DOES MODERN INFORMATION TECHNOLOGY AFFECT ASYMMETRIC V-SHAPE DISPOSITION EFFECT?

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ABSTRACT

I test how the new acquirable information affects individual investors' disposition effect. By using the Electronic Data Gathering Analysis and Retrieval system (EDGAR) implementation as a policy change, I find individual investors tend to be more hesitant on selling the stocks and more aggressive on buying additional shares they currently own after the stocks become EDGAR filers. These opposite impacts are concentrated on investors who trade with higher frequency and the stocks whose value is hard to be estimated. The opposite impacts could be driven by investors' overconfidence.

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Contents

1 Introduction

What makes people trade and how could new acquirable information affect their trading behavior? Previous studies show that investors' trading behavior seems to follow some patterns. For example, studies related to the disposition effect state that investors are more willing to sell the past winners than past losers (Shefrin and Statman 1985). Ben-David and Hirshleifer (2012) first point out that investors' probabilities of selling and buying additional shares are both positively related to the magnitude of the paper gains and losses. They, therefore, introduce the " V-shape" disposition effect that the probabilities of selling and buying additional shares as the function of unrealized profits are V-shape. They attribute this asymmetric V-shape disposition effect to speculative motive by stating that investors will trade when their beliefs been updated. Since investors have limited attention, it is more likely that they will pay attention and adjust their positions, either buying additional shares or liquidating their current holdings, when there are substantial gains or losses changes in their accounts.

However, with the fast-spreading digital revolution, information related to stocks and the financial market can be disseminated in a more efficient way to retail investors. In this case, pronounced stock return changes may not be the only ones that could draw investors' attention and further affect their trading behavior. Investors' attention may also be attracted by new acquirable information that they could obtain in their daily life with modern computer technology. Therefore, information, by itself, may also have visible and distinctive effects on investors' trading behavior. Investors' initial assessments about certain stocks may be updated once there is more acquirable disclosed information. But how will those investors revise their

beliefs and further trigger trading once they could obtain more disclosed information? This is the question answered by this thesis.

In this thesis, I test how new acquirable information by itself affects individual investors' disposition effect, with the changes of gains and losses constant. To do that, I first replicate the main results from Ben-David and Hirshleifer (2012). Following their methods, I run the probit regression of selling and buying additional shares separately. In both probit regression models, the major independent variable is unrealized profits, representing by positive returns and negative returns separately. The dependent variable is a dummy variable which equals one if investors sell or buy additional shares. I find that speculative investors' probabilities of selling and buying additional shares indeed have positive relations with the magnitude of paper gains and paper losses, where speculative investors are defined as investors who trade for capital gains. For example, with a one-standard-deviation increase in the magnitude of paper gains and paper losses, the probabilities of selling increase by 0.29% and 0.2% respectively, which are 40% and 27% increases relative to the unconditional probability of selling (0.72%) in the same sample.

Then, to test how new acquirable information would affect this V-shape disposition effect, I introduce the Electronic Data Gathering Analysis and Retrieval system (EDGAR) implementation in 1993-1996 as a shock and flag the observations whose underlying policy stocks have become the EDGAR filers with dummy variable "Post-EDGAR" equals 1. Stocks becoming EDGAR filers means firms are required by SEC to disclose their filings electronically

following the EDGAR system implementation schedule. This implementation schedule follows a so-called "Phase-in" pattern that all the U.S. public firms are divided randomly by SEC into 10 groups and mandatory to disclose firm filings electronically group by group, with firms in the first group starting to file in April 1993 and firms in the last group starting in May 1996. EDGAR implementation facilities the information dissemination, since before EDGAR implementation, firms transmit their filings as paper copies to the SEC public office (in Washington DC, New York, and Chicago), at where those filings be stored and available for public to check (Gao and Huang 2020).

By adding the interactive variable between unrealized returns and Post-EDGAR to the previous probit regression models, I find new information affects selling and buying additional shares in different ways, with the probability of selling decreases and the probability of buying additional shares increases after the stocks become EDGAR filers. The "strength of V" (difference between the slopes on positive and negative branches of the V) decreases from 8.61 to 7.12 (17%) for selling and increases from 4.47 to 5.58 (25%) for buying additional shares after the stocks become EDGAR filers, with more acquirable online information. Since the V-shape disposition effect once been attributed to overconfidence-driven speculation by Ben-David and Hirshleifer (2012), the changes of overconfidence level of speculative investors induced by new information may potentially explain the changes of V-shape disposition effect. To explain these opposite impacts brought by EDGAR implementation to selling and buying behavior, I borrow the findings from overconfidence studies in psychology. In the overconfidence literature, researchers find people's overconfidence level is related to the clearness of

feedback. People tend to be more overconfident in solving the difficult tasks with obscure and deferred feedback (Griffin and Tversky 1992; K.D. Daniel, Hirshleifer, and Subrahmanyam 2001), but less overconfident when the feedback is clear and certain (Keren 1987).

Therefore, to test whether changes of overconfidence level induced by new information could explain the opposite impacts of EDGAR implementation on the V-shape disposition effect of selling and buying additional shares, I run the probit regression of indicator of selling and buying on unrealized returns and other control variables, conditional on investors trading frequency and firms information uncertainty. Previous studies find investors with high trading frequency are tend to be more speculative and overconfidence (Ben-David and Hirshleifer 2012; Odean 1998). For firms' information uncertainty, if the stocks' value is more ambiguity by itself, the new information may generate more obscure feedback. Following Zhang (2006), I use firms age, firm size and number of analyst coverage as measurements for stocks' information uncertainty. If the increase of overconfidence level could explain such opposite impacts of new information, we should expect to observe more pronounced opposite impacts in the subsample where investors tend to be more overconfident to new information (investors trading in higher frequency and stocks with high information uncertainty). As the result, I find these opposite impacts on the probability of selling and buying additional shares brought by EDGAR implementation are concentrated on frequent investors and the young, small and less analyst-coverage firms, with deferred stock price responses to the new information (See Figure 1 and Figure 2).

The remainder of the thesis is organized as follows. Section 2 discusses the related literature about disposition effect and overconfidence. Section 3 describes the transaction data structure and EDGAR implementation background. Section 4 examines the changes of the V-shape disposition effect of selling and buying additional shares separately before and after EDGAR implementation in different subsamples, and Section 5 concludes.

2 Literature Review

2.1 Disposition effect

Both individual and institutional investors have preferences to sell the past winners and hold past losers. Shefrin and Statman (1985) first name such behavior as disposition effect. After that, the disposition effect has been widely found by researchers using worldwide data across different investor types. Using 1995-1996 Taiwan Stock Exchange data, Barber et al. (2007) find individual investors have the strongest disposition effect compared with institutional investors, including dealers and mutual funds. During the same period, Brown et al. (2006) prove the existence of disposition effect among individual and institutional investors in the Australian IPO market (1995-2000). Investors in the U.S., Finland and China also been proved having preferences to sell the past winners and holds the past losers. (Grinblatt and Keloharju 2001; Odean 1998; Feng and Seasholes 2005; Chen et al. 2007).

As the empirical evidence of the disposition effect become robust, researchers start to un-

derstand the underlying reasons for this trading preference. There are two main explanations. The first one is the preference-based explanation, whose central idea is that investors are reluctant to realize their losses, either due to the disutility or reasons from prospect theory preference. Grinblatt and Han (2005) state that disposition effect could be driven by prospect theory (Kahneman and Tversky 1979) and mental accounting (Thaler 1980). Because of the S-shaped prospective theory value function, investors' demand for certain stocks increases as the wealth realizations become smaller. Therefore, investors tend to hold the losers and sell the winners. Henderson (2012) further build a model to capture this link between prospect theory and disposition effect by allowing partial liquidation of stocks and find investors are more likely to realize gains instead of losses. Barberis and Xiong (2009, 2012) develop the model called "realization utility" and find if investors evaluate the realized gains and losses, they would willing to sell the stocks when the selling price is higher than the purchase price. Moreover, Frydman et al. (2011) creatively use the neural data from magnetic resonance imaging and find that utility increases sharply at the exact moment when people sell stocks with gains.

The majority studies related to this realization preference explanation, either providing theoretical models or empirical evidence, derive from the central idea of prospect theory (Kahneman and Tversky 1979) that investors evaluate their investments by considering gains and losses instead of the wealth levels and have different value functions on gains and losses, with concave for gains and convex for losses. In this case, investors should prefer gains than losses and be more willing to realize the large gains than small gains and realize small losses than

large losses. However, Ben-David and Hirshleifer (2012) find that: 1) there is the minimal difference in investors' selling probability when the stock returns are just above zero and just below zero. This finding implies that investors' preference of realizing gains over losses, which only based on the "sign" difference of returns, maybe not enough to explain and predict the disposition effect. Therefore, it is important to consider the magnitude of realized gains and losses. 2) Once they consider the magnitude of realized gains and losses, the empirical results are still not consistent with what implied by prospect theory. For both gains and losses, investors are more willing to realize the return with larger magnitudes.

