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Nico B. Rottke · Jan Mutl *Hrsg.*

RESEARCH

Anna Mathieu

Essays on the Impact of Sentiment on Real Estate Investments

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Essays on the Impact of Sentiment on Real Estate Investments

With a Preface of the Editors by
Prof. Dr. Nico B. Rottke and Prof. Dr. Matthias Thomas

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Preface of the Editor

The tremendous downturn of the U.S. housing market was one of the drivers for the current global financial crisis, which had originated in the U.S. market for mortgage backed securities in 2007. Until April 2009, the crash of the U.S. banking and its related shadow banking system, in conjunction with the confidence crisis, has caused a direct loss of nearly 3 Trillion dollars. Once more, the asset class "real estate" had demonstrated its crucial role in global economics.

Against this background, the current crisis of the European Monetary Union has illustrated very well which large impact sentiment has for stock markets as well as for physical markets: reactions of market participants can hardly be explained with underlying fundamentals and efficient market theory.

Thus, the author of this Ph.D.-thesis, Ms. Dipl.-Kffr. Anna Mathieu, has chosen a very current topic which she applies in the context of real estate, more specifically, US Real Estate Investment Trusts and direct residential real estate in the U.S. and investigates the sentiment of various market participants. Therefore, the main part of her dissertation is composed of three essays investigating the impact of sentiment on real estate investments as follows:

- Impact of Investor Sentiment on U.S. REIT returns
- Investor Sentiment and the Return and Volatility of U.S. REITs and Non-REITs during the Financial Crisis
- Impact of Consumer Sentiment on the Number of New Home Sales in the U.S.

The first stand-alone study (chapter 2) deals with the impact of investor sentiment on REIT returns: after an introduction which tries to motivate the study and the topic, defined as REITS being a special investment class, the author conducts a literature review and summarizes the existing results of sentiment research.

In this part of the thesis, the aim of the study is characterized as an extension of the literature on REIT returns and volatility by considering the impact of investor sentiment on REIT returns and volatility. The author then describes her data set and her methodology using US Equity REIT total returns and employing several GARCH-models with and without sentiment. The author concludes that REIT returns and return volatility are influenced by investor sentiment being itself asymmetric: bearish sentiment having a stronger impact on the volatility of REITs.

The second study, chapter 3, deals with investor sentiment and the return and volatility of REITs and Non-REITs during the financial crisis and the hypothesis is postulated that more sales happen when consumer sentiment is high and less sales in unstable market environments.

In this part as well, the aim of the study is to extend the literature on sentiment by considering the impact of institutional investor sentiment on returns and conditional volatility of different asset classes in an unstable market environment using U.S. Equity REIT returns, S&P 500 returns, and NASDAQ returns. The theoretical background of the paper is described explaining four different effects (the “holdmore- effect”, the “price pressure effect”, the “create space effect” as well as the “Friedman effect”) which are then empirically tested using the aforementioned data in connection with a GARCH-M model. The hypothesis is stated that market sentiment has a higher impact in extreme market environments such as the 2008-financial crisis. The hypothesis is then tested and confirmed (with the exception of NASDAQ-returns) using the aforementioned effects as explanations.

The third study of this thesis, the fourth chapter of the disseration, analyzes the impact of consumer sentiment on the number of new home sales. At this point, the object of study changes from indirect real estate – REITs – to direct real estate though.

The aim of the study is described with the investigation if consumer sentiment has an impact on the decision of a household to buy a new home. After a brief literature review, the author uses a data set from 1978 to 2010 is used with a total of 385 monthly observations from the Federal Reserve Bank of St. Louis. Methodologically, unobserved component models (instead of OLS regressions) are used to utilize their advantage to identify coefficients of some observable determinants of the dependent variable even if some independent variables are omitted. Results show that consumer (here instead of investor) sentiment has a significantly positive impact on the number of new one-family home sales in the U.S. Next to consumer sentiment, the mortgage rate is identified as critical variable with a strong and significant impact. The analysis thereby illustrates that 2008-financial crisis cannot be predicted by the data.

The dissertation at hand has been accepted at EBS Business School in autumn 2011 and graded with distinction. It provides practical results for investigating the sentiment of two different market participants (investors and consumers) in the U.S. residential market and shows up room for further research to be conducted against this background.

Therewith, we sincerely do hope that this research project will be well appreciated by both, real estate researchers and practitioners, alike.

Wiesbaden, November 21st, 2012

Prof. Dr. Nico Rottke FRICS CRE

Aareal Endowed Chair
Real Estate Investment & Finance

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Endowed Chair
Real Estate Management

Real Estate Management Institute
EBS Business School
EBS Universität für Wirtschaft und Recht

Preface of the Author

The dissertation at hand was created in the years 2008 to 2011 during the time as internal doctorate candidate at the Endowed Chair of Real Estate Investment and Finance of Prof. Dr. Nico B. Rottke at Real Estate Management Institue at the former European Business School – now EBS Business School -

Many people supported me during the time of my dissertation and I like to to express my greatest gratitude to them.

However, the greatest gratitude is dedicated to my family, first and foremest my father and my mother who always believed in me and who made this education possible at all. Both experienced all up and downs in the creation of this doctoral thesis and supported me with motivation and energy. Also, I'd like to thank my husband Matthias, who moved close to my parents during my disseration and pregnancy with our first daughther Charlotte as a favor for me. In return, he did not only accept additional traveling but also supported me with spiritual succor to finsish this work successfully. Finally, I like to express my gratitude to my siblings Ulf and Elise for their motivation and the recessary provision of diversion in desperate times.

In particular I have to thank my doctoral advisor and academic teacher Mr. Prof. Dr. Nico B. Rottke as well as my second referee Mr. Prof. Dr. Joachim Zietz for their acadamic supervision of my work.

Both supervisors were always available to me and did actively support me at anytime. Professor Rottke gave me the required academic liberty in the creation process and supported my progress with valuable discussions. Despite the huge spatial distance to Professor Zietz in the United States of Amercia and the given time lag he was a great constant I could count on at anytime though.

I received great support from my doctoral fellows at the Endowed Chair of Real Estate Investment and Finance: I was able to discuss the content of my thesis in several doctoral seminars and conversations and got very useful hints and advice.

Dr. Anna Mathieu

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List of Abbreviations

AAII	Association of Individual Investors
ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
DSSW	DeLong Shleifer Summers Waldmann
EMH	Efficient Market Hypothesis
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
II	Investor Intelligence
KPSS	Kwiatkowski–Phillips–Schmidt–Shin
NAV	Net Asset Value
NSA	Not Seasonally Adjusted
REIT	Real Estate Investment Trust
SA	Seasonally Adjusted
SAAR	Seasonally Adjusted Annual Rate
UCM	Unobserved Component Model

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1 Introduction

In real estate capital markets several phenomena are observable that are difficult to explain with the efficient market hypothesis. Property companies typically offer market capitalizations that are smaller than their net asset value (NAV), closed-end funds are usually traded at a discount to their NAV and real estate investment trusts are often mispriced. Attempts to explain these anomalies are at least incomplete.

In financial markets, anomalies, such as excessive volatility of and mean reversion in stock prices, are partly explained by the noise trader theory. Black (1986) identifies noise traders to be responsible for mispricing in financial markets. Noise traders suffer from cognitive biases and disturb the market with their irrational trading. A trigger for this is their reliance on investor sentiment, which is defined by Baker and Wurgler (2007) as a prospect about the development of future cash flows and investment risks based on information that is not explained by fundamentals. This misguided belief may be based, for example, on general market commentaries. In what follows, we distinguish between investor sentiment and consumer sentiment. Investor sentiment is specified as an aggregate measurement of investors' attitude towards prevalent market conditions. It is usually determined as bullish, bearish or neutral.

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Consumer sentiment, by contrast, reflects the perceptions individual consumers have about the short-term and long-term prospects of the economy in general and their personal financial situation in particular.

De Long et al. (1990) first model the influence of noise trading on assets considering the existence of arbitrage limits caused by noise traders. In their model, noise traders act in concert on irrelevant information, let prices deviate from fundamental values, and introduce a systematic risk that is priced. This noise trader risk is unpredictable as the beliefs of noise traders are uncertain. In the short run, arbitrageurs face the risk that sentiment becomes more extreme and prices deviate further from their fundamental values. Arbitrageurs, who have to liquidate before the prices recover, risk to lose money. The risk aversion and the short time horizon of arbitrageurs in this model limit their willingness to take arbitrary positions and impede the complete elimination of mispricing. Thus, sentiment, respectively noise trading, has a persistent impact on financial markets.

The importance of sentiment to understand the effectiveness of financial markets is extensively studied in the financial literature. However, until now only few studies exist investigating the impact of sentiment on real estate markets or direct and indirect real estate investments.

Among indirect real estate investments, REITs have gained in importance over the past years. The National Association of Real Estate Investment Trusts (NAREIT) reports that the equity market capitalization of U.S. REITs has increased from $90 billion to roughly $200 billion during the last decade. A characteristic of REITs is that they provide a form of mixed investment, located between equities and the fixed-income securities. Compared to other asset classes, such as small or large cap stocks, they offer significant diversification benefits.[1] Further, REITs are subject to a specific regulatory and tax framework. They are restricted in their investment decisions, their gross income derivation is predetermined and they are mandated to pay high dividends.[2]

We expect REITs to be sensitive to changes in sentiment for the following reasons. REITs and closed-end funds feature structural similarities, since it is possible to gauge their market values by valuing their underlying assets. In addition, REIT prices usually suffer from being mispriced and also closed-end funds are traded at a discount to NAV.[3] Another reason is that the volatility of REITs is generally strongly influenced by the volatility in small cap stocks.[4] According to several studies, closed-end funds and small cap stocks

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1 See, for example, Anderson et al., 2005; Lee and Stevenson, 2007; Simon and Ng, 2009.

2 REITs have to invest at least 75 percent of total assets in real estate, 2) at least 75 percent of gross income has to derive as rents from real property or interest from mortgages on real property, 3) and at least 90 percent of taxable income has to be distributed annually to shareholders in the form of dividends.

3 For detailed information see Gentry et al., (2004) and Clayton and MacKinnon (2001).

4 Compare Stevenson (2002).

are susceptible to the influence of investor sentiment.[5] Since REITs are to some degree similar to closed-end funds and related to small cap stocks, it is likely that REIT returns and REIT return volatility are also influenced by investor sentiment.

As REITs gain in importance and are often used as a hedging instrument in a mixed-asset portfolio, it is important for shareholders as well as for REIT managers to fully understand the return generating process as well as the risk related to this investment class. As investor sentiment is known to have significant influence in financial markets, the relationship between sentiment and the real estate capital market is important to be determined. Sentiment is a factor that cannot be changed by actions of the REIT management or by shareholders. Thus it is necessary to know how to handle this factor and to anticipate its impact on the real estate capital market.

To provide an overall picture of the impact of sentiment on real estate markets, it is helpful to consider not only indirect real estate investments but also direct real estate investments. Direct real estate markets are substantially different from financial markets. They are characterized by heterogeneity, illiquidity, high transaction costs and a lack of information.[6] Unlike for stocks, no perfect substitutes exist for properties. This makes a comparison of prices difficult. Further, a

5 Several studies investigate that closed-end funds and small cap stocks are influenced by investor sentiment, e.g. Lee et al. (1991), Chopra et al. (1993), Glushkov (2006).

6 Lin and Vandell (2007) identified these characteristics of real estate markets in their study.

new home requires a high capital commitment and is not easily resold quickly. We expect that these imperfections make real estate markets susceptible to the influence of sentiment. In financial markets, small imperfections, such as less liquidity, can cause more activity of noise traders. Insecurity and risk combined with cognitive biases let individuals rely on sentiment, when serves as an orientation. As real estate markets are characterized by several imperfections implying more risk and insecurity, they should be even more prone to the influence of sentiment.

From a practitioner's point of view our work is of interest because we illustrate for individuals as well as for real estate companies how and to what degree sentiment influences direct real estate investment decisions. A better understanding of the influencing factors of investment decisions enables real estate companies to better anticipate the demand and individuals to determine the optimal investment date.

The purpose of the dissertation is to elucidate the impact of sentiment on direct and indirect real estate investments. To achieve this aim we compose three papers. In Paper one (Chapter two), we analyze the impact of individual and institutional investor sentiment on REIT returns. Our study applies a new methodology that enables us to analyze simultaneously the impact of investor sentiment on both the return and conditional return volatility of REITs. As bullish and bearish sentiment may have a different impact on REIT returns and REIT return volatility, we allow for asymmetries in our model.

We expect that an increase in sentiment raises REIT returns, whereas a decrease in sentiment may lower REIT returns. Further we anticipate that both an increase and a decrease in investor sentiment raise REIT return volatility.

In Paper two (Chapter three), we discuss a question that has so far received no attention in the literature. We investigate the impact of institutional investor sentiment on the formation of conditional volatility and expected return both in a stable and an unstable market environment. In particular, we compare an ordinary market situation to the financial crisis that started in 2007. To capture different investment classes, we analyze US Equity REIT returns, S&P 500 returns (large cap stocks) and NASDAQ returns (small cap stocks). In an extreme market environment, we expect investor sentiment to have a higher impact on the return generating process of REITs and on REIT return volatility. Previous empirical tests of the impact of investor sentiment have only considered ordinary market situations. But noise traders enter the market in force in extreme market situations. The financial crisis provides us a good opportunity to test the behavior and the impact of noise traders under extreme market conditions.

After a systematic analysis about the influence of investor sentiment on indirect real estate investments, we turn in Paper three (Chapter four) towards direct real estate markets. Our study is the first that analyzes the impact of sentiment on residential real estate investments. For this purpose, we investigate to what extent consumer sentiment and other key macroeconomic variables influence the number of sales of new one-family homes in the U.S. If households suffer from the same cognitive biases as financial investors, consumer sentiment is bound to have an impact on their decision process. We expect that a positive consumer sentiment increases the number of new home sales, whereas a negative consumer sentiment is attended by a decrease in sales of new homes. In a positive market environment, employment is more stable and households feel more confident to take on a large investment. Negative consumer sentiment would indicate an unstable market environment and would probably prevent households from investing directly in real estate. The analysis is based on an unobserved component model (UCM), which allows including observed explanatory variables in a time series model along with unobserved components, which absorb the impact of variables left out of the study. This is important since it is not possible to obtain data for all influencing variables or even to know what all the relevant variables are, given the lack of a theory that relates sentiment to direct real estate investments.

The remainder of the dissertation proceeds as follows. In Chapter two we present Paper one. Using an asymmetric threshold GARCH model, we test the impact of investor sentiment on the formation of conditional volatility and expected return of REITs. We distinguish between two different weekly sentiment indicators, one for individual investor sentiment and one for institutional investor sentiment and use weekly US Equity REIT returns from December 1998 to May 2009.

Paper two is provided in Chapter three. In this study we use a GARCH-M model to investigate the impact of institutional investor sentiment on the formation of conditional volatility and expected return both in an ordinary market situation and during the financial crisis that started in 2007. We use a weekly sentiment indicator for institutional investor sentiment, as well as weekly US Equity REIT returns, S&P 500 returns and NASDAQ returns from December 1998 to December 2010.

