Essays on Efficiency of Capital Markets

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Pavel Lesnevski

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Prodekan:	Prof. Dr. Moritz Fleischmann
Referent:	Prof. Dr. Stefan Ruenzi
Korreferent:	Prof. Dr. Erik Theissen

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To my parents, my brothers and my wife

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Introduction

This PhD thesis comprises three research papers that contribute to the literature on market efficiency. All papers cover some aspects of the arbitrage process. The first paper, titled "A Name That Rings a Bell: Spillover Effects in Companies with Similar Names", documents irrational spillover effects in equity markets due to similarities in company names. It shows that investors' confusion of company names is a source of uninformed demand shocks that drive prices away from their fundamental levels. These price deviations are the first aspect of the arbitrage process. The second paper, titled "Do Short Sellers Exploit Stock Mispricing Smartly?", demonstrates that market participants who engage in short selling identify and exploit market anomalies and, as a result, contribute to market efficiency. Thus, this paper shows that arbitrageurs are able to identify stock misvaluations and, at least partially, push the prices back to their fundamental levels, which is the second aspect of the arbitrage process. Finally, in the third paper, titled "Surprise in Short Interest", I construct a new measure of informed short selling and find that information contained in this measure is not fully priced by market participants.[1] The results imply that limits to arbitrage, at least partially, hinder other investors from following short-sellers' positions that are associated with abnormal returns. This type of market friction prevent prices from converging to their fair values over extended period of time. Thus, the last paper highlights market frictions as an important third aspect of the arbitrage process. I summarize all three papers in more details below.

Summary of "A Name That Rings a Bell: Spillover Effects in Companies with Similar Names"

In the first paper, I demonstrate that retail investors exhibit behavioral biases and confuse stocks with similar company names. In particular, they accidently trade similarly named peer stocks instead of intended focal stocks. As the result of these trades, the stock prices of peer companies experience price pressure and comove with those of the focal stocks.

First, I consider attention spillover effects after the substantial value-relevant events (earnings announcements and 8-K filings) over the period of 1996 - 2015. Attention is measured as views of company Wikipedia pages (e.g., Focke, Ruenzi, and Ungeheuer, 2018) and searches of company tickers from Google (e.g., Da, Engelberg, and Gao, 2011) as proxies for retail investors attention, and downloads of SEC filings from EDGAR (e.g., Drake, Roulstone, and Thornock, 2015) as a proxy for institutional investors attention. After controlling for other factors on the event days

[1] This paper is a joint work with Esad Smajlbegovic.

of focal stocks, peer stocks experience abnormal attention as measured by Wikipedia page views but not Google search volume or Edgar downloads. This increase in attention is associated with an increase in trading volume. The results are consistent with the spillovers of retail investors attention and trading to peer companies.

To distinguish between fundamentals-based and mispricing-based explanations of these spillovers, I consider the reaction of peer stock prices around these events. I expect some substantial price reaction in peer stock prices to events in focal companies only in case of significant events. Given a price reaction for peer stocks on an event date, fundamentals-driven explanation predicts persistent price change as the result of the event. In contrast, if the price reaction is the result of mispricing, the price should revert back to its initial level. Consistent with the mipricing-based explanation, I show a strong price reversal pattern for peer stocks after the event date for the strongest 5 percent focal stock events, measured by the 3-days cumulative abnormal return (CAR) around the event. The stock price reaction is statistically and economically much weaker for all other events.

In the next step, I hypothesize that the documented price pressure should result in the excessive return comovement for companies with similar names. I test this hypothesis using a longer time period from 1972 to 2016. I show that prices of stocks with similar company names comove excessively after controlling for other known sources of comovement. In general, it is challenging to control for all possible sources of the excess comovement. To show that it is the firm names that drive the documented excess comovement, I run a quasi-natural experiment using a sample of corporate name changes. Following Green and Jame (2013), I focus on rebranding-driven name changes without confounding corporate events. These name changes are not associated with changes in companies' business strategies and therefore can be considered as quasi-exogenous (Wu, 2010). I show that the excess comovement happens for the same companies in those months when their names are similar but not in the months when they are not. To address the existing critique in the comovement literature (Chen, Singal, and Whitelaw, 2016), I control for nonsynchronous trading and estimate comovement before and after the name-changing events in separate regressions. Finally, I compare the results to the control group that is matched by stock characteristics, in particular, past stock momentum returns.

The time-series and cross-sectional tests show that the excess comovement is predominantly present on days when stocks experience large price movements and days with high levels of trading. Moreover, the comovement is more pronounced for younger stocks with larger retail investor ownership and with higher limits of arbitrage. These results are consistent with the price-pressure interpretation of the observed excess comovement.

This paper contributes to the literature on the behavioral biases of retail investors (e.g., Odean, 1998; Barber and Odean, 2000), on the sources of stock return comovement (e.g., Barberis, Shleifer, and Wurgler, 2005; Pirinsky and Wang, 2006; Green and Hwang, 2009; Boyer, 2011; Grullon, Underwood, and Weston, 2014; Kumar, Page, and Spalt, 2016; Chen, Singal, and Whitelaw, 2016), on the effect of investor attention in the financial markets (e.g., Gervais, Kaniel, and Mingelgrin, 2001; Da, Engelberg, and Gao, 2011; Kumar, Ruenzi, and Ungeheuer, 2016), and spillovers of investor attention (e.g., Rashes, 2001; Drake, Jennings, et al., 2016;

Leung et al., 2016). All in all, I identify a behavioral bias that drives irrational demand shocks and results in significant deviations of stock prices from their fundamental levels.

Summary of "Do Short Sellers Exploit Stock Mispricing Smartly?"

In this paper, I examine whether short sellers profit from mispricing opportunities in the stock market. Using Stambaugh, Yu, and Yuan (2015) mispricing score as a proxy for stock level mispricing, and the ratio of shares shorted to shares outstanding as a measure of short positions, I document novel results. First, I find a strong monotonic relation between abnormal short interest and the mispricing score: The more overpriced a stock according to the mispricing score the larger its short interest ratio. Moreover, the most underpriced stocks are associated with abnormally low short interest, meaning that short sellers avoid entering short positions in these stocks. Second, I show that the difference in the short interest between the most overpriced and the most underpriced stocks increases dramatically after periods of high sentiment. This result means that arbitrageurs allocate more capital to the mispricing based strategies when the profitability of these strategies is higher. Third, motivated by the fact that idiosyncratic volatility (IVOL) is a common proxy for arbitrage risk that deters arbitrageurs (Shleifer and Vishny, 1997; Pontiff, 2006; Stambaugh, Yu, and Yuan, 2015; Drechsler and Drechsler, 2016), I test the relationship between this proxy and the short interest ratio. Stambaugh, Yu, and Yuan (2015) show significant anomaly returns for stocks with high mispricing score in the months following months of high idiosyncratic volatility. Consistent with arbitrageurs' stock picking skill, the short interest ratio increases by 0.11 p.p. for a one standard deviation increase in IVOL for these stocks. In an alternative setting of the Regulation SHO, Chu, Hirshleifer, and Ma (2016) show a decrease in anomaly returns associated with the mispricing score for randomly chosen pilot stocks that were exempted from short sale tests. Consistent with arbitrageurs' ability to identify mispriced stocks, I show a decrease of 2.86 p.p in exposure to these stocks relative to control stocks. The difference is not observed pre- and post-pilot program and is driven by the short leg of the anomaly.

Finally, to test whether short sellers' activity leads to more efficient markets, I reconsider the relation of spread in short interest between the short and the long leg of the composite mispricing anomaly to future corresponding strategy returns. I find a significantly negative relationship between these variables prior to 2008. This result is consistent with the interpretation of Hanson and Sunderam (2014) that the rise of arbitrage capital is associated with a decline in arbitrage profits. On the other hand, I document a positive relationship after 2008. This strong change in the relationship manifests a structural break in the behavior of short sellers. This positive relationship means higher strategy returns for a higher level of short interest spread and is consistent with the spread reflecting arbitrageurs' expectations of future strategy profitability.

This paper contributes to the literature on the role of arbitrageurs and institutional investors in stock market anomalies (DeVault, Sias, and Starks, 2016; Akbas, Armstrong, et al., 2015; Edelen, Ince, and Kadlec, 2016; Jiao, Massa, and Zhang, 2016), their effect on market efficiency (Hanson and Sunderam, 2014; McLean and Pontiff, 2016), general predictive power of short interest (Desai et al., 2002; Boehmer, Huszar, and Jordan, 2010; Diether, Lee, and Werner, 2009;

Hwang and Liu, 2014; Wu and Zhang, 2014; Drechsler and Drechsler, 2016), and the literature on limits to arbitrage (Shleifer and Vishny, 1997; Pontiff, 2006; Drechsler and Drechsler, 2016; Chu, Hirshleifer, and Ma, 2016; Stambaugh, Yu, and Yuan, 2012). All in all, this study provides evidence for "smart" arbitrageurs, and thus corroborates the predictions of theoretical models and the results of empirical papers.

Summary of "Surprise in Short Interest"

This paper contributes to the ongoing discussion on the informational efficiency of capital markets. We propose a new measure of informed short selling. The idea for this measure is based on our observation of two features in the distribution of the short interest ratio, the ratio of shares shorted to shares outstanding. First, the level of the short interest ratio is highly persistent over time and differs dramatically across companies. Second, the short interest ratio of some companies exhibits a larger time-series variation than of other companies. These differences in distributional properties may arise because certain stocks are mainly used for market making and hedging while other stocks are primarily targeted by arbitrageurs (Desai et al., 2002; Diether, Lee, and Werner, 2009). In this paper, we account for these differences by calculating the standardized unexpected short interest ratio ($SUSIR$), or simply surprise in short interest. For stock i and month t, it is defined as:

$$SUSIR_{i,t} = \frac{SR_{i,t} - \overline{SR}_{i,t-1,t-12}}{\sigma^{SR}_{i,t-1,t-12}},$$

where $\overline{SR}_{i,t-1,t-12}$ is the twelve months moving window of short interest ratio and $\sigma^{SR}_{i,t-1,t-12}$ is the volatility of short interest ratio over the same period.

Using surprise in short interest as a proxy for informed short selling, we provide several new insights. First, we show that the information from short-interest reports is not instantly incorporated into stock prices after public announcements. Stocks with top (bottom) 30 percent surprises in short interest experience a strong price drift of around -0.25% (+0.27%) within 30 days of the dissemination. Second, we construct a measure that is updated on a monthly basis to capture this price drift. A portfolio strategy that involves buying stocks with the 10 percent lowest surprise in short interest (unexpectedly high short covering) and sells stocks with the 10 percent highest surprise in short interest (unexpectedly high short selling) yields a statistically significant risk-adjusted return of around 4 to 6 percent p.a. over the next month. The effect is present on both the long and short side of the portfolio. The predictive ability of $SUSIR$ is not captured by standard risk factors, mispricing-related anomalies, or other proxies of informed short selling and short-selling impediments.

Evidence suggests that our measure identifies market mispricing that stems from biased beliefs of market participants and persists due to limits to arbitrage, such as illiquidity and idiosyncratic volatility. Thus, the surprise in short interest represents a mispricing-related anomaly that is not identified in the prior literature.

This paper contributes to the literature on the predictive power of short interest (e.g., Desai et al., 2002; Cohen, Diether, and Malloy, 2007; Boehmer, Jones, and Zhang, 2008; Diether, Lee, and Werner, 2009; Hirshleifer, Teoh, and Yu, 2011; Akbas, Boehmer, et al., 2013), on market efficiency (e.g., Ball and Brown, 1968; Jones and Litzenberger, 1970; Bernard and Thomas, 1990; Mendenhall, 2004; Senchack and Starks, 1993), on the existence and source of capital asset pricing anomalies (Stambaugh, Yu, and Yuan, 2012; Engelberg, Mclean, and Pontiff, 2018; Stambaugh, Yu, and Yuan, 2015; Stambaugh and Yuan, 2017; McLean and Pontiff, 2016) and the literature on limits to arbitrage (Shleifer and Vishny, 1997; Pontiff, 2006; Drechsler and Drechsler, 2016; Chu, Hirshleifer, and Ma, 2016; Stambaugh, Yu, and Yuan, 2012). Overall, our results suggest that the market does not efficiently price the information from short-sale reports.

Chapter 1

A Name That Rings a Bell: Spillover Effects in Stocks with Similar Company Names

1.1 Introduction

Investors exhibit behavioral biases and make suboptimal investment decisions (Thaler, 2016). These biases result in unintended effects in the financial markets, such as mispricing of attention-grabbing stocks (Barber and Odean, 2008; Da, Engelberg, and Gao, 2011; Kumar, Ruenzi, and Ungeheuer, 2016; Ben-Rephael et al., 2018), underreaction to accounting information (Hirshleifer, Lim, and Teoh, 2009; Dellavigna and Pollet, 2009), sentiment-driven return comovement (Kumar and Lee, 2006) and fund window dressing (Solomon, Soltes, and Sosyura, 2014).

In this paper, I study spillover effects resulting from investors' confusion of similarly named companies. Anecdotal evidence is a 122 percent price jump of Snap Interactive stock after Snap Inc., an owner of a multimedia messaging app Snapchat, filed for its initial public offering in February 2017. Snap Interactive is a publicly traded company that does not have any direct or indirect links to Snap Inc. except for the similarity in the names. In fact, the CEO of Snap Interactive had foreseen possible confusion and tried to stop the peer company from changing its original name "Snapchat" to "Snap Inc.". In the end, the name change took place a few months before the IPO announcement.[1]

In this study, I focus on publicly traded firms. I construct a sample of similarly named US firms over 1996 - 2015 and document novel attention and return spillover effects between them. Following the literature, I use Google search volume of company tickers (Da, Engelberg,

[1] One more example is a 70 percent premium over its net asset value of a closed-end fund with a ticker "CUBA" right after the United States announced re-initiation of its diplomatic and potentially economic relations with Cuba (Thaler, 2016). Historically, the CUBA fund traded at a 10 percent discount to NAV. The fund did not invest in Cuba or profited from the announced changes in relations with this country. Finally, there is an example from the book publishing industry. A new attention-grabbing book titled "Fire and Fury: Inside the Trump White House" devoted to the first year of Donald Trump's presidency was published in early January 2018. Surprisingly, another historical book titled "Fire and Fury: The Allied Bombing of Germany, 1942 - 1945" also unexpectedly reached the rank of bestseller the same days. Published in 2008, this book differed only by a subtitle but had nothing to do with the politics of the American president.

and Gao, 2011) and Wikipedia views of company pages (Focke, Ruenzi, and Ungeheuer, 2018; Hillert and Ungeheuer, 2016) as proxies for retail investor attention and EDGAR downloads of company filings (Drake, Roulstone, and Thornock, 2015) as a proxy for institutional investor attention. Moreover, I use company earnings announcements and 8-K filings as events that attract investor attention. I show that high attention to one company experiencing an event is associated with abnormally high attention to a similarly named peer. The effect is not explained by economic or geographical links. The surge in attention is associated with an increase in trading and price changes. The increase in Wikipedia page views and trading volume are around 1.37% and 1.90% relative to their average values, respectively. The effect is more than two times stronger for the top half of the most similar names and for the top quarter of the strongest events in terms of the announcing firm $CAR(-1, 1)$. Consistent with no new fundamental information for peer companies, I find no statistically significant change in EDGAR filings downloads for these companies. The return reaction of peer stocks is statistically and economically significant 0.39% on the announcement day for the most extreme 2.5% events and reverts after forty to sixty days after the event. The reversal pattern is a piece of evidence in favor of a price pressure driven mispricing due to investor confusion. The reaction and reversal are more pronounced for positive news than for negative news. This asymmetry is consistent with a higher propensity to buy attention-grabbing stocks than to sell them (Barber and Odean, 2008) and a difficulty to arbitrage away mispricing in overpriced securities relative to underpriced ones (Miller, 1977; Diamond and Verrecchia, 1987; Stambaugh, Yu, and Yuan, 2015; Engelberg, Reed, and Ringgenberg, 2018).

An important implication of spillover effects is excess returns comovement in stocks of companies with similar names. To show the causal effect of similar names on this comovement, I use corporate name changes over 1980-2008 from Green and Jame (2013) that are not confounded with any other corporate events. I find statistically and economically stronger comovement for the same pair of companies when the names are similar than when the names are dissimilar. The difference in comovement is on average 0.032 that is statistically significant at 5% significance level. Importantly, the effect is driven by the name changes that are not associated with changes in companies' fundamentals. To rule out spurious correlation, I control for nonsynchronous trading, estimate comovement before and after the name-changing events in separate regressions and, finally, compare the results to a control group of companies that are matched to the companies from the peer group by stock characteristics, in particular, past stock momentum returns. The change in comovement for the matched group is statistically insignificant and has an opposite sign.

I measure economic significance and test the robustness of excess comovement using an extended sample period from 1972 to 2016. I control for a number of characteristics that could explain the effect, such as size, book-to-market, momentum, short-term reversal, transaction costs (Boyer, 2011), price (Green and Hwang, 2009), industries (Kallberg and Pasquariello, 2008) and headquarters location (Pirinsky and Wang, 2006). To measure the economic magnitude I compare the comovement measure based on raw excess returns to the comovement measure that accounts for observable stock characteristics. The estimated excess comovement due to similar names is between 6.45% and 13.33% of the total comovement. In absolute terms, these values correspond to excess comovement between 0.0120 and 0.0248, which are economically meaningful values. I run a number of further robustness check to show that the excess comovement is not driven by the similarity of tickers (Rashes, 2001), economic links (Cohen and Frazzini, 2008), alternative industry definition (Hoberg and Phillips, 2010), alphabetical bias (Jacobs, 2016) and S&P 500 index participation (Barberis, Shleifer, and Wurgler, 2005). An additional analysis compares the magnitude of excess comovement in the cross-section of stocks. In particular, I show that return comovement is stronger for stocks experiencing high trading volume and large absolute returns. Moreover, the effect is stronger for stocks with higher limits to arbitrage as proxied by residual institutional ownership, idiosyncratic volatility and different measures of liquidity. Thus, the results of this analysis are consistent with the price pressure channel of the documented excess comovement.

This paper contributes to the literature on the sources of stock return comovement (e.g., Barberis, Shleifer, and Wurgler, 2005; Pirinsky and Wang, 2006; Kumar and Lee, 2006; Kallberg and Pasquariello, 2008; Green and Hwang, 2009; Boyer, 2011; Kumar, Page, and Spalt, 2013; Grullon, Underwood, and Weston, 2014; Muslu, Rebello, and Xu, 2014; Kumar, Ruenzi, and Ungeheuer, 2016; Chen, Singal, and Whitelaw, 2016; Hameed and Xie, 2018). Moreover, this paper contributes to the literature on the relevance of company names in the context of financial markets (e.g., Cooper, Dimitrov, and Rau, 2001; Head, Smith, and Wilson, 2009; Wu, 2010; Green and Jame, 2013). In particular, it reveals asset pricing irregularities due to similarity in company names. Finally, this paper contributes to the literature on the effects of investor attention on financial markets (e.g., Gervais, Kaniel, and Mingelgrin, 2001; Da, Engelberg, and Gao, 2011; Ungeheuer, 2017; Ben-Rephael et al., 2018) and, in particular, on the effect of spillovers in investor attention (e.g., Rashes, 2001; Drake, Jennings, et al., 2016; Leung et al., 2016).

Papers by Leung et al. (2016), Rashes (2001) and Drake, Jennings, et al. (2016) are the most closely related to this study. Leung et al. (2016) use Yahoo! Finance co-searches to reveal collective investor attention to different subsets of stocks. The authors find that co-searched stocks comove together. My study shows a potential source of excess attention and return comovement. In a case study, Rashes (2001) documents excess return comovement for two particular securities with similar tickers (MCI and MCIC) and attributes this comovement to confusion among investors. The focus of my study is on company names in the full cross-section of stocks. In fact, I show that the effect in my paper is not driven by the similarity in tickers and therefore is a new phenomenon. Drake, Jennings, et al. (2016) document attention and return spillovers due to related fundamentals for companies in the same industries. In contrast, I show that return comovement between companies with similar names is due to mispricing and is not explained by industry relations.

This paper is structured as follows. In Section 1.2, I introduce a name matching algorithm, compare the matched stocks to the stocks from the full sample and describe data sources. In Section 1.3, I show spillover effects for attention, trading and returns. In Section 1.4, I define a measure of return comovement and show that it changes as the result of changes in company names. Next, I quantify the economic magnitude of excess comovement and test robustness of the effect. I conclude in Section 1.5.

1.2 Data

1.2.1 Data sources

In this study, I combine data from different sources. The company names and equity market data on the stock level are obtained from CRSP, whereas the accounting and S&P 500 index constituents data come from Compustat. Fama and French (1997) classification of 48 industries is based on SIC codes from CRSP. The most recent headquarters states of the companies are from Compustat. Historical headquarters states over the period of 1996-2010 are from the headers of 10-K filings at EDGAR and were graciously made available online by Bill McDonald. The 8-K events announcements dates are from EDGAR. The data on earnings announcements and analyst coverage are from IBES. The Hoberg and Phillips (2010) text-based industry classification based on products' description in 10-K filings are downloaded from the authors' website. I obtain the Pástor and Stambaugh (2003) liquidity measure (γ^{PS}) and the Gibbs estimate of trading costs (c^{Gibbs}) over the period of 1926 - 2009 from Hasbrouck (2009). The Amihud (2002) illiquidity ratio is calculated following the original study using one year of daily data. I obtain the Corwin and Schultz (2012) spread, the bid-ask spread estimator calculated using daily high and low prices (*hlspread*), directly from the authors. The residual institutional ownership (*rio*) is calculated as a residual in the cross-sectional regression of the logit-transformed institutional ownership ratio on log size and log size squared following Nagel (2005). Idiosyncratic volatility (*ivola*) is the standard deviation of residuals over the past month in the daily regression of excess return on Fama and French (1993) three factors, as in Ang et al. (2006). Various asset pricing factors are obtained either from the corresponding authors' websites or calculated based on publicly available data. The mispricing score (*misp*) is from Robert Stambaugh's website. In the robustness tests, I control for the supplier-customer links used in Cohen and Frazzini (2008). The data over the period of 1980-2005 are downloaded from Andrea Frazzini's website. Green and Jame (2013) name changes data set is kindly provided by the authors. Attention measures used in the study over the period of 2008-2015 are Wikipedia page views (*wiki*), Google search volume (*gsv*) and EDGAR filings requests (*edgar*). Wikipedia page views of firms with common stocks in CRSP's NYSE, AMEX and NASDAQ universe used in Ungeheuer (2017) and Hillert and Ungeheuer (2016) are graciously provided by the authors. The Google search volume is downloaded from Google Trends and calculated following Da, Engelberg, and Gao (2011). EDGAR filings requests are calculated following Ryans (2018) and are downloaded from the author's website. Other standard control variables, such as log size, the log book-to-market ratio, momentum and short-term reversal, are defined as it is common in the literature. A more detailed description of variables is given in the Appendix in Table A1.1.

The sample period of this study is from December 1972 to December 2016. The starting date of the sample period is determined by the date when NASDAQ stocks were added to CRSP. Before this date, I obtain a smaller number of matched firms. I limit my analyses to

AMEX/NYSE/NASDAQ stocks with share codes 10 and 11. To ensure that my results are economically meaningful and not driven by penny stocks, I drop stocks with prices below 5$ and stocks with market capitalization below the 5th NYSE percentile the most recent month. The sample period with earnings announcements and 8-K filings is constrained to 1996-2015. The limited availability of attention measures leads to an even shorter period from 2008 to 2015.

1.2.2 Name matching algorithm

I prepare data from CRSP for name matching. First, I change all names to the upper case. Second, I drop all words that reflect the legal entities of the firms (e.g., "CORP", "INC", "GROUP", HLDG","LLC"). Third, I drop "NEW" that reflects a change of the name and drop the headquarters state of the firm (e.g., "DEL", "NY") that are usually the last words in the CRSP name. Finally, if the name contains an abbreviation, I add spaces between the letters of the abbreviation.

The matching procedure consists of the following steps. At the end of each year, I consider the cross-section of companies' names. I identify key words in the names and supplementary words. The supplementary words are the words that are common to many companies and often designate the type of services or products that these companies produce (e.g., "SOLUTIONS", "AIRLINES", "PARTNERS", "STORES", "TECHNOLOGIES") or its geographical operations ("WORLDWIDE", "AMERICAN", "INTERNATIONAL"). Where possible, I account for possible different spellings, typos and abbreviations. I compare company names using the key words only and using their full names (key words together with the supplementary words). I turn these names into the sets of bigrams (e.g. "EMCORE" becomes ["EM","MC","CO","OR","RE"] and EMCOR becomes ["EM","MC","CO","OR"]). The measure of similarity of two names is the Jaccard distance between two corresponding sets of bigrams, which is the number of common bigrams in two sets over the geometric mean of bigram counts in these sets (e.g., $Similarity\{\text{"EMCORE","EMCOR"}\} = 4/\sqrt{4 \cdot 5} = 0.8944$). This way, I calculate similarity using key words only, $Similarity^{Key}$, and similarity using all words, $Similarity^{All}$. I impose a stricter similarity criteria for $Similarity^{Key}$ (> 0.6) than for $Similarity^{All}$ (> 0.5) to ensure significant similarity in key words. For each year, I identify pairs of companies that are *mutually* the most similar to each other according to $Similarity^{Total} = 1/2(Similarity^{Key} + Similarity^{All})$. Thus, each company has only maximum one matched peer in a given year. Finally, because some financial firms have complicated structure and have many related firms with closely related names, I exclude pairs that contain financial firms (based on the Fama and French 48 industry classification) from my analysis.

1.2.3 Stock characteristics of companies with matched names

Table 1.1 gives examples of resulting pairs matched at the end of 2015. In particular, it demonstrates company names that are the most similar according to the total similarity score (Panel A), weakly similar that marginally make it in the final sample of mutually similar companies (Panel B) and dissimilar companies that marginally do not make it to the final sample (Panel C).

[Table 1.1 about here.]

Table 1.2 describes companies in the final sample of mutually similar firms over the period of 1972-2016. Panel A presents summary statistics for stock characteristics. Panel B compares characteristics of these stocks to all traded stocks. This table provides some insights into the matched stocks. First, around 20% of all stocks have peers with similar names. The companies with similarly named peers are on average larger, older, less volatile and have better analyst coverage. On the other hand, these stocks are less liquid and their trading is associated with higher transaction costs. The average value of $sameIND$ dummy indicates that the peers are more frequently coming from the same industry than for an average firm. This observation is not fully explained by the fact that these stocks are concentrated in industries with a larger share of firms. The peers are also more probably to come from the same headquarters states. These results indicate a close relation between matched firms in terms of industries and geography. Therefore, I control for this relatedness in my further analysis.

[Table 1.2 about here.]

1.3 Attention and return spillovers

I start my empirical analysis by testing the relationship between abnormal investor attention in stocks with similar names around 8-K events and earnings announcements. These events have accurate announcement dates and represent attention-grabbing news.

1.3.1 Summary statistics of events dummies and attention proxies

Table 1.3 describes event dummies over the period of 1996-2015 and measures of abnormal attention for the period of 2008-2015. It covers all firms in the CRSP universe.

[Table 1.3 about here.]

Panel A displays the mean, standard deviation, 1st, 10th, 50th, 90th and 99th percentiles of variables. Abnormal attention is defined as attention on a given day minus the average attention for the same weekday over the past 10 weeks divided by this average attention over the past 10 weeks, following Drake, Roulstone, and Thornock (2012) and Da, Engelberg, and Gao (2011). This measure can be interpreted as a percentage increase in today's attention relative to the average attention on the same day of the week over the past 10 weeks. Abnormal turnover, $aturn$, reflects both investor attention (Barber and Odean, 2008) and trading activity. $CAR(-1, 1)$, a 3-day abnormal return reaction around the event, serves as a measure of investor surprise. The event dummies $eventD^{focal}$, $eventD^{peer}$, $eventD^{ind}$ and $eventD^{state}$ are defined as either earnings announcements or 8-K fillings of focal firms, peer firms, any firms in the same industries and any firms in the same headquarters states, respectively. The averages of measures of abnormal attention are slightly above zero due to skewness in their distributions. Event dummies show that considered events on average happen on around 5% of trading days for focal and peer stocks, and around 90% days for any stocks in the same industries and the same headquarters states.

Panel B provides Spearman correlations between all variables. *Aedgar*, a proxy for institutional attention, is strongly correlated with abnormal trading, *aturn*, with a correlation coefficient of 0.14. Moreover, *aedgar* is much higher on firm's own news days (correlation of 0.16), but also higher on the event days of firms from the same industry or the same headquarter state (both correlation coefficients are 0.02). Its correlation coefficient with $eventD^{peer}$ is 0.01. *awiki*, which proxies for retail investor attention, exhibit a similar but weaker pattern. Its correlation coefficients with *aturn*, $eventD^{focal}$, $event^{peer}$, $eventD^{ind}$ and $eventD^{state}$ are 0.10, 0.05, 0.01, 0.02 and 0.02, respectively. *Agsv*, an alternative proxy of retail investor attention, is strongly related to *aturn* and *agsv* with correlation coefficients of 0.06 and 0.04, respectively, weaker to *aedgar* and $eventD^{focal}$ with correlation coefficients of 0.03 and 0.02, respectively, and almost not related to the other event dummies. All in all, the descriptive analysis shows the relation of investor attention to market events but does not reveal any strong changes in attention due to events in similarly named peer companies. Controlling for potentially confounding variables in a multivariate setting could be necessary to identify the effect.

1.3.2 Attention spillovers

To estimate the spillovers of investor attention, I regress abnormal attention measures of stock j at date t on the event dummies in the following regression:

$$\begin{aligned}\text{attention}_{jt}^{focal} &= a_m + a_d + a_i + a_s + peerD_{jt} + b^{focal}\cdot\text{eventD}_{jt}^{focal} + b^{ind}\cdot\text{eventD}_{jt}^{ind} \\ &+ b^{state}\cdot\text{eventD}_{jt}^{state} + b^{peer}\cdot\text{eventD}_{jt}^{peer} + \mathbf{b_{jt}^{controls\prime}}\cdot\mathbf{controls_{jt}} + \epsilon_{jt},\end{aligned} \tag{1.1}$$

where a_m, a_d, a_i, a_s are year-month, day of the week, industry, headquarters state fixed effects, and $eventD^{focal}$, $eventD^{peer}$, $eventD^{ind}$, $eventD^{state}$ are event dummies of focal firms, peer firms, the same industry firms and the same headquarters state firms, respectively. $\mathbf{Controls_{jt}}$ is the vector of controls that contains log size, log book-to-market, momentum, short-term reversal, momentum, mispricing score, idiosyncratic volatility, institutional ownership and log analyst coverage.[2] Around 20% of all firms have similarly named peers. In order to keep a representative sample without affecting the inference of the coefficient on $eventD^{peer}$, I introduce a peer dummy, *peerD*, that is equal to one if a company has a similarly named peer and zero otherwise, and assume $eventD^{peerD}$ to be zero for all stocks without peers. By using this approach, I follow closely Pontiff and Woodgate (2008) and McLean, Pontiff, and Watanabe (2009), who make adjustments for the missing book-to-market ratios in their analyses. The coefficient on $eventD^{peer}$ is the coefficient of our main interest. It reflects the change in abnormal attention given an event in a firm with a similar name. If positive and significant, this coefficient reflects an increase in attention on days when peer firms experience events after controlling for the other drivers of investor attention. I account for possible heteroscedasticity and autocorrelation by clustering standard errors by firm and date following Petersen (2009).

[2] I also run a specification without fixed effects and controls. The results are quantitatively similar and are presented in Table A1.4

[Table 1.4 about here.]

Table 1.4 shows estimation results for *awiki*, *agsv*, *aedgar* and *aturn*. The first two are proxies for retail investor attention. *Aedgar* is a proxy for institutional investor attention and *aturn* is a measure of abnormal trading. Consistent with the literature, company's own events attract both institutional and retail investor attention. The coefficients on $eventD^{focal}$ are all economically and highly statistically significant. The largest coefficient is for abnormal EDGAR filing requests, which is equal to 0.6658 with the t-statistic of 89.66. This coefficient reflects on average a 67% increase in filings request compared to the average on the same day of the week over the past 10 weeks. The coefficient on the *aturn* is comparable and is equal to 0.5327. The coefficients on *awiki* and *agsv* are 0.0917 and 0.0839, respectively. The effect of the same industry and the same headquarters states events are around 5 to 10 times weaker than for the firm own events.[3] But all coefficients remain economically and statistically significant. There is a large difference in coefficients on $eventD^{peer}$. The coefficients are insignificant for *agsv* and *aedgar* but are both economically and statistically significant for *awiki* and *aturn*, with the values (t-statistics) of 0.0137 (4.18) and 0.0190 (3.48), respectively. These results show that retail investors pay more attention to focal companies, as proxied by Wikipedia page views, on the event days of similarly named companies. This increase in attention is associated with an increase in trading volume.[4] The insignificant changes in EDGAR filings requests are consistent with no reaction from institutional investors and the absence of additional fundamental information from peer companies' events. Google search volume is based on the search queries of company tickers, not names. Given that similar names do not imply similar tickers, the insignificant result for *agsv* is an evidence that it is company names that play an important role in documented attention spillovers.[5] All in all, I find evidence in favor of spillovers of retail investor attention.

In the next step, I test whether the spillover effects are stronger for more similarly named firms. To test this hypothesis, I first define a dummy variable $HsimilarD$ that is equal to 1 for the most similar 50% pairs in the sample of name matched firms and zero otherwise. I introduce this dummy and its interaction with the $eventD^{peer}$ to the regression. The coefficient on the interaction term reflects additional abnormal attention on the event date of peer firms for more similar pairs.

[Table 1.5 about here.]

The estimation results are reported in Table 1.5. Consistent with the hypothesis, the spillover

[3] By default, I use Fama-French 48 industries. I test the robustness of these results by using the Hoberg and Phillips (2010) industries definition based on product descriptions in 10-K filings.

[4] I also run regressions for 8-K filings and earnings announcements separately. The estimation results reveal that the spillover effects are significant for both types of events but up to twice stronger for earnings announcements. The statistical significance decreases for both types of events. These results are presented in Table A1.5 and Table A1.6 of the appendix.

[5] A possible caveat of this interpretation is a less accurate measurement of *agsv* due to noise in the data that might result in the insignificant outcome. One possible source of such noise comes from the fact that Google replaces the search volume with zero when it is below an uncertain threshold, which is time- and firm-varying. Another source of noise could be that the search volume is not an accurate number but an estimate from a random subsample. See Fink and Johann (2014) for more details. As a result, R^2 in the regression with *agsv* as a dependent variable is much lower compared to the regressions with the other measures. Thus, for my analysis, *awiki* is a better proxy for retail investor attention than *agsv*.

effects for *awiki* and *aturn* are more than two times stronger for highly similar firms. These results support the definition of the similarity measure introduced in this paper. There is no significant interaction effect for *agsv* and *aedgar*.

Next, I test whether attention spillovers are more prevalent for peer events that are associated with larger surprises as proxied by larger price movements. For this, I define a $Hpeer\_retD$ dummy that is equal to one for the peer firms events that are in the top quarter of the absolute $CAR(-1,1)$ returns and zero otherwise. I add its interaction with $eventD^{peer}$ to the baseline Regression (1.1). The coefficient on this interaction term reflects the additional attention spillovers if the news in peer firms are especially important.

[Table 1.6 about here.]

The estimation results are reported in Table 1.6. The attention spillovers for *awiki* and *aturn* are two and a half times stronger for events with larger surprises. There are no significant effects for *agsv* and *aedgar* on these days. Thus, consistent with larger surprises attracting more retail investor attention, attention spillovers are stronger for stocks with events associated with larger absolute cumulative abnormal returns.

1.3.3 Return spillovers

In this subsection, I test whether spillovers of investor attention and trading affect stock prices. Barber and Odean (2008) and Ungeheuer (2017) document that stocks experiencing the most extreme returns attract the largest share of investor attention. Moreover, Kumar, Ruenzi, and Ungeheuer (2016) show that this abnormal attention has implications for stock prices. Motivated by these studies and by the results of the previous subsection, I focus on the events associated with the most extreme stock returns. In particular, I use earnings announcements and 8-K fillings of peer stocks with the most extreme 2.5% CAR(-1, 1) from 1996 to 2015 as events. I keep only pairs from different industries and headquarters states to make sure that the return reaction is not driven by simple observable geographical or economic closeness of firms. I calculate cumulative abnormal returns of focal and peer stocks after the event following Hirshleifer, Lim, and Teoh (2009):

$$CAR(-1,T)_i = \prod_{k=-1}^{T}(1+R_{ik}) - \prod_{k=-1}^{T}(1+R_{pk}), \tag{1.2}$$

where R_{pk} is the return of of the matching size-BM portfolio on day k relative to the announcement date.

If documented attention spillovers are strong enough to have an impact on stock prices, three different reaction patterns are possible. First, in the case the similarity measure captures companies that are related in their fundamentals, then a shock to the value of a peer company should result in a persistent change in the value of the related focal company. This pattern is consistent with economic links between firms documented by Cohen and Frazzini (2008), Menzly and Ozbas (2010), Müller (2017) and Smajlbegovic (2018). Second, in the case the attention spillovers result in the attention driven overpricing described in Kumar, Ruenzi, and Ungeheuer

(2016), the price of a focal stock should experience a short-term increase and a long-term decrease irrespective of the direction of the initial shock. Finally, the attention spillovers might result in price pressure due to investor confusion. In this case, a shock to a peer company should result in a temporary mispricing and a subsequent reversal for the focal company in the same direction as for the peer company. This way, the reaction should depend on the direction of the shock.

[Figure 1.1 about here.]

I start testing these hypotheses by considering the reaction of peer stocks to their own extreme events. Figure 1.1 depicts the cumulative abnormal returns of peer stocks experiencing extreme events starting at the event date with holding periods of up to 60 days. As far as the definition of the extreme event is based on the firm's $CAR(-1,1)$, it is not surprising that the initial reaction yields a large spread of close to 60% between the extremely positive and the extremely negative shocks on the announcement date. If any, the post-event drift is weak and there are no signs of significant price reversal. These results are consistent with well-functioning efficient markets when new significant value-relevant information is quickly incorporated in the prices of the announcing firms.

[Figure 1.2 about here.]

The price reaction of focal companies to significant events of the peer companies is presented on Figure 1.2. This reaction is economically and statistically significant. The positive shock is associated with a price appreciation of 0.432% after one day and of 0.664% after five days. Both numbers are significant at 1% significance level. Afterwards, there is a gradual price reversal until 40-60 days after the event date. A symmetric but weaker pattern arises for significant negative shocks. A significant price reaction around the announcement of -0.348% with the t-statistics of -2.17 becomes statistically insignificant -0.320% five days after the announcement and reverts fully 60 days after the announcement. The spread between significant positive and significant negative shocks reaches up to 1% five days after the event and decrease to 0.122% after 60 days.[6] Moreover, the effect should be stronger for positive shocks that is consistent with the ease of buying unknown stocks compared to selling or short selling (Barber and Odean, 2008) and the difficulty to correct overpricing compared to underpricing (Stambaugh, Yu, and Yuan, 2015). Thus, the results are consistent with the price pressure driven temporary mispricing due to investor confusion of company names.

[Figure 1.3 about here.]

For comparison, Figure 1.3 presents the results for all other events, i.e. events that are not associated with top 2.5% $CAR(-1,1)$. Although significant at 5% level, the spread at the announcement of 10 basis points is almost 8 times weaker than the spread around the significant events and driven mostly by positive shocks. This spread becomes essentially zero after 10 days.

[6] In Figure A1.1 and Figure A1.2 of the appendix, I show separate results for earnings announcements and 8-K filings. Results from both figures present similar patterns with the difference that extreme *negative* earnings announcements to peer stocks are not associated with significant negative returns in focal stocks.

This result confirms that focusing on the most extreme events is the key to identifying significant attention-driven price pressure.

Thus, these findings support the price pressure driven return spillovers between companies with similar names. The temporary mispricing is prevalent for events associated with large price reactions, stronger for positive shocks and reverses after 40 to 60 trading days. All in all, I contribute to the literature by showing that name similarity is a new important channel of attention spillovers that results in trading spillovers and subsequently return spillovers.

1.4 Return comovement

According to results of the previous section, abnormal returns of similarly named stocks are highly correlated on the days of attention-grabbing events. In the absence of events, abnormal returns of these stocks do not exhibit any clear correlation pattern. Thus, in aggregate, return spillovers might result in excess comovement of the respective stocks. In this section, I test this prediction.

