BEHAVIORAL EXPLANATIONS OF INVESTORS' TRADING IN FINANCIAL MARKETS

by

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DISSERTATION

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ABSTRACT

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In the first essay, I examine the effect of social media sentiment on the trading behavior of individual investors. I document a positive association between sentiment and retail order imbalances (i.e., individual investors tend to buy more than they sell as they become more optimistic about stocks). The association between retail investor activity and sentiment is stronger for hard-to-value stocks (small cap, low institutional ownership, and low analyst coverage firms). Finally, the association between retail order imbalances and stock returns exists only in conjunction with investor sentiment.

In the second essay, I consider the effect of firm-level sentiment extracted from a social network platform on the presence of herding behavior in the US equity market. Applying a quantile regression model enables me to investigate the existence of herding during both quiet periods and extreme market movements. I also benefit from using different sampling frequencies (daily, weekly, and monthly) for detecting investor herding. I document an asymmetric association between herding and investor sentiment. Herding is present in low-optimism portfolios but not in high-optimism portfolios. I also find evidence of herding in intermediate

quantiles (i.e., relatively quiet market periods but not during extreme market movements). The degree of investor attention has a moderating impact on the relationship between investor optimism and the tendency to herd, with herding being more intense among low-optimism stocks. I also find evidence that trading volume drives herding behavior.

In the third essay, I estimate the impact of investor sentiment in the stock market on the return and volatility spillover risks between real estate investment trusts (REITs) and a broader equity index. The total return spillover risk from equity market to real estate is higher for low-optimism portfolios (45.76%) relative to high-optimism portfolios (41.41%). I do not document any significant impact of investor sentiment on the volatility spillover risk between REITs and the equity market (34.85% versus 34.17%). My results highlight the importance of considering investor sentiment in the stock market when constructing multi-asset portfolios that include REITs in addition to other asset classes.

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DEDICATION

To my family, who made me the man that I am.

To Professor Ram Venkataraman, who made me the scholar that I am.

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CHAPTER 1

INTRODUCTION

Now, the question is no longer, as it was a few decades ago, whether investor sentiment affects stock prices, but rather how to measure investor sentiment and quantify its effects.

—Malcolm Baker and Jeffrey Wurgler (2007, p. 130)

What effect does investor sentiment have on asset prices? Friedman (1953) and Fama (1965) argue that the demand of irrational investors is offset by rational investors (arbitrageurs) who trade against them. Consequently, arbitrageurs prevent noise traders from affecting stock prices, which results in asset prices that are close to their fundamental value. Friedman and Fama argue further that even if the noise traders could affect asset prices, the duration of the effect would be short. Thus, classical theory states that asset prices are equal to the (rationally) discounted value of expected cash flow and that cross-sectional variation in expected returns depends solely on the cross-sectional variation in systematic risks.

De Long et al. (1990) show how risk aversion can keep informed traders from taking arbitrage positions to offset the demand effect of noise traders (i.e., those acting on sentiment instead of on fundamental information, such as a firm's sales prospects, or other information relevant to a firm's expected cash flow prospects or risk). De Long et al. (1990) assume that two types of investors operate in the market: (1) rational investors who trade on fundamentals only and (2) those who trade on noisy signals without fundamental information. Investors who trade while unusually bullish or bearish with no rational basis for that sentiment could affect asset prices. If noise traders act in large numbers, then their trading can cause asset prices to deviate from their fundamental values. Because deviations from fundamental values could increase, arbitrage is now risky, and rational traders will choose not to fully restore prices to their fundamental levels. In short, noise traders create an additional source of systematic risk priced in the market because their actions increase price volatility.

Several empirical studies document how sentiment traders affect stock price formation. French and Roll (1986) show that stock price volatility is lower when the market is closed on Wednesdays compared with when the market is open on Wednesdays, consistent with a failure of arbitrageurs to offset the shift of intraday demand. Roll (1988) finds evidence of substantial stock price movements that cannot be explained by overall market movements on days with no fundamental news to justify the price movements. Cutler, Poterba, and Summers (1989) find that the largest aggregate market movements do not occur on days on which the most important fundamental news occurs and vice versa.

This dissertation explores the role of investor sentiment in equity markets in general and the behavior of retail investors in particular. I begin by investigating how the level of investor sentiment affects the investment decisions of individual investors. I find evidence that individual investors buy (sell) when they are bullish (bearish) about a particular stock. The impact of sentiment on retail investor trading is more pronounced when investors buy or sell stocks that they consider hard to value.

I then study the effect of firm-level sentiment extracted from a social network platform on the presence of herding behavior in the US equity market. The evidence shows that investors are more likely to herd when they are less optimistic about stocks. In addition, the level of investor attention intensifies the impact of sentiment on herding behavior. Investors herd more among attention-grabbing stocks when investors are not optimistic about those stocks. Trading volume is the main driver of herding behavior in the stock market.

I go on to estimate the impact of investor sentiment in the stock market on the return and volatility spillover risks between real estate investment trusts (REITs) and a broader equity index. The total return spillover risk is higher for low-optimism portfolios (45.76%) relative to high-optimism portfolios (41.41%). My results highlight the importance of considering investor sentiment in the stock market when constructing multi-asset portfolios that include REITs in addition to other asset classes.

The dissertation is organized as follows. Chapter 2 reviews relevant literature. Using evidence from a social network of investors, Chapter 3 considers the impact of investor sentiment on the trading behavior of individual investors and Chapter 4 examines the impact of investor sentiment on herding behavior. Chapter 5 studies spillover risk in REITs and the equity market, asking: Does investor sentiment matter? Chapter 6 concludes.

CHAPTER 2

RELEVANT LITERATURE

2.1 Investor sentiment and retail investors' trading behavior

Trading correlation by retail investors is important, as these investors represent either dumb money or smart money. Uncorrelated trading by retail investors has a much lower impact on the market compared with their trading in concert. Hence, market participants should assess and understand the trading activities and behavior of retail investors.

Institutional trading relies more on analysts' opinions and professional expertise, whereas retail investors base their trades on either historical information or attention-grabbing news—and they ignore fundamental facts. Retail investors make systematic mistakes because they are prone to behavioral biases.

The efficient-market hypothesis assumption that noise traders cancel the actions of each other can be challenged if a correlation exists among retail investors' trading. Consequently, retail investors may influence market prices if they have significantly similar opinions and trading correlations exist among them.

Barber, Odean, and Zhu (2009b) examine the trading behavior of individual and institutional investors at two large brokers. They find high correlation (about 75%) between those stocks that individual investors are buying and selling. They attribute the high correlation of individual investors' trading to behavioral biases, such as the disposition effect and limited attention. They conclude that even though the impact of individual investors on asset prices is negligible, individual trading may influence the market because investors' noise trading is systematic.

Dorn, Huberman, and Sengmueller (2008) examine the behavior of retail investors using transaction-level data from the three largest German discount brokerages. They document that retail investors follow a positive-feedback trading strategy in which they buy recent winners and sell recent losers. Contrary to Barber, Odean, and Zhu (2009b), Dorn, Huberman, and Sengmueller (2008) find evidence of a positive correlation between retail trading and contemporaneous, as well as future, returns.

Schmitz, Glaser, and Weber (2007) construct a measure of individual investor sentiment–based order imbalance that is derived from bank-issued warrants using data from German discount brokerages. They examine the relationship between investor sentiment and stock returns using vector autoregression (VAR) models and the Granger causality test. They find a short-term (one to two days) mutual influence between investor sentiment and stock returns. On the one hand, returns have a negative impact on sentiment. On the other hand, investor sentiment has a positive and stronger influence on stock returns for the next trading day.

Several researchers have investigated the relationship between individual investor trading and behavior and short-term stock return movements. For example, Kaniel, Saar, and Titman (2008), using a large cross section of stocks traded on the NYSE, find evidence indicating that individual investors tend to buy stocks following declines in the previous month and to sell following price increases. In addition, intense buying (selling) by individuals is followed by positive (negative) excess returns in the next month.

Barber, Odean, and Zhu (2009a) report that the ability of retail order imbalance to predict future stock returns varies based on what horizon is used to measure those returns. When measured annually, stocks bought intensely outperform stocks sold heavily only for small stocks. When measured weekly, stocks bought heavily have positive returns and can predict a future positive return for up to two weeks, and stocks sold heavily earn a negative return and continue to earn a negative return for the following two weeks. Those returns reverse over the following several months.

Hvidkjaer (2008) examines the relationship between individual investor trading behavior and a cross section of future stock returns. He finds that intensely selling stocks outperform intensely bought stocks up to two years. These results persist for the third year among small and medium-size firms.

Subrahmanyam (2008) provides an empirical analysis that order imbalances at longer horizons (monthly and bimonthly) are associated with future negative returns in a manner consistent with inventory control by market makers. The results are more pronounced for larger firms and negative imbalances, which is consistent with the notion that short-selling constraints may cause negative sentiment to build up to high levels, and the spurt of selling accompanying the sentiment crossing a threshold, may cause significant inventory problems for market makers.

Boehmer and Wu (2008) differentiate among the order imbalances of individuals, institutions (regular versus program), and market makers using proprietary data on a broad panel of stocks traded on the NYSE. They document that both institutions and retail are contrary with respect to past returns. They find that individual trading is positively associated with contemporaneous returns and that institutional imbalances are negatively related to current returns. They show that both regular institutional and individual imbalances have predictive power for next trading-day excess returns. Institutional program imbalances are negatively related to next-day returns.

2.2 Investor sentiment and herding behavior

Bikhchandani, Hirshleifer, and Welch (1992), Banerjee (1992), and Welch (1992) were the first to discuss herd behavior based on theoretical frameworks. Their seminal papers characterize herd behavior by explaining how agents make decisions in a sequence based on private information. The inference was that many agents make similar decisions primarily by imitating their predecessors instead of by using their own private information. Later research (e.g., Lee, 1998; Cipriani and Guarino, 2008) empirically characterizes herding behavior in financial markets. The main analysis of these studies includes the trading of a security of unknown value between informed and uninformed traders. In such a situation, the price of the security is set based on order flow in the market. This price mechanism thus prevents herding from arising in the market. Avery and Zemsky (1998) find that herding behavior may occur because of the unpredictability of an event, such as the uncertainty about an asset's value.

Theoretical research has described processes that can lead to herd behavior. Empirical research follows a different approach. Major empirical works (Lakonishok, Shleifer, and Vishny, 1992; Grinblatt, Titman, and Wermers, 1995; Weimers, 1999) examine herding in financial markets based only on statistical measures of clustering. Therefore, they do not directly validate the theoretical herding models. These works conclude that, in several financial markets, the clustering of investment decisions by fund managers is more than what is anticipated when they act independently. The empirical works on herding are crucial not only for revealing the behavior of participants in economic markets but also for determining whether market participants make a synchronized pattern of decisions.

Decisions may arise for reasons other than herding. Under certain circumstances, clustering could be due to market participants reacting to public declarations. In addition, differentiating between specious herding and actual herding behaviors is extremely difficult (Bikhchandani and Sharma, 2000; Hirshleifer and Teoh, 2009).

The field of empirical research on herding has two types of studies. The first branch examines group-based herding, which focuses on specific clusters of investors: mutual fund managers or financial analysts. The biggest hurdle in analyzing this kind of herding is the need for comprehensive archives of the trading activities of investors. For example, Lakonishok, Shleifer, and Vishny (1992) measure the herding tendency of pension fund managers in simultaneously buying or selling stocks and then compare the results with those anticipated if managers acted individually. Clement and Tse (2005), Gleason and Lee (2003), Welch (2000), Graham (1999), and Wermers (1999) conduct investigations of group-based herding.

The second branch of empirical research focuses on market-wide herding, which arises from the combined behaviors of market participants toward the market. In the same fashion as group-based herding, herding based on markets can ensure that specific assets are mispriced. Market-wide herding can be examined in the context of the cross-sectional distributions of stock returns. In markets characterized by herding, in durations of market stress, cross-stock return dispersion is likely to decrease as herding increases. In markets characterized by herding, cross-stock return dispersion is likely to decrease as herding increases in periods of market stress. Consequently, herding causes the return of individual stocks to cluster around the overall market return.

The examination of the association between market returns and dispersion has shed light on the presence of stock market herding. However, research along this line fails to provide conclusive results. For example, Christie and Huang (1995, hereafter CH) find that return dispersion increases significantly during periods of extreme market movement, suggesting that stock returns do not cluster around the overall market return during periods of market stress. Using the CH model, Chang, Cheng, and Khorana (2000, hereafter CCK) show the presence of nonlinearity between market returns and dispersion. Surprisingly, the results did not exhibit any evidence for herding in the United States, contrary to earlier research. CCK did find notable evidence of herding in South Korea and Taiwan. More recent studies by Tan et al. (2008) and Chiang, Li, and Tan (2010), applying the CCK methodology, show the presence of herding in the Chinese stock markets. Despite using different methodologies, the existing literature concludes that the tendency to herd can be observed more actively in developing markets.

2.3 The impact of investor sentiment on REITs market

Recent literature in finance has investigated the effects of spillover risks for various financial assets and markets. Many studies analyze either return or volatility spillover for similar assets across different countries. For example, Diebold and Yilmaz (2012) examine volatility spillovers between four asset classes in the US market: stocks, bonds, foreign exchange, and commodities. They find that even though the volatility fluctuation was significant in all four markets, the cross-market volatility spillover in the four markets was triggered only when the financial crisis began in 2007. The volatility spillover was more intense from the stock market compared with the other markets during the global financial crisis.

Bubák, Kočenda, and Žikeš (2011) use high-frequency (intraday) data to examine the volatility spillover between Central European currencies and the euro to dollar foreign exchange market. They find insignificant volatility spillover between the euro to dollar and Central European currencies, with the exception of the Czech currency. They document evidence of significant volatility spillovers among the Central European foreign exchange markets. These results are stronger during times of market uncertainty.

Antonakakis (2012) examines how the introduction of the euro affects return co-movements and volatility spillover for four major currencies (euro, British pound, Japanese yen, and Swiss franc) traded against the US dollar. He finds that the magnitude of return co-movements and volatility spillover is lower in the post-euro era compared with the pre-euro period.

Liow and Newell (2012) investigate the volatility spillover and correlation between the securitized real estate markets in Mainland China, Hong Kong, and Taiwan in Greater China (GC) and their relationship with the real estate market in the United States. Liow and Newell report a high level of integration among the GC markets. This level of integration also is found between the GC markets and the US markets. The volatility spillover and correlation between those markets intensified during the 2007–2009 financial crisis.

Chen and Liow (2006) investigate the transmission of returns and volatility among world stock markets and major real estate markets. Applying the matrix-exponential generalized autoregressive conditional heteroskedasticity in mean (MEGARCH-M) model, they find that volatility spillover effects are more significant within Asian countries than across the world.

Stevenson (2002) applies the generalized autoregressive conditional heteroskedasticity (GARCH) and exponential generalized autoregressive conditional heteroskedasticity (EGARCH) models to examine the volatility spillover between the stock equity, fixed-income, and REITs market. He documents that the REITs market is influenced by equity subsectors, such as small-cap and value stocks. The volatility spillover from the equity market to mortgage REITs is stronger than that from the fixed-income market. He finds no evidence of volatility spillover between the equity and fixed-income markets and REIT sectors.

Cotter and Stevenson (2006) examine the volatility spillover between different REIT subsectors and between the REIT and equity markets. They find that the linkages both within the REIT sector and between REITs and related sectors in the equity market, such as value stocks, are weaker when they use daily frequency data than when they use monthly data used in prior literature. Further, the spillover from the equity market to REITs is stronger when the relationship is tested using daily data.

Elyasiani, Mansur, and Wetmore (2010) find evidence of volatility spillover from the REITs market to other markets of financial institutions, including savings, loan, and life insurance companies. Michayluk, Wilson, and Zurbruegg (2006) document a volatility spillover between US and UK REITs market. They also find evidence of an asymmetric impact of volatility spillover between the two markets; that is, negative spillovers have a stronger effect than positive spillovers.

CHAPTER 3

THE IMPACT OF INVESTOR SENTIMENT ON THE TRADING BEHAVIOR OF INDIVIDUAL INVESTORS: EVIDENCE FROM A SOCIAL NETWORK OF INVESTORS

3.1 Introduction

Investors' rationality is the cornerstone of traditional economic models in finance. Investors choose a diversified portfolio of assets that maximize their wealth while minimizing their exposure to risk (Grossman and Stiglitz, 1980; Kyle, 1985). Empirical studies report that individual investors behave differently from investors in those rational models. Real investors are more likely to sell winning stocks while holding on to their losing investments—a behavior dubbed the "disposition effect" (Shefrin and Statman, 1985; Odean, 1998). Individual investors tend to hold stocks of companies close to their home base and invest heavily in the stock of firms where they work (Benartzi, 2001; Liang and Weisbenner, 2002). Moreover, individual investors are influenced by limited attention bias. They tend to buy, not sell, attention-grabbing stocks (Barber and Odean, 2008; Engelberg and Parsons, 2011; Dougal et al., 2012; Gurun and Butler, 2012; Solomon, 2012). Being subject to all these biases, individual investors construct an investment portfolio far from the efficient portfolio proscribed by the rational models. Consequently, exposing individual investors to unnecessarily high levels of risk.

Many theoretical models of financial markets treat buying and selling as two sides of the same coin. Informed investors observe the same signal whether they are deciding to buy or to sell. In symmetric models, investors are equally likely to sell securities with negative signals as they are to buy those securities with positive signals. Uninformed noise traders are equally likely to make random purchases or random sales. In formal models, the decisions to buy and to sell often differ only by a minus sign. For investors, the decisions to buy and to sell are fundamentally different. I explore the asymmetry of decisions by associating social media–based proxies of investor sentiment with estimates of retail investor buy-sell imbalances. My analysis allows for inferences about the independence of sentiment relative to retail investor trading activity, as well as the interaction between the two.

A rapidly growing body of research documents how social media–based measures of investor sentiment are positively associated with stock returns (Antweiler and Frank, 2004; Sprenger et al., 2014; Renault, 2017). Of the social media–based measures of sentiment, Twitter and StockTwits have been shown to capture information from retail investors. I use StockTwits to construct a measure of retail investor sentiment.

Economic measures of trading activity often suffer from the problem that they capture a combination of liquidity, information, and sentiment. Chordia, Roll, and Subrahmanyam (2002) describe order volume as a good measure of liquidity, but a poor indicator of information or sentiment. They also describe order imbalances as being superior to volume in many empirical settings because imbalances capture aspects of information and sentiment that are absent from traditional measures of trading activity such as volume and spreads. An established body of research shows how order imbalances determine returns in a manner that is distinct from that of volume: Chan and Fong (2000), Hasbrouck and Seppi (2001), and Brown, Walsh, and Yeun (1997).

3.2 Data, sample, research design, and hypothesis development

3.2.1 StockTwits

A formal study of how investors' trading activity depends on sentiment requires data that accurately capture the sentiment of those investors who are known to be influential on financial markets, as well as trading activity data from which trading imbalances can be estimated. The social media platform StockTwits is a good source of such data, as it provides social media posts by users who are explicitly providing semiprofessional investment advice. I obtain data on StockTwits from a company called PsychSignal. StockTwits, which was founded in 2008, is the largest social network for investors and traders to connect with each other and share their opinions about stocks. The website has a Twitter-like format, with users posting messages of up to 140 characters. To link a user's message to a stock, the website uses cashtags with the stock ticker symbol (for example, $AMZN for Amazon). According to Alexa, a website analytics tool, StockTwits was ranked as the 1,150th most popular website in the United States as of September 2018.

PsychSignal provides StockTwits data on individual securities at intraday frequencies. The original data set spans from January 1, 2009, until September 30, 2016. For each observation, I gather the number of messages and how many of those messages are bullish, bearish, or unclassified, as well as a score (0 to 4) on how bullish or bearish each message is.

3.2.2 Retail investors' order imbalance trades

To identify transactions initiated by retail customers, I follow the Boehmer, Jones, and Zhang (2017) methodology. Let $P_{i,t}$ be the transaction price of stock *i* at time *t*, and let $Z_{i,t} \equiv 100 * \text{mod}(P_{i,t}, 0.01)$. A transaction is identified as retail seller initiated if $Z_{i,t}$ is in the interval (0, 0.4), and a transaction is categorized as retail buyer initiated if $Z_{i,t}$ is in the interval (0.6, 1).[1]

To measure retail investors' directional trades, I compute order imbalance measures for each stock *i* on each day *t* as

$$BSI_{i,t} = \frac{\sum_{i=1}^{n} VB_{i,t} - \sum_{i=1}^{n} VS_{i,t}}{\sum_{i=1}^{n} VB_{i,t} + \sum_{i=1}^{n} VS_{i,t}} \tag{1}$$

[1] For details of the procedure to categorize each transaction as retail buyer or retail seller initiated, see Boehmer, Jones, and Zhang (2017).

where $VB_{i,t}$ is the volume of purchases of stock *i* on day *t* and $VS_{i,t}$ is the volume of sales of stock *i* on day *t*.

3.2.3 Measure of investors' sentiment

Following Antweiler and Frank (2004), I combine individual opinions into one measure of sentiment, which is the arithmetic average of bearish and bullish messages at firm-day levels:

$$AvgSentiment_{i,t} = \frac{N_{i,t}^{bullish} - N_{i,t}^{bearish}}{N_{i,t}^{bullish} + N_{i,t}^{bearish}} \tag{2}$$

The measure of sentiment ranges from −1 (all bearish) to +1 (all bullish). To account for messages that are posted after the market closes, *AvgSentiment* is calculated for day *t* from messages posted between the market close of day $t - 1$ to the market close of day *t*.

3.2.4 Measure of investors' attention

Using a nontraditional measure, such as Google searches (Da, Engelberg, and Gao, 2011), to capture retail investor attention helps to determine the direct impact of attention on investors using an online platform to communicate with each other.

Following Da, Engelberg, and Gao (2011), I calculate the abnormal retail attention measure as the natural log of the ratio of *DSVI* on day *t* to the average of *DSVI* over the previous month, where *DSVI* is Google's daily Search Volume Index (SVI). Then, I construct an indicator variable (*ADSVI*) with a potential value of 0, 1, 2, 3, or 4 using the firm's past 30 trading days' *DSVI* values (Ben-Rephael, Da, and Israelsen, 2017).[2] I assign *ADSVI* a score of 1, 2, 3, or 4 if the previous 30 trading days' *DSVI* average is between 80% and 90%, 90% and 94%, 94% and 96%, or greater than 96%, respectively.

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[2] I thank the authors for providing the daily Google search volume data used in their paper.

3.2.5 Research design

3.2.5.1 Sorts methodology

I examine the extent to which the tendency to buy stocks increases on days of highly positive sentiment. I begin by sorting stocks into five deciles based on *AvgSentiment* as calculated in Eq. (2). I then calculate the time series mean of abnormal retail investors imbalances (*Abn-BSI*) for the days with trading data. *Abn-BSI* is the difference between *BSI* in time period *t* and the average *BSI* from *t-140* to *t-20*. I use the Newey-West approach to calculate the standard deviation of the time series correcting for serial dependence.

3.2.5.2 Multivariate analysis

To examine whether the measure of investors' sentiment forecasts the future order imbalances of retail investors, I estimate the following regression specification:

$$Abn\text{-}BSI_{i,t} = \alpha + \beta_1 AvgSentiment_{i,t} + \beta_2 BSI_{i,t-1} + Control\ Variables + TimeFEs + FirmFEs + \varepsilon_{i,t} \quad (3)$$

where $AvgSentiment_{i,t}$ is the sentiment measure for firm *i* at time *t*. Because *BSI* tends to be autocorrelated, I also control for abnormal *BSI* on day $t-1$. I include year, month, day of the week, and firm fixed effects. The standard errors are clustered at the date and firm levels. Control variables for each stock *i* include log (firm size), firm age, and a dividend-paying dummy, because small stocks, young stocks, and non-dividend-paying stocks are more likely to be sensitive to investor sentiment (Baker and Wurgler, 2007). I control for momentum because stock past returns might drive the retail investor's decision to buy or sell (Odean, 1999). In addition to clustering in date level, I control for earning announcement day as both investor sentiment and trading decision might be influenced by the nature of the news (Kaniel et al., 2012). I also control for institutional ownership, analyst's coverage, market volatility, stock price, and bid-ask spread.

3.2.5.3 Hypothesis development

I am interested in empirically examining the impact of investor sentiment on the activities of retail investors. Shiller (1984) suggests that investors are more likely to trade in response to pseudo signals, such as historical price movements, volume patterns, or experts' opinion. Using earning announcements as a proxy for news in the market, Lee (1992) shows that investors respond to good (bad) earning news with a period of intense buying (selling) that persists only for a short time.

Odean (1999) finds evidence that retail investors tend to buy, not sell, securities that have depreciated or appreciated in value over the previous six months. Meanwhile, they tend to sell securities that have risen rapidly in recent weeks. In addition, they sell previous winners while holding onto previous losers. Barber and Odean (2007) suggest that at least a portion of retail investors' trading is induced by pseudo signals. I present my first hypothesis.

H1: I expect to observe aggregate individual investor buying (selling) following positive (negative) sentiment.

Psychology studies find that individuals are more likely to use heuristics when they are presented with difficult problems in which the feedback is delayed or even noisy. In recent theoretical behavioral-finance models (e.g., Daniel, Hirshleifer, and Subrahmanyam, 1998, 2001; Hirshleifer, 2001), this intuition has been formalized in the context of investment decisions and suggests that investors' behavior is stronger when they invest in hard-to-value stocks that operate in informationally sparse environments. Later empirical studies in the behavioral-finance literature either implicitly or explicitly assume that investors' behavioral biases are stronger when stocks are more difficult to value because of the intuitive appeal of this conjecture. Surprisingly, very little direct empirical support exists for this theoretical conjecture. Kumar

(2009) finds empirical evidence that individual investors exhibit stronger behavioral biases when they encounter an investing decision regarding a hard-to-value stock. In line with my predictions, I formulate my second hypothesis.

H2: I expect the association between retail investor activity and sentiment is stronger for hard-to-value stocks.

3.3 Empirical findings

Table 3.1 presents summary statistic of my measurement of retail investors' trading (*BSI*) as well as other main variables I use in my analysis. My sample includes 147,026 stock-day observations. Over my sample period, there is slightly more selling than buying by retail investors (*BSI* average is -0.006). Moreover, *BSI* exhibits a significant kurtosis, and hence is not normally distributed. In addition, investors are, on average, optimistic over the sample period with *AvgSentiment* averaging around 0.42. Finally, the correlation analysis presented in Table 3.2 reveals a positive and significant correlation between retail investors' activity and sentiment.

3.3.1 Investor sentiment and individual investors' trading activity

If sentiment is a factor considered by retail investors, more buying (positive imbalances) should be evident when investors are more optimistic about stocks even after correcting for the time series trend in order imbalances. The results reported in Table 3.3 show that the coefficient of *AvgSentiment* is positive and significant for different models' specifications. The positive and significant coefficient indicates that investors' imbalances are positive (i.e., investors buy more than they sell) when they are optimistic about stocks, which is consistent with the finding of the univariate results shown in Figure 3.1. The figure clearly depicts investors' tendency to buy, not sell, stocks that they have optimistic sentiment about. The results presented in this section add to the literatures examining the questions of which stocks individual investors choose to buy (sell) and what motivates retail investors to invest in one stock over another. I provide robust evidence of intense buying (selling) by retail investors following bullish (bearish) sentiment about a particular stock.

3.3.2 Stock-level characteristics and the impact of sentiment on individual investors' trading activity

Results reported in Table 3.4 show that the impact of sentiment on investors' trading imbalances is higher in the low-ownership tercile compared with the high-ownership tercile (0.0138 versus 0.0117). Results reported in Table 3.5 show that the coefficient of sentiment is positive and significant (0.0189) in the small-cap tercile, and the coefficient of sentiment is insignificant in the large-cap tercile. By construction, I expect retail investors' activity to be greater in the low-ownership tercile compared with the high-ownership tercile. The combined evidence from Tables 3.4 and 3.5 as well as the distribution of retail investors' activity shown in Figures 3.2 and 3.3 confirms that the impact of sentiment on retail order imbalances for the different size and institutional ownership tercile does not stem from the intensity of retail investors trading. The measures of sentiment are stronger for low-ownership and small firms.

Table 3.6 shows that the impact of sentiment on investors' trading imbalances is higher in the low analyst coverage tercile compared with the high analyst coverage tercile (0.0163 versus 0.00479).

Collectively, these results indicate that the impact of sentiment on retail investor's decision is amplified when investors are uncertain about the value of a stock. In addition, the results provide evidence to support the theoretical prediction that individual are more likely to use heuristics when encounter an investment decision to trade in hard to value stocks (Daniel, Hirshleifer, and Subrahmanyam (1998, 2001), Hirshleifer (2001).

3.3.3 The role of limited attention and the impact of sentiment on individual investors' trading activity

Recent literature in finance provides evidence of the consequences of investors not paying enough attention to important information in the market. For example, Hirshleifer, Lim, and Teoh (2009) find that, on days when investors' attention is limited, investors tend to underreact to earnings announcements that result in a smaller earning surprise and greater post-earnings-announcement drift. DellaVigna and Pollet (2009) find that, due to limited investor attention, earnings announcements made on Friday are muted and, consequently, their post-earnings drift is greater.