Since their empirical findings can not be explained by the first realization preference perspective, Ben-David and Hirshleifer (2012) point out the second explanation that the disposition effect may derive from belief-based tradings. The main idea is that investors' trading decisions could be attributed to their belief revision. Ben-David and Hirshleifer (2012) find the relation between investors' trading probabilities and magnitude of unrealized profits is a V shape by using the U.S. retail investor transaction data. For example, the probability of selling stocks will increase if the magnitudes of both paper gains and paper losses increase. Moreover, this V shape is asymmetric, with the branch in positive region higher than in negative region, meaning with the same amount of paper gains and paper losses, retail investors have a higher probability to sell the winners than the losers. To explain these findings, they state that investors will close their positions or bet more on the stocks they currently own once their initial belief of stocks value been updated by large amount changes of unrealized returns. Therefore, they could observe higher probabilities of selling or buying additional shares when

the size of unrealized returns is larger. Following their finding, An (2016) further shows that this V-shape disposition effect is priced by the equity market. She finds stocks with large paper gains and large paper losses outperform others in the following months. Because those stocks face higher selling pressures and thus have lower current stock prices and higher future returns. Moreover, by using institutional fund managers' transaction data during a three-day window around earnings announcements, Weisbrod (2019) find disposition effect can affect stock prices by causing an underreaction to the disclosed information.

Another trading pattern closely related to disposition effect," Rank Effect ", is proposed by Hartzmark (2015) which documents that retail investors are more willing to sell the extreme winners and losers inside their portfolios. Like the V-shape disposition effect, rank effect also provides supportive evidence to the argument that investor's trading behavior could be motivated by their belief updating. However, the sample structure and constructions of the variable of interest are different. Hartzmark (2015) follows Odean (1998) where only the day when there are trading transactions been observed is included in the sample, whereas my thesis, following Ben-David and Hirshleifer (2012), includes all the business days during the holding periods, which could answer not only why investors want to selling stock A instead of stock B at a given day but also the timing uncertainty of investors' trading behavior.

2.2 Overconfidence

This thesis extends the main findings from Ben-David and Hirshleifer (2012), where disposition effect is V-shape and could be attributed to speculative motive (belief revisions). Spec-

ulative traders are investing for gains, which could be triggered by overconfidence. In psychology, studies related to overconfidence could be classified into three groups based on the various definitions (Moore and Healy 2008). The first definition captures the belief that people overestimate their actual ability or chance of success, which been labeled as overestimation. The second kind of overconfidence is when people think they are better than the median, which also been called as better-than-average effect. The third definition of overconfidence is when people trust their beliefs with excessive certainty, labeled as overprecision. Both better-than-average effect and overprecision as two types of overconfidence play important roles in explaining the V-shape disposition effect and its changes with information dissemination changes. I will further discuss it in section 4.1.3.

Overconfidence has visible effects on investors' trading behavior and their performance. Theoretical studies already built the models assuming investors are overconfident (Benos 1998; K. Daniel, Hirshleifer, and Subrahmanyam 1998; Kyle and Wang 1997; Gervais and Odean 2001). Those models imply that when investors are overconfident, they tend to trade more with worse performance. Empirical evidence also proves this relation. B. Barber and T. Odean (2000, 2001) show that overconfident investors, such as men, trade with high frequency but lower returns.

3 Data and Summary statistics

3.1 Stock transactions data

To test how EDGAR implementation affects individual investors' trading behavior, I use the retail investors' trading data set as used by Ben-David and Hirshleifer (2012), which is also the same data used by Odean (1998). This data set provides U.S. retail investors' stock transaction information of 77,037 unique accounts, from January 1991 to December 1996. For each trading observation, the trading action (whether it is a sell or buy) is given and the initial unit of observation is investor-transaction.

Following Ben-David and Hirshleifer (2012), I randomly select 10,000 accounts as the sample used in all empirical tests and clean the transaction data in several steps. First, I only retain the transactions whose underlying securities are common shares. If the underlying security in a given account is not the common stock, I delete all observations for that investor-stock. Then, I remove the potential short transactions by deleting the investor-stocks once accumulated share positions for that investor-stocks become negative at any time point covered by the whole sample, with stock split being considered. The negative accumulated share position means investors either open that position before the start of the sample period and close it during the sample period, or short selling. Finally, to solve the microstructure frictions problem, I remove the observations of any stocks that are not actively traded at least for one day during the previous 250 trading days.

Then I build the investor-stock-date data structure by using the screened initial investor-transaction data following previous literature (Ben-David and Hirshleifer 2012; An 2016). To illustrate, If an investor buys stock A on March 12, 1992 and sells all the shares on April 23, 1992, there will be 30 investor-stock-date observations for the 30 business days, with the initial buying date, selling date and buying additional shares date been flagged. I use CRSP to calculate returns since prices in the data set are not adjusted for split and dividend. To handle the outliers issue in regression, I winsorize independent variables at 1^{st} and 99^{th} return percentiles for each prior holding period. After these adjustments, there are around 21 million investor-stock-date observations in the sample.

3.2 EDGAR implementation

Before EDGAR implementation start (1993), when public firms disclose their filings to SEC, they need to submit the paper copies documents by mail or personal delivery. After reviewing by SEC, those paper copies are stored at the three SEC office rooms (public reference room) located in three different cities in United States . Due to the limited number of paper copies for one filing, usually one or two in each office room, and restricted files checking policy that one paper copy can be inspected by one person at each time, it is time-consuming and even impossible for investors, especially retail investors, to acquire that information on time. In the worst situation, some paper copies may be at risk of loss (Gao and Huang 2020).

The implementation of the EDGAR system helps to bring firms' information dissemination from print age to digital age (Gao and Huang 2020). With EDGAR system, according to 58

FR 14628 (Mar.18, 1993) Federal Register citation (Page 14640), " Generally, as noted in the Proposing Release, public filings will be received, accepted and disseminated electronically on the same day." And as been further confirmed by SEC's annual report, investors could obtain " 10K/Q and all other corporate filings instantly on home computer screens" (Liu 2019). More importantly, the retail investors indeed obtain firms' disclosure through the EDGAR system. Gao and Huang (2020) manually identify the retail investors' domain name when they search the filings through the EDGAR system during the EDGAR implementation period and find 24.45% of the total number of requests are made by retail investors, which accounts for 31.39% of the total amount of data requests.

The EDGAR implementation follows the phase-in schedule that all U.S. public firms are categorized into 10 groups and firms in the same group are required to submit their fillings to SEC during same period of time. According to appendix A of SEC Release No.33-6977 (released on February 23, 1993), firms in the first group (Group CF-01) have to commence the electronic filing requirements in April 1993 and firms in the last group (Group CF-10) need to file in May 1996. I obtained a detailed EDGAR implementation phase-in schedule from appendix B of SEC Release No.33-6977. Timetable for the EDGAR implementation is provided in appendix B. I am able to obtain firms' CIK codes, firm names and the number of groups they belong to.

3.3 Summary statistics

Table 1 shows the summary statistics of the transaction data set. Panel A and Panel B show the estimated probabilities of selling and buying additional shares that investors own for EDGAR

filers and non-EDGAR filers. EDGAR filers are defined if the date of investor-stock-date observation is later than the first date of the next quarter after the stocks start filling in SEC as required by the EDGAR implementation timetable. To illustrate, if stock A is in the first EDGAR implementation group and required to fill in SEC in April 1993, stock A would be defined as EDGAR filers after July 1^{st},1993, which is the first date of the next quarter of April 1993. Since the timetable of EDGAR implementation for the first group (CF-01) is April 1993 and for the second group (CF-02) is July 1993, the exact time for certain firms in group one (CF-01) to fill in SEC could be anytime from April to July in 1993. Therefore, I choose the first date of the next quarter of the initial timetable as the anchor to define the EDGAR filers. I also use the initial timetable to redefine the EDGAR filers, the results remain consistent. Following Ben-David and Hirshleifer (2012), I test the probabilities of selling and buying additional shares for four different prior holding periods. They are 20 days after initial purchase, from 21 to 250 days after purchase, over 250 days after purchase and the whole sample. Using the randomly selected sample and same testing methods, I find consistent results as Ben-David and Hirshleifer (2012) present.

