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**Fictitious Price Falls and the Buying Activity of Retail
Investors**

**Quedas de Preço Imateriais e a Atividade de
Investidores Individuais**

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Fictitious Price Falls and the Buying Activity of Retail Investors

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Resumo

Neste trabalho, é mostrada evidência de que investidores individuais respondem positivamente à quedas de preços de ações *em si*, isto é, quedas de preços que não refletem nenhuma informação relevante a respeito daquele ativo em particular. Para tanto, é utilizado o banco de dados da TAQ entre 2010 e 2017. Para identificar negócios realizados por indivíduos através deste banco, lança-se mão de um recente algoritmo proposto por [Boehmer, Jones and Zhang \(2017\)](#). São explorados dois eventos distintos que produzem quedas de preço *imateriais* em ações. O primeiro evento se dá em datas ex-dividendo de ações: nestes dias, o preço de abertura de uma ação é ajustado mecanicamente em relação ao preço de fechamento do dia anterior, tendo-se em vista que, a partir daquele dia, novos acionistas não serão contemplados pelo pagamento do próximo dividendo distribuído pela empresa. Mostra-se que indivíduos reagem positivamente a estas quedas de preços e, de fato, compram ações em datas ex-dividendo, a despeito do fato dessa queda de preço não ter significado material. Tal resultado é consistente para diferentes especificações; além disso, quando é levada em conta a quantidade de vendas de ações feitas por indivíduos em datas ex-dividendo, encontra-se que, em termos líquidos, indivíduos também reagem positivamente a quedas de preços imateriais. O segundo exercício realizado consiste em avaliar se indivíduos apresentam viés do dígito da esquerda quando compram ações: é mostrada evidência de que quando o preço de um ativo flutua em torno de um número inteiro, indivíduos compram ativos em proporção maior quando o preço do ativo está ligeiramente abaixo daquele número inteiro, apesar dessa diferença ser insignificante em termos relativos. Também é mostrada evidência de que esse viés ocorre para diferentes preços nominais de ativos. Ambos exercícios sugerem que indivíduos negligenciam o conteúdo informacional contido nos preços dos ativos, uma vez que os mesmos reagem positivamente a quedas de preços imateriais e sem significado econômico.

Palavras-chave: investidores individuais, mercado de ativos, viés do dígito da esquerda.

Códigos JEL: G00, G11, G12, G40, G41.

Abstract

This work shows that retail investors respond positively to stock prices' drops *in itself*, that is, price drops that do not reflect any relevant information about that particular stock. To do so, I use TAQ data between 2010 and 2017 and identify retail trades using a recent innovation proposed by [Boehmer, Jones and Zhang \(2017\)](#). I explore two distinct events that produce *immaterial* price drops on stock prices. The first one is the *mechanical* price drop of a stock during its ex-dividend date: I document that retailers increase their buying activity of a stock during its ex-dividend date, regardless of the fact that this price drop is meaningless and is just an adjustment to the next cash dividend payout that its new shareholders are not entitled to receive. This result is consistent for different specifications; also, when I take into account the selling activity of retailers, I find that the *net* buying activity also respond positively to these price drops. The second exercise consists in evaluating if individuals display left-digit bias when they purchase stocks: indeed, when the price of a stock fluctuates around an integer number, individuals focus their purchases on trade prices just below that integer number, in spite of the fact that the difference between the trade price and its next integer number is meaningless in relative terms. I also find that individuals display left-digit bias for different nominal stock prices. Both exercises suggest that individuals neglect the informational role of stock prices, as they react positively to price falls that are non-material.

Key-words: retail investors, stock market, left-digit bias.

JEL Codes: G00, G11, G12, G40, G41.

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1 Introduction

Should individuals *necessarily* buy a stock when its price fall? The answer to this question is not straightforward, as individuals should account for the reasons why the price of the stock has fallen, e.g. a change in the expected present value of the dividend cash flow, some negative news regarding the company books etc. If individuals indeed ignore that some negative news are driving the drop of the stock's price, they will be more willing to buy that particular stock. Theoretical models assume the existence of these individuals: [Eyster, Rabin and Vayanos \(2019\)](#) assume that individuals neglect the information contained in stock prices to explain their (high) trading activity. Also, lab experiments deduce that this kind of investor exist, such as [Corgnet, DeSantis and Porter \(2015\)](#). The fact that individuals may ignore the information behind stock prices' drops is also a possible explanation for the poor performance of individuals in the stock market, as shown by [Barber and Odean \(2000\)](#), [Barber, Lee, et al. \(2008\)](#), [Grinblatt and Keloharju \(2000\)](#), [Odean \(1999\)](#) and so on.

Another set of evidence shows that investors overestimate the room to grow for low-priced stocks relatively to high-priced stocks: [Birru and Wang \(2016\)](#) argue that investors overestimate the skewness of low-priced stocks and, therefore, its skewness when the stock's nominal price falls. The same pattern is shown theoretically by [Barberis and Huang \(2008\)](#), as they use cumulative prospect theory preferences to argue that investors overprice positively skewed securities. Analogously, [Kumar \(2009\)](#) finds that individuals invest in stocks with higher skewness and lower prices even when these stocks have lower mean returns. These evidences indicates that investors are somehow influenced by stocks' (low) nominal prices; however, they do not provide any kind of *causal* effect between nominal stock prices' drops and individuals' demand for stocks.

This work shows that there is a *causal* effect between stock prices' drops and individual investors' demand for stocks using data from the US stock market; this *causality* may be due to the fact that individuals ignore the informational content of stock prices. The chronology is as follows: an investor connects to her home broker account in her computer in the morning, sees that the price of stock s is falling and immediately purchases that stock. Ideally, one would need to follow all the decision process from this investor, from the moment she sees the stock's price falling to the moment when she decides to purchase that stock, along with the information she (does not) incorporate between these two instants of time on her information set. Unfortunately, it is not possible to do such thing. Instead, I follow [Chague, De-Losso and Giovannetti \(2018\)](#) strategy to define a "Fictitious Price Fall (FPF)" event. Such event is characterized by an *immaterial* price fall, that is, a price fall that has no material meaning. [Chague, De-Losso and Giovannetti \(2018\)](#) use a data set on the activity of all

individual investors in Brazil to show that prices falls *in itself* (i.e., price falls that do not contain any information about the stock) are followed by an increase of the buying activity of individuals. They use two identification strategies to present this result: the first one shows that individuals' buying activity on ex-dividend dates increases stock prices fall *mechanically*. I.e., although there is no new information on the stock that might trigger individuals' purchases, individuals' buying activity increases on these dates. The second one shows that individuals display left-digit bias, i.e., they focus their purchases on stocks when their price are just below an integer number (e.g., \$ 24.95) rather than when their prices are just above that same integer number (e.g., \$ 25.05).

The first FPF event I explore (henceforth, FPF1) is the *mechanical* adjustment on stock prices during ex-dividend dates. Suppose that a stock s has its ex-dividend date on t_{ex} . It means that, from t_{ex} onwards, investors that purchase that stock s are not entitled to receive the very next cash dividend amount paid by the company that issues stock s . Thus, it is natural that the stock's s open price on t_{ex} will be lower than the closing price on the previous day and this lower amount should be equal to (or very close to) the cash dividend amount that will be paid to the shareholders of that company. [Chague, De-Losso and Giovannetti \(2018\)](#) show that, in spite of the fact these price falls are meaningless, individual investors' buying activity increases on ex-dividend dates. In order to do this same exercise for the US stock market, a first challenging task is to identify the activity of individual investors inside the US. Since there is no such data available as the one [Chague, De-Losso and Giovannetti \(2018\)](#) use for recent years¹, I use the Daily Trades and Quotes (henceforth, TAQ) data set, openly available at the Wharton Research Data Services (henceforth, WRDS). In order to identify the trading activity of retailers using TAQ, I apply a recent innovation developed by [Boehmer, Jones and Zhang \(2017\)](#) for data between 2010 and 2017. The algorithm that [Boehmer, Jones and Zhang \(2017\)](#) developed relies on the assumption that retail order flow receive price improvement and these kind of orders are easily identifiable on TAQ data set. Important to my results, this algorithm is able to identify only *marketable* orders placed by individuals; that is, *limit* orders are not used as retail flow activity within this work. I first apply the algorithm of [Boehmer, Jones and Zhang \(2017\)](#) for every trading day between 2010 and 2017. This allows me to set up a stock-day data set: for each pair stock-day, I aggregate information on the (i) number of purchases made by retailers, (ii) number of sales made by retailers, (iii) volume purchased by retailers (number of shares), (iv) volume sold by retailers, (v) value purchased by retailers (trade price $\times$ quantity purchased) and (iv) value sold

¹Here, I consider "recent years" as a period when individuals are able to trade stocks using Internet and a broker account at home. A very popular data set on the literature of individual investors is the one used by [Barber and Odean \(2000\)](#) and [Barber and Odean \(2001\)](#), which tracks the trading activity of 78,000 households between 1991 and 1996, therefore a period before the widespread of Internet and home broker services.

by retailers. I then merge this data set with a stock-day data set on information about returns and dividend-related events, also obtained through WRDS.

These two operations enable me to somehow relate stock prices' *immaterial* drops and retailers' trading activity. To do so, I define $N_{s,t}$ as the total number of individual purchases (standardized by stock) of stock s on day t . I also define $R_{s,t}^*$ as the overnight return of stock s on day t and run stock-day panel regressions of $N_{s,t}$ on $\widehat{R_{s,t}^*}$, the projection of $R_{s,t}^*$ on $DivYield_{s,t}$, a variable that I define to be equal to the dividend yield of stock s on day t if $t = t_{ex}$ and to be equal to zero otherwise. That is, the variable $\widehat{R_{s,t}^*}$ is a measure of the size of the mechanical price drop that occurs on ex-dividend dates. I find that when the price drops by 5% on ex-dates, individuals' buying activity increases significantly by 0.6 to 0.82 standard deviations, depending on the regression specification I use. I also define $V_{s,t}$ as the total volume purchased by individuals (standardized by stock) of stock s on day t and do the same exercise described above. My findings are similar: when the price drops by 5% on ex-dates, individuals' buying volume increases significantly by 0.5 to 0.72 standard deviations, depending on the regression specification I used.

The second FPF event I explore (FPF2, henceforth) are fluctuations of stock prices around integer numbers during trading days. Suppose that during a trading day t , stock s is being traded at prices around \$ 25.00, sometimes below, sometimes above. There is no reason *a priori* for individuals to buy that stock when its price is just below \$ 25.00 rather than when it is just above \$ 25.00; that is, there is no relevant information of common knowledge among investors that induce individuals to buy the stock at a \$ 24.99 price rather than at a \$ 25.01 price. Therefore, they should read as something *immaterial* the difference between these two prices during day t and look for other relevant information about the stock before they purchase it. If individuals focus their purchases on stocks negotiated at prices just below \$ 25.00 when stock's s price is around this integer number, one must conclude that they are biased by non-leading digits of prices. I then argue that this left-digit bias possibly displayed by individuals is additional evidence on the fact that stock prices' drops (being so *immaterial* as they are) are followed by (or at least associated to) increases in the buying activity of individuals.

I find that the left-digit bias exists among individual investors when they purchase stocks. To do so, for each trading day between 2010 and 2017, I select all stocks that fluctuated around an integer price (e.g., \$ 25.00). The criteria² that I adopt to consider a price fluctuation around an integer number is as follows: (i) at least 5,000 trades (by institutions and individuals) made within

²This criteria was chosen *ad hoc* and other thresholds can be used to test the consistency of my results. The goal of this work, however, is to show non-exhaustively the existence of left-digit bias among individuals. A future work may test exhaustively if my result is consistent for other set of thresholds.

the interval [24.90, 24.94], (ii) at least 5,000 trades made within the interval [24.95, 24.99], (iii) at least 5,000 trades made within the interval [25.01, 25.05] and (iv) at least 5,000 trades made within the interval [25.06, 25.10]. With this criteria, I define a FPF2 event as a pair stock-day: on day t , a stock s that fluctuated around an integer price. I obtain a total of 16,727 FPF2 events between 2010 and 2017; considering only common stocks, I obtain 9,657 FPF2 events. Then, for all trades realized for each FPF2 pair, I use [Boehmer, Jones and Zhang \(2017\)](#) algorithm to identify retailers' trades and count (i) the number of individual purchases that were made below the integer price (using our example, all trades with prices between \$ 24.90 and \$ 24.99) and (ii) the number of individual purchases that were made above the integer price (using our example, all trades with prices between \$25.01 and \$25.10). Finally, for each FPF2 event, I calculate the *proportion* of purchases that were made below that integer price, that is, I divide the number of individuals' below purchases by the sum of individuals' below and above purchases. I then take the average across these proportions for all 9,657 FPF2 events and find that this average is significantly higher than the average proportion of just-above purchases. Moreover, I initially find that individuals only display left-digit bias for high-priced stocks, but when I take into account the fact that some stocks are more *attention-grabbing* than others, for instance in terms of trading volume and market capitalization, individuals also display left-digit bias for low-priced stocks. The proportion of individual purchases just-below integer prices range between 50.5% and 51.3%; when I take into account the market capitalization of stocks, this proportion range between 51.7% and 57.7%.

Overall, I document two identification strategies suggesting that individuals neglect the informational role of stock prices before purchasing them. This conclusion stems from the fact that if they did not, I would not find significant (and consistent for other specifications) estimates for both FPF1 and FPF2 events. Looking for similar patterns as the ones [Chague, De-Losso and Giovannetti \(2018\)](#) found but using a different data set allows us to answer a set of questions. Is this pattern restricted to the *brazilian* investor or is it possible to find that feature for investors from other countries, such as US? The answer to that question being *yes* enable us to state that indeed there is enough evidence supporting the idea that individuals *in general*, not specific ones, ignore the information behind stock prices' drops and this might be related to other behavioral biases displayed by individuals, as showed by [Chague, De-Losso and Giovannetti \(2018\)](#). If the answer happened to be *no*, then one would be tempted to investigate the reasons why the pattern [Chague, De-Losso and Giovannetti \(2018\)](#) document happens only with the *brazilian* investors. The present work, therefore, corroborates a very important finding using a different data set and establishes a contribution to the literature of individual investors.

