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Essays on Sentiment Analysis through Textual Analysis in Real Estate Markets

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1. Introduction

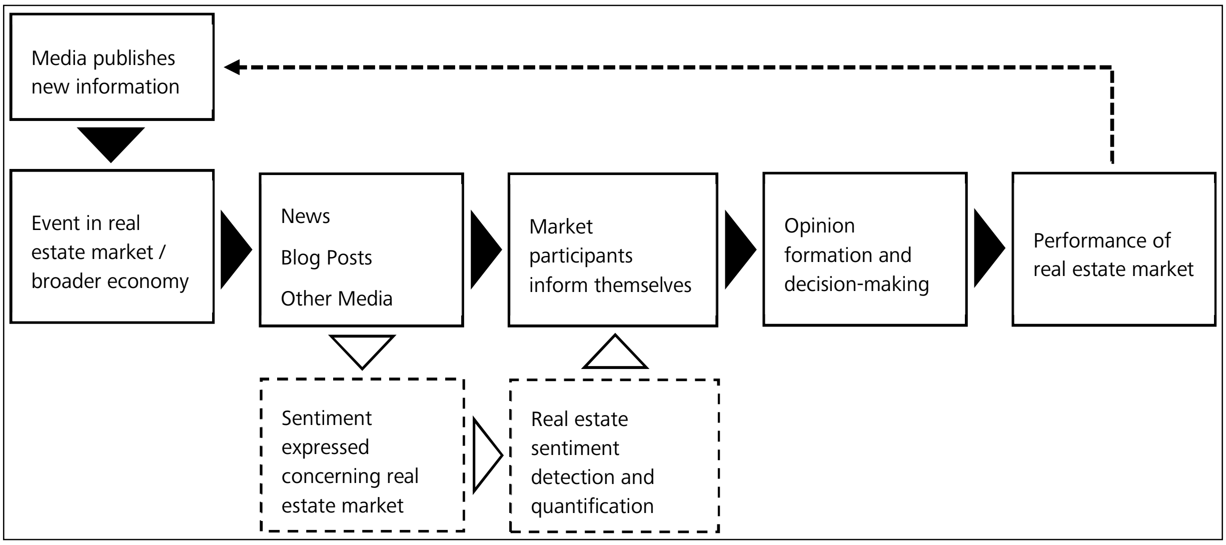
1.1 General Motivation

Previous research (Clayton et al., 2009; Ling et al., 2014; Das et al., 2015) reports that fundamentals, such as economic variables and risk factors, do not account for all observed price changes in commercial real estate markets. Other studies (Baker and Wurgler 2007; Seiler et al., 2012) provide clear evidence that the investment decisions of real estate investors are not based solely on economic fundamentals, but also on personal beliefs and emotions. Despite these considerations, only limited research directly investigates the role of investor sentiment in real estate markets. To date, surveys are the most common approach to measuring investor sentiment directly in the realm of real estate. For example, recent research (Clayton et al., 2009; Das et al., 2015; Freybote, 2016) has employed the quarterly published *Real Estate Research Corporation* sentiment indicator. However, surveys are associated with several inherent disadvantages. They are costly and labor-intensive, have a limited sample size and are highly dependent on the truthfulness of the respondents (Tourangeau et al., 2000). In addition, they are not ideal for time-series modeling, due to their low frequency and time-lag bias.

Sentiment analysis uses textual analysis to determine the sentiment expressed in text corpora regarding a certain entity, such as a particular product or stock. In short, it helps bridge the gap between qualitative information in texts and quantitative analysis for various purposes. Due to its great potential, sentiment analysis has recently drawn increased attention from companies, organizations and academia, and from various disciplines, as it enriches their analytical capabilities. In fact, textual analysis is an emerging field of research in accounting and finance, where studies have found text-based sentiment measures to affect the aggregate market as well as individual stock performance (Tetlock, 2007; Loughran and McDonald, 2011; Heston and Sinha, 2016).

The digitalization of information and professionalization of the internet support sentiment analysis efforts, as a wealth of information worth investigating is created every day. The text data can come from several sources, such as news websites, social media platforms or corporate disclosures. However, with his assessment "*News media do play an important role both in setting the stage for market moves and in instigating the moves themselves*", Robert J. Shiller (2000), Nobel Prize Winner and Yale University Professor, highlights the importance of news for today's markets. In addition, a considerable number of finance studies have found news to influence investor sentiment, hence the risk-return characteristics of assets (Tetlock, 2007; Schumaker and Chen, 2009; Heston and Sinha, 2016). Lately, real estate research has also started investigating the impact of text-based sentiment on decision-making processes and residential asset prices (Walker, 2014; Soo, 2015; Nowak and Smith, 2017). For example, Walker (2014) found text-based sentiment, captured from national newspapers, to Granger-cause house price changes in the UK. Similarly, Soo (2015) showed sentiment expressed in local housing news to have a significant effect on U.S. housing prices. Yet, no existing research directly investigates the role of any text-based sentiment in commercial real estate markets in the United States. Thus, the present dissertation addresses this gap in the literature and particularly captures text-based sentiment from real estate news published by leading financial and real estate news outlets. Consequently, the News-Impact Model (Figure 1.1) depicts the theoretical framework of the present dissertation. In simplified terms, different types of media report on certain events in the real estate markets or the broader economy. This model assumes that the information to which real estate investors are exposed – consciously or unconsciously – affects their opinion-formation and decision-making processes. In this context, the news-based sentiment is assumed to impact on investor sentiment. Subsequently, investors' expectation-based actions influence the commercial real estate market. Ultimately, the resulting real estate market events might be newsworthy and reported on again.

Figure 1.1: News-Impact Model



Accordingly, this dissertation aims to detect and quantify the sentiment expressed in real estate news stories published by several authoritative news outlets, such as *The Wall Street Journal* or *S&P Global Market Intelligence*. In this context, the dissertation proposes a novel approach to capturing news-based sentiment through various methodologies of textual analysis, i.e. the dictionary-based approach and a supervised machine-learning algorithm. Specifically, the three papers in this dissertation examine *whether* and *to what extent* news-based sentiment predicts returns from the securitized and direct commercial real estate market in the United States.

1.2 Research Questions

This section provides an overview of the three papers in the dissertation and the respective research questions.

Paper 1: Real Estate Media Sentiment Through Textual Analysis

- What is the status quo of textual analysis in the finance and real estate literature?
- Is it possible to capture the sentiment expressed in real-estate-related news headlines using the dictionary-based approach?
- Does news-based sentiment predict future movements of the securitized real estate market in the U.S.?
- Is a sentiment measure which considers media optimism and pessimism, more appropriate than a measure which accounts only for either one?
- Is a domain-specific dictionary more appropriate for domain-specific sentiment analysis tasks?

Paper 2: On the Relationship Between Market Sentiment and Commercial Real Estate Performance – A Textual Analysis Examination

- What is the current state of research on sentiment analysis in the real estate literature?
- Can the dictionary-based approach successfully capture sentiment expressed in real-estate-related news abstracts?
- Does news-based sentiment predict returns from the direct commercial real estate market?
- Is a weighted sentiment measure better suited as a leading market indicator, than an absolute measure?
- Is there a feedback loop between news-based sentiment and the direct commercial real estate market?
- Are direct commercial real estate markets more susceptible to sentiment during decelerating and/or bear markets?

Paper 3: News-Based Sentiment Analysis in Real Estate: A Machine-Learning Approach Via Support Vector Networks

- What is the current state of research on text-based sentiment analysis for real estate markets?
- Can sentiment expressed in real-estate-related news headlines be captured via a machine-learning approach?
- Does text-based sentiment, captured via a supervised machine learning approach, predict returns from the securitized and direct commercial real estate market?
- What are the intertemporal linkages between news-based sentiment and the securitized and direct U.S. real estate markets?
- Do the text-based sentiment measures provide additional information beyond that provided by established sentiment indicators?
- Are market participants influenced more strongly by pessimism rather than optimism expressed in news? Hence, is there empirical evidence of a negativity bias?

1.3 Course of Analysis

This section provides a chronological overview of the course of analysis with regard to the research purpose, the authors and the current publication status of the respective paper.

Paper 1: Real Estate Media Sentiment Through Textual Analysis

For the first time, the first paper in the dissertation examines the relationship between news-based sentiment and the securitized real estate market in the United States. In order to capture sentiment expressed in more than 125,000 real-estate-related news headlines from *Bloomberg*, *The Financial Times*, *Forbes* and *The Wall Street Journal*, a dictionary-based approach is deployed. Subsequently, the intertemporal linkages between different text-based sentiment measures and monthly returns from the securitized real estate market are analyzed in a vector autoregressive framework.

Authors: Jessica Ruscheinsky, Marcel Lang and Wolfgang Schaefers

Submission to: Journal of Property Investment and Finance

Status: Forthcoming, Vol. 36 No. 5 (July 2018)

This paper was presented at the 2016 Annual Conference of the European Real Estate Society (ERES) in Regensburg, Germany, and the 2017 Annual Conference of the American Real Estate Society (ARES) in San Diego, USA. The paper received the 'Best Paper Award in the PhD Session' at ERES Conference, 2016.

Paper 2: On the Relationship Between Market Sentiment and Commercial Real Estate Performance – A Textual Analysis Examination

Inspired by the findings from the first study, this paper is the first to characterize the bi-directional relationship between news-based sentiment and the performance of U.S. direct commercial real estate from 2001 to 2016. The direct commercial real estate market is expected to be less efficient than the securitized and/or public market, and hence more susceptible to the impact of sentiment. Using the dictionary-based approach, optimism and pessimism expressed in approximately 65,000 real-estate-related news abstracts of *The Wall Street Journal* is quantified and aggregated on a quarterly basis.

Authors: Eli Beracha, Jochen Hausler and Marcel Lang

Submission to: Journal of Real Estate Research

Status: Under Review

This paper was presented at the 2018 Annual Conference of the ARES in Bonita Springs, USA.

Paper 3: News-Based Sentiment Analysis in Real Estate: A Machine-Learning Approach Via Support Vector Networks

The third and final paper of the dissertation aims to characterize the relationship between news-based sentiment and the securitized as well as the direct commercial real estate market in the United States from 2005 to 2016. This paper is unique in its approach, as for the first time, approximately 54,500 real-estate-related news headlines from *S&P Global Market Intelligence* were analyzed concerning their respective sentiment, deploying a supervised machine-learning algorithm, i.e. a support vector machine.

Authors: Jochen Hausler, Jessica Ruscheinsky and Marcel Lang

Submission to: Journal of Property Research

Status: Under Review

This paper was presented at the 2017 Annual Conference of the ERES in Delft, Netherlands, the 2017 Annual Conference of the ARES in San Diego, USA, as well as at the 2018 Annual Conference of the ARES in Bonita Springs, USA.

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2. Real Estate Media Sentiment Through Textual Analysis

Abstract

Purpose

The purpose of this paper is to determine systematically the broader relationship between news media sentiment, extracted through textual analysis of articles published by leading U.S. newspapers, and the securitized real estate market.

Methodology

The methodology is divided into two stages. First, roughly 125,000 U.S. newspaper article headlines from *Bloomberg*, *The Financial Times*, *Forbes* and *The Wall Street Journal* are investigated with a dictionary-based approach, and different measures of sentiment are created. Secondly, a vector autoregressive framework is used to analyse the relationship between media-expressed sentiment and REIT market movements over the period 2005 – 2015.

Findings

The empirical results provide significant evidence for a leading relationship between media sentiment and future REIT market movements. Furthermore, applying the dictionary-based approach for textual analysis, the results exhibit that a domain-specific dictionary is superior to a general dictionary. In addition, better results are achieved by a sentiment measure incorporating both positive and negative sentiment, rather than just one polarity.

Practical Implications

In connection with fundamentals of the REIT market, these findings can be utilized to further improve the understanding of securitized real estate market movements and investment decisions. Furthermore, this paper highlights the importance of paying attention to new media and digitalization. The results are robust for different REIT sectors and when conventional control variables are considered.

Originality

This study demonstrates for the first time, that textual analysis is able to capture media sentiment from news relevant to the U.S. securitized real estate market. Furthermore, the broad collection of newspaper articles from four different sources is unique.

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2.1. Introduction

'A simple remark from him could cause the stock market and the dollar to rise or fall', commented Abe (2011), who analysed the changes in Alan Greenspan's language use during his period as chairman of the Federal Reserve Board. The message behind this concise proposition is one sound reason for intensified research efforts assessing how decision-making is often not based solely on fundamentals.

A substantial body of literature focuses predominantly on quantifying the effects of sentiment captured through the textual analysis of stock market related text corpora. The most important works on text-based sentiment analysis include Tetlock (2007), Das and Chen (2007), Tetlock et al. (2008) and Loughran and McDonald (2011), who found significant correlations with stock returns, return volatility and trading volume. However, there is little research investigating the role of text-based sentiment in a real estate context and in particular none in relation to the securitized real estate market. Understanding the behaviour of Real Estate Investment Trust (REIT) price movements, using text-based sentiment measures, is especially relevant for two main reasons. Firstly, as an asset class, REITs are information-intensive. This derives from the aspect that both stock and real estate market characteristics must be taken into account due to the underlying asset class on the one hand and the stock exchange listing of REITs on the other hand. Secondly, real estate market information is mainly backward-looking and lacks expectations about future market conditions, for example, the NCREIF property index or Real Capital Analytics transactions.

Until recently, no attention has been paid to the extraction of sentiment through the textual analysis of online text corpora related to the REIT market. Especially interesting and promising is the investigation of online newspaper articles as a newly available source. Hence, this paper aims at filling this research gap by analysing newspaper article headlines from leading U.S. financial newspapers to evaluate the question of whether news media sentiment influences future securitized real estate market movements. The use of *news analytics* is defined by Das (2014) as a special subfield of textual analysis, which is associated with distinct advantages, in comparison to the traditional survey-based sentiment measures. Not only the immediate availability and objectivity of results is a key aspect, but also the option of scaling the methodology to a large data set and a wide variety of topics. Concerning the text corpus, news headlines offer several advantages compared to Twitter messages, blog posts or forum entries that have been explored in previous studies. News headlines are written more professionally and therefore contain (almost) no typographical errors, normally no slang or abbreviations, and extraction can be limited to a specific language. Additionally, with respect to news, it is more likely that published information is reliable and read by a broad and, equally important, a relevant audience.

The newspaper sample consists of about 125,000 market-specific U.S. news article headlines from *Bloomberg*, *The Financial Times*, *Forbes* and *The Wall Street Journal*. These newspaper headlines are analysed by applying the dictionary-based approach. The adequacy of a general psychological dictionary is compared to a domain-specific dictionary. Subsequently, different sentiment measures are derived and tested in a vector autoregressive model on their linkage to the REIT market.

The empirical results suggest a significant relationship between media-expressed sentiment and REIT returns. The findings are robust when conventional control variables are considered. Specifically, a leading relationship of the created real estate media sentiment by three to four months is identified. Moreover, the development of a domain-specific real estate dictionary, leads to a superior fit of the model. The findings are relevant to various market participants, for example for investors' decision-making processes, as media sentiment is forward-looking, contrary to traditional sentiment measures.

The remainder of this paper is structured as follows. Section 2.2 reviews the relevant literature in the context of textual analysis, as well as sentiment analysis in REIT markets. Section 2.3 presents a description of the data set. Having described the basics and the methodology of textual analysis in Section 4, a vector autoregressive model is derived and the results are analysed in Section 2.5. Afterwards, these results are tested regarding their robustness in Section 2.6. Finally, Section 2.7 contains conclusions and the implications of the findings.

2.2. Literature Review

2.2.1 Sentiment in the Context of REIT Market Movements

Over the last few years, the theory of behavioural finance has replaced the efficient market hypothesis, introduced by Fama in 1970, which is based on the idea that asset prices incorporate 'all existing, new, and even hidden information' about fundamental values. Behavioural finance, which refers to as the collaboration between finance and a broader social science perspective, has led to new insights into actual financial markets. The real estate literature has evolved accordingly over the last years, augmenting traditional asset pricing models with behavioural factors. Relevant evidence in the direct real estate market was among others found by Ling et al. (2015). They constructed sentiment measures applying surveys of homebuyers, builders and mortgage lenders in order to predict movements in the Case Shiller U.S. National Home Price Index and ascertained a significant evidence in the following quarter. The direct commercial property market showed supportive results testing different investor sentiment measures and the effects on the NCREIF (Ling et al. 2014).

Likewise the securitized real estate market research developed. For instance, Lin et al. (2009) examined the return-generating process of REITs and showed that REIT returns become higher, or lower, when investors are more optimistic or pessimistic. Das et al. (2015) supplement the earlier findings by introducing institutional real estate investor sentiment as a non-fundamental component into REIT-pricing.