We can find from Panel A of Table 1 that the probability of selling winners (PSW) is higher than the probability of selling losers (PSL) for both EDGAR filers and non-EDGAR filers. The disposition effect (PSW $-$ PSL) is positive and statistically significant, which accounts for more than 55% and more than 22% of unconditional probability of selling for EDGAR filers and non-EDGAR filers respectively. The disposition effect decreases with the increase of the time since the initial purchase. Panel B presents the probability of buying additional

shares. We can find a mirror-version disposition effect compared with the disposition effect of selling in Panel A. The probability of buying additional winners (PBW) is lower than the probability of buying additional losers (PBL) for both EDGAR filers and non-EDGAR filers. The disposition effect for additional buying (PBW $-$ PBL) is negative and statistically significant for all prior holding periods. Panel C shows the summary statistics for variables used in the probit regressions.

4 Empirical Results

4.1 How EDGAR implementation affects disposition effect

To test the impacts brought by EDGAR implementation to the probability of selling and buying additional shares, I first follow Ben-David and Hirshleifer (2012) without introducing EDGAR implementation to estimate the probabilities of selling and buying additional shares separately and find consistent results. The probabilities of selling and buying additional shares as the function of unrealized returns are V-shape. Following Ben-David and Hirshleifer (2012), I run the probit regression of a trading indicator on stocks unrealized returns and control variables. Unrealized returns are separated by their signs. The positive return, Ret^{+}, is the maximum return between return since purchase and zero. The negative return, Ret^{-}, is the minimum return between return since purchase and zero.

To measure the impacts of EDGAR implementation, I then introduce a new dummy variable $Post\text{-}EDGAR$, which equals one if the stocks been traded are EDGAR filers. EDGAR

filers are defined if the date of investor-stock-date observation is later than the first date of the next quarter after the stocks start filling in SEC as required by the EDGAR implementation timetable. The interactive terms between unrealized return and this EDGAR filer indicator ($Ret^{+} \times Post\text{-}EDGAR$, $Ret^{-} \times Post\text{-}EDGAR$) capture how the slopes of V change once stocks become EDGAR filers with more acquirable online information. The control variables in probit regression include an indicator if the return is zero, an indicator if the return is positive, the square root of prior holding period measured in holding days, logged purchase price, stocks volatility for positive return and negative return separately.

4.1.1 The probability for selling

Table 2 Panel A shows the probit regression results for selling stocks. The dependent variable is the dummy variable which equals one if there is a selling and zero otherwise. Columns 1 to 3 present the asymmetric V shape around the origin with a steeper branch in the positive return region compared with the branch in the negative return region, when we do not consider the EDGAR implementation. The results are consistent with Ben-David and Hirshleifer (2012). After introducing EDGAR implementation, this asymmetric V-shape disposition effect still holds (Column 4-6). As we can see from the opposite coefficients of interactive term between returns and Post-EDGAR with coefficients of corresponding returns, probability of selling stocks become lower given the constant magnitude of return once those stocks become EDGAR filers than before, making the V shape become flatter.

To illustrate, consider column 4. The coefficient (marginal effect $\times$ 100) of interactive term

between positive return and Post-EDGAR ($Ret^{+} \times Post\text{-}EDGAR$) is -0.48, meaning one standard deviation increase in the magnitude of return for EDGAR filers is associated with the 0.03%(=0.48*0.068) decrease in the probability of selling. Given that the unconditional probability of selling is 0.72% (not report) for this 1 to 20 prior holding period, this is an around 4% decrease relative to the unconditional probability of selling once the stocks become EDGAR filers than before.

4.1.2 The probability for buying additional shares

Table 2 Panel B shows the probit regression results for buying additional shares that investors already owned. The dependent variable is the dummy variable which equals one if there is an additional buying and zero otherwise. Columns 1-3 show the analogous but reverse asymmetric V shape around the origin. Retail investors have a higher probability to buy additional shares for past losers than for past winners, as we can find that the slope in the negative return region (-3.08) is higher than slope in the positive slope region (1.73) from column 1, which is consistent with Ben-David and Hirshleifer (2012). From columns 4-6 we can find that the probability of buying additional shares increases conditional on both positive returns and negative returns once the firms become EDGAR filers. The coefficients of the interactive term between returns and Post-EDGAR have the same sign as coefficients of corresponding returns, which is opposite to the results for selling stocks.

For example, in column 4, the coefficient (marginal effect $\times$ 100) of interactive term between positive return and Post-EDGAR ($Ret^{+} \times Post\text{-}EDGAR$) is 0.72, meaning one stan-

dard deviation increase in the magnitude of return for EDGAR filers is associated with the 0.05%(=0.72*0.068) increase in the probability of buying additional shares. Given that the unconditional probability of buying is 0.24% (not report) for this 1 to 20 prior holding period, this is an around 20% increase relative to the unconditional probability of buying additional shares once the stocks become EDGAR filers than before.

4.1.3 Discussion

By using EDGAR implementation as the policy change, I find the asymmetric V-shape disposition effect for selling and buying additional shares as found by Ben-David and Hirshleifer (2012) still hold before and after stocks become EDGAR filers. However, the impacts brought by EDGAR implementations to retail investors' selling decision is different from that to buying additional shares. For selling, after firms become EDGAR filers and start fill in SEC electronically, meaning more acquirable information is available to the public, retail investors on average are not as willing to sell the stocks as before when they have the same amount of unrealized gains or losses in their account. But for buying additional shares, with more acquirable information of stocks investors already owned, they are more likely to buy additional shares given the same amount of unrealized gains and losses.

At first glance, the impacts of EDGAR implementation on probabilities of selling and buying additional shares are opposite. With more acquirable information of stocks that retail investors own, they are more hesitant to sell stocks and more aggressive to buy additional shares given the same amount of paper gains and paper losses. However, such opposite changes in trad-

ing decisions might be explained by the same argument that retail investors tend to be more overconfident once they have more information. With the different thought processes behind buying and selling, the specific manifestations of overconfidence could be various. B. M. Barber and Terrance Odean (2013) state that buying is a forward-looking process and selling is a backward-looking process. This argument is further testified by Grosshans, Zeisberger, and Langnickel (2017) using laboratory evidence.

As stated by Ben-David and Hirshleifer (2012), V-shape disposition effect of both selling and buying additional shares could be attributed to speculative trading. Speculative traders trade for gains. Therefore, it is not hard to imagine that the underlying reason for speculative traders' initial buying could be that they think the stocks are undervalued and the stock prices will increase in the future, since that is the way they could earn the capital gains by buying stocks today and selling it in the future. The reason for their assessments that stocks may be undervalued is that speculators think that they know better than the market what the stock is worth, either because they own private information or they are overconfident (Ben-David and Hirshleifer 2012). More specifically speaking, if the stock price reflects investors' average belief of the stock value, such overconfidence that motivates speculative trading belongs to the " better than average" effect according to psychological studies.

Under V-shape disposition effect, for selling, when the stock price goes up, investors may think the undervaluation of stock has been removed and close the current position with paper gains. If investors now hold EDGAR filers, with more acquirable information, they may

have excessive certainty about their initial judgment (defined as overprecision, one type of overconfidence), which is reinforced by more information, and still believe the existence of undervaluation of stocks they hold. Therefore, they are less likely to sell the current winners given the same size of paper gains when they hold EDGAR filers than non-EDGAR filers. When the stock price goes down, investors may think there is dis-confirmation with their initial assessment and close the position. If investors become overprecision once they know more about the stocks they hold, they may be less willing to sell the current stocks given the same size of paper losses than when they invest in less informative non-EDGAR filers.

For buying additional shares, when stock price increases, speculative investors may become more confident about their initial assessment or intuition and buy more. If now they have more information and become more overprecision, they may buy additional shares with higher probability given the same magnitude of paper gains. In other words, investors do not need that large paper gains to grab their attention and convince themselves about their initial judgments and buy additional shares, since they are investing in the more informative EDGAR filers and information may partially play the role as paper gains did in the sense of updating investors' beliefs and induce trading. Similarly, when stock prices decrease, they may remain confident and think it is a good chance to bet more. When investors hold EDGAR filers, their overconfidence could be intensified by more acquirable information. This explanation is also consistent with the previous finding that investors tend to be forward-looking when they need to buy instead of sell (B. M. Barber and Terrance Odean 2013; Grosshans, Zeisberger, and Langnickel 2017).

4.2 Additional tests of disposition effect conditional on investors and firms characteristics

In this section, I further test the impacts of EDGAR implementation on probability of selling and buying additional shares, conditional on investors' type and clearness of firms' value. If investing on more informative EDGAR filers makes speculative investors more overconfident, which leads to opposite changes on selling and buying additional shares, we should expect to find such difference concentrated on highly speculative investors and stocks with high information uncertainty. Investors would be more overconfident when the feedback of information is deferred and obscure, which happens when firms value is hard to be estimated (K.D. Daniel, Hirshleifer, and Subrahmanyam 2001; Zhang 2006).