This work is organized as follows. In Section 2, I bring the literature related to the activity of individual investors in the stock market, from their behavioral biases to their performance, explaining how these themes are related to what I document in this work. Section 3 describes the data that I use in both FPF exercises. Section 4 shows the results for both FPF exercises. Finally, section 5 concludes.

2 Related Literature

This section will be used to bring the literature related to the activity of individual investors in the stock market. Here, I review non-exhaustively (i) how individuals perform in the stock market, (ii) the behavioral aspects associated with individual investors that were documented and (iii) the models and experiments that deal with investors' decision making process. The goal of this section is to somehow argue how the work that is done here fits the existing literature and to which extent the contribution that I propose is a valid one.

2.1 Performance

A very large class of papers shed light on the performance of individuals in the stock market. [Barber and Odean \(2000\)](#) use a data set on the activity of 65,000 households from a large discount brokerage firm inside US, from 1991 to 1996, to show that the 20% investors that trade most actively earn an annual return rate of 11.4%, while the market return is far from a 17% annual rate. [Barber, Lee, et al. \(2008\)](#) use data from all investors in Taiwan to document that the individuals' losses in the stock market are equivalent to 2.2% of Taiwan's GDP and 2.8% of the total personal income in that country. [Grinblatt and Keloharju \(2000\)](#) use a data set on the activity of individuals from Finland, from 1995 to 1997, to show that household investors follow contrarian strategies and have negative average performance. [Barber, Odean and Zhu \(2009\)](#) also use data from taiwanese investors, from 1995 to 1999, to show that stocks bought by individuals have further poor performance, while stocks sold by individuals have further strong returns. [Chague, De-Losso and Giovannetti \(2018\)](#) show that individuals who (i) respond to ex-dividend dates by increasing their buying activity and (ii) display left-digit bias have a worse stock-picking performance.

Generically speaking, there is strong and consistent evidence on the poor performance of individuals investors in the stock market, using data from different places and different periods of time. But what drives this poor performance? The next subsection of this section will be used to discuss some behavioral aspects displayed by individuals and how they are associated with the poor performance of individual investors. The evidence that I provide in this work, like [Chague, De-Losso and Giovannetti \(2018\)](#), can shed light on explanations for the bad performance of retailers in the stock market.

2.2 Behavioral Aspects Behind Individuals' Activity

Why do individuals perform poorly in the stock market? A first explanation relies on the fact that individuals are overconfident. Overconfidence is defined by [Gabaix \(2017\)](#) in terms of inattention: individuals are inattentive to their true ability. [Barber and Odean \(2013\)](#) state that overconfidence can be labeled as “overprecision” or “miscalibration”. [Odean \(1998b\)](#) and [Gervais and Odean \(2001\)](#) developed theoretical models based on findings and guesses that investors are overconfident. A number of works corroborates this idea: using intense trading activity as a measure of overconfidence, [Barber and Odean \(2000\)](#) show that who trade the most perform the worst. [Barber and Odean \(2001\)](#) use the same data as [Barber and Odean \(2000\)](#) to show that men trade more and perform worse than women and this may be due to the fact that men are more prone to be overconfident than women. [Dorn and Huberman \(2005\)](#) use data on a german retail brokerage firm to show that investors that think themselves as more knowledgeable than the average investor churn their portfolios of stocks more. I also cite [Grinblatt and Keloharju \(2009\)](#) as a paper that also deals with this matter and use data on finnish investors to find that investors that has a inflated perspective of their true abilities trade more. [Chague, De-Losso and Giovannetti \(2018\)](#) show that individuals who respond positively to ex-dividend dates and display left-digit bias trade more than individuals who do not.

A second approach that I bring to this section is the one that was labeled by [Shefrin and Statman \(1985\)](#) as the *disposition effect*, the act of selling winner stocks too early and to hold loser stocks too long. [Odean \(1998a\)](#) use data on 10,000 household accounts at a large US discount brokerage firm between 1987 and 1993 to find that investors realize their gains at a 50% higher rate than their losses. [Grinblatt and Keloharju \(2001\)](#) use data on all finish individual investors between 1995 and 1996 to show that investors have a tendency to hold losers. Rationally, one source of explanation for the existence of the disposition effect is the fact that some investors may have information that recent winners will subsequently perform poorly and also have information that recent losers will perform well. However, [Odean \(1998a\)](#) show that this does not happen: the prior winners that individuals sell perform better than the prior losers that they choose to hold on their portfolios. [Shefrin and Statman \(1985\)](#) state that the prospect theory developed by [Kahneman and Tversky \(1979\)](#) can explain the disposition effect: basically, the fact that the value function of an individual is concave over gain regions and convex over loss regions makes the investors more risk averse after a gain than after a loss, therefore more likely to sell a winner stock. Some papers test this argument of [Shefrin and Statman \(1985\)](#): for that matter, I cite [Barberis and Xiong \(2009\)](#), [Meng and Weng \(2017\)](#) and [Andrikogiannopoulou and Papakonstantinou \(2018\)](#) as good references.

The third evidence on individuals' activity in the stock market that I review in this section is the *contrarian behavior* of individual investors. The Webster Dictionary defines *contrarian* specifically as "an investor who buys shares of stock when most others are selling and sells when others are buying". The literature uses a common definition that relates price movements and the net buying activity of individuals: an individual is a contrarian if her net buying activity of a stock and the price of this stock are negatively related. [Kaniel, Saar and Titman \(2008\)](#) use data on a large cross-section of NYSE stocks to show that individuals tend to buy stocks following price declines in the previous month and sell following price increases. [Grinblatt and Keloharju \(2000\)](#) also document that Finnish investors pursue contrarian strategies to both short-term and intermediate-term past returns. [Grinblatt and Keloharju \(2000\)](#) also argue that there is no *causality* between contrarian behavior and poor performance of individual investors, although when they adjust the performance of individuals for the impact of contrarian strategies, households still exhibit inferior performance. Different from the prior papers I cited, [Barber, Odean and Zhu \(2009\)](#) do not consider the net buying activity of investors; instead, they analyze separately the buying and the selling activity of investors. To do so, they use data from 66,465 households at a large discount brokerage firm and data from 665,533 investors at a large retail brokerage firm and document that there is a positive relation between both buying and selling activity of investors and lagged returns up to 12 quarters. I finally cite [Chague, De-Losso and Giovannetti \(2018\)](#) as a paper that also documents that individual investors are contrarians: they show that proportion of contrarian purchases from Brazilian individual investors range from 56% to 71%, depending on the time horizon before individuals' purchases dates. Overall, the evidence supporting the contrarian behavior of individuals is compelling and all papers well document it for different places and periods of time.

A fourth and last aspect that plays a central role in the trading activity of individuals and may be related to their performance is *limited attention*, that is, the (lack of) attention that individuals can devote to a large number of stocks that are being traded. According to [Barber and Odean \(2013\)](#), lack of attention can lead to delayed reactions by individuals to important information regarding stocks; on the other hand, devoting too much attention to (irrelevant) information about stocks can lead to overreaction by individuals. [Barber and Odean \(2007\)](#) argue that individuals face a search problem when choosing to buy stocks and therefore are led to buy attention-grabbing stocks. To show that this holds empirically, [Barber and Odean \(2007\)](#) use data on 78,000 households at a large discount brokerage firm and (i) abnormal trading volume, (ii) previous day's return and (iii) new coverage as proxies for attention to show that individuals execute more buy orders to attention-grabbing stocks. [Hirshleifer, Lim and Teoh \(2009\)](#) show that investors' reaction to earnings surprises is smaller and post-

earnings announcement drift is higher for firms that announce their earnings on days that other firms announce earnings (PEAD, henceforth); that is, investors are distracted as extraneous news inhibits market reactions to relevant news. [DellaVigna and Pollet \(2009\)](#) argue that investors are distracted on Fridays and are unable to process relevant information regarding earnings announcements; they show that the market reaction to earning announcements on Fridays are muted and the PEAD is higher. These findings, according to them, support the idea of limited attention by investors. Like [Barber and Odean \(2007\)](#), a set of papers relate investors' attention and media coverage. [Engelberg and Parsons \(2011\)](#) find a causal relation between the *local* media coverage and *local* trading activity of individual investors by using data from 78,000 households at a large discount brokerage firm and their location across the United States' territory. [Engelberg, Sasseville and Williams \(2012\)](#) study the overnight market reaction to buy and sell recommendations made by a TV show called *Mad Monday* inside US and find that market reaction is greater following stock recommendations when the audience of that show is higher. It is clear, as exposed here, that individuals' (limited) attention and its drivers play an important role on the trading activity of individual investors.

All the papers I mentioned in this subsection support the idea that individuals display a number of behavioral biases. These biases were exhaustively documented by the literature and might explain the poor performance of individuals, although it is not straightforward that there is a *causality* between those biases and individuals' performance. It is clear these papers and the evidence presented by them are broadly related to the scope of my work: contrarian strategies, (in) attention and overconfidence may be related to the fact that individuals buy stocks after price falls (contrarians, therefore) without looking for any information behind that price fall (inattentive, therefore). But is it possible to find, theoretically and experimentally, that these individuals do exist? I will dedicate the next subsection to analyze theoretical models and experiments that might answer that question.

2.3 Models and Experiments: What Do They Say?

What do models and experiments have shown about the activity of individuals and how they incorporate information about prices into their information sets? A first class of papers developed theoretical models to explain anomalies observed in the stock market. [Eyster, Rabin and Vayanos \(2019\)](#) assume the existence of individuals that neglect the informational role of prices to explain the high trading activity in the stock market. They argue that an investor “neglects disagreements in beliefs”, ignoring others' information about assets. [Carrillo and Palfrey \(2011\)](#) develop a model to study the interaction between two agents that can trade an asset and are unable to derive any ex-post

utility from that trade. This model also presumes that an individual neglects the information that the other individual has on the asset but, differently from [Eyster, Rabin and Vayanos \(2019\)](#), a no-trade equilibrium is found.

A set of experiments were also made to study the relationship between agents' private information and how they (dis) consider others' information about asset prices. [Biais et al. \(2005\)](#) study how individuals overestimate the precision of one's information (miscalibration) through a lab experiment and find that miscalibration reduces the trading performance of individuals. [Corgnet, DeSantis and Porter \(2015\)](#) study how agents aggregate information and find that traders use their private information but fail to use market prices to infer about other traders' information. [Magnani and Oprea \(2017\)](#) propose an experiment where three channels of biases (overconfidence on one's private information, lack of sophistication and noisy responses to weak incentives) are used to explain excess trading activity of individuals. They find that when all these three channels are available as explanations for the excess trading, individuals trade in excess of 70% of the time.

All the studies I mentioned in this subsection share the feature of considering (or finding) individuals as *cursed*, in the sense that they ignore that asset prices reflect the information *all* agents have about a particular asset. In other words, individuals are unable to infer that asset prices (and its movements) are the reflection also of others' information, not only their own. Finding a *causal effect* between price drops and the buying activity of investors using field data, as I attempt to do with this work, constitutes one good contribution to the existing literature, mainly the one I presented in this subsection. Also, finding that this effect indeed exist for the US stock market could provide another reason for the poor performance of individuals in the stock market. [Chague, De-Losso and Giovannetti \(2018\)](#) are able to find this *causal effect* and relate this feature to other behavioral biases displayed by individuals: they show that individuals that buy stocks after *immaterial* price falls (i) trade more (a good *proxy* for overconfidence), (ii) are less sophisticated and (iii) are more contrarians than investors that do not buy after *immaterial* price falls. Although the data set used in this work does not track the activity of each individual investors from US, it enables me to use [Chague, De-Losso and Giovannetti \(2018\)](#) methodology and evaluate if individuals buy more stocks after *immaterial* price falls; if they do, as I argued in the first section, there will be evidence supporting the idea that individuals ignore the information behind asset prices.

3 Data Set

This section describes the data that was used within this work. First, I describe the algorithm proposed by [Boehmer, Jones and Zhang \(2017\)](#) that identifies the activity of retail investors. Then, I show descriptive statistics that were obtained after applying the algorithm of [Boehmer, Jones and Zhang \(2017\)](#) for the sample period that was chosen.

3.1 Identifying Retail Investors' Activity

The first challenging task is identifying the activity of retail investors using TAQ data. As I mentioned previously, there is no recent data available that tracks the activity of specific individuals through time, as the one used by [Barber and Odean \(2000\)](#) and [Barber and Odean \(2001\)](#). Also, by using TAQ, one would wrongly use the trade volume as a good proxy of retail trades using, for example, [Lee and Radhakrishna \(2000\)](#) criteria, since the spread of computer algorithms used by institutions to place small orders sequentially may produce a confusion between an order placed by an individual or an institution. To circumvent both problems, I use the algorithm recently developed by [Boehmer, Jones and Zhang \(2017\)](#) for data between 2010 and 2017. Their algorithm relies on the assumption that retail orders receive *price improvement*.

Retail order flow receives *price improvement* when a retailer places either a buying or a selling order of a stock. To illustrate the mechanism of *price improvement*, suppose investor *A* places a buying order for a stock *s* negotiated at \$ 100.00. Her wholesaler, instead of withdrawing \$ 100.00 from her broker account, will withdraw \$ 99.996. In that case, investor *A* received a price improvement of 0.4 cents. If she had placed a selling order for that stock negotiated at \$ 100.00 and her wholesaler paid her a price improvement of 0.4 cents, she would receive \$ 100.004 in her broker account after the sale.