1.4.1 Measuring comovement

To measure return comovement, I first calculate returns adjusted for Davis, Fama, and French (2000) four factors. These factors represent important sources of covariation in stock returns. For each stock and date, I first estimate factors' exposures over one year using the most recent daily returns by running the following regression:

$$R_\tau - rf_\tau = a + b^{mktrf} \cdot mktrf_\tau + b^{smb} \cdot smb_t + b^{hml} \cdot hml_\tau + b^{umd} \cdot umd_\tau + \epsilon_\tau \tag{1.3}$$

Daily alpha on the next trading day, $\text{Alpha}_{it}^{focal}$, is the difference between the stock return in excess of the risk free rate and the predicted return, calculated as the factor returns on day t multiplied by the estimated factors' exposure coefficients, b, from Equation (1.3) estimated over the most recent 252 days.[7]

Return comovement is measured as the sum of coefficients from the following pooled regression:

$$\text{Alpha}_{it}^{focal} = \sum_{k=-3}^{3} b_k^{peer} \cdot \text{Alpha}_{it+k}^{peer} + \epsilon_{it}, \tag{1.4}$$

where $Alpha_{it}^{focal}$ is a residual of a focal stock and $Alpha_{it}^{peer}$ is a residual of the corresponding peer stock. The measure of comovement $b^{peer} = \sum_{k=-3}^{3} b_k^{peer}$ accounts for the non-synchronicity in trades.

[7] This methodology is equivalent to the one employed in Amihud and Goyenko (2013) to calculate return residuals as a measure of fund performance. Antón and Polk (2014) also calculate residuals from Davis, Fama, and French (2000) four-factor model to calculate comovement of stock returns. In contrast to our approach, the authors estimate these residuals in-sample using one month of daily data and calculate comovement for each stock pair every month.

1.4.2 Name changes and changes in comovement

I test whether company names are associated with excess return correlation. If the similarity in names results in excess comovement, then stock returns of chosen companies at a fixed point of time should on average experience higher comovement if company names are similar compared to the case if these names are dissimilar. It is not possible to observe both cases simultaneously. But it is possible to measure changes in comovement around events associated with corporate name changes. I use name changes from Green and Jame (2013) over the period 1980-2008 as a quasi-natural experiment.[8] Importantly, I focus on the name changes that are not associated with corporate events and changes in company strategy. Thus, changes in return comovement are unlikely to be driven by fundamentals.

Overall, I identify 547 name changing events that involve stocks with similarly named peers and are not associated with any other corporate events. I follow Green and Jame (2013) and classify these events into three categories: broad focus, narrow focus, and rebranding. 177 broad focus name changes are motivated by an expansion of business (e.g., Apple Computers → Apple). 96 narrow focus name changes are motivated by narrowing focus on a particular business line (e.g., Epix Medical → Epix Pharmaceutical). The most important type of name changes for this study is rebranding because these name changes are not associated with fundamental shifts in business strategy (e.g., Kaufman and Broad Home Corporation → KB Home). There are 274 such events in our sample.

An alternative classification of events is based on whether the stocks are similar before or after the name change. 230 focal stocks are leaving comovement with similarly named peer, 235 are entering comovement and 82 are changing from one peer firm to another. Thus, leaving firms are similar to the peers in terms of their names before the name changes, but dissimilar after the name changes. Entering focal firms are dissimilar to the peers in terms of their names before the name changes but become similar after the name changes. The focal firm that is changing peers is similar to one peer before the name change and become similar to a different one after the event. I decompose each such event into two events: a focal company leaving comovement with one peer and the same company entering comovement with the other peer. Figure 1.4 illustrates name changes and the corresponding changes in comovement.

[Figure 1.4 about here.]

Chen, Singal, and Whitelaw (2016) criticize the existing comovement literature. In addition to the usage of univariate regressions and non-synchronicity robust (Dimson (1979) corrected) coefficients, the authors emphasize the importance of comparing results to a sample of firms matched on stock characteristics, in particular, return momentum. I follow authors' recommendations and construct a sample of matched firms that are similar to peer firms in terms of size, book-to-market, industry and momentum, but have different names. In particular, for each peer firm in the sample of firms with name changes, I choose a group of stocks from the same size and BM quintiles and Fama-French 5 industry. The final control firm is the firm that is the closest to the peer firm in terms of momentum.

[8] I thank the authors for providing the data.

[Table 1.7 about here.]

I present the difference between similarly named peer stocks and stocks matched on characteristics in Table 1.7. The stocks are very close in almost all characteristics, except for institutional ownership, analyst coverage and idiosyncratic volatility. Matched stocks have average institutional ownership of 31% compared to 24% for similarly named peers and have 4.2 analysts compared to 1.8 for similarly named peers. The differences are statistically significant at any reasonable significance level. The difference in idiosyncratic volatility is 0.004 and is significant at 10% significance level.

To estimate return comovement of involved stocks, I incorporate suggestions of Chen, Singal, and Whitelaw (2016) and run separate pooled panel regressions for the cases when firm names are similar and when they are dissimilar:

$$\begin{aligned} \text{Alpha}_{it}^{focal} &= \sum_{k=-3}^{3} b_k^{peer,\,similar} \cdot \text{Alpha}_{it+k}^{peer,\,similar} + \epsilon_{it} \\ \text{Alpha}_{it}^{focal} &= \sum_{k=-3}^{3} b_k^{peer,\,nonsimilar} \cdot \text{Alpha}_{it+k}^{peer,\,nonsimilar} + \epsilon_{it} \end{aligned} \tag{1.5}$$

I limit the estimation window to two years before and two year after the name change. Additionally, I skip two months right before and two months right after the event to make sure that a possible reaction in prices around the event does not influence the estimation results. Finally, the name changing events with less than 100 observations either before or after the event are not included. $\Delta b = \sum_{k=-3}^{3} b_k^{peer,\,similar} - \sum_{k=-3}^{3} b_k^{peer,\,nonsimilar}$ is the difference in comovement between two periods. I run these regressions for similarly named peers and matched firms and compare the results.

[Table 1.8 about here.]

The estimation results are presented in Table 1.8. For all events together, the average comovement between stocks decreases from 0.050 when the stocks have similar names to 0.018 when the stock names are dissimilar. The difference of 0.032 is statistically significant at 5% significance level. Splitting by type of name changing event reveals that the results are heterogeneous. In particular, the results are especially strong and significant for rebranding and narrow focus events. The differences in the comovement coefficients are 0.041 and 0044 with the p-values of 0.055 and 0.098, respectively. The change in comovement for broad focus name changes has an opposite sign and insignificant. The changes in the comovement coefficients for the matched group confirm that the results are not associated with observable stock characteristics. In particular, the change in comovement is insignificant -0.009 for the pooled analysis. The changes in comovement coefficients for rebranding, narrow focus and broad focus name changes are -0.016, -0.020 and 0.029, respectively. All changes are statistically insignificant.

Table 1.8 presents the results for an alternative classification. In particular, in the case of leaving comovement, the comovement coefficients between focal and peer stocks decreases from 0.046 before the event to 0.34 after the event. The change of 0.12 is consistent with the change in comovement but is statistically insignificant. This result could be explained by the idea that it takes longer for market participants to forget the previous names even after the name change of the company is announced. In contrast, in the case of name changes that result in stocks' entering comovement due to name similarities, the comovement coefficient increases from zero to 0.054 after the event, the result significant at 1% significance level. This result is consistent with the idea that it is easier to confuse firms with new unknown names. For comparison, the results for the stocks in the group matched to peers on stock characteristics, the changes in the comovement coefficients have opposite signs and are not significant.

All in all, given that rebranding motivated name changes could be considered as quasi-exogenous to company's strategy and fundamentals, my results serve as evidence in favor of a significant relation between company names and stock return comovement. Spillovers of attention, trading and returns documented in this study favor behavioral explanation of this comovement.

1.4.3 Return comovement - economic significance and alternative explanations

In this section, I analyze the economic significance of return comovement and the robustness of this effect. The literature documents different causes of return comovement. To measure stock return comovement after accounting for these sources, I run a number of panel regressions with fixed effects at a daily frequency. The baseline version of the regression is:

$$\text{Alpha}_{it}^{focal} = a_t + \sum_{k=-3}^{3} b_k^{peer} \cdot \text{Alpha}_{it+k}^{peer} + \sum_{k=-3}^{3} \mathbf{b_k^{controls\prime}} \cdot \mathbf{controls_{it+k}} + \epsilon_{it},$$

where $Alpha_{it}^{focal}$ is a stock's residual from Davis, Fama, and French (2000) four factor model on day t with factors exposures estimated using 1 year of the most recent daily data, $Alpha_{it}^{peer}$ is the $Alpha_{it}$ of the peer stock, a_t is the time fixed effect. $\mathbf{Controls_{it+k}}$ is a vector of controls that consists of equally-weighted returns on the price, size, book-to-market, momentum, short-term reversal decile portfolios and Fama-French 48 industry portfolio. Extended controls additionally include equally-weighted returns on the transaction costs decile portfolio and headquarters state portfolio. The sample period for the analysis with extended controls is limited to 1996 to 2010 due to data availability. By including these control variables, I account for price driven comovement (Green and Hwang, 2009), style-related comovement (Boyer, 2011), geography driven comovement (Pirinsky and Wang, 2006) and industry driven comovement (Kallberg and Pasquariello, 2008; Menzly and Ozbas, 2010). The measure of comovement $b^{peer} = \sum_{k=-3}^{3} b_k^{peer}$ accounts for the non-synchronicity of trades. Standard errors are clustered by focal stock and day.

For this analysis, I keep only stocks that have similarly named peers. Moreover, I keep only one observation per each pair because, otherwise, the regression overestimates the significance of coefficients. To increase the number of observations, I extend the sample period back to 1972, when NASDAQ enters the CRSP sample.[9]

[Table 1.10 about here.]

The estimation results are presented in Table 1.10. Reported are the coefficients on leads and lags of the abnormal returns of the peer stocks together with the t-statistics in the parentheses and the sum of these coefficients together with the F-statistics and the p-values. The column (1) shows the results for raw excess returns without any controls. All leads and lags are economically and statistically significant and add up to 0.186. This total comovement coefficient serves as a benchmark, as it uncovers comovement between stocks in the absence of any other controls. In the column (2), I regress the out-of-sample residuals from Davis, Fama, and French (2000) model of focal stocks on the leads and lags of these residuals of the corresponding peer stocks. This change in the calculation of abnormal returns has a dramatic impact on the results. Two leads and one lag of $Alpha_t^{peer}$ are statistically significant and the sum of coefficients decreases to 0.028. This number, if compared to the benchmark comovement coefficient, means that around 85 % of comovement is explained by the market, size, book-to-market, and momentum factors. The coefficient is nevertheless highly significant at any reasonable significance level. Column (3) includes date fixed effect that decreases the comovement coefficient to 0.0248. Adding control variables for peer stocks or focal stocks decreases the comovement coefficient even further to 0.209. Extended controls additionally include transaction costs decile portfolio returns and headquarter states portfolio returns. These controls do not have any strong effect, except that the significance decreases due to decreased sample size. I do not include the controls for both focal and peer stocks, because, otherwise, multicollinearity becomes an issue.

An alternative approach is to introduce interacted fixed effects. In columns (8) to (12), I include date times industry and date times headquarters state fixed effects. The comovement coefficient stays significant for all specifications. The most conservative specification that includes all mentioned interacted fixed effects together yields the comovement coefficient of 0.022 with the p-value of 0.0368. The R^2 in this specification reaches 0.702. In this specification, the estimated share of total comovement due to the similarity in names is $0.022/0.186*100 = 11.83\%$ of the total stock comovement.

[Table 1.11 about here.]

For comparison, Table 1.11 reports results on comovement between focal stocks and stocks that are matched to peer stocks on characteristics. The return comovement coefficient based on raw excess returns is 0.162, which is by 0.024 smaller than for the peer group. Changing to out-of-sample residuals and including controls in the regression results in the comovement coefficients that are two to three times smaller than the corresponding coefficients for the peer group. Finally, the significance of comovement coefficients fully disappears once I control for interacted fixed effects. In the most conservative specification, the comovement coefficient becomes negative but indistinguishable from zero.

[9]Before 1972 much smaller number of firms results in a smaller number of firms with similar names.

All in all, the results of this analysis reveal that excess comovement due to similar names explains around 10% of total return comovement between similar stocks. This effect is robust to a number of stock characteristics. The effect is not present for stocks from the matched group.

1.4.4 Return comovement - robustness checks

A number of alternative explanations of excess comovement are possible. Rashes (2001) documents excess comovement of two particular stocks with similar tickers (MCI-MCIC). I use my matching algorithm to match companies based on the similarity of their tickers. The estimation results are presented in Table A1.3 of the appendix. The results show very weak comovement for stocks with similar tickers, meaning that the documented comovement is not driven by the similarity of tickers. The results of further tests are unreported. Cohen and Frazzini (2008) show mutual return predictability between companies with customer-supplier links. To ensure that excess comovement is not driven by these economic links, I limit the sample period to 1980-2004 and keep the companies that do not have customer-supplier relationships using the authors' data. The results are not influenced by this restriction. I also run the analysis using alternative industry definition of Hoberg and Phillips (2010) that is based on products description in companies' 10-K Fillings. The implications of the analysis do not change. Jacobs (2016) find that stocks of the companies whose names start with the letters that are near the top of an alphabetical listing experience higher trading activity and have higher liquidity. To exclude that the comovement effect is due to the alphabetical bias, I drop pairs whose names start with the same letters. The comovement effect is robust to this test. Finally, return comovement due to S&P 500 index participation (Barberis, Shleifer, and Wurgler, 2005), does not explain the effect either. Excluding pairs with both stocks constituting the index does not change the inference.

1.4.5 Return comovement - cross-sectional tests

In my further analysis, I compare the strength of the effect for stocks with different characteristics. I extend the baseline methodology by adding stock characteristics dummies and their interactions with the peer stock's leads and lags of daily Davis, Fama, and French (2000) alphas. In particular, I run the following panel regression with time fixed effects and a number of controls at a daily frequency:

$$\begin{aligned}\text{Alpha}_{it}^{focal} = a_t &+ \sum_{k=-3}^{3} b_k^{peer} \cdot \text{Alpha}_{it+k}^{peer} + \sum_{k=-3}^{3} b_k^{interact} \cdot D_{it}^{CS,focal} \times \text{Alpha}_{it+k}^{peer} \\ &+ b^{CS} \cdot D_{it}^{CS,focal} + \sum_{k=-3}^{3} \mathbf{b_k^{controls\prime}} \cdot \mathbf{controls_{it+k}} + \epsilon_{it},\end{aligned} \tag{1.6}$$

where $D_{it}^{CS,focal}$ is a dummy variable equal to one for above median values of other cross-sectional variables of a focal stock (absolute trading volume, residual institutional ownership, liquidity measures, idiosyncratic volatility, age and institutional ownership) or above 75th percentile of stock's absolute abnormal daily return. The vector of controls, $\mathbf{controls_{it+k}}$, consists of equally-weighted returns on the price, size, book-to-market, momentum, short-term reversal decile portfolios and Fama-French 48 industry portfolios of the focal firm. The baseline level of comovement is $b^{peer} = \sum_{k=-3}^{3} b_k^{peer}$. The sum of coefficients on the interaction variable, $b^{interact} = \sum_{k=-3}^{3} b_k^{interact}$, reflects by how much the comovement is stronger for stocks for $D_{it}^{CS} = 1$. I keep both observations for each pair in this analysis because the regression includes the characteristics of one company at a time. Thus, the observations are not repeated twice. For more conservative estimation, standard errors are clustered by stock-pair and day.

[Table 1.12 about here.]

The estimation results are reported in Table 1.12. The first important finding is that stock return comovement is fully concentrated in the stocks that experience large price movements. The value of b^{peer} is negative but insignificant. The value of $b^{interact}$ reflects the return comovement to be 0.0666 for the stocks in the top 25% of absolute returns. This result echoes one of the first findings of this study that attention, trading and returns spillovers are predominant for pairs experiencing large price shocks. Also consistent with this interpretation, excess return comovement is seven times stronger for stocks experiencing high abnormal trading, *aturn*. The baseline effect $b^{peer} = 0.0041$ increases to $b^{peer} + b^{interact} = 0.0041 + 0.0246 = 0.0287$ for the top 50% *aturn*. Considered proxies for limits to arbitrage are residual institutional ownership (*rio*), the Amihud (2002) illiquidity ratio (*amihud*), the Pástor and Stambaugh (2003) liquidity measure (γ^{PS}), the Corwin and Schultz (2012) bid-ask spread (*hlspread*) and idiosyncratic volatility (*ivol*). The estimation results for these variables are consistent with return comovement to be stronger for stocks with higher limits to arbitrage. In particular, $b^{interact}$ is significantly negative for *rio* and γ^{PS}, with the values of -0.01 and -0.012, respectively. These values mean that the effect is weaker for stocks with lower short sale constraints and for more liquid stocks in terms of the Pástor and Stambaugh (2003) price pressure measure. The sums of interaction coefficients for *hlspread* and *ivol* are positive and significant, reflecting that higher bid-ask spreads and idiosyncratic volatility are associated with stronger return comovement by 0.0084 and 0.0116, respectively. The interaction effect for the Amihud (2002) illiquidity ratio is insignificant. The reason could be that, as noticed by Lou and Shu (2017), this illiquidity measure is negatively correlated with trading volume. In its turn, trading volume is positively related to return comovement, potentially attenuating the effect of *amihud*. The other variables used in the analysis are *age* and *io*. The results reveal a weaker effect for older stocks and stocks with larger institutional ownership. These results are consistent with the idea that unsophisticated investors are more prone to irrational behavior and easier confuse new unknown firms. Thus, the set of cross-sectional tests supports the hypothesis that return comovement results from the price pressure induced by retail investors.

1.5 Conclusion

In this study, I use a name matching algorithm to identify stocks with similar names and find that investor attention spills over from one stock to its similarly named peer. Using earnings announcements and 8-K filings as attention-grabbing events, I show that these attention spillovers result in excess trading and return spillovers to similarly named peers. The pattern is consistent with price pressure driven temporary mispricing that reverts after 40 to 60 days. The result of such price pressure is the excess comovement of similarly named stocks. This effect is not explained by economic relatedness, geographical proximity or similarity in stock characteristics. Corporate name changes serve as a natural experiment to test the relationship between return comovement and similarity of company names. Quasi-exogenous name changes that are not driven by changes in business strategies are associated with changes in return comovement. Further analysis reveals the economic magnitude of this excess return comovement to be at 10% of total stock return comovement. Finally, cross-sectional tests support the price pressure channel of this comovement. These tests reveal a stronger effect for stocks that experience large price movements and abnormally high trading, and stocks that are characterized by higher limits to arbitrage and a larger share of retail investors.

If truly exogenous to firm fundamentals, documented attention spillovers might serve as an instrument to investor attention. This feature enables testing attention related hypotheses, for instance, distinguishing between fundamentals based and attention based explanations of anomalies in the financial markets. This opportunity remains for future research.

Tables and Figures of Chapter 1

Table 1.1:

Results of Name Matching - Examples of Similar and Dissimilar Firms

The table consists of three sets of companies matched by their names at the end of 2015. Panel A contains companies with the highest similarity score in the given year. Panel B contains companies that are marginally similar enough to be included in the sample of similar firms. Finally, Panel C contains matched companies that are not included in the sample of similar firms. All panels display name, industry and size of the matched companies together with the similarity score.

Panel A: Companies with the Most Similar Names						
Focal Company Name	Peer Company Name	FF 48 Industry	FF 48 Industry Peer	Size ($Mio)	Size Peer($Mio)	Similarity
GRAHAM CORP	GRAHAM HOLDINGS CO	Machinery	Printing and Publishing	167.359	2365.199	1
BSQUARE CORP	SQUARE INC	Business Services	Business Services	73.64637	406.4445	0.913
MASTECH HOLDINGS INC	MASTEC INC	Business Services	Construction	31.82043	1388.453	0.913
E S C O TECHNOLOGIES INC	T E S S C O TECHNOLOGIES INC	Electronic Equipment	Wholesale	933.1348	160.5496	0.900
EMCORE CORP	EMCOR GROUP INC	Electronic Equipment	Construction	157.6268	3013.261	0.894
EMPIRE RESOURCES INC DEL	EMPIRE RESORTS INC	Computers	Entertainment	29.66151	172.098	0.885
Panel B: Companies with Less Similar Names						
Focal Company Name	Peer Company Name	FF 48 Industry	FF 48 Industry Peer	Size ($Mio)	Size Peer($Mio)	Similarity
CENVEO INC	GENVEC INC	Business Services	Pharmaceutical Products	59.1454	31.76576	0.600
DIODES INC	BIODEL INC	Electronic Equipment	Pharmaceutical Products	1106.441	21.9771	0.600
FLOWERS FOODS INC	1 800 FLOWERS COM INC	Food Products	Retail	4559.34	252.7762	0.595
RUBICON PROJECT INC	RUBICON TECHNOLOGY INC	Business Services	Electronic Equipment	730.0346	30.46422	0.587
DELTA AIR LINES INC	DELTA APPAREL INC	Transportation	Wholesale	39866.37	108.5152	0.584
CAREDX INC	CAREER EDUCATION CORP	Healthcare	Personal Services	89.3504	247.1994	0.571
Panel C: Companies with Dissimilar Names						
Focal Company Name	Peer Company Name	FF 48 Industry	FF 48 Industry Peer	Size ($Mio)	Size Peer($Mio)	Similarity
SMITH A O CORP	SMITH MICRO SOFTWARE INC	Electrical Equipment	Business Services	5737.399	33.33644	0.538
W E C ENERGY GROUP INC	C E C O ENVIRONMENTAL CORP	Utilities	Machinery	16197.75	260.4902	0.537
ANADIGICS INC	ANALOGIC CORP	Electronic Equipment	Electronic Equipment	55.88835	1024.983	0.535
VERMILLION INC	MILLER HERMAN INC	Business Services	Business Supplies	93.8034	1722.172	0.535
FUEL TECH INC	TETRA TECH INC	Wholesale	Business Services	43.78563	1532.812	0.533
DR PEPPER SNAPPLE GROUP INC	APPLE INC	Candy & Soda	Computers	17604.73	583612.7	0.533

Table 1.2:
Summary Statistics for Firms with Similarly Named Peers and Comparison to All Firms
This table summarizes stock characteristics for the sample of similarly named peers over the period from 1972 to 2016. Panel A displays the mean, standard deviation, 1st, 10th, 50th, 90th and 99th percentiles. Panel B compares mean and standard deviation of the variables to the overall sample of stocks. Last three rows contain the difference in the characteristics and the t-statistic of the unpaired t-test under assumption of unequal variances and the p-values. The detailed description of the variables is in the Table A1.1 of the appendix.

Panel A: Summary Statistics for Firms with Similarly Named Peers

Variable	Mean	SD	1st	10th	Median	90th	99th
size	1932.2	13856.1	1.1	5.9	88.1	2147.7	33799.3
bm	0.846	0.999	0.000	0.154	0.619	1.704	4.098
mom	0.144	0.747	-0.815	-0.482	0.039	0.765	2.779
st_rev	0.011	0.190	-0.401	-0.167	0.000	0.184	0.609
misp	49.922	13.645	21.460	32.640	49.270	68.200	82.880
turn	0.110	0.258	0.002	0.009	0.054	0.253	0.783
amihud	3.717	29.046	0.000	0.001	0.138	7.246	59.074
γ^{PS}	25.5	456.9	-495.2	-13.2	0.2	62.3	995.9
c^{Gibbs}	0.014	0.017	0.001	0.002	0.007	0.033	0.079
hlspread	0.038	0.079	0.002	0.004	0.014	0.082	0.400
ivol	0.031	0.028	0.002	0.009	0.024	0.060	0.134
io	0.346	0.283	0.001	0.020	0.284	0.776	1.000
age	177.485	188.569	3	18	115	439	860
analyst	4.160	6.447	0	0	1	13	29
similarity	0.714	0.083	0.570	0.612	0.707	0.831	0.913
sameIND	0.189	0.392	0	0	0	1	1
sameHQ	0.117	0.321	0	0	0	1	1

Panel B: Comparison of Firms with Peers to Firms without Peers

	All		With Peers		With Peers - All		
Variable	Mean	SD	Mean	SD	Diff	t-stat	p-value
size	1610.6	10976.0	1932.2	13856.1	321.6	13.84	0.0000
bm	0.8565	1.0219	0.8463	0.9994	-0.0102	-5.64	0.0000
mom	0.1364	0.7699	0.1438	0.7474	0.0074	5.50	0.0000
st_rev	0.0113	0.1975	0.0109	0.1900	-0.0003	-1.07	0.2831
misp	49.517	13.590	49.922	13.645	0.405	13.76	0.0000
turn	0.1139	0.3133	0.1096	0.2581	-0.0042	-8.97	0.0000
amihud	3.8174	22.3458	3.7172	29.0460	-0.1002	-1.89	0.0581
γ^{PS}	27.614	722.645	25.549	456.938	-2.064	-1.93	0.0531
c^{Gibbs}	0.0139	0.0171	0.0137	0.0168	-0.0002	-5.23	0.0000
hlspread	0.0411	0.0857	0.0380	0.0792	-0.0031	-22.25	0.0000
ivol	0.0316	0.0305	0.0311	0.0281	-0.0005	-10.86	0.0000
io	0.3510	0.2882	0.3461	0.2831	-0.0048	-8.76	0.0000
age	167.689	177.906	177.485	188.569	9.796	30.58	0.0000
analyst	3.992	6.289	4.160	6.447	0.169	15.31	0.0000
w^{ind}	0.0489	0.0419	0.0492	0.0412	0.0003	4.80	0.0000
w^{state}	0.0684	0.0631	0.0681	0.0628	-0.0003	-1.67	0.0939
peerD	0.1956	0.3966	1.0000	0.0000	0.8044	2959.74	0.0000

Table 1.3:
Descriptive Statistics and Correlation Table of Attention Measures and Event Dummies
The table displays the mean, standard deviation, 1st, 10th, 50th, 90th and 99th percentiles of variables over the period from 1996 to 2015. Panel A consists of event dummies, a return reaction and proxies for abnormal investor attention. All these variables are at a daily frequency. The events are defined as either earnings announcements or 8-K fillings of the corresponding firms. Due to data availability, the sample period for the attention measures is from 2008 to 2015. Panel B displays the correlation matrix of all variables. The detailed description of the variables is in the Table A1.1 of the appendix.

Panel A: Descriptives

Variable	Mean	SD	1st	10th	Median	90th	99th
$awiki$	0.024	0.377	-0.719	-0.359	-0.023	0.421	1.714
$agsv$	0.021	0.651	-1.000	-0.640	-0.017	0.504	3.211
$aedgar$	0.080	0.830	-0.912	-0.688	-0.127	1.053	3.800
$aturn$	0.072	1.036	-0.997	-0.674	-0.171	0.887	5.716
$CAR(-1,1)$	0.002	0.090	-0.234	-0.076	-0.001	0.077	0.258
$eventD$	0.049	0.216	0	0	0	0	1
$eventD^{peer}$	0.044	0.204	0	0	0	0	1
$eventD^{ind}$	0.909	0.287	0	1	1	1	1
$eventD^{state}$	0.925	0.263	0	1	1	1	1

Panel B: Correlations

	$awiki$	$agsv$	$aedgar$	$aturn$	$CAR(-1,1)$	$eventD$	$eventD^{peer}$	$eventD^{ind}$	$eventD^{state}$
$awiki$	1.00								
$agsv$	0.04	1.00							
$aedgar$	0.09	0.03	1.00						
$aturn$	0.10	0.06	0.14	1.00					
$CAR(-1,1)$	0.02	0.00	-0.01	0.04	1.00				
$eventD$	0.05	0.02	0.16	0.10	0.00	1.00			
$eventD^{peer}$	0.01	0.00	0.01	0.01	0.00	0.01	1.00		
$eventD^{ind}$	0.02	-0.00	0.02	0.01	-0.01	0.02	0.02	1.00	
$eventD^{state}$	0.02	-0.00	0.02	0.01	-0.00	0.02	0.02	0.13	1.00

Table 1.4:
Attention Spillovers
This table reports the estimation results of a panel regression of the daily abnormal investor attention (*awiki*, *agsv*, *aedgar* and *aturn*) on the focal stock event dummy ($eventD^{focal}$), the same industry event dummy ($eventD^{ind}$), the same headquarters state event dummy ($eventD^{state}$), and a number of control variables. If the peer stock experiences an event ($eventD^{peer} = 1$) and comes from the same industry and/or the same state as the focal stock, the corresponding event dummies ($eventD^{ind}$ and/or $eventD^{state}$) are also equal to one. To estimate the regression for the full cross-section of firms, I assume $eventD^{peer}$ to be zero for firms without peers with similar names and allow a separate intercept (*peerD*) for these firms. The events are earnings announcements and 8-K filings. The sample period is 2008-2015. The regressions are estimated with year-month, day of the week, industry and headquarters state fixed effects. The standard errors are clustered by date and firm. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

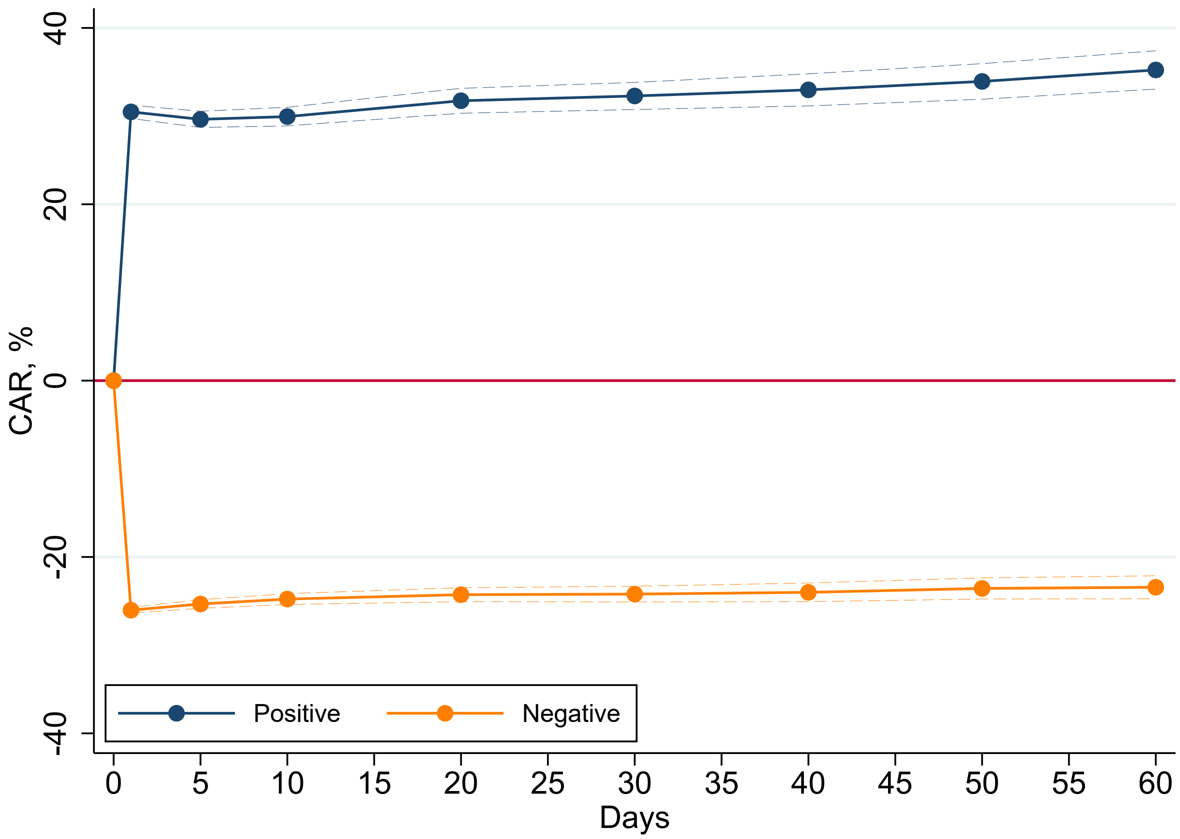
	(1) *awiki*	(2) *agsv*	(3) *aedgar*	(4) *aturn*
peerD	-0.0000	-0.0005	-0.0009	-0.0021
	(-0.01)	(-0.23)	(-0.88)	(-1.35)
ln_size	-0.0038***	-0.0045***	-0.0076***	-0.0145***
	(-8.09)	(-5.51)	(-12.67)	(-14.51)
ln_bm	-0.0007	-0.0016	-0.0007	0.0002
	(-1.52)	(-1.53)	(-1.26)	(0.24)
mom	0.0018	-0.0022**	-0.0030***	-0.0009
	(1.47)	(-1.96)	(-2.80)	(-0.50)
st_rev	-0.0007	0.0361***	-0.0138*	0.0084
	(-0.15)	(5.83)	(-1.91)	(0.77)
misp	0.0002***	0.0001	-0.0003***	-0.0001
	(4.64)	(1.55)	(-5.93)	(-1.45)
ivola	-0.5589***	-0.3092***	-0.8494***	-2.1507***
	(-11.24)	(-4.62)	(-11.38)	(-17.01)
io	0.0050**	0.0163***	-0.0059**	-0.0439***
	(2.16)	(3.69)	(-2.03)	(-7.29)
ln_nanalyst	0.0010	0.0040**	-0.0032***	-0.0044**
	(1.26)	(2.22)	(-3.57)	(-2.34)
$eventD^{focal}$	0.0917***	0.0839***	0.6658***	0.5327***
	(37.58)	(21.04)	(89.66)	(59.29)
$eventD^{ind}$	0.0196***	0.0066***	0.0444***	0.0606***
	(6.59)	(3.37)	(8.77)	(8.75)
$eventD^{state}$	0.0186***	0.0062**	0.0428***	0.0658***
	(4.91)	(2.52)	(6.94)	(7.88)
$\boldsymbol{eventD^{peer}}$	**0.0137*** **	**0.0025**	**0.0078**	**0.0190*** **
	(4.18)	**(0.59)**	**(1.43)**	**(3.48)**
Year - Month FE	Yes	Yes	Yes	Yes
Day of the Week FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
HQ State FE	Yes	Yes	Yes	Yes
R2	0.0478	0.0022	0.0922	0.0317
N	2'696'867	3'262'755	3'657'172	3'795'003

Table 1.5:
Attention Spillovers for Highly Similar Pairs
This table reports the estimation results of a panel regression of the daily abnormal investor attention ($awiki$, $agsv$, $aedgar$ and $aturn$) on the focal stock event dummy ($eventD^{focal}$), the same industry event dummy ($eventD^{ind}$), the same headquarters state event dummy ($eventD^{state}$), the peer stock event dummy ($event^{peer}$), its interaction with highly similar pairs dummy ($HsimilarD$) and a number of control variables. $HsimilarD$ is equal to one for top fifty percent similar firms and zero otherwise. If the peer stock experiences an event ($eventD^{peer} = 1$) and comes from the same industry and/or the same state as the focal stock, the corresponding event dummies ($eventD^{ind}$ and/or $eventD^{state}$) are also equal to one. To estimate the regression for the full cross-section of firms, I assume $eventD^{peer}$ to be zero for firms without peers with similar names and allow a separate intercept ($peerD$) for these firms. The events are earnings announcements and 8-K filings. The sample period is 2008-2015. The regressions are estimated with year-month, day of the week, industry and headquarters state fixed effects. The standard errors are clustered by date and firm. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1) *awiki*	(2) *agsv*	(3) *aedgar*	(4) *aturn*
$peerD$	0.0004	-0.0013	-0.0002	-0.0022
	(0.26)	(-0.42)	(-0.13)	(-1.00)
$HsimilarD$	0.0008	-0.0015	0.0013	-0.0002
	(0.38)	(-0.40)	(0.68)	(-0.06)
ln_size	-0.0038***	-0.0044***	-0.0076***	-0.0145***
	(-8.09)	(-5.49)	(-12.66)	(-14.51)
ln_bm	-0.0007	-0.0016	-0.0007	0.0002
	(-1.51)	(-1.53)	(-1.26)	(0.24)
mom	0.0018	-0.0022*	-0.0030***	-0.0009
	(1.47)	(-1.96)	(-2.80)	(-0.50)
st_rev	-0.0007	0.0361***	-0.0138*	0.0084
	(-0.15)	(5.83)	(-1.91)	(0.77)
misp	0.0002***	0.0001	-0.0003***	-0.0001
	(4.64)	(1.55)	(-5.93)	(-1.45)
ivola	-0.5585***	-0.3093***	-0.8493***	-2.1505***
	(-11.23)	(-4.62)	(-11.38)	(-17.01)
io	0.0049**	0.0163***	-0.0059**	-0.0439***
	(2.15)	(3.69)	(-2.04)	(-7.29)
ln_nanalyst	0.0010	0.0040**	-0.0032***	-0.0044**
	(1.26)	(2.22)	(-3.56)	(-2.34)
$eventD^{focal}$	0.0917***	0.0839***	0.6658***	0.5327***
	(37.58)	(21.04)	(89.66)	(59.29)
$eventD^{ind}$	0.0196***	0.0066***	0.0444***	0.0606***
	(6.59)	(3.37)	(8.77)	(8.75)
$eventD^{state}$	0.0186***	0.0062**	0.0428***	0.0658***
	(4.91)	(2.52)	(6.94)	(7.88)
$\boldsymbol{eventD^{peer}}$	**0.0082****	**0.0026**	**0.0062**	**0.0110**
	(2.19)	**(0.39)**	**(0.85)**	**(1.57)**
$\boldsymbol{HsimilarD \times eventD^{peer}}$	**0.0118***	**-0.0002**	**0.0034**	**0.0172***
	(1.82)	**(-0.03)**	**(0.31)**	**(1.66)**
Year - Month FE	Yes	Yes	Yes	Yes
Day of the Week FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
HQ State FE	Yes	Yes	Yes	Yes
R2	0.0478	0.0022	0.0922	0.0317
N	2'696'867	3'262'755	3'657'172	3'795'003

