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DO BEARS PREFER THE WEAK AND THE DOWNTRODDEN? THE EFFECTS OF THE 52-WEEK LOW AND FINANCIAL STRENGTH ON SHORT-SELLER BEHAVIOR

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DO BEARS PREFER THE WEAK AND THE DOWNTRODDEN? THE EFFECTS OF THE 52-WEEK LOW AND FINANCIAL STRENGTH ON SHORT-SELLER BEHAVIOR

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ABSTRACT

This dissertation investigates the effects of a company's financial strength on short-seller behavior around a non-information-producing event. The distance of a stock price to its 52-week high or low does not provide fundamental information, but the price extremes serve as salient price points upon which investors anchor their expectations of future stock performance. Using a large sample of daily short sales data, I investigated the effects of both the proximity to the 52-week low and the financial strength of the underlying company on short-seller behavior. I found that short-selling volume increases as the price nears its 52-week low and that the financial strength of the underlying stock has little effect on short sellers near the 52-week low.

DEDICATION

This dissertation and degree is dedicated to my mom, Jean Carol Rogers Miller, and her late siblings: my uncles Frank, Ralph, and Kenneth, and my aunt Julianne. Their fights for education and education leadership paved the road for me and many others.

LIST OF ABBREVIATIONS

ADR	American Depository Receipts
AMEX	American Stock Exchange
ARCA	Archipelago Exchange
BTD	Book-Tax Difference
CBOE	Chicago Board Options Exchange
CRSP	Center for Research in Security Prices
ETF	Exchange Traded Fund
FINRA	Financial Industry Regulatory Authority
FTD	Fail - to - Deliver
ICI	Investment Company Institute
NASD	National Association of Securities Dealers
NASDAQ	National Association of Securities Dealers Automated Quotations
NMS	National Market System
NYSE	New York Stock Exchange
REIT	Real Estate Investment Trust
SEC	Securities and Exchange Commission
SSR	Short Sale Restricted

ACKNOWLEDGEMENTS

The list of people and organizations to whom I am indebted is rather lengthy, and contrary to what appears to be an accounting school tradition of succinct acknowledgements, I will attempt to thank them all.

First and foremost, I give special thanks to my dissertation co-chairs, Victoria “Vicky” Dickinson and Morris Stocks, who have helped push, pull, and carry me to the finale of this academic odyssey. I am also indebted to my committee members, Dean Mark Wilder and Robert Van Ness. Each has provided steadfast support and direction in this endeavor. Undeniably, my committee’s time, consideration, and guidance have left an indelible mark on my future career in academia as well as life. Last, but not least, I would like to acknowledge the hard work of the PhD program directors, Dale Flesher and Kendall Bowlin.

The path towards a second PhD starts sometime after the completion of the first. I would be amiss if I did not mention my first dissertation’s committee: Bill Werner, Robert Woods, Grace Chatfield, and Michael Sullivan. Without them, there would not have been a first doctorate.

The decision to leave my job in the beautiful town of Monterey Bay, California and to go for another doctorate was greatly influenced by Sharon Lasser, who after a few phone conversations, made me realize that it was just “me and my truck” and that this would be an ideal time to go for “number 2.” She then informed me about the PhD Project and the upcoming annual AAA meeting in San Francisco. There, I met Carolyn Callahan. If there was any remaining doubt of if I should pursue a PhD in accounting, Dr. Callahan eliminated it. There was nothing that was going to get in the way of me getting on this path. Well, except for not having a degree in accounting. It seemed that having one PhD already, but not having a degree in accounting, was too much for some committees. I guess an undergraduate degree in finance, an MBA, Level I of the CFA, a 690 GMAT, and industry experience as a financial analyst and stockbroker was not enough for me to specialize in Capital Markets research in an accounting program. Who knew, right? Next stop: College Station, Texas.

There are many people to whom I owe thanks to at Texas A&M University, but a few I will mention here (more later) are Michael Kinney, Annie McGowan, and Chris Wolfe. The much-needed pep talks (or grants) during my master's in science program and annual AAA meetings during my doctoral studies were invaluable in keeping this mission going. A special thanks must go out to Bret and Laura Scott. Our candid conversations, cigars, and home brews helped bring clarity and confidence in times that were uncertain. I still gather perspective from these conversations, both past and present. From my cohort, Josh Wagner and Katie Koop still drop the occasional pearl on any subject, from homemade gym equipment to anti-aging lotions. I am fortunate for the experiences, friends, and mentors that College Station brought into my life. I wear my Aggie ring with pride.

My fellow University of Mississippi doctoral students, with whom I shared many challenges and triumphs, made this PhD a memorable one. I want to thank Brian Goodson for being the cool voice of reason during my emotional upheavals; Ryan Seay for being the one to “tell it like it is,” as most great auditors are known to do; Derrick Barr-Pulliam, who helped open the door to what was possible and likely; Sydney Manley, a pillar of strength who always had an encouraging word; Chevonne Alston, who always reminded us that a little fun was necessary to get through any graduate program; Andy Almand, who was on a mission from day one, and who showed us how to get in, get done, and get out in an efficient and timely manner; Sara Gochnauer, who always played a great devil’s advocate in helping me formulate research and teaching ideas; Emily Hornock, whose occasional desserts and other goodies brightened everyone’s day; and Josh Simer, who would often discuss the realizations that one only discovers by living through a doctoral program. Special thanks goes to Tyler Williams, who was always good for a practical joke and hosted a number of steak and cigar nights, much needed distractions from PhD life.

PhD programs tend to create friends for life, and my first was no exception. I am grateful for Dr. John Farrish, who was always willing to share a story, a laugh, or give some sound advice. Having already gone through a doctoral program makes for lively conversations, especially comparing and contrasting the world of hospitality to the world of accounting.

They say that sitting at your desk is the new smoking. If that is the case, I was averaging three packs a day. From data gathering on WRDS, to programming in SAS, to waiting for STATA to crunch through 35 million observations, doctoral studies and faculty life can take a toll on the body. I am incredibly grateful for my personal trainers, physical therapists, and personal coaches over these years. K. K. Anderson’s early morning “Abs & Glutes” class made me realize that some personal goals need outside help; Dr. Michael Meurrier seemed to be able to relieve any misalignment pain by getting me to “breathe correctly”; Pamela Hyde guided me to lose 52 pounds in 8 weeks and win $5,000 for my efforts; personal trainer and Baseball Hall of Famer Katie Brownell helped me keep this body “more dateable” in these trying times. Thanks to Laurie Hubbs and Matt Campbell for their support in letting me know that I was not any more (or less) crazy than their other clients.

One of the lessons I have learned on this odyssey is to be willing to go on what us gamers call a “side quest.” I consider side quests in academia to include skills workshops. I am very grateful for Michael Drake’s SAS 2014 workshop and Andy Leone’s PERL/Python 2014 course. Both of these courses continue to benefit me in a number of ways. A boatload of gratitude must go out to Earl Avery and his Strategies for Success in the College Classroom 2017 workshop at Bentley University. Though I consider myself adept at the instructing arts, this program allowed for more growth in areas of which I was not previously aware.

I am grateful to the “Miller Alumni Association,” my former students from every institution at which I have had the pleasure of teaching. To see the active members “after the degree” and “pre-another degree” helps keep my perspective. Through many conversations about school, life, and other things, my alumni help keep me abreast of trends that remain unseen in the world of academia and formal instruction. Special thanks go to Carter M., Katelyn H., Marcus H., Matt S., Kate R. K., and Meredith P. for sharing your experiences, and reminding me to follow my own “Millerisms” that I share in class.

Almost everyone thanks their parents; mine deserve more than just thanks because their work on me started a long time before I was born. They helped create the opportunities for me when there were none. Dad organized sit-ins in the late ’50s and early ’60s and Mom was in the first batch of teachers to desegregate Hillsborough County (Tampa, Florida). Facing and confronting challenges in those days opened up opportunities for me and many others for decades to come. Instilling in me the idea that I would have to “work twice as hard and be twice as smart, to get half the pay, and one quarter of the credit” made it easy to do many of the things that I have done this point. When Dad passed in 1992, Mom did not miss a beat. She made sure the magnitude of their combined support never wavered and was forever present. Life is a little bit easier and new challenges are not as daunting when you have unconditional emotional (and many times financial) support. A simple “thank you” (or 170 words in my acknowledgements) does not do enough; I am forever indebted to you.

To my sister Alicia and her daughter Ashley, who is more like the little sister I never had than a niece: thank you for being there when I needed parental advice but did not want the parental lecture. Thank you for sharing your ups and downs; it gave me a chance to compare and contrast ways to deal with petty situations (or people). Additional gratitude to Ashley who always reminds me to “ask for another 10%” in every type of relationship. Thank you for being there for Mom when I was gallivanting across country earning degrees and spreading business knowledge.

There is family that you are born into and there is family that you choose. I call them "Framily." Joe "The Real Doctor" Robison has been my brother since Cub Scouts in third grade. He and his wife (my sister-in-law), Stephanie, have always been only a call, text, or Facebook posting away. High level logical advice is rare these days, even in the world of academia. I am fortunate to have had you on the team for this long. The strategic financial team of my framily is headed by Frank "Tony" Jones, Jason Smith, and Dr. Dee Newson. They have kept my eye on the set of overall goals and have set the bar in many cases. Burnout is a real issue in any job, and when you have taught as many courses as I have, it is good to have framily that will force a much-needed break. I thank my West Coast framily, Annie, Billy, Je, Jenn, Jay, and Kerry for introducing me (after twisting my arm for 3 years) to music festivals that reset and rehumanize the soul. I cannot wait to be back under the electric sky with this crew. My new life in the Northeast has been greatly improved by Cori and Kim Whittingham. Who knew I would find my University of Florida roommate up here in the Northeast? And to Daniella Rodriguez, whose abundant positive energy, world travels, and rave motherhood have kept the life in me even in these interesting times by persuading me to "buy those tickets and book that trip." And then there is Tylor "Top Billing" Birthisel. If I were to author a book about getting an on-campus graduate degree, I would advise having a friend who is also in an on-campus graduate program but in a totally different field and section of the country. To be able to vent about shenanigans in our respective worlds of academia, finances, and people in general, helped me get through the years knowing that I was not the only one experiencing them. These deep conversations about the worthiness of these situations over numerous rounds of Halo (3, 4, and 5) helped keep me on task with an uplifting persona.

I was fortunate that my talents and experiences in the classroom caught the eyes of George Plesko and Josh Racca. The opportunity to teach in the great state of Connecticut has been an honor and a privilege. I appreciate the opinions and support given to me by Trent Krupa and Sarah Parsons. The sharing of doctoral stories and the occasional proofread is quite reassuring in the final stages of the process.

One of the traits of a great professor/teacher/instructor/coach is the ability to create energy within the minds of your students/players. Jay Thibodeaux may be the best there is and I have worked with and attended seminars of many of the great motivators, coaches, and military leaders of the day. There has never been a conversation with Jay that ended where I did not feel that I could take the entire world head on. Conversations with Jay were instrumental in getting me to this point. I do not think I would have finished this year without his guidance. I am fortunate to have Jay as a colleague, mentor, and friend.

This odyssey could not have been undertaken without generous financial support from a number of organizations. First, the graduate funding from the Patterson School of Accountancy and the Graduate School at the University of Mississippi formed the core of funding I received in while on campus. Special thanks to Royce Kurtz in the AICPA library, helping solve accounting research problems for accountants in the field not only kept me abreast on current issues, but it also provided a nice flow of income during the lean summers. Scholarships from KPMG and the

AICPA were instrumental in allowing me to stay solvent in tight times. Working as a tutor for the FedEx Student-Athlete Academic Support Center allowed me to fund many of my aforementioned side quests. The resources provided by the University of Connecticut for my services were instrumental in strengthening my financial position going into these last days of this process. I am truly indebted to my unnamed option trading mentor as well as the people at Maverick Trading for their unmatched options trading training program during the quarantine.

If there was one factor, one variable, that helped bind all of this together, it would be the PhD Project. Bernie Milano, Marie Zara, Myrna Varner, Cristina Pazos, and Tara Perino helped create the atmosphere with conferences, mentorships, funding, social gatherings, and workshops that helped this doctoral student successfully navigate and complete the process. The value from the colleagues that I have met, the conversations that I have had, and the camaraderie that has been formed, I will carry with me forever.

Many times, I was questioned and ridiculed for the pursuit of a second PhD. They would ask, “Your background is finance, why accounting?” My reply would be: “Why would an assassin go to med. school?” Today, the traditional large employers of accounting graduates are looking for new employees with “other skills in addition to some familiarity with accounting methods.” I am fortunate for my mentors in both academia and industry who reminded me of the upcoming trends that I predicted several years ago.

Sometimes, motivation is needed until something becomes a habit. I leave with words from people who have gone through tougher challenges than a mere second doctoral degree and found high levels of success. The sources of these words vary but are effective, nonetheless.

From Bruce Lee (1940–1973): “If you follow the classical pattern, you are understanding the routine, the tradition, the shadow – you are not understanding yourself.”

The second is the fourth law of the Navy:

On the strength of one link of the cable
Dependeth the might of the chain.
Who knows when thou mayest be tested?
So live that thou bearest the strain!

From David Goggins: “Be uncommon amongst uncommon people.” The last is a recent one given to me by a great friend and Halo fire team member; it is a clever mix of military history and science fiction: “Chris, you have armor and shields! Turn into the torpedoes and engage at point blank range! Concentrate all fire on that Super-Star Destroyer!”

And for anyone that I have forgotten to thank, I’ll get you next time.

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I. INTRODUCTION

One thesis in the body of literature on investor behavior posited that the long investor uses salient points of a stock’s price series to initiate trading decisions (George & Hwang, 2004; Grinblatt & Keloharju, 2001; Huddart et al., 2009; Li & Yu, 2012). Additionally, research based upon laboratory experiments showed that prior price extremes affect both buying and selling (to close) decisions. But the literature addressing short-seller behavior at these extremes is scarce. Lee and Scotto-Piqueira (2016) examined short-seller behavior around 52-week highs and found that short selling is negatively associated with the nearness of the 52-week high. However, research has not addressed short-seller behavior around the 52-week low. Research has shown that psychological heuristics, such as anchoring and adjustment (Tversky & Kahneman, 1974) and disposition theory (Shefrin & Statman, 1985), influenced investor trading. The traditional accounting and finance literature provided numerous studies on how the stock market reacts to the release of new financial information; less prevalent is research on how reference points influence behavior to non-fundamental events. In this dissertation, I demonstrated that proximity to the 52-week low, a non-fundamental information-producing event, affects short-seller behavior. This behavior is conditional on the financial strength of the underlying firm.

Short sellers are sophisticated, well-informed investors that use fundamental and non-fundamental data in their decision making (Dechow et al., 2001; Diamond & Verrecchia, 1987; Drake et al., 2011). Examining how short sellers behave around 52-week lows conditional on the financial strength of the underlying company allowed me to analyze how and when short seller integrate prior financial statement–based information with non-fundamental stock price movement. The difference between the highest and lowest prices of a stock over a set period, typically a year, defines its trading range. Although comparing the current price to a prior price extreme does not yield new fundamental information, prior literature maintained that investors use price extremes as salient reference points in making trading decisions.

However, fundamental information regarding the underlying company also affects short-selling behavior (Dechow et al., 2001; Drake et al., 2011, 2015). Accordingly, I investigated whether financial strength, calculated using fundamental data, affects short-seller behavior as stock price approaches and crosses its 52-week low. By incorporating fundamental data into my investigation, I provided evidence to whether existing fundamentals (i.e., financial strength) are a factor in short sellers' decision-making around stock events that do not involve new fundamental information.

This dissertation reports the results of several regression models using three measures of short-selling activity as the dependent variable. I found that short-selling volume increases near the 52-week low. Models show that this relationship holds for short-selling volume before and after the stock price has crossed the 52-week low. I further investigated the effects of financial strength on short-seller behavior near the 52-week low. The results show that short sellers do not consider the fundamental strength of the company when the stock's price is near the 52-week low. These results are robust to various sensitivity analyses. These analyses include price levels, 52-week price ranges, time windows, and dividend policies. This dissertation fills the gap in the literature by investigating short-seller behavior at the lower ends of price extremes. Specifically, I investigated the effects of both non-fundamental and fundamental data on short-seller behavior by investigating short interest, daily short sale volume, current stock prices, and a financial strength variable based on Piotroski's FSCORE (2000).

This dissertation contributes to the literature by studying the activity of short sellers around an important salient reference point. Knowledge about patterns in short selling has important implications for both short and long investors, as either type of investor could be on the other side of a trade. Specifically, this study contributes to our understanding of short sellers by helping form future short sale volume expectations based on recent financial and pricing and fundamental information of the underlying company. Securities lending markets are decentralized and opaque (Cohen et al., 2007). Participants in these markets look for any evidence that can explain or predict demand. Evidence that short sellers behave differently around 52-week lows due to potential biases in response to publicly available information allows brokerages, stock lending institutions, and large individual investors to negotiate lending fees more efficiently and thus match prices and supply with expected demand.[1] The model I developed will allow investors to better form expectations on short-selling volume around 52-week lows.

The findings in this dissertation will aid investment managers in optimizing decision making with respect to stocks near their 52-week lows. Though managers may not be able to sell the stock, they will know that—by lending the shares to short sellers—there is an alternative means of earning income. Adams et al. (2014) found that 70 percent of mutual funds studied engaged in some level of securities lending and that the typical fund lends about eight percent of its portfolio. Adams et al. (2014) also discovered that short seller demand spikes increase

[1] "The income which a customer receives in exchange for shares lent depend upon loan rates established in the over-the-counter securities lending market. These rates can vary significantly not only by the particular security loaned but also by the loan date." See https://ibkb.interactivebrokers.com/node/1838/.

abnormal loan fees by 18.5 basis points (3.2 to 21.7). Given that U.S. mutual fund total assets are greater than $15.65 trillion (ICI, 2016), and investment managers try to enhance returns by lowering management fees (an average of 67 basis points) (Adams et al., 2014; Oey & West, 2016), the findings of this study are economically significant. Moreover, the financial service industry is allowing less sophisticated investors to participate in stock lending, such that my findings will help individual investors develop better trading and lending strategies as well.[2]

The rest of this dissertation is organized as follows: Section II reviews the prior literature and presents the development of hypotheses. Section III provides a summary of models, data, and methods, while Section IV discusses the related findings. Section V provides conclusions, limitations, and opportunities for future research.

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[2] Investment brokers allow clients to willingly lend their shares to short sellers for the purpose of increasing client income. These accounts can be as small as $50,000. For an example, see https://ibkb.interactivebrokers.com/node/1838/.

II. BACKGROUND AND HYPOTHESES DEVELOPMENT

Short Selling

Short selling is the process of selling something that one does not already own with the intent of buying the asset later for a lower price. In other words, one wants to "sell high and then buy low" instead of the better known "buy low and then sell high." For this dissertation, the assets are stocks, but many items are sold short.

The short seller creates a position by first borrowing the shares from a stock lender. Lenders typically consist of brokerage houses or large financial institutions but can include individual investors and pension funds. Borrowing shares creates lending fees (costs) for the borrower and income for the lender. The short seller then takes the borrowed shares and sells them in the market. When short sellers want to close their position, they then buy the stock and deliver the purchased shares to the borrower. Short sellers earn a profit if they buy back the shares for less than they initially sold them for, net of fees. In other words, "winners" for short sellers consist of stocks that have decreased in price (net of fees). By construction, short sellers have limited profit potential (the amount the shares were sold for) and unlimited loss potential since a stock's price has no upper bound.

Due to the elevated levels of risk to the short seller, the lender, and the market, the Federal Reserve Board heavily regulates the process of short selling. The Federal Reserve Board, through Regulation T, requires that short sale transactions of stocks are executed in a margin account. Regulation T requires a margin of at least 150 percent of the market value of the security on all short sales, which means that 100 percent of the proceeds of the short sale plus 50 percent must be deposited into the margin account. Short sellers do not receive the proceeds from their short sales until the position is closed out.

Since 1934, the Federal Reserve has changed the initial margin requirements in stocks twenty-three times. The current rate, set in 1974, is 50 percent (Kwan, 2000). The additional 50 percent requirement can rise due to the rule that a minimum of $5 per share must be held in margin when shorting a stock priced at $5 or more. Stocks priced less than $5 per share require the greater of 100 percent or $2.50 per share to be held in the margin account. Short sellers regard the mandatory initial deposit as a trading expense. The following example helps illustrate the effect of low-priced stocks on the margin deposit requirement: Investor A wants to short 1,000 shares of ABC stock priced at $20 per share ($20,000). The amount that Investor A would need to deposit to execute this transaction is $10,000 (50 percent of $20,000). Investor B wants to short 2,500 shares of XYZ stock priced at $8 per share (again, $20,000). The amount Investor B would need to deposit to execute this transaction is $12,500 (the greater of, $5 per share times 2,500 shares or 50 percent of $20,000).

The lower-priced stock of Investor B creates an effective initial deposit of 62.5 percent as compared to Investor A’s 50 percent.

Due to the expensive nature of short selling, short sellers place significant effort into stock selection and trade timing. Unlike long investors, short investors lose value due to fees when “holding” a position open. Research frequently assessed the effect of borrowing fees on short-selling behavior and found that fees influence short sellers to close their positions quickly (Cohen et al., 2007; Kolasinski et al., 2013).

Uptick Rules and Bans

To prevent the abusive use of short selling, the Securities Exchange Act of 1934 created Rule 10a-1. The SEC adopted the rule in 1938. The rule only allowed short sales to take place at an uptick or a zero-uptick for exchange-listed stocks. This required short sales to only be executed above the last trade price or at the same price if the last trade price was higher than the most recent trade at a different price. This rule was created when trading volume was smaller and strategies not as complex. The primary tick size, or the minimum price increment for a listed stock, was 1/8 of a dollar.

In 1994, the National Association of Securities Dealers introduced a “bid test” for NASDAQ National Market stocks since the NASDAQ was not operating as an exchange. This bid test, more formally known as NASD Rule 3350, specified that whenever the bid is a downtick relative to the previous bid, traders may only short sell at prices no lower than one penny above the bid.

The SEC elimination of the original uptick rule went effective July 6, 2007. After extensive studies by third-party researchers, it was found that prices of stocks subject to the uptick rule did not fall any slower than stocks that were not subject to the uptick rule during times of market stress. It seemed that the market, buyers, long and short sellers, were able to find equilibrium prices despite having a limit on short selling.

After years of creating, collecting, and inflating assets tied to real estate, the solvency of many financial institutions was put into question in late 2007 and early 2008. The assets that the financial institutions used to create income and to bolster balance sheets were being revalued for less. Subsequently, the market viewed the stocks of these financial institutions as overpriced and acted accordingly. As with many prior significant declines in overall market valuation, short selling received a significant amount of the blame. On September 19, 2008, under pressure from the Federal Reserve and the United States Treasury Department, the SEC, along with the Financial Services Authority of the United Kingdom created a ban to prohibit short selling securities of financial services companies. The temporary ban included 799 financial institutions and went into effect immediately with an initial termination date of October 2, 2008. The SEC emergency order included a requirement that institutional managers report new short sales of certain securities. The order also temporarily eased the ability of security issuers to buy back their securities. This was believed to help provide liquidity during a time of “unusual and extraordinary market volatility” (SEC, 2008, para. 8).