4.2.1 Conditional on investors trading frequency

Previous studies find investors with high trading frequency tend to be more speculative and overconfident (Odean 1998; B. Barber and T. Odean 2000, 2001). Following Ben-David and Hirshleifer (2012), I focus on a subsample in which the prior holding period is from 1 to 20 days for the strongest V shape of the disposition effect, and use the difference between the slopes (i.e. the coefficient of return) in positive branch and negative branch as a proxy for the strength of the V shape ($\beta^+ - \beta^-$). The larger the difference is, the steeper the V shape will be. To test the impacts of EDGAR implementation, I divide the whole subsample into the EDGAR group and the non-EDGAR group, and further divide each group based on investors' trading frequency.

In Table 3, trading frequency increase from Q1 to Q4. Consistent with findings in Ben-David and Hirshleifer (2012), the V-shape of both selling and buying additional shares become stronger as trading frequency increases (from Q1 to Q4) for both the EDGAR group and non-EDGAR group. The opposite impacts brought by EDGAR implementation to the probability of selling and probability of buying additional shares can only be found when retail investors have the highest trading frequency (Q4). For selling, among investors with the highest trading frequency, the strength of V-shape disposition effect is 18.63 for transactions in non-EDGAR group and 10.72 in EDGAR group, with the negative change after firms become EDGAR filers (-7.91). For buying additional shares, the strength of V-shape disposition effect is 6.39 for transactions in non-EDGAR group and 8.07 in EDGAR group, with the positive change after firms become EDGAR filers (1.68).

Figure 1 shows the V-shape disposition effect of selling and buying additional shares for EDGAR group and non-EDGAR group, conditional on investors' trading frequency. Figure (a) and figure (b) show the changes of disposition effect after firms become EDGAR filers for infrequent traders (Q1-Q3). We can find EDGAR group (red curves) have flatter V-shapes for both selling and buying additional shares. However, from the figure (c) and figure (d), we can observe the opposite impacts of EDGAR implementation for selling and buying additional shares when investors have higher trading frequency (Q4). In figure (c), the V-shape of selling shares becomes flatter when the stocks been traded are EDGAR filers (red curves). But in figure (d), the V-shape of buying additional shares becomes steeper for EDGAR filers (red curves). The opposite impacts of EDGAR implementations for selling and buying additional

shares are only shown on frequent traders.

Since speculative investors with higher trading frequency (Q4) tend to be overconfident and their trading decisions are sensitive to their overconfidence level, results in Table 3 and Figure 1 support the argument that the opposite impacts brought by EDGAR implementation to selling and buying could be attributed to intensified overconfidence of retail investors when they know that they have more disclosed information and they may also think not everyone has the ability to access the information they have (the average percentage of internet trading is 12% in this sample during EDGAR implementation).

4.2.2 Conditional on trading frequency and information uncertainty

Investors also tend to be more overconfident when the feedback of new information is weak and obscure (Griffin and Tversky 1992; K.D. Daniel, Hirshleifer, and Subrahmanyam 2001). If the opposite impacts of EDGAR implementation could be explained by the increased overconfidence of speculative investors, these impacts should be more significant when investors tend to be more overconfident with the new acquirable information. Kent Daniel, David Hirshleifer, and Avanidhar Subrahmanyam (1998) state that investors tend to be more overconfident when the firms' businesses are hard to value. Following Zhang (2006), I use analyst coverage, firm size and firm age as proxies for firms' information uncertainty. Firms having low analyst coverage, small size or young age are those with high information uncertainty, whose value is hard to be estimated by investors.

Panel A of Table 4 shows the change of V-shape strength ($\Delta Strength$) between EDGAR group and non-EDGAR group ($EDGAR - non\text{-}EDGAR$) conditional on both firms' analyst coverage and investors' trading frequency. Firms with below-median analyst coverage are classified as lower analyst coverage firms and firms with above-median analyst coverage are classified as higher analyst coverage firms. Only the coefficients of negative and positive returns in probit regressions are reported.

In Panel A, we can only observe the opposite impacts on V shape changes ($\Delta Strength$) after firms become EDGAR filers between selling and buying additional shares in Column 4. Column 4 presents the probit regression results for subsample in which investors are most likely to be motivated by speculation (Q4) and firms business value is more obscure (low analyst coverage). For selling, the strength of V becomes weaker after the firms become EDGAR filers ($\Delta Strength = -7.97$), but the strength of V for buying additional shares becomes stronger after the firms become EDGAR filers ($\Delta Strength = 3.52$) for the same subsample. However, we can not find such opposite impacts among firms covered by the above-median level of analyst even for the most speculative investors (Column 8). The changes of V shape strength ($\Delta Strength$) have the same directions in selling (-8.44) and buying additional shares(-3.22) in Column 8.

Even though the speculative investors with the highest trading frequency (Q4) tend to have opposite changes of V strength for selling and buying additional shares after firms become EDGAR filers as we found in Table 3, with the relative clear business value of firms, which

represented by above-median analyst coverage, those speculative investors may not be more overconfidence once they have more information of stocks they hold. Therefore, we can not obverse the opposites changes of V ($\Delta Strength$) between selling and buying additional shares in Column 8, where investors are highly speculative motivated but firms are covered by more analysts. Since investors tend to be more overconfident to the new information when the firms have lower analyst coverage, the findings from Panel A are consistent with the argument that such opposite impacts of EDGAR implementation for selling and buying additional shares are attributed to investors overconfidence once they have more information of the stocks they own.

Panel B and Panel C of Table 4 provide consistent results. Panel B and Panel C show the changes of V-shape strength ($\Delta Strength$) between EDGAR group and non-EDGAR group ($EDGAR-non\text{-}EDGAR$) conditional on both firm size and firm age respectively, as well as investors' trading frequency. Consistent with Panel A, we can only observe the opposite impacts on V shape changes ($\Delta Strength$) after firms become EDGAR filers between selling and buying additional shares in Column 4, where investors are most likely be motivated by speculation (Q4) and firms business value is more obscure (represented by small firms in Panel B and young firms in Panel C), but not in Column 8, where investors are most likely be motivated by speculation (Q4) but firms business value is less obscure (represented by large firms in Panel B and old firms in Panel C). To illustrate, in Column 4 of Panel B, the strength of V becomes weaker for selling after the small firms become EDGAR filers ($\Delta Strength = -7.98$), but the strength of V for buying additional shares becomes stronger ($\Delta Strength = 3.73$). However, the changes of V shape strength ($\Delta Strength$) have the same directions for selling (-9.9) and

buying additional shares(-4.3) for large firms in Column 8.

Figure 2 shows the V-shape disposition effect of selling and buying additional shares for EDGAR group and non-EDGAR group with various firms' information uncertainty, holding the investors' trading frequency constant (Q4). Figure (a) and Figure (b) show the changes of disposition effect after firms become EDGAR filers for stocks with high information uncertainty. We can find a significant opposite impact brought by EDGAR on selling and buying additional shares. Consistent with the probit regression results in Column 4 of Table 4, investors are more hesitant to sell stocks once these stocks become EDGAR filers (see the flatter red curve in Figure (a)) but more willing to buy additional shares when firms start to fill in EDGAR (see the steeper red curve in Figure (b)). However, for investors with the same trading frequency (Q4), once they trade on stocks with low information uncertainty and clear feedback to new information, the opposite impacts brought by EDGAR implementation on selling and buying additional shares are less pronounced (see Figure (c) and Figure (d)). Maybe because the overconfidence of investors with higher trading frequency (Q4) is partially offset by the stocks' low information uncertainty.

Overall, by adding the interactive term between Post-EDGAR and unrealized returns in probit regression models, we can find the EDGAR implementation affects probabilities of selling and buying additional shares differently. Retail investors on average have a lower probability of selling once the stocks become EDGAR filers, but have a higher probability of buying additional shares after the stocks starting fill in SEC electronically, holding the unrealized

profits constant. These opposite impacts may be explained by the increased overconfidence of investors. Additional probit regressions conditional on investors and firms characteristics further provide supportive evidence that we could only observe such opposites impacts when investors are more overconfident to new information, with high trading frequency and trading on stocks with more obscure businesses.

5 Conclusion

This thesis presents that the V-shape disposition effect of retail investors would change differently for selling stocks and buying additional shares when investors have higher overconfidence levels induced by more acquirable disclosed information by using U.S. retail investors' transaction data from 1991 to 1996. This finding further provides new supportive evidence to the previous argument that the V-shape disposition effect could be attributed to overconfidence-driven speculation. By introducing the EDGAR implementation as a policy shock, I am able to flag the stocks with more acquirable online information following the timetable of the implementation and test the changes of disposition effect before and after firms become EDGAR filers. Empirical results show that retail investors have a lower probability of selling stocks but a higher probability of buying additional shares after the stocks become EDGAR filers, holding the unrealized profits constant. Such opposite impacts could be attributed to intensified overconfidence brought by more information, supported by the observations that those opposite impacts are concentrated on investors with high trading frequency and stocks with weak feedback to new information.