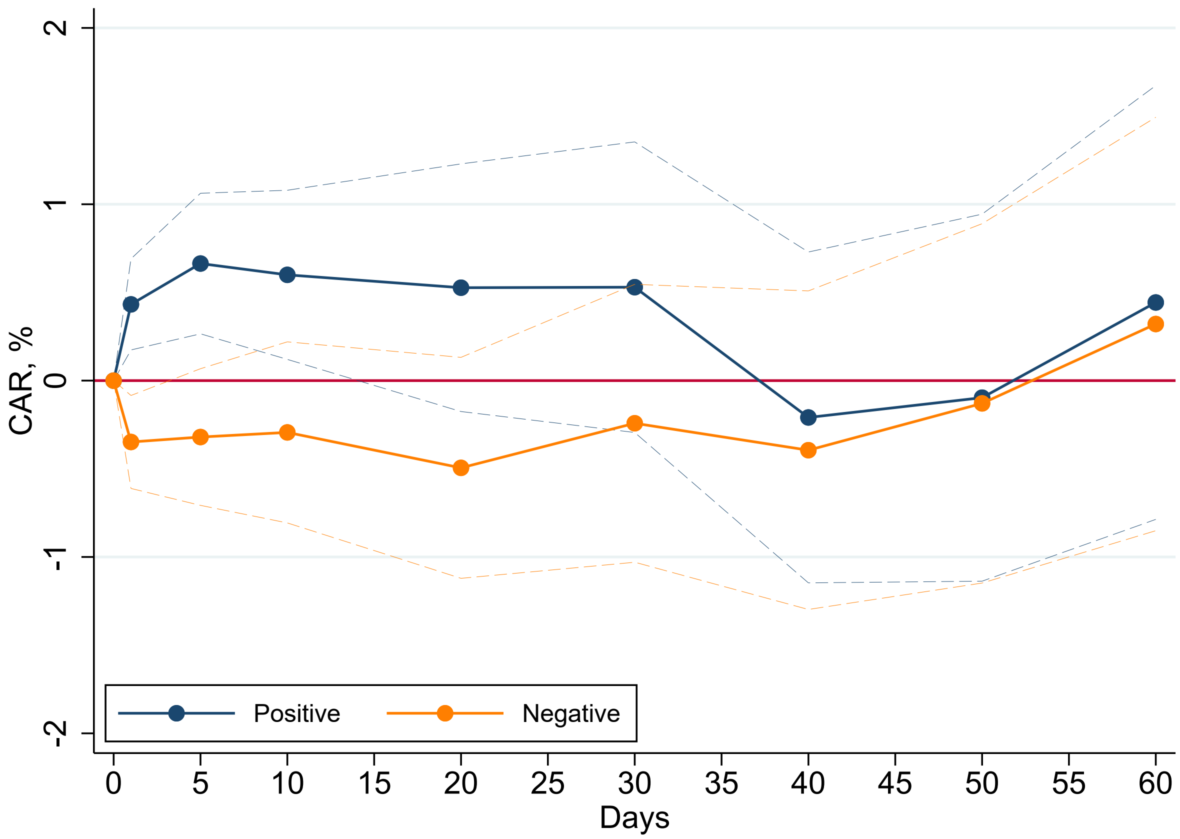
Table 1.6:
Attention Spillovers for Significant News
This table reports the estimation results of a panel regression of the daily abnormal investor attention (*awiki*, *agsv*, *aedgar* and *aturn*) on the focal stock event dummy ($eventD^{focal}$), the same industry event dummy ($eventD^{ind}$), the same headquarters state event dummy ($eventD^{state}$), the peer stock event dummy ($event^{peer}$), its interaction with significant news dummy (*Hpeer_retD*) and a number of control variables. *Hpeer_retD* is one for the top quarter of absolute 3-days cumulative abnormal returns around peer stock events and zero otherwise. If the peer stock experiences an event ($eventD^{peer} = 1$) and comes from the same industry and/or the same state as the focal stock, the corresponding event dummies ($eventD^{ind}$ and/or $eventD^{state}$) are also equal to one. To estimate the regression for the full cross-section of firms, I assume $eventD^{peer}$ to be zero for firms without peers with similar names and allow a separate intercept (*peerD*) for these firms. The events are earnings announcements and 8-K filings. The sample period is 2008-2015. The regressions are estimated with year-month, day of the week, industry and headquarters state fixed effects. The standard errors are clustered by date and firm.*, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1) *awiki*	(2) *agsv*	(3) *aedgar*	(4) *aturn*
peerD	-0.0000	-0.0005	-0.0009	-0.0022
	(-0.01)	(-0.23)	(-0.88)	(-1.35)
ln_size	-0.0038***	-0.0045***	-0.0076***	-0.0145***
	(-8.09)	(-5.51)	(-12.67)	(-14.50)
ln_bm	-0.0007	-0.0016	-0.0007	0.0002
	(-1.52)	(-1.53)	(-1.26)	(0.24)
mom	0.0018	-0.0022**	-0.0030***	-0.0009
	(1.47)	(-1.96)	(-2.80)	(-0.50)
st_rev	-0.0007	0.0361***	-0.0138*	0.0084
	(-0.15)	(5.83)	(-1.91)	(0.77)
misp	0.0002***	0.0001	-0.0003***	-0.0001
	(4.64)	(1.55)	(-5.93)	(-1.45)
ivola	-0.5589***	-0.3092***	-0.8494***	-2.1508***
	(-11.24)	(-4.62)	(-11.38)	(-17.01)
io	0.0050**	0.0163***	-0.0059**	-0.0439***
	(2.16)	(3.69)	(-2.03)	(-7.29)
ln_nanalyst	0.0010	0.0040**	-0.0032***	-0.0044**
	(1.25)	(2.22)	(-3.57)	(-2.34)
$eventD^{focal}$	0.0917***	0.0839***	0.6658***	0.5327***
	(37.58)	(21.04)	(89.66)	(59.29)
$eventD^{ind}$	0.0196***	0.0066***	0.0444***	0.0606***
	(6.58)	(3.37)	(8.77)	(8.75)
$eventD^{state}$	0.0186***	0.0062**	0.0428***	0.0658***
	(4.91)	(2.52)	(6.94)	(7.88)
$\boldsymbol{eventD^{peer}}$	**0.0099*** **	**0.0022**	**0.0076**	**0.0135*** *
	(2.86)	**(0.49)**	**(1.30)**	**(2.14)**
$\boldsymbol{Hpeer\_retD \times eventD^{peer}}$	**0.0154*** *	**0.0008**	**0.0008**	**0.0213***
	(2.30)	**(0.09)**	**(0.07)**	**(1.75)**
Year - Month FE	Yes	Yes	Yes	Yes
Day of the Week FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
HQ State FE	Yes	Yes	Yes	Yes
R2	0.0478	0.0022	0.0922	0.0317
N	2'696'867	3'262'755	3'657'172	3'795'003



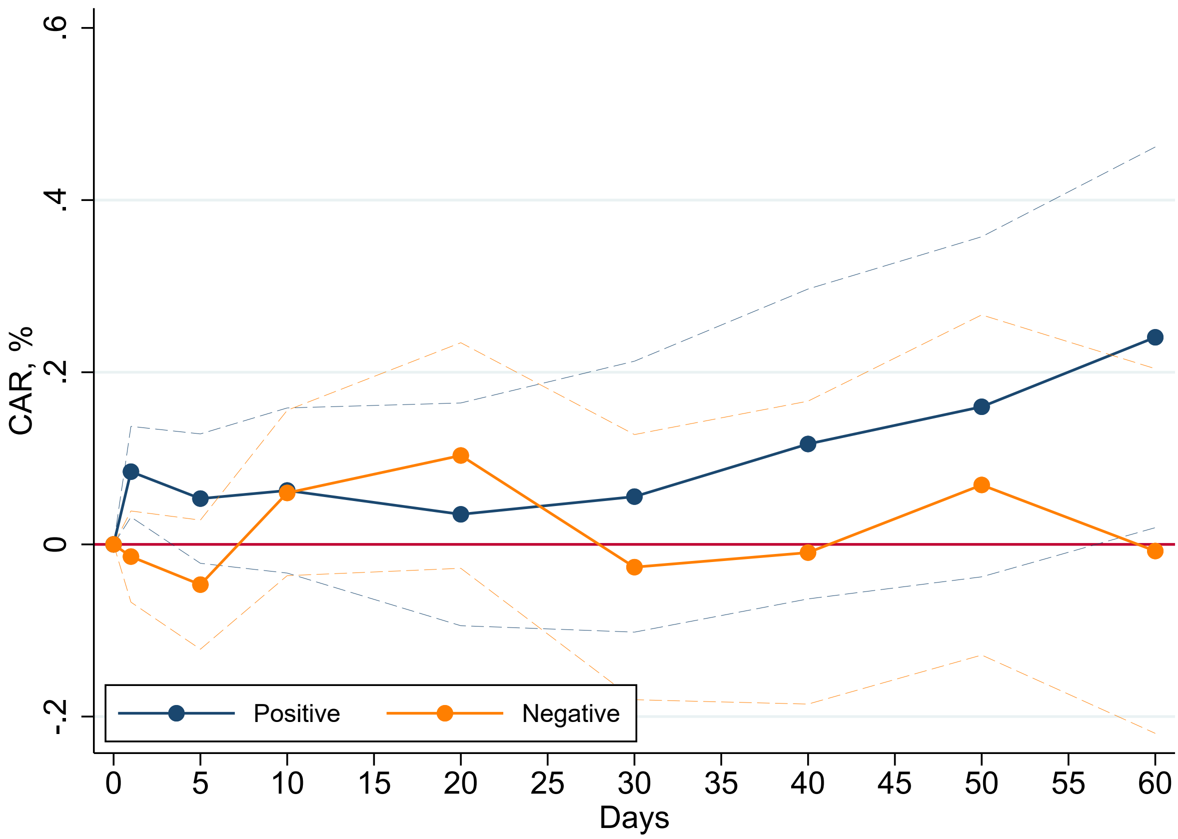
	CAR(-1,1)	CAR(-1,5)	CAR(-1,10)	CAR(-1,20)	CAR(-1,30)	CAR(-1,40)	CAR(-1,50)	CAR(-1,60)
Positive	30.48***	29.63***	29.94***	31.74***	32.28***	32.97***	33.93***	35.23***
N = 2152	(66.75)	(53.21)	(46.70)	(37.00)	(34.61)	(29.85)	(27.66)	(26.71)
Negative	-26.03***	-25.33***	-24.77***	-24.27***	-24.21***	-24.00***	-23.56***	-23.44***
N = 1960	(-135.77)	(-86.24)	(-65.99)	(-50.78)	(-44.74)	(-37.36)	(-32.38)	(-29.56)
Difference	56.512***	54.961***	54.717***	56.012***	56.489***	56.978***	57.496***	58.669***
	(110.32)	(84.90)	(71.86)	(55.57)	(51.10)	(43.49)	(39.36)	(37.23)

Figure 1.1:
Peer Company's Own Stock Price Reaction to Its Significant News
This figure depicts cumulative abnormal returns around companies' own announcement events with significant positive and negative news as a function of holding period. Cumulative abnormal returns are defined as the difference between the buy-and-hold returns of the announcing company and returns of a portfolio of firms matched on size and book-to-market, following Hirshleifer, Lim, and Teoh (2009). Significant news event is defined as an event in top 2.5% of absolute $CAR(-1,1)$ in response to earnings announcements or 8-K filings and classified as positive or negative depending on the sign of the $CAR(-1,1)$. The holding period starts one day before the event and ends in 1 day to 60 days after the event. The table under the figure presents cumulative abnormal returns for positive, negative news and the difference between them. In parentheses are the t-statistics of the t-test on the statistical difference from zero of cumulative abnormal returns. The sample period is from January 1996 to December 2015. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.



	CAR(-1,1)	CAR(-1,5)	CAR(-1,10)	CAR(-1,20)	CAR(-1,30)	CAR(-1,40)	CAR(-1,50)	CAR(-1,60)
Positive	0.432***	0.664***	0.600**	0.527	0.530	-0.209	-0.0965	0.443
N = 2242	(2.76)	(2.74)	(2.06)	(1.23)	(1.06)	(-0.37)	(-0.15)	(0.59)
Negative	-0.348**	-0.320	-0.293	-0.494	-0.242	-0.394	-0.129	0.321
N = 1963	(-2.17)	(-1.36)	(-0.94)	(-1.30)	(-0.50)	(-0.72)	(-0.21)	(0.45)
Difference	0.780***	0.984***	0.893**	1.021*	0.771	0.186	0.032	0.122
	(3.47)	(2.89)	(2.09)	(1.77)	(1.11)	(0.23)	(0.04)	(0.12)

Figure 1.2:
Focal Company's Stock Price Reaction to Peer's Significant News
This figure depicts cumulative abnormal returns around peer companies' announcement events with significant positive and negative news as a function of holding period. Cumulative abnormal returns are defined as the difference between the buy-and-hold returns of the announcing company and returns of a portfolio of firms matched on size and book-to-market, following Hirshleifer, Lim, and Teoh (2009). Significant news event is defined as an event in top 2.5% of absolute $CAR(-1,1)$ in response to earnings announcements or 8-K filings and classified as positive or negative depending on the sign of the $CAR(-1,1)$. The holding period starts one day before the event and ends in 1 day to 60 days after the event. The table under the figure presents cumulative abnormal returns for positive, negative news and the difference between them. In parentheses are the t-statistics of the t-test on the statistical difference from zero of cumulative abnormal returns. The pairs from the same industry and headquarters state as the focal company are not included in the analysis. The sample period is from January 1996 to December 2015.*, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.



	CAR(-1,1)	CAR(-1,5)	CAR(-1,10)	CAR(-1,20)	CAR(-1,30)	CAR(-1,40)	CAR(-1,50)	CAR(-1,60)
Positive	0.0845***	0.0532	0.0626	0.0349	0.0555	0.117	0.160	0.241*
N = 41453	(2.64)	(1.16)	(1.07)	(0.44)	(0.58)	(1.07)	(1.33)	(1.79)
Negative	-0.0141	-0.0468	0.0598	0.103	-0.0264	-0.00953	0.0691	-0.00770
N = 43046	(-0.44)	(-1.03)	(1.02)	(1.30)	(-0.28)	(-0.09)	(0.57)	(-0.06)
Difference	0.099**	0.100	0.003	-0.068	0.082	0.126	0.091	0.248
	(2.17)	(1.55)	(0.03)	(-0.61)	(0.61)	(0.82)	(0.53)	(1.33)

Figure 1.3:
Focal Company's Stock Price Reaction to Peer's Weak News
This figure depicts cumulative abnormal returns around peer companies' announcement events with weak positive and negative news as a function of holding period. Cumulative abnormal returns are defined as the difference between the buy-and-hold returns of the announcing company and returns of a portfolio of firms matched on size and book-to-market, following Hirshleifer, Lim, and Teoh (2009). Weak news event is defined as an event *not* in top 2.5% of the absolute $CAR(-1,1)$ in response to earnings announcements or 8-K filings and classified as positive or negative depending on the sign of the $CAR(-1,1)$. The holding period starts one day before the event and ends in 1 day to 60 days after the event. The table under the figure presents cumulative abnormal returns for positive, negative news and the difference between them. In parentheses are the t-statistics of the t-test on the statistical difference from zero of cumulative abnormal returns. The pairs from the same industry and headquarters state as the focal company are not included in the analysis. The sample period is from January 1996 to December 2015. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

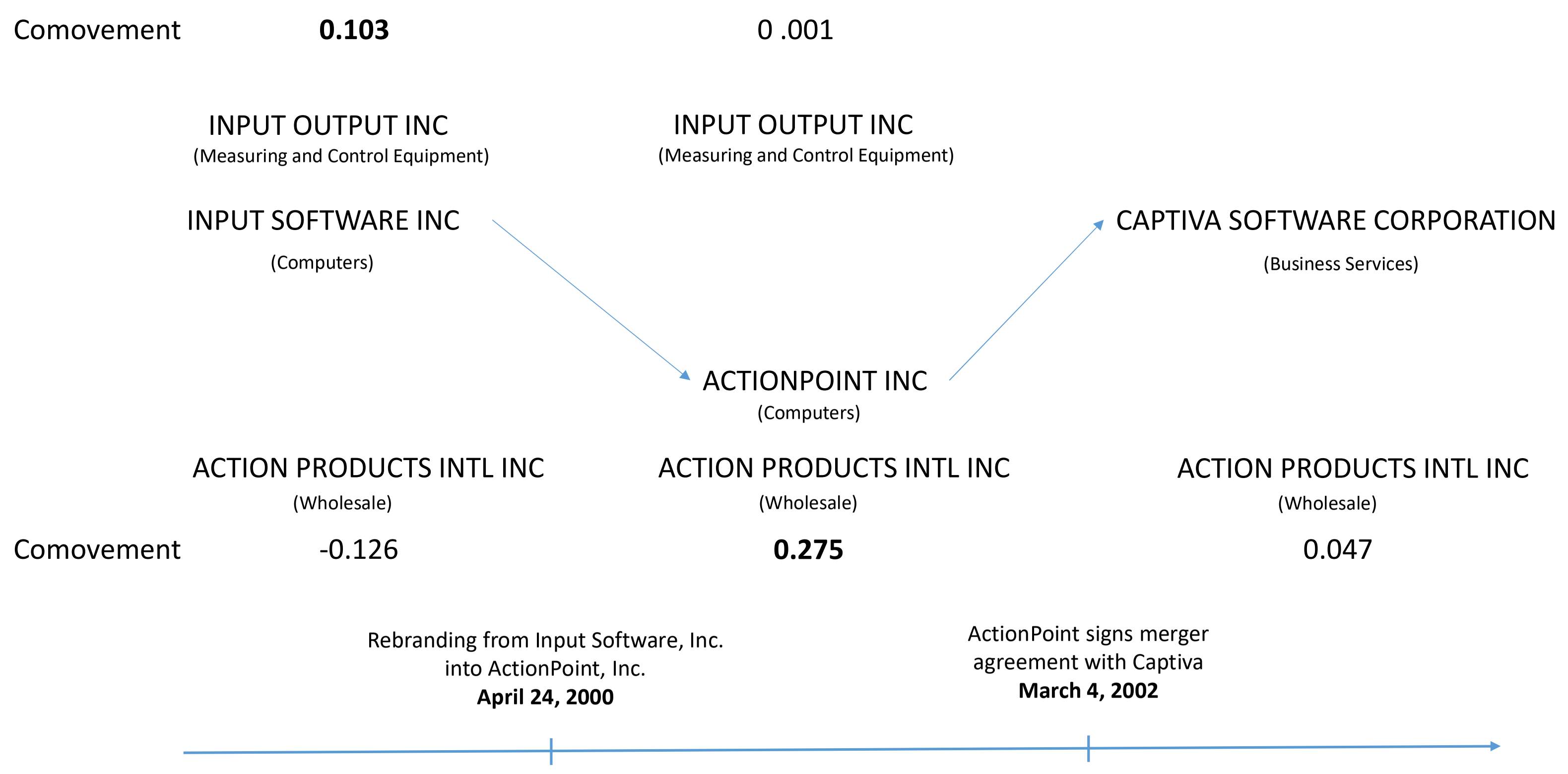


Figure 1.4:
Name Changes Analysis - Illustration
This figure illustrates name changing events and the corresponding changes in comovement. INPUT SOFTWARE, INC. developed and marketed software products that "intelligently capture customer, supplier, and business partner information ... into formats compatible with enterprise computing systems and the Internet". Name matching algorithm matched this company to INPUT/OUTPUT, INC, the company that provided "products and services that are used in the exploration for, and development ... of oil and gas reserves." Before the name change, INPUT/OUTPUT, INC comoved with INPUT SOFTWARE with the comovement coefficient of 0.103. Input Software changed its name to ACTIONPOINT on April 24, 2000 to more efficiently communicate its focus on commercial interaction management software. After the name change the comovement coefficient became close to zero. The company that is matched by name after the name change is ACTION PRODUCTS INTERNATIONAL, which produced games and toys. Before the event the comovement coefficient of these two companies was -0.126. After the name change, it increased to 0.275. On March 4, 2002 ACTIONPOINT signs merger agreement CAPTIVA. This name changing event is associated with another corporate event (merger), and therefore is not considered in this study.

Table 1.7:
Comparison of Peer Firms to Matched Firms in the Name Changes Sample
This table contains the mean and standard deviation of the selected stock characteristics for stocks that are in the sample of similarly named peers to matched stocks from the control group. The matched stocks are from the same size quintile, BM quintile, FF 5 industry and are the closest in terms of momentum to the peer stocks. Last three rows contain the difference in the characteristics, the t-statistic and the p-value.

	Matched		Peers		Peers - Matched		
Variable	Mean	SD	Mean	SD	Diff	t-stat	p-value
$size$	1687.9	14252.8	1074.3	6875.2	-613.5	-0.69	0.491
bm	0.6211	0.5622	0.6677	0.6936	0.0466	0.88	0.382
mom	0.1744	0.8489	0.2842	1.0066	0.1098	1.41	0.160
st_rev	0.0171	0.2285	0.0025	0.2131	-0.0145	-0.89	0.376
$misp$	49.301	13.260	51.014	14.218	1.714	0.80	0.427
$turn$	0.1382	0.2582	0.1219	0.1663	-0.0164	-1.04	0.299
$amihud$	2.5050	6.7362	7.2213	75.5637	4.7163	1.09	0.277
γ^{PS}	30.088	283.608	36.722	137.968	6.634	0.32	0.746
c^{Gibbs}	0.0150	0.0161	0.0174	0.0179	0.0024	1.57	0.117
$hlspread$	0.0392	0.0772	0.0380	0.0509	-0.0012	-0.24	0.811
$ivol$	0.0386	0.0297	0.0428	0.0284	0.0042	1.96	0.051
io	0.3141	0.2739	0.2422	0.2501	-0.0719	-3.45	0.001
age	146.596	155.678	146.173	168.567	-0.422	-0.04	0.972
$nanalyst$	4.179	6.337	1.833	4.047	-2.347	-5.66	0.000
w^{ind}	0.0554	0.0510	0.0558	0.0513	0.0004	0.10	0.918
w^{state}	0.0644	0.0639	0.0740	0.0627	0.0097	1.17	0.244

Table 1.8:
Name Changes and Changes in Comovement by Type

This table reports the results of the pooled panel regressions of the daily four-factor abnormal returns of focal stocks on the leads and lags of abnormal returns of the corresponding peer stocks around name changing events that are not associated with any other corporate events. Name changes are from Green and Jame (2013) and divided into three categories (Rebranding, Narrow Focus and Broad Focus) depending on how these events are related to changes in company strategy. I estimate two separate regressions for the cases when the company names are similar and not similar, and calculate the difference in comovement:

$$\text{Alpha}_{it}^{focal} = \sum_{k=-3}^{3} b_k^{peer,\,similar} \cdot \text{Alpha}_{it+k}^{peer,\,similar} + \epsilon_{it}$$

$$\text{Alpha}_{it}^{focal} = \sum_{k=-3}^{3} b_k^{peer,\,nonsimilar} \cdot \text{Alpha}_{it+k}^{peer,\,nonsimilar} + \epsilon_{it}$$

$$\Delta b = \sum_{k=-3}^{3} b_k^{peer,\,similar} - \sum_{k=-3}^{3} b_k^{peer,\,nonsimilar}$$

Displayed are the estimated comovement coefficients, F-statistics and p-values for all groups. For the change in comovement, the chi2 statistics and p-values of the difference in estimates are reported. I skip two months right before and two months right after the name changes. The estimation window is limited to two years before and two years after the event (excluding skipped months). The standard errors are clustered on the event level. The sample period is 1980 - 2008.

Panel A: Peer Group

	All			Rebranding			Narrow Focus			Broad Focus		
	Similar	Nonsimilar	Difference	Similar	Nonsimilar	Difference	Similar	Nonsimilar	Difference	Similar	Nonsimilar	Difference
b^{peer}	0.050	0.018	**0.032**	0.068	0.027	**0.041**	0.046	0.002	**0.044**	0.009	0.023	**-0.014**
F_stat	20.31	3.31	**4.17**	16.12	3.34	**3.67**	6.11	0.01	**2.73**	0.22	0.96	**0.12**
p_val	0.000	0.069	**0.041**	0.000	0.069	**0.055**	0.014	0.907	**0.098**	0.641	0.331	**0.726**
R2	0.00029	0.00010		0.00052	0.00018		0.00043	0.00020		0.00031	0.00013	
N	160,979	151,896		78,707	76,009		54,222	51,376		28,050	24,511	

Panel B: Matched Group

	All			Rebranding			Narrow Focus			Broad Focus		
	Similar	Nonsimilar	Difference	Similar	Nonsimilar	Difference	Similar	Nonsimilar	Difference	Similar	Nonsimilar	Difference
b^{contol}	0.016	0.025	**-0.009**	0.008	0.024	**-0.016**	0.020	0.041	**-0.020**	0.025	-0.003	**0.029**
F_stat	2.60	5.39	**0.32**	0.30	1.98	**0.48**	1.26	7.46	**0.51**	1.85	0.02	**0.50**
p_val	0.108	0.021	**0.572**	0.586	0.161	**0.487**	0.264	0.007	**0.474**	0.178	0.899	**0.480**
R2	0.00005	0.00007		0.00003	0.00012		0.00008	0.00051		0.00041	0.00031	
N	155,508	140,167		75,787	67,959		53,304	46,986		26,417	25,222	

Table 1.9:
Name Changes and Changes in Comovement - Leaving versus Entering
This table reports the results of the pooled panel regressions of the daily four-factor abnormal returns of focal stocks on the leads and lags of abnormal returns of the corresponding peer stocks around name changing events that are not associated with any other corporate events. Name changes are from Green and Jame (2013) and divided into three categories (Leaving and Entering) depending on whether the companies are similar before the event or become similar after the event. I estimate two separate regressions for the cases when the company names are similar and not similar, and calculate the difference in comovement:

$$\text{Alpha}_{it}^{focal} = \sum_{k=-3}^{3} b_k^{peer,\,similar} \cdot \text{Alpha}_{it+k}^{peer,\,similar} + \epsilon_{it}$$

$$\text{Alpha}_{it}^{focal} = \sum_{k=-3}^{3} b_k^{peer,\,nonsimilar} \cdot \text{Alpha}_{it+k}^{peer,\,nonsimilar} + \epsilon_{it}$$

$$\Delta b = \sum_{k=-3}^{3} b_k^{peer,\,similar} - \sum_{k=-3}^{3} b_k^{peer,\,nonsimilar}$$

Displayed are the estimated comovement estimates, F-statistics and p-values for all groups. For the change in comovement, the chi-squared and p-values of the difference in estimates are reported. I skip two months right before and two months right after the name changes. The estimation window is limited to two years before and two years after the event (excluding skipped months). The standard errors are clustered on the event level. The sample period is 1980 - 2008.

Panel A: Peer Group

	Leaving			Entering			All		
	Similar	Nonsimilar	Difference	Similar	Nonsimilar	Difference	Similar	Nonsimilar	Difference
b^{peer}	0.046	0.034	**0.012**	0.054	0.000	**0.054**	0.050	0.018	**0.032**
F_stat	8.63	5.37	**0.30**	12.29	0.00	**6.84**	20.31	3.31	**4.17**
p_val	0.004	0.021	**0.582**	0.001	0.996	**0.009**	0.000	0.069	**0.041**
R2	0.00027	0.00017		0.00032	0.00009		0.00029	0.00010	
N	81,236	79,034		79,743	72,862		160,979	151,896	

Panel B: Matched Group

	Leaving			Entering			All		
	Similar	Nonsimilar	Difference	Similar	Nonsimilar	Difference	Similar	Nonsimilar	Difference
b^{contol}	0.019	0.036	**-0.018**	0.013	0.013	**-0.001**	0.016	0.025	**-0.009**
F_stat	2.12	5.28	**0.48**	0.75	0.87	**0.00**	2.60	5.39	**0.32**
p_val	0.146	0.023	**0.487**	0.387	0.352	**0.972**	0.108	0.021	**0.572**
R2	0.00006	0.00014		0.00010	0.00012		0.00005	0.00007	
N	75,505	69,111		80,003	71,056		155,508	140,167	

Table 1.10:
Return Comovement

This table presents panel regression results of the daily abnormal returns of focal stocks on the leads and lags of abnormal returns of the corresponding peer stocks and a number of controls. Reported are the coefficients on the abnormal returns of the peer stocks together with the t-statistics in the parentheses and the sum of these coefficients together with the F-statistics and the p-values. The Column (1) shows the results for the raw excess returns and all other columns show the results for Davis, Fama, and French (2000) four-factor abnormal returns. Columns (2) to (7) include time fixed effects and different sets of control variables. The control variables are equally-weighted returns on the price, size, book-to-market, momentum, short-term reversal decile portfolios and FF 48 industry portfolios. The extended controls include additionally equally weighted returns on transaction costs decile portfolios and HQ state portfolios. Specifications in columns (8) to (12) contain more conservative date times industry and date times HQ state fixed effects of focal and peer stocks in different combinations. The sample period is 1972 to 2016. The sample period for the regressions with extended controls is limited to 1996 - 2010 due to data availability. The standard errors are clustered on date and stock-pair level. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1) retd	(2) alpha	(3) alpha	(4) alpha	(5) alpha	(6) alpha	(7) alpha	(8) alpha	(9) alpha	(10) alpha	(11) alpha	(12) alpha
$perf^{peer}_{+3}$	0.0056***	0.0001	0.0000	-0.0002	-0.0001	0.0008	0.0005	-0.0002	-0.0004	0.0013	0.0004	0.0029
	(2.70)	(0.07)	(0.05)	(-0.23)	(-0.12)	(0.49)	(0.31)	(-0.18)	(-0.45)	(0.67)	(0.21)	(0.78)
$perf^{peer}_{+2}$	0.0048*	0.0016*	0.0017**	0.0015*	0.0015*	0.0005	0.0005	0.0009	0.0016*	-0.0001	-0.0005	-0.0034
	(1.95)	(1.88)	(1.98)	(1.77)	(1.73)	(0.35)	(0.38)	(0.95)	(1.69)	(-0.04)	(-0.27)	(-0.89)
$perf^{peer}_{+1}$	0.0223***	0.0049***	0.0046***	0.0039***	0.0038***	0.0035**	0.0037**	0.0035***	0.0033***	0.0024	0.0015	0.0018
	(9.29)	(5.00)	(4.76)	(4.14)	(4.05)	(2.14)	(2.38)	(3.43)	(3.11)	(1.21)	(0.76)	(0.48)
$perf^{peer}_{0}$	0.1197***	0.0149***	0.0128***	0.0110***	0.0109***	0.0134***	0.0115***	0.0086***	0.0070***	0.0097***	0.0068***	0.0033
	(25.69)	(7.92)	(6.87)	(6.20)	(6.23)	(4.79)	(4.28)	(5.08)	(4.50)	(3.54)	(2.72)	(0.79)
$perf^{peer}_{-1}$	0.0231***	0.0042***	0.0037***	0.0030***	0.0030***	0.0023	0.0033**	0.0020*	0.0031***	0.0018	0.0044**	0.0076**
	(8.74)	(4.15)	(3.69)	(3.01)	(3.06)	(1.26)	(2.04)	(1.87)	(2.87)	(0.82)	(2.14)	(2.03)
$perf^{peer}_{-2}$	0.0052**	0.0015	0.0013	0.0011	0.0012	0.0001	0.0008	0.0010	0.0013	0.0011	-0.0002	0.0040
	(1.98)	(1.64)	(1.42)	(1.17)	(1.33)	(0.05)	(0.53)	(1.02)	(1.33)	(0.54)	(-0.09)	(1.09)
$perf^{peer}_{-3}$	0.0053**	0.0010	0.0007	0.0006	0.0006	0.0013	0.0003	0.0005	0.0005	0.0019	-0.0001	0.0057
	(2.45)	(1.02)	(0.77)	(0.63)	(0.66)	(0.84)	(0.18)	(0.46)	(0.50)	(0.91)	(-0.07)	(1.47)
Date FE			Yes	Yes	Yes	Yes	Yes					
Controls Peer				Yes								
Controls Focal					Yes							
Controls Peer Ext						Yes						
Controls Focal Ext							Yes					
Date*Industy FE Peer								Yes		Yes		Yes
Date*Industy FE Focal									Yes		Yes	Yes
Date*HQ State FE Peer										Yes		Yes
Date*HQ State FE Focal											Yes	Yes
b^{peer}	**0.186**	**0.0281**	**0.0248**	**0.0209**	**0.0209**	**0.022**	**0.0205**	**0.0164**	**0.0164**	**0.018**	**0.012**	**0.022**
F_stat	480.00	67.23	53.43	40.56	41.63	16.19	15.19	23.07	25.01	9.11	4.57	4.37
p_val	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0001**	**0.0001**	**0.0000**	**0.0000**	**0.0026**	**0.0327**	**0.0368**
r2	0.015	0.000	0.007	0.008	0.013	0.011	0.018	0.158	0.167	0.316	0.316	0.702
N	2,266,324	1,993,346	1,993,346	1,993,307	1,991,278	675,868	697,994	1,914,441	1,912,919	590,393	602,734	383,316

Table 1.11:
Return Comovement - Matched Sample

This table presents panel regression results of the daily abnormal returns of focal stocks on the leads and lags of abnormal returns of the control stocks that are matched to corresponding peer stocks and a number of controls: Reported are the coefficients on the abnormal returns of the peer stocks together with the t-statistics in the parentheses and the sum of these coefficients together with the F-statistics and the p-values. The Column (1) shows the results for the raw excess returns and all other columns show the results for Davis, Fama, and French (2000) four-factor abnormal returns. Columns (2) to (7) include time fixed effects and different sets of control variables. The control variables are equally-weighted returns on the price, size, book-to-market, momentum, short-term reversal decile portfolios and FF 48 industry portfolios. The extended controls include additionally equally weighted returns on transaction costs decile portfolios and HQ state portfolios. Specifications in columns (8) to (12) contain more conservative date times industry and date times HQ state fixed effects of focal and matched stocks in different combinations. The sample period is 1972 to 2016. The sample period for the regressions with extended controls is limited to 1996 - 2010 due to data availability. The standard errors are clustered on date and stock-pair level. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1) retd	(2) alpha	(3) alpha	(4) alpha	(5) alpha	(6) alpha	(7) alpha	(8) alpha	(9) alpha	(10) alpha	(11) alpha	(12) alpha
$perf_{+3}^{matched}$	0.0056***	0.0010	0.0010	0.0008	0.0009	0.0015	0.0027**	0.0012	0.0013	0.0022	0.0029*	0.0027
	(2.89)	(1.19)	(1.18)	(1.03)	(1.08)	(1.11)	(1.97)	(1.34)	(1.45)	(1.29)	(1.72)	(1.01)
$perf_{+2}^{matched}$	0.0038*	-0.0002	-0.0003	-0.0004	-0.0004	-0.0008	-0.0006	-0.0006	-0.0004	-0.0004	-0.0013	0.0003
	(1.70)	(-0.19)	(-0.33)	(-0.47)	(-0.48)	(-0.55)	(-0.47)	(-0.66)	(-0.41)	(-0.22)	(-0.77)	(0.11)
$perf_{+1}^{matched}$	0.0194***	0.0031***	0.0027***	0.0024***	0.0023***	0.0026*	0.0026**	0.0016*	0.0023***	0.0015	0.0022	0.0018
	(8.69)	(3.77)	(3.24)	(2.94)	(2.81)	(1.91)	(2.03)	(1.83)	(2.58)	(0.89)	(1.35)	(0.67)
$perf_{0}^{matched}$	0.1011***	0.0048***	0.0024***	0.0016*	0.0016*	0.0028*	0.0027*	-0.0010	-0.0003	-0.0007	0.0005	-0.0055*
	(21.59)	(4.98)	(2.58)	(1.75)	(1.72)	(1.83)	(1.76)	(-1.00)	(-0.27)	(-0.35)	(0.25)	(-1.75)
$perf_{-1}^{matched}$	0.0205***	0.0012	0.0006	0.0002	0.0002	-0.0003	0.0002	-0.0001	0.0001	-0.0013	0.0010	-0.0007
	(8.83)	(1.41)	(0.76)	(0.27)	(0.28)	(-0.22)	(0.14)	(-0.07)	(0.09)	(-0.74)	(0.59)	(-0.27)
$perf_{-2}^{matched}$	0.0054**	0.0007	0.0006	0.0004	0.0005	0.0013	0.0018	-0.0000	0.0001	0.0005	0.0002	-0.0032
	(2.27)	(0.89)	(0.74)	(0.54)	(0.63)	(0.96)	(1.34)	(-0.01)	(0.16)	(0.31)	(0.11)	(-1.13)
$perf_{-3}^{matched}$	0.0059***	0.0014*	0.0013	0.0012	0.0012	0.0024*	0.0022	0.0019**	0.0011	0.0033*	0.0009	0.0042
	(2.93)	(1.71)	(1.54)	(1.43)	(1.48)	(1.72)	(1.60)	(2.07)	(1.25)	(1.94)	(0.56)	(1.44)
Date FE			Yes	Yes	Yes	Yes	Yes					
Controls Matched				Yes								
Controls Focal					Yes							
Controls Matched Ext						Yes						
Controls Focal Ext							Yes					
Date*Industy FE Matched								Yes		Yes		Yes
Date*Industy FE Focal									Yes		Yes	Yes
Date*HQ State FE Matched										Yes		Yes
Date*HQ State FE Focal											Yes	Yes
$b^{control}$	**0.162**	**0.012**	**0.0083**	**0.00633**	**0.00634**	**0.00961**	**0.0117**	**0.00306**	**0.00429**	**0.00519**	**0.00649**	**-0.000342**
F_stat	312.80	28.43	14.06	8.45	8.54	6.99	9.95	1.60	3.31	1.24	2.08	0.00
p_val	**0.0000**	**0.0000**	**0.0002**	**0.0037**	**0.0035**	**0.0083**	**0.0016**	**0.2060**	**0.0691**	**0.2650**	**0.1490**	**0.9660**
r2	0.011	0.000	0.006	0.007	0.012	0.008	0.016	0.143	0.146	0.286	0.278	0.625
N	2’699’347	2’352’923	2’352’923	2’352’878	2’349’841	831’607	834’506	2’278’835	2’274’740	752’595	745’049	531’904

Table 1.12:
Return Comovement - Cross-Sectional Tests
This table presents panel regression results of the daily abnormal returns of focal stocks on the leads and lags of abnormal returns of the corresponding peer stocks and their interaction with a focal stock characteristic dummy :

$$\text{Alpha}_{it}^{focal} = a_t + \sum_{k=-3}^{3} b_k^{peer} \cdot \text{Alpha}_{it+k}^{peer} + \sum_{k=-3}^{3} b_k^{interact} \cdot D_{it}^{CS,focal} \times \text{Alpha}_{it+k}^{peer} + b^{CS} \cdot D_{it}^{CS,focal} + \sum_{k=-3}^{3} \mathbf{b_k^{controls\,\prime}} \cdot \mathbf{controls_{it+k}} + \epsilon_{it}$$

Reported are the sum of coefficients on the abnormal returns of the peer stocks and the sum of coefficients on the abnormal returns of the peer stocks interacted with the characteristic dummy together with the F-statistics and the p-values. The stock characteristic dummies are equal to one for the top 50 % in daily abnormal trading (*aturn*), residual institutional ownership (*rio*), Amihud (2002) illiquidity ratio (*amihud*), Pástor and Stambaugh (2003) liquidity measure (γ^{PS}), Corwin and Schultz (2012) bid-ask spread (*hlspread*), idiosyncratic volatility (*ivol*), age (*age*) and insitutional ownership (*io*) and for the top 25% in absolute daily alpha (|*alpha*|). The regressions include date fixed effects and standard controls for the focal stock characteristics. The standard errors are clustered on date and stock-pair level. The sample period is 1972 to 2016.

	Type of Days		Limits to Arbitrage					Other	
D^{CS} =	$\|alpha\|$	*aturn*	*rio*	*amihud*	γ^{PS}	*hlspread*	*ivol*	*age*	*io*
	(1) alpha	(2) alpha	(4) alpha	(5) alpha	(7) alpha	(6) alpha	(8) alpha	(9) alpha	(10) alpha
$b^{peer}(\text{Alpha}^{peer})$	-0.0011	**0.0041**	**0.0222**	**0.0165**	**0.0235**	**0.0127**	**0.0108**	**0.0225**	**0.0220**
F_stat	1.24	4.33	30.16	18.61	35.00	24.09	21.20	37.80	31.72
p_val	0.2660	**0.0375**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**
$b^{interact}(D^{CS} \times \text{Alpha}^{peer})$	**0.0666**	**0.0246**	**-0.0099**	0.0003	**-0.0120**	**0.0084**	**0.0116**	**-0.0120**	**-0.0097**
F_stat	76.92	33.99	4.46	0.00	7.35	4.06	8.87	7.16	4.25
p_val	**0.0000**	**0.0000**	**0.0349**	0.9510	**0.0067**	**0.0441**	**0.0029**	**0.0075**	**0.0394**
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls Focal	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
r2	0.0127	0.0142	0.0116	0.0114	0.00899	0.0108	0.011	0.0109	0.0116
N	3'945'686	3'733'608	3'125'964	3'298'359	2'829'184	3'759'353	3'881'621	3'823'049	3'127'921

Appendix to Chapter 1

Table A1.1:
Definitions of Variables

Variable:	Description:	Source:
awiki	Wikipedia page views of company i on a given day minus the same company's average page views for the same weekday over the past 10 weeks divided by this average term: $awiki_{i,t} = \frac{wiki_{i,t} - mean_{k\in\{7,14,...70\}}(wiki_{i,t-k})}{mean_{k\in\{7,14,...70\}}(wiki_{i,t-k})}$.	Authors
agsv	Google search volume of company i on a given day minus the average company search volume for the same weekday over the past 10 weeks divided by this average term: $agsv_{i,t} = \frac{gsv_{i,t} - mean_{k\in\{7,14,...70\}}(gsv_{i,t-k})}{mean_{k\in\{7,14,...70\}}(gsv_{i,t-k})}$.	Google Trends
aedgar	EDGAR requests of company i filings on a given day minus the average company filings requests for the same weekday over the past 10 weeks divided by this average term: $aedgar_{i,t} = \frac{edgar_{i,t} - mean_{k\in\{7,14,...70\}}(edgar_{i,t-k})}{mean_{k\in\{7,14,...70\}}(edgar_{i,t-k})}$.	EDGAR, Authors
aturn	Company's share turnover on a given day minus the average share turnover for the same weekday over the past 10 weeks divided by this average term: $aturn_{i,t} = \frac{turn_{i,t} - mean_{k\in\{7,14,...70\}}(turn_{i,t-k})}{mean_{k\in\{7,14,...70\}}(turn_{i,t-k})}$.	CRSP
$CAR(-1,1)$	Cumulative abnormal return over the three-day window around the event date adjusted for *size* and *bm* following Hirshleifer, Lim, and Teoh (2009).	CRSP, IBES
eventD	An event dummy that is equal to one on the day of either earnings announcement or 8-K filing of the *focal* company and zero otherwise.	Compustat, EDGAR
$eventD^{peer}$	An event dummy that is equal to one on the day of either earnings announcement or 8-K filing of the *peer* company and zero otherwise.	Compustat, CRSP, EDGAR
$eventD^{ind}$	An event dummy that is equal to one on the day of either earnings announcement or 8-K filing of the company from the same *industry* (the default is Fama French 48 industries based on FIC codes) and zero otherwise.	Compustat, CRSP, EDGAR
$eventD^{state}$	An event dummy that is equal to one on the day of either earnings announcement or 8-K filing of the company from the same *state* and zero otherwise.	Compustat, EDGAR, Authors
ln_size	The log market capitalization is calculated as the number of shares outstanding times price per share (in $Mio).	CRSP

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Table A1.1 – *Continued from previous page*

Variable:	**Description:**	**Source:**
ln_bm	The log book-to-market ratio is calculated following Davis, Fama, and French (2000). The book-to-market ratio in year t is the total book value at the end of fiscal year ending in year $t-1$ divided by total market capitalization on the last trading day of the calendar year $t-1$, as reported by CRSP. The total book value is the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit minus the book value of preferred stock. To estimate the book value of preferred stock, we use the redemption, liquidation , or par value, in this order (depending on data availability).	CRSP, Compustat
mom	Return momentum is the cumulative return from month $t-12$ to $t-2$.	CRSP
st_rev	Return reversal is the return over the month $t-1$.	CRSP
misp	The mispricing score from Stambaugh, Yu, and Yuan (2015).	Authors
turn	The monthly turnover ratio over the previous month.	CRSP
amihud	The Amihud (2002) illiquidity ratio is calculated following the original study using one year of daily data.	CRSP
γ^{PS}	The Pástor and Stambaugh (2003) gamma liquidity variable that measures the correlation of stock's return and the liquidity factor.	Authors
c^{Gibbs}	The Gibbs estimate calculated using the market model applied to the daily CRSP prices over the past year as in Hasbrouck (2009).	Authors
hlspread	The bid-ask spread of Corwin and Schultz (2012).	Authors
ivol	Idiosyncratic volatility is defined as the standard deviation of the most recent month's daily residuals obtained from the regression of the excess stock returns on Fama-French three factors.	CRSP
io	Institutional ownership is a ratio of shares held by institutional investors in a given company to the total number of company's shares.	13F
rio	Residual institutional ownership is calculated as a residual in the cross-sectional regression of the logit-transformed institutional ownership ratio on log size and log size squared following Nagel (2005).	13F, EST
age	Number of months since the appearance in CRSP.	CRSP
analyst	Number of analysts making earnings forecast of a given company.	IBES
similarity	Names similarity measured as a Jaccard distance between two sets of bi-grams from two companies' names. See more detailed description in Subsection 1.2.2.	CRSP, EST
sameIND	A dummy variable equal to one if the peer company is in the same Fama-French 48 industry.	CRSP

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Table A1.1 – *Continued from previous page*

Variable:	**Description:**	**Source:**
sameHQ	A dummy variable equal to one if the peer company is in the same US state.	Authors, EST
w^{ind}	Share of companies in the same Fama-French 48 industry as a given company.	CRSP
w^{state}	Share of companies in the same US state as a given company.	Authors, EST
peerD	A dummy variable equal to one for companies from the sample of companies with similar names.	CRSP, EST

Table A1.2:
Comparison of Firms with Peers to Matched - Whole Sample
This table contains mean and standard deviation of the selected stock characteristics for the stocks that are in the full sample to the matched stocks from the control group. The matched stocks are from the same size quintile, BM quintile, FF 5 industry and the closest in terms of momentum to the peer stocks. Last three rows contain the difference in the characteristics, the t-statistic and the p-value.