Economists have proposed and tested a broad range of measures to proxy for market sentiment. Firstly, there are indirect measures such as the closed-end fund discount (Clayton and MacKinnon, 2003b, Barkham and Ward, 1999), the buy-sell-imbalance (Freybote and Seagraves, 2016) or mortgage flows (Ling et al., 2014; Clayton et al., 2009). Secondly, direct measures as survey-based proxies have been applied, such as the *Real Estate Research Corporation* sentiment measure (Das et al., 2015; Freybote, 2016; Clayton et al., 2009), a quarterly survey of institutional investors, the *American Association of Institutional Investors Investor Sentiment Survey (AAII)* or the *U.S. Investor Intelligence sentiment indicator* (Mathieu, 2016). With new possibilities opening up through digitalization, new ways of capturing sentiment are being introduced. Recently, several attempts have been made to use internet search volume data – *Google Trends* – to track investor sentiment, e.g. one of the first research papers is Hohenstatt et al. in 2011. Following on from that work, Rochdi and Dietzel (2015) and Braun (2016) found that Google-augmented models improve the predictability of REIT market movements and volatility.

However, many of the measures that are intended to indicate sentiment, are backward looking because they simply report information about the past. Sentiment extracted from newspaper articles focuses on published information in the past as well. However, there is a crucial difference: newspaper articles not only reflect the past, but they do also discuss the implications from past events or announcements on the future. Furthermore, there are newspaper articles in the form of outlooks, forecasts or opinions about events in the future. Hence, market participants might get affected in their beliefs, which might affect decisions accordingly.

Beyond that, traditional survey-based sentiment measures are labour-intensive, rarely available and depend on the honesty of respondents. So far, there have been few empirical investigations using new online text corpora and none at all in the field of REIT market movements. Consequently, this paper seeks to go one step further and fill this knowledge gap by creating a media-expressed sentiment that is captured from REIT-related newspaper articles by means of textual analysis. Hence, in the following Section, research on textual analysis is reviewed.

2.2.2 Textual Analysis

Probably, Tetlock (2007) represents the pioneering paper applying textual analysis to capture sentiment in the finance literature. Deploying the dictionary-based approach to capture sentiment in *Wall Street Journal*'s column 'Abreast of the Market', he found a significant relationship between pessimism reflected in news and price changes of the Dow Jones Industrial Average Index, as well as its trading volume. A number of researchers have used the dictionary-based approach, for example Henry and Leone (2010), Feldman et al. (2010) or Davis et al. (2012). This approach can be described as counting the number of positive and negative words in a text corpus according to a chosen dictionary that contains words considered to carry sentiment.

Tetlock (2007) used the Harvard GI word list, which subsequently became popular for further language processing research (Tetlock et al., 2008; Kothari and Short, 2009; Heston and Sinha, 2016). For example, Kothari and Short (2009) employed the *Harvard GI* word list to analyse firm-specific disclosures, discovering that positive disclosures are followed by declining firm risk measures and vice versa. Heston and Sinha (2016) made use of this dictionary, analysing news articles, and found that positive net sentiment for a specific firm (positive – negative frequency of words) is related to future high returns of that company.

A further milestone in dictionary-based textual analysis was conducted by Loughran and McDonald (2011), who demonstrated the relevancy of a domain-specific dictionary. They developed a financial-dictionary which was later used by many other researchers, for example Boudoukh et al. (2013), Jagadeesh and Wu (2013) or lately, Heston and Sinha (2016). Loughran and McDonald (2016) highlight two main advantages of the dictionary-based approach relevant for this paper. The first refers to subjectivity as a common problem within textual analysis. Once a dictionary-approach is applied, subjective decisions by researchers are avoided, as the evaluation process is bound strictly to the classifications within the dictionary. Second, and equally important for this research, the method can be scaled to a large sample. In summary, the literature has studied three main sources of digital information: public corporate disclosures/fillings, newspaper articles, internet messages as blog posts, tweets or forum entries.

Recently, some first attempts in the context of real estate were conducted to examine the impact of sentiment by analysing text corpora. First, Walker (2014) found a significant positive relationship between newspaper articles in the *Financial Times* and returns of listed companies engaged in the UK housing market. Soo (2013) investigated the sentiment expressed in 37,500 local housing news articles of 34 U.S. cities, in order to predict future house prices. She found that the measured sentiment leads housing price movements by more than two years. In accordance with his earlier findings, Walker (2016) subsequently analysed the direct housing market in the UK, and ascertained that news media granger-caused real house price changes from 1993 to 2008.

Based on the literature review and the highlighted research gap, this paper developed the following hypotheses:

Hypothesis 1: Media-expressed sentiment affects future REIT market movements.

Hypothesis 2: A domain-specific dictionary creates more efficient sentiment scores.

Hypothesis 3: The incorporation of both positive and negative sentiment creates a more accurate measure than solely negative sentiment.

2.3. Dataset

For this paper, two different datasets are relevant: (1) a text corpus consisting of news headlines and (2) a U.S. REIT index, as well as economic time series. In order to analyse the impact of media-expressed sentiment not solely for a specific market phase, an eleven-year period from 01/01/2005 to 12/31/2015 is considered. A monthly analysis is performed, to obtain a sufficient amount of news containing sentiment per aggregation period. Furthermore, monthly frequency is also chosen because some variables are not available at a higher frequency.

2.3.1 Text Corpus

Identifying the relevant information source – newspaper articles in this case – is essential for performing a meaningful sentiment analysis. In this context, a news source is considered 'relevant', if it has a significant readership by informed individuals or professional investors, who are expected to influence REIT prices. Consequently, this paper captures real estate-related sentiment expressed by the leading U.S. (financial) newspapers. In order to determine the relevance of a particular newspaper, the following aspects were considered: firstly, news sources from research already conducted in the literature (Wuthrich et al., 1998; Rachlin et al., 2007; Tetlock et al., 2008; and Chatrath et al., 2014 among others). Secondly, the most popular and frequently visited newspaper websites were identified using the *Alexa*[1] U.S. ranking. Thirdly, the REIT-related news coverage of each newspaper was analysed.

Consequently, the text corpus consists of news articles from the following four leading U.S. newspapers: *Bloomberg*, *The Financial Times*, *Forbes* and *The Wall Street Journal*. Gathering articles from multiple newspapers is advantageous, as it decreases the probability of obtaining biased sentiment from one source. The next step is the detection of real estate-related news, and excluding irrelevant news and noise. Therefore, specifically articles containing either the keywords 'real estate' and/or 'REIT' were retrieved from the digital archive of the respective news websites.[2] This way, the data set includes news about the REIT market itself, as well as news about the underlying asset of REITs, namely real estate. Furthermore, the data queries were limited geographically to U.S. news. Overall, 124,685 news articles were collected. Furthermore, it is important to note that this paper examines exclusively the headlines of the newspaper articles. This is in accordance with Permanuetilleke and Wong (2002), who argued that news headlines are usually more straight-to-the-point, more straightforward and contain fewer irrelevant words than full articles. Over the eleven-year period, *Bloomberg* (34.7%) and *The Wall Street Journal* (29.86%) account for the largest shares of real-estate-related news coverage, while the *Financial Times* and *Forbes* account for 22.57% and 13.43% of the dataset. On average, 945 headlines were published per month.

2.3.2 Time Series Variables

To analyse whether sentiment influences the aggregate U.S. securitized real estate market, the FTSE/NAREIT All Equity REITs U.S. Total Return Index (*REIT*) is selected, due to its comprehensive

[1] www.alexa.com/about; Alexa offers a country-specific ranking, which measures the relative popularity of websites in a particular country, combining a site's average of daily unique visitors and its estimated number of page views.

[2] www.bloomberg.com, www.ft.com, www.forbes.com, www.wsj.com.

market coverage and long history. At the end of 2015, the index had a net market capitalization of $937 billion, consisting of 166 constituents covering all property sectors. Monthly closing prices were used to track the movements of the REIT index.

Besides media-expressed sentiment, this study controls for potential fundamental and economic sources of variation in REIT market movements, according to the theory and previous empirical evidence. The significance of media-expressed sentiment must be tested in a multivariate setting to determine whether the created sentiment measures contribute independently to REIT returns, or whether they are simply picking up the impact of other missing variables. First, as several studies detect high correlations of REITs with common stocks (Clayton and MacKinnon, 2003a; Sebastian and Schaetz, 2009; Hoesli and Oikarinnen, 2012; Das et al,. 2015; Mathieu, 2016), the S&P 500 Price Index (*SP500*) controls for the U.S. stock market development. Second, the Aruoba-Diebold-Scotti Business Conditions Index (*ADSI*) and the Disposable Income (*DISPOSINC*) are considered as proxies for business conditions and the potential spending power of individuals. More precisely, the *ADSI* is a measure of economic activity at high frequency, covering the term structure of interest rates, defined by the spread between the 10-year and 3-month U.S. Treasury yields. In addition, it includes labour market developments by considering initial claims for unemployment insurance and real GDP, the latter representing general economic growth among others. To control for the direct commercial real estate market, this paper uses the U.S. Costar Commercial Repeat-Sale Index *(CCRSI)*, a transaction-based index that is published monthly. Finally, the U.S. Consumer Confidence Index *(CONCON)* is a survey which accounts for consumer attitude towards the general state of the economy. All time series are derived from Thomson Reuters Eikon.

Table 2.1 provides descriptive statistics about the monthly REIT return data and the control variables. Mean, median, standard deviation, minimum and maximum of levels are reported in decimal form. Since the sample period covers part of a boom phase (2005/01 – 2007/06), the recent bust of the bubble (2007/07 – 2009/01) and the subsequent recession (2009/02 – 2015/12), the total returns of the securitized real estate market (*REIT*) show a wide range with extreme minimum (-31.67%) and maximum (31.02%) values. The REIT market averages at a monthly return of 0.96%. All control variables were transformed into growth rates to address non-stationarity issues.

Table 2.1: Descriptive Statistics

	Mean	Median	SD	Min	Max
REIT (%)	0.96	1.31	7.07	-31.67	31.02
SP500 (%)	0.51	1.07	4.21	-16.94	10.77
ADSI (%)	-0.37	-0.18	0.84	-3.95	0.85
DISPOSINC (%)	0.32	0.37	0.87	-6.05	5.27
CCRSI (%)	0.14	0.49	1.37	-3.70	2.93
CONCON (%)	0.51	0.32	10.83	-36.81	51.67

Notes: This table reports descriptive statistics of the monthly variables. *REIT* is the growth rate of the NAREIT All Equity total return index. *SP500* is the growth rate of the S&P 500 Price Index. *ADSI* is the first difference of the Aruoba-Diebold-Scotti Business Conditions Index. *DISPOSINC* is the growth rate of the Disposable Income. *CCRSI* is the growth rate of the U.S. Costar Commercial Repeat-Sale Index. *CONCON* is the growth rate of the U.S. Consumer Confidence Index. Percentages are expressed in decimal form. The sample period is from January 2005 to December 2015.

2.4. Textual Analysis of News

2.4.1 Dictionary-based Approach

Applying the dictionary-based approach, the ‘bag-of-words’-technique is the basis for counting the number of positive and negative words. This technique is described by Nassirtoussi et al. (2014) as breaking the text corpora down into its individual words, meaning that the order and co-occurrence of the resulting features are not considered. Subsequently, the number of positive and negative words is summed for each text entity, delivering a sentiment score for each headline.

This paper uses two different dictionaries, first, the Harvard General Inquirer Word List and second, the financial dictionary of Loughran and McDonald (2011), adjusted for real estate specifics.

Harvard General Inquirer Dictionary

The established sociology and psychology dictionary Harvard General Inquirer (GI) Word List is a merger of the Harvard-IV-4 and Lasswell dictionaries and is freely available to all.[3]

The Harvard GI word list assembles 182 categories in total, such as words referring pleasure, pain, arousal or motivation-related words, such as need, goal, persist, and other categories such as words of cognitive orientation. This paper focuses on the classification categories positive and negative, which contain 1,915 words of positive and 2,291 words of negative outlook, after deleting duplicates. The decision to focus solely on the categories positive and negative, is based on the assumption that the allocation within these two categories is more precise and thus less error-prone compared to other categories.

Real Estate Dictionary

Loughran and McDonald (2011) showed that dictionaries should be sector-specific in order to classify text corpora successfully. Subsequently, many researchers have used the financial-language-orientated dictionary of Loughran and McDonald. As REITs are a financial product, the financial sector vocabulary is presumably applicable to the REIT context. Loughran and McDonald (2011) published six word lists – negative, positive, uncertainty, litigious, strong modal and weak modal – trying to capture the most likely interpretation of a word in a business context (McDonald, 2015). This dictionary is also freely available.[4] The two main advantages of this dictionary are firstly, that the words are selected based on financial communication from managers and secondly, they claim to be quite comprehensive. For subsequent analysis, the positive (354 words) and negative (2,355) word lists from Loughran and McDonald (2011) are used for the purpose of unambiguousness.

Following on from this, the financial dictionary was adapted to the context of real estate. First, the dictionary was controlled for its accuracy in a real estate context. If the given classification was not definite, words were deleted. Therefore, all words occurring more than 30 times within the complete text corpora were analysed. 43 out of 250 were found to have a rather different or unclear classification within a real estate context, and were subsequently removed. Second, over 10,000 newspaper articles were analysed manually regarding sentiment classification. Words appearing on

[3] See http://www.wjh.harvard.edu/~inquirer/homecat.html.
[4] See http://www.nd.edu/mcdonald/Word_Lists.html.

a regular basis and considered to convey a specific sentiment were added to the dictionary. In the end, 199 words, which 62 were positive and 137 negative, are included in the dictionary. For example, ‘bubble’ can be listed as a real-estate-specific word; it became popular in a real estate context during the recent financial crisis. Similarly, words like ‘crash’ and ‘depression’ were also included, since they are regarded as relevant, but missing in the financial dictionary. Ultimately, the real estate dictionary contains 410 positive and 2,455 negative words.

2.4.2 Sentiment Measures

Applying the dictionary-based approach, positive words are counted as '+1' and negative words as '-1'; this facilitates calculating a sentiment score for each headline by summation. Negation is considered in the following way: the value of a positive or negative annotated word is reversed, multiplied by -1, if up to five words in front of the sentiment annotated word a negation word is present. This paper uses the following words from Loughran and McDonald (2012) as negation words: *no, not, none, neither, never and nobody.* The evaluation of the dictionary-based approach is performed with RapidMiner Studio.[5] As a result, the predominantly represented sentiment in a headline defines the *final sentiment score* of a headline. More precisely, each headline is translated into a numerical sentiment value based on its overall classification: '1' if the headline is positive (sentiment score ≥ 1), '-1' if negative (sentiment score ≤ -1), and '0' if neutral. Note, either of two circumstances can cause a score of '0'. First, no positive or negative word was found in a headline at all. Second, the number of positive and negative words is equal and hence, the scores neutralize each other.

After assigning each news headline individually with a sentiment score, this paper deploys three different ways of aggregating the scores into monthly sentiment measures: the Sentiment Quotient Positive *(SQ),* the Negative Count *(NCount)* and the Positive Count (*PCount*).

Equation 2.1: Sentiment Measure 1 – Sentiment Quotient (*SQ*)

$$SQ_t = \frac{positive\ headlines_t}{positive\ headlines_t\ +\ negative\ headlines_t} \tag{1}$$

The *SQ* is a relative measure and considers headlines of both polarities, positive and negative, inspired by a company, offering sentiment analysis products (yukkalab 2017). Hence, the *SQ* indicates the degree of media optimism and pessimism for a given period, excluding all neutral headlines. The *SQ* is defined as the ratio of the number of positive headlines to the number of positive and negative headlines for a given period *t*. Consequently, one can easier identify whether a period is relatively positive or negative. If the number of positive headlines exceeds the number of negative ones, the *SQ* is greater than 0.5, indicating media optimism and vice versa.

In order to investigate the positive media sentiment and the negative media sentiment separately from each other, the subsequent two measures are calculated.

Equation 2.2: Sentiment Measure 2 – Negative Count (*NCount*)

$$NCount_t = \frac{negative\ headlines_t}{number\ of\ headlines_t} \tag{2}$$

The *NCount* is based on the *negativity bias*, which states that human psychology is affected more strongly by negative, rather than positive influences – even when the two are of equal intensity. The *NCount* yields to quantify relative media-expressed pessimism; and is defined as the number of negative headlines divided by the overall number of headlines for a given period *t*. This leads to the *NCount* ranging from 0 to 1; if the relative number of negative headlines increases, the *NCount* indicates increasing media pessimism.

[5] RapidMiner Studio is a Data Science Software Platform.