Christopher Cox, SEC Chairman said:

> The Commission is committed to using every weapon in its arsenal to combat market manipulation that threatens investors and capital markets. The emergency order temporarily banning short selling of financial stocks will restore equilibrium to markets. This action, which would not be necessary in a well-functioning market, is temporary in nature and part of the comprehensive set of steps being taken by the Federal Reserve, the Treasury, and Congress. (SEC, 2008, para. 3)

Though these actions seemed to quell the anxiety of the market, it would take fewer than three months for Christopher Cox to comment on the ban: “While the actual effects of this temporary action will not be fully understood for many more months, if not years, knowing what we know now, I believe on balance the commission would not do it again.” Cox continued, “The costs appear to outweigh the benefits” (Younglai, 2008, para 6).

One of the benefits of the actions taken by the SEC in the fall of 2008 was the adoption of Rule 204T. 204T addressed the close-out requirement, which, along with Rule

203(b)(1)and(2), reinforced proper short selling transactions. There were short sale transactions initiated by investors that did not possess or have located, borrowed shares to be delivered on the date of delivery. These transactions were called “naked” short sales. If the short sale was not closed out quickly and the borrowed shares did not exist, then the short seller would Fail-To-Deliver. In the fall of 2008, the SEC stated that “the Commission adopted Rule 10b-21, referred to as the “naked” short selling antifraud rule. Those who deceive about their intention or ability to deliver securities in time for settlement are committing fraud, in violation of Rule 10b-21, when they fail to deliver securities by the settlement date” (SEC, 2015, para 20). Additionally, the SEC stated that “Selling stock short and failing to deliver shares at the time of settlement to drive down the security’s price [is a] manipulative activity, in general, [and] would violate various securities laws, including Rule 10b-5 under the Exchange Act” (SEC, 2015, para 21).

As seen in Liu (2012), the number of naked short sales dropped significantly in the fall of 2008. The naked short interest percentage (number of naked shares per shares outstanding) fell to less than 1% of 1%. The SEC provides the Fail-to-Deliver data on their website. Furthermore, the amounts of transactions that fall into FTD are typically financially insignificant and more likely due to error than malicious intent.

To further bolster investor confidence in the markets, the SEC adopted Rule 201 of Regulation SHO. According to the SEC, “The rule is designed to preserve investor confidence and promote market efficiency, recognizing short selling can potentially have both a beneficial and a harmful impact on the market” (SEC, 2010, para 3). This rule “restricts the price at which short sales may be affected when a stock has experienced significant downward price pressure. Rule 201 is designed to prevent short selling, including potentially manipulative or abusive short selling, from driving down further the price of a security that has already experienced a significant intra-day price decline, and to facilitate the ability of long sellers to sell first upon such a decline" (SEC, 2015, para 9).

> Rule 201 generally requires trading centers to establish, maintain, and enforce written policies and procedures that are reasonably designed to prevent the execution or display of a short sale at an impermissible price when a stock has triggered a circuit breaker by experiencing a price decline of at least 10 percent in one day. Once the circuit breaker in Rule 201 has been triggered, the price test restriction will apply to short sale orders in that security for the remainder of the day and the following day, unless an exception applies. (SEC, 2015, para 11)

The “impermissible price” is a price at or below the national best bid.

The following examples help visualize the effect of the Rule 201 Short Sale Restriction on a short seller wanting to place an aggressive short sell:

Non-Restricted trade:

Investor A is looking to aggressively short stock ABC. ABC closed the prior day at $75.46 and is currently trading with a bid/ask of 70.55/.65. Investor A decides to put in the short sell order for 70.55. This is called “hitting the bid.” This technique of hitting the bid allows sellers (long and short) to execute trades immediately. Once executed at 70.55, this reduces the number of buyers at the 70.55 price level. Lowering the number of shares at the bid also lowers the chance of execution for the other sellers waiting for orders to fill at the higher ask. This may put pressure on the other sellers (long and short) to lower their asks, which would put downward pressure on the price.

Restricted trade:

Investor A is looking to aggressively short Stock ABC. ABC closed the prior day at $75.46 and is currently trading with a bid/ask of 62.45/.55. Because the stock is trading more than 10% below its previous day closing price (or the trading day before), the stock is said to be trading SSR or Short Sale Restricted. Per Rule 201, Investor A will not have an order at the bid posted, so Investor A decides to put in the short sell order for 62.46[3]. Though not the bid, the trade will probably not get executed immediately, but it may entice a buyer to purchase at the slightly higher "bid plus a penny." Just as in the non-SSR trade, selling at the "bid plus a penny" puts pressure on the other sellers to lower their asks. This would put pressure on long sellers to "hit the bid" to get in front of the short sellers. The effectiveness of Rule 201 is still in question. Short sellers can still place pressure on a stock by influencing long sellers to "hit the bids" for them. Additionally, investors, both buyers and sellers, will tend to buy/sell at or near the ask/bid when timeliness of execution is desired.

Fundamental Analysis

Research shows that long investors distinguish winning investments from losing investments by comparing their intrinsic value to their market value. Frankel and Lee (1998) advised long investors to buy stocks that lag their fundamental value, which produces positive abnormal gains over three-year investment windows. Other research indicated that long investors can use specific financial performance signals to refine their trading strategy.[4] Many of these strategies seek to create returns better than the overall market by taking advantage of the market's inability to immediately and fully adjust to these financial signals. Examples of these

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3 The decimalization of the tick size in 2001 allows for more frequent "upticks" and easier selling at or near the bid.

[4] A signal refers to a specific configuration of several fundamental variables (Lev & Thiagarajan, 1993).

strategies include the use of unexpected earnings (Bernard & Thomas, 1989), total accruals (Sloan, 1996), capital expenditures (Beneish et al., 2001), market capitalization (Fama & French, 1992), revenue growth (Lakonishok et al., 1994), and dividend decreases (Michaely et al., 1995). Subsequent research incorporates multiple fundamental signals simultaneously. Ou and Penman (1989) explored sixty-eight financial statement variables univariately to determine which signals relate to future earnings increases. They combine the significant variables to compute predicted performance for each stock and then use that information to form two-year-long and short portfolios. They find that financial statement information is not fully priced by the market. Ou and Penman (1989) further used the associated fundamental signals to predict value in combination with the price to earnings (PE) ratio. They found that these measures impact future earnings but differentially affect stock prices.

Lev and Thiagarajan (1993) employed twelve financial signals, used by financial professionals, to create a composite score. They found that the composite score more fully captures investors' assessments of a company's future financial performance than a time-series of earnings measure. Abarbanell and Bushee (1997) examined the underlying relationship between fundamental signals and security prices by investigating the relationship between accounting-based fundamental data and changes in future earnings. They found evidence that supports many, but not all, of the financial variables studied by Lev and Thiagarajan (1993) that evaluated future earnings performance. Unlike Lev and Thiagarajan (1993), Abarbanell and Bushee (1997) did not aggregate the financial signals into a single score. Piotroski (2000) used a composite score of accounting-based fundamental data (FSCORE) on a broad portfolio of high book-to-market firms (i.e., value stocks) to create a trading strategy that earned at least 7.5

percent annually.[5] Piotroski (2000) also found that the FSCORE was less effective with low book-to-market firms (i.e., glamour firms) than with high book-to-market firms. Conversely, Mohanram (2005) used a composite score (GSCORE) that combines five commonly used fundamentals, including cash flow, assets, revenue, and earnings, with variables tailored for growth firms, such as R&D spending, capital expenditure, and advertising, to study the earnings-returns relation. Of these eight signals, five (two) are defined to equal 1 if the firm's value is greater (less) than the contemporaneous median for all low book-to-market firms in the same industry, and 0 otherwise. Mohanram (2005) also found that the GSCORE does not capture value as well when used with high book-to-market firms rather than with low book-to-market firms.

Short Seller Fundamental Analysis

Prior research found that short sellers behave as if they use fundamental-to-price ratios to short a stock (Dechow et al., 2001; Diether et al., 2009; Drake et al., 2011). Dechow et al. (2001) used a short interest-based variable as a proxy for short-seller behavior and found evidence that short sellers use accounting information to distinguish between firms that have poor fundamentals and firms with low fundamental-to-price ratios due to temporarily elevated stock prices. Dechow et al. (2001) used ratios that research shows are positively correlated with future returns. They used cash flows-to-price (Basu, 1983; Lakonishok et al., 1994; Sloan, 1996), earnings-to-price (Basu, 1983; Fama & French, 1992), book-to-market (Fama & French, 1992; Rosenberg et al., 1985; Stattman, 1980), and value-to-market ratios (Dechow et al., 1999; Ohlson, 1995) to evaluate short-seller behavior. They found that short-sellers position

[5] Piotroski's (2000) FSCORE is a composite score of nine variables. Each of the variables receives a value of 1 if return-on-assets is positive, cash flow from operations is positive, change in return-on-assets (annual) is positive, accruals are negative, leverage decreases or is zero, increase in current ratio, no issuance of common equity, increase in gross margin, and positive change in asset turnover, otherwise zero. Higher FSCORE values indicate a stronger financial condition.

themselves in the stocks they deem overpriced in relation to the company's fundamentals. Short sellers then close their positions as the company's market value falls toward a price better supported by its fundamentals. Dechow et al. (2001) also found that short sellers use information beyond that of the fundamental-to-price ratios in their trading actions. They found that short sellers also consider transaction costs when selecting stocks to short.

On January 2, 2005, the SEC introduced Regulation SHO (Reg SHO), a set of new regulations governing short sales in U.S. markets. Along with the creation of rules to reduce the occurrence of unethical trading, Reg SHO required the dissemination of short selling trade data to the public.[6] Diether et al. (2009) used 2005 SEC-mandated short selling trade data as well as short interest data to study the relationship between short selling and returns (preceding and future). By analyzing the data along with corresponding fundamental data, they found evidence that short sellers can locate and trade on short-term deviations of a company's stock price from its fundamental value. They also found that significant increases in short-selling volume precede negative abnormal returns (for longs) as much as five days out from the increase in short-selling volume.

Drake et al. (2011) extended the work of Dechow et al. (2001) by comparing the use of 11 fundamental and fundamental-to-price variables between analysts and short sellers.[7] Drake et al. (2011) found these 11 ratios that analysts use are also significant to short-seller behavior.

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[6] A 2010 revision of Reg SHO (Rule 201) created an "Alternative Uptick Rule" which requires markets to only allow short sales on an uptick. This rule is triggered when the price of the stock falls 10% from the previous trading day's close. To ensure an order is filled, a short seller simply needs to place their order for 1 cent (or smaller) above the current best bid. Theoretically, this helps prevent short sellers from accelerating the downward momentum of a security's stock decline by putting sell orders at the bid. The trigger stays in effect for the remainder of the trading day and the following trading day.

[7] The following is the list of variables and each variable's normative correlation with subsequent returns. Drake et al. (2011) used unexpected earnings (positive), total accruals (negative), capital expenditures (negative), market capitalization (negative), earnings-to-price (positive), book-to-market (positive), stock turnover (negative), sales growth (negative), long-term-growth forecast (negative), forecast revision (positive), and stock momentum (positive).

Drake et al. (2011) found that short sellers and analysts interpret the information provided by fundamentals differently regarding future returns. Analysts tend to recommend stocks with high recent growth, low book-to-market, and high accruals, which prior research shows is negatively related to future returns. Short sellers use all 11 fundamental signals in line with prior research. Their findings also suggested that short interest provides information about future returns beyond the eleven fundamental ratios used and find a highly profitable trading strategy that allows investors to trade with short sellers when the short interest signals strongly conflict with consensus analyst recommendations. In a more recent study, Chi et al. (2014) used Piotroski's (2000) composite FSCORE as a control for accounting predictors of future returns when analyzing the relationship between short-seller behavior and the mispricing of book-tax differences. They found FSCORE to have a significant effect on the interaction between short-seller behavior and book-tax differences. The authors posited that short sellers are more likely to use and comprehend book-tax difference information better than the "average less-attentive" investor. Moreover, they found that short sellers profitably take advantage of BTD mispricing by entering positions against less-sophisticated investors.

Behavioral Finance and Economics

> *Even apart from the instability due to speculation, there is the instability due to the characteristic of human nature that a large proportion of our positive activities depend on spontaneous optimism rather than mathematical expectations, whether moral or hedonistic or economic. Most, probably, of our decisions to do something positive, the full consequences of which will be drawn out over many days to come, can only be taken as the result of animal spirits—a spontaneous urge to action rather than inaction, and*

not as the outcome of a weighted average of quantitative benefits multiplied by quantitative probabilities.

–John Maynard Keynes, *The General Theory of Employment, Interest, and Money*

The traditional capital market research paradigm assumes that "rational" agents exist in financial markets (Barberis & Thaler, 2003). Rationality implies the immediate use of new information such that agents adjust their beliefs and actions correctly and accordingly. These actions would support the normative findings of utility maximization[8] consistent with Von Neumann and Morgenstern (1947) and Savage (1972). However, neither the market nor its agents necessarily behave rationally: numerous studies examining stock returns and individual trading behavior have provided evidence of irrationality (Barberis & Thaler, 2003; Lee, 2001).

For example, DeBondt and Thaler (1985, 1987) found that investors show a tendency to overreact to information when making investment decisions. They document that stock prices are biased with excessive optimism or pessimism and that these biases shift prices away from fundamental values. Specifically, the authors analyzed the returns of prior winning and losing stocks and determined that investors overreact to short-term earnings changes. These overreactions create opportunities for both the long and short investor.

Both behavioral finance and behavioral economics have evolved due to the limitations of the traditional efficient markets paradigm. Supporters of efficient markets believe that by using arbitrage, rational investors will prevent irrational investors from influencing prices for extended periods of time.[9] Arbitrage provides markets a mechanism to ensure that investment prices do

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[8] Utility refers to the total satisfaction received from consuming a good or service. A consumer's utility is determined with behavioral theories which assume that the consumer will strive to maximize their utility.
[9] Arbitrage is an investment process that offers riskless profits at no cost. Many textbooks define arbitrage as "the simultaneous purchase and sale of the same, or similar, investment in two different markets for advantageously different prices. Arbitrage exists due to inefficiencies in the market and would not exist in an efficient market" (Sharpe & Alexander, 1990).

not deviate from fundamental value in the long run. However, when rational and irrational investors interact, irrational investors can have significant effects on prices. In fact, prior research has found that price does not correct to its fundamental value expeditiously or sometimes at all (Barberis & Thaler, 2003; Keynes, 1936; Shiller, 2003; Shleifer, 2000), thus providing evidence of the limits of arbitrage (Lee, 2001; Shleifer, 2000; Shleifer & Vishny, 1997).

To explain investor irrationality, behavioral economists typically rely on psychology-based theories on cognitive bias. People form specific types of beliefs—known as heuristics—to make judgments and reach decisions with relative speed (Barberis & Thaler, 2003; Tversky & Kahneman, 1974;). These heuristics may result in cognitive biases. Financial scientists believe that overlapping factors of overconfidence, optimism, wishful thinking, belief perseverance, anchoring, and information availability contribute to the formation of beliefs that, in turn, influence the financial markets. Research provides extensive evidence that overconfidence affects judgments. For example, Davis et al. (1994) found that redundant information increases subjects' self-assurance in their investment decisions. Slovic et al. (1977) showed the effects of unwarranted certainty on decision-making, determining that people regard events with an 80 percent likelihood of occurrence as certainties, while events with a 20 percent likelihood of occurrence are presumed impossible.

Likewise, research revealed that subjects tend to hold unrealistic and optimistic views of their own skill and forecasting ability (Weinstein, 1980). In a number of experiments, Weinstein found that his subjects overestimated (underestimated) the probability that they will experience positive (negative) future events. Moreover, Lord et al. (1979) demonstrated that people excessively adhered to their initial opinions even in light of new evidence to the contrary. In their seminal capital punishment study, they documented that subjects willingly accepted "confirming" evidence to their initial positions on complex social issues while simultaneously rejecting "disconfirming "evidence. They also found that people were reluctant to search for contradictory evidence to their initial opinion. Another example of belief perseverance is when a proponent of the efficient markets hypothesis does not revise their beliefs in the face of contrary evidence of inefficient markets.

Like belief perseverance, confirmation bias affects the way subjects interpret and recall information. Confirmation bias takes place when subjects interpret additional evidence as support for existing beliefs even when new evidence contradicts the initial belief. For example, suppose an investor is privy to information suggesting that a company is about to be acquired by a larger, more successful firm. Because the public announcement of the acquisition should increase the target's stock price, the investor considers buying shares of stock in the target. As the investor searches for additional information related to the possible acquisition, they tend to overweight articles that confirm the likelihood of the acquisition while underweighting articles reporting the contrary. Additionally, confirmation biases drive polarization. Instead of additional information reducing disagreement between two groups, repeated instances of information can fortify each opponent's views.

Anchoring occurs when a person uses an initial piece of information to make subsequent decisions or judgments (Tversky & Kahneman, 1974). People attach or "anchor" themselves to the initial piece of information. This is problematic if subjects insufficiently correct decisions thereafter in light of new information. An example of anchoring bias occurs when an investor purchases stock of XYZ company for $75 a share, then the investor becomes fixated on that price for future transactions of the same stock, regardless of subsequent changes to the fundamental value of the stock. This can happen even when the “anchor,” though salient, is completely irrelevant (Tversky & Kahneman, 1974).

In 1974, Kahneman and Tversky, using nine separate studies, found that people tend to use more readily available facts to form beliefs, resulting in availability bias. Availability bias in investing occurs when information that is most recent, relevant, or extreme influences future investing beliefs or decisions. In 2008, the Standard and Poor’s 500 Index declined 37 percent but increased 26.5 percent in 2009. In 2010, Franklin Templeton Investments performed a survey on investors’ views on the performance of the market. Due to the devastating performance of 2008, two-thirds of respondents believed that the market declined or remained flat for 2009. This showed how the disturbing results of the recent past affects views of later events.

Time limitations also restrict decision makers’ processing abilities and attention. When facing many possibilities, people narrow the opportunity choice set to options that hold their attention. In other words, attention biases form when subjects are “led” to a subset of options. An example of attention bias is when the volume of a stock immediately increases due to a well-known financial journalist mentioning the stock during her newscast. Though this heuristic can expedite decision making, it can also lead to sub-optimal choices (Gabaix et al., 2003; Pashler, 1989; Pashler & Johnston, 1998).

Many of the biases previously discussed interact with one another. Due to the rapid pace of information exchange within financial markets, investors must make decisions quickly. If a trusted source guides their attention to a specific investment, they may execute a trade prior to verifying the accuracy of the information. Moreover, the overlapping biases shape expectations. Biased expectations result in irrational behavior. Differences in expectations across investors manifest in price and volume fluctuations in the market (Bamber, 1986).

Investor Preferences

Research that studies human behavior and risky choices must make assumptions about subjects' preferences. Many models assume that investors use an expected utility framework. An expected utility framework governs preferences under uncertainty. Von Neumann and Morgenstern (1947) posited that if preferences satisfy four axioms (completeness, transitivity, continuity, and independence),[10] the statistical expectation of outcomes represent these preferences. However, prior research demonstrated that individuals systematically violate expected utility theory (Akerlof & Shiller, 2009; De Bondt & Thaler, 1985; Keynes, 1936; Scitovsky, 1976; Thaler et al., 1997). Understanding these violations is essential to interpreting financial market phenomena (Barberis & Thaler, 2003; Lee, 2001; Shiller, 2015). Additionally, these anomalies have led to theories that better explain experimental and real-world phenomena. Prospect theory is one such theory (Barberis et al., 2001; Barberis & Thaler, 2003; Kahneman & Tversky, 1979; Tversky & Kahneman, 1992).

Prospect Theory

> Prospect theory has no aspirations as a normative theory: it simply tries to capture people's attitudes to risky gambles as parsimoniously as possible. Indeed, Tversky and Kahneman (1986) argue convincingly that normative approaches are doomed to failure because people routinely make choices that are simply impossible to justify on normative grounds, in that they violate dominance or invariance.[11]
>
> –Barberis and Thaler, *A Survey of Behavioral Finance*.

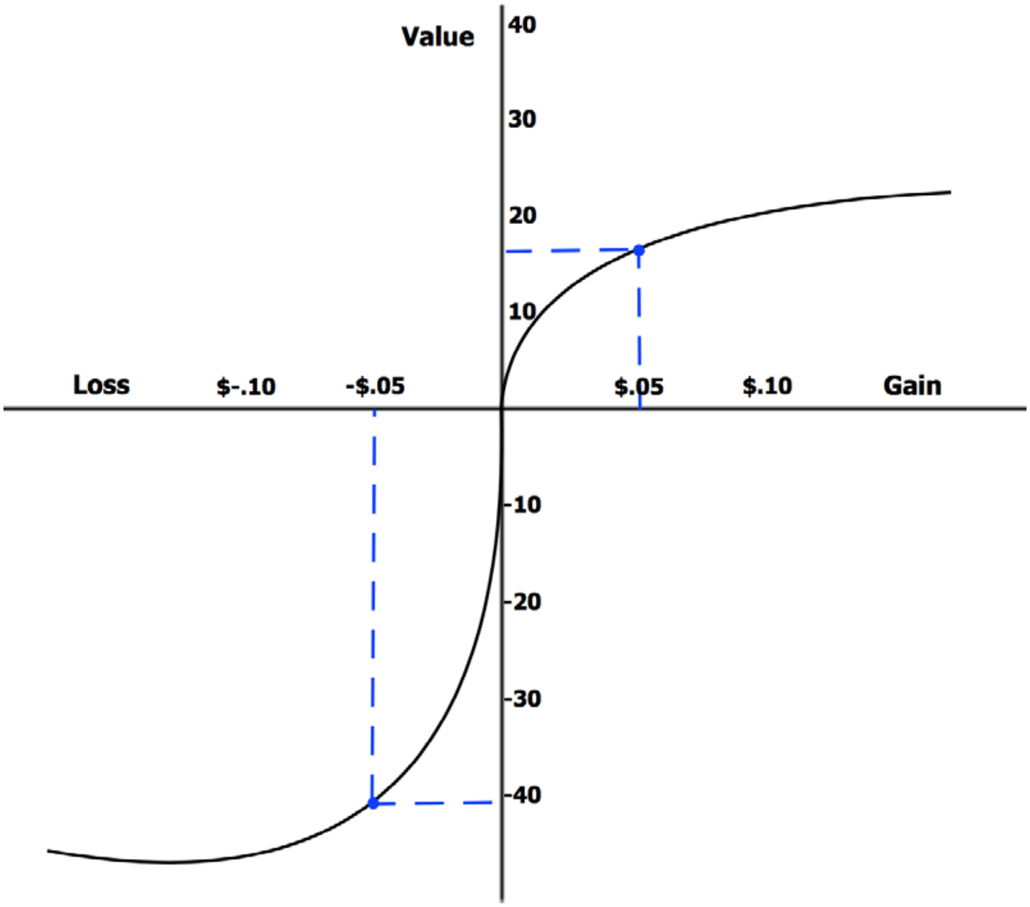
[10] Completeness assumes the decision-maker has defined preferences. Between outcomes A and B, the individual either prefers outcome A, outcome B, or is indifferent. Transitivity assumes that preferences stay consistent. If A is preferred to B and C is preferred to A, then C is preferred to B. Continuity assumes that there is a defined point between being "worse than" and being "better than" a given middle choice. Independence (of irrelevant alternatives) assumes that the preference between outcome A and B holds stable in the presence of an unrelated outcome.

