells (HFTD)			0.00743%	<0.0001			0.00748%	<0.0001
HFTD			0.00724%	<0.0001			0.00629%	<0.0001
Firm fixed effects	Yes		Yes		Yes		Yes	
Month fixed effects	Yes		Yes		Yes		Yes	
Price level fixed effects	Yes		Yes		Yes		Yes	
Trade size fixed effects	Yes		Yes		Yes		Yes	
N	498,340,508		498,340,508		498,340,508		498,340,508	

Table 6: Stock Returns by Price Point Dummies, by Trade Volume and Firm Size

This table presents the regression results for Equation (3) by subsamples of three groups of firm size (Panels A through C) and three groups of trade volume (Panels D through F). Dependent variables are the stock returns to closing positions at the daily closing prices. Columns (1) and (2) use the daily closing bid (ask) if the trade was a purchase (sale) to compute returns, while Columns (3) and (4) use the daily closing midpoint. Independent variables are conditional dummy variables of when the trades have occurred, and their definitions are provided in Section 4. Coefficients reported are difference in coefficients of integer dummy variables and their corresponding nickel variables. *(HFTD)* indicates an interaction of the conditional dummy variables and *HFTD*, which is a dummy variable that equals to 1 if liquidity demander is a HFT and 0 if it is an nHFT. All regression models include fixed effect controls for firm, month, and price level, while Panels A–C also include trade size fixed effects. *N* indicates the sample size.

	(1)		(2)		(3)		(4)	
	Trade Price	p-value	Trade Price	p-value	Midpoint	p-value	Midpoint	p-value
Panel A: Small Firm Size								
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys	-0.08540%	<0.0001	-0.09375%	<0.0001	-0.08955%	<0.0001	-0.09894%	<0.0001
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys (HFTD)			0.03406%	0.0095			0.03822%	0.0035
Ask Falls to Integer Buys – Ask Falls to Nickel Buys	0.10492%	<0.0001	0.12401%	<0.0001	0.10354%	<0.0001	0.12100%	<0.0001
Ask Falls to Integer Buys – Ask Falls to Nickel Buys (HFTD)			-0.10008%	0.0023			-0.09694%	0.0029
Bid Rises to Integer Sells – Bid Rises to Nickel Sells	-0.03989%	0.0041	-0.05266%	0.0006	-0.04604%	0.0007	-0.06014%	<0.0001
Bid Rises to Integer Sells – Bid Rises to Nickel Sells (HFTD)			0.06128%	0.0807			0.06453%	0.0648
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells	0.00263%	0.8670	-0.01821%	0.3152	0.00102%	0.9478	-0.02079%	0.2498
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells (HFTD)			0.08090%	0.0254			0.08440%	0.0192
HFTD			0.00417%	0.0747			-0.00050%	0.8292
Firm fixed effects	Yes		Yes		Yes		Yes	
Month fixed effects	Yes		Yes		Yes		Yes	
Price level fixed effects	Yes		Yes		Yes		Yes	

Trade size fixed effects	Yes		Yes		Yes		Yes	
N	11,772,718		11,772,718		11,772,718		11,772,718	
Panel B: Medium Firm Size								
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys	-0.06972%	<0.0001	-0.09388%	<0.0001	-0.06630%	<0.0001	-0.09102%	<0.0001
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys (HFTD)			0.06069%	<0.0001			0.06190%	<0.0001
Ask Falls to Integer Buys – Ask Falls to Nickel Buys	-0.02228%	0.0006	-0.01852%	0.0189	-0.01640%	0.0109	-0.01321%	0.0931
Ask Falls to Integer Buys – Ask Falls to Nickel Buys (HFTD)			-0.01348%	0.3277			-0.01183%	0.3889
Bid Rises to Integer Sells – Bid Rises to Nickel Sells	0.00800%	0.2618	0.00700%	0.4201	0.00900%	0.1606	0.00800%	0.3341
Bid Rises to Integer Sells – Bid Rises to Nickel Sells (HFTD)			0.00148%	0.9196			0.00319%	0.8266
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells	-0.00300%	0.1756	-0.02100%	<0.0001	-0.00500%	0.0626	-0.02300%	<0.0001
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells (HFTD)			0.04288%	<0.0001			0.04351%	<0.0001
HFTD			-0.00773%	<0.0001			-0.01033%	<0.0001
Firm fixed effects	Yes		Yes		Yes		Yes	
Month fixed effects	Yes		Yes		Yes		Yes	
Price level fixed effects	Yes		Yes		Yes		Yes	
Trade size fixed effects	Yes		Yes		Yes		Yes	
N	47,077,623		47,077,623		47,077,623		47,077,623	
Panel C: Large Firm Size								
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys	-0.00582%	<0.0001	-0.00790%	<0.0001	-0.00540%	<0.0001	-0.00752%	<0.0001
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys (HFTD)			0.00481%	0.0008			0.00489%	0.0007