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Appendix

A. Variable Definitions

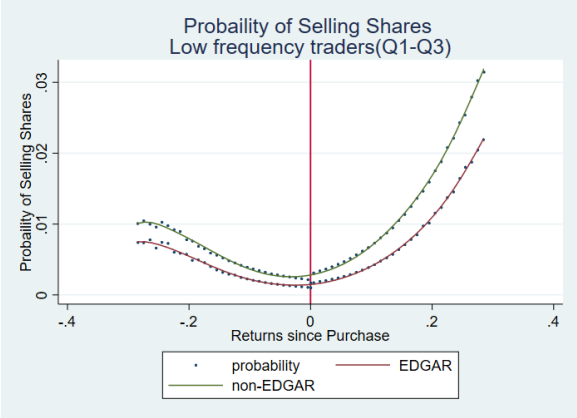
Variable	Definition
$Ret^{-}(Ret^{+})$	The return since purchase is negative(positive), zero otherwise.
$Post\text{-}EDGAR$	Dummy variable if the stocks are EDGAR filers
$I(ret < 0)$	An indicator for whether the return since purchase is negative
$I(ret = 0)$	An indicator for whether the return since purchase is zero
$I(ret > 0)$	An indicator for whether the return since purchase is positive
$log(Buy\ price)$	The logged purchase price
$sqrt(Time\ owned)$	The square root of the number of days since purchase
$Volatility^{-}(Volatility^{+})$	The standard deviation of 250 days daily return prior to the purchase if the return since purchase is negative (positive), zero otherwise
$Trading\ Frequency$	The number of new stocks positions opened by investors scaled by the interval lengths that investors hold open positions, from first day to last day between 1991 to 1996.

B. Timetable for Implementation of EDGAR Division of Corporation Finance Filings

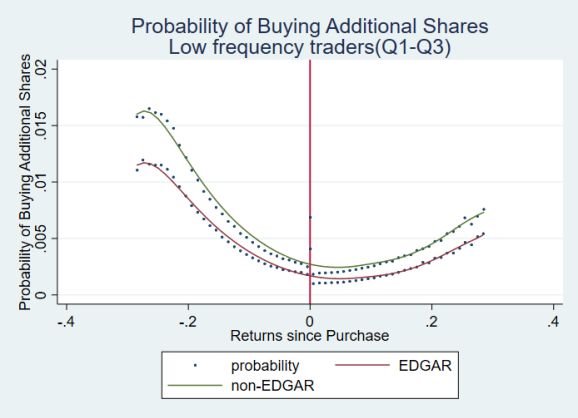
Time	Group
April 26, 1993	Phase-in of Group CF-01
July 19, 1993	Phase-in of Group CF-02
October 4, 1993	Phase-in of Group CF-03
December 6, 1993	Phase-in of Group CF-04
August 1994	Phase-in of Group CF-05
November 1994	Phase-in of Group CF-06
May 1995	Phase-in of Group CF-07
August 1995	Phase-in of Group CF-08
November 1995	Phase-in of Group CF-09
May 1996	Phase-in of Group CF-10

C. Figures and Tables

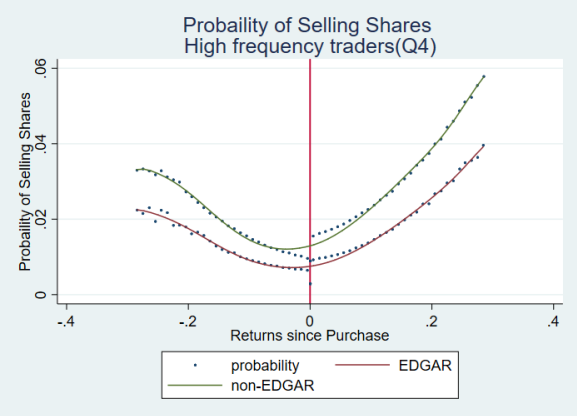
Figure 1: V-shapes conditional on investors type



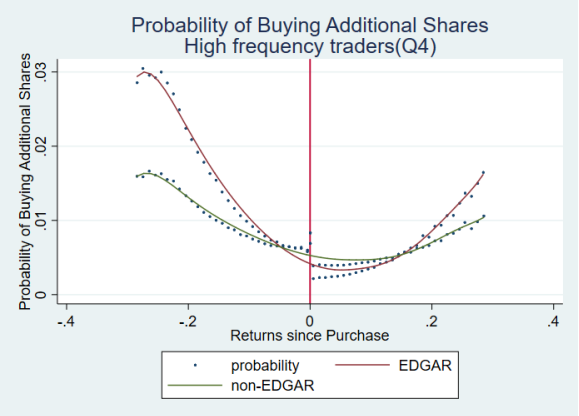
(a) Probability of selling shares for infrequent traders



(b) Probability of buying additional shares for infrequent traders



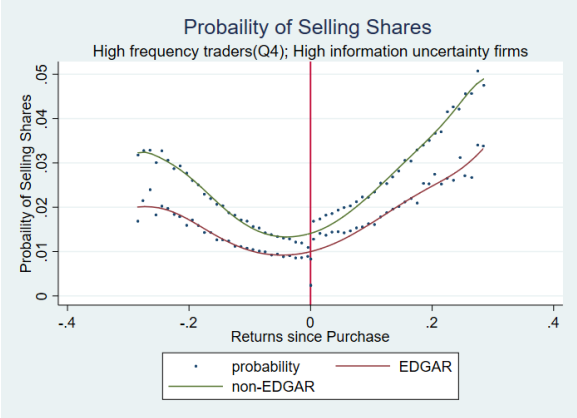
(c) Probability of selling shares for frequent traders



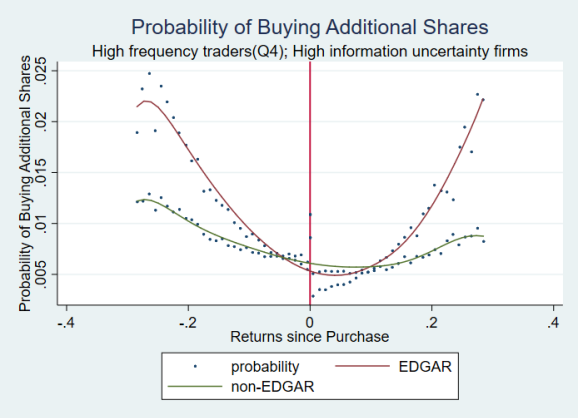
(d) Probability of buying additional shares for frequent traders

The figures present the estimated 4^{th}-degree polynomials in both positive and negative region separately for selling and buying additional shares as a function of returns for EDGAR and non-EDGAR group, conditional on investors trading frequency for prior holding 1 to 20 days. EDGAR group includes EDGAR traders, defined as investors who have more than half of the investor-stock-date observations with Post-EDGAR equals 1. non-EDGAR group includes non-EDGAR traders, defined as investors who have less than half of the investor-stock-date observations with Post-EDGAR equals 1. Following Ben-David and Hirshleifer (2012), trading frequency is the number of new stocks positions opened by investors scaled by the interval lengths that investors hold open positions, from the first day to the last day between 1991 and 1996.

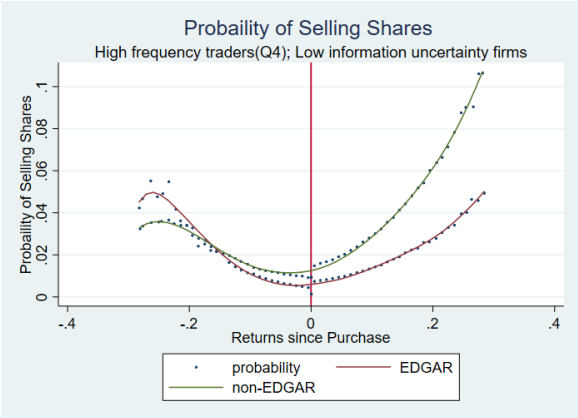
Figure 2: V-shapes conditional on firms characteristics with trading frequency controlled



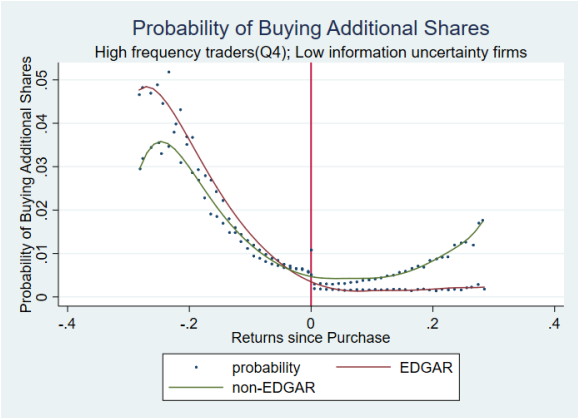
(a) Probability of selling shares for frequent traders and firms with high information uncertainty



(b) Probability of buying additional shares for frequent traders and firms with high information uncertainty



(c) Probability of selling shares for frequent traders and firms with low information uncertaint



(d) Probability of buying additional shares for frequent traders and firms with low information uncertainty

The figures present the estimated 4^{th}-degree polynomials in both positive and negative region separately for selling and buying additional shares as a function of returns for EDGAR and non-EDGAR group, conditional on firms information uncertainty for prior holding 1 to 20 days. Investors in four subfigures are frequent investors (Q4). EDGAR group includes EDGAR traders, defined as investors who have more than half of the investor-stock-date observations with Post-EDGAR equals 1. non-EDGAR group includes non-EDGAR traders, defined as investors who have less than half of the investor-stock-date observations with Post-EDGAR equals 1. High information uncertainty firms are defined as firms that have below-median size, age and analyst coverage. Low information uncertainty firms are defined as firms that have above-median size, age and analyst coverage. Following Ben-David and Hirshleifer (2012), trading frequency is the number of new stock positions opened by investors scaled by the interval lengths that investors hold open positions, from the first day to the last day between 1991 and 1996.