In Chapter four we introduce Paper three. While Paper one and two concentrate on the impact of investor sentiment on indirect real estate markets, Paper three considers direct real estate markets. Using an unobserved component model (UCM) we investigate the impact of several macroeconomic influencing factors, particularly consumer sentiment, on the number of new one-family home sales in the U.S. We use monthly U.S. data from August 1978 to August 2010. Five different explanatory variables are considered: consumer sentiment, the mortgage rate, real estate loans, the inflation rate and the disposable personal income.

Chapter five summarizes the results.

2 The Impact of Investor Sentiment on REIT Returns

Co-authors of this chapter are N. Rottke and J. Zietz.

2.1 Introduction

The behavior of real estate investment trust (REIT) returns and REIT return volatility is a key topic in the real estate literature. Various studies concentrate on the return generating process of REITs. Chui et al. (2003), for instance, examine the cross-sectional determinants of expected REIT returns. Hsieh and Peterson (1997) find that risk premiums on equity REITs are related to their market capitalization and the book to market ratio. Clayton and MacKinnon (2003) analyze the link between REIT prices and the value of direct real estate owned by REITs.

Other papers focus on the volatility of REIT returns. Stevenson (2002) examines volatility spillovers of REITs. Devaney (2001) investigates the relationship between REIT volatility and interest rates. Cotter and Stevenson (2004) analyze the volatility dynamics in daily equity REIT returns and Hung and Glascock (2010) studies momentum returns in REITs.

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Several stylized facts have emerged thus far. First, according to several studies REIT prices deviate from net asset values (for example, Gentry et al., 2004; Clayton and MacKinnon, 2001). Second, REITs provide a form of mixed investment, located between equities and the fixed-income sector. They are unique in that they offer significant diversification benefits over other asset classes, such as small or large cap stocks and bonds.[7] Third, following Stevenson (2002) the volatility of REITs is generally influenced more strongly by volatility in small cap stocks and in firms classified as value stocks.

These stylized facts raise the question if REITs - as closed-end-funds and small cap stocks - are exposed to the influence of investor sentiment. There appear to be few studies that relate explicitly to REITs. Most focus on small caps or closed-end funds. For example, Lee et al. (1991) examine whether changes in closed-end fund discounts are caused by market sentiment. Glushkov (2006) investigates whether small cap and more volatile stocks with low dividend yields are influenced by sentiment.

REITs are similar to closed-end funds, since it is possible to gauge the market value of REITs by valuing the underlying assets. Further, REIT prices usually suffer from being undervalued and closed-end funds are traded at a discount to NAV. The basic characteristic that

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7 See, for example, Anderson et al., 2005; Lee and Stevenson, 2007; Simon and Ng, 2009.

distinguishes REITs from closed-end funds is the illiquid asset that REITs own. Since REITs are similar to closed-end funds in terms of their structure, and their volatility is influenced by small cap stock volatility, REITs are probably influenced by market sentiment. To what extent that is true, is the focus of this study.

More precisely, the current paper extends the literature on REIT returns and volatility by considering the impact of investor sentiment on REIT returns and volatility. Our main findings suggest that individual investor sentiment is a significant factor in explaining REIT returns and REIT return volatility. We can also identify asymmetric sentiment threshold values for both the return and the conditional volatility parts of the model. REIT returns increase in bullish sentiment stages, whereas bearish sentiment has no impact on the returns. The volatility increases in both sentiment stages, but bad news tends to have a larger effect.

The remainder of the study proceeds as follows. Section two gives an overview of the literature on investor sentiment as it is relevant to REITs. Section three describes the data and the different empirical models that are estimated. Section four discusses the empirical results and section five concludes with a summary of the study's most important results.

2.2 Literature Review

The idea to analyze REIT returns and REIT return volatility in different sentiment stages is based on the noise trader theory (for example, Black, 1986; DeLong et al., 1990). Noise traders seem to act primarily in extreme sentiment stages. Accordingly, extreme sentiment stages may cause changes in REIT returns and REIT return volatility.

The aim of the noise trader theory has been to find explanations for market anomalies, such as excessive volatility of and mean reversion in stock prices, the small firm effect and under- or overreaction of stock prices. These anomalies are difficult to explain with the efficient market hypothesis.

The empirical evidence suggests that not all investors buy and hold the market portfolio as recommended by economists. Instead, according to Lease et al. (1974) some investors pick their stocks by their own research and do not diversify their portfolio. Black (1986) ascertains that these investors seem to form their beliefs on anything but fundamentals and act irrationally on noise as if it were profitable information. In other words, noise traders' decisions to buy, sell, or hold an asset are based on a "noisy" signal. Kahneman and Tversky (1974) provide a multiplicity of possible cognitive biases in their studies, such as anchoring, representativeness or availability that try to explain reasons for the behavior of these investors.

Early studies (Friedman, 1953; Fama, 1965) attach no importance to the existence of so-called noise traders.[8] They assume that an investor trading on anything but fundamentals would be forced out of the market by arbitrageurs. This would let prices return to their fundamental values. However, continuing market anomalies challenge the efficient market hypothesis.

DeLong et al. (1990) first model the influence of noise trading on assets considering the existence of arbitrage limits caused by noise traders. In their model, noise traders act in concert on irrelevant information, let prices deviate from fundamental values, and introduce a systematic risk that is priced. This noise trader risk is unpredictable as the beliefs of noise traders are uncertain. In the short run, arbitrageurs face the risk that sentiment becomes more extreme and prices deviate further from their fundamental values. Arbitrageurs, who have to liquidate before the prices recover, risk to lose money. The risk aversion and the short time horizon of arbitrageurs in this model limit their willingness to take arbitrary positions and impede the complete elimination of mispricing. Investor sentiment influences the behavior of noise traders: in positive (negative) sentiment stages noise traders become extremely optimistic (pessimistic) and buy (sell) more of the asset. In summary, extreme sentiment stages let noise traders act and their trading has an persistent impact on returns and raises return volatility.

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[8] Kyle (1985) first uses the term “noise trader” in their study.

Noise traders react asymmetrically in positive and negative sentiment stages. Bad news tends to have a larger negative effect on the return and the conditional volatility than good news has a positive effect. According to Barberis and Huang (2001) reasons for these effects are the loss aversion and the narrow framing of individuals. Loss aversion is the tendency of individuals to be more sensitive to losses than to gains. Narrow framing indicates the bias of individuals to focus on narrowly defined gains and losses.

The relationship between investor sentiment and noise trading is well investigated for closed-end funds and small cap stocks, but there has been little research for REITs. The question is whether and to what extent REITs are also exposed to the influence of investor sentiment. This is an important question because REITs have historically been viewed as providing investors protection during market downturns.

In the literature, noise traders have not yet been exactly identified as individual or institutional investors. DeLong et al. (1990) assume that individual investors are more likely to be noise traders because they tend to be less sophisticated and more prone to cognitive biases. According to Weiss (1989), closed-end fund shares are primarily held by individual investors. Following up on Weiss, Lee et al. (1991) find a possible explanation for the closed-end fund puzzle presented by Zweig (1973), which is one of the most persistent puzzles related to the efficient market hypothesis. Lee et al. (1991) discover that changes in closed-end fund discounts are highly correlated with returns of small stocks that are mainly held by individual investors and infer that the previously unexplained discounts are caused by market sentiment. Swaminathan (1996) and Neal and Wheatley (1998) suggest that closed-end fund discounts predict small firm returns. Glushkov (2006) reports that more sentiment sensitive stocks have higher individual ownership and Brown (1999) investigates the price volatility of closed-end funds and finds a close relation to unusual levels of sentiment.

Chen et al. (1993) and Brown and Cliff (2005) do not support the conventional wisdom that sentiment primarily affects individual investors and small stocks. Hughen and McDonald (2005) further show that the order-flow imbalances of small investors do not cause large changes in fund discounts. Instead, fluctuations in fund discounts are strongly correlated with trading activity of institutional investors that have enough market power to strongly affect prices.

REIT institutional ownership is quite high. Clayton and MacKinnon determine that, during the 1990-1998 period, institutional ownership in REITs increased to over fifty percent. This stands in contrast to closed-end funds, which are mainly held by individual investors. It is, therefore, not clear if an indicator for individual or institutional investor sentiment is better suited to measure the influence of sentiment on REITs. To allow for this fact, we use both an individual investor sentiment measure and an institutional investor sentiment measure. The analysis will show which measure is more appropriate.

Although there is a growing number of theoretical and empirical studies that investigates the role of investor sentiment in financial markets (for example, DeLong et al., 1990, Lee et al., 1991, Brown and Cliff, 2004), only few have focused on the real estate sector. Lin et al. (2009), for example, find that sentiment has a significant positive impact on REIT returns. Clayton and MacKinnon (2001) report that the discount to NAV in REIT pricing is caused by noise. Falzon (2002) suggests a strong relationship between REITs and small capital stocks, and finds the relationship is especially strong with small capital value stocks. The relationship between sentiment and REIT return volatility appears to be unexplored so far.

To investigate the relationship between REITs and sentiment, we estimate several generalized autoregressive conditional heteroscedasticity (GARCH) models, introduced by Bollerslev (1986), with sentiment as the key explanatory variable. We distinguish two sentiment indicators, one for individual investors and one for institutional investors. For each indicator, we test for nonlinearities that may arise from threshold effects. Not every movement in the sentiment index may have a proportionate impact on REIT return or volatility; only sentiment changes beyond a certain critical value may have an impact. Our study is the first one that analyses sentiment threshold values. Furthermore, we are the first to allow the impact of positive and negative sentiment on REIT return and volatility to be asymmetric. In studies about stocks, such asymmetries are found to be important (for example, Barberis and Huang, 2001, Kirchler, 2009).

2.3 Data and Methodology

In this section we describe the data and several GARCH models that we estimate to analyze the impact of individual and institutional investor sentiment on REIT returns and REIT return volatility.

2.3.1 Data

The data consist of US equity REIT total returns and two different US sentiment indicators. The REIT returns are derived as $\Delta \ln p$, where p is the stock price of the REITs.

The first sentiment indicator is based on a survey regularly conducted by the American Association of Individual Investors (AAII) since July 1987. The association asks each week a random sample of its members where they think the stock market will be in six months. The responses, which are coded as up, down or the same, are interpreted as bullish, bearish or neutral market sentiments. Within the observation period, the responses are on average 39 percent bullish, 30 percent bearish and 31 percent neutral. Since the association asks mainly individuals, this indicator is often interpreted as a measure of individual investor sentiment.

The second sentiment measure relies on the survey of Investor Intelligence (II) founded in 1963. The association studies over a hundred independent market newsletters every week and assesses each author's current stance on the market: bullish, bearish or waiting for a correction. On average, 48 percent of the newsletters expect future market movements to be bullish and 30 percent expect bearish market movements within the observation period. Since many of the authors of these market newsletters are market professionals, this indicator is interpreted as a measure of institutional investor sentiment. For both indicators, the percentage of bullish investors minus the percentage of bearish investors (bull-bear spread) is used to identify the market sentiment.

All variables consist of 544 observations and are observed weekly from December 31, 1998 to May 28, 2009. The REIT data are derived from the SNL Financial database and the data of the two sentiment indicators are from Thomson Reuters Datastream.

2.3.2 The GARCH Model without Sentiment

We first estimate a GARCH model without sentiment to provide a basis of comparison for the following models. The return equation of the model takes the form

$$r_t = \mu + \varepsilon_t \qquad (1)$$

where r_t is the weekly return on US equity REITs, μ a time invariant constant, and ε_t a disturbance term. The conditional volatility equation of the model is given in standard format as

$$h_t = \omega + \sum_{i=0}^{I} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=0}^{J} \beta_j h_{t-j},$$

where h_t is the conditional volatility of US equity REIT returns.

2.3.3 The Sentiment Threshold GARCH Model

The base model consisting of Equations (1) and (2) is expanded by allowing for threshold values for the sentiment variable (S_t). We allow for asymmetric reactions with positive and negative threshold values. The return equation of the model including investor sentiment and asymmetry effects takes the form

$$r_t = \alpha_0 + \alpha_1 S_t + \beta_1 S_t I(S_t < \eta_1) + \gamma_1 S_t I(S_t > \eta_2) + \varepsilon_t,$$

where $I(S_t < \eta_1)$ is an indicator variable, which is unity if $S_t < \eta_1$ and zero if $S_t \geq \eta_1$. The scalar η_1 denotes the threshold value for negative changes in sentiment. $I(S_t > \eta_2)$ is an indicator variable, which is unity if $S_t > \eta_2$ and zero if $S_t \leq \eta_2$. η_2 is the threshold value for positive changes in sentiment. The conditional volatility equation of the model is given as

$$h_t = \omega + \sum_{i=0}^{I} \alpha_i \varepsilon_{t-i}^2 + \alpha_2 S_t \varepsilon_{t-1}^2 + \alpha_3 S_t I(S_t < \eta_3) \varepsilon_{t-1}^2$$

$$+ \alpha_4 S_t I(S_t > \eta_4) \varepsilon_{t-1}^2 + \sum_{j=0}^{J} \beta_j h_{t-j},$$

where $I(S_t < \eta_3)$ and $I(S_t > \eta_4)$ are indicator variables, which are unity for the specified conditions and zero otherwise.

The zero/one indicator variables (I) in the mean and the conditional volatility equations allow for asymmetric reactions to changes in the direction and magnitude of the sentiment variable. The rationale for the asymmetric terms is simple: they allow investors to react differently to changes in bullish and bearish sentiment. This is in line with the finance literature (for example, Glosten et al., 1993; Backus and Gregory, 1993), which find bearish sentiment to have a larger impact than periods of bullish sentiment.

The estimation of threshold values for both the mean return equation and the conditional volatility equation enables us to compare the relative sentiment sensitivity of the return and the conditional volatility. The lower the sentiment threshold value is the higher is the sentiment sensitivity. We expect the conditional volatility to have lower threshold values compared to the returns of REITs, as relatively small changes in sentiment may cause buy/sell actions of investors and thus increase conditional volatility. The return however may be only affected by more severe changes in investor sentiment.

2.4 Empirical Results

This section presents the empirical evidence on the impact of sentiment on mean returns and conditional volatility.

2.4.1 Augmented Dickey-Fuller Test and KPSS Test

Table 2.1 shows the results of the augmented Dickey-Fuller (ADF) tests for a unit root. Stationarity requires a rejection of the null hypothesis of a unit root. This is the case if the p-value of the ADF test statistic is lower than the significance level α = 1%. The ADF test with constant reveals that all variables are stationary. We also estimate the KPSS test, which has the null hypothesis of stationarity. The null hypothesis is rejected if the critical value of 0.739 is exceeded. This is the case for $AAII_t$ and II_t. The variables r_t, Δr_t, $\Delta AAII_t$ and ΔII_t are stationary.

Since both tests do not have the same conclusion, we use r_t in level form and for both sentiment indicators we employ first differences. This ensures that all variables are stationary. Furthermore, it makes economic sense to use the first differences of the sentiment variables because changes in the sentiment variable are of primary interest.

2.4.2 Summary Statistics

As reported in Table 2.2 $\Delta AAII_t$ and ΔII_t measure changes in investor sentiment and therefore capture innovations in individual and institutional investor sentiment. The mean of both sentiment indicators are small and negative over the sample period. r_t has a small, positive mean and displays a skewed, leptokurtic pattern. $\Delta AAII_t$ and ΔII_t show a skewed and platykurtic distribution. The relatively high standard deviation - particularly for $\Delta AAII_t$ -indicates that the low mean is due to the fact that positive and negative changes in sentiment are offsetting.