Ask Falls to Integer Buys – Ask Falls to Nickel Buys	0.03042%	<0.0001	0.02382%	<0.0001	0.03049%	<0.0001	0.02377%	<0.0001
Ask Falls to Integer Buys – Ask Falls to Nickel Buys (HFTD)			0.01695%	<0.0001			0.01726%	<0.0001
Bid Rises to Integer Sells – Bid Rises to Nickel Sells	0.00003%	0.9870	0.00383%	0.1478	-0.00061%	0.7679	0.00322%	0.2234
Bid Rises to Integer Sells – Bid Rises to Nickel Sells (HFTD)			-0.00946%	0.0255			-0.00957%	0.0238
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells	-0.01676%	<0.0001	-0.01741%	<0.0001	-0.01686%	<0.0001	-0.01752%	<0.0001
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells (HFTD)			0.00162%	0.2611			0.00162%	0.2595
HFTD			0.00945%	<0.0001			0.00872%	<0.0001
Firm fixed effects	Yes		Yes		Yes		Yes	
Month fixed effects	Yes		Yes		Yes		Yes	
Price level fixed effects	Yes		Yes		Yes		Yes	
Trade size fixed effects	Yes		Yes		Yes		Yes	
N	439,490,167		439,490,167		439,490,167		439,490,167	
Panel D: Small Trade Volume (Less than 500 Shares)								
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys	-0.01369%	<0.0001	-0.01962%	<0.0001	-0.01318%	<0.0001	-0.01921%	<0.0001
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys (HFTD)			0.01335%	<0.0001			0.01357%	<0.0001
Ask Falls to Integer Buys – Ask Falls to Nickel Buys	0.02743%	<0.0001	0.02403%	<0.0001	0.02835%	<0.0001	0.02482%	<0.0001
Ask Falls to Integer Buys – Ask Falls to Nickel Buys (HFTD)			0.00892%	0.0298			0.00926%	0.0240
Bid Rises to Integer Sells – Bid Rises to Nickel Sells	-0.00256%	0.2166	0.00020%	0.938	-0.00304%	0.1415	-0.00031%	0.9062
Bid Rises to Integer Sells – Bid Rises to Nickel Sells (HFTD)			-0.00712%	0.0947			-0.00706%	0.0974

Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells	-0.01830%	<0.0001	-0.02159%	<0.0001	-0.01849%	<0.0001	-0.02183%	<0.0001
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells (HFTD)			0.00753%	<0.0001			0.00762%	<0.0001
HFTD			0.00652%	<0.0001			0.00557%	<0.0001
Firm fixed effects	Yes		Yes		Yes		Yes	
Month fixed effects	Yes		Yes		Yes		Yes	
Price level fixed effects	Yes		Yes		Yes		Yes	
Trade size fixed effects	No		No		No		No	
N	458,735,578		458,735,578		458,735,578		458,735,578	
Panel E: Medium Trade Volume (500 to 2,000 Shares)								
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys	-0.01537%	<0.0001	-0.01952%	<0.0001	-0.01458%	<0.0001	-0.01916%	<0.0001
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys (HFTD)			0.01138%	0.0187			0.01253%	0.0096
Ask Falls to Integer Buys – Ask Falls to Nickel Buys	0.03295%	<0.0001	0.02962%	<0.0001	0.03267%	<0.0001	0.02853%	0.0001
Ask Falls to Integer Buys – Ask Falls to Nickel Buys (HFTD)			0.00946%	0.4761			0.00998%	0.4521
Bid Rises to Integer Sells – Bid Rises to Nickel Sells	-0.00796%	0.2091	-0.01536%	0.0447	-0.00890%	0.1600	-0.01657%	0.0303
Bid Rises to Integer Sells – Bid Rises to Nickel Sells (HFTD)			0.02702%	0.0482			0.02784%	0.0417
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells	-0.01137%	<0.0001	-0.01398%	<0.0001	-0.01210%	<0.0001	-0.01453%	<0.0001
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells (HFTD)			0.00814%	0.0927			0.00763%	0.1152
HFTD			0.01402%	<0.0001			0.01322%	<0.0001
Firm fixed effects	Yes		Yes		Yes		Yes	
Month fixed effects	Yes		Yes		Yes		Yes	
Price level fixed effects	Yes		Yes		Yes		Yes	

Trade size fixed effects	No		No		No		No	
N	36,701,915		36,701,915		36,701,915		36,701,915	
Panel F: Large Trade Volume (More than 2,000 Shares)								
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys	-0.00603%	0.4347	-0.01089%	0.2344	-0.00542%	0.4826	-0.01047%	0.2527
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys (HFTD)			0.01660%	0.3286			0.01725%	0.3097
Ask Falls to Integer Buys – Ask Falls to Nickel Buys	0.01523%	0.4212	0.03009%	0.1649	0.01222%	0.5187	0.02671%	0.2129
Ask Falls to Integer Buys – Ask Falls to Nickel Buys (HFTD)			-0.06507%	0.1493			-0.06471%	0.1515
Bid Rises to Integer Sells – Bid Rises to Nickel Sells	0.01448%	0.4605	0.02383%	0.2840	0.01388%	0.4789	0.02357%	0.2891
Bid Rises to Integer Sells – Bid Rises to Nickel Sells (HFTD)			-0.03683%	0.4368			-0.03839%	0.4175
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells	-0.00222%	0.7742	-0.01103%	0.2288	-0.00376%	0.6273	-0.01223%	0.1819
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells (HFTD)			0.03216%	0.0599			0.03097%	0.0699
HFTD			0.02520%	<0.0001			0.02481%	<0.0001
Firm fixed effects	Yes		Yes		Yes		Yes	
Month fixed effects	Yes		Yes		Yes		Yes	
Price level fixed effects	Yes		Yes		Yes		Yes	
Trade size fixed effects	No		No		No		No	
N	2,903,015		2,903,015		2,903,015		2,903,015	