[11] Dominance, one of the four assumptions of expected utility theory, states that if one option, A, is better than option B in one state and at least as good in all other states, the dominant choice is option A. Invariance, another assumption of expected utility theory, claims that the preference between options is independent of their descriptions.

Kahneman and Tversky (1979) found that people are risk averse—as demonstrated by an "S"-shaped value function, generally (see Figure 1). The center of the graph is a reference point by which to measure gains and losses in wealth utility. The concave function in quadrant I represents gains, while the convex function in quadrant III represents losses. The resulting diagram reflects risk aversion in the gain quadrant and risk-seeking in the loss quadrant. Simply put, individuals, on average, weight losses to a greater degree than an equivalent amount of gains. As seen in Figure 1, the magnitude of perceived value is at least twice as large for losses when compared to an equivalent gain—as seen in the steepness of the loss portion of the value function. This outcome signifies that subjects view losses as more painful than the pleasure of an equivalent gain. Kahneman and Tversky characterized this loss aversion as "prospect theory." A salient example of prospect theory is when investors do not deposit their cash in an interest-bearing account because they want to avoid paying taxes on the interest. Even though the interest outweighs the tax, they are more averse to the loss.

Figure 1

Illustration of Prospect Theory



Disposition Theory: Holding on too long or selling too soon…

> *One of the most significant and unique features in Kahneman and Tversky's approach to choice under uncertainty is aversion to loss realization.*
>
> *–Shefrin and Statman, The Disposition to Sell Winners too Early and Ride Losers too Long: Theory and Evidence*

Shefrin and Statman (1985) extended prospect theory to the area of investor behavior, finding that investors will display behavior inconsistent with expected utility maximization. Long investors tend to hold on to their losing investments too long and sell their winners too soon. The “disposition effect,” so labeled by Shefrin and Statman (1985), represented the tendency to hold a declining investment in the hope of a turnaround. They related this phenomenon to prospect theory’s steepness of the loss region of the value function. As found in Kahneman and Tversky (1979), investors are less willing to accept the pain of being wrong than they are the satisfaction of being right. They provided evidence that people view losses twice as painfully as they view an equivalently sized gain. Odean (1998) offered additional evidence of the disposition effect on investor decision making. Odean investigated ten thousand accounts at a large discount brokerage from 1987 to 1993 and found a significant preference for selling winners and retaining losers. He determined that the proportion of gains realized was 14.8 percent compared to 9.8 percent for the proportion of losses realized—a significant difference. Moreover, Jordan and Diltz (2004) noted that 62 percent of day traders in one study held losing trades longer than winning trades for significant amounts of time. They tested the possibility mentioned by Odean (1999), “The investors who believe in trend may buy previous winners to which their attention has been directed, while those who believe in reversion buy previous losers to which their attention has been directed.” Jordan and Diltz (2004) provided evidence that the disposition effect better explains day trader behavior than belief in mean reversion by regressing trade profitability versus holding time. They found a significant inverse relation between profitability and time held and inferred that the disposition effect better explains the phenomena.

Grinblatt and Keloharju (2001) offered another cause for the disposition effect, suggesting that long investors hesitate to realize their losses because selling at a loss corroborates that they made a wrong decision. O’Neil and Morales (2005) described the actions and reasoning of long investors who fall victim to the disposition effect when the value of their investments starts trending lower:

> Once caught in a bear market, many [long] investors, both individuals and institutional alike, employ the face-saving crutch that they are actually long-term investors and therefore correct in their judgement because they are still getting dividends on their stock holdings. This is not only naïve, but foolish and risky, since the money received in dividends can be wiped out in one day's correction. This person who sells nothing at all when a bear market begins will find the pressure building steadily as the months of decline continue. It is just this person who may be finally overcome by fear and panic, only to sell out at the bottom with tremendous losses. (p. 5)

Dhar and Zhu (2006) investigated the individual characteristics of the investor and uncovered that trading heuristics such as the disposition effect correlate to specific investor characteristics. They found that wealthier investors, those with greater investment knowledge, those who trade more often, and those who work in professional occupations show a significantly smaller disposition effect.

Shifting Reference Points

> *There are situations in which gains and losses are coded relative to an expectation or aspiration level that differs from the status quo (entry price) . . .*
>
> *–Kahneman and Tversky, Prospect Theory: An Analysis of Decision Under Risk*

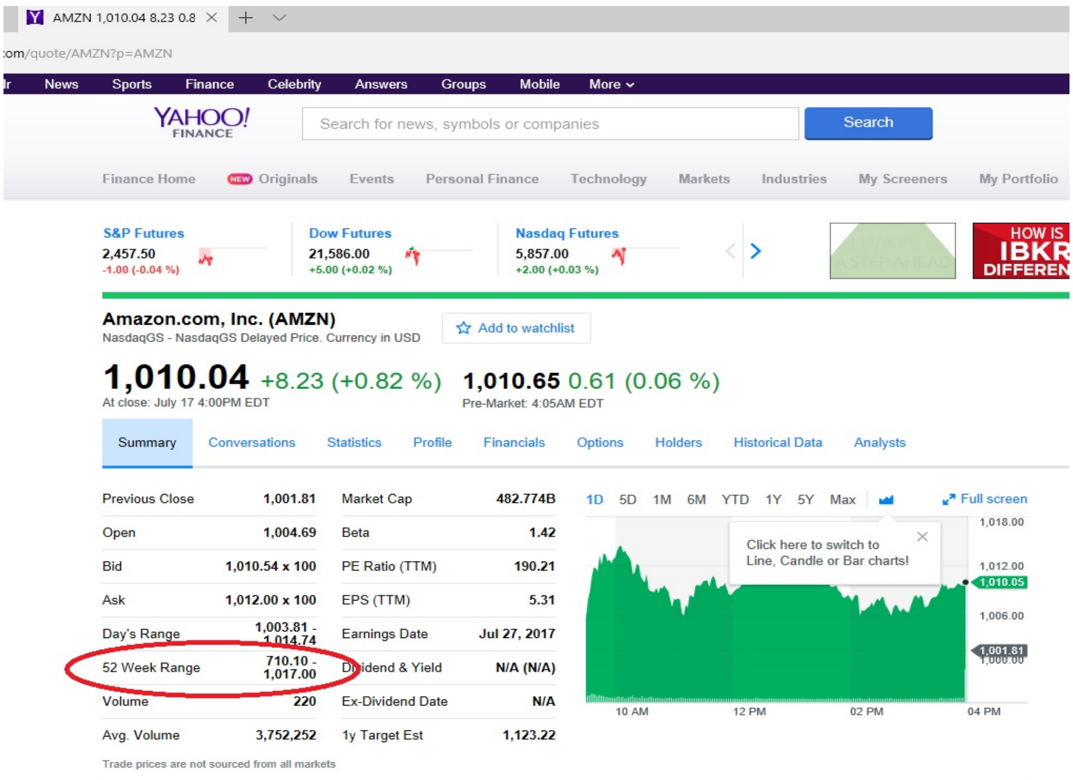
Many studies investigating stock prices have shown that investigators' assuming the cost of trade initiation represents the status quo or reference point; however, the price path may lead to a shifting reference point. Odean (1998) described this scenario as follows: someone who bought a house for $200,000 before a spike in real estate prices and has the house appraised for $350,000 a year later may not feel he is breaking even if he was forced to sell the house for $200,000. Changes in value influence the investor's reference points, even when that change in value is unrealized. Additionally, Raghubir and Das (2010) found that people perceive maxima and minima values as salient points of information by performing three experiments using graphical representations of a stock's performance. They noted that investors use price trends to make investment decisions and that these trends use the recent highs and lows to shift reference points.

52–Week Highs and Lows

Business media and investment software provide the 52-week high and low prices for stocks (see Figures 2, 3, and 4). The 52-week high (low) is the highest (lowest) price at which a security has traded over the previous year. Investors use the 52-week high and low as a technical indicator. Investors use these price extremes as reference points in determining a stock's current value or predicting future price movement. George and Hwang (2004) provided evidence that long investors use the 52-week high coupled with the stock's current price to influence their trading behavior. They showed that traders are initially unwilling to sell their shares when bad news pushes the price away from its 52-week high. Their results showed that investors anchor on the 52-week high. In their conclusion, George and Hwang (2004) suggested "that models in which agents' valuations depend on nearness of the share price to an anchor will be successful in explaining price dynamics." (p. 2161). Grinblatt and Keloharju (2001) showed that investors are likely to buy stocks whose prices are near their monthly lows. Li and Yu (2012) showed that investors will also anchor on the 52-week highs and lows of an aggregate market index such as the Dow Jones Industrial Average. Huddart et al. (2009) found that total volume increases when the stock price crosses the 52-week high as well as the 52-week low. Their findings suggested that stocks crossing their price extremes creates an increase in attention. Moreover, they concluded that the increased levels of attention lead more investors to trade the stock. Likewise, Bamber (1986) found that total trading volume reflects investors' activity and lack of consensus, whereas prices reflect the market's aggregated belief. Beaver (1968) argued that changes in trading volume capture variations in the individual investor's expectations while price changes reflect changes in expectations of the market as a whole.

Figure 1

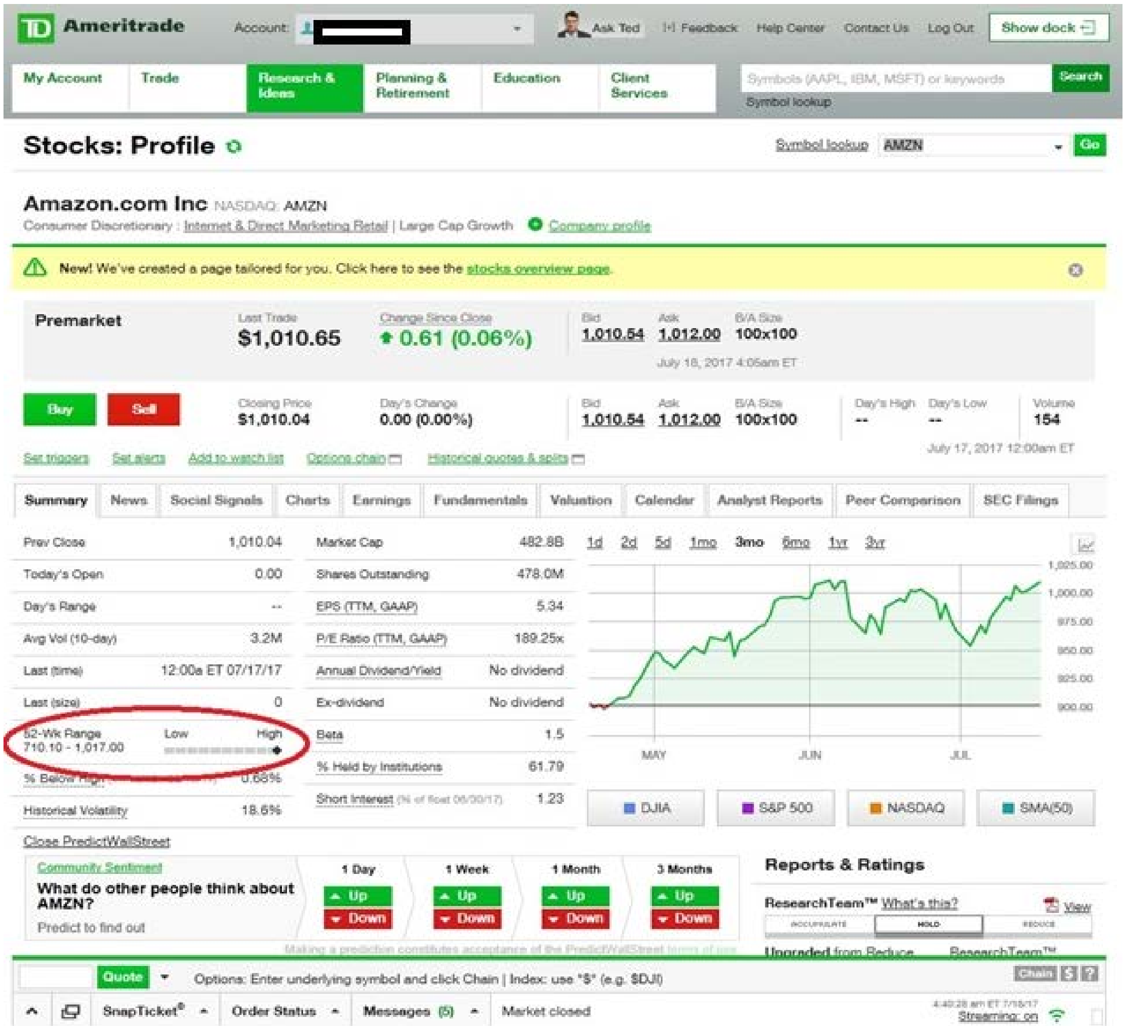
Example of Financial Media and the 52-week Range



Note. Example of online business media providing 52-week range information.

Figure 2

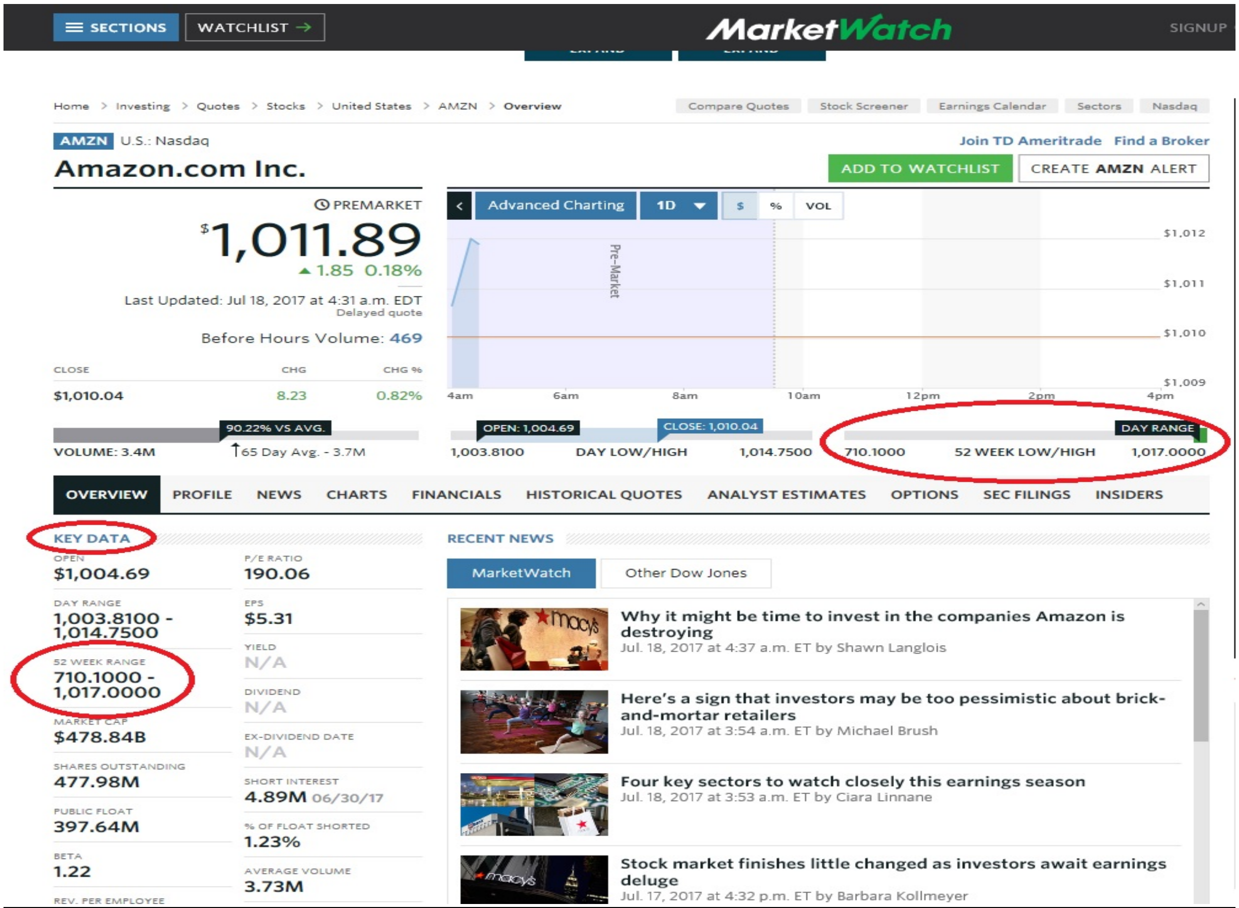
Example of Online Broker Providing 52-week Range Information



Note. Example of online brokers providing 52-week range information to its clients.

Figure 4

Example of Financial Media and Trading Ranges



Note. Example of online business media suggesting that the 52-week range is "Key Data."

Hypothesis Development

Short Sellers

Short selling incorporates processes that are more complex and expensive than long investing. Though short-selling volume makes up a fraction of total volume (Diether et al., 2009) up to 49% (SEC, 2014), researchers view short sellers as informed and sophisticated investors (Dechow et al., 2001; Drake et al., 2011). Declining prices provide short sellers a higher probability for capital gains. However, research provides evidence that price declines follow increases in short-selling volume (Boehmer et al., 2008; Cohen et al., 2007; Diether et al., 2009), such that it is critical to equity forecasting to understand what drives short-selling behavior.

Short Seller Non-Fundamental Analysis

Research demonstrates that short sellers use fundamental (Dechow et al., 2001; Drake et al., 2011) and non-fundamental (Lee & Scotto-Piqueira, 2016) information to make investment decisions. One source of non-fundamental information is knowledge about cognitive biases. Prior studies document that short sellers will make decisions based on the biases of other short sellers (Massa & Von Beschwitz, 2015) as well as take advantage of heuristics used by long investors (Lee & Scotto-Piqueira, 2016).

Massa and Von Beschwitz (2015) used a novel dataset of short selling closing positions to show that some short sellers tend to hold on to their positions too long and close their positions too early, thus presenting evidence of the disposition effect. Closing winning positions too soon leads to a loss (potential) of profits. Additionally, a short seller falls victim to the disposition effect by not closing a losing position soon enough. Losses in these situations become realized. Conversely, Lee and Scotto-Piqueira (2016) used short interest and stock return patterns to conclude that short sellers exploit long investors' biases associated with the 52-week and historical highs. Furthermore, they found evidence that short-seller behavior near the 52-week and historical highs does not adhere to behavioral biases. In fact, the authors found evidence that short sellers exploit the overreaction to good news near the historical highs of long investors. Moreover, short-seller behavior near the 52-week highs contributes to price discovery by correcting long investor overreactions.

Research concerning short-selling behavior near price extremes remains limited to Lee and Scotto-Piqueira (2016), yet they do not address short-seller behavior near the 52-week low.

Given earlier research of long investors at both price extremes and short sellers at 52-week highs, I explored the gap in the research to provide insights into the behavior of short sellers at the 52-week low. The 52-week low provides a salient reference point where short sellers (long investors) possess winning (losing) positions. Further, the 52-week low creates a situation where (1) business media and investment management software draw investor attention to the current stock price and the salient price extreme, and (2) short and long investors may be prone to disposition effect biases. As prices decline, short sellers hold “winners” and run the risk of possibly closing out too soon, while long investors retain “losers” that should have already been sold.

Huddart et al. (2009) provided evidence that total abnormal volume and stock price rise after a stock crosses its 52-week low. Based on the evidence in Lee and Scotto-Piqueira (2016) that short sellers take advantage of long investors’ disposition effects, I hypothesized that short sellers will take advantage of long investors’ tendency to hold “losers” too long by increasing their short position as the stock decreases to the 52-week low. Because investment strategies promote buying at the 52-week low, new long investors target the 52-week low as an optimal entry point. Upward pressure is applied to stock price (i.e., downward pressure on shorts’ profits); thus, short sellers will reduce their short-selling activity and close out their positions. These actions will elevate short-selling volume as the price approaches the 52-week low. Due to new long investors’ initiating positions at the 52-week low, I expected short-selling activity to decline after the 52-week low is crossed. The first set of hypotheses is as follows:

H1a: Short-seller volume is positively correlated to the approach of the 52-week low.

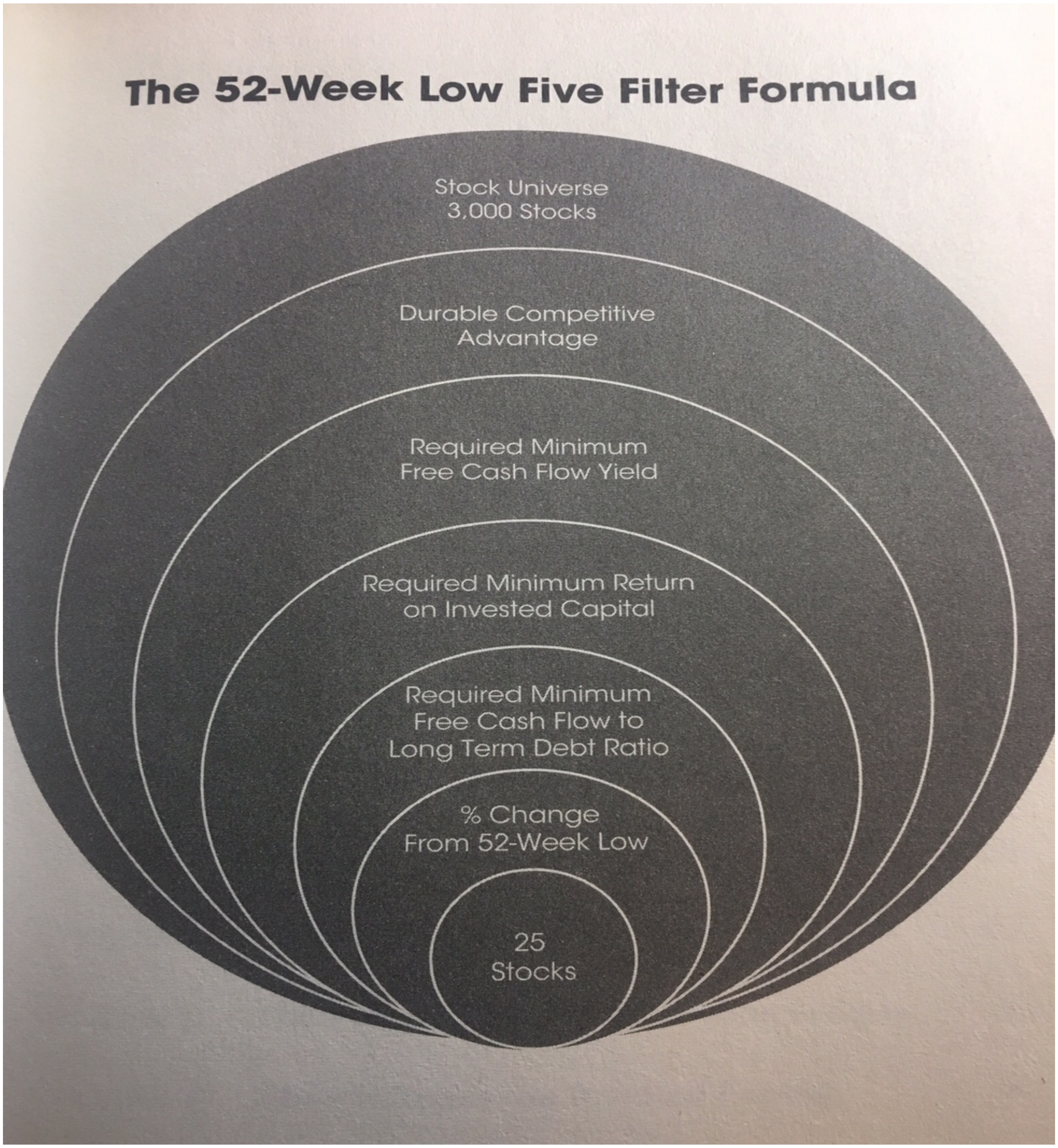
H1b: Short-seller volume will decrease after crossing the 52-week low.