Table 1: **Summary Statistics**

Panel A: Estimated probabilities of selling stocks

	Estimated probability of selling							
	EDGAR filers				non-EDGAR filers			
Prior holding period (days)	1 to 20	21 to 250	>250	All	1 to 20	21 to 250	>250	All
Unconditional Probability	0.20	0.13	0.04	0.10	0.52	0.33	0.05	0.20
	(15.80)	(34.51)	(49.16)	(20.97)	(25.86)	(51.26)	(43.75)	(27.90)
PSW(%)	0.32	0.14	0.05	0.14	0.76	0.33	0.04	0.29
	(12.13)	(31.41)	(43.44)	(22.61)	(20.01)	(44.98)	(35.37)	(32.18)
PSL (%)	0.19	0.06	0.03	0.08	0.55	0.17	0.03	0.17
	(9.55)	(21.09)	(29.70)	(16.54)	(13.87)	(32.86)	(29.41)	(22.91)
Disposition effect	0.13	0.09	0.02	0.07	0.19	0.16	0.01	0.12
	(4.32)	(18.92)	(18.06)	(8.99)	(3.99)	(21.30)	(8.02)	(10.58)
(PSW-PSL)/Unconditional Probability (%)	62.38	71.76	55.52	65.35	37.59	50.33	22.47	59.14
No.of selling	2,182	8,316	6,620	17,118	4,525	16,287	5,159	25,971
No.of observation	1,065,221	8,237,441	11,521,511	20,824,173	1,065,221	8,237,441	11,521,511	20,824,173

Panel B: Estimated probabilities of buying additional shares of stocks already owned

	Estimated probability of buying additional shares							
	EDGAR filers				non-EDGAR filers			
Prior holding period (days)	1 to 20	21 to 250	>250	All	1 to 20	21 to 250	>250	All
Unconditional Probability	0.06	0.02	0.01	0.05	0.18	0.04	0.01	0.09
	(14.69)	(17.44)	(14.61)	(13.8)	(22.86)	(28.89)	(15.94)	(16.61)
PBW(%)	0.03	0.01	0.01	0.02	0.14	0.03	0.004	0.04
	(8.88)	(13.07)	(12.04)	(7.9)	(7.36)	(17.21)	(10.56)	(8.42)
PBL (%)	0.09	0.02	0.01	0.03	0.18	0.05	0.01	0.06
	(7.84)	(13.62)	(12.11)	(9.51)	(15.84)	(22.5)	(13.36)	(11.37)
Disposition effect	-0.05	-0.01	-0.001	-0.01	-0.04	-0.02	-0.003	-0.02
	(-4.82)	(-7.58)	(-1.5)	(-3.57)	(-1.92)	(-8.62)	(-4.69)	(-3.02)
(PBW-PBL)/Unconditional Probability (%)	-89.06	-68.72	-13.02	-30.90	-24.14	-48.45	-42.60	-21.34
No.of buying additional shares	1,270	2,747	1,597	5,614	2,605	5,102	1,353	9,060
No.of observation	1,065,221	8,237,441	11,521,511	20,824,173	1,065,221	8,237,441	11,521,511	20,824,173

Panel C: Summary statistics for regression variables means and standard deviations

	Prior holding period (days)			
	1 to 20	21 to 250	>250	All
N	1,065,221	8,237,441	11,521,511	20,824,173
I (ret<0)	0.461	0.438	0.33	0.379
	[0.499]	[0.496]	[0.47]	[0.485]
I (ret=0)	0.048	0.012	0.005	0.01
	[0.214]	[0.107]	[0.067]	[0.097]
I (ret>0)	0.491	0.55	0.666	0.611
	[0.5]	[0.497]	[0.472]	[0.487]
Ret^-	-0.027	-0.074	-0.096	-0.084
	[0.051]	[0.131]	[0.186]	[0.162]
Ret^+	0.032	0.117	0.442	0.293
	[0.068]	[0.229]	[0.813]	[0.644]
log(Buy price)	3.247	3.258	3.272	3.265
	[0.815]	[0.803]	[0.804]	[0.804]
sqrt(Time owned)	3.164	10.558	24.468	17.876
	[0.902]	[3.156]	[5.693]	[8.844]
$Volatility^-$	0.013	0.012	0.009	0.01
	[0.018]	[0.017]	[0.015]	[0.016]
$Volatility^+$	0.013	0.013	0.014	0.013
	[0.016]	[0.014]	[0.013]	[0.014]
Post-EDGAR	0.322	0.367	0.581	0.483
	[0.467]	[0.482]	[0.493]	[0.499]

This table presents the summary statistics for the transaction data sample of retail investors. The sample includes randomly selected 10,000 retail investors who trade in U.S. broker from January 1991 to December 1996. Panel A and Panel B show the frequencies of selling and buying additional shares of the stocks investors own for four different prior holding periods, conditional on whether the stocks been traded are EDGAR filers or not. EDGAR filers have been defined if the date of investor-stock-date observation is later than the first date of the next quarter after the stocks start filling in SEC as required by the EDGAR implementation timetable. Furthermore, Panel A and Panel B also show the probabilities of selling winning stocks (PSW), the probabilities of selling losing stocks (PSL), the probabilities of buying winning stocks (PBW) and the probabilities of buying losing stocks (PLW). The disposition effect for selling is PSW − PSL and the disposition effect for buying additional shares is PBW − PBL. T-statistics are in parentheses. Standard errors are clustered at the investor level. *, ** and *** denote significance levels at 10%, 5%, 1%. Panel C shows the mean and standard deviation (in brackets) for the variables used in probit regression.

Table 2: V-Shape disposition effect under EDGAR implementation

Panel A: Probability of selling stocks

	Depended variables : I (Sell stocks) × 100					
Prior holding period (Days)	1 to 20	21 to 250	>250	1 to 20	21 to 250	>250
	(1)	(2)	(3)	(4)	(5)	(6)
Ret^{-}	-3.93***	-0.30***	-0.04***	-4.21***	-0.29***	-0.05***
	(-21.59)	(-13.73)	(-4.71)	(-21.17)	(-12.14)	(-5.41)
Ret^{-} × Post-EDGAR				1.01***	-0.02	0.02**
				(3.28)	(-0.74)	(2.12)
Ret^{+}	4.28***	0.23***	0.00***	4.40***	0.22***	0.01***
	(33.91)	(21.48)	(2.80)	(31.75)	(18.02)	(3.77)
Ret^{+} × Post-EDGAR				-0.48**	0.02	-0.01***
				(-2.21)	(1.21)	(-2.96)
Post-EDGAR				0.09***	-0.01**	0.02***
				(4.33)	(-2.38)	(7.73)
I (ret=0)	0.01	0.17***	0.03*	0.01	0.17***	0.03*
	(0.28)	(7.68)	(1.75)	(0.27)	(7.64)	(1.89)
I (ret>0)	0.07***	0.01	-0.03***	0.06**	0.01	-0.02***
	(2.65)	(1.00)	(-6.27)	(2.40)	(1.03)	(-6.08)
sqrt(Time Owned)	-0.18***	-0.03***	-0.01***	-0.18***	-0.03***	-0.01***
	(-22.56)	(-49.54)	(-40.98)	(-22.50)	(-49.39)	(-41.38)
log(Buy price)	0.16***	0.03***	0.01***	0.16***	0.03***	0.01***
	(17.06)	(12.28)	(6.97)	(16.67)	(12.38)	(5.87)
$Volatility^{-}$	5.17***	2.28***	0.76***	5.11***	2.27***	0.79***
	(11.15)	(13.82)	(6.89)	(11.02)	(13.68)	(7.13)
$Volatility^{+}$	11.37***	7.33***	2.72***	11.51***	7.31***	2.73***
	(17.09)	(41.42)	(28.01)	(17.29)	(41.09)	(28.07)
Observations	1,065,221	8,237,441	11,521,511	1,065,221	8,237,441	11,521,511
Pseudo R^2	0.0404	0.0207	0.0154	0.0407	0.0207	0.0158