Barber and Odean (2008) document that the investors' decision to buy is more influenced by their attention level than by their decision to sell. Seasholes and Wu (2007) use transaction-level data on stocks traded on the Shanghai Stock Exchange and confirm individual investors' tendency to buy stocks that hit upper (even attention-grabbing) price limits. Engelberg and Parsons (2011) show that individual investors trade more following earnings announcements that are covered in their local newspapers. They find that both buying and selling increase, with investors more likely to buy than to sell. Engelberg, Sasseville, and Williams (2011) examine buy and sell recommendations on the CNBC television show *Mad Money*. They show that the overnight market reaction is higher for recommendations made on nights when viewership is higher. In addition, they find evidence in support of the Barber and Odean (2008) argument regarding the asymmetric impact of attention on investors' trading behavior. Greater reaction is paid to first-time buying recommendations than to first-time selling recommendations. Da, Engelberg, and Gao (2011) use a novel proxy for investor attention (i.e., Google search frequency) to examine the role of investor attention in causing price pressure effects similar to that documented in Barber and Odean (2008). Da, Engelberg, and Gao show that a higher level of investor attention can predict higher returns in the succeeding two weeks. They also document return reversal within one year.

Investors' level of attention can affect how individuals trade in the stock market. On the one hand, investors delay their reactions to important information because they pay little attention to that relevant information. On the other hand, investors' devoting too much attention to irrelevant or stale information results in their overreaction.

To ensure that investors' attention does not drive my results, I adjust Eq. (3) as follows:

$$Abn\text{-}BSI_{i,t} = \alpha + \beta_1 AvgSentiment_{i,t} + \beta_2 BSI_{i,t-1} + \beta_2 ADSVI_{i,t} + Control\ Variables + TimeFEs + FirmFEs + \varepsilon_{i,t} \quad (4)$$

where $AvgSentiment_{i,t}$ is the sentiment measure for firm *i* at time *t* and *ADSVI* measures the level of individual investor attention for firm *i* at time *t*.

The results of running Eq. (4), reported in Table 3.7, show that the coefficient of *AvgSentiment* is positive and significant for full sample, high-attention, and low-attention sub-samples even after controlling for the level of investor attention. This indicates that the relationship between investor sentiment and retail investors' activity is not driven by limited attention bias.

I replicate my analysis using other traditional measures of investor attention (i.e., abnormal volume and lagged returns). The results in Appendix 2 show robustness regarding the choice of investor-attention proxies.

3.3.4 The impact of order imbalance and investor sentiment on stock price formation

Eq. (3) provides estimates of how sentiment is associated with retail order imbalances. The more important issue to understand is how investor sentiment translates into trading activity and, thus, security price changes. I therefore build on the estimates to form a fuller mapping of sentiment to trading activity and then to security returns. I isolate the component of order imbalances that are correlated with sentiment:

$$BSI_{i,t} = \alpha+\beta_1\ AvgSentiment_{i,t} + Control\ Variables + TimeFEs + FirmFEs + \varepsilon_{i,t} \quad (5)$$

I take $\varepsilon_{i,t}$ as the component of retail order flow that is independent of sentiment and notate this as $BSI\_nosent_{i,t}$. To evaluate how order flow and sentiment are associated with returns, after correcting for the dynamic relationship between order flow and sentiment, I estimate

$$Return_{i.t} = \alpha+\beta_1\ BSI_{i,t-1} + \beta_2\ BSI\_nosent_{i,t-1} + Control\ Variables + TimeFEs + FirmFEs + \varepsilon_{i,t} \quad (6a)$$

and

$$Return_{i.t} = \alpha+\beta_1\ AvgSentiment_{i,t-1} + \beta_2\ BSI\_nosent_{i,t-1} + + Control\ Variables + TimeFEs + FirmFEs + \varepsilon_{i,t} \quad (6b)$$

The estimation of Eqs. (6a) and (6b) allows me to test the extent to which sentiment is transmitted through retail order flow and into the price discovery process.

In a world where retail investors are completely informed and *BSI* accurately captures retail order flow, a significant estimate for β_1 and an insignificant estimate for β_2 can be observed.

Table 3.8 shows that *BSI* predicts returns only when *BSI* is combined with sentiment. The coefficients of $BSI_{i,t-1}$ and $AvgSentiment_{i,t-1}$ are both positive and significant, and the coefficient of $BSI\_nosent_{i,t}$ is insignificant in both models.

For the control variables, the coefficient of lagged return is either positive or insignificant, which indicates no return reversal for a one-day horizon. Meanwhile, the positive coefficients on the other longer-horizon returns show a presence of momentum. In my models, the results are robust even after controlling for firm size, analyst coverage, and market volatility, which indicates that the predictability I find is not simply a manifestation of some size or volatility anomaly.

BSI represents only partially informed retail order flow (Boehmer, Jones, and Zheng, 2017). Retail investors trade for both information and liquidity motivations. Measures of retail order flow, such as *BSI*, would be far more useful if they could be decomposed into liquidity- and information-based components. To examine if *BSI* matters more for price discovery when it represents perceived retail information, I interact *BSI* with an indicator for sentiment:

$$Return_{i.t} = \alpha + \beta_1\, BSI_{i,t} + \beta_2\, BSI{*}Bullish_{i,t-1} + Control\ Variables$$
$$+ TimeFEs + FirmFEs + \varepsilon_{i,t} \qquad (7)$$

where *Bullish* is an indicator that takes a value of one when retail investor sentiment is above median for all stocks at day *t* and zero otherwise. From an estimation of Eq. (7), I can examine if *BSI* exerts an influence on prices that is independent of sentiment or if *BSI* matters only in conjunction with (bullish) investor sentiment.

Consistent with the results reported in Table 3.8, results presented in Table 3.9 show that the predictability of order imbalance to future returns is contingent on investor sentiment. Specifically, the coefficient of the interaction term between sentiment and order imbalance is positive and significant, which confirms this prediction. Moreover, the coefficient of lagged return is insignificant, which reveals that no return reversal is detected for one-day horizon. On the other hand, the positive coefficients on the other longer-horizon returns, which shows a present of momentum. To summarize, order imbalance measures from retail investors strongly and positively predict one-day-ahead stock returns only when it is combined with investor sentiment.

3.4 Concluding remarks

In this chapter, I examine the impact of investor sentiment on the behavior of retail investors' trading. Using univariate and multivariate analysis, I find evidence of investors' tendency to buy, not sell, stocks that they have optimistic sentiment about.

To control for the level of attention—to ensure that investors' attention does not drive the results—I use different measures of investor attention (abnormal volume, lagged returns, and Google searches) and report robust findings showing a positive relationship between investor sentiment and retail individual order imbalance.

Finally, I show that the impact of sentiment on investors' trading imbalances is higher for hard-to-value stocks. The impact of sentiment is more pronounced among small, low institutional ownership, and low analyst coverage firms.

Chapter 3 Figures and Tables

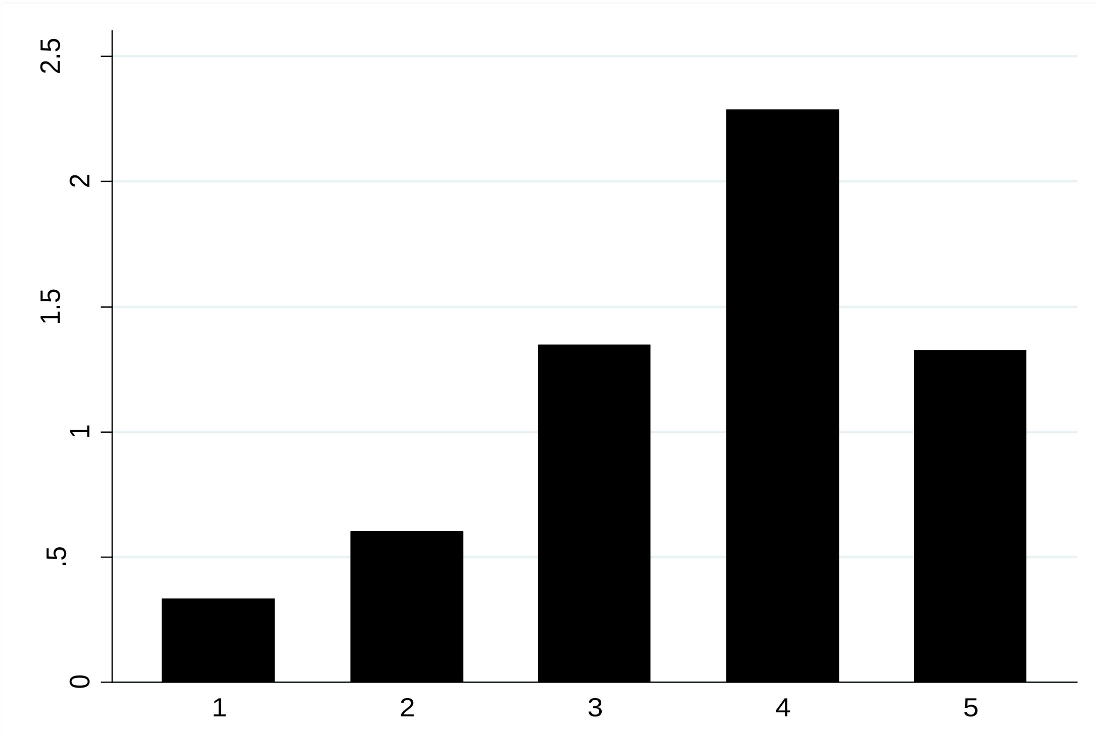

Figure 3.1. The average abnormal imbalances for five *AvgSentiment* quintiles.

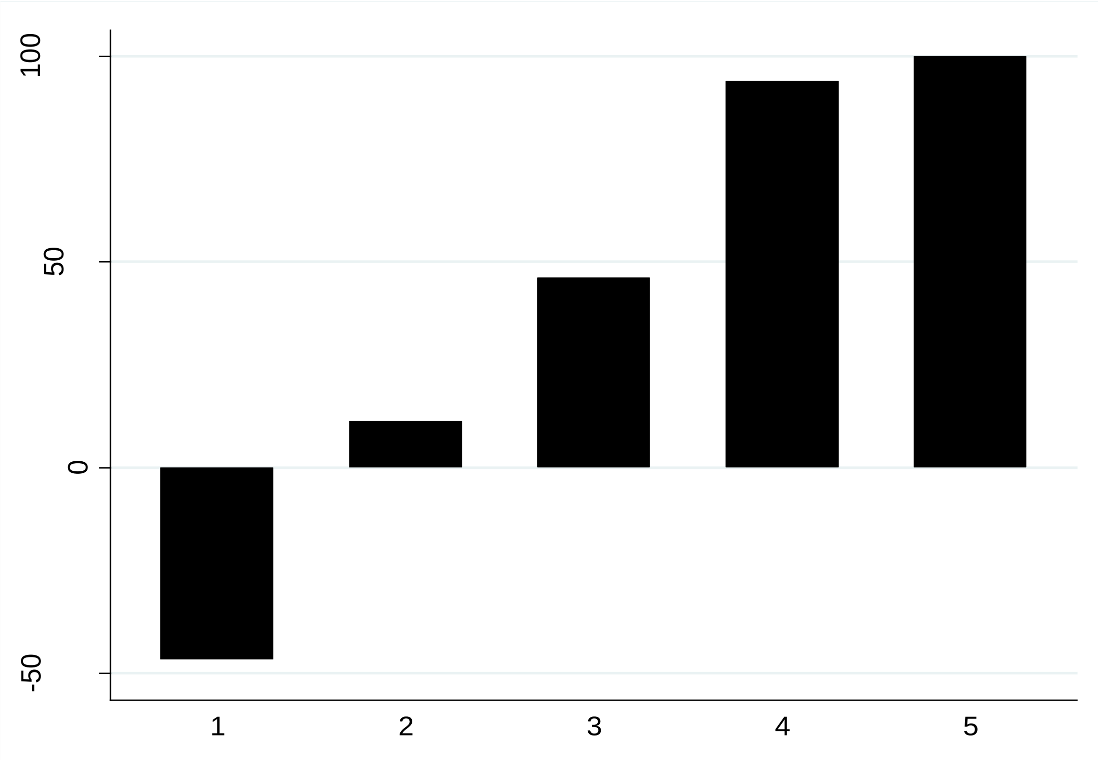

Figure 3.2. The average *AvgSentiment* for five *AvgSentiment* quintiles.

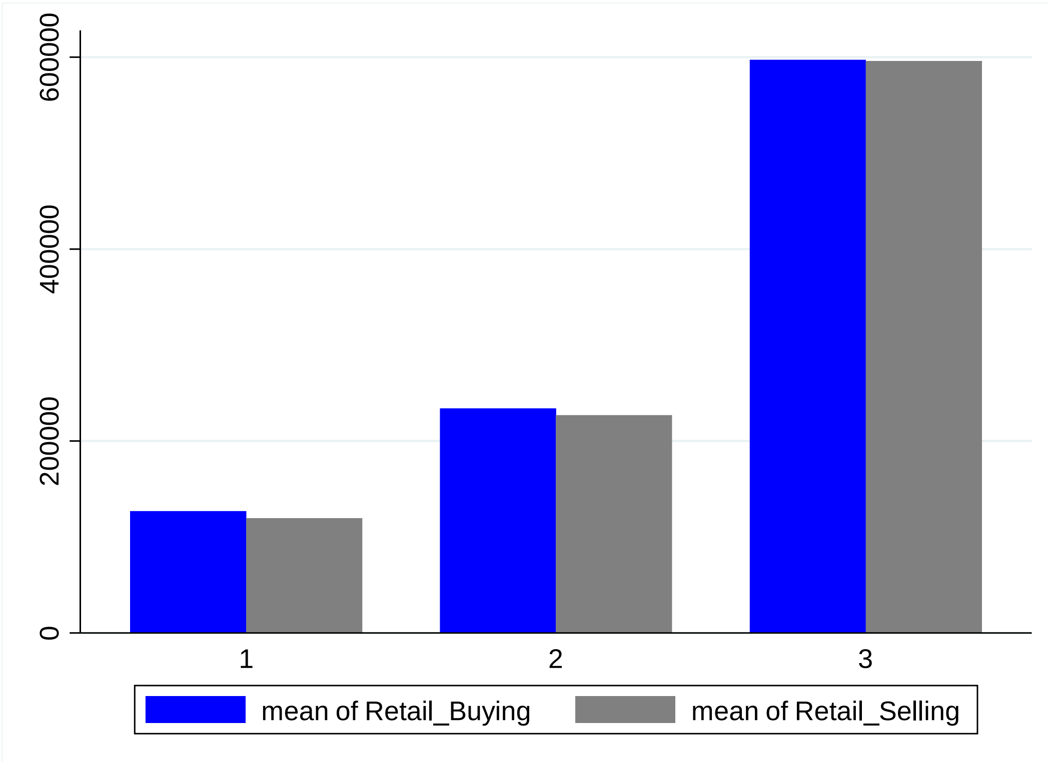

Figure 3.3. The average retail buying and retail selling for firm-size terciles.

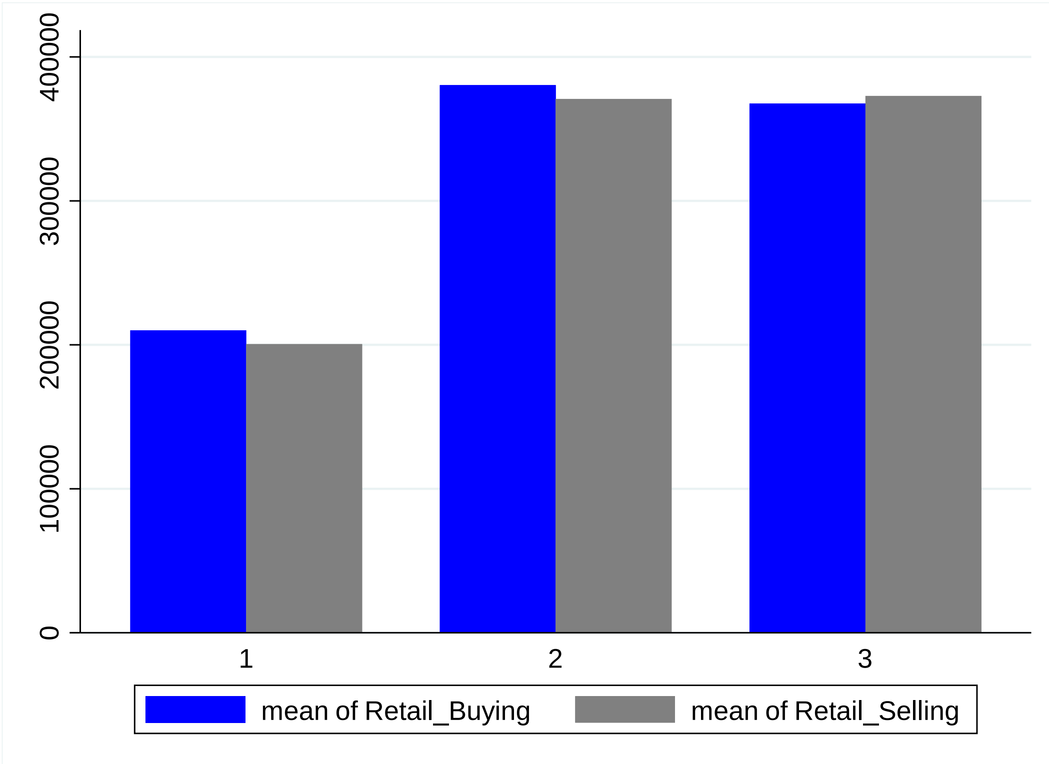

Figure 3.4. The average retail buying and retail selling for analyst coverage terciles.

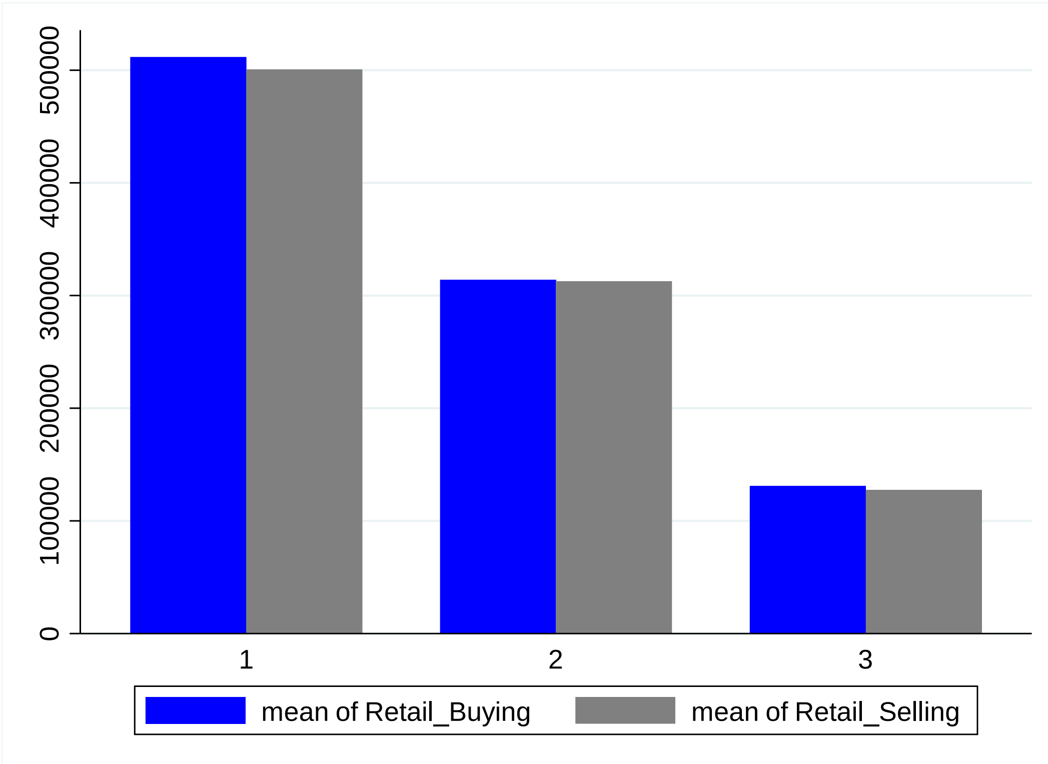

Figure 3.5. The average retail buying and retail selling for institutional ownership terciles.

Table 3.1

Descriptive statistics

This table provides sample descriptive statistics for all stocks in our sample. I calculate one time series value for each stock within our sample and present the cross-sectional mean, median, minimum, maximum, standard deviation, skewness, and kurtosis. I define all variables in detail in Chapter 3 Appendix 1.

Variable	N	Mean	Min	Max	SD	Skewness	Kurtosis
AvgSentiment	147,026	.422	-1	1	.589	-.793	2.862
BSI	147,026	-.006	-1	1	.205	-.203	5.543
Abn-BSI	145,276	.012	-1.132	1.365	.205	.03	5.591
ADSVI	147,026	.426	0	4	1.083	2.630	8.613
Firm age	147,026	23.469	0	63	18.029	.94	2.675
Institutional ownership	147,026	.74	0	1	.226	-1.089	3.664
NASDAQ dummy	147,026	.479	0	1	.5	.083	1.007
Earning-day dummy	147,026	.001	0	1	.031	32.018	1026.155
Dividend-paying dummy	147,026	.491	0	1	.5	.036	1.001
Log(firm size)	147,008	8.327	.754	13.131	2.094	-.077	2.583
Log(1 + analyst coverage)	147,026	1.228	0	2.89	.769	-.15	2.084
Stock price	147,026	50.78	.6	2403.25	64.566	4.32	38.003
Bid-ask spread	147,026	1.552	0	84.51	1.985	5.219	70.666
Momentum	140,751	.431	-.935	81.8	1.009	16.055	982.836
Market volatility	147,026	.008	.005	.023	.004	2.15	7.074

Table 3.2

Correlation matrix between *BSI* and other variables used in the analysis

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) *AvgSentiment*	1.000											
(2) *BSI*	0.030*	1.000										
(3) *Abn-BSI*	0.037*	0.966*	1.000									
(4) *ADSVI*	-0.018*	0.005	0.005	1.000								
(5) *Log(firm size)*	-0.065*	-0.051*	-0.041*	0.135*	1.000							
(6) *Log(1 + analyst coverage)*	-0.057*	-0.039*	-0.023*	0.075*	0.651*	1.000						
(7) *Institutional ownership*	-0.011*	-0.019*	-0.009*	0.037*	0.240*	0.313*	1.000					
(8) *Market volatility*	-0.018*	0.010*	0.008*	0.005	0.063*	0.130*	0.023*	1.000				
(9) *Firm age*	-0.005	-0.034*	-0.020*	0.083*	0.492*	0.159*	0.077*	-0.010*	1.000			
(10) *Stock price*	-0.053*	-0.009*	-0.018*	0.042*	0.434*	0.405*	0.193*	0.015*	0.066*	1.000		
(11) *Bid-ask spread*	-0.075*	0.009*	-0.006	0.042*	0.196*	0.246*	0.178*	0.097*	-0.084*	0.728*	1.000	
(12) *Momentum*	0.035*	0.019*	0.015*	-0.035*	-0.188*	-0.141*	-0.056*	-0.059*	-0.122*	0.034*	0.099*	1.000

* indicates significant level at 1 %

Table 3.3

Panel regression estimates with the abnormal imbalance for a given stock on day *t* as the dependent variable

AvgSentiment is used as the primary independent variable. To estimate the impact of sentiment on retail investors' trading behavior, I run the following model:

$$Abn\text{-}BSI_{i,t} = \alpha + \beta_1 AvgSentiment_{i,t} + \beta_2 BSI_{i,t-1} + Control\ Variables + TimeFEs + FirmFEs + \varepsilon_{i,t} \quad (3)$$

Variable	(1) *Abn-BSI*	(2) *Abn-BSI*	(3) *Abn-BSI*	(4) *Abn-BSI*	(5) *Abn-BSI*	(6) *Abn-BSI*
AvgSentiment	0.0105***	0.0123***	0.0100***	0.0116***	0.00962***	0.0104***
	(0.00120)	(0.00123)	(0.00117)	(0.00120)	(0.00118)	(0.00121)
BSI-Lag			0.116***	0.119***	0.116***	0.117***
			(0.00525)	(0.00523)	(0.00535)	(0.00533)
Log(firm size)					-0.00501*	-0.00333***
					(0.00274)	(0.000740)
Log(1 + analyst coverage)					-0.00191	0.000665
					(0.00247)	(0.00161)
Institutional ownership					0.0328**	-0.00146
					(0.0132)	(0.00428)
Market volatility					1.035***	0.849**
					(0.388)	(0.387)
Firm age					0.00373	0.000160***
					(0.00314)	(5.88e-05)
NASDAQ dummy					0.0152	0.00554***
					(0.0102)	(0.00199)
Earning-day dummy					0.0253*	0.0327**
					(0.0135)	(0.0142)
Dividend-paying dummy					-0.0188***	-0.00567***
					(0.00600)	(0.00210)
Stock price					6.32e-05**	-7.14e-06
					(2.87e-05)	(1.34e-05)
Bid-ask spread					0.000204	-0.000103
					(0.000405)	(0.000392)
Momentum					0.000905	0.000952
					(0.00129)	(0.00101)
Constant	0.00766***	0.00682***	0.00836***	0.00761***	-0.0712	0.0255***

	(0.000887)	(0.00111)	(0.000865)	(0.00109)	(0.0742)	(0.00707)
Observations	144,966	145,276	144,966	145,276	139,644	139,953
R-squared	0.056	0.005	0.070	0.020	0.071	0.022
TIME *FE*	YES	YES	YES	YES	YES	YES
INDUSTRY FE	NO	YES	NO	YES	NO	YES
FIRM FE	YES	NO	YES	NO	YES	NO

Robust standard errors are in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.4

Panel regression estimates with the abnormal imbalance for a given stock on day *t* as the dependent variable

AvgSentiment is used as the primary independent variable. To estimate the impact of sentiment on retail investors' trading behavior for different terciles of institutional ownership, I run the following model for each institutional ownership tercile:

$$Abn\text{-}BSI_{i,t} = \alpha + \beta_1 AvgSentiment_{i,t} + \beta_2 BSI_{i,t-1} + Control\ Variables + TimeFEs + FirmFEs + \varepsilon_{i,t} \qquad (3)$$

	(1)	(2)	(3)	(4)	(5)	(6)
	Abn-BSI	*Abn-BSI*	*Abn-BSI*	*Abn-BSI*	*Abn-BSI*	*Abn-BSI*
Variable	*Low Ownership*		*Mid Ownership*		*High Ownership*	
AvgSentiment	0.0138***	0.0143***	0.00310*	0.00433**	0.0117***	0.0126***
	(0.00247)	(0.00253)	(0.00181)	(0.00179)	(0.00174)	(0.00174)
BSI-Lag	0.105***	0.108***	0.132***	0.135***	0.104***	0.109***
	(0.0118)	(0.0116)	(0.00756)	(0.00751)	(0.00622)	(0.00627)
Log(firm size)	-0.00856*	-0.00479***	-0.00550	-0.00247*	-0.00451	-0.00168
	(0.00478)	(0.00129)	(0.00510)	(0.00139)	(0.00469)	(0.00161)
Log(1 + analyst coverage)	-0.00545	0.00199	-0.00673	-0.000607	0.0101**	0.000650
	(0.00540)	(0.00346)	(0.00425)	(0.00280)	(0.00393)	(0.00249)
Institutional ownership	0.0358	-0.0203*	0.168***	0.0369	0.0722	-0.00890
	(0.0299)	(0.0103)	(0.0512)	(0.0266)	(0.0478)	(0.0285)
Market volatility	0.844	0.491	1.350***	1.054**	0.980**	1.009**
	(0.648)	(0.621)	(0.506)	(0.479)	(0.460)	(0.461)
Firm age	-0.00279	0.000320***	0.00380	0.000170*	0.00442	3.97e-05
	(0.00903)	(0.000121)	(0.00564)	(8.91e-05)	(0.00605)	(0.000103)
NASDAQ dummy	0.0258**	0.00884**	-0.0235	0.00459	0.0322	0.00396
	(0.0124)	(0.00429)	(0.0244)	(0.00358)	(0.0215)	(0.00301)
Earning-day dummy	0.0263	0.0363	0.0398**	0.0590**	0.0116	0.00481
	(0.0299)	(0.0301)	(0.0197)	(0.0243)	(0.0214)	(0.0197)
Dividend-paying dummy	-0.00312	-0.00764*	-0.0163*	-0.00320	-0.0343***	-0.00678**
	(0.0123)	(0.00438)	(0.00903)	(0.00392)	(0.0105)	(0.00322)
Stock price	4.25e-05	9.00e-06	2.04e-05	-8.94e-06	4.54e-05	-3.34e-05
	(8.28e-05)	(2.92e-05)	(4.72e-05)	(3.26e-05)	(4.44e-05)	(2.41e-05)
Bid-ask spread	0.00207**	0.000793	-0.000479	-0.000429	-8.95e-05	-0.000423
	(0.00101)	(0.000887)	(0.000734)	(0.000690)	(0.000485)	(0.000501)
Momentum	0.000905	0.000307	0.000473	-0.000472	0.00295**	0.00336**