Table 7: Opportunistic Stock Returns by Price Point Dummies

This table presents the regression results for Equation (4). Dependent variables are the stock returns to closing positions at the daily closing prices. Column (1) uses the daily closing bid (ask) if the trade was a purchase (sale) to compute returns, while Column (2) use the daily closing midpoint. Independent variables are conditional dummy variables of when the trades have occurred, and their definitions are provided in Section 4. Coefficients reported are difference in coefficients of integer dummy variables and their corresponding nickel variables. *(HFTD)* indicates an interaction of the conditional dummy variables and *HFTD*, which is a dummy variable that equals to 1 if liquidity demander is a HFT and 0 if it is an nHFT. All regression models include fixed effect controls for firm, month, trade size, and price level. *N* indicates the sample size.

	(1)		(2)	
	Trade Price	p-value	Midpoint	p-value
Ask Falls Below Integer Sells – Ask Falls Below Nickel Sells	0.01093%	<0.0001	0.01130%	<0.0001
Ask Falls Below Integer Sells – Ask Falls Below Nickel Sells (HFTD)	-0.00409%	0.0017	-0.00387%	0.0029
Ask Falls to Integer Sells – Ask Falls to Nickel Sells	-0.01582%	<0.0001	-0.01624%	<0.0001
Ask Falls to Integer Sells – Ask Falls to Nickel Sells (HFTD)	0.00836%	0.0170	0.00841%	0.0162
Bid Rises to Integer Buys – Bid Rises to Nickel Buys	0.02722%	<0.0001	0.02754%	<0.0001
Bid Rises to Integer Buys – Bid Rises to Nickel Buys (HFTD)	0.00033%	0.9265	0.00013%	0.9715
Bid Rises Above Integer Buys – Bid Rises Above Nickel Buys	0.02998%	<0.0001	0.03002%	<0.0001
Bid Rises Above Integer Buys – Bid Rises Above Nickel Buys (HFTD)	0.00839%	<0.0001	0.00841%	<0.0001
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys	-0.00526%	<0.0001	-0.00499%	<0.0001
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys (HFTD)	0.01249%	<0.0001	0.01281%	<0.0001
Ask Falls to Integer Buys – Ask Falls to Nickel Buys	0.02644%	<0.0001	0.02695%	<0.0001
Ask Falls to Integer Buys – Ask Falls to Nickel Buys (HFTD)	0.00526%	0.1817	0.00572%	0.1458
Bid Rises to Integer Sells – Bid Rises to Nickel Sells	-0.00260%	0.3000	-0.00317%	0.2053
Bid Rises to Integer Sells – Bid Rises to Nickel Sells (HFTD)	-0.00538%	0.1878	-0.00523%	0.2001
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells	-0.03435%	<0.0001	-0.03467%	<0.0001
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells (HFTD)	0.00441%	0.0016	0.00449%	0.0013
HFTD	0.01129%	<0.0001	0.01026%	<0.0001
Firm fixed effects	Yes		Yes	
Month fixed effects	Yes		Yes	
Price level fixed effects	Yes		Yes	
Trade size fixed effects	Yes		Yes	
N	498,335,921		498,335,921	

Table 8: Opportunistic Stock Returns by Price Point Dummies, by Trade Volume and Firm Size

This table presents the regression results for Equation (4) by subsamples of three groups of firm size (Panels A through C) and three groups of trade volume (Panels D through F). Dependent variables are the stock returns to closing positions at the daily closing prices. Column (1) uses the daily closing bid (ask) if the trade was a purchase (sale) to compute returns, while Column (2) use the daily closing midpoint. Independent variables are conditional dummy variables of when the trades have occurred, and their definitions are provided in Section 4. Coefficients reported are difference in coefficients of integer dummy variables and their corresponding nickel variables. *(HFTD)* indicates an interaction of the conditional dummy variables and *HFTD*, which is a dummy variable that equals to 1 if liquidity demander is a HFT and 0 if it is an nHFT. All regression models include fixed effect controls for firm, month, and price level, while Panels A–C also include trade size fixed effects. *N* indicates the sample size.