It is worth mentioning that these *price improvements* are paid by the wholesaler that executes the order of the retail investors, since retail orders usually takes place-off exchange. The chronology is as follows. First, retail orders are reported to a Trade Reporting Facility (TRF); this TRF provide broker-dealers with a mechanism to report these transactions that take place off-exchange. Second, when these orders are included in a consolidated tape of all transactions, it is identified as an order with its exchange code equals to "D". This identification enables me to identify these kind of orders using TAQ: each transaction in that data set has a variable that identifies the exchange code of the transaction.

After that, it is used the size of the price improvement, usually a fraction of penny, to identify

if the trade took place after a buying order or a selling order made by that individual: let $P_{s,t}$ be the transaction price of stock s on time t and define $Z_{s,t}$ as the fraction of penny associated with that price, that is, $Z_{s,t} = 100 \times \text{mod}(P_{s,t}, 0.01)$. We know that $Z_{s,t}$ can take on any value in the interval $[0, 1)$. If the value of $Z_{s,t}$ is in the interval $(0, 0.4)$, then we identify the trade as a retail *seller-initiated* transaction. On the other hand, if $Z_{s,t}$ is in the interval $(0.6, 1)$, then we identify the trade as a retail *buyer-initiated* transaction. According to [Boehmer, Jones and Zhang \(2017\)](#), if the value of $Z_{s,t}$ is equal to zero or in the interval $[0.4, 0.6]$, then that trade is not assigned as a retail transaction.

Important to my exercise, this algorithm is able to identify only marketable orders made by individuals, as only marketable orders receive price improvements. That is, it is not possible to identify transactions that are triggered by limit orders placed by individuals. On the one hand, this feature of [Boehmer, Jones and Zhang \(2017\)](#) algorithm loses a large fraction of retail's activity, since limit orders are widely popular between individuals. On the other hand, however, using only marketable orders placed by individuals helps me to identify the behavioral biases that I evaluate during ex-dividend dates and when the price of a stock fluctuates around integer numbers: the individual "attacks" an offer in real time, instead of placing an order and waiting for something to happen.

I apply this algorithm to TAQ data between 2010 and 2017³, therefore a broader period than the one [Boehmer, Jones and Zhang \(2017\)](#) use in their paper (from 2010 to 2015). After all, I obtain 7,663,529 stock-day observations considering only common stocks, that is, stocks with share code that equals 10 or 11. Each observation is a pair stock-day with a day, a stock identifier, the number of retail purchases of that stock on that day, the number of retail sales, the volume purchased by retailers, the volume sold by retailers, the value purchased by retailers and the value sold by retailers. Panel A of Table 1 presents summary statistics on the stock-level in terms of retail activity. It shows that the average stock had, between 2010 and 2017, 114.31 individual purchases and 110.95 individual sales per day. Also, 48,565 shares were bought and 48,727 share were sold by individuals, and their value (in US dollars) were at a level of 1,426,100 dollars and 1,415,272, respectively. Panel B of Table 1 shows how individuals' activity evolved over time, in terms of purchases, volume and value. Finally, Figure 1 shows the evolution of the trading activity on a daily frequency. It is possible to note that the time-series of both buying and selling activity of retail investors have a stationary aspect with few outliers. Also, the valley points are typically seasonal and related to days before Thanksgiving and Christmas events.

³At first, I applied their algorithm for data between 2007 and 2017. The reason why I did not consider the first three years of this period is due to a non-stationary behavior for the time-series of the number of retail purchases. I discussed this issue with Terry Odean and he endorsed that it is the right procedure to adopt in such cases.

Table 1: Retail Investors' Trading Activity

This table provides descriptive statistics of the trading activity of retail investors between 2010 and 2017. Panel A shows stock-level distribution of retailers' activity: number of purchases, number of sales, volume purchased, volume sold, value purchased and value sold. Panel B shows retailers' buying activity over time: their (i) number of purchases (in million units), (ii) volume purchased (in million units) and (iii) value purchased (in US\$ billions) for each year of our sample.

Panel A: Stock-level distribution of retailers' activity						
	pct5	pct25	pct50	pct75	pct95	mean
N. of purchases	0	5	22	82	461	114.31
N. of sales	0	5	24	84	454	110.95
Vol. purchased	0	1,129	5,651	23,429	176,441	48,565.89
Vol. sold	0	1,270	6,026	24,356	176,912	48,272.95
Val. purchased (US\$)	0	11,138	80,613	476,272	5,120,657	1,426,100
Val. sold (US\$)	0	12,339	85,887	491,053	5,127,807	1,415,272

Panel B: Retailers' buying activity over time			
Year	Retail Purchases (mi)	Volume Purchased (mi)	Value Purchased (US\$ bi)
2010	104.06	55,854.52	1,149.49
2011	101.29	45,105.66	1,178.36
2012	88.55	39,773.73	1,152.13
2013	85.57	40,836.73	1,225.60
2014	97.93	41,068.10	1,359.75
2015	108.94	39,099.38	1,376.05
2016	124.55	46,524.34	1,407.23
2017	120.64	45,022.88	1,525.28

Overall, the innovation proposed by [Boehmer, Jones and Zhang \(2017\)](#) allows us to identify most of the marketable orders from retail investors. They also cross-validate their algorithm with proprietary data from [Kelley and Tetlock \(2013\)](#) and with an intraday transaction data set from October 2010 provided by NASDAQ; both exercises confirm the accuracy of their algorithm. It is also worth mentioning that the descriptive statistics I presented on Table 1 are similar to the ones [Boehmer, Jones and Zhang \(2017\)](#) obtained. To the best of my knowledge, this work is the first one that uses their algorithm to identify retail investors' activity for a broader period.

Figure 1: Retailers' trading activity over time

This figure shows the daily time-series of the trading activity of retailers between 2010 and 2017. The top graph shows the daily number of retail purchases (in thousands) and the bottom graph shows the daily number of retail sales (in thousands).

4 Fictitious Price Falls (FPF) and Investors' Activity

In this section, I show that individuals may ignore negative news that might be behind stock prices' falls. First, I show that when they face an *immaterial* price fall caused by an ex-dividend date event, they increase their buying activity on that particular stock. This exercise reveals that indeed individuals are ignoring the content of the price fall, since this fall has no additional information on one's information set: the stock price falls because investors are no longer entitled to receive the next cash dividend amount and, therefore, the price's expected drop is close to the next cash dividend amount. Second, I show that individuals focus their purchases on stocks with prices just-below integer numbers, i.e., I show evidence that they display *left-digit bias* also in the stock market.

4.1 FPF1: ex-dividend dates and individuals' buying activity

The first identification strategy to show that individuals may ignore the information behind price falls relies on the fact that on ex-dividend dates, the price of a stock s falls *mechanically* by the amount of the dividend D that will be paid. The chronology is as follows: on day t_{dec} , the announcement date, company s announces that (i) will pay D dollars as cash dividends to its shareholders, (ii) the shareholders that are entitled to receive dividends are the ones that hold stocks of company s one day before day t_{ex} , the ex-dividend date and (iii) these shareholders will receive their cash dividend amount on day t_{pay} , the payment date. Important to our strategy is the number of days between t_{ex} and t_{dec} to be more than or equal to one: there is absolutely no new information available to investors on t_{ex} , day when their home-broker screen shows a negative return on stock's s price. The overnight return on day t_{ex} is necessarily negative and the individual is not told that this negative return is due to the ex-dividend event.

To be able to reproduce [Chague, De-Losso and Giovannetti \(2018\)](#) first identification strategy, it is necessary to collect data on dividend events for every common stock I previously obtained using [Boehmer, Jones and Zhang \(2017\)](#) algorithm. To do so, I use the CRSP database and obtain, for each common stock and for all sample period, every (i) dividend event, (ii) dividend amount, (iii) declaration date, (iv) ex-dividend date and (v) payment date. Overall, there are 44,205 dividend events for all common stocks between 2010 and 2017.

Figure 2: Distribution of ex-dates over time

This figure shows the distribution of ex-dates between 2010 and 2017. I aggregate, for each day t , the number of different stocks that had on t their ex-dividend date and plot this number on the vertical axis. The horizontal axis represents day t .

Important to my identification strategies are all the ex-dividend dates associated with these 44,205 dividend events. Figure 2 shows the distribution over time of ex-dividend dates: each dot represents the number of stocks that has on t its ex-dividend date. Table 2 also reports the evolution of ex-dividend dates over time. Panel A shows the number of ex-dividend dates per year and over the years of our sample. It is possible to see that they are evenly distributed over the sample period. Panel B shows the distribution of ex-dividend dates across the months of the year. Panel C shows the distribution of ex-dates over weekdays. It is possible to see that there is some seasonality in the distribution of ex-dividend dates over the months: they have higher values one month prior to the end of each quarter (March, June, September and December) and also during those same months. This may be due to the fact that companies (i) usually pay dividends in a quarterly frequency and (ii) usually announce their ex-dates and payment days more than 10 days prior to cash their dividends into

shareholders accounts, which is shown on Table 3: besides showing that most of the dividend events have declaration dates (at least one day) in advance to their ex-dividend dates, it shows descriptive statistics on the average cash dividend amounts paid by those firms and the average annualized dividend yield (in %), for each interval (Δt) between the declaration date (t_{dec}) and the ex-dividend date (t_{ex}), that is, $\Delta t = t_{ex} - t_{dec}$.

Table 2: Distribution of Ex-dividend Events

This table provides descriptive statistics of the distribution of ex-dividend events over time. Panel A shows how ex-dates are distributed between 2010 and 2017. Panel B shows how ex-dividend dates are distributed between the 12 months of the year for all the years of our sample. Panel C shows how ex-dates are distributed over weekdays.

Panel A: Ex-dividend events over the years

Year	Frequency	Percent	Cumulative
2010	4,987	11.28	11.28
2011	5,129	11.60	22.88
2012	5,599	12.66	35.55
2013	5,383	12.17	47.72
2014	5,821	13.16	60.89
2015	5,881	13.30	74.19
2016	5,746	12.99	87.19
2017	5,659	12.80	100.00

Panel B: Ex-dividend events over months

Month	Frequency	Percent	Cumulative
January	1,746	3.94	3.94
February	4,432	10.02	13.97
March	4,510	10.20	24.17
April	1,928	4.36	28.53
May	4,969	11.24	39.78
June	4,070	9.20	48.98
July	1,998	4.51	53.50
August	5,023	11.36	64.87
September	3,805	8.60	73.47
October	2,047	4.63	78.10
November	5,338	12.07	90.18
December	4,339	9.81	100.00

Panel C: Ex-dividend events over weekdays

Day of Week	Frequency	Percent	Cumulative
Monday	5,669	12.82	11.28
Tuesday	7,113	16.09	28.91
Wednesday	15,289	34.58	63.50
Thursday	10,424	23.58	87.08
Friday	5,710	12.91	100.00

Table 3: Cash Dividend Statistics

	$\Delta t = 0$	$\Delta t \geq 1$	Δt								
	1	2	3	4	5	6	7	8	9	10+	
All dividends events											
# of dividend events	40	54	174	790	2,459	4,069	3,379	3,963	2,782	26,491	
dividend average value	0.132	0.343	0.241	0.308	0.269	0.276	0.234	0.198	0.219	0.247	
average dividend yield (%)	3.85	4.44	3.84	3.70	3.77	3.70	3.66	3.14	3.19	3.51	

The strategy is to evaluate how individuals respond to negative overnight returns on ex-dates. If negative overnight returns *causes* an increase in the buying activity of individual investors, we will be able to affirm that there is some evidence pointing to the fact that they ignore the information contained on stock prices, since this price drop is absent of negative news. The main dependent variable is the total number of individual purchases of stock s on day t , $N_{s,t}$, standardized by stock. First, I show the buying activity of individuals five days prior and five days after ex-dividend dates on Figure 3. Here, I consider all dividend events that were announced at least 5 days before the ex-dividend date; that is, investors were aware of the ex-dividend date 5 days in advance of the *mechanical* price drop that occurs on ex-dates.

It can be seen that individuals' buying activity is significantly higher on the "cum-dividend date", that is, one day prior to the ex-date their buying activity is high (0.15 standard deviations). This is not surprising: individuals may take advantage of the fact that prices often fall less than the dividend amount on ex-dates, as shown by Frank and Jagannathan (1998). This strategy of buying before ex-dates is popular among investors and is known as "dividend stripping". Also, this pattern can be seen for all four days prior to the cum-dividend date: their buying activity is also significantly higher. This result can be explained by two main drivers: (i) individuals may want to receive dividends and, therefore, purchase stock s before the ex-dividend date in order to be entitled to receive dividends, as suggested by Dong, Robinson and Veld (2005) and Graham and Kumar (2006) or (ii) dividend-related announcements (news) are attention-driven events and individuals' buying activity increases after that, as suggested by Barber and Odean (2007). The surprising feature of Figure 3, however, is the activity of individuals on the ex-date (0.05 standard deviations): there is no new information and no dividend-related issue during ex-dates and, therefore, no reason to believe that they should increase their buying activity during that date. Also, there is no strategy such as the "dividend stripping" on ex-dates. I will now argue that individuals are actually responding to the ex-date's *mechanical* price drop.

Figure 3: Individuals' buying activity around ex-dates

This figure shows individuals' buying activity around ex-dividend dates. For each day t of the sample, I compute the number of individual purchases of stock s and standardize it by stock, computing $N_{s,t}$. Then, I take the average of $N_{s,t}$ across all stocks for each day around the ex-date from five days before to five days after the ex-date, along with a 99% confidence interval. I only consider all 43,143 dividends that were announced at least 5 days prior to their ex-dividend date. Vertical axis displays the average values of $N_{s,t}$ around ex-dates and horizontal axis shows which day is being considered, with t_{ex} being equal to 0. See Table A1 of Appendix A for values of each average and their standard errors.

