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The Price Tag Illusion

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Abstract:

We find that a stock price fall in itself induces more individuals to buy the stock. Used to temporary sales in the goods market, individuals have the illusion that buying a stock at a lower price is also a better deal, ignoring the fact that a price fall usually reflects negative news. We call this illusion the "Price Tag Illusion" (PTI). To identify the PTI, we use two distinct events which generate "fictitious price falls". The first is the mechanical stock price adjustment on ex-dividend dates. The second is the fluctuation of stock prices around integer numbers. The PTI can cause severe losses to individuals in the stock market.

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JEL Codes: G11; G12; G40.

The Price Tag Illusion*

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Abstract

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1 Introduction

Consumers like to wait for temporary sales to find better deals and pay lower prices. We argue in this paper that individuals may inadvertently bring this "retail mindset" to the stock market. It is common to hear among friends "Stock XYZ is too expensive; I will wait for a price fall to buy it." However, different from the goods market, there are no temporary sales in the stock market. A price fall usually reflects negative news. Individual investors seem to ignore that and to believe that buying a stock at a lower price is a better deal. We call this the "Price Tag Illusion" (PTI). The PTI provides a simple explanation for individuals' well-documented poor stock-picking performance.[1]

In our main empirical exercise, we show that a price fall *in itself* induces more individuals to buy the stock. That is, individuals see a price fall and decide to buy the stock without considering any other relevant piece of information. This is consistent with the PTI. In a complementary analysis, we document that individuals become much more attracted to price falls in the stock market when temporary sales are heavily advertised in the goods market. This suggests that the PTI may originate from individuals' retail mindset. Our study is based on a comprehensive dataset that contains the complete daily trading activity of all individual investors in Brazil from January 2012 to December 2015. Individuals purchased US$ 99.4 billion in stocks during this period across more than ten million individual-stock-day purchases.

There is evidence that individual investors are contrarians, i.e., they buy stocks when their prices fall.[2] This does not necessarily imply that individuals suffer from the PTI. For instance, individuals may be following contrarian strategies based on their interpretations of market reactions to bad news. Ideally, to show that individuals see a price fall and decide to buy the stock without considering any other relevant piece of information, one would need

[1] A large number of papers shows that individuals tend to buy stocks that present poor future performance. See, for instance, Odean (1999), Barber and Odean (2000), Grinblatt and Keloharju (2000), and Barber, Odean, and Zhu (2009).

[2] See, for instance, Choe, Kho, and Stulz (1999), Grinblatt and Keloharju (2000), Kaniel, Saar, and Titman (2008), and Foucault, Sraer, and Thesmar (2011).

to observe all pieces of information that individuals consider. Since this is not possible, we resort to the following identification strategy. We focus on events that we call “fictitious price falls” (FPFs). An FPF consists of an unreal price fall that may be perceived as real by investors. Since prices do not actually change, there is no new relevant piece of information to be considered. We find that individuals do buy consistently more when FPFs occur.

We explore two distinct but complementary FPFs. The first FPF is the fictitious fall of stock prices on ex-dividend dates. On ex-dates, the opening price of a stock mechanically falls with respect to the closing price of the previous day. Investors who only look at stock prices should perceive the FPF as a real price fall. Indeed, prices displayed on websites and home-broker accounts are not adjusted for dividends and may delude individuals that a stock is available at a discount. The second FPF is the fluctuation of stock prices around round prices (integer numbers). Lacetera, Pope, and Sydnor (2012) find strong evidence of the so-called “left-digit effect:” individuals disproportionally focus on left digits when evaluating numbers.[3] Therefore, a very small stock price fall from \$30.05 to \$29.95 may be perceived as more significant by individuals. Consistent with PTI, we find robust evidence that more individuals buy stocks (i) on ex-dates and (ii) at prices just below round numbers if compared to just above round numbers.

More specifically, in our first FPF identification strategy, we study individuals' trading activity on ex-dates. For each stock-day we compute the total number of distinct individual buyers (N). We then run stock-day panel regressions of N on $\widehat{R}$, the projection of the stock overnight return, unadjusted for dividends, on a variable that equals the stock dividend yield on ex-dates and is zero on other dates. That is, $\widehat{R}$ measures the FPF that occurs when the market opens on ex-dates. Since the ex-date and the dividend amount are announced days in

[3]There is also a large literature in marketing and consumers behavior documenting the left-digit effect. Holdershaw, Gendall, and Garland (1997) shows that most prices in advertising material end in the digit 9. Anderson and Simester (2003) show that the practice of ending prices in the digit 9 does increase demand. Manning and Sprott (2009) show that changing price endings can disproportionally affect consumer choices. Englmaier, Schmöller, and Stowasser (2017) also find clear discontinuities in the prices paid for used cars around round odometer thresholds. See Thomas and Morwitz (2005) for a discussion about the left-digit effect behavior of consumers.

advance, no actual new information is released to investors on ex-dates. Therefore, there is no information-related reason for more individuals to buy on ex-dates. We find that when a stock price mechanically falls by 5% on ex-dates, the number of individuals buying the stock significantly increases by 0.5 to 0.9 standard deviations, depending on the specification. We also run the same regression with the net number of buyers (the total number of buyers minus the total number of sellers) and find similar results. A possible confounding effect is that some individuals could decide to postpone buying the stock until the ex-date to avoid taxes.[4] To address this, we also consider non-taxable dividend payouts as an instrument and find similar results.[5] Finally, we run regressions considering only professional investors and, differently from individuals, we find no evidence of changes in their buying activity on ex-dates.

In our second FPF identification strategy, we study the trading activity of individuals on days when stock prices fluctuate around round numbers. For each stock-day on which we observe the stock price fluctuating around a round number, we compute the number of individuals who buy the stock at prices "just below" (at most ten cents below) and "just above" (at most ten cents above) round numbers.[6] We find that the proportion of just-below individuals is 54%, significantly higher than the proportion of just-above individuals, 46%. Importantly, the same asymmetric buying behavior is absent around prices that end at 50 cents, where the left-digit effect is turned off. When we compute the same proportions using instead number of buyers per seller, we find that the proportion of just-below buyers per seller is 57%, also significantly higher than the proportion of just-above buyers per seller, 43%. Finally, when the same analysis is performed for professional investors, we find no asymmetric buying behavior around round prices.

Taken together, these results are consistent with the existence of the PTI. In a comple-

[4] An investor who pay higher taxes on dividends than on capital gains may have the incentive to postpone the purchase of the stock to the ex-date.

[5] In Brazil there are two types of dividends, taxable dividends (called "Interest on Equity") and nontaxable dividends.

[6] To ensure that only small intervals are being considered, we keep only stock prices that are above $10 in this exercise.

mentary analysis, we then suggest that individuals' contrarian behavior in the stock market may be related to their retail mindset. We document that individuals become much more contrarian in the stock market in periods of heavy temporary sales in the goods market. Since 2012, Brazilian retailers started advertising temporary discounts following in the US Black Friday tradition. Perhaps because of its novelty, Black Friday campaigns have been very successful in getting the attention of Brazilian consumers weeks before the Black Friday day.[7] Differently from the US, Black Friday discount campaigns start as early as October and, during the actual Black Friday week, the stock market functions regularly (Thanksgiving is not a holiday in Brazil). To gauge consumers interest in Black Friday sales campaigns, we look at internet searches for the term "Black Friday" from computers located in Brazil. As conjectured, we find that individuals become much more contrarian in the stock market as Black Friday campaigns become stronger. Importantly, this finding is robust to investor-level fixed effects, different horizons, different specifications, and placebo exercises.

We contribute to the literature that investigates why individuals underperform in the stock market (Odean, 1999, Barber and Odean, 2000, Grinblatt and Keloharju, 2000, Barber and Odean (2002), Barberis and Thaler (2003), and Barber, Odean, and Zhu, 2009). Barber and Odean (2013) provide a list of behavioral biases that may be related to individuals' poor performance: overconfidence (see, for instance, Odean, 1999, Barber and Odean, 2000, Barber and Odean, 2001, and Moore and Healy, 2008), sensation seeking (see, for instance, Grinblatt and Keloharju, 2009, Dorn and Sengmueller, 2009, Kumar, 2009, Dorn, Dorn, and Sengmueller, 2014, and Barber, Lee, Liu, and Odean, 2014), local-bias (see, for instance, Ivković and Weisbenner, 2005, Massa and Simonov, 2006, Seasholes and Zhu, 2010), and disposition-effect (see, for instance, Shefrin and Statman, 1985, Odean, 1998, Grinblatt and Keloharju, 2001, Barberis and Xiong, 2009, and Seru, Shumway, and Stoffman, 2010).

In conjunction with a growing body of articles that document that asset prices display

[7] A number of news articles highlight the increasing notoriety of Black Friday sales campaigns in Brazil. See, for instance, "Black Friday – Brazilian style" (Financial Times, November 23, 2012), "Brazil retail sales rise in November as Black Friday takes root" (Business News section from Reuters.com, January 14, 2015), "Black Friday Still on Rise in Brazil, No Thanksgiving Required" (Bloomberg.com, November 25, 2016).

time-series momentum[8]—price falls tend to be followed by further price falls particularly at the typical investment horizon of individuals—the PTI provides a direct explanation of individuals' poor stock-picking performance. Buying recent losers without any further analysis is clearly a bad stock-picking strategy. To show that the PTI indeed leads to significant losses, we simulate the performance of a PTI portfolio using a 50-year sample of US stocks (from January 1967 to July 2017). A portfolio that is long on the PTI portfolio and short on the market portfolio yields an average return of -5.42% per year.

Our paper relates to a recent set of papers that shows that individuals overpay for lottery-like stocks (Barberis and Huang, 2008, Kumar, 2009, Baker, Greenwood, and Wurgler, 2009, Green and Hwang, 2009, and Eraker and Ready, 2015). Lottery-like stocks have low nominal prices as opposed to high nominal prices, and because of this, individuals believe that they have more "space" to grow. These papers show that individuals prefer, for instance, a $4 stock than a $40 stock just because of the nominal price difference. Birru and Wang (2016) name this bias "nominal price illusion" and compare the skewness (a measure for space to grow) implicit in option prices of low- and high-priced stocks. They find that the skewness of low-priced stocks is indeed overestimated. Consistent with this literature, our paper also shows that individuals care about nominal prices when buying stocks. However, the PTI, differently from the preference for lottery-like stocks, occurs on stocks at *any* price level (not only low-priced stocks) and after regular price falls. That is, according to the PTI, a regular price fall during a week can induce individuals to buy the stock. As such, the PTI is able to explain the well-documented contrarian behavior of individuals.

The PTI may also explain the fact that individuals prefer to place limit orders instead of market orders. Using trading records from individual investors in Finland, Linnainmaa (2010) finds that 76% of all orders by individuals are limit orders. An investor who chooses to place a buy limit order may suffer from the PTI since by doing so she is avoiding the current

[8]According to Moskowitz, Ooi, and Pedersen (2012), an asset class' own past return (from one to 12 months) is highly positively correlated with its future return (from one to 12 months). Hurst, Ooi, and Pedersen (2017) extend this time-series momentum evidence to global market indexes since 1880.

price and bidding a lower price. She may well be thinking "Stock XYZ is too expensive; I will wait for a price fall to buy it" and ignoring that at a lower price, the stock will likely be a "different" stock. Indeed, a very popular website about investments illustrates in a video the use of buy limit orders as follows: "... Mary wants to buy ABC stock but does not want to pay more than $45 a share. Currently, ABC stock trades at $49 a share. Mary places a buy limit order with her broker to purchase ABC at $45. If ABC stock drops to $45 or below, then Mary's order will be triggered..."[9] This sentence captures the essence of the PTI. If the stock drops from $49 to $45 and Mary's order is triggered, Mary is very likely buying a "different" stock than the one she once valued at $45.

The remainder of the paper is organized as follows. In Section 2, we describe our data set and show that individuals are contrarian investors. In Section 3, we present the main empirical findings suggesting the existence of the PTI among investors. In Section 4, we show that individuals' contrarian behavior has three characteristics common to behavioral biases. Finally, Section 5 concludes.

2 Data Set

Our dataset contains the daily trading activity of *all* individual investors in Brazil from January 2012 to December 2015. The observations are at the investor-stock-day level and we follow each investor over time. The dataset comes from the "Comissão de Valores Mobiliários" (CVM), the Brazilian equivalent to the Securities and Exchange Commission in the US (SEC). Since our data come from the regulator of the Brazilian financial market, they are extremely reliable. At the investor-stock-day level, we observe the quantity of shares the investor buys and sells, and the respective financial volumes. To focus on individuals' buy-and-hold decisions we exclude day-trades (i.e., individual-stock-day observations with both buys and sells).

Our sample contains 10,637,788 individual-stock-day purchase observations. It is the

[9] https://www.investopedia.com/video/play/buy-limit-order/ as on November, 08th 2017.

result of the buying activity of 391,184 individual investors on 432 different stocks. In monetary terms, these purchases correspond to a total volume of US$ 99.4 billion over the four years. Panel A of Table 1 shows the evolution of these numbers over the years.

[Table 1 about here]

Panel B of Table 1 presents the distribution of four individual-level variables: total number of (stock-day) purchases, average volume purchased per stock-day, total volume purchased during the four years, and number of different stocks purchased during the four years. The median individual investor made seven purchases, purchased four different stocks, and invested US$ 2,199 per stock-day and US$ 17,205 during the four years.

Figure 1 presents two graphs. The first graph displays the daily value-weighted cumulative return of the stocks in our sample. As we can see, between January 2012 and December 2015 the Brazilian stock market experienced no overall trend, with considerable volatility. The second graph displays the daily number of distinct individual buyers. The time-series average of this variable is 7,877 individuals per day buying some stock, the minimum value is 2,905 on July 4th 2014 (the day Brazil played the quarter-final against Colombia in the 2014 FIFA World Cup), and the maximum value is 19,318 on October 27th 2014 (the first trading day after Ms. Rousseff was reelected president, a day with a large negative market return of -2.8%).

[Figure 1 about here]

2.1 Individuals are contrarian

There is substantial international evidence showing that individual investors are contrarians, i.e., they buy after recent price falls (Choe, Kho, and Stulz, 1999, Grinblatt and Keloharju, 2000, Kaniel, Saar, and Titman, 2008, and Foucault, Sraer, and Thesmar, 2011). We show that individuals are also contrarian in our sample in a rather direct way.

For each one of the 10,637,788 purchases by individual investors, we compute R_{-h}, the cumulative stock return h days prior to its purchase (excluding the purchase date). We say a purchase is contrarian if $R_{-h} < -\tau_h$, where τ_h is a threshold that varies with horizon h. Panel A of Table 2 shows the proportion of contrarian purchases by individuals. The proportions are computed as the ratio between the number of contrarian purchases and the number of all purchases with either $R_{-h} < -\tau_h$ or $R_{-h} > \tau_h$. We allow for different horizons, $h = 1$, 5, and 20 days, and for different thresholds, $\tau_h = 0$, $0.5\sigma_h$, and $1.0\sigma_h$, where σ_h is the standard error of the h-day cumulative returns of all stocks in our sample. Just for comparison purposes, we also compute the same proportions for "professional investors"—a total of 976 institutions which made more than 50 purchases in each year of our sample and have good stock-picking performance.[10] Proportions of contrarian purchases by professional investors are presented in Panel B of Table 2.