	(0.00265)	(0.00144)	(0.00265)	(0.00187)	(0.00139)	(0.00149)
Constant	0.106	0.0382***	-0.156	-0.00834	-0.143	0.0223
	(0.218)	(0.0106)	(0.155)	(0.0233)	(0.127)	(0.0317)
Observations	44,414	44,693	47,285	47,415	47,772	47,845
R-squared	0.101	0.025	0.082	0.030	0.062	0.020
TIME FE	YES	YES	YES	YES	YES	YES
INDUSTRY FE	NO	YES	NO	YES	NO	YES
FIRM FE	YES	NO	YES	NO	YES	NO

Robust standard errors in are parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.5

Panel regression estimates with the abnormal imbalance for a given stock on day *t* as the dependent variable

AvgSentiment is used as the primary independent variable. To estimate the impact of sentiment on retail investors' trading behavior for different terciles of firm size, I run the following model for each size tercile:

$$Abn\text{-}BSI_{i,t} = \alpha + \beta_1 AvgSentiment_{i,t} + \beta_2 BSI_{i,t-1} + Control\ Variables + TimeFEs + FirmFEs + \varepsilon_{i,t} \quad (3)$$

	(1)	(2)	(3)	(4)	(5)	(6)
	Abn-BSI	*Abn-BSI*	*Abn-BSI*	*Abn-BSI*	*Abn-BSI*	*Abn-BSI*
Variable	*Small Cap*		*Mid Cap*		*Large Cap*	
AvgSentiment	0.0189***	0.0190***	0.0105***	0.0110***	-0.00106	-0.000405
	(0.00225)	(0.00236)	(0.00180)	(0.00177)	(0.00183)	(0.00181)
BSI-Lag	0.0946***	0.0962***	0.122***	0.127***	0.151***	0.152***
	(0.00855)	(0.00836)	(0.00683)	(0.00692)	(0.0112)	(0.0110)
Log(firm size)	-0.00901*	0.00738***	0.00149	-0.000982	0.0109	0.000188
	(0.00527)	(0.00218)	(0.00500)	(0.00261)	(0.00837)	(0.00164)
Log(1 + analyst coverage)	-0.00198	0.000256	-0.00315	-0.00272	0.000919	0.00293
	(0.00568)	(0.00350)	(0.00355)	(0.00221)	(0.00436)	(0.00303)
Institutional ownership	0.0294*	-0.00144	0.0983***	0.0228**	0.0737	0.0211**
	(0.0178)	(0.00755)	(0.0291)	(0.00985)	(0.0649)	(0.00851)
Market volatility	0.842	0.319	1.412***	1.353***	0.797	0.752
	(0.602)	(0.574)	(0.485)	(0.485)	(0.530)	(0.527)
Firm age	0.00846	0.000336**	0.000625	-3.97e-05	0.00181	0.000101
	(0.00793)	(0.000158)	(0.00513)	(9.00e-05)	(0.00448)	(7.80e-05)
NASDAQ dummy	0.0114	0.00678*	0.0103	0.00275	-0.00238	0.00289
	(0.0178)	(0.00406)	(0.0135)	(0.00298)	(0.0383)	(0.00344)
Earning-day dummy	-0.0251	0.0181	0.00745	0.00688	0.0657***	0.0682***
	(0.0280)	(0.0360)	(0.0226)	(0.0220)	(0.0186)	(0.0186)
Dividend-paying dummy	-0.0185	-0.00816*	-0.0102	-0.00312	-0.0222**	-0.00730*
	(0.0162)	(0.00420)	(0.00884)	(0.00273)	(0.00914)	(0.00409)
Stock price	0.000485**	2.42e-05	7.04e-05	-8.63e-06	3.05e-05	-3.06e-05**
	(0.000219)	(0.000122)	(5.69e-05)	(3.28e-05)	(4.10e-05)	(1.50e-05)
Bid-ask spread	0.00163	0.00191	4.22e-05	-0.000453	0.000120	-2.74e-05
	(0.00127)	(0.00123)	(0.000608)	(0.000602)	(0.000410)	(0.000418)
Momentum	0.00158	0.000634	0.00129	0.00142	-0.000399	0.00177
	(0.00215)	(0.00128)	(0.00186)	(0.00143)	(0.00389)	(0.00291)

Constant	-0.0776	0.0452***	-0.116	-0.0114	-0.220	-0.0196
	(0.116)	(0.0132)	(0.116)	(0.0236)	(0.146)	(0.0195)
Observations	46,145	46,471	46,485	46,523	46,957	46,958
R-squared	0.098	0.019	0.061	0.024	0.045	0.033
TIME FE	YES	YES	YES	YES	YES	YES
INDUSTRY FE	NO	YES	NO	YES	NO	YES
FIRM FE	YES	NO	YES	NO	YES	NO

Robust standard errors are in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.6

Panel regression estimates with the abnormal imbalance for a given stock on day *t* as the dependent variable

AvgSentiment is used as the primary independent variable. To estimate the impact of sentiment on retail investors' trading behavior for different terciles of firm analysts' coverage, I run the following model for each analyst coverage tercile:

$$Abn\text{-}BSI_{i,t} = \alpha + \beta_1 AvgSentiment_{i,t} + \beta_2 BSI_{i,t-1} + Control\ Variables + TimeFEs + FirmFEs + \varepsilon_{i,t} \quad (3)$$

	(1)	(2)	(3)	(4)	(5)	(6)
	Abn-BSI	*Abn-BSI*	*Abn-BSI*	*Abn-BSI*	*Abn-BSI*	*Abn-BSI*
Variable	*Low Coverage*		*Mid Coverage*		*High Coverage*	
AvgSentiment	0.0163***	0.0159***	0.00764***	0.00907***	0.00479***	0.00550***
	(0.00221)	(0.00234)	(0.00184)	(0.00182)	(0.00184)	(0.00181)
BSI-Lag	0.0999***	0.106***	0.121***	0.127***	0.118***	0.121***
	(0.00941)	(0.00906)	(0.00708)	(0.00724)	(0.00822)	(0.00794)
Log(firm size)	-0.00809*	0.00667***	-0.00237	-0.00145	-0.0107**	-0.000989
	(0.00475)	(0.00146)	(0.00472)	(0.00126)	(0.00506)	(0.00141)
Log(1 + analyst coverage)	0.000799	0.00112	-0.00815	-0.00389	0.00229	0.00220
	(0.00683)	(0.00507)	(0.00701)	(0.00571)	(0.00717)	(0.00495)
Institutional ownership	0.0389**	0.000103	0.0453**	0.0191**	0.0484	0.0122
	(0.0183)	(0.00664)	(0.0222)	(0.00922)	(0.0317)	(0.00753)
Market volatility	0.523	0.256	1.660***	1.582***	0.560	0.625
	(0.621)	(0.604)	(0.536)	(0.511)	(0.452)	(0.449)
Firm age	0.00230	0.000177*	0.00457	8.42e-05	0.00514	8.79e-05
	(0.00613)	(0.000108)	(0.00599)	(8.76e-05)	(0.00455)	(0.000101)
NASDAQ dummy	0.0175	0.00532	-0.00151	0.00298	0.0373	0.00516*
	(0.0130)	(0.00422)	(0.0172)	(0.00346)	(0.0468)	(0.00273)
Earning-day dummy	0.00153	0.0281	0.0128	0.0131	0.0517**	0.0542***
	(0.0281)	(0.0310)	(0.0216)	(0.0210)	(0.0200)	(0.0193)
Dividend-paying dummy	-0.0140	-0.0113***	-0.0172	-0.00584*	-0.0160*	-0.00170
	(0.0116)	(0.00392)	(0.0111)	(0.00350)	(0.00832)	(0.00326)
Stock price	2.15e-05	4.79e-06	1.59e-05	-6.94e-06	5.87e-05*	-1.93e-05
	(0.000138)	(7.29e-05)	(7.53e-05)	(3.96e-05)	(3.19e-05)	(1.47e-05)
Bid-ask spread	0.000741	0.00120	-0.000525	-0.00102	0.000672	0.000203
	(0.00109)	(0.00106)	(0.000782)	(0.000767)	(0.000410)	(0.000383)
Momentum	0.00127	0.000591	0.00387*	0.00485**	-0.00212	-0.00288
	(0.00186)	(0.00112)	(0.00231)	(0.00190)	(0.00277)	(0.00294)

Constant	-0.0168	0.0474***	-0.124	-0.00248	-0.0832	-0.00547
	(0.117)	(0.0108)	(0.160)	(0.0159)	(0.119)	(0.0166)
Observations	46,737	47,099	50,523	50,671	42,116	42,183
R-squared	0.108	0.022	0.081	0.026	0.052	0.025
TIME FE	YES	YES	YES	YES	YES	YES
INDUSTRY FE	NO	YES	NO	YES	NO	YES
FIRM FE	YES	NO	YES	NO	YES	NO

Robust standard errors are in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.7

Panel regression estimates with the abnormal imbalance for a given stock on day *t* as the dependent variable

AvgSentiment is used as the primary independent variable. To control for the impact of attention on investors' trading behavior, I run the following model:

$$Abn\text{-}BSI_{i,t} = \alpha + \beta_1 AvgSentiment_{i,t} + \beta_2 BSI_{i,t-1} + \beta_2 ADSVI_{i,t} + Control\ Variables + TimeFEs + FirmFEs + \varepsilon_{i,t} \quad (4)$$

	(1) *Abn-BSI*	(2) *Abn-BSI*	(3) *Abn-BSI*	(4) *Abn-BSI*	(5) *Abn-BSI*	(6) *Abn-BSI*
Variable	*Full Sample*		*Low Attention*		*High Attention*	
AvgSentiment	0.00963***	0.0104***	0.00970***	0.0106***	0.00646*	0.00706**
	(0.00118)	(0.00121)	(0.00123)	(0.00126)	(0.00377)	(0.00357)
ADSVI	0.00171***	0.00159***	0.00254**	0.00228*	0.0309	0.0426*
	(0.000494)	(0.000493)	(0.00123)	(0.00121)	(0.0217)	(0.0223)
BSI-Lag	0.116***	0.117***	0.116***	0.117***	0.108***	0.118***
	(0.00535)	(0.00533)	(0.00498)	(0.00502)	(0.0247)	(0.0216)
Log(firm size)	-0.00498*	-0.00345***	-0.00575**	-0.00355***	0.0133	-0.000663
	(0.00274)	(0.000739)	(0.00277)	(0.000754)	(0.00846)	(0.00207)
Log(1 + analyst coverage)	-0.00185	0.000715	-0.00244	0.000786	0.00363	-0.00180
	(0.00247)	(0.00161)	(0.00255)	(0.00168)	(0.00618)	(0.00404)
Institutional ownership	0.0329**	-0.00146	0.0333**	-0.00212	0.0231	0.0169
	(0.0132)	(0.00428)	(0.0132)	(0.00438)	(0.0418)	(0.0115)
Market volatility	1.037***	0.850**	1.077***	0.881**	0.578	0.379
	(0.389)	(0.388)	(0.378)	(0.378)	(0.871)	(0.856)
Firm age	0.00375	0.000161***	0.00363	0.000172***	0.000370	-2.96e-05
	(0.00314)	(5.88e-05)	(0.00315)	(6.03e-05)	(0.00866)	(0.000148)
NASDAQ dummy	0.0151	0.00577***	0.0206*	0.00558***	-0.0394	0.00903
	(0.0102)	(0.00199)	(0.0117)	(0.00205)	(0.0386)	(0.00566)
Earning-day dummy	0.0246*	0.0321**	0.0139	0.0237	0.0713*	0.0646*
	(0.0134)	(0.0141)	(0.0132)	(0.0148)	(0.0393)	(0.0359)
Dividend-paying dummy	-0.0189***	-0.00568***	-0.0176***	-0.00628***	-0.0343*	0.000900
	(0.00601)	(0.00209)	(0.00605)	(0.00219)	(0.0201)	(0.00599)
Stock price	6.51e-05**	-5.23e-06	6.62e-05**	-3.61e-06	1.44e-05	-6.04e-05
	(2.86e-05)	(1.33e-05)	(2.91e-05)	(1.35e-05)	(8.76e-05)	(4.68e-05)
Bid-ask spread	0.000134	-0.000166	0.000121	-0.000129	-0.000164	1.36e-05
	(0.000406)	(0.000394)	(0.000431)	(0.000421)	(0.000793)	(0.000818)

Momentum	0.000917	0.000959	0.00129	0.00124	-0.00509*	0.00556**
	(0.00129)	(0.00101)	(0.00136)	(0.00108)	(0.00304)	(0.00231)
Constant	-0.0727	0.0256***	-0.0663	0.0262***	-0.234	-0.163*
	(0.0742)	(0.00707)	(0.0731)	(0.00711)	(0.255)	(0.0898)
Observations	139,644	139,953	129,570	129,891	9,848	10,062
R-squared	0.071	0.022	0.074	0.022	0.151	0.033
TIME FE	YES	YES	YES	YES	YES	YES
INDUSTRY FE	NO	YES	NO	YES	NO	YES
FIRM FE	YES	NO	YES	NO	YES	NO

Robust standard errors are in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.8

Panel regression estimates with the abnormal imbalance for a given stock on day *t* as the dependent variable

AvgSentiment is used as the primary independent variable. To control for the impact of attention on investors' trading behavior, I run the following models:

$$Return_{i,t} = \alpha + \beta_1 BSI_{i,t-1} + \beta_2 BSI\_nosent_{i,t-1} + Control\ Variables + TimeFEs + FirmFEs + \varepsilon_{i,t} \quad (6.a)$$

and

$$Return_{i,t} = \alpha + \beta_1 AvgSentiment_{i,t-1} + \beta_2 BSI\_nosent_{i,t-1} + Control\ Variables + TimeFEs + FirmFEs + \varepsilon_{i,t} \quad (6.b)$$

Variable	(1) *Return*	(2) *Return*	(3) *Return*	(4) *Return*
BSI-Lag	0.00249**	0.00205*		
	(0.00102)	(0.00109)		
AvgSentiment-Lag			0.00186***	0.00182***
			(0.000261)	(0.000265)
BSI-nosent-Lag	-0.000400	-0.000703	-0.000318	-0.000722
	(0.000802)	(0.000801)	(0.000802)	(0.000801)
Ret-Lag	-0.0145	0.0202*	-0.0368	0.0174
	(0.0123)	(0.0118)	(0.0267)	(0.0128)
Log(firm size)	-0.00906***	-0.00332***	-0.00928***	-0.00345***
	(0.000905)	(0.000225)	(0.000955)	(0.000268)
Log(1 + analyst coverage)	0.000143	8.47e-05	0.000149	0.000153
	(0.000552)	(0.000405)	(0.000558)	(0.000416)
Institutional ownership	-0.0235***	-0.0114***	-0.0237***	-0.0120***
	(0.00422)	(0.00143)	(0.00430)	(0.00158)
Market volatility	0.347*	0.270	0.365**	0.279
	(0.184)	(0.185)	(0.185)	(0.184)
Firm age	0.00153*	0.000110***	0.00160*	0.000118***
	(0.000830)	(1.58e-05)	(0.000844)	(1.85e-05)
NASDAQ dummy	5.00e-05	0.000336	8.02e-05	0.000354
	(0.00324)	(0.000537)	(0.00325)	(0.000549)
Earning-day dummy	0.00354	0.00290	0.00364	0.00294
	(0.00656)	(0.00663)	(0.00656)	(0.00663)
Dividend-paying dummy	-0.000180	0.00122**	-0.000111	0.00130**

	(0.00128)	(0.000532)	(0.00131)	(0.000552)
Stock price	4.97e-05***	-1.14e-07	5.06e-05***	-2.05e-07
	(1.58e-05)	(9.45e-06)	(1.62e-05)	(9.51e-06)
Bid-ask spread	0.00129***	0.000871**	0.00133***	0.000913**
	(0.000501)	(0.000422)	(0.000507)	(0.000427)
Momentum	0.00265***	0.00245***	0.00273***	0.00261***
	(0.000519)	(0.000404)	(0.000540)	(0.000453)
Constant	0.0550***	0.0347***	0.0545***	0.0350***
	(0.0193)	(0.00274)	(0.0196)	(0.00302)
Observations	136,036	136,346	136,041	136,351
R-squared	0.079	0.024	0.090	0.024
YEAR FE	YES	YES	YES	YES
INDUSTRY FE	NO	YES	NO	YES
FIRM FE	YES	NO	YES	NO

Robust standard errors are in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.9

Panel regression estimates with the return for a given stock on day *t* as the dependent variable

*BSI*Bullish* is used as the primary independent variable. To examine the role of *BSI* on stock prices independently, as well as in conjunction with sentiment, I run the following model:

$$Return_{i,t} = \alpha + \beta_1 BSI_{i,t} + \beta_2 BSI_{i,t} * Bullish_{i,t-1} + Control\ Variables + TimeFEs + FirmFEs + \varepsilon_{i,t} \quad (7)$$

Variable	(1) *Return*	(2) *Return*	(3) *Return*	(4) *Return*
BSI	-0.00390***	-0.00516***	-0.00830***	-0.00885***
	(0.00143)	(0.00140)	(0.00193)	(0.00191)
*BSI*Bullish-Lag*			0.00796***	0.00663***
			(0.00186)	(0.00184)
Bullish-Lag			0.0106***	0.0109***
			(0.000503)	(0.000494)
Ret-Lag	-0.0381	0.0151	-0.0420	0.0108
	(0.0259)	(0.0124)	(0.0258)	(0.0123)
Log(firm size)	-0.00928***	-0.00348***	-0.00898***	-0.00325***
	(0.000956)	(0.000269)	(0.000935)	(0.000263)
Log(1+ analyst coverage)	6.98e-05	0.000148	1.28e-05	0.000106
	(0.000556)	(0.000412)	(0.000547)	(0.000390)
Institutional ownership	-0.0227***	-0.0120***	-0.0225***	-0.0130***
	(0.00449)	(0.00157)	(0.00450)	(0.00157)
Market volatility	0.354*	0.271	0.324*	0.241
	(0.185)	(0.183)	(0.188)	(0.187)
Firm age	0.00158*	0.000116***	0.00156*	0.000111***
	(0.000831)	(1.82e-05)	(0.000844)	(1.74e-05)
NASDAQ dummy	-0.000296	0.000300	-6.77e-05	0.000405
	(0.00304)	(0.000552)	(0.00297)	(0.000541)
Earning-day dummy	0.00331	0.00259	0.00328	0.00239
	(0.00636)	(0.00644)	(0.00624)	(0.00632)
Dividend-paying dummy	-0.000244	0.00130**	-0.000158	0.00107**
	(0.00129)	(0.000557)	(0.00119)	(0.000537)
Stock price	5.16e-05***	1.49e-07	4.99e-05***	-2.75e-08
	(1.66e-05)	(9.38e-06)	(1.47e-05)	(1.00e-05)
Bid-ask spread	0.00131***	0.000903**	0.00148***	0.00113**

	(0.000499)	(0.000418)	(0.000518)	(0.000437)
Momentum	0.00262***	0.00256***	0.00249***	0.00246***
	(0.000539)	(0.000445)	(0.000534)	(0.000431)
Constant	0.0553***	0.0362***	0.0483**	0.0302***
	(0.0195)	(0.00302)	(0.0198)	(0.00297)
Observations	140,424	140,733	140,424	140,733
R-squared	0.089	0.024	0.098	0.033
YEAR FE	YES	YES	YES	YES
INDUSTRY FE	NO	YES	NO	YES
FIRM FE	YES	NO	YES	NO

Robust standard errors are in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Chapter 3 Appendix 1

Variable definitions

Variable	Description	Source
AvgSentiment	The number of bullish messages minus the number of bearish messages divided by the sum of bullish and bearish messages for firm i at day t.	PsychSignal
BSI	The volume of purchases of stock i on day t minus the volume of sales of stock i on day t divided by the sum of purchases of stock i on day t and the volume of sales of stock i on day t.	TAQ
Abn-BSI	The difference between *BSI* in time period t and the average *BSI* from $t - 140$ to $t - 20$ trading days (a six-month period, skipping a month).	TAQ
ADSVI	A categorical variable that takes a score of 1, 2, 3, or 4 if the previous 30 trading days' *DSVI* average is between 80% and 90%, 90% and 94%, 94% and 96%, or greater than 96%, respectively.	Google
Log(1+analyst coverage)	The natural log of 1 plus the number of analysts covering the firm for the fiscal quarter.	I/B/E/S
Firm age	The number of years since the stock first appeared in the Compustat database.	Compustat
Log(firm size)	The natural log of the market value of equity (Compustat item *PRCC_F*CSHO*).	Compustat
Market volatility	Following Busse (1999), a root mean-squared error from a rolling 90-day, one-factor model, including a one-day lagged market excess return factor.	CRSP
Dividend-paying dummy	An indicator variable that takes the value of 1 if a stock pays a dividend and zero otherwise.	CRSP
Earning-day dummy	An indicator variable that takes the value of 1 if a daily observation takes place on an earnings-announcement day and zero otherwise.	Compustat
NASDAQ dummy	An indicator variable that takes the value of 1 if the stock trades on the NASDAQ exchange and zero otherwise.	CRSP
Stock price	The daily closing price of a stock.	CRSP
Institutional ownership	The total institutional ownership ratio in terms of the percentage of market capitalization.	Factset
Bid-ask spread	The difference between the bid and ask prices.	CRSP
Momentum	The past 12-months' stock return from $t - 12$ to $t - 1$.	CRSP

CRSP = Center for Research in Security Prices.

I/B/E/S = Institutional Brokers' Estimate System.

TAQ = Trade and Quote database.

Chapter 3 Appendix 2

Panel regression estimates with the abnormal imbalance for a given stock on day *t* as the dependent variable

AvgSentiment is used as the primary independent variable. To control for the impact of attention on investors' trading behavior using alternative measures of investors' attention, I run the following two models:

$$AbBSI_{i,t} = \alpha + \beta_1 AvgSentiment_{i,t} + \beta_2 BSI_{i,t-1} + \beta_2 Abn\text{-}Vol_{i,t} + Control\ Variables + TimeFEs + FirmFEs + \varepsilon_{i,t}$$

and

$$AbBSI_{i,t} = \alpha + \beta_1 AvgSentiment_{i,t} + \beta_2 BSI_{i,t-1} + \beta_2 Return_{i,t-1} + Control\ Variables + TimeFEs + FirmFEs + \varepsilon_{i,t}$$

Abn-Vol is defined as the trading volume for stock *i* on day *t* divided by the average trading volume over the previous one year (i.e., 252 trading days).

Variable	(1) *Abn-BSI*	(2) *Abn-BSI*	(3) *Abn-BSI*	(4) *Abn-BSI*
AvgSentiment	0.00964***	0.0104***	0.00947***	0.0103***
	(0.00120)	(0.00123)	(0.00119)	(0.00122)
Abn-Vol	4.62e-07	-0.000417		
	(0.000310)	(0.000297)		
Ret-Lag			0.0216	0.0186
			(0.0141)	(0.0145)
BSI-Lag	0.115***	0.117***	0.116***	0.117***
	(0.00540)	(0.00539)	(0.00535)	(0.00533)
Log(firm size)	-0.00456	-0.00340***	-0.00487*	-0.00328***
	(0.00287)	(0.000753)	(0.00274)	(0.000740)
Log(1 + analyst coverage)	-0.00202	0.000715	-0.00189	0.000668
	(0.00252)	(0.00165)	(0.00247)	(0.00161)
Institutional ownership	0.0334**	-0.00241	0.0332**	-0.00131
	(0.0137)	(0.00434)	(0.0133)	(0.00428)
Market volatility	1.062***	0.877**	1.027***	0.843**
	(0.387)	(0.386)	(0.387)	(0.386)
Firm age	0.00443	0.000170***	0.00370	0.000159***
	(0.00316)	(5.93e-05)	(0.00314)	(5.88e-05)
NASDAQ dummy	0.0162	0.00564***	0.0151	0.00553***
	(0.0105)	(0.00201)	(0.0102)	(0.00199)
Earning-day dummy	0.0252*	0.0333**	0.0253*	0.0327**
	(0.0137)	(0.0143)	(0.0135)	(0.0142)
Dividend-paying dummy	-0.0200***	-0.00568***	-0.0189***	-0.00569***
	(0.00623)	(0.00212)	(0.00600)	(0.00209)
Stock price	5.97e-05*	-1.12e-05	6.17e-05**	-7.71e-06
	(3.11e-05)	(1.41e-05)	(2.89e-05)	(1.34e-05)
Bid-ask spread	0.000175	2.65e-05	0.000214	-9.24e-05
	(0.000427)	(0.000416)	(0.000405)	(0.000392)

Momentum	0.00187*	0.00183*	0.000875	0.000918
	(0.00103)	(0.00100)	(0.00128)	(0.00101)
Constant	-0.0924	0.0265***	-0.0717	0.0250***
	(0.0748)	(0.00719)	(0.0742)	(0.00708)
Observations	137,952	138,259	139,644	139,953
R-squared	0.071	0.022	0.071	0.022
YEAR FE	YES	YES	YES	YES
INDUSTRY FE	NO	YES	NO	YES
FIRM FE	YES	NO	YES	NO

Robust standard errors are in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

CHAPTER 4

THE IMPACT OF INVESTOR SENTIMENT ON HERDING BEHAVIOR: EVIDENCE FROM A SOCIAL NETWORK OF INVESTORS

4.1 Introduction

In the recent behavioral-finance literature, significant attention has been directed to herd behavior in financial markets. Researchers have since looked for both a theoretical explanation and empirical evidence of herding. However, there is considerable disagreement regarding how the theoretical and empirical literature explains the herding phenomenon. On one hand, the theoretical literature provides possible purposes for herding in abstract models that are difficult to examine using archive data; on the other hand, the empirical works use statistical evidence of trade clustering and interpret this as herding.

The main findings of our study can be summarized as follows. First, even though I did not detect any presence of herding in the overall stock market, by dividing the universe of stocks into high-optimism and low-optimism portfolios, I was able to show that herding presents an asymmetric reaction to investor sentiment. Specifically, herding is present in low-optimism portfolios but not in high-optimism portfolios. Second, the level of investor attention has a moderating impact on the relationship between investors' optimism and their tendency to herd by causing the presence of herding to be more intensified among low-optimism stocks. Finally, I find evidence that herding behavior, whenever it exists, is driven by trading volume.

My study makes several direct contributions to the literature on behavioral finance and, specifically, to the areas of investor sentiment and its impact on asset prices. First, to the best of my knowledge, I am the first to use firm-specific sentiment to study the impact of investor sentiment on herding behavior. Second, I also investigate the impact of using different sampling frequencies on detecting the presence of herding in the equity market. The majority of previous studies use a low-frequency (monthly or quarterly) market-level sentiment measure, whereas I use daily, weekly, and monthly frequency data that are more aligned with changes in investor sentiment. Contrary to previous findings, I document that herding may occur when the overall market is quiet.

4.2 Date, sample, and hypothesis development

4.2.1 Market-wide herding measure

Chang, Cheng, and Khorana (2000) characterize herding with cross-sectional absolute deviation of returns (*CSAD*), which is calculated as

$$CSAD_t = \frac{1}{N} \sum_{i=1}^{N} \left| R_{i,t} - R_{m,t} \right| \tag{1}$$

CSAD is preferable over other measures of herding, such as Christie and Huang's (1995) measure of herding, because return outliers have a less significant effect on it. Moreover, CSAD considers the nonlinear relationship between return dispersion and market returns. To test for the presence of herding in the stock market, CCK examine the presence of herding in markets by estimating the following equation:

$$CSAD_t = \gamma_0 + \gamma_1 \mid R_{m,t} \mid + \gamma_2 R^2_{m,t} + \varepsilon_t \tag{2}$$

CSAD and R_m are the cross-sectional absolute deviation of equity returns and cross-sectional average return, respectively. In the CCK method, the justification for introducing the nonlinear term $R^2_{m,t}$ is that the association between market returns and return dispersion is not just an increasing function but is linear. However, the presence of herding will cause this relationship to be nonlinear, which indicates that return dispersion would be less if herding were present.

Because I am interested in exploring the presence of herding in normal market periods, not simply during periods of market distress, and because I want to take into consideration the nonlinear relationship between return dispersion and market returns, I apply the CCK methodology in my analysis.

4.2.2 Sample creation and descriptive statistic

I obtain daily security-level data from the Center for Research in Security Prices database. I limit my sample to common stocks with share codes 10 and 11 (which excludes mainly exchange-traded funds, American depositary receipts, and REITs) listed on the three primary exchanges: NYSE, NYSEMKT (formerly Amex), and NASDAQ. Based on the daily data, a series of weekly (monthly) returns is calculated by selecting the first available observation of each week (month). Thus, the robustness of herding behavior across sampling frequencies is studied.

Figures 4.1 and 4.2 plot the time series of R_m and *CSAD* for the high- and low-optimism portfolios, respectively, at three data frequencies (daily, weekly, and monthly), all of which display a spike at the start of the sample. This can be attributed to the ongoing financial crisis.