	(1)		(2)	
	Trade Price	p-value	Midpoint	p-value
Panel A: Small Firm Size				
Ask Falls Below Integer Sells – Ask Falls Below Nickel Sells	0.05735%	<0.0001	0.04906%	<0.0001
Ask Falls Below Integer Sells – Ask Falls Below Nickel Sells (HFTD)	-0.04305%	0.0002	-0.04065%	0.0005
Ask Falls to Integer Sells – Ask Falls to Nickel Sells	-0.08725%	<0.0001	-0.09423%	<0.0001
Ask Falls to Integer Sells – Ask Falls to Nickel Sells (HFTD)	-0.04111%	0.1588	-0.04044%	0.1641
Bid Rises to Integer Buys – Bid Rises to Nickel Buys	0.00493%	0.7563	0.00333%	0.8333
Bid Rises to Integer Buys – Bid Rises to Nickel Buys (HFTD)	-0.03212%	0.2970	-0.03513%	0.2523
Bid Rises Above Integer Buys – Bid Rises Above Nickel Buys	0.04500%	<0.0001	0.04508%	<0.0001
Bid Rises Above Integer Buys – Bid Rises Above Nickel Buys (HFTD)	0.03083%	0.0095	0.03193%	0.0070
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys	-0.05965%	<0.0001	-0.06606%	<0.0001
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys (HFTD)	0.01817%	0.1701	0.02265%	0.0859
Ask Falls to Integer Buys – Ask Falls to Nickel Buys	0.14593%	<0.0001	0.14225%	<0.0001
Ask Falls to Integer Buys – Ask Falls to Nickel Buys (HFTD)	-0.11603%	0.0004	-0.11305%	0.0006
Bid Rises to Integer Sells – Bid Rises to Nickel Sells	-0.06438%	<0.0001	-0.07311%	<0.0001
Bid Rises to Integer Sells – Bid Rises to Nickel Sells (HFTD)	0.05701%	0.1046	0.06022%	0.0853
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells	-0.10235%	<0.0001	-0.10425%	<0.0001
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells (HFTD)	0.03214%	0.0160	0.03312%	0.0127
HFTD	0.02284%	<0.0001	0.01759%	<0.0001
Firm fixed effects	Yes		Yes	
Month fixed effects	Yes		Yes	
Price level fixed effects	Yes		Yes	

Trade size fixed effects	Yes		Yes	
N	11,772,585		11,772,585	
Panel B: Medium Firm Size				
Ask Falls Below Integer Sells – Ask Falls Below Nickel Sells	0.03030%	<0.0001	0.03243%	<0.0001
Ask Falls Below Integer Sells – Ask Falls Below Nickel Sells (HFTD)	0.01032%	0.0335	0.01171%	0.0156
Ask Falls to Integer Sells – Ask Falls to Nickel Sells	0.01388%	0.0871	0.01524%	0.0596
Ask Falls to Integer Sells – Ask Falls to Nickel Sells (HFTD)	0.01454%	0.2422	0.01286%	0.2997
Bid Rises to Integer Buys – Bid Rises to Nickel Buys	0.00300%	0.7497	0.00500%	0.5066
Bid Rises to Integer Buys – Bid Rises to Nickel Buys (HFTD)	0.02015%	0.1167	0.01804%	0.1588
Bid Rises Above Integer Buys – Bid Rises Above Nickel Buys	0.04300%	<0.0001	0.04200%	<0.0001
Bid Rises Above Integer Buys – Bid Rises Above Nickel Buys (HFTD)	-0.01241%	0.0114	-0.01256%	0.0102
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys	-0.04845%	<0.0001	-0.04596%	<0.0001
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys (HFTD)	0.05495%	<0.0001	0.05605%	<0.0001
Ask Falls to Integer Buys – Ask Falls to Nickel Buys	0.00706%	0.3717	0.01220%	0.1213
Ask Falls to Integer Buys – Ask Falls to Nickel Buys (HFTD)	-0.02411%	0.0802	-0.02244%	0.1025
Bid Rises to Integer Sells – Bid Rises to Nickel Sells	0.00200%	0.8348	0.00300%	0.7184
Bid Rises to Integer Sells – Bid Rises to Nickel Sells (HFTD)	-0.00280%	0.8484	-0.00108%	0.9409
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells	-0.04200%	<0.0001	-0.04300%	<0.0001
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells (HFTD)	0.03311%	<0.0001	0.03364%	<0.0001
HFTD	0.01035%	<0.0001	0.00800%	<0.0001
Firm fixed effects	Yes		Yes	
Month fixed effects	Yes		Yes	
Price level fixed effects	Yes		Yes	
Trade size fixed effects	Yes		Yes	
N	47,077,296		47,077,296	
Panel C: Large Firm Size				
Ask Falls Below Integer Sells – Ask Falls Below Nickel Sells	0.00665%	<0.0001	0.00713%	<0.0001
Ask Falls Below Integer Sells – Ask Falls Below Nickel Sells (HFTD)	-0.00331%	0.0144	-0.00341%	0.0116
Ask Falls to Integer Sells – Ask Falls to Nickel Sells	-0.01699%	<0.0001	-0.01744%	<0.0001
Ask Falls to Integer Sells – Ask Falls to Nickel Sells (HFTD)	0.00813%	0.0264	0.00830%	0.0234
Bid Rises to Integer Buys – Bid Rises to Nickel Buys	0.03136%	<0.0001	0.03147%	<0.0001