[Table 2 about here]

According to Table 2, most purchases by individuals occur following price falls. The proportion of contrarian purchases by individuals range from 55% to 65%. By contrast, the proportion of contrarian purchases by professional investors range from 43% to 49%. When we use past market-adjusted returns to compute R_{-h}, we obtain similar results. The proportion of contrarian purchases by individuals range from 56% to 71%, while the proportion of contrarian purchases by professional investors range from 49% to 51%.

3 The Price Tag Illusion

Are individuals contrarian because they are able to detect market mispricings? Are they able to run intelligent contrarian strategies? Not really. In this section we show that, actually,

[10] To compute the stock-picking performance of an institution, we first calculate the 20-day ahead market-adjusted return of each one of its purchases. We then compute the t-statistic of this variable. If it is greater than two, we say the institution has good stock-picking performance. There are 976 institutions classified as "professional investors."

many individuals buy when prices fall just because prices have fallen.[11] Then, we suggest that they may be doing that because they are being influenced by their retail mindset. We document that individuals are more attracted to stocks with negative past returns during periods when they are more exposed to temporary sales campaigns in the goods market.

Showing that many individuals decide to buy a stock just because of a price fall is challenging. We cannot hope to observe investors' information set nor how they use it. To circumvent this, we study the response of individuals to events that we call "fictitious price falls" (FPFs). An FPF consists of an unreal price fall that may be perceived as real by investors. Since prices do not actually change, there is no new relevant piece of information to be considered by investors. Therefore, if we find that individuals consistently buy more when FPFs occur, we can conclude that they like to buy when prices fall without considering any new relevant information.

3.1 FPF 1: ex-dividend dates

The first FPF that we propose is the fictitious price fall that mechanically occurs on ex-dividend dates. The typical chronology of a dividend payout is as follows. On day t_1, the "declaration date" or "announcement date", a firm announces (i) that it will pay D dollars per share as cash dividends, (ii) the "ex-dividend date," t_2, the date on which new buyers are cut off from receiving dividend, and (iii) the "payment date," t_3, the date that the cash dividend will be credited into the shareholders bank account. When $t_2 > t_1$, there is no new information disclosed to investors on t_2, the ex-date (the only date that brings new information to investors is t_1). On the ex-date, all that happens is a mechanical adjustment of stock prices. The opening price of the stock mechanically falls with respect to the closing price of the trading day before t_2 because, from the ex-date onward, new owners of the stock

[11] We emphasize that this is different from saying that the aggregate demand curve for stocks is downward sloping, as showed by Shleifer (1986) and Kaul, Mehrotra, and Morck (2000). These papers show that there is dispersion of opinion among investors. That is, *ceteris paribus*, investors valuations of a given stock are different. In other words, the aggregate demand curve for *a given stock* at *a given point in time* is negatively slopped. In turn, we look at the reaction of investors to a price fall.

are not entitled to the dividend payout anymore.

Important to the effectiveness of our identification strategy, prices displayed on websites and home-brokers accounts are not adjusted for dividends. As a result, price charts and home-brokers screens display price falls on ex-dates. This reinforces the possibility of individuals perceiving the FPF on ex-dates as real.

There are 2,412 cash dividend payments during our sample period. However, for 1,405 of these, we have $t_2 = t_1$, i.e., the ex-date coincides with the declaration date.[12] Crucial to our identification hypothesis is the fact that on the ex-date there is no relevant disclosure of information. Hence, we exclude such dividend payments from our analysis and use the 1,007 dividend payments for which we have $t_2 > t_1$.

In our main specification we consider all 1,007 dividend payments with $t_2 > t_1$. However, in principle, some individuals could decide to buy stocks on ex-dates to avoid taxes. An investor who pays higher taxes on dividends than on capital gains could have the incentive to postpone the stock purchase to the ex-date.[13] To account for this possibility, we also use non-taxable dividends in our analyses (differently from the US, there are both taxable and non-taxable dividends in Brazil).

Table 3 presents some descriptive statistics of the dividend payouts. Panel A shows the number of dividend payouts, the average dividend value per stock, and the average dividend yield. The statistics are also presented conditional on $\Delta t = t_2 - t_1$, the number of days between the declaration date and the ex-date. Panel B of Table 3 shows the same statistics but considering only non-taxable dividend payouts.

[12] In such cases, the firm announces that it will pay dividends on trading day t after markets close and sets the ex-date to be trading day $t + 1$.

[13] According to the Brazilian tax system, income tax on capital gains obtained by individuals from the sale of stocks have a flat rate of 15%. However, in some cases individuals are exempt: (i) if the individual traded less than R$20,000.00 in the month (regardless of the amount of the realized capital gain), or (ii) if the individual accumulated capital losses in previous months. With respect to income taxes on dividends for individuals in Brazil, there are non-taxable dividends (called simply "Dividends") and taxable dividends (called "Interest on Equity"), which have a flat tax rate of 15%. Therefore, the following individuals would have the incentive to postpone the stock purchase to the ex-date: individuals who expect to be exempt of capital gains income taxes (either because of (i) or (ii)), and who would receive Interest on Equity payments.

[Table 3 about here]

To study if more individuals decide to buy on ex-dates, for each stock-day we compute $N_{s,t}$, the total number of individual buyers of stock s on day t (standardized by stock). We then run stock-day panel regressions of $N_{s,t}$ on $\widehat{R^*_{s,t}}$, where $\widehat{R^*_{s,t}}$ is the projection from a first-step regression of $R^*_{s,t}$, the overnight return (not adjusted for dividends) of stock s on day t, on $DivYield_{s,t}$, a variable that equals the dividend yield on the ex-dates and is zero on all other dates. That is, $\widehat{R^*_{s,t}}$ measures the FPF that occurs when the market opens on ex-dates. To control for a possible joint seasonality of ex-dates and individuals' trading preferences, we include in the regression day-of-the-week dummies as controls. We also include as controls the stock lagged returns to avoid the following possible confounding effect. Suppose that declaration dates during our sample period brought, on average, bad news to the investors. That is, on average, stock prices fell on declaration dates. This would induce contrarian investors to buy the stock after the declaration date, e.g., on ex-dates.

Table 4 presents the first and second steps of the regression. In columns (1) and (2) we use both taxable and non-taxable dividends. In columns (3) and (4) we use only non-taxable dividends. The results are similar across the different dividend types. With respect to the first step results, the opening return on the ex-date is 66% (71%) of the dividend yield considering all dividend types (only non-taxable dividends).[14] With respect to the second step results, we find that when a stock price mechanically falls by 5% on ex-dates, the number of individuals buying the stock significantly increases by 0.88 standard deviation ($0.88 = 5 \times 0.175$); considering only non-taxable dividends, it increases by 0.90 standard deviation ($0.90 = 5 \times 0.179$). The coefficients on the control variables show, as expected, that individuals are contrarian investors—all estimates for lagged returns R_{-h}, $h = 1$, 5, and 20 day, are negative—and that their buying activity is higher on Tuesdays and Wednesdays.

[Table 4 about here]

[14] The fact that the stock price fall on ex-dates is lower than the dividend yield is not uncommon (see, for instance, Frank and Jagannathan, 1998).

The dividend payments considered in Table 4 have $\Delta t \geq 1$. That is, investors have at least one day to process any new information released on the declaration day. However, one day may not be enough and the information released on the declaration date can still affect investors decisions on the ex-date. To account for this, in Table 5 we run the same regressions but using only dividend payments with $\Delta t \geq 5$. The results are qualitatively the same. In column (2), which uses taxable and non-taxable dividends, we find that after a stock price fall of 5% on ex-dates, the number of individuals buying the stock significantly increases by 0.62 standard deviation ($0.62 = 5 \times 0.123$). In column (4), which uses only non-taxable dividends, the number of individuals buying the stock significantly increases by 0.55 standard deviation ($0.55 = 5 \times 0.109$).

[Table 5 about here]

For comparison purposes, we run the same regressions considering the same 976 professional investors used in Section 2.1. Professionals should be aware that the price falls on the ex-dates are immaterial and should not change their behavior on these dates. Indeed, this is what we see in Table 6. Variable $\widehat{R^*_{s,t}}$ has no explanatory power on the number of professional investors buying the stock. Moreover, the coefficients on the lagged returns show that the professional investors are not contrarian as a group; in fact, the 20-day lagged return coefficient is statistically positive.

[Table 6 about here]

Finally, we use the net number of buyers on each stock-day, $net(N_{s,t})$, as the dependent variable. We compute $net(N_{s,t})$ as the total number of individuals buying stock s on day t minus the total number of individuals selling stock s on day t, standardized by stock. As Table 7 shows, the net number of buyers increases on ex-dates. The effects are smaller than the ones estimated before, what suggests that the number of sellers also increases on ex-dates, although less than the number of buyers. However, differently from the buying activity, there may be a reason for the selling activity to increase on ex-dates. The fact that stock prices usually fall less than the dividend yield on ex-dates can lead some investors to sell their stocks on these dates—indeed, a well-known trading strategy is to buy the stock one day before the ex-date and to sell it on the ex-date (the so-called "dividend stripping" strategy).

[Table 7 about here]

Summing up, we find that more individuals buy a stock on ex-dates. On average, all that happens during these days is a mechanical price fall. Hence, we conclude that individuals like to buy when prices fall. Moreover, since these price falls are information-empty, we conclude that they buy when prices fall without considering any piece of information. This is consistent with the PTI. We next, explore a second identification strategy to test the existence of the PTI.

3.2 FPF 2: left-digit effect

Studying the used cars market in the US, Lacetera, Pope, and Sydnor (2012) find strong evidence of the "left-digit effect:" individuals disproportionally focus on left digits. They report discontinuous drops in sale prices at 10,000-mile odometer thresholds.[15] A large literature on marketing and consumer behavior also highlights the relevance of the left-digit effect. Holdershaw, Gendall, and Garland (1997) show that approximately 60% of prices in advertising material in their sample ended in the digit 9, 30% ended in the digit 5, 7% ended in the digit 0, and the remaining seven digits combined accounted for only slightly over 3% of prices evaluated. Using evidence from field experiments, Anderson and Simester (2003) show that the practice of ending prices in the digit 9 does increase demand. Manning and

[15] Similarly, using data from a large online marketplace for used cars in Europe, Englmaier, Schmöller, and Stowasser (2017) also find clear discontinuities in the prices paid for cars around round odometer thresholds.

Sprott (2009) also find that changing price endings can disproportionally affect consumer choices. See Thomas and Morwitz (2005) for a discussion about how the left-digit effect affects the behavior of consumers.

Our second FPF relies on this left-digit cognitive limitation of individuals. There should be in general no relevant piece of information attached to a small stock price fall from, for instance, \$30.05 to \$29.95. However, due to the left-digit effect, individuals may perceive \$29.95 as significantly cheaper than \$30.05. So, do individuals buy more at prices just below round prices than at prices just above? To answer this question, we study the buying behavior of individuals when stock prices fluctuate around round numbers. If individuals do buy more at prices just below round numbers, they should be buying just because they perceive a lower stock price.

We proceed as follows. First, we identify the stock-days during which the FPF occurs. We say that a stock price fluctuates around a round number on a particular day, for instance around \$30, if more than 50 investors (individuals or institutions) purchase the stock at a price within *each one* of the following four intervals: $[\$29.90, \$29.94]$, $[\$29.95, \$29.99]$, $[\$30.01, \$30.05]$, and $[\$30.06, \$30.10]$. We observe 1,090 FPF events from 2012 to 2015. Next, for each one of the 1,090 FPF events, we count the number of individuals who purchased the stock at a price just below the round price (at most 10 cents below, i.e., from \$(x-1).90 to \$(x-1).99 cents) and just above the round price (at most 10 cents above, i.e., from \$x.01 to \$x.10 cents). To ensure that the 10 cents price interval is small in relative terms, we consider only stock prices above \$10. We then compute the proportion of just-below and just-above individuals for each stock-day.

As a placebo exercise, we also identify the stock-days during which a placebo-FPF occurs, namely, the fluctuation of the stock price around \$10.50, \$11.50, and so on. Around these 50-cent-ending prices the left-digit effect is turned off. As before, we say that a stock price fluctuated around a 50-cent-ending price during the day, for instance \$30.50, if more than 50 investors (either individuals or institutions) purchase the stock on that day at a price within each one of the following intervals: [$30.40, $30.44], [$30.45, $30.49], [$30.51, $30.55], and [$30.56, $30.60]. We observe 1,002 placebo-FPF events. For each one of the 1,002 stock-days, we compute the proportion of just-below and just-above individuals.

Figure 2 shows the average proportions across all 1,090 FPFs events and across all 1,002 placebo-FPFs events, along with the corresponding 95% confidence intervals. Considering the FPFs events, the proportion of just-below individuals is significantly higher than the proportion of just-above individuals (54.20% vs. 45.80%). Considering the placebo-FPFs events, we find no statistical difference between these proportions, although the proportion of just-below individuals is slightly higher than the proportion of just-above individuals (50.78% vs. 49.21%).

[Figure 2 about here]

For comparison purposes, we also compute both just-below and just-above proportions considering the 976 professional investors. As Lacetera, Pope, and Sydnor (2012) show, professionals should not suffer from the left-digit effect. Accordingly, Figure 3 shows no statistical difference between just-below and just-above proportions; in fact, the proportion of just-below professionals is slightly lower than the proportion of just-above professionals (49.36 vs. 50.64%).

[Figure 3 about here]

Figure 4 shows the same buying proportions for each cent around round prices. That is, for each FPF we count the number of individuals who purchase the stock at a price equal to x.90, x.91, ..., x.99, (x+1).01, (x+1).02, ..., (x+1).10 and compute the proportions within each stock-day. We then average the proportions across the 1,090 stock-days with the FPF. Consistent with Bhattacharya, Holden, and Jacobsen (2011), Figure 4 shows a concentration of purchases at the 90, 95, 05, and 10 cents. Importantly, by pairwise comparing the symmetric proportions, we find that individuals consistently buy more just below than just above round prices at every cent considered. The proportion of purchases at 90 cents *vs* at 10 cents is 62.7% higher ($0.627 = 0.103/0.063 - 1$); at 91 cents *vs* at 09 cents is 9.5% higher ($0.095 = 0.039/0.035 - 1$); at 92 cents *vs* at 08 cents is 8.3% higher ($0.083 = 0.042/0.038 - 1$); at 93 cents *vs* at 07 cents is 14.6% higher ($0.146 = 0.043/0.037 - 1$); at 94 cents *vs* at 06 cents is 9.9% higher ($0.099 = 0.042/0.038 - 1$); at 95 cents *vs* at 05 cents is 29.2% higher ($0.292 = 0.080/0.062 - 1$); at 96 cents *vs* at 04 cents is 10.3% higher ($0.103 = 0.047/0.042 - 1$); at 97 cents *vs* at 03 cents is 15.8% higher ($0.158 = 0.048/0.041 - 1$); at 98 cents *vs* at 02 cents is 14.7% higher ($0.147 = 0.054/0.047 - 1$); finally, at 99 cents *vs* at 01 cents is 10.6% higher ($0.106 = 0.051/0.046 - 1$).