2.4.3 The GARCH Model without Sentiment

First, we estimate several basic GARCH models, as described by Equations (1) and (2). The coefficient estimates are reported in Table 2.3. For the purpose of comparison these models exclude sentiment variables in the mean and conditional volatility equation. Across the different GARCH models, most of the estimated GARCH coefficients are significant. The analysis shows that GARCH effects exist in both REIT returns and REIT return volatility.

To compare the different models and to select the most appropriate one, we use the Akaike information criterion (AIC). It indicates that a simple GARCH (2,3) model is the most appropriate one for the data. For all GARCH models, the Ljung-Box p-values indicate that no serial correlation exists in either the standardized residuals or the squared standardized residuals. That means the null hypothesis of no autocorrelation cannot be rejected. The models fit the data well.

2.4.4 The Sentiment Threshold GARCH Model

Next, we include investor sentiment in both the mean return and conditional volatility equation of our model. Our purpose is to detect asymmetries in the impact of sentiment as well as to investigate if certain sentiment threshold values exist. Accordingly, we use a GARCH model that allows for positive and negative sentiment threshold values. We estimate two models, one with an indicator for individual investor sentiment (AAII) and one with an institutional investor sentiment indicator (II).

AAII Sentiment Thresholds

The first model includes individual investor sentiment as an explanatory variable in the mean and conditional volatility equations, as described by Equations (3) and (4). The coefficient estimates are reported in Table 2.4. We start with the estimation of the complete model with all possible threshold effects. The results show primarily significant coefficients, indicating a widespread impact of individual investor sentiment on REIT returns. We estimate further models, which exclude insignificant variables to improve the Akaike information criterion (AIC) and get the optimal model.

For all three models of Table 2.4, the Ljung-Box p-values suggest the absence of serial correlation in the standardized and squared standardized residuals. We find that Model III is most suitable for the data, since it has the lowest AIC value. To identify the threshold values for the mean and the conditional volatility equations, we estimate values in the range from 0 to 30 and from 0 to -30. These ranges for the threshold values are determined on the basis of the kernel density function of the sentiment changes in Figure 2.1. Approximately at the points +30 and -30 are inflection points of the graph, indicating the maximal respectively minimal range for the threshold values.

The threshold values for the mean equation (-21; 25) and for the conditional volatility (-3; 8) equation do not differ between the three models. The relatively small threshold values of the conditional volatility equation suggest that even small changes in sentiment influence the conditional volatility of REITs. Nearly every positive or negative news seems to bias the trading behavior of REIT investors. REIT returns however are only affected by relatively strong changes in individual investor sentiment.

In the mean equation of the preferred Model III, positive and negative changes in sentiment have almost no impact at the extreme ends of the distribution of the sentiment variable, as the return is not affected by changes in sentiment that are smaller than the negative threshold value (-21) or larger than the positive threshold value (25).[9] If changes in sentiment are greater than the negative threshold value (-21) or smaller than the positive threshold value (25), the return increases approximately by 0.001 units. By contrast, we find that sentiment has a significant impact on volatility. Bullish changes in sentiment that exceed the positive threshold value result in statistically significant increases in volatility; in particular, the volatility changes approximately by 0.106. Bearish changes in sentiment that fall below the negative threshold value let the volatility increase by approximately 0.272. This finding is in line with Glosten et al. (1993) who report that the magnitude of the

[9] The addition of α_1 and β_1 respectively of α_1 and γ_1 is approximately zero.

change in market volatility is greater in bearish than in bullish sentiment stages.

In summary, we can say that individual investor sentiment does indeed capture the influence of market sentiment on REIT returns and REIT return volatility. In the mean equation, we find only a small influence of sentiment. In the conditional volatility equation, we detect an asymmetric impact. In particular, the negative threshold value is smaller and the negative sentiment has a stronger impact on the conditional volatility of REITs than the positive one.

II Sentiment Thresholds

We estimate a sentiment threshold GARCH model with institutional investor sentiment as the explanatory variable in the mean and conditional volatility equations (Equations (3) and (4)). The estimates of the coefficients are reported in Table 2.5. In Model I, we estimate the complete model with all possible threshold effects. Some of the coefficients are insignificant, which we remove in Model II from the mean and volatility equation. The Ljung-Box p-values report no serial correlation for either the standardized residuals or the squared standardized residuals for the two models. The models fit the data as serial correlation is effectively absent. We find again that a GARCH (1,1) is most suitable for the data. Threshold values are tested for the mean and the conditional volatility equations in the range from 0 to 20 and from 0 to -20. The ranges for the threshold values are determined on the basis of the kernel density function of the sentiment changes (Figure 2.2). In Model I the threshold values for the mean equation are -15 and 18, but the corresponding coefficients are not significant. Therefore, we remove the insignificant variables in Model II. Changes in sentiment without consideration of threshold effects raise the return by approximately 0.001. Furthermore, we find that the threshold values of the conditional volatility equation are smaller compared to the model with the individual investor sentiment indicator, namely -2 and 1. In Model II, a one unit change in bullish sentiment raises the volatility approximately by 0.245[10]. Bearish changes in sentiment let the volatility increase by approximately 0.210[11]. These findings contradict the results of Lee et al, who detect a negative correlation between changes in investor sentiment and stock market volatility. It is apparent that the two sentiment indicators, described in Table 2.4 and Table 2.5, behave differently. The indicator of individual investor sentiment fits the data better according to the information criteria and provides more reasonable results. Since investors are risk averse, bearish changes in sentiment should have a stronger impact on conditional volatility than bullish changes in sentiment; this is only the case for the individual investor sentiment indicator. The results are interesting as institutional investors primarily invest in REITs. Therefore, one would expect the indicator

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[10] The value 0.245 is derived from the addition of α_2 and α_4.
[11] The value 0.240 is derived from the addition of α_2 and α_3.

for institutional investor sentiment to be the more appropriate explanatory variable for REIT returns and REIT return volatility.

Overall, our results contradict the conventional wisdom that only small stocks are affected by noise trading (Baker and Wurgler, 2007). The results are, however, in line with the findings of Brown and Cliff (2004), which do not support the conventional view. REITs also seem to be sensitive to sentiment changes although they are primarily held by institutions and not individuals. To measure the influence of sentiment on REITs, the indicator for individual investor sentiment is the most appropriate.

2.5 Conclusions

The purpose of this study has been to analyze the influence of investor sentiment on REIT returns and REIT return volatility. This is the first study to investigate if the impact of sentiment on REIT returns and REIT return volatility is asymmetric. In studies about stocks such asymmetries are found (for example, Barberis, N. and Huang, M., 2001; Kirchler, M., 2009). This is also the first study to analyze if nonlinear effects of the threshold type exist for sentiment.

In our analysis we use two different weekly sentiment indicators, one for individual investor sentiment (AAII) and one for institutional investor sentiment (II), as well as weekly US Equity REIT returns from December 1998 to May 2009. We apply a GARCH framework to test the influence of investor sentiment on REIT returns and conditional volatility. We find that including a sentiment variable as an explanatory variable into a basic GARCH model improves the fit. The same applies to including threshold effects for the sentiment variables. For the indicator of individual investor sentiment, we identify a small positive influence on REIT returns. In the conditional volatility equation, we detect some weak asymmetry. Negative sentiment changes have a stronger impact on the conditional volatility of REITs. However, in bullish and bearish sentiment stages, sentiment changes that exceed the threshold values tend to increase volatility.

The inclusion of institutional investor sentiment in the model leads to inferior models compared to the analysis with individual investor sentiment. In the mean equation, we find again a small positive influence of institutional investor sentiment on REIT returns. In the volatility equation, positive and negative sentiment changes raises volatility by a similar magnitude. Sentiment changes that fall below the positive threshold value respectively exceed the negative threshold value have a negative impact on the conditional volatility.

In summary, we ascertain that REIT returns and REIT return volatility are influenced by investor sentiment. The indicator for individual investor sentiment is the most appropriate indicator for REITs. The impact of individual investor sentiment on REIT returns and REIT return volatility is asymmetric: bearish sentiment has a stronger impact on the volatility of REITs. This is consistent with

Barberis and Huangs' (2001) finding that investors are loss averse and focus on narrowly defined gains and losses. Furthermore, the influence of sentiment on the conditional volatility is higher than on the mean return, as the corresponding threshold values are smaller for the conditional volatility equation.

Sentiment is, contrary to conventional wisdom, not an individual investor problem that only affects small capitalization stocks and closed-end funds. It also affects REITs.

2.6 Appendix for Chapter Two

Table 2.1: Augmented Dickey-Fuller tests and KPSS tests, 544 weekly observations, observation period 1998/12/31 - 2009/05/28

Variable	ADF test		KPSS test
r_t	0.002	(14)	0.318
Δr_t	0.004	(4)	0.009
$AAII_t$	< 0.001	(6)	2.439
$\Delta AAII_t$	0.001	(13)	0.009
II_t	< 0.001	(1)	1.062
ΔII_t	< 0.001	(15)	0.015

Notes: This table provides augmented Dickey-Fuller (ADF) tests and KPSS tests for the return, sentiment indices, changes in returns and changes in sentiment indices. The ADF test statistic is calculated with a constant, no time trend is used, the p-values are shown and the optimal lag choice is in parentheses. The KPSS test is done without time trend and the critical values at different significance levels are: 10% (0.347), 5% (0.463), 2.5% (0.574), 1% (0.739). The weekly data consists of 544 observations from December 1998 to May 2009.

Table 2.2: Summary Statistics, 544 weekly observations, observation period 1998/12/31 - 2009/05/28

Variable	Mean	Median	Standard deviation	Skewness	Kurtosis
r_t	0.001	0.002	0.041	0.339	15.357
$\Delta AAII_t$	-0.050	0.320	16.893	-0.073	0.413
ΔII_t	-0.029	0.200	4.740	0.159	1.213

Notes: All data relate to the U.S. for the time period of December 1998 to May 2009. We have 544 weekly observations.

Table 2.3: Basic GARCH models, 544 weekly observations, observation period 1998/12/31 - 2009/05/28

Variable	GARCH (1,1)	GARCH (1,2)	GARCH (1,3)	GARCH (2,3)	GARCH (3,3)
Return:					
μ	0.004 ***	0.004 ***	0.004 ***	0.004 ***	0.004 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Conditional Volatility:					
ω	<0.001 ***	<0.001 **	<0.001 **	<0.001	<0.001
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
ε_{t-1}^2	0.172 ***	0.222 ***	0.292 ***	0.419 ***	0.420 ***
	(0.023)	(0.034)	(0.039)	(0.066)	(0.066)
ε_{t-2}^2				-0.372 ***	-0.022
				(0.067)	(0.184)
ε_{t-3}^2					-0.284 *
					(0.163)
h_{t-1}	0.813 ***	0.343 *	0.208 **	1.110 ***	0.264
	(0.025)	(0.201)	(0.095)	(0.124)	(0.438)
h_{t-2}		0.423 **	0.118	-0.077	0.650
		(0.181)	(0.143)	(0.193)	(0.502)
h_{t-3}			0.382 ***	-0.073	-0.014
			(0.120)	(0.129)	(0.148)
Akaike criterion:	-3393.487	-3395.856	-3397.784	-3402.408	-3399.825
Ljung-Box p-value: $\frac{\varepsilon}{\sqrt{h}}$					
(lag 1)	0.843	0.816	0.726	0.499	0.511
(lag 3)	0.627	0.643	0.499	0.478	0.406
(lag 10)	0.924	0.910	0.831	0.735	0.711
Ljung-Box p-value: $(\frac{\varepsilon}{\sqrt{h}})^2$					
(lag 1)	0.587	0.677	0.760	0.511	0.455
(lag 3)	0.829	0.903	0.814	0.854	0.416
(lag 10)	0.964	0.970	0.981	0.928	0.791

*Notes: This table reports different GARCH models, described by Equation (1) und (2), based on weekly data from December 1998 to May 2009 and consisting of 544 observations. The models do not include the effect of sentiment on the mean and conditional volatility equation. The dependent variable is the return of REITs. The Ljung-Box Q-statistics tests for serial correlation in standardized residuals and squared standardized residuals for lags up to 27. The p-value indicates if serial correlation exists. Parameter estimates and standard errors (in parentheses) are listed. * Indicates significance at the*

*10% level, ** indicates significance at the 5% level, *** indicates significance at the 1% level.*

Table 2.4: AAII sentiment threshold GARCH model, 544 weekly observations, 1998/12/31 - 2009/05/28

Variable	Coefficient	Model I: base model	Model II: insignificant variables removed	Model III: more insignificant variables removed
Return:				
α_0		0.002 *	0.002 **	0.002 **
		(0.001)	(0.001)	(0.001)
ΔS_t	α_1	<0.001***	<0.001***	<0.001***
		(<0.001)	(<0.001)	(<0.001)
$\Delta S_t I(\Delta S_t < \eta_1)$	β_1	<-0.001 ***	<-0.001***	<-0.001***
		(<0.001)	(<0.001)	(<0.001)
$\Delta S_t I(\Delta S_t > \eta_2)$	γ_1	<-0.001 **	<-0.001 **	<-0.001**
		(<0.001)	(<0.001)	(<0.001)
Conditional Volatility:				
ω		<0.001**	<0.001**	<0.001**
		(<0.001)	(<0.001)	(<0.001)
ε_{t-1}^2	α_i	-0.035		
		(0.025)		
$\Delta S_t \varepsilon_{t-1}^2$	α_2	0.004*	0.004	
		(0.002)	(0.002)	
$\Delta S_t I(\Delta S_t < \eta_3)$	α_3	0.254***	0.223 ***	0.272 ***
		(0.061)	(0.047)	(0.032)
$\Delta S_t I(\Delta S_t > \eta_4)$	α_4	0.128 ***	0.107 **	0.106 ***
		(0.047)	(0.052)	(0.034)
h_{t-1}	β_j	0.881***	0.863 ***	0.870 ***
		(0.014)	(0.016)	(0.014)
Akaike criterion:		-3411.896	-3412.874	-3412.621
Threshold values:				
Return:		-21; 25	-21; 25	-21;25
Conditional volatility:		-3 ; 8	-3; 8	-3 ; 8
Ljung-Box p-value: $\frac{\varepsilon}{\sqrt{h}}$				
(lag 1)		0.558	0.693	0.770
(lag 3)		0.409	0.464	0.513
(lag 10)		0.800	0.870	0.922
Ljung-Box p-value: $(\frac{\varepsilon}{\sqrt{h}})^2$				
(lag 1)		0.197	0.404	0.443
(lag 3)		0.168	0.705	0.538
(lag 10)		0.566	0.913	0.894

Notes: This table reports a threshold GARCH model, described by Equation (5) und (6), based on weekly data from December 1998 to May 2009 and consisting of 544 observations. The dependent variable is the return of REITs. First the complete model is estimated with all possible threshold effects, and then the optimal model without insignificant variables is developed. Positive and negative threshold values for the mean *and the conditional volatility equations are reported. The Ljung-Box Q-statistics tests for serial correlation in standardized and squared standardized residuals for lags up to 27. The p-value indicates if serial correlation exists. Estimates and standard errors (in parentheses) are listed. *Indicates significance at the 10% level, **indicates significance at the 5% level, ***indicates significance at the 1% level.*