I estimate the effect that the price drop on ex-dates has on individuals' buying activity. The goal is to somehow relate $N_{s,t}$ and $R_{s,t}^*$, the overnight return of stock s on day t during ex-dates. This will enable us to see how individuals react when they see, in the morning of day t_{ex} , that the price of stock s has fallen from day $t_{ex} - 1$ to day t_{ex} . To do so, I use the dividend yield of stock s on day t_{ex} as an instrument. I define $DivYield_{s,t}$ as a variable that equals the dividend yield⁴ on ex-dates and equals zero otherwise. Then, I run stock-day fixed effect panel regressions of $N_{s,t}$ on $\widehat{R_{s,t}^*}$, the projection of $R_{s,t}^*$ on the instrument $DivYield_{s,t}$. Therefore, the first stage of our strategy is running stock-day panel regressions of $R_{s,t}^*$ on $DivYield_{s,t}$ and the second stage is running stock-day panel regressions of $N_{s,t}$ on $\widehat{R_{s,t}^*}$, both with a vector $x_{s,t}$ of control variables. As one can see, my measure

⁴To be precise, I define here that the dividend yield is equal to $D_{s,t}/P_{s,t-1}$, where $D_{s,t}$ is the dividend amount of dollars per share of stock s at day t and $P_{s,t-1}$ is the closing price of stock s at day $t - 1$.

of the fictitious price fall that occurs when the market opens on ex-dates is $\widehat{R_{s,t}^*}$. The equations, therefore, are:

$$R_{s,t}^* = \delta + \gamma DivYield_{s,t} + x'_{s,t}\theta + a_s + \varepsilon_{s,t} \quad (1st\ stage)$$

$$N_{s,t} = \alpha + \phi \widehat{R_{s,t}^*} + x'_{s,t}\lambda + a_s + \varepsilon_{s,t} \quad (2nd\ stage)$$

Table 4 shows the results of the first and the second stages that were described above. Column (1) shows the results of the first stage: the coefficient estimated shows that the price drop on ex-dates is 87.08% of the dividend payout, which is consistent to the fact that the price drop is less than the dividend payout. Column (2) shows the direction and the magnitude of the price drop on individuals' buying activity. The negative sign shows that the price drop and individuals' buying activity are related in the way: the more the price *mechanically* falls (negative $R_{s,t}^*$), the more individuals' buying activity increases. The coefficient shows the magnitude of this relation: a 5% price drop significantly increases individuals' buying activity in 0.71 standard deviations ($0.71 = 0.142 \times 5$). Column (3) shows the same relation, but instead of the number of individuals purchases, I relate *mechanical* price falls with the volume $V_{s,t}$ (number of shares) purchased by individuals of stock s on day t . As it happens with $N_{s,t}$, the volume purchased by individuals also increases after *mechanical* price falls: a 5% price drop increases individuals' buying volume by 0.605 standard deviations ($0.605 = 0.121 \times 5$).

Columns (4), (5) and (6) of Table 4 include lagged returns, R_{-h} , with $h = 1, 5$ and 20 days. I include lagged returns to control for (i) possible contrarian strategies by individuals after possible negative news attached to dividend announcements, including during ex-dividend dates, (ii) individuals' slowly reaction after positive earnings surprises (PEAD anomaly) and (iii) individuals' extrapolative beliefs. The first effect refers to the fact that dividend announcements may bring negative news and, in the case that individuals engage on contrarian strategies, they will increase their buying activity on stocks, even on ex-dividend dates. The second effect refers to the fact that dividend announcements may bring positive news and because investors have a slow reaction to these news⁵, they delay their purchases to days after the announcement (possibly, that day would be the ex-dividend date). Finally, the third effect is related to the fact that investors have extrapolative beliefs and may expect future returns to be a weighted average of past returns, weighting more recent past returns⁶. I also include day-of-the-week dummies to control for a possible joint seasonality between ex-dividend dates and individuals' trading preferences (supposing, for instance, that ex-dates occur

⁵See, for instance, [Rendleman, Jones and Latane \(1982\)](#) and [Jones and Litzenberger \(1970\)](#).

⁶See, for instance, [Amromin and Sharpe \(2013\)](#) and [Greenwood and Shleifer \(2014\)](#).

Table 4: FPF1: Buying Activity of Retail Investors

This table shows the estimates of stock-day panel regressions of $N_{s,t}$, the number of individual purchases of stock s on day t standardized by stock, on $\widehat{R_{s,t}^*}$, the projection of the overnight return, $R_{s,t}^*$, on $DivYield_{s,t}$, an instrument that equals the dividend yield on ex-dividend dates and equals zero otherwise. I include day-of-the-week dummies and stock lagged returns on columns (4), (5) and (6) as controls variables. Standard errors were clustered by stock and are shown in parentheses below each estimate.

All dividends						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. variable:	1st stage $R_{s,t}^*$	2nd stage $N_{s,t}$	2nd stage $V_{s,t}$	1st stage $R_{s,t}^*$	2nd stage $N_{s,t}$	2nd stage $V_{s,t}$
$DivYield_{s,t}$	-0.8708 (0.0545)			-0.8707 (0.0546)		
$\widehat{R_{s,t}^*}$		-0.1417 (0.0106)	-0.1209 (0.0114)		-0.1415 (0.0106)	-0.1217 (0.0114)
R_{-1}				-0.0020 (0.0009)	0.0002 (0.0002)	0.0001 (0.0002)
R_{-5}				-0.0007 (0.0002)	-0.0001 (0.0001)	-0.0001 (0.0001)
R_{-20}				-0.0005 (0.0005)	-0.0001 (0.0001)	-0.0001 (0.0001)
Monday				0.0282 (0.0256)	0.0187 (0.0012)	-0.0517 (0.0015)
Tuesday				0.0123 (0.0268)	0.0317 (0.0013)	-0.0352 (0.0016)
Wednesday				0.0150 (0.0268)	0.0220 (0.0013)	-0.0439 (0.0015)
Thursday				0.0094 (0.0245)	0.0184 (0.0012)	-0.0455 (0.0015)
Constant	0.1457 (0.0002)	0.0201 (0.0015)	0.0171 (0.0016)	0.1326 (0.0192)	0.0003 (0.0016)	0.0512 (0.0018)
# of Stocks	5718	5718	5718	5700	5700	5700
R^2 (%)	0.01	0.03	0.02	0.01	0.05	0.07
Obs. (mi)	7.27	7.27	7.27	7.24	7.24	7.24

more on Mondays and individuals like to purchase stocks on that same day). The results, however, remain basically the same.

I also take into account the fact that some individuals like to receive dividends and increase their buying activity after dividend announcements. Therefore, their buying activity on ex-dates would be a delayed response to the dividend announcement and they would not be attentive to the fact that buying stocks on ex-dates does not entitle them to receive dividends. Now, I redefine $DivYield_{s,t}$ to be equal to the dividend yield on ex-dates of dividends that were announced at least 5 days before the ex-date. Then, I run the same stock-day panel regressions and obtain similar results than the ones I obtained before. Table 5 shows these results for the first and second stages in columns (1), (2) and (3), respectively. The estimates are almost equal to the ones of Table 4: (i) column (1) shows that the price drop on ex-dates is 87.04% of the dividend payout; (ii) also, column (2) shows that a 5% on the price increases individuals' buying activity on 0.705 standard deviations ($0.705 = 0.141 \times 5$), (iii) column (3) shows that the buying volume of individuals increases by 0.6 standard deviations after a 5% price drop on ex-dates ($0.60 = 0.120 \times 5$). When I control for lagged returns and day-of-the-week dummies, the results are basically the same. It is important to say that the results presented on Table 5 are similar to the ones of Table 4 because a large fraction of the dividend events in our sample is announced 5 days before the ex-dividend date, as showed on Table 3.

Table 5: FPF1: Buying Activity of Retail Investors

This table shows the estimates of stock-day panel regressions of $N_{s,t}$, the number of individual purchases of stock s on day t standardized by stock, on $\widehat{R_{s,t}^*}$, the projection of the overnight return, $R_{s,t}^*$, on $DivYield_{s,t}$, an instrument that equals the dividend yield on ex-dividend dates for dividends that were announced 5 days before the ex-date and equals zero otherwise, i.e., $\Delta t \geq 5$, with $\Delta t = t_{ex} - t_{dec}$. I include day-of-the-week dummies and stock lagged returns on columns (4), (5) and (6) as controls variables. Standard errors were clustered by stock and are shown in parentheses below each estimate.

	Dividends with $\Delta t \geq 5$					
	(1)	(2)	(3)	(4)	(5)	(6)
	1st stage	2nd stage	2nd stage	1st stage	2nd stage	2nd stage
Dep. variable:	$R_{s,t}^*$	$N_{s,t}$	$V_{s,t}$	$R_{s,t}^*$	$N_{s,t}$	$V_{s,t}$
$DivYield_{s,t}$	-0.8704 (0.0557)			-0.8703 (0.0557)		
$\widehat{R_{s,t}^*}$		-0.1411 (0.0108)	-0.1198 (0.0116)		-0.1409 (0.0108)	-0.1207 (0.0116)
R_{-1}				-0.0020 (0.0009)	0.0002 (0.0002)	0.0001 (0.0002)
R_{-5}				-0.0007 (0.0002)	-0.0001 (0.0001)	-0.0001 (0.0001)
R_{-20}				-0.0005 (0.0005)	-0.0001 (0.0001)	-0.0001 (0.0001)
Monday				0.0282 (0.0256)	0.0187 (0.0012)	-0.0517 (0.0015)
Tuesday				0.0122 (0.0268)	0.0317 (0.0013)	-0.0352 (0.0016)
Wednesday				0.0148 (0.0268)	0.0220 (0.0013)	-0.0439 (0.0015)
Thursday				0.0091 (0.0245)	0.0184 (0.0012)	-0.0455 (0.0015)
Constant	0.1456 (0.0002)	0.0200 (0.0015)	0.0170 (0.0016)	0.1326 (0.0192)	0.0002 (0.0016)	0.0511 (0.0018)
# of Stocks	5718	5718	5718	5700	5700	5700
R^2 (%)	0.01	0.03	0.02	0.01	0.05	0.07
Obs. (mi)	7.27	7.27	7.27	7.24	7.24	7.24

Another possible confounding effect is the fact that retailers postpone their purchases to ex-dates in order to avoid taxes. For instance, an individual may want to wait the ex-date before buying a particular stock to avoid paying tax on dividends. Unlike Chague, De-Losso and Giovannetti (2018), my analysis does not have to consider taxable and non-taxable dividends: different from Brazil’s case, every dividend gain in US is subject to tax filling by individuals, although retailers get taxed at lower rates if the dividend gained is a qualified one. A dividend is qualified⁷ to be taxed at lower rates if (i) that dividend is distributed by a US corporation and (i) an individual owns that stocks 60 days before the ex-dividend date. In any case, that issue does not affect individuals’ activity *during* ex-dates and, therefore, does not require a special concern.

When I consider the selling activity of individuals, the results point in the same direction: the *net* buying activity of individuals also increases on ex-dates. Table 6 shows the results of these estimations. I define $net(N_{s,t})$ as the difference between individuals’ purchases of stock s on day t and individuals’ sales of stock s on day t , standardized by stock; similarly, $net(V_{s,t})$ is the net volume purchased by individuals on stock s on day t . Columns (1) and (3) show the results of the second stage estimation (the first stage is equal to the ones I presented on column (5) of Tables 4 and 5, respectively). Column (1) shows the estimation when I consider the instrument $DivYield_{s,t}$ to be equal to dividend yield for ex-dates with $\Delta t \geq 1$, as I did on Table 4. Column (3) shows the estimation when I consider the instrument $DivYield_{s,t}$ to be equal to the dividend yield only for ex-dates with $\Delta t \geq 5$, as I did on Table 5. As we see, the *net* individuals’ purchases also respond positively to *mechanical* price falls, although in a smaller magnitude than when I do not consider the selling activity of individuals. An explanation is that individuals may increase their selling activity on ex-dates to take advantage of the fact that prices fall less than the dividend amount and, therefore, adopt the “dividend stripping” strategy. I do not find similar results, however, for the *net* volume purchased by individuals. Columns (2) and (4) of Table 6 show that the estimates of the response of individuals in terms of volume to price falls are not statistically different from zero. This may be due to the fact that skilled individuals (e.g., the ones that know the dividend stripping strategy) trade more volume than non-skilled individuals.

All stock-day panel regressions above were run considering all trading days between 2010 and 2017, including ex-dividend dates and regular dates. A next exercise consist in restricting the sample only to ex-dividend dates. This procedure is made so that I can evaluate if the buying activity of retailers increase with the size of the price fall that occurs on ex-dates, that is, do we observe a greater

⁷More details on that qualification can be found on Topic 404 of the Internal Revenue Services (IRS): <https://www.irs.gov/taxtopics/tc404>

Table 6: FPF1: Net Buying Activity of Retail Investors

This table shows the estimates of stock-day panel regressions of $net(N_{s,t})$ and $net(V_{s,t})$, respectively, (i) the net number of individual purchases of stock s on day t standardized by stock and (ii) the net volume purchased by individuals on stock s at day t standardized by stock, on $\widehat{R}_{s,t}^*$, the projection of the overnight return, $R_{s,t}^*$, on $DivYield_{s,t}$, an instrument that first equals the dividend yield on ex-dividend dates for dividends that were announced at least one day before the ex-date ($\Delta t \geq 1$) and zero otherwise and then equals the dividend yield on ex-dividend dates for dividends that were announced 5 days before the ex-date and equals zero otherwise, i.e., $\Delta t \geq 5$, with $\Delta t = t_{ex} - t_{dec}$. I include day-of-the-week dummies and stock lagged returns as controls variables. Standard errors were clustered by stock and are shown in parentheses below each estimate.