[Figure 4 about here]

Finally, we include in the analysis the selling activity of individuals. For each one of the 1,090 FPF events, we divide the number of individuals who purchase just below round prices by the number of individuals who sell just below round prices. This gives us the number of buyers per seller at prices just below round numbers. We also compute the number of buyers per seller at prices just above round numbers. Next, with these two ratios, we calculate the proportion of just-below and just-above buyers per seller for each stock-day. Figure 5 shows the average of these proportions across the 1,090 FPFs events, along with 95% confidence intervals. The result is qualitatively the same. The proportion of buyers per seller just below round numbers is 57.32%, statistically greater than the proportion of buyers per sellers just above round numbers (42.68%). The fact that this proportion is higher than the one computed using only purchases (54.20%), suggests that individuals may also suffer from the left-digit-effect when deciding at which price to sell their stocks.

[Figure 5 about here]

Summing up, we find that individuals buy more at prices just below round numbers. In turn, around prices that end at 50 cents, we see no asymmetric buying activity. We interpret these findings as follows. Individuals buy more just below round numbers because, given the well-documented left-digit effect, they perceive a price fall. Hence, we conclude that individuals like to buy when prices fall. Moreover, given the negligibly small variation in prices within the intervals used, we can conclude that they buy when prices fall without considering any other piece of information. This is also consistent with the PTI.

3.3 The PTI and the contrarian behavior of individuals

We now relate the exposure of each individual to both FPFs with their contrarian behavior. We show that individuals who do not buy on ex-dates and show no preference for prices just below round numbers are not significantly contrarians. In turn, individuals who buy on ex-dates and show a preference for prices just below round numbers are significantly contrarians. This suggests that the PTI explains a relevant portion of individuals' contrarian behavior.

We first compute how contrarian each individual is. For each purchase in the sample we compute R_{-h}, the cumulative stock return h days prior to its purchase. Then we aggregate it to the individual level. For each individual with more than ten purchases (171,080 individuals), we compute $\overline{R_{-h}}^i$, the average R_{-h} across all purchases by individual i, and $t\left(\overline{R_{-h}}^i\right)$, the t-statistic of $\overline{R_{-h}}^i$. We define an individual with $t\left(\overline{R_{-h}}^i\right) < -2$ to be "significantly contrarian." At $h = 1$, 21% of the individuals are significantly contrarians, while only 8% have $t\left(\overline{R_{-1}}^i\right) > 2$. At $h = 5$, these proportions are 29% and 8% and, at $h = 20$, 33% and 10%.[16]

We then define two dummy variables, $FPF1_i$ and $FPF2_i$, that determine whether individual i responds to the FPFs events. $FPF1_i$ equals one if individual i made at least one purchase on an ex-date. $FPF2_i$ equals one if individual i buys significantly more at just

[16] Considering the simple averages, at $h = 1$, 61% of the individuals have $\overline{R_{-h}}^i < 0$, while 39% have $\overline{R_{-h}}^i \geq 0$. At $h = 5$ and $h = 20$, 65% of the individuals have $\overline{R_{-h}}^i < 0$ while 35% have $\overline{R_{-h}}^i \geq 0$.

below round prices than at just above round prices—more precisely, if individual i closed at least ten purchases around round prices and her ratio of just-below to just-above purchases is greater than two (there are 26,518 individuals who closed at least ten purchases around round prices).

Next, we run cross-sectional regressions of $\overline{R_{-h}}^{i}$ and $t\left(\overline{R_{-h}}^{i}\right)$ on $FPF1_i$ and $FPF2_i$. We highlight that there is no mechanical relation between $\overline{R_{-h}}^{i}$ and $t\left(\overline{R_{-h}}^{i}\right)$ and the dummies. Particularly with respect to $FPF1$, the lagged returns (R_{-h}) used to compute $\overline{R_{-h}}^{i}$ and $t\left(\overline{R_{-h}}^{i}\right)$ are adjusted for dividends and, therefore, do not mechanically fall on ex-dates. Panel A of Table 8 shows the results for $\overline{R_{-h}}^{i}$ as the dependent variable, with $h = 1$, 5, and 20. Considering $h = 1$ and the regression with both dummies (column 3), we have that an individual with $FPF1 = 0$ and $FPF2 = 0$—i.e., an individual who presents no signs of PTI—has $\overline{R_{-1}}^{i} = -0.15\%$; an individual with $FPF1 = 1$ and $FPF2 = 0$ has $\overline{R_{-1}}^{i} = -0.24\%$; an individual with $FPF1 = 0$ and $FPF2 = 1$ has $\overline{R_{-1}}^{i} = -0.26\%$; and, finally, an individual with $FPF1 = 1$ and $FPF2 = 1$—i.e, and individual who presents strong signs of PTI—has $\overline{R_{-1}}^{i} = -0.35\%$. A similar pattern arises at the other horizons as we switch on the dummies. Considering 5-day past returns (column 6), we have that an individual with no signs of PTI has $\overline{R_{-5}}^{i} = -0.54\%$; and an individual with strong signs of PTI has $\overline{R_{-5}}^{i} = -0.94\%$. Considering 20-day past returns (column 9), we have that an individual with no signs of PTI has $\overline{R_{-20}}^{i} = -0.86\%$; and an individual with strong signs of PTI has $\overline{R_{-20}}^{i} = -1.73\%$. These numbers allow us to conclude that individuals who display stronger signs of PTI, as measured by their responses to different FPFs, are also the individuals who display stronger contrarian behavior.

[Table 8 about here]

As Panel B of Table 8 shows, the conclusion is similar when we consider $t\left(\overline{R_{-h}}^{i}\right)$ as the dependent variable. Considering 1-day past returns (column 3), we have that an individual with no signs of PTI has $t\left(\overline{R_{-1}}^{i}\right) = -0.58$; an individual with $FPF1 = 1$ and $FPF2 = 0$ has

$t\left(\overline{R_{-1}}^{i}\right) = -1.31$; an individual with $FPF1 = 0$ and $FPF2 = 1$ has $t\left(\overline{R_{-1}}^{i}\right) = -0.94$; and, finally, an individual with strong signs of PTI has $t\left(\overline{R_{-1}}^{i}\right) = -1.67$. Considering 5-day past returns (column 6), we have that an individual with no signs of PTI has $t\left(\overline{R_{-5}}^{i}\right) = -1.01$; an individual with $FPF1 = 1$ and $FPF2 = 0$ has $t\left(\overline{R_{-5}}^{i}\right) = -1.80$; an individual with $FPF1 = 0$ and $FPF2 = 1$ has $t\left(\overline{R_{-5}}^{i}\right) = -1.34$; and, finally, an individual with strong signs of PTI has $t\left(\overline{R_{-5}}^{i}\right) = -2.13$. Finally, considering 20-day past returns (column 9), we have that an individual with no signs of PTI has $t\left(\overline{R_{-20}}^{i}\right) = -0.85$; an individual with $FPF1 = 1$ and $FPF2 = 0$ has $t\left(\overline{R_{-20}}^{i}\right) = -1.62$; an individual with $FPF1 = 0$ and $FPF2 = 1$ has $t\left(\overline{R_{-20}}^{i}\right) = -1.36$; and, finally, an individual with strong signs of PTI has $t\left(\overline{R_{-20}}^{i}\right) = -2.13$. These numbers allow us to conclude that only the group of individuals with strong signs of PTI—i.e., those who respond to both FPFs—are significantly contrarians.

3.4 Where does the PTI come from?

We now suggest that the PTI originates from investors experiences as consumers. Consumers often wait for temporary sales to pay lower prices in the goods market. We conjecture that individuals inadvertently bring this retail mindset to the stock market. Consistent with that, we document that during periods of Black Friday temporary sales campaigns individual investors display much stronger contrarian behavior in the stock market.

Since 2012, Brazilian retailers started advertising large attention-getting discounts following in the US Black Friday tradition. Such campaigns have been very successful; they received large publicity and have been widely and rapidly incorporated by Brazilian retailers marketing campaigns. A number of media articles highlight the notoriety of Black Friday sales campaigns in Brazil (see, for instance, "Black Friday – Brazilian style", in the Financial Times, November 23, 2012, "Brazil retail sales rise in November as Black Friday takes root", in Business News section from Reuters.com, January 14, 2015, "Black Friday Still on Rise in Brazil, No Thanksgiving Required", in Bloomberg.com, November 25, 2016). Differently from the US, however, there is no Thanksgiving holiday in Brazil and sales peak occurs during regular trading days. This is convenient since it allows us to analyze individuals' trading behavior during the entire Black Friday campaigns.

To gauge individuals interest on the Black Friday sales campaigns, we use Google Trends to obtain an index of the number of internet searches for the term "Black Friday."[17] To ensure the searches are from Brazilian consumers, we restrict the index to consider only searches by computers (their IP addresses) located in Brazil. Because the term "Black Friday" used by Brazilian retailers is written in English, it is very unlikely that there is ambiguity about the actual intended search. Figure 6 plots the index from January of 2012 to December of 2015. As can be seen, the Black Friday index becomes positive as early as in October of each year and solidly increase until the Black Friday day, in the last week of November. Importantly, the time-series evolution of the index is consistent with the timing of the campaigns.

[Figure 6 about here]

Based on the values of the Black Friday index, we classify each day in our sample into three groups that reflect the intensity of the searches: (i) "Peak-BF" (which contains a total 36 days), (ii) "Pre-BF" (195 days), and (iii) "No-BF" (757 days). Days during the actual Black Friday week and the previous week are classified as Peak-BF; days which are not classified as Peak-BF but have a positive value for the Black Friday index are classified as Pre-BF; finally, all other days with a zero value for the Black Friday index are classified as No-BF.

We then run purchase-by-purchase regressions of R_{-h}, the cumulative stock return h days prior to its purchase, on dummy variables that indicate whether the day is a Peak-BF, Pre-BF or No-BF day. In a different specification, we use the original Black Friday index as explanatory variable. To control for changing market conditions, we include the market return in the respective horizon as an additional explanatory variable. Table 9 shows the

[17] The higher available frequency is weekly. We convert it to the daily frequency by assigning the weekly values to the corresponding days.

results. Column (3) shows that the average R_{-5} on "no-BF" days is -1.11%, on "pre-BF" days is -1.50%, and on "peak-BF" days is -2.15%. Consistently, column (4) shows that R_{-5} is decreasing on the original Black Friday index. Column (5) shows that the average R_{-20} on "no BF" days is -2.33%, on "pre-BF" days is -4.05%, and on "peak-BF" days is -4.88%. As before, column (6) shows that R_{-20} is consistently decreasing on the original Black Friday index. Columns (1) and (2) also show negative coefficients, although they are statistically insignificant. The results in Table 9, particularly for $h = 5$ and 20, indicate that individuals do become more contrarian during periods when consumers face exogenous changes in their retail mindset.

[Table 9 about here]

Our results could be driven by a changing market participation of investors during the Black Friday days. This would be the case if, for example, the investors who display the strongest contrarian behavior also trade relatively more during Black Friday days. To rule our this possibility, we run the same purchase-by-purchase panel regressions but now controlling for investors fixed-effects. As the results in Table 10 show, the conclusions remain qualitatively the same. Column (3) shows that the average R_{-5} on "no-BF" days is -1.10%, on "pre-BF" days is -1.49%, and on "peak-BF" days is -2.09%. Consistently, column (4) shows that R_{-5} is decreasing on the original Black Friday index. Column (5) shows that the average R_{-20} on "no BF" days is -2.32%, on "pre-BF" days is -3.82%, and on "peak-BF" days is -5.09%. As before, column (6) shows that R_{-20} is consistently decreasing on the original Black Friday index. Columns (1) and (2) also show negative coefficients, although they are statistically insignificant.

[Table 10 about here]

Since we only observe few Pre-BF and Peak-BF days, a possible concern is that our results are obtained by chance. To address this concern, we run 500 placebo purchase-by-purchase regressions, with R_{-5} as the dependent variable and dummy variables that identify

36 “fake-peak-BF” days and 195 “fake-pre-BF” days as the explanatory variables. As in our main regression, we also include the 5-day market return to control for changing market conditions. In each one of the 500 regressions, we use a different set of randomly constructed “fake-BF” dummy variables. To ensure we do not use any Black Friday campaign days, we exclude the months of October and November of each year from this analysis.

Figure 7 shows the histograms of the 500 estimates for the “fake-peak-BF” and “fake-pre-BF” dummy variables, along with an indication of the original estimates. Remarkably, in no placebo regression the estimate of the “fake-peak-BF” coefficient is more negative than the original one (-1.05). With respect to the estimate of the “fake-pre-BF” coefficient, only in 7 out of the 500 regressions we obtain a lower estimate than the original (-0.39).

[Figure 7 about here]

4 Further discussion

Is the contrarian behavior of individuals indeed related to a behavioral bias? In this section we further discuss this possibility. Specifically, we see if the contrarian behavior of individuals shares three common characteristics to behavioral biases, namely, that (i) it results in losses, (ii) it is a somewhat stable behavior within an individual, and (iii) it eventually diminishes with experience. These characteristics are the ones analyzed by Seru, Shumway, and Stoffman (2010) to conclude that the disposition effect is a behavioral bias.

4.1 Contrarian behavior leads to poor stock-picking

Consistent with international evidence (Odean, 1999, Barber and Odean, 2000, Grinblatt and Keloharju, 2000, and Barber, Odean, and Zhu, 2009), individuals are bad stock-pickers in our sample. To show this, for each purchase in our sample we compute R_{+h}, the cumulative market-adjusted stock return h days after its purchase (excluding the purchase date). Constructed in this way, R_{+h} measures the realized stock-picking performance relative to the current market conditions. Then, for each individual we compute $\overline{R_{+h}}^{i}$, the average R_{+h} across all purchases by individual i. In this analysis, we consider only individuals with more than ten stock-day purchases. An individual with a poor stock-picking performance will have a negative $\overline{R_{+h}}^{i}$. As an alternative measure of stock-picking performance, we also compute $t\left(\overline{R_{+h}}^{i}\right)$, the t-statistic of $\overline{R_{+h}}^{i}$.