To assess properly the relationship of media-expressed optimism and REIT returns, this paper deploys the Positive Count (*PCount*) as the third sentiment measure:

Equation 2.3: Sentiment Measure 3 – Positive Count (*PCount*)

$$PCount_t = \frac{positive\ headlines_t}{number\ of\ headlines_t} \tag{3}$$

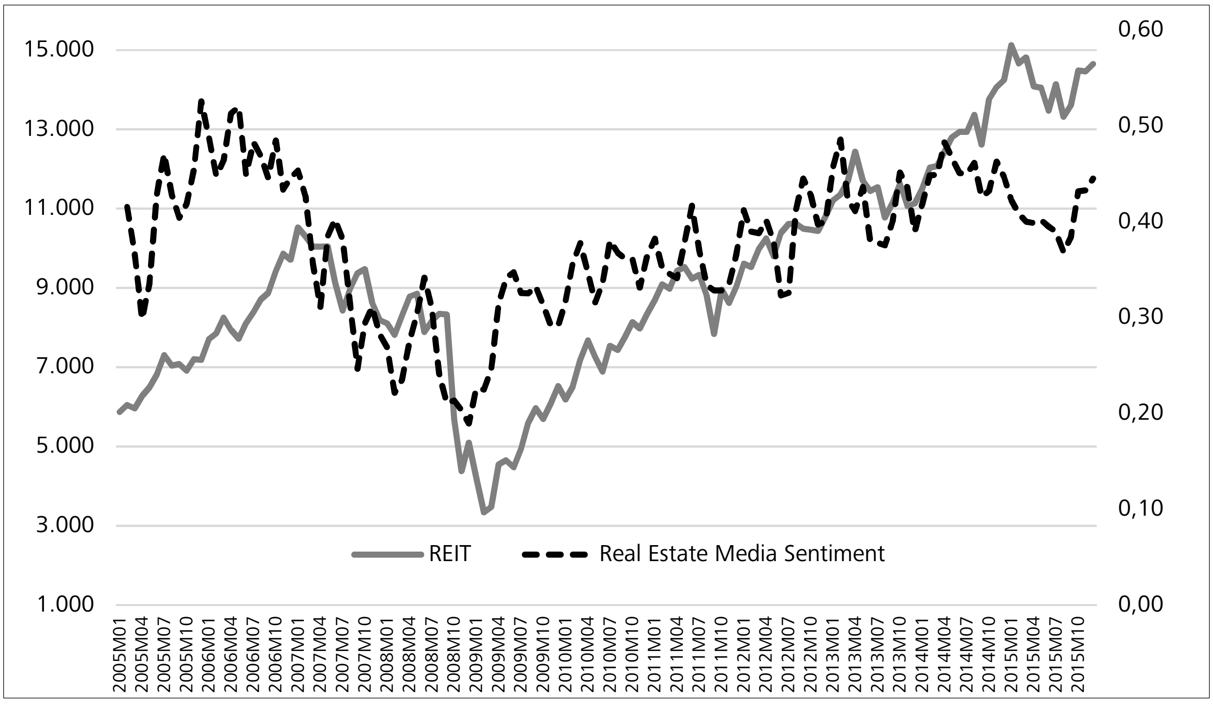
The PCount is defined as the number of positive headlines divided by the overall number of headlines for a given period *t*. It ranges from 0 to 1 and increases with a relative increase in positive headlines indicating increasing media optimism.

2.5 Relationship Between Real Estate Media Sentiment and REIT Market Movements

2.5.1 Preliminary Analysis

Similarly to the findings of Walker (2014), who analysed the relationship between the UK housing market by means of 30,000 articles on local housing markets, the data of this paper shows an increase in the number of topic-specific newspaper articles published over time. However, the percentage of positive or negative news does not change. In 2005, the data set includes on average about 450 published articles per month. Over time, the number grew to a monthly average of about 1,100 articles in 2015. The number of articles peaked in November 2010 at 1,653 articles. A possible explanation for the sharp increase in 2007 can be the increased media attention due to the beginning of the U.S. subprime mortgage crisis, which led to the global financial crisis. Looking at 2010, a possible explanation is the enormous growth in web usage. In 2000, only 400 million users were connected to the Internet, by 2005, the number grown to 1 billion and then doubled to 2 billion people by 2010 (Internet Live Stats, 2017). Possibly, traditional journalism adapted by increasing the publication of digital news, as more people consume news online. This is reflected in the data set by a rise of 67% in the average yearly news coverage, when comparing the periods 2005 – 2009 and 2010 – 2015.

Figure 2.1: RE Media Sentiment vs. REIT Total Return



Notes: This figure plots the *FTSE/NAREIT All Equity REITs U.S. Total Return Index* (*REIT*) against the 2-month moving average of the *Sentiment Quotient* deploying the real estate dictionary (Real Estate Media Sentiment). The sample period is January 2005 to December 2015.

Figure 2.1 plots the positive sentiment quotient and the REIT total return index over the whole sample period. This gives a first impression about their relationship. The graph suggests the media sentiment measure to lead the REIT return index. For instance, the lowest value of the media sentiment can be found in December 2008, while the lowest value of the REIT is in February 2009. Following, this initial idea is assessed statistically in a vector autoregressive framework.

2.5.2 Empirical Analysis: Vector Autoregressive Model

The relationship between REIT market movements and media-expressed sentiment possibly faces a so-called endogeneity problem. Similarly, macroeconomic variables often cannot be regarded as strictly exogenous. Furthermore, it is useful to investigate the additional explanatory power of the sentiment indices for the *REIT returns* over time. Therefore, a vector autoregressive model (VAR) is chosen. The dependent variables are each represented as a linear function of their own and each other's lagged values, plus potential exogenous control variables.

Accordingly, the REIT index and the respective media sentiment indices are included as endogenous variables. To capture other potential sources of variation in REIT market movements, five different variants of the model were run, controlling for different factors influencing the model at each pass. The control variables described in Section 2.3.2 are supplemented by a dummy variable for the recent financial crisis. The period is motivated by the findings of Walker (2016) and Brunnermeier (2009), who chose July 2007 as the starting point of the financial crisis; consistently, the end of the crisis is defined as January 2009.

An important assumption within the VAR framework is the stationarity of all variables. To test for stationarity, the *Augmented Dickey-Fuller* and *Philipps Perron unit root tests* are employed. Results from these tests suggest the use of first differences; all variables are found to be stationary in their first differences or growth rates.

A crucial step in constructing a VAR model is the appropriate selection of the lag length. This selection needs to be done with care, as it faces a trade-off; the curse of dimensionality reduces the degrees of freedom on the one side, whereas choosing a lag length that is too short, fails to correctly specify the model on the other side. To consider this trade-off, the *Akaike Information Criterion (AIC),* the *Schwarz Information Criterion* and the *Hanna-Quinn Information Criterion* were chosen. They are measurements that minimize the variance of the error terms by punishing at the same time for included parameters to estimate. The basic functional form VAR framework looks as follows:

Equation 2.4: VAR Model

$$\begin{pmatrix} REIT_t \\ SI_t \end{pmatrix} = \begin{pmatrix} \beta_0 \\ \beta_1 \end{pmatrix} + \boldsymbol{A} \begin{pmatrix} REIT_{t-i} \\ SI_{t-i} \end{pmatrix} + \boldsymbol{B} \begin{pmatrix} SP500_t \\ ADSI_t \\ DISPONIC_t \\ CCRSI_t \\ CONCON_t \\ Crisis_t \end{pmatrix} + \begin{pmatrix} u_{REIT_t} \\ u_{SI_t} \end{pmatrix} \qquad (4)$$

As all three information criterions suggest a lag length of four; both endogenous variables enter the equation system with four lags: I = {1,..,4}. This is also confirmed by the likelihood ratio selection criteria and the Akaike's final prediction error. **A** and **B** represent the respective coefficient matrix of the endogenous and exogenous variables. u_t are the error terms in each equation.

One of the most important aspects is to test each model for autocorrelation. Each model output presented within this paper was tested for autocorrelation with the *Autocorrelation LM Test* and found not to be autocorrelated.

2.5.3 Results of VAR Models

Real Estate Sentiment Quotient

To ensure the comparability of results, a model is developed by controlling for different factors influencing REIT market movements at each pass. The analysis starts with the sentiment quotient, which is calculated by using the real estate dictionary, *SQ_RE*. Table 2.2 contains the results of the estimated VAR models. The main findings strongly imply a positive relationship between the generated real estate sentiment quotient *SQ_RE* and future REIT prices, even after controlling for common market factors. Considering the bigger picture, this means that media-expressed sentiment exerts an influence on REIT market movements.

Model (1) analyses the endogenous variables and the general stock market (*SP500)* as a control variable. Looking at the results, the *SQ_RE* exerts a statistically significant positive influence on three and four-month-ahead REIT returns. This result is backed by the associated Granger causality, which shows that the *SQ_RE* influences the REIT return movements, which is not already explained by the past of the *REIT* itself. In addition, there is a significant relation between lagged REIT returns and current period media sentiment. Hence, the relationship between media sentiment and REIT returns is bi-directional. This is in accordance with the idea, that newspaper articles among others report about past real estate events or performance. It would have been surprising to see the sentiment decoupled from the REIT returns. According to expectations, the past REIT total return values ($REIT_{t-2}$ and $REIT_{t-4}$) exert an explanatory power on the current values. This is also in line with expectations. Hence, the results give an inherently consistent overall picture.

Table 2.2: VAR Results – Sentiment Quotient

Model	(1)		(2)		(3)		(4)	
Endogenous Variable	*REIT*	*SQ_RE*	*REIT*	*SQ_RE*	*REIT*	*SQ_RE*	*REIT*	*SQ_RE*
$REIT_{t-1}$	-0.0334	0.1323*	-0.0490	0.1354**	0.0505	0.1377**	-0.0957*	0.1385*
$REIT_{t-2}$	-0.1127*	-0.0779	-0.1285**	-0.0757	-0.1326**	-0.0694	-0.1689***	-0.0687
$REIT_{t-3}$	-0.0306	-0.0135	-0.0185	-0.0203	-0.0161	-0.0161	0.0142	-0.0245
$REIT_{t-4}$	0.1546***	-0.1444**	0.1282**	-0.1483**	0.1306**	-0.1520**	0.1565***	-0.1524**
SQ_RE_{t-1}	0.0456		0.0677		0.0793		0.0860	
SQ_RE_{t-2}	0.0871		0.0504		0.0679		0.0654	
SQ_RE_{t-3}	0.2421***		0.1856**		0.1992***		0.1727**	
SQ_RE_{t-4}	0.1750**		0.1840***		0.1917***		0.1796***	
SQ X^2 (4) Joint	10.6987**		10.4938**		11.3741**		9.9092**	
REIT X^2 (4) Joint		8.1418*		8.7472*		9.2865*		8.3367*
C	0.0032		-0.0010		-0.0018		-0.0028	
SP500	1.2088***		1.1189***		1.1130***		1.9073***	
ADSI			0.0413***		0.0414***		0.0342***	
DISPOSINC			1.5266***		1.4328***		1.5187***	
CCRSI					0.4048		0.4692*	
CONCON							0.1039***	
CRISIS	-0.0070		0.0018		0.0062		0.0086	
Adj R^2	0.6218		0.6889		0.6919		0.7092	
AIC	-3.326		-3.507		-3.5100		-3.5608	
Loglikelihood	222.2010		235,7215		236,8900		241,1106	

Notes: This table shows the coefficients of the estimated VAR models (1) - (4) with 4 lags. The lag length was based on AIC, BC and HQ criterion. *REIT* is the NAREIT All Equity total return index. *SQ* is the Sentiment Quotient. RE stands for the usage of the real estate dictionary. *ADSI* and *CCRSI* are included with a second lag, *DISPOSINC* with fourth and *CONCON* with a first lag. The regression is based on 127 observations from January 2005 to December 2015 on a monthly basis. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level. Furthermore, granger causality x^2 with its p-probability is given.

Extending the model with control variables for the general economy, adding the *ADSI* and the *DISPOSINC*, delivers consistent results (model 2). Lags 3 and 4 of the *SQ_RE* remain statically significant at the 5% level and the Granger causality is significant at a 5% level as well. Due to REIT specific characteristics, the paper next controls for the direct real estate market by subsequently including *CCRSI COMM* in the model (3). The results hold at a 1% significance level of the SQ_RE_{t-3} and SQ_RE_{t-4}. Finally, the inclusion of a measure for consumer optimism or pessimism *CONCON* does not render the *SQ_RE* insignificant. Model (4) is subsequently referred to in this paper as the *main model*. The R-squared of 74.15% and the adjusted R-squared of 70.92% suggest that the main model is well specified. The *SQ_RE* exhibits in all models (1) – (4) a significant Granger causality at a 5% level. Likewise, the REIT returns granger-cause the media sentiment measure at a 10% significance level in all model variations. That gives further proof of a robust relationship. In conclusion, the above findings confirm Hypothesis 1 of a positive influence of the created real estate news sentiment on future REIT prices. The results are consistent, independently of the order the control variables are included in the model. An improvement in the goodness of fit is reported with the adjusted R-squared increasing by including the control variables in Model (1) to (4). The evidence found, shows that the created media sentiment measure contains not only information already incorporated into prices or the control variables; otherwise the *SQ_RE* would not significantly explain REIT returns. Taken together, sentiment extracted from newspaper articles enhances information about REIT market movements.

A possible explanation for the time reference found, could be the opinion formation process. In other words, the opinion of an individual might not change by simply reading one article containing positive or negative sentiment about a specific topic. It can be assumed that it takes some time, and further information, until an individual changes his/her opinion about a certain topic. In addition, the reaction capability of REIT managers is bound to the real estate asset-specific transaction period. Hence, the underlying asset allocation of REITs cannot be adapted right away. Another explanation is the statement from Devos et al. (2013), that traditionally, institutional investors which hold an increasing share of REITs, are both long-term and passive investors.

Furthermore, the findings contribute to answering the question in REIT analysis 'do REITs behave more like real estate or equity investments?', as investigated by Sebastian and Schaetz (2009), Hoesli and Moreno (2007) and Wang et al. (1995) among others. More precisely, the results of this paper are consistent with Morawski et al. (2008), who found interdependencies between REITs and the direct real estate market over the long-run. Accordingly, Wang et al. (1995) found REIT stocks to have a significantly smaller turnover ratio, less financial analyst coverage and to receive less attention from institutional investors.

Further Sentiment Measures

All models referred to in this section are based on the *main model*, adjusted each time by another respective sentiment measure, see Table 2.3. The results of model (4) are repeated in this table for reasons of clarity and comprehensibility. First, the theory that market participants are affected more strongly by negative than positive influences, because investors tend to be risk averse, is tested. Initially, the idea of a media pessimism measure was investigated by Tetlock (2007), who constructed a pessimism factor from the content of the WSJ column using the dictionary-based approach. He found evidence for media pessimism predicting downward pressure on market prices in future periods. Accordingly, the *main model* is consulted, simply substituting the sentiment measure with the negative count based on the real estate dictionary, referred to as *NCount_RE*. In accordance with Tetlock (2007), the results indicate a relationship between pessimistic media sentiment and the U.S. REIT market. The first and the fourth lag of the *NCount_RE* are statistically significant on the 10% and 5% level. Collectively, all four lags significantly granger-cause REIT total returns. Furthermore, the relationship is bi-directional similarly to the results in model (4) with the *SQ_RE*. As can be seen in Table 2.3*,* the impact of the *NCount_RE* is slightly smaller than the impact of the *SQ_RE* and less significant.

Next, the corresponding positive measure, the *PCount_RE,* solely focussing on positive assigned newspaper articles is tested in model (6). The *PCount_RE* exerts a statistically significant positive influence on three and four-month-ahead REIT prices. Hence, the *PCount_RE* granger-causes REIT return changes. Interestingly, the *REIT* does not granger-cause the *PCount_RE*. A possible theory is that positive changes in REIT returns or positive events influencing REIT returns positively are not discussed that often in news than negative ones. Summing up, the results confirm Hypothesis 3: both positive and negative news have a significant relationship with REIT market movements, nevertheless, the incorporation of both positive and negative sentiment at the same time creates a more accurate measure than solely focussing on one polarity.

Furthermore, this paper examines the importance of choosing an adequate dictionary to extract sentiment from real estate specific newspaper articles, formulated in Hypothesis 2. As a general dictionary the sociology and psychology dictionary Harvard General Inquirer (GI) Word List is considered. The Sentiment Quotient that is calculated by classifying the headlines with the general Harvard Dictionary (*SQ_HAV)* is significant in its third and fourth lag. However, collectively, the lags have no robust granger-causal impact on REIT returns. The same is true for the *NCount_HAV* and the *PCount_HAV.* Even though some of the lags ($NCount\_HAV_{t-4}$ *and* $PCount\_HAV_{t-1}$) indicate an existing relationship to REIT returns, jointly they do not show a robust Granger causality. These findings are in accordance with Loughran and McDonald (2011) and Heston and Sinha (2016), who point out that a domain-specific dictionary is superior to a general psychology word list, such as the Harvard General Inquirer. Consequently, Hypothesis 2 can be confirmed.