Panel B: Probability of buying additional shares

	Depended variables : I (Buy additional shares) × 100					
Prior holding period (Days)	1 to 20	21 to 250	>250	1 to 20	21 to 250	>250
	(1)	(2)	(3)	(4)	(5)	(6)
Ret^-	-3.08***	-0.21***	-0.03***	-2.96***	-0.21***	-0.03***
	(-28.45)	(-22.81)	(-7.96)	(-24.55)	(-20.98)	(-6.95)
Ret^- × Post-EDGAR				-0.39**	0.01	0.00
				(-2.25)	(0.98)	(0.28)
Ret^+	1.73***	0.09***	0.01***	1.51***	0.10***	0.00***
	(15.55)	(13.50)	(8.39)	(12.09)	(12.38)	(2.95)
Ret^+ × Post-EDGAR				0.72***	-0.01	0.00**
				(4.13)	(-1.03)	(2.05)
Post-EDGAR				0.00	0.01**	0.00
				(0.24)	(2.55)	(0.55)
I (ret=0)	0.16***	-0.02**	-0.01*	0.16***	-0.02**	-0.01*
	(5.73)	(-2.58)	(-1.87)	(5.72)	(-2.52)	(-1.87)
I (ret>0)	-0.27***	-0.09***	-0.01***	-0.27***	-0.09***	-0.01***
	(-12.64)	(-21.26)	(-5.58)	(-12.75)	(-21.09)	(-5.57)
sqrt(Time Owned)	-0.18***	-0.01***	-0.00***	-0.18***	-0.01***	-0.00***
	(-32.92)	(-37.98)	(-20.53)	(-32.97)	(-38.04)	(-20.42)
log(Buy price)	0.00	0.00*	-0.00	-0.00	0.00	-0.00
	(0.46)	(1.81)	(-0.84)	(-0.12)	(1.61)	(-1.17)
$Volatility^-$	-0.82*	-0.47***	0.00	-0.79*	-0.46***	-0.00
	(-1.86)	(-4.64)	(0.08)	(-1.78)	(-4.54)	(-0.04)
$Volatility^+$	5.10***	1.48***	0.20***	5.23***	1.50***	0.21***
	(9.38)	(13.14)	(3.46)	(9.63)	(13.15)	(3.67)
Observations	1,065,221	8,237,441	11,521,511	1,065,221	8,237,441	11,521,511
Pseudo R^2	0.0404	0.0207	0.0154	0.0407	0.0207	0.0158

This table presents the probit regression results. The sample includes randomly selected 10,000 retail investors who trade in U.S. broker from January 1991 to December 1996. The coefficients are the marginal effect on the average times 100. Observations are at the investor-stock-date level. Panel A presents probit regression results of indicator whether the investor-stock-date observation is a sell. Panel B presents probit regression in which the dependent variable is an indicator of whether additional shares are bought of stocks that are currently owned by investors. Ret^- is the minimum return since purchase between return and zero.Ret^+ maximum return since purchase between return and zero. $Post\text{-}EDGAR$ is dummy variable equals 1 if the stocks of investor-stock-date observations are EDGAR filers and zero otherwise. $I(ret = 0)$ is the indicator for zero return since purchase. $I(ret > 0)$ indicator for positive return since purchase. $sqrt(TimeOwned)$ is the square root of the prior holding period measured in holding days. $log(Buyprice)$ is logged purchase price. $Volatility^-$ is stock volatility when return is negative. $Volatility^+$ is stock volatility when return is positive. T-statistics are in parentheses. *, ** and *** denote significance levels at 10%, 5%, 1%.

Table 3: Subsample tests conditional on trading frequency

	EDGAR				Non-EDGAR			
Trading Frequency	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Breakpoint	n/a	0.0064	0.0133	0.0279	n/a	0.0056	0.0118	0.0245
N	119,613	119,802	119,508	119,286	147,162	146,642	147,193	146,015
Selling								
Ret^-	-0.65***	-1.17***	-2.81***	-5.34***	-1.00***	-2.31***	-4.64***	-9.57***
	(-3.53)	(-3.80)	(-6.18)	(-6.71)	(-5.05)	(-5.90)	(-8.89)	(-10.68)
Ret^+	0.73***	2.11***	2.88***	5.38***	1.34***	3.33***	6.54***	9.06***
	(5.78)	(11.15)	(10.35)	(9.72)	(9.88)	(14.72)	(17.89)	(14.08)
Strength ($\beta^+ - \beta^-$)	1.38	3.28	5.69	10.72	2.34	5.64	11.18	18.63
ΔStrength								
(EDGAR−non-EDGAR)	-0.96	-2.36	-5.49	-7.91				
Buying additional shares								
Ret^-	-1.23***	-1.68***	-2.79***	-4.86***	-1.76***	-3.14***	-4.28***	-3.98***
	(-6.07)	(-7.17)	(-9.77)	(-12.52)	(-8.13)	(-12.40)	(-12.37)	(-9.14)
Ret^+	0.57**	0.96***	1.48***	3.21***	0.68***	2.02***	1.51***	2.41***
	(2.22)	(3.68)	(5.54)	(7.91)	(3.04)	(9.36)	(3.69)	(5.62)
Strength ($\beta^+ - \beta^-$)	1.8	2.64	4.27	8.07	2.44	5.16	5.79	6.39
ΔStrength								
(EDGAR−non-EDGAR)	-0.64	-2.52	-1.52	1.68				

This table shows the probit regression results of selling or buying additional shares on positive returns and negative returns for EDGAR traders and non-EDGAR traders, conditional on investors' trading frequency for prior holding 1 to 20 days subsample. EDGAR subsample includes EDGAR traders, defined as investors who have more than half of the investor-stock-date observations with Post-EDGAR equals 1. non-EDGAR subsample includes non-EDGAR traders, defined as investors who have less than half of the investor-stock-date observations with Post-EDGAR equals 1. The coefficients are the marginal effect on the average times 100. Observations are at the investor-stock-date level. The dependent variables are the indicators that equal 1 if the investor-stock-date observation is a sell (or an additional buy in the lower part of the table). The independent variables are not all shown in the table. Independent variables include: maximum return since purchase between return and zero, minimum return since purchase between return and zero, the indicator for zero return since purchase, the indicator for positive return since purchase, square root of prior holding period measured in holding days, logged purchase price, stock volatility when return is positive, stock volatility when return is negative. Variable definitions are in Appendix A. T-statistics are in parentheses. *, ** and *** denote significance levels at 10%, 5%, 1%.

Table 4: Subsample tests conditional on trading frequency and firm characteristics

Panel A: Subsample tests conditional on trading frequency and firm analyst coverage

Trading Frequency		Low analyst coverage firms				High analyst coverage firms			
		Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Selling								
EDGAR	Ret-	-1.13***	-1.44***	-3.52***	-5.00***	-0.21	-0.87**	-2.04***	-5.78***
		(-2.95)	(-3.04)	(-5.23)	(-4.70)	(-0.99)	(-1.98)	(-2.98)	(-4.76)
	Ret+	1.14***	2.05***	3.15***	5.17***	0.52***	2.11***	3.01***	5.59***
		(4.42)	(6.39)	(7.65)	(6.78)	(3.61)	(9.23)	(7.08)	(6.88)
	Strength ($\beta^+ - \beta^-$)	2.27	3.49	6.67	10.17	0.73	2.98	5.05	11.37
non-EDGAR	Ret-	-0.89***	-2.11***	-4.58***	-9.51***	-1.01***	-2.54***	-3.82***	-9.48***
		(-3.84)	(-4.31)	(-6.88)	(-8.80)	(-2.83)	(-3.93)	(-4.15)	(-5.82)
	Ret+	1.47***	3.07***	6.31***	8.63***	1.05***	3.76***	7.03***	10.33***
		(8.70)	(11.14)	(13.47)	(10.84)	(4.61)	(9.31)	(11.96)	(9.37)
	Strength ($\beta^+ - \beta^-$)	2.36	5.18	10.89	18.14	2.06	6.3	10.85	19.81
	ΔStrength								
	(EDGAR$-$non-EDGAR)	-0.09	-1.69	-4.22	-7.97	-1.33	-3.32	-5.8	-8.44
	Buying additonal shares								
EDGAR	Ret-	-0.81**	-1.66***	-3.08***	-4.52***	-1.45***	-1.71***	-2.60***	-5.19***
		(-2.30)	(-3.94)	(-6.99)	(-8.41)	(-6.07)	(-6.28)	(-6.86)	(-9.53)
	Ret+	0.69*	1.29***	1.33***	4.50***	0.45	0.65*	1.90***	0.23
		(1.89)	(3.28)	(3.55)	(9.09)	(1.25)	(1.65)	(4.37)	(0.30)
	Strength ($\beta^+ - \beta^-$)	1.5	2.95	4.41	9.02	1.9	2.36	4.5	5.42
non-EDGAR	Ret-	-1.83***	-2.81***	-4.96***	-3.49***	-1.82***	-3.50***	-3.59***	-5.19***
		(-6.25)	(-8.83)	(-9.81)	(-6.50)	(-5.70)	(-9.05)	(-7.21)	(-7.03)
	Ret+	0.55*	1.34***	1.96***	2.01***	1.25***	2.95***	0.87	3.45***
		(1.94)	(4.94)	(3.49)	(3.93)	(3.27)	(8.00)	(1.22)	(4.45)
	Strength ($\beta^+ - \beta^-$)	2.38	4.15	6.92	5.5	3.07	6.45	4.46	8.64
	ΔStrength								
	(EDGAR$-$non-EDGAR)	-0.88	-1.2	-2.51	3.52	-1.17	-4.09	0.04	-3.22