Table 4.3 provides the statistical summary of R_m and *CSAD* at three data frequencies for the full-sample portfolio, which consists of all publicly traded stocks with valid data each period, a high-optimism portfolio, which consists of stocks with average daily sentiment above the median for all stocks at time t, and a low-optimism portfolio, which consists of stocks with average daily sentiment below the median for all stocks at time t. As shown in the table, the time series mean of the full-sample portfolio return R_m is negative in all three data frequencies. The time series mean for *CSAD* increases as sampling frequency decreases from daily to monthly. *CSAD* has significant skewness and kurtosis, especially for the high-optimism portfolio compared with the full-sample and low-optimism portfolios. Therefore, it is not normally distributed.

4.2.3 Hypothesis development

4.2.3.1 Investor sentiment and herding behavior

According to the literature in psychology, the sentiments of individuals influence their judgments regarding future events, which affects decision-making. The literature indicates that persons with positive (negative) sentiments tend to make optimistic (pessimistic) decisions (Arkes, Herren, and Isen, 1988; Bower, 1981; Wright and Bower, 1992). Because sentiment involves measuring the emotive condition of the capital market, it likely affects herding behavior.

Several authors have applied numerous proxies for sentiment. Among the most popular is that of Baker and Wurgler (2006), who develop a sentiment proxy based on multiple factors, namely, trading volume measured by NYSE turnover, closed-end fund discount, the dividend premium, the number of initial public offerings (IPOs), first-day returns on IPOs, and equity shares in new issues.

De Long et al. (1990) conclude that investors are affected by sentiment, which is related to their confidence regarding the certainty of future cash flows. According to Shleifer and Vishny (1997), competing with sentimental investors can be expensive because their decisions influence the market price of securities. Eichengreen and Mody (1998) find evidence that investor sentiment has a contagion effect on the stock market, particularly in the short term. Baek and Bandopadhyaya (2005) document that changes in investor sentiment can predict the short-term movements in asset prices better than any other set of fundamental factors.

An increasing number of empirical studies uncover a noteworthy association between investor sentiment and market returns (Baker and Wurgler, 2006, 2007; Brown and Cliff, 2005; Lee, Jiang, and Indro, 2002). The findings highlight the role of sentiment on the decision-making process of individual investors, which eventually has an impact on asset prices and market returns.

Motivated by the literature, I examine the association between herding intensity and investor sentiment. If sentiment is low (high), several (few) investors reproduce the actions of other investors, who are presumed to have more reliable information on the market. Based on this argument, I formulate an alternative hypothesis regarding the influence of investors' sentiment on the presence of herding.

H1: Herding is more likely to be present in low-optimism portfolios than in high-optimism portfolios.

4.2.3.2 Investor attention and asset prices

Recent empirical evidence reveals that investor attention fluctuates over time and has a significant impact on the trading decisions of investors and, thus, affects asset prices (Da, Engelberg, and Gao, 2011). High levels of attention cause buying pressures and sudden drops in stock price (Barber and Odean, 2008; Barber, Odean, and Zhu, 2009a), and low levels of attention generate underreaction to firms' public announcements (DellaVigna and Pollet, 2009).

H2: The level of investors' attention will have a moderating effect on the impact of investors' sentiment on the presence of herding in stock markets.

4.2.3.3 Herding behavior and trading volume

The variation in trading volume often triggers a change in stock price. The degree of delay and the nature of the correlation between the change in a price and the trading volume require further empirical investigation. Little is known about the dual-influencing relationship between trading volume and herding, as measured by stock return dispersion.

Hachicha (2010) uses a measure of trading volume dispersion in examining the herding behavior of investors in the Toronto Stock Exchange. He finds that investors tend to intensely and sustainably herd on this market. Using a sample of stocks traded in Chinese markets, Fu and Lin (2010) and Lan and Lai (2011) investigate the impact of trading turnover on herding and find supporting evidence that trading volume contributes to triggering herding behavior among investors. Based on these arguments, I formulate a hypothesis on the relationship between herding behavior and trading volume.

H3: I expect a positive and significant correlation between market trading volume and herding. In addition, I expect trading volume to be a main factor in triggering the presence of herding.

4.2.3.4 Regression methodology

To conduct my analysis, I use the CCK method, which has been widely applied in the finance literature (Demirer and Kutan, 2006; Tan et al., 2008; Chiang, Li, and Tan, 2010). The underlying idea behind the CCK model is that it tests for herding by examining whether the cross-sectional return dispersion decreases or increases as market returns increase. To examine the presence of herding in stock markets, researchers apply an ordinary least squares (OLS) regression approach, whereas I prefer the use of quantile regression (QR; Koenker and Bassett, 1978).

If I compare both OLS and QR, QR seems more appropriate for discussion for two fundamental reasons. First, it can perform a thorough regression analysis over the entire distribution of the dependent variable. It shows a broader picture of how herding functions across diverse quantiles. Because market turmoil arises, the probability of a herding occurrence is more likely to exist in the high quantiles of the distribution compared with the low quantiles. The issue with using an OLS (mean-based) regression technique is that it becomes difficult to distinguish between diverse quantiles and, hence, increases the possibility of herding being overlooked as existing only in certain quantiles.

Second, QR mitigates some of the statistical drawbacks of OLS (Barnes and Hughes, 2002), such as abnormal distributions, sensitivity to outliers, errors in variables, and omitted-variable bias. Out of all these problems, the ability of QR to cope with abnormal distribution deserves the most attention. Here the return dispersion is not normally distributed, showing significant skewness and kurtosis. As such, when dealing with abnormal distributions, the QR model depicts more efficient estimators than those of OLS (Buchinsky, 1998).

4.3 Empirical results

4.3.1 Cross-validating the measurement of sentiment

I compare the measurement of sentiment with different classifications of investor sentiment measures as suggested by related research and sentiment measures in practice. I consider only sentiment measurements with high-frequency (i.e., daily) data availability. I seek answers to two questions: Does the measurement of investor sentiment pick up the same signals as other existing measures of sentiment and, if so, do they correlate with each other? Is the investor sentiment measure correlated to market returns and, if so, does it explain part of the movements of the market?

4.3.2 Comparison with other measures of sentiment

I consider eight different measures of wide-market sentiment: (1) the ADV/DEC ratio calculated as the number of advancing stocks on the NYSE divided by the number of declining stocks on the NYSE; three versions of the Put/Call ratio calculated as the trading volume of puts options divided by the trading volume of calls options, namely, (2) the total Put/Call ratio, (3) the equity Put/Call ratio, and (4) the index Put/Call ratio; the ISEE Sentiment Index calculated for (5) all securities (ISEE All), (6) single equity options (ISEE Equity), and (7) all index options (ISEE Index); and (8) the Volatility Index (VIX). Table 4.1, Panel A, provides summary statistics for those sentiment measures.

The measure of sentiment is positively correlated with measures of market-wide sentiment, such as the ADV/DEC ratio and the ISEE Sentiment Index. I expect to detect a negative correlation between *AvgSentiment* and measures of market fear, such as VIX and the Put/Call ratio of short-term options.

The correlations reported in Table 4.1, Panel B, indicate that *AvgSentiment* is consistent with what would be expected from a measure of sentiment. The correlation between *AvgSentiment* and the ADV/DEC ratio measure is positive (3.7%). The correlations between *AvgSentiment* and the ISEE Index, ISEE Equity, and ISEE All are 1.5%, 3.4%, and 3.5%, respectively. The correlations between *AvgSentiment* and total Put/Call ratio, equity Put/Call ratio, and index Put/Call ratio are negative (−4.7%, −1.1%, and −5.5%, respectively).

4.3.3 Comparison with market returns

Another evaluation method of sentiment measures is the comparison with market returns. Because investor sentiment incorporates investors' expectations and opinions about the market, sentiment measures and market returns should be correlated. Results reported in Table 4.2 confirm this reasoning and find that my measure of sentiment is correlated with market returns, as well as lagged market returns.

4.3.4 Herding in the equity market

I examine the presence of herding in the US equity market. The results reported in Table 4.4 present the estimation of herding based on Eq. (2). My focus is on the herding coefficient γ_2

because a significantly negative value of γ_2 suggests that herding is present in the market. The OLS results indicate that γ_2 is positive and significant. These findings hold across the different sampling frequencies (daily, weekly, and monthly), which suggests that herding does not exist in the US equity market. Moreover, the results based on QR support this finding. That is, γ_2 is positive and significant across all quantiles, as well as different sampling frequencies. These results are in line with existing empirical works that did not detect herding in the US equity market.

4.3.5 Herding in the up and down market

Several studies have shown that stocks' return dispersion tends to behave differently in rising and falling markets (see, e.g., Bekaert and Wu, 2000; Duffee, 2000; Longin and Solnik, 2001). To test whether the existence of herding presents an asymmetric reaction on days when the market is rising vis-à-vis days when the market is falling, I modify Eq. (2) as follows:

$$CSAD_t = \gamma_0 + \gamma_1(1 - D) \mid R_{m,t} \mid + \gamma_2 D \mid R_{m,t} \mid + \gamma_3(1 - D)R^2_{m,t} + \gamma_4 D R^2_{m,t} + \varepsilon_t \qquad (3)$$

where *CSAD* is the cross-sectional absolute deviation of equity returns, R_m is the cross-sectional average return, and D is a dummy variable that equals one when $R_{m,t} < 0$ and zero otherwise.

Table 4.5 reports the estimation results of herding in the up and down markets according to Eq. (3). A negative significant coefficient γ_3 (γ_4) indicates the existence of herding behavior in up (down) markets. The overall results, based on both OLS and QR, do not support the presence of herding-behavior asymmetry. The coefficients of γ_3 and γ_4 are either positive or insignificant across all sampling frequencies.

4.3.6 Impact of investor sentiment on herding behavior

I examine the impact of investor sentiment on the existence of herding behavior in the market. I create two portfolios: high optimism and low optimism. At day *t,* I assign a stock to a high- (low-)optimism portfolio if *AvgSentiment* for that stock is above (below) the median for all stocks on that day. I apply Eq. (2) to the two portfolios using different sampling frequencies (daily, weekly, and monthly).

Table 4.6 presents the results for herding in the high-optimism portfolio. The coefficient γ_2 is either positive or insignificant, which means that herding cannot be detected in the high-optimism portfolio across all sampling frequencies and using both OLS and QR. The picture is different for the low-optimism portfolio (Table 4.7).

Based on OLS estimates, I cannot detect the presence of herding behavior in the high-optimism portfolio (the coefficient γ_2 is positive and significant). When applying the QR approach, the coefficient γ_2 is negative and significant in lower quantiles (e.g., q = 10% and 25%), which is indicative of herding behavior when the market is quiet. The coefficient γ_2 becomes positive and significant in extreme quantiles (e.g., q = 50%, 75%, and 90%).

More convincing evidence for the impact of sentiment on herding behavior is obtained by examining the coefficient γ_2 for weekly frequency (Table 4.7, Panel B), which is negative and significant over a wider distribution range (e.g., q = 10% to q = 75%). The result obtained from OLS support the results using QR. These findings reinforce the notion that herding behavior can take place not only in extreme market movements but also in periods of quiet (Hwang and Salmon, 2004). Using QR instead of OLS thus is needed to estimate the presence of herding behavior in stock markets.

The monthly frequency sampling, using both OLS and QR, confirms that herding behavior cannot be detected in a portfolio of low-optimism stocks. The coefficient γ_2 is insignificant for OLS and across all quantiles. This finding can be attributed to the momentum impact of investor sentiment on stock returns.

4.3.7 Impact of investors' attention on herding behavior

To examine the impact of the level of investor attention on herding behavior, I construct two portfolios: high attention and low attention. At day *t*, I assign a stock to the high- (low-)attention portfolio if the stock's *DADSVI* equals one (zero) at day *t*. I then apply Eq. (2) to both portfolios using different sampling frequencies (daily, weekly, and monthly).

Tables 4.8 and 4.9 present the estimation of herding in high- and low-attention portfolios, respectively. The coefficient is either positive or insignificant across different models (OLS and QR) and different sampling frequencies (daily, weekly, and monthly). This indicates that the limited attention bias has no direct impact on the presence of herding in stock markets.

4.3.8 The joint impact of investor sentiment and attention on herding behavior

Investors' attention level by itself has no impact on the presence of herding in the stock market. Can investor attention play a moderating role in the relationship between sentiment and herding behavior? To examine if such an impact exists, I construct two portfolios: a high-attention/low-optimism portfolio and a low-attention/low-optimism portfolio.

Table 4.10 summarizes the estimation results for herding in the high-attention/low-optimism portfolio. For the daily frequency, the coefficient γ_2 is negative in the intermediate quantiles (e.g., q = 25%, 50%, and 75%). The OLS estimation for γ_2 also supports the QR estimates (γ_2 is negative and significant, which is indicative of herding behavior). In comparison with the results reported in Table 4.6, Panel A (the low-optimism portfolio), investors' high level of attention causes the presence of herding to be more intense in the low-optimism portfolio. For low sampling frequencies (weekly and monthly), the coefficient γ_2 is either positive or insignificant.

Table 4.11 presents the estimation of herding in the low-attention/low-optimism portfolio. The coefficient is either positive or insignificant across different models (OLS and QR) and different sampling frequencies (daily, weekly, and monthly). In line with my predication, the level of investor attention only contributes to investor decision to herd if investors pay more attention to the pessimistic stocks.

4.3.9 Causality between trading volume and herding behavior

To determine the dual-influencing relationship between trading volume and herding behavior, I follow the Granger (1980) methodology. According to Granger, the random variable *X* can help to explain *Y* if the coefficients of the lagged difference of *X* are jointly statistically significant. Formally, Granger causality equations are expressed as

$$CSAD_t = \alpha_0 + \sum_i^P \alpha_i CSAD_{t-i} + \sum_i^j \beta_j Vol_{p,t-j} + \varepsilon_t \tag{4}$$

and

$$Vol_{t,p} = \alpha'_0 + \sum_i^P \alpha'_i Vol_{p,t-i} + \sum_i^j \beta'_j CSAD_{t-j} + \varepsilon'_t \tag{5}$$

where *CSAD* is the cross-sectional absolute deviations of equity returns and $Vol_{p,t}$ is the natural log of daily, weekly, or monthly trading volume scaled by market capitalization. To determine the number of lags “p and q,” I use the Akaike information criterion (AIC) and the Bayesian information criterion. The volume-herding relationship can be assessed based on the estimated parameters of α_i and β_i , which capture the impact of lagged-period trading volume on current-period herding and vice versa.

Table 4.12 reports the results estimating the VAR model and Granger causality test for the low-optimism portfolio. The results reported in Table 4.12 Panel A and B show that volume is a main driver for herding. The Wald statistics test for low-optimistic portfolio at daily and weekly frequency reject the null hypothesis that VOL does not Granger cause market return dispersion (CSAD) since p-value for daily (monthly) frequency is 0.000 (.0019) , which is less than 5%

significant level. The insignificant results for monthly frequency should not come at surprise since I do not find any evidence of herding in low-optimistic portfolio using data at monthly frequency.

4.4 Conclusion

I document evidence of social media sentiment's impact on investors' herding behavior. Herding exists in low-optimism portfolios but not in high-optimism portfolios. In addition, these results are contingent on model selection and sampling frequency. For example, OLS does not capture the existence of herding for the daily frequency, and QR detects that herding behavior is taking place in periods of quiet markets. These results are more pronounced with weekly frequency measures, as both OLS and QR confirm the existence of herding behavior in the low-optimism portfolio. I do not find any evidence of herding behavior when using monthly frequency data, thus highlighting the importance of data sampling frequency when testing for investors' herding behavior in financial markets. I also investigate how investors' attention affects the relationship between sentiment and herding behavior. A high level of investor attention intensifies the presence of herding in the low-optimism portfolio. Finally, I find evidence that trading volume drives herding behavior.

Chapter 4 Figures and Tables

A *Rm* **B** *CSAD*

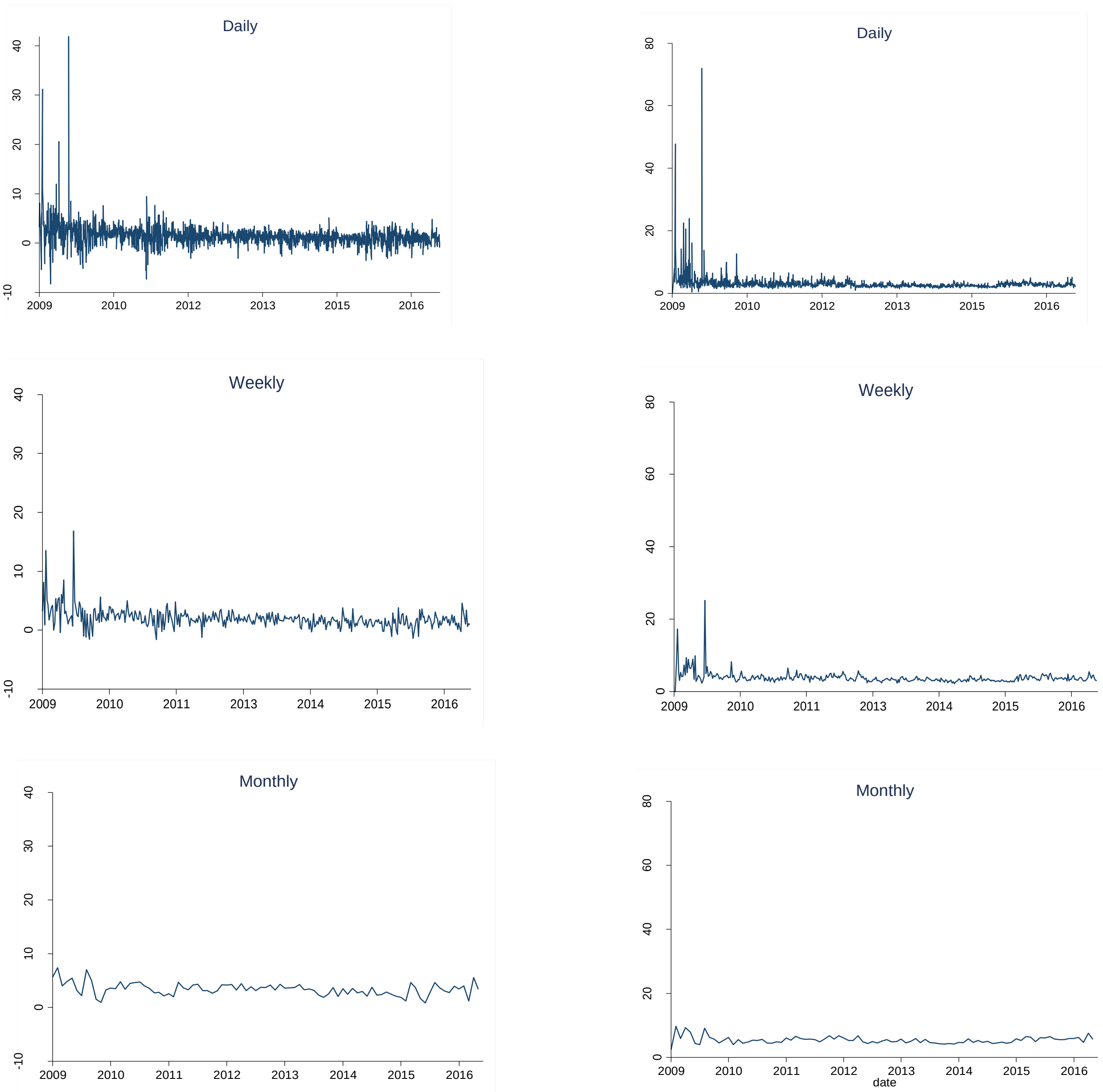

Figure 4.1. Time series plots of R_m and *CSAD*. This figure plots R_m (the cross-sectional average returns) and *CSAD* (the cross-sectional absolute deviations of the returns) for the high-optimism portfolio at three data frequencies (daily, weekly, and monthly). Data range from 2009 to 2016.

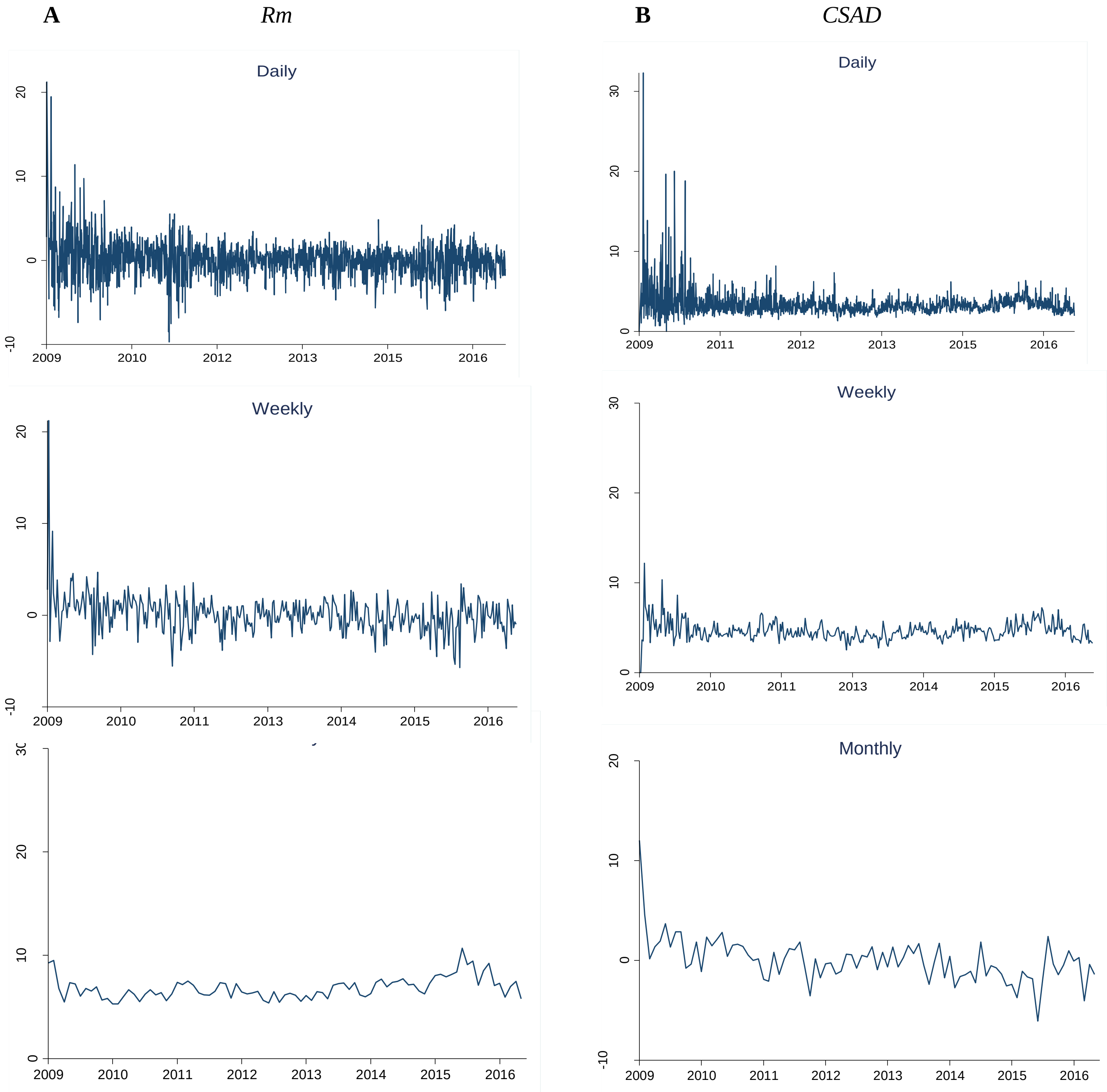

Figure 4.2. Time series plots of R_m and *CSAD*. This figure plots R_m (the cross-sectional average returns) and *CSAD* (the cross-sectional absolute deviations of the returns) for the low-optimism portfolio at three data frequencies (daily, weekly, and monthly). Data range from 2009 to 2016.

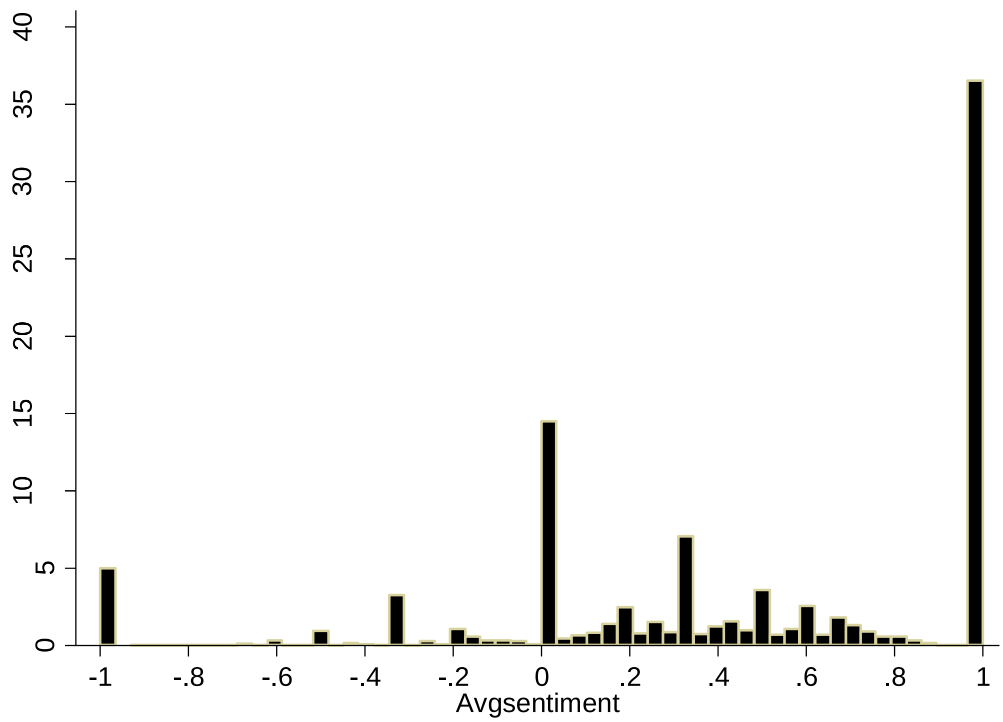

Figure 4.3. Sample distribution of the measurement of investor optimism (*AvgSentiment*) for the full sample.

Table 4.1

Panel A

Summary statistics of market-based sentiment measures.

Variable	N	Mean	Min	Max	SD
ADV/DEC	1,852	1.457	.037	9.277	1.281
VIX	1,852	18.206	10.32	48	5.861
ISEE Index	1,852	62.506	13	228	26.006
ISEE Equity	1,852	160.36	45	410	41.866
ISEE All	1,852	103.926	31	230	27.636
Total Put/Call	1,852	.943	.55	1.69	.153
Equity Put/Call	1,852	1.163	.35	2.39	.284
Index Put/Call	1,852	.638	.32	1.21	.104

Panel B

Correlation between *AvgSentiment* and alternative measures of sentiment.

Variable	Expected Sign	*AvgSentiment*
ADV/DEC	+	0.037*
VIX	-	-0.041*
ISEE Index	+	0.015*
ISEE Equity	+	0.034*
ISEE All	+	0.035*
Total Put/Call	-	-0.047*
Equity Put/Call	-	-0.011*
Index Put/Call	-	-0.055*

* Shows significance at the .01 level.

Table 4.2

Correlation between *AvgSentiment* and market returns, as well as lagged market returns

Variable	Expected Sign	*AvgSentiment*
EW_RET	+	0.055*
VW_RET	+	0.047*
SP500_RET	+	0.044*
Lag(EW_RET)	+	0.052*
Lag(VW_RET)	+	0.048*
Lag(SP500_RET)	+	0.046*

* Shows significance at the .01 level.

Table 4.3

Summary statistics for the full sample, high-optimism portfolio, and low-optimism portfolio

This table reports the summary statistics of the cross-sectional average return (R_m) and the cross-sectional absolute deviation (*CSAD*) at three data frequencies (daily, weekly, and monthly) for the full sample, which consists of all publicly traded stocks (Panel A); the high-optimism portfolio, which consists of stocks with average daily sentiment above the median for all stocks at time *t* (Panel B); and the low-optimism portfolio, which consists of stocks with average daily sentiment below the median for all stocks at time *t* (Panel C). The sample covers the period from 2009 to 2016.

Variable	T	Mean	Min	Max	SD	Skewness	Kurtosis
			Panel A: *Full sample*				
R_m							
Daily	2014	.091	-7.899	7.056	1.229	-.154	7.01
Weekly	416	.442	-9.318	14.769	2.761	-.063	5.25
Monthly	96	1.906	-10.952	19.945	2.436	.279	4.035
CSAD							
Daily	2014	1.98	1.092	6.286	.638	2.643	11.853
Weekly	416	4.342	2.609	12.652	1.27	2.596	12.234
Monthly	96	9.314	6.788	19.945	2.436	2.617	10.483
			Panel B: *High-optimism portfolio*				
R_m							
Daily	1766	1.356	-8.282	41.892	2.129	6.003	103.019
Weekly	384	1.968	-1.59	16.857	1.626	3.236	27.458
Monthly	89	3.421	0.864	7.362	1.176	.487	4.146
CSAD							
Daily	1766	2.986	0.000	71.971	2.412	18.22	455.476
Weekly	384	3.8	0.000	25.199	1.668	7.366	83.884
Monthly	89	5.456	2.434	9.709	1.13	1.318	6.513
			Panel C: *Low-optimism portfolio*				
R_m							
Daily	1848	.017	-9.703	21.246	2.052	1.065	15.196
Weekly	384	.082	-5.728	21.246	2.09	2.673	30.07
Monthly	89	.02	-6.088	12.005	2197	1.589	11.819
CSAD							
Daily	1848	3.39	0.000	32.326	1.519	7.006	98.791
Weekly	384	4.642	0.000	12.176	1.007	1.389	12.182
Monthly	89	6.843	5.288	10.668	1.05	1.098	4.461

Table 4.4

Estimation results of herding in the US stock equity market

This table reports the estimation results of herding in the US stock equity market according to the model:

$$CSAD_t = \gamma_0 + \gamma_1 \mid R_{m,t} \mid + \gamma_2 R^2_{m,t} + \varepsilon_t \qquad (2)$$

where *CSAD* is the cross-sectional absolute deviation of equity returns and R_m is the cross-sectional average return. A significant negative value of γ_2 suggests the existence of herding.