Fundamentals Near a Non-Fundamental Event

As stated above, research found that short sellers use both fundamental and non-fundamental information to make trading decisions. Research that considers the effects of the underlying company's financial strength on trading behavior near specific non-fundamental events is scarce. Lee and Scotto-Piqueira (2016) only considered two of the eleven financial ratios analyzed by Drake et al. (2011), book-to-market and market value of equity, in their analysis of short-seller behavior near the 52-week high, while Huddart et al. (2009) only used market value of equity in their analyses. Practitioners possess stock picking strategies that use stock fundamentals near price extremes. For example, Wiley (2014) provided an example of a trading strategy that focuses on trading near the 52-week low that incorporates different fundamental signals as filters to refine stock selection. As seen in Figure 5, Wiley (2014) incorporated the fundamental data signals of free cash flow, return on invested capital, and long-term debt to allocate attention to a reduced number of stocks. Dechow et al. (2001) suggested that short sellers take positions in stocks with lower expected future returns. They documented that short sellers increase short positions in stocks with weak fundamental ratios. Drake et al. (2011) maintained that changes in short-seller behavior are significantly associated with the expected direction of the eleven fundamental signals examined. Companies with stronger fundamentals tend to be shorted less than companies with weaker fundamentals. Moreover, research demonstrates that financially stronger companies tend to earn abnormal stock returns (Abarbanell & Bushee, 1997; Lev & Thiagarajan, 1993; Mohanram, 2005; Piotroski, 2000).

Figure 5

Example of 52-Week Low Buy Strategy



Note. Diagram depicting the screens used in Wiley's (2014) "52-Week Low Formula: A Contrarian Strategy that Lowers Risk, Beats the Market, and Overcomes Human Emotion."

Although these studies focus on investor behavior and fundamentals, none restrict their analyses to the region around the 52-week low. Due to long investors providing upward pricing pressure for fundamentally stronger stocks and their willingness to target stocks at their 52-week low (to open new positions in the “buy low” strategy), I expected the financial strength of the companies’ underlying fundamentals will have a negative effect on short selling levels as the price nears the 52-week low. Once the stock crosses the 52-week low, I expected fundamental strength to continue to have a negative effect on short-selling volume. This expectation suggests the following hypotheses.

> **H2a**: Fundamental strength has a negative effect on short-selling volume when the price is approaching the 52-week low.
>
> **H2b:** Fundamental strength has a negative effect on short-selling volume after the price has crossed the 52-week low.

III. DATA AND ANALYSIS

Though short selling research has increased over time, event studies using contemporary short-selling volume remain sparse. Many recent short selling studies used short interest as their variable of investigation (Beaver et al., 2016; Chi et al., 2014; Griffin et al., 2016; Kecskés et al., 2013; Park, 2017). Like Arif et al. (2016), Blau et al. (2013), Drake et al. (2015), and Thornock (2013), I used daily short-selling volume for each firm, which allows for the investigation of short sellers' reaction to discrete events. Use of short-selling volume allows for analysis over the relatively short investing periods typical of short sellers (Boehmer et al., 2008; Diether, 2008).

My tests investigate the association of abnormal short-selling volume near the lower price range for specific stocks over a rolling benchmark period. Similar to Heath et al. (1999) and Huddart et al. (2009), I defined the previous 52-week low as the lowest daily closing stock price in the prior 252 trading days. However, in light of the short investment window of short sellers, I used firm-days instead of firm-weeks. Diether (2008) found that securities lending contracts' median length was eleven days[12]. He also reported that short sellers cover their positions in 5.4 and 4.4 days for NYSE and NASDAQ stocks, respectively. A lag of any length may introduce internal validity concerns.

I obtained data from the following databases: CRSP Daily, FINRA Short Sale, NASDAQ short sale, CBOE short sale, NYSE sale, Compustat Short Interest, and Compustat Quarterly Fundamentals. I started with the CRSP dataset to compute the 52-week lows. When acquiring

[12] Borrowing stock is one of the initial steps to short selling (Diether, 2008).

data from the CRSP database, I considered only common shares (SHRCD = 10 and 11) traded on the NYSE, AMEX, NASDAQ, and ARCA (EXCHCD = 1 to 4). These two filters eliminate shares that are ADRs, limited partnerships, REITs, ETFs, and other closed-end funds when the databases are merged. To calculate prior 52-week lows, I retained observations for the dates October 1, 2008 to August 31, 2016 (9,761,602 observations).

Like Jain et al. (2013), I obtained daily short sale trade data from the Financial Industry Regulatory Authority (FINRA) website.[13] Per Securities and Exchange Commission (SEC) Release No. 34-60807, File No. SR-FINRA-2009-064, the SEC granted FINRA approval relating to publication of certain daily and monthly short sale data on the FINRA website. FINRA's proposal, signed by Stephanie Dumont, Senior Vice President and Director of Capital Markets and dated September 29, 2009, requested a change to Rule 19b-4 under the Securities Exchange Act of 1934. Letters and conversations with SEC staff shaped the proposed changes. SEC staff requested FINRA to publish certain short sale data to increase market transparency to help bolster investor confidence and thereby help promote capital formation. Additionally, as stated in the proposal:

> FINRA believes that the proposed rule change is consistent with the provisions of Section 15A(b)(6) of the Act (15 U.S.C. 78o-2(b)(6)), which requires, among other things, that FINRA rules must be designed to prevent fraudulent and manipulative acts and practices, to promote just and equitable principles of trade, and, in general, to protect investors and the public interest. FINRA believes that the publication of the requested short sale data will result in increased market transparency, providing additional market information to investors and other interested parties. (SEC, 2009, para 14)

[13] http://www.finra.org/industry/trade-reporting-facility-trf

FINRA began providing public access to monthly short sale reports in September 2009. These files provide data, such as transaction times, price, and number of shares per trade for every national market stock (NMS) short sale. Due to the SEC actions, specifically Rule 204T of Regulation SHO, to protect the markets from abusive short sales, these data files provide increased market transparency. I also used the short sale volume data provided by the CBOE, NASDAQ, and NYSE. Combined, the short sales volume databases correspond to over 98% of total market volume. September 3, 2009 was the earliest common starting date for these databases, and I gathered data until August 31, 2016.[14,15] I computed daily short-selling volume by summing the individual short sales per stock for each trading day. This data set contains 15,111,624 daily short sale volume observations.

Due to FINRA's time and access limitations to the short interest data files, I utilized the Compustat Short – Interest file for data on short interest levels.[16] Starting in 2007, the Short Interest file includes two data points per month (15th and end of the month) for each stock. I used both the short selling and the short interest datasets to provide both "stock and flow" short data. The dataset with a starting date of January 15, 2008 to December 30, 2016 contains 1,713,042 semi-monthly stock observations.

After calculating the needed variables in each dataset, I linked the database of the CRSP observations with the short selling and short interest database (mentioned above). When matching the datasets, I required that the short interest data be at least eight trading days old in

[14] FINRA's 5-Cent Tick Pilot Program went live on October 3, 2016. This changed the minimum trading increment from 1 cent to 5 cents for approximately 1200 stocks.
[15] Investors Exchange was founded in 2012 and launched as a national exchange in September of 2016. IEX does not provide short-selling volume data.
[16] FINRA's website only provides short interest data of OTC equities. The start date of this database is November 14, 2014.

reference to the trade date to account for data dissemination.[17] To calculate variables that require prior years' data, I gathered quarterly financial data from the Compustat quarterly financial database for U.S. firms from 2006 to 2016, inclusive (355,619 observations). I linked the quarterly financial data on the closest financial release date (RDQ) preceding the trade date of the Security-Daily database.

Linking the observations from the above datasets and eliminating observations with missing regression variable data provide 4,295,352 million firm-trade day observations. Combining the above datasets produces a sample of 12,832,306 observations. Missing data involving the financial strength score eliminates 8,536,954 observations. The sample loses 179,962 observations due to missing total daily volume data; 67,138 observations are lost due to missing 52-week high data; 184,110 observations are lost due to missing short interest data; 29 more observations are lost due to duplicate observations. To avoid introducing an effect produced by the higher percentage of margin for stocks priced below $10, I eliminated all stocks that had a price or 52-week low below $10 (2,090,885 observations) in the sample. Another 1,935 observations were eliminated due to stocks that experienced a split (forward or reverse) within the sample time period, which leaves 1,771,293 observations from 3,959 stocks for the initial sample for investigation (see Table 1).

[17] FINRA member firms are required to report their short positions as of settlement on (1) the 15th of each month or the preceding business day if the 15th is not a business day, and (2) as of settlement on the last business day of the month. The reports must be filed by the second business day after the reporting settlement date. FINRA compiles the short interest data and provides it for publication on the eighth business day after the reporting settlement date.

Table 1

Sample and Data Attrition

Combined dataset (FINRA, CRSP, COMPUSTAT, SHORT INTEREST)	12,832,306
Less:	
Missing financial strength data	(8,536,954)
Missing short-selling volume data	(179,962)
Missing 52-week high data	(67,138)
Missing short interest data	(184,110)
Duplicate observations	(29)
Stocks priced/52-week low below $10	(2,090,885)
Stocks that experienced a split within the time period	(1,935)
Total remaining observations	1,771,293
Number of unique companies	3,959

Note. Presents the details of the sample obtained from merging CRSP, Compustat, and FINRA databases.

Research Design

The development of my short-selling volume models started with the work of Christophe et al. (2004). In their seminal paper, they used short-selling volume to investigate short-seller behavior prior to earnings announcements. Christophe et al. (2004) aggregated their short sale transaction data to a daily level for each stock. I defined SSVOL as:

$$SSVOL_{i,t} = \left[\sum_{1}^{n} ssvo\,l_{i,t}\right] \tag{1}$$

and Christophe et al. (2004) defined RELSS, a ratio of short sale volume to total volume, as:

$$RELSS_{i,t} = \left[\frac{\text{SSVOL}}{\text{VO}L_{i,t}}\right] \tag{2}$$

where $SSVOL_{i,t,}$ represents the daily short-selling volume for company *i* on day t. $RELSS_{i,t}$ was created to assess the robustness of the short-selling volume by examining the change in the ratio of short-selling volume to total volume of company *i* on day *t*. $VOL_{i,t}$ represents total volume of shares traded of company *i* on day t. Additionally, I included $SSRATIO_{i,t}$ to further test the robustness of the models. Whereas SSVOL represents the raw number of shares shorted in a day and RELSS represents the percentage of shares shorted to total share volume, neither consider the availability of shares to be shorted. SSRATIO incorporates this availability factor by scaling SSVOL by common shares outstanding. Similar to Blau et al. (2011), I calculated SSRATIO as:

$$SSRATIO_{i,t} = \left[\frac{\text{SSVOL}}{CSHOC_{i,t}}\right] \tag{3}$$

Where $CSHOC_{i,t}$ represents the common shares outstanding for firm *i* on day t.

Non-Fundamental Testing – Proximity to the 52-Week Low

I started my analysis with a basic regression of short-selling volume on the variable NEARLOW. This indicator variable is coded 1 if the stock price is in the lower 25% of its rolling 52-week range, zero otherwise.

The first model uses the following form:

$$SSVOL(RELSS, SSRATIO) \quad = \beta_{FE} + \beta_1 NEARLOW \ + \in_{,} \qquad (4, 5, 6)$$

Next, I included the latest short-interest ratio for each company. I calculated the short-interest ratio (SIR) by dividing the latest reported short interest by the number of shares outstanding. I included SIR to account for any effect that prior short interest levels may have had on current short-selling activity. Prior short-interest levels control for short interest sentiment (Christensen et al., 2014) and are associated with subsequent abnormal short selling.[18] For example, Drake et al. (2015) found that prior short-interest ratio levels have a negative effect on subsequent short-selling volume. I used the latest SIR data point that is at least eight days old (relative to the trading day) due to the time it takes for FINRA to release the data to the public. I predicted SIR to have a negative relationship with short-selling volume.

Therefore, the second model is:

$$SSVOL(RELSS, SSRATIO) = \beta_{FE} + \beta_1 NEARLOW + \beta_2 SIR + \epsilon, \qquad (7, 8, 9)$$

Consistent with Drake et al. (2015), the market value of equity (LnMVE) and book-to-market ratio (BTM) are included to control for changes in firm valuation and size. Prior research, such as Dechow et al. (2001) and Drake et al. (2011, 2015), showed that these variables are

[18] Using short interest along with short-selling volume allows for the analysis of “levels and changes” in investor behavior. Similarly, Easton and Harris (1991) used prior book and market values as their “levels” variables when investigating their effects on earnings and market returns (“change variables”). Burgstahler and Dichev (1997) used book value as their adaptation (levels) variable and earnings as the recursion (change) variable to investigate their effects on a firm’s market value.

associated with changes in short interest levels. However, I utilized BTM and LnMVE in altered forms. Drake et al. (2015) calculated BTM and LnMVE by using the closing stock price at the end of the fiscal year. With short sellers' shorter investment horizons and the assumption that well-informed investors would use more timely information, I calculated BTM and LnMVE using the last reported quarterly book value along with the current day's opening stock price and last reported common shares outstanding. Additionally, the use of daily values for LnMVE and BTM allows for the departure away from stock return variables. Including both daily return variables along with market capitalization variables may lead to multicollinearity issues. I predicted LnMVE will have a negative relationship with short selling. Lower market values are more likely to indicate a stock that short sellers are driving down. Based on prior studies (Dechow et al., 2001; Drake et al., 2011) that find short-sellers position themselves in stocks with low BTM values, I predicted that the relationship between BTM and short selling would be negative. Though BTM and LnMVE are commonly used together in short selling models (Dechow et al., 2001; Drake et al., 2011; Lee & Scotto-Piqueira, 2016), there exists uncertainty in the influence each variable has on short-selling behavior due to insignificant coefficient values in prior research results (Drake et al., 2015; Lee & Scotto-Piqueira, 2016). The following three models represent the above:

$$SSVOL(RELSS, SSRATIO)_{i,t} = \beta_{FE} + \beta_1 NEARLOW_{i,t} + \beta_2 SIR_{i,t} + \beta_3 BTM_{i,t} \qquad (10, 11, 12)$$

$$SSVOL(RELSS, SSRATIO)_{i,t} = \beta_{FE} + \beta_1 NEARLOW_{i,t} + \beta_2 SIR_{i,t} + \beta_3 LnMVE_{i,t} \qquad (13, 14, 15)$$

$$SSVOL(RELSS, SSRATIO)_{i,t} = \beta_{FE} + \beta_1 NEARLOW_{i,t} + \beta_2 SIR_{i,t} + \beta_3 BTM_{i,t} + \beta_4 LnMVE_{i,t} \qquad (16, 17, 18)$$

I tested models four through 18 on the full sample of observations for H1a. However, for H1b, I hypothesized that short-seller volume will decrease after crossing the 52-week low. I used the same models as for hypothesis H1a but used a subsample that only included observations of stocks that had crossed its 52-week low. Unlike the sample for hypothesis H1a, the sample for H1b will only contain observations in the lower 25% of the trading range.

Though this hypothesis is of an exploratory nature, I predicted that short seller volume to decrease after crossing the 52-week low. There exist long investor strategies (buyer) that target stocks hitting their 52-week low. They purport the 52-week low as a target entry point to increase or initiate a long position.

Fundamental Strength Testing

I tested Hypotheses 2a and 2b by replacing NEARLOW from the above models with FSCORE. The resulting model,

$$SSVOL(RELSS, SSRATIO)_{i,t} \tag{19, 20, 21}$$

$$= \beta_{FE} + \beta_1 FSCORE_{i,t} + \beta_2 SIR_{i,t} + \beta_3 BTM_{i,t}$$

$$+ \beta_4 LnMVE_{i,t}$$

where FSCORE = Σ (positive cash flow from operations, positive return on assets, increasing return on assets, zero or decreasing long-term debt, negative accruals, increase in current ratio, no issuance of common equity, increasing gross margin, and increasing asset turnover).[19] Based on the findings of Drake et al. (2011) and Dechow et al. (2001) that supported the position that short sellers are attracted to weaker companies, I predicted FSCORE to have a negative effect on short selling and remained agnostic concerning the control variables. I applied the sample of observations that consists of the bottom 25% of the

[19] See Appendix for a more detailed description of Piotroski's (2000) FSCORE

trading range to H2a that have not crossed the 52-week low. For H2b, I used a non-overlapping sample of observations that have crossed the 52-week low.

IV. RESULTS

Descriptive Statistics and Correlations

Summary statistics are presented in Table 2 for the regression variables in the full sample. I winsorized all continuous variables, except for FSCORE, at the 2 and 98 percent levels to mitigate effects of extreme outliers. The average daily short sale volume for a stock is 583,000 shares. This value is significantly greater than the average in Blau et al. (2011) (237,551 shares). This could be due to the differences in the time periods of the samples or the method of sample selection. The data used in Blau et al. (2011) was a sample provided by the Securities and Exchange Commission for studies to determine the effectiveness of proposed regulations (Regulation SHO). The Regulation SHO Pilot Program data sample contains short sale volume data for a select group of companies from January 2005 to August 2007. The sample used in this dissertation draws from a wider population. The percentage of a stock's short-selling volume to total share volume is 43.2% (.432). This is close to the 49% the SEC (2014) reported for all listed equity share volume. I speculated the reason for the difference is due to sample selection.

Table 2

Descriptive Statistics: Full Sample

	N	Mean	St.Dev	p25	Median	p75
SSVOL	1,771,293	583,000	967,000	57,762	200,685	628,022
RELSS	1,771,293	.432	.152	.348	.444	.536
SSRATIO	1,771,293	.003	.003	.001	.002	.004
NEARLOW	1,771,293	.164	.37	0	0	0
FSCORE	1,771,293	5.908	1.441	5	6	7
SIR	1,771,293	.045	.045	.015	.029	.057
BTM	1,771,293	.409	.274	.21	.354	.553
LnMVE	1,771,293	22.035	1.542	20.927	21.903	23.038
PRICE	1,771,293	52.314	33.803	28.8	43.16	65.04
PRICE(Split adj)	1,771,293	48.951	31.787	26.7	40	61.1
52-Week HIGH	1,771,293	60.1	37.41	34.25	49.95	74.19
52-Week LOW	1,771,293	39.616	25.388	21.7	32.53	49.16
RANGEPCT	1,771,293	.47	.43	.281	.379	.527
NODIVIDEND	1,771,293	.363	.481	0	0	1
NEXTDIVYLD	1,246,086	.007	.007	.003	.005	.009

The reported statistics for FSCORE are mean (5.91), 25th percentile (5), median (6), 75th percentile (7), and the range includes all scores (0 to 9). These results indicate that most firm-days are related to companies with many positive performance metrics. The short-interest ratio (SIR) mean is 4.5 percent whereas the means for Drake et al. (2011, 2015) were 3.2 and 4.9 percent, respectively. Moreover, Diether et al. (2009) and Lee and Scotto-Piqueira (2016) SIR means were 5.4 and 4.2 percent, respectively. BTM and LnMVE means are .41 and 22.03, respectively. The book-to-market value remains in the range of previous short selling studies.

Drake et al. (2011, 2015) BTM means were both .5 and both Lee and Scotto-Piqueira (2016) and Diether et al. (2009) provided BTM means of .65. The LnMVE value of 20.45 corresponds to companies that have a market capitalization of approximately $3.71 billion. This value is similar to other studies. Drake et al. (2011, 2015) mean market capitalization values were $3.6 billion and $2.9 billion, respectively. Moreover, Lee and Scotto-Piqueira's (2016) and Diether et al.'s (2009) mean market capitalization values are $3.2 billion and $7.4 billion, respectively.

For univariate correlations (Table 3), the main variable of interest FSCORE is significant and negatively correlated with RELSS (Pearson, -0.04) and SSRATIO (Pearson, -0.04). This indicates that short sellers prefer weaker firms to short. Drake et al. (2011) supported this finding et al. as well as Dechow et al. (2001). Additionally, FSCORE is negatively and significantly correlated with SIR (Pearson, -0.10). This finding is supported by the results of Dechow et al. (2001) and Drake et al. (2011). Short sellers avoid firms with stronger financial positions.

Table 3

Pearson/Spearman Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13
SSVOL	1.00	0.36	0.65	0.05	0.04	0.06	-0.13	0.70	-0.09	0.15	0.17	0.18	0.17
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
RELSS	0.22	1.00	0.47	0.01	-0.04	0.22	-0.03	0.08	-0.01	0.01	0.01	0.03	0.02
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
SSRATIO	0.39	0.39	1.00	0.11	-0.02	0.51	-0.05	0.10	0.17	0.07	0.09	0.15	0.05
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NEARLOW	0.05	0.01	0.15	1.00	-.10	0.08	0.12	-.08	0.03	-.16	-.13	0.02	-.04
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
FSCORE	0.04	-0.04	-0.04	-0.10	1.00	-0.10	-0.08	0.11	-0.06	0.11	0.09	0.06	0.08
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
SIR	-0.05	0.18	0.47	0.10	-0.10	1.00	-0.05	-0.30	0.31	-0.07	-0.05	-0.00	-0.10
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BTM	-0.03	-0.04	-0.03	0.14	-0.09	-0.05	1.00	-0.27	-0.09	-0.34	-0.30	-0.30	-0.27
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LnMVE	0.57	0.08	0.02	-0.08	0.11	-0.25	-0.27	1.00	-0.26	0.50	0.47	0.46	0.52

	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NODIVIDEND	-.13	-.02	0.19	0.03	-.07	0.29	-.06	-.25	1.00	-.10	-.09	-.06	-.17
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PRICE	0.01	0.00	0.03	-0.12	0.10	-0.06	-0.32	0.43	-0.05	1.00	0.91	0.95	0.94
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PRICE(Split adj)	0.02	0.00	0.03	-.10	0.08	-.05	-.30	0.42	-.05	0.92	1.00	0.87	0.87
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
52 Week High	0.03	0.02	0.11	0.02	0.05	0.00	-0.28	0.40	-0.02	0.96	0.89	1.00	0.93
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
52 Week Low	0.04	0.01	0.00	-.03	0.08	-0.08	-.27	0.46	-.11	0.95	0.89	0.94	1.00
	0.00	0.00	0.34	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: Pearson correlation coefficients are presented above the diagonal and Spearman below.