Table 2.3: VAR Results – Various Different Sentiment Measures

Model	(4)		(5)		(6)		(7)		(8)		(9)	
Endogenous Variable	*REIT*	*SQ_RE*	*REIT*	*NCount_RE*	*REIT*	*PCount_RE*	*REIT*	*SQ_HAV*	*REIT*	*NCount_HAV*	*REIT*	*PCount_HAV*
$REIT_{t-1}$	-0.0957*	0.1385*	-0.0734	-0.0583*	-0.1048*	0.0347	-0.0636	0.0886*	-0.0635	-0.0336	-0.0733	0.0643**
$REIT_{t-2}$	-0.1689***	-0.0687	-0.1624***	0.0097	-0.1723***	-0.0252	-0.1831***	-0.0250	0.1684***	-0.0015	-0.1943***	-0.0280
$REIT_{t-3}$	0.0142	-0.0245	0.0086	-0.0162	0.0211	-0.01763	0.0132	0.0497	0.0197	-0.0070	0.0221	0.0364
$REIT_{t-4}$	0.1565***	-0.1524**	0.1552***	0.1036***	0.1726***	-0.6681	0.1512	-0.0560	0.1553***	-0.0072	0.1517**	-0.0679***
$Sentiment_{t-1}$	0.0860		-0.2407*		0.2296		0.1347		-0.0450		0.3899**	
$Sentiment_{t-2}$	0.0654		0.0516		0.4402		0.0500		0.1951		0.2188	
$Sentiment_{t-3}$	0.1727**		-0.2080		0.8007***		0.1889*		-0.2481		0.3366	
$Sentiment_{t-4}$	0.1796***		-0.2806**		0.5102**		0.1942**		-0.2859*		0.1980	
X^2 (4) Joint	9.9092**	8.3367*	9.1851*	13.0666**	8.7063*	6.3746	7.0301	3.8530	4.3052	1.4497	6.8091	9.8284**
CONTROL VARIABLES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: The table shows the coefficients of the estimated VAR models (4) - (9) with 4 lags. *REIT* is the NAREIT All Equity total return index. *SQ* is the Sentiment Quotient. *PCount* is the Positive Count and *NCount* is the Negative Count. RE stands for the usage of the real estate dictionary, HAV for the usage of the Harvard GI dictionary. All regressions were run with the total set of control variables including: *SP500*, *ADSI(-2)*, *DISPOSINC(-4)*, *CCRSI(-2)*, *CONCON(-1)* and dummy variable *CRISIS*. The regression is based on 127 observations from January 2005 to December 2015 on a monthly basis. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level. Furthermore, granger causality x^2 with its p-probability is given.

REIT Sector Specific Analysis

According to the categorization of equity REITs by the National Association of Real Estate Investment Trusts, there are several subsectors: industrial, office, retail, residential and health care, among others. In order to further analyse the relationship between media sentiment and the REIT market, subsectors of the REIT market are examined. This paper is not interested in explaining the distinct characteristics of each category, instead, the general linkage to media sentiment is worthwhile. Therefore, the same control variables of the *main model* are included to enhance the comparability of all regressed models.

Regarding the lag length of the equation system and the non-presence of autocorrelation, the subcategories differ in their characteristics and consequently, the VAR framework has to be adjusted. Hence, each model is optimized individually by the information criteria. This explains why model (12) examining the Residential REIT market has five lags; all other models include four lags. A possible explanation for this emergence is, that the residential real estate market is established to move slower than the other asset classes.

Overall, the results hold and confirm Hypothesis 1. Table 2.4 reports that there is a constant relationship between media-expressed sentiment and the REIT market. More specifically, the *SQ_RE* still exerts a statistically significant positive influence on three and four-month-ahead REIT subcategories: diversified, residential, office and retail. Media Sentiment significantly granger-causes just mentioned REIT sectors. The results hold independently of the included lag length. Residential, office and retail can broadly speaking be summarized as rather traditional real estate asset classes, which have the largest market coverage. As might be reasonably expected, many newspaper articles will be about these asset classes. The remaining REIT categories resemble alternative investments, which might not be linked to the same market drivers. Interestingly, for the office subsectors, the first lag of *SQ_RE* shows a significant positive influence at the 10% level.

However, the created media sentiment shows no significant linkage to the sub sectors NAREIT Healthcare. This might be due to the unique risk-return characteristics of this asset class. For example, Healthcare REITs own and sometimes operate health care properties such as senior living facilities, nursing homes, medical office building, and hospitals. It can be argued that they do not have a linkage with real estate sentiment, because there is a steady demand for health care facilities, especially increasing due to demographics.

Table 2.4: VAR Results – Specific REIT Sectors

Variables	*NAREIT Diversified*	*NAREIT Residential*	*NAREIT Office*	*NAREIT Retail*	*NAREIT Industrial*	*NAREIT Self Storage*	*NAREIT Healthcare*
Model	(10)	(11)	(12)	(13)	(14)	(15)	(16)
REIT $_{t-1}$	-0.0542	-0.1442	-0.1144	-0.1137	-0.2209***	-0.1094	-0.1786***
REIT $_{t-2}$	-0.1797***	-0.1190*	-0.0964**	-0.1487**	-0.3235***	-0.0898	-0.1840***
REIT $_{t-3}$	0.0949	0.0507	0.0084	-0.0832	-0.0344	0.0295	0.1230
REIT $_{t-4}$	0.1910***	0.1850***	0.2164***	0.1756***	0.0552	0.0582	0.0667
REIT $_{t-5}$		0.0960					
SQ_RE $_{t-1}$	0.0962	0.1372	0.1294*	0.0776	0.1055	-0.0286	-0.0273
SQ_RE $_{t-2}$	0.1295	0.1527	0.1242	0.0630	0.1216	-0.0882	-0.0556
SQ_RE $_{t-3}$	0.2129**	0.2998***	0.2028**	0.2189**	0.1419	0.1575*	0.1671
SQ_RE $_{t-4}$	0.2023***	0.3255***	0.2258***	0.1907**	0.0870	0.1608*	0.2185*
SQ_RE $_{t-5}$		0.1888**					
x^2 (4) Joint	9.5836**	13.8275**	11.2665**	7.8559*	1.3054	9.2808*	6.0170
C	-0.0071	-0.0017	-0.0050	-0.0016	-0.0030	0.0058	-0.0043
CONTROL VARIABLES	YES	YES	YES	YES	YES	YES	YES
R^2	0.7093	0.6090	0.7046	0.6814	0.6483	0.4995	0.5581
Adj R^2	0.6730	0.5516	0.6677	0.6416	0.6043	0.4370	0.4877

Notes: The table shows the coefficients of the estimated VAR models (10), (12), (13), (14), (15), (16) with 4 and model (11) with 5 lags. The lag length was based on AIC, BC and HQ criterion. *REIT* is the NAREIT All Equity total return index. *SQ* is the Sentiment Quotient. RE stands for the usage of the real estate dictionary. All regressions were run with the total set of control variables including: *SP500*, *ADSI(-2)*, *DISPOSINC(-4)*, *CCRSI(-2)*, *CONCON(-1)* and *CRISIS*. The regressions are all from January 2005 to December 2015 on a monthly basis, except for NAREIT Healthcare this regression is from January 2007 to December 2017. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level. Furthermore, granger causality x^2 with its p-probability is given. Only the outcome from the REIT equation in the VAR system is reported.

2.6 Robustness

As the results are highly sensitive to the lag-length specification, robustness can be tested using different lengths of lag, according to Walker (2016). Therefore, the *main model* was run, gradually increasing the number of lags to 8. The main finding of this paper is thus confirmed. Looking at Table 2.5, as in all lag specifications, the generated newspaper sentiment granger-causes REIT prices. More importantly, the time linkage of the real estate sentiment quotient is confirmed for all model variations; as $SQ\_ RE_{t-3}$ and $SQ\_ RE_{t-4}$ remain significant.

Furthermore, to test whether the results are dependent solely on outliers, the FTSE EPRA/NAREIT Index is winsorized at the 1% level and afterwards included in the *main model*. The results show that this does not change the main findings. As a further robustness check, the real estate-related media sentiment was replaced with established stock market sentiment indicators of individual and institutional investors – American Association of Individual Investors (*AAII*) and Investors Intelligence (*II*). Referring to the abovementioned REIT literature, one would expect either a weak or no long-term impact at all of a stock market sentiment indicator on REIT returns. Contrary to the real estate media sentiment, neither *AAII* nor *II* have a significant relationship with the REIT market.

As a final robustness check, a falsification test was applied, to establish whether a significant relationship could be identified by regressing a new variable that has no theoretical link to the REIT index. Hence, the Dow Jones U.S. Oil and Gas Index (*DJ OIL*) was chosen as a representation of a different market / asset class. As Table 2.5 also shows, no significant relationship was found with any of the media sentiment variables, indicating that the media coverage does not capture an unknown effect. In summary, the tests for robustness support the abovementioned findings.

Table 2.5: Robustness Tests

(1) Robustness of Granger Causality with Varying Lag Length									
	SQ_RE_{t-1}	SQ_RE_{t-2}	SQ_RE_{t-3}	SQ_RE_{t-4}	SQ_RE_{t-5}	SQ_RE_{t-6}	SQ_RE_{t-7}	SQ_RE_{t-8}	x^2
Modell w/ 5 lags	0.1135	0.1177	0.2287***	0.2475***	0.0924				11.9846**
Modell w/ 6 lags	0.0884	0.0937	0.2325**	0.2527***	0.1051	0.0296			11.2841*
Modell w/ 7 lags	0.1029	0.1231	0.2786***	0.2825***	0.1304	0.0528	0.0272		12.4307*
Modell w/ 8 lags	0.1060	0.1395	0.3033***	0.2796**	0.1009	0.0163	0.0267	-0.0747	14.2503*
(2) Winzorising FTSE NAREIT 1%									
	SQ_RE_{t-1}	SQ_RE_{t-2}	SQ_RE_{t-3}	SQ_RE_{t-4}					x^2
NAREIT WIN 99	0.0488	0.0309	0.1234*	0.1575***					7.8890*
(3) Testing the REIT Model with different Stock Market Sentiment Indices									
Institutional Investor Sentiment	II_{t-1}	II_{t-2}	II_{t-3}	II_{t-4}					x^2
II_bearish	-0.0048	0.0546	-0.0787	-0.0023					1.9456
II_bullish	0.0066	-0.0667	0.0088	-0.0058					1.4357
Individual Investor Sentiment	$AAII_{t-1}$	$AAII_{t-2}$	$AAII_{t-3}$	$AAII_{t-4}$					x^2
AAII_bearish	0.0111	0.0059	0.0078	-0.0183					0.5641
AAII_bullish	-0.0474	-0.0483	-0.0006	0.0332					2.8746
(4) Falsification with Variable not theoretically linked to REIT market: Dow Jones U.S. Oil and Gas Index									
	$SQ\ RE_{t-1}$	$SQ\ RE_{t-2}$	$SQ\ RE_{t-3}$	$SQ\ RE_{t-4}$					x^2
DJ OIL	0.0713	0.0707	-0.1050	-0.0601					5.8741

Notes: The table shows the coefficients for our robustness checks (1) - (4). The lag length was based on AIC, BC and HQ criterion. *SQ* is the Sentiment Quotient. RE stands for the usage of the real estate dictionary. All regressions were run with the total set of control variables including: *SP500*, *ADSI(-2)*, *DISPOSINC(-4)*, *CCRSI(-2)*, *CONCON(-1)* and *CRISIS*. The regression is based on 127 observations from January 2005 to December 2015 on a monthly basis. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level. Furthermore, granger causality x^2 with its p-probability is given.

2.7 Conclusion

This paper was designed to systematically examine the relationship between news media sentiment, extracted through textual analysis from newspaper articles, and the securitized real estate market from 2005 to 2015. It contributes not only to the contemporary literature on textual analysis, but at the same time, adds to the growing research on sentiment analysis in the context of REIT models. Investigating about 125,000 U.S. news-media article headlines from *Bloomberg*, *The Financial Times*, *Forbes* and *The Wall Street Journal* with a dictionary-based approach, different measures of sentiment were created. Using a vector autoregressive framework, significant evidence of a positive relationship between media-expressed sentiment and future REIT market movements is found. More precisely, the results suggest a leading relationship of the derived real estate media sentiment by three to four months. Hence, sentiment seems to be one explanation for prices deviating from fundamentals. Consequently, this study demonstrated for the first time, that textual analysis is able to capture media-expressed sentiment on the U.S. REIT market. Applying the dictionary-based approach for textual analysis, the results show that a domain-specific dictionary is superior to a general one. In addition, different measures of sentiment were created. Better results were achieved by the sentiment measure incorporating both, positive and negative sentiment, rather than just one polarity.

The significant constant relationship found, indicates that both positive and negative changes in real estate media sentiment induces upward and downward pressure on REIT returns three to four months later. Individuals' thinking processes are not altered after reading a few positive / negative articles about a certain topic, rather it might take time and further information to change an opinion. The time interval between publication of news and the changes in REIT returns gives investors the chance to change their portfolio orientation and reallocate it accordingly. In connection with fundamentals of the REIT market, the findings can be utilized to further improve the understanding of the securitized real estate market. Gaining further insights can assist to make better allocation decisions that lead to higher returns in the future. Another aspect considering today's global economy is the avoidance of financial crises like in 2008 with new insights into market behaviour.

The findings of this paper are in accordance with current behavioural finance and investor sentiment theory, establishing that investors' decisions are influenced by whether they feel optimistic or pessimistic about future market changes. Going one step further, and comparing the results to Ling et al. (2014), who found a positive relation between investor sentiment and the following quarter returns in direct real estate markets, the theory of *style investing* can legitimately be encouraged. Taken together, one can argue that there is such a thing as media-expressed real estate sentiment. This does not conflict with other research findings, which showed that there is a correlation between REIT market changes and the stock market. Two sentiment effects might occur within different periods; sentiment present in the stock market might influence REIT prices in the short run, and real estate-related sentiment more in the long term.

The average institutional ownership rate of U.S. REITs steadily increased over the last decade (Devos et al. 2013). Financial professionals manage the investments of institutional investors. Hence, for future research, it might be interesting to examine news feeds, which provide information in real time about the REIT sector and are not accessible to everyone. An information asymmetry might be ascertained.

Considering the bigger picture, this study highlights the importance of paying sufficient attention to new media and digitalization. The information behaviour of society is changing due to new possibilities; everybody can inform themselves about everything, everywhere in the world, and within minutes. This project is only a first step and is intended to encourage research to remain abreast of the rapid changes occurring over the last decade and which will surely continue into the future. Future research in this field of analysis could think about separating different forms of articles. There might be news categories including more sentiment than others do. Furthermore, it would be interesting to find a way to filter and exclude news, which are likely to be influenced by certain market participants for their purposes. For example, there are press releases from companies which shall, needless to say, influence other market participants to think more positive about the company's future.

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3. On the Relationship Between Market Sentiment and Commercial Real Estate Performance – A Textual Analysis Examination

Abstract

We examine *whether* and the *extent to which* news-based sentiment, captured by textual analysis, can predict the performance of the direct commercial real estate market in the United States. Our results show that sentiment reflected in news abstracts of the *Wall Street Journal* predicts returns of commercial real estate two to three quarters in advance. These findings are statistically significant and persist even when controlling for other related factors. This suggests that news-based sentiment can serve as an early market indicator. This paper is the first to examine the bi-directional relationship between sentiment, measured by textual analysis, and the performance of the direct U.S. commercial real estate market. The findings presented in this paper not only contribute to the academic literature, but also carry practical implications for real estate professionals.

3.1 Introduction

Empirical evidence by Baker and Wurgler (2007) as well as Seiler et al. (2012) suggests that real estate investors bear not only economic, but also emotional factors in mind when making real estate investment decisions. A variety of other studies also show that economic fundamentals do not account for all observed price changes in commercial or residential real estate markets and much of the expectations about future cash flow are tied to information that is related to other factors (Shiller, 2007; Clayton et al., 2009; Ling et al., 2014). That said, only limited academic research directly investigates the role of sentiment in the commercial real estate (CRE) markets. In this study, we look to address this underexplored topic and examine the bi-directional relationship between sentiment and market returns of the direct CRE in the U.S.. We do so by analyzing real estate sentiment gathered from news data of a leading financial newspaper in the U.S., which is a new source of sentiment to be used for this type of analysis.

The direct CRE suffers from several obvious market inefficiencies. Compared with the securitized real estate markets, the transparency of the direct CRE market is limited, causing asymmetric information situations to be more frequent. All else equal, asymmetric information leads to high information and transaction costs, which results in a less efficient market, overall. The heterogeneity of properties and the lengthy decision-making and transaction processes provide additional challenges to investors. Therefore, it is reasonable to expect that investors in direct CRE market are especially vulnerable to the influence of sentiments and opinions expressed in the news items that they consume. The tendency of the direct CRE to adjust slower to new information and its vulnerability to non-economic fundamentals makes it particularly worth examining under the light of textual sentiment analysis.

In this study, we gather more than 65,000 real-estate related news articles from *The Wall Street Journal (WSJ),* spanning the 2001 through 2016 time period, and analyze them in order to detect real-estate related sentiment. Specifically, a dictionary-based textual analysis approach is used to quantify the level of optimism and pessimism expressed through the abstracts of these articles. The intertemporal links between this sentiment and the direct CRE market over the 16-year sample period are then examined to determine whether media-expressed real estate sentiment can help predict direct CRE returns.

Our findings indeed suggest that sentiment reflected in news articles can help predict returns on the direct CRE market in the U.S. even after controlling for other macroeconomic factors. On average, our measure for media-expressed sentiment leads total returns on direct CRE properties by two to three quarters. Additionally, we also provide some evidence for a feedback loop, where information on the performance of direct CRE is reflected in future textual media-expressed sentiment.

This study contributes to the existing literature by being the first to employ a real estate specific word dictionary to construct a real estate sentiment measure and determine whether and the extent to which such measure can help predict direct CRE returns. More broadly, the results reported in this paper can be generalized to other less efficient asset classes.

The rest of this paper is organized as follows. In Section 3.2, we discuss the importance of sentiment in CRE markets and review relevant literature on investors' sentiment and textual analysis in the realm of real estate research. Section 3.3 presents the data set employed in this paper as well as a description of the sentiment-extraction procedure. In Section 3.4, we detail the methodology used for the analysis and present the hypotheses. Sections 3.5 and 3.6 report the results and assess their robustness, while section 3.7 concludes and discusses the implications of the findings.