The results in Table 11 clearly shows that most individuals are bad at stock-picking. Panel A shows the mean and the 5th, 25th, 50th, 75th, and 95th percentiles of the empirical distribution of $\overline{R_{+h}}^{i}$ across all individuals. At the horizon of 20 days, $h = 20$, 70% of the individuals show poor stock-picking performance—i.e., have $\overline{R_{+20}}^{i} < 0$—; the average (median) individual has $\overline{R_{+20}}^{i} = -1.8\%$ (-1.2%). At $h = 120$, 75% of the individuals display poor stock-picking performance; the average (median) individual has $\overline{R_{+120}}^{i} = -6.8\%$ (-5.1%). At $h = 250$, 76% of the individuals display poor stock-picking performance; the average (median) individual has $\overline{R_{-250}}^{i} = -10.8\%$ (-8.8%). Panel B of Table 11 shows the results when we consider t-statistics. At $h = 20$, 22% of the individuals display statistically poor stock-picking performance—i.e., have $t\left(\overline{R_{+20}}^{i}\right) < -2$. This fraction contrasts with the 3% of individuals who display statistically good stock-picking performance—i.e., $t\left(\overline{R_{+20}}^{i}\right) > 2$. At $h = 120$, 38% of the individuals display statistically poor stock-picking performance, while only 4% display statistically good stock-picking performance. Finally, at $h = 250$, 43% of the individuals display statistically poor stock-picking performance, while only 6% display statistically good stock-picking performance. These results are consistent with the international evidence of individuals' poor stock-picking performance.

[Table 11 about here]

Next, we relate individuals' contrarian behavior to their poor stock-picking performance. Panel A of Table 12 shows all pairwise correlations of the variables $\overline{R_{-h}}^{i}$, $h = 1$, 5, and 20, with $\overline{R_{+h}}^{i}$, $h = 20$, 120, and 250. All estimates are positive and statistically significant, with their values ranging from 0.11 to 0.33. That is, more contrarian individuals tend to display poorer stock-picking performance. Panel B of Table 12 shows all pairwise correlations of the corresponding t-statistics. As before, in all cases the t-statistics present positive correlation, with the values ranging from 0.12 to 0.33.

[Table 12 about here]

We next show in a more controlled setting that a contrarian behavior induced by the PTI, i.e., buying stocks just looking at price falls, is indeed harmful to investors. To do so, we simulate an investment strategy based on an investor with PTI and apply it to a longer sample of Brazilian stocks (from January of 2000 to July 2015), and to a 50-year sample of US stocks (from January 1967 to July 2017).[18] The simulation of a PTI-based contrarian strategy is relatively straightforward. On the first day of each month, we form a portfolio with the stocks that presented negative returns in the previous month. This is a PTI-based contrarian strategy because it looks only at prices and the purchases take place only after a recent stock price fall. We consider three different price falls as the thresholds that trigger the purchases. The "light-contrarian" threshold is the 75th percentile of the distribution of the *negative* monthly returns; for the Brazilian sample it is -3.07%, for the US sample, -3.45%. The "medium-contrarian" threshold is the 50th percentile; for the Brazilian sample it is -6.94%, for the US sample, -7.41%. Finally, the "heavy-contrarian" threshold is the 25th percentile; for the Brazilian sample it is -13.33%, for the US sample, -14.06%. For instance, on the first trading day of each month, a heavy-contrarian American investor buys all US stocks that presented a return in the previous month lower than -14.06%. The portfolios are value-weighted to ensure that the results are not driven by small firms. To measure performance, we consider holding period horizons varying from 2 to 12 months.

Figure 8 shows the cumulative performance, relative to the market, of one dollar invested according to PTI-based contrarian strategies; the variants are the light-, medium-, and heavy-contrarian thresholds that trigger the purchases, and the six holding horizons 2, 4, 6, 8, 10,

[18] The US data come from the CRSP dataset. It contains all firms in the NYSE, Amex, and Nasdaq with share codes 10 and 11.

and 12 months. Figure 9 shows the corresponding performances using US stocks. PTI-based contrarian strategies lead to poor stock-picking performance in almost all cases using both US and Brazilian data. Importantly, at the typical holding horizon of individuals of about six months[19], the PTI-based contrarian strategy, considering the medium-contrarian threshold, yields 43.24% of the market during the same period. That is, a portfolio that is long in the PTI-based contrarian strategy and is short on the market portfolio yields -56.76%, an average return of -4.55% per year. Similarly, considering the 50-year sample of US stocks, the PTI-based contrarian strategy with the medium-contrarian thresholds yields only 6.18% of the market during the same period. That is, the long-short portfolio with the market portfolio on the short side yields -93.82%, an average return of -5.42% per year.

[Figures 8 and 9 about here]

The poor performance of PTI-based contrarian strategies is not surprising. A growing body of articles documents that asset prices display time-series momentum: price falls tend to be followed by further price falls. Moskowitz, Ooi, and Pedersen (2012) show that an asset class' own past return (from 1 to 12 months) is positively correlated with its future return (from 1 to 12 months). The authors analyze a set of 58 different futures and forward contracts that include country equity indexes, currencies, commodities, and sovereign bonds over more than 25 years of data. Hurst, Ooi, and Pedersen (2017) document the presence of time-series momentum across global market indexes since 1880. At the stock-level, Figures 8 and 9 show that idiosyncratic shocks may lead to some level of reversion up to 2-month future returns (mainly for the light-contrarian strategy). After that, however, time-series momentum kicks in, more than compensating the initial reversion. Therefore, under time-series momentum, buying a stock just because of a recent price fall is in general a poor strategy.

[19] Articles that study individuals investment performance consider the typical investment horizon of individuals to be around six months (see, for instance, Odean, 1999, Barber and Odean, 2000, Grinblatt and Keloharju, 2000, and Barber, Odean, and Zhu, 2009).

4.2 Contrarian behavior is somewhat stable

Besides being costly, a behavioral bias should also be persistent over time. Accordingly, we next see if an individual who is contrarian tend to continue being contrarian. We compute for each individual i the variable $\overline{R_{-5}}^{i,t}$, the average 5-day past returns of all purchases by individual i in year t. For this analysis, we consider only individuals who traded in all four years of our sample (60,128 individuals). If the PTI is a somewhat stable behavior, the variables $\overline{R_{-5}}^{i,2012}$, $\overline{R_{-5}}^{i,2013}$, $\overline{R_{-5}}^{i,2014}$, and $\overline{R_{-5}}^{i,2015}$ should be positively correlated.

Consistent with the contrarian behavior being persistent, Panel A of Table 13 shows all positive and significant pairwise correlations of $\overline{R_{-5}}^{i,t}$, $t = 2012, 2013, 2014,$ and 2015. The correlations range from 0.17 to 0.23. Interestingly, the correlations diminish as the interval between the years increase. Panel B of Table 13 shows the rank-correlations—i.e., all pairwise correlations of $rank\left(\overline{R_{-5}}^{i,t}\right)$, $t = 2012, 2013, 2014,$ and 2015, a ranking variable that starts at one for the most contrarian individual (i.e., the one with the lowest $\overline{R_{-5}}^{i,t}$), and ends at 60,128 for the least contrarian individual. The results are similar. The rank-correlations are statistically significant, range from 0.22 to 0.33, and diminish as the interval between the years increase. The fact that the correlations decrease over time suggests that some form of learning by trading may also be at play. Indeed, next we show that individuals become less contrarian as they trade more.

[Table 13 about here]

4.3 Learning by trading

Since being contrarian leads to losses, it is reasonable to expect that individuals who keep trading eventually learn to become less contrarian. To see if this is the case, we order chronologically all the purchases by an individual—from the first to the last—and search for a declining pattern in their contrarian behavior. To ensure that we are looking at the first purchase ever made by an individual (or at least the first after a very long period), we consider only individuals who made no purchases in 2012 and 2013 (a total 53,169 individuals).

The graph in Figure 10 shows the averages $\overline{R_{-h}}^{k}$, $k = 1, ..., 30$, where k indicates the k-th purchase by an individual, along with 95% confidence intervals (i.e., the average of R_{-h} across all first purchases, across all second purchases, and so on). If an individual made more than one purchase in a day, we consider the average of R_{-h} across these purchases. The plots on the top row consider raw returns. The plots on the bottom row consider market-adjusted returns. For all horizons, we see that the initial purchases tend to be more contrarian and that there is a clear declining pattern of this contrarian intensity. For instance, considering raw returns and $h = 5$, the first purchase by individuals occurs after a large fall in prices, -2.7%, the second after a smaller fall, -1.9%, the third after an even smaller fall, -1.6%, and so on until the 30th purchase, that occurs after a prices fall of -0.6%.

[Figure 10 about here]

It is possible that a number of individuals learn by trading and decide to quit the market after the first few purchases. Indeed, while 53,169 different individuals made a first purchase in either 2014 or 2015, only 38,527 made a second purchase, 31,010 made a third purchase, and 26,172 made a forth purchase. Therefore, the pattern in the graph captures both learning outcomes: individuals who learn and quit the market, and individuals who learn and become less contrarian.

5 Conclusion

There is substantial evidence of individuals' contrarian behavior in the stock market (Choe, Kho, and Stulz, 1999, Grinblatt and Keloharju, 2000, Kaniel, Saar, and Titman, 2008, and Foucault, Sraer, and Thesmar, 2011). This is puzzling for two reasons. First, a contrarian strategy to be successful requires the investor either to be able to detect market overreactions to bad news or to profit by providing liquidity to the market. Given the amount of information and risk management skills required to do so, it is unlike that individuals are running intelligent contrarian strategies. Second, stock prices tend to display momentum at the typical holding period of individuals. In fact, a popular rule of thumb often advocated by specialists is "The trend is your friend," which implies that investors should actually do the opposite of being contrarian. So, why are individuals contrarian?

The main contribution of this paper is to show that individuals simply like to buy stocks after their prices fall. We find that a price fall *in itself* induces more individuals to buy the stock. Our identification strategy exploits what we call "fictitious price falls" (FPF) events, i.e, events during which individuals see a price fall but no new information exists. We analyze two distinct but complementary FPFs. The first FPF is the fictitious fall of stock prices during ex-dividend dates. The second FPF is based on the so-called left-digit effect and on the fluctuation of stock prices around round numbers. Consistent with individuals looking only at price falls to decide when to buy, we find that they do buy consistently more when FPFs occur.

Individual investors are also consumers. As such, they are used to wait for temporary sales to find better deals and pay lower prices. Inadvertently, they may bring this retail mindset to the stock market. Interestingly, we document that individuals are more attracted to stock price falls when heavy sales campaigns are advertised to consumers.

A natural extension of this paper is to test the existence of the Price Tag Illusion (PTI) in other markets and countries. Another extension is to examine individuals' preference for buy limit orders in further detail. While institutions who provide liquidity are expected to place buy limit orders to provide liquidity to buyers, the determinants of individuals preference for buy limit orders are less clear. How much of this preference could be traced back to the PTI? We leave this for future research.

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A Tables and Graphs

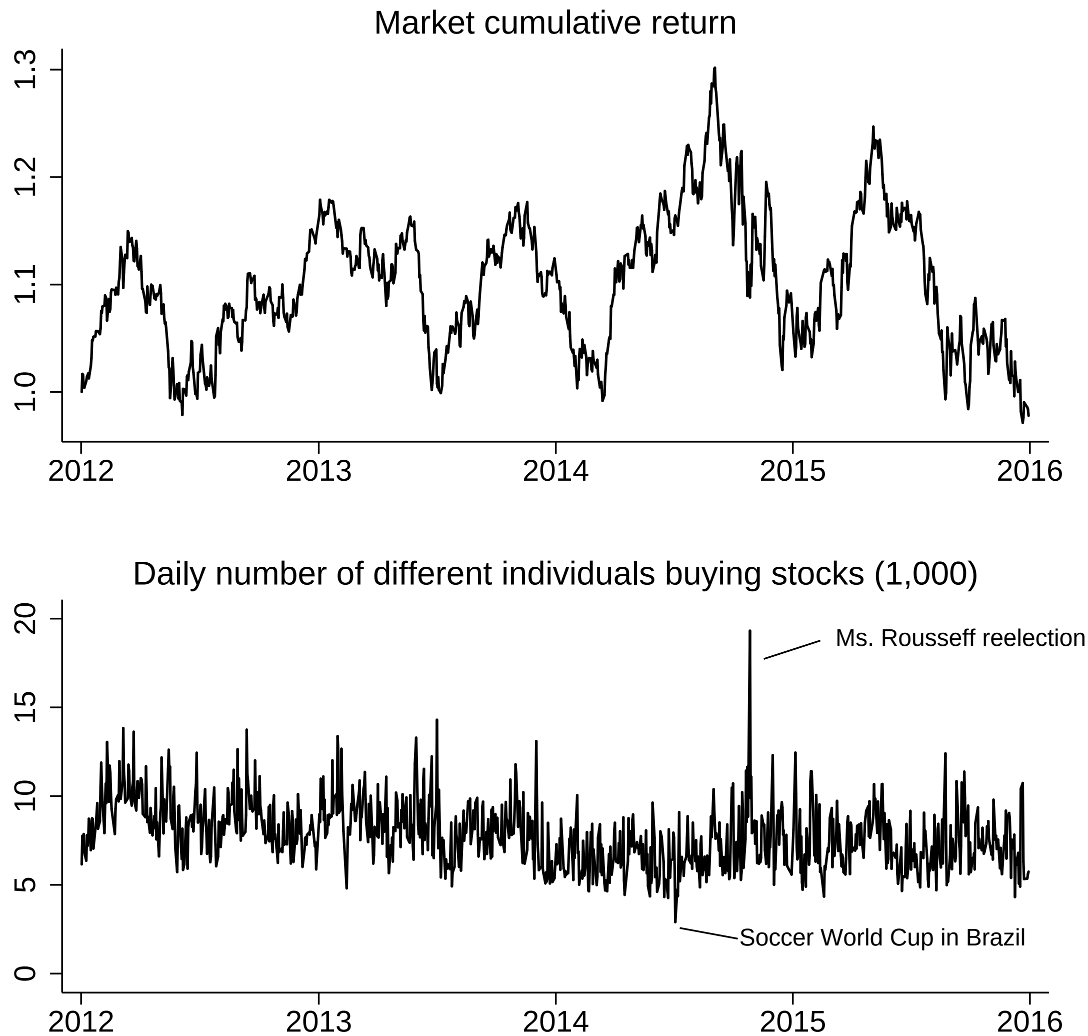

Figure 1: **The stock market and individuals buying activity**
The top graph shows the daily time-series of the cumulative value-weighted return of the portfolio using all 432 stocks in our sample, from January 2nd 2012 to December 30th 2015. The bottom graph shows the total number of individuals (in thousands) who purchased at least one stock on each day. We do not consider day trades.