Regression Results

This dissertation evaluates the impact of the proximity of a stock's 52-week low as well as a stock's fundamental strength on short-selling volume. While the academic literature has explored short-seller behavior near 52-week highs (Lee & Scotto-Piqueira, 2016) and the effects of fundamental strength on short-seller behavior in general (Dechow et al., 2001; Drake et al., 2011; Lui, 2012), no known studies have investigated the effects of fundamental strength on short-seller behavior near the 52-week low. This study first explores the effect of the proximity of the 52-week low on short-seller behavior. It then investigates the influence of the company's fundamental strength using a well-known and used proxy, the Piotroski F-Score, on short-seller behavior near the 52-week low. I furthered my investigation to explore the effects of fundamental strength on those stocks that hit their 52-week on the 10 days surrounding the event.

Proximity to 52-Week Low

In this subsection**,** I used regression analyses to investigate the relationships between abnormal short-selling volume and multiple independent variables. Hypothesis 1a examines the effect of nearness to the 52-week low on abnormal short selling. The sample starts with the overall sample described in the previous subsection and eliminates the daily-stock observations that follow crossing the 52-week low (1,235,911 observations). Table 4 presents the descriptive statistics for the sample used for the regressions for Hypothesis 1A. Tables 5-8 present the results of three regressions based on Hypothesis H1A's equations (16-18). I found the coefficient for NEARLOW, my proxy for nearness to the 52-week low, is positive and significant for all regressions with SSVOL and SSRATIO as the independent variable. From the results of column (5) in Table 5, the coefficient of 71.9 represents the expected increase in daily shares shorted (in thousands) when a stock gets near its 52-week low. The results of the coefficient of NEARLOW for SSRATIO results further support these findings. The NEARLOW coefficient of .044 represents the increase in shares (percentage) shorted with respect to the company's shares outstanding. The regressions with RELSS as the independent variable is significant but negative. The coefficient of -0.016 represents the percentage change in short sell volume with respect to total volume. This result provides evidence that short-selling volume becomes a smaller percentage of total volume when nearing the 52-week low. When the results of the three regressions are combined, I posited that total volume increases at a higher rate than the increase in short-selling volume as a stock nears its 52-week low.

Table 4

Descriptive Statistics: Hypothesis 1a

	N	Mean	St.Dev	p25	Median	p75
SSVOL	535,382	577,000	1,000,000	48,467	180,000	584,070
RELSS	535,382	.423	.154	.342	.437	.527
SSRATIO	535,382	.003	.003	.001	.002	.004
NEARLOW	535,382	.058	.233	0	0	0
FSCORE	535,382	6.131	1.417	5	6	7
SIR	535,382	.042	.042	.014	.028	.055
BTM	535,382	.358	.242	.18	.314	.477
LnMVE	535,382	22.067	1.538	20.962	21.932	23.018
PRICE	535,382	55.157	34.478	31.69	46.17	67.65
PRICE(Split adj)	535,382	50.261	32.496	27.83	41.154	61.89
52-Week HIGH	535,382	60.83	37.867	35.488	50.95	73.92
52-Week LOW	535,382	39.611	25.126	22.35	32.74	48.29
RANGEPCT	535,382	.46	.316	.288	.387	.524
NODIVIDEND	535,382	.4	.49	0	0	1
NEXTDIVYLD	371,613	.007	.007	.003	.005	.008

Table 5

Regression of Short-Selling Volume on Proximity to 52-Week Low (H1a)

	(1) SSVOL	(2) SSVOL	(3) SSVOL	(4) SSVOL	(5) SSVOL
NEARLOW	53.9^{***}	50.6^{***}	39.0^{***}	90.0^{***}	71.9^{***}
	(5.94)	(5.58)	(3.50)	(6.22)	(5.45)
SIR		9.52^{***}	9.31^{***}	12.1^{***}	12.1^{***}
		(4.23)	(4.07)	(5.66)	(5.53)
BTM			195.5^{*}		420.3^{***}
			(1.76)		(3.20)
LnMVE				258.3^{***}	303.0^{***}
				(3.74)	(4.06)
N	535,374	535,374	535,374	535,374	535,374
adj. R^2	0.836	0.836	0.836	0.838	0.838

Note: SSVOL is the daily short sale volume of the stock; NEARLOW is a binary variable and is equal to 1 if the stock's price is in the lower 25 percent of its 52-week range, otherwise equals zero; SIR is the short-interest ratio reported at least 8 days prior to the observation date; BTM is the book-to-market ratio; LnMVE = natural log of the market value of equity. To make the regression results more salient, the SSVOL variable was reduced to thousands (x 1/1000) and the variables of SIR and SSRATIO were converted to percentages (x100). All continuous variables except those related to returns are winsorized at the top and bottom 2% *t* statistics in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6

Regression of Relative Short-Selling Volume on Proximity to 52-Week Low (H1a)

	(1) RELSS	(2) RELSS	(3) RELSS	(4) RELSS	(5) RELSS
NEARLOW	-0.017***	-0.019***	-0.020***	-0.014***	-0.016***
	(-7.94)	(-8.92)	(-7.89)	(-5.95)	(-6.80)
SIR		0.0050***	0.0050***	0.0053***	0.0053***
		(10.74)	(10.69)	(11.45)	(11.43)
BTM			0.011		0.039
			(0.44)		(1.41)
LnMVE				0.034***	0.038***
				(4.67)	(4.18)
N	535,374	535,374	535,374	535,374	535,374
adj. R^2	0.427	0.430	0.430	0.431	0.431

Note: RELSS is the daily short sale volume of the stock divided by total daily trading volume of the stock.

Table 7

Regression of Short Selling Ratio on Proximity to 52-week Low (H1a)

	(1) SSRATIO	(2) SSRATIO	(3) SSRATIO	(4) SSRATIO	(5) SSRATIO
NEARLOW	0.037***	0.032***	0.032***	0.048***	0.044***
	(7.49)	(6.92)	(6.20)	(7.00)	(7.28)
SIR		0.016***	0.016***	0.017***	0.017***
		(12.51)	(12.45)	(13.63)	(13.56)
BTM			0.0052		0.091*
			(0.13)		(1.78)
LnMVE				0.11***	0.12***
				(3.37)	(3.34)
N	535,374	535,374	535,374	535,374	535,374
adj. R^2	0.573	0.580	0.580	0.583	0.583

Note: SSRATIO is the ratio of SSVOL divided by the stock’s common shares outstanding.

Table 8

Summary of Regressions of Short Selling on Proximity to 52-Week Low (H1a)

	(1) SSVOL	(2) RELSS	(3) SSRATIO
NEARLOW	71.9***	-0.016***	0.044***
	(5.45)	(-6.80)	(7.28)
SIR	12.1***	0.0053***	0.017***
	(5.53)	(11.43)	(13.56)
BTM	420.3***	0.039	0.091*
	(3.20)	(1.41)	(1.78)
LnMVE	303.0***	0.038***	0.12***
	(4.06)	(4.18)	(3.34)
N	535,374	535,374	535,374
adj. R^2	0.838	0.431	0.583

The coefficients for SIR are all positive and significant. These results provide evidence that the latest short interest data has a positive influence on short-selling volume. A 1% increase in SIR (3.0% to 4.0%) would cause an increase of 12.1 (thousands) in short-selling volume, a 0.53% increase in short-selling volume relative to total volume, and an increase .017% in short-selling volume relative to shares outstanding.

Crossing the 52-week low-NEARLOW

In this subsection**,** I used regression analyses to investigate the relationships between abnormal short-selling volume and multiple independent variables after the stock has crossed its

52-week low. Hypothesis 1b examines the effect of nearness to the 52-week low on abnormal short selling after the stock has crossed its 52-week low. The sample starts with the overall sample and then eliminates the daily-stock observations that have not crossed the 52-week low (535,374 observations). Table 9 presents the descriptive statistics for the sample used for the regressions for Hypothesis 1B. Table 13 presents the results of three regressions based on equation (1).

Table 9

Descriptive Statistics: Hypothesis 1B

	N	Mean	St.Dev	p25	Median	p75
SSVOL	1,235,911	586,000	952,000	62,105	209,962	646,293
RELSS	1,235,911	.436	.15	.351	.448	.54
SSRATIO	1,235,911	.004	.003	.001	.003	.005
NEARLOW	1,235,911	.209	.407	0	0	0
FSCORE	1,235,911	5.812	1.441	5	6	7
SIR	1,235,911	.046	.046	.015	.029	.058
BTM	1,235,911	.432	.284	.225	.374	.584
LnMVE	1,235,911	22.021	1.543	20.914	21.891	23.049
PRICE	1,235,911	51.082	33.431	27.71	41.86	63.81
PRICE(Split adj)	1,235,911	48.383	31.457	26.22	39.5	60.76
52-Week HIGH	1,235,911	59.784	37.206	33.77	49.55	74.35
52-Week LOW	1,235,911	39.618	25.501	21.4	32.39	49.64
RANGEPCT	1,235,911	.475	.471	.278	.374	.528
NODIVIDEND	1,235,911	.347	.476	0	0	1
NEXTDIVYLD	874,473	.007	.007	.003	.006	.009

I found the coefficient for NEARLOW, my proxy for nearness to the 52-week low, is positive and significant for all regressions with SSVOL and SSRATIO as the independent variable. From the result of equation (5) in Table 10, the coefficient of 65.2 represents the expected increase in daily shares (in thousands) shorted when a stock gets near its 52-week low. The results of the coefficient of NEARLOW for SSRATIO further support these findings. The NEARLOW coefficient of .046, when investigating SSRATIO, represents the percentage increase in shares shorted with respect to the company's shares outstanding. The coefficients for the regressions with RELSS as the independent variable are significant but negative. The coefficient of -0.014 represents a .014% change in short sell volume with respect to total volume. This result provides evidence that short-selling volume becomes a smaller percentage of total volume when near the 52-week low. When the results of the three regressions are combined, I posited that total volume increases at a higher rate than the increase in short-selling volume as a stock nears its 52-week low.

Table 10

Regression of Short-Selling Volume on Proximity to 52-Week Low After Crossing the 52-Week Low (H1b)

	(1) SSVOL	(2) SSVOL	(3) SSVOL	(4) SSVOL	(5) SSVOL
NEARLOW	93.3***	85.2***	64.5***	76.7***	65.2***
	(12.09)	(11.52)	(9.21)	(10.35)	(9.15)
SIR		20.2***	19.3***	19.4***	19.4***
		(10.72)	(10.41)	(10.95)	(10.88)
BTM			248.0***		257.8***
			(4.88)		(4.40)
LnMVE				-52.6**	9.19
				(-2.01)	(0.31)
N	1,235,911	1,235,911	1,235,911	1,235,911	1,235,911
adj. R^2	0.776	0.778	0.779	0.778	0.779

Table 11

Regression of Relative Short-Selling Volume on Proximity to 52-Week Low After Crossing the 52-Week Low (H1b)

	(1)	(2)	(3)	(4)	(5)
	RELSS	RELSS	RELSS	RELSS	RELSS
NEARLOW	-0.011***	-0.013***	-0.014***	-0.014***	-0.014***
	(-7.89)	(-9.90)	(-9.21)	(-8.90)	(-9.06)
SIR		0.0057***	0.0057***	0.0057***	0.0057***
		(16.36)	(16.17)	(15.80)	(15.78)
BTM			0.0081		0.0068
			(0.91)		(0.58)
LnMVE				-0.0028	-0.0012
				(-0.51)	(-0.17)
N	1,235,911	1,235,911	1,235,911	1,235,911	1,235,911
adj. R^2	0.395	0.402	0.402	0.402	0.402

Table 12

Regression of Short-Selling Ratio on Proximity to 52-week Low After Crossing the 52-Week Low

	(1) SSRATIO	(2) SSRATIO	(3) SSRATIO	(4) SSRATIO	(5) SSRATIO
NEARLOW	0.059***	0.051***	0.046***	0.048***	0.046***
	(16.02)	(15.59)	(14.00)	(13.16)	(13.07)
SIR		0.021***	0.021***	0.021***	0.021***
		(20.56)	(20.44)	(19.65)	(19.74)
BTM			0.053**		0.047
			(2.21)		(1.63)
LnMVE				-0.017	-0.0060
				(-1.18)	(-0.35)
N	1,235,911	1,235,911	1,235,911	1,235,911	1,235,911
adj. R^2	0.542	0.561	0.561	0.561	0.561

Table 13

Summary of Regressions of Short Selling on Proximity to 52-Week Low After Crossing the 52-Week Low (H1b)

	(1) SSVOL	(2) RELSS	(3) SSRATIO
NEARLOW	65.2^{***}	-0.014^{***}	0.046^{***}
	(9.15)	(-9.06)	(13.07)
SIR	19.4^{***}	0.0057^{***}	0.021^{***}
	(10.88)	(15.78)	(19.74)
BTM	257.8^{***}	0.0068	0.047
	(4.40)	(0.58)	(1.63)
LnMVE	9.19	-0.0012	-0.0060
	(0.31)	(-0.17)	(-0.35)
N	1,235,911	1,235,911	1,235,911
adj. R^2	0.779	0.402	0.561

Crossing the 52-Week Low, a Closer Look

In this subsection**,** to mitigate against the possible influence from time-based omitted variables, I refined the previous sample to include only the observations that occur up to 10 days after the 52-week low has been crossed. The sample starts with the overall sample and then eliminates the daily-stock observations that have not crossed the 52-week low (535,374 observations) and eliminates the observations that are more than 10 days after (173,298 observations). Table 14 presents the descriptive statistics for the sample used for the regressions for Hypothesis 1B. Table 18 presents the results of three regressions based on equation (1).

Table 14

Descriptive Statistics: Hypothesis 1b – Limited to 10 Days After 52-Week Low

	N	Mean	St.Dev	p25	Median	p75
SSVOL	1,062,613	571,000	934,000	58,788	201,161	624,592
RELSS	1,062,613	.435	.152	.349	.447	.54
SSRATIO	1,062,613	.004	.003	.001	.003	.005
NEARLOW	1,062,613	.236	.425	0	0	0
FSCORE	1,062,613	5.757	1.438	5	6	7
SIR	1,062,613	.047	.047	.016	.029	.06
BTM	1,062,613	.444	.287	.235	.386	.599
LnMVE	1,062,613	21.962	1.537	20.851	21.827	22.987
PRICE	1,062,613	49.559	32.287	27	40.75	62.01
PRICE(Split adj)	1,062,613	47.444	30.676	25.72	38.84	59.73
52-Week High	1,062,613	58.814	36.274	33.54	48.8	73.34
52-Week Low	1,062,613	38.698	24.737	20.95	31.82	48.34
RANGEPCT	1,062,613	.485	.493	.284	.382	.538
NODIVIDEND	1,062,613	.352	.478	0	0	1
NEXTDIVYLD	749,513	.008	.007	.003	.006	.009

I found the coefficient for NEARLOW, my proxy for nearness to the 52-week low, is positive and significant for all regressions with SSVOL and SSRATIO as the independent variable. From the result of equation (5) in Table 15, the coefficient of 62.1 represents the expected increase in daily shares (in thousands) shorted when a stock gets near its 52-week low. The results of the coefficient of NEARLOW for SSRATIO results further support these findings. The NEARLOW coefficient of .043, when investigating SSRATIO, represents the percentage increase in shares shorted with respect to the company's shares outstanding. The coefficients for the regressions with RELSS as the independent variable are significant but negative. The coefficient of -0.014 represents the percentage change in short sell volume with respect to total volume. This result provides evidence that short-selling volume becomes a smaller percentage of total volume when near the 52-week low. Again, when the results of the three regressions are combined, I posited that total volume increases at a higher rate than the increase in short-selling volume as a stock nears its 52-week low.

Table 15

Regressions of Short-Selling Volume on Proximity to 52-Week Low Within 10 Days After Crossing the 52-Week Low

	(1) SSVOL	(2) SSVOL	(3) SSVOL	(4) SSVOL	(5) SSVOL
NEARLOW	92.5***	84.9***	63.1***	72.6***	62.1***
	(11.95)	(11.44)	(9.14)	(9.82)	(8.93)
SIR		20.6***	19.7***	19.4***	19.5***
		(10.10)	(9.76)	(10.20)	(10.18)
BTM			259.5***		247.4***
			(5.09)		(4.05)
LnMVE				-73.3***	-11.7
				(-2.76)	(-0.38)
N	1,062,613	1,062,613	1,062,613	1,062,613	1,062,613
adj. R^2	0.770	0.773	0.773	0.773	0.773

Table 16

Regression of Relative Short-Selling Volume on Proximity to 52-Week Low Within 10 Days After Crossing the 52-Week Low

	(1) RELSS	(2) RELSS	(3) RELSS	(4) RELSS	(5) RELSS
NEARLOW	-0.011***	-0.013***	-0.014***	-0.014***	-0.014***
	(-7.62)	(-9.34)	(-8.72)	(-9.28)	(-9.27)
SIR		0.0056***	0.0056***	0.0055***	0.0055***
		(14.97)	(14.85)	(14.60)	(14.58)
BTM			0.0068		0.0022
			(0.76)		(0.17)
LnMVE				-0.0050	-0.0044
				(-1.00)	(-0.65)
N	1,062,613	1,062,613	1,062,613	1,062,613	1,062,613
adj. R^2	0.406	0.413	0.413	0.413	0.413

Table 17

Regression of Short-Selling Ratio on Proximity to 52-Week Low Within 10 Days After Crossing the 52-Week Low (H1b)

	(1) SSRATIO	(2) SSRATIO	(3) SSRATIO	(4) SSRATIO	(5) SSRATIO
NEARLOW	0.057***	0.050***	0.045***	0.044***	0.043***
	(15.41)	(14.93)	(13.38)	(12.81)	(12.60)
SIR		0.021***	0.021***	0.021***	0.021***
		(20.36)	(20.04)	(19.54)	(19.56)
BTM			0.056**		0.032
			(2.31)		(1.13)
LnMVE				-0.031**	-0.023
				(-2.26)	(-1.41)
N	1,062,613	1,062,613	1,062,613	1,062,613	1,062,613
adj. R^2	0.554	0.572	0.572	0.573	0.573

Table 18

Summary of Regressions of Short Selling on Proximity to 52-Week Low Within 10 Days After Crossing the 52-Week Low (H1b)

	(1) SSVOL	(2) RELSS	(3) SSRATIO
NEARLOW	62.1***	-0.014***	0.043***
	(8.93)	(-9.27)	(12.60)
SIR	19.5***	0.0055***	0.021***
	(10.18)	(14.58)	(19.56)
BTM	247.4***	0.0022	0.032
	(4.05)	(0.17)	(1.13)
LnMVE	-11.7	-0.0044	-0.023
	(-0.38)	(-0.65)	(-1.41)
N	1,062,613	1,062,613	1,062,613
adj. R^2	0.773	0.413	0.573

Fundamental Strength

I used regression analyses to investigate the relationships between abnormal short-selling volume and multiple independent variables. Hypothesis 2a examines the effect of financial strength on short selling in a sample of stocks near their 52-week low. The sample starts with the overall sample described in Hypothesis 1a and eliminates the daily-stock observations where the stock's price is not near the stock's 52-week low (504,580 observations). Table 22 presents the results of three regressions based on equations (19-21). I found the coefficient for FSCORE, my proxy for fundamental strength, is insignificant with all three main regression columns (5) in Tables 19-21. From the result of column (5) in Table 19, the coefficients of SIR and LnMVE are highly significant and positive. A positive and significant coefficient for SIR provides further evidence that short sellers may view higher short interest as confirmation to short shares further. Furthermore, the positive and significant coefficient for LnMVE provides evidence that short sellers prefer shorting larger capitalized and more liquid stocks. When the results of the three regressions in Table 22 are collectively analyzed, I posited that short sellers do not consider a stock's fundamental strength when the price is near the 52-week low. Short sellers may be using other factors to influence their trading behavior.

Table 19

Hypothesis 2a - Regression of Short-Selling Volume on Financial Strength Score

	(1) SSVOL	(2) SSVOL	(3) SSVOL	(4) SSVOL	(5) SSVOL
FSCORE	60.2***	53.4***	51.4***	-8.17	-9.10
	(3.00)	(2.71)	(2.67)	(-0.59)	(-0.66)
SIR		-17.9***	-21.0***	9.83**	12.8***
		(-2.90)	(-3.41)	(2.48)	(3.08)
BTM			-488.5***		304.3***
			(-4.61)		(3.23)
LnMVE				446.9***	462.7***
				(15.69)	(16.20)
N	30,760	30,760	30,760	30,760	30,760
adj. R^2	0.044	0.051	0.065	0.433	0.438

Note. FSCORE is the Financial Strength score based on Piotroski (2000) it is defined simply as the sum of the 9 individual signals or *FSCORE = F_ROA + F_CFO + F_ΔROA + F_ACCRUAL + F_LEVER + F_ΔLIQUID + F_ISSUANCE + F_ΔMARGIN + F_ΔTURNOVER*; F_ROA is a binary variable that is equal to one if the ratio of the firm's income before extraordinary items for the last four quarters divided by beginning quarter's total assets is positive, zero otherwise; If subtracting last year's ROA from current year's ROA results in a positive result F_ΔROA equals to one, otherwise zero. F_CFO equals one if the cash flow from operations of the last four quarters is positive after being scaled by beginning of the year total assets, zero otherwise; F_ACCRUAL is equal to one if cash flow from operations from the last four quarters is greater than net income from the last four quarters, otherwise zero. F_ ΔLEVERAGE is equal to one, zero otherwise; F_ ΔLIQUIDITY is equal to one if the current ratio (current assets divided by current liabilities) increased from last year to current year, zero otherwise; F_ISSUANCE is equal to one if the firm did not issue any common equity in the previous four quarters, zero otherwise; F_ΔMARGIN is one if subtracting last year's gross margin from this year's gross margin is positive, zero otherwise. F_ΔTURNOVER is one if subtracting last year's asset turnover ratio (total sales divided by total assets) from this year's asset turnover ratio is positive, zero otherwise.