Bid Rises to Integer Buys – Bid Rises to Nickel Buys (HFTD)	-0.00288%	0.4377	-0.00279%	0.4508
Bid Rises Above Integer Buys – Bid Rises Above Nickel Buys	0.02656%	<0.0001	0.02675%	<0.0001
Bid Rises Above Integer Buys – Bid Rises Above Nickel Buys (HFTD)	0.01156%	<0.0001	0.01157%	<0.0001
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys	0.00217%	0.0265	0.00245%	0.0123
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys (HFTD)	0.00584%	<0.0001	0.00594%	<0.0001
Ask Falls to Integer Buys – Ask Falls to Nickel Buys	0.02214%	<0.0001	0.02202%	<0.0001
Ask Falls to Integer Buys – Ask Falls to Nickel Buys (HFTD)	0.01565%	0.0002	0.01596%	0.0001
Bid Rises to Integer Sells – Bid Rises to Nickel Sells	0.00268%	0.3157	0.00208%	0.4344
Bid Rises to Integer Sells – Bid Rises to Nickel Sells (HFTD)	-0.00974%	0.0226	-0.00985%	0.0211
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells	-0.02999%	<0.0001	-0.03014%	<0.0001
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells (HFTD)	-0.00079%	0.5849	-0.00076%	0.6017
HFTD	0.01049%	<0.0001	0.00971%	<0.0001
Firm fixed effects	Yes		Yes	
Month fixed effects	Yes		Yes	
Price level fixed effects	Yes		Yes	
Trade size fixed effects	Yes		Yes	
N	439,486,040		439,486,040	
Panel D: Small Trade Volume (Less than 500 Shares)				
Ask Falls Below Integer Sells – Ask Falls Below Nickel Sells	0.01070%	<0.0001	0.01107%	<0.0001
Ask Falls Below Integer Sells – Ask Falls Below Nickel Sells (HFTD)	-0.00451%	0.0009	-0.00431%	0.0016
Ask Falls to Integer Sells – Ask Falls to Nickel Sells	-0.01308%	<0.0001	-0.01341%	<0.0001
Ask Falls to Integer Sells – Ask Falls to Nickel Sells (HFTD)	0.00578%	0.1156	0.00575%	0.1168
Bid Rises to Integer Buys – Bid Rises to Nickel Buys	0.02461%	<0.0001	0.02498%	<0.0001
Bid Rises to Integer Buys – Bid Rises to Nickel Buys (HFTD)	0.00458%	0.2196	0.00433%	0.2449
Bid Rises Above Integer Buys – Bid Rises Above Nickel Buys	0.03033%	<0.0001	0.03043%	<0.0001
Bid Rises Above Integer Buys – Bid Rises Above Nickel Buys (HFTD)	0.00853%	<0.0001	0.00852%	<0.0001
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys	-0.00509%	<0.0001	-0.00480%	<0.0001
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys (HFTD)	0.01271%	<0.0001	0.01296%	<0.0001
Ask Falls to Integer Buys – Ask Falls to Nickel Buys	0.02642%	<0.0001	0.02710%	<0.0001
Ask Falls to Integer Buys – Ask Falls to Nickel Buys (HFTD)	0.00518%	0.2103	0.00556%	0.1779
Bid Rises to Integer Sells – Bid Rises to Nickel Sells	-0.00184%	0.4888	-0.00237%	0.3721
Bid Rises to Integer Sells – Bid Rises to Nickel Sells (HFTD)	-0.00748%	0.0815	-0.00738%	0.0851

Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells	-0.03488%	<0.0001	-0.03517%	<0.0001
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells (HFTD)	0.00415%	0.0048	0.00425%	0.0038
HFTD	0.01092%	<0.0001	0.00990%	<0.0001
Firm fixed effects	Yes		Yes	
Month fixed effects	Yes		Yes	
Price level fixed effects	Yes		Yes	
Trade size fixed effects	Yes		Yes	
N	458,731,602		458,731,602	
Panel E: Medium Trade Volume (500 to 2,000 Shares)				
Ask Falls Below Integer Sells – Ask Falls Below Nickel Sells	0.01424%	<0.0001	0.01469%	<0.0001
Ask Falls Below Integer Sells – Ask Falls Below Nickel Sells (HFTD)	0.00366%	0.4322	0.00396%	0.3959
Ask Falls to Integer Sells – Ask Falls to Nickel Sells	-0.03988%	<0.0001	-0.04094%	<0.0001
Ask Falls to Integer Sells – Ask Falls to Nickel Sells (HFTD)	0.02839%	0.0216	0.02887%	0.0194
Bid Rises to Integer Buys – Bid Rises to Nickel Buys	0.04873%	<0.0001	0.04872%	<0.0001
Bid Rises to Integer Buys – Bid Rises to Nickel Buys (HFTD)	-0.04106%	0.0010	-0.04106%	0.0010
Bid Rises Above Integer Buys – Bid Rises Above Nickel Buys	0.02599%	<0.0001	0.02538%	<0.0001
Bid Rises Above Integer Buys – Bid Rises Above Nickel Buys (HFTD)	0.00508%	0.2760	0.00507%	0.2769
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys	-0.00784%	0.0080	-0.00758%	0.0103
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys (HFTD)	0.00863%	0.0766	0.00983%	0.0436
Ask Falls to Integer Buys – Ask Falls to Nickel Buys	0.02455%	0.0013	0.02372%	0.0019
Ask Falls to Integer Buys – Ask Falls to Nickel Buys (HFTD)	0.01446%	0.2849	0.01502%	0.2663
Bid Rises to Integer Sells – Bid Rises to Nickel Sells	-0.01217%	0.1171	-0.01324%	0.0883
Bid Rises to Integer Sells – Bid Rises to Nickel Sells (HFTD)	0.02382%	0.0873	0.02462%	0.0771
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells	-0.02935%	<0.0001	-0.02993%	<0.0001
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells (HFTD)	0.00963%	0.0481	0.00919%	0.0591
HFTD	0.01522%	<0.0001	0.01424%	<0.0001
Firm fixed effects	Yes		Yes	
Month fixed effects	Yes		Yes	
Price level fixed effects	Yes		Yes	
Trade size fixed effects	Yes		Yes	
N	36,701,357		36,701,357	