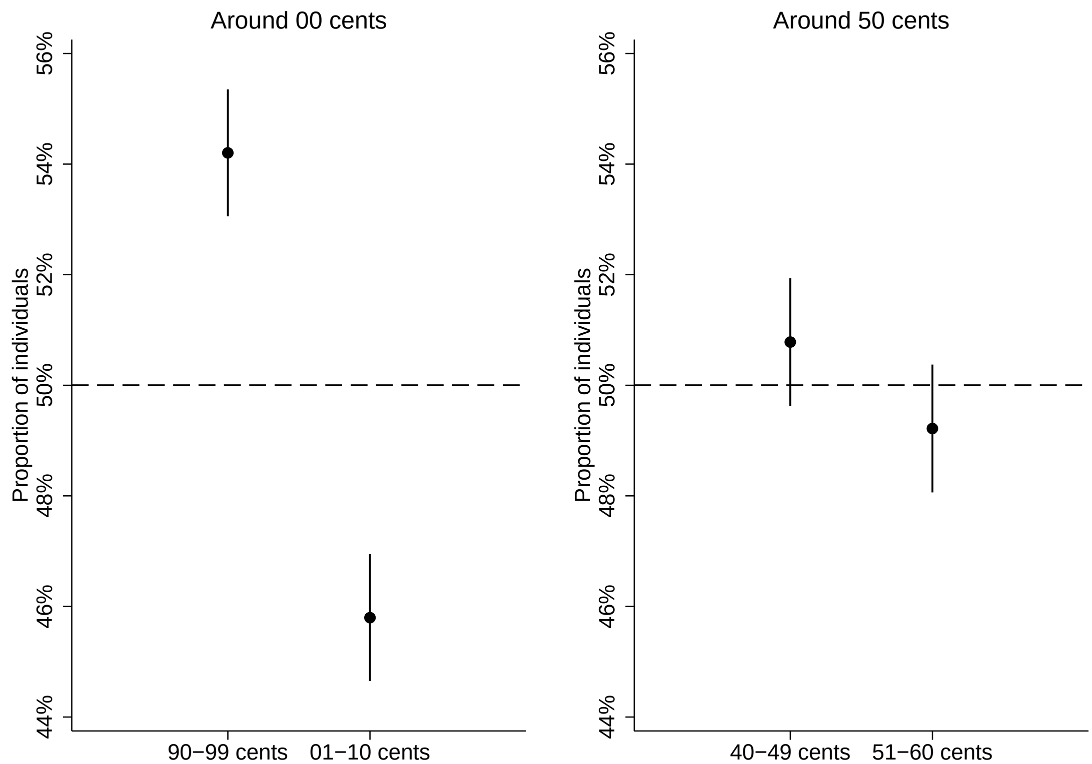

Figure 2: **Proportion of purchases just below and just above 0 cents and 50 cents**
This Figure compares the proportion of purchases by individuals at prices "just below" and "just above" round prices. First, we identify the stock-days during which the stock price fluctuated around round numbers, i.e., when a FPF occurs. We say that a stock price fluctuates around a round number on a particular day, for instance around \$30, if more than 50 investors (either individuals or institutions) purchase the stock at a price within each one of the following four intervals: [\$29.90, \$29.94], [\$29.95, \$29.99], [\$30.01, \$30.05], and [\$30.06, \$30.10]. We observe 1,090 FPF events from 2012 to 2015. Next, for each one of the 1,090 FPF events, we count the number of individuals who purchased the stock at a price just below the round price (at most 10 cents below, i.e., from \$(x-1).90 to \$(x-1).99 cents) and just above the round price (at most 10 cents above, i.e., from \$x.01 to \$x.10 cents). To ensure that the 10-cent interval is small in relative terms, we consider only stock prices above \$10. We then compute the proportion of just-below and just-above individuals for each stock-day. The left-graph presents the averages of these proportions across all stock-days and their 95%-confidence bands. The right graph presents the placebo exercise: the same average proportions computed using the 1,002 stock-days during which stock prices fluctuated around 50-cent-ending prices.

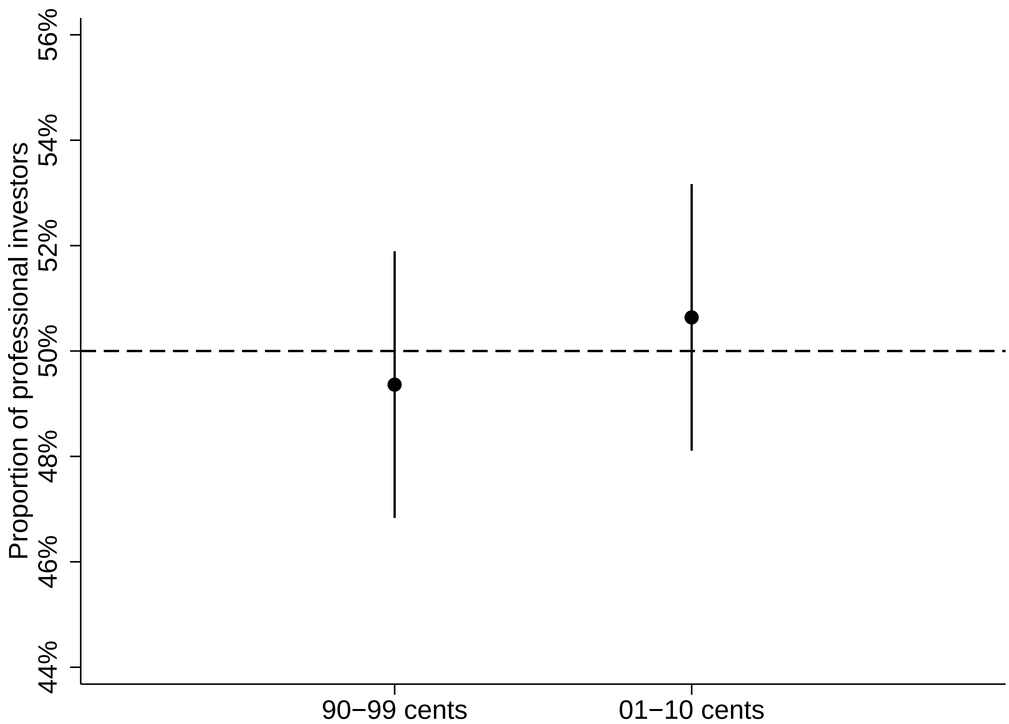

Figure 3: **Proportion of purchases just below and just above round prices: professional investors**

This Figure compares the proportion of purchases by professional investors at prices "just below" and "just above" round prices. We define "professional investors" as institutions that closed more than 50 purchases in each year of our sample and presented positive stock-picking performance. First, we identify the stock-days during which the stock price fluctuated around round numbers, i.e., when a FPF occurs. We say that a stock price fluctuates around a round number on a particular day, for instance around $30, if more than 50 investors (either individuals or institutions) purchase the stock at a price within each one of the following four intervals: [$29.90, $29.94], [$29.95, $29.99], [$30.01, $30.05], and [$30.06, $30.10]. We observe 1,090 FPF events from 2012 to 2015. Next, for each one of the 1,090 FPF events, we count the number of individuals who purchased the stock at a price just below the round price (at most 10 cents below, i.e., from $(x-1).90 to $(x-1).99 cents) and just above the round price (at most 10 cents above, i.e., from $x.01 to $x.10 cents). To ensure that the 10-cent interval is small in relative terms, we consider only stock prices above $10. We then compute the proportion of just-below and just-above individuals for each stock-day. The graph presents the averages of these proportions across all stock-days and their 95%-confidence bands.

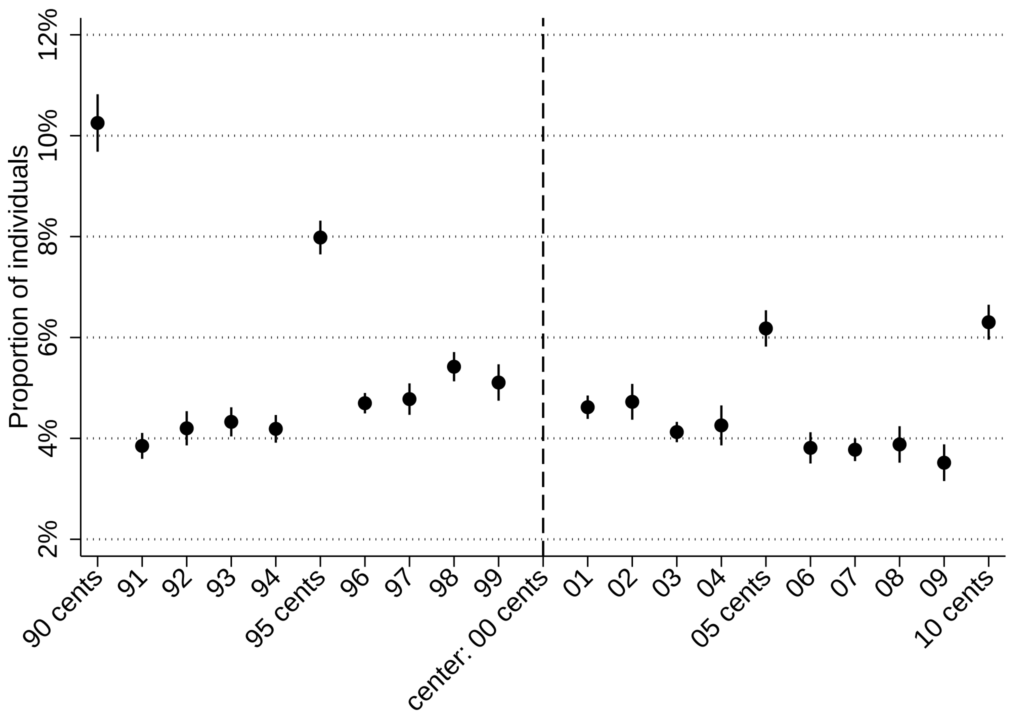

Figure 4: **Proportion of purchases on each cent around round numbers**

This Figure compares the proportion of purchases by individuals at prices "just below" and "just above" round prices. First, we identify the stock-days during which the stock price fluctuated around round numbers, i.e., when a FPF occurs. We say that a stock price fluctuates around a round number on a particular day, for instance around \$30, if more than 50 investors (either individuals or institutions) purchase the stock at a price within each one of the following four intervals: [\$29.90, \$29.94], [\$29.95, \$29.99], [\$30.01, \$30.05], and [\$30.06, \$30.10]. We observe 1,090 FPF events from 2012 to 2015. Next, for each one of the 1,090 FPF events, we count the number of individuals who purchase the stock at a price equal to x.90, x.91, ..., x.99, (x+1).01, (x+1).02, ..., (x+1).10. To ensure that the 10-cent interval is small in relative terms, we consider only stock prices above \$10. We then compute the proportion of just-below and just-above individuals for each stock-day at each cent. The graph presents the averages of these proportions across all 1,090 stock-days and their 95%-confidence bands.

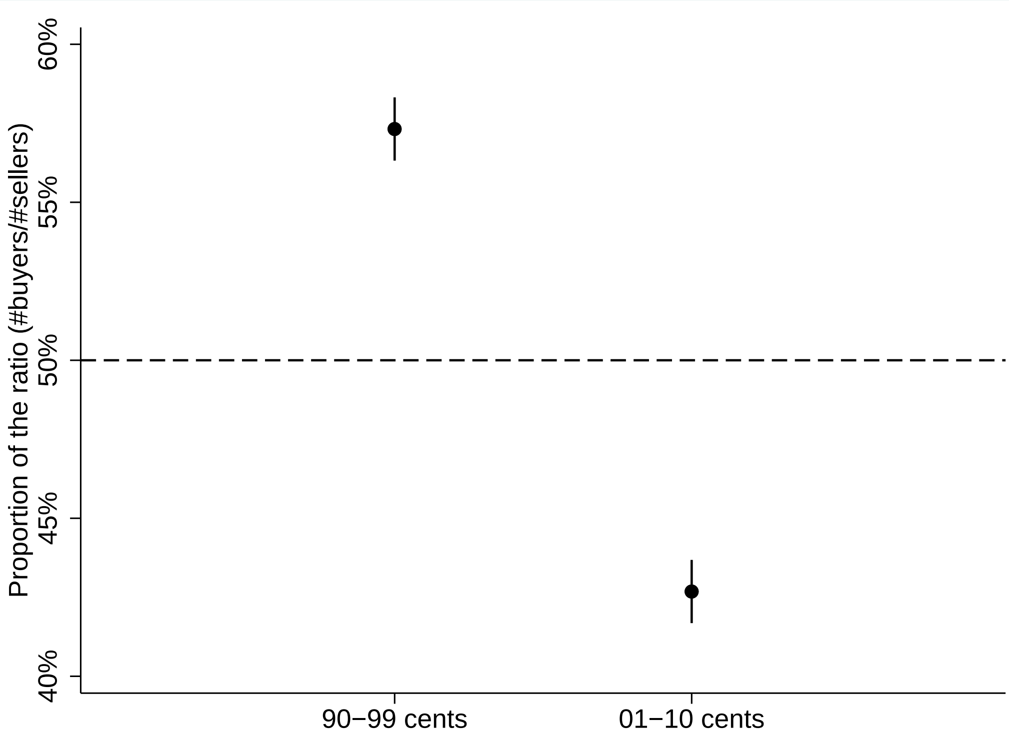

Figure 5: **Proportion of purchases per sell just below and just above round prices**
This Figure compares the proportion of "just-below" and "just-above" buyers per seller for each stock-day. First, we identify the stock-days during which the stock price fluctuated around round numbers, i.e., when a FPF occurs. We say that a stock price fluctuates around a round number on a particular day, for instance around \$30, if more than 50 investors (either individuals or institutions) purchase the stock at a price within each one of the following four intervals: $[\$29.90, \$29.94]$, $[\$29.95, \$29.99]$, $[\$30.01, \$30.05]$, and $[\$30.06, \$30.10]$. We observe 1,090 FPF events from 2012 to 2015. Next, for each one of the 1,090 FPF events, we count how many individuals purchased and how many individuals sold the stock at a price just below the round price (at most 10 cents below, i.e., from \$(x-1).90 to \$(x-1).99 cents) and just above the round price (at most 10 cents above, i.e., from \$x.01 to \$x.10 cents). To ensure that the 10-cent interval is small in relative terms, we consider only stock prices above \$10. We then divide the number of individuals who purchase just below round prices by the number of individuals who sell just below round prices. Next, with these two ratios, we calculate the proportion of just-below and just-above buyers per seller for each stock-day. The graph presents the averages of these proportions across all 1,090 stock-days and their 95%-confidence bands.