Table 20

Hypothesis 2a - Regression of Relative Short-Selling Volume on Financial Strength Score

	(1) RELSS	(2) RELSS	(3) RELSS	(4) RELSS	(5) RELSS
FSCORE	-0.0022	0.00047	0.00036	-0.0019	-0.0019
	(-1.09)	(0.26)	(0.20)	(-1.09)	(-1.09)
SIR		0.0069^{***}	0.0067^{***}	0.0080^{***}	0.0080^{***}
		(9.13)	(8.89)	(10.07)	(9.90)
BTM			-0.026^{*}		0.0040
			(-1.94)		(0.30)
LnMVE				0.017^{***}	0.018^{***}
				(8.48)	(7.88)
N	30,760	30,760	30,760	30,760	30,760
adj. R^2	0.095	0.144	0.146	0.173	0.173

Table 21

Hypothesis 2a - Regression of Short-Selling Ratio on Financial Strength Score

	(1) SSRATIO	(2) SSRATIO	(3) SSRATIO	(4) SSRATIO	(5) SSRATIO
FSCORE	-0.0059	0.0079	0.0072	-0.00025	-0.000091
	(-0.68)	(1.31)	(1.25)	(-0.05)	(-0.02)
SIR		0.036^{***}	0.035^{***}	0.040^{***}	0.039^{***}
		(15.46)	(15.29)	(17.89)	(17.38)
BTM			-0.15^{***}		-0.051^{*}
			(-4.60)		(-1.73)
LnMVE				0.059^{***}	0.056^{***}
				(10.82)	(10.08)
N	30,760	30,760	30,760	30,760	30,760
adj. R^2	0.082	0.285	0.294	0.335	0.336

Table 22

Hypothesis 2a - Summary of Regressions of Short Selling on Financial Strength Score

	(1) SSVOL	(2) RELSS	(3) SSRATIO
FSCORE	-9.10	-0.0019	-0.000091
	(-0.66)	(-1.09)	(-0.02)
SIR	12.8^{***}	0.0080^{***}	0.039^{***}
	(3.08)	(9.90)	(17.38)
BTM	304.3^{***}	0.0040	-0.051^{*}
	(3.23)	(0.30)	(-1.73)
LnMVE	462.7^{***}	0.018^{***}	0.056^{***}
	(16.20)	(7.88)	(10.08)
N	30,760	30,760	30,760
adj. R^2	0.438	0.173	0.336

Crossing the 52-Week Low - FSCORE

Similar to Hypothesis 1B, I used regression analyses to investigate the relationships between abnormal short-selling volume and multiple independent variables after the stock has crossed its 52-week low. Hypothesis 2B examined the effect of the stock's fundamental strength on short-selling volume after the stock has crossed its 52-week low. The sample started with the overall sample and then eliminated the daily-stock observations not in the stock's lowest 25% of its trading range (535,374 observations), I then eliminated the observations where the stock has not crossed its 52-week low (276,527 observations). Table 23 presents the descriptive statistics for the sample used for the regressions for Hypothesis 1B. Table 24 presents the results of the five regressions of short-selling volume (SSVOL) on the Piotroski financial strength score (FSCORE).

Table 23

Descriptive Statistics: Hypothesis 2b

	N	Mean	St.Dev	p25	Median	p75
SSVOL	258,847	707,000	1,080,000	67,325	250,084	826,515
RELSS	258,847	.445	.152	.359	.458	.55
SSRATIO	258,847	.005	.004	.002	.003	.006
FSCORE	258,847	5.448	1.462	4	5	6
SIR	258,847	.057	.054	.019	.038	.079
BTM	258,847	.529	.328	.281	.47	.734
LnMVE	258,847	21.684	1.543	20.543	21.51	22.662
PRICE	258,847	40.238	28.434	21.19	31.88	48.59
PRICE(Split adj)	258,847	39.192	27.26	20.6	31.22	47.73
52-Week High	258,847	60.737	37.903	34.21	49.95	75.63
52-Week Low	258,847	37.08	24.936	19.34	29.92	45.78
RANGEPCT	258,847	.73	.84	.371	.55	.832
NODIVIDEND	258,847	.397	.489	0	0	1
NEXTDIVYLD	169,376	.009	.008	.004	.007	.011

The regressions of SSVOL on FSCORE find the coefficient for FSCORE, my proxy for financial strength, is not significant for columns (1-3) and (5). From the result of equation (4) in Table 24, the coefficient for FSCORE is significant and negative. When comparing the results of columns (3-5), Column (4) does not include the BTM variable and represents the possibility that FSCORE may be significantly associated with BTM. Considering the calculation of BTM includes the difference of assets and liabilities scaled by market capitalization value and FSCORE is a composite score that contains elements of leverage, liquidity, and issuance of equity capital, I therefore examined the differences in the *adj* R^2 scores of columns (4) and (5) (.362 v. .377) and posited that column (5) better explains the variability of SSVOL with changes in SIR, BTM, and LnMVE.

Table 25 presents the results of the five regressions of relative short-selling volume (RELSS) on the Piotroski financial strength score (FSCORE). Columns (1-5) show the coefficients of FSCORE to be negative and significant. Using the Equation (5) coefficient of RELSS, one could expect a decrease in RELSS of .43% (coefficient of -0.0043) for every unit increase in a company's FSCORE. Both SIR and LnMVE are significant and positive, thus providing evidence that increases in a company's short-interest ratio and market capitalization increase a company's RELSS.

Table 26 presents the results of the five regressions of short selling ratio (SSRATIO) on the Piotroski financial strength score (FSCORE). The coefficients for FSCORE are slightly significant ($p < .10$) for equations (2) and (3) and are insignificant for equations (1), (4), and (5). Again, the coefficients for SIR and LnMVE are positive and significant, providing evidence of the positive correlation of recently reported short interest levels and stock capitalization on current short-selling volume.

Table 24

Hypothesis 2b - Regression of Short-Selling Volume on Financial Strength Score After Crossing 52-Week Low

	(1) SSVOL	(2) SSVOL	(3) SSVOL	(4) SSVOL	(5) SSVOL
FSCORE	19.2	19.2	17.7	-23.8**	-13.5
	(1.30)	(1.29)	(1.19)	(-2.23)	(-1.29)
SIR		-0.35	-0.56	27.7***	31.0***
		(-0.08)	(-0.12)	(8.24)	(9.10)
BTM			-48.0		425.3***
			(-0.52)		(5.45)
LnMVE				427.0***	448.4***
				(17.94)	(18.31)
N	258,847	258,847	258,847	258,847	258,847
adj. R^2	0.024	0.024	0.024	0.362	0.377

Table 25

Hypothesis 2b – Regression of Relative Short-Selling Volume on Financial Strength Score After Crossing 52-Week Low

	(1) RELSS	(2) RELSS	(3) RELSS	(4) RELSS	(5) RELSS
FSCORE	-0.0043***	-0.0026**	-0.0032**	-0.0042***	-0.0043***
	(-3.20)	(-2.06)	(-2.48)	(-3.42)	(-3.46)
SIR		0.0060***	0.0059***	0.0070***	0.0070***
		(13.42)	(13.27)	(16.09)	(16.00)
BTM			-0.019**		-0.0024
			(-2.33)		(-0.30)
LnMVE				0.016***	0.016***
				(10.03)	(9.43)
N	258,847	258,847	258,847	258,847	258,847
adj. R^2	0.100	0.144	0.145	0.167	0.167

Table 26

Hypothesis 2a - Regression of Short-Selling Ratio on Financial Strength Score After Crossing 52-Week Low

	(1) SSRATIO	(2) SSRATIO	(3) SSRATIO	(4) SSRATIO	(5) SSRATIO
FSCORE	-0.0045	0.0068*	0.0077*	0.0023	0.0042
	(-0.77)	(1.70)	(1.91)	(0.59)	(1.11)
SIR		0.041***	0.042***	0.044***	0.045***
		(25.27)	(25.37)	(27.35)	(27.72)
BTM			0.030		0.082***
			(1.16)		(3.23)
LnMVE				0.045***	0.049***
				(9.50)	(9.96)
N	258,847	258,847	258,847	258,847	258,847
adj. R^2	0.052	0.324	0.324	0.348	0.352

When I considered the regression equations of the three dependent variables of Hypothesis 2b (SSVOL, RELSS, SSRATIO), I posited again that the fundamental strength of a company, as measured by the Piotroski FSCORE, does not have significant influence over short-seller behavior after a stock has crossed its 52-week low. The negative and significant coefficient value for FSCORE with RELSS as the dependent variable provides evidence that it is not the short sellers affected by the FSCORE but the long investors that increase their selling.

Table 27

Hypothesis 2a - Summary of Regression of Short Selling on Financial Strength Score After Crossing 52-Week Low

	(1) SSVOL	(2) RELSS	(3) SSRATIO
FSCORE	-13.5	-0.0043^{***}	0.0042
	(-1.29)	(-3.46)	(1.11)
SIR	31.0^{***}	0.0070^{***}	0.045^{***}
	(9.10)	(16.00)	(27.72)
BTM	425.3^{***}	-0.0024	0.082^{***}
	(5.45)	(-0.30)	(3.23)
LnMVE	448.4^{***}	0.016^{***}	0.049^{***}
	(18.31)	(9.43)	(9.96)
N	258,847	258,847	258,847
adj. R^2	0.377	0.167	0.352

Crossing the 52-Week Low with FSCORE, a Closer Look

In this subsection, to mitigate against the possible influence from time-based omitted variables, I refined the previous sample to include only the observations that occur up to 10 days after the 52-week low has been crossed. The sample started with the sample used in Hypothesis 2b and then eliminated the observations occurring more than 10 days after (173,298 observations) the stock crosses the 52-week low. Table 28 presents the descriptive statistics for the sample used for the regressions for Hypothesis 1b. Table 29 presents the results of five regressions based on equations (19-21).

Table 28

Descriptive Statistics: Hypothesis 2b Limited to 10 Days after 52-Week Low

	N	Mean	St.Dev	p25	Median	p75
SSVOL	251,094	701,000	1,070,000	66,224	246,000	819,468
RELSS	251,094	.444	.152	.358	.457	.55
SSRATIO	251,094	.005	.004	.002	.003	.006
FSCORE	251,094	5.435	1.461	4	5	6
SIR	251,094	.057	.054	.019	.038	.078
BTM	251,094	.529	.328	.28	.471	.736
LnMVE	251,094	21.679	1.544	20.535	21.504	22.661
PRICE	251,094	40.156	28.38	21.1	31.85	48.51
PRICE(Split adj)	251,094	39.172	27.265	20.51	31.23	47.75
52 Week High	251,094	60.673	37.847	34.22	49.87	75.56
52 Week Low	251,094	37.022	24.896	19.25	29.89	45.74
RANGEPCT	251,094	.731	.847	.373	.551	.833
NONDIVIDEND	251,094	.394	.489	0	0	1
NEXTDIVYLD	165,251	.009	.008	.004	.007	.011

Table 29 provides the results of the regressions of short-selling volume (SSVOL) on FSCORE, the proxy for financial strength of the company on a sample of the observations for the 10 days following the stock's initial crossing of the 52-week low. The regressions of SSVOL on FSCORE find the coefficient for FSCORE not significant for columns (1-3) and (5). From the result of column (4) in Table 29, the coefficient for FSCORE is significant and negative. When comparing the results of columns (3-5), column (4) does not include the BTM variable and represents the possibility that FSCORE may be significantly associated with BTM. Considering the calculation of BTM includes the difference of assets and liabilities scaled by market capitalization value and FSCORE is a composite score that contains elements of leverage, liquidity, and issuance of equity capital, I, therefore, examined the differences in the *adj* R^2 scores of columns (4) and (5) (.358 v. .373) and posited that column (5) better explains the variability of SSVOL with changes in SIR, BTM, and LnMVE.

Table 30 presents the results of the five regressions of relative short-selling volume (RELSS) on the Piotroski financial strength score (FSCORE). Columns (1-5) show the coefficients of FSCORE are negative and significant. Using the column (5) coefficient of RELSS (-0.0044), one could expect a decrease in RELSS of .44% for every unit increase in a company's FSCORE. Both SIR and LnMVE are significant and positive, thus providing further evidence that increases in a company's short-interest ratio and market capitalization increase a company's RELSS.

Table 31 presents the results of the five regressions of short selling ratio (SSRATIO) on the Piotroski financial strength score (FSCORE). The coefficients for FSCORE are slightly significant ($p < .10$) for column (3) and are insignificant for columns (1), (2), (4), and (5). Again, the coefficients for SIR and LnMVE are positive and significant, providing evidence of the positive correlation of recently reported short interest levels and stock capitalization on current short-selling volume.

Table 29

Hypothesis 2b - Regression of Short-Selling Volume on Financial Strength Score the 10 Days After Crossing 52-Week Low

	(1)	(2)	(3)	(4)	(5)
	SSVOL	SSVOL	SSVOL	SSVOL	SSVOL
FSCORE	15.8	15.9	14.5	-25.0**	-14.5
	(1.05)	(1.06)	(0.96)	(-2.30)	(-1.36)
SIR		0.39	0.18	28.0***	31.3***
		(0.08)	(0.04)	(8.19)	(8.99)
BTM			-45.8		422.9***
			(-0.49)		(5.33)
LnMVE				423.3***	444.4***
				(17.56)	(17.93)
N	251,094	251,094	251,094	251,094	251,094
adj. R^2	0.023	0.023	0.023	0.358	0.373

Table 30

Hypothesis 2b - Regression of Short-Selling Volume on Financial Strength Score the 10 Days After Crossing 52-Week Low

	(1)	(2)	(3)	(4)	(5)
	RELSS	RELSS	RELSS	RELSS	RELSS
FSCORE	-0.0045^{***}	-0.0028^{**}	-0.0034^{**}	-0.0043^{***}	-0.0044^{***}
	(-3.29)	(-2.13)	(-2.57)	(-3.41)	(-3.47)
SIR		0.0059^{***}	0.0059^{***}	0.0070^{***}	0.0069^{***}
		(12.91)	(12.75)	(15.47)	(15.37)
BTM			-0.020^{**}		-0.0036
			(-2.42)		(-0.44)
LnMVE				0.016^{***}	0.016^{***}
				(9.82)	(9.20)
N	251,094	251,094	251,094	251,094	251,094
adj. R^2	0.098	0.141	0.143	0.164	0.164

Table 31

Hypothesis 2b – Regression of Short-Selling Ratio on Financial Strength Score the 10 Days After Crossing 52-Week Low

	(1) SSRATIO	(2) SSRATIO	(3) SSRATIO	(4) SSRATIO	(5) SSRATIO
FSCORE	-0.0053	0.0063	0.0070*	0.0019	0.0038
	(-0.91)	(1.56)	(1.74)	(0.49)	(0.99)
SIR		0.041***	0.041***	0.044***	0.045***
		(24.51)	(24.57)	(26.67)	(26.98)
BTM			0.024		0.077***
			(0.95)		(3.03)
LnMVE				0.046***	0.050***
				(9.43)	(9.84)
N	251,094	251,094	251,094	251,094	251,094
adj. R^2	0.050	0.319	0.319	0.344	0.347

The results from the regression equations of the three dependent variables of Hypothesis 2B (SSVOL, RELSS, SSRATIO), I posited that the fundamental strength of a company, as measured by the Piotroski FSCORE, does not have significant influence over short-seller behavior after a stock has crossed its 52-week low. The negative and significant coefficient value for FSCORE with RELSS as the dependent variable provides evidence that it is not the short sellers affected by the FSCORE but the long investors that increase their buying and selling in the 10 days that follow the stock crossing the 52-week low.

Table 32

Hypothesis 2b - Summary of Regressions of Short Selling on Financial Strength Score the 10 Days After Crossing 52-Week Low

	(1) SSVOL	(2) RELSS	(3) SSRATIO
FSCORE	-14.5	-0.0044***	0.0038
	(-1.36)	(-3.47)	(0.99)
SIR	31.3***	0.0069***	0.045***
	(8.99)	(15.37)	(26.98)
BTM	422.9***	-0.0036	0.077***
	(5.33)	(-0.44)	(3.03)
LnMVE	444.4***	0.016***	0.050***
	(17.93)	(9.20)	(9.84)
N	251,094	251,094	251,094
adj. R^2	0.373	0.164	0.347

Sensitivity Analyses and Robustness Checks

To rule out potential alternative explanations for the results already found, I performed several sensitivity and robustness checks. These checks and analyses included testing for any influence due to “abnormally high-priced” stocks, the proximity of earnings announcements, persistence of a stock placement within the portions of the lower 52-week price range, dividends, decomposition of the FSCORE, size of the 52-week range relative to current price, and finally, different trading day intervals. I made no ex-ante predictions for these alternative measures.

Though none of these additional studies bore any significant findings that changed or altered results in any significant manner, one can feel more assured that they have been investigated.

"Abnormally" High-priced Stocks

A number of studies using the 2005 to 2006 Regulation SHO database restricted their samples to exclude "abnormally" high-priced stocks. There are a growing number of companies that have decided not to split their shares when the price of their stock rise to "abnormal levels." High-priced stocks make it more difficult for the retail investor to buy shares, thus putting possible downward pressure on overall volume. Tables (33-36) provide the regression results of using a sample that only includes the lower 90 percentile of stocks based on price. There are no significant changes in direction or level of significance in the variables of interest of any hypotheses.

Table 33

Hypothesis 1a - Summary of Regressions of Short-Selling Volume on Proximity to 52-Week Low Using Lower 90 Percentile of Closing Price

	(1) SSVOL	(2) RELSS	(3) SSRATIO
NEARLOW	62.1***	-0.015***	0.042***
	(5.64)	(-6.03)	(7.94)
SIR	12.0***	0.0054***	0.017***
	(4.35)	(9.82)	(10.18)
BTM	291.0**	0.050	0.078
	(2.35)	(1.61)	(1.58)
LnMVE	248.6***	0.051***	0.11***
	(5.42)	(4.41)	(5.30)
N	389,379	389,379	389,379
adj. R^2	0.848	0.413	0.563

Table 34

Hypothesis 1b - Summary of Regressions of Short Selling on Proximity to 52-Week Low the 10 Days After Crossing the 52-Week Low Using Lower 90 Percentile of Closing Price Sample

	(1) SSVOL	(2) RELSS	(3) SSRATIO
NEARLOW	58.0***	-0.014***	0.044***
	(7.99)	(-9.07)	(12.19)
SIR	19.8***	0.0058***	0.021***
	(9.31)	(15.70)	(18.77)
BTM	256.7***	0.0036	0.032
	(4.16)	(0.28)	(1.10)
LnMVE	-3.71	-0.0051	-0.0091
	(-0.11)	(-0.70)	(-0.52)
N	883,276	883,276	883,276
adj. R^2	0.782	0.411	0.579

Table 35

Hypothesis 2a - Summary of Regressions of Short Selling on Financial Strength Score Using Lower 90 Percentile of Closing Price Sample

	(1) SSVOL	(2) RELSS	(3) SSRATIO
FSCORE	-3.41	-0.0039**	-0.0014
	(-0.24)	(-1.97)	(-0.24)
SIR	11.5***	0.0082***	0.037***
	(2.74)	(10.07)	(15.68)
BTM	294.9***	0.0073	-0.053*
	(3.00)	(0.47)	(-1.76)
LnMVE	506.0***	0.021***	0.064***
	(14.82)	(7.94)	(10.07)
N	25,605	25,605	25,605
adj. R^2	0.464	0.178	0.334

Table 36

Hypothesis 2b - Summary of Regressions of Short Selling on Financial Strength Score the 10 Days After Crossing 52-Week Low Using Lower 90 Percentile of Closing Price Sample

	(1) SSVOL	(2) RELSS	(3) SSRATIO
FSCORE	-10.6	-0.0048***	0.0038
	(-0.97)	(-3.63)	(0.96)
SIR	31.0***	0.0068***	0.045***
	(9.00)	(14.54)	(25.90)
BTM	417.8***	-0.0027	0.092***
	(5.22)	(-0.33)	(3.54)
LnMVE	469.8***	0.018***	0.054***
	(17.00)	(9.39)	(9.49)
N	226,600	226,600	226,600
adj. R^2	0.390	0.166	0.351

Earnings Announcements

I investigated the sample of observations within a 10-day [-5,+5] window of an earnings announcement to see if there is a significant change in direction or significance in the variables of interest. I then investigated the sample not within the 10-day window. The results of the regressions are in Tables 38-44. I found no changes in significance of the variables of interest. My conclusions remained the same.