Net purchases regressions with all dividends				
Dep. variable:	(1)	(2)	(3)	(4)
	$\Delta t \geq 1$		$\Delta t \geq 5$	
	$net(N_{s,t})$	$net(V_{s,t})$	$net(N_{s,t})$	$net(V_{s,t})$
$\widehat{R}_{s,t}^*$	-0.0532 (0.0188)	-0.0295 (0.0199)	-0.0538 (0.0191)	-0.0299 (0.0203)
R_{-1}	0.0002 (0.0001)	0.0001 (0.0001)	0.0002 (0.0001)	0.0001 (0.0001)
R_{-5}	-0.0001 (0.0001)	-0.0001 (0.0001)	-0.0001 (0.0001)	-0.0001 (0.0001)
R_{-20}	-0.0001 (0.0001)	-0.0001 (0.0001)	-0.0001 (0.0001)	-0.0001 (0.0001)
Monday	-0.0103 (0.0013)	-0.0117 (0.0015)	-0.0103 (0.0013)	-0.0117 (0.0015)
Tuesday	-0.0073 (0.0012)	-0.0159 (0.0014)	-0.0073 (0.0012)	-0.0159 (0.0014)
Wednesday	-0.0050 (0.0012)	-0.0125 (0.0014)	-0.0050 (0.0012)	-0.0125 (0.0014)
Thursday	-0.0092 (0.0011)	-0.0155 (0.0013)	-0.0092 (0.0011)	-0.0155 (0.0013)
Constant	0.0136 (0.0025)	0.0153 (0.0028)	0.0137 (0.0026)	0.0153 (0.0028)
# of Stocks	5702	5702	5702	5702
R^2 (%)	0.01	0.01	0.01	0.01
Obs. (mi)	7.24	7.24	7.24	7.24

buying activity when the price drop is higher? To do so, I run the same stock-day fixed effect panel regressions, considering (i) dividends that were announced 1 day prior to the ex-date, that is, $\Delta t \geq 1$ and (ii) dividends that were announced 5 days prior to the ex-date, that is, $\Delta t \geq 5$. In such cases, the variable $DivYield_{s,t}$ is defined to be equal to the dividend yield for those dividends that were announced 1 or 5 days before the ex-date.

The results are presented in Table 7. Columns (1), (2) and (3) consider all the 44,201 dividends with $\Delta t \geq 1$. Column (1) shows the estimates of the first stage for dividends with $\Delta t \geq 1$. Since all observations I consider are ex-dividend dates, the price drop between $t_{ex} - 1$ and t_{ex} is equal to 88.2% of the dividend amount payed ($100 \times (-1.168 + 0.286)$), after controlling for lagged returns and day-of-the-week dummies. Columns (2) and (3) show negative and significant estimates of $\widehat{R}_{s,t}^*$ on $N_{s,t}$ and $V_{s,t}$: the buying activity of retailers increases by 0.61 standard deviations ($0.61 = 0.122 \times 5$) when the mechanical price drop is equal to 5%. When I consider the 43,143 dividends that were announced five days before the ex-dividend date, the results are qualitatively the same: column (4) shows that the mechanical price drop equals 88.1% of the dividend amount payed ($100 \times (-1.177 + 0.296)$). Moreover, column (5) shows that when the price drop is 5%, the buying activity of individuals increases by 0.595 standard deviations ($0.595 = 0.119 \times 5$). Overall, I found that the buying activity of retailers also increases with the magnitude of the mechanical price drop on ex-dates.

In short words, the opening price of a stock *mechanically* falls during ex-dividend dates. Retailers are unaware that this price drop is mechanical, since their home broker screen only shows a negative sign, not indicating that that day is an ex-dividend one. I showed that retailers respond positively to these *immaterial* price drops, even when controlling for confounding effects. In the next subsection, I explore a different fictitious price fall and how individuals respond to it.

Table 7: FPF1: Buying Activity of Retail Investors Only on Ex-Dates

This table show the estimates of stock-day fixed effect panel regressions of $N_{s,t}$ and $V_{s,t}$, respectively, the number of individual purchases and the volume purchased by individuals, both standardized by stock, on $\widehat{R}_{s,t}^*$, the projection of the overnight return, $R_{s,t}^*$, on $DivYield_{s,t}$. Here, I consider a stock-day data set with only the 44,205 ex-dividend dates between 2010 and 2017. The variable $DivYield_{s,t}$ first equals the dividend yield for stocks that announced their ex-dividend dates at least 1 day before the ex-dividend date, that is, $\Delta t \geq 1$, with $\Delta t = t_{ex} - t_{dec}$. Columns (1), (2) and (3) shows the estimates of the first stage and the second stages for that definition. Second, $DivYield_{s,t}$ equals the dividend yield for stocks that announced their ex-dividend dates at least 5 day before the ex-dividend date, that is, $\Delta t \geq 5$. Columns (4), (5) and (6) shows the estimates of the first stage and the second stages for that definition. I include day-of-the-week dummies and stock lagged returns as controls variables. Standard errors were clustered by stock and are shown in parentheses below each estimate.

Regressions with only on ex-dates						
	(1)	(2)	(3)	(4)	(5)	(6)
	1st stage	2nd stage	2nd stage	1st stage	2nd stage	2nd stage
	$\Delta t \geq 1$			$\Delta t \geq 5$		
Dep. variable:	$R_{s,t}^*$	$N_{s,t}$	$V_{s,t}$	$R_{s,t}^*$	$N_{s,t}$	$V_{s,t}$
$DivYield_{s,t}$	-1.1679 (0.3943)			-1.1772 (0.4050)		
$\widehat{R}_{s,t}^*$		-0.1221 (0.0140)	-0.1036 (0.0131)		-0.1195 (0.0140)	-0.1010 (0.0130)
R_{-1}	-0.0538 (0.0088)	-0.0047 (0.0047)	-0.0043 (0.0047)	-0.0543 (0.0091)	-0.0033 (0.0046)	-0.0031 (0.0047)
R_{-5}	-0.0128 (0.0038)	0.0003 (0.0026)	-0.0025 (0.0020)	-0.0132 (0.0040)	0.0005 (0.0026)	-0.0026 (0.0020)
R_{-20}	0.0021 (0.0022)	-0.0013 (0.0011)	-0.0008 (0.0010)	0.0026 (0.0024)	-0.0013 (0.0012)	-0.0008 (0.0010)
Monday	0.0744 (0.0750)	0.0267 (0.0223)	-0.0312 (0.0219)	0.0768 (0.0766)	0.0228 (0.0223)	-0.0333 (0.0219)
Tuesday	0.0060 (0.0989)	0.0221 (0.0208)	-0.0366 (0.0222)	-0.0051 (0.1019)	0.0184 (0.0208)	-0.0387 (0.0222)
Wednesday	-0.0369 (0.1386)	-0.0370 (0.0197)	-0.0643 (0.0207)	-0.0373 (0.1430)	-0.0347 (0.0198)	-0.0643 (0.0207)
Thursday	0.0380 (0.1096)	0.0192 (0.0208)	-0.0390 (0.0218)	0.0290 (0.1142)	0.0146 (0.0212)	-0.0448 (0.0220)
Constant	0.2869 (0.3857)	-0.0127 (0.0174)	0.0124 (0.0185)	0.2962 (0.3951)	-0.0108 (0.0174)	0.0137 (0.0184)
# of Stocks	2213	2213	2213	2203	2203	2203
R^2 (%)	13.63	2.47	2.11	13.59	2.42	2.07
Obs.	44,201	44,201	44,201	43,143	43,143	43,143

4.2 FPF2: left-digit bias

Now, I show that individuals display left-digit bias when they purchase stocks. This behavioral pattern has been pointed out by [Gabaix \(2017\)](#) as a kind of inattention to non-leading digits and shown to exist among individuals in several markets. [Lacetera, Pope and Sydnor \(2012\)](#) analyze millions of used-car transactions to show that individuals focus their attention on the left digit of odometers when they purchase used cars: there is a discontinuous drop in sale prices at 10,000 mile odometer thresholds. [Chava and Yao \(2017\)](#) show that properties with left-digit prices are more likely to be sold than other properties and stay fewer days available to the market. [Anderson and Simester \(2003\)](#) show that ending prices in the digit 9 (e.g., \$ 19.99 instead of \$ 20.00) increase retail sales. [Shlain \(2018\)](#) develop a theoretical model and use retail scanner data on products and retailers to explain the tendency of consumers to perceive a \$ 4.99 product as much cheaper than a \$ 5.00 product: he finds that consumers respond to a 1 cent increase from a 99-ending price as if it were something between 15 and 25 cents. Other evidence-based works corroborate these evidences, justifying the study of the buying activity of individuals when they face the choice of picking a stock which price is fluctuating around an integer number.

As I did in the Introduction of this work, I argue that this kind of event qualifies as a fictitious price fall: individuals *wrongly* perceive a stock priced at \$ 24.99 as being much more cheaper than if the stock were priced at \$ 25.01. That is, there is no information or event *a priori* that justifies that individuals should focus their purchases on stock if its price is \$ 24.99 instead of \$ 25.01. This 2-cent difference between both prices is, at some point, *immaterial* and meaningless, probably reflecting noises in the stock market microstructure. Also, the fact that retailers do not ignore the *immateriality* of this price difference may indicate that they ignore the informational content of stock prices; that is, if they did not ignore, they would not focus their purchases on stocks priced at 99-ending prices rather than 01-ending prices. My goal is to provide evidence that individuals display this bias and indeed focus their purchases on just-below integer number prices.

To do so, I also use TAQ data between 2010 and 2017 to identify this potential bias displayed by individuals. Again, I use [Boehmer, Jones and Zhang \(2017\)](#) algorithm to identify marketable orders made by individuals in my identification strategy. First, I define a *FPF2 event* as a pair stock-day: on day t , stock's s price fluctuated around an integer number (for instance, \$ 25) if at least 5,000 trades (by institutions and individuals) were made within each of the following intervals: [24.90, 24.94], [24.95, 24.99], [25.01, 25.05], [25.06, 25.10]. To be consistent with [Boehmer, Jones and Zhang \(2017\)](#)

algorithm, I consider trades that were registered in TAQ with price improvements⁸. I obtain a total of 16,727 FPF2 events between 2010 and 2017, that is, I observe, by that *ad hoc* criteria, that stocks fluctuated around integer prices 16,727 times during my sample period. Considering only common stocks, I obtained a total of 9,657 FPF2 events.

For each FPF2 event, I use [Boehmer, Jones and Zhang \(2017\)](#) to identify all retail traders and then I count (i) the number of individual purchases that were made below the integer price (using the previous example, all trades with prices between \$ 24.90 and \$ 24.99) and (ii) the number of individual purchases that were made above the integer price (using the previous example, all trades with prices between \$ 25.01 and \$ 25.10). Finally, I calculate the *proportion* of purchases that were made below that integer price, that is, I divide the number of individuals' below purchases by individuals' below and above purchases.

I also do a placebo exercise and call it a Placebo FPF2 event. A Placebo FPF2 event is pair stock-day: on day t , a stock s that fluctuates around the 50 cent (e.g., \$ 24.50) price. Note that around this 50-cent ending price, there is no left-digit effect, thus a “placebo” exercise. I used the same criteria to identify a Placebo FPF2 than before: at least 5,000 trades (by institutions and individuals) were made within each of the following intervals: [24.40, 24.44], [24.45, 24.49], [24.51, 24.55], [24.56, 24.60]. I obtained a total of 16,129 Placebo FPF2 events; from these, I will only consider the 9,146 Placebo FPF2 events that happened with common stocks. Then, for each Placebo FPF2 events, I count (i) the number of individual purchases that were made below the placebo integer price (using the previous example, all trades with prices between \$ 24.40 and \$ 24.49) and (ii) the number of individual purchases that were made above the integer price (using the previous example, all trades with prices between \$ 24.51 and \$ 24.60). Then, I calculate the *proportion* of purchases that were made below that placebo integer price, that is, I divide the number of individuals' below purchases by individuals' below and above purchases.

To test if individuals display left-digit bias when they purchase stocks, I take the average across the above mentioned proportions for all 9,657 FPF2 events and for all 9,146 Placebo FPF2 events. That is, I calculate the average proportion of just-below purchases made by individuals for all FPF2 events and for all Placebo FPF2 events. Figure 4 compares the averages of the proportions of just below and just above purchases along with their 99% confidence interval. Considering the FPF2 events, the proportion of just-below purchases is significantly higher than the proportion of just-above purchases (50.56% vs 49.44%); considering the Placebo FPF2 events, the proportion of

⁸A trade that was made by a retailer with its trading price at \$24.898 was a purchase *placed* at \$24.90. Therefore, I assign this trade to have being made at the first interval. I proceed like this with every interval.

just-below purchases is significantly lower than the proportion of just-above purchases (49.50% vs 50.50%). This first result is a first evidence of left-digit bias displayed by individuals: individuals are buying significantly more stocks that are priced just-below integer numbers. The magnitude of this result is closely related to the fact that our algorithm only consider marketable orders by individuals; it is very likely that the magnitude of the left-digit bias that I found would be higher if I were able to also identify limit orders placed by individuals. Although I found significant results for the “true” FPF2, the Placebo FPF2 shows results in the opposite way, also significantly. [Chague, De-Losso and Giovannetti \(2018\)](#), for instance, find that the proportions of just-below and just-above purchases are statistically the same, considering their confidence interval. Here, I found that these proportions are statistically different and individuals buy more stocks that are priced just-above 50 cents. A priori, I expected to find no statistical difference between the two average proportions. I will further show that when I consider a narrower interval of purchases just-above and just-below integer prices, this difference of the Placebo exercise disappears. In any case, the Placebo exercise confirms that there is only left-digit bias among stocks priced around integer prices, not for stocks priced around 50-cents.