Panel F: Large Trade Volume (More than 2,000 Shares)				
Ask Falls Below Integer Sells – Ask Falls Below Nickel Sells	-0.00218%	0.7903	-0.00235%	0.7742
Ask Falls Below Integer Sells – Ask Falls Below Nickel Sells (HFTD)	0.00590%	0.7183	0.00611%	0.7087
Ask Falls to Integer Sells – Ask Falls to Nickel Sells	-0.06105%	0.0046	-0.06213%	0.0039
Ask Falls to Integer Sells – Ask Falls to Nickel Sells (HFTD)	0.03927%	0.3525	0.03958%	0.3486
Bid Rises to Integer Buys – Bid Rises to Nickel Buys	0.07916%	0.0002	0.07770%	0.0003
Bid Rises to Integer Buys – Bid Rises to Nickel Buys (HFTD)	-0.14767%	0.0005	-0.14648%	0.0006
Bid Rises Above Integer Buys – Bid Rises Above Nickel Buys	0.03286%	<0.0001	0.03134%	0.0001
Bid Rises Above Integer Buys – Bid Rises Above Nickel Buys (HFTD)	-0.00322%	0.8434	-0.00335%	0.8372
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys	0.00117%	0.8993	0.00141%	0.8785
Ask Falls Below Integer Buys – Ask Falls Below Nickel Buys (HFTD)	0.01379%	0.4198	0.01467%	0.3906
Ask Falls to Integer Buys – Ask Falls to Nickel Buys	0.01937%	0.3780	0.01639%	0.4556
Ask Falls to Integer Buys – Ask Falls to Nickel Buys (HFTD)	-0.03519%	0.4458	-0.03510%	0.4467
Bid Rises to Integer Sells – Bid Rises to Nickel Sells	0.03226%	0.1546	0.03214%	0.1560
Bid Rises to Integer Sells – Bid Rises to Nickel Sells (HFTD)	-0.04025%	0.4072	-0.04172%	0.3901
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells	-0.02492%	0.0069	-0.02619%	0.0045
Bid Rises Above Integer Sells – Bid Rises Above Nickel Sells (HFTD)	0.03500%	0.0419	0.03396%	0.0484
HFTD	0.02464%	<0.0001	0.02379%	<0.0001
Firm fixed effects	Yes		Yes	
Month fixed effects	Yes		Yes	
Price level fixed effects	Yes		Yes	
Trade size fixed effects	Yes		Yes	
N	2,902,962		2,902,962	

Table 9: Wealth Transfer

This table presents the wealth transfer among trades that occur in the directions of and against the psychological effects, which is calculated by multiplying the abnormal stock returns from regular and opportunistic trades by their corresponding aggregate dollar value of trades. I report the scaled calculations, which is derived by multiplying corresponding results by 3,000 (the number of stocks in Russell 3000) and divided by 238 (119 stocks multiplied by 2 years of sample), to estimate annual wealth transfer in the Russell 3000 index from the buy-sell imbalances on and around round numbers. The percentage abnormal return for each category with respect to the corresponding dollar volume is reported in the parentheses.

Condition	HFTD Gain (Trade Price)	nHFTD Gain (Trade Price)	HFTD Gain (Midpoint)	nHFTD Gain (Midpoint)
Ask Falls Below Integer Buys	$22,475,963	-$24,272,440	$24,314,482	-$23,036,216
	(0.0072%)	(-0.0053%)	(0.0078%)	(-0.005%)
Ask Falls to Integer Buys	$12,270,334	$21,158,184	$12,648,544	$21,569,551
	(0.0317%)	(0.0264%)	(0.0327%)	(0.027%)
Bid Rises to Integer Sells	-$2,768,452	-$1,936,260	-$2,915,256	-$2,364,385
	(-0.008%)	(-0.0026%)	(-0.0084%)	(-0.0032%)
Bid Rises Above Integer Sells	-$91,460,966	-$158,377,186	-$92,191,065	-$159,843,257
	(-0.0299%)	(-0.0344%)	(-0.0302%)	(-0.0347%)
Ask Falls Below Integer Sells	$24,145,262	$63,051,026	$26,217,680	$65,186,198
	(0.0068%)	(0.0109%)	(0.0074%)	(0.0113%)
Ask Falls to Integer Sells	-$4,040,191	-$12,821,354	-$4,235,623	-$13,156,839
	(-0.0075%)	(-0.0158%)	(-0.0078%)	(-0.0162%)
Bid Rises to Integer Buys	$14,527,568	$21,738,917	$14,589,266	$21,992,066
	(0.0275%)	(0.0272%)	(0.0277%)	(0.0275%)
Bid Rises Above Integer Buys	$132,119,745	$169,169,099	$132,316,029	$169,377,880
	(0.0384%)	(0.03%)	(0.0384%)	(0.03%)
Total	$107,269,263	$77,709,986	$110,744,057	$79,724,998
	(0.0072%)	(0.0033%)	(0.0074%)	(0.0034%)