	γ_0	γ_1	γ_2	R^2
Panel A: *Daily*				
OLS	1.670***	0.271***	0.048***	0.387
QR				
q = .10	1.363***	0.175***	0.027***	0.141
q = .25	1.485***	0.128***	0.059***	0.163
q = .50	1.644***	0.110***	0.085***	0.198
q = .75	1.798***	0.207***	0.086***	0.242
q = .90	1.982***	0.427***	0.086***	0.283
Panel B: *Weekly*				
OLS	3.652***	0.223***	0.028***	0.429
QR				
q = .10	3.106***	0.116***	0.024***	0.158
q = .25	3.322***	0.126***	0.024***	0.191
q = .50	3.654***	0.092***	0.035***	0.209
q = .75	4.025***	0.086	0.054***	0.251
q = .90	4.368***	0.218	0.084***	0.343
Panel C: *Monthly*	8.491***	-0.065	0.032***	0.526
OLS				
QR				
q = .10	7.747***	-0.294***	0.041***	0.178
q = .25	7.847***	-0.153*	0.034***	0.194
q = .50	8.214***	-0.054	0.028***	0.257
q = .75	9.129***	-0.136	0.041***	0.324
q = .90	9.988***	-0.365	0.086***	0.409

Table 4.5

Estimation results of herding in the up and down equity stock markets

This table reports the estimation results of herding in the up and down equity stock markets according to the model:

$$CSAD_t = \gamma_0 + \gamma_1(1 - D) \mid R_{m,t} \mid + \gamma_2 D \mid R_{m,t} \mid + \gamma_3(1 - D)R^2_{m,t} + \gamma_4 D R^2_{m,t} + \varepsilon_t \qquad (3)$$

where *CSAD* is the cross-sectional absolute deviations of equity returns, R_m is the cross-sectional average return, and *D* is a dummy variable, which equals one when $R_{m,t} < 0$ and zero otherwise.

		Up market		Down market		
	γ_0	γ_1	γ_3	γ_2	γ_4	R^2
Panel A: *Daily*						
OLS	1.673***	0.240***	0.077***	0.289***	0.020***	0.407
QR						
q = .10	1.370***	0.122***	0.080***	0.177***	0.013***	0.163
q = .25	1.480***	0.112***	0.083***	0.172***	0.025***	0.180
q = .50	1.631***	0.114***	0.097***	0.181***	0.035***	0.203
q = .75	1.822***	0.123***	0.151***	0.165***	0.074***	0.250
q = .90	1.973***	0.445***	0.085***	0.542***	0.003	0.288
Panel B: *Weekly*						
OLS	3.595***	0.236***	0.033***	0.353***	0.0003	0.441
QR						
q = .10	3.098***	0.065	0.039***	0.184***	0.007	0.176
q = .25	3.312***	0.087***	0.037***	0.171***	0.014*	0.204
q = .50	3.606***	0.107***	0.034***	0.233***	0.009	0.216
q = .75	4.048***	-0.026	0.085***	0.238	0.020	0.259
q = .90	4.355***	0.128	0.106***	0.348*	0.039	0.350
Panel C: *Monthly*						
OLS	8.529***	-0.119	0.035***	-0.037	0.036	0.535
QR						
q = .10	6.068***	-0.289***	0.041***	-0.191	0.039***	0.219
q = .25	6.139***	-0.232***	0.037***	-0.058	0.025	0.211
q = .50	6.594***	-0.108	0.030***	-0.122	0.048*	0.270
q = .75	7.824***	-0.105	0.040***	-0.168	0.076***	0.327
q = .90	8.081***	-0.181	0.041	-0.365	0.086	0.439

Table 4.6

Estimation results of herding in the high-optimism portfolio

This table reports the estimation results of herding in the high-optimism portfolio, which consists of stocks with a daily average of sentiment above the median for all stocks at day *t* according to the model:

$$CSAD_t = \gamma_0 + \gamma_1 \mid R_{m,t} \mid + \gamma_2 R_{m,t} + \varepsilon_t \quad (2)$$

where *CSAD* is the cross-sectional absolute deviation of equity returns and R_m is the cross-sectional average return. A significant negative value of γ_2 suggests the existence of herding.

	γ_0	γ_1	γ_2	R^2
Panel A: *Daily*				
OLS	2.244***	0.305***	0.034***	0.781
QR				
q = .10	1.919***	-0.021	0.034***	0.077
q = .25	2.077***	0.066***	0.038***	0.137
q = .50	2.305***	0.155***	0.036***	0.198
q = .75	2.625***	0.264***	0.038***	0.269
q = .90	3.273***	0.048	0.102***	0.383
Panel B: *Weekly*				
OLS				
QR	3.437***	-0.077	0.080***	0.672
q = .10	2.706***	-0.094	0.085***	0.069
q = .25	2.969***	-0.114***	0.085***	0.161
q = .50	3.171***	-0.005	0.078***	0.238
q = .75	3.636***	0.030	0.074***	0.312
q = .90	4.191***	-0.040	0.093***	0.403
Panel C: *Monthly*				
OLS	5.639***	-0.664***	0.160***	0.403
QR				
q = .10	5.032***	-0.679	0.146	0.052
q = .25	5.322***	-0.854***	0.197***	0.162
q = .50	5.150***	-0.528	0.157***	0.249
q = .75	6.054***	-0.615*	0.155***	0.321
q = .90	6.724***	-0.802	0.187	0.433

Table 4.7

Estimation results of herding in the low-optimism portfolio

This table reports the estimation results of herding in the low-optimism portfolio, which consists of stocks with a daily average of sentiment below the median for all stocks at day *t* according to the model:

$$CSAD_t = \gamma_0 + \gamma_1 \mid R_{m,t} \mid + \gamma_2 R^2_{m,t} + \varepsilon_t \qquad (2)$$

where *CSAD* is the cross-sectional absolute deviation of equity returns and R_m is the cross-sectional average return. A significant negative value of γ_2 suggests the existence of herding.

	γ_0	γ_1	γ_2	R^2
Panel A: *Daily*				
OLS	2.804***	0.344***	0.020***	0.257
QR				
q = .10	2.216***	0.111***	-0.010***	0.010
q = .25	2.465***	0.192***	-0.014***	0.019
q = .50	3.000***	-0.033	0.079***	0.057
q = .75	3.403***	0.084***	0.074***	0.137
q = .90	3.898***	0.112*	0.144***	0.267
Panel B: *Weekly*				
OLS	3.939***	0.595***	-0.034***	0.240
QR				
q = .10	3.322***	0.315***	-0.022***	0.082
q = .25	3.583***	0.412***	-0.027***	0.088
q = .50	3.950***	0.538***	-0.034***	0.100
q = .75	4.379***	0.623***	-0.039***	0.153
q = .90	4.933***	0.422***	0.040***	0.168
Panel C: *Monthly*				
OLS	6.179***	0.480***	-0.015	0.269
QR				
q = .10	5.300***	0.330*	-0.000	0.109
q = .25	5.781***	0.295***	-0.001	0.103
q = .50	6.231***	0.297*	-0.004	0.131
q = .75	6.731***	0.456*	-0.021	0.112
q = .90	7.200***	0.664***	-0.016	0.256

Table 4.8

Estimation results of herding in the high-attention portfolio

This table reports the estimation results of herding in the high-attention portfolio, which consists of stocks that have a *DADSVI* equaling one at day *t* according to the model:

$$CSAD_t = \gamma_0 + \gamma_1 \,|\, R_{m,t} \,|\, + \gamma_2 R^2_{m,t} + \varepsilon_t \qquad (2)$$

where *CSAD* is the cross-sectional absolute deviation of equity returns and R_m is the cross-sectional average return. A significant negative value of γ_2 suggests the existence of herding.

	γ_0	γ_1	γ_2	R^2
Panel A: *Daily*				
OLS	1.363***	0.159***	0.006	0.134
QR				
q = .10	0.961***	0.129***	0.011***	0.090
q = .25	1.105***	0.133***	0.009***	0.089
q = .50	1.286***	0.134***	0.008	0.079
q = .75	1.534***	0.151***	0.008	0.078
q = .90	1.789***	0.323***	-0.022	0.071
Panel B: *Weekly*				
OLS	1.903***	0.174	0.114*	0.164
QR				
q = .10	1.511***	-0.123	0.204***	0.065
q = .25	1.646***	-0.004	0.158***	0.081
q = .50	1.823***	0.089	0.127***	0.089
q = .75	2.133***	0.100	0.159	0.107
q = .90	2.443***	0.501	0.010	0.101
Panel C: *Monthly*				
OLS	2.435***	0.454	0.179	0.229
QR				
q = .10	2.351***	-0.560	0.529	0.070
q = .25	2.396***	0.172	0.112	0.070
q = .50	2.472***	0.463	-0.000	0.099
q = .75	2.669***	0.491	0.464	0.166
q = .90	3.331***	0.631	0.362	0.193

Table 4.9

Estimation results of herding in the low-attention portfolio

This table reports the estimation results of herding in the low-attention portfolio, which consists of stocks that have a *DADSVI* equaling zero at day *t* according to the model:

$$CSAD_t = \gamma_0 + \gamma_1 \mid R_{m,t} \mid + \gamma_2 R^2_{m,t} + \varepsilon_t \qquad (2)$$

where *CSAD* is the cross-sectional absolute deviation of equity returns and R_m is the cross-sectional average return. A significant negative value of γ_2 suggests the existence of herding.

	γ_0	γ_1	γ_2	R^2
Panel A: *Daily*				
OLS	1.168***	0.135***	0.015***	0.408
QR				
q = .10	0.957***	0.121***	0.010***	0.145
q = .25	1.040***	0.125***	0.013***	0.170
q = .50	1.148***	0.125***	0.016***	0.198
q = .75	1.280***	0.115***	0.023***	0.227
q = .90	1.419***	0.136***	0.024***	0.258
Panel B: *Weekly*				
OLS	2.671***	0.084*	0.018***	0.325
QR				
q = .10	2.073***	0.115*	0.012	0.129
q = .25	2.329***	0.070	0.019***	0.146
q = .50	2.515***	0.127***	0.012	0.153
q = .75	2.916***	0.036	0.028***	0.185
q = .90	3.202***	0.037	0.033	0.222
Panel C: *Monthly*				
OLS	5.933***	0.036	0.011	0.230
QR				
q = .10	5.457***	-0.178	0.025*	0.111
q = .25	5.934***	-0.175	0.025***	0.078
q = .50	5.981***	0.004	0.013	0.133
q = .75	6.003***	0.183	0.000	0.194
q = .90	6.806***	0.216	-0.006	0.160

Table 4.10

Estimation results of herding in the high-attention/low-optimism portfolio

This table reports the estimation results of herding in the high-attention/low-optimism portfolio, which consists of stocks that have a *DADSVI* equaling one at day *t* and daily average sentiment below the median for all stocks at day *t* according to the model:

$$CSAD_t = \gamma_0 + \gamma_1 \mid R_{m,t} \mid + \gamma_2 R^2_{m,t} + \varepsilon_t \qquad (2)$$

where *CSAD* is the cross-sectional absolute deviation of equity returns and R_m is the cross-sectional average return. A significant negative value of γ_2 suggests the existence of herding.

	γ_0	γ_1	γ_2	R^2
Panel A: *Daily*				
OLS	1.851***	0.801***	-0.013***	0.272
QR				
q = .10	0.872***	-0.064	0.001	0.006
q = .25	1.280***	0.310***	-0.005***	0.025
q = .50	1.654***	0.791***	-0.013***	0.119
q = .75	2.378***	1.152***	-0.019***	0.221
q = .90	3.751***	1.109***	0.009***	0.307
Panel B: *Weekly*				
OLS	3.421***	0.431***	0.035***	0.327
QR				
q = .10	1.946***	0.353***	-0.022	0.021
q = .25	2.548***	0.325***	0.012	0.063
q = .50	3.152***	0.518***	0.033***	0.112
q = .75	4.061***	0.749***	0.014	0.191
q = .90	5.201***	0.447*	0.097***	0.295
Panel C: *Monthly*				
OLS	4.422***	0.365	0.046	0.200
QR				
q = .10	2.819***	1.238	-0.258	0.050
q = .25	3.620***	0.407	0.070	0.101
q = .50	4.103***	0.490	0.045	0.157
q = .75	4.629***	0.972***	-0.043	0.212
q = .90	5.144***	0.820	-0.031	0.208

Table 4.11

Estimation results of herding in the low-attention/low-optimism portfolio

This table reports the estimation results of herding in the low-attention/low-optimism portfolio, which consists of stocks that have a *DADSVI* equaling zero at day *t* and daily average sentiment below the median for all stocks at day *t* according to the model:

$$CSAD_t = \gamma_0 + \gamma_1 \mid R_{m,t} \mid + \gamma_2 R^2_{m,t} + \varepsilon_t \qquad (2)$$

where *CSAD* is the cross-sectional absolute deviation of equity returns and R_m is the cross-sectional average return. A significant negative value of γ_2 suggests the existence of herding.

	γ_0	γ_1	γ_2	R^2
Panel A: *Daily*				
OLS	1.925***	0.183***	0.010	0.130
QR				
q = .10	1.408***	0.036	0.017***	0.026
q = .25	1.594***	0.109***	0.010*	0.039
q = .50	1.842***	0.198***	0.001	0.060
q = .75	2.194***	0.205***	0.018*	0.081
q = .90	2.611***	0.193***	0.046***	0.110
Panel B: *Weekly*				
OLS	2.800***	0.167	0.056	0.187
QR				
q = .10	2.168***	0.135	0.055	0.074
q = .25	2.408***	0.115	0.069***	0.114
q = .50	2.759***	0.081	0.083*	0.106
q = .75	3.049***	0.302*	0.024	0.134
q = .90	3.676***	-0.017	0.142	0.121
Panel C: *Monthly*				
OLS	3.909***	0.579*	-0.025	0.265
QR				
q = .10	3.484***	0.117	0.119	0.083
q = .25	3.743***	0.183	0.108	0.138
q = .50	3.799***	0.590*	-0.013	0.158
q = .75	4.124***	0.706	-0.029	0.250
q = .90	4.416***	0.988	-0.142	0.164

Table 4.12

Estimation results of the causal relationship between herding and trading volume

This table reports the results estimating the VAR model and Granger causality test in the low-optimism portfolio for three data frequencies (daily, weekly, and monthly) according to the models:

$$CSAD_t = \alpha_0 + \sum_i^P \alpha_i \, CSAD_{t-i} + \sum_i^j \beta_j \, Vol_{p,t-j} + \varepsilon_t \quad (4)$$

$$Vol_{p,t} = \alpha'_0 + \sum_i^P \alpha'_i \, Vol_{p,t-i} + \sum_i^j \beta'_j \, CSAD_{t-j} + \varepsilon'_t \quad (5)$$

where *CSAD* is the cross-sectional absolute deviation of equity returns and $Vol_{p,t}$ is the natural log of daily trading volume scaled by market capitalization. Numbers in parentheses are standard errors based on the Newey-West (1987) heteroskedasticity and autocorrelation consistent standard errors.

Panel A: *Daily frequency*

VAR estimation	$CSAD_t$	$VOL_{p,t}$
$CSAD_{t-1}$	0.134***	1.365***
	(0.0367)	(0.445)
$CSAD_{t-2}$	0.0863**	0.0750
	(0.0375)	(0.345)
$CSAD_{t-3}$	0.0766	0.286
	(0.0579)	(0.450)
$CSAD_{t-4}$	0.00373	0.502
	(0.0409)	(0.432)
$VOL_{p,t-1}$	0.00124***	0.242***
	(0.000336)	(0.0385)
$VOL_{p,t-2}$	0.000919**	0.192***
	(0.000360)	(0.0285)
$VOL_{p,t-3}$	0.000660*	0.142***
	(0.000389)	(0.0297)
$VOL_{p,t-4}$	0.000926**	0.130***
	(0.000360)	(0.0346)
Adjusted R^2	0.0682	0.305
F-Statistic	17.879	102.233

Granger causality test	F-Statistic	P-value
CSAD does not Granger cause *VOL*	0.918	0.452
VOL does not Granger cause *CSAD*	5.877	0.000

Panel B: *Weekly frequency*		
VAR estimation	$CSAD_t$	$VOL_{p,t}$
$CSAD_{t-1}$	0.268***	8.289
	(0.0499)	(6.756)
$CSAD_{t-2}$	0.153***	2.005
	(0.0553)	(5.590)
$CSAD_{t-3}$	-0.0865	-0.489
	(0.112)	(5.042)
$VOL_{p,t-1}$	0.000490**	0.532***
	(0.000225)	(0.0721)
$VOL_{p,t-2}$	-0.000191	0.0729
	(0.000273)	(0.0608)
$VOL_{p,t-3}$	0.000738**	0.227***
	(0.000330)	(0.0716)
Adjusted R^2	0.188	0.581
F-Statistic	15.678	88.971
Granger causality test		
	F-Statistic	P-value
CSAD does not Granger cause *VOL*	0.39213	0.7587
VOL does not Granger cause *CSAD*	5.05714	0.0019

Panel C: *Monthly frequency*		
VAR estimation	$CSAD_t$	$VOL_{p,t}$
$CSAD_{t-1}$	0.662***	60.53
	(0.0923)	(67.06)
$VOL_{p,t-1}$	-0.000123	0.696***
	(0.000104)	(0.0893)
Adjusted R^2	0.393	0.454
F-Statistic	29.145	37.222
Granger causality test		
	F-Statistic	P-value
CSAD does not Granger cause *VOL*	0.65183	0.4217
VOL does not Granger cause *CSAD*	1.03429	0.3120

CHAPTER 5

SPILLOVER RISK IN REITS AND THE EQUITY MARKET: DOES INVESTOR SENTIMENT MATTER?

5.1 Introduction

Diebold and Yilmaz (2012) show that volatility and return shocks in the asset market are not generated in isolation but rather are amplified by volatility spillovers from shocks transmitting from other asset markets. In the same way, volatility shocks can spill over to other receiving asset markets. Hence, volatility shocks increase in these asset markets. Diebold and Yilmaz (2009, 2012) measure the direction and intensity of return and volatility shocks of various asset classes belonging to various countries by proposing spillover indices. Liu et al. (1990) find that the REITs market, as it matures, becomes more integrated with other markets. Consequently, REIT investors more likely are affected by the spillover risks transmitted from other asset markets.

I apply the Diebold and Yilmaz (2012) methodology to find return and volatility spillovers between REITs and the equity market and to examine the investor sentiment impact on return and volatility spillovers in the equity markets. The spillover measures not only determine the intensity of risks but also define the direction of incoming and outgoing spillovers. They measure the intensity of risks within asset markets as well.

5.2 Measuring return and volatility spillovers

I apply the Diebold and Yilmaz (2012) methodology to examine the effects of investor sentiment in the equity market on the return and volatility transmitted from the equity market to REITs. Following Diebold and Yilmaz (2012), I employ the VAR framework introduced by Koop, Pesaran, and Potter (1996) to forecast the errors in returns and volatility for different VAR models used to estimate the spillover risks between the equity and REITs markets (see also Pesaran and Shin, 1998). Next, I apply the variance decompensation procedure, which is invariant to the ordering of variables in the Cholesky factorization, to compute the Diebold and Yilmaz (2012) spillover index that is used to estimate both the intensity and the direction of return and volatility spillovers.

5.2.1 Variance decompensation

Variance shares are defined as the fractions of the H-step-ahead error variances to forecast *ix* owing to shocks as *ix* for all $i \in N$, where *N* is a set of natural numbers (1, 2, 3, …). To forecast the cross-variance shares, or spillovers, I let the fractions of the H-step-ahead error variances in forecasting *ix* due to shocks be *jx* , for $i, j \in N$, in a way that *i* and *j* are always unequal.

The Koop, Pesaran, and Potter (1996) H-step-ahead forecast error variance decompositions are denoted by $\theta_{ij}^{g}(H)$, where $H \in N$. Hence,

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{\hbar=0}^{H-1} (e\prime_i A_\hbar \Sigma e_j)^2}{\sum_{\hbar=0}^{H-1} (e\prime_i A_\hbar \Sigma A\prime_\hbar e_i)} \tag{1}$$

where $\sum$ is the variance matrix for the error vector ε, σ_{jj} is the standard deviation of the error term for the *j*th equation, and e_j is the selection vector, with one as the *i*th element and zero otherwise.

5.2.2 Total, direction, net, and net pairwise spillovers

Using the variance decompensation methodology, Diebold and Yilmaz (2012) estimate measures of total, direction, net, and net pairwise spillovers. Total spillovers are calculated as

$$S^g(H) = \frac{\sum_{i,j=1, i\neq j}^{N} \theta_{ij}^{\sim g}(H)}{\sum_{i,j=1}^{H} \theta_{ij}^{\sim g}(H)} * 100 = \frac{\sum_{i,j=1, i\neq j}^{N} \theta_{ij}^{\sim g}(H)}{N} * 100 \tag{2}$$

By construction, $\sum_{j=1}^{N} \theta_{ij}^{\sim g}(H) = 1$ and $\sum_{i,j=1}^{N} \theta_{ij}^{\sim g}(H) = N$. I can calculate the direction spillovers received by asset *i* from all other assets *j* as

$$S_{i.}^{g}(H) = \frac{\sum_{j=1, i\neq j}^{N} \theta_{ij}^{\sim g}(H)}{\sum_{i,j=1}^{N} \theta_{ij}^{\sim g}(H)} * 100 = \frac{\sum_{j=1, i\neq j}^{N} \theta_{ij}^{\sim g}(H)}{N} * 100 \tag{3}$$

Direction spillovers transmitted by asset *i* to all other assets *j* are calculated as

$$S_{.i}^{g}(H) = \frac{\sum_{j=1, i\neq j}^{N} \theta_{ji}^{\sim g}(H)}{\sum_{i,j=1}^{N} \theta_{ji}^{\sim g}(H)} * 100 = \frac{\sum_{j=1, i\neq j}^{N} \theta_{ji}^{\sim g}(H)}{N} * 100 \tag{4}$$

The net spillover measures the difference between gross return and volatility transmitted to and those received from all other assets. The net spillover can be estimated as

$$S_{i}^{g}(H) = S_{.i}^{g}(H) - S_{i.}^{g}(H)\ . \tag{5}$$

I calculate the net pairwise spillover as

$$S_{ij}^{g}(H) = \left(\frac{\theta_{ji}^{\sim g}(H)}{\sum_{i,k=1}^{N} \theta_{ik}^{\sim g}(H)} - \frac{\theta_{ij}^{\sim g}(H)}{\sum_{j,k=1}^{N} \theta_{jk}^{\sim g}(H)}\right) * 100 = \left(\frac{\theta_{ji}^{\sim g}(H) - \theta_{ij}^{\sim g}(H)}{N}\right) * 100 \tag{6}$$

5.2.3 Volatility measure

The daily volatility for asset *i* at day *t* is calculated as

$$\sigma_{it}^{\sim 2} = 0.361\ [\ln(P_{it}^{max}) - \ln(P_{it}^{min})]^2 \tag{7}$$

where P_{it}^{max} is the highest price for asset *i* on day *t* and P_{it}^{min} is the lowest price for asset *i* on day *t*. Then, I estimate the annualized daily percentage standard deviation (or volatility) as

$$\hat{\sigma_{it}} = 100\sqrt{365\ .\ \sigma_{it}^{\sim 2}} \tag{8}$$

5.3 Empirical findings

5.3.1 Summary statistics and correlation analysis

Table 5.1 provides summary statistics for the stock market, REIT equity, REIT mortgage, the high-optimism portfolio, and the low-optimism portfolio. The cross-sectional average return for all asset classes is positive except for the low-optimism portfolio. The high-optimism portfolio has the best performance, with an average daily return of 1.36%, and the low-optimism portfolio has the lowest return, with an average daily return of −0.06%. In terms of volatility, the high-optimism portfolio has a relatively high standard deviation of 2.13%, and REIT equity and REIT mortgage have low standard deviations of 1.22% and 1.09%, respectively. In addition, all asset classes, except REIT equity, exhibit positive skewness return distribution. All assets returns exhibit sharp peakness with a kurtosis statistic greater than 3.

I also report in Table 5.1 the daily annualized standard deviation and the percentage (volatility) for all asset classes. The low-optimism portfolio has the most volatile assets, with an average annualized standard deviation of 64.55%. REIT equity and REIT mortgage are the least volatile asset classes, with an average daily standard deviation of 28.30% and 26.375%, respectively.

Table 5.2 shows the correlation matrices between returns and volatility for the stock market, REIT equity, REIT mortgage, the high-optimism portfolio, and the low-optimism portfolio. The stock market return is positively correlated with REIT equity and REIT mortgage, with a pairwise correlation of 0.608 and 0.576, respectively. A strongly positive correlation exists between stock market volatility and other asset classes.

Figures 5.1 and 5.2 plot cross-sectional average returns and daily annualized standard deviation, respectively, for all asset classes from September 2009 to December 2016. I observe a clear spike in returns and volatility at the beginning of the sample caused by the ongoing financial crisis.

5.3.2 Lag selections

In the generalized VAR models, decomposed variances are used to calculate the Diebold and Yilmaz (2012) spillover indices from the H-step-ahead forecast return errors. In the analyses of variance decomposition, the optimum lag structure is determined with the help of three unrestricted VAR models. Tables 5.3 and 5.4 contain the summary of results based on information criteria. The summary of results incorporate the sequential modified likelihood ratio (LR) test, AIC, final prediction error (FPE), the Schwarz information criterion (SC), and the Hannan-Quinn information criterion (HQ). The four lags are selected based on most of the information criteria as the optimum lag structure for all models.

5.3.3 Return spillover risk

The return spillover matrices are constructed in Table 5.5. Panel A reports the return spillover for the stock market, REITs equity, and REITs mortgage; Panel B, the return spillover for the high-optimism portfolio, REITs equity, and REITs mortgage; Panel C, the return spillover for the low-optimism portfolio, REITs equity, and REITs mortgage. In Table 5.5, the asset in the first row is denoted as i, and the asset in the column as j. Hence, the cell (i, j) represents the forecast return error variance transmitted from the asset market i to the asset market j. For example, in cell (1, 2), forecast return error variance is estimated as 31.20, which is transmitted from REITs mortgage to REITs equity. The sum of the off-diagonal row represents the directional spillovers from the asset market i to the other asset market j, where $i \neq j$. The sum of the off-diagonal column represents the directional spillovers transmitted to asset market i from the other asset market j, where $i \neq j$. Net return spillover is defined as the difference between the “from” directional spillovers and the “to” directional spillovers. The diagonal cells in Table 5.5, indicating $i = j$, represent the within-asset market i return spillovers.

Panel A reports the return spillover for the stock market, REITs equity, and REITs mortgage. REITs equity receives the maximum return spillovers from the other two assets in the model (50.20%), and the stock market is the market least affected by return spillovers (41.05%).

The REITs equity market is the strongest transmitter of return variance to the other markets (53.58%). The stock market has the strongest within-market return spillover (58.95%).

Panel B reports the return spillover for the high-optimism portfolio, REITs equity, and REITs mortgage. REITs equity receives the maximum return spillovers from the other two assets in the model (46.92%), and the high-optimism portfolio is the market least affected by return spillovers (31.53%). The REITs equity market is the strongest transmitter of return variance to the other markets (50.86%). The high-optimism portfolio has the strongest within-market return spillover (68.47%).

Panel C reports the return spillover for the low-optimism portfolio, REITs equity, and REITs mortgage. REITs equity receives the maximum return spillovers from the other two assets in the model (49.17%), and the low-optimism portfolio is the market least affected by return spillovers (39.56%). The REITs equity market is the strongest transmitter of return variance to the other markets (52.88%). The low-optimism portfolio has the strongest within-market return spillover (60.45%).

The return spillover risk for each model is calculated by taking the ratio of the grand off-diagonal column sum to the grand column sum. For each model, I present the return spillover risk in the lowest right-hand corner of each spillover table. The results indicate that total return spillover risks are higher for the low-optimism portfolio (45.76%) relative to the high-optimism portfolio (41.41%).