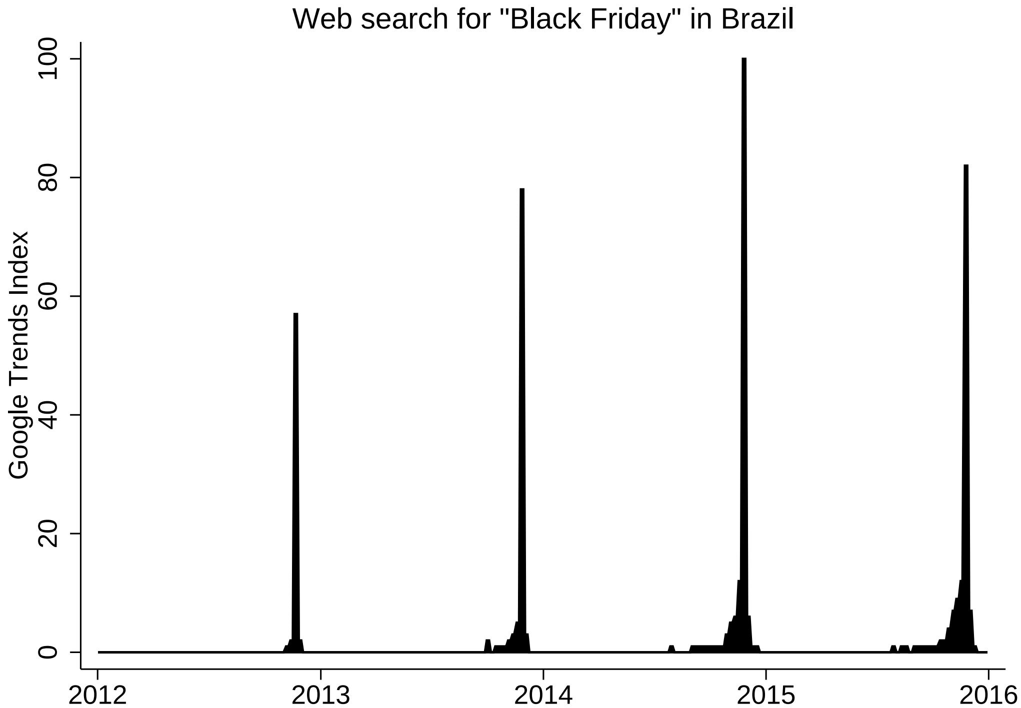

Figure 6: **Intensity of Black Friday campaigns in Brazil along the years**
This Figure plots the Google Trends Index based on internet searches for the "Black Friday" from computers located in Brazil from January of 2012 to December of 2015.

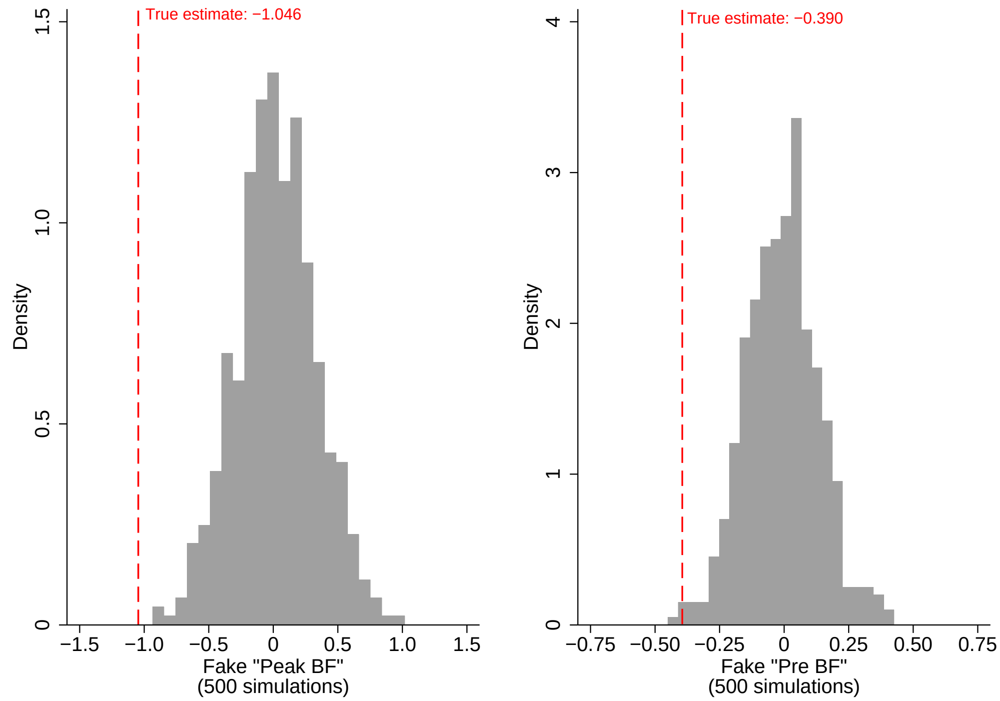

Figure 7: **Estimates of contrarian behavior around "fake" Black Friday days**
This Figure presents the histograms of the 500 estimated coefficients on two dummy variables, "fake-peak-BF" and "fake-pre-BF" dummies. We run 500 placebo purchase-by-purchase regressions, with R_{-5} (the stock return five days prior to a purchase by an individual) as the dependent variable and dummy variables that identify 36 "fake-peak-BF" days and 195 "fake-pre-BF" days as the explanatory variables that resemble (in their quantity of days) the "peak-BF" and "pre-BF" groups of days defined in Figure **??**. We also include the 5-day market return to control for changing market conditions. In each one of the 500 regressions, we use a different set of randomly constructed "fake-BF" dummy variables. To ensure we do not use any Black Friday campaign days, we exclude the months of October and November of each year from this analysis. The red-pointed line indicates the estimates of the coefficients using the original dummy variables.

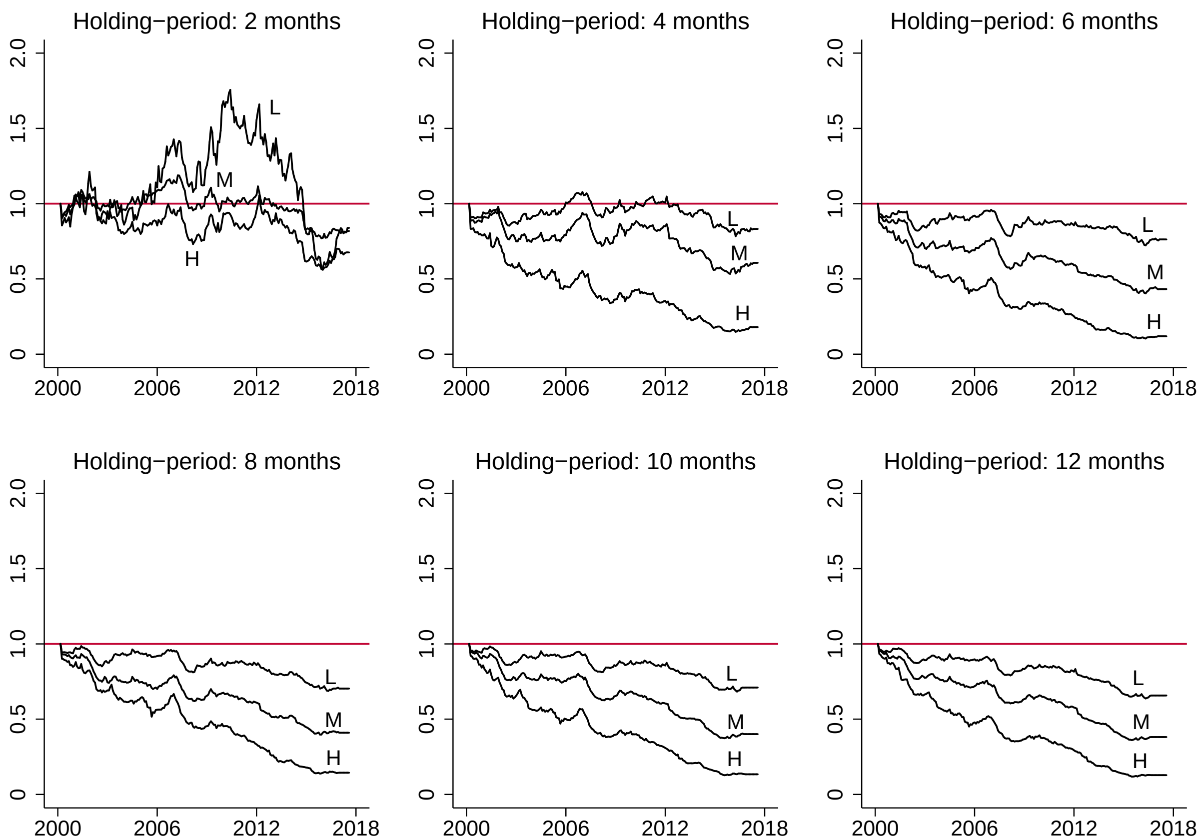

Figure 8: **Simulation of PTI-based contrarian strategies in Brazil (from 2000 to 2015)**

This Figure shows the cumulative performance, relative to the market, of one dollar invested according to PTI-based contrarian strategies. On the first day of each month, we form a portfolio with the stocks that presented negative returns in the previous month. We consider three different price falls as the thresholds that trigger the purchases. The "light-contrarian" (L) threshold is the 75th percentile of the distribution of the negative monthly returns (-3.07%); the "medium-contrarian" (M) threshold is the 50th percentile (-6.94%); the "heavy-contrarian" (H) threshold is the 25th percentile (-13.33%). The portfolios are value-weighted. Six holding horizons are considered: 2, 4, 6, 8, 10, and 12 months. The sample considered includes all stocks listed in the Brazilian market from January of 2000 to July 2015.

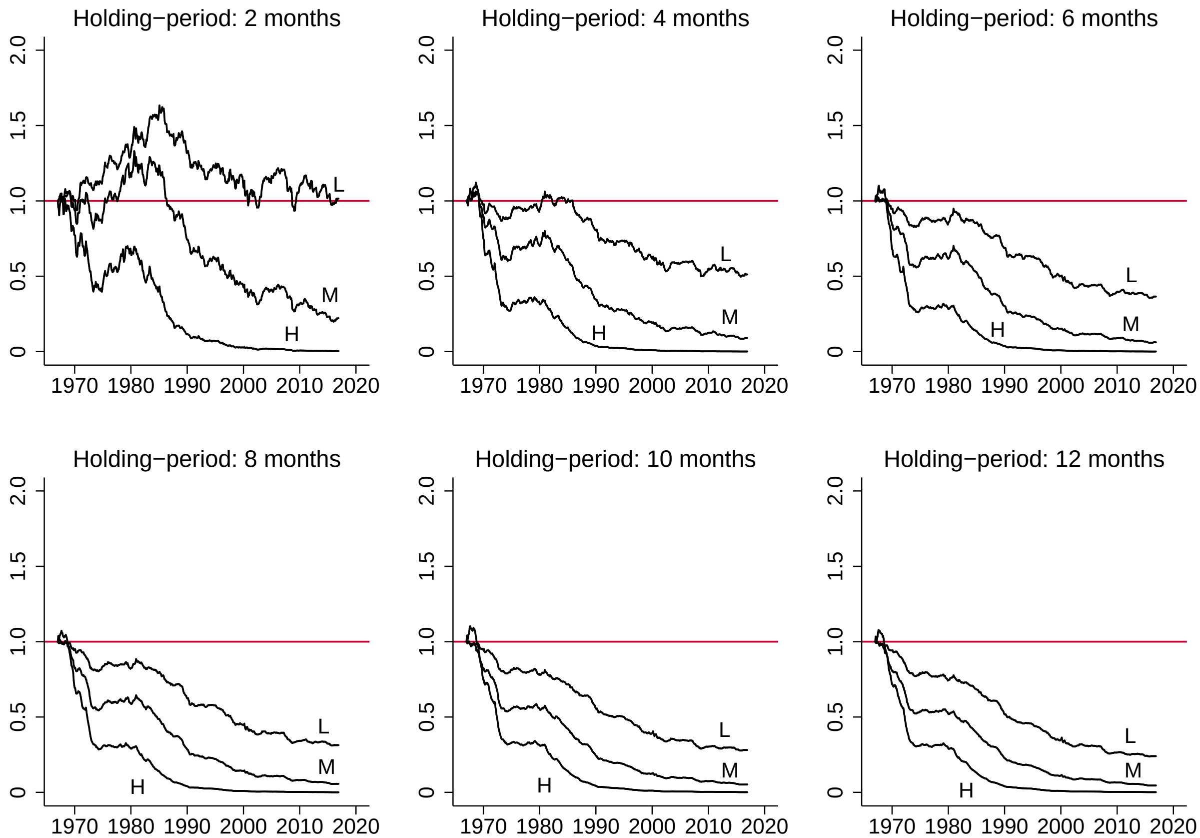

Figure 9: **Simulation of PTI-based contrarian strategies in the US (from 1967 to 2017)**

This Figure shows the cumulative performance, relative to the market, of one dollar invested according to PTI-based contrarian strategies. On the first day of each month, we form a portfolio with the stocks that presented negative returns in the previous month. We consider three different price falls as the thresholds that trigger the purchases. The "light-contrarian" (L) threshold is the 75th percentile of the distribution of the negative monthly returns (-3.45%); the "medium-contrarian" (M) threshold is the 50th percentile (-7.41%); the "heavy-contrarian" (H) threshold is the 25th percentile (-14.06%). The portfolios are value-weighted. Six holding horizons are considered: 2, 4, 6, 8, 10, and 12 months. The sample considered includes all stocks listed in the NYSE, Amex, and Nasdaq stock markets from January of 1967 to July 2017.

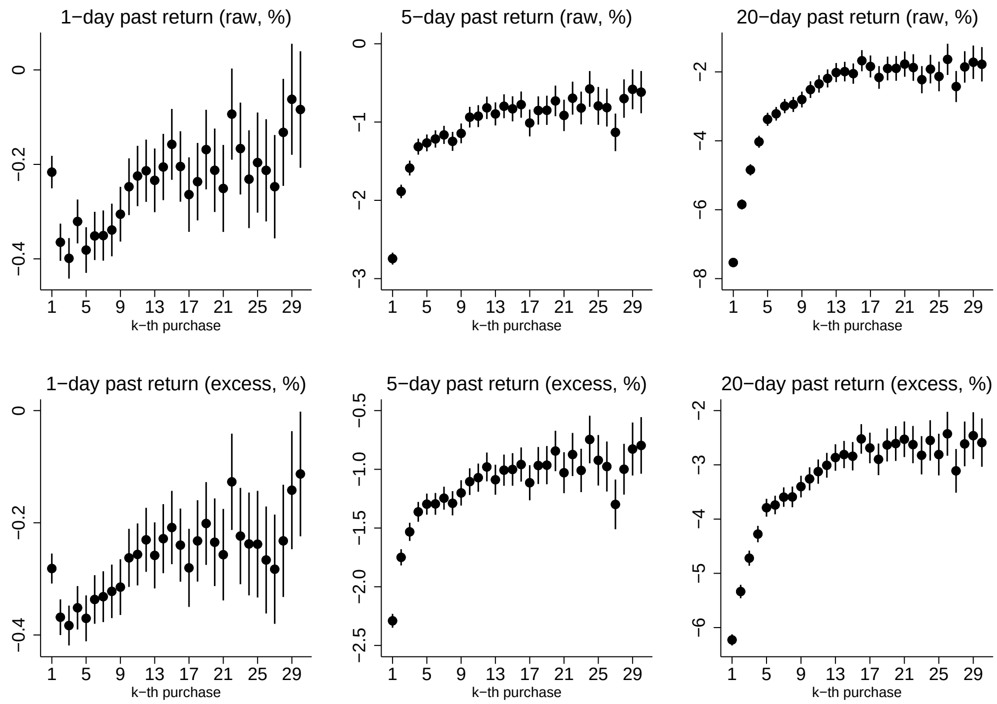

Figure 10: **Learning by trading**

This Figure shows that individuals learn by trading. We order chronologically all the purchases by an individual—from the first to the last one we observe. To ensure that we are looking at the first purchase ever made by an individual (or at least the first after a very long period), we consider only individuals who made no purchases in the first two years of our sample, 2012 and 2013 (a total 53,169 individuals). Then, for each purchase we compute R_{-h}, the stock return five days prior to the date of purchase. If an individual made more than one purchase in a day, we consider the average of R_{-h} across these purchases instead. The graph shows the averages $\overline{R_{-h}}^{k}$, $k = 1$, ..., 30, where k indicates the k-th purchase by an individual (i.e., the average of R_{-h} across all first purchases, across all second purchases, and so on), along with 95% confidence intervals. The plots on the top row consider R_{-h} computed using raw returns for horizons $h = 1$, 5, and 20 days. The plots on the bottom row consider R_{-h} computed using market-adjusted returns for horizons $h = 1$, 5, and 20 days.