Panel B: Subsample tests conditional on trading frequency and firm size

Trading Frequency		Small firms				Large firms			
		Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Selling								
EDGAR	Ret-	-0.86**	-1.16**	-3.33***	-4.87***	-0.28	-1.12***	-2.34***	-6.00***
		(-2.55)	(-2.20)	(-4.74)	(-4.48)	(-1.09)	(-2.92)	(-3.51)	(-5.05)
	Ret+	1.32***	2.46***	3.26***	5.50***	0.31**	1.87***	3.00***	5.19***
		(5.21)	(7.91)	(7.71)	(7.20)	(2.23)	(7.55)	(6.94)	(6.32)
	Strength ($\beta^+ - \beta^-$)	2.18	3.62	6.59	10.37	0.59	2.99	5.34	11.19
non-EDGAR	Ret-	-1.17***	-1.86***	-4.40***	-9.83***	-0.47	-3.26***	-4.64***	-8.94***
		(-4.77)	(-3.84)	(-6.59)	(-9.22)	(-1.08)	(-4.96)	(-4.88)	(-5.11)
	Ret+	1.55***	3.19***	6.75***	8.52***	1.02***	3.84***	6.77***	12.15***
		(8.62)	(12.22)	(14.84)	(11.23)	(4.56)	(7.97)	(10.15)	(9.38)
	Strength ($\beta^+ - \beta^-$)	2.72	5.05	11.15	18.35	1.49	7.1	11.41	21.09
	ΔStrength								
	(EDGAR−non-EDGAR)	-0.54	-1.43	-4.56	-7.98	-0.9	-4.11	-6.07	-9.9
	Buying additonal shares								
EDGAR	Ret-	-1.13***	-1.65***	-3.32***	-4.99***	-1.34***	-1.70***	-2.35***	-4.63***
		(-3.38)	(-3.71)	(-7.01)	(-9.35)	(-5.36)	(-6.72)	(-6.36)	(-8.43)
	Ret+	0.61*	1.43***	1.77***	4.63***	0.69*	0.41	1.33***	-0.04
		(1.66)	(3.50)	(4.78)	(9.40)	(1.77)	(0.98)	(2.68)	(-0.05)
	Strength ($\beta^+ - \beta^-$)	1.74	3.08	5.09	9.62	2.03	2.11	3.68	4.59
non-EDGAR	Ret-	-1.98***	-3.16***	-4.75***	-3.73***	-1.48***	-3.31***	-3.73***	-4.98***
		(-6.81)	(-9.32)	(-9.89)	(-6.93)	(-4.55)	(-8.64)	(-6.97)	(-6.55)
	Ret+	0.66**	2.24***	1.73***	2.16***	0.87**	1.75***	1.28*	3.91***
		(2.36)	(8.68)	(3.23)	(4.28)	(2.15)	(3.37)	(1.66)	(4.45)
	Strength ($\beta^+ - \beta^-$)	2.64	5.4	6.48	5.89	2.35	5.06	5.01	8.89
	ΔStrength								
	(EDGAR−non-EDGAR)	-0.9	-2.32	-1.39	3.73	-0.32	-2.95	-1.33	-4.3

Panel C: Subsample tests conditional on trading frequency and firm age

Trading Frequency		Young firms				Old firms			
		Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Selling								
EDGAR	Ret-	-0.99***	-1.53***	-3.34***	-4.97***	-0.17	-0.51	-2.46***	-7.50***
		(-2.90)	(-3.10)	(-4.96)	(-4.36)	(-0.58)	(-0.94)	(-3.40)	(-5.97)
	Ret+	1.04***	2.71***	3.40***	5.73***	0.62***	1.56***	2.61***	5.61***
		(4.06)	(7.97)	(7.66)	(7.10)	(4.22)	(7.39)	(7.00)	(6.69)
	Strength ($\beta^+ - \beta^-$)	2.03	4.24	6.74	10.7	0.79	2.07	5.07	13.11
non-EDGAR	Ret-	-0.99***	-2.39***	-4.56***	-10.12***	-1.09***	-2.55***	-4.69***	-9.32***
		(-3.54)	(-4.81)	(-6.57)	(-9.15)	(-3.66)	(-3.90)	(-5.10)	(-5.62)
	Ret+	1.52***	3.30***	7.01***	8.66***	1.11***	3.37***	6.06***	10.68***
		(7.66)	(10.56)	(14.23)	(10.57)	(5.98)	(10.37)	(10.90)	(9.83)
	Strength ($\beta^+ - \beta^-$)	2.51	5.69	11.57	18.78	2.2	5.92	10.75	20
	ΔStrength								
	(EDGAR−non-EDGAR)	-0.48	-1.45	-4.83	-8.08	-1.41	-3.85	-5.68	-6.89
	Buying additonal shares								
EDGAR	Ret-	-1.53***	-2.18***	-3.55***	-6.39***	-0.90***	-1.45***	-2.30***	-3.93***
		(-5.36)	(-5.63)	(-7.93)	(-10.37)	(-2.86)	(-4.63)	(-5.69)	(-7.09)
	Ret+	0.81**	1.34***	2.43***	4.24***	0.42	0.67*	0.73*	2.20***
		(2.11)	(3.25)	(5.39)	(6.56)	(1.22)	(1.81)	(1.78)	(3.86)
	Strength ($\beta^+ - \beta^-$)	2.34	3.52	5.98	10.63	1.32	2.12	3.03	6.13
non-EDGAR	Ret-	-2.22***	-3.03***	-4.64***	-3.72***	-1.01***	-3.60***	-4.08***	-4.97***
		(-7.86)	(-9.54)	(-9.93)	(-6.63)	(-2.60)	(-8.45)	(-7.11)	(-6.77)
	Ret+	1.03***	2.89***	1.69***	2.53***	0.02	1.00***	1.40**	2.39***
		(3.57)	(9.24)	(3.00)	(4.68)	(0.05)	(2.82)	(2.19)	(3.17)
	Strength ($\beta^+ - \beta^-$)	3.25	5.92	6.33	6.25	1.03	4.6	5.48	7.36
	ΔStrength								
	(EDGAR−non-EDGAR)	-0.91	-2.4	-0.35	4.38	0.29	-2.48	-2.45	-1.23

This table shows the probit regression results of selling or buying additional shares on positive returns and negative returns for EDGAR traders and non-EDGAR traders, conditional on investors trading frequency and firms' information uncertainty for prior holding 1 to 20 days subsample. EDGAR subsample includes EDGAR traders, defined as investors who have more than half of the investor-stock-date observations with Post-EDGAR equals 1. non-EDGAR subsample includes non-EDGAR traders, defined as investors who have less than half of the investor-stock-date observations with Post-EDGAR equals 1. The coefficients are the marginal effect on the average times 100. Observations are at the investor-stock-date level. The dependent variables are the indicators that equal 1 if the investor-stock-date observation is a sell (or an additional buy in the lower part of table). The independent variables are not all shown in the table. Independent variables include: maximum return since purchase between return and zero, minimum return since purchase between return and zero, the indicator for zero return since purchase, the indicator for positive return since purchase, square root of prior holding period measured in holding days, logged purchase price, stock volatility when return is positive, stock volatility when return is negative. Panel A shows the probit regressions results conditional on the trading frequency and firms' analyst coverage. Panel B shows the probit regressions results conditional on the trading frequency and firms size. Panel C shows the probit regressions results conditional on the trading frequency and firms age. Variable definitions are in Appendix A. T-statistics are in parentheses. *, ** and *** denote significance levels at 10%, 5%, 1%.