5.3.4 Volatility spillover risk

The volatility spillover matrices are constructed in Table 5.6. Panel A reports the volatility spillover for the stock market, REITs equity, and REITs mortgage. REITs mortgage receives the maximum volatility spillovers from the other two assets in the model (47.09%), and the stock market is the market least affected by volatility spillovers (30.83%). The REITs equity market is the strongest transmitter of volatility variance to the other markets (49.34%). The stock market has the strongest within-market volatility spillover (69.17%).

Panel B reports the volatility spillover for the high-optimism portfolio, REITs equity, and REITs mortgage. REITs mortgage receives the maximum volatility spillovers from the other two assets in the model (43.06%), and the high-optimism portfolio is the market least affected by volatility spillovers (27.22%). The REITs equity market is the strongest transmitter of volatility variance to the other markets (50.56%). The high-optimism portfolio has the strongest within-market volatility spillover (72.78%).

Panel C reports the volatility spillover for the low-optimism portfolio, REITs equity, and REITs mortgage. REITs mortgage receives the maximum volatility spillovers from the other two assets in the model (42.20%), and the low-optimism portfolio is the market least affected by volatility spillovers (22.86%). The REITs equity market is the strongest transmitter of volatility variance to the other markets (44.32%). The low-optimism portfolio has the strongest within-market volatility spillover (77.12%).

For each model, I present the volatility spillover risk in the lowest right-hand corner of each spillover table. I do not document any significant impact of investor sentiment on the volatility spillover risk between REITs and the stock market (34.85% versus 34.17%).

5.4 Conclusion

I apply the Diebold and Yilmaz (2012) methodology to examine return and volatility spillovers between REITs and a broad equity market index. I am interested in examining how the level of investor sentiment in the equity market impacts returns and volatility spillovers transmitted between the REITs market and the broad equity markets. The spillover index allows me to measure the intensity of spillover risk as well as the directions of that spillover risk. I can estimate the intensity of risks within asset markets and apply the spillovers index.

I find that the total return spillover risk is higher for the low-optimism portfolio (45.76%) relative to the high-optimism portfolio (41.41%). I do not document any significant impact of investor sentiment on the volatility spillover risk between REITs and the equity market (34.85% versus 34.17%). My results highlight the importance of considering investor sentiment in the stock market when constructing multi-asset portfolios that include assets such as REITs in addition to other asset classes.

Chapter 5 Figures and Tables

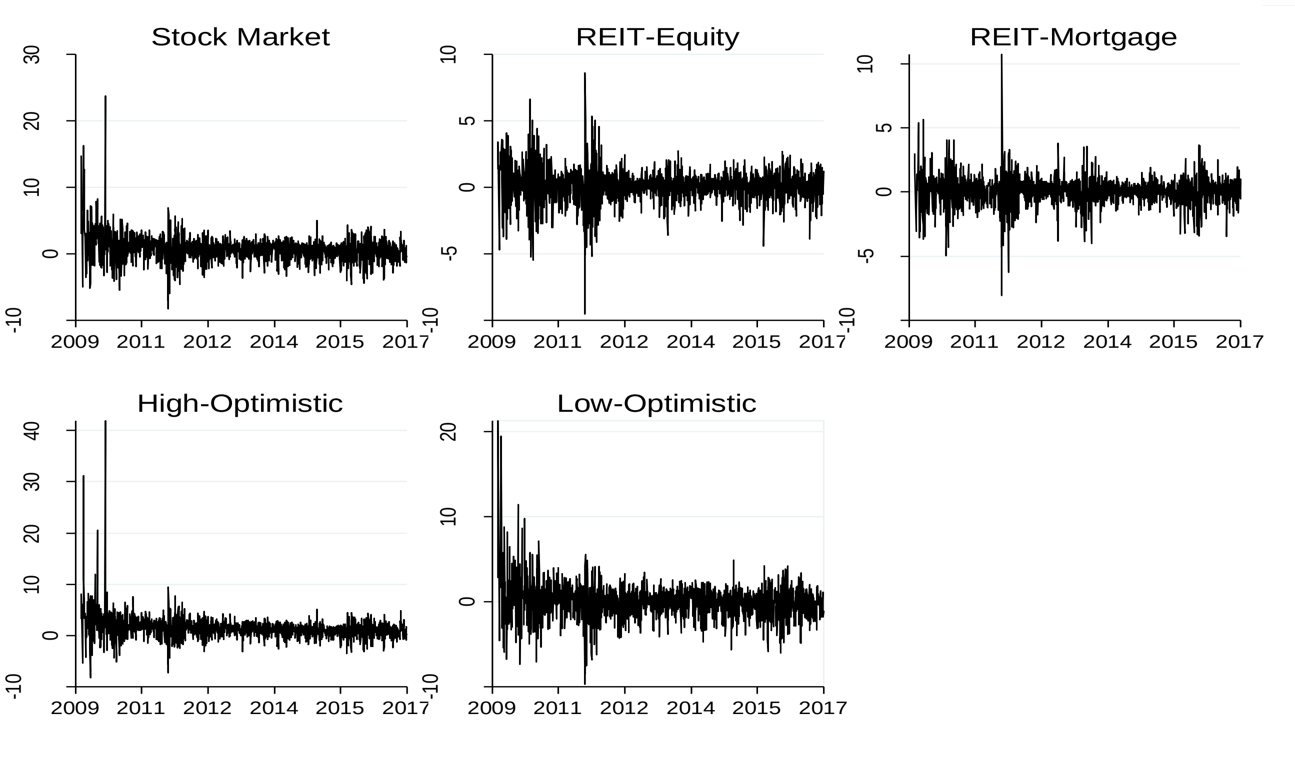

Figure 5.1. The cross-sectional average return as a percentage (*Return*) for the stock market, REIT equity, REIT mortgage, the high-optimism portfolio, and the low-optimism portfolio.

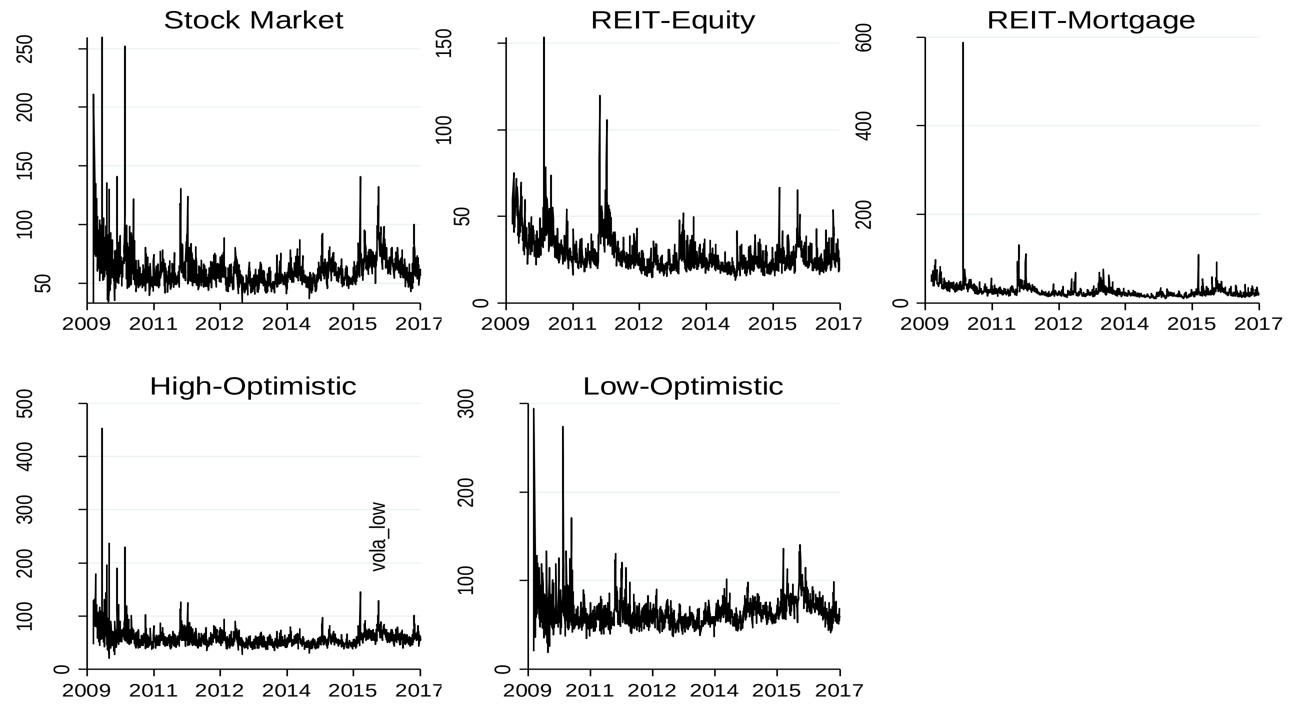

Figure 5.2. Daily annualized standard deviation as a percentage (*Volatility*) for the stock market, REIT equity, REIT mortgage, the high-optimism portfolio, and the low-optimism portfolio.

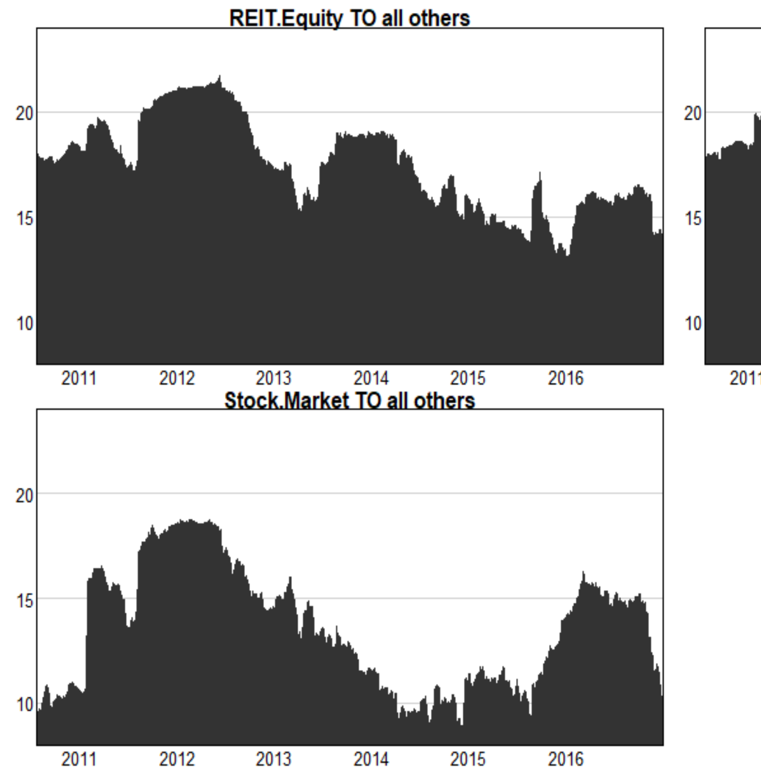

Figure 5.3.a. Directional return spillovers *to* REIT equity, REIT mortgage, and the stock market.

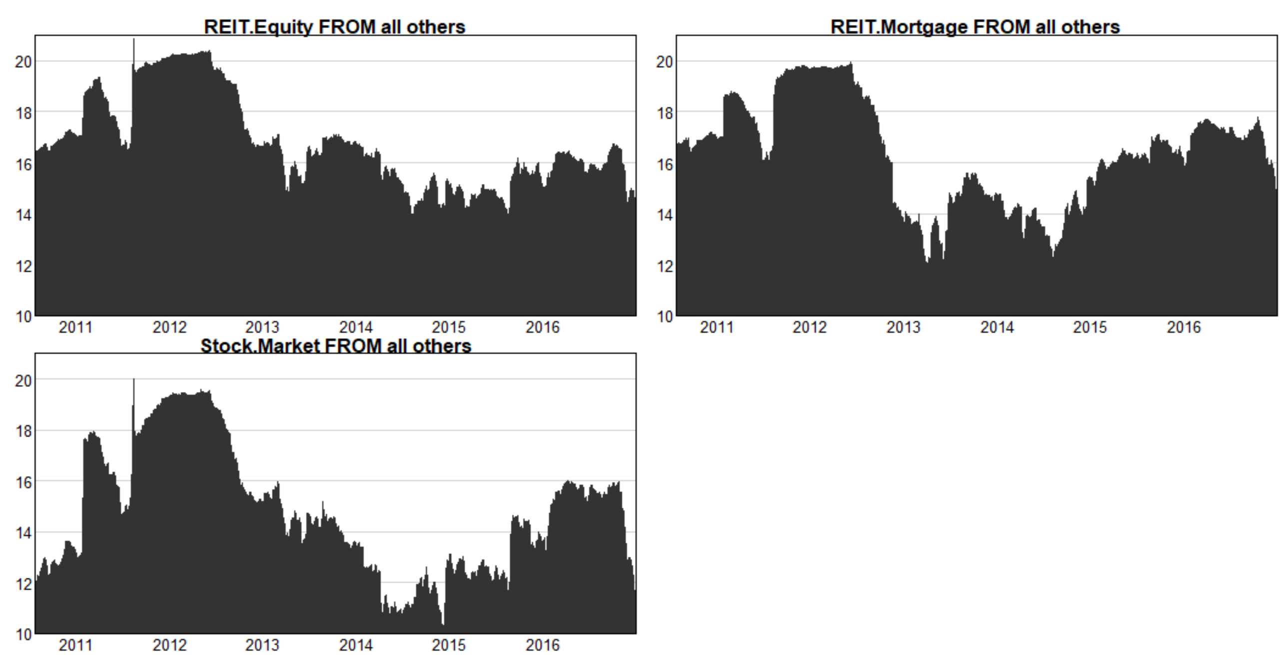

Figure 5.3.b. Directional return spillovers *from* REIT equity, REIT mortgage, and the stock market.

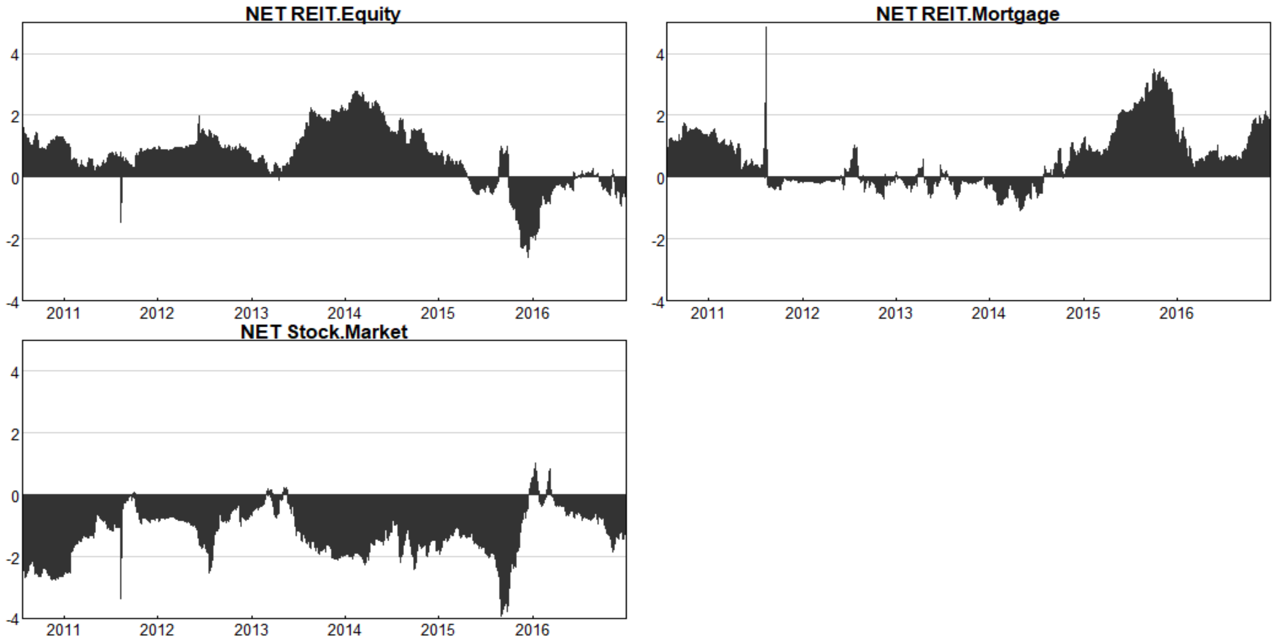

Figure 5.3.c. Net return spillovers for REIT equity, REIT mortgage, and the stock market.

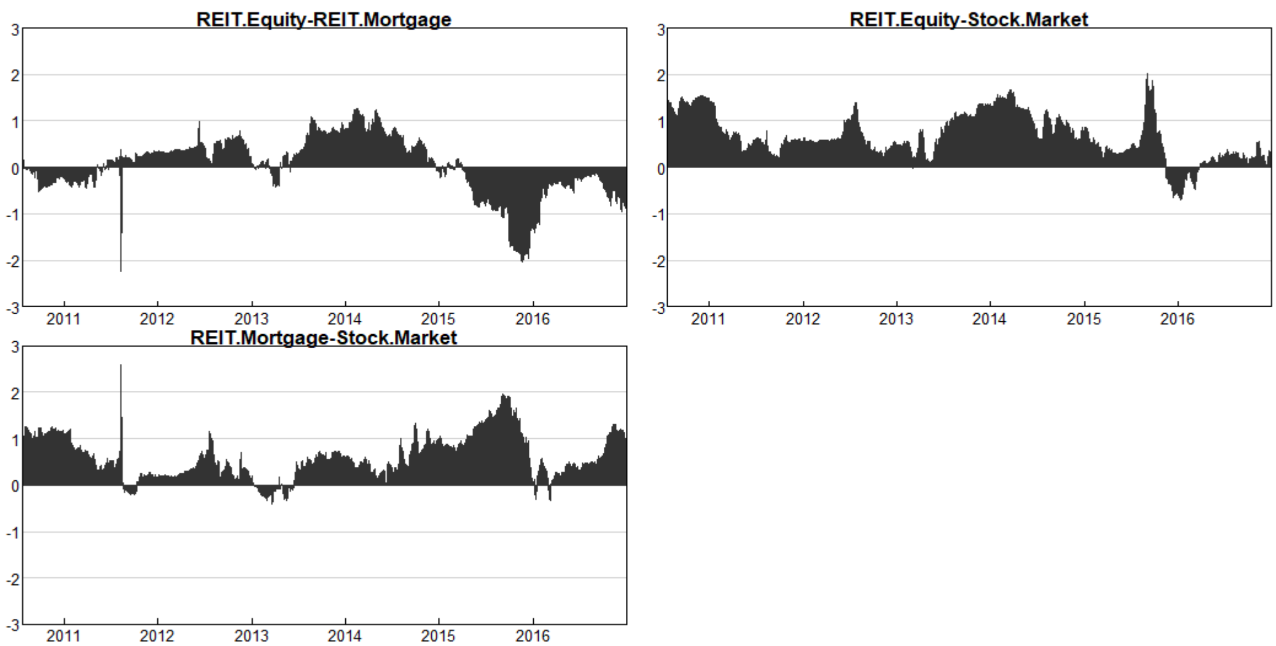

Figure 5.3.d. Net pairwise return spillovers for REIT equity, REIT mortgage, and the stock market.

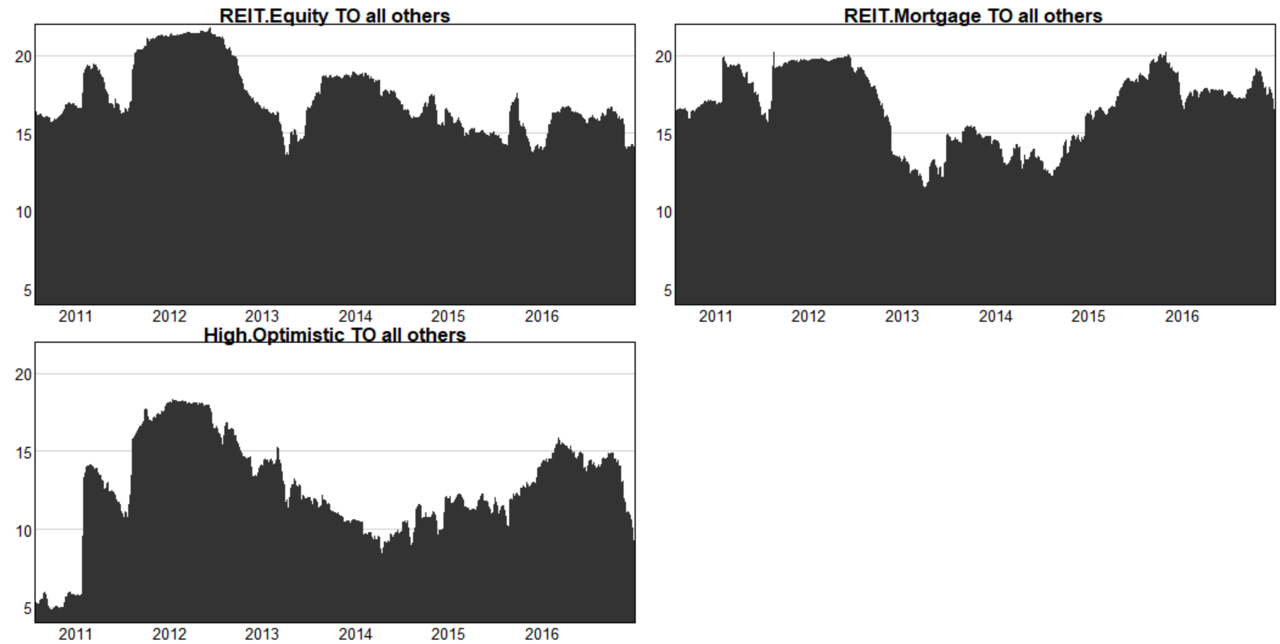

Figure 5.4.a. Directional return spillovers *to* REIT equity, REIT mortgage, and the high-optimism portfolio.

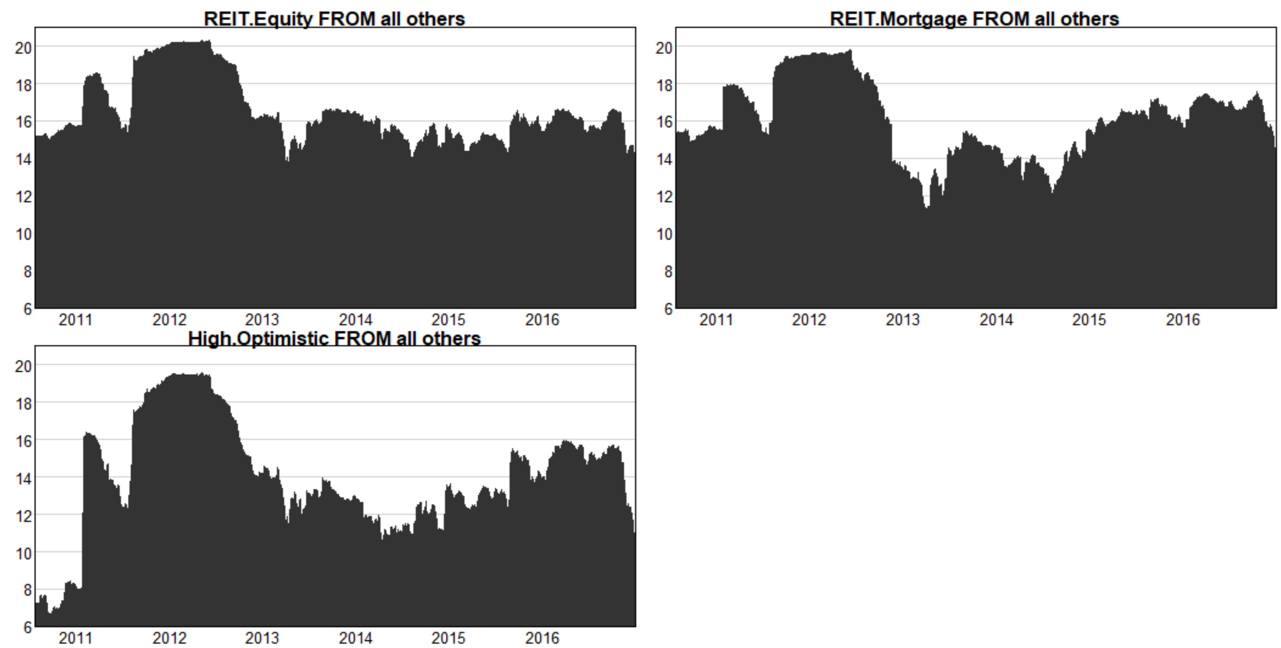

Figure 5.4.b. Directional return spillovers *from* REIT equity, REIT mortgage, and the high-optimism portfolio.

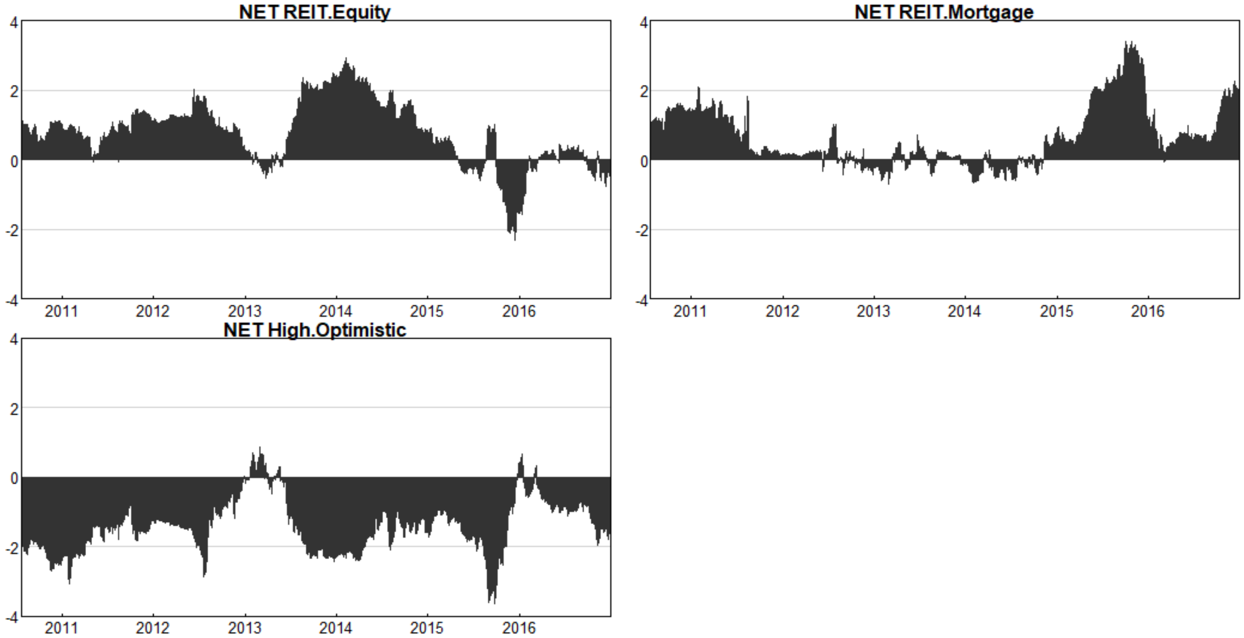

Figure 5.4.c. Net return spillovers for REIT equity, REIT mortgage, and the high-optimism portfolio.

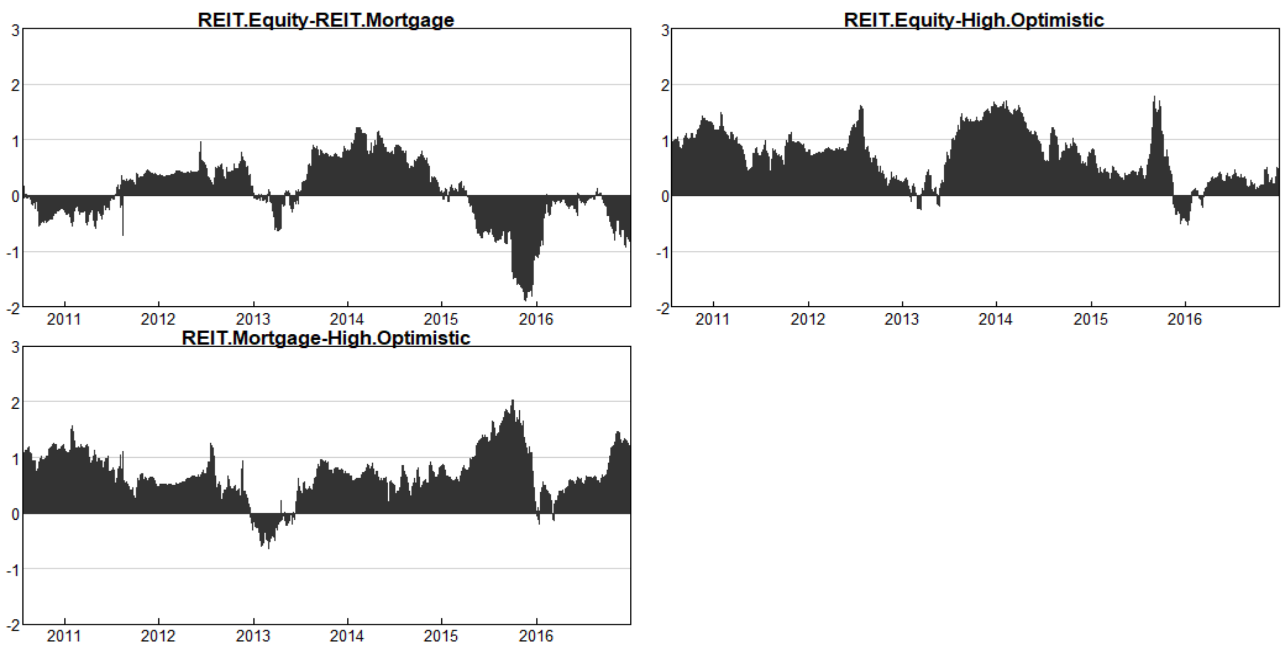

Figure 5.4.d. Net pairwise return spillovers for REIT equity, REIT mortgage, and the high-optimism portfolio.