	Matched		With Peers		With Peers - Matched		
Variable	Mean	SD	Mean	SD	Diff	t-stat	p-value
size	1746.0	11334.4	1974.7	14075.0	228.6	7.78	0.000
bm	0.8509	1.0885	0.8503	1.0153	-0.0006	-0.22	0.825
mom	0.1407	0.7374	0.1463	0.7494	0.0056	3.29	0.001
st_rev	0.0113	0.1949	0.0110	0.1899	-0.0003	-0.78	0.433
misp	49.435	13.502	49.649	13.511	0.214	4.57	0.000
turn	0.1145	0.3623	0.1140	0.2674	-0.0005	-0.61	0.540
amihud	3.3688	15.5521	3.6873	30.5314	0.3186	5.08	0.000
γ^{PS}	21.965	431.548	23.307	379.477	1.342	1.09	0.275
c^{Gibbs}	0.0139	0.0173	0.0138	0.0171	-0.0001	-1.18	0.238
hlspread	0.0377	0.0770	0.0379	0.0791	0.0001	0.88	0.381
ivol	0.0310	0.0283	0.0311	0.0280	0.0001	0.95	0.343
io	0.3557	0.2864	0.3550	0.2859	-0.0007	-1.10	0.273
age	173.119	181.856	178.017	188.430	4.898	12.24	0.000
analyst	4.300	6.593	4.164	6.458	-0.136	-9.66	0.000
w^{ind}	0.0488	0.0416	0.0492	0.0412	0.0004	4.26	0.000
w^{state}	0.0699	0.0647	0.0688	0.0638	-0.0010	-3.78	0.000

Table A1.3:
Correlation of Stock Characteristics
This table displays the correlation matrix of stock characteristics. The sample period is from 1972 to 2016. The detailed description of the variables is in the Table A1.1 of the appendix.

	size	*bm*	*mom*	*st_rev*	*misp*	*turn*	*amihud*	γ^{PS}	c^{Gibbs}	*hlspread*	*ivol*	*io*	*age*	*analyst*	*similarity*	*sameIND*	*sameHQ*
size	1.00																
bm	-0.27	1.00															
mom	0.12	0.10	1.00														
st_rev	0.04	0.05	0.04	1.00													
misp	-0.09	-0.02	-0.30	-0.05	1.00												
turn	0.43	-0.32	0.10	0.08	0.09	1.00											
amihud	-0.93	0.23	-0.16	-0.05	0.06	-0.55	1.00										
γ^{PS}	-0.25	0.03	-0.07	-0.03	0.02	-0.06	0.28	1.00									
c^{Gibbs}	-0.75	0.04	-0.26	-0.10	0.16	-0.14	0.76	0.29	1.00								
hlspread	-0.72	0.01	-0.30	-0.12	0.16	-0.15	0.67	0.27	0.86	1.00							
ivol	-0.43	-0.13	-0.27	-0.03	0.20	0.13	0.49	0.20	0.69	0.57	1.00						
io	0.76	-0.08	0.13	0.06	-0.10	0.46	-0.74	-0.23	-0.59	-0.55	-0.39	1.00					
age	0.39	0.17	0.11	0.06	-0.22	-0.07	-0.30	-0.09	-0.38	-0.45	-0.35	0.28	1.00				
analyst	0.81	-0.21	0.11	0.06	-0.03	0.44	-0.79	-0.18	-0.56	-0.56	-0.33	0.69	0.29	1.00			
similarity	-0.01	0.01	0.01	0.00	0.03	-0.04	0.01	0.01	-0.00	0.01	-0.01	-0.02	0.03	-0.01	1.00		
sameIND	0.04	-0.01	0.00	0.00	0.05	0.02	-0.04	-0.01	-0.02	-0.01	-0.01	-0.01	-0.02	0.03	0.02	1.00	
sameHQ	0.03	-0.01	0.00	0.00	-0.03	0.01	-0.02	0.01	-0.02	-0.01	0.00	-0.00	-0.00	0.02	0.01	0.09	1.00

Table A1.4:
Attention Spillovers - No Controls

This table reports the estimation results of a panel regression of the daily abnormal investor attention ($awiki$, $agsv$, $aedgar$ and $aturn$) on the focal stock event dummy ($eventD^{focal}$), the same industry event dummy ($eventD^{ind}$), the same headquarters state event dummy ($eventD^{state}$). If the peer stock experiences an event ($eventD^{peer} = 1$) and comes from the same industry and/or the same state as the focal stock, the corresponding event dummies ($eventD^{ind}$ and/or $eventD^{state}$) are also equal to one. To estimate the regression for the full cross-section of firms, I assume $eventD^{peer}$ to be zero for firms without peers with similar names and allow a separate intercept ($peerD$) for these firms. The events are earnings announcements and 8-K filings. The sample period is 2008-2015. The standard errors are clustered by date and firm.

	(1) *awiki*	(2) *agsv*	(3) *aedgar*	(4) *aturn*
$peerD$	0.0006	-0.0016	-0.0016	-0.0033
	(0.56)	(-0.87)	(-1.20)	(-1.34)
$eventD^{focal}$	0.0904***	0.0818***	0.6830***	0.5243***
	(36.71)	(24.95)	(94.10)	(67.12)
$eventD^{ind}$	0.0211***	0.0117***	0.0378***	0.0410***
	(6.12)	(4.62)	(6.70)	(6.43)
$eventD^{state}$	0.0164***	0.0059**	0.0338***	0.0376***
	(4.23)	(2.03)	(5.54)	(5.29)
$eventD^{peer}$	0.0146***	0.0051	0.0100*	0.0147**
	(4.58)	(1.38)	(1.90)	(2.45)
Year - Month FE	No	No	No	No
Day of the Week FE	No	No	No	No
Industry FE	No	No	No	No
HQ State FE	No	No	No	No
$R2$	0.0033	0.0007	0.0327	0.0122
N	3'376'063	4'642'550	5'130'453	5'409'946

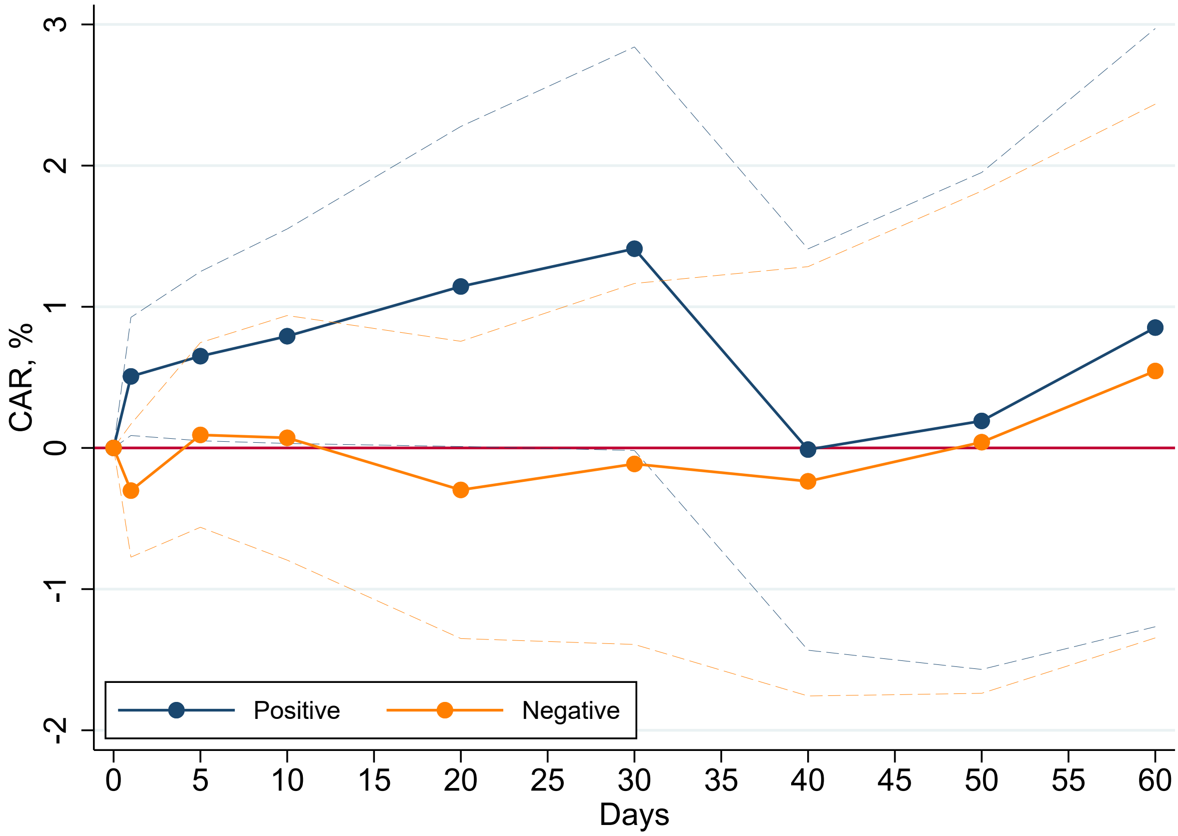
Table A1.5:
Attention Spillovers - Earnings Announcements
This table reports the estimation results of a panel regression of the daily abnormal investor attention ($awiki$, $agsv$, $aedgar$ and $aturn$) on the focal stock event dummy (eaD^{focal}), the same industry event dummy (eaD^{ind}), the same headquarters state event dummy (eaD^{state}), and a number of control variables. If the peer stock experiences an event ($eaD^{peer} = 1$) and comes from the same industry and/or the same state as the focal stock, the corresponding event dummies (eaD^{ind} and/or eaD^{state}) are also equal to one. To estimate the regression for the full cross-section of firms, I assume eaD^{peer} to be zero for firms without peers with similar names and allow a separate intercept ($peerD$) for these firms. The events are earnings announcements. The sample period is 2008-2015. The regressions are estimated with year-month, day of the week, industry and headquarters state fixed effects. The standard errors are clustered by date and firm.

	(1) $awiki$	(2) $agsv$	(3) $aedgar$	(4) $aturn$
$peerD$	0.0004	-0.0004	-0.0004	-0.0016
	(0.37)	(-0.19)	(-0.43)	(-0.99)
ln_size	-0.0036***	-0.0042***	-0.0061***	-0.0131***
	(-7.68)	(-5.21)	(-10.69)	(-13.32)
ln_bm	-0.0008*	-0.0016	-0.0010**	-0.0002
	(-1.66)	(-1.55)	(-2.26)	(-0.20)
mom	0.0019	-0.0020*	-0.0020*	-0.0002
	(1.53)	(-1.85)	(-1.75)	(-0.11)
st_rev	-0.0004	0.0365***	-0.0129*	0.0100
	(-0.08)	(5.89)	(-1.74)	(0.91)
$misp$	0.0002***	0.0001*	-0.0001***	-0.0000
	(4.99)	(1.70)	(-3.46)	(-0.25)
$ivola$	-0.5290***	-0.2784***	-0.6873***	-1.9903***
	(-10.67)	(-4.16)	(-9.30)	(-16.01)
io	0.0051**	0.0161***	-0.0060**	-0.0441***
	(2.25)	(3.66)	(-2.18)	(-7.39)
$ln\_nanalyst$	0.0009	0.0037**	-0.0047***	-0.0064***
	(1.04)	(2.01)	(-5.56)	(-3.42)
eaD^{focal}	0.1416***	0.1760***	0.9437***	0.9707***
	(26.68)	(20.10)	(58.69)	(45.39)
eaD^{ind}	0.0221***	0.0047***	0.0469***	0.0479***
	(10.20)	(4.16)	(13.99)	(10.70)
eaD^{state}	0.0194***	0.0057***	0.0463***	0.0404***
	(8.36)	(4.66)	(12.44)	(8.09)
$\boldsymbol{eaD^{peer}}$	**0.0161*** **	**0.0080**	**0.0113**	**0.0360*** **
	(2.72)	**(1.13)**	**(1.04)**	**(2.91)**
Year - Month FE	Yes	Yes	Yes	Yes
Day of the Week FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
HQ State FE	Yes	Yes	Yes	Yes
r2	0.0484	0.0025	0.0812	0.0332
N	2'696'867	3'262'755	3'657'172	3'795'003

Table A1.6:
Attention Spillovers - 8-K

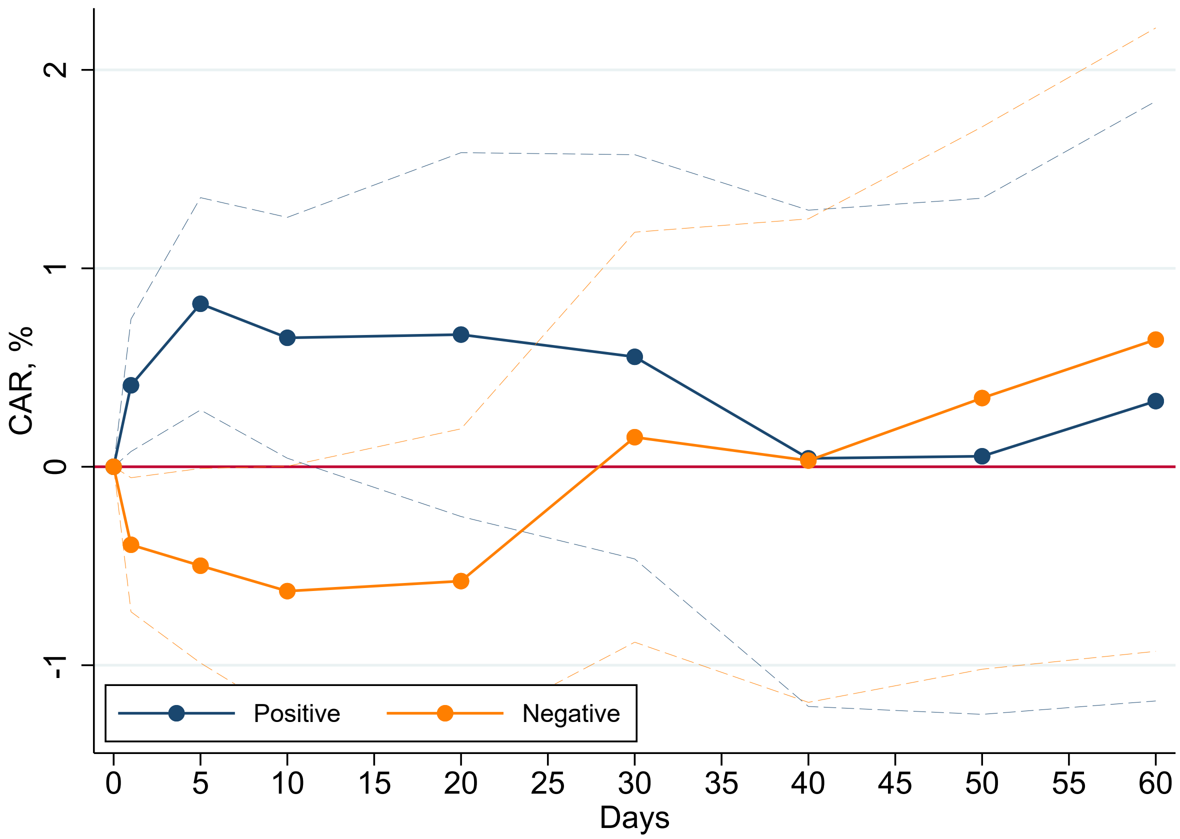
This table reports the estimation results of a panel regression of the daily abnormal investor attention (*awiki*, *agsv*, *aedgar* and *aturn*) on the focal stock event dummy ($8kD^{focal}$), the same industry event dummy ($8kD^{ind}$), the same headquarters state event dummy ($eventD^{state}$), and a number of control variables. If the peer stock experiences an event ($8kD^{peer} = 1$) and comes from the same industry and/or the same state as the focal stock, the corresponding event dummies ($8kD^{ind}$ and/or $eventD^{state}$) are also equal to one. To estimate the regression for the full cross-section of firms, I assume $8kD^{peer}$ to be zero for firms without peers with similar names and allow a separate intercept ($peerD$) for these firms. The events are 8-K filings. The sample period is 2008-2015. The regressions are estimated with year-month, day of the week, industry and headquarters state fixed effects. The standard errors are clustered by date and firm.

	(1) *awiki*	(2) *agsv*	(3) *aedgar*	(4) *aturn*
peerD	0.0001	-0.0004	-0.0007	-0.0019
	(0.05)	(-0.20)	(-0.74)	(-1.22)
ln_size	-0.0038***	-0.0045***	-0.0080***	-0.0148***
	(-8.16)	(-5.57)	(-13.32)	(-14.73)
ln_bm	-0.0007	-0.0016	-0.0007	0.0002
	(-1.50)	(-1.53)	(-1.24)	(0.27)
mom	0.0018	-0.0021*	-0.0030***	-0.0008
	(1.48)	(-1.95)	(-2.75)	(-0.45)
st_rev	-0.0008	0.0360***	-0.0144**	0.0080
	(-0.16)	(5.82)	(-1.98)	(0.73)
misp	0.0002***	0.0001	-0.0003***	-0.0001
	(4.70)	(1.59)	(-5.65)	(-1.22)
ivola	-0.5636***	-0.3136***	-0.8841***	-2.1775***
	(-11.32)	(-4.68)	(-11.79)	(-17.17)
io	0.0050**	0.0163***	-0.0059**	-0.0438***
	(2.16)	(3.69)	(-2.03)	(-7.29)
ln_nanalyst	0.0011	0.0041**	-0.0028***	-0.0041**
	(1.29)	(2.26)	(-3.16)	(-2.15)
$8kD^{focal}$	0.0896***	0.0806***	0.6669***	0.5190***
	(37.20)	(20.60)	(89.00)	(57.08)
$8kD^{ind}$	0.0148***	0.0059***	0.0367***	0.0531***
	(4.84)	(3.23)	(7.36)	(7.45)
$8kD^{state}$	0.0123***	0.0052**	0.0297***	0.0544***
	(3.06)	(2.31)	(4.73)	(5.99)
$\mathbf{8kD^{peer}}$	**0.0125*** **	**0.0013**	**0.0062**	**0.0165*** **
	(3.84)	**(0.29)**	**(1.13)**	**(2.94)**
Year - Month FE	Yes	Yes	Yes	Yes
Day of the Week FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
HQ State FE	Yes	Yes	Yes	Yes
r2	0.0474	0.0021	0.0902	0.0295
N	2’696’867	3’262’755	3’657’172	3’795’003



	CAR(-1,1)	CAR(-1,5)	CAR(-1,10)	CAR(-1,20)	CAR(-1,30)	CAR(-1,40)	CAR(-1,50)	CAR(-1,60)
Positive	0.507**	0.650*	0.792*	1.144*	1.411	-0.0112	0.191	0.853
N = 844	(1.99)	(1.79)	(1.72)	(1.66)	(1.63)	(-0.01)	(0.18)	(0.66)
Negative	-0.302	0.0923	0.0718	-0.297	-0.113	-0.236	0.0409	0.545
N = 802	(-1.06)	(0.23)	(0.14)	(-0.47)	(-0.15)	(-0.26)	(0.04)	(0.47)
Difference	0.809**	0.558	0.720	1.441	1.524	0.225	0.150	0.307
	(2.12)	(1.04)	(1.03)	(1.53)	(1.30)	(0.18)	(0.10)	(0.18)

Figure A1.1:
Focal Company's Price Reaction to Peer's Significant News - Earnings Announcements
This figure depicts the cumulative abnormal returns around the peer companies' announcement events with significant positive and negative news as the function of holding period. The cumulative abnormal returns are defined as the difference between the buy-and-hold return of the focal company and that of a matching portfolio based on size and book-to-market, following Hirshleifer, Lim, and Teoh (2009). Significant news event is defined as an event in top 2.5% of absolute $CAR(-1,1)$ in response to earnings announcements and classified as positive or negative depending on the sign of the $CAR(-1,1)$. The holding period starts one day before the event and ends in 1 day to 60 days after the event. The table under the figure presents the cumulative abnormal returns for positive, negative news and the difference between them. In parentheses are the t-statistics of the t-test on the statistical difference from zero of cumulative abnormal returns. The pairs from the same industry and headquarters state as the focal company are not included in the analysis. The sample period is from January 1996 to December 2015.*, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.



	CAR(-1,1)	CAR(-1,5)	CAR(-1,10)	CAR(-1,20)	CAR(-1,30)	CAR(-1,40)	CAR(-1,50)	CAR(-1,60)
Positive	0.410**	0.821**	0.650*	0.666	0.554	0.0425	0.0528	0.331
N = 1382	(2.02)	(2.53)	(1.76)	(1.20)	(0.90)	(0.06)	(0.07)	(0.36)
Negative	-0.393*	-0.499*	-0.627	-0.576	0.149	0.0311	0.346	0.641
N = 1127	(-1.92)	(-1.67)	(-1.64)	(-1.24)	(0.24)	(0.04)	(0.42)	(0.67)
Difference	0.803***	1.320***	1.277**	1.242*	0.405	0.011	-0.293	-0.310
	(2.76)	(2.94)	(2.39)	(1.66)	(0.46)	(0.01)	(-0.25)	(-0.23)

Figure A1.2:
Focal Company's Price Reaction to Peer's Significant News - 8-K Filings
This figure depicts the cumulative abnormal returns around the peer companies' announcement events with significant positive and negative news as the function of holding period. The cumulative abnormal returns are defined as the difference between the buy-and-hold return of the focal company and that of a matching portfolio based on size and book-to-market, following Hirshleifer, Lim, and Teoh (2009). Significant news event is defined as an event in top 2.5% of absolute $CAR(-1,1)$ in response to 8-K filings and classified as positive or negative depending on the sign of the $CAR(-1,1)$. The holding period starts one day before the event and ends in 1 day to 60 days after the event. The table under the figure presents the cumulative abnormal returns for positive, negative news and the difference between them. In parentheses are the t-statistics of the t-test on the statistical difference from zero of cumulative abnormal returns. The pairs from the same industry and headquarters state as the focal company are not included in the analysis. The sample period is from January 1996 to December 2015.*, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Figure A1.3:
Comovement - Similar Tickers
This table presents panel regression results of the daily abnormal returns of focal stocks on the leads and lags of abnormal returns of the corresponding stocks with similar tickers and a number of controls. Reported are the coefficients on the abnormal returns of the peer stocks together with the t-statistics in the parentheses and the sum of these coefficients together with the F-statistics and the p-values. The Column (1) shows the results for the raw excess returns and all other columns show the results for Davis, Fama, and French (2000) four-factor abnormal returns. Columns (2) to (7) include time fixed effects and different sets of control variables. The control variables are equally-weighted returns on the price, size, book-to-market, momentum, short-term reversal decile portfolios and FF 48 industry portfolios. The extended controls include additionally equally weighted returns on transaction costs decile portfolios and HQ state portfolios. Specifications in columns (8) to (12) contain more conservative date times industry and date times HQ state fixed effects of focal and peer stocks in different combinations. The sample period is 1972 to 2016. The sample period for the regressions with extended controls is limited to 1996 - 2010 due to data availability. The standard errors are clustered on date and stock-pair level. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1) retd	(2) alpha	(3) alpha	(4) alpha	(5) alpha	(6) alpha	(7) alpha	(8) alpha	(9) alpha	(10) alpha	(11) alpha	(12) alpha
$perf_{+3}^{peer}$	0.0053**	-0.0003	-0.0005	-0.0005	-0.0005	-0.0003	-0.0001	-0.0007	-0.0010	-0.0001	-0.0000	0.0010
	(2.46)	(-0.40)	(-0.62)	(-0.71)	(-0.73)	(-0.24)	(-0.07)	(-0.80)	(-1.16)	(-0.07)	(-0.01)	(0.44)
$perf_{+2}^{peer}$	0.0027	-0.0007	-0.0007	-0.0008	-0.0007	-0.0017	-0.0029**	-0.0013	-0.0012	-0.0024	-0.0018	0.0001
	(1.09)	(-0.91)	(-0.86)	(-1.03)	(-0.86)	(-1.31)	(-2.27)	(-1.47)	(-1.43)	(-1.55)	(-1.12)	(0.05)
$perf_{+1}^{peer}$	0.0142***	-0.0005	-0.0008	-0.0009	-0.0008	-0.0010	-0.0006	-0.0011	-0.0007	-0.0007	-0.0000	-0.0001
	(6.05)	(-0.64)	(-1.07)	(-1.23)	(-1.09)	(-0.77)	(-0.47)	(-1.30)	(-0.83)	(-0.46)	(-0.01)	(-0.05)
$perf_{0}^{peer}$	0.1149***	0.0047***	0.0028***	0.0026***	0.0026***	0.0029*	0.0030*	0.0027***	0.0022**	0.0034**	0.0030*	0.0028
	(26.26)	(4.81)	(2.89)	(2.77)	(2.73)	(1.90)	(1.96)	(2.83)	(2.36)	(2.01)	(1.75)	(1.18)
$perf_{-1}^{peer}$	0.0166***	0.0012	0.0008	0.0007	0.0007	0.0000	0.0007	0.0002	0.0010	-0.0006	0.0011	0.0019
	(6.48)	(1.46)	(1.04)	(0.86)	(0.90)	(0.01)	(0.57)	(0.22)	(1.15)	(-0.36)	(0.68)	(0.85)
$perf_{-2}^{peer}$	0.0030	-0.0001	-0.0002	-0.0002	-0.0002	-0.0009	-0.0011	-0.0006	0.0004	-0.0025	-0.0013	-0.0038*
	(1.13)	(-0.19)	(-0.23)	(-0.26)	(-0.21)	(-0.74)	(-0.89)	(-0.66)	(0.51)	(-1.64)	(-0.92)	(-1.73)
$perf_{-3}^{peer}$	0.0062***	0.0012	0.0011	0.0012	0.0012	-0.0002	-0.0003	0.0010	0.0012	0.0002	-0.0018	-0.0011
	(2.72)	(1.57)	(1.54)	(1.57)	(1.57)	(-0.17)	(-0.30)	(1.21)	(1.43)	(0.15)	(-1.20)	(-0.49)
Date FE			Yes	Yes	Yes	Yes	Yes					
Controls Peer				Yes								
Controls Focal					Yes							
Controls Peer Ext						Yes						
Controls Focal Ext							Yes					
Date*Industy FE Peer								Yes		Yes		Yes
Date*Industy FE Focal									Yes		Yes	Yes
Date*HQ State FE Peer										Yes		Yes
Date*HQ State FE Focal											Yes	Yes
b^{peer}	**0.1630**	**0.0055**	**0.0027**	**0.0020**	**0.0023**	**-0.0012**	**-0.0013**	**0.0003**	**0.0019**	**-0.0026**	**-0.0009**	**0.0008**
F_stat	411.5471	6.2990	1.5189	0.8602	1.1285	0.1176	0.1509	0.0173	0.7398	0.4008	0.0479	0.0184
p_val	**0.0000**	**0.0121**	**0.2179**	**0.3537**	**0.2882**	**0.7317**	**0.6977**	**0.8953**	**0.3898**	**0.5268**	**0.8267**	**0.8920**
r2	0.0121	0.0000	0.0064	0.0064	0.0114	0.0078	0.0156	0.1359	0.1348	0.2667	0.2569	0.5726
N	2.9e+06	2.5e+06	2.5e+06	2.5e+06	2.5e+06	9.8e+05	9.8e+05	2.5e+06	2.5e+06	9.1e+05	9.1e+05	7.1e+05

Chapter 2

Do Short Sellers Exploit Mispricing Smartly?

2.1 Introduction

The finance literature documents a number of stylized facts in equity markets that appear to be at odds with standard asset pricing models. These stylized facts are commonly referred to as market anomalies.[1] Understanding why these anomalies exist and persist requires a careful study of the arbitrage process. This process usually consists of three components. The first component is investors' demand shocks that push prices in the underlying securities away from their fundamental values. The second component is arbitrageurs that identify the demand imbalances and return the security prices back to their fundamental values. The third component is limits to arbitrage that prevent arbitrageurs from correcting mispricing. Many papers are devoted to the demand shocks and limits to arbitrage components.[2] Less attention is paid to arbitrageurs and their ability to identify and exploit mispricing.

In this paper, I use monthly aggregate short interest to track arbitrageurs' positions and the mispricing score of Stambaugh, Yu, and Yuan (2015) as a measure of mispricing to fill this gap in the literature. Short interest predominantly reflects short positions of hedge funds, a group of informed arbitrageurs that actively engage in short selling (Boehmer, Jones, and Zhang, 2013; Ben-David, Franzoni, and Moussawi, 2012). The mispricing score of Stambaugh, Yu, and Yuan (2015) is a well-established proxy for stock-level mispricing that is related to investor sentiment (Stambaugh, Yu, and Yuan, 2012) and is associated with anomalous returns around the globe (Jacobs, 2016). In this study, I show that arbitrageurs are able to identify and profit from mispricing. I measure stocks' short interest ratios (the ratios of shares shorted to shares outstanding) in the middle of the month following the measurement of the composite mispricing score. The short interest ratio in the short leg of the mispricing anomaly exceeds the short interest ratio in the long leg by 0.98 p.p. after accounting for other determinants and stock fixed effects. This spread is economically highly significant given the median short interest ratio of 1.72%. I use this spread as a measure of shortsellers' exposure to the composite mispricing

[1] See McLean and Pontiff (2016) and Jacobs and Müller (2018) for reviews of anomalies in the US and around the globe, respectively.
[2] See Gromb and Vayanos (2010) and Barberis and Thaler (2003) for the review of theoretical and empirical findings.

strategy. Consistent with arbitrageurs' ability to time strategy returns, this spread is 0.54 p.p. larger after periods of high sentiment, when the mispricing anomaly returns are especially high. I also analyze the effect of limits to arbitrage on arbitrageurs' short selling activity. Stambaugh, Yu, and Yuan (2015) show that higher idiosyncratic volatility is associated with significantly larger anomaly returns in the following months. Consistent with arbitrageurs' stock picking skill, the spread increases by 0.11 p.p. for a one standard deviation increase in the most recent month's idiosyncratic volatility. In an alternative setting of the Regulation SHO, Chu, Hirshleifer, and Ma (2016) show a decrease in abnormal returns associated with the mispricing score for randomly chosen pilot stocks that were exempted from short sale tests as the result of the pilot program. The exemption from short sale tests looses short-selling constraints and prevents building up of mispricing. Consistent with arbitrageurs' ability to identify mispriced stocks, I show a decrease of 2.86 p.p in exposure to these pilot stocks relative to control stocks. In accordance with the implications of Chu, Hirshleifer, and Ma (2016), the difference is not observed pre- and post-pilot program and is driven by the short leg of the anomaly.

Finally, I reconsider the relationship between the short interest spread and future mispricing strategy returns. Hanson and Sunderam (2014) use the quarterly short interest spread as a measure of constrained arbitrage capital and show that its increase is associated with lower future long-short returns of book-to-market and momentum strategies. The interpretation is that the more arbitrage capital is exploiting anomalies the lower is the profitability of these anomalies. I confirm this result for the mispricing anomaly for the earlier period but document a significant structural break in 2008. After 2008 the relationship turns positive. This positive correlation means higher strategy returns for a higher level of short interest spread and is consistent with the spread reflecting arbitrageurs' expectations of future strategy profitability. I document a related structural break in the same year. The correlation between the short interest spread and assets under management of market neutral hedge funds drops from 0.85 before 2008 to a statistically insignificant 0.13 after 2008. This finding strengthens the alternative interpretation of the short interest spread.

This study contributes to the literature on a number of dimensions. First, it contributes to the discussion on the ability of institutional investors to exploit market anomalies. DeVault, Sias, and Starks (2016) provide evidence that it is institutional investors, in particular, the hedge funds, not the retail investors whose demand shocks drive the deviation of stock prices from their fundamental levels associated with Baker and Wurgler (2006) sentiment index. Edelen, Ince, and Kadlec (2016) document another surprising result. They show that institutional investors are in aggregate on the wrong side of mispricing-based anomalies in their long positions. Akbas, Armstrong, et al. (2015) use money flow to distinguish between different types of institutional investors. The authors show that money flows to mutual funds exacerbate market anomalies, whereas money flows to hedge funds attenuate these anomalies. From the short side perspective, Dechow et al. (2001) and Hanson and Sunderam (2014) show arbitrageurs' ability to exploit book-to-market and momentum anomalies. My study contributes to this discussion by documenting short sellers' superior ability to identify mispricing based anomalies and exploit them.

This study also contributes to the strand of literature on the general predictive ability of short positions. Desai et al. (2002) are first to show that a high short interest ratio is associated with negative future abnormal returns. Boehmer, Huszar, and Jordan (2010) propose that a low short interest ratio is good news for a company and show that it is associated with positive future returns. Boehmer, Jones, and Zhang (2008) use proprietary daily data on short trades and show that they are informed and deliver high abnormal returns. Diether, Lee, and Werner (2009) study trading patterns used by short sellers and document their trading on short-term overreaction of stock prices. Hwang and Liu (2014) find that short sellers shy away from risky and prefer low-volatility high-return strategies that have weak correlations with other strategies. Wu and Zhang (2014) observe that short interest contains increasingly more return predictive information beyond discovered anomalies, especially in more recent years. Jiao, Massa, and Zhang (2016) show that short positions of hedge funds contain complementing information to their long positions about future stock performance. Drechsler and Drechsler (2016) argue that short sales are profitable even after accounting for lending fees. I contribute to this strand of literature by showing short sellers' informational advantages in exploiting mispricing.

I also contribute to the literature on the effect of arbitrageurs on market efficiency. McLean and Pontiff (2016) documents an increase in short sellers' activity after anomalies are published in academic journals. The authors show that this increase in activity is associated with lower anomaly returns. The short sellers' activity is measured as the spread in the short interest ratio between the short leg and the long leg of an anomaly. Hanson and Sunderam (2014) confirm the findings of McLean and Pontiff (2016) by showing that higher activity for momentum and book-to-market anomalies results in lower anomaly profits over time. My study emphasizes an alternative way to interpret short sellers' activity. In particular, I argue that in recent years it reflects short seller expectations of future anomaly profits. Consistent with this interpretation, after 2008 I document an increase in short sellers' activity to lead to higher future anomaly returns for the composed mispricing anomaly of Stambaugh, Yu, and Yuan (2015).

Finally, my paper contributes to the literature on limits of arbitrage. Shleifer and Vishny (1997), Pontiff (2006), and Drechsler and Drechsler (2016) develop models that emphasize the role of such limits to arbitrage as constraints on equity capital, non-fundamental risk and short-selling costs, correspondingly. Many empirical studies, in particular Chu, Hirshleifer, and Ma (2016), Stambaugh, Yu, and Yuan (2015), Stambaugh, Yu, and Yuan (2012) and Baker and Wurgler (2006) use these models to interpret their results. Findings of my study confirm the assumption of "smart" arbitrageurs underlying these theoretical and empirical papers.

This paper is structured in the following way. In Section 2.2, I introduce the data and define my main and control variables. In Section 2.3, I document short sellers' ability to identify and time returns of the mispricing strategy using publicly available information. In Section 2.4, I show the effect of limits on arbitrage on short sellers' behavior and document their stock picking skills. In Section 2.5, I consider the relationship between short sellers' activity and future mispricing strategy returns. Finally, I conclude and make suggestions for future research in Section 2.6.

2.2 Data

2.2.1 Data sources

Stock level data are obtained from CRSP and accounting data are from the Compustat annual file. The number of shares shorted is from the Compustat supplementary short interest file. The short interest ratio (SR) is the mid-month ratio of the number of shares shorted over the number of shares outstanding. Idiosyncratic volatility ($IVOL$) is the standard deviation of residuals over the past month in regression of the excess returns on the Fama and French (1993) three factors using daily data, as in Ang et al. (2006). The mispricing score ($MISP$) of Stambaugh, Yu, and Yuan (2015) is from Robert Stambaugh's website. It is a composite score equal to the arithmetic average of the ranking percentile over eleven mispricing based anomalies. The mispricing score is an ordinal value, i.e. it shows only that one stock is more or less overpriced relative to another stock in the cross-section but does not show whether the mispricing increased or decreased over time. Stock analyst coverage ($ACOVERAGE$) is from IBES. Other standard control variables, such as log size, log book-to-market ratio and momentum are defined as it is common in the literature. The sentiment index of Baker and Wurgler (2006) is obtained from the author's website. The data on assets under management of equity market-neutral hedge funds (AUM^{MN}) is available starting the first quarter of 2000 and comes from Barclay Hedge database. A more detailed description of all variables is given in the Appendix in Table A2.1

My sample period is from March 1980 to December 2013. The starting date of the sample is determined by the availability of reliable data on institutional ownership. To construct the universe of the U.S. equity market, I consider stocks with share codes 10 and 11 that are traded at AMEX, NYSE and NASDAQ. The NASDAQ stock data starts in June 2003 due to limited availability of short interest data in Compustat. To ensure that my results are not driven by penny stocks, I drop stocks with a previous month's price below 1$ and stocks below the 5th NYSE market capitalization percentile.

2.2.2 Summary statistics

Table 2.1 presents descriptive statistics. Panel A reports the mean, standard deviation, 10th, 50th, and 90th percentiles of the variables. All variables are winsorized at 0.1% and 99.9% levels. The variable of our main interest is the short interest ratio. Its distribution is skewed with a mean of 3.55% and a median of 1.72%. SR is highly correlated with the lagged turnover ratio, institutional ownership and illiquidity with correlation coefficients of 0.74, 0.54 and -0.42, respectively. The strong correlations show the importance to control for these variables in a regression analysis. The correlation of the short interest ratio with the mispricing score is weaker but also positive. In the next sections, I consider the relationship of mispricing and short interest in a multiple linear regression.