Table 1: Individuals' trading activity

This Table shows descriptive statistics of individuals trading activity in our final sample. Our dataset contain individual-stock-day level observations on the trading activity by all individual investors in Brazil from 2012 to 2015. Panel A reports the number of individual investors, the number of individual-stock-day purchase observations, and the total financial volume of all purchases. Panel B reports selected percentiles of the empirical distribution of the following variables at the individual level: total number of purchases, average purchase volume per stock-day (in US$), total volume of purchases (in US$), and number of different stocks purchased.

Panel A: Individuals' aggregate buying activity

Year	Number of Individuals	Number of purchases	Volume (in US$ billion)
2012	203,476	2,961,225	30.1
2013	201,090	2,834,936	25.9
2014	187,247	2,368,282	22.6
2015	194,754	2,473,345	20.8
2012-2015	391,184	10,637,788	99.4

Panel B: Individual-level variables distributions

	pct 5	pct 10	pct 25	pct 50	pct 75	pct 90	pct 95	pct 99
Total number of purchases	1	1	2	7	23	60	105	297
Average volume per stock-day	155	354	882	2,199	5,794	14,303	25,230	78,359
Total volume purchased	384	893	3,482	17,205	85,608	365,504	843,167	3,833,923
Number of different stocks purchased	1	1	1	4	10	21	32	63

Table 2: Individuals are contrarian investors

This Table shows the proportions of contrarian purchases. For each purchase in our sample, we compute R_{-h}, the stock return (or the market-adjusted stock return) h days prior to the purchase date. We say a purchase is contrarian if $R_{-h} < -\tau_h$, where τ_h is a threshold that varies with horizon h. Panel A shows the proportion of contrarian purchases by individuals. The proportions are computed as the ratio between contrarian purchases and all purchases with either $R_{-h} < -\tau_h$ or $R_{-h} > \tau_h$. We allow for different horizons, $h = 1$, 5, and 20 days, and for different thresholds, $\tau_h = 0$, $0.5\sigma_h$, and $1.0\sigma_h$, where σ_h is the standard error of the h-day cumulative returns of all stocks in our sample. Panel B shows the same proportions for "professional investors"—a total of 976 institutions which made more than 50 purchases in each year of our sample and has good stock-picking performance. To compute the stock-picking performance of an institution, we calculate the 20-day ahead market-adjusted return of each one of its purchases and compute the corresponding t-statistic. We say the institution has good stock-picking performance if the computed t-statistic is greater than two.

Panel A: Individual investors

	Proportion of contrarian purchases					
	Raw returns			Market-adj. returns		
	$h = 1$	$h = 5$	$h = 20$	$h = 1$	$h = 5$	$h = 20$
$\tau_h = 0$	55%	57%	58%	56%	60%	62%
$\tau_h = 0.5\sigma_h$	58%	61%	61%	60%	65%	68%
$\tau_h = \sigma_h$	58%	62%	65%	60%	66%	71%

Panel B: Professional investors

	Proportion of contrarian purchases					
	Raw returns			Market-adj. returns		
	$h = 1$	$h = 5$	$h = 20$	$h = 1$	$h = 5$	$h = 20$
$\tau_h = 0$	49%	49%	47%	50%	50%	51%
$\tau_h = 0.5\sigma_h$	49%	48%	45%	50%	50%	50%
$\tau_h = \sigma_h$	48%	47%	43%	49%	50%	49%

Table 3: Cash dividends statistics

This Table presents some descriptive statistics of the dividend payouts. Panel A shows the number of dividend payouts, the average dividend value per stock (in US$), and the average dividend yield (in %). The same number are also presented conditional on $\Delta t = t_2 - t_1$, the number of days between the declaration date, t_1, and the ex-date, t_2. Panel B of Table presents the same statistics but considering only non-taxable dividend payouts. In Brazil, there are non-taxable dividends (called simply "Dividends") and taxable dividends (called "Interest on Equity"), which have a flat income tax rate of 15%.

			Δt (# of days between declaration and ex-date)									
Panel A: both types of dividends	$\Delta t = 0$	$\Delta t \geq 1$	1	2	3	4	5	6	7	8	9	10 +
# of dividend events	1,405	1,007	220	93	61	46	79	46	85	94	49	234
dividend average value	0.35	0.32	0.38	0.44	0.39	0.34	0.36	0.31	0.30	0.20	0.35	0.21
average dividend yield	2.0	1.7	2.3	2.2	2.0	2.0	1.6	1.6	1.1	0.9	1.3	1.2

			Δt (# of days between declaration and ex-date)									
Panel B: only tax-free dividends	$\Delta t = 0$	$\Delta t \geq 1$	1	2	3	4	5	6	7	8	9	10 +
# of dividend events	838	338	90	32	15	12	30	14	35	51	11	48
dividend average value ($)	0.40	0.43	0.53	0.79	0.38	0.34	0.54	0.25	0.36	0.10	0.31	0.47
average dividend yield (%)	2.0	2.2	3.3	3.6	2.1	1.1	2.1	1.3	1.5	0.7	1.5	2.4

Table 4: Ex-dates fictitious price falls

This Table shows the estimates of stock-day panel regressions of $N_{s,t}$, the total number of individual buyers of stock s on day t (standardized by stock), on $\widehat{R^*_{s,t}}$. $\widehat{R^*_{s,t}}$ is the projection from a first-step regression of $R^*_{s,t}$, the overnight return (not adjusted for dividends) of stock s on day t, on $DivYield_{s,t}$, a variable that equals the dividend yield on the ex-dividend dates and is zero on all other dates. That is, $\widehat{R^*_{s,t}}$ measures the FPF that occurs when the market opens on ex-dates. To control for a possible joint seasonality of ex-dates and individuals' trading preferences, we include in the regression day-of-the-week dummies as controls. We also include as controls stock lagged returns, R_{-h}, $h = 1$, 5, and 20. Columns (1) and (2) considers $DivYield_{s,t}$ with all dividends and columns (3) and (4) considers only non-taxable dividends. Columns (1) and (3) present the first-step regressions and columns (2) and (4) present the second-step regressions. Standard errors are shown in parentheses and are clustered by stock. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	All dividends		Only non-taxable	
	1st stage	2nd stage	1st stage	2nd stage
Dep. variable:	$R^*_{s,t}$	$N_{s,t}$	$R^*_{s,t}$	$N_{s,t}$
	(1)	(2)	(3)	(4)
$DivYield_{s,t}$	-0.655***		-0.709***	
	(0.097)		(0.076)	
$\widehat{R^*_{s,t}}$		-0.175***		-0.179***
		(0.028)		(0.031)
R_{-1}	-0.099***	-0.019***	-0.099***	-0.019***
	(0.010)	(0.003)	(0.010)	(0.003)
R_{-5}	-0.016***	-0.006***	-0.016***	-0.006***
	(0.002)	(0.001)	(0.002)	(0.001)
R_{-20}	0.008***	-0.002**	0.008***	-0.002**
	(0.003)	(0.001)	(0.003)	(0.001)
Monday	-0.055***	-0.004	-0.055***	-0.004
	(0.019)	(0.004)	(0.019)	(0.005)
Tuesday	-0.025	0.018***	-0.025	0.018***
	(0.019)	(0.005)	(0.019)	(0.005)
Wednesday	-0.009	0.020***	-0.009	0.020***
	(0.021)	(0.005)	(0.021)	(0.005)
Thursday	-0.011	0.004	-0.012	0.004
	(0.020)	(0.004)	(0.020)	(0.004)
Constant	2.794***	0.470***	2.791***	0.482***
	(0.186)	(0.083)	(0.186)	(0.091)
R2	0.01	0.01	0.01	0.01
N	381,990	381,990	381,990	381,990

Table 5: Ex-dates fictitious price falls: Only dividends with $\Delta t \geq 5$

This Table shows the estimates of stock-day panel regressions of $N_{s,t}$, the total number of individual buyers of stock s on day t (standardized by stock), on $\widehat{R^*_{s,t}}$. $\widehat{R^*_{s,t}}$ is the projection from a first-step regression of $R^*_{s,t}$, the overnight return (not adjusted for dividends) of stock s on day t, on $DivYield_{s,t}$, a variable that equals the dividend yield on the ex-dividend dates and is zero on all other dates. That is, $\widehat{R^*_{s,t}}$ measures the FPF that occurs when the market opens on ex-dates. To control for a possible joint seasonality of ex-dates and individuals' trading preferences, we include in the regression day-of-the-week dummies as controls. We also include as controls stock lagged returns, R_{-h}, $h = 1$, 5, and 20. Columns (1) and (2) considers $DivYield_{s,t}$ with all dividends with $\Delta t \geq 5$ and columns (3) and (4) considers only non-taxable dividends with $\Delta t \geq 5$, where $\Delta t = t_2 - t_1$, the number of days between the declaration, t_1, date and the ex-date, t_2. Columns (1) and (3) present the first-step regressions; columns (2) and (4) present the second-step regressions. Standard errors are shown in parentheses and are clustered by stock. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	All dividends		Only non-taxable	
	1st stage	2nd stage	1st stage	2nd stage
Dep. variable:	$R^*_{s,t}$	$N_{s,t}$	$R^*_{s,t}$	$N_{s,t}$
	(1)	(2)	(3)	(4)
$DivYield_{s,t}$	-0.909***		-1.064***	
	(0.177)		(0.153)	
$\widehat{R^*_{s,t}}$		-0.123***		-0.109***
		(0.032)		(0.036)
R_{-1}	-0.099***	-0.014***	-0.099***	-0.013***
	(0.010)	(0.004)	(0.010)	(0.004)
R_{-5}	-0.016***	-0.005***	-0.016***	-0.005***
	(0.002)	(0.001)	(0.002)	(0.001)
R_{-20}	0.008***	-0.002***	0.008***	-0.002***
	(0.003)	(0.001)	(0.003)	(0.001)
Monday	-0.054***	-0.001	-0.054***	-0.001
	(0.019)	(0.004)	(0.019)	(0.004)
Tuesday	-0.025	0.019***	-0.025	0.020***
	(0.019)	(0.005)	(0.019)	(0.004)
Wednesday	-0.009	0.019***	-0.009	0.020***
	(0.021)	(0.005)	(0.021)	(0.004)
Thursday	-0.011	0.005	-0.011	0.005
	(0.020)	(0.004)	(0.020)	(0.004)
Constant	2.794***	0.326***	2.794***	0.288***
	(0.186)	(0.093)	(0.186)	(0.104)
R2	0.01	0.01	0.01	0.01
N	381,990	381,990	381,990	381,990

Table 6: Ex-dates fictitious price falls: Professional investors regressions

This Table shows the estimates of stock-day panel regressions of $N_{s,t}$, the total number of professional investors buyers of stock s on day t (standardized by stock), on $\widehat{R^*_{s,t}}$. A professional investor is an institutions which made more than 50 purchases in each year of our sample and has good stock-picking performance. $\widehat{R^*_{s,t}}$ is the projection from a first-step regression of $R^*_{s,t}$, the overnight return (not adjusted for dividends) of stock s on day t, on $DivYield_{s,t}$, a variable that equals the dividend yield on the ex-dividend dates and is zero on all other dates. That is, $\widehat{R^*_{s,t}}$ measures the FPF that occurs when the market opens on ex-dates. To control for a possible joint seasonality of ex-dates and individuals' trading preferences, we include in the regression day-of-the-week dummies as controls. We also include as controls stock lagged returns, R_{-h}, $h = 1$, 5, and 20. Columns (1) and (2) considers $DivYield_{s,t}$ with all dividends and columns (3) and (4) considers only non-taxable dividends. Columns (1) and (3) present the first-step regressions; columns (2) and (4) present the second-step regressions. Standard errors are shown in parentheses and are clustered by stock. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	All dividends		Only non-taxable	
	1st stage	2nd stage	1st stage	2nd stage
Dep. variable:	$R^*_{s,t}$	$N_{s,t}$	$R^*_{s,t}$	$N_{s,t}$
	(1)	(2)	(3)	(4)
$DivYield_{s,t}$	-0.711***		-0.738***	
	(0.055)		(0.070)	
$\widehat{R^*_{s,t}}$		-0.011		-0.013
		(0.011)		(0.013)
R_{-1}	-0.099***	-0.001	-0.099***	-0.001
	(0.010)	(0.001)	(0.010)	(0.001)
R_{-5}	-0.016***	0.001	-0.016***	0.001
	(0.002)	(0.001)	(0.002)	(0.001)
R_{-20}	0.007***	0.004***	0.008***	0.004***
	(0.003)	(0.001)	(0.003)	(0.001)
Monday	-0.057***	-0.068***	-0.055***	-0.068***
	(0.019)	(0.006)	(0.019)	(0.006)
Tuesday	-0.025	-0.029***	-0.025	-0.029***
	(0.019)	(0.005)	(0.019)	(0.005)
Wednesday	-0.008	-0.015***	-0.009	-0.015***
	(0.021)	(0.005)	(0.021)	(0.005)
Thursday	-0.011	-0.017***	-0.012	-0.017***
	(0.020)	(0.004)	(0.020)	(0.004)
Constant	2.790***	0.051**	2.791***	0.055**
	(0.186)	(0.021)	(0.186)	(0.025)
R2	0.01	0.01	0.01	0.01
N	318,358	318,358	318,358	318,358