Figure 4: Proportion of individual purchases just-below and just-above integer prices

This figure shows the average proportion of just-below and just-above integer prices purchases made by individuals. Here, I consider that just-below purchases are the ones made between 90-cent prices and 99-cent prices; just-above purchases are the ones made between 01-cent prices and 10-cent prices. The left side of the figure shows the averages of these proportions, along with their 99% confidence interval, for all 9,657 FPF2 events: the just-below average proportion equals 50.56% and the just-above average proportion equals 49.44%. Then, I consider a placebo exercise where just-below purchases are the ones made between 40-cent prices and 49-cent prices; just-above purchases are the ones made between 51-cent prices and 60-cent prices. The right side of the figure shows the averages of these proportions, along with their 99% confidence interval, for all 9,147 FPF2 events. See Table A2 of Appendix A for values of each average and their standard errors.

When I assess the proportion of individual purchases at each cent around integer prices, it is possible to see that indeed there is a strong digit bias in marketable orders made by individuals, specially when one compares the concentration of individuals' purchases at 90, 95, 05 and 10 cent-priced stocks; also, when one compares 99-cent purchases against 01-cent purchases. Figure 5 shows these proportions along with their 99% confidence intervals. It is also remarkable that (i) the proportion of purchases at 90, 95, 05 and 10 cent-priced stocks “jump” from the trend of the other proportions and (ii) individuals are buying significantly more when prices are very close to the 00-cent cutoff: at 99 cents, the average proportion of purchases is significantly higher than the proportion of individuals buying at 01 cents (5.81% vs 5.44%). Finally, when I pairwise compare symmetric proportions, I also find that individuals purchase more for cents below the integer threshold, specially when I consider a narrow interval around the integer threshold: the proportion of purchases at 95 cents *vs* at 05 cents is 2.13% higher ($0.0213 = 0.0527/0.0516 - 1$); at 96 cents *vs* at 04 cents is 2.57% higher ($0.0257 = 0.05133/0.05004 - 1$); at 97 cents *vs* at 03 cents is 5.48% higher ($0.0548 = 0.05267/0.04993 - 1$); at 98 cents *vs* at 02 cents is 8.86% higher ($0.0886 = 0.05487/0.05040 - 1$); finally, at 99 cents *vs* at 01 cents is 6.69% higher ($0.0669 = 0.05814/0.05449 - 1$).

Figure 5: Proportion of individual purchases at each cent around integer prices

This figure shows the average proportion of individual purchases made at each cent around integer prices, along with their 99% confidence interval. First, for each FPF2 event, I count the number of individual purchases at each cent. Then, I calculate the proportion of individual purchases that were made at each cent. Finally, I take the average of these proportions for all 9,657 FPF2 events. See Table A3 of Appendix A for values of each average and their standard errors.

I also include in the analysis the selling activity of individuals. To do so, for each FPF2 event, I (i) count the number of individual purchases made just-below integer prices, (ii) count the number of individual sales made just-below integer prices and (iii) divide these two numbers, obtaining the number of purchases per sale just-below integer prices. I do the same exercise for just-above purchases and obtain the number of individual purchases per sale just-above integer prices. With this two ratios, for each FPF2 event, I calculate the proportion of individual purchases per sale just-below and just-above integer prices. Then, I take the average of this proportion across all FPF2 events. Figure 6 compares the average proportions of just-below and just-above purchases per sale made by individuals. It is possible to see that the result I previously obtained is consistent even when I consider the selling activity of individuals around integer prices, although the magnitude is smaller: now, the average proportion of just-below purchases per sale is equal to 50.47% and the average proportion of just-above purchases per sale is equal to 49.53%. Again, it is reasonable to think that this proportion would be higher if I could identify limit orders placed by individuals.

Figure 6: Proportion of individual purchases per sale just-below and just-above integer prices

This figure shows the average proportion of just-below and just-above integer prices purchases per sale made by individuals. Here, I consider that just-below trades are the ones made between 90-cent prices and 99-cent prices; just-above trades are the ones made between 01-cent prices and 10-cent prices. First, for each FPF2 event, I count the number of purchases and sales made by individuals just-below integer prices. Then, I divide these two numbers to obtain the number of purchases per sale made just-below integer prices. Second, I count the number of purchases and sales made by individuals just-above integer prices. Then, I divide these two numbers to obtain the proportion of purchases per sale just-below integer price for each stock-day and, finally, I take the average for these proportions across all 9,657 FPF2 events. See Table A4 of Appendix A for values of each average and their standard errors.

Another exercise that was made has to do with the *definition* of just-below and just-above purchases. As I previously showed on Table 1, it is being considered a very large number of retail traders and, as a consequence, I obtained a large number of FPF2 events. This feature enables me to analyze the buying activity of individuals for a narrower interval of prices when they are fluctuating around an integer number. That is, it is possible for us to test the consistency of the previous results I showed, changing what is considered “just-below” integer prices. Now, I consider that just-below purchases are the ones made for prices that end between 95 cents and 99 cents; analogously, just-above purchases are the ones made for prices that end between 01 and 05 cents. Figure 7 shows the average proportion of just-below and just-above purchases made by individuals across all 9,657 FPF2 events and across all 9,147 Placebo FPF2 events, along with their 99% confidence interval. Now, the average proportion of just-below purchases is higher than the one I previously calculated using a broader interval of purchases around the integer threshold (51.31% vs 48.69%). Also, the average proportions of just-below and just-above purchases for the placebo exercise are statistically the same, although the average proportion of just-below purchases is numerically higher than the average proportion of just-above purchases (50.27% vs 49.73%).

Figure 7: Proportion of purchases just-below and just-above integer prices made by individuals

This figure shows the average proportion of just-below and just-above integer prices purchases made by individuals. Here, I consider that just-below purchases are the ones made between 95-cent prices and 99-cent prices; just-above purchases are the ones made between 01-cent prices and 05-cent prices. The left side of the figure shows the averages of these proportions, along with their 99% confidence interval, for all 9,657 FPF2 events: the just-below average proportion equals 51.31% and the just-above average proportion equals 48.69%. Then, I consider a placebo exercise where just-below purchases are the ones made between 45-cent prices and 49-cent prices; just-above purchases are the ones made between 51-cent prices and 55-cent prices. The right side of the figure shows the averages of these proportions, along with their 99% confidence interval, for all 9,147 FPF2 events: the just-below average proportion equals 50.27% and the just-above average proportion equals 49.73%. See Table A5 of Appendix A for values of each average and their standard errors.

4.2.1 FPF2 and Stock Prices: heterogeneous effects?

The argument for using the left-digit bias as a fictitious price fall misperceived by individuals on the stock market was built on the fact that a small price difference around an integer price is *immaterial* and does not reflect any new information publicly available that should induce individuals to focus their purchases on that particular stock, specially when the price is just below an integer number. For instance, the price of stock *A* on day *t* is around \$ 25.00 and some individual purchases that stock when its price equals \$ 24.95; our argument is that this 5-cent difference, relatively to the trade price, is meaningless. A first feature that may bias the results that I previously presented is the fact that this 5-cent difference is not necessarily meaningless, depending on the size of the prices that are being considered. For instance, if it happens that the price of stock *B* on day *t* is around \$ 5.00 and some individual purchases that stock when its price equals \$ 4.95, the 5-cent difference is not *as meaningless* as it was for stock *A*. The main concern, therefore, is to evaluate if the left-digit bias displayed by individuals happens for different stock prices.

To avoid a confounding effect for the left-digit bias driven by different prices of stocks, I compare the proportion of retail purchases just-below integer prices for low-priced and high-priced stocks. To do so, for each FPF2 event, I calculate the average trade price of the corresponding stock on the corresponding day, weighted by the number of shares for each trade. Then, I divide all 9,657 FPF2 events into ten deciles, based on the average trade price of each FPF2 event. Finally, I calculate the average proportion of individual purchases just-below integer prices for all FPF2 events within the first decile of all average trade prices, then for the second decile etc ⁹. Figure 8 shows these average proportions when I consider purchases made between 90-cent and 10-cent ending prices and between 95-cent and 05-cent ending prices. In both cases, I found that the proportion of individual purchases just-below integer prices is not statistically different from 50% for the first eight deciles of trade prices and are significantly higher than 50% for the last two deciles. Differently from what it was expected, the proportion of individuals purchasing stocks just-below integer prices is way higher if the nominal price of that stock is high. That is, the more *meaningless* a 5-cent difference is, the higher is the proportion of individuals buying stocks just-below integer prices: the proportion of just-below purchases for the tenth decile equals 54.14% when I consider purchases between 90-cent and 10-cent ending prices and equals 56.39% for purchases made only between 95-cent and 05-cent ending prices. Both proportions are significantly higher than the proportions I found on the previous exercises.

A possible explanation for the fact that I found a high number of just-below purchases made by

⁹See Table A6 of Appendix A for the values of each decile of the average trade price distribution.

Figure 8: FPF2 and stock prices: heterogeneous effects?

This figure shows the average proportion of individual purchases made just-below integer prices for different trade prices. For each one of the 9,657 FPF2 events, I calculate the average trade price of the corresponding stock during the corresponding day, weighted by the number of shares traded at each trade. Then, I sort all 9,657 FPF events by its average trade price and divide them into ten deciles. Finally, for each decile, I calculate the average proportion of individual purchases just-below integer prices, along with its 99% confidence interval. The first panel shows these proportions when I consider all purchases between 90-cent and 10-cent ending prices. The second panel shows these proportions when I only consider purchases between 95-cent and 05-cent ending prices. See Table A7 of Appendix A for values of each average and Table A6 for each decile of the average trade price distribution.

individuals for high-priced stocks relies on *attention*: these stocks might be attention-grabbing stocks and, therefore, individuals focus their purchases on them. Barber and Odean (2007), for instance, use stock's abnormal daily trading volume as a proxy of *attention*: investors are more attentive than usual to a particular stock when its trading volume is unusual or abnormal. Now, I calculate the proportion of purchases just-below integer prices for low-priced and high-priced stocks controlling for a possible source of attention-grabbing. To do so, first I use the measure of abnormal daily trading volume proposed by Barber and Odean (2007). I define abnormal trading volume for stock s on day t , $AV_{s,t}$, to be:

$$AV_{s,t} = \frac{V_{s,t}}{\overline{V_{s,t}}} \quad (1)$$

where $V_{s,t}$ is the trading volume of stock s on day t and $\overline{V_{s,t}}$ is the average trading volume of the 252 trading days previous to t of stock s :

$$\overline{V_{s,t}} = \sum_{d=t-252}^{t-1} \frac{V_{s,d}}{252} \quad (2)$$

Second, I calculate the abnormal daily trading volume $AV_{s,t}$ for each FPF2 event. Table A8 of Appendix A shows descriptive statistics of $AV_{s,t}$ for all 9,657 FPF2 events. Third, I sort all 9,657 FPF2 events based on their (i) average trading price and (ii) abnormal daily trading volume $AV_{s,t}$. Now, I am able to calculate proportions of just-below integer prices purchases made by individuals controlling for the abnormal daily trading volume of each stock, as a measure of *attention*. The results, however, remain qualitatively the same: I still find that the proportion of just-below purchases is only significant for the last two deciles of the average trade price distribution. Figure 9 shows the average proportions of just-below integer prices purchases made by individuals, along with their 99% confidence interval, for stocks with difference levels of attention. The first panel consider all FPF2 events with $AV_{s,t}$ below its median value, whilst the second panel consider all FPF2 events with $AV_{s,t}$ above its median value. Both panels are considering purchases between 90-cent and 10-cent price endings. As one can see, the pattern found is very similar to the ones presented on Figure 8: they differ only on the magnitude. Considering all FPF2 events within the first half of $AV_{s,t}$ distribution, only the FPF2 events for the ninth and the tenth deciles of the average trade price distribution have significant proportions of just-below purchases made by individuals, just like I showed previously on Figure 8: they are equal to 51.50% and 52.83%, respectively. When I consider all FPF2 events within the second half of $AV_{s,t}$ distribution, I found significant proportions for just-below purchases made by individuals only for the

last decile of the average price distribution: 55.42%. Although not significantly higher than 50%, I still find proportions for just-below purchases higher than 50% for the first, the second, the sixth, the seventh and the eighth deciles when $AV_{s,t}$ is below its median value and for the second, the third, the sixth and the eighth deciles when $AV_{s,t}$ is above its median value. All average proportions of this exercise are presented on Table A9 of Appendix A.

To corroborate these findings, I run the same exercise, but now I first consider all FPF2 events with $AV_{s,t}$ below its first quartile (25th percentile) and then above its third quartile (75th percentile). My findings are qualitatively the same and are shown on Figure 10. The first panel shows the average proportion of just-below purchases made by individuals for each decile of the average trade price distribution, considering all FPF2 events with $AV_{s,t}$ below its first quartile. I find that the proportion of just-below purchases is not statistically different from 50% for any of the ten deciles of the average trade price distribution. The second panel shows the average proportion of just-below purchases made by individuals for each decile of the average trade price distribution, but considering all FPF2 events with $AV_{s,t}$ above its third quartile. Now, the same pattern of Figures 8 and 9 is found: the ninth and the tenth deciles of the average trade price distribution have proportions of just-below purchases made by individuals significantly higher than 50%, respectively, equal to 51.73% and 55.20%. All average proportions of this exercise are presented on Table A10 of Appendix A.

A second explanation for the results I presented on Figure 8 is *attention* related to the market capitalization of stocks. That is, stocks with higher market cap are *salient* and individuals focus their purchase on these kind of stocks. Bordalo, Gennaioli and Shleifer (2012), Bordalo, Gennaioli and Shleifer (2013) and Bordalo, Coffman, et al. (2016), for instance, develop theoretical models of context-dependent choices, in which consumers face have their attention drawn to consumption goods that are *salient*, i.e., goods that have attributes unusual to a given reference frame. I argue that the market value of stocks can be considered as a salient factor: stocks with high market capitalization are (i) widely known among investors, (ii) more likely to be on the news and draw attention and (iii) more likely to have their stock prices with high values. These attribute of stocks, therefore, may be related to the pattern I found on Figure 8 and have to be taken into consideration. Thus, the next exercise I present evaluates the proportion of just-below integer prices purchases made by individuals for different stock prices, but now controlling for the market value of those stocks.