[Insert Table 2.1]

2.3 Short sellers and mispricing

2.3.1 Short interest ratio over misprcing deciles

Short sellers are shown to predict future stock returns (e.g., Desai et al., 2002; Boehmer, Jones, and Zhang, 2008). In this section, I test whether this predictive ability of short sellers is related to their ability to identify and exploit mispricing, $MISP$, as defined in Stambaugh, Yu, and Yuan (2015). To test this hypothesis, I run a panel regression adopted from Hanson and Sunderam (2014):

$$SR_{i,t} = Time_t + Stock_i + \boldsymbol{\beta}^{MISP\prime}\boldsymbol{D}_{it-1}^{MISP} + \boldsymbol{\beta}^{BM\prime}\boldsymbol{D}_{it-1}^{BM} + \boldsymbol{\beta}^{Size\prime}\boldsymbol{D}_{it-1}^{Size} + \boldsymbol{\gamma}'\boldsymbol{x}_{it-1} + \varepsilon_{i,t}, \quad (2.1)$$

where $Time_t$ and $Stock_i$ are month and stock fixed effects, respectively, $\boldsymbol{D}_{it-1}^{MISP}$ is a vector of decile dummies based on the mispricing score at the end of the previous month and $\boldsymbol{\beta}_{it}^{MISP}$ is a vector of coefficients on mispricing dummies. A dummy variable for the fifth decile is not included in the regression. Stocks from this decile serve as reference stocks, i.e., coefficients on the decile dummies measure short interest ratio relative to the short interest ratio of stocks from this decile. Decile 10 is the short side of the mispricing strategy (stocks with the highest mispricing score), and decile 1 is the long side of the mispricing strategy (stocks with the lowest mispricing score). Following Hanson and Sunderam (2014), I control for a potential non-linear impact of size and the book-to-market ratio by including decile dummies, $\boldsymbol{D}_{it-1}^{BM}$ and $\boldsymbol{D}_{it-1}^{Size}$. These dummies are defined similarly to $\boldsymbol{D}_{it-1}^{MISP}$. $\boldsymbol{x}_{it}$ is a set of control variables that includes turnover ($Turn$), institutional ownership (IO), illiquidity ($Illiq$), idiosyncratic volatility ($IVOL$), a convertible debt dummy ($D\_convert$), dummies for stock exchanges (D_nasdaq, D_nyse), and analyst coverage ($Acoverage$). The standard errors are clustered by stock and date as advocated by Petersen (2009).

The estimation results are presented in Table 2.2. The regression specification in Column (1) does not include stock fixed effects. The coefficients on the mispricing dummies increase monotonically from -0.341 for decile 1 to 1.200 for decile 10. The difference between the two extreme deciles of 1.541% is economically and statistically significant. This result is consistent with short sellers' ability to exploit the mispricing anomaly.

[Insert Table 2.2]

The specification in Column (2) introduces stock fixed effects. This specification measures within stock variation in the level of the short interest ratio depending on stock characteristics. The spread in short interest ratios between the extreme underpriced and the extreme overpriced decile decreases to 0.977%. The relation of abnormal short interest over mispricing deciles stays monotonic. It is graphically depicted on Figure 2.1.[3] Other significant control variables are trading volume, institutional ownership, convertible dummy, S&P 500 dummy and analyst coverage. The coefficients on control variables are in line with the literature. R^2 increases from

[3] The coefficients on size and book-to-market decile dummies are depicted on Figure A2.1 and Figure A2.2, respectively. Observable patterns confirm the necessity to control for the non-monotonicity in relationships.

0.503 in Column (1) to 0.705 in Column (2). This increase in explanatory power is consistent with Lesnevski and Smajlbegovic (2018) who document strong persistence in short interest on the stock level. Based on this insight, the authors show that a deviation of stock's short interest from its persistent level is informative about stock's future performance. If not stated otherwise, further in this study, I include stock fixed effects as important control variables. Overall, my results confirm that the predictive ability of the short interest ratio comes, at least partially, from short sellers' ability to exploit mispricing.

[Insert Figure 2.1]

2.3.2 Short interest ratio, mispricing and sentiment

In this subsection, I test whether short sellers can time anomaly returns, in the sense of being able to increase their exposure when the profitability of anomalies increases. The literature documents a substantial role of sentiment in mispricing-based anomalies. In particular, Stambaugh, Yu, and Yuan (2012) document that the profitability of the underlying anomalies composing the mispricing score is significantly stronger after periods of high sentiment, as proxied by the Baker and Wurgler (2006) sentiment index, and is predominantly driven by the short side. To test whether short sellers react to changes in profitability due to investor sentiment, I remove time fixed effects and add interaction terms between the high sentiment dummy and the mispricing decile dummies to the baseline regression:

$$\begin{aligned} SR_{i,t} = Stock_i + \boldsymbol{\beta}^{MISP\prime}\boldsymbol{D}_{it-1}^{MISP} + \boldsymbol{\beta}^{HsentD} HsentD_{t-1} + \boldsymbol{\beta}^{MISP\times HsentD\prime}\boldsymbol{D}_{it-1}^{MISP} \times HsentD_{t-1} + \\ + \boldsymbol{\beta}^{BM\prime}\boldsymbol{D}_{it-1}^{BM} + \boldsymbol{\beta}^{Size\prime}\boldsymbol{D}_{it-1}^{Size} + \boldsymbol{\gamma}'\boldsymbol{x}_{it-1} + \varepsilon_{i,t}, \end{aligned} \tag{2.2}$$

where $HsentD_{t-1}$ is the high sentiment dummy which is equal to 1 if the average sentiment index over the three most recent months is above the sample median and $\boldsymbol{D}_{it}^{MISP} \times HsentD_{t-1}$ is the interaction term between mispricing decile dummies and the high sentiment dummy.

Estimation results are presented in Column (2) of Table 2.3. For comparison, Column (1) displays the results of the baseline regression with time fixed effects. The coefficient on $HsentD$ reflects the change in short selling activity after the periods of high sentiment for the reference mispricing decile 5. Its value reflects on average a 0.366 p.p. increase in the short selling ratio for the stocks that are correctly priced according to the Stambaugh, Yu, and Yuan (2015) mispricing score. The increase is stronger by 0.268 p.p. for the most overpriced decile (coefficient on the $MISP_{Decile=10} \times HsentD$), adding up to 0.634 p.p, and weaker by -0.271 p.p for the most underpriced decile (coefficient on the $MISP_{Decile=1} \times HsentD$), amounting to economically insignificant 0.095 p.p. In total, the spread in short interest between the most extreme deciles increases from 0.724% after periods of low sentiment to 1.263% after periods of high sentiment. Overall, my results are consistent with short sellers' ability to time anomaly returns by using the publicly available sentiment index.

[Insert Table 2.3]

2.4 Short sellers and limits to arbitrage

Theoretical models developed by Shleifer and Vishny (1997), D'Avolio (2002) and Pontiff (2006) show that limits to arbitrage prevent arbitrageurs from correcting mispricing. These models predict higher limits to arbitrage to be associated with larger future mispricing returns. Two prominent studies that use the mispricing score to test this prediction empirically are Stambaugh, Yu, and Yuan (2015) and Chu, Hirshleifer, and Ma (2016).

Stambaugh, Yu, and Yuan (2015) assume that idiosyncratic volatility (IVOL) represents an important source of limits to arbitrage. The authors find that among overpriced stocks, those with high IVOL experience abnormally lower future returns than those with low IVOL. The reason for this finding is that high-IVOL stocks stay overpriced longer due to higher limits to arbitrage. An opposite pattern is documented for the underpriced stocks, i.e. high-IVOL underpriced stocks deliver higher abnormal positive returns than high-IVOL underpriced stocks.

Chu, Hirshleifer, and Ma (2016) use a pilot program under Rule 202T of Regulation SHO, adopted by the Securities and Exchange Commission (SEC) in July 2004, as a natural experiment to show the causal effect of short sale constraints on anomaly profits. The authors find that relaxed short sale constraints associated with the new regulation result in lower profitability of anomaly returns.

In this study, I employ both settings to test whether short sellers are able to profit from the return predictability associated with the corresponding types of limits to arbitrage.

2.4.1 Short sellers and idiosyncratic volatility

Idiosyncratic volatility is a common proxy for limits to arbitrage (Shleifer and Vishny, 1997; Pontiff, 2006; Stambaugh, Yu, and Yuan, 2015; Drechsler and Drechsler, 2016). Stambaugh, Yu, and Yuan (2015) use the mispricing score to show that among overpriced stocks, those with higher idiosyncratic volatility deliver more negative abnormal returns. They document a return spread of -1.5% between the 5th and the 1st IVOL quintiles for the most overpriced quintile of stocks in the month following the portfolio formation. To test whether short sellers are profiting from these abnormal returns, I add the interaction terms between IVOL and the mispricing decile dummies to the baseline regression:

$$\begin{aligned} SR_{i,t} = {} & Stock_i + Time_t + \boldsymbol{\beta}^{MISP\prime}\boldsymbol{D}_{it-1}^{MISP} + \boldsymbol{\beta}^{IVOL} IVOL_{t-1} + \\ & + \boldsymbol{\beta}^{MISP\times IVOL\prime}\boldsymbol{D}_{it-1}^{MISP} \times IVOL_{t-1} + \boldsymbol{\beta}^{BM\prime}\boldsymbol{D}_{it-1}^{BM} + \boldsymbol{\beta}^{Size\prime}\boldsymbol{D}_{it-1}^{Size} + \boldsymbol{\gamma}'\boldsymbol{x}_{it} + \varepsilon_{i,t}, \end{aligned} \tag{2.3}$$

where $IVOL_{t-1}$ is the standard deviation of the most recent month's daily benchmark-adjusted returns following Stambaugh, Yu, and Yuan (2015), and $\boldsymbol{D}_{it}^{MISP} \times IVOL_{t-1}$ are interaction terms between the mispricing decile dummies and IVOL. As in the baseline specification, both stock and date fixed effects are included. Moreover, the interaction term for the 5th decile is skipped as $IVOL$ already captures the effect of idiosyncratic volatility on short interest ratio for stocks in this decile.

Estimation results are presented in Column (1) of Table 2.4. The effect of volatility on the short interest ratio for decile 5 is -6.351, which is weakly significant at the 10 percent significance level. Given the standard deviation of IVOL in my sample of 0.01, this coefficient corresponds to a 0.06 p.p. decrease in the short interest ratio for a one standard deviation increase in idiosyncratic volatility in stocks which are not mispriced. The pattern is similar for the underpriced deciles. All interaction terms for theses deciles are insignificant. In contrast, there is a monotonic increase in the coefficients on the interaction terms for overpriced stocks. The coefficient for the tenth decile, 18.28, implies an overall 0.11 p.p. increase in the short interest ratio for a one standard deviation increase in idiosyncratic volatility. The documented pattern is consistent with the following interpretation: If high IVOL stops arbitrageurs from arbitraging away mispricing at initiation, then high-IVOL stocks are associated with higher mispricing in the following period, as documented by Stambaugh, Yu, and Yuan (2015). Short-sellers profit from these more mispriced stocks, whose value converges to its fundamental value during the observed period. Thus, my results are consistent with the short sellers' ability to profit from this variation in abnormal returns. In Column (2), I substitute the mispricing decile dummies with a piecewise linear function of the mispricing score with ten intervals corresponding to the mispricing deciles. This adjustment allows addressing further concerns of potential non-linearities with respect to the mispricing score. The results stay qualitatively similar.

[Insert Table 2.4]

To show that changes in short positions are intentional, I test how the short interest ratio evolves during the 24 months around stocks' entering the extreme deciles. I split stocks into two groups, a group with above median IVOL ($ivolH = 1$) and a group with below median IVOL ($ivolL = 1$) right before the event, and follow the procedure of Hanson and Sunderam (2014). In particular, I run the following regression:

$$\begin{aligned} SR_{i,t} = & [h^{-24} D_{it}^{-24}(MISP) + \ldots + h^{0} D_{it}^{0}(MISP) + \ldots + h^{+24} D_{it}^{+24}(MISP)] \times 1\{ivolH = 1\} + \\ & + [l^{-24} D_{it}^{-24}(MISP) + \ldots + l^{0} D_{it}^{0}(MISP) + \ldots + l^{+24} D_{it}^{+24}(MISP)] \times 1\{ivolL = 1\} + \\ & + \boldsymbol{\beta}^{IVOL\prime} \boldsymbol{D}_{it}^{IVOL} + \boldsymbol{\beta}^{BM\prime} \boldsymbol{D}_{it}^{BM} + \boldsymbol{\beta}^{Size\prime} \boldsymbol{D}_{it}^{Size} + \boldsymbol{\gamma}' \boldsymbol{x}_{it} + Time_t + Stock_i + \varepsilon_{i,t}, \end{aligned} \tag{2.4}$$

where $D_{it}^{0}(MISP)$ is a dummy which is equal to one when a stock is in the extreme mispricing decile in month t. If a stock spends more than one month in the extreme decile, then $D_{it}^{0}(MISP)$ is one for all of these months. $D_{it}^{-k}(MISP)$ is a dummy that is equal to one if a stock enters the extreme mispricing decile in k months from t, and $D_{it}^{+k}(MISP)$ is a dummy that is equal to one k months after the stock leaves the extreme mispricing decile. Thus, the coefficients h^{-k} and l^{-k} reflect the abnormal short interest ratio k months before entering the extreme decile for the stocks with high IVOL and low IVOL right before the event, correspondingly. The coefficients h^{+k} and l^{+k} reflect the abnormal short interest ratio k months after leaving the extreme decile for the stocks with high IVOL and low IVOL right after the event, correspondingly. The regression is estimated separately for stocks entering the mispricing decile 10 and 1, respectively.

Results are presented in Figure 2.2. Panel (a) depicts the estimated coefficients for the stocks entering the most overpriced decile. There are significant differences depending on the level of idiosyncratic volatility. For highly volatile stocks, the abnormal short interest ratio increases almost monotonically prior to entering the extreme decile, reaching 0.75% one month prior to the event. The ratio jumps to 1.72% on the event months and reverts to 0.63% right after leaving the extreme decile. It is insignificantly different from zero after 12 months. The increase in abnormal short interest ratio upon the event month is much weaker for non-volatile stocks. It jumps from 0.39% to 0.62% and returns back to 0.35% right after leaving the decile of overpriced stocks. Moreover, for these stocks, the abnormal short interest ratio has higher levels months prior to the event that might indicate higher arbitrageurs' activity in advance of the event. Results in Panel (b) show that short sellers also react to stocks' entering the underpriced decile. The jump of around 0.4% is economically much weaker and does not differ with the level of idiosyncratic volatility. Overall, my results indicate that short sellers are able to profit from the return predictability arising from limits of arbitrage associated with idiosyncratic volatility.

[Insert Figure 2.2]

2.4.2 Short sellers and Regulation SHO

According to the pilot program under Rule 202T of Regulation SHO announced in July 2004, from May 2, 2005, to July 6, 2007, every third stock in the Russell 3000 index ranked by its average daily trading volume was exempted from short sale tests. Stocks at NYSE/AMEX stock exchanges were exempted from the uptick rule that limited a short sale to be placed exclusively on a minus tick and therefore impeded short-selling activity. In comparison, Nasdaq stocks were exempted from the bid price test that was used at this exchange instead of the uptick rule. I focus on NYSE/AMEX stocks because the NASDAQ's bid price test was less restrictive and its removal had little effect on the short sale constraints.[4] Chu, Hirshleifer, and Ma (2016) document that as the result of the exemption from the short sale tests the combined mispricing anomaly long-short portfolio returns for pilot NYSE/AMEX stocks decreased by 77 basis points per month. In my further analysis, I compare short sellers' exposure to the mispricing score for pilot stocks relative to control stocks around the event period to test their ability to adjust to the new regulation.

I follow SEC's procedure (Securities Exchange Act Release No. 50104) to identify pilot (treated) and non-pilot (control) stocks. The final sample consists of 1363 NYSE/AMEX stocks. In accordance with the design of the experiment, approximately one-third of these stocks are pilot and two-thirds are non-pilot. If short sellers are able to understand the implication of the program, they should decrease their exposure to the mispricing anomaly in these stocks. To reduce estimation noise, I measure time-varying exposure of short sellers to the mispricing score at a quarterly frequency. Using all monthly observation in quarter t, I run the following pooled regression separately for pilot and control stocks:

$$SR_{i,\tau} = \boldsymbol{\beta}_t^{MISP\prime}\boldsymbol{D}_{i\tau-1}^{MISP} + \boldsymbol{\beta}_t^{BM\prime}\boldsymbol{D}_{i\tau-1}^{BM} + \boldsymbol{\beta}_t^{Size\prime}\boldsymbol{D}_{i\tau-1}^{Size} + \boldsymbol{\gamma}_t'\boldsymbol{x}_{i\tau-1} + \varepsilon_{i,\tau}, \tag{2.5}$$

where $SR_{i,\tau}$ is the short interest ratio of stock i in the middle of month τ, and $\boldsymbol{D}_{i\tau-1}^{MISP}$ are mispricing dummies based on the mispricing score at the end of month $\tau-1$. From this regression, I obtain quarterly estimates of $\boldsymbol{\beta}_t^{MISP}$ for pilot and control stocks. Alternatively, I designate these coefficients as $\beta_{l,t}^{MISP}$, where l takes values of 1 for the long leg or 10 for the short leg of

[4]See Diether, Lee, and Werner (2009) for more details on Regulation SHO.

mispricing anomaly. The difference $\beta_{10,t}^{MISP} - \beta_{1,t}^{MISP}$ is the spread in abnormal short interest ratios between the short and long leg.

Figure 2.3 depicts the evolution of long-short spreads in abnormal short interest ratios for pilot and control stocks over time. The timeline is divided by into four periods: the pre-announcement period (before July 2004), the announcement period (July 2004 - April 2005), the Reg SHO period (May 2005 - June 2007), and the post-Reg SHO period (after July 2007). The figure shows no significant difference in the long-short short interest spread in the pre-announcement period of the pilot program, with the level of spread around 1%. After the announcement, the spread goes down for the pilot stocks, but not for the control stocks. The difference becomes substantial after the program initiation. In particular, the spread drops to zero for the pilot stocks and stays highly positive for the non-pilot stocks. This pattern is consistent with short sellers' avoiding the stocks that do not deliver abnormal returns. The difference in spreads vanishes after the program termination, with the spreads dropping for both pilot and non-pilot stocks. The last result is consistent with the fact that after the termination of the pilot program SEC eliminated the price test for all stocks.

[Insert Figure 2.3]

Next, I compare the effect of the regulation separately for the long and the short leg of the mispricing anomaly. I define $\beta_{l,t}^{MISP}(Pilot) - \beta_{l,t}^{MISP}(Control)$ as a measure of the difference in exposures to the anomaly between pilot and control stocks, and run the following regression:

$$\begin{aligned} \beta_{l,t}^{MISP}(Pilot) - \beta_{l,t}^{MISP}(Control) = b_{0,l} \cdot preD_t + b_{1,l} \cdot announcementD_t + \\ + b_{2,l} \cdot duringD_t + b_{3,l} \cdot postD_t + \varepsilon_{l,t}, \end{aligned} \tag{2.6}$$

where $preD_t$ is one for the pre-announcement period and zero, otherwise, $announcementD_t$ is one for the announcement period, $duringD_t$ is one for the period during the pilot program (May 2005 - June 2007), and $postD_t$ is the period after the program, when the SEC eliminated the short sale price test for all exchange-listed stocks (July 2007 - December 2010). The regression is estimated with robust standard errors.

The results of the regression for the short leg, long leg, and the spread between long and short legs are presented in Columns (1), (2) and (3) of Table 2.5, correspondingly. For the short leg, the difference in short interest between pilot and control stocks is as small as -0.390% before the Reg SHO announcement. It reaches -1.074% after the announcement and becomes -2.608% during the pilot program. The difference reverts to insignificant 0.307% after the program termination. For the long leg, the difference in exposures is close to zero before the announcement, significantly positive after the announcement and stays significantly positive after the pilot program is finished. Column (3) reports the difference in long-short spreads between pilot and control stocks. Corroborating results of Figure 2.3, this difference is insignificant before the announcement and after the termination of the program, and is significantly negative after the announcement and especially during the pilot program with the corresponding values of -1.480% and -2.858%. The difference between the coefficient on $duringD_t$ and $preD_t$ is equal to -2.529%, highly significant and is equivalent to the difference-in-difference estimate of the effect of Reg

SHO, as shown in Chu, Hirshleifer, and Ma (2016). Overall, these results show that short sellers decrease their exposure to the mispricing anomaly in affected stocks as a reaction to lower anomaly profitability. The effect is driven by the short leg and does not exist before and after the pilot program. The pattern is consistent with the short sellers' ability to predict the effect of the regulation on strategy returns.

[Insert Table 2.5]

Overall, results for both proxies to limits of arbitrage show that short sellers are able to adjust their positions to the changing profitability of the mispricing anomaly. These findings are broadly consistent with arbitrageurs' informational advantage assumed in theoretical models (Drechsler and Drechsler, 2016; Pontiff, 2006; Shleifer and Vishny, 1997) and empirical studies (Stambaugh, Yu, and Yuan, 2015; Chu, Hirshleifer, and Ma, 2016).

2.5 Short sellers' activity and arbitrage profits

Results in previous sections show the arbitrageurs' ability to exploit stock mispricing and time their exposure in return maximizing manner. In this section, I analyze the relationship between arbitrage activity and future mispricing strategy returns. Hanson and Sunderam (2014) use the spread in short interest as a proxy for arbitrage activity and document a negative relationship between short interest activity and abnormal returns for a number of anomalies, in particular value and momentum. Similarly, McLean and Pontiff (2016) show a decline in strategy returns and a simultaneous increase in the short-long short interest spread after the academic publication of discovered anomalies. Both studies assume the spread in short interest to be a proxy for arbitrage capital allocated to the exploitation of the corresponding strategies. Results of these studies are consistent with an increase in arbitrage capital as investors learn about mispricing, leading to lower subsequent strategy profitability. In this section, I revisit the findings of the literature by testing the relationship between the short interest spread and mispricing strategy returns. In particular, I show that larger short interest spreads might not only serve as a measure of arbitrage capital but also reflect arbitrageurs' opinion about future anomaly returns.

As in subsection 2.4.2, I turn to quarterly frequency and use short minus long abnormal short interest on the extreme mispricing score deciles as a measure for short sellers activity. This measure, S^{MISP}, is calculated every quarter as a difference between the coefficients, $\beta_{10}^{MISP} - \beta_1^{MISP}$, from the following pooled regression with monthly observations from Equation (2.5):

$$SR_{i,\tau} = \boldsymbol{\beta}^{MISP\prime}\boldsymbol{D}_{i\tau-1}^{MISP} + \boldsymbol{\beta}^{BM\prime}\boldsymbol{D}_{i\tau-1}^{BM} + \boldsymbol{\beta}^{Size\prime}\boldsymbol{D}_{i\tau-1}^{Size} + \boldsymbol{\gamma}'\boldsymbol{x}_{i\tau-1} + \varepsilon_{i,\tau}$$

I start my analysis by plotting quarterly misprcing strategy returns against lagged estimated short interest spreads. The results are presented in Figure 2.4. The plot reveals the following pattern. First, there is a decrease in strategy returns over time that is especially significant after 2000. On the other hand, the short interest spread grows only until around 2007-2008, reaching 3% at the peak, and then dramatically drops to around 1%. An upward trend in the spread and a downward trend in strategy returns are cosistent with the negative relationship between these variables documented by Hanson and Sunderam (2014) and McLean and Pontiff (2016).

[Insert Figure 2.4]

I test shifts in relationships formally by running two linear regressions and conducting supremum Wald tests on the structural break in coefficients with an unknown break date following Andrews (1993). In the first regression, mispricing strategy returns are regressed on a constant to estimate average strategy returns. The second regression takes the following form:

$$Ret_t^{MISP} = \alpha + \beta_1 S_{t-1}^{MISP} + \beta_2 Ret_{t-1}^{MISP} + \beta_3 Sent_{t-1} + \varepsilon_t, \tag{2.7}$$

where S_{t-1}^{MISP} is the short interest spread over the previous quarter, Ret_{t-1}^{MISP} is the recent performance of the strategy to control for possible momentum in the strategy performance, and $Sent_{t-1}$ is the average sentiment index of Baker and Wurgler (2006) over the most recent quarter to control for the effect of investor sentiment. Standard errors are adjusted for time series correlation following Newey and West (1987). The test for structural breaks in all regression coefficients consists of performing Wald tests for each potential date and yields the most probable break date. To test the null hypothesis of no structural break, I compute p-values for the non-standard limiting distributions using the method of Hansen (1997).[5] After the break dates are determined, I estimate regression coefficients before and after the structural breaks.

Regression results are presented in Table 2.6. The left panel of the table presents the results of the regression on the intercept. The coefficient on the intercept reflects the mean returns. Regression coefficient in Column (1) reveals 3.61% average quarterly strategy returns over the whole sample period. The supremum Wald test indicates a significant shift in returns in 2002Q3. The null hypothesis of no structural break is rejected with the p-value of 0.009 (untabulated). Results in Columns (2) and (3) reveal a substantial 5.05% average return prior and an insignificant return of 0.918% after the break date. This result echoes findings of Green, Hand, and Zhang (2017), who document close to zero long-short returns for a number of anomalies starting 2003 outside small caps. The authors list a number of regulatory and technological changes that could drive this change. In particular, adoption of Regulation Fair Disclosure in October 2000 and NYSE's introduction of an autoquoting software in January 2003 dramatically reduced trading frictions and costs. Moreover, passing of Sarbanes-Oxley Act in November 2002 increased auditing quality and managers' responsibilities, and changed the filing procedure of annual and quarterly SEC reports resulted in more timely data availability that improved information flow from companies to investors. As Figure 2.4 shows, the drop in anomaly returns is also associated with the growth of short sellers' activity.

The right panel of Table 2.6 present estimation results for the regression (2.7). For the whole sample period, there is no significant relationship between the short-long spread and mispricing strategy returns. The coefficient on S_{t-1}^{MISP} is negative but insignificantly different from zero. The only significant coefficients in Column (4) are on the constant and S_{t-1}^{MISP} with the values of 0.353 and 0.0320, correspondingly. The supremum Wald test identifies a structural break in the

[5]For literature review of the methods estimating structural break with unknown date see Perron (2006).

coefficients in 2008Q1 with a p-value of 0.0595 (untabulated). Splitting the sample period before and after this date reveals a significant difference in coefficients. In particular, the coefficient on the spread in abnormal short interest before 2008Q1 is -0.0175 and highly statistically significant. One standard deviation (equal to 0.74%) in this spread is associated with 1.3% lower future strategy quarterly performance. This result is consistent with the literature that higher short sellers activity leads to lower arbitrage profitability. From 2008Q2 to 2013Q4, the respective coefficient, 0.0930, is positive and highly statistically and economically significant. This result is consistent with short sellers' ability to increase their exposure to the mispricing anomaly prior to strategy's larger abnormal returns. In Column (7), I estimate the same regression with the period starting in 2010Q2 to show that the results are not driven by the financial crisis. The coefficient is economically slightly weaker, with one standard deviation increase in the short-long spread leading to 4.5% higher future quarterly returns.[6]

[Insert Table 2.6]

To take a closer look at the structural break, I plot Wald test statistics for all quarters used for the estimation of regression (2.7). The results are presented in Figure 2.5. The graph reveals that the test statistic is especially high for any point between the Quant Meltdown in 2007Q3 and the collapse of Lehman Brothers in 2008Q3. Both events are relevant for short sellers employing long-short strategies as they revealed new sources of systematic and liquidity risks associated with arbitrage strategies and resulted in regulatory changes in the financial markets.[7] Finally, on July 3, 2007, the uptick rule and the short-sale price tests were removed for all stocks, as the result of Regulation SHO described in subsection 2.4.2. This cofounding event could additionally contribute to the observed structural break.[8]

[Insert Figure 2.5]

Additionally, I consider the relationship between assets under management of market neutral hedge funds and the moving average of short interest spread over the most recent four quarters. Market neutral hedge funds were documented to exploit strategies similar to the mispricing strategy on both the long and the short side and therefore serve as a perfect example of arbitrageurs. The results are presented in Table 2.7. The average correlation between AUM_Q^{MN} and S_Y^{MISP} over the period of 2000Q1 to 2014Q3 is 0.295 and is significant at 5% significance level. The test on structural breaks reveals that the hypothesis of no structural break is rejected at any

[6] The results are qualitatively similar if three-factor Fama and French (1993) alphas are used as a measure of strategy performance.

[7] The events on August 6, 2007, resulted in poor performance of long-short equity strategies that revealed an additional systematic risk in the hedge fund industry (Khandani and Lo, 2007). The financial crisis of 2008 was associated with severe market declines, liquidity dry-ups, bailouts and disruptions in short selling markets (Brunnermeier, 2009; Saffi and Sigurdsson, 2011). See Ben-David, Franzoni, and Moussawi (2012) for the review of hedge fund trading around these events.

[8] In Figure A2.3 of the Appendix, I depict the dynamics of the test statistics for the regression with the constant only. The figure reveals a less clear break date for the strategy returns. This result could be reconciled by observing that the mispricing score consists of multiple anomalies that could have different dynamics. In Table A2.2 I estimate structural break dates for each anomaly separately. The results reveal qualitatively similar relationship for all of these anomalies.

common significance level. The most probable break date according to the test is 2008Q3. This break date is consistent with the previously found structural break for the relationship between short interest spread and strategy returns. The correlation before 2008Q3 is 0.846. After this date, the correlation decreases to a statistically insignificant level of 0.130. The result of the analysis is consistent with the change in the behavior of the short interest spread.

[Insert Table 2.7]

Overall, the results of this section emphasize the possibility of different interpretations of the short interest spread. Until the third quarter of 2008, the spread is highly correlated with assets under management of market neutral hedge funds. Moreover, higher arbitrageurs' activity is associated with lower anomaly returns. Consistently with Hanson and Sunderam (2014), for this period, the short interest spread could be interpreted as the measure of constrained arbitrage capital. After this period, the short interest spread is positively associated with future strategy returns and is uncorrelated with assets under management of market neutral hedge funds. These results support an alternative interpretation of the short interest spread for the later period, in particular, that it reflects the opinion of short sellers about the future performance of the mispricing strategy. Earned abnormal returns are consistent with the compensation to arbitrageurs for the generation of private information (Grossman and Stiglitz, 1980) and with a general predictive power of short interest (Desai et al., 2002; Drechsler and Drechsler, 2016).

2.6 Conclusion

In this study, I show that short sellers are smart in exploiting mispricing. First, short sellers have a high exposure to stocks belonging to the short leg of the mispricing strategy and avoid stocks in the long leg. This result is consistent with their ability to capture abnormal returns associated with the mispricing strategy. The effect is stronger after periods of high sentiment and for stocks with a high level of idiosyncratic volatility, i.e. when the mispricing strategy is especially profitable. Moreover, I analyze a change in short sellers' exposure to pilot stocks due to a change in limits to arbitrage around the Regulation SHO. Arbitrageurs predict a decrease in anomaly profits due to the new regulation and decrease their exposure to these stocks. All these results are consistent with arbitrageurs' strategy timing and stock picking skills. Finally, to test whether short sellers activity leads to more efficient markets, I reconsider the relation of the short interest spread with future strategy returns. I find a significantly negative relationship between these variables prior to 2008. This result is consistent with the interpretation of Hanson and Sunderam (2014) that the rise of arbitrage capital is associated with a decline in arbitrage profits. On the other hand, I document a positive relationship after 2008. Such a strong change in the relationship manifests a structural break in the behavior of short sellers and financial markets but also confirms arbitrageurs' ability to time strategy returns. All in all, my findings support existing theoretical models, such as Drechsler and Drechsler (2016), Pontiff (2006), and Shleifer and Vishny (1997) and reinforce the results of empirical studies, such as Chu, Hirshleifer, and Ma (2016), Stambaugh, Yu, and Yuan (2015), Stambaugh, Yu, and Yuan (2012) and Baker and Wurgler (2006). This study also complements McLean and Pontiff (2016) and Hanson and Sunderam (2014) by emphasizing an alternative interpretation of the short interest spread.

There is a number of questions that remain unanswered. One important question is on the causes of the documented structural break in the relationship between short interest spread and future strategy returns. Another important question is why the mispricing is not arbitraged away when it is initiated and what role short sellers play in this process. My study employs monthly snapshots of short interest that do not allow more detailed analysis. Data of higher frequency would be helpful to address this question. Among potential data sources are Markit (Saffi and Sigurdsson, 2011; Prado, Saffi, and Sturgess, 2016) , ANcerno (Puckett and Yan, 2011; Choi et al., 2017) and other proprietary data sources (Cohen, Diether, and Malloy, 2007; Boehmer, Jones, and Zhang, 2008; Kelley and Tetlock, 2016). Markit's data on the lending market would be helpful to address one more concern, in particular, that lending fees (Drechsler and Drechsler, 2016) and short selling risks (Engelberg, Reed, and Ringgenberg, 2018) could outweigh the abnormal returns earned by short sellers. Answering these questions is a potential agenda for future research.

Tables and Figures of Chapter 2

Table 2.1:
Descriptive Statistics
This table summarizes stock characteristics over the period from March 1980 to December 2013. Panel A displays the mean, standard deviation, 10th, 50th and 90th percentiles. Panel B displays the correlation matrix of all variables. The detailed description of the variables is in the Table A2.1 of the appendix.

Panel A: Descriptives

			Percentiles		
Variable	Mean	SD	10th	Median	90th
SR	3.55	4.95	0.10	1.72	9.29
$MISP$	48.90	12.74	32.80	48.31	65.87
$IVOL$	0.017	0.010	0.008	0.015	0.029
$SIZE$	4600	17430	138	853	8425
BM	0.637	0.512	0.189	0.542	1.159
$TURN$	0.133	0.163	0.023	0.083	0.295
IO	0.566	0.258	0.195	0.582	0.905
$ILLIQ$	0.090	0.782	0.000	0.006	0.167
$ACOVERAGE$	9.58	8.02	1	7	21
$D\_CONVERT$	0.16	0.37	0	0	1
D_SP500	0.27	0.44	0	0	1
D_NASDAQ	0.23	0.42	0	0	1
D_NYSE	0.70	0.46	0	1	1
$SENT$	0.33	0.62	-0.36	0.25	0.96
Ret^{MISP}	0.011	0.034	-0.026	0.012	0.051

Panel B: Correlations

	SR	$MISP$	$IVOL$	$SIZE$	BM	$TURN$	IO	$ILLIQ$	$ACOVER$	$D\_CONVERT$	D_SP500	D_NASDAQ	D_NYSE
SR	1.00												
$MISP$	0.13	1.00											
$IVOL$	0.14	0.17	1.00										
$SIZE$	0.18	-0.20	-0.35	1.00									
BM	-0.21	0.12	-0.08	-0.24	1.00								
$TURN$	0.74	0.06	0.22	0.32	-0.21	1.00							
IO	0.54	-0.08	-0.03	0.42	-0.16	0.65	1.00						
$ILLIQ$	-0.42	0.13	0.27	-0.91	0.26	-0.58	-0.59	1.00					
$ACOVERAGE$	0.06	-0.09	-0.20	0.72	-0.16	0.26	0.30	-0.69	1.00				
$D\_CONVERT$	0.09	0.12	0.06	0.01	0.01	0.11	0.06	-0.05	0.07	1.00			
D_SP500	-0.13	-0.19	-0.22	0.60	-0.04	0.03	0.10	-0.52	0.59	0.04	1.00		
D_NASDAQ	0.41	0.07	0.10	-0.11	-0.17	0.31	0.20	-0.03	-0.12	-0.05	-0.24	1.00	
D_NYSE	-0.26	-0.09	-0.15	0.29	0.15	-0.14	-0.01	-0.18	0.29	0.04	0.31	-0.82	1.00

Table 2.2:
Determinants of Short Interest Ratio
This table reports the estimation results of a panel regression of the short interest ratio (SR) on the mispricing score decile dummies ($MISP_{Decile=k}$) and other determinants of the short interest ratio. Column (1) presents results without stock fixed effects. Column (2) includes stock fixed effects. Coefficients on the size and book-to-market decile dummies are not reported. The sample period is from March 1980 to December 2013. The regressions are estimated with time fixed effects. The standard errors are clustered by date and stock.*, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1) SR	(2) SR
$MISP_{Decile=10}$	1.200***	0.739***
	(12.88)	(10.92)
$MISP_{Decile=9}$	0.598***	0.397***
	(9.57)	(8.75)
$MISP_{Decile=8}$	0.413***	0.297***
	(8.21)	(7.83)
$MISP_{Decile=7}$	0.173***	0.144***
	(4.16)	(4.56)
$MISP_{Decile=6}$	0.0701**	0.0538**
	(2.41)	(2.46)
$MISP_{Decile=4}$	-0.0354	-0.0246
	(-1.23)	(-1.08)
$MISP_{Decile=3}$	-0.143***	-0.118***
	(-3.58)	(-3.66)
$MISP_{Decile=2}$	-0.239***	-0.158***
	(-4.87)	(-4.23)
$MISP_{Decile=1}$	-0.341***	-0.238***
	(-5.01)	(-4.36)
$Turn$	13.29***	11.25***
	(11.82)	(12.40)
IO	3.059***	6.242***
	(12.11)	(18.10)
$IVOL$	-2.219	-2.458
	(-0.46)	(-0.95)
$D\_convert$	0.641***	0.758***
	(7.55)	(9.52)
D_sp500	-0.463***	-0.520***
	(-5.21)	(-4.19)
D_nasdaq	0.920***	0.490
	(6.11)	(1.37)
D_nyse	0.365***	0.362**
	(3.12)	(2.08)
$Illiq$	-0.0615**	-0.0321*
	(-2.11)	(-1.86)
$Acoverage$	0.0305***	0.0449***
	(4.12)	(7.76)
SIZE Decile Dummies	Yes	Yes
BM Decile Dummies	Yes	Yes
Time Fixed Effects	Yes	Yes
Stock Fixed Effects	No	Yes
N	575371	575279
R-sq	0.503	0.705

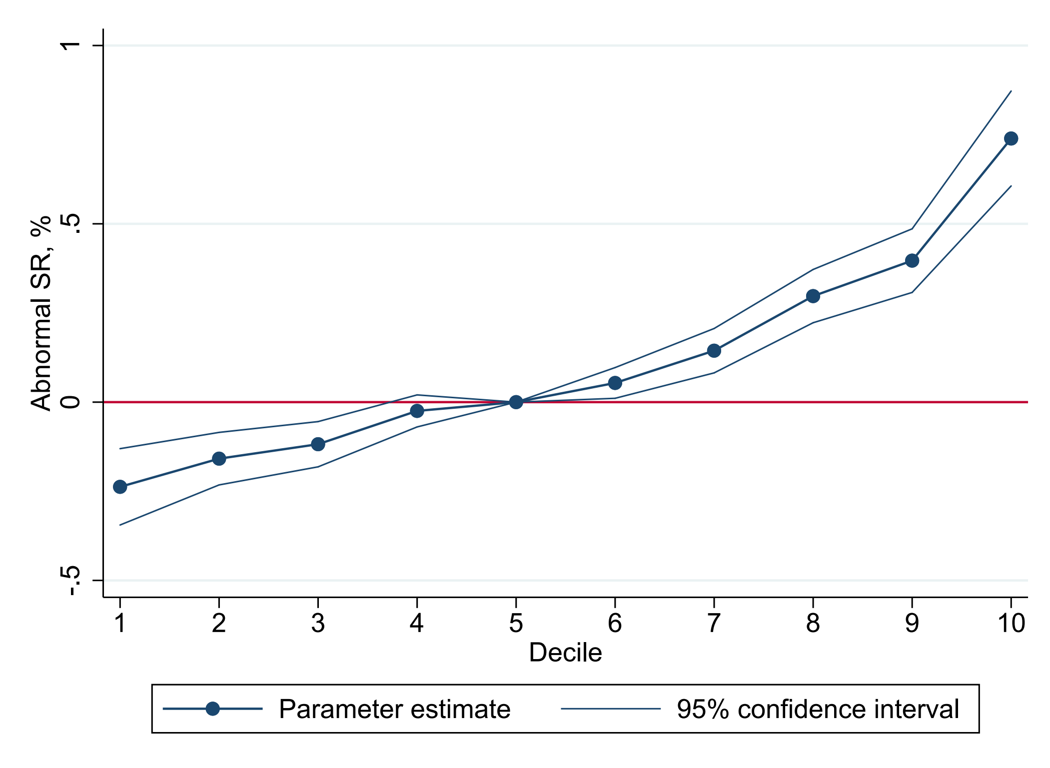


Figure 2.1:
Abnormal Short Interest Over Misprcing Score Deciles.
This figure shows the dynamics of the abnormal short interest over misprcing score deciles. Abnormal short interest for a given decile is estimated as a coefficient on the corresponding decile dummy from the following panel regression:

$$SR_{i,t} = Time_t + Stock_i + \boldsymbol{\beta}^{MISP\prime}\boldsymbol{D}^{MISP}_{it-1} + \boldsymbol{\beta}^{BM\prime}\boldsymbol{D}^{BM}_{it-1} + \boldsymbol{\beta}^{Size\prime}\boldsymbol{D}^{Size}_{it-1} + \boldsymbol{\gamma}'\boldsymbol{x}_{it-1} + \varepsilon_{i,t},$$

This specification includes both time and stock fixed effects. The standard errors are clustered by stock and date. The 95% confidence intervals are shown.