Table 10: Buy-Sell Ratio by Price Point Dummies, Liquidity Supply Side

This table presents the regression results for Equation (1), separated by trades that an HFT is the liquidity supplier and those that are not. The dependent variable is the buy-sell ratio, which is defined as (*buys* – *sells*) / (*buys* + *sells*), of liquidity demanders for each firm-year. In Panel A, *buys* and *sells* are defined respectively as number of buyer-initiated and seller-initiated trades, while in Panels B and C they are defined as number of shares bought and sold and dollar volume of buyer-initiated and seller-initiated trades. The independent variables are dummy variables for price points: *Below Integers* equals to 1 if *pp* = .99 and 0 otherwise, *Above Integers* equals to 1 if *pp* = .01 and 0 otherwise, *Below Half-Dollars* equals to 1 if *pp* = .49 and 0 otherwise, *Above Half-Dollars* equals to 1 if *pp* = .51 and 0 otherwise, *Below Quarters* equals to 1 if *pp* ϵ {.24, .74} and 0 otherwise, *Above Quarters* equals to 1 if *pp* ϵ {.26, .76} and 0 otherwise, *Below Dimes* equals to 1 if *pp* ϵ {.09, .19, .29, .39, .59, .69, .79, .89} and 0 otherwise, *Above Dimes* equals to 1 if *pp* ϵ {.11, .21, .31, .41, .61, .71, .81, .91} and 0 otherwise, *Below Nickels* equals to 1 if *pp* ϵ {.04, .14, .34, .44, .54, .64, .84, .94} and 0 otherwise, and *Above Nickels* equals to 1 if *pp* ϵ {.06, .16, .36, .46, .56, .66, .86, .96} and 0 otherwise. Column (1) only includes trades that an HFT is the liquidity supplier and Column (2) only includes trades that an nHFT is the liquidity supplier. *N* indicates the sample size.

	(1) HFTS Trades	p-value	(2) nHFTS Trades	p-value
Panel A: Number of Buys and Sells				
Intercept	0.0092	<0.0001	-0.0035	<0.0001
Below Integers	0.0407	<0.0001	-0.0537	<0.0001
Above Integers	-0.0663	<0.0001	0.0144	0.0063
Below Half-Dollars	0.0352	<0.0001	-0.0221	<0.0001
Above Half-Dollars	-0.0462	<0.0001	0.0053	0.3148
Below Quarters	0.0219	0.0001	-0.0099	0.0080
Above Quarters	-0.0212	0.0002	-0.0032	0.4000
Below Dimes	0.0118	<0.0001	-0.0117	<0.0001
Above Dimes	-0.0172	<0.0001	-0.0042	0.0309
Below Nickels	0.0111	0.0002	-0.0048	0.0136
Above Nickels	-0.0068	0.0232	-0.0060	0.0023
N	23,700		23,700	
Panel B: Shares Bought and Sold				
Intercept	0.0080	<0.0001	-0.0041	<0.0001
Below Integers	0.0487	<0.0001	-0.0478	<0.0001
Above Integers	-0.0702	<0.0001	0.0029	0.6423
Below Half-Dollars	0.0428	<0.0001	-0.0140	0.0267

Above Half-Dollars	-0.0620	<0.0001	-0.0011	0.8616
Below Quarters	0.0290	<0.0001	-0.0055	0.2202
Above Quarters	-0.0179	0.0057	-0.0065	0.1463
Below Dimes	0.0124	0.0003	-0.0087	0.0002
Above Dimes	-0.0218	<0.0001	-0.0096	<0.0001
Below Nickels	0.0109	0.0014	-0.0039	0.1026
Above Nickels	-0.0081	0.0171	-0.0082	0.0005
N	23,700		23,700	
Panel C: Dollars Bought and Sold				
Intercept	0.0096	<0.0001	-0.0028	0.0007
Below Integers	0.0502	<0.0001	-0.0468	<0.0001
Above Integers	-0.0717	<0.0001	0.0024	0.7041
Below Half-Dollars	0.0453	<0.0001	-0.0141	0.0269
Above Half-Dollars	-0.0627	<0.0001	-0.0027	0.6758
Below Quarters	0.0283	<0.0001	-0.0068	0.1356
Above Quarters	-0.0181	0.0058	-0.0076	0.0946
Below Dimes	0.0134	0.0001	-0.0095	<0.0001
Above Dimes	-0.0220	<0.0001	-0.0110	<0.0001
Below Nickels	0.0108	0.0017	-0.0054	0.0244
Above Nickels	-0.0075	0.0305	-0.0100	<0.0001
N	23,700		23,700	

Table 11: Buy-Sell Ratio by Price Point Dummies, Broken Down by Each Trade Types

This table presents the regression results for Equation (1), separated by trade types. The dependent variable is the buy-sell ratio, which is defined as (*buys* – *sells*) / (*buys* + *sells*), of liquidity demanders for each firm-year. In Panel A, *buys* and *sells* are defined respectively as number of buyer-initiated and seller-initiated trades, while in Panels B and C they are defined as number of shares bought and sold and dollar volume of buyer-initiated and seller-initiated trades. The independent variables are dummy variables for price points: *Below Integers* equals to 1 if *pp* = .99 and 0 otherwise, *Above Integers* equals to 1 if *pp* = .01 and 0 otherwise, *Below Half-Dollars* equals to 1 if *pp* = .49 and 0 otherwise, *Above Half-Dollars* equals to 1 if *pp* = .51 and 0 otherwise, *Below Quarters* equals to 1 if *pp* ϵ {.24, .74} and 0 otherwise, *Above Quarters* equals to 1 if *pp* ϵ {.26, .76} and 0 otherwise, *Below Dimes* equals to 1 if *pp* ϵ {.09, .19, .29, .39, .59, .69, .79, .89} and 0 otherwise, *Above Dimes* equals to 1 if *pp* ϵ {.11, .21, .31, .41, .61, .71, .81, .91} and 0 otherwise, *Below Nickels* equals to 1 if *pp* ϵ {.04, .14, .34, .44, .54, .64, .84, .94} and 0 otherwise, and *Above Nickels* equals to 1 if *pp* ϵ {.06, .16, .36, .46, .56, .66, .86, .96} and 0 otherwise. Column (1) only includes trades that both liquidity demander and supplier are an HFT. Column (2) only includes trades that an HFT is the liquidity demander while an nHFT is the liquidity supplier. Column (3) only includes trades that an nHFT is the liquidity demander while an HFT is the liquidity supplier. Column (4) only includes trades that both liquidity demander and supplier are an nHFT. *N* indicates the sample size.