3.2 Literature Review

This study relates to two separate streams of literature. The first stream is the role of investors' sentiment with respect to the commercial real estate markets and its performance. The second stream refer to the textual analysis methodology used in this paper and the most recent developments in text-based sentiment measures in the realm of real estate.

3.2.1 Investors' Sentiment and Commercial Real Estate

Investors' sentiment is often measured directly or indirectly using two types of proxies. The most common direct measure approach is survey-based, such as the *Real Estate Research Corporation* sentiment measure that is employed in a few recent studies (Clayton et al., 2009; Das et al., 2015; Freybote, 2016). While claiming to capture investors' sentiment directly, survey-based indicators, by their very nature, are associated with several material disadvantages. The surveys are not only costly and time consuming, but are also subject to the possibility that the answers provided by the respondents do not reflect their true sentiment. This might be due to the fact that respondents are not incentivized to take the surveys seriously or intentionally do not provide accurate and honest answers.

Indirect sentiment measures do not usually suffer from the disadvantages associated with the direct measures, because they are proxied by the actual behavior of market participants, which is fundamentally incentivized. These measures include, for example, closed-end fund discounts (Barkham and Ward, 1999; Clayton and MacKinnon, 2003), buy-sell-imbalances (Freybote and Seagraves, 2016), mortgage fund flows (Clayton et al., 2009; Ling et al., 2014) or search engine volumes and trends (Beracha and Wintoki, 2013).

While many studies have examined the role of sentiment with relation to the residential real estate market[6], only a few studies have sought to investigate how investors' sentiment is related to the performance of direct CRE. Three recent studies that identify the relationship between sentiment and CRE performance in the U.S. are closely related to this study. Clayton et al. (2009) analyzed the impact of fundamentals and their sentiment index – constructed from sentiment-related proxies – on CRE values over the 1997 – 2007 time period. Their results suggest that investors' sentiment does play a role in CRE pricing at the national as well as MSA-level and is robust to relevant macroeconomic factors. Similarly, Ling et al. (2014) examined the relationship between investor sentiment – measured via direct and indirect real estate sentiment measures – and direct as well as securitized CRE market returns over the 1992 – 2009 period. Using VAR models, the authors provide evidence for a positive relation between investor sentiment and direct market performance in subsequent quarters. However, the relationship between investor sentiment and public real estate market returns in subsequent periods was negative. The authors supported their findings with the argument that, in the short term, sentiment drives prices away from fundamentals, i.e. causes sentiment-induced mispricing. Furthermore, assessing various survey-based sentiment measures, their study concluded that real-estate-specific sentiment measures are of high importance, when quantifying the influence of sentiment on real estate. The third related study is by Tsolacos et al. (2014). Their study deploys a probit and Markov-switching model to predict rental growth in CRE

[6] See e.g. Marcato and Nanda's (2016) recent article in the *Journal of Real Estate Research* for a comprehensive analysis of sentiment indicators with respect to the U.S. housing market.

and apartment rent series in the U.S.. The authors illustrate the prediction power of several sentiment-based leading indicators on commercial rent price movements.

Each of the above-mentioned studies contributes to our knowledge on investors' sentiment and CRE performance, but is also associated with its respective drawbacks. Specifically, these studies ignore the impact of other unperceived, but valuable, factors on investors' decision-making processes. For example, Price et al. (2017) showed that executive emotions during earnings conference calls are positively related to investors' initial reactions. Analyzing the vocal cues of managers with a voice analysis software revealed that investors do indeed react to this emotionally charged information. Similarly, professional news outlets publish daily thousands of news articles on the real estate market. These publications range from reports and opinions to views and perspectives and are likely to, consciously or unconsciously, influence investors' action and, by extension, CRE performance.

In this study, we exploit this valuable source of information by applying textual analysis to published real estate news articles. This approach has already been applied in mainstream finance, but should be even more relevant to the direct CRE market, which is arguably less efficient compared with the public market for common stocks. Section 3.2.2 provides a concise overview of related research using textual analysis conducted to date.

3.2.2 Sentiment Measure Using Textual Analysis

In the finance literature, Tetlock (2007) is regarded as one of the pioneers in applying textual analysis in order to capture market sentiment. Tetlock employs a sentiment dictionary on the 'Abreast of the Market' column of the *Wall Street Journal* and successfully shows a relationship between pessimism reflected in news items and price changes of the Dow Jones Industrial Average Index, as well as its trading volume. A few other studies followed with a similar methodology and facilitated dictionary-based approaches using sentiment-annotated word-lists in order to extract sentiment from news items (e.g. Henry and Leone, 2010; Feldman et al., 2010; Davis et al., 2012). While Tetlock (2007) uses the Harvard GI word list from the field of psychology, Loughran and McDonald (2011) set a further cornerstone by highlighting the importance of a domain-specific dictionary. The authors develop a dictionary relevant to financial text corpora, which Boudoukh et al. (2013) and Heston and Sinha (2016) successfully utilize in their research.

Recently, a few studies examine the impact of sentiment extracted from text corpora in the context of real estate. Soo (2013) investigates the sentiment expressed in 37,500 local housing news articles of 34 U.S. cities in order to predict future house prices. The author finds that the measured sentiment has predictability power and leads housing price movements by more than two years. Walker (2014) illustrates a material positive relationship between newspaper articles in the *Financial Times* and returns of listed companies engaged in the UK housing market. In accordance with his earlier findings, Walker (2016) subsequently analyzes the direct housing market in the UK, and ascertains that news media granger-caused real house price changes from 1993 to 2008.

This paper aims to fill a gap in the literature and examines the relationship between text-based sentiment and the performance of direct CRE in the U.S. rather than the housing market or foreign publicly traded real estate firms. Investigating sentiment in the context of the direct CRE market, which is expected to be less efficient than the public market, provides a meaningful contribution to the literature and the results can be generalized to other less efficient markets.

3.3 Data

The dataset complied for the empirical analysis conducted in this study is based on three main sources: (1) a news media corpus to extract sentiment, (2) U.S. commercial real estate market performance and (3) general macroeconomic factors.

3.3.1 News Data

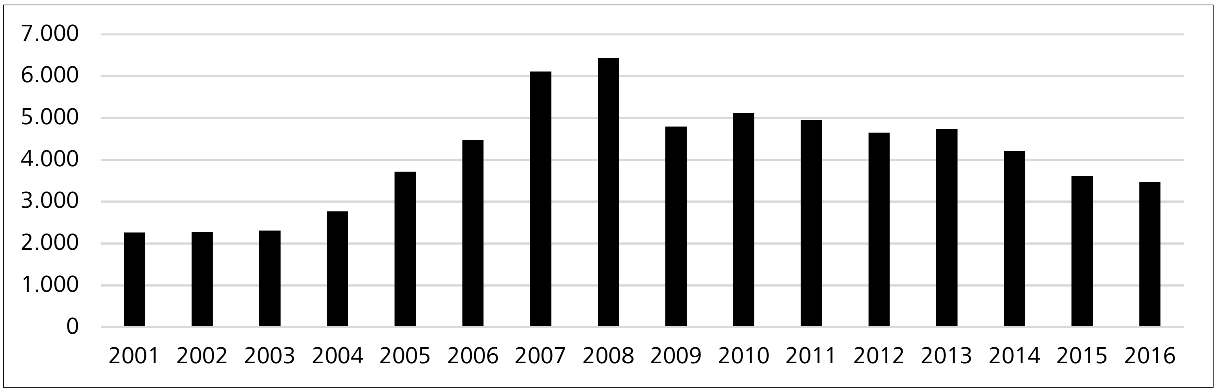
Our news data source used for the analysis in this study is *The Wall Street Journal*. Founded in New York City in 1889, the WSJ is nowadays the largest newspaper in the U.S. in terms of its daily circulation.[7] Nationally and internationally, the *WSJ* is considered by many as one of the leading sources of business and financial news and it includes a dedicated real estate section. The *WSJ* has a broad readership, ranging from retail to institutional investors as well as managers and real estate professionals. Given its corporate news, political and economic reporting as well as its financial and real estate market coverage, the *WSJ* is of great importance to the CRE market. Although Tetlock (2007) pioneered textual analysis based on the 'Abreast of the Market' column of the *WSJ* in mainstream finance, the real estate literature still lacks an attempt to capture its sentiment.

Considering the aforementioned aspects, we use news items from the *WSJ* to capture and quantify media-expressed sentiment concerning the direct CRE market. Specifically, via *ProQuest* (www.proquest.com), we accessed *WSJ*'s digital archive of the period that spans January 2001 until December 2016 and retrieved articles containing either the keywords 'real estate', 'REIT' or 'housing'. This 16-year period is a representative and worthwhile time span as it contains the real estate boom market phase until 2007, the real estate bust and the global financial crisis (GFC) from 2007 to 2010, as well as the subsequent recovery market phase from 2011. We further limited the data queries geographically to the U.S. and to news reported in the English language. Over the sample period, the *WSJ* published 65,870 real estate-related news, which – on average – translates to more than 1,000 news items per calendar quarter. It is worth mentioning, that we exclusively analyze the abstracts of the newspaper articles. We assume, that these abstracts contain all relevant information of the articles themselves but exclude noise in terms of irrelevant words and additional information, which are not necessary in order to capture the 'tone' or sentiment expressed.

Figure 3.1 shows the annual number of real estate-related news published by the *WSJ* over the sample's 16-year time period that spans 2001 to 2016. The graph depicts a significant increase in news coverage during the boom market phase starting with around 2,762 news in 2004 and ending with 6,108 articles in 2007. During the real estate bust period, the amount of articles reached its peak with 6,440 news items released in 2008 and then gradually declined. 3,462 news items were included in 2016, which is still above the average number of articles during the pre-crisis period. This general increase in real estate news coverage may suggests an overall rise of attention for real estate as an asset class.

[7] According to the WSJ's June 2017 10-K Filing, it had a paid circulation of more than 2.2 million subscribers whereof more than 50% were digital subscriptions.

Figure 3.1: WSJ Real Estate News Coverage



Notes: This figure plots the sample distribution with respect to the number of real-estate related news published by the *WSJ* per annum. All *WSJ* news were retrieved using *ProQuest*; retrieving articles containing the keywords 'real estate', 'REIT' or 'housing'. The sample period is 2001:Q1 to 2016:Q4.

3.3.2 Sentiment Measures Construction

To extract the sentiment from news abstracts, a dictionary-based sentiment classifier is used. Hence, we compare a pre-defined sentiment dicti onary i.e. a word list annotated by sentiments such as positive or negative to every single news item and aggregate the sentiment of the identified words. This allows us to measure the overall 'tone' of the abstracts.

Following Loughran and McDonald (2011), we apply a domain-specific dictionary by extending their pure finance dictionary to real estate specific terms. In the end, our word list contains 408 positive and 2,455 negative terms. To ease the process of sentiment extraction, words in the dictionary and in the news abstracts are pre-processed, i.e. converted in well-defined sequences of linguistically meaningful units following Uysal and Gunal (2014).[8]

For every abstract, we count positive and negative words. Hereby, each positive word is counted as a '+1' and each negative word as a '-1'. Because the sentiment dictionary does not consist of an equal number of positive and negative words, positive scores are multiplied by the inverse of the total number of positive terms divided by the total number of negative words in the dictionary. This calibrates the likelihood of that positive and negative words have similar impact on total count. This procedure allows us to calculate the overall sentiment score of each abstract by addition of the numeric values from the positive and negative words. An abstract can be viewed as positive, if the sentiment score is greater or equal to 1, negative if the sentiment score is smaller or equal to -1, and neutral if it is 0.

Subsequently, all positive, negative and neutral abstracts are added up for a defined period in order to arrive with a total periodic score of the positive, negative and neutral categories, respectively. This value is calculated on an absolute or weighted basis. The absolute basis only considers the raw number of positive and negative news items. For example, if there are 56 positive abstracts published during a given period, the positive periodic score for that period would simply be 56. On the other hand, the weighted approach uses the actual sentiment scores assigned to every abstract. This means that two negative abstracts with a score of '-5' and '-2' are added up for a score of '-

[8] For more details on this process, please see the technical appendix.

7'. This periodical aggregation of sentiment scores further allows us to generate a sentiment measure for every period during our sample period.

Using the absolute and the weighted sentiment measures, we calculate a Positive-Negative-Ratio *(PNR)* for each period. This ratio expresses the amount of positive sentiment relative to total amount of negative sentiment. A higher ratio suggests a more positive sentiment and a lower ratio suggests a more negative sentiment with respect to the commercial real estate market. More formally, the *PNR* is calculated as the following:

Equation 3.1: Sentiment Measure – Positive-Negative-Ratio (PNR)

$$PNR_t = \frac{\sum_1^I positive\ Sentiment\ Score_{i,t}}{|\sum_1^J negative\ Sentiment\ Score_{i,t}|} \tag{1}$$

where *i* and *j* represent the abstracts with positive and negative scores respectively and *t* is the time period during which the published abstracts are accounted for. We calculate this ratio on an absolute as well as a weighted basis.

3.3.3 Other Data

The data on the performance of the direct CRE market in the U.S. used in this paper is the NPI series extracted from the *National Council of Real Estate Investment Fiduciaries (NCREIF)*. The NPI is an unleveraged total return index for direct CRE properties held by contributing institutional investors. Published with quarterly frequency since 1977, the NPI is transaction-based where each property's performance is weighted by its market value. Though it is available for different property types, we use the national composite NPI to measure total returns of the direct U.S. CRE market, incorporating all relevant property types i.e. apartments, hotels, industrial, office and retail.

To control for economic factors that are likely to affect CRE returns, we follow Clayton et al. (2009) and Ling et al. (2014) and include in our dataset macroeconomic variables proven to affect CRE returns. These variables include: the term structure of interest rates (defined as the spread between the ten-year U.S. Treasury Constant Maturity rate and the 3-Month Treasury Bill yield), the percentage change in the Consumer Price Index (CPI) and the spread between BAA- and AAA-rated corporate bonds yields. We obtained all these economic variables from the *Federal Reserve Bank of St. Louis* with quarterly frequency.

Table 3.1 provides descriptive statistics about the quarterly NPI total returns (*NPI*), absolute and weighted Positive-Negative-Ratios (*PNR_A* and *PNR_W*) and our macroeconomic control variables. For each variable, we report the mean, median, standard deviation, minimum and maximum. The average quarterly total returns of the direct CRE during our sample period is 2.19% and ranges between -8.40% to 5.49% given the high volatility during the boom and bust phases that are part of our sample period. For robustness, in our analysis we also consider the annual NPI total returns to smooth out potential quarterly measurement errors and noise. The average *PNR_W* value (7.31) is more than three times of the *PNR_A* value (2.25), which depicts the importance of distinguishing between the two measures and sheds light on the strength of the respective sentiment.

Table 3.1: Descriptive Statistics

	Mean	Median	SD	Min	Max
NPI (%)	2.19	2.68	2.55	-8.40	5.49
PNR_A	2.25	1.55	1.12	0.99	4.58
PNR_W	7.31	5.07	4.10	2.37	16.59
INFLATION (%)	0.52	0.58	1.02	-3.91	2.48
TERM (%)	2.09	2.15	1.01	-0.29	3.80
SPREAD (%)	1.10	0.98	0.45	0.55	3.38

Notes: This table reports summary statistics of variables used in the analysis on a quarterly basis. *NPI* is the total return of the NPI. *PNR_A* and *PNR_W* are the absolute and weighted Positive-Negative-Ratio sentiment measures, respectively. *INFLATION* is the percentage change of the Consumer Price Index (CPI). *TERM* is the spread between the ten-year U.S. Treasury Bond and the 3-Month Treasury Bill yields. *SPREAD* is the spread between BAA- and AAA-rated corporate bonds yields. The sample period is 2001:Q1 to 2016:Q4.

3.4 Methodology and Hypothesis Formation

3.4.1 Visual and Correlation Analysis

As our preliminary visual analysis, we plot the media-expressed sentiment measures against the returns of the direct CRE market. Specifically, we plot the deviation of the sentiment measure from its 1-year moving average relative to the quarterly CRE total returns. This type of plot would illustrate the general relationship between changes in market sentiment and CRE returns and highlight whether market sentiment leads or lags returns. Additionally, we calculate the respective correlations between our quarterly sentiment values and CRE quarterly and annual returns.

3.4.2 Regression Analysis

We begin our empirical analysis by investigating the ability of real-estate related sentiment, expressed in the news, to predict total returns on the direct CRE market in the U.S.. To do so, we regress the NPI total return on the lagged absolute and weighted Positive-Negative-Ratios. By regressing CRE returns on our lagged media-expressed sentiment values, we test the hypothesis that market sentiment predicts future returns of the direct CRE market.

Hypothesis 1*:* Real estate market sentiment predicts future returns of the direct CRE market.

In addition to lagged media-expressed real estate sentiment, the regression specifications also control for other relevant macroeconomic variables proven to affect CRE market returns (e.g. Clayton et al., 2009; Ling et al., 2014). Controlling for the term structure of interest rates is relevant because it is related to commercial real estate financing cost and expectations of future economic developments. Accounting for the percentage changes in the Consumer Price Index (CPI) is important because many commercial rental contracts are linked to inflation and therefore affects future returns. The spread between BAA- and AAA-rated corporate bonds yields reflects the overall business conditions and general default risk in the economy. Finally, we include a dummy variable to control for any factors associated with the global financial crisis (GFC) from 2007:Q3 to 2008:Q4. Autocorrelation and heteroscedasticity issues are accounted for by using Newey and West (1987) robust standard errors.