Table 2.5: II sentiment threshold GARCH model, 544 weekly observations, 1998/12/31 - 2009/05/28

Variable	Coefficients	Model I: base model	Model II: insignificant variables removed
Return:			
α_0		0.004 ***	0.004 ***
		(0.001)	(0.001)
ΔS_t	α_1	<0.001**	<0.001**
		(<0.001)	(<0.001)
$\Delta S_t I(\Delta S_t < \eta_1)$	β_1	0.004	
		(0.006)	
$\Delta S_t I(\Delta S_t > \eta_2)$	γ_1	-0.001	
		(<0.001)	
Conditional Volatility:			
ω		<0.001***	<0.001***
		(<0.001)	(<0.001)
ε_{t-1}^2	α_i	0.044	
		(0.045)	
$\Delta S_t \varepsilon_{t-1}^2$	α_2	-0.019 ***	-0.015 **
		(0.007)	(0.007)
$\Delta S_t I(\Delta S_t < \eta_3)$	α_3	0.177 *	0.225 ***
		(0.100)	(0.085)
$\Delta S_t I(\Delta S_t > \eta_4)$	α_4	0.236 ***	0.260 ***
		(0.064)	(0.054)
h_{t-1}	β_j	0.794 ***	0.798 ***
		(0.028)	(0.027)
Akaike criterion:		-3400.660	-3398.800
Threshold values:			
Return:		-15; 18	
Conditional volatility:		-2 ; 1	-2 ; 1
Ljung-Box p-value: $\frac{\varepsilon}{\sqrt{h}}$			
(lag 1)		0.229	0.209
(lag 3)		0.560	0.612
(lag 10)		0.835	0.874
Ljung-Box p-value: $(\frac{\varepsilon}{\sqrt{h}})^2$			
(lag 1)		0.935	0.905
(lag 3)		0.976	0.932
(lag 10)		0.997	0.985

Notes: This table reports a threshold GARCH model, described by Equation (5) und (6), based on weekly data from December 1998 to May 2009 and consisting of 544 observations. The dependent variable is the return of REITs. First the complete model is estimated with all possible threshold effects, and then the optimal model without insignificant variables is developed. Positive and negative threshold values for the mean *and the conditional volatility equations are reported. The Ljung-Box Q-statistics tests for serial correlation in standardized and squared standardized residuals for lags up to 27. The p-value indicates if serial correlation exists. Estimates and standard errors (in parentheses) are listed. *Indicates significance at the 10% level, **indicates significance at the 5% level, ***indicates significance at the 1% level.*

Figure 2.1: Kernel density function of AAII sentiment indicator

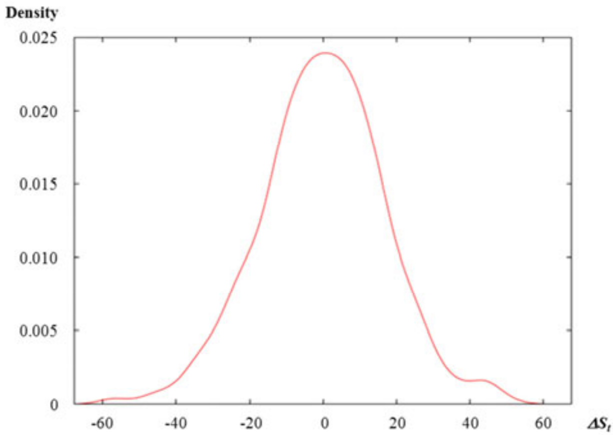
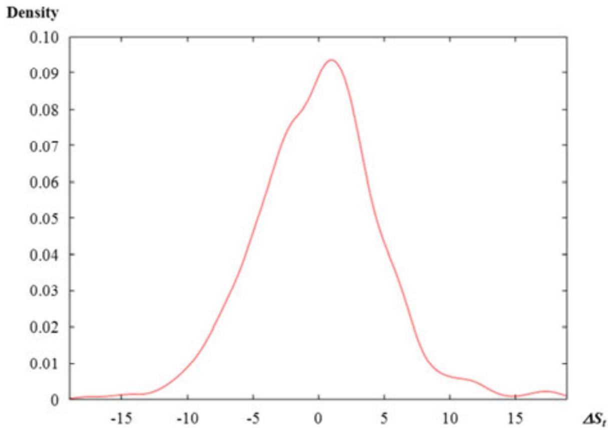


Figure 2.2: Kernel density function of II sentiment indicator



3 Investor Sentiment and the Return and Volatility of REITs and Non-REITs during the Financial Crisis

Co-authors of this chapter are N. Rottke and J. Zietz.

3.1 Introduction

The participation of noise traders in financial markets has different effects for returns and return volatility. Noise traders participate in the market is based on an external, noisy signal that conveys no information about fundamentals. Investor sentiment is such a signal. Sentiment reflects the optimism or pessimism of the market and does not need to be completely rational. The more extreme the sentiment is, the more noise traders act in the market; their trading lets prices deviate from their fundamental values. This deviation is persistent and introduces a new kind of risk - the noise trader risk (Shleifer and Summers, 1990, Sias et al., 2001, De Long et al., 1989).

The current paper extends the literature on sentiment by considering the impact of institutional investor sentiment on returns and conditional volatility of different asset classes in an unstable market environment. We use a GARCH-M model to identify to what extent returns and conditional volatilities are influenced by investor

A. Mathieu, *Essays on the Impact of Sentiment on Real Estate Investments,*
Essays in Real Estate Research 9, DOI 10.1007/978-3-658-11637-8_3,

sentiment. To capture different investment classes, we analyze US Equity REIT returns, S&P 500 returns (large cap stocks) and NASDAQ returns (small cap stocks). As noise traders are more active in extreme sentiment stages, we allow the impact of sentiment on returns and return volatility to be different during the financial crisis that started in 2007 than during tranquil times.

Our main findings suggest that for REIT and S&P 500 returns the impact of investor sentiment on returns and return volatility is higher during the financial crisis than in a tranquil market environment. Further, the impact of return volatility on contemporaneous REIT and S&P 500 returns is significantly higher during the financial crisis. Generally, REIT returns and S&P 500 returns behave similarly with regard to investor sentiment. NASDAQ returns are influenced by market sentiment at large, with no particular difference observable during the financial crisis.

The remainder of the study proceeds as follows. Section two specifies the theoretical background of the study. Section three describes the data, the methodology and the individual hypotheses. Section four discusses the empirical results and section five concludes with a summary of the study's most important results.

3.2 Theoretical Background

Several theoretical models have been developed to show that irrational trading has a long term impact on asset prices (Hirshleifer et al., 2006, Dumas et al., 2005). De Long et al. (1990) (DSSW hereafter) first model theoretically the influence of noise trading on expected returns and conditional volatility. In their model, noise traders act in concert with sentiment signals, let prices deviate from fundamental values, and introduce a systematic risk that is priced. This noise trader risk is unpredictable as the beliefs of noise traders are prone to cognitive biases and thus uncertain.

Arbitrageurs face the risk, at least in the short run, that sentiment becomes more extreme and prices deviate further from their fundamental values. They risk losing money if they have to liquidate before the prices recover. The risk aversion and the short time horizon of arbitrageurs (Shleifer and Vishny, 1997), limit their willingness to take arbitrary positions and impede the complete elimination of mispricing. Consequently, investor sentiment has a sustainable impact on asset prices.

Following the noise trader model of DSSW, several empirical analyses test the theoretical framework for stocks and closed-end funds. Lee et al. (1991) discover that changes in closed-end fund discounts are highly correlated with returns of small stocks, which are mainly held by individual investors. They infer that the previously unexplained discounts are caused by market sentiment.

Brown and Cliff (2004) find that sentiment levels are strongly correlated with contemporaneous market returns, but sentiment has little predictive power for near-term future stock returns. Kelly (1997) examines the influence of noise trader participation on returns.[12] He finds that a higher participation of noise traders is a negative predictor of stock returns. Baker and Wurgler (2007) suggest that speculative stocks, which are difficult to value and to arbitrage, are likely to be disproportionately sensitive to broad waves of investor sentiment. Brown (1999) first investigates the correlation between changes in sentiment and return volatility. He suggests that unusual levels of individual investor sentiment are associated with greater volatility in closed-end fund returns.

In their noise trader model DSSW identify four effects noise trading has on returns and return volatility. They identify four effects: the so called "hold more" effect implies that noise traders with bullish (bearish) sentiment increase (decrease) their demand for a particular risky asset and thus raise (lower) the market risk. The higher (lower) risk results in higher (lower) expected returns, which noise traders may earn. The "price pressure" effect works in the opposite direction. As noise traders overreact to optimistic or pessimistic sentiment, the asset prices either over- or undershoot the fundamental value. This mispricing induces "price pressure" and

[12] According to Kelly (1997), noise traders tend to be lower-income individuals.

lowers expected returns. Depending on which effect dominates the market returns increase or decrease.

Additionally, DSSW determine the “create space” effect. If the variability of noise traders’ sentiment increases, sophisticated investors must bear a greater price risk. Since these investors are risk averse, they tend to limit their bets against noise traders, who thus can earn higher expected returns. But noise traders typically act in concert, namely they buy (sell) when other noise traders are buying or selling. Consequently they buy high and sell low. The more volatile noise traders’ sentiment is the higher is the capital loss they suffer from their misperception (“Friedman effect”). Depending on which effect dominates, a rise in conditional volatility lets market returns increase or decrease.

Lee et al. (2002) first empirically test the four DSSW noise trader effects for three different market indices. They find that sentiment is an important factor in explaining market volatility, as volatility increases (decreases) when the sentiment becomes more bearish (bullish).

The activity of noise traders is positively correlated with the strength of the market sentiment. The more positive or negative the market sentiment is, the higher is the signal noise traders act on, and the more are noise traders active in the market. For this reason we investigate the influence of sentiment on returns also in the unstable environment of the financial crisis that started in 2007. We analyze if the influence of market sentiment on returns differs during the crisis compared to more tranquil market periods.

Some assets are more susceptible to the influence of sentiment. But it is still a matter of dispute which asset is the most sentiment sensitive. Baker and Wurgler (2007) find that smaller stocks tend to be more sensitive to changes in sentiment. Glushkov (2006) considers more stock characteristics and identifies those stocks as more sentiment-sensitive that are smaller, younger, with greater short-sales constraints, higher idiosyncratic volatility, and lower dividend yields. But Chen et al. (1993) and Brown and Cliff (2005) both do not find a confirmation of the conventional wisdom that sentiment primarily affects small stocks.

REITs have a similar structure as closed-end funds and closed-end funds have been shown to be sentiment sensitive according to Lee et al. (1991) and Chopra et al. (1993). Peterson and Hsieh (1997) report that the REIT return behavior is similar to that of a portfolio of small stocks. Lin et al. (2009) analyze sentiment and REITs and find that sentiment has a significantly positive impact on REIT returns. Further, Clayton and MacKinnon (2001) identify a relationship between noise and the discount in REIT pricing. Hughen and McDonald (2005) show that fluctuations in fund discounts are strongly correlated with trading activity of institutional investors. Following them, institutional investors mainly invest in large cap stocks and have -compared to individual investors- enough market power to strongly affect prices.

According to previous empirical studies, investor sentiment or noise trading seem to influence the returns of small cap stocks as well as large cap stocks and closed-end funds as well as REITs. These studies analyze the influence of investor sentiment in ordinary market situations. According to previous theoretical studies, investor sentiment should affect returns as well as conditional return volatility. Both appear to react most to the impact of extreme optimism or pessimism. We add to this literature by testing explicitly the impact of investor sentiment on both returns and conditional volatility in the extremely pessimistic market environment of the financial crisis. We use a GARCH-M model that enables us to also test the four DSSW noise trader effects in this extreme situation. We compare different investment classes in order to determine their particular sentiment sensitivity.

3.3 Data and Methodology

In this section we describe the data and the model that we estimate to analyze the impact of institutional investor sentiment on returns and return volatility.

3.3.1 Data

The data consist of US Equity REIT returns, NASDAQ Composite returns, S&P 500 returns and the US Investor Intelligence sentiment indicator. The returns are derived as $\Delta \ln p$, where p is the stock price. The market indices NASDAQ Composite and S&P 500 are used to characterize the overall market performance in comparison to the performance of REITs. Both are value-weighted indices that reflect the return of small (NASDAQ Composite) and large (S&P 500) capitalization stocks.

The sentiment measure relies on the survey of Investor Intelligence (II) founded in 1963. The association studies over a hundred independent market newsletters every week and assesses each author's current stance on the market: bullish, bearish or waiting for a correction. On average, 48 percent of the newsletters expect future market movements to be bullish and 29 percent expect bearish market movements within the observation period. Since many of the authors of these market newsletters are market professionals, this indicator is interpreted as a measure of institutional investor sentiment. The percentage of bullish investors minus the percentage of bearish investors (bull-bear spread) is used to identify the market sentiment.

The variables consist of 627 observations and are observed weekly from December 31, 1998 to December 29, 2010. The REIT, NASDAQ and S&P 500 data are derived from the SNL Financial database and the data of the sentiment indicator are from Thomson Reuters Datastream.

3.3.2 The GARCH-M Model

We employ the GARCH-M model as introduced by Engle et al. (1987). It includes a heteroskedasticity term in the mean equation and allows for a time varying risk premium.

The return equation of the model takes the form

$$r_t = \alpha_0 + \alpha_1 r_{t-1} + \alpha_2 h_t^{0.5} + \alpha_3 \Delta S_t^r + \varepsilon_t, \tag{1}$$

where α_0 is a time invariant constant, α_1 is an autoregressive lag parameter, α_2 measures the influence of own conditional volatility on returns, and α_3 indicates the influence of investor sentiment on the return generating process. We allow each of the parameters α_0, α_2 and α_3 to vary in a linear and non-stochastic way between the financial crisis (denoted as D_t^{cr} and equal to unity between 2007 and 2010) and before. This can be written as

$$r_t = (a_1 + a_2 D_t^{cr}) + \alpha_1 r_{t-1} + (b_1 + b_2 D_t^{cr}) h_t^{0.5} + (c_1 + c_2 D_t^{cr}) \Delta S_t^r + \varepsilon_t \tag{2}$$

or, if we multiply out, as

$$r_t = a_1 + a_2 D_t^{cr} + \alpha_1 r_{t-1} + b_1 h_t^{0.5} + b_2 D_t^{cr} h_t^{0.5} + c_1 \Delta S_t^r + c_2 D_t^{cr} \Delta S_t^r + \varepsilon_t.$$

In Equation (1) to (3), r_t is the weekly return on US Equity REITs or on one of the two market indices (NASDAQ Composite, S&P 500). ΔS_t^r denotes the weekly change in sentiment, as measured by the Investor Intelligence (II) sentiment indicator. ε_t is a disturbance term and $\varepsilon_t \sim N(0, h_t)$. Our GARCH-M model allows the return r_t to be determined by the market sentiment ΔS_t^r and own conditional volatility h_t.The parameters α_0, α_2 and α_3 of Equation (1) are divided into crisis-independent terms (a_1, b_1, c_1) and crisis-dependent terms $(a_2 D_t^{cr}, b_2 D_t^{cr}, c_2 D_t^{cr})$.