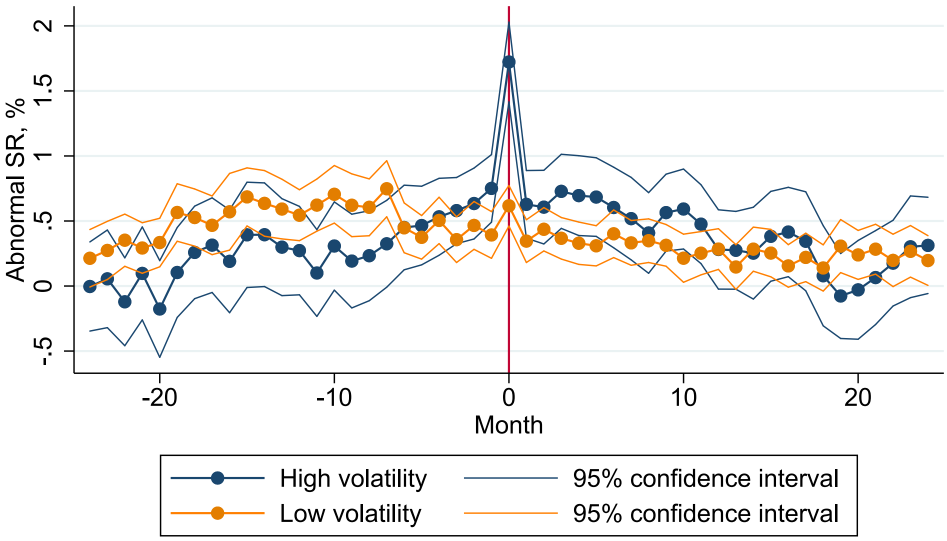
Table 2.3:
Impact of Sentiment on Short Selling Activity
This table reports the estimation results of a panel regression of the short interest ratio (SR) on high investor sentiment dummy ($HsentD$) and its interaction with mispricing score decile dummies ($MISP_{Decile=k} \times HsentD$), and other control variables. $HsentD$ is equal to one if the average sentiment index of Baker and Wurgler (2006) over the three most recent months is above the sample median and zero, otherwise. Column (1) presents results without sentiment for comparison. Column (2) introduces the high sentiment dummy and its interaction terms with mispricing score decile dummies. The sample period is from March 1980 to December 2013. The regressions are estimated with stock fixed effects. Column (1) also includes time fixed effects. The standard errors are clustered by date and stock.*, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1) SR	(2) SR
$MISP_{Decile=10}$	0.739***	0.625***
	(10.92)	(7.96)
$MISP_{Decile=9}$	0.397***	0.312***
	(8.75)	(5.37)
$MISP_{Decile=8}$	0.297***	0.215***
	(7.83)	(4.49)
$MISP_{Decile=7}$	0.144***	0.0661
	(4.56)	(1.57)
$MISP_{Decile=6}$	0.0538**	0.0144
	(2.46)	(0.47)
$MISP_{Decile=4}$	-0.0246	-0.0167
	(-1.08)	(-0.54)
$MISP_{Decile=3}$	-0.118***	-0.0678
	(-3.66)	(-1.60)
$MISP_{Decile=2}$	-0.158***	-0.0756
	(-4.23)	(-1.50)
$MISP_{Decile=1}$	-0.238***	-0.0990
	(-4.36)	(-1.50)
$HsentD$		0.366***
		(4.60)
$MISP_{Decile=10} \times HsentD$		0.268**
		(2.26)
$MISP_{Decile=9} \times HsentD$		0.185**
		(2.31)
$MISP_{Decile=8} \times HsentD$		0.189***
		(2.74)
$MISP_{Decile=7} \times HsentD$		0.168***
		(2.93)
$MISP_{Decile=6} \times HsentD$		0.0891**
		(2.22)
$MISP_{Decile=4} \times HsentD$		-0.0136
		(-0.32)
$MISP_{Decile=3} \times HsentD$		-0.0957*
		(-1.87)
$MISP_{Decile=2} \times HsentD$		-0.164***
		(-2.81)
$MISP_{Decile=1} \times HsentD$		-0.271***
		(-3.91)
Control Variables	Yes	Yes
SIZE Decile Dummies	Yes	Yes
BM Decile Dummies	Yes	Yes
Time Fixed Effects	Yes	No
Stock Fixed Effects	Yes	Yes
N	575279	575279
R-sq	0.705	0.687

Table 2.4:
Impact of Idiosyncratic Volatility on Short Selling Activity
This table reports the estimation results of a panel regression of short interest ratio (SR) on stock's idiosyncratic volatility ($IVOL$) and its interaction terms with mispricing score decile dummies ($MISP_{Decile=k} \times IVOL$) and other control variables. Column (1) includes mispricing decile dummies to control for stock's mispricing. Column (2) includes a piecewise linear function of mispricing score with breakpoints equal to cutoff points of mispricing score deciles to control for non-linearities inside of mispricing deciles. The sample period is from March 1980 to December 2013. The regressions are estimated with month and stock fixed effects. The standard errors are clustered by date and stock.*, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1) SR	(2) SR
$IVOL$	-6.351*	-5.837*
	(-1.74)	(-1.80)
$MISP_{Decile=10} \times IVOL$	18.28***	16.44***
	(3.89)	(4.06)
$MISP_{Decile=9} \times IVOL$	10.56**	10.98***
	(2.47)	(3.30)
$MISP_{Decile=8} \times IVOL$	15.52***	10.67***
	(3.98)	(3.84)
$MISP_{Decile=7} \times IVOL$	3.453	2.635
	(1.13)	(1.31)
$MISP_{Decile=6} \times IVOL$	-0.654	-0.567
	(-0.25)	(-0.39)
$MISP_{Decile=4} \times IVOL$	0.879	2.155
	(0.34)	(1.43)
$MISP_{Decile=3} \times IVOL$	3.503	1.071
	(1.09)	(0.50)
$MISP_{Decile=2} \times IVOL$	1.360	1.410
	(0.36)	(0.52)
$MISP_{Decile=1} \times IVOL$	2.032	2.764
	(0.46)	(0.76)
Other Control Variables	Yes	Yes
MISP Decile Dummies	Yes	
MISP Piecewise Linear		Yes
Stock Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
N	575279	575279
R-sq	0.705	0.705

(a) Entering the extreme *overpriced* decile



(b) Entering the extreme *underpriced* decile

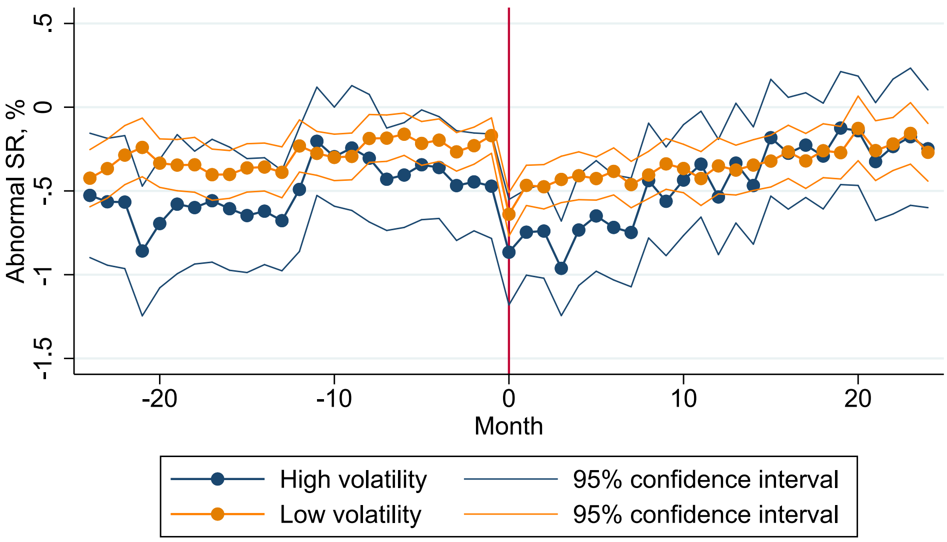


Figure 2.2:
Abnormal Short Interest for High- and Low-Volatility Stocks Entering Extreme Mispricing Deciles

This figure displays the abnormal short interest ratio for high-IVOL and low-IVOL stocks around entering the extreme mispricing deciles. Panel (a) plots the abnormal short interest around entering the most overpriced decile, whereas Panel (b) plots the abnormal short interest around entering the most underpriced decile. The abnormal short interest is estimated as coefficients h^k and l^k from the following regression:

$$\begin{aligned} SR_{i,t} = {} & [h^{-24} D_{it}^{-24}(MISP) + \ldots + h^0 D_{it}^0(MISP) + \ldots + h^{+24} D_{it}^{+24}(MISP)] \times 1\{ivolH = 1\} + \\ & + [l^{-24} D_{it}^{-24}(MISP) + \ldots + l^0 D_{it}^0(MISP) + \ldots + l^{+24} D_{it}^{+24}(MISP)] \times 1\{ivolL = 1\} + \\ & + \boldsymbol{\beta}^{IVOL\prime} \boldsymbol{D}_{it}^{IVOL} + \boldsymbol{\beta}^{BM\prime} \boldsymbol{D}_{it}^{BM} + \boldsymbol{\beta}^{Size\prime} \boldsymbol{D}_{it}^{Size} + \boldsymbol{\gamma}' \boldsymbol{x}_{it} + Time_t + Stock_i + \varepsilon_{i,t}, \end{aligned}$$

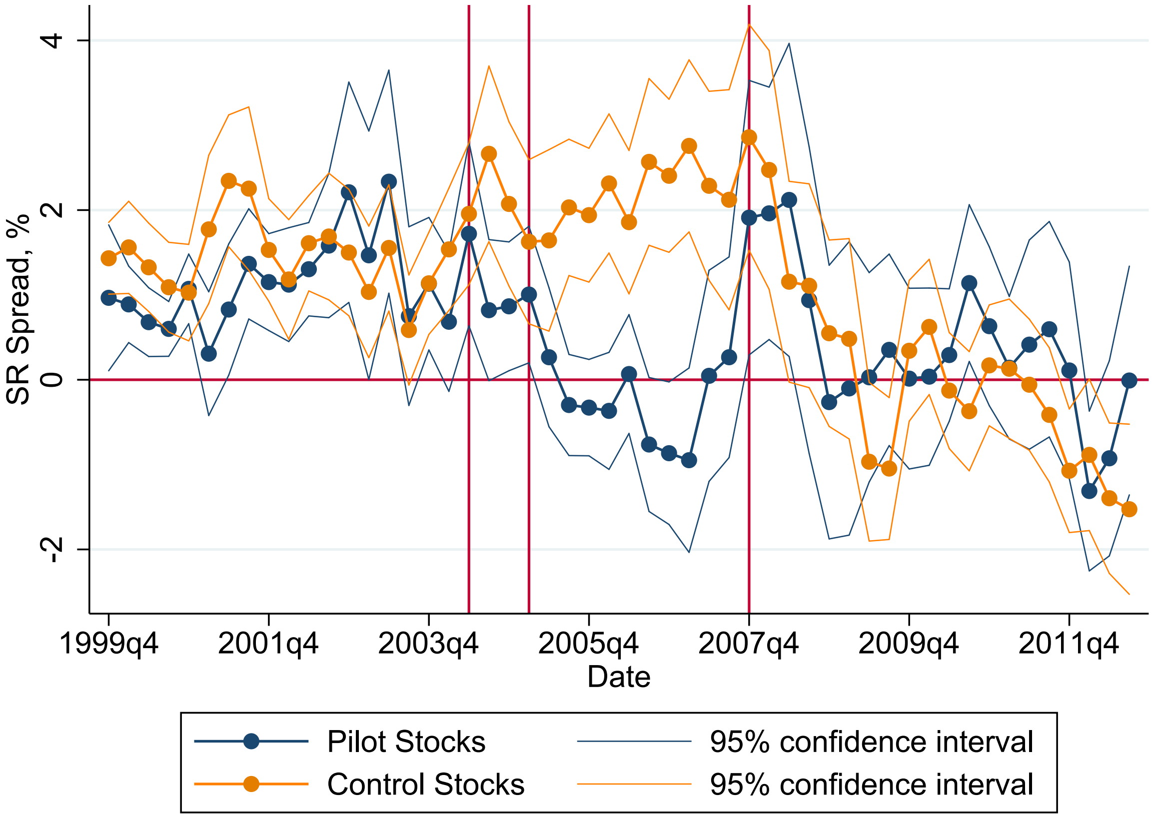


Figure 2.3:
Abnormal Short Interest Ratio Around the Implementation of Regulation SHO
This figure presents the dynamics of the mispricing strategy short interest ratio spread for affected and non-affected stocks around the implementation of the pilot program under Rule 202T of Regulation SHO. The short interest ratio short-long spread is estimated every quarter as a difference between coefficients, $\beta_{10}^{MISP} - \beta_{1}^{MISP}$, from the following pooled regression with monthly observations:

$$SR_{i,\tau} = \boldsymbol{\beta}^{MISP\prime}\boldsymbol{D}_{i\tau-1}^{MISP} + \boldsymbol{\beta}^{BM\prime}\boldsymbol{D}_{i\tau-1}^{BM} + \boldsymbol{\beta}^{Size\prime}\boldsymbol{D}_{i\tau-1}^{Size} + \boldsymbol{\gamma}'\boldsymbol{x}_{i\tau-1} + \varepsilon_{i,\tau}$$

The sample consists of 1363 NYSE/AMEX stocks from Russell 3000 over 2000-2012. The timeline is divided into four periods: the pre-announcement period (before July 2004), the announcement period (July 2004 - April 2005), the Reg SHO period (May 2005 - June 2007), and the post-Reg SHO period (after July 2007). In addition to the estimates depicted are 95% confidence intervals.

Table 2.5:
Difference in Abnormal Short Positions Between Pilot and Control Stocks Around the SHO Regulation for Long and Short Leg of Mispricing Strategy
This table presents an average difference in the abnormal short interest ratio for extreme deciles of the mispricing strategy between affected and non-affected stocks around the implementation of the pilot program under Rule 202T of Regulation SHO. The average difference by period is estimated from the following regression:

$$\beta_{l,t}^{MISP}(Pilot) - \beta_{l,t}^{MISP}(Control) = b_{0,l} \cdot preD_t + b_{1,l} \cdot announcementD_t + \\ + b_{2,l} \cdot duringD_t + b_{3,l} \cdot postD_t + \varepsilon_{l,t},$$

$preD_t$ is one for the pre-announcement and zero, otherwise, $announcementD_t$ is one for the announcement period, $duringD_t$ is one for the period during pilot program (May 2005 - June 2007), and $postD$ is the period after the program, when the SEC eliminated short sale price test for all exchange-listed stocks (July 2007 - December 2010).

	(1) Short Leg	(2) Long Leg	(3) Short - Long
preD	-0.390**	-0.0606	-0.329
	(-2.46)	(-0.90)	(-1.60)
announcementD	-1.074***	0.407***	-1.480***
	(-5.49)	(3.89)	(-5.00)
duringD	-2.608***	0.250**	-2.858***
	(-11.70)	(2.36)	(-11.18)
postD	0.307	0.729***	-0.422
	(1.66)	(5.70)	(-1.63)
N	52	52	52

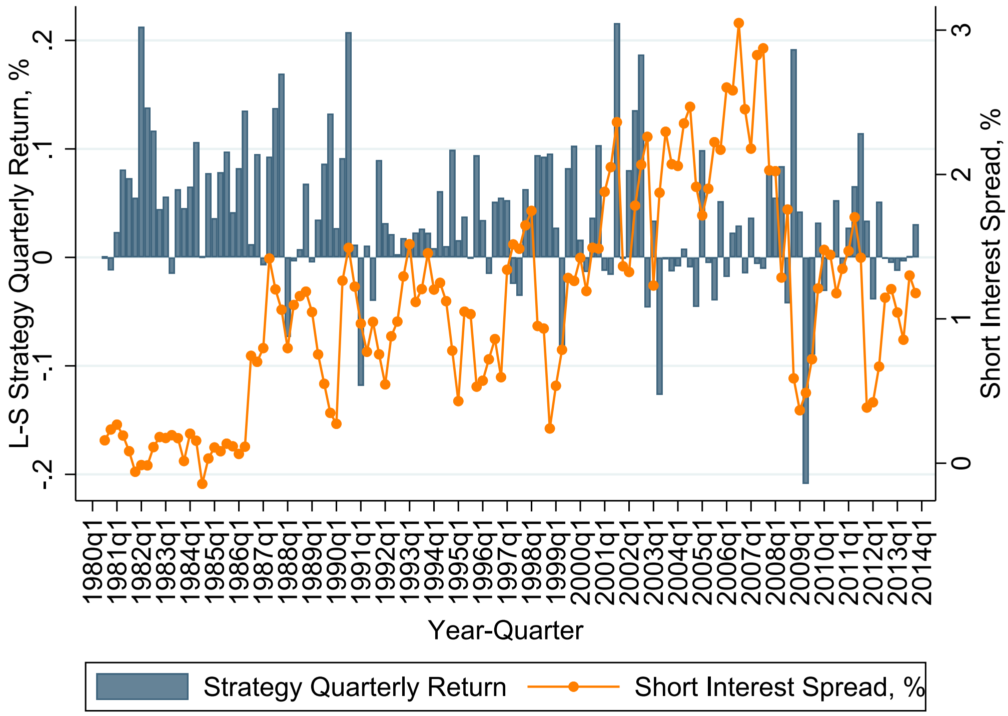


Figure 2.4:
Profitability of Mispricing-based Long-Short Strategy and Short Interest Spread
The figure depicts the dynamics of mispricing strategy quarterly returns and the spread in abnormal short interest between short and long leg of the mispricing strategy. The sample period is 1980 to 2013.

Table 2.6:
Short Interest Spread and Mispricing Returns.
This table presents results of the time-series regression of mispricing quarterly long minus short strategy returns on a constant, spread in the abnormal short interest, past quarter strategy performance and the sentiment index of Baker and Wurgler (2006). Regression split dates of 2002Q3 and 2008Q1 are determined using supremum Wald test for a structural break at an unknown break date following Andrews (1993). The sample period is 1980 to 2013. The standard errors are adjusted for serial correlation following Newey and West (1987).

	(1) 1980-2013	(2) 1980-2002q3	(3) 2002q4-2013	(4) 1980-2013	(5) 1980-2008q1	(6) 2008q2-2013	(7) 2010q2-2013
	Ret_t^{MISP}	Ret_t^{MISP}	Ret_t^{MISP}	Ret_t^{MISP}	Ret_t^{MISP}	Ret_t^{MISP}	Ret_t^{MISP}
$\_const$	0.0361***	0.0503***	0.00918	0.0353***	0.0513***	-0.0769**	-0.0415
	(5.58)	(7.35)	(1.09)	(2.79)	(5.86)	(-2.23)	(-1.67)
S_{t-1}^{MISP}				-0.00880	-0.0175***	0.0930***	0.0610**
				(-1.13)	(-3.38)	(3.11)	(2.47)
Ret_{t-1}^{MISP}				0.00563	-0.0379	-0.0195	-0.157
				(0.08)	(-0.48)	(-0.20)	(-1.32)
$Sent_{t-1}$				0.0320***	0.0248***	0.0631***	0.0296
				(3.13)	(2.65)	(3.25)	(1.11)
N	134	89	45	133	110	23	14

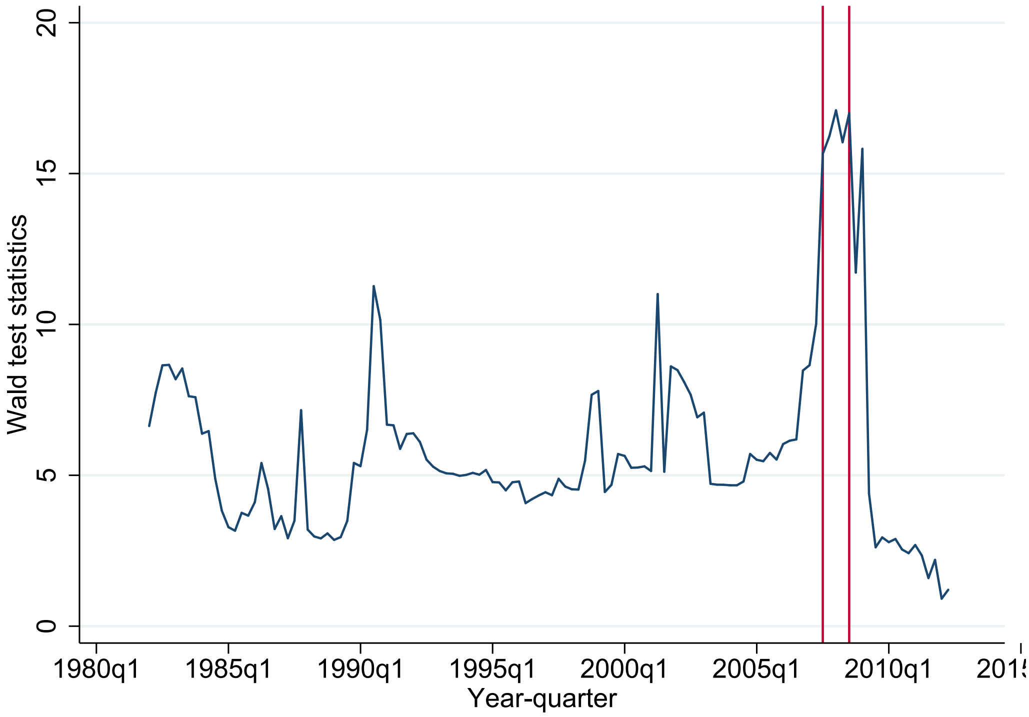


Figure 2.5: Wald Test for a Structural Break in Relationship between Short Interest Spread and Mispricing Strategy Quarterly Returns
This figure displays the test statistic of Wald test for a structural break at an unknown break date as a function of a quarter. The structural break test is performed jointly for all coefficients of the following relationship:

$$Ret_t^{MISP} = \alpha + \beta_1 S_{t-1}^{MISP} + \beta_2 Ret_{t-1}^{MISP} + \beta_3 Sent_{t-1} + \varepsilon_t$$

The sample period is 1980 to 2013. Two lines mark the quarters of the quant meltdown and the start of the financial crisis. These events happened in the 3rd quarter of 2007 and the 3rd quarter of 2008, correspondingly.

Table 2.7:
Relation between Average Short Interest Spread and AUM
The table shows the estimation results of the regression of four quarters moving average of the strategy short interest spread and assets under management of market neutral hedge funds. Additionally, the corresponding correlation between the variables is presented. The sample period is from 2000Q1 to 2014Q3. The time line is split into two periods, before and after 2008Q3. The standard errors are adjusted for serial correlation following Newey and West (1987).

	2000Q1-2014Q3 S_Y^{MISP}	2000Q1-2008Q3 S_Y^{MISP}	2008Q4-2014Q3 S_Y^{MISP}
_cons	1.237***	1.405***	0.871***
	(6.51)	(10.72)	(3.90)
AUM_Q^{MN}	0.0186**	0.0300***	0.00939
	(2.33)	(5.92)	(0.97)
Correlation	0.295	0.846	0.130
N	59	35	24

Appendix to Chapter 2

Table A2.1:
Definitions of Variables

Variable:	Description:	Source:
SR	The short interest ratio is the mid-month reported short interest divided by shares outstanding. To aggregate on PERMNO level, we sum short interest over global issue key. We use the version of short interest variable from Compustat supplementary file that is not adjusted for stock splits. Short interest for NASDAQ stocks is available starting June 2003.	CRSP/Compustat.
$MISP$	The mispricing score from Stambaugh, Yu, and Yuan (2015).	Authors
$IVOL$	Idiosyncratic volatility is defined as the the log of the standard deviation of residuals obtained in the the most recent month's daily regression of the excess stock returns on Fama-French 3-factors.	CRSP
$Size$	Market capitalization is calculated as the number of shares outstanding times price per share (in $Mio).	CRSP
BM	The book-to-market ratio is calculated following Davis, Fama, and French (2000). The book-to-market ratio in year t is the total book value at the end of fiscal year ending in year $t-1$ divided by total market capitalization on the last trading day of the calendar year $t-1$, as reported by CRSP. The total book value is the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit minus the book value of preferred stock. To estimate the book value of preferred stock, we use the redemption, liquidation , or par value, in this order (depending on data availability).	CRSP/Compustat
$Turn$	The monthly turnover ratio averaged over past quarter.	CRSP
IO	Aggregate institutional ownership from 13-F fillings. Being reported once per quarter, insitutional ownership is assumed to be constant over three-month period prior to the next report.	13F
$Illiq$	The Amihud (2002)) illiquidity ratio calculated using one year of daily data.	CRSP
$Acoverage$	Number of analysts making firm's earnings forecasts.	IBES
$D\_convert$	A convertible debt dummy is equal to 1 if the company has convertible debt outstanding.	Compustat
D_sp500	An S&P 500 index membership dummy is 1 for stocks included to the S&P 500 index.	CRSP
D_nasdaq	A NASDAQ dummy is equal to 1 if the stock is listed on NASDAQ.	CRSP
D_nyse	A NYSE dummy is equal to 1 if the stock is listed on NYSE.	CRSP

Continued on next page

Table A2.1 – *Continued from previous page*

Variable:	**Description:**	**Source:**
Sent	An orthogonalized version of the Baker and Wurgler (2006) sentiment index that is constructed as the first principal component of six sentiment proxies that have been orthogonalized to macroeconomic factors that capture business cycle component.	Authors
Ret^{MISP}	Monthly returns of equally-weighted long-short strategy based on the Stambaugh, Yu, and Yuan (2015) misprcing score. The strategy is long in stocks from decile with the most underpriced stocks according to the misprcing score and is short in stocks from decile with the most overpriced stocks.	CRSP/Authors
S^{MISP}	The spread between abnormal short interest ratios for the short side and for the long side of the mispricing anomaly calculated at quarterly frequency.	Compustat
AUM^{MN}	Aggregate assets under management of equity market neutral hedge funds.	Barclay Hedge

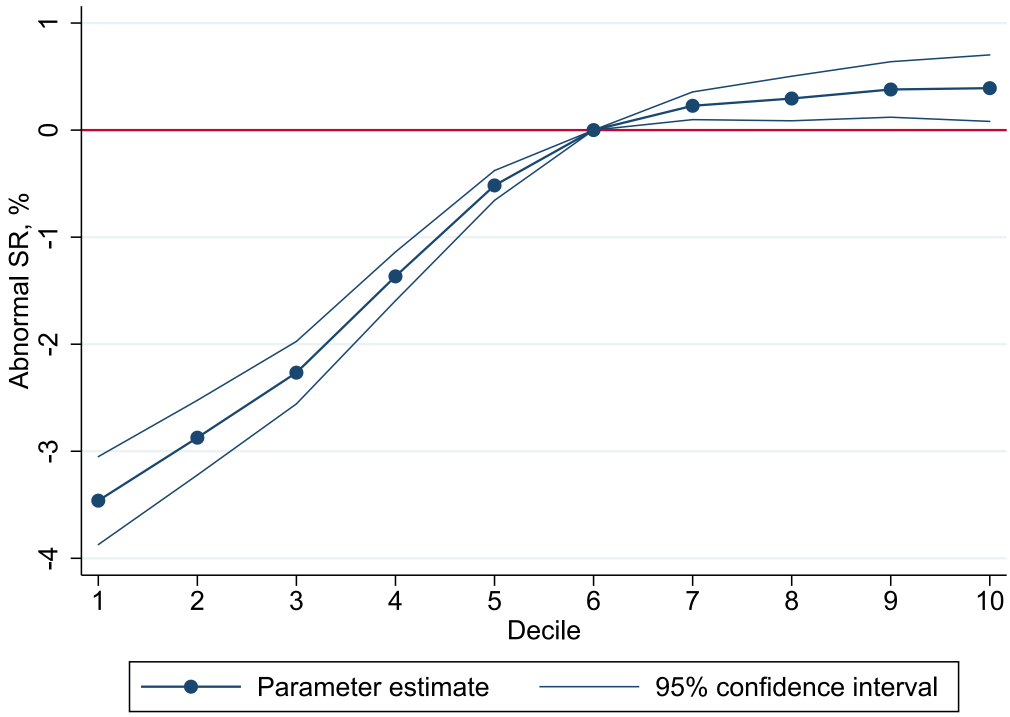


Figure A2.1:
Abnormal Short Interest Over Size Deciles
This figure shows the dynamics of abnormal short interest over size deciles. Abnormal short interest for a given decile is estimated as the coefficient on the corresponding decile dummy from the following panel regression:

$$SR_{i,t} = Time_t + Stock_i + \boldsymbol{\beta}^{MISP\prime}\boldsymbol{D}^{MISP}_{it-1} + \boldsymbol{\beta}^{BM\prime}\boldsymbol{D}^{BM}_{it-1} + \boldsymbol{\beta}^{Size\prime}\boldsymbol{D}^{Size}_{it-1} + \boldsymbol{\gamma}'\boldsymbol{x}_{it-1} + \varepsilon_{i,t},$$

This specification includes both time and stock fixed effects. The standard errors are clustered by stock and date. The 95% confidence intervals are shown.

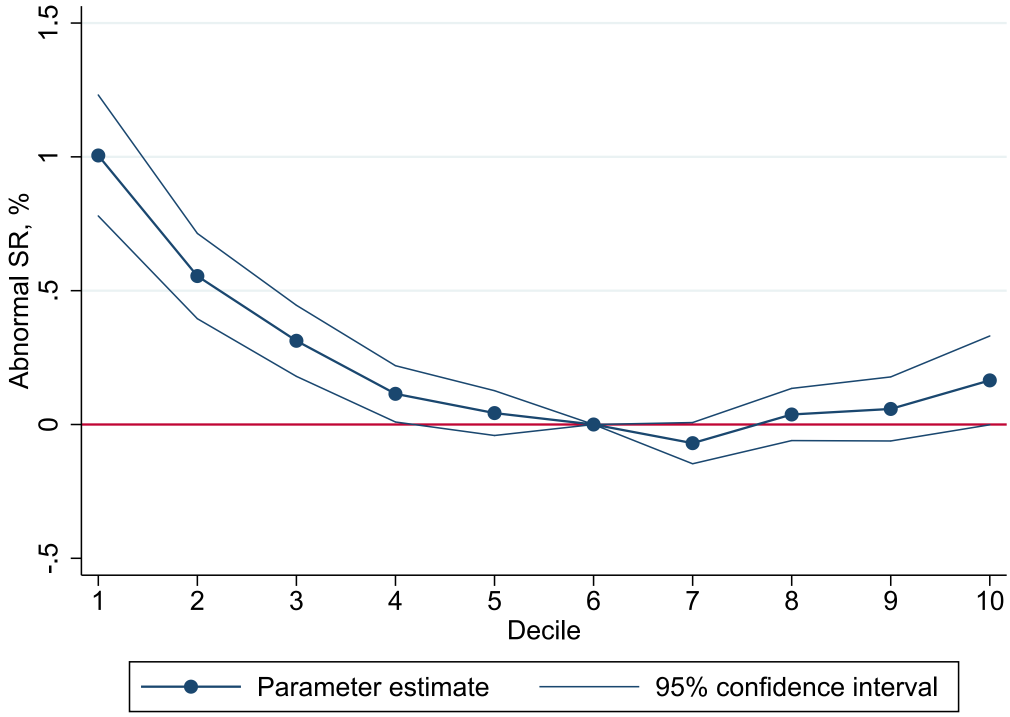


Figure A2.2:
Abnormal Short Interest Over Book-To-Market Ratio Deciles
This figure shows the dynamics of abnormal short interest over book-to-market deciles. Abnormal short interest for a given decile is estimated as the coefficient on the corresponding decile dummy from the following panel regression:

$$SR_{i,t} = Time_t + Stock_i + \boldsymbol{\beta}^{MISP\prime}\boldsymbol{D}^{MISP}_{it-1} + \boldsymbol{\beta}^{BM\prime}\boldsymbol{D}^{BM}_{it-1} + \boldsymbol{\beta}^{Size\prime}\boldsymbol{D}^{Size}_{it-1} + \boldsymbol{\gamma}'\boldsymbol{x}_{it-1} + \varepsilon_{i,t},$$

This specification includes both time and stock fixed effects. The standard errors are clustered by stock and date. The 95% confidence intervals are shown.

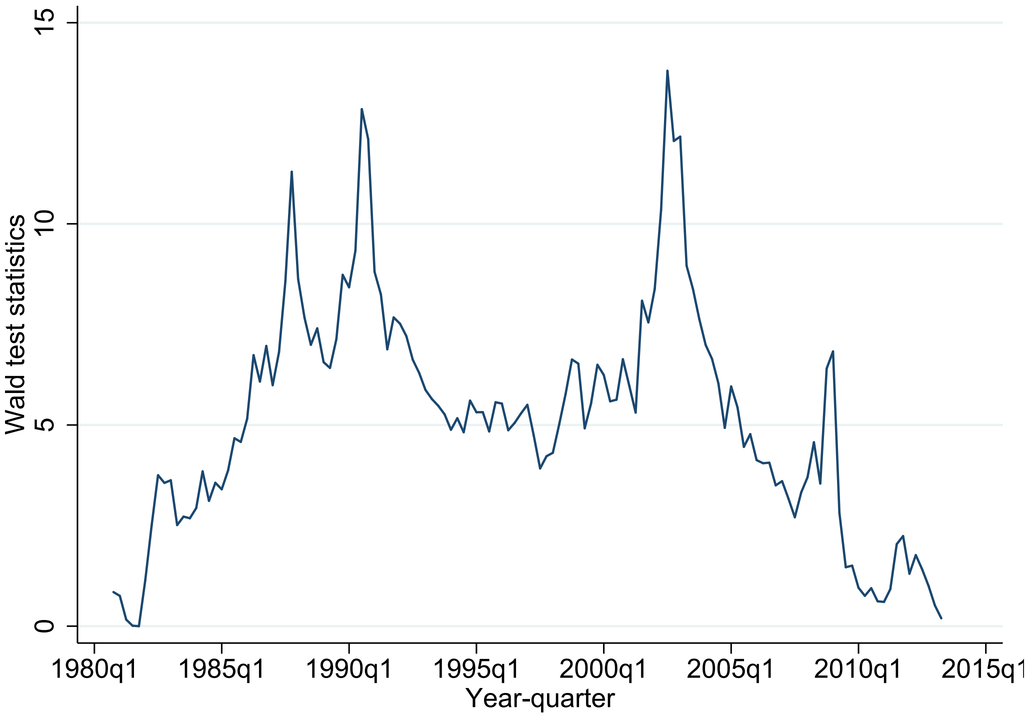


Figure A2.3: Wald Test for a Structural Break in Mispricing Strategy Quarterly Returns
This figure displays the test statistic of Wald test for a structural break in mispricing strategy returns at an unknown break date as a function of a quarter.

Table A2.2:
Structural Break in Anomaly Returns and Anomaly Relationship
This table presents the results of Wald tests on structural breaks with unknown date for anomalies that are included in the construction of the mispricing score. Panel A publication contains an anomaly publication year. Panel B contains an estimated year of structural break for anomaly returns, change in average anomaly returns and the statistic of the t-test on its significance. Panel C contains an estimated year of structural break for the relationship between anomaly returns and spread in the abnormal short interest, difference in the coefficients on the short interest spread and the corresponding t-statistic.

	A: Publication Year	B: Structural Break in Returns			C: Structural Break in Relationship		
Anomaly	Published	Break Year	Δ Ret	t-stat	Break Year	ΔS	t-stat
MISP	2012	2002	-0.035	-4.05	2008	0.075	2.84
NI	1991	1987	-0.022	-3.89	2002	0.023	1.81
CEI	2006	1998	0.015	1.70	2008	0.047	2.66
ACC	1996	2000	-0.017	-2.50	2008	0.025	0.88
NOA	2004	1999	-0.020	-2.20	1998	0.003	0.15
AG	2008	2000	-0.013	-1.71	1986	0.009	0.24
ITA	2004	1999	-0.021	-2.56	2008	0.009	0.38
FD	2008	1986	-0.048	-3.16	2007	0.029	1.90
OS	1980	1985	-0.033	-3.20	1997	0.023	1.80
MOM	1993	2008	-0.062	-2.63	2001	0.010	0.53
GPP	2010	1990	-0.028	-2.97	1998	0.019	1.17
ROA	2006	1986	-0.052	-4.31	1999	0.022	1.55

Chapter 3

Surprise in Short Interest

3.1 Introduction

Short selling has become an essential feature of arbitrageurs' trading strategies. The average level of shares shorted has rapidly increased over recent years. This phenomenon has been related to an increase in capital devoted to arbitrage strategies but also to the expanded use of short selling for market making and hedging activities. An increase in supply of lendable stocks is driven by the growth of institutional ownership (Lewellen, 2011).

This paper studies the informational role of short sellers in the equity market. Many recent studies have examined the ability of short sellers to detect deviations of stock prices from fundamentals and to arbitrage them away. Although most of these studies find evidence that to suggest that there is informed trading by short sellers, there are three major concerns. First, the key measure of short sellers' positions employed in the literature is the level of short interest ratio (i.e., shares shorted relative to shares outstanding). However, as argued by Asquith, Pathak, and Ritter (2005)), for instance, the negative relation between short interest ratio and future stock returns is also consistent with Miller's (1977) view that short-sale constraints impede the trades of investors with negative beliefs, causing stocks to be overvalued. In other words, stocks that are already heavily shorted are the most difficult to short and are consequently overvalued. Overpricing, in turn, mechanically leads to future negative returns. Second, even if the short interest ratio does reflect arbitrageurs' view on stock prospects, profits from following this view might be captured by high lending fees (Drechsler and Drechsler, 2016). Finally, using similar arguments to those used in the literature on institutional trading (e.g., Bennett, Sias, and Starks, 2003), if short sellers can forecast returns, then cross-sectional variation in future returns should be related to *changes in the short interest ratio* as a proxy for informed short selling. However, previous research provides at best inconclusive evidence on the predictive power of changes in the short interest ratio for stock returns after controlling for the level of short interest ratio (Boehmer, Huszar, and Jordan, 2010).

This paper proposes a new measure of informed *short selling* (or short covering). The simple intuition behind the proxy is based on the distribution of the short interest ratio in the cross section of stocks. Namely, two prevalent two main features become apparent when analyzing the short interest ratio. First, the level of the short interest ratio differs dramatically across firms and it is highly persistent over time. As a consequence, informed short-selling in response to (short-term) mispricing is difficult to capture by the cross section of the short interest ratio. Second, certain companies exhibit a greater time-series variation in the share of shorted stocks than others. Therefore, even when the short interest ratio deviates from the expected or usual level of short selling, this may not be sufficient to pick out informed trading from the noise of the short interest ratio. Namely, if two stocks exhibit the same increase in short interest ratio relative to their previous levels, we expect that an increase for a stock whose level of short interest is normally stable will be more informative than a one for a stock that typically has a far higher level of variation in short selling. These distribution differences may arise because certain stocks are ideal for market making or hedging while others primarily attract arbitrageurs (Desai et al., 2002; Diether, Lee, and Werner, 2009). In this paper, we account for these differences between stocks and offer a novel proxy for informed short selling: the standardized unexpected short interest ratio (SUSIR), or simply *surprise in short interest.*

Using surprise in short interest as a proxy for informed short selling, we provide several new insights. First, we show that the information from short-interest reports is not incorporated into stock prices instantly after public announcements. Stocks with top (bottom) 30 percent surprises in short interest experience a strong price drift of around -0.25% (+0.27%) within 30 days of the dissemination. Second, we construct a measure that is updated on a monthly basis to capture this price drift. A portfolio strategy that involves buying stocks with the 10 percent lowest surprise in short interest (unexpectedly high short covering) and sells stocks with the 10 percent highest surprise in short interest (unexpectedly high short selling) yields a statistically significant risk-adjusted return of around 4 to 6 percent p.a. over the next month. This return spread is statistically and economically significant for both the equal- and value-weighted long-short portfolios. Most notably, the effect is present on both the long and short side of the portfolio. The predictive ability of $SUSIR$ is not captured by standard risk factors, mispricing-related anomalies, or other proxies of informed short selling and short-selling impediments.

Third, we find that the return predictability stems from the ability of short sellers to predict changes in a company's fundamental value. In particular, positive surprises in short interest are predictive of lower unexpected earnings and lower cumulative abnormal returns around earnings announcements. Moreover, the profitability of the long-short strategy based on the surprises is particularly strong around earnings announcements when valuation-relevant news is released and this fundamental news is incorporated into prices. These findings suggest that short sellers trade on mispricing that arises from biased beliefs in the overall market about company fundamentals.