I proceed as follows: for all stocks from all 9,657 FPF2 events, I calculate the market value of the corresponding company on the corresponding day by taking the product of the closing price of that stock on that day and the number of shares outstanding. Table A11 of Appendix A shows descriptive statistics of the market value distribution for all 9,657 FPF2 events. Then, I sort all FPF2 events

Figure 9: FPF2, stock prices and attention: abnormal volume

This figure shows the average proportion of individual purchases made just-below integer prices for different trade prices, considering different attention-grabbing stocks. For each one of the 9,657 FPF2 events, I calculate the average trade price of the corresponding stock during the corresponding day, weighted by the number of shares traded at each trade. Then, I sort all 9,657 FPF events by its average trade price and divide them into ten deciles. Finally, for each decile, I calculate the average proportion of individual purchases just-below integer prices, along with its 99% confidence interval. Then, for each FPF2 event, I calculate $AV_{s,t}$, the abnormal trading volume of stock s on day t and sort all FPF2 events based on their $AV_{s,t}$. The first panel shows all FPF2 events within the first half of $AV_{s,t}$ distribution; the second panel shows all FPF2 events within the second half of $AV_{s,t}$ distribution. See Table A8 of Appendix A for descriptive statistics of $AV_{s,t}$, Table A9 of Appendix A for values of all the average proportions showed below and Table A6 for values of each decile of the average trade price distribution.

based on their average trade prices and on the market capitalization of their stocks. Finally, I take the average proportion of just-below integer prices purchases made by individuals for three different groups of FPF2 events: first, for the FPF2 events with stocks below the 25th percentile of the market cap distribution (first quartile); second, for the FPF2 events with stocks above the 25th percentile and below the 75th percentile of market value distribution (second and third quartiles); third, for the FPF2 events with stocks above the 75th percentile of the market cap distribution (last quartile).

Results are presented on Figure 11. The first panel shows the average proportions of just-below integer prices purchases made by individuals for different average trade prices and for stocks within the first quartile of the market cap distribution, considering only the stocks of the 9,657 FPF2 events. Like on Figure 8, I find that the proportion of just-below purchases made by individuals are significant only for high-priced stocks, specifically the ones on the ninth and the tenth decile of the average trade price distribution: these proportions are equal to 54.66% and 57.70%, respectively. The second panel shows the average proportions for stocks within the second and the third quartile of the market cap distribution. Now, I find that the proportion of just-below purchases made by individuals is also significantly higher than 50% for low-priced stocks, specifically the ones on the second decile of the average trade price distribution: on this decile, the proportion is equal to 51.69%. I also find that this proportion is significantly higher than 50% for stocks priced at the eighth, ninth and tenth decile of the average trade price distribution, respectively, equal to 51.67%, 51.85% and 55.33%. Furthermore, it is possible to see that, although not significantly different from 50%, the proportion of just-below purchases is higher than 50% for almost every trade price when I consider stocks in the middle part of the market cap distribution. The last panel shows these proportions for stocks within the last quartile of the market cap distribution; again, the same pattern of Figure 8 is found: the proportion of individual purchases is significantly higher than 50% for the ninth and the tenth decile: these proportions are equal to 51.95% and 56.64%, respectively. Values of every proportion are on Table A12 of Appendix A. It is worth mentioning that the standard errors for the average proportions are higher for the last deciles and lower for the first deciles of the average trade price distribution when I consider less-valued stocks and are lower for the last deciles and higher for the first deciles of the average trade price distribution when I consider high-valued stocks: this is due to the fact that high-priced stocks are frequently associated to large cap companies. I also mention that I did not depict the average proportion for the first decile on the last panel of Figure 11 due to the fact that there is no FPF2 event that qualifies for that position, that is, on the first decile of average trade prices and within the last quartile of the market cap distribution.

Overall, I found initially that the left-digit bias was concentrated on high-priced stocks, mainly

on stocks on the ninth and the tenth decile of the average trade price distribution of all 9,657 FPF2 events. To be precise, for prices above \$ 75.96 and mainly above \$ 115.50, as I show on Table A6. This result is consistent when I control for abnormal trading volume as a measure of *attention*. That is, one possible driver of the concentration of the left-digit bias among high-priced stocks could be that these stocks are *attention-grabbing* stocks. Figures 9 and 10 showed that this result is not driven by trading volume; however, when I use the market value of the companies that issues those stocks as a measure of *attention*, I find that the left-digit bias is not concentrated only on high-priced stocks. Figure 11 showed that there is also left-digit bias displayed by individuals on low-priced stocks, specially the ones on the second decile of the average trade price distribution and on the middle of the market cap distribution. To be precise, using the values of Table A6, individuals also display left-digit bias for stocks within \$ 12.90 and \$ 19.02. The conclusion, therefore, is that the left-digit bias is not concentrated on a specific kind of stock: there is evidence that individuals buy stocks that fluctuates around integer prices regardless of its nominal prices.

Figure 10: FPF2, stock prices and attention: abnormal volume

This figure shows the average proportion of individual purchases made just-below integer prices for different trade prices, considering different attention-grabbing stocks. For each one of the 9,657 FPF2 events, I calculate the average trade price of the corresponding stock during the corresponding day, weighted by the number of shares traded at each trade. Then, I sort all 9,657 FPF events by its average trade price and divide them into ten deciles. Finally, for each decile, I calculate the average proportion of individual purchases just-below integer prices, along with its 99% confidence interval. Then, for each FPF2 event, I calculate $AV_{s,t}$, the abnormal trading volume of stock s on day t and sort all FPF2 events based on their $AV_{s,t}$. The first panel shows all FPF2 events within the first quarter of $AV_{s,t}$ distribution; the second panel shows all FPF2 events within the last quarter of $AV_{s,t}$ distribution. See Table A8 of Appendix A for descriptive statistics of $AV_{s,t}$, Table A10 of Appendix A for values of all the average proportions showed below and Table A6 for values of each decile of the average trade price distribution.

Figure 11: FPF2, stock prices and attention: market capitalization

This figure shows the average proportion of individual purchases made just-below integer prices for different trade prices, considering different attention-grabbing stocks. For each one of the 9,657 FPF2 events, I calculate the average trade price of the corresponding stock during the corresponding day, weighted by the number of shares traded at each trade. Then, I sort all 9,657 FPF events by its average trade price and divide them into ten deciles. Then, for each FPF2 event, I calculate the market capitalization of the corresponding stock on the corresponding day and sort all FPF2 events also based on their market cap. Finally, I take the average proportion of individual purchases just-below integer prices, along with its 99% confidence interval, for each decile of the average trade price distribution. The first panel shows all FPF2 events within the first quartile of the market cap distribution. The second panel shows all FPF2 events within the second and the third quartile of the market cap distribution. The last panel shows all FPF2 events within the last quartile. See Table A11 of Appendix A for descriptive statistics of the market cap distribution, Table A12 of Appendix A for values of all the average proportions showed below and Table A6 for values of each decile of the average trade price distribution.

5 Conclusion

Through this work, I provided evidence on a *causal* relation between retail investors' buying activity and stock prices' drops using data from the US stock market. To do so, I did two exercises relating the buying activity of investors when they face *immaterial* price falls, that is, price falls that (i) are not attached to any kind of new information publicly available or (ii) meaningless in monetary terms.

The first exercise consisted on evaluating the reaction of individual investors after mechanical price drops of ex-dividend dates. As known, the opening price of a stock s on an ex-dividend date is mechanically lower than the closing price on the previous day, as investors are not entitled to receive the very next dividend cash amount; the price drop, therefore, equals (or is very close to) the dividend amount that will be paid. Individuals, however, seem to ignore the fact that the price drop is an automatic adjustment to the next dividend amount and increase their buying activity on that stock, even considering the fact that all information about ex-dividend dates were available prior to the ex-date. My identification strategy used the dividend cash amount paid by companies as an instrument to the overnight return of stocks on ex-dates. I showed that individuals react positively after mechanical price drops; this result was consistent for different regression specifications.

The second exercise consisted on evaluating if retailers display left-digit bias when they purchase stocks. To do so, I defined an event when stock prices fluctuate around integer prices and calculated the proportion of individual purchases below and above that integer price. I found that individuals display left-digit bias and buy more stocks below integer prices than above integer prices. I argued that this bias can be characterized as a *meaningless* price fall, that is, individuals significantly buy more stocks, for instance, when a stock is priced on \$ 24.95 than when it is priced on \$ 25.05. This 10-cent difference should be interpreted as insignificant relatively to the price of that stock, probably reflecting noises in the microstructure of the stock market rather than some public information about the company that issues that stock. Furthermore, I showed that the left-digit bias is consistent for different stock prices, that is, individuals display the mentioned bias for low-priced and high-priced stocks, when I take into account differences in the market capitalization of stocks.

Both exercises can be interpreted as an evidence on the fact that individuals may ignore the informational content of stock prices. Considering the first exercise, if they did consider the information behind the stock price's drop, they would not react positively after ex-dividend dates' price falls, since this price fall is in fact *mechanical* and does not reflect any information regarding the state of the companies. Considering the second exercise, if they did consider the information behind stock prices,

they would not focus their purchases on just-below prices, since this price difference between the actual trade price and the very next integer number is relatively *meaningless* and, like the previous exercise, does not reflect new information regarding the companies.

This work contributes to the literature of retail investors in different ways. First, I corroborated the findings from [Chague, De-Losso and Giovannetti \(2018\)](#) using a different data set; as they consider the activity of individuals from Brazil, I considered the activity of retailers from the US stock market. The fact that our results are similar indicates that individuals reacting to price falls *in itself* is not a feature of a singular stock market; instead, it happens on two different markets and may be considered a bias displayed by individuals *in general*, not specific ones. Second, a set of evidence relates individuals' trading activity after price drops (i.e., contrarian behavior of individuals): [Kaniel, Saar and Titman \(2008\)](#), [Grinblatt and Keloharju \(2000\)](#), [Foucault, Sraer and Thesmar \(2011\)](#) etc. This work, instead, provided a *causal* relation between individuals' trading activity and price drops: they buy stocks after price drops with no further analysis, ignoring the information behind stock prices. Third, this is the very first work that applied the algorithm of [Boehmer, Jones and Zhang \(2017\)](#) on a broader period to identify retailers' activity on the US stock market with TAQ data.

A future research agenda that can be developed consists on identifying the mechanism behind individuals' decision making of buying stocks after *immaterial* price drops. That is, is there any factor that trigger investors' buying activity on stock prices that are falling? Is it some kind of *retail mindset* that they import from the real economy? A second extension of this work is testing the consistency of my results by considering limit orders placed by individuals; in my case, because there is a limitation of the algorithm from [Boehmer, Jones and Zhang \(2017\)](#), it was only possible to identify marketable orders placed by individuals. Overall, I documented two sets of evidence supporting the idea that individuals ignore the informational content of stock prices: future research can provide experimental, theoretical or other empirical explanations to this feature.

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A Appendix

Table A1: Individuals' buying activity around ex-dates

This table provides the average values of $N_{s,t}$ 5 days prior and 5 days after ex-dividend dates, along with their standard errors and the 99% confidence interval. $N_{s,t}$ is the number of individual purchases of stock s on day t , standardized by stock. The first column shows which day is being considered around the ex-date (t_{ex}), with $t_{ex} = 0$. These values are represented on Figure 3.

Day ($t_{ex} = 0$)	Mean	Std. Error	CI of 99%
-5	0.1003	0.0054	[0.0863, 0.1142]
-4	0.0815	0.0049	[0.0688, 0.0941]
-3	0.0650	0.0048	[0.0526, 0.0773]
-2	0.0744	0.0048	[0.0620, 0.0867]
-1	0.1471	0.0050	[0.1342, 0.1600]
0	0.0558	0.0049	[0.0431, 0.0684]
1	0.0071	0.0045	[-0.0045, 0.0187]
2	0.0030	0.0045	[-0.0086, 0.0146]
3	0.0008	0.0045	[-0.0108, 0.0124]
4	-0.0028	0.0046	[-0.0146, 0.0090]
5	-0.0060	0.0047	[-0.0181, 0.0061]

Table A2: Proportion of Individual Purchases Around Integer Prices

This table provides the average proportions, their standard errors and their 99% confidence intervals for just-below and just-above integer prices purchases made by individuals. These proportions were represented on Figure 4. Panel A shows these statistics when I consider all 9,657 FPF2 events and Panel B shows these statistics when I consider all 9,146 Placebo FPF2 events. Both panels consider purchases made between 90-cent and 10-cent ending prices.

Panel A: 9,657 FPF2 Events				
	Mean	Std. Error	CI of 99%	FPF2 Events
Just Below	0.5056	0.0011	[0.5027, 0.5084]	9,657
Just Above	0.4944	0.0011	[0.4915, 0.4972]	9,657

Panel B: 9,146 Placebo FPF2 Events				
	Mean	Std. Error	CI of 99%	FPF2 Events
Just Below	0.4950	0.0012	[0.5019, 0.5080]	9,146
Just Above	0.5050	0.0012	[0.4919, 0.4980]	9,146

Table A3: Proportion of Individual Purchases Around Integer Prices at Each Cent

This table provides the average proportions, their standard errors and their 99% confidence intervals for purchases made by individuals at each cent around an integer price, from 90-cent to 10-cent ending prices. These proportions were represented on Figure 5.