The conditional volatility equation of the model is given as

$$h_t = \beta_0 + \beta_1 \Delta S_t^v \varepsilon_{t-1}^2 + \sum_i \delta_i \varepsilon_{t-i}^2 + \sum_i \gamma_i h_{t-i}$$

where the parameters $\beta_0, \beta_1, \delta_i, \gamma_i$ are allowed to vary with the financial crisis, such that $\beta_0 = d_1 + d_2 D_t^{cv}$, $\beta_1 = e_1 + e_2 D_t^{cv}$, $\delta_i = f_{1i} + f_{2i} D_t^{cv}$ and $\gamma_i = g_{1i} + g_{2i} D_t^{cv}$. Inserting the determining equations of parameters into Equation (4) gives

$$h_t = (d_1 + d_2 D_t^{cv}) + (e_1 + e_2 D_t^{cv}) \Delta S_t^v \varepsilon_{t-1}^2 + \sum_i (f_{1i} + D_t^{cv}) \varepsilon_{t-i}^2 + \sum_i (g_{1i} + g_{2i} D_t^{cv}) h_{t-i}$$

this can be multiplied out to give

$$h_t = d_1 + d_2 D_t^{cv} + e_1 \Delta S_t^v \varepsilon_{t-1}^2 + e_2 D_t^{cv} \Delta S_t^v \varepsilon_{t-1}^2 +$$

$$\Sigma_i (f_{1i} + f_{2i} D_t^{cv}) \varepsilon_{t-i}^2 + \Sigma_i (g_{1i} + g_{2i} D_t^{cv}) h_{t-i}. \qquad (6)$$

The conditional volatility of the return (h_t) is defined as a function of squared values of the past residuals (ARCH factor), lagged conditional volatility (GARCH factor) and the product of weekly shifts in investor sentiment and lagged squared errors.[13] As in Eq. (1) each coefficient $(\beta_0, \beta_1, \delta_i, \gamma_i)$ of equation (4) is split up into crisis-independent terms (d_1, e_1, f_1, g_1) and crisis-dependent terms $(d_2 D_t^{cv}, e_2 D_t^{cv}, f_2 D_t^{cv}, g_2 D_t^{cv})$ with the volatility dummy variable being D_t^{cv}.

In GARCH-M models the mean of the return series is specified as an explicit function of the conditional volatility of the process and permits risk to be time-invariant. The coefficient α_2 in Eq. (1) captures the dynamic pattern of the changing risk premium over time. Following Merton (1980) and Campbell and Hentschel (1992), α_2 is interpreted as the coefficient of the relative risk aversion of investors. Periods of instability $(b_2 D_t^{cr})$, for example the financial crisis, may cause a different α_2 compared to periods of stability (b_1).[14] As noise traders overreact to good and bad news, their misperceptions increase during the financial crisis. These misperceptions raise price uncertainty and crowd out risk-averse

13 Although the results are not reported herein, we find that without the squared and lagged error term in the sentiment terms the model does not estimate.

14 $\alpha_2 = b_1 + b_2 D_t^{cr}$

informed investors (Lee et al., 2002). When the coefficient is equal to zero, the model reduces to a simple GARCH model.

3.3.3 Empirical Hypotheses

Market sentiment is an important factor in explaining the return generating process of financial assets according to DSSW (1990), Lee et al. (1991), and Brown and Cliff (2004). We expect that this effect deepens in an extreme market environment such as the financial crisis. To test this fact, we develop two hypotheses concerning the impact of investor sentiment on volatility and returns during the financial crisis. Further we test the hypothesis that the impact of conditional volatility on contemporaneous returns increases during the financial crisis. All hypotheses are based on the model specified in Equations (3) and (6). The hypotheses are summarized in Table 3.1.

3.4 Empirical Results

This section presents the empirical evidence on the impact of institutional investor sentiment on mean returns and conditional volatility of US Equity REITs, S&P 500 index and NASDAQ index in a tranquil as well as in a turbulent market environment.

3.4.1 Summary Statistics

As reported in Table 3.2 the three different returns have similar summary statistics. The returns are all negatively skewed and the mean (<0.1) and the standard deviation (<4) are small compared to those of the sentiment variable. The US Equity REIT returns and S&P 500 returns display a leptokurtic, the NASDAQ returns a platykurtic pattern.

The sentiment variable offers a high mean and standard deviation as well as a negatively skewed, platykurtic pattern. The first difference of the sentiment variable however has a positively skewed platykurtic pattern.

The relatively high standard deviation for the sentiment indicator indicates that the low mean is due to the fact that positive and negative changes in sentiment are offsetting each other.

3.4.2 The GARCH-M Model

For each of the three financial assets we estimate a GARCH-M model with investor sentiment as an explanatory variable in the mean and conditional volatility equations. The coefficients and standard errors for Equations (3) and (6) are shown in Table 3.3.

The S&P 500 and NASDAQ indices reflect the returns of large and small capitalization stocks, respectively. REITs can be viewed as one homogeneous industry of medium capitalization size. According to previous studies (Hughen and McDonald, 2005, Glushkov, 2006, Lin et al., 2008), each of the three returns should provide a good opportunity to study the impact of investor sentiment. In the REIT and S&P 500 models we exclude variables to the extent that they lower the Log-Likelihood value. We test the exclusion restrictions with the Likelihood Ratio Test and the corresponding p- values are mentioned at the bottom of Table 3.3. However, all variables that are relevant for the hypotheses tests are included. When we compare the results for the three assets, REIT returns and S&P 500 returns seem to behave similarly to each other, while the NASDAQ returns appear to behave differently. These results contradict the analysis of Peterson and Hsieh (1997), who report that REIT returns behave similar to a portfolio of small stocks.

First we consider the impact of investor sentiment on returns (b_1), on conditional volatility (c_1), and the impact of conditional volatility on contemporaneous returns before and after the crisis (e_1).

b_1 is positive for each return series, but only significant for REIT (at the 1 percent level) and S&P 500 (at the 5 percent level) returns; an increase of conditional volatility increases contemporaneous returns. In the absence of any crisis, the "create space" effect dominates the "Friedman" effect as indicated by the positive sign of b_1. Higher volatility means higher risk and higher returns. As risk averse, sophisticated investors limit their bets, noise traders create their own space and earn higher returns.

The impact of investor sentiment on returns before and after the crisis (c_1) is not tested for REIT returns, because the exclusion of this parameter improves the model. For S&P 500 and NASDAQ returns, c_1 is positive and significant. Bullish changes in sentiment increase returns and bearish changes in sentiment decrease returns.

The impact of changes in investor sentiment on conditional return volatility (e_1) is significant and negative for S&P 500 and NASDAQ returns. Bullish (bearish) changes in sentiment result in a decrease (increase) of return volatility. This suggests that a rise in sentiment is treated by investors similar to a reduction in volatility. In the model for REIT returns only the impact of sentiment during the financial crisis is tested.[15]

Next we compare the results before and after the financial crisis with those during the crisis. We consider the three hypotheses summarized in Table 3.1. The corresponding results are reported in Table 3.4. Hypothesis 1 (H1: $b_2 = 0$) tests whether conditional volatility has an impact on contemporaneous returns during the financial crisis. (b_2) is negative for each return series, but only significant for REIT and S&P 500 returns. Since Hypothesis 1 (H1: $b_2 = 0$) can be rejected for REIT and S&P 500 returns, conditional volatility has a negative impact on returns during the financial

[15] The inclusion of the variable $e_1 \Delta S_t^v \varepsilon_{t-1}^2$ that tests the impact before and after the crisis worsens the information criteria and is therefore excluded.

crisis.[16] The negative sign of b_2 indicates that the “Friedman” effect tends to dominate the “create space” effect during the financial crisis. Returns seem to be negatively affected when noise traders’ misperceptions are more severe. In a turbulent market environment this effect becomes even stronger as the misperceptions strengthen. These results are in line with Lee et al. (2002). They find a dominating Friedman effect in bearish sentiment shifts. Nelson (1991) also detects that the relation between volatility and expected returns is negative, which means that investors require a lower risk premium when volatility is high. As mentioned before, in ordinary market situations the “create space” effect dominates the “Friedman” effect, and higher volatility results in higher returns.

Hypothesis 2 (H2: $c_2 = 0$) tests the impact of investor sentiment on returns during the financial crisis. A significant positive correlation between returns and changes in sentiment during the crisis is found for REIT (at the one percent level) and S&P 500 (at the five percent level) returns; a positive change in sentiment increases REIT returns and S&P 500 returns by approximately 0.2518 respectively 0.1401. A negative change in sentiment decreases REIT returns and S&P 500 returns by 0.2518 respectively 0.1401[17]. Both results are contradictory to conventional wisdom that noise trading only affects small stocks (Lee et al., 1991); but they are in line with Hughen and

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16 The impact of conditional volatility on returns is the sum of b_1 and b_2; for example, for REIT returns: 6.7854 - 20.2055 = -13.4201.

17 0.0730 + 0.0671 = 0.1401.

McDonald (2005), who find that large stocks are also exposed to noise trader risk. The positive correlation between returns and changes in sentiment indicates that the "hold-more" effect tends to dominate the "price-pressure" effect. Noise traders' optimism (pessimism) in bullish (bearish) sentiment stages let hold them more (less) of the asset than fundamentals would indicate and provide them a higher (lower) risk premium due to increased (decreased) demand. In ordinary market situations also the "hold-more" effect dominates.

Hypothesis 3 (H3: $e_2 = 0$) examines the impact of investor sentiment on conditional return volatility during the financial crisis. As it is the case before and after the financial crisis, the impact during the financial crisis is significant and negative for all three indices. If we compare the impact of investor sentiment on conditional volatility before and after (e_1) as well as during ($e_1 + e_2$) the financial crisis in Table 3.3, we see that the negative impact of investor sentiment triples for S&P 500 returns and quadruples for NASDAQ returns during the crisis. These results are in line with the noise trader theory. In extreme sentiment stages (for example, the financial crisis) more noise traders are active in financial markets and increase return volatility.

A direct impact of the financial crisis on the returns (D_t^{cr}) and the conditional return volatility (D_t^{cv}) is only tested in the NASDAQ return model as the inclusion in the REIT and S&P 500 return models worsens the information criteria. The results are insignificant for NASDAQ returns. We conclude that sentiment is more extreme during the financial crisis and that sentiment affects returns. The more extreme the sentiment is, the more pronounced is its impact on returns and conditional return volatility. However, the financial crisis does not directly influence returns or conditional return volatility.

3.5 Conclusions

This study investigates the impact of investor sentiment on the formation of returns and conditional return volatility using a GARCH-M model. In contrast to prior empirical studies, we test this impact as a function of the market environment. In particular, we compare an ordinary market situation to the financial crisis that started in 2007. We do this for REITs and non-REITs in order to represent the overall performance of the market and to identify differences. Previous empirical tests of the noise trader theory only consider ordinary market situations. But noise traders enter the market in particular in extreme market situations. The financial crisis provides us a good opportunity to test the behavior and the impact of noise traders under extreme market conditions. We use a weekly sentiment indicator for institutional investor sentiment, as well as weekly US Equity REIT returns, S&P 500 returns and NASDAQ returns from December 1998 to December 2010.

The results of our analysis indicate that investor sentiment has a significant impact on all three returns. In ordinary market situations the impact of investor sentiment is smaller compared to the impact during the financial crisis and all three returns we examine behave in a similar manner. This result is inconsistent with Lee et al. (2002) who find that sentiment has the most profound impact on NASDAQ returns. During the financial crisis, however, investor sentiment has no impact on NASDAQ returns, but a significantly stronger impact on REIT returns and S&P 500 returns. The correlation between the returns and changes in sentiment is positive in both market situations. That means the “hold-more” effect appears to dominate the “price-pressure” effect. Noise traders’ optimism (pessimism) increases (decreases) their demand and provides a higher (lower) risk premium.

The impact of investor sentiment on conditional return volatility is significant and negative for all three indices. Bullish (bearish) changes in sentiment result in a decrease (increase) of return volatility. Again the impact is higher during the crisis.

Our analysis also shows that conditional volatility has a negative impact on contemporaneous REIT and S&P 500 returns during the financial crisis. This indicates that the “Friedman” effect tends to dominate the “create space” effect. Returns decrease when noise traders’ misperceptions are more severe.

In summary, we find that both REIT and S&P 500 returns and conditional return volatilities are strongly influenced by institutional investor sentiment; and that applies in particular during extreme market situations. In ordinary market situations, the influence of institutional investor sentiment on all return classes we examine is significantly smaller. The strength and the direction of the impact of investor sentiment differ as a function of different market situations. We conclude that investor sentiment should be considered for investment decisions especially in an extreme market environment.

3.6 Appendix for Chapter Three

Table 3.1: Hypotheses, 627 weekly observations, observation period 1998/12/28 - 2010/12/27

Hypotheses	
H1:	The impact of volatility on returns is unaffected by the crisis $(b_2 = 0)$
H2:	The impact of sentiment on returns is unaffected by the crisis $(c_2 = 0)$
H3:	The impact of sentiment on return volatility is unaffected by the crisis $(e_2 = 0)$

Notes: This table shows three research hypotheses concerning the impact of sentiment on mean returns and conditional volatility during the financial crisis of 2007. The weekly data consists of 627 observations from December 1998 to December 2010.

Table 3.2: Summary Statistics, 627 weekly observations, observation period 1998/12/28 - 2010/12/27

Variables	Mean	Median	Standard deviation	Minimum	Maximum	Skewness	Kurtosis
Returns:							
US Equity REIT	0.0847	0.1054	3.6458	-23.7580	21.2050	-0.7171	8.4046
S&P 500	0.0040	0.1513	2.5726	-16.4510	10.1830	-0.4870	4.0472
NASDAQ	0.0327	0.3151	3.7072	-19.0660	14.7340	-0.5553	2.7079
Sentiment:							
S_t	19.4860	21.8000	14.0840	-32.2000	44.1000	-0.9001	0.7432
ΔS_t	0.0141	0.2000	4.8472	-17.5000	18.1000	0.0344	1.1005

Notes: This table shows summary statistics for the data used in the analysis. The weekly data consists of 627 observations from December 1998 to December 2010. The returns are multiplied by 100 as the sentiment variable is huge compared with the returns.