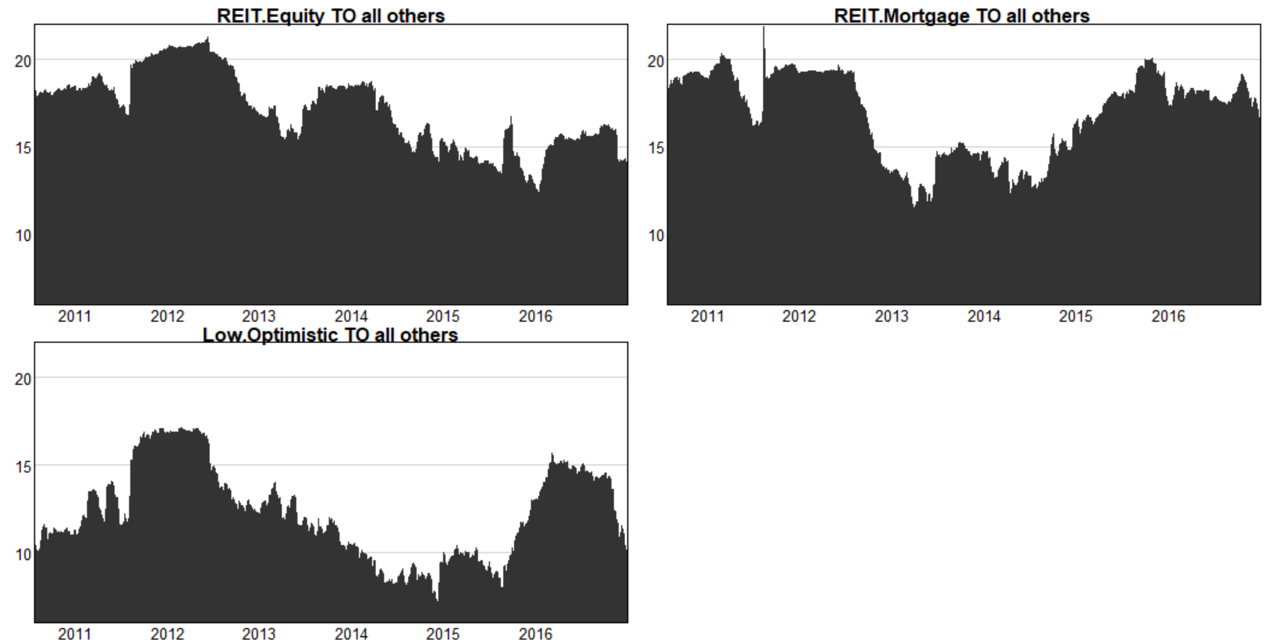

Figure 5.5.a. Directional return spillovers *to* REIT equity, REIT mortgage, and the low-optimism portfolio.

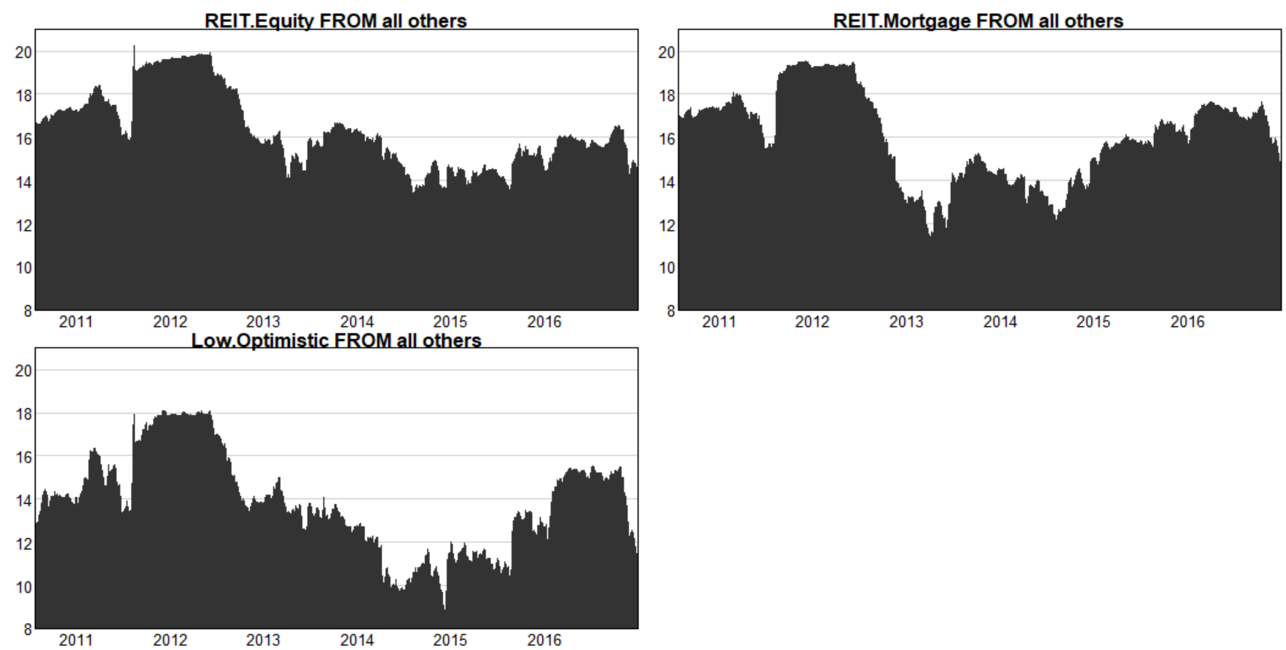

Figure 5.5.b. Directional return spillovers *from* REIT equity, REIT mortgage, and the low-optimism portfolio.

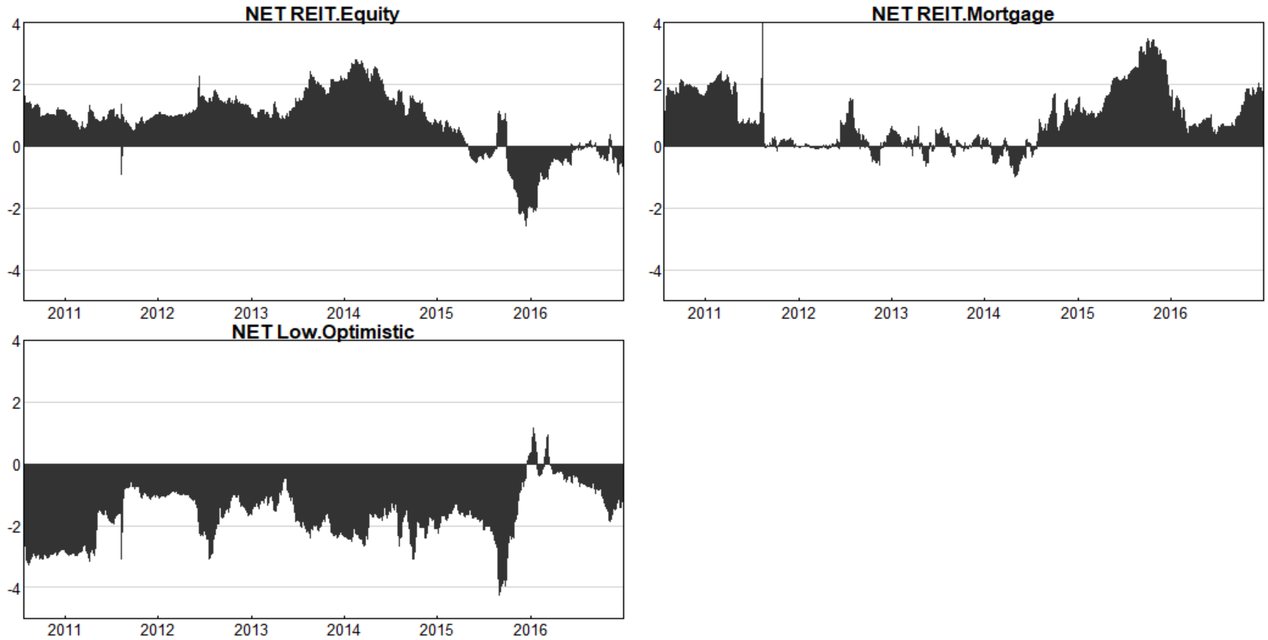

Figure 5.5.c. Net return spillovers for REIT equity, REIT mortgage, and the low-optimism portfolio.

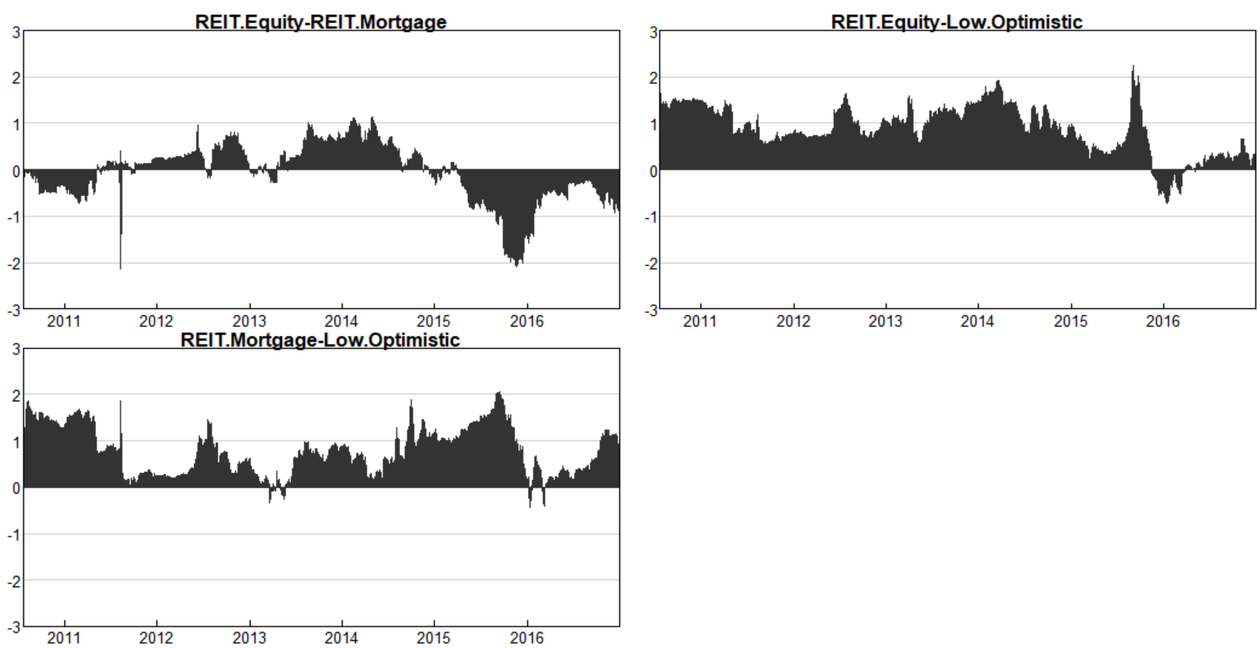

Figure 5.5.d. Net pairwise return spillovers for REIT equity, REIT mortgage, and the low-optimism portfolio.

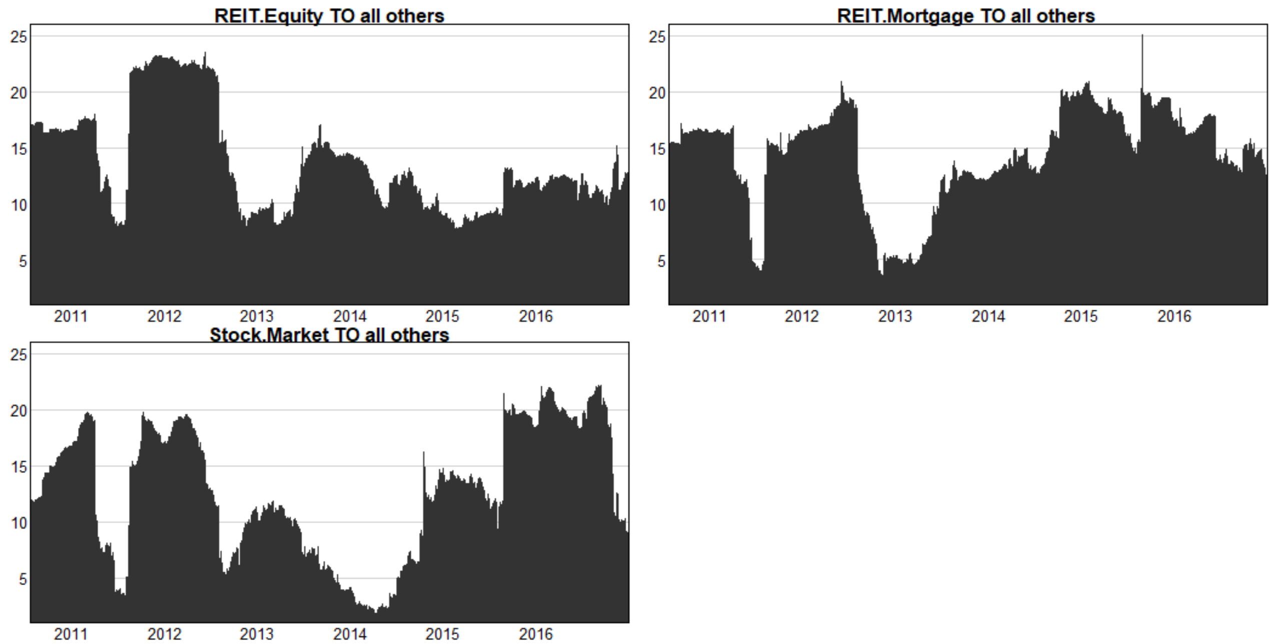

Figure 5.6.a. Directional volatility spillovers *to* REIT equity, REIT mortgage, and the stock market.

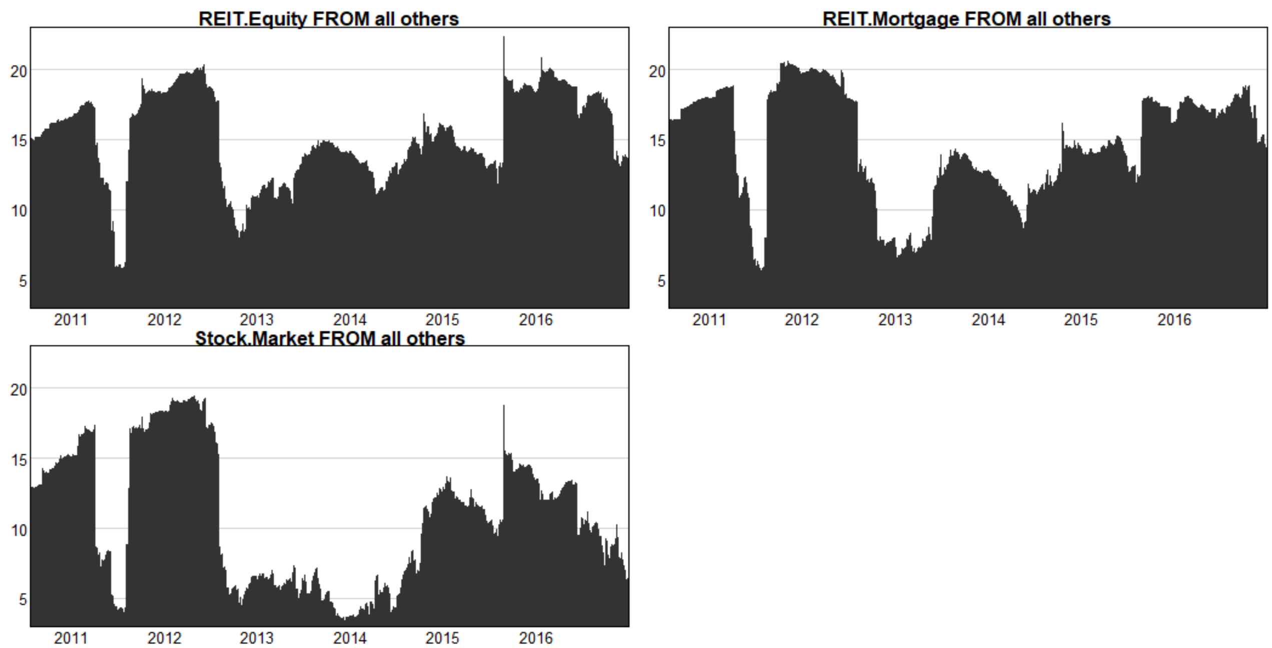

Figure 5.6.b. Directional volatility spillovers *from* REIT equity, REIT mortgage, and the stock market.

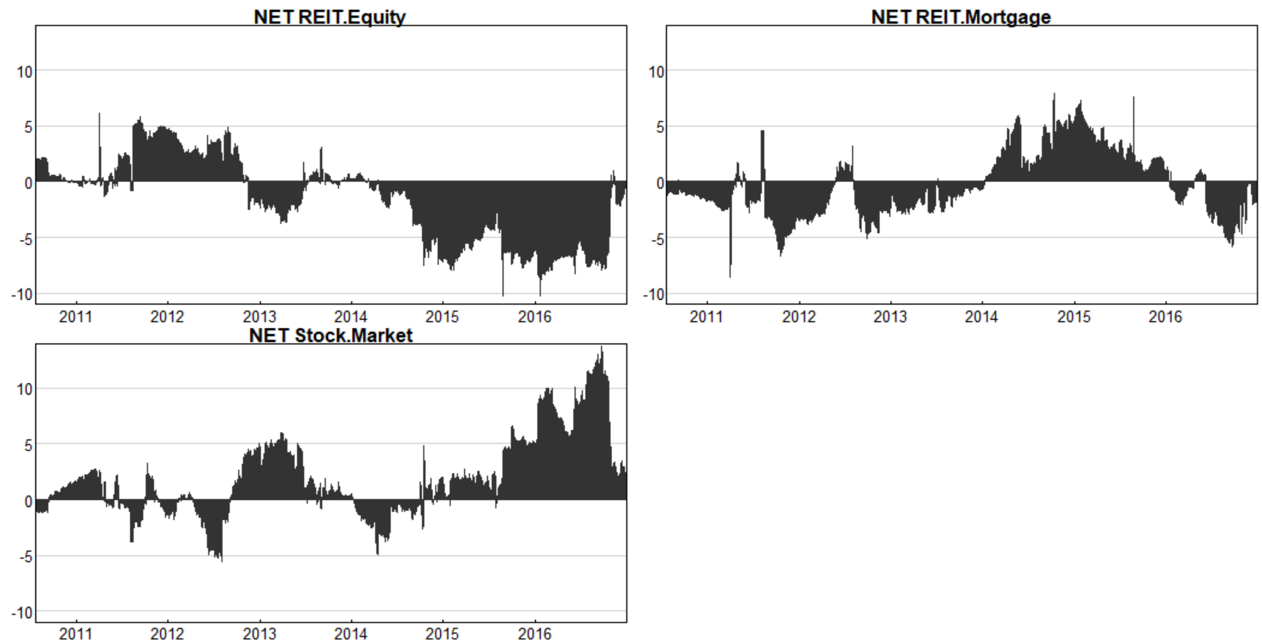

Figure 5.6.c. Net volatility spillovers for REIT equity, REIT mortgage, and the stock market.

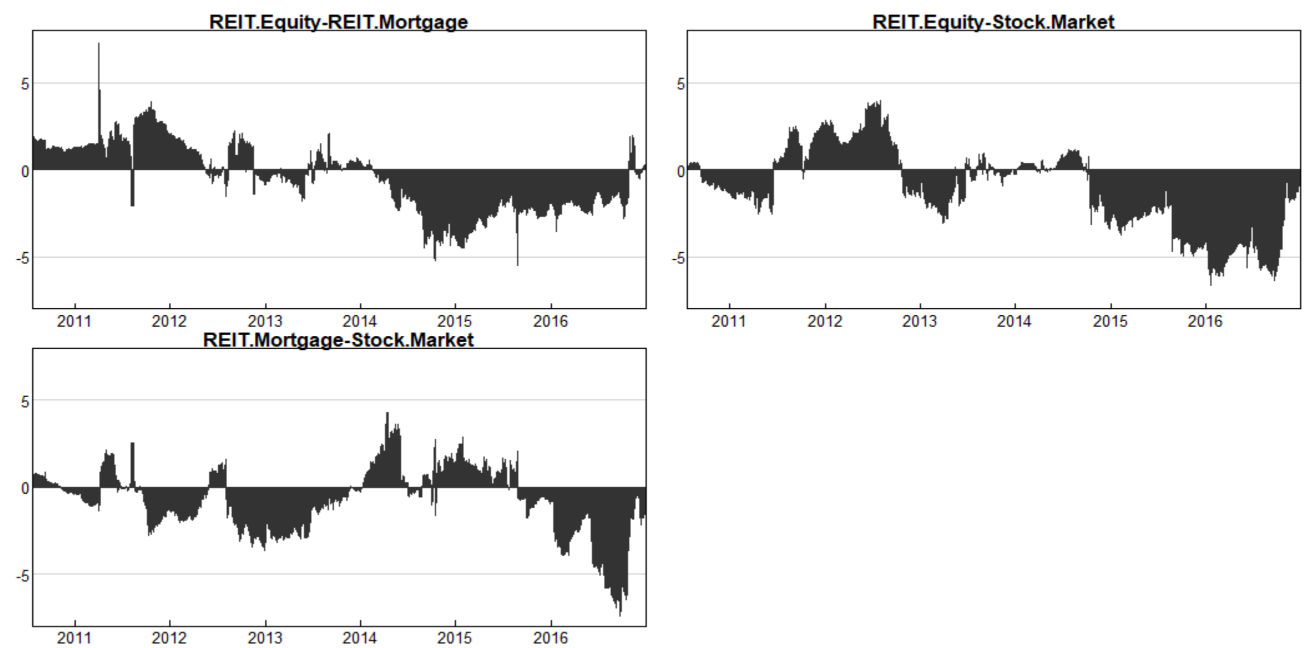

Figure 5.6.d. Net pairwise volatility spillovers for REIT equity, REIT mortgage, and the stock market.

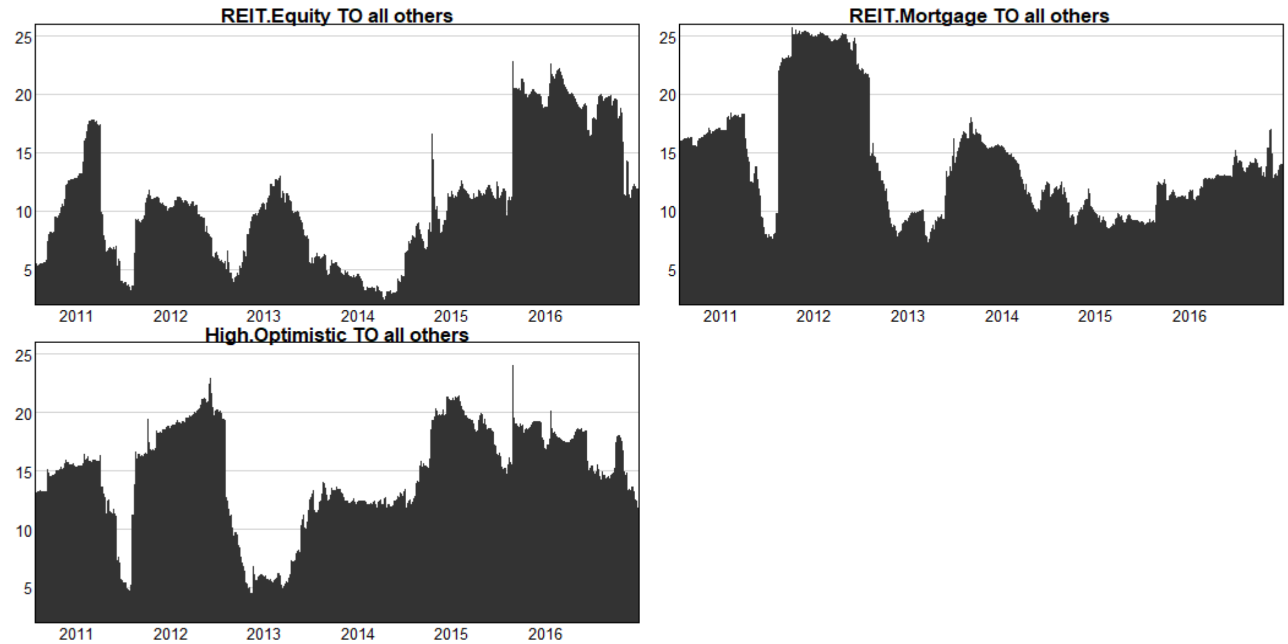

Figure 5.7.a. Directional volatility spillovers *to* REIT equity, REIT mortgage, and the high-optimism portfolio.

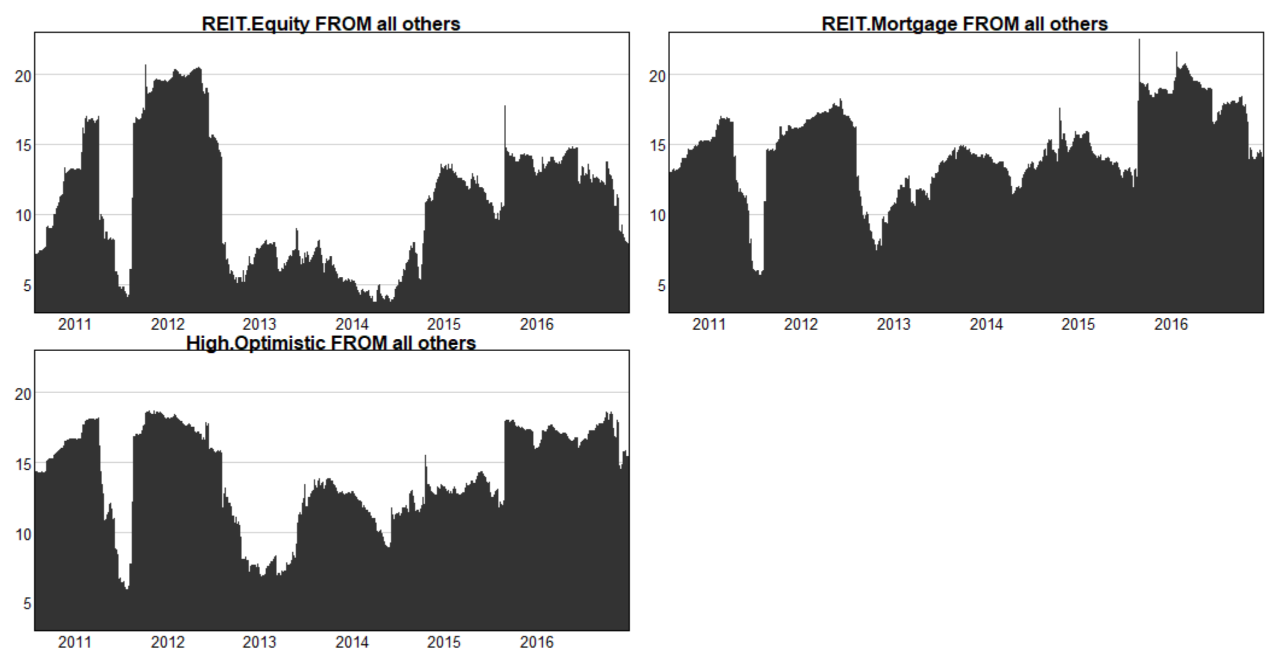

Figure 5.7.b. Directional volatility spillovers *from* REIT equity, REIT mortgage, and the high-optimism portfolio.