Finally, our final analysis provides evidence that the persistence of mispricing and, as a consequence, the return predictability are partially explained by Shleifer and Vishny's (1997) limits-to-arbitrage argument. That is, general trading impediments such as illiquidity and idiosyncratic volatility are positively associated with the magnitude of the predicted returns.

Interestingly, a low supply of stocks to borrow – a common proxy for short-sale constraints (Nagel, 2005) – is essentially unrelated to the predictive power of the surprise in short interest, suggesting that $SUSIR$ captures short sellers' informed trading rather than purely overpricing due to short-sale constraints.

The findings of this paper contribute to the literature in several important ways. First, by employing the surprise in short interest, we provide new evidence on informed trading by short sellers. Previous studies relate short selling to future negative stock returns (e.g., Desai et al., 2002; Cohen, Diether, and Malloy, 2007; Boehmer, Jones, and Zhang, 2008; Diether, Lee, and Werner, 2009) and future changes in fundamentals (e.g., Hirshleifer, Teoh, and Yu, 2011; Akbas, Boehmer, et al., 2013). Rapach, Ringgenberg, and Zhou (2016) find similar results for aggregate short interest. In particular, they show that detrended aggregate short interest predicts market returns and that this predictability stems from the cash flow channel. Although it has been shown that the level of short selling predicts both stock returns and company fundamentals, this predictability might have different interpretations. Namely, stocks with a high level of short interest tend to be more difficult to short, which automatically leads to predictability due to short-sale constraints (e.g., Asquith, Pathak, and Ritter, 2005). Moreover, even if a high level of short selling is an indicator of bearish views, it is associated with a high risk of short selling (Engelberg, Reed, and Ringgenberg, 2018) and high lending fees (Drechsler and Drechsler, 2016) casting doubt on the risk-adjusted net profitability of strategies based on the level of short interest ratio. If short sellers are informed investors, who are smart about how they enter and cover short positions, we should also expect that an increase (decrease) in short interest is also related to future negative (positive) returns. Interestingly, while changes in short interest ratio have been shown to predict future fundamentals (Deshmukh, Gamble, and Howe, 2015), to the best of our knowledge there has been little or no convincing evidence of their incremental ability to predict stock returns (Boehmer, Huszar, and Jordan, 2010). In this paper we first put forward the *surprise in short interest* as a novel and intuitive proxy for informed short selling. Second, we show that this proxy predicts *both* stock returns and changes in fundamentals beyond the level of short interest and other standard determinants. Lastly, this predictability is not explained by common proxies for short-sale constraints.

We also contribute to the literature on market efficiency. In contrast to the extensive literature on earnings reports (e.g., Ball and Brown, 1968; Jones and Litzenberger, 1970; Bernard and Thomas, 1990; Mendenhall, 2004), to our knowledge, Senchack and Starks (1993) is the only paper that considers market reaction to short-interest reports. The authors document negative market returns around announcement periods for stocks with a reported large increase in short interest. Our results extend this picture. We show that not only are large increases in short interest associated with abnormal returns but so too are large decreases, as captured by the surprise in short interest. More importantly, we observe that there is a price drift for longer than 30 days after the public announcement of short interest.

In a related paper, Cohen, Diether, and Malloy (2007) employ a detailed proprietary data set on lending activity at a daily frequency and show that shorting demand, which reflects intended changes of arbitrageurs' short positions, is a strong predictor of future stock returns. The data from that study is not publicly available and therefore could not be observed and processed by investors. In contrast, the data used in our study is published by stock exchanges on regular basis and is available to all market participants. If we take this fact into account, the return predictability documented in our study calls into question the market's ability to incorporate information from short-sale reports efficiently into stock prices.

Finally, a recent strand of literature studies the existence and source of capital asset pricing anomalies (Stambaugh, Yu, and Yuan, 2012; Engelberg, Mclean, and Pontiff, 2018; Stambaugh, Yu, and Yuan, 2015; Stambaugh and Yuan, 2017; McLean and Pontiff, 2016). These anomalies may arise due to behavioral biases as a result of mispricing combined with limits to arbitrage (Nagel, 2013; Shleifer and Vishny, 1997). Although it has been shown in the literature that arbitrageurs, in particular short sellers, exploit well-known and profitable capital market anomalies (Hanson and Sunderam, 2014; Akbas, Armstrong, et al., 2015; Akbas, Armstrong, et al., 2016; Jank and Smajlbegovic, 2016), we find that returns from informed short selling, as proxied by the surprise in short interest, cannot be entirely explained by trading on these anomalies. Therefore, we contribute to this stream of the literature by revealing a previously undocumented anomaly based on the informed trading by short sellers.

The remainder of the paper is structured as follows. Section 3.2 describes the data set, introduces the proxy for informed short selling, and provides initial descriptive statistics of the variables. Section 3.3 presents evidence of informed trading by short sellers, focusing particularly on analyses on short sellers' ability to predict future stock returns and changes in company fundamentals. Section summarizes the key findings and suggests a number of avenues for future research.

3.2 Data

3.2.1 Data sources

In our study, we use standard data sources. Equity market data on the stock level are obtained from CRSP, whereas accounting data come from the Compustat annual file. Information about the number of shares shorted is drawn from the Compustat supplementary short interest file. Short interest ratio (SR) is defined as the mid-month short interest over the number of shares outstanding.[1] Other short-interest-based control variables are days-to-cover ratio (Hong et al., 2016) and short interest over institutional ownership (Drechsler and Drechsler, 2016). Days to cover (DTC) is defined as short interest ratio over average daily turnover in the same month. To calculate short interest over institutional ownership (SR_{IO}), we divide the short interest ratio by the institutional ownership ratio. We retrieve institutional ownership in individual stocks from Thomson Reuters institutional (13F) holdings. Residual institutional ownership (RIO) is calculated as a residual in the cross-sectional regression of the logit-transformed institutional ownership ratio on log size and log size squared, following Nagel (2005). We obtain the Corwin and Schultz (2012) spread – the bid-ask spread estimator calculated using daily high and low prices ($HLSPREAD$) – directly from the authors.[2]. Idiosyncratic volatility ($IVOLA$) is the standard deviation of residuals over past month in the daily regression of excess return on Fama and French (1993) three factors, as in Ang et al. (2006). Various pricing factors are obtained either from the corresponding authors' websites or calculated based on publicly available data.

[1]Starting from 2007 the short interest data is reported bimonthly. For consistency, we use only mid-month figures.

[2]We thank Shane Corwin for providing these data.

For instance, the underpriced minus overpriced (UMO) factor is calculated following Stambaugh and Yuan (2017) using the mispricing score ($MISP$) from Robert Stambaugh's website. Analyst data including forecasts and observed earnings are collected from IBES. Market beta ($MBETA$) is the slope coefficient in the regression of daily excess stock returns on the market factor, based on the daily data over the past year. Return on assets (ROA) is income before extraordinary items divided by total assets. Investment (INV) is the asset growth measure used by Cooper, Gulen, and Schill (2008). Other standard control variables, such as log size, log book-to-market ratio, momentum and short-term reversal, are defined as is common in the literature. A more detailed description of variables is given in the Appendix, in Table A3.1. Our sample period is from March 1980 to December 2013. The starting date of our sample is determined by the availability of reliable data on the 13F filings, an essential ingredient in one of our important control variables. To construct our universe of the U.S. equity market, we apply a number of filters. In particular, we include in our analyses stocks with share codes 10 and 11. We consider all AMEX, NYSE and NASDAQ stocks. The NASDAQ sample, however, starts in June 2003, and is limited by the availability of short-interest data in Compustat. To ensure that our results are economically meaningful and not driven by penny stocks, we exclude stocks with a previous month's price below 5$ and stocks below the 5th NYSE market capitalization percentile. Finally, we ensure that our sample stocks have a non-missing mispricing score, which is an important control variable in our study.

3.2.2 Surprise in short interest

We introduce a new measure of arbitrageurs' opinions about stock misvaluation: the surprise in short interest. This measure has two important ingredients. The first is based on the observation that the short interest ratio is persistent over time. There are a few potential reasons for such persistence. On the demand side, it could be driven by market-making and hedging activities involving equity short selling. On the supply side, the rise of institutional investors, and especially exchange-traded funds, boosts short selling by pushing lending fees down. Such a persistent component in the short interest ratio does not necessary reflect investors' views about stock future performance. We extract an unexpected component of short interest ratio by subtracting a twelve-month moving window mean from the short interest ratio.[3] An implicit assumption is that investors rely on a twelve-month window to form their expectations about the level of shorting activity. The second ingredient is based on the observation that the short interest ratio is volatile and this volatility varies across stocks. Thus, an unexpected change in the short interest ratio could be small but significant relative to the volatility level of the ratio. Inversely, a large and unexpected change in the short interest ratio could be negligible if compared to volatility. To address this issue, we divide the unexpected change in the short interest ratio by the volatility of the ratio. In particular, we use past twelve-month moving window standard deviation of the short interest ratio. Formally, for stock i and month t, the

[3] We also use different window lengths and alternative procedures – for example, autoregressive models – to estimate the unexpected component of the short interest ratio. The results remain qualitatively similar.

surprise in short interest is defined as:

$$SUSIR_{i,t} = \frac{SR_{i,t} - \overline{SR}_{i,t-1,t-12}}{\sigma^{SR}_{i,t-1,t-12}}, \tag{3.1}$$

where $\overline{SR}_{i,t-1,t-12}$ is the twelve months moving window mean of short interest ratio and $\sigma^{SR}_{i,t-1,t-12}$ is the volatility of short interest ratio over past 12 months.[4] This proxy serves as our main variable of interest.

3.2.3 Summary statistics

We start our analysis with descriptive statistics, and these are presented in Table 3.1. Panel A reports the mean, standard deviation, and the 1st, 10th, 50th, 90th and 99th percentiles of the variables. All variables are winsorized at the 0.1% and 99.9% levels. Surprise in short interest has a mean of 0.332 and a median of 0.006, with a standard deviation of 2.069. Thus it is slightly skewed towards positive surprises. This result can be explained by the fact that short interest is limited by zero from below. Slight positive skewness is also observed for the short interest ratio, days to cover, and short interest over institutional ownership. The mean and median for these variables are 0.035 and 0.016, 6.085 and 3.721, and 0.067 and 0.033 respectively. The average market beta is around 1. Firm size is highly skewed, its median value being 826 $Mio and its mean around 4,498 $Mio. For this reason, we apply log transformation to this variable. The mispricing score ranges by construction from 0 to 100. A mispricing score close to 0 indicates strong underpricing of a stock, whereas a score of 100 indicates strong overpricing. The bid-ask spread varies from 0.2% for the 1st percentile to 2.5% for the 99th percentile. Mean institutional ownership ratio is 56.1% and increases to 100% for the top 1% of stocks. Other summary results are consistent with the literature.

[Insert Table 3.1]

Panel B shows Spearman correlations between variables. As expected, the $SUSIR$ is related to measures based on short interest. Its correlation coefficients with SR, DTC and SR_{IO} are equal to 0.22, 0.26 and 0.26 respectively. It is of great importance to control for these variables in order to test for the incremental effect of SUSIR on our dependent variables. Drechsler and Drechsler (2016) show that SR_{IO} serves as a good proxy for lending fees. Thus, $SUSIR$ tends to be only weakly correlated with shorting costs. Moreover, it is not correlated with proxies for limits to arbitrage, such as size, idiosyncratic volatility, bid-ask spread and institutional ownership ratio. In contrast, the other short interest-based variables clearly are related in some way to $SUSIR$. For instance, the correlation coefficients for these variables with $HLSPREAD$ and IO are 0.27, 0.13 and 0.31, and 0.55, 0.22 and 0.24 respectively. The results for the mispricing score go in a similar direction. The score's correlation coefficient with $SUSIR$ is 0.02. In comparison, the correlation coefficients with SR, DTC and SR_{IO} are 0.13, 0.13 and

[4]This definition is somewhat similar to the definition of standardized unexpected earnings surprises (SUE) that serves as a proxy for earnings surprises in the accounting and finance literature (see, for example, Foster, Olsen, and Shevlin (1984)). Such similarity in the definitions explains the similarity in the names.

0.19 respectively. Thus, our measure is less related to the aggregate mispricing score than existing short-interest-based measures.

3.3 Results

3.3.1 Surprise in short interest, short interest announcements, and stock returns

As a first step, we strive to understand how stock prices react to surprises in short interest. In particular, we take a closer look at the announcement period and investigate how fast this unexpected information on short interest is incorporated into prices. To conduct this analysis, we use the announcement dates of short- interest data for stocks traded primarily on the NYSE from 1995 to the end of our sample period. This sample choice is defined by the availability of historical short-interest dissemination dates. It is worth noting that there is a significant time gap of several days between the settlement date (when the short interest data is measured), which is always in the middle of the month, and the dissemination date (when the information is published by the NYSE), which usually scheduled for the last week of that same month. This time gap varies over the years. It is possible that some information is diffused before the exchange's official dissemination date. Therefore, the NYSE dissemination date is the last possible date on which the surprise in short selling may become available to the market. Consequently, we define the seven trading days prior to the NYSE's publication as the dissemination period. To test the price effects of the surprise in short interest, we calculate our surprise measure for each individual stock and month using the short interest data measured in the middle of the month. Then, at each NYSE dissemination date, we define one portfolio that consists of stocks with the top 30 percent surprises in short interest and one portfolio with the lowest 30 percent surprises. In the next step, for each announcement day, we calculate the abnormal and cumulative abnormal returns of the two portfolios around the announcement period using the equal-weighted market return as a benchmark. Finally, we calculate the cumulative average abnormal return across all events for each of the portfolios.

[Insert Figure 3.1]

Figures 3.1(a) and 3.1(b) display the cumulative average abnormal returns of the two portfolios from 10 trading days before the NYSE dissemination day to 30 days afterwards. Several important findings emerge. First, stocks with a high/positive surprise in short interest went through a significant price increase before the dissemination period, whereas stocks with a low/negative surprise in short interest decreased significantly in price before the dissemination period. Second, during the dissemination period, prices of stocks with high and low surprises start to revert to their previous level. Stocks with high surprises in short interest start to decrease in value whereas those with low short interest start to increase in value. Third and most interestingly, these negative and positive price reactions continue even after the publication of short interest data. In economic terms, stocks with high values of $SUSIR$ decrease in value by 0.25% within 30 trading days of the NYSE dissemination day, whereas those with low $SUSIR$

increase in value by 0.27% over that period. These values are not just economically meaningful but also statistically significant at the 1% level. Thus, we observe a strong price drift, but only a weak reaction, if any, to the short interest report on the day of the public announcement. There are a few possible explanations for this finding. First, some market participants might obtain the short-sale data before the NYSE's public announcement – for instance, from commercial data providers. As a result, reaction to the new information is incorporated into prices on different days within the dissemination period. Second, limits to arbitrage might prevent the information from being incorporated instantly. The drift might be a result of investors avoiding stocks that are more difficult to trade or that are prone to noise trader risk (De Long et al., 1990; Shleifer and Vishny, 1997). However, the fact that we observe a *positive* price drift even for stocks where the short interest surprise is low suggests that short-sale constraints are unlikely to play a crucial role. These stocks are also associated with a weak announcement effect, and an investment strategy that exploits this drift does not involve any of the costs or risks associated with short selling. Finally, our measure is constructed using a time series of 13F figures on short interest per stock and this type of calculation might represent significant signal extraction costs for many market participants. This explanation would be in line with Rapach, Ringgenberg, and Zhou's (2016) interpretation of market return predictability using detrended aggregate short interest.

In sum, the results of positive surprises in short interest are consistent with the findings of Senchack and Starks (1993), who analyze the reaction of stock prices to large increases in short interest. However, the positive price reaction after negative surprises is novel and contributes to a better understanding of the role of short-selling information in financial markets. More importantly, we document a long-run price drift following announcements of surprises in short interest. In the next part of our analysis we focus our analysis on this price drift and study the predictive power of SUSIR on a monthly basis. We explore whether the return predictability can be explained by well-known risk factors or common anomalies. In further analyses we investigate whether this return predictability reflects mispricing and a delayed price response to fundamental news. Lastly, we study the role of limits to arbitrage in explaining the existence of this return predictability.

3.3.2 Portfolio sorts and long-short strategies

In this part of the paper, we employ the portfolio approach on a monthly basis to test whether the surprise in short interest predicts future returns in the cross section of U.S. stocks. In particular, each month we sort the stocks into deciles according to the standardized unexpected short interest ratio, which is measured in the middle of the previous month and announced at the end of that month. If $SUSIR$ captures long-lived information about stock performance, we expect that stocks with a positive surprise in short interest associated with lower abnormal returns in the next month than stocks with a negative surprise in short interest.

[Insert Table 3.2]

Table 3.2 reports the average excess returns of the individual deciles and risk-adjusted returns across different factor models. Panel A shows the returns of equal-weighted portfolio, whereas Panel B shows the corresponding returns if stocks are weighted according to their market capitalization within the portfolios. As evident from Column (1), we find that stocks in the highest decile earn on average lower future returns compared to stocks in the lowest decile. Consistent with our expectation that SUSIR captures informed trading by short sellers, the difference between the two extreme equal-weighted portfolios amounts to 0.44%. This result is of meaningful economic magnitude and statistically significant at any conventional level. Moreover, the relation between the surprise in short interest and return is not only reflected in the extreme portfolios. Namely, the average return decreases almost monotonically in the surprise in short interest, with a minor exception only for the ninth and tenth portfolios. A similar return pattern emerges for the value-weighted portfolios in Panel B, though slightly more noisily in economic and statistical terms.

Next, to ensure that the difference in return observed above is not explained by standard risk or mispricing-related factors, we regress the time series of the long-short portfolio returns on a number of factors. We first employ the following risk-based factor models: the seminal Capital Asset Pricing Model (CAPM) by Sharpe (1964) and Lintner (1965), the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, the Carhart (1997) model with the Pástor and Stambaugh (2003) liquidity factor, and the two more recent models, namely Fama and French (2015) and Hou, Xue, and Zhang (2014). The results are reported in Columns (2) to (7). Most importantly, the risk-adjusted returns are positive and statistically different from zero across all the factor models, suggesting that classical risk -factors are unable to explain the predictive power of $SUSIR$.

Moreover, to ensure that the surprises in short interest do not simply mimic the arbitrageurs' trading on well-known mispricing factors, we also account for factors that have been recently related to misvaluation rather than to traditional explanations of risk. Namely, in Column (8) we employ the Carhart (1997) model, and include two additional factors: quality minus junk (QMJ) (Asness, Frazzini, and Pedersen, 2018) and betting against beta (BAB) (Frazzini and Pedersen, 2014). We choose these factors because, first, Jank and Smajlbegovic (2016) document that they are associated with the actual trading of short sellers, and, second, Harvey and Liu (2018)show that they, especially QMJ, are of great importance in explaining the cross section of stock returns when returns are value-weighted. The alpha in Column (8) suggests that the surprise in short interest does not simply capture trading on these two prominent mispricing factors. In the last specification, we control for the mispricing factor recently proposed by Stambaugh and Yuan (2017), who combine 11 different anomalies into one score reflected in the factor underpriced minus overpriced (UMO). Although the adjusted return of the value-weighted long-short *SUSIR* portfolio decreases slightly relative to the raw portfolio return, it remains economically large and statistically significant.

As a robustness check, we form a more conservative long-short portfolio using the top and bottom 30 percent of stocks instead of deciles. This sorting exercise largely reduces the difference between the average surprise in short interest of the two extreme portfolios and thereby makes it more difficult to identify a significant difference in returns. Nonetheless, the average returns of the portfolio across all models are positive and statistically significant. This result demonstrates that the predictive relation between surprise in short interest and stock returns is not driven by extreme observations.

[Insert Table 3.3]

Next we explore whether the return spread between stocks with low and high surprise in short interest can be explained by other measures related to short-sale constraints. Namely, previous empirical research finds that the level of short interest predicts future negative abnormal returns (Desai et al., 2002; Boehmer, Jones, and Zhang, 2008; Diether, Lee, and Werner, 2009; Asquith, Pathak, and Ritter, 2005). This predictive relationship has been associated with two mutually non-exclusive explanations.: On the one hand, the predictability suggests there is informed trading by short sellers; on the other hand, the effect might also stem from the fact that stocks with a high level of short interest are more difficult to short, resulting in overpricing and predictability of negative future returns. To address the concern that $SUSIR$ captures solely the level effect of short interest, we now add the return of the long-short portfolio based on the two extreme short interest ratio deciles to the Carhart (1997) model (Column (1)) to a still statistically significant return of around 0.255 percent for the equal-weighted portfolio and 0.288 percent for the value-weighted portfolio.

In a recent study, Hong et al. (2016) show that days to cover (DTC), the ratio of short interest to trading volume, measures the costliness of exiting crowded trades such that arbitrageurs require a premium for trading stocks with high DTC. In Column (3) we analyze whether this premium can explain the return spread that arises from the surprise in short interest. We document a positive relation between our portfolio and the DTC long-short portfolio. Also, more importantly for our study, this relation does not entirely explain the return based on surprise in short interest.

Lastly, Drechsler and Drechsler (2016) find that the ratio between short interest (demand for shorting) and shares held by institutional investors (lending supply) negatively predicts the cross section of stock returns. The authors justify this predictability as a premium that compensates short sellers for their limited risk-bearing capacity. Including a long-short portfolio based on this ratio in our time-series regression in Column (4), we find that shorting premium does not entirely explain the effect of surprise in short interest.

Finally, in the last specification, we add all three of the short-interest-related factors previously discussed to the Carhart (1997) four-factor model. We observe that the effect of informed short selling, as proxied by the surprise in short interest, remains economically and statistically significant even in the full specification.

3.3.3 The cross section of individual stock returns

So far, the results of the portfolio sorting suggest there is a negative relation between surprise in short interest and future stock returns. In this part of the paper we employ the returns of individual U.S. stocks and conduct a regression analysis along the lines of Fama and MacBeth (1973), with monthly excess returns as the dependent variable. Compared to the portfolio approach, this stock-specific approach allows us to account more easily for other firm characteristics and rule out other possible explanations for the effect of $SUSIR$. Formally, we run a cross-sectional regression for each month t:

$$Ret_{i,t} = \alpha_t + \beta_t SUSIR_{i,t-1} + \mathbf{x'_{i,t-1}} \mathbf{b_t} + \varepsilon_{i,t}, \tag{3.2}$$

where $SUSIR_{i,t-1}$ denotes the stock-specific surprise in short interest as defined in Equation (3.1) and $\mathbf{x_i}$ represents a vector of control variables depending on the specification. All the explanatory variables are standardized with a mean of zero and a standard deviation of one. We then calculate the time-series average of each estimated regression coefficient and its t-statistic. To account for autocorrelation and heteroskedasticity in the error terms, we use the Newey and West (1987) correction with twelve lags. If a positive surprise in short interest reflects informed short selling and has predictive power for stock returns, we expect there to be a significant negative estimate for β. We report the estimation results for different specifications of Equation (3.2) in Table 3.4.

[Insert Table 3.4]

The first specification in Column (1) of Table 3.4 considers only $SUSIR$ considers only SUSIR and the standard control variables as explanatory variables. Using this simple design, we find that the surprise in short interest negatively predicts individual stock returns. The regression coefficient associated with the proxy is 0.114, with a corresponding t-value of 5.73. Therefore, the average return spread between a stock that is one standard deviation below the mean of $SUSIR$ and a stock that is one standard deviation above the mean is around 0.23%. This result is consistent with the portfolio sort findings in Table 3.2 using the top and bottom 30 percent $SUSIR$ in the cross section of stocks.

Next, we account for the level of short interest ratio and proxies of short-sale constraints in the regression framework. In Columns (2) to (4), we add the level of short interest, days to cover, and the ratio between short interest and shares held by institutional investors respectively. As is evident from the table, for all three specifications the coefficient of surprise in short interest decreases slightly but remains economically and statistically significant. Moreover, in line with the existing studies, we find that all three control variables negatively predict the cross section of future stock returns.

We then test whether the two recent prominent factors, investment and profitability (Fama and French, 2015; Hou, Xue, and Zhang, 2014), affect the predictive power of $SUSIR$. In Column (5) we observe that the coefficients of both variables have the expected signs, but the effect of surprise in short interest is essentially unchanged relative to our benchmark specification in Column (1).

Our next step is to account for the possibility that surprise in short interest simply reflects the trading of short sellers on well-known mispricing factors. Similar to the portfolios sorts, we rely on the mispricing score of Stambaugh and Yuan (2017). A high score indicates that a stock is overpriced, whereas a low score suggests underpricing. We therefore expect the coefficient to the mispricing score to be negative. As is evident in Column (6), we find that the proxy of

Stambaugh and Yuan (2017) negatively predicts stock returns. More important for this study, we observe that the surprise in short interest remains a significant cross-sectional predictor of future stock returns.

In Column (7) we include the idiosyncratic volatility of the individual stock to control for the low-volatility anomaly. Most notably, it does not affect our $SUSIR$ result. However, consistent with previous research (e.g., Ang et al., 2006), we document that high idiosyncratic volatility is associated with lower future returns. Lastly, in Column (8), we include all previously introduced variables in one specification and find that the surprise in short interest is still a meaningful and important predictor of the cross section of future stock returns.

Both the portfolio approach and the analysis of the level of individual stock returns suggest that $SUSIR$ captures the informed trading by short sellers. In the remaining part of this paper, we strive to better understand the source and channels of this return predictability.

3.3.4 The time-series dimension of return predictability

To understand the source of return predictability, we turn to the time-series properties of the SUSIR long-short strategy. We check the stability of monthly returns delivered by the strategy over time. In particular, we calculate and then analyze the cumulative returns. Severe crashes in returns would be consistent with a risk-based explanation of the strategy's abnormal profits. Momentum (Daniel and Moskowitz, 2016) and days-to-cover (Hong et al., 2016) strategies are well-known examples of risky strategies that experienced severe crashes, in particular, around the 2008 financial crisis. Second, we look at the performance of the $SUSIR$ long-short portfolio up to 24 months after portfolio formation. The main purpose of this exercise is to rule out the possibility that the negative relation between $SUSIR$ and future stock returns is the result of temporary price changes due to short-sellers' overreaction or uninformed demand shocks. If these explanations were to apply, we would expect a reversal in the strategy's return in the long run.

Figure 3.2 illustrates the overall performance of the SUSIR long-short strategy over time. We plot the logarithmic cumulative raw returns to ensure comparability between performance at different time periods. The plot indicates that the strategy does not exhibit strong negative returns or crashes over the sample period. This finding serves as the first evidence that supports the mispricing-based explanation of the strategy's profits.[5]

[Insert Figure 3.2]

Is the profitability of the $SUSIR$ long-short strategy the result of temporary or permanent price changes? To answer this question we analyze the long-run performance of the $SUSIR$ buy-and-hold portfolio. First, we form decile portfolios based on $SUSIR$ in every month t. Next, we calculate equal- and value-weighted raw excess returns of the first minus tenth decile portfolios in month $t + k$, where $k \in \{1, ..., 24\}$. Finally, we run the following time-series regression for

[5]In unreported results we examine the impact of Baker and Wurgler's (2006) investor sentiment index on the returns of $SUSIR$-based long-short strategy. Our results reveal no significant relation.

each holding period month k:

$$LS\_SUSIR_{t+k} = \alpha_k + \beta_{MKTRF,k}MKTRF_{t+k} + \beta_{SMB,k}SMB_{t+k} + \\ + \beta_{HML,k}HML_{t+k} + \beta_{UMD,k}UMD_{t+k} + \varepsilon_{k,t+k}, \tag{3.3}$$

where LS_SUSIR_{t+k} is the raw excess return in month $t+k$ of the long-short portfolio formed in month t, and $MKTRF_{t+k}$, SMB_{t+k}, HML_{t+k}, UMD_{t+k} are the returns on the four factors of the Carhart (1997) model in month $t+k$. The intercept of the regression (α_k) is the alpha of the buy-and-hold strategy k months after portfolio formation.

[Insert Figure 3.3]

Figure 3.3 presents equal-weighted and value-weighted average holding period alpha obtained by accumulating over the months of the holding period the four-factor alphas from Equation (3.3). The figure reveals a pattern that is consistent with $SUSIR$ predicting permanent price changes. The long-short portfolio delivers abnormal returns up to 18 months after portfolio formation and the returns do not revert to previous levels, as it would be the case for temporary price changes. Surprisingly, the performance of the equal-weighted and value-weighted portfolios are very similar until month 8. After this point, the cumulative alpha of the value-weighted portfolio hovers around 2%, whereas the equal-weighted portfolio continues to deliver abnormal performance until month 18, when it reaches 3.6%. Thus, the ability of surprise in short interest to predict stock returns is not limited to the first months and is not associated with price reversal in the long run.

3.3.5 Surprise in short interest, biased expectations and fundamental news

In this section we ask whether the ability of surprise in short interest to predict the cross section of stock returns is the manifestation of risk or mispricing. Return predictability might arise if market participants have biased expectations. However, when the information becomes available to the market, the firm's value should converge to its fundamental level. To be consistent with this type of mispricing-based explanation, $SUSIR$ should satisfy the following two conditions. First, it should predict future changes in fundamentals (cash-flow news). Second, the ability to predict stock returns should be stronger on the days when such valuation-relevant news is released. We use quarterly earnings announcements to test our two hypotheses. Companies' quarterly earnings reports contain valuable information about firm fundamentals. We use earnings surprises as a proxy for fundamental news in these reports. Market participants update their expectations when reports are released. Consequently, these changes in expectations are reflected in equity prices.

To test our first hypothesis, we check whether surprises in short interest can predict future surprises in announced earnings. Using data on 196,719 earnings announcements, we run a panel regression of earnings surprises on the most recent $SUSIR$ measure and other controls including month-fixed effects:

$$Earnings\_Surprise_{i,t} = \alpha_t + \beta_t SUSIR_{i,t-1} + \mathbf{x'_{i,t-1}b_t} + \varepsilon_{i,t}, \tag{3.4}$$

where $SUSIR_{i,t-1}$ is the stock-specific surprise in short interest in month $t-1$ and $\mathbf{x_{i,t-1}}$ is a vector of control variables depending on the specification.

We use three measures of earnings surprises. The first measure is standardized unanticipated earnings based on past earnings (SUE^{PE}). This measure is equal to the difference between current earnings per share and earnings per share reported four quarters previously, divided by the standard deviation of this difference over the past eight quarters. It is derived on the assumption that earnings follow a seasonal random walk and it performs well in terms of capturing earnings news (Foster, Olsen, and Shevlin, 1984). The second measure is standardized unanticipated earnings based on analyst forecasts (SUE^{AF}), also known as analyst forecast errors. In contrast to SUE^{PE}, this measure uses analyst forecasts as a proxy for the market expectation of EPS. It is defined as an actual EPS net of the most recent mean analyst forecasts over the standard deviation of analyst forecasts. This measure is obtained directly from IBES. Finally, the third measure, CAR, is the cumulative market-adjusted return over the earnings announcement window $[-1, 1]$. The CRSP value-weighted portfolio is used as a benchmark index. In some specifications we control for two measures of stock misevaluation: short interest ratio and mispricing score. There are two reasons to include short interest ratio. First, the short interest ratio predicts stock returns and its predictive power might also come from the fundamental news channel (Akbas, Boehmer, et al., 2013). Second, $SUSIR$ is derived using information from the short interest ratio. We also control for mispricing score that aggregates misvaluation-related information (Stambaugh, Yu, and Yuan, 2015; Stambaugh and Yuan, 2017). If surprise in short interest is not simply loading on known factors, it should have significant predictive power on top of these factors. The explanatory variables are standardized to have zero mean and unit standard deviation to ensure the comparability of coefficients.

Regression results are reported in Table 3.5. The sample period starts in May 1985 for SUE^{PE}, in May 1992 for SUE^{AF}, and in May 1980 for CAR. The sample period is limited by data availability. All earnings surprise variables are multiplied by 100 to improve the readability of the table. All earnings surprise measures are winsorized at the 1% and 99% levels. The standard errors are double-clustered by month and stock. The standard control variables are market beta, log size, log book-to-market ratio, momentum and short-term reversal. The left panel of the table reports results for SUE^{PE}. The coefficient on $SUSIR$ in the specification that includes only month-fixed effects is -0.0302 with a t-statistic of -3.51. The negative sign of the coefficient means that an increase in surprise in short interest predicts lower earnings surprises, all else being equal. The inclusion of standard controls makes the predictive power of $SUSIR$ even stronger (Column (2)). Controlling for $MISP$ and SR slightly decreases the significance of $SUSIR$ (Columns (3) and (4)). As expected, SR and $MISP$ are also significant predictors of earnings surprises. Coefficients on other control variables are in line with the literature. Regression results for SUE^{AF} are presented in the middle panel. Two additional controls are added: number of analysts producing the forecast ($NUMEST$) and standard deviation of forecasts ($STDEV$). The coefficients on the variables are qualitatively similar to those for SUE^{PE}. Regression with CAR as the dependent variable produces statistically weaker but nevertheless significant results. They are reported in the right panel. Regression coefficient allows easy interpretation of the economic importance of $SUSIR$. In the specification with solely month-fixed effects, the coefficient -0.0515 (t-stat -3.08) means that, all other things being equal, an increase of two standard deviations in $SUSIR$ results in announcement returns that are 10.3 basis points lower. Accounting for $MISP$ and SR slightly decreases this number to 7.3 basis points. The statistical significance of $SUSIR$ stays above the 95% confidence level in all the specifications that we considered. Interestingly, the predictive power of SR is much stronger when using CAR as a measure of earnings surprises. It has more than double the predictive power of $SUSIR$ and is even stronger than for $MISP$. Overall, the tests show that surprise in short interest is a statistically and economically significant predictor of earnings surprises. This result is in line with our first hypothesis.

[Insert Table 3.5]

To test the second hypothesis, we turn to a daily frequency and adopt the methodology of Engelberg, Mclean, and Pontiff (2018). The sample contains 12,552,943 day-stock observations. The earnings announcement dates are from the Compustat quarterly file. Our goal is to compare the predictive power of short interest surprise on announcement days to non-announcement days. We first define an earnings announcement period dummy (EAP) equal to 1 for the days that are within the three-day window around the earnings announcement. We run a panel regression of raw daily stock returns on EAP, the most recent $SUSIR$, the interaction between them ($SUSIR \times EAP$) and other control variables:

$$Ret_{i,t} = \alpha_t + \beta_{1,t} EAP_{i,t} + \beta_{2,t} SUSIR_{i,t-1} + \beta_{3,t} SUSIR_{i,t-1} \times EAP_{i,t} + \mathbf{x'_{i,t-1}} \mathbf{b_t} + \varepsilon_{i,t}, \quad (3.5)$$

The coefficient on $SUSIR_{i,t-1}$ reflects the average predictive power of $SUSIR$ on non-announcement days. The coefficient on the interaction variable shows an additional predictive power of $SUSIR$ upon earnings announcements. The mispricing-based explanation commands a significant negative coefficient on this variable.

We report the estimation results in Table 3.6. In all specifications, standard errors are clustered by month. The regression specification in Column (1) includes only EAP, $SUSIR$ and the interaction between them as explanatory variables, together with day-fixed effects. The significantly positive coefficient on EAP is the manifestation of an earnings announcement premium first discovered by Beaver (1968). $SUSIR$ is a significant predictor of stock returns on both announcement and non-announcement days. However, the predictability is almost five times stronger upon announcements days. The introduction of four lags of return, return squared and daily turnover has no significant impact (Column (2)). Controlling for mispricing and short interest ratio slightly weakens the results but does not change the implications (Column (3)). Consistent with the mispricing-related nature of the short interest ratio (Akbas, Boehmer, et al., 2013) and mispricing score (Stambaugh, Yu, and Yuan, 2015), the interaction coefficients of these variables with EAP are also significant and imply around 3.5 times stronger return predictability upon news arrival. Further specifications address some possible risk-based explanations of the effect. Savor and Wilson (2016) argue that firms that are making announcements have higher exposure to fundamental risk than firms that are not doing so. To control for this risk heterogeneity, we include day-EAP fixed effects. As is evident from Column (4), the announcement risk premium does not drive our results. In Column (5), we analyze whether the increase in exposure to systematic risk for earnings announcers documented by Patton and Verardo (2012) might influence our inference. That is, we test whether stocks with more negative surprises in short interest (associated with higher future returns) experience a larger increase in market beta around earnings announcements. For that, we introduce market return, proxied by the CRSP value-weighted index (MKT), to our baseline specification from Column (2). We interact MKT with EAP and $SUSIR$ and add triple interaction of these variables. The coefficient on MKT confirms that average market beta is around 1. The coefficient on $MKT \times EAP$ reveals the average effect of earnings announcements on market beta to be positive but statistically insignificant (t-stat of 0.54). The insignificant coefficient on $MKT \times SUSIR$ of -0.00567 (t-stat of -1.27) suggests that market exposure is not significantly correlated with $SUSIR$. Surprisingly, the coefficient on triple interaction is positive and significant, meaning that high $SUSIR$ stocks experience an increase in market beta on announcement days, while low stocks experience a decrease. Given that $SUSIR$ is normalized to have zero mean and unit standard deviation, the coefficient of 0.0204 means that a stock whose $SUSIR$ is one standard deviation above (or below) its average experiences an increase (or decrease) in its market beta by 0.02 around earnings announcements. A $SUSIR$ long-short strategy is long in low-$SUSIR$ stocks and short in high-$SUSIR$ stocks, meaning that the market exposure of this strategy actually decreases on days when announcements are made. Thus, if anything, the strategy gets less risky on these days. All in all, our tests show that $SUSIR$'s predictive ability is economically and statistically stronger on earnings announcement days. This effect is not explained by an earnings announcement premium or an increase in exposure to market risk.

[Insert Table 3.6]

To conclude, in this subsection we find that information contained in $SUSIR$ is relevant for identifying misvalued stocks. We formulate two hypotheses that are consistent with the informational advantage of arbitrageurs. The first hypothesis states that return predictability stems from biased expectations, which are corrected when news arrives. The second hypothesis states that if biased expectations are the main channel of return predictability, then return predictability should be stronger on days when new valuation-relevant information is released. We find support for both hypotheses. First, we show that stocks with higher $SUSIR$ experience lower earnings surprises, while those with lower $SUSIR$ experience higher earnings surprises. This conclusion holds for various measures of earnings surprises. Second, we find that the ability of $SUSIR$ to predict stock returns becomes almost five-fold stronger around earnings announcements. Moreover, this effect is not explained by an increase in systematic risk. Our results are thus consistent with the mispricing-based explanation of $SUSIR$'s ability to predict stock returns.

3.3.6 Limits to arbitrage

Our results so far indicate that $SUSIR$ reflects information on misvaluation. This naturally prompts the question: Why do investors not arbitrage away this misvaluation? Certain limits to arbitrage might sustain short-term deviations of stock prices from fundamental values. The seminal work of Shleifer and Vishny (1997) provides an important framework and justification for the persistence of mispricing and predictability of stock returns. These authors argue that arbitrage opportunities should vanish immediately as a large number of investors take positions against the mispricing, driving the stock price back to its fundamental value. However, in reality, due to noise trading, the stock price might diverge in short-run even further from the fundamental value, inducing losses to the arbitrageur. This fact could prevent the investors from trading on mispricing in the first place and could set certain limits to arbitrage.

To test whether the predictability arises, at least in part, from these limits to arbitrage (Shleifer and Vishny, 1997), we define variables that have been related in previous research to trading impediments. Then, for each of the variables, we sort the stocks into quintiles. Finally, we include dummy variables for each quintile, except the first one, and incorporate their interactions with $SUSIR$ into a Fama and MacBeth (1973) regression framework:

$$\begin{aligned} Ret_{i,t} = \alpha_t + \beta_1 SUSIR_{i,t-1} + \sum_{k=2}^{5} \beta_k M_{Quintile=k,i,t-1} + \\ + \sum_{k=2}^{5} \gamma_k SUSIR_{i,t-1} \times M_{Quintile=k,i,t-1} + \mathbf{x_i'b} + \varepsilon_{i,t}, \end{aligned} \tag{3.6}$$

where $M_{Quintile=k}$ denotes the dummy variable equal to one if the limits-to-arbitrage variable M is in the kth quintile. The coefficients γ_2 to γ_5 are of most interest in this subsection. In particular, we expect that the negative predictability associated with $SUSIR$ is the strongest in the quintile with the highest limits to arbitrage. Also, note that the estimate β_1 denotes the effect of $SUSIR$ in the lowest quintile of variable M. We now consider three different variables that are closely related to the mechanism of limits to arbitrage and commonly used in the literature: The spread estimator of Corwin and Schultz (2012) as a proxy for illiquidity, idiosyncratic volatility as a proxy for arbitrage risk (Pontiff, 2006; Stambaugh, Yu, and Yuan, 2015), and residual institutional ownership as a proxy for short-sale constraints (Nagel, 2005). If limits to arbitrage are important for the persistence of mispricing, we expect that predictability is the strongest (more negative) for stocks with high illiquidity, high idiosyncratic volatility, or lower residual institutional ownership.