Table 3.3: Investor sentiment and the financial crisis 2007, observation period 1998/12/28 - 2010/12/27

Variables	Coefficients	US Equity REIT returns	S&P 500 returns	NASDAQ returns
Mean return				
$h_t^{0.5}$	b_1	6.7854 ***	7.0949 **	4.8903
		(0.0245)	(0.0332)	(97.0924)
$h_t^{0.5} D_t^{cr}$	b_2	-20.2055 *	-17.9060 *	-0.4834
		(0.1199)	(0.0923)	(<0.0001)
ΔS_t^r	c_1		0.0730 ***	0.1193 ***
			(0.0002)	(0.0002)
$\Delta S_t^r D_t^{cr}$	c_2	0.2518 ***	0.0671 **	-0.0476
		(0.0005)	(0.0003)	(0.0006)
D_t^{cr}	a_2			-0.0941
				(0.0019)
Conditional Volatility				
ΔS_t^v	e_1		-1.2010 ***	-0.8878 **
			(0.0025)	(0.0035)
$\Delta S_t^v D_t^{cv}$	e_2	-2.7003 **	-2.7850 *	-3.1834 *
		(0.0110)	(0.0155)	(0.0177)
D_t^{cv}	d_2			0.0288 *
				(0.0002)
Log-Likelihood		1952.987	2085.181	1867.622
Diagnostic tests on standardized residuals:				
Ljung-Box p-value: $\frac{\varepsilon}{\sqrt{h}}$				
(lag1)		0.956	0.376	0.304
(lag 5)		0.296	0.386	0.917
(lag10)		0.458	0.342	0.980
Ljung-Box p-value: $\left(\frac{\varepsilon}{\sqrt{h}}\right)^2$				
(lag1)		0.837	0.822	0.975
(lag 5)		0.879	0.762	1.000
(lag10)		0.965	0.863	1.000
Exclusion restrictions relative to complete model: p-value		0.9018	0.4821	

Notes: We find the following models to be most appropriate to the data: GARCH (2,1) for REIT returns, GARCH (2,2) for S&P 500 returns and GARCH (3,3) for NASDAQ returns. Each model contains an autoregressive term AR(1) in the return equation. The NASDAQ model is estimated in its original form, the models of the REIT returns and S&P 500 returns are reduced according to the log-likelihood value. The p-values of the Likelihood Ratio Test show that the exclusion restrictions are supported by the data. The dependent variable r is multiplied by 100 as the sentiment variable is huge compared with r. The dummy variable D_t is unity from December 3, 2007 to January 25, 2010 and zero otherwise. The dependent *variables are the returns of REITs, S&P 500 and NASDAQ. The Ljung-Box Q-statistics tests for serial correlation in standardized residuals and squared standardized residuals for lags up to 27. Parameter estimates and standard errors (in parentheses) are listed. * Indicates significance at the 10% level, ** indicates significance at the 5% level, *** indicates significance at the 1% level.*

Table 3.4: Hypotheses tests, 627 weekly observations, observation period 1998/12/28 - 2010/12/27

Hypotheses	Variable	REITs	S&P 500	NASDAQ
H1: $b_2 = 0$	$h_t^{0.5} D_t^{cr}$	-20.2055 *	-17.9060 *	-0.4834
H2: $c_2 = 0$	$\Delta S_t^r D_t^{cr}$	0.2518 ***	0.0671 **	-0.0476
H3: $e_2 = 0$	$\Delta S_t^v D_t^{cv}$	-2.7003 **	-2.7850 *	-3.1834 *

*Notes: This table shows the results of the three research hypotheses concerning the impact of sentiment on mean returns and conditional volatility during the financial crisis of 2007. The hypotheses are reported in Table 3.1 and as follows: H1: The impact of volatility on returns is unaffected by the crisis, H2: The impact of sentiment on returns is unaffected by the crisis, H3: The impact of sentiment on return volatility is unaffected by the crisis. The weekly data consists of 627 observations from December 1998 to December 2010. * Indicates significance at the 10% level, ** indicates significance at the 5% level, *** indicates significance at the 1% level.*

4 The Impact of Consumer Sentiment on the Number of New Home Sales

Co-author of this chapter is J. Zietz.

4.1 Introduction

In financial markets the assumption that investors act fully rationally and build their decisions on all available information has often been challenged by phenomena that appear to contradict this paradigm, such as excessive volatility or mean reversion of stock prices. One explanation for these phenomena are the actions of so called noise traders (Black, 1986). Noise traders suffer from cognitive biases, such as overconfidence or overreaction.[18] They rely to some degree on sentiment and disturb the market with their irrational trading. Baker and Wurgler (2007) define investor sentiment as a prospect about the development of future cash flows and investment risks based on information that is not justified by fundamentals. This misguided belief may be based, for example, on general market commentaries.

[18] These cognitive biases have been researched by psychologists such as Tversky and Kahneman (1974, 1981), DeBondt and Thaler (1985), Barberis et al. (1998).

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Efficient market theory assumes that the mispricing caused by noise traders is quickly eliminated by the countertrading of sophisticated arbitrageurs.[19] But the trading of noise traders is unpredictable as the beliefs of noise traders are uncertain. According to Daniel et al. (2001) arbitrageurs are risk-averse; in the short run, however, they face the risk that sentiment becomes more extreme and prices deviate further from their fundamental values. The so called systematic “noise trader risk” (DeLong et al. 1990) and the accruing transaction costs (Shleifer and Vishny, 1997) prevent sophisticated arbitrageurs to fully offset the mispricing. Thus, noise trading has a persistent impact on financial markets.

Real estate markets are substantially different from financial markets. They are characterized by heterogeneity, illiquidity, high transaction costs and a lack of information (Lin and Vandell, 2007). Unlike for stocks, for properties no perfect substitute exists. This makes a comparison of prices difficult. Further, a new home requires a high capital commitment and is not easily resold quickly. Information on fundamentals is asymmetric between the seller and the buyer of the property. In contrast to the builder the buyer does not exactly know the quality and basic structure of the building.

According to Palomino (1996), noise traders in financial markets primarily invest in small stocks that tend to be less liquid and more

[19] Fama (1965) developed the efficient market hypothesis, Samuelson (1965) published a proof of the hypothesis and Fama (1970) improved the theory.

volatile than large stocks. Thus, if small imperfections, such as less liquidity, can cause more activity of noise traders in financial markets, real estate markets that are characterized by several imperfections should be even more prone to the influence of sentiment than financial markets.

Even though real estate markets and stock markets differ, the investors in these markets are not necessarily different. In capital markets, noise traders are often identified as individual investors (Glushkov, 2006). They are more prone to cognitive biases and, therefore, more sensitive to changes in sentiment. New one-family homes are not in the focus of institutional investors, but they are interesting for individuals. As individuals react irrationally in their stock investment decisions, why should they behave differently in their real estate investment decisions? The risk that triggers irrational behavior is similar in both markets (illiquidity, high transaction costs) and even more pronounced in direct real estate markets. Thus, if individuals rely on investor sentiment in capital markets, they probably rely on consumer sentiment in direct real estate markets.

In our study we investigate if consumer sentiment has an impact on the decision of a household to buy a new home. If consumer sentiment has an impact, one would expect that positive consumer sentiment is attended by more sales of new one-family homes. In a positive market environment, employment is more stable and households feel more confident to take on a large investment, such as a house. Negative consumer sentiment would indicate an unstable market environment and would probably prevent households from investing directly in real estate.

The decision of a household to buy a new one-family house depends on several factors. Some of these factors are not easy measurable or no relevant data exist. As not all influencing factors are available and we are primarily interested in one variable, the consumer sentiment, we use an unobserved component model (UCM) that can deal with omitted variables far better than least squares.

We find that two of our five tested macroeconomic variables have a statistically significant impact on the number of new one-family home sales in the U.S. from 1978 to 2010. The consumer sentiment has a significantly positive impact and the mortgage rate a strongly negative impact on the number of new home sales. Taken together both variables explain approximately 23 percent of the variation in the number of new one-family home sales. Our analysis shows that apart from monetary aspects expectations also strongly influence investment decisions of individuals.

The remainder of the study proceeds as follows. In the literature review we discuss sentiment studies in the field of real estate and, more generally, studies relating to potential cognitive biases of individuals. The methodology section presents different unobserved component models that are used for our analysis. The results section contains our empirical findings and the concluding section summarizes the main aspects of the study.

4.2 Literature Review

Behavioral finance literature has developed several cognitive biases in the beliefs of investors that allow sentiment to play a role in financial markets. Daniel et al. (1998 and 2001) explain patterns in stock returns using two cognitive biases in investors' beliefs: "overconfidence" and "self-attribution". "Overconfidence" about private information lets investors overreact and causes long-lag autocorrelations or excessive volatility. "Self-attribution" bias (attributing success to their own expertise and failures to external factors) extends overreaction and implies short-term momentum as well as long-term reversals.

Barberis and Huang (2001) analyze the "mental accounting", which describes the evaluation of individuals concerning financial transactions. Accordingly, individuals assign their assets to discrete, non-transferable groups and each group is related to a different level of utility. Investors' attitude towards risk is described by the cognitive biases "loss aversion" and "narrow framing". Kahneman and Tversky (1979) develop in their prospect theory the idea of "loss aversion", meaning that individuals are more sensitive to losses than to gains. "Narrow framing" indicates that individuals look after narrowly defined gains and losses. Barberis and Huang (2001) find evidence that the beliefs of investors in individual stocks as well as in a stock portfolio are influenced by both cognitive biases: "loss aversion” and “narrow framing”. All these cognitive biases let some financial investors become susceptible to the impact of investor sentiment. Their irrational trading causes financial markets to become inefficient.

The impact of investor sentiment on indirect real estate investments, such as real estate investment trusts or stocks of property companies, has been analyzed in few studies. Barkham and Ward (1999) investigate the discount of property company shares to their net asset value (NAV). They conclude that, in addition to agency costs, contingent taxation, and the liquidity of assets, investor sentiment explains a significant part of these discounts. Other studies analyze the relationship between investor sentiment and REIT returns. Lin et al. (2009) find a strong impact of investor sentiment on the return generating process of REITs. Clayton and MacKinnon (2002) identify a relationship between sentiment and the discount to net asset value in REIT pricing.

There has been only little research on the impact of sentiment on direct real estate investment. Gallimore and Gray (2002) design a questionnaire survey and ask UK investment decision makers if investor sentiment plays a role in their decision making. They find strong support for investor sentiment as an important source of information. Ling (2005) analyzes the ability of institutional managers to predict commercial real estate return performance. One result of the study is the evidence for cognitive biases in the beliefs of commercial real estate investors. The behavioral finance literature describes the associated behavior as “representativeness bias”, which means that recent returns are overweighted and long-term performance is underweighted. Clayton et al. (2009) investigate the impact of fundamentals and investor sentiment on commercial real estate valuation using an error correction model. They find evidence that investor sentiment has a significant impact on real estate pricing.

As financial investors are susceptible to cognitive biases, households may also be. A new home investment decision is of course different from the decision to sell or buy stocks. An investment in a new home is long-term; it implies higher capital spending and a resale is more difficult given the illiquidity of the real estate market. But “loss aversion” and “narrow framing” may also affect the beliefs of individuals and, hence, influence their investment decision for direct real estate investments. If households suffer from the same cognitive biases as financial investors, consumer sentiment is bound to have an impact on their decision process.

4.3 Data

We use monthly data from August 1978 to August 2010 on the number of new home sales in the U.S., the consumer sentiment, the mortgage rate, the inflation rate, real estate loans and the disposable personal income. All data are from the Federal Reserve Bank of St.

Louis data bank. The variables consist of 385 observations. Table 4.1 provides variable names and their definitions.

The Bureau of the Census publishes every month data on "new home sales", which reports sales of newly constructed one-family homes in the U.S. This variable seems to be appropriate for our analysis because it relates to transactions, unlike variables, such as building permits or housing starts, which are only declarations of intent. The data are reported at seasonally adjusted annual rates. Hamilton (2008) also uses this variable to identify the impact of monetary policy on new home sales.

To capture sentiment, we use a consumer sentiment index instead of an investor sentiment index because it is primarily individuals and not institutional investors who buy new one-family houses. We employ the University of Michigan Consumer Sentiment Index published monthly by the University of Michigan and Thomson Reuters Datastream. The base year of the index (a value of 100) is 1966. Each month, the University of Michigan's survey research center interviews a random sample of approximately 500 U.S. households. 50 core questions are asked with focus on the prospects of the personal financial situation, the short-term general economy and the long-term economic outlook. The data are not seasonally adjusted. The consumer sentiment variable is a common variable in studies that try to explain the relationship between movements in consumer sentiment and the economic development (for example, Souleles, 2004, Otoo, 1999).

The mortgage rate is the 30-year conventional mortgage rate in percentage format. It has a direct impact on the costs that accrue with the purchase of a new home. The lower the mortgage rate is the lower are the corresponding costs. Dua and Smyth (1995) analyze the usefulness of the mortgage rate amongst other macroeconomic variables to predict sales of homes.

The real estate loans variable is seasonally adjusted and based on information from all commercial banks in the U.S. Real estate loans are loans secured by real estate. Thus, we expect a positive relationship between real estate loans and new home sales.

The University of Michigan inflation expectation is part of the survey for the consumer sentiment index. Since 1977, the U.S. households have been asked about their expectation concerning the rise in prices over the next year and the next five to ten years. Bond and Seiler (1998) find that residential real estate is a significant hedge against expected and unexpected inflation. Thus, we expect a positive relationship between the number of new home sales and the inflation rate.

Disposable income is the difference between total personal income and personal current taxes; the data are reported at seasonally adjusted annual rates. Dua et al. (1999) also use this variable to analyze the usefulness of different leading indicators in predicting U.S. home sales. As a higher disposable income enables more individuals to buy a new home, we expect a positive relationship between both variables.

Figure 4.1 shows time-plots of each data series. The new home sales rate has its peak in 2005 and then declines until the end of 2008 from approximately 1400 to 150; it shows five to ten year cyclical behavior. The time series of the mortgage rate and the inflation rate are similar with peaks in 1981 and 1980, when the U.S. were in a deep recession. Consumer sentiment shows ten year cyclical behavior and has its low in 1980 and in 2008, both times preceding a recession. Real estate loans and disposable personal income behave similarly and rise continuously.

4.4 Methodology

For our analysis we rely on an UC model instead of an OLS regression. The key advantage of the UCM in our particular application is the fact that it is possible to reliably identify the coefficients of some observable determinants of the dependent variable even if some independent variables are omitted. These other independent variable may be known to play a role in determining the dependent variable, but may be impossible to measure; alternatively, and more to the point for the current application, there may not be a reliable or generally accepted theory to suggest which these other variables are. In any case, the influence of these omitted independent variables are absorbed by the unobserved components assuming they are properly specified, at least in terms of the general class of component, such as trend, seasonal or cycle.[20] In an OLS regression these omitted variables would appear in the residuals and could induce biased parameter estimates.

4.4.1 The Basic Unobserved Component Model (UCM)

For our analysis we use an unobserved component model (UCM) in which the dependent variable is explained by a combination of several unobserved components and fixed regression coefficients.[21] The general model can be written for given *t* as

$$y_t = \mu_t + \alpha' x_t + \varepsilon_t, \qquad \varepsilon_t \sim NID(0, \sigma_\varepsilon^2),$$

where y_t is the observed series of new home sales in the U.S., μ_t a stochastic trend component and ε_t an irregular component or disturbance term with zero mean and a constant variance. The term x_t represents a vector of observed regression variables, including consumer sentiment, the mortgage rate, the inflation rate, real estate

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[20] Details of the specification of any unobserved component can be checked against the data, for example, by testing a more general unobserved component with more parameters against a simpler one. This is not just a minor advantage. It is also the key reason why UCM modeling can forego pretesting of degrees of integration for the included variables. By simply including sufficiently flexible trend component it is possible to easily eliminate the problem of spurious correlation that results from regressing trended variables on each other.

[21] See Harvey (1989), Harvey and Jaeger (1993). An elementary discussion of the UCM technique is presented in Commandeur and Koopman (2007). An advanced treatment can be found in Durbin and Koopman (2001).

loans and disposable personal income; α is an appropriately dimensioned vector of regression coefficients.

In the so-called local linear trend model the term μ is modeled as a random walk with a stochastic drift term (β_t),

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \qquad \eta_t \sim NID(0, \sigma_\eta^2) \tag{2}$$

$$\beta_t = \beta_{t-1} + \zeta_t \qquad \zeta_t \sim NID\left(0, \sigma_\zeta^2\right), \tag{3}$$

where the level disturbance (η_t), and the slope disturbance (ζ_t) are assumed uncorrelated with each other and also with the irregular term (ε_t). The stochastic drift term β_t also follows a random walk. The trend component μ_t is fully determined by the variances σ_η^2 and σ_ζ^2, which are the only estimable parameters in the trend Equations (2) and (3). In all of our models we set σ_η^2 equal to zero; this is similar to the approach taken by the Hodrick-Prescott filter and generates a *smooth trend model* with a fixed level and a stochastic drift. The only estimable parameter left for the stochastic trend is σ_ζ^2.

4.4.2 A Model with Additional Components

In models where significant autocorrelation arises in the irregular component, we supplement the trend component with a first-order autoregressive component. The AR(1) component captures the fact that the number of new home sales tends to be persistent over time. For given observation *t*, Equation (1) then takes the form

$$\gamma_t = \mu_t + \vartheta_t + \alpha' x_t + \varepsilon_t, \quad \varepsilon_t \sim NID(0, \sigma_\varepsilon^2)$$

where the AR term ϑ_t can be written as

$$\vartheta_t = \tau \vartheta_{t-1} + \omega_t, \qquad \omega_t \sim NID(0, \sigma_\omega^2)$$

The AR(1) coefficient τ is restricted to be less than unity to represent a stationary process. This is necessary to avoid a situation where the AR(1) coefficient is confounded with the random walk component in the stochastic trend.[22] Instead of an AR(1) component we also try a stochastic cycle component (ψ_t) in some of our models. This alternative unobserved component can be incorporated for given *t* as follows:

$$\gamma_t = \mu_t + \psi_t + \alpha' x_t + \varepsilon_t, \qquad \varepsilon_t \sim NID(0, \sigma_\varepsilon^2)$$

with

$$\psi_t = \rho(\cos \lambda_c \psi_{t-1} + \sin \lambda_c \psi_{t-1}^*) + \kappa_t,$$

$$\psi_t^* = \rho(-\sin \lambda_c \psi_{t-1} + \cos \lambda_c \psi_{t-1}^*) + \kappa_t^*,$$

where the stochastic cycle component ψ_t is constructed as a sine-cosine wave with the disturbances κ_t and κ_t^* and a damping factor ρ, which satisfies $0 < \rho \leq 1$. λ_c is the frequency (in radians) with $0 < \lambda_c < \pi$. If λ_c becomes zero or π , the stochastic cycle becomes an AR(1) process. The two disturbances κ_t and κ_t^* are white noise and assumed mutually uncorrelated with zero means and common

22 See Koopman et al. (2009) STAMP 8.2

variance σ_{k}^{2} . The period in months is $2\pi / \lambda_{c}$. Stochastic cycles of this type are appropriate to model the "pseudo-cyclical behavior" of many time series (Koopman et al., 2009).

4.5 Empirical Results

In this section we present the empirical evidence on the impact of consumer sentiment and other explanatory variables on the number of sales of new one-family homes in the U.S. In our analysis we test four different models. Model I and Model II differ in the number of the regression coefficients. In Model I we include all of our five variables. In Model II and in Models III and IV we remove the variables with insignificant coefficients and only analyze the impact of consumer sentiment and the mortgage rate on the number of new one-family home sales. Model III is similar to Model II, but the AR(1) component is omitted. In Model IV we include a stochastic cycle component.

4.5.1 Summary Statistics

Table 4.2lists the summary statistics for all variables. All variables except for the *inflation rate* have a kurtosis smaller than three and, therefore, display a platykurtic pattern; the *inflation rate*, however, is leptokurtic, distributed with a kurtosis of approximately 3.97. The *consumer sentiment* is the only negatively skewed variable; the other variables are positively skewed. A negative skew means that the distribution has relatively few low values. In Figure 4.2 we see that the left tail of the density distribution of the *consumer sentiment* is longer compared with the density distribution of the *mortgage rate* or the *new home sales*. The distribution of the consumer sentiment is left-skewed. The other variables are right-skewed and have relatively few high values but many low values.

4.5.2 UCM with all Variables

Model I in Table 4.3 includes a trend component, a first-order autoregressive component, and a regression component with five variables. The variables *consumer sentiment* and *disposable personal income* have a positive sign whereas the *mortgage rate*, *real estate loans* and *inflation rate* are negatively related to the number of new home sales. The *consumer sentiment* and the *mortgage rate* are the only variables with statistically significant coefficients; the three other explanatory variables are insignificant and therefore excluded from the further analysis. The statistical insignificance of the inflation rate is interesting because several studies, for example Hartzell et al. (1987) and Bond and Seiler (1998), identify real estate investments as a good hedging instrument against anticipated and unanticipated inflation. In Figure 4.1 we see that *disposable personal income* and *real estate loans* increases continuously from 1978 until 2010 and the sales of new homes fluctuate relative intensely. This can explain the result that no relation exists between the dependent variable and the two explanatory variables. The Durbin Watson test has a value of approximately two, which means that no autocorrelation of the residuals exists. To compare the different models we use R^2 and Rd^2 and the two information criteria Akaike (AIC) and Bayesian (BIC). Rd^2 compares the fit of the model with a random walk plus drift. It reveals how much of the variation in the number of "new home sales" is explained by the regression variables alone, whereas R^2 measures how much is explained by the whole right side of the equation, which includes all unobserved components.

4.5.3 UCM with Significant Variables

As three of the five explanatory variables are insignificant in Model I, we include in Model II only the significant explanatory variables *consumer sentiment* and the *mortgage rate*. The structure of the model does not change, we have again a smooth trend model with a fixed level and a stochastic drift, an AR(1) component and the regression component. The variable *consumer sentiment* is now significant at the five percent level; in Model I it is significant only at the ten percent level. The *mortgage rate* is significant at the one percent level in both models. To get an economic interpretation of the estimated coefficients, we calculate elasticities at the mean for all models and coefficients. The elasticities are listed in Table 4.4. The impact of the *mortgage rate* is higher compared to that of the *consumer sentiment*. A one percent increase in the *mortgage rate* in Model II will lower *new home sales* by approximately 0.64 percent. This result is intuitive as lower mortgage rates offer more people the opportunity to buy a new home. The elasticity for *consumer sentiment* of Model II is 0.13. A one percent increase in *consumer sentiment* raises *new home sales* by approximately 0.13 percent. This finding is in line with Weber and Devaney (1996), who ascertains that consumer sentiment is useful to improve forecasts of housing starts. Model II is the preferred model compared to Model I. Although the coefficients of determination, Rd^2 and R^2, are larger in Model I, the three additional included regression coefficients are insignificant. As a consequence, the information criteria AIC and BIC are lower in Model II, which makes it the preferred model.

4.5.4 Other Models

Model III provides a variation of Model II: the autoregressive component is omitted. This lowers the Rd^2 measure of fit compared to Model II. As the two information criteria BIC and AIC are larger in Model III compared to Models I and II, Model III is the inferior model. Also, the Durbin Watson test has a value of approximately 1.5, which implies some residual autocorrelation.

Model IV modifies Model II by replacing the autoregressive component with a stochastic cycle component. The stochastic cycle component is specified in Equations (6)-(8). A cycle of the length of twenty years appears appropriate for the data.[23] In terms of the coefficients of determination, Rd^2 and R^2, there is little change relative to Model II. The same applies to the information criteria AIC and BIC. As the coefficients of Model IV are also very close to those of Model II, there is little point going from a simpler model, with an autoregressive component, to a more complicated one, with a cycle component.[24] Thus, Model II remains the preferred model.

In Figure 4.3 we show for each model how much of the variation of *new home sales* is explained by: (1) the stochastic trend, (2) the stochastic trend plus the regression component, (3) the stochastic

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[23] We also try models with a cycle of five and ten years as well as multiple cycles; all of these models suffer from only weak convergence. As the time series of *"new home sales"* shows relatively irregular cycles, only a large cycle seems to be able to capture all the different structures.

[24] We also test a model where we include both components, the autoregressive and the cycle component. But that does not change the results either.

trend plus the autoregressive or cycle components and (4) by the regression component alone. It is apparent that the regression component alone can explain closely the downturn in new home sales in the early 1980s and the subsequent upturn in the middle of the 1980s. It can also capture the ups and downs during the 1990s. However, the regression component (*consumer sentiment* and *mortgage rate*) fails to predict the downturn around 1990 and, in particular, the crisis around 2008. That means that the two recent downturns (1990 and 2008) in new home sales are not predictable by sentiment or the mortgage rate. There are other forces at work. These are captured by our stochastic trend component. As a result, the trend and the regression component taken together well approximate the behavior of new home sales over time, either one alone does not.

Figure 4.4 provides some graphical evidence on the residual fit of Models I through IV. The autocorrelation functions (ACF's) show no autocorrelation of the residuals of Model I, II and IV. In Model III however the ACF's display some autocorrelation of the residuals at lags one and four. The QQ normality plots of Model II and IV reveal that the residuals are nearly normally distributed. The Cusum plot identifies no sign of a structural change as the upper and lower limits are not crossed.

In summary, Model II is appropriate to explain the variation of the number of new one-family home sales in the U.S. The variables *consumer sentiment* and the *mortgage rate* explain together approximately 23 percent of the variation.[25] If the stochastic trend component and the first-order autoregressive component are added 96 percent of the variation is explained. Other possible explanatory regression variables, such as the *inflation rate*, *real estate loans* or the *disposable personal income*, are insignificant. The *mortgage rate* has a negative impact on the number of *new home sales*. *Consumer sentiment* has the expected positive influence on the real estate investment decisions of individuals.

4.6 Conclusion

This study investigates to what extent consumer sentiment and other key macroeconomic variables influence the number of sales of new one-family homes in the U.S. Our analysis is based on an unobserved component model (UCM) that allows including observed explanatory variables in a time series model along with unobserved components, which absorb the impact of variables left out of the study due to measurement problems or the lack of a proper theory. We use monthly U.S. data from August 1978 to August 2010. Five different explanatory variables are considered: consumer sentiment, the mortgage rate, real estate loans, the inflation rate and the disposable personal income.

[25] In a separate analysis with sentiment as the only regression variable, we find that 7 percent of the variation is explained by the consumer sentiment alone.

We analyze UCMs with various structures: the models differ in the number of explanatory variables and the inclusion of different unobserved components. A *smooth trend model* together with an AR(1) component and the two observed regression variables *consumer sentiment and mortgage rate* appear to be most appropriate for the data. The other explanatory regression variables are insignificant. That includes the inflation rate, which is somewhat surprising as it is often thought that inflation motivates individuals to invest in real estate.

The results of our analysis indicate that consumer sentiment has a significantly positive impact on the number of new one-family home sales in the U.S. An increase in the consumer sentiment index suggests that people expect a positive development of their personal financial situation, both in the short-term and the long-term. These prospects positively influence their investment decision concerning a new home. A decrease in the consumer sentiment index, however, suggests negative prospects and leads to a reduction in the number of new home sales.

The mortgage rate is also significant and has the expected strongly negative impact on the number of new home sales. Lower mortgage rates offer the opportunity to buy a new home at lower costs. In contrast to the consumer sentiment, the mortgage rate has a directly calculable impact on the number of new home sales. The impact of consumer sentiment on the investment decisions of individuals is indirect and expressed in the expectations of individuals. Both variables taken together explain approximately 23 percent of the variation in the number of new one-family home sales.

We further determine that the regression component (*consumer sentiment* and *mortgage rate*) taken together with the stochastic trend component well approximate the behavior of new home sales over time. The regression component alone however captures only partly the variation in new home sales. In particular it fails to predict the crisis around 2008.

In summary, our study is the first to investigate the relation between residential real estate and consumer sentiment. We add to the understanding of private investment decisions and show that the impact of sentiment is not a topic exclusively of interest for financial markets. The results of the study show that the imperfections of direct real estate markets, such as heterogeneity, illiquidity, high transaction costs and insufficient information, induce risk and make real estate markets susceptible to the impact of sentiment.

4.7 Appendix for Chapter Four

Table 4.1: Variable Definitions, 385 monthly observations, observation period 1978/08 - 2010/08

Variables	Variable Definition
New home sales	New one-family homes sold: United States, in thousands, seasonally adjusted annual rate (SAAR)
Consumer sentiment	University of Michigan: Consumer Sentiment Index, first quarter 1966 = 100, not seasonally adjusted (NSA)
Mortgage rate	30- year conventional mortgage rate, in percent
Real estate loans	Real estate loans at all commercial banks, billions of dollars, seasonally adjusted (SA)
Inflation rate	University of Michigan inflation expectation, in percent
Disposable personal income	Disposable personal income: per capita: current dollars, seasonally adjusted annual rate (SAAR)

Notes: All data are collected from the Federal Reserve Bank of St. Louis.

Table 4.2: Summary Statistics, 385 monthly observations, observation period 1978/08 - 2010/08

Variables	Mean	Standard Deviation	Minimum	Maximum	Skewness	Kurtosis
New home sales	681.1500	211.4300	282.0000	1389.0000	0.8418	0.6234
Consumer sentiment	86.2790	13.0640	51.7000	112.0000	-0.4493	-0.5264
Mortgage rate	8.9370	2.8430	4.4300	18.4500	1.0997	0.9245
Real estate loans	877.6800	1071.9000	24.9000	3877.7000	1.4768	1.1403
Inflation rate	3.7490	1.8490	0.4000	10.4000	2.1653	3.9687
Disposable personal income	14407.0000	10883.0000	1938.0000	37419.0000	0.5416	-0.9723

Notes: All data relate to the U.S. for the time period of August 1978 to August 2010. We have 385 monthly observations.

Table 4.3: Results of the UCMs, 385 monthly observations, observation period 1978/08 - 2010/08

Variables	Model I	Model II	Model III	Model IV
Consumer sentiment	0.9526 *	1.0257 **	1.0792 **	1.0286 **
	(0.5300)	(0.5202)	(0.4747)	(0.5203)
Mortgage rate	-49.4396 ***	-48.8059 ***	-50.6575 ***	-48.7972 ***
	(5.3679)	(5.2038)	(4.6202)	(5.2047)
Real estate loans	-0.1200			
	(0.1204)			
Inflation rate	-1.2902			
	(5.3044)			
Disposable personal income	0.0147			
	(0.0131)			
Rd^2	0.2399	0.2291	0.1710	0.2292
R^2	0.9621	0.9616	0.9587	0.9616
AIC	7.6518	7.6423	7.7151	7.6422
BIC	7.7339	7.6936	7.7665	7.6936
Durbin-Watson	2.0015	1.9961	1.5450	2.0034

*Notes: All models contain a smooth stochastic trend – a combination of a fixed level and a stochastic slope. All data relate to the U.S. for the time period of August 1978 to August 2010. We have 385 monthly observations. The dependent variable is the number of new one-family home sales in the U.S. Each model shows strong convergence. Model I-IV are unobserved component models. Parameter estimates and root mean squared errors (in parentheses) are listed. * Indicates significance at the 10% level, ** indicates significance at the 5% level, *** indicates significance at the 1% level.*

Table 4.4: Elasticities, 385 monthly observations, observation period 1978/08 - 2010/08

Variables	Model I	Model II	Model III	Model IV
Consumer sentiment	0.12	0.13	0.14	0.13
Mortgage rate	-0.65	-0.64	-0.66	-0.64
Real estate loans	-0.15			
Inflation rate	-0.01			
Disposable personal income	0.31			

Notes: All data relate to the U.S. for the time period of August 1978 to August 2010. We have 385 monthly observations. The dependent variable is the number of new one-family home sales in the U.S. Coefficient elasticities at the mean for each model and each coefficient are listed.

Figure 4.1: Dependent and explanatory variables over time

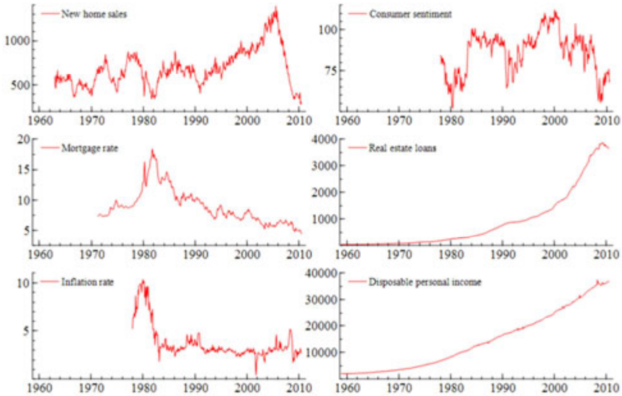
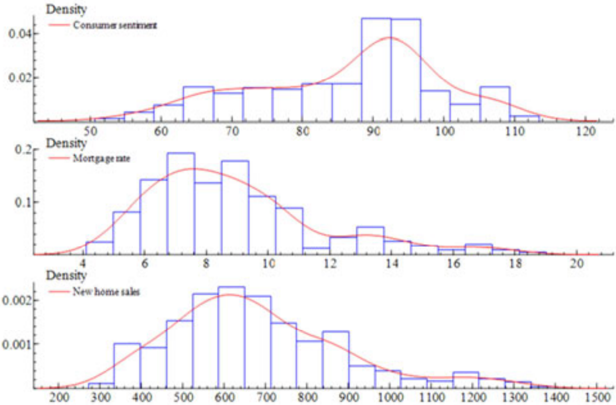


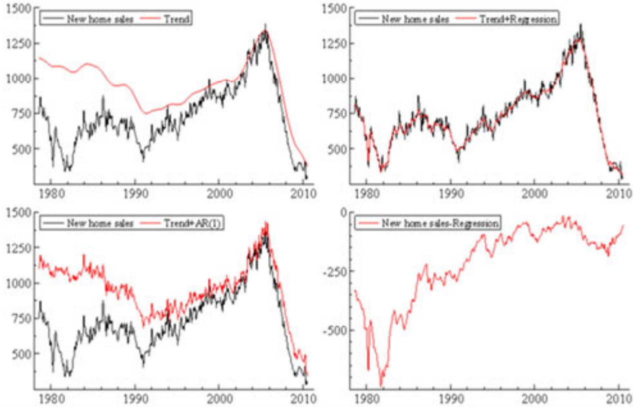
Figure 4.2: Estimated density and histogram



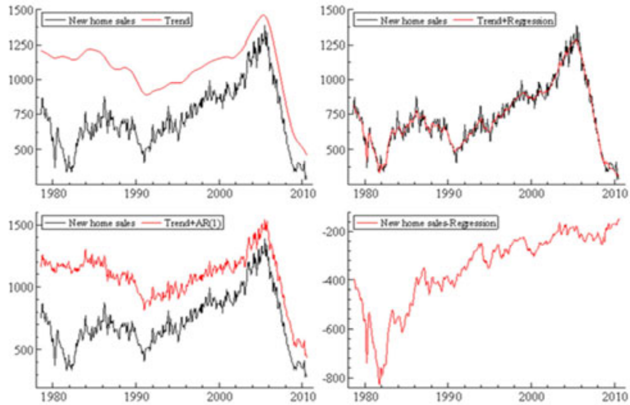
Notes: "Consumer sentiment" and "mortgage rate" are (significant) explanatory variables and "new home sales" is the dependent variable.

Figure 4.3: Graphics of the different model results (Model I-IV)

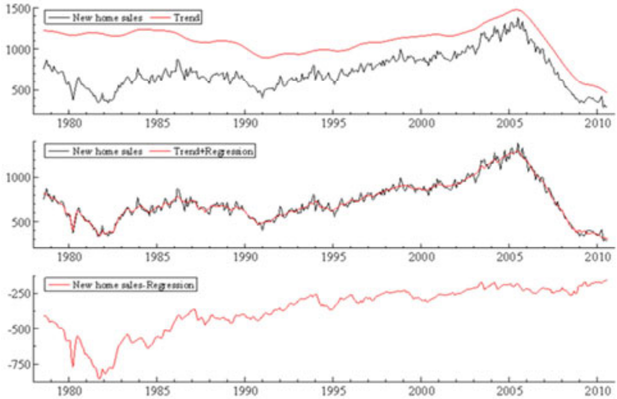
Model I: contains a smooth stochastic trend, five explanatory regression variables and an AR(1) component



Model II: contains a smooth stochastic trend, two explanatory regression variables and an AR(1) component



Model III: contains a smooth stochastic trend, two explanatory regression variables and no AR(1) component



Model IV: contains a smooth stochastic trend, two explanatory regression variables and a cycle component (20 years)

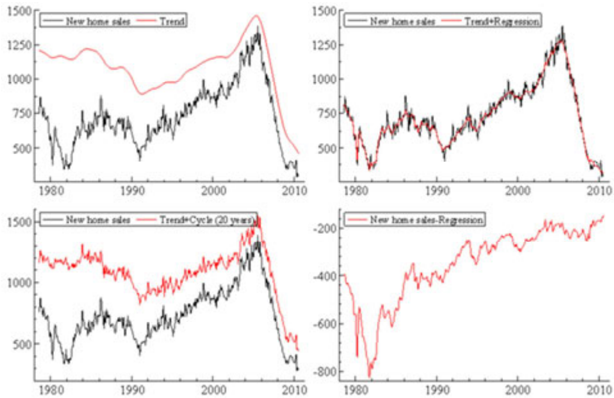
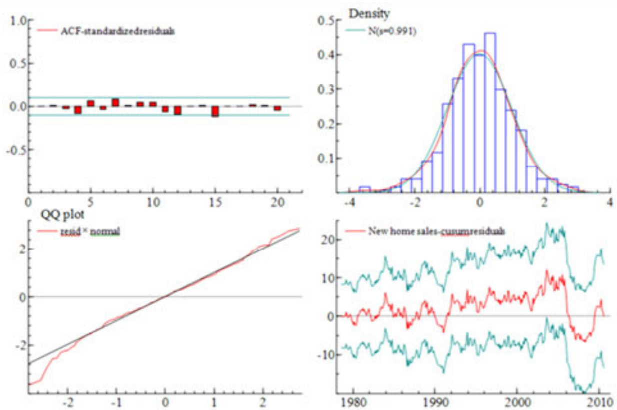
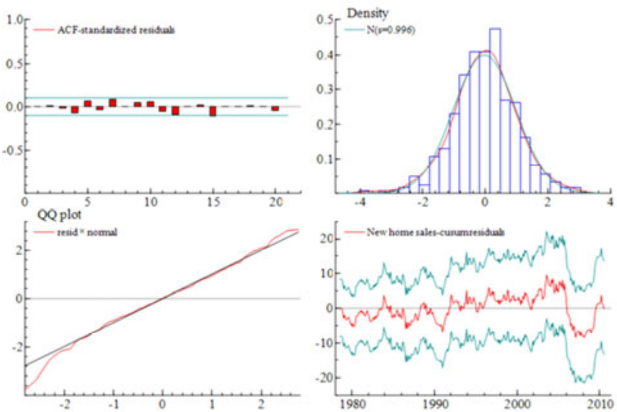


Figure 4.4: Residual graphics of the different models (Model I-IV)

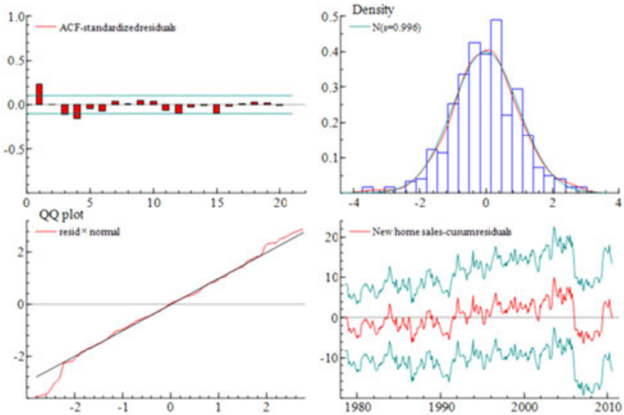
Model I: contains a smooth stochastic trend, five explanatory regression variables and an AR(1) component



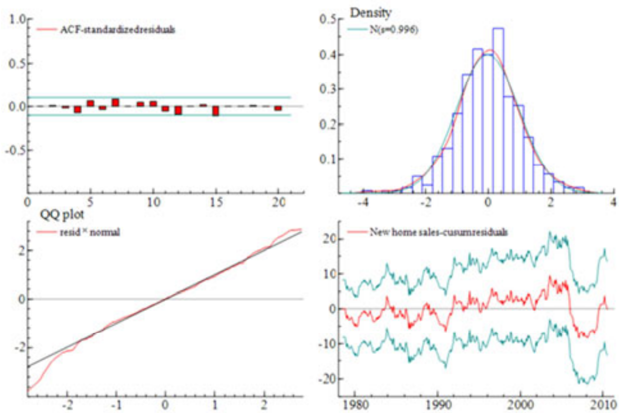
Model II: contains a smooth stochastic trend, two explanatory regression variables and an AR(1) component



Model III: contains a smooth stochastic trend, two explanatory regression variables and no AR(1) component



Model IV: contains a smooth stochastic trend, two explanatory regression variables and a cycle component (20 years)



5 Dissertation Conclusions

This dissertation is composed of three papers that examine the impact of sentiment on direct and indirect real estate investments. Papers one (Chapter two) and two (Chapter three) analyze the impact of investor sentiment on real estate investment trusts (REITs) and Paper three (Chapter four) investigates the relationship between direct real estate investments and consumer sentiment.

In Paper one we analyze, on weekly data for the time period December 1998 to May 2009, the influence of investor sentiment on the returns and return volatilities of U.S. Equity REITS. We use two different weekly sentiment indicators, one for individual investor sentiment and one for institutional investor sentiment. Our main findings suggest that individual investor sentiment is a significant factor in explaining REIT returns and REIT return volatilities. We can also identify asymmetric sentiment threshold values for both the return and the conditional volatility parts of the model. Bad news tends to have a more significant effect on the conditional volatility of REITs than good news. In other words, bearish sentiment increases REIT return volatility more than bullish sentiment does. This is consistent with Barberis and Huangs' (2001) finding that investors are loss averse and focus on narrowly defined gains and losses.

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In terms of the mean return equation, we find that REIT returns increase in bullish sentiment stages, whereas bearish sentiment has no impact on REIT returns. This result is surprising as we expect a decrease in REIT returns in bearish sentiment stages.

The results suggest that even small changes in sentiment have a significant impact on the conditional volatility of REITs, as indicated by relatively small corresponding threshold values. The threshold values of the mean equation, however, are higher, which indicates that not every small change in sentiment has an impact on REIT returns.

In Paper two we investigate the differential impact of investor sentiment on the formation of returns and conditional return volatility of a REIT index as opposed to non-REIT market indices. In contrast to prior empirical studies, we test this differential impact as a function of the market environment and compare an ordinary market situation to the financial crisis that started in 2007. We use a weekly sentiment indicator for institutional investor sentiment and study its impact on US Equity REIT returns, S&P 500 returns and NASDAQ returns over the period from December 1998 to December 2010.

The results of our analysis indicate that investor sentiment has a significant impact on the returns of all three asset classes. In ordinary market situations, our different asset classes behave in a similar manner. This result is inconsistent with Lee et al. (2002) who find that sentiment has the most profound impact on small cap stocks, which are primarily listed in the NASDAQ index.

During the financial crisis, the influence of investor sentiment on REIT and S&P 500 returns is significantly stronger. NASDAQ returns, however, are only affected by sentiment in tranquil markets, indicating that these stocks are less influenced by extreme market sentiment.

The correlation between the returns and changes in sentiment is positive in both market situations. That means that noise traders' optimism increases their demand and provides a higher risk premium, which results in a higher return. However, if noise traders are pessimistic they decrease their demand, lower the risk premium and reduce the return.

We also find that REIT and S&P 500 returns are negatively influenced by contemporaneous conditional volatility during the financial crisis. This indicates that if noise traders' misperceptions are more severe and conditional volatility increases, then returns decrease.

With regard to the conditional return volatility, we find a significant and negative impact of investor sentiment for all three indices. Bullish changes in sentiment result in a decrease of return volatility, whereas bearish changes in sentiment lead to an increase of return volatility. Again, the impact is significantly higher during the crisis.

Our analysis shows that REIT returns and conditional REIT return volatility are significantly influenced by investor sentiment especially in extreme sentiment stages. Therefore, although REITs are subject to a specific regulatory and tax framework and offer significant diversification benefits compared to other asset classes, they should be treated similar to stocks. Shareholders and the management of REITs should consider the development of investor sentiment to better anticipate the return and conditional volatility of REITs.

In Paper three we investigate to what extent consumer sentiment and other key macroeconomic variables influence the number of sales of new one-family homes in the U.S. Our analysis is based on an unobserved component model (UCM) that allows omitting the influence of variables that are difficult to obtain due to measurement problems or the lack of a proper theory. We use monthly U.S. data from August 1978 to August 2010. Five different explanatory variables are considered: consumer sentiment, the mortgage rate, real estate loans, the inflation rate and the disposable personal income.

The results of our analysis indicate that only two of our five explanatory variables are significant: consumer sentiment and the mortgage rate. Consumer sentiment has a significantly positive impact on the number of new one-family home sales in the U.S. An increase in the consumer sentiment index suggests that people expect a positive development of their personal financial situation, both in the short-term and the long-term. These prospects positively influence their investment decision concerning a new home. Likewise, a decrease in the consumer sentiment index suggests negative prospects and leads to a reduction in the number of new home sales.

The mortgage rate is also significant and has the expected strongly negative impact on the number of new home sales. Lower mortgage rates offer the opportunity to buy a new home at lower costs. In contrast to the consumer sentiment variable, the mortgage rate has a directly calculable impact on the number of new home sales. The impact of consumer sentiment on the investment decisions of individuals is indirect and expressed in the expectations of individuals. Both variables taken together explain approximately 23 percent of the variation in the number of new one-family home sales.

We further determine that the regression component (sentiment variable and mortgage rate) taken together with the stochastic trend component well approximate the behavior of new home sales over time. The regression component alone, however, captures only part of the variation in new home sales. In particular, it fails to predict the crisis around 2008.

Paper three adds to the understanding of private investment decisions in real estate markets and shows that the impact of sentiment is not a topic exclusively of interest for financial markets. The results of the study show that the imperfections of direct real estate markets, such as heterogeneity, illiquidity, high transaction costs and insufficient information, induce risk and make real estate markets susceptible to the impact of sentiment. This knowledge enables building companies to consider consumer sentiment as an influencing factor in their demand forecasts. Further, it can help individuals to optimize their investment date, although there are several other non-measurable factors besides sentiment that have an impact on this decision.

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