Table 7: Ex-dates fictitious price falls: Net purchases regressions

This Table shows the estimates of stock-day panel regressions of $net(N_{s,t})$, the total number of individuals buying stock s on day t minus the total number of individuals selling stock s on day t (standardized by stock), on $\widehat{R^*_{s,t}}$. $\widehat{R^*_{s,t}}$ is the projection from a first-step regression of $R^*_{s,t}$, the overnight return (not adjusted for dividends) of stock s on day t, on $DivYield_{s,t}$, a variable that equals the dividend yield on the ex-dates and is zero on all other dates. That is, $\widehat{R^*_{s,t}}$ measures the FPF that occurs when the market opens on ex-dates. To control for a possible joint seasonality of ex-dividend dates and individuals' trading preferences, we include in the regression day-of-the-week dummies as controls. We also include as controls stock lagged returns, R_{-h}, $h = 1$, 5, and 20. Columns (1) and (2) considers $DivYield_{s,t}$ with all dividends and columns (3) and (4) considers only non-taxable dividends. Columns (1) and (3) present the first-step regressions and columns (2) and (4) present the second-step regressions. Standard errors are shown in parentheses and clustered by stock. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	All dividends		Only non-taxable	
	1st stage	2nd stage	1st stage	2nd stage
Dep. variable:	$R^*_{s,t}$	$net\,(N_{s,t})$	$R^*_{s,t}$	$net\,(N_{s,t})$
	(1)	(2)	(3)	(4)
$DivYield_{s,t}$	-0.670***		-0.723***	
	(0.060)		(0.070)	
$\widehat{R^*_{s,t}}$		-0.107***		-0.097***
		(0.026)		(0.029)
R_{-1}	-0.099***	-0.020***	-0.099***	-0.019***
	(0.010)	(0.003)	(0.010)	(0.003)
R_{-5}	-0.016***	-0.011***	-0.016***	-0.011***
	(0.002)	(0.001)	(0.002)	(0.001)
R_{-20}	0.008***	-0.004**	0.008***	-0.005**
	(0.003)	(0.001)	(0.003)	(0.001)
Monday	-0.055***	-0.002	-0.055***	-0.001
	(0.019)	(0.005)	(0.019)	(0.005)
Tuesday	-0.025	0.005	-0.025	0.005
	(0.019)	(0.005)	(0.019)	(0.005)
Wednesday	-0.009	0.004	-0.009	0.004
	(0.021)	(0.005)	(0.021)	(0.005)
Thursday	-0.012	0.000	-0.012	0.000
	(0.020)	(0.005)	(0.020)	(0.005)
Constant	2.721***	0.285***	2.771***	0.259***
	(0.186)	(0.076)	(0.009)	(0.084)
R2	0.01	0.01	0.01	0.01
N	381,990	381,990	381,990	381,990

Table 8: The PTI explains individuals' contrarian behavior

This Table shows the estimates of individual-level regressions of two contrarian measures at the individual level, $\overline{R_{-h}}^i$ and $t\left(\overline{R_{-h}}^i\right)$, on two dummy variables, $FPF1_i$ and $FPF2_i$. $\overline{R_{-h}}^i$ is the average across all purchases by individual i of R_{-h}, the cumulative stock return h days prior to its purchase; $t\left(\overline{R_{-h}}^i\right)$ is its corresponding t-statistic. $FPF1_i$ equals one if individual i made at least one purchase on an ex-dividend date. $FPF2_i$ equals one if individual i buys significantly more at just below round prices than at just above round prices—more precisely, if individual i closed at least ten purchases around round prices and her ratio of just-below to just-above purchases is greater than two. Panel A shows the regressions with $\overline{R_{-h}}^i$ and Panel B the regressions with $t\left(\overline{R_{-h}}^i\right)$. Horizons $h = 1$, 5, and 20 days are considered. Robust standard errors are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A

Dep. variable:		$\overline{R_{-1}}$			$\overline{R_{-5}}$			$\overline{R_{-20}}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FPF1	-0.081***		-0.086***	-0.145***		-0.156***	-0.287***		-0.310***
	(0.008)		(0.008)	(0.020)		(0.021)	(0.044)		(0.049)
FPF2		-0.107***	-0.114***		-0.232***	-0.246***		-0.535***	-0.562***
		(0.012)	(0.012)		(0.031)	(0.031)		(0.068)	(0.068)
Constant	-0.168***	-0.196***	-0.149***	-0.583***	-0.626***	-0.542***	-0.955***	-1.028***	-0.861***
	(0.006)	(0.004)	(0.006)	(0.015)	(0.011)	(0.015)	(0.032)	(0.023)	(0.034)
R2	0.004	0.003	0.007	0.002	0.002	0.005	0.002	0.003	0.005
N	26,518	26,518	26,518	26,518	26,518	26,518	26,518	26,518	26,518

Panel B

Dep. variable:		$t(R_{-1})$			$t(R_{-5})$			$t(R_{-20})$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FPF1	-0.715***		-0.729***	-0.768***		-0.782***	-0.756***		-0.777***
	(0.040)		(0.040)	(0.047)		(0.047)	(0.057)		(0.056)
FPF2		-0.294***	-0.355***		-0.265***	-0.331***		-0.447***	-0.512***
		(0.054)	(0.053)		(0.064)	(0.064)		(0.077)	(0.076)
Constant	-0.642***	-0.974***	-0.583***	-1.068***	-1.432***	-1.013***	-0.931***	-1.262***	-0.845***
	(0.024)	(0.023)	(0.026)	(0.028)	(0.026)	(0.031)	(0.034)	(0.031)	(0.036)
R2	0.011	0.001	0.013	0.010	0.001	0.007	0.002	0.001	0.008
N	26,518	26,518	26,518	26,518	26,518	26,518	26,518	26,518	26,518

Table 9: Contrarian behavior is stronger around Black Friday

This Table shows the estimates of purchase-level regressions of R_{-h}, the stock return h days prior to the purchase date, on dummy variables that indicate whether the day is a Peak-BF, Pre-BF or No-BF day (Columns (1), (3), and (5)), or on the Black Friday Search Index (Columns (2), (4), and (6)). To control for changing market conditions, we include R_{-h}^{MKT}, the market return in the respective horizon as an additional explanatory variable. The Black Friday Search Index is the Google Trend Index for the term "Black Friday" from computers located in Brazil. We define the Peak-BF, Pre-BF or No-BF dummies as follows. We classify each day in our sample into three groups that reflect the intensity of the Black Friday Search Index: (i) "Peak-BF" (the days with highest search intensity, it contains a total 36 days), (ii) "Pre-BF" (days with moderate search intensity, 195 days), and (iii) "No-BF" (days with no searches, 757 days). Horizons $h = 1$, 5, and 20 days are considered. Robust standard errors are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	R_{-1}		R_{-5}		R_{-20}	
	(1)	(2)	(3)	(4)	(5)	(6)
Peak-BF days	-0.199*		-1.046***		-2.549***	
	(0.110)		(0.226)		(0.479)	
Pre-BF days	-0.060		-0.390***		-1.714***	
	(0.065)		(0.152)		(0.239)	
Black Friday Search Index		-0.0004		-0.011***		-0.021***
		(0.002)		(0.004)		(0.007)
R_{-h}^{MKT}	1.236***	1.235***	1.284***	1.292***	1.205***	1.237***
	(0.022)	(0.022)	(0.024)	(0.024)	(0.029)	(0.029)
Constant	-0.323***	-0.341***	-1.107***	-1.201***	-2.332***	-2.735***
	(0.023)	(0.024)	(0.057)	(0.053)	(0.111)	(0.098)
R2	0.18	0.18	0.19	0.19	0.10	0.10
N	10,344,665	10,344,665	10,344,665	10,344,665	10,344,665	10,344,665

Table 10: Contrarian behavior is stronger around Black Friday (with ID fixed-effects)

This Table shows the estimates of purchase-level regressions of R_{-h}, the stock return h days prior to the purchase date, on dummy variables that indicate whether the day is a Peak-BF, Pre-BF or No-BF day (Columns (1), (3), and (5)), or on the Black Friday Search Index (Columns (2), (4), and (6)). To control for changing market conditions, we include R_{-h}^{MKT}, the market return in the respective horizon as an additional explanatory variable. We also include investor-level fixed effects. The Black Friday Search Index is the Google Trend Index for the term "Black Friday" from computers located in Brazil. We define the Peak-BF, Pre-BF or No-BF dummies as follows. We classify each day in our sample into three groups that reflect the intensity of the Black Friday Search Index: (i) "Peak-BF" (the days with highest search intensity, it contains a total 36 days), (ii) "Pre-BF" (days with moderate search intensity, 195 days), and (iii) "No-BF" (days with no searches, 757 days). Horizons $h = 1$, 5, and 20 days are considered. Robust standard errors are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	R_{-1}		R_{-5}		R_{-20}	
	(1)	(2)	(3)	(4)	(5)	(6)
Peak-BF days	-0.192*		-0.989***		-2.409***	
	(0.102)		(0.212)		(0.417)	
Pre-BF days	-0.036		-0.388***		-1.501***	
	(0.061)		(0.139)		(0.206)	
Black Friday Search Index		-0.0005		-0.010**		-0.016**
		(0.002)		(0.004)		(0.007)
R_{-h}^{MKT}	1.182***	1.181***	1.213***	1.219***	1.068***	1.092***
	(0.025)	(0.021)	(0.022)	(0.021)	(0.025)	(0.025)
Constant	-0.327***	-0.339***	-1.097***	-1.190***	-2.322***	-2.684***
	(0.025)	(0.022)	(0.052)	(0.047)	(0.109)	(0.083)
Individuals FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.25	0.25	0.28	0.28	0.22	0.22
N	10,344,665	10,344,665	10,344,665	10,344,665	10,344,665	10,344,665

Table 11: Stock-picking performance of individuals

This Table shows individuals' stock-picking realized performance. Panel A shows the mean and the 5th, 25th, 50th, 75th, and 95th percentiles of the empirical distribution of $\overline{R_{+h}}^{i}$ across all individuals (in %), as well as the fraction of individuals with positive and negative performance. $\overline{R_{+h}}^{i}$ is the average R_{+h} across all purchases by individual i, where R_{+h} is the cumulative stock return h days after the purchase. Panel B shows the mean and the 5th, 25th, 50th, 75th, and 95th percentiles of the empirical distribution of $t\left(\overline{R_{+h}}^{i}\right)$ across all individuals, as well as the fraction of individuals with t-statistics above 2 and below -2. $t\left(\overline{R_{+h}}^{i}\right)$ is the corresponding t-statistic of $\overline{R_{+h}}^{i}$. We consider only individuals with more than ten stock-day purchases. Horizons $h = 20$, 120, and 250 days are considered.

Panel A: $\overline{R_{+h}}^{i}$ distribution across individuals with at least 10 purchases (171,080 individuals)

Future horizon	Mean	5 pct	25 pct	50 pct	75 pct	95 pct	Ind. with $\overline{R_h} < 0$	Ind. with $\overline{R_h} > 0$
$h = 20$	-1.8	-8.1	-3.4	-1.2	0.3	2.9	70%	30%
$h = 120$	-6.8	-26.7	-12.2	-5.1	-0.1	7.4	75%	25%
$h = 250$	-10.8	-42.5	-20.2	-8.8	-0.3	13.8	76%	24%

Panel B: $t\left(\overline{R_{+h}}^{i}\right)$ distribution across individuals with at least 10 purchases (171,080 individuals)

Future horizon	Mean	5 pct	25 pct	50 pct	75 pct	95 pct	Ind. with $t(R_h) < -2$	Ind.with $t(R_h) > 2$
$h = 20$	-0.87	-3.71	-1.81	-0.76	0.21	1.59	21.6%	2.7%
$h = 120$	-1.70	-6.59	-2.91	-1.31	-0.01	1.86	37.7%	4.4%
$h = 250$	-2.19	-8.61	-3.56	-1.56	-0.05	2.17	43.4%	5.6%

Table 12: Contrarian behavior and poor stock-picking performance

Panel A of this Table shows all pairwise correlations of the variables $\overline{R_{-h}}^i$, $h = 1$, 5, and 20, with $\overline{R_{+h}}^i$, $h = 20$, 120, and 250. $\overline{R_{-h}}^i$ is the average R_{-h} across all purchases by individual i, where R_{-h} is the cumulative stock return h days prior to the purchase. $\overline{R_{+h}}^i$ is the average R_{+h} across all purchases by individual i, where R_{+h} is the cumulative stock return h days after the purchase. Panel B of this Table shows all pairwise correlations of their corresponding t-statistics, $t\left(\overline{R_{-h}}^i\right)$, $h = 1$, 5, and 20, with $t\left(\overline{R_{+h}}^i\right)$, $h = 20$, 120, and 250. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A

		$\overline{R_{+h}}^i$ 20-day	120-day	250-day
$\overline{R_{-h}}^i$	1-day	0.15***	0.08***	0.09***
	5-day	0.21***	0.11***	0.12***
	20-day	0.33***	0.19***	0.19***

Panel B

		$t\left(\overline{R_{+h}}^i\right)$ 20-day	120-day	250-day
$t\left(\overline{R_{-h}}^i\right)$	1-day	0.20***	0.13***	0.12***
	5-day	0.24***	0.14***	0.13***
	20-day	0.33***	0.20***	0.19***

Table 13: Contrarian is behavior is somewhat stable

Panel A of this Table shows all pairwise correlations of the variables $\overline{R_{-5}}^{i,t}$, $t = 2012$, 2013, 2014, and 2015. We consider only individuals who made purchases in all four years of our sample (a total of 60,128 individuals). Panel B of this Table shows the rank-correlations—i.e., all pairwise correlations of $rank\left(\overline{R_{-5}}^{i,t}\right)$, $t = 2012$, 2013, 2014, and 2015, a ranking variable that starts at one at the most contrarian individual (i.e., with the lowest $\overline{R_{-5}}^{i,t}$), and ends at 60,128, the least contrarian individual in our sample. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A

	$\overline{R_{-5}}^{i,2012}$	$\overline{R_{-5}}^{i,2013}$	$\overline{R_{-5}}^{i,2014}$	$\overline{R_{-5}}^{i,2015}$
$\overline{R_{-5}}^{i,2012}$	1			
$\overline{R_{-5}}^{i,2013}$	0.23***	1		
$\overline{R_{-5}}^{i,2014}$	0.19***	0.23***	1	
$\overline{R_{-5}}^{i,2015}$	0.17***	0.18***	0.22***	1

Panel B

	$rank\left(\overline{R_{-5}}^{i,2012}\right)$	$rank\left(\overline{R_{-5}}^{i,2013}\right)$	$rank\left(\overline{R_{-5}}^{i,2014}\right)$	$rank\left(\overline{R_{-5}}^{i,2015}\right)$
$rank\left(\overline{R_{-5}}^{i,2012}\right)$	1			
$rank\left(\overline{R_{-5}}^{i,2013}\right)$	0.33***	1		
$rank\left(\overline{R_{-5}}^{i,2014}\right)$	0.26***	0.32***	1	
$rank\left(\overline{R_{-5}}^{i,2015}\right)$	0.22***	0.26***	0.29***	1