	(1) HH Trades	p-value	(2) HN Trades	p-value	(3) NH Trades	p-value	(4) NN Trades	p-value
Panel A: Number of Buys and Sells								
Intercept	0.0100	<0.0001	-0.0035	0.0011	0.0080	<0.0001	-0.0048	<0.0001
Below Integers	-0.0137	0.3411	-0.1492	<0.0001	0.0906	<0.0001	0.0043	0.4545
Above Integers	0.0099	0.4874	0.1060	<0.0001	-0.1100	<0.0001	-0.0390	<0.0001
Below Half-Dollars	-0.0015	0.9163	-0.0936	<0.0001	0.0701	<0.0001	0.0178	0.0018
Above Half-Dollars	0.0247	0.0849	0.0729	<0.0001	-0.0768	<0.0001	-0.0326	<0.0001
Below Quarters	-0.0248	0.0153	-0.0501	<0.0001	0.0399	<0.0001	0.0118	0.0037
Above Quarters	0.0034	0.7402	0.0305	<0.0001	-0.0355	<0.0001	-0.0226	<0.0001
Below Dimes	0.0055	0.3019	-0.0470	<0.0001	0.0265	<0.0001	0.0074	0.0005
Above Dimes	0.0030	0.5744	0.0276	<0.0001	-0.0320	<0.0001	-0.0214	<0.0001
Below Nickels	0.0032	0.5479	-0.0266	<0.0001	0.0174	<0.0001	0.0048	0.0252
Above Nickels	-0.0002	0.9657	0.0080	0.0113	-0.0130	<0.0001	-0.0133	<0.0001
N	23,517		23,700		23,700		23,700	
Panel B: Shares Bought and Sold								
Intercept	0.0111	<0.0001	-0.0030	0.0167	0.0061	<0.0001	-0.0054	<0.0001
Below Integers	-0.0139	0.3748	-0.1658	<0.0001	0.1028	<0.0001	0.0136	0.0461

Above Integers	0.0046	0.7675	0.1128	<0.0001	-0.1175	<0.0001	-0.0503	<0.0001
Below Half-Dollars	0.0022	0.8874	-0.0954	<0.0001	0.0804	<0.0001	0.0265	0.0001
Above Half-Dollars	0.0349	0.0254	0.0858	<0.0001	-0.0947	<0.0001	-0.0435	<0.0001
Below Quarters	-0.0237	0.0333	-0.0567	<0.0001	0.0472	<0.0001	0.0175	0.0003
Above Quarters	0.0015	0.8928	0.0349	<0.0001	-0.0312	<0.0001	-0.0284	<0.0001
Below Dimes	0.0070	0.2329	-0.0486	<0.0001	0.0284	<0.0001	0.0106	<0.0001
Above Dimes	0.0007	0.9098	0.0289	<0.0001	-0.0360	<0.0001	-0.0287	<0.0001
Below Nickels	0.0037	0.5217	-0.0309	<0.0001	0.0168	<0.0001	0.0067	0.008
Above Nickels	-0.0019	0.7502	0.0101	0.0061	-0.0140	0.0002	-0.0173	<0.0001
N	23,517		23,700		23,700		23,700	
Panel C: Dollars Bought and Sold								
Intercept	0.0114	<0.0001	-0.0033	0.0097	0.0080	<0.0001	-0.0036	<0.0001
Below Integers	-0.0168	0.2885	-0.1680	<0.0001	0.1048	<0.0001	0.0162	0.019
Above Integers	0.0003	0.9842	0.1133	<0.0001	-0.1183	<0.0001	-0.0517	<0.0001
Below Half-Dollars	0.0033	0.8370	-0.0965	<0.0001	0.0835	<0.0001	0.0265	0.0001
Above Half-Dollars	0.0309	0.0513	0.0855	<0.0001	-0.0955	<0.0001	-0.0451	<0.0001
Below Quarters	-0.0254	0.0244	-0.0578	<0.0001	0.0468	<0.0001	0.0163	0.0009
Above Quarters	0.0039	0.7332	0.0340	<0.0001	-0.0309	<0.0001	-0.0295	<0.0001
Below Dimes	0.0076	0.1963	-0.0499	<0.0001	0.0294	<0.0001	0.0099	0.0001
Above Dimes	0.0018	0.7668	0.0281	<0.0001	-0.0363	<0.0001	-0.0302	<0.0001
Below Nickels	0.0051	0.3846	-0.0331	<0.0001	0.0170	<0.0001	0.0052	0.0421
Above Nickels	-0.0022	0.7053	0.0087	0.0192	-0.0129	0.0006	-0.0193	<0.0001
N	23,517		23,700		23,700		23,700	