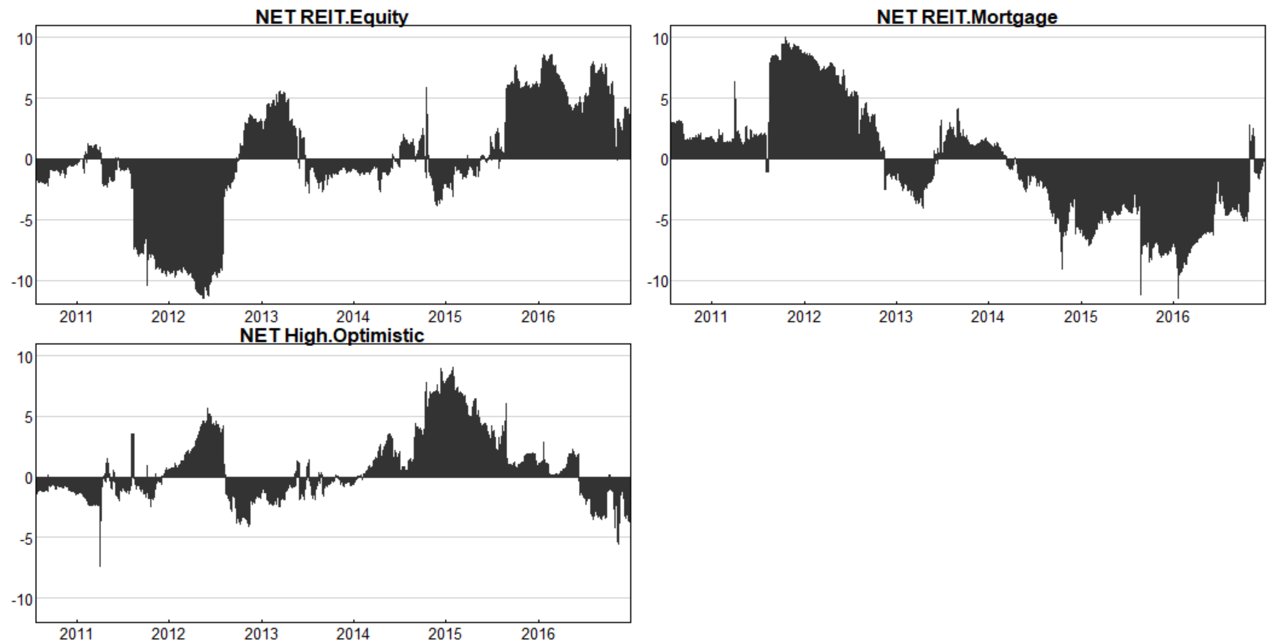

Figure 5.7.c. Net volatility spillovers for REIT equity, REIT mortgage, and the high-optimism portfolio.

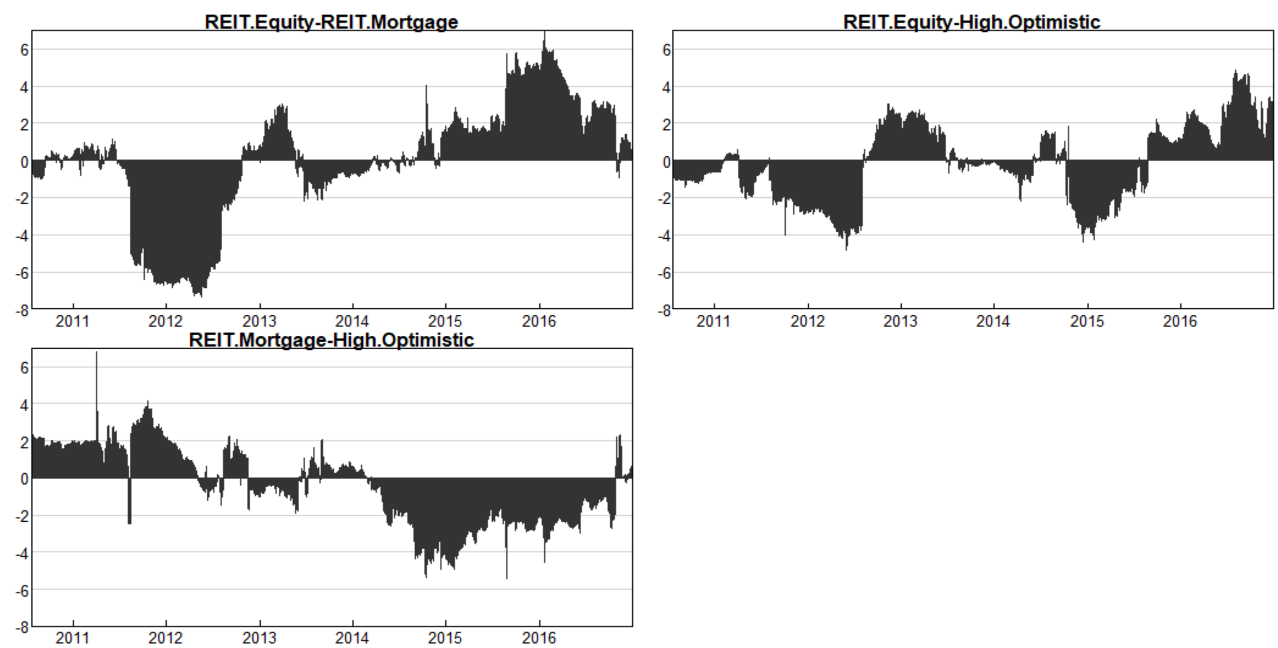

Figure 5.7.d. Net pairwise volatility spillovers for REIT equity, REIT mortgage, and the high-optimism portfolio.

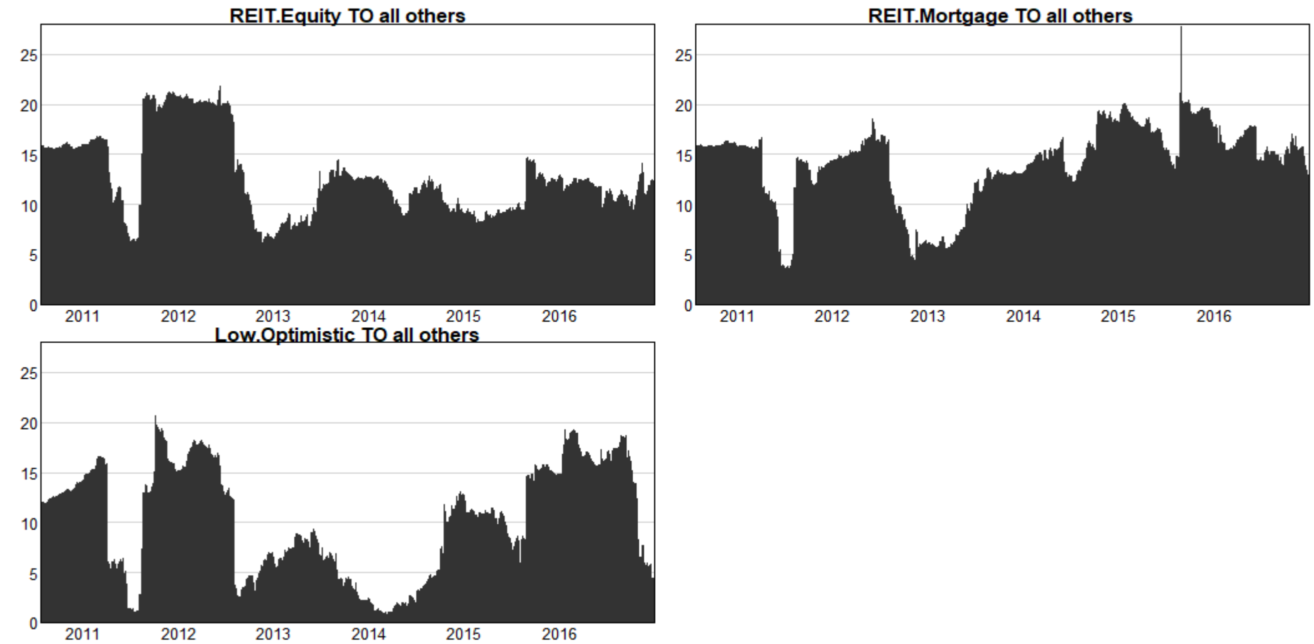

Figure 5.8.a. Directional volatility spillovers *to* REIT equity, REIT mortgage, and the low-optimism portfolio.

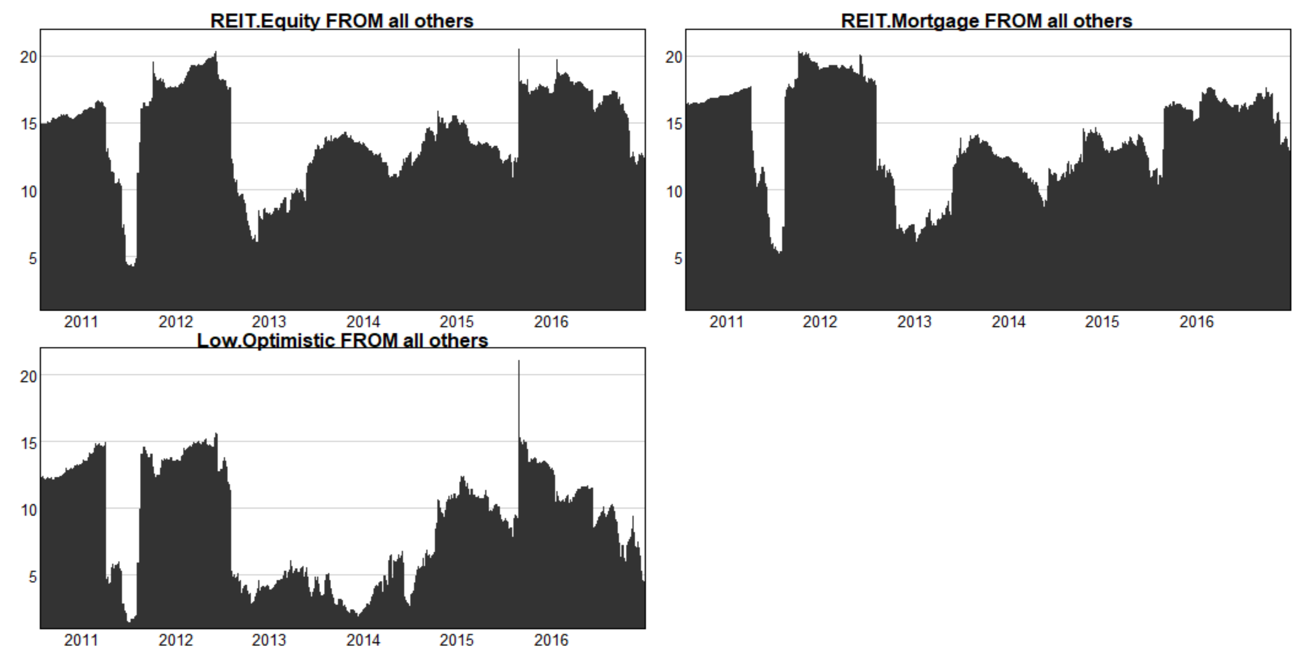

Figure 5.8.b. Directional volatility spillover *from* REIT equity, REIT mortgage, and the low-optimism portfolio.

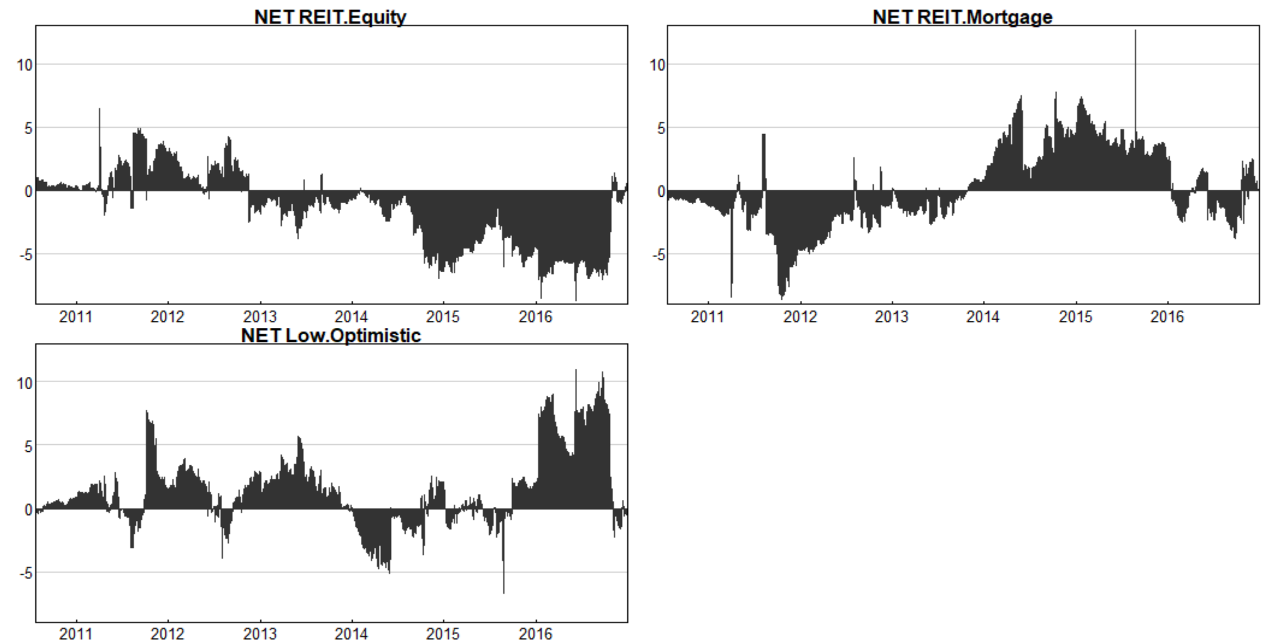

Figure 5.8.c. Net volatility spillovers for REIT equity, REIT mortgage, and the low-optimism portfolio.

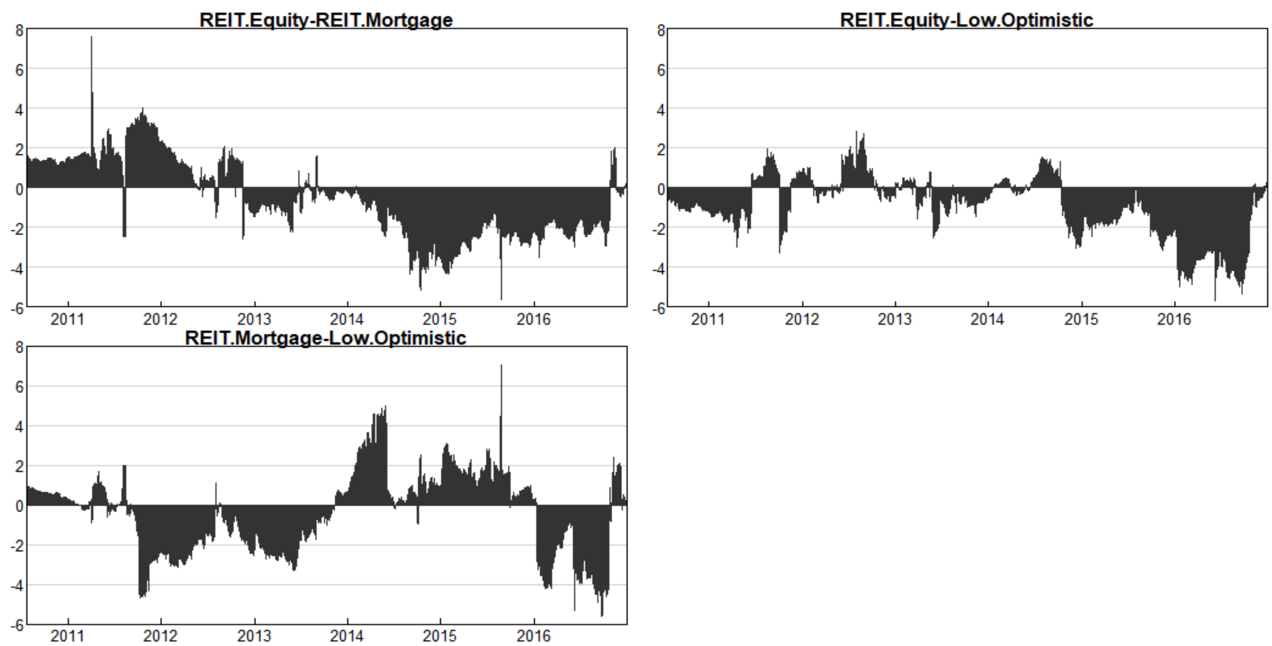

Figure 5.8.d. Net pairwise volatility spillovers for REIT equity, REIT mortgage, and the low-optimism portfolio.

Table 5.1

Summary statistics for the stock market, REIT equity, REIT mortgage, high-optimism portfolio, and low-optimism portfolio

This table reports the summary statistics of the cross-sectional average return, percentage (*Return*), and daily annualized standard deviation, or percentage (*Volatility*) for the full sample, which consists of all publicly traded stocks with share codes 10 and 11 (Panel A); REIT equity (Panel B); REIT mortgage (Panel C); the high-optimism portfolio, which consists of stocks with average daily sentiment above the median for all stocks at time *t* (Panel D); and the low-optimism portfolio, which consists of stocks with average daily sentiment below the median for all stocks at time *t* (Panel E). The sample covers the period from 2009 to 2016.

Variable	N	Mean	Min	Max	SD	Skewness	Kurtosis
Panel A: *Stock market*							
Return	1766	.662	-8.226	23.764	1.837	1.744	23.376
Volatility	1766	61.513	33.071	259.645	14.802	4.259	44.607
Panel B: *REIT equity*							
Return	1766	.059	-9.516	8.615	1.217	-.168	9.061
Volatility	1766	28.029	13.169	153.44	10.691	3.111	22.706
Panel C: *REIT mortgage*							
Return	1766	.051	-8.05	10.735	1.094	.027	12.485
Volatility	1766	26.368	9.493	588.178	17.925	18.155	549.641
Panel D: *High-optimism portfolio*							
Return	1766	1.356	-8.282	41.892	2.129	6.003	103.019
Volatility	1766	58.316	20.032	453.011	18.436	7.85	135.351
Panel E: *Low-optimism portfolio*							
Return	1766	-.061	-9.703	21.246	2.02	1.128	16.614
Volatility	1766	64.545	18.975	294.07	16.843	3.54	37.763

Table 5.2

Correlation matrices between *Return* and *Volatility* of the stock market, REIT equity, REIT mortgage, high-optimism portfolio, and low-optimism portfolio

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Stock market *Return*	1.000									
(2) Stock market *Volatility*	0.041	1.000								
(3) REIT equity *Return*	0.608*	-0.085*	1.000							
(4) REIT equity *Volatility*	0.004	0.573*	-0.094*	1.000						
(5) REIT mortgage *Return*	0.576*	-0.123*	0.792*	-0.098*	1.000					
(6) REIT mortgage *Volatility*	-0.029	0.544*	-0.112*	0.742*	-0.150*	1.000				
(7) High-optimism *Return*	0.885*	0.110*	0.505*	0.043	0.468*	0.008	1.000			
(8) High-optimism *Volatility*	0.077*	0.855*	-0.078*	0.520*	-0.101*	0.466*	0.206*	1.000		
(9) Low-optimism *Return*	0.878*	-0.044	0.568*	-0.046	0.548*	-0.068*	0.589*	-0.055	1.000	
(10) Low-optimism *Volatility*	-0.020	0.813*	-0.063*	0.435*	-0.104*	0.444*	-0.014	0.424*	-0.006	1.000

* Shows significance at the .01 level.

Table 5.3

VAR lag selection criteria for estimating return spillover risk models

Lag	Log. Likelihood	LR	FPE	AIC	SC	HQ
Panel A: *Lag selection for returns spillover between the stock market and REITs*						
0	-7717.021	NA	1.282951	8.762794	8.772114	8.766238
1	-7655.460	122.8422	1.208648	8.703133	8.740415*	8.716910
2	-7630.888	48.95035	1.187471	8.685457	8.750700	8.709567*
3	-7618.804	24.02964	1.183323	8.681957	8.775162	8.716400
4	-7607.963	21.52266*	1.180853*	8.679867*	8.801033	8.724642
Panel B: *Lag selection for returns spillover between the high-optimism portfolio and REITs*						
0	-8168.472	NA	2.141684	9.275223	9.284544	9.278668
1	-8134.284	68.21987	2.081321	9.246634	9.283915*	9.260411*
2	-8118.309	31.82299	2.064908	9.238717	9.303960	9.262826
3	-8104.963	26.54201	2.054745	9.233783	9.326987	9.268225
4	-8092.912	23.92366*	2.047643*	9.230320*	9.351486	9.275095
Panel C: *Lag selection for returns spillover between the low-optimism portfolio and REITs*						
0	-7913.546	NA	1.603570	8.985864	8.995184	8.989308
1	-7864.902	97.06754	1.533011	8.940865	8.978147*	8.954642*
2	-7857.282	15.17919	1.535414	8.942431	9.007674	8.966541
3	-7848.485	17.49325	1.535769	8.942662	9.035867	8.977105
4	-7837.217	22.37104*	1.531820*	8.940087*	9.061253	8.984862

* Indicates lag order selected by the criterion.

VAR = vector autoregression; LR = sequential modified LR test statistic (each test at 5% level); FPE = Final prediction error; AIC = Akaike information criterion; SC = Schwarz information criterion; HQ = Hannan-Quinn information criterion; REITs = real estate investment trusts;

Table 5.4

VAR lag selection criteria for estimating volatility spillover risk models

Lag	Log. Likelihood	LR	FPE	AIC	SC	HQ
Panel A: *Lag selection for volatility spillover between the stock market and REITs*						
0	-20322.40	NA	2099484.	23.07083	23.08015	23.07428
1	-19323.86	1992.548	682829.3	21.94763	21.98491	21.96141
2	-19239.48	168.1037	626829.8	21.86206	21.92730	21.88617
3	-19199.57	79.36605	605219.2	21.82698	21.92018	21.86142
4	-19143.05	112.2019*	573440.9*	21.77304*	21.89421*	21.81782*
Panel B: *Lag selection for volatility spillover between the high-optimism portfolio and REITs*						
0	-20866.46	NA	3893198.	23.68837	23.69769	23.69182
1	-20050.08	1629.043	1557062.	22.77194	22.80922	22.78572
2	-19975.35	148.8670	1445120.	22.69733	22.76258*	22.72144
3	-19942.82	64.68984	1407035.	22.67063	22.76383	22.70507
4	-19913.30	58.61396*	1374635.*	22.64733*	22.76849	22.69210*
Panel C: *Lag selection for volatility spillover between the low-optimism portfolio and REITs*						
0	-20670.08	NA	3115310.	23.46547	23.47479	23.46891
1	-19650.15	2035.222	988914.7	22.31799	22.35528	22.33177
2	-19523.48	252.3397	865269.1	22.18443	22.24967	22.20854
3	-19486.76	73.02947	838465.1	22.15296	22.24616	22.18740
4	-19441.00	90.83149*	804206.2*	22.11124*	22.23241*	22.15602*

* Indicates lag order selected by the criterion.

VAR = vector autoregression; LR = sequential modified LR test statistic (each test at 5% level); FPE = final prediction error; AIC = Akaike information criterion; SC = Schwarz information criterion; HQ = Hannan-Quinn information criterion; REITs = real estate investment trusts.

Table 5.5

Return spillover risk

The off-diagonal column sums (contributions to others) or row sums (contributions from others) are the “to” and “from” directional spillovers, and the “from minus to” differences are the net return spillovers. In addition, the total return spillover, expressed as a percentage, is approximately the grand off-diagonal column sum (or row sum) relative to the grand column sum including diagonals (or row sum including diagonals).

Panel A: *Returns Spillover Between Stock Markets and REITs*

	"Transmitted from"			
"Transmitted to"	REIT-Equity	REIT-Mortgage	Stock Market	From Others
REIT-Equity	49.802	31.196	19.002	50.198
REIT-Mortgage	31.72	50.894	17.385	49.106
Stock Market	21.858	19.19	58.952	41.048
Contribution to Others	53.578	50.386	36.387	140.352
Contribution Including Own	103.38	101.28	95.34	300.00
		Spillover Index = (140.352/300)		46.78

Panel B: *Returns Spillover Between High-Optimistic Portfolio and REITs*

	"Transmitted from"			
"Transmitted to"	REIT-Equity	REIT-Mortgage	High-Optimistic	From Others
REIT-Equity	53.085	33.286	13.629	46.915
REIT-Mortgage	33.842	54.228	11.93	45.772
High-Optimistic	17.016	14.517	68.467	31.533
Contribution to Others	50.859	47.803	25.558	124.22
Contribution Including Own	103.944	102.031	94.025	300.00
		Spillover Index = (124.22/300)		41.41

Panel C: *Returns Spillover Between Low-Optimistic Portfolio and REITS*

	"Transmitted from"			
"Transmitted to"	REIT-Equity	REIT-Mortgage	Low-Optimistic	From Others
REIT-Equity	50.834	31.917	17.249	49.166
REIT-Mortgage	32.13	51.446	16.425	48.554
Low-Optimistic	20.746	18.806	60.449	39.551
Contribution to Others	52.876	50.723	33.673	137.272
Contribution Including Own	103.71	102.169	94.122	300.00
		Spillover Index = (137.272/300)		45.76

Table 5.6

Volatility spillover risk

The off-diagonal column sums (contributions to others) or row sums (contributions from others) are the “to” and “from” directional spillovers, and the “from minus to” differences are the net volatility spillovers. In addition, the total volatility spillover, expressed as a percentage, is approximately the grand off-diagonal column sum (or row sum) relative to the grand column sum including diagonals (or row sum including diagonals).

Panel A: *Volatility Spillover Between Stock Market and REITs*

	"Transmitted from"			
"Transmitted to"	REIT-Equity	REIT-Mortgage	Stock Market	From Others
REIT-Equity	61.905	21.344	16.751	38.095
REIT-Mortgage	31.589	52.912	15.499	47.088
Stock Market	17.753	13.078	69.169	30.831
Contribution to Others	49.342	34.422	32.249	116.014
Contribution Including Own	111.248	87.335	101.418	300.00
	Spillover Index = (116.014/300)			38.671

Panel B: *Volatility Spillover Between High-Optimistic Portfolio and REITs*

	"Transmitted from"			
"Transmitted to"	REIT-Equity	REIT-Mortgage	High-Optimistic	From Others
REIT-Equity	65.736	22.76	11.504	34.264
REIT-Mortgage	33.959	56.937	9.104	43.063
High-Optimistic	16.627	10.596	72.778	27.222
Contribution to Others	50.585	33.356	20.608	104.549
Contribution Including Own	116.321	90.293	93.386	300.00
	Spillover Index = (104.549.22/300)			34.85

Panel C: *Volatility Spillover Between Low-Optimistic Portfolio and REITs*

	"Transmitted from"			
"Transmitted to"	REIT-Equity	REIT-Mortgage	Low-Optimistic	From Others
REIT-Equity	65.706	22.799	11.496	34.294
REIT-Mortgage	32.862	54.798	12.34	45.202
Low-Optimistic	11.455	11.43	77.115	22.885
Contribution to Others	44.317	34.228	23.836	102.382
Contribution Including Own	110.023	89.027	100.95	300.00
	Spillover Index = (102.382/300)			34.13

CHAPTER 6

CONCLUSION AND FUTURE WORK

Section 6.1 reviews the research questions from Chapter 3 and briefly summarizes the answers provided in it and subsequent chapters. Section 6.2 provides an overview of open questions and avenues for future research.

6.1 Conclusion

In Chapter 3, I examine the role of social media sentiment on the trading behavior of individual investors. I document a positive association between sentiment and retail order imbalances (i.e., investors tend to buy more than they sell as they become more optimistic about stocks). Investors are more likely to be influenced by sentiment when they invest in hard-to-value stocks (small, low institutional ownership, and low analyst coverage firms). The impact of retail order imbalances on stock returns is only in conjunction with investor sentiment.

In Chapter 4, I consider the effect of firm-level sentiment extracted from a social network platform on the presence of herding behavior in the US equity market. Applying a quantile regression model enables me to investigate the existence of herding in both periods of quiet and periods of extreme market movements. I also benefit from using different sampling frequencies (daily, weekly, and monthly) for detecting investor herding. I document an asymmetric association between herding and investor sentiment. That is, herding is present in low-optimism portfolios but not in high-optimism portfolios. I also find evidence of herding in intermediate quantiles (i.e., relatively quiet market periods but not during extreme market movements). The degree of investor attention has a moderating impact on the relationship between investor optimism and the tendency to herd, with the presence of herding being more intensified among low-optimism stocks. I also find evidence that trading volume drives herding behavior.

In Chapter 5, I estimate the impact of investor sentiment in the stock market on the return and volatility spillover risks between REITs and a broader equity index. I find that the total return spillover risk is higher for low-optimism portfolios (45.76%) compared with high-optimism portfolios (41.41%). I do not document any significant impact of investor sentiment on the volatility spillover risk between REITs and the equity market (34.85% versus 34.17%). My results highlight the importance of considering investor sentiment in the stock market when constructing multi-asset portfolios that include assets such as REITs in addition to other asset classes.

6.2 Future work

Some questions remain unanswered, which can provide direction for future researchers.

A combined theory of investor sentiment, which discusses both theoretical and experimental studies, could be developed. A combined theory of investor sentiment has been attempted in the research, but it still cannot explain all the empirical findings. A theory should especially consider both short-term and long-term effects, because empirical research mentions that short-term effects are different from long-term effects. Therefore, these different patterns are yet to be explained by market microstructure theory.

To comprehend the trading motivation of retail investors, studies of individual investor behavior should be carried out. The data set utilized in existing research reflects retail investor behavior, but it lacks a link to individual account data. Future work on individual account data could be gathered from large brokers. These data would enable researchers to track submitted orders to individual accounts, and research should concentrate on retail investor motivation to submit orders for particular stocks. In addition, individual account data provide an opportunity to find out the profit or loss of individual investors from trading, identified by investigating the holding period and account settlement data. Account data of individual retail investors enable researchers to identify high-performance investors who earn considerable profits from trading decisions. The data also enable the identification of low-performance investors who do not earn profits due to bad decisions. Therefore, this concept provides a platform for future research to analyze the reason behind the profit difference if this difference remains consistent.

To understand the behavior of retail investors, field or laboratory experiments could be conducted that determine the motivation of individual investors' investment decisions, as well as the timing associated with these decisions.

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