	Mean	Std. Error	CI of 99%	FPF2 Events
90-cent	0.0466	0.00029	[0.0459, 0.0474]	9,657
91-cent	0.0447	0.00026	[0.0440, 0.0454]	9,657
92-cent	0.0461	0.00024	[0.0455, 0.0467]	9,657
93-cent	0.0482	0.00024	[0.0475, 0.0488]	9,657
94-cent	0.0499	0.00023	[0.0493, 0.0505]	9,657
95-cent	0.0527	0.00026	[0.0520, 0.0534]	9,657
96-cent	0.0513	0.00024	[0.0506, 0.0519]	9,657
97-cent	0.0526	0.00024	[0.0520, 0.0533]	9,657
98-cent	0.0548	0.00026	[0.0542, 0.0555]	9,657
99-cent	0.0581	0.00028	[0.0574, 0.0588]	9,657
01-cent	0.0544	0.00030	[0.0537, 0.0552]	9,657
02-cent	0.0504	0.00025	[0.0497, 0.0510]	9,657
03-cent	0.0499	0.00024	[0.0493, 0.0505]	9,657
04-cent	0.0500	0.00024	[0.0494, 0.0506]	9,657
05-cent	0.0516	0.00025	[0.0509, 0.0522]	9,657
06-cent	0.0489	0.00024	[0.0483, 0.0496]	9,657
07-cent	0.0478	0.00024	[0.0472, 0.0484]	9,657
08-cent	0.0468	0.00024	[0.0462, 0.0475]	9,657
09-cent	0.0462	0.00025	[0.0455, 0.0468]	9,657
10-cent	0.0479	0.00029	[0.0471, 0.0487]	9,657

Table A4: Proportion of Individual Purchases Per Sale Around Integer Prices

This table provides the average proportions, their standard errors and their 99% confidence intervals for just-below and just-above integer prices purchases per sale made by individuals. These proportions were represented on Figure 6. It shows these statistics when I consider all 9,657 FPF2 events and purchases made between 90-cent and 10-cent ending prices.

Panel A: 9,657 FPF2 Events				
	Mean	Std. Error	CI of 99%	FPF2 Events
Just Below	0.5047	0.0008	[0.5026, 0.5067]	9,657
Just Above	0.4952	0.0008	[0.4932, 0.4973]	9,657

Table A5: Proportion of Individual Purchases Around Integer Prices

This table provides the average proportions, their standard errors and their 99% confidence intervals for just-below and just-above integer prices purchases made by individuals. These proportions were represented on Figure 7. Panel A shows these statistics when I consider all 9,657 FPF2 events and Panel B shows these statistics when I consider all 9,146 Placebo FPF2 events. Both panels consider purchases made between 95-cent and 05-cent ending prices.

Panel A: 9,657 FPF2 Events				
	Mean	Std. Error	CI of 99%	FPF2 Events
Just Below	0.5131	0.0012	[0.5100, 0.5161]	9,657
Just Above	0.4869	0.0011	[0.4838, 0.4899]	9,657

Panel B: 9,146 Placebo FPF2 Events				
	Mean	Std. Error	CI of 99%	FPF2 Events
Just Below	0.5027	0.0012	[0.4996, 0.5057]	9,146
Just Above	0.4972	0.0012	[0.4941, 0.5002]	9,146

Table A6: Descriptive Statistics for Average Trade Prices

This table provides descriptive statistics of the average trade prices of all 9,657 FPF2 events. The average trade price is calculated by taking the average of the price of all trades of stock s on day t , weighted by the volume of each trade. Then, for all 9,657 FPF2 events, I sort them from the lowest average trade price to the highest one and calculate each decile of that distribution. Values are depicted in US dollars (USD).

Decile	1	2	3	4	5	6	7	8	9
Average Trade Price	12.90	19.02	25.25	30.07	35.33	43.73	54.05	75.96	115.50

Table A7: FPF2 for Different Stock Prices

This table provides the average proportions, their standard errors and their 99% confidence intervals for purchases made by individuals at each cent around an integer price, from 90-cent to 10-cent ending prices (Panel A) and from 95-cent to 05-cent ending prices (Panel B), for different average trade prices. These trade prices were divided into ten deciles. These proportions were represented on Figure 8.

Panel A: 90-10 cents				
Decile	Mean	Std. Error	CI of 99%	FPF2 Events
1	0.5016	0.0044	[0.4902, 0.5129]	955
2	0.5034	0.0046	[0.4915, 0.5152]	955
3	0.4971	0.0043	[0.4860, 0.5081]	955
4	0.4955	0.0041	[0.4849, 0.5060]	955
5	0.4937	0.0040	[0.4833, 0.5040]	955
6	0.5036	0.0036	[0.4943, 0.5128]	955
7	0.5008	0.0035	[0.4917, 0.5098]	955
8	0.5062	0.0032	[0.4979, 0.5144]	955
9	0.5121	0.0027	[0.5051, 0.5190]	955
10	0.5414	0.0022	[0.5357, 0.5470]	955

Panel B: 95-05 cents				
Decile	Mean	Std. Error	CI of 99%	FPF2 Events
1	0.5045	0.0045	[0.4928, 0.5161]	955
2	0.5091	0.0047	[0.4969, 0.5212]	955
3	0.5042	0.0044	[0.4928, 0.5155]	955
4	0.5049	0.0043	[0.4938, 0.5159]	955
5	0.5003	0.0042	[0.4894, 0.5111]	955
6	0.5098	0.0037	[0.5002, 0.5193]	955
7	0.5049	0.0036	[0.4956, 0.5141]	955
8	0.5098	0.0033	[0.5012, 0.5183]	955
9	0.5202	0.0028	[0.5129, 0.5274]	955
10	0.5639	0.0025	[0.5574, 0.5703]	955

Table A8: Descriptive Statistics for $AV_{s,t}$

This table provides descriptive statistics of $AV_{s,t}$, defined as the abnormal daily trading volume of stock s on day t , for all 9,657 FPF2 events. $AV_{s,t}$ is a measure of *attention* proposed by [Barber and Odean \(2007\)](#) and equals $\frac{V_{s,t}}{\bar{V}_{s,t}}$, where $V_{s,t}$ is the trading volume of stock s on day t and $\bar{V}_{s,t} = \sum_{d=t-252}^{t-1} \frac{V_{s,d}}{252}$.

	pct5	pct25	pct50	pct75	pct95	mean
$AV_{s,t}$	0.561	0.905	1.373	2.486	11.328	3.997

Table A9: FPF2 for Different Stock Prices and Attention: Abnormal Volume

This table provides the average proportions, their standard errors and their 99% confidence intervals for purchases made by individuals at each cent around an integer price, from 90-cent to 10-cent ending prices, for different average trade prices and different levels of attention. These trade prices were divided into ten deciles. Here, the measure of attention used is the one proposed by [Barber and Odean \(2007\)](#), the abnormal trading volume of stock s on day t , $AV_{s,t}$, as showed on equations 1 and 2. Panel A shows these proportions for stocks within the first half of $AV_{s,t}$ distribution, that is, below its median value. Panel B shows these proportions for stocks within the second half of $AV_{s,t}$ distribution, that is, above its median value. The below proportions were represented on Figure 9.

Panel A: $AV_{s,t} < 1.373$				
Decile	Mean	Std. Error	CI of 99%	FPF2 Events
1	0.5067	0.0090	[0.4834, 0.5299]	276
2	0.5042	0.0065	[0.4874, 0.5209]	489
3	0.4910	0.0062	[0.4750, 0.5069]	494
4	0.4991	0.0055	[0.4849, 0.5132]	565
5	0.4928	0.0055	[0.4786, 0.5069]	543
6	0.5001	0.0053	[0.4864, 0.5137]	474
7	0.5057	0.0053	[0.4920, 0.5193]	475
8	0.5066	0.0049	[0.4939, 0.5192]	467
9	0.5150	0.0042	[0.5041, 0.5258]	463
10	0.5283	0.0036	[0.5190, 0.5375]	471

Panel B: $AV_{s,t} > 1.373$				
Decile	Mean	Std. Error	CI of 99%	FPF2 Events
1	0.4995	0.0050	[0.4866, 0.5124]	682
2	0.5026	0.0064	[0.4860, 0.5191]	463
3	0.5037	0.0059	[0.4884, 0.5189]	461
4	0.4903	0.0062	[0.4743, 0.5062]	390
5	0.4948	0.0060	[0.4793, 0.5102]	412
6	0.5071	0.0050	[0.4942, 0.5200]	481
7	0.4959	0.0044	[0.4845, 0.5072]	480
8	0.5058	0.0042	[0.4949, 0.5166]	488
9	0.5094	0.0035	[0.5003, 0.5184]	492
10	0.5542	0.0025	[0.5477, 0.5606]	484

Table A10: FPF2 for Different Stock Prices and Attention: Abnormal Volume

This table provides the average proportions, their standard errors and their 99% confidence intervals for purchases made by individuals at each cent around an integer price, from 90-cent to 10-cent ending prices, for different average trade prices and different levels of attention. These trade prices were divided into ten deciles. Here, the measure of attention used is the one proposed by [Barber and Odean \(2007\)](#), the abnormal trading volume of stock s on day t , $AV_{s,t}$, as showed on equations 1 and 2. Panel A shows these proportions for stocks within the first quarter of $AV_{s,t}$ distribution, that is, below its 25th percentile value. Panel B shows these proportions for stocks within the last quarter of $AV_{s,t}$ distribution, that is, above its 75th percentile value. The below proportions were represented on Figure 10.

Panel A: $AV_{s,t} < 0.905$				
Decile	Mean	Std. Error	CI of 99%	FPF2 Events
1	0.4915	0.0137	[0.4561, 0.5268]	111
2	0.4953	0.0091	[0.4718, 0.5187]	264
3	0.4952	0.0093	[0.4712, 0.5191]	244
4	0.5000	0.0076	[0.4803, 0.5196]	320
5	0.4938	0.0076	[0.4741, 0.5134]	290
6	0.5005	0.0070	[0.4824, 0.5185]	256
7	0.4927	0.0077	[0.4728, 0.5125]	227
8	0.5088	0.0075	[0.4894, 0.5281]	222
9	0.5130	0.0060	[0.4975, 0.5284]	227
10	0.5071	0.0057	[0.4923, 0.5218]	198

Panel B: $AV_{s,t} > 2.486$				
Decile	Mean	Std. Error	CI of 99%	FPF2 Events
1	0.5044	0.0058	[0.4894, 0.5193]	445
2	0.4931	0.0087	[0.4706, 0.5155]	228
3	0.4958	0.0080	[0.4751, 0.5164]	226
4	0.4821	0.0086	[0.4599, 0.5042]	185
5	0.5002	0.0085	[0.4782, 0.5221]	214
6	0.5050	0.0067	[0.4877, 0.5222]	263
7	0.4953	0.0067	[0.4780, 0.5125]	218
8	0.5044	0.0055	[0.4902, 0.5185]	271
9	0.5173	0.0050	[0.5044, 0.5302]	240
10	0.5520	0.0042	[0.5411, 0.5628]	191

Table A11: Descriptive Statistics for the Market Cap from all 9,657 FPF2 Events

This table provides descriptive statistics of the market capitalization of all stocks from the 9,657 FPF2 events. I calculate market cap as the product of the closing price of stock s on day t and the number of shares outstanding on day t , for each pair s and t of the corresponding FPF2 event. Values are depicted in million US dollars (USD).

	pct5	pct25	pct50	pct75	pct95	mean
Market Cap. (mi)	2.700	25.275	90.615	197.535	579.153	148.670

Table A12: FPF2 for Different Stock Prices and Attention: Market Cap

This table provides the average proportions, their standard errors and their 99% confidence intervals for purchases made by individuals at each cent around an integer price, from 95-cent to 05-cent ending prices, for different average trade prices and different levels of attention. These trade prices were divided into ten deciles. Here, the measure of attention used is the market capitalization of stocks, calculated by the product of the closing price of stock s on day t and its number of shares outstanding on day t . Panel A shows these proportions for stocks within the first quartile of the market cap distribution. Panel B shows these proportions for stocks within the second and the third quartile of the market cap distribution. Panel C shows these proportions for stocks within the last quartile of the market cap distribution. The below proportions were represented on Figure 11.

Panel A: First Quartile				
Decile	Mean	Std. Error	CI of 99%	FPF2 Events
1	0.5027	0.0047	[0.4905, 0.5148]	820
2	0.5036	0.0059	[0.4883, 0.5188]	527
3	0.5044	0.0062	[0.4883, 0.5204]	360
4	0.5023	0.0081	[0.4814, 0.5231]	171
5	0.5143	0.0105	[0.4870, 0.5415]	124
6	0.5129	0.0080	[0.4921, 0.5336]	160
7	0.4947	0.0116	[0.4646, 0.5247]	93
8	0.5020	0.0107	[0.4743, 0.5296]	70
9	0.5466	0.0168	[0.5032, 0.5899]	37
10	0.5770	0.0181	[0.5303, 0.6236]	25

Panel B: Second and Third Quartile				
Decile	Mean	Std. Error	CI of 99%	FPF2 Events
1	0.5170	0.0143	[0.4801, 0.5538]	137
2	0.5169	0.0060	[0.5014, 0.5323]	412
3	0.5068	0.0069	[0.4889, 0.5246]	464
4	0.5064	0.0053	[0.4927, 0.5200]	624
5	0.4963	0.0048	[0.4839, 0.5086]	728
6	0.5073	0.0044	[0.4959, 0.5186]	697
7	0.5029	0.0041	[0.4923, 0.5134]	625
8	0.5167	0.0042	[0.5058, 0.5275]	562
9	0.5185	0.0043	[0.5074, 0.5295]	328
10	0.5533	0.0049	[0.5406, 0.5659]	198

Panel C: Last Quartile				
Decile	Mean	Std. Error	CI of 99%	FPF2 Events
1	-	-	-	0
2	0.4879	0.0464	[0.3680, 0.6077]	13
3	0.4942	0.0132	[0.4601, 0.5282]	131
4	0.5015	0.0128	[0.4684, 0.5345]	160
5	0.5114	0.0149	[0.4729, 0.5498]	103
6	0.5223	0.0140	[0.4861, 0.5584]	98
7	0.5140	0.0083	[0.4925, 0.5354]	237
8	0.4995	0.0061	[0.4837, 0.5152]	323
9	0.5195	0.0037	[0.5099, 0.5290]	590
10	0.5664	0.0029	[0.5589, 0.5738]	732