Table 37

Hypothesis 1b - Summary of Regressions of Short Selling on Proximity to 52-Week Low when an Earnings Announcement is Close (<10 Days)

	(1) SSVOL	(2) RELSS	(3) SSRATIO
NEARLOW	150.7***	-0.017***	0.091***
	(7.91)	(-4.96)	(9.35)
SIR	16.3***	0.0049***	0.022***
	(6.52)	(8.07)	(12.75)
BTM	575.5***	0.034	0.14**
	(3.92)	(1.15)	(2.47)
LnMVE	342.0***	0.035***	0.14***
	(4.63)	(3.37)	(4.49)
N	59,032	59,032	59,032
adj. R^2	0.804	0.442	0.571

Table 38

Hypothesis 1b - Summary of Regressions of Short Selling on Proximity to 52-Week Low the 10 Days after Crossing the 52-Week Low when an Earnings Announcement is Close (<10 Days)

	(1) SSVOL	(2) RELSS	(3) SSRATIO
NEARLOW	99.1***	-0.013***	0.067***
	(10.76)	(-6.75)	(14.01)
SIR	28.4***	0.0061***	0.025***
	(12.56)	(14.57)	(20.01)
BTM	285.8***	0.00080	0.029
	(4.23)	(0.06)	(0.83)
LnMVE	-28.9	-0.0094	-0.019
	(-0.81)	(-1.32)	(-0.97)
N	119,351	119,351	119,351
adj. R^2	0.756	0.428	0.581

Table 39

Hypothesis 2a - Summary of Regressions of Short Selling on Financial Strength Score when an Earnings Announcement is Close (<10 Days)

	(1) SSVOL	(2) RELSS	(3) SSRATIO
FSCORE	7.23	-0.0048	0.0066
	(0.36)	(-1.64)	(0.74)
SIR	24.0***	0.0069***	0.052***
	(4.07)	(5.99)	(16.16)
BTM	283.2**	0.026	-0.011
	(2.11)	(1.42)	(-0.24)
LnMVE	549.5***	0.016***	0.078***
	(15.36)	(4.84)	(8.38)
N	2,828	2,828	2,828
adj. R^2	0.450	0.126	0.334

Table 40

Hypothesis 2b - Summary of Regressions of Short Selling on Financial Strength Score the 10 Days After Crossing 52-Week Low when an Earnings Announcement is Close (<10 Days)

	(1) SSVOL	(2) RELSS	(3) SSRATIO
FSCORE	-15.1	-0.0050***	0.0052
	(-1.19)	(-3.64)	(1.15)
SIR	51.2***	0.0074***	0.056***
	(11.33)	(16.77)	(32.02)
BTM	430.7***	0.011	0.039
	(4.65)	(1.28)	(1.34)
LnMVE	535.2***	0.016***	0.060***
	(20.32)	(8.72)	(9.34)
N	26,656	26,656	26,656
adj. R^2	0.390	0.177	0.360

Table 41

Hypothesis 1a - Summary of Regressions of Short Selling on Proximity to 52-Week Low when an Earnings Announcement is not Close (>10 Days)

	(1) SSVOL	(2) RELSS	(3) SSRATIO
NEARLOW	63.0***	-0.016***	0.038***
	(4.68)	(-6.61)	(6.10)
SIR	11.5***	0.0054***	0.016***
	(5.22)	(11.56)	(13.00)
BTM	394.9***	0.040	0.080
	(3.03)	(1.44)	(1.55)
LnMVE	296.4***	0.038***	0.11***
	(3.95)	(4.22)	(3.12)
N	476,277	476,277	476,277
adj. R^2	0.850	0.432	0.607

Table 42

Hypothesis 1b - Summary of Regressions of Short Selling on Proximity to 52-Week Low the 10 Days After Crossing the 52-Week Low when an Earnings Announcement is not Close (>10 Days)

	(1) SSVOL	(2) RELSS	(3) SSRATIO
NEARLOW	57.8***	-0.014***	0.040***
	(8.26)	(-9.15)	(11.54)
SIR	18.5***	0.0055***	0.020***
	(9.67)	(14.31)	(19.05)
BTM	243.8***	0.0025	0.033
	(3.97)	(0.20)	(1.17)
LnMVE	-8.98	-0.0038	-0.023
	(-0.29)	(-0.56)	(-1.42)
N	943,218	943,218	943,218
adj. R^2	0.788	0.413	0.593

Table 43

Hypothesis 2a - Summary of Regressions of Short Selling on Financial Strength Score when an Earnings Announcement is not Close (>10 Days)

	(1) SSVOL	(2) RELSS	(3) SSRATIO
FSCORE	-9.72	-0.0019	-0.0013
	(-0.70)	(-1.04)	(-0.24)
SIR	11.9***	0.0081***	0.038***
	(2.87)	(9.86)	(16.56)
BTM	312.1***	0.0027	-0.046
	(3.29)	(0.19)	(-1.56)
LnMVE	455.3***	0.018***	0.055***
	(15.77)	(7.72)	(9.99)
N	27,632	27,632	27,632
adj. R^2	0.443	0.178	0.345

Table 44

Hypothesis 2b - Summary of Regressions of Short Selling on Financial Strength Score the 10 Days After Crossing 52-Week Low When an Earnings Announcement is not Close (>10 Days)

	(1) SSVOL	(2) RELSS	(3) SSRATIO
FSCORE	-14.5	-0.0044***	0.0035
	(-1.38)	(-3.44)	(0.92)
SIR	28.9***	0.0069***	0.044***
	(8.63)	(14.92)	(25.96)
BTM	426.2***	-0.0052	0.083***
	(5.45)	(-0.62)	(3.30)
LnMVE	433.9***	0.016***	0.048***
	(17.64)	(9.06)	(9.79)
N	224,300	224,300	224,300
adj. R^2	0.378	0.163	0.355

Price Persistence

Price persistence is the tendency of a stock's price to stay on trend relative to a reference point. I investigated the stocks' persistence in staying in the upper or lower halves of the area close to the 52-week low. I further split the sample into persistence levels of high and low which is determined by the number of days a stock's price stays in the half described above. Low persistence is defined by a stock staying in the region less than six days and High is six days or more. The use of six days is based on findings from the literature showing that short sellers stay in a position for an average of 11 days. I do not expect to see any significant changes in direction or statistical significance from the main regressions. Tables 45-48 show the results of the regressions for the four subsamples. No significant overall changes were found.

Table 45

Hypothesis 2a Summary of Regressions of Short Selling on Financial Strength Score, Persistence Upper Low Range, Low Persistence

	(1) SSVOL	(2) RELSS	(3) SSRATIO
FSCORE	-6.24	-0.00072	0.011
	(-0.42)	(-0.33)	(1.51)
SIR	16.2***	0.0079***	0.041***
	(2.82)	(13.32)	(15.61)
BTM	336.4**	0.0097	-0.051
	(2.48)	(0.66)	(-1.16)
LnMVE	493.6***	0.018***	0.055***
	(17.18)	(5.62)	(7.98)
N	10,993	10,993	10,993
adj. R^2	0.428	0.127	0.263

Table 46

Hypothesis 2a Summary of Regressions of Short Selling on Financial Strength Score, Persistence Upper Low Range, High Persistence

	(1) SSVOL	(2) RELSS	(3) SSRATIO
FSCORE	-9.66	-0.0030	-0.011
	(-0.54)	(-1.25)	(-1.64)
SIR	5.73	0.0080***	0.036***
	(1.20)	(8.54)	(13.13)
BTM	273.3*	0.014	-0.018
	(1.76)	(0.85)	(-0.40)
LnMVE	429.5***	0.018***	0.054***
	(10.61)	(5.39)	(8.28)
N	10,645	10,645	10,645
adj. R^2	0.455	0.148	0.324

Table 47

Hypothesis 2a Summary of Regressions of Short Selling on Financial Strength Score, Persistence Lower Low Range, Low Persistence

	(1) SSVOL	(2) RELSS	(3) SSRATIO
FSCORE	5.90	0.0017	0.014
	(0.30)	(0.67)	(1.39)
SIR	39.1***	0.0083***	0.052***
	(4.11)	(10.07)	(14.44)
BTM	421.9**	0.020	-0.091
	(2.50)	(1.05)	(-1.54)
LnMVE	578.8***	0.019***	0.064***
	(17.57)	(5.33)	(6.53)
N	2,498	2,498	2,498
adj. R^2	0.440	0.138	0.278

Table 48

Hypothesis 2a Summary of Regressions of Short Selling on Financial Strength Score, Persistence Lower Low, High Persistence

	(1) SSVOL	(2) RELSS	(3) SSRATIO
FSCORE	-13.5	-0.0014	-0.0052
	(-0.70)	(-0.62)	(-0.68)
SIR	12.7**	0.0078***	0.040***
	(2.16)	(8.16)	(12.32)
BTM	279.3**	-0.013	-0.063
	(2.08)	(-0.51)	(-1.58)
LnMVE	420.3***	0.017***	0.058***
	(11.46)	(3.17)	(5.36)
N	6,487	6,487	6,487
adj. R^2	0.431	0.159	0.364

Range Size

To investigate the effects of the size of the range on the variables of interest, I introduced RANGEPCT to represent the ratio of the 52-week range divided by the current stock price. Conceptually, RANGEPCT can be viewed as a measure of long-term volatility. Since short

Table 49

Hypothesis 1a Summary of Regressions of Short Selling on Proximity to 52-Week Low with RANGEPCT

	(1) SSVOL	(2) RELSS	(3) SSRATIO
NEARLOW	61.9***	-0.011***	0.030***
	(4.94)	(-4.42)	(5.29)
SIR	12.2***	0.0053***	0.017***
	(5.63)	(11.35)	(14.30)
BTM	427.9***	0.035	0.10**
	(3.24)	(1.27)	(2.03)
LnMVE	293.4***	0.043***	0.10***
	(4.06)	(4.54)	(3.08)
RANGEPCT	116.3**	-0.057***	0.17***
	(1.97)	(-6.07)	(7.21)
N	535,374	535,374	535,374
adj. R^2	0.838	0.432	0.585

sellers prefer stocks that move forcefully, I expected that the coefficient of the variable would be positive. I did not expect it to have a significant effect on the variables of interest. Tables 49-52 provide the results of the regressions with variable RANGEPCT added to the main regressions. The tables show RANGEPCT to be positive and highly significant in regressions that have SSVOL and SSRATIO as the dependent variable. Based on these results, one would expect short-selling volume to be higher near the 52-week low for stocks with larger 52-week ranges with respect to the current stock price.

Table 50

Hypothesis 1b Summary of Regressions of Short Selling on Proximity to 52-Week Low with RANGEPCT 10 Days After 52-Week Low

	(1) SSVOL	(2) RELSS	(3) SSRATIO
NEARLOW	36.1***	-0.015***	0.023***
	(5.26)	(-10.70)	(7.02)
SIR	18.6***	0.0055***	0.020***
	(10.08)	(14.42)	(20.14)
BTM	188.7***	-0.00019	-0.012
	(3.19)	(-0.01)	(-0.46)
LnMVE	19.4	-0.0032	0.00092
	(0.64)	(-0.47)	(0.06)
RANGEPCT	171.5***	0.0069*	0.13***
	(6.58)	(1.81)	(8.46)
N	1,062,613	1,062,613	1,062,613
adj. R^2	0.775	0.413	0.579

Table 51

Hypothesis 2a Summary of Regressions of Short Selling on Financial Strength Score with RANGEPCT

	(1) SSVOL	(2) RELSS	(3) SSRATIO
FSCORE	1.07	-0.0016	0.0064
	(0.08)	(-0.91)	(1.32)
SIR	7.23*	0.0078***	0.036***
	(1.74)	(9.71)	(16.95)
BTM	336.6***	0.0051	-0.030
	(3.66)	(0.38)	(-1.07)
LnMVE	481.2***	0.018***	0.068***
	(16.42)	(7.94)	(12.09)
RANGEPCT	436.1***	0.014	0.28***
	(3.64)	(1.21)	(6.89)
N	30,760	30,760	30,760
adj. R^2	0.450	0.173	0.373

Table 52

Hypothesis 2b Summary of Regressions of Short Selling on Financial Strength Score with RANGEPCT 10 Days After 52-Week Low

	(1) SSVOL	(2) RELSS	(3) SSRATIO
FSCORE	-2.23	-0.0045***	0.011***
	(-0.22)	(-3.47)	(3.17)
SIR	23.6***	0.0070***	0.040***
	(6.78)	(15.25)	(25.75)
BTM	381.9***	-0.0035	0.052**
	(4.84)	(-0.43)	(2.14)
LnMVE	452.9***	0.016***	0.055***
	(18.11)	(9.12)	(11.14)
RANGEPCT	273.0***	-0.00091	0.16***
	(6.15)	(-0.27)	(8.47)
N	251,094	251,094	251,094
adj. R^2	0.390	0.164	0.387

Dividends

Those that do and those that do not.

Literature has provided evidence that short-seller behavior is affected by dividend policy. I first investigated the effect of dividend-paying status. I inserted the binary variable, NODIVIDEND, into the main regressions. If the stock has not announced a dividend, NODIVIDEND is given a value of one, zero otherwise. The results of the regressions are in Tables 53-58. The regressions provided no evidence that the significance or direction of the variables of interest are affected.

Table 53

Hypothesis 1a - Summary of Regressions of Short Selling on Proximity to 52-Week Low with NODIVIDEND

	(1) SSVOL	(2) RELSS	(3) SSRATIO
NEARLOW	71.8***	-0.016***	0.044***
	(5.45)	(-6.80)	(7.28)
SIR	12.2***	0.0053***	0.017***
	(5.58)	(11.41)	(13.58)
BTM	422.1***	0.039	0.091*
	(3.22)	(1.42)	(1.77)
LnMVE	302.5***	0.038***	0.12***
	(4.05)	(4.18)	(3.34)
NODIVIDEND	-44.2	-0.0027	0.0083
	(-1.63)	(-0.40)	(0.52)
N	535,374	535,374	535,374
adj. R^2	0.838	0.431	0.583

Table 54

Hypothesis 1b - Summary of Regressions of Short Selling on Proximity to 52-Week Low with NODIVIDEND

	(1) SSVOL	(2) RELSS	(3) SSRATIO
NEARLOW	62.5***	-0.014***	0.043***
	(8.93)	(-9.29)	(12.64)
SIR	19.6***	0.0055***	0.021***
	(10.21)	(14.53)	(19.64)
BTM	245.2***	0.0024	0.032
	(4.02)	(0.19)	(1.12)
LnMVE	-11.2	-0.0045	-0.023
	(-0.36)	(-0.66)	(-1.40)
NODIVIDEND	39.4	-0.0039	0.012
	(1.15)	(-0.57)	(0.71)
N	1,062,613	1,062,613	1,062,613
adj. R^2	0.773	0.413	0.573

Table 55

Hypothesis 2a - Summary of Regressions of Short Selling on Financial Strength Score with NODIVIDEND

	(1) SSVOL	(2) RELSS	(3) SSRATIO
FSCORE	-7.80	-0.0022	0.00086
	(-0.57)	(-1.26)	(0.16)
SIR	10.7***	0.0084***	0.038***
	(2.66)	(10.32)	(16.91)
BTM	325.1***	-0.00038	-0.036
	(3.38)	(-0.03)	(-1.23)
LnMVE	470.2***	0.016***	0.062***
	(16.05)	(7.05)	(10.81)
NODIVIDEND	90.3*	-0.019***	0.067***
	(1.90)	(-2.66)	(4.14)
N	30,760	30,760	30,760
adj. R^2	0.440	0.176	0.341

Table 56

Hypothesis 2b - Summary of Regressions of Short Selling on Financial Strength Score with NODIVIDEND 10 Days After 52-Week Low

	(1) SSVOL	(2) RELSS	(3) SSRATIO
FSCORE	-14.5	-0.0044***	0.0036
	(-1.36)	(-3.45)	(0.94)
SIR	31.2***	0.0072***	0.043***
	(8.49)	(14.86)	(25.04)
BTM	423.5***	-0.0049	0.085***
	(5.37)	(-0.60)	(3.35)
LnMVE	444.8***	0.015***	0.054***
	(17.90)	(8.55)	(10.37)
NODIVIDEND	5.18	-0.0099*	0.063***
	(0.13)	(-1.92)	(3.76)
N	251,094	251,094	251,094
adj. R^2	0.373	0.165	0.351

Table 57

Hypothesis 2a - Summary of Regressions of Short Selling on Financial Strength Score with EXDIVCLOSE

	(1) SSVOL	(2) RELSS	(3) SSRATIO
FSCORE	7.06	-0.0034	0.018***
	(0.34)	(-1.33)	(2.60)
SIR	4.60	0.010***	0.035***
	(0.72)	(10.04)	(10.38)
BTM	483.4***	0.0051	-0.011
	(3.30)	(0.31)	(-0.28)
LnMVE	496.6***	0.018***	0.042***
	(14.12)	(7.56)	(7.07)
EXDIVCLOSE	46.8	-0.0097*	0.021*
	(1.45)	(-1.92)	(1.94)
N	17,122	17,122	17,122
adj. R^2	0.453	0.177	0.272

Note. EXDIVCLOSE is a binary variable equal to one if the stock is within 5 days [-5, +5] of its ex-dividend date and zero otherwise.

Table 58

Hypothesis 2b - Summary of Regressions of Short Selling on Financial Strength Score the 10 Days After Crossing 52-Week Low with EXDIVCLOSE

	(1) SSVOL	(2) RELSS	(3) SSRATIO
FSCORE	-12.8	-0.0041**	0.0081*
	(-0.78)	(-2.57)	(1.70)
SIR	41.9***	0.0083***	0.047***
	(6.47)	(10.88)	(17.00)
BTM	561.1***	-0.0036	0.10***
	(4.80)	(-0.33)	(3.12)
LnMVE	460.3***	0.015***	0.039***
	(15.25)	(7.25)	(7.17)
EXDIVCLOSE	57.8***	0.0016	0.018***
	(3.41)	(0.78)	(3.47)
N	152,239	152,239	152,239
adj. R^2	0.381	0.163	0.331

Dividend Yield

I furthered my investigation of dividends by including a dividend yield variable. NEXTDIVYLD is calculated by dividing the next expected dividend divided by the current stock price. Tables 59 and 60 show the results of adding variable NEXTDIVYLD to the main regressions of H2a and H2b. The results show that NEXTDIVYLD is negative and significant in the three main regressions for each hypothesis. The results provide evidence that stocks that pay a higher dividend with respect to their price have lower short-selling volume than those stocks with lower dividend yields. The coefficient for FSCORE in equation (3) is positive and significant. This result implies that fundamentally stronger stocks get short sold more than weaker dividend-paying stocks. Considering the coefficient for FSCORE in equation (1) is insignificant, I posited that the results are mixed, and the difference may be caused by share buybacks of the underlying companies.

Table 59

Hypothesis 2a - Summary of Regressions of Short Selling on Financial Strength Score with NEXTDIVYLD

	(1) SSVOL	(2) RELSS	(3) SSRATIO
FSCORE	3.19	-0.0037	0.015**
	(0.15)	(-1.50)	(2.40)
SIR	-0.89	0.0093***	0.032***
	(-0.14)	(10.07)	(10.00)
BTM	432.4***	-0.0054	-0.035
	(2.86)	(-0.34)	(-0.95)
LnMVE	492.2***	0.017***	0.039***
	(13.67)	(7.63)	(6.90)
NEXTDIVYLD	-17126.2**	-2.17***	-9.78***
	(-2.26)	(-4.75)	(-7.91)
N	17,004	17,004	17,004
adj. R^2	0.462	0.186	0.308

Note. NXTDIVYLD is calculated by dividing the next expected dividend payment by the stock's current price.

Table 60

Hypothesis 2a - Summary of Regressions of Short Selling on Financial Strength Score the 10 Days After Crossing 52-Week Low with EXDIVCLOSE

	(1) SSVOL	(2) RELSS	(3) SSRATIO
FSCORE	-18.9	-0.0048***	0.0058
	(-1.15)	(-3.01)	(1.26)
SIR	40.1***	0.0081***	0.046***
	(6.13)	(10.66)	(16.73)
BTM	569.7***	-0.0029	0.10***
	(4.84)	(-0.27)	(3.18)
LnMVE	463.5***	0.015***	0.040***
	(15.48)	(7.48)	(7.23)
NEXTDIVYLD	-11432.0**	-0.99***	-5.08***
	(-2.57)	(-3.32)	(-3.87)
N	151,319	151,319	151,319
adj. R^2	0.386	0.166	0.338

Tasting Each Ingredient of the Cake – Testing the Components of FSCORE

The FSCORE, as stated before, is a composite of nine binary variables. It represents an overall assessment of the underlying company's fundamentals. The score was meticulously created by Piotroski (2000) by testing several variables and their many combinations. Knowing the limitations of using only one variable, Piotroski chose 9 variables grouped into 3 categories of Profitability, Leverage/Source of Capital, and Operating Efficiency. I investigated the effect of each indicator variable of the FSCORE composite variable on short-seller volume near the 52-week low. Tables 61-66 show the results of the regressions. The only indicators that remain significant for regressions testing SSVOL and SSRATIO are F_ROA and F_TURNOVER. These two variables, though associated with profits and revenues, do not represent the overall fundamental strength of a company. Though the findings may hold some interest for a future study not focused on overall financial strength but specific variables, these limited findings contributed little to this dissertation.

Table 61

Hypothesis 2a - Regression of Short-Selling Volume on Financial Strength Score with FSCORE DECOMPOSED

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	SSVOL	SSVOL	SSVOL	SSVOL	SSVOL	SSVOL	SSVOL	SSVOL	SSVOL
F_ROA	-205.8***								
	(-2.60)								
F_ΔROA		95.0**							
		(2.44)							
F_CFO			-159.0**						
			(-2.19)						
F_ACCRUAL				-42.6					
				(-0.81)					
F_ ΔLEVERAGE					-96.2**				
					(-2.34)				
F_ ΔLIQUIDITY						69.7*			
						(1.66)			
F_ISSUANCE							-18.0		
							(-0.33)		
F_ΔMARGIN								-6.96	
								(-0.11)	
F_ΔTURNOVER									-2.42

									(-0.06)
SIR	11.3***	12.8***	11.5***	12.8***	13.1***	12.5***	12.8***	13.0***	12.9***
	(2.70)	(3.05)	(2.89)	(3.12)	(3.15)	(2.96)	(3.05)	(3.11)	(3.09)
BTM	329.7***	310.4***	311.2***	302.1***	314.4***	300.8***	305.0***	302.1***	303.4***
	(3.45)	(3.36)	(3.30)	(3.23)	(3.36)	(3.21)	(3.23)	(3.17)	(3.23)
LnMVE	466.2***	462.4***	463.7***	462.8***	463.9***	461.2***	462.4***	461.5***	461.6***
	(16.04)	(16.19)	(16.14)	(16.24)	(16.21)	(16.20)	(15.97)	(16.11)	(16.11)
N	30760	30760	30760	30760	30760	30760	30760	30760	30760
adj. R^2	0.441	0.440	0.439	0.438	0.440	0.439	0.438	0.438	0.438

Table 62

Hypothesis 2a - Regression of Relative Short-Selling Volume on Financial Strength Score with FSCORE DECOMPOSED

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	RELSS	RELSS	RELSS	RELSS	RELSS	RELSS	RELSS	RELSS	RELSS
F_ROA	0.00053								
	(0.05)								
F_ΔROA		-0.0095*							
		(-1.69)							
F_CFO			0.0032						
			(0.27)						
F_ACCRUAL				-0.0030					
				(-0.43)					
F_ ΔLEVERAGE					-0.0044				
					(-0.81)				
F_ ΔLIQUIDITY						-0.00095			
						(-0.17)			
F_ISSUANCE							0.0033		
							(0.53)		
F_ΔMARGIN								-0.0031	
								(-0.44)	
F_ΔTURNOVER									-0.0018

									(-0.31)
SIR	0.0081***	0.0081***	0.0081***	0.0081***	0.0081***	0.0081***	0.0081***	0.0081***	0.0081***
	(9.92)	(10.03)	(9.80)	(9.95)	(9.95)	(9.96)	(9.93)	(9.99)	(9.94)
BTM	0.0038	0.0031	0.0037	0.0037	0.0043	0.0039	0.0035	0.0032	0.0038
	(0.28)	(0.23)	(0.27)	(0.28)	(0.32)	(0.29)	(0.26)	(0.24)	(0.28)
LnMVE	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***
	(7.74)	(7.77)	(7.75)	(7.69)	(7.77)	(7.77)	(7.70)	(7.75)	(7.76)
N	30,760	30,760	30,760	30,760	30,760	30,760	30,760	30,760	30,760
adj. R^2	0.172	0.173	0.172	0.173	0.173	0.172	0.173	0.173	0.173

Table 63

Hypothesis 2a - Regression of Short-Selling Ratio on Financial Strength Score with FSCORE DECOMPOSED

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	SSRATIO	SSRATIO	SSRATIO	SSRATIO	SSRATIO	SSRATIO	SSRATIO	SSRATIO	SSRATIO
F_ROA	-0.061**								
	(-2.05)								
F_ΔROA		0.048***							
		(3.51)							
F_CFO			-0.070*						
			(-1.89)						
F_ACCRUAL				-0.026					
				(-1.25)					
F_ ΔLEVERAGE					-0.012				
					(-0.84)				
F_ ΔLIQUIDITY						0.0041			
						(0.31)			
F_ISSUANCE							-0.026*		
							(-1.72)		
F_ΔMARGIN								0.021	