[Insert Table 3.7]

Column (1) of Table 3.7 shows the time-series average of the cross-sectional regression coefficients employing the standard control variables, surprise in short interest, dummy variable for each quintile of illiquidity (except the first one), and the interaction terms of $SUSIR$ with the dummy variables. In line with our prediction, we find that the predictive power of surprise in short interest is strongest for the highest quintile of illiquidity. In terms of economic magnitude, the return spread associated with surprise in short interest is around three times larger for the most illiquid stocks than for the most liquid. Also, except for the second quintile, this effect of illiquidity is monotonic across the quintiles. The intuition behind this finding is that the more illiquid the stock, the slower and more costly it will be to trade on the market. These additional costs could prevent investors from fully exploiting arbitrage opportunities and from taking advantage of the return predictability.

Next, we examine the role of idiosyncratic volatility for predictability of returns. In the framework of Shleifer and Vishny (1997), stocks with greater volatility are less attractive to arbitrageurs and exhibit larger predictable returns than stocks with less volatility. Column (2) shows results that are in line with this hypothesis. The predictability in the quintile with the most volatile stocks is five times higher than that of the least volatile stocks. Interestingly, this relation is monotonic, and the predictability using $SUSIR$ is statistically significant across four of the five volatility quintiles.

Lastly, we employ the residual of institutional ownership as a proxy for limits to arbitrage. More specifically, Nagel (2005) suggests that this variable serves as a meaningful proxy for the supply of stocks to borrow in the lending market. In the case of low supply, arbitrageurs face higher impediments to short the stock, resulting in stronger predictability in the event of overpricing. In Column (3), we do not find any evidence of stronger return predictability for stocks with low lending supply. The effect is essentially the same across all five rio quintiles. There are two mutually non-exclusive possible explanations for this non-finding. First, the supply of stocks to borrow is particularly important for anomalies that are driven by the short leg. Given that the strategy based on $SUSIR$ yields profitable returns on both the long and the short leg, short-sale constraints cannot represent the ultimate explanation in the first place. Second, the construction of the surprise in short interest is based on abnormal changes of short interest compared to the usual variation in the past. Consequently, an extreme negative or positive change in the level of short interest implies that this particular stock is most probably *not* short-sale-constrained.[6]

Overall, in line with Shleifer and Vishny's (1997) limits-to-arbitrage argument, we find evidence that general trading impediments (Gromb and Vayanos, 2010), such as illiquidity and idiosyncratic volatility, are positively related to the strength of predictability. However, we also document that short-sale constraints cannot explain the effect of $SUSIR$. Therefore, the predictive ability of $SUSIR$ is unlikely to be due to a low supply of lendable shares or high lending fees (Drechsler and Drechsler, 2016).

3.4 Conclusion

This paper contributes to the ongoing discussion of the impact of short sellers on the informational efficiency of capital markets. We introduce a new measure of informed trading, surprise

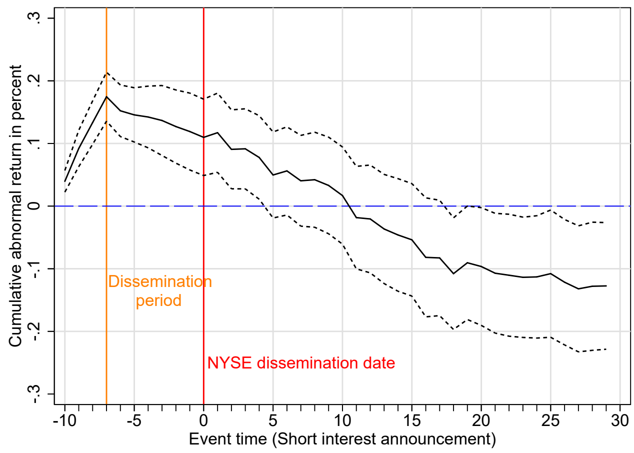
[6] In untabulated tests we find similar results for other short-sale constraint proxies such as the level of short interest ratio (Asquith, Pathak, and Ritter, 2005) or the short interest relative to institutional shares (Drechsler and Drechsler, 2016)

in short interest, that incorporates two regular features of the short interest data: strong persistence in the levels of short interest ratio and large cross-sectional differences in volatility. The long-short strategy based on this measure delivers up to 6% in annualized risk-adjusted returns that are not explained by standard stock characteristics, by other known short interest-based strategies or short-sale constraints. Evidence suggests that our measure identifies market mispricing that stems from biased beliefs of market participants and persists due to trading impediments, such as illiquidity and idiosyncratic volatility. Thus, surprise in short interest represents a mispricing-related anomaly that is not identified in the prior literature.

Our findings have wide-reaching implications for future studies on the informational role of short sellers. For instance, one important question remains: What is the source of arbitrageurs' informational advantage? Therefore, an interesting avenue for future research is to study the relation between the surprise in short interest and future corporate events and news (e.g., Engelberg, Reed, and Ringgenberg, 2012), insider trades, and capital market anomalies.

Tables and Figures of Chapter 3

(a) CAAR for stocks with high surprise in short interest



(b) CAAR for stocks with low surprise in short interest

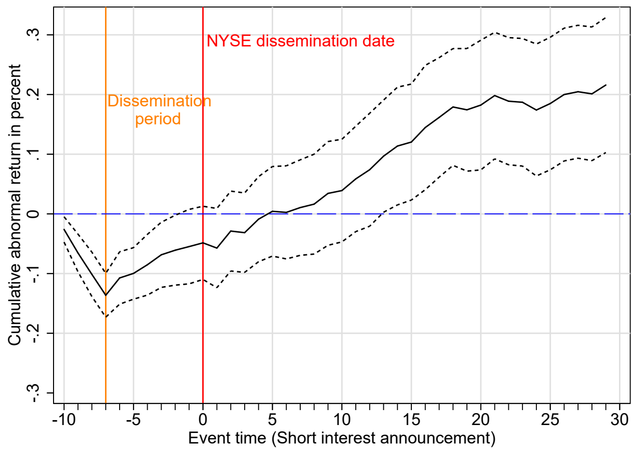


Figure 3.1:
Cumulative Average Abnormal Returns Around Short Interest Announcement
This figure displays the cumulative average abnormal returns (CAARs) of two portfolios based on the surprise in short interest. The benchmark is the market return and the time window is 10 days before and 30 days after the NYSE's short interest dissemination day. Figure 3.1(a) plots the CAAR for stocks with the highest 30% of surprises in short interest at each event day, whereas Figure 3.1(b) plots the CAAR for stocks with the lowest 30% of surprises in short interest at each event day. The dashed lines represent the upper and lower 90% confidence intervals. The sample starts in January 1995 and contains stocks traded on the NYSE.

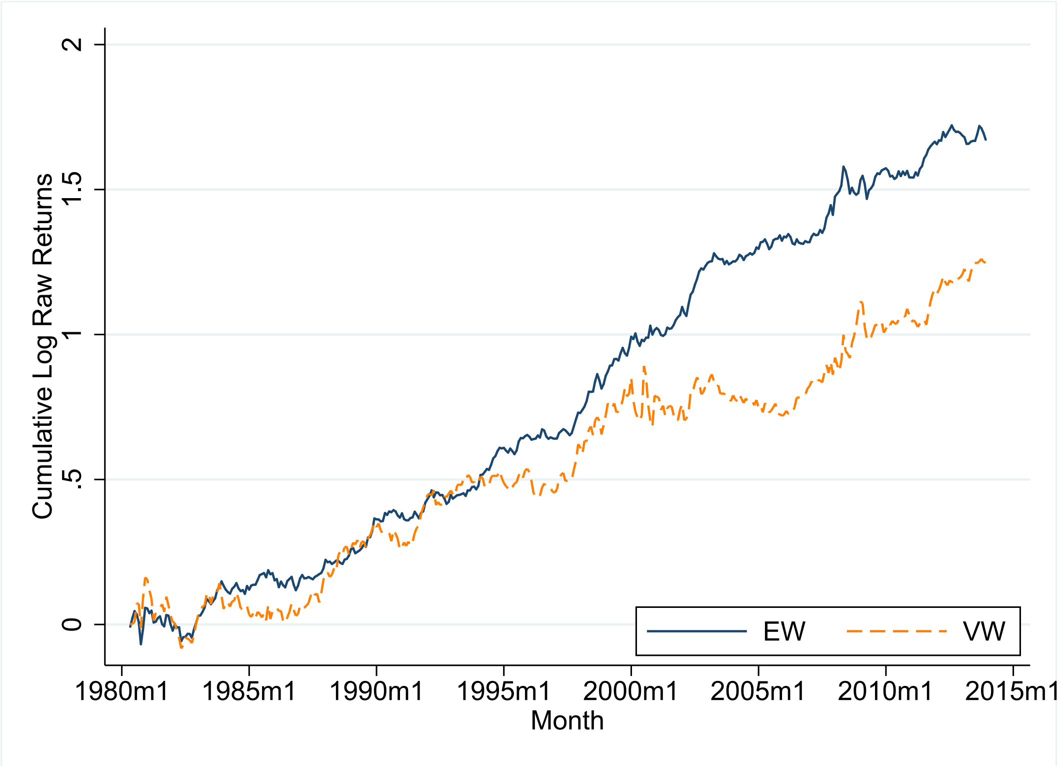


Figure 3.2:
Cumulative Logarithmic Raw Returns
This figure shows the monthly cumulative sums of log raw returns for equal-weighted and value-weighted *SUSIR* long-short strategies over the period from March 1980 to December 2013.

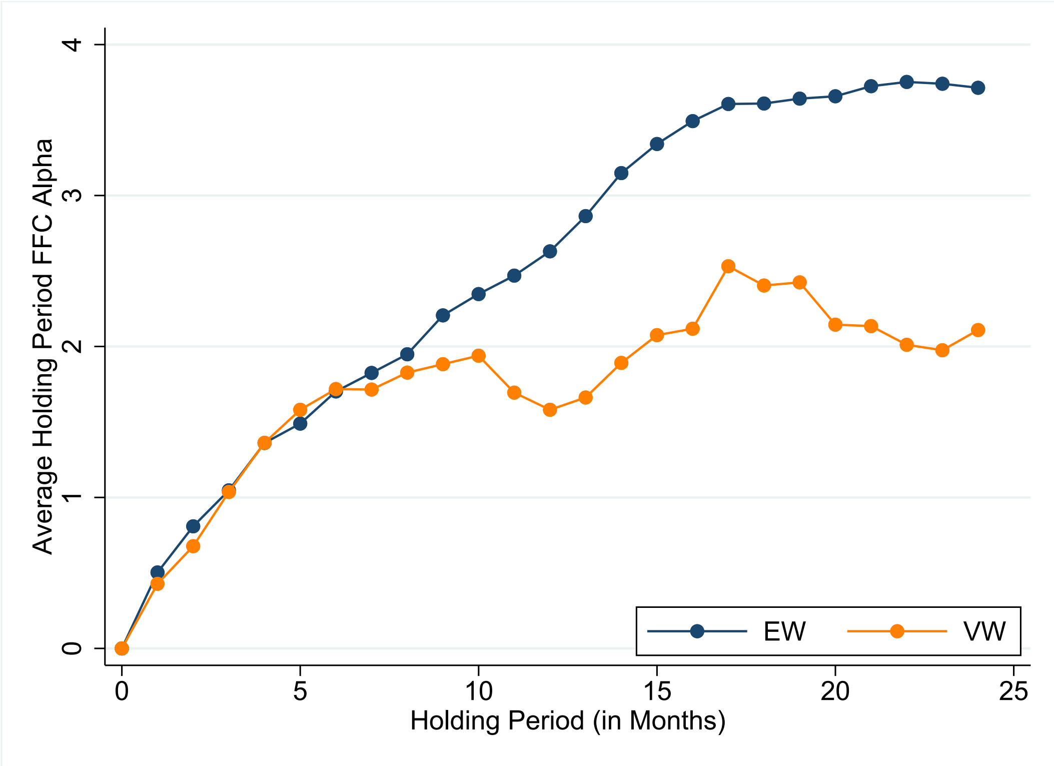


Figure 3.3:
Holding Period Performance of $SUSIR$ Long-Short Strategy
This figure plots the average cumulative Carhart (1997) four-factor alpha of long-short portfolios over the holding period. We first construct the long-short portfolio each month according to $SUSIR$ and calculate monthly returns in the month $t+k$, where $k \in \{1, ..., 24\}$. Second, we run a time-series regression for each holding period month k of the $SUSIR$ long-short strategy on four factors. The corresponding strategy average four-factor alpha at month k is the intercept (α_k) in the following regression:

$$LS\_SUSIR_{t+k} = \alpha_k + \beta_{MKTRF,k} MKTRF_{t+k} + \beta_{SMB,k} SMB_{t+k} + \\ + \beta_{HML,k} HML_{t+k} + \beta_{UMD,k} UMD_{t+k} + \epsilon_{k,t+k}.$$

In the final step, the alphas are accumulated over months in the holding period . The sample period is from March 1980 to December 2013.

Table 3.1:
Descriptive Statistics
Panel A of this table reports univariate summary statistics (mean, standard deviation and 1st, 10th, 50th, 90th, 99th percentiles) of the variables used in this study. The first set of variables in Panel A is based on short interest data. Standardized unexpected short interest ratio ($SUSIR$) is the short interest ratio net of its 12-month moving average over its 12-month moving standard deviation. Short interest ratio (SR) is the short interest over shares outstanding. The days-to-cover measure (DTC) is equal to short interest divided by daily turnover. SR_{IO} is short interest ratio over institutional ownership ratio. The second set of variables in Panel A is the set of stock characteristics known to predict stock returns. Market beta ($MBETA$) is calculated using 12 months of daily data. Size ($SIZE$) and book-to-market ratio (BM) are constructed as in Fama and French (1992). Return reversal (RET_RV) is the return over the month $t-1$. Return momentum (RET_MOM) is the cumulative return from month $t-12$ to $t-2$. Investment (INV) is the asset growth measure of Cooper, Gulen, and Schill (2008). Return on assets (ROA) is equal to income before extraordinary items over assets. $MISP$ is the mispricing score of Stambaugh, Yu, and Yuan (2015). The third set of variables in Panel A is the set of proxies for the limits to arbitrage. Idiosyncratic volatility ($IVOLA$) is constructed using 12 months of daily data as in Ang et al. (2006). $HLSPREAD$ is the bid-ask spread of Corwin and Schultz (2012). Institutional ownership ratio (IO) is the proportion of shares outstanding owned by institutional investors. All variables are winsorized at the 0.1% and 0.99% levels. Panel B of this table reports Spearman correlations of variables.

Panel A: Summary Statistics							
			Percentiles				
Variable	Mean	SD	1st	10th	Median	90th	99th
$SUSIR$	0.332	2.069	-2.935	-1.484	0.006	2.338	6.452
SR	0.035	0.049	0.000	0.001	0.016	0.091	0.239
DTC	6.085	7.509	0.015	0.496	3.721	13.951	37.831
SR_{IO}	0.067	0.122	0.000	0.003	0.033	0.153	0.498
$MBETA$	1.042	0.452	0.018	0.505	1.018	1.607	2.283
$SIZE$	4498.113	17182.012	33.312	126.298	826.032	8202.445	69739.656
BM	0.643	0.528	0.000	0.190	0.545	1.169	2.338
RET_RV	0.012	0.113	-0.291	-0.113	0.009	0.138	0.342
RET_MOM	0.196	0.518	-0.606	-0.280	0.121	0.688	2.126
INV	0.158	0.397	-0.327	-0.065	0.081	0.399	1.722
ROA	0.049	0.117	-0.386	-0.015	0.048	0.143	0.326
$MISP$	48.934	12.735	22.150	32.830	48.360	65.880	79.990
$IVOLA$	0.019	0.012	0.005	0.008	0.016	0.032	0.061
$HLSPREAD$	0.008	0.005	0.002	0.003	0.007	0.014	0.025
IO	0.561	0.261	0.026	0.184	0.578	0.903	1.000

Panel B: Correlation Table

	$SUSIR$	SR	DTC	SR_{IO}	$MBETA$	$SIZE$	BM	RET_RV	RET_MOM	INV	ROA	$MISP$	$IVOLA$	$HLSPREAD$	IO
$SUSIR$	1.00														
SR	0.22	1.00													
DTC	0.26	0.76	1.00												
SR_{IO}	0.26	0.91	0.79	1.00											
$MBETA$	0.00	0.17	0.05	0.15	1.00										
$SIZE$	-0.02	0.22	0.04	0.07	0.05	1.00									
BM	-0.03	-0.22	-0.13	-0.19	-0.03	-0.25	1.00								
RET_RV	0.02	-0.02	-0.03	-0.02	-0.01	0.06	0.03	1.00							
RET_MOM	0.01	-0.07	-0.09	-0.06	-0.02	0.08	0.01	0.01	1.00						
INV	0.04	0.03	0.00	0.05	0.03	0.02	-0.22	-0.02	-0.04	1.00					
ROA	0.00	-0.05	-0.11	-0.09	-0.07	0.16	-0.38	0.01	-0.01	0.38	1.00				
$MISP$	0.02	0.13	0.13	0.19	0.10	-0.20	0.12	-0.02	-0.27	0.42	-0.31	1.00			
$IVOLA$	0.03	0.12	-0.07	0.16	0.25	-0.34	-0.08	-0.01	-0.11	0.07	-0.07	0.17	1.00		
$HLSPREAD$	0.01	0.27	0.13	0.31	0.21	-0.26	-0.06	-0.09	-0.18	-0.02	-0.15	0.19	0.56	1.00	
IO	-0.02	0.55	0.22	0.24	0.12	0.43	-0.17	0.00	-0.03	-0.02	0.08	-0.08	-0.04	0.05	1.00

Table 3.2:
Performance of $SUSIR$ Sorted Portfolios.
This table reports performance of equal-weighted (Panel A) and value-weighted portfolios (Panel B) formed by monthly sorting stocks into deciles on $SUSIR$ measure. The lower part of each panel reports performance and t-statistics of the long-short strategy that is long in stocks with the 10% (30%) lowest values of $SUSIR$ and short in stocks with the the 10% (30%) highest values of $SUSIR$. The performance measures are raw returns (RawRet) and factor model alphas. Estimated models are CAPM (CAPM), Fama and French (1993) 3-factor model (FF3), Carhart (1997) 4-factor model (C4), Carhart (1997) 4-factor model augmented by Pástor and Stambaugh (2003) liquidity factor (C4+LIQ), Fama and French (2015) 5-factor model (FF5), Hou, Xue, and Zhang (2014) q-factor model (HXZ4), Carhart (1997) 4-factor model augmented by quality-minus-junk and betting-against-beta factors (C4+Q+B) and Stambaugh and Yuan (2017) 3-factor model (UMO3).

Panel A: Equal-Weighted Portfolio									
Decile	RawRet	CAPM	FF3	C4	C4+LIQ	FF5	HXZ4	C4+Q+B	UMO3
1 (Long)	1.002	0.359	0.163	0.239	0.234	-0.034	0.077	-0.030	0.374
2	0.936	0.290	0.066	0.121	0.144	-0.139	-0.058	-0.194	0.259
3	0.875	0.233	0.025	0.079	0.097	-0.218	-0.104	-0.246	0.176
4	0.849	0.215	-0.007	0.032	0.047	-0.240	-0.165	-0.295	0.157
5	0.786	0.151	-0.057	-0.018	-0.019	-0.260	-0.192	-0.309	0.101
6	0.790	0.151	-0.046	-0.006	-0.005	-0.278	-0.189	-0.332	0.086
7	0.659	-0.002	-0.210	-0.172	-0.176	-0.424	-0.382	-0.452	-0.016
8	0.634	-0.031	-0.254	-0.208	-0.200	-0.446	-0.387	-0.470	-0.054
9	0.517	-0.149	-0.355	-0.276	-0.276	-0.530	-0.448	-0.541	-0.110
10 (Short)	0.572	-0.098	-0.310	-0.250	-0.242	-0.495	-0.428	-0.470	-0.065
1-10	0.430	0.458	0.473	0.489	0.475	0.461	0.505	0.440	0.439
	(5.287)	(5.498)	(5.451)	(5.703)	(5.419)	(4.882)	(5.396)	(4.074)	(4.664)
L 30% - H 30%	0.363	0.387	0.391	0.391	0.397	0.360	0.392	0.337	0.346
	(6.633)	(6.892)	(6.57)	(6.526)	(6.673)	(5.595)	(6.325)	(4.397)	(5.121)

Panel B: Value-Weighted Portfolio

Decile	RawRet	CAPM	FF3	C4	C4+LIQ	FF5	HXZ4	C4+Q+B	UMO3
1	0.862	0.278	0.246	0.220	0.196	0.163	0.134	0.123	0.250
2	0.830	0.249	0.200	0.249	0.237	0.107	0.133	0.095	0.263
3	0.640	0.048	-0.028	-0.051	-0.051	-0.151	-0.148	-0.156	-0.020
4	0.636	0.019	-0.015	-0.045	-0.037	-0.205	-0.253	-0.231	-0.061
5	0.598	0.004	-0.040	-0.017	-0.027	-0.142	-0.140	-0.172	0.004
6	0.729	0.124	0.079	0.104	0.110	-0.042	-0.009	-0.048	0.069
7	0.604	0.040	-0.016	-0.040	-0.052	-0.201	-0.249	-0.275	-0.054
8	0.356	-0.229	-0.330	-0.339	-0.334	-0.477	-0.562	-0.539	-0.293
9	0.580	-0.016	-0.085	-0.054	-0.041	-0.194	-0.197	-0.164	0.026
10	0.515	-0.073	-0.182	-0.147	-0.132	-0.310	-0.332	-0.332	-0.050
1-10	0.347	0.350	0.428	0.368	0.327	0.474	0.466	0.455	0.300
	(3.304)	(3.012)	(3.81)	(3.132)	(2.855)	(3.64)	(2.927)	(2.832)	(2.279)
L 30% - H 30%	0.293	0.297	0.337	0.313	0.287	0.358	0.393	0.353	0.267
	(3.582)	(3.186)	(3.814)	(3.538)	(3.357)	(3.57)	(3.244)	(3.297)	(2.84)

Table 3.3:
Abnormal Returns of $SUSIR$ Long-Short Strategy
The returns of the $SUSIR$-based long-short strategy are regressed on the four factors from Carhart (1997) model and long-short strategies based on SR, DTC and SR_{IO}. All strategies are long in stocks from the lowest decile of the corresponding variable and are short in stocks from the highest decile of the corresponding variable. In Panel A (Panel B) the returns of all strategies are calculated using an equal-weighting (value-weighting) procedure. The t-statistics are adjusted for autocorrelation following Newey and West (1987) with the lag of twelve months. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Equal-Weighted Strategy					
	(1)	(2)	(3)	(4)	(5)
$\_CONS$	0.489***	0.255***	0.330***	0.279***	0.242***
	(5.70)	(2.74)	(3.82)	(3.10)	(2.63)
LS_SR		0.267***			0.242***
		(4.76)			(3.33)
LS_DTC			0.183***		0.0330
			(3.02)		(0.56)
LS_SR_{IO}				0.214***	0.00699
				(4.19)	(0.13)
$MKTRF$	-0.0562**	0.0572**	-0.0331	0.00761	0.0527**
	(-2.23)	(2.22)	(-1.54)	(0.38)	(1.97)
SMB	0.00318	0.0489	0.00466	0.0526	0.0464
	(0.08)	(1.36)	(0.14)	(1.30)	(1.23)
HML	-0.0400	-0.0584**	-0.0330	-0.0489*	-0.0557*
	(-1.17)	(-1.99)	(-1.08)	(-1.68)	(-1.93)
UMD	-0.0179	-0.0438	-0.0236	-0.0356	-0.0430
	(-0.43)	(-1.35)	(-0.60)	(-0.89)	(-1.31)
N	404	404	404	404	404
Panel B: Value-Weighted Strategy					
	(1)	(2)	(3)	(4)	(5)
$\_CONS$	0.368***	0.288**	0.328***	0.251**	0.254**
	(3.13)	(2.36)	(2.69)	(2.11)	(2.02)
LS_SR		0.166**			0.0362
		(2.48)			(0.58)
LS_DTC			0.183***		0.100
			(2.62)		(1.55)
LS_SR_{IO}				0.201***	0.128**
				(2.86)	(2.00)
$MKTRF$	-0.0358	0.0319	-0.0352	0.0204	0.0152
	(-0.81)	(0.82)	(-0.85)	(0.52)	(0.38)
SMB	0.0379	0.0623	0.00938	0.0654	0.0452
	(0.81)	(1.15)	(0.21)	(1.25)	(0.82)
HML	-0.150**	-0.162**	-0.162***	-0.158**	-0.165***
	(-2.17)	(-2.50)	(-2.66)	(-2.54)	(-2.72)
UMD	0.0684	0.0602	0.0710	0.0538	0.0587
	(1.12)	(1.08)	(1.25)	(0.96)	(1.08)
N	404	404	404	404	404

Table 3.4:

Fama-MacBeth Regression of Stock Returns on $SUSIR$

This table reports the results of the Fama-MacBeth regression of raw monthly stock returns on the $SUSIR$ measure and other stock characteristics. All explanatory variables are normalized to have mean equal to zero and standard deviation equal to one. Additional control variables are market beta, log size, log book-to-market ratio, momentum and short-term reversal. The t-statistics are Newey and West (1987) adjusted. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$SUSIR$	-0.114***	-0.0852***	-0.0928***	-0.0812***	-0.113***	-0.107***	-0.0998***	-0.0766***
	(-5.73)	(-4.55)	(-4.60)	(-3.97)	(-5.71)	(-5.61)	(-5.20)	(-4.04)
SR		-0.404***						0.168*
		(-4.77)						(1.70)
DTC			-0.169***					-0.0998**
			(-4.98)					(-2.28)
SR_{IO}				-0.234***				-0.168***
				(-6.55)				(-3.14)
INV					-0.161***			0.0280
					(-6.42)			(0.85)
ROA					0.134***			-0.0673
					(2.61)			(-1.20)
$MISP$						-0.274***		-0.222***
						(-6.64)		(-4.75)
$IVOLA$							-0.430***	-0.318***
							(-5.89)	(-4.95)
$MBETA$	-0.0208	0.00346	-0.0196	-0.00113	-0.0118	0.0154	0.0521	0.0636
	(-0.36)	(0.06)	(-0.34)	(-0.02)	(-0.21)	(0.27)	(0.93)	(1.17)
LN_SIZE	0.0276	0.00421	0.00166	-0.0368	0.00513	-0.0218	-0.102	-0.167***
	(0.43)	(0.07)	(0.03)	(-0.58)	(0.08)	(-0.35)	(-1.62)	(-2.66)
LN_BM	0.0958*	0.0843*	0.0905*	0.0707	0.0992**	0.113**	0.0524	0.0428
	(1.91)	(1.67)	(1.78)	(1.37)	(2.06)	(2.32)	(1.06)	(0.91)
RET_RV	-0.335***	-0.342***	-0.338***	-0.381***	-0.347***	-0.350***	-0.329***	-0.392***
	(-6.35)	(-6.46)	(-6.28)	(-6.93)	(-6.54)	(-6.58)	(-6.12)	(-6.96)
RET_MOM	0.249**	0.242**	0.240**	0.230*	0.246**	0.141	0.242**	0.124
	(2.09)	(2.02)	(2.03)	(1.88)	(2.05)	(1.23)	(2.14)	(1.04)
N	577088	577088	577056	475372	571201	577088	576894	470396
R^2	0.058	0.062	0.061	0.061	0.065	0.062	0.065	0.084

Table 3.5:
***SUSIR*, Biased Expectations and Fundamental News**
This table shows estimation results for the panel regression of earnings surprises measures on the most recent $SUSIR$ and other control variables. All specifications include month-fixed effects. For the calculation of the first dependent variable, SUE^{PE}, past earnings per share (EPS) are used to estimate earnings surprises. SUE^{PE} is equal to the difference between current earnings per share and earnings per share reported 4 quarter ago divided by the standard deviation of this difference over past 8 quarters. For the calculation of the second dependent variable, SUE^{AF}, analyst forecasts are used as a proxy for market expectations. SUE^{AF} is equal to EPS announced at month t net of the most recent mean analyst forecast divided by standard deviation of the most recent analyst forecasts. The third dependent variable, CAR, is the cumulative market-adjusted return over the earnings announcement window $[-1, 1]$. Analyst forecasts are obtained from IBES database and are required to be not older than 90 days. All earnings surprises measures are winsorized at the 1% and 99% levels. All explanatory variables are normalized to have mean equal to zero and standard deviation equal to one. The standard errors are double-clustered by month and stock. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. The sample period starts in May 1985 for SUE^{PE}, in May 1992 for SUE^{AF}, and in May 1980 for CAR.

	(1) SUE^{PE}	(2) SUE^{PE}	(3) SUE^{PE}	(4) SUE^{PE}	(1) SUE^{AF}	(2) SUE^{AF}	(3) SUE^{AF}	(4) SUE^{AF}	(1) CAR	(2) CAR	(3) CAR	(4) CAR
$SUSIR$	-0.0302***	-0.0366***	-0.0342***	-0.0254***	-0.0515***	-0.0579***	-0.0494***	-0.0419***	-0.0515***	-0.0513***	-0.0495***	-0.0364**
	(-3.51)	(-4.71)	(-4.42)	(-3.31)	(-3.61)	(-4.41)	(-3.85)	(-3.09)	(-3.08)	(-2.99)	(-2.91)	(-2.17)
$MISP$			-0.117***	-0.110***			-0.316***	-0.311***			-0.0931***	-0.0815***
			(-10.61)	(-9.94)			(-17.05)	(-16.92)			(-4.00)	(-3.59)
SR				-0.0539***				-0.0413**				-0.111***
				(-4.90)				(-2.05)				(-3.40)
$MBETA$		-0.0537***	-0.0393***	-0.0341***		0.0239	0.0603***	0.0639***		0.00423	0.0166	0.0276
		(-5.20)	(-3.88)	(-3.34)		(1.30)	(3.37)	(3.53)		(0.16)	(0.65)	(1.09)
LN_SIZE		0.156***	0.132***	0.124***		0.157***	0.0720***	0.0570**		0.0406*	0.0222	0.0114
		(10.20)	(8.98)	(8.58)		(5.47)	(2.62)	(2.03)		(1.70)	(0.95)	(0.48)
LN_BM		-0.111***	-0.0972***	-0.104***		-0.0592***	-0.0184	-0.0229		0.0273	0.0344	0.0232
		(-9.46)	(-8.42)	(-8.86)		(-2.90)	(-0.95)	(-1.19)		(1.17)	(1.47)	(1.00)
RET_RV		0.149***	0.148***	0.148***		0.268***	0.268***	0.268***		0.0167	0.0153	0.0153
		(9.08)	(9.14)	(9.34)		(11.63)	(11.95)	(12.10)		(0.59)	(0.54)	(0.54)
RET_MOM		0.411***	0.379***	0.380***		0.398***	0.318***	0.319***		0.0319	0.00625	0.00817
		(15.32)	(14.22)	(14.29)		(12.61)	(10.50)	(10.55)		(0.85)	(0.17)	(0.22)
$NUMEST$						0.00758*	0.0108***	0.0122***				
						(1.95)	(2.92)	(3.28)				
$STDEV$						-0.00403***	-0.00350***	-0.00325***				
						(-3.73)	(-4.02)	(-3.90)				
$FixedEffects$	Month	Month	Month	Month	Month	Month	Month	Month	Month	Month	Month	Month
N	145038	140366	140366	140366	124262	119874	119874	119874	195840	189153	189153	189153
R^2	0.028	0.080	0.084	0.084	0.013	0.031	0.038	0.038	0.007	0.007	0.007	0.007

Table 3.6:
Anomaly Returns on Earnings Announcement Days
This table reports the results of the panel regression of raw stock returns on the $SUSIR$ measure, the earnings announcement period (EAP) dummy and the interaction between them. Column (1) includes day-fixed effects. Column (2) adds four lags of stock return, return squared and turnover ($Controls$), coefficients are not displayed. In Column (3) SR and $MISP$ and their interactions with EAP are included. In Column (4) day-fixed effects are replaced with more restrictive day-EAP fixed effects. In Column (5) the return of the CRSP value-weighted index (MKT), its interaction with $SUSIR$ and EAP and their triple interaction are added but day-fixed effects are removed. The standard errors are clustered by month. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
EAP	0.0633***	0.0611***	0.0612***		0.0460***
	(9.26)	(8.93)	(9.00)		(4.71)
$SUSIR$	-0.00441***	-0.00500***	-0.00361***	-0.00507***	-0.00410*
	(-3.79)	(-4.36)	(-3.21)	(-4.41)	(-1.90)
$SUSIR \times EAP$	-0.0174***	-0.0180***	-0.0141**	-0.0151***	-0.0172***
	(-2.99)	(-3.11)	(-2.47)	(-2.68)	(-2.70)
$MISP$			-0.0109***		
			(-5.29)		
$MISP \times EAP$			-0.0264***		
			(-3.84)		
SR			-0.0109***		
			(-3.43)		
$SR \times EAP$			-0.0292***		
			(-3.14)		
MKT					1.005***
					(105.04)
$MKT \times EAP$					0.00793
					(0.54)
$MKT \times SUSIR$					-0.00567
					(-1.27)
$MKT \times SUSIR \times EAP$					0.0204**
					(2.35)
$Controls$	None	Yes	Yes	Yes	Yes
$FixedEffects$	Day	Day	Day	Day*EAP	None
R^2	0.207	0.208	0.208	0.210	0.181
N	12552943	12537383	12537383	12537348	12537383

Table 3.7:
Analysis of Limits to Arbitrage
This table reports the estimation results for the Fama-MacBeth regression of monthly stock returns on the $SUSIR$ measure and its interactions with variables that proxy for limits to arbitrage. These proxies are the Corwin and Schultz (2012) spread ($HLSPREAD$), idiosyncratic volatility ($IVOLA$) and the residual institutional ownership ratio (RIO). The interaction variables are sorted into quintiles. $SUSIR$ is normalized to have zero mean and unit standard deviation. It is interacted with the quintile dummies of the interaction variable. Dummies for the lowest quintile of the interaction variable are omitted. Additional control variables are market beta, log size, log book-to-market ratio, momentum and short-term reversal (coefficients are not displayed). The t-statistics are Newey and West (1987) adjusted. ***, ** and * indicate significance at 1%, 5% and 10% levels, respectively.

	$M = HLSPREAD$ (1)	$M = IVOLA$ (2)	$M = RIO$ (3)
$SUSIR$	-0.0816**	-0.0352	-0.0893***
	(-2.49)	(-1.06)	(-2.84)
$SUSIR \times M_{Quintile=2}$	0.0339	-0.0618*	-0.0164
	(0.87)	(-1.74)	(-0.35)
$SUSIR \times M_{Quintile=3}$	-0.0287	-0.0837*	-0.0267
	(-0.57)	(-1.79)	(-0.58)
$SUSIR \times M_{Quintile=4}$	-0.0545	-0.0928*	-0.0687
	(-1.16)	(-1.87)	(-1.35)
$SUSIR \times M_{Quintile=5}$	-0.154***	-0.141**	-0.0209
	(-3.07)	(-2.38)	(-0.32)
$M_{Quintile=2}$	0.0348	0.0551	0.260***
	(0.75)	(0.92)	(4.77)
$M_{Quintile=3}$	0.0120	-0.00641	0.205***
	(0.26)	(-0.08)	(2.91)
$M_{Quintile=4}$	0.00578	-0.0927	0.254***
	(0.08)	(-0.91)	(3.10)
$M_{Quintile=5}$	-0.298**	-0.641***	0.189*
	(-2.55)	(-3.81)	(1.83)
$Controls$	Yes	Yes	Yes
R^2	0.0684	0.0719	0.0689
N	577088	576894	575995

Appendix to Chapter 3

Table A3.1:
Definitions of Variables

Variable:	Description:	Source:
SR	Short interest ratio is the mid-month reported short interest divided by shares outstanding. To aggregate on PERMNO level, we sum short interest over global issue key. We use the version of short interest variable from Compustat supplementary file that is not adjusted for stock splits. Short interest for NASDAQ stocks is available starting June 2003.	CRSP/Compustat
$SUSIR$	Standardized unanticipated short interest ratio is defined as $\frac{SR_t - \overline{SR}_{t-1,t-12}}{\sigma^{SR}_{t-1,t-12}}$, where $\overline{SR}_{t-1,t-12}$ is a 12-month moving window mean and $\sigma^{SR}_{t-1,t-12}$ is a 12-month moving window standard deviation of short interest ratio. $SUSIR$ is set to missing if fewer than five observations of short interest ratio are available.	CRSP/Compustat
DTC	Days-to-cover equals to short interest divided by daily turnover.	CRSP/Compustat
SR_{IO}	Short interest over institutional ownership equals to short interest ratio over institutional ownership ratio.	Compustat/13F
$MBETA$	Market beta is a slope coefficient in the time series regression of the stock's return on the market excess return (MKTRF), with a rolling window of 252 trading days.	CRSP
LN_SIZE	Log market capitalization is calculated as the number of shares outstanding times the price per share (in \$Mio).	CRSP
LN_BM	Log book-to-market ratio is calculated following Davis, Fama, and French (2000). The book-to-market ratio in year t is the total book value at the end of the fiscal year ending in year $t-1$ divided by total market capitalization on the last trading day of the calendar year $t-1$, as reported by CRSP. The total book value is the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit minus the book value of preferred stock. To estimate the book value of preferred stock, we use the redemption, liquidation, or par value, in this order (depending on data availability).	CRSP/Compustat
RET_MOM	Return momentum is the cumulative return from month $t-12$ to $t-2$.	CRSP
RET_REV	Return reversal is the return over the month $t-1$.	CRSP
ROA	Return on assets equals to to income before extraordinary items over assets.	Compustat
INV	Assets growth is defined as $\frac{TA_{t-1} - TA_{t-2}}{TA_{t-2}}$ following Cooper, Gulen, and Schill (2008).	Compustat

Continued on next page

Table A3.1 – *Continued from previous page*

Variable:	**Description:**	**Source:**
$IVOLA$	Idiosyncratic volatility is defined as the standard deviation of the recent month's daily residuals obtained in the regression of the excess stock returns on Fama-French 3-factors, with a rolling window of 252 trading days.	Compustat
$HLSPREAD$	The bid-ask spread of Corwin and Schultz (2012).	Authors
RIO	Residual institutional ownership is the residual from the following monthly cross-sectional regression: $ln(\frac{IO_{i,t}}{1-IO_{i,t}}) = \alpha_t + \beta_{1,t} \times ln(SIZE_{i,t}) + \beta_{2,t} \times ln(SIZE_{i,t})^2 + \epsilon_{i,t}$. Being reported once per quarter, insitutional ownership is assumed to be constant over three-month period prior to the next report.	CRSP/13F
SUE^{PE}	Standardized unanticipated earnings surprises are defined as a forecast error in quarter t divided by the volatility of forecast error over last eight quarters. Forecast error is calculated as the difference between the EPS announced at t and the EPS four quarters prior to that. Thus, $SUE^{PE} = \frac{EPS_t - EPS_{t-4}}{\sigma^{\Delta EPS}_{t-1,t-8}}$.	IBES
SUE^{AF}	Earnings forecasts error is equal to EPS announced at month t net of the most recent mean analyst forecast divided by the standard deviation of the most recent analyst forecasts.	IBES
CAR	Cumulative abnormal return over 3-day earnings announcement window is defined as $\sum_{t=-1}^{1}(ret_t - MKT_t)$, where MKT_t is the CRSP value-weighted portfolio.	CRSP/Compustat
$NUMEST$	Number of analyst forecasts used to calculate the mean forecast.	IBES
$STDEV$	Dispersion in analyst earnings estimates.	IBES
EAP	Earnings announcement period dummy is equal to one for a 3-day window around earnings announcement.	Compustat

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Curriculum Vitae

September, 2012 - August, 2019	**University of Mannheim**, Mannheim, Germany Graduate School of Economic and Social Sciences *PhD Candidate in Finance*
September, 2009 - December, 2011	**Humboldt University of Berlin - Higher School of Economics in Moscow** *Double Master of Science in Economics and Management*
September, 2005 - June, 2009	**Moscow Institute of Physics and Technology**, Moscow, Russian Federation *Bachelor of Science in Applied Physics and Mathematics*
June, 2005	**Lyceum at the Belarusian State University**, Minsk, Belarus *School Leaving Examination (A-Levels equivalent)*