Formally, we estimate the following equation:

Equation 3.2: Linear Regression Model

$$\Delta NPI_t = c + \sum_{i=2}^{i=5} \propto_i * (\Delta PNR_{t-i}) + \beta_1 * (\Delta INFL_t) + \beta_2 * (\Delta TERM_t) + \beta_3 * (\Delta SPREAD_t) + GFC_t + \varepsilon_t \quad (2)$$

where NPI_t is the total return during quarter t; PNR_{t-i} is the Positive-Negative-Ratio to measure media-expressed sentiment with i quarterly lags; $INFL_t$ is the inflation rate, $TERM_t$ the interest term structure and $SPREAD_t$ the spread between BAA and AAA- rated corporate bonds. GFC is a dummy variable to indicate the global financial crisis and ε_t represents the error term. Except of the crisis dummy, all variables are applied in first differences to ensure stationarity. The first lag included in Equation 3.2 is t-2. t-1 is omitted from the regression because we assume that even if the effect of media-expressed sentiment is immediate, it would still take at least one quarter for this information to be reflected in CRE prices, given the time required for due diligence and other transaction related delays.

3.4.3 Vector Autoregressive Analysis

The multiple linear regression model described above estimates the value of the dependent variable (*NPI*) using several, supposedly independent, variables. However, it could be presumed that our media-expressed sentiment measures also contain information about past CRE market performance. Consequently, we examine the bi-directional relationship between media-expressed sentiment and the performance of the direct U.S. CRE market using a Vector Autoregressive (VAR) framework. According to this model, each variable is a linear function of lags of itself and lags of other variables. Hence, the VAR model allows us to estimate the intertemporal links between media-expressed sentiment and the direct CRE market and address the potential endogeneity problem. Furthermore, the VAR model enables us to analyze whether the media-expressed sentiment predicts returns on direct CRE, even when controlling for the lags of the *NPI* itself, which is shown to contain momentum (Beracha and Downs, 2015). Formally, the VAR model used in our analysis is specified as the following:

Equation 3.3: VAR Model

$$\begin{aligned} \Delta NPI_t &= \alpha_1 + \sum_{i=2}^{i=5} \beta_{1i} * (\Delta NPI_{t-i}) + \sum_{i=2}^{i=5} \gamma_{1i} * (\Delta PNR_{t-i}) + \delta_1 * (\Delta Exog_t) + \varepsilon_{1t} \\ \Delta PNR_t &= \alpha_2 + \sum_{i=2}^{i=5} \beta_{2i} * (\Delta PNR_{t-i}) + \sum_{i=2}^{i=5} \gamma_{2i} * (\Delta NPI_{t-i}) + \delta_2 * (\Delta Exog_t) + \varepsilon_{2t} \end{aligned} \tag{3}$$

The variables are as described above and defined in Equation 3.2. Note that for brevity all control variables ($INFL_t$, $TERM_t$, $SPREAD_t$ and $CRISIS$) are summarized in $Exog_t$. ε_{1t} and ε_{2t} are error terms. The endogenous variables are quarterly *NPI* returns (NPI_{t-i}) and the media-expressed sentiment (*PNR_A* or *PNR_W*). We include lags up to t-5 based on the Akaike Information Criteria (AIC) for various choices of the lag length *p.* Consistent with our OLS model, we assume that it takes at least one quarter for information in the news to reach direct CRE markets and trickle from the decision making process to execution. Hence, we exclude the first lag from our analysis. Applying the Augmented-Dickey-Fully unit root test suggests using first differences of all variables to ensure stationarity.

3.4.4 Granger Causality Tests

We further examine the bi-directional relationship between media-expressed sentiment and CRE returns, by conducting pairwise Granger-causality tests (Granger, 1969). This type of analysis helps us better understand the lead-lag relationships between sentiment in real estate related news and the direct CRE market. We hypothesize that media-expressed sentiment drives total returns of the direct CRE market but not the other way around. We base our hypothesis on evidence from the literature that the CRE market is not fully efficient and is slow to react to new market information. Formally, our hypothesis is stated as the following:

Hypothesis 2*:* Media-expressed sentiment predicts future returns of direct commercial real estate, but returns on direct commercial real estate do not predict future media-expressed sentiment.

Formally, the model for testing Granger-causality between real estate market sentiment and returns is defined as follows:

Equation 3.4: Granger Causality Test

$$\Delta NPI_t = \propto_0 + \sum_{i=2}^{i=5} \beta_i * (\Delta NPI_{t-i}) + \sum_{i=2}^{i=5} \gamma_i * (\Delta PNR_{t-i}) + \delta_1 * (Exog_t) + \varepsilon_t \tag{4}$$

$$\Delta PNR_t = \propto_0 + \sum_{i=2}^{i=5} \beta_i * (\Delta PNR_{t-i}) + \sum_{i=2}^{i=5} \gamma_i * (\Delta NPI_{t-i}) + \delta_1 * (Exog_t) + \varepsilon_t \tag{5}$$

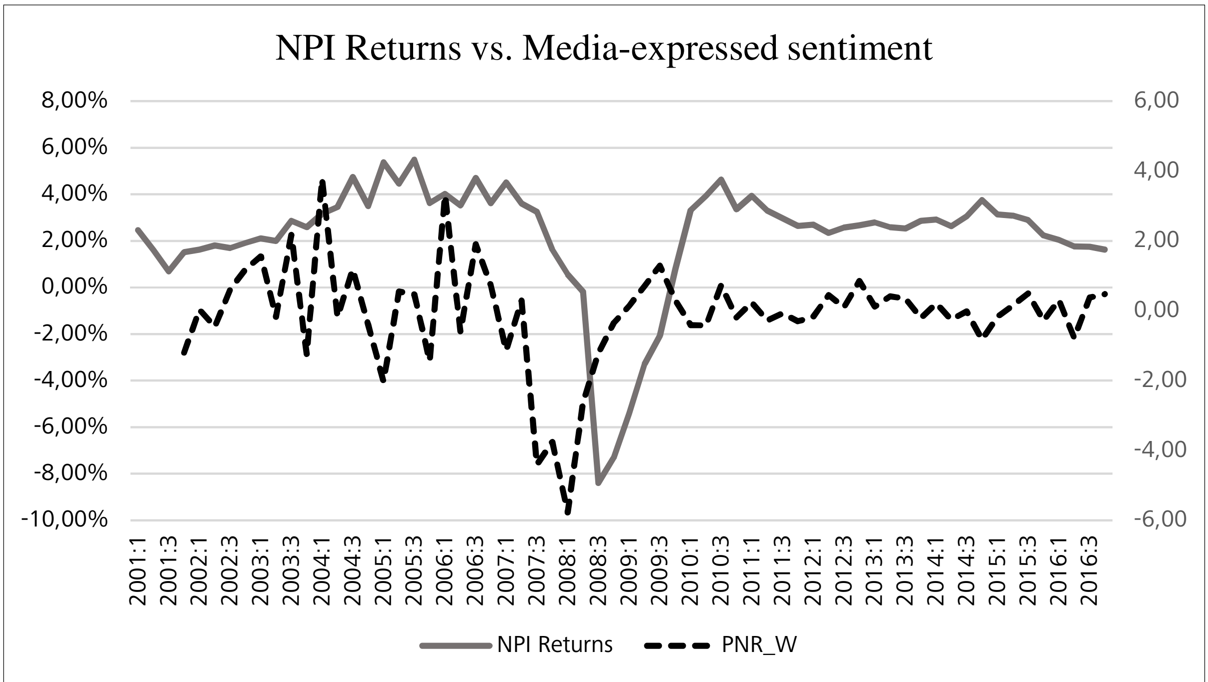
The variables included in Equation 3.4 are as described and defined earlier in the text. Consistent with our previous models, we conduct the tests for 2 to 5 lags and report the X^2 (Wald) statistics for the joint significance of each of the other lagged endogenous variables in both equations.

3.5 Results

3.5.1 Visual and Correlation Results

Figure 3.2 provides visual illustration of the relationship between our weighted media-expressed sentiment measure (*PNR_W*) and the returns on the direct CRE market.[9] A glance at the figure reveals that the two variables are correlated and that *PNR_W* seems to lead the direct CRE market returns. For example, a substantial drop in sentiment occurred late 2007 and early 2008 and was followed by meaningful negative returns in the CRE market. More specifically, the *PNR_W* drops from 0.29 in 2007:Q2 to -5.78 in 2008:Q1 and *NPI* total return bottomed in 2008:Q3 (-8.40%). Similarly, the sentiment seems to also be a leading indicator in periods of recovery and expansion. Following the drop in real estate market sentiment the measure improved from 2008:Q1 to 2009:Q3 while returns on the direct CRE market gradually recovered from 2008:Q3 to 2010:Q3. That said, the relationship in pre-crisis years is less clear as the sentiment measures show a high level of fluctuation relative to the performance of the CRE market.

Figure 3.2: Direct Commercial Real Estate Returns and Media-Expressed Sentiment



Notes: This figure plots levels of real estate media-expressed sentiment and the total returns on the CRE market. The media-expressed sentiment is quantified using the weighted Positive-Negative-Ratio (*PNR_W*) measure described in the text. The sentiment is plotted based on the difference between current PNR (PNR_W_t) and the simple average of the weighted PNR of the last 4 quarters (PNR_{t-1} to PNR_{t-4}). The sample period is 2001:Q1 to 2016:Q4.

Table 3.2 presents the correlations between the level and change in media-expressed sentiment (*PNR_A* and *PNR_W*) and direct CRE returns (*NPI*). Returns based on the *NPI* are calculated on a quarterly as well as annual basis. When the level of media-expressed sentiment is considered, the correlations between the *PNR_A* and *PNR_W* and the quarterly *NPI* are positive with the second quarterly lag and gradually dissipate through the fifth lag. The correlation results for the annual *NPI*

[9] A figure using our absolute sentiment measure was also conducted and appears qualitatively similar. It is omitted from this version of the paper for brevity.

behave in a similar manner, but dissipates more quickly, which is expected given that each lag accounts for the four most recent quarters. When the change in media-expressed sentiment is considered, the correlations of the *PNR_A* and *PNR_W* and the quarterly *NPI* are mostly positive in the early lags, but volatile. On the other hand, the correlations with the annual NPI are positive in the second lag and dissipates gradually. Overall, the results presented in Table 3.2 reveal that quarterly and annual returns on CRE are correlated with the level and the change in the level of past media expressed real estate sentiment.

Table 3.2: Correlations – Sentiment and Direct CRE Market

	NPI (quarterly)		*NPI (annual)*	
	Level	Change in level	Level	Change in level
PNR_A_{t-2}	0.40	0.49	0.24	0.17
PNR_A_{t-3}	0.28	-0.03	0.09	0.02
PNR_A_{t-4}	0.16	0.25	-0.06	-0.11
PNR_A_{t-5}	-0.03	-0.27	-0.20	-0.30
PNR_W_{t-2}	0.44	0.41	0.27	0.17
PNR_W_{t-3}	0.32	-0.07	0.11	0.07
PNR_W_{t-4}	0.21	0.45	-0.06	-0.03
PNR_W_{t-5}	-0.02	-0.38	-0.24	-0.31

Notes: This table reports the correlations between the level and change in level for lags 2 to 5 of the absolute and weighted Positive-Negative-Ratio (*PNR_A* and *PNR_W*) and the quarterly and annual CRE returns (NPI). The sample period is 2001:Q1 to 2016:Q4.

3.5.2 Regression Analysis Results

Table 3.3 presents the results of several regressions specifications as per Equation 3.2. Specifications (I) and (II) examine the ability of our absolute media-expressed sentiment measure to predict quarterly CRE returns with and without our macroeconomic control variables, respectively. When the control variables are excluded, the coefficient of the first two sentiment measure lags are positive and statistically significant at the 5% or 10% level. The coefficients then turn insignificant for the following lag. However, when the control variables are included only the first sentiment measure lag is statistically significant with the expected sign. Specifications (III) and (IV) repeat the analysis from specifications (I) and (II), but with our weighted rather than absolute media-expressed sentiment measure. In both specifications, regardless of whether the control variables are included, the first two sentiment measure lags are positive and statistically significant at the 1% or 5% level. The next lag (t-4) remains positive, but statistically insignificant, and the last lag (t-5) turns negative with statistical significance. The negative sign of the fifth lag in specifications (I) to (IV) may indicate a potential reversal or correction effect of the media-expressed sentiment. Moreover, the adjusted R^2 for specifications (III) and (IV) are materially larger than the R^2 in the specifications where the absolute measure is employed (over 50% compared with about 35%).

Table 3.3: Regression Results – Predicting Quarterly NPI Returns Using Media-Expressed Sentiment

	Regressand: NPI (quarterly)			
	Absolute PNR		*Weighted PNR*	
	(I)	*(II)*	*(III)*	*(IV)*
PNR_{t-2}	0.017**	0.015*	0.005***	0.005***
PNR_{t-3}	0.010*	0.005	0.004***	0.004**
PNR_{t-4}	0.003	0.000	0.002	0.002
PNR_{t-5}	-0.009*	-0.008*	-0.004***	-0.004***
INFLATION		0.272*		0.138
TERM		0.119		0.131
SPREAD		0.462		0.048
GFC		-0.010		0.004
Adj. R^2	0.333	0.357	0.509	0.503
AIC	-5.941	-5.918	-6.248	-6.177

Notes: This table reports the coefficients of the estimated AR models with quarterly *NPI* returns as the dependent variable on the lagged media-expressed sentiment (*PNR*) as well as macroeconomic control variables. The set of control variables in our regression are the CPI growth (*INFLATION*), the spread between the ten-year U.S. Treasury Bond and the 3-Month Treasury Bill yields (*TERM*), the spread between BAA- and AAA-rated corporate bonds yields (*SPREAD*) and a dummy variable that captures the effect of the great financial crisis (*GFC*), which is set to 1 during the 2007:Q3 to 2008:Q4 time period and 0 otherwise. We use Newey and West (1987) standard errors that are robust to heteroscedasticity and autocorrelation. We transformed all variables to their first differences. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level. The sample period is 2001:Q1 to 2016:Q4.

To account for potential measurement errors and noise in the quarterly CRE returns, we repeat the analysis from Table 3.3 with annual CRE returns. The results of this analysis are presented in

Table ***3.4***. Columns (I) and (II) presents the results of the analysis using the absolute media-expressed sentiment measure while columns (III) and (IV) presents the results using the weighted measure. Overall, the results presented in

Table ***3.4*** are more robust than the results presented in the previous table that considered quarterly CRE returns. Specifically, in each of the four specifications, regardless of the media-expressed sentiment measure used (absolute or weighted) or whether control variables are included, the coefficients of the first two lags are positive and statistically significant at the 1% or 5% level. This positive relation dissipates over time and the coefficients of the previous two lags (t-4 and t-5) are no longer positive with statistical significance. Overall, the results of the different specifications presented in Table 3.3 and

Table ***3.4*** suggest that real estate sentiment predicts future returns of direct CRE market and provide support to Hypothesis 1.

Table 3.4: Regression Results – Predicting Annual NPI Returns Using Media-Expressed Sentiment

	Regressand: NPI (annual)			
	Absolute PNR		Weighted PNR	
	(I)	(II)	(III)	(IV)
PNR_{t-2}	0.032**	0.028***	0.012***	0.009***
PNR_{t-3}	0.027***	0.024***	0.010***	0.008***
PNR_{t-4}	-0.002	0.003	-0.001	0.000
PNR_{t-5}	-0.014	-0.010	-0.006**	-0.004
INFLATION		0.189		0.280
TERM		-0.040		-0.301
SPREAD		-1.064		-0.506
GFC		-0.047***		-0.039***
Adj. R^2	0.189	0.412	0.350	0.476
AIC	-4.103	-4.363	-4.326	-4.478

Notes: This table reports the coefficients of the estimated AR models with annual *NPI* returns as the dependent variable on the lagged media-expressed sentiment (*PNR*) as well as macroeconomic control variables. The set of control variables in our regression are the CPI growth (*INFLATION*), the spread between the ten-year U.S. Treasury Bond and the 3-Month Treasury Bill yields (*TERM*), the spread between BAA- and AAA-rated corporate bonds yields (*SPREAD*) and a dummy variable that captures the effect of the great financial crisis (*GFC*), which is set to 1 during the 2007:Q3 to 2008:Q4 time period and 0 otherwise. We use Newey and West (1987) standard errors that are robust to heteroscedasticity and autocorrelation. We transformed all variables to their first differences. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level. The sample period is 2001:Q1 to 2016:Q4.

3.5.3 Vector Autoregressive (VAR) Analysis Results

Table 3.5 reports the VAR estimation outputs as per Equation 3.3. Like in the previous tables, columns (I) and (II) presents the estimation results using the absolute media-expressed sentiment measure and columns (III) and (IV) for the weighted measure. The purpose of this analysis is to examine the ability of media-expressed real estate sentiment to predict the returns of direct CRE while controlling for possible momentum behaviour embedded within CRE returns. Overall, the results presented in Table 3.5 are consistent with the results presented in the previous tables and provide support to Hypothesis 1, showing that real estate sentiment helps predict the returns of the CRE market and that the results of our prior regression models hold within the VAR framework. Moreover, the results suggest that our weighted sentiment measure is better suited, compared with the absolute sentiment measure, as a predictor. Specifically, the coefficients of the first two media-expressed sentiment measure lags are positive and statistically significant when the weighted measure is employed (columns III and IV). These coefficients are positive, but with weaker or no statistical significance at traditional levels when the absolute sentiment measure is employed. The positive statistical significance dissipates after these two lags. These results highlight the importance of a measure that not only accounts for the occurrence of optimism and pessimism in the news, but also its respective intensity. The adjusted R^2 and AIC values in these VAR specifications are also materially higher with the weighted compared to the absolute sentiment measure is used.

Table 3.5*:* VAR Results – Quarterly NPI Returns and Media-Expressed Sentiment

	Dependent variable: NPI (quarterly)			
	(I) *PNR_A*	(II) *PNR_A*	(III) *PNR_W*	(IV) *PNR_W*
	w/o CV	*w/ CV*	*w/o CV*	*w/CV*
NPI_{t-2}	0.061	0.163	0.046	0.022
NPI_{t-3}	0.064	0.055	0.106	0.113
NPI_{t-4}	-0.015	-0.100	-0.007	-0.052
NPI_{t-5}	-0.200***	-0.171**	-0.205*	-0.179***
PNR_{t-2}	0.016*	0.016*	0.004***	0.004***
PNR_{t-3}	0.010*	0.008	0.004***	0.004**
PNR_{t-4}	0.003	-0.001	0.002	0.001
PNR_{t-5}	-0.009	-0.008	-0.004**	-0.004**
Adj. R^2	0.329	0.362	0.521	0.518
AIC	-5.876	-5.887	-6.212	-6.166

Notes: This table reports the estimated coefficients from the VAR models with quarterly NPI total returns (*NPI*) and Positive-Negative-Ratio (PNR) as endogenous variables. The lag length of the VAR is based on the leg-length-criteria test, looking at the AIC, SIC and the likelihood ratio for various choices. The set of the macroeconomic control variables (*CV*) in our regression are the CPI growth (*INFLATION*), the spread between the ten-year U.S. Treasury Bond and the 3-Month Treasury Bill yields (*TERM*), the spread between BAA- and AAA-rated corporate bonds yields (*SPREAD*). We use Newey and West (1987) standard errors that are robust to heteroscedasticity and autocorrelation. We transformed all variables to their first differences. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level. The sample period is 2001:Q1 to 2016:Q4.

3.5.4 Granger Causality Tests Results

Table 3.6 presents the results of our Granger causality tests conducted in order to test the null hypotheses that media-expressed sentiment dos not cause CRE returns and that CRE returns does not cause media expressed sentiment. Specifically, columns (I) and (II) test the null hypothesis that the coefficients of the lagged media-expressed sentiment variables are equal to zero. Conversely, columns (III) and (IV) test the null hypothesis that the coefficients of the lagged CRE return variables are equal to zero.

The results presented in columns (I) and (II) reject the null hypothesis and suggest that there is a significant causality running from media-expressed real estate sentiment (*PNR*) to direct CRE returns (*NPI*). This relationship is statistically significant at a 1% level and holds when control variables are included, regardless of the sentiment measure (absolute or weighted *PNR*). Column (III) and (IV) suggest that the CRE market does not drive media-expressed sentiment when proxied using the PNR sentiment measures. However, when the weighted PNR sentiment measure and macroeconomic controls are used, there is some evidence (with statistical significance at the 5% level) that the returns on CRE Granger causing media-expressed sentiment. Hence, it can be argued that there is some feedback loop between media-expressed sentiment and CRE returns. Overall, real estate related news contain new information and sentiment that may affect CRE returns and the news, at least partially, reflect the sentiment driven by past market performance.

Table 3.6: Granger Causality Test Results

	H_0: Media-expressed sentiment does not cause NPI		H_0: NPI does not cause Media-expressed sentiment	
Sentiment	(I) *Absolute PNR*	(II) *Weighted PNR*	(III) *Absolute PNR*	(IV)*Weighted PNR*
X^2*(w/o CV)*	27.07***	57.47***	4.33	5.50
X^2*(w CV)*	20.39***	41.75***	6.47	10.94**

Notes: This table reports the Granger causality results of the estimated VAR models of specifications (I) to (IV) of Table 3.5. Granger-causality results test the joint significance of all lags for a given variable. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level. The sample period spans 2001:Q1 – 2016:Q4.

3.6 Robustness Checks

The prospect theory presented by Kahneman and Tversky (1979) describes how individuals are more prone to avoid losses than to achieve economic gains. In accordance, empirical evidence in real estate research suggests that investors yield to avoid experiencing regret by deviating from rational behavior. On the residential real estate side, for example, Seiler et al. (2010) found that the willingness of investors to sell a residential property increases most when their investment breaks even. Following a similar logic, it can also be argued that direct CRE markets are particularly prone to media-expressed sentiment during downward markets and recessions. Therefore, we hypothesize the following:

Hypothesis 3: Commercial real estate prices are more susceptible to sentiment when markets are slowing down.

To investigate whether the sentiment-based predictability of *NPI* total returns is asymmetric, i.e. higher predictability power during periods of slower market growth, we run two separate regressions (based on Equation 3.2) using the portion of the sample when the market is accelerating or decelerating. Hence, the samples include only the quarters of growing and shrinking total *NPI* returns, respectively.

Table *3.7*: Regression Results – Sentiment in Accelerating vs. Decelerating Markets

Panel A: Up-Market Trend

presents the results of the *up market* vs. *down market* trend analysis in panel A and B, respectively.

The results reported in Panel A indicate that our absolute real estate sentiment measure (columns I and II) has very little predictability power with respect to future CRE performance. The only coefficient that carries the anticipated sign with statistical significance (at the 10% level) is the coefficient of PNR_{t-2} where our macroeconomic control variables are excluded. When our weighted real estate sentiment measure is considered (columns III and IV) the predictability power improves somewhat. In these specifications, we observe a positive and statistically significant coefficient for the second and third quarter lag when the control variables are excluded and for the second lag when the control variables are included. In comparison, the results reported for the down-market trend portion of the sample suggest that our sentiment real estate measure has high level of predictability during these periods. In each of the specifications (columns V though VIII) the coefficients of the second, third and forth quarter lag of the real estate sentiment measure (absolute or weighted) are positive and statistically significant at the 1% or 5% level (with the exception of the third lag in column VI). These findings are consistent with our third hypothesis and suggest that commercial real estate prices are better predicted by sentiment during periods of decelerating markets compared with up market trends. Our results are also consistent with the findings of Beracha and Wintoki (2013) for the role of sentiment in the residential properties during up versus down markets.

Table 3.7: Regression Results – Sentiment in Accelerating vs. Decelerating Markets

Panel A: Up-Market Trend

	Regressand: NPI (quarterly)			
	(I)	(II)	(III)	(IV)
	Absolute	*Absolute*	*Weighted*	*Weighted*
PNR_{t-2}	0.007*	0.004	0.003***	0.003***
PNR_{t-3}	0.000	-0.011**	0.002**	0.001
PNR_{t-4}	-0.002	-0.008	-0.001	-0.001
PNR_{t-5}	-0.009**	-0.007**	-0.003***	-0.003***
INFLATION		0.087		0.025
TERM		0.347		0.437
SPREAD		-0.276		-0.225
GFC		-0.013		-0.002
Adj. R^2	0.236	0.230	0.354	0.330
AIC	-6.766	-6.667	-6.935	-6.805

Panel B: Down-Market Trend

	Dependent variable: NPI (quarterly)			
	(V)	(VI)	(VII)	(VIII)
	Absolute	*Absolute*	*Weighted*	*Weighted*
PNR_{t-2}	0.022***	0.013**	0.006***	0.005***
PNR_{t-3}	0.022***	0.011*	0.007***	0.005***
PNR_{t-4}	0.026***	0.022***	0.006***	0.006***
PNR_{t-5}	0.007	0.009**	0.000	0.000
INFLATION		0.231		0.095
TERM		-0.052		-0.239
SPREAD		-1.043		-0.912
GFC		-0.023**		-0.010
Adj. R^2	0.597	0.698	0.808	0.816
AIC	-6.028	-6.220	-6.771	-6.715

Notes: This table reports the coefficients of the estimated AR models with quarterly *NPI* returns as the dependent variable on media-expressed sentiment (*PNR*) and a set of macroeconomics control variables: CPI growth (*INFLATION*), the spread between the ten-year U.S. Treasury Bond and the 3-Month Treasury Bill yields (*TERM*), the spread between BAA- and AAA-rated corporate bonds yields (*SPREAD*) and a dummy variable that captures the effect of the great financial crisis (*GFC*), which is set to 1 during the 2007:Q3 to 2008:Q4 time period and 0 otherwise. Panel A presents the results using the up-market trend portion of the sample and Panel B for the down-market trend portion of the sample. We use Newey and West (1987) standard errors that are robust to heteroscedasticity and autocorrelation. We transformed all variables to their first differences. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level. The sample period is 2001:Q1 to 2016:Q4.

3.7 Conclusion

The existing literature shows that sentiment plays an important role in pricing different asset classes, independent of fundamentals. In this paper, we employ a real estate specific sentiment measure that is based on news articles in order to determine the extent to which media-expressed sentiment can help predict direct CRE returns in the U.S.. The results of our analysis show that media-expressed sentiment predicts returns of commercial real estate up to three quarters in advance, even when macroeconomic factors are accounted for. When analyzing the bi-directional relationship between media-expressed sentiment and CRE returns, our results show clear evidence that information is flowing from the media-expressed sentiment to the direct CRE market, but also show some evidence that news reflect information on the past performance of CRE.

Our findings contribute to the literature on market sentiment and direct CRE performance and should be of interest to academics as well as real estate professionals. Specifically, the results of this paper highlight the importance for real estate investors and other market participants to monitor real estate related news as a valuable leading market indicator. This study also set the foundation for future research on advanced methods of textual analysis and machine learning algorithms with respect to investments, in general, and CRE, in particular.

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3.9 Appendix

Creation of a Real-Estate Specific Dictionary

While different sentiment related word lists and dictionaries are available, this paper follows Loughran and McDonald (2011) who find that sentiment dictionaries should be domain-specific in order to classify text corpora adequately. Thus, as a starting point, we deploy their finance dictionary based on the assumption that the terminology in the realm of real estate should be linked to vocabulary used in finance. Albeit the lexicon distinguishes between the sentiment categories of positive, negative, uncertain, litigious, constraining, superfluous, interesting and modal terms, only the first two categories of positivity (354 words) and negativity (2,355 words) are used. In the second step, this basic finance dictionary is adapted to real estate. More specifically, we perform the following tasks: First, the dictionary is revised in terms of its accuracy in a real estate related context. If a word's classification as positive or negative is ambiguous, it was removed, leading to the elimination of 43 words. We continue and manually analyze over 10,000 real estate-related headlines of a second news source – the *Financial Times* - regarding real-estate specific words indicating sentiment. As a result, 190 words are added to the dictionary, whereof 61 are positive and the remaining 136 are negative. For example, the terms 'bubble', 'crisis' and 'crash' were included in the real estate dictionary as they were missing in the finance dictionary but can be considered highly relevant in the context of real estate. In the end, the final real estate dictionary consists of 408 positive and 2,455 negative words and is slightly larger than the finance dictionary.

Text Pre-Processing

Given the abstracts from the *WSJ*, we pre-process the text of each abstract and convert them into well-defined sequences of linguistically meaningful units. This procedure is done in order to ensure that the computer can 'understand' the language input for the following steps of the analysis and improves the quality of the dictionary-based approach. Following Uysal and Gunal (2014), the pre-processing procedure consists of four steps: lowercase conversion, stop-word removal, stemming and tokenization. Additionally, numbers and punctuations were eliminated. Stop-words removal is concerned with words such as 'and', 'in' and 'the', which are usually conjunctions, prepositions, articles etc. and considered irrelevant to text classification. Stemming replaces each word within a sentence by its stem or root form as derived word forms should typically have a similar semantic meaning as their original root.[10] Finally, tokenization segments the text into smaller meaningful units called tokens. Note, that the real estate dictionary must be pre-processed accordingly to allow a comparison of news abstracts and dictionary terms. This leads to a reduced form of 959 negative and 189 positive tokens as some words in the original list are stemmed to the same root.

The example below illustrates each of the text pre-processing tasks.

We begin with the following sentence:

'Sales of US homes show a 2.7% rise.'

Eliminating numbers and punctuation leaves us with

[10] We follow Porter (1980) using a suffix stripping algorithm, which is widely used for analyzing text corpora in English.

'Sales of US homes show a rise'.

Stop-word removal and lowercase conversion reduce the sentence to

'sales us homes show rise',

which can be stemmed and tokenized to the final version of:

' sale - us – home – show – rise '.

Every single token of this string is then compared to the terms included in the reduced form real estate dictionary in order to measure the sentence's tone or attitude as described in Section 3.3.2.

4. News-Based Sentiment Analysis in Real Estate: A Machine-Learning Approach Via Support Vector Networks

Abstract

This paper examines the relationship between news-based sentiment, captured through a machine-learning approach, and the U.S. securitized and direct commercial real estate markets. Thus, we contribute to the literature on text-based sentiment analysis in real estate by creating and testing various sentiment measures by utilizing trained support vector networks. Using a vector autoregressive framework, we find the constructed sentiment indicators to predict the total returns of both markets. The results show a leading relationship of our sentiment, even after controlling for macroeconomic factors and other established sentiment proxies. Furthermore, empirical evidence suggests a shorter response time of the securitized market in relation to the direct one. The findings make a valuable contribution to real estate research and industry participants, as we demonstrate the successful application of a sentiment-creation procedure that enables short and flexible aggregation periods. To the best of our knowledge, this is the first study to apply a machine-learning approach to capture textual sentiment relevant to U.S. real estate markets.

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4.1 Introduction

Over the past decade, real estate researchers have intensified their efforts to investigate how sentiment affects individual decision-makers (Freybote and Seagraves, 2017), institutions (Das et al. 2015) and hence, property markets themselves (Ling et al., 2014; Marcato and Nanda, 2016). There is general consensus on the complexity of influencing factors, and that investors should not be considered as rational utility-maximizers only, thus indicating the overall importance of sentiment. Furthermore, real estate investors may be especially sensitive to sentiment, due to real estate market characteristics such as the relatively low market transparency and long transaction periods, leading to information asymmetries. Conducting a survey on decision-making among individuals actively involved in the property investing process, Gallimore and Gray (2002) found that individuals are in fact aware of the importance of sentiment for their own decisions.

Recent works further support the notion, that the augmentation of sentiment proxies in fundamental market models enhances their explanatory power. For example, Ling et al. (2014) confirm a relationship between investor sentiment and subsequent returns in the direct commercial real estate market, which drives prices away from fundamentals. Walker (2014) showed similar findings for the UK housing market, suggesting media sentiment to have a significant impact on real house price changes.

This paper seeks to deepen the knowledge of a rather new field of sentiment analysis based on news items instead of traditional indicators such as investor surveys. Some initial research by Soo (2015), Walker (2014, 2016) and Nowak and Smith (2017) has assessed the relationship between textual sentiment measures and the residential real estate market, deploying sentiment-annotated word lists. However, no study evidently uses supervised machine learning to extract news-based sentiment relevant to the U.S. real estate market. Therefore, this paper examines the relationship between news-based sentiment, captured through a classification algorithm, and the U.S. securitized and direct commercial real estate markets.

After training a support vector machine (SVM), we analyze approximately 54,500 real estate (RE) news headlines from the *S&P Global Market Intelligence* database (SNL) concerning their inherent sentiment. Thereby, the machine-learning algorithm assigns either a positive, negative or neutral score to each news headline, which is subsequently aggregated to different monthly measures of market sentiment. Based on psychological theory and existing research, we introduce an optimism indicator (*OI*), a pessimism indicator (*PI*) and a weighted sentiment quotient (*SQ*). A vector autoregressive framework (VAR) enables us to investigate the dynamic relationship between these three created sentiment measures and the securitized and direct real estate markets in the United States.

The findings indeed indicate strong and consistent evidence of a significant relationship between our sentiment indicators and real estate market movements. For both markets, especially the pessimism indicator provides additional information to macroeconomic fundamentals in explaining market returns. The predictive power of our indicator remains intact, even when controlling for the influence of other traditional sentiment measures, such as the *Survey of Consumers* of the University of Michigan or the *American Association of Individual Investors* (*AAII*) *Investor Sentiment Survey*. The *PI* drives total returns of the securitized and direct real estate market by one and by two, three and eight months, respectively. As comparable results were not found for the optimism indicator, these findings indicate a negativity bias of real estate market participants. As the analysis does not reveal any significant impact of past market performance on current sentiment measures, a bi-directional relationship cannot be claimed.

These results provide an additional opportunity to better understand influences on real estate market returns that are not based on fundamental value changes. Furthermore, a new technique for extracting sentiment from one of the most widespread information sources – news – is applied, contrasted and discussed. The knowledge gained can be applied to every form of text corpora, such as earnings press releases, annual reports, IPO prospectus, corporate disclosures, analyst reports, tweets or blog posts. Hence, the study makes a valuable contribution to the extraction of sentiment itself and participates in the recently emerging strand of literature concerning textual analysis in real estate. Additionally, it sheds light on real estate news analytics, as an innovative source of sentiment and an opportunity to construct a leading market indicator.

This paper itself is organized as follows. In Section 4.2, we provide a synopsis of the relevant literature on textual analysis finding its way into the broad field of sentiment analysis. Furthermore, recent research on sentiment analysis in the context of real estate is discussed. The subsequent section introduces various datasets, while Section 4.4 presents the machine-learning approach, as well as the methods of aggregating the sentiment measures. Furthermore, the VAR framework is derived. Section 4.5 shows the empirical results and the conclusion draws upon the entire work and discusses implications of our findings for the industry, as well as future research.

4.2 Literature Review

4.2.1 Sentiment Analysis and the Subcategory of Textual Analysis

'The effects of noise on the world, and on our views of the world, are profound' (Black, 1986, p. 529). According to Black, noise has several meanings and impacts on economic activity in various ways; noise entails expectations, which do not follow any rational rules, is a form of uncertainty that changes investment flows, is information not yet arrived at every market participant, and subsumes the reasons for markets to be inefficient. Hence, noise enables trading in financial markets (Black, 1986). What Black laconically describes as 'noise', can nowadays be considered at least partially as sentiment.

Following this rationale, there have been several attempts since the mid-1980s to explain asset prices deviating from intrinsic values, which are not based on underlying value changes (Brown and Cliff, 2004). After 2000, the debate on how to quantify sentiment intensified (Liu, 2012). In general, one can now distinguish between two different ways of measuring sentiment. On the one hand, there are indirect indicators, which are market-based, claiming to proxy sentiment such as closed-end fund discounts, buy-sell imbalance or mortgage fund flows (Brown and Cliff, 2004). On the other hand, one can rely on surveys as a direct measure of investor sentiment. Qiu and Welch (2004) discuss several survey-based sentiment indices, for example, the consumer confidence index or the AAII index, a survey of individual investors.

Recently, researchers have shown an increased interest in a new subcategory of sentiment analysis, so-called textual analysis. The digitalization of information and news, increasing computational power, and new techniques for analyzing text corpora fuel the rapid growth of this research area (Liu, 2012). A diverse variety of textual documents such as earnings press releases (Henry, 2008; Henry and Leone, 2016), news articles (Tetlock, 2007; Sinha, 2016; Hanna et al., 2017), annual reports (Li, 2006) or IPO prospectus (Ferris et al., 2013), corporate disclosures (Rogers et al., 2011; Ozik and Sadka, 2012), and analyst reports (Twedt and Rees, 2012) were analyzed in order to extract sentiment and draw conclusions about market events.

When analyzing the relationship between sentiment and the market, textual analysis provides promising results for a wide range of domains such as market indices (Schumaker and Chen, 2009; Bollen et al., 2011), exchange rates (Jin et al., 2013; Chatrath et al., 2014), company stock prices (Tetlock et al., 2008), earnings (Li, 2010), trading volume or market volatility (Tetlock, 2007).

4.2.2 Dominant Methodologies in Textual Analysis

In recent years, two methodologies for conducting textual analysis have been predominant. Originally, the dictionary-based approach was introduced to the finance literature by Tetlock in 2007. Examining news articles from *The Wall Street Journal*, he found that high media pessimism temporarily leads to downward pressure on market prices and higher market volatility. In a subsequent paper, Tetlock et al. (2008) again made use of the *Harvard University's General Inquirer (GI)* as sentiment dictionary in order to forecast firm earnings. Several papers followed his approach and applied both the methodology and the GI/Harvard dictionary in the most diverse contexts. Among others, Kothari et al. (2009) investigated the relationship between company disclosures and the return volatility, as well as cost of capital and analyst forecast dispersion. Arguing that the meaning of words may depend on certain circumstances, Loughran and McDonald (2011) developed a financial-language-orientated word list especially for business communication. Based on their findings, researchers started to compare domain-specific dictionaries to general ones (Henry and Leone, 2016; Rogers et al., 2011; Doran et al., 2012) or added domain-specific words (Hanna et al., 2017). Henry and Leone (2016) report that the investigation of financial disclosures with a domain-specific word list leads to superior results.

The second methodology focuses on sentiment classification algorithms such as support vector machines (SVM) or the Naïve Bayes classifiers. Two of the earliest works of Pang et al. (2002) and Antweiler and Frank (2004) conducted an analysis with both techniques. Classifying movie reviews as positive or negative, Pang et al. (2002) showed that Naïve Bayes as well as SVM led to good results, whereby the SVM provided the most promising findings. Antweiler and Frank (2004) investigated more than 1.5 million message board postings on *Yahoo! Finance* and *Raging Bull* about a group of 45 companies and determined the predictive power of their sentiment measure on next day returns and volatility. Furthermore, they report that disagreement in sentiment during the period under consideration is linked to increased trading volume. At firm level, Li (2010) analyzed MD&As from 1994 to 2007 with the Naïve Bayes algorithm. The extracted tone is linked significantly to future earnings and liquidity and has predictive power with respect to future performance. Further techniques categorized by Khadjeh et al. (2014) are regression algorithms (Schumaker et al., 2012), decision rules or decision trees (Rachlin et al., 2007), combinatory algorithms and multi-algorithm experiments (Das and Chen, 2007).

4.2.3 Sentiment Analysis in the Context of Real Estate

As early papers only extend back to the beginning of 2000 (Barkham and Ward, 1999; Gallimore and Gray, 2002), the real estate sentiment literature lags behind related research in finance. However, there has lately been an increasing amount of literature on sentiment analysis in the context of real estate.

Conducting a survey among 983 UK property investors about their decision-making, Gallimore and Gray (2002) make the astounding discovery that personal feelings and the views of other market participants are almost equally important to fundamental market information. Subsequent research confirms these initial findings across real estate market sectors. Clayton et al. (2009) and Ling et al. (2014) examine the commercial real estate market, and find evidence that investor-sentiment measures among others in the form of the *Real Estate Research Corporation Investment Survey* have a significant linkage to pricing and market returns in subsequent periods. Lin et al. (2009) and

Das et al. (2015) took a closer look at REIT performance, and Marcato and Nanda (2016) among others, at residential real estate returns.

Similar to the financial literature, real estate sentiment research was traditionally conducted facilitating direct and indirect sentiment measures, as so do all the abovementioned research papers. Over time however, new ways of measuring sentiment have emerged. Online search engine volume provided by Google Trends have been successfully established as a new way of measuring real estate market sentiment (Hohenstatt et al., 2011; Dietzel et al., 2014; Rochdi and Dietzel, 2015). Equivalently, the stream of textual-analysis-based sentiment measures is slowly finding its way into real estate research. Some first attempts were made by Walker (2014), making use of the dictionary-based approach. He found that past newspaper articles about the housing market Granger-cause house price changes in the UK, even when controlling for different control variables. His findings were confirmed on a city level in the US. With 37,500 local housing news articles, Soo (2015) successfully applied the dictionary-based approach and argues that her sentiment measure leads house-price movements by more than two years. In accordance with his findings in 2014, Walker (2016) found further evidence that the media is a reliable source of sentiment in the real estate housing market.

Together, these studies provide insights into sentiment analysis in the field of real estate, but little is known about the potential of other methods to investigate text corpora. Extracting relevant real estate sentiment is still limited mainly to dictionary-based approaches. No study has so far applied a machine-learning approach in a real estate context. Hence, the present paper is the first to use a sentiment classification algorithm to extract sentiment from qualified news items and quantify the performance in relation to the securitized and the direct commercial real estate markets.

Thus, we state our first research question as follows: *(1) Can sentiment measures created via machine learning predict the securitized commercial real estate market?*

Furthermore, it is worth investigating, whether the results deviate, when switching to the direct real estate market. Hence, the second research question follows directly: *(2) Is the predictive power different for the direct real estate market?*

As there have been several attempts at measuring sentiment with direct and indirect indicators, the third research question considers measuring the relative quality: *(3) How do the created sentiment indicators perform in addition to established sentiment measures?*

Finally, research question 4 is based on the notion of an existing negativity bias (Rozin and Royzman, 2001), which refers to the idea that the human psychological state is affected more strongly by negative entities – in this case, news stories – than by positive ones. Given that Tetlock (2007) found corresponding evidence of a negativity bias in terms of stock market sentiment, we construct various sentiment measures accordingly and formulate the fourth research question as: *(4) Is there evidence of a negativity bias on the part of market participants?*

4.3 Data

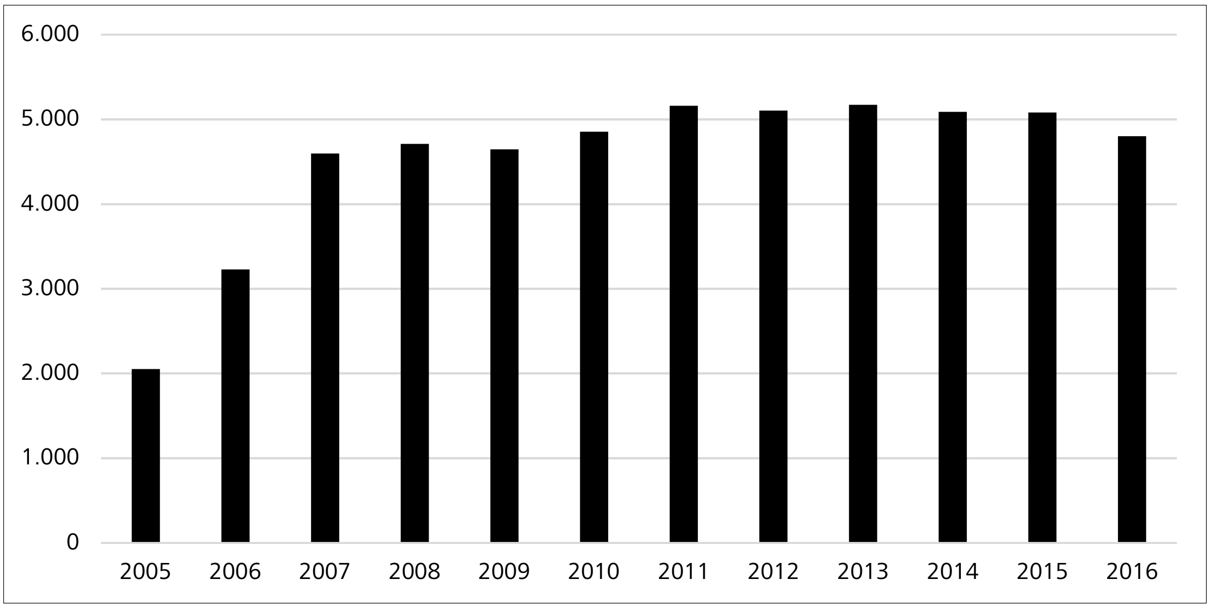
To examine the relationship between news-based sentiment and the real estate market in the United States, we use two types of dataset: (1) a news text corpus and (2) real estate return data, as well as further economic time series. The availability of historic news in the digital archive of our data source restricts the overall research period. Thus, we collect all data from January 1st, 2005 to December 31st, 2016. This 12-year period is worth investigating, since it contains a boom phase (until 2007), the housing bubble bust and the recession from 2007 to 2009, as well as the pronounced recovery market phase in the subsequent years.

4.3.1 News Data

The identification of a suitable text corpus that is relevant to the commercial real estate market is decisive to building an accurate real estate market sentiment measure. Hence, we base our sentiment analysis upon professional financial news from the *S&P Global Market Intelligence* platform. The platform offers real-time updates, trends, market activities and reporting which is specific to the real estate market. Due to the expertise of reporting on SNL, we assume the news to be more comprehensive and reliable than news usually directed to the public. Over the 12-year time span, 54,530 articles including the keyword 'real estate' were collected. This corresponds to more than 370 real estate news items per month. Following Peramunetilleke and Wong (2002), who argue that headlines are normally short and straight-to-the-point, this paper analysis news headlines only.

Figure 4.1 presents the amount of real estate-related news published by SNL over the 12-year research period. During the boom market, from 2005 to 2007, the news coverage more than doubles from about 2,050 to 4,595 annual news. This might be the result of an increased interest in real estate, but probably also due to the rise of the internet and hence, more and more people reading news online. During the bust of the subprime mortgage crisis, the annual news coverage stabilizes at around 4,700 news items, and reaches its peak in 2011 with 5,158 news annually. In comparison, the post-crisis level of annual news coverage is steadily higher than the prior bust-level in 2007/08. This may indicate an increased attention-level concerning real estate as an asset class.

Figure 4.1: SNL Real Estate News Coverage



Notes: This figure plots the sample distribution of real-estate-related news published by *S&P Global Market Intelligence* (SNL) over the sample period, 2005:M1 to 2016:M12. All news was retrieved using the digital archive of SNL by selecting articles that contain the keyword 'real estate'.

4.3.2 Real Estate Data

The return data of the direct real estate market stems from a repeat-sales index provided by *CoStar*. More specifically, we select the *CoStar Commercial Repeat-Sale Index* (*CCRSI*) as an accurate and comprehensive measure of commercial real estate prices in the United States. As a measure of overall market performance, the value-weighted U.S. Composite Price Index is chosen. The index is published monthly and is available at www.costargroup.com.

Furthermore, we derive the return data of the securitized market from the *National Association of Real Estate Investment Trusts* (*NAREIT*), selecting the *FTSE/NAREIT All Equity REIT Total Return Index* as a market-capitalization-weighted, free-float-adjusted index of equity REITs in the United States (www.reit.com). We use the monthly percentage changes of both indices to measure the total returns from the direct and securitized commercial real estate market, respectively.

4.3.3 Further (Economic) Data

To control for other potential influencing factors causing variations in real estate sentiment and returns, a selected set of control variables is included. All variables relevant to the direct and securitized real estate market are inspired by existing findings of other researchers. Two distinct sets of control variables are used for the direct and securitized market, respectively. For the VAR framework, the set of control variables firstly consists of a measure of overall economic default risk (*SPREAD*), defined as the difference between Moody's Seasoned Baa- and Aaa-rated corporate bonds (e.g. Lin et al., 2009; Ling et al., 2014). Secondly, we include a term structure variable (*TERM*), as a mean for expectations of future economic developments, defined as the difference between the yields on the 10-year Treasury bond and the 3-month Treasury bill (e.g. Clayton et al., 2009; Freybote and Seagraves, 2017). The analysis controls for percentage changes of the Consumer Price

Index (*CPI*) since real estate is often regarded as a hedge against inflation (e.g. Hoesli et al., 2008). To account for the performance of the general stock market, we incorporate the return of the S&P500 composite index (*SP500*) in our analysis (e.g. Schaetz and Sebastian, 2010, Das et al., 2015). Furthermore, incorporating initial claims of unemployment insurance (*UNEMPL*) controls for labor market developments and total construction spending (*CONSTR*) for the supply side of the real estate market (e.g. Dietzel et al., 2014).

Table 4.1 presents the descriptive statistics of monthly returns and other variables. We state the mean, median, standard deviation, minimum and maximum. Total returns range from -6.87% to 3.18% and -31.67% to 31.02% for the direct and securitized market, respectively. The volatility, measured per standard deviation of the securitized market is more than four times greater than of the direct one. The overall volatility in returns is the result of the boom and bust phases included in our sample period.

Table 4.1: Descriptive Statistics – Real Estate Returns and Economic Time Series

	Mean	Median	SD	Min	Max
CCRSI (%)	0.34	0.59	1.59	-6.87	3.18
NAREIT (%)	0.88	1.25	6.91	-31.67	31.02
SPREAD (%)	1.13	0.96	0.51	0.55	3.38
TERM (%)	1.87	2.01	1.08	-0.52	3.69
INFL (%)	0.17	0.19	0.43	-1.92	1.22
SP500 (%)	0.51	1.02	4.10	-16.94	10.77
UNEMPL	350,036	318,466	102,575	200,456	717,000
CONSTR	83,815	82,235	15,204	50,973	110,020

Notes: This table reports summary statistics of our monthly real estate return data and macroeconomic time series. *CCRSI* is the total return of the CoStar Commercial Repeat-Sale Index. *NAREIT* is the total return of the FTSE/NAREIT All Equity REIT Total Return Index. *SPREAD* is the difference between BAA- and AAA-rated corporate bonds yields. *TERM* is the difference between the 10-year U.S. Treasury bond and the 3-Month Treasury bill yields. *CPI* is the percentage change of the Consumer Price Index (CPI). *SP500* is the total return of the S&P 500 Composite Index. *UNEMPL* is the amount of unemployment initial claims in the number of persons. *CONSTR* is the amount of construction spending in millions of dollars. Percentages are expressed in decimal form. The sample period is 2005:M1 to 2016:M12.

To test the robustness of our sentiment measures, we further control for a set of more 'general' and well-established sentiment indicators such as the *Surveys of Consumers* of the University of Michigan (*CONSUSENTI*). We also incorporate the bullish and bearish measures of the *American Association of Individual Investors (AAII) Investor Sentiment Survey* (*AAIIBULL*, *AAIIBEAR*) as well as of the *Investors Intelligence US