								(1.00)	
F_ΔTURNOVER									0.021
									(1.52)
SIR	0.039***	0.039***	0.039***	0.039***	0.039***	0.039***	0.039***	0.039***	0.039***
	(16.92)	(17.37)	(17.51)	(17.57)	(17.41)	(17.37)	(17.35)	(17.34)	(17.52)
BTM	-0.043	-0.048	-0.048	-0.052*	-0.050*	-0.051*	-0.049*	-0.047	-0.051*
	(-1.47)	(-1.61)	(-1.61)	(-1.76)	(-1.68)	(-1.74)	(-1.66)	(-1.57)	(-1.71)
LnMVE	0.057***	0.057***	0.057***	0.057***	0.056***	0.056***	0.057***	0.056***	0.056***
	(10.13)	(10.09)	(10.17)	(10.12)	(10.08)	(10.03)	(10.19)	(10.05)	(9.99)
N	30,760	30,760	30,760	30,760	30,760	30,760	30,760	30,760	30,760
adj. R^2	0.337	0.339	0.337	0.336	0.336	0.336	0.336	0.336	0.336

Table 64

Hypothesis 2b - Regression of Short-Selling Volume on Financial Strength Score with FSCORE DECOMPOSED 10 Days After 52-Week Low

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	SSVOL	SSVOL	SSVOL	SSVOL	SSVOL	SSVOL	SSVOL	SSVOL	SSVOL
F_ROA	-187.5***								
	(-3.48)								
F_ΔROA		17.7							
		(0.61)							
F_CFO			-126.7**						
			(-2.25)						
F_ACCRUAL				46.4					
				(1.32)					
F_ ΔLEVERAGE					-51.7*				
					(-1.86)				
F_ ΔLIQUIDITY						13.2			
						(0.53)			
F_ISSUANCE							-39.9		
							(-1.05)		
F_ΔMARGIN								-37.4	
								(-1.00)	

F_ΔTURNOVER									67.2**
									(2.28)
SIR	30.5***	31.6***	31.1***	31.6***	31.3***	31.6***	31.6***	31.7***	31.6***
	(8.91)	(9.06)	(9.03)	(9.08)	(8.97)	(9.09)	(9.07)	(9.15)	(9.07)
BTM	423.1***	433.6***	432.1***	430.6***	434.8***	429.9***	428.5***	420.4***	437.6***
	(5.39)	(5.44)	(5.48)	(5.46)	(5.51)	(5.46)	(5.45)	(5.22)	(5.54)
LnMVE	447.8***	443.7***	445.4***	442.8***	443.9***	443.6***	446.1***	442.5***	444.4***
	(17.93)	(17.90)	(17.87)	(17.94)	(17.94)	(17.86)	(17.79)	(17.87)	(17.93)
N	251,094	251,094	251,094	251,094	251,094	251,094	251,094	251,094	251,094
adj. R^2	0.376	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.374

Table 65

Hypothesis 2b - Regression of Relative Short-Selling Volume on Financial Strength Score with FSCORE DECOMPOSED 10 Days After 52-Week Low

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	RELSS	RELSS	RELSS	RELSS	RELSS	RELSS	RELSS	RELSS	RELSS
F_ROA	-0.0089*								
	(-1.80)								
F_ΔROA		-0.0056							
		(-1.56)							
F_CFO			-0.018**						
			(-2.30)						
F_ACCRUAL				-0.012**					
				(-2.27)					
F_ ΔLEVERAGE					-0.0032				
					(-0.99)				
F_ ΔLIQUIDITY						-0.0033			
						(-1.05)			
F_ISSUANCE							-0.0068*		
							(-1.71)		
F_ΔMARGIN								-0.0086*	
								(-1.94)	

F_ΔTURNOVER									0.0011
									(0.32)
SIR	0.0070***	0.0070***	0.0070***	0.0070***	0.0070***	0.0070***	0.0070***	0.0071***	0.0070***
	(15.56)	(15.58)	(15.38)	(15.58)	(15.66)	(15.66)	(15.73)	(15.86)	(15.66)
BTM	-0.0017	-0.0024	-0.0011	-0.0014	-0.0011	-0.0012	-0.0017	-0.0036	-0.0012
	(-0.21)	(-0.29)	(-0.13)	(-0.17)	(-0.13)	(-0.15)	(-0.20)	(-0.43)	(-0.15)
LnMVE	0.016***	0.015***	0.016***	0.016***	0.015***	0.015***	0.016***	0.015***	0.015***
	(9.07)	(8.93)	(9.13)	(9.12)	(9.02)	(8.97)	(9.19)	(8.85)	(9.00)
N	251,094	251,094	251,094	251,094	251,094	251,094	251,094	251,094	251,094
adj. R^2	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163

Table 66

Hypothesis 2b - Regression of Short-Selling Ratio on Financial Strength Score with FSCORE DECOMPOSED 10 Days After 52-Week Low

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	SSRATIO	SSRATIO	SSRATIO	SSRATIO	SSRATIO	SSRATIO	SSRATIO	SSRATIO	SSRATIO
F_ROA	-0.045**								
	(-2.42)								
F_ΔROA		0.019*							
		(1.85)							
F_CFO			-0.031						
			(-1.30)						
F_ACCRUAL				-0.022					
				(-1.37)					
F_ ΔLEVERAGE					-0.0020				
					(-0.21)				
F_ ΔLIQUIDITY						-0.010			
						(-1.17)			
F_ISSUANCE							0.0037		
							(0.28)		
F_ΔMARGIN								0.027**	

								(2.24)	
F_ΔTURNOVER									0.038***
									(3.55)
SIR	0.045***	0.045***	0.045***	0.045***	0.045***	0.045***	0.045***	0.045***	0.045***
	(26.93)	(27.12)	(26.90)	(27.17)	(27.05)	(27.11)	(27.06)	(27.11)	(27.14)
BTM	0.073***	0.078***	0.075***	0.075***	0.075***	0.075***	0.075***	0.082***	0.079***
	(2.92)	(3.10)	(3.00)	(2.97)	(3.00)	(2.99)	(2.99)	(3.19)	(3.14)
LnMVE	0.051***	0.050***	0.050***	0.050***	0.050***	0.050***	0.050***	0.051***	0.050***
	(10.00)	(9.96)	(9.93)	(10.05)	(9.92)	(9.88)	(9.54)	(10.06)	(10.05)
N	251,094	251,094	251,094	251,094	251,094	251,094	251,094	251,094	251,094
adj. R^2	0.348	0.347	0.347	0.347	0.347	0.347	0.347	0.348	0.349

Event Study

The literature used a number of methods to investigate the behavior of market participants around events. I leaned on Drake et al.'s (2015) study of short-selling behavior around restatement announcements to create several periods around and including the crossing of the 52-week low. Additionally, I introduced a Standardized Short Ratio variable, SSVRATIOBVN, used in Blau et al. (2011) that is calculated by taking the difference of the days' short-selling volume and the 21-day average of short-selling volume and dividing the difference by the 21-day standard deviation in daily short ratio for the stock.

$$SSVRATIOBVN_{i,t} = \left[\left(SSRATIO_{i,t} - \overline{SSRATIO_i} \right) / \sigma(SSRATIO_i) \right] \quad (20)$$

Where $SSRATIO_{i,t}$ is as defined before, short-selling volume divided by common shares outstanding for company i at day t, $\overline{SSRATIOi}$ is the 21-day mean of SSRATIO for company i surrounding and including the day the stock initially crosses the 52-week low, and $\sigma(SSRATIO_i)$ is the 21-day standard deviation of SSRATIO surrounding and including the day the stock initially crosses the 52-week low. Tables 67-72 report the results for the 21-day window surrounding the days that stocks have crossed the 52-week low. Columns 1-3 on each of these tables support previous findings in this study and support the idea that FSCORE is an insignificant factor in affecting short-seller volume near the 52-week low.

Table 67

Summary of Regressions of Short Selling on Financial Strength Score with Daily Ranges [-10, -7]

	(1) SSVOL[-10,-7]	(2) RELSS[-10,-7]	(3) SSRATIO[-10,-7]	(4) SSVRATIOBVN[-10,-7]
FSCORE	-5.68	-0.0048	0.0024	-0.0043
	(-0.25)	(-1.30)	(0.26)	(-0.39)
SIR	22.1***	0.0074***	0.046***	-0.00021
	(4.19)	(7.70)	(9.87)	(-0.05)
BTM	281.9***	-0.00078	-0.021	-0.021
	(2.74)	(-0.05)	(-0.49)	(-0.27)
LnMVE	502.5***	0.015***	0.073***	-0.040**
	(11.54)	(4.33)	(7.98)	(-2.45)
NODIVIDEND	135.9**	-0.012	0.12***	-0.011
	(2.27)	(-1.19)	(4.86)	(-0.34)
N	969	966	969	931
adj. R^2	0.365	0.117	0.333	0.382

Table 68

Summary of Regressions of Short Selling on Financial Strength Score with Daily Ranges [-6, -3]

	(1) SSVOL[-6,-3]	(2) RELSS[-6,-3]	(3) SSRATIO[-6,-3]	(4) SSVRATIOBVN[-6,-3]
FSCORE	2.92	-0.0026	0.0046	0.0034
	(0.12)	(-0.74)	(0.46)	(0.25)
SIR	28.9***	0.0078***	0.053***	-0.00066
	(4.63)	(7.55)	(10.74)	(-0.17)
BTM	387.5**	0.014	-0.038	-0.036
	(2.22)	(0.80)	(-0.65)	(-0.64)
LnMVE	598.8***	0.015***	0.088***	0.0011
	(9.34)	(4.30)	(8.12)	(0.07)
NODIVIDEND	97.4	-0.0093	0.12***	0.039
	(1.49)	(-0.95)	(5.43)	(0.86)
N	969	966	969	931
adj. R^2	0.334	0.115	0.273	0.167

Table 69

Summary of Regressions of Short Selling on Financial Strength Score with Daily Ranges [-2, 0]

	(1) SSVOL[-2,0]	(2) RELSS[-2,0]	(3) SSRATIO[-2,0]	(4) SSVRATIOBVN[-2,0]
FSCORE	6.33	-0.0017	0.0077	0.0061
	(0.24)	(-0.42)	(0.41)	(0.41)
SIR	40.4***	0.0081***	0.084***	0.0077
	(4.96)	(9.43)	(6.62)	(1.41)
BTM	500.1***	0.025	-0.092	0.0047
	(2.88)	(1.57)	(-0.83)	(0.07)
LnMVE	711.0***	0.011***	0.13***	0.044***
	(8.75)	(3.12)	(6.51)	(2.70)
NODIVIDEND	77.4	-0.025***	0.12***	-0.051
	(1.19)	(-2.71)	(3.23)	(-1.01)
N	969	969	969	931
adj. R^2	0.376	0.160	0.263	0.311

Table 70

Summary of Regressions of Short Selling on Financial Strength Score with Daily Ranges [+1, +3]

	(1) SSVOL[+1,+3]	(2) RELSS[+1,+3]	(3) SSRATIO[+1,+3]	(4) SSVRATIOBVN[+1,+3]
FSCORE	11.6	-0.0039	0.0032	0.013
	(0.41)	(-1.09)	(0.22)	(0.98)
SIR	38.3^{***}	0.0068^{***}	0.069^{***}	0.0046
	(4.41)	(7.78)	(8.23)	(0.69)
BTM	497.9^{***}	0.0081	-0.11	-0.098
	(2.78)	(0.50)	(-1.16)	(-1.10)
LnMVE	752.5^{***}	0.016^{***}	0.11^{***}	0.030
	(10.70)	(4.84)	(6.18)	(1.53)
NODIVIDEND	58.9	-0.0051	0.11^{***}	-0.025
	(0.76)	(-0.52)	(3.56)	(-0.60)
N	969	969	969	931
adj. R^2	0.347	0.140	0.285	0.334

Table 71

Summary of Regressions of Short Selling on Financial Strength Score with Daily Ranges [+4, +6]

	(1) SSVOL[+4,+6]	(2) RELSS[+4,+6]	(3) SSRATIO[+4,+6]	(4) SSVRATIOBVN[+4,+6]
FSCORE	4.98	-0.0032	-0.0013	-0.014
	(0.20)	(-0.71)	(-0.10)	(-1.21)
SIR	28.6^{***}	0.0059^{***}	0.063^{***}	-0.0057
	(4.14)	(6.21)	(8.20)	(-1.29)
BTM	482.0^{***}	-0.0077	-0.062	0.067
	(2.74)	(-0.49)	(-0.79)	(1.22)
LnMVE	669.0^{***}	0.020^{***}	0.10^{***}	0.0032
	(11.80)	(5.17)	(7.68)	(0.21)
NODIVIDEND	104.6	0.0093	0.15^{***}	0.056
	(1.32)	(0.78)	(5.31)	(1.00)
N	969	969	969	931
adj. R^2	0.314	0.092	0.284	0.255

Table 72

Summary of Regressions of Short Selling on Financial Strength Score with Daily Ranges [+7, +10]

	(1) SSVOL[+7,+10]	(2) RELSS[+7,+10]	(3) SSRATIO[+7,+10]	(4) SSVRATIOBVN[+7,+10]
FSCORE	0.023	0.0020	0.0064	-0.0026
	(0.00)	(0.45)	(0.56)	(-0.17)
SIR	28.2***	0.0066***	0.062***	-0.0041
	(4.37)	(6.46)	(8.13)	(-0.97)
BTM	483.8***	-0.0033	-0.0020	0.077
	(2.86)	(-0.18)	(-0.02)	(1.02)
LnMVE	625.3***	0.018***	0.096***	-0.019
	(10.85)	(5.83)	(7.33)	(-1.42)
NODIVIDEND	107.8	0.0021	0.12***	-0.013
	(1.38)	(0.21)	(5.05)	(-0.31)
N	969	969	969	931
adj. R^2	0.321	0.101	0.299	0.264

V. CONCLUSION, LIMITATIONS, AND FUTURE RESEARCH

I examined short-selling activity in proximity to the stock's 52-week lows. I investigated the influence of the proximity of the 52-week as well as the financial strength, as determined by fundamental data on short-selling behavior while the stock is near its 52-week low. I used a broad sample of U.S. stocks and found that abnormal short selling increases as the 52-week low draws near and that the level of abnormal short selling continues after the breach. My results showed that proximity to the 52-week low affects short-seller behavior. My results also found that financial strength is insignificant on short-seller behavior near the stock's 52-week lows. It would be difficult to believe that all short sellers use these cues, but the 52-week low seems sufficiently salient to enough short sellers to create results discoverable in aggregate short selling data. These results are fascinating when one considers that the 52-week low, or a stock crossing it, conveys no information about firm fundamentals.

From the results of this study, I provided evidence into how and when short sellers make their investment decisions around the 52-week low. Boehmer et al. (2008) stated that short sellers are held in "an exalted place in the pantheon of investors" due to their behavior that suggests they are informed and have superior analytical skills. This article adds to the literature that short sellers not only are sophisticated investors, but their investment strategies differ depending on accounting fundamentals around stock events. Consistent with Lee and Scotto-Piqueira (2016), this study suggests that short sellers resist psychological biases found in other investors. It supports prior literature in accounting and behavioral finance that sophisticated and rational investors are less vulnerable to behavioral biases.

For practitioners, I provided information for individual and institutional investors. Both types of short sellers are aided by knowing information about different factors that will and will not affect shorting demand. My findings may allow investors to develop and execute different trading strategy techniques and algorithms. These findings may also help investors involved in stock lending. Stock lending rates are based on expected demand for the shares from short sellers. Similar to a revenue manager at a resort or property manager at an apartment complex, any factor that can help predict future demand will assist in setting rates. A portfolio manager who wished to add income to their portfolio by lending shares to short sellers now has additional variables to consider. Future studies investigating the role of analysts and institutional ownership may shed greater light on the short selling phenomena around 52-week lows.

Limitations

My study may suffer from limitations typical of archival studies. For example, the FINRA short selling dataset started in late 2009, which was a few months from the market bottom of the Great Recession and the start of a ten-year bull market. This timing may have caused the number of observations of stocks near their 52-week lows to be skewed. The sample itself may have filtered out companies that are typically affected by other variables not controlled for. Since the larger, more analyst-covered, index membered stocks are traditionally the stocks to rebound first, my sample in the early years may have included companies in which analyst coverage and index membership do not produce “noise” in the study. Another limitation is the relatively short time period used. Typical capital market papers use longer time periods. For example, Huddart et al. (2009) used a sample that spans twenty-five years. However, many seminal short-selling research articles published in the top-tier accounting and finance journals have used a dated two-year sample provided by the SEC or FINRA that does not incorporate the changes in recent securities laws and policies.

Implications for Additional Research

My findings suggested many avenues for research in behavioral capital markets research in accounting. I discussed two possible streams of research. First, my study avoided mention of stock analysts due to a lack of efficient access to an analyst database. Though Huddart et al. (2009) did not mention analysts, many studies have shown how coverage can influence short-selling behavior. Conversely, a substream would be to study the effect of short selling on analyst behavior. Though I contributed to the prior literature by filling the gap left by Lee and Scotto-Piqueira (2016) and Huddart et al. (2009), incorporating analyst data may lead to additional or more precise findings. Second, various trading techniques simulate shorting. Some of them use options. Exploring the concurrent volume of calls and puts with recent financial statement data may unlock hidden relationships between trading and fundamentals.

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APPENDIX

Piotroski's FSCORE Statistic

This dissertation utilizes an aggregate statistic, FSCORE, based on Piotroski (2000) to differentiate stocks based on financial strength. This aggregate measure is constructed from nine financial signals from three separate dimensions of a company's financial condition: profitability, liquidity, and operating efficiency. Moreover, the allure of using the FSCORE comes from the relative ease in measuring, interpreting, and implementing it as an overall performance statistic. Each of the nine signals are classified as "good" or "bad" and given a value of 1 or 0, respectively. The aggregate measure, FSCORE, is simply the sum of the nine binary values.

Profitability

Piotroski (2000) used four signals to measure profitability: return on assets (ROA), cash flow from operations (CFO), change in net income, and accrual adjustments. To calculate ROA, one takes the firm's income before extraordinary items and divides it by the beginning of the year's total assets. If the ROA is positive, the indicator F_ROA equals one, zero otherwise. Equally, F_CFO is calculated the same way. If the cash flow from operations is positive after being scaled by beginning of the year total assets, then F_CFO equals one, zero otherwise.
To measure trends in profitability, Piotroski (2000) measured the change in annual income by subtracting last year's ROA from the current year's ROA. If the result is positive, F_ΔROA equals one, zero otherwise. Additionally, Piotroski (2000) considered earnings quality by

comparing a company's net income before extraordinary items against cash flow from operations. The variable ACCRUAL is calculated by subtracting cash flow from operations from net income. If ACCRUAL is less than zero, the indicator variable F_ACCRUAL is equal to one, zero otherwise.

Liquidity

ΔLEVERAGE, ΔLIQUIDITY, and ISSUANCE are three signals designed to measure the firm's ability to meet future obligations and gauge changes in capital structure. ΔLEVERAGE is measured by calculating the change in long-term debt to total assets ratio. If the firm's long-term debt to asset ratio decreases, it is deemed positive and F_ ΔLEVERAGE is equal to one, zero otherwise. ΔLIQUIDITY is measured by calculating the change in the firm's current ratio (current assets divided by current liabilities) and is used to gauge the firm's ability to service current debt and working capital obligations. F_ ΔLIQUIDITY is equal to one if the current ratio increased, zero otherwise. Finally, F_ISSUANCE is equal to 1 if the firm did not issue any common equity in the reported year, zero otherwise. Raising additional equity can be viewed as a sign that the firm is unable to generate needed funds internally.

Operating Efficiency

The last two signals, ΔMARGIN and ΔTURNOVER, measure the firm's operating efficiency. ΔMARGIN is measured by subtracting last year's gross margin from this year's gross margin. If ΔMARGIN is positive, F_ΔMARGIN is one, zero otherwise. Similarly, ΔTURNOVER is calculated by subtracting last year's asset turnover ratio (total sales divided by total assets) from this year's asset turnover ratio. If the difference is positive, then F_ΔTURNOVER is one, zero otherwise.

Aggregate Score

FSCORE is defined simply as the sum of the individual signals, or

$$FSCORE = F\_ROA + F\_CFO + F\_\Delta ROA + F\_ACCRUAL + F\_LEVER + F\_\Delta LIQUID + F\_ISSUANCE + F\_\Delta MARGIN + F\_\Delta TURNOVER$$

The value of FSCORE can range from zero to nine, where a firm with a high (low) FSCORE represents a firm with many (few) signals of financial well-being.

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RESEARCH: PUBLICATIONS

A Pandemic Case Study of Stress and Modality in an Accounting Course: A Success Story with J. Racca, Business Education Innovation Journal. Vol. 12, No. 2, December 2020.

Is Customer Satisfaction a Relevant Metric for Short Sellers (with Doug Vorhies and Todd Griffith). Proceedings of the2017 Winter AMA Annual Conference

- Presented at the Accounting Doctoral Students Association - AAA Annual Meeting (Chicago, IL)

Research Interests: Short Seller Behavior; Capital Markets, Financial Analysts

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WORKS IN PROGRESS

Teaching Case – Stop the Gaslighting! Short Interest over 100% is OK: Explaining “140% Short Interest of GameStop” to Business Students (Useful Metaphors)

- Writing Phase

Short Seller Behavior and Earnings Acceleration

- Data collection and analysis stage

An Innovative Look at the CAN SLIM model: Bears CAN SWIM

- Data collection and programming/analysis stage

SCHOLARLY PRESENTATIONS

2016: Washington University in St. Louis (St. Louis, MS), Accounting Doctoral Students Association- AAA Annual Meeting (New York City, NY)

2015: PhD Project, Accounting Doctoral Students Association - AAA Annual Meeting (Chicago, IL)

2014: AAA Diversity Section (Atlanta, GA); Accounting Doctoral Students Association (Atlanta, GA).

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AAA Annual Meeting – 2012 – 2016
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ACADEMIC EXPERIENCE

In-Residence Instructor, University of Connecticut	2017 – 2020
Research/Teaching Assistant, University of Mississippi	2012 - 2017
AICPA Library Research Assistant, University of Mississippi	2012 – 2017
Tenure-Track Assistant Professor, California State University, Monterey Bay	2009 – 2011
Graduate Teaching and Visiting Instructor, University of Nevada, Las Vegas	2003 - 2009

TEACHING EXPERIENCE (Over 80 sections taught, 28 at UCONN):

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ACCT 5123 Cost Analysis FMBA (Live)
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California State University, Monterey Bay, School of Business, Seaside, California

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Realtor® 2007 - 2009
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Credit Collections Account Manager 2002 – 2003
Household Credit (now HSBC), Las Vegas

Personal and Small Business Banker 2001 – 2002
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Financial Investments Advisor – Stockbroker 1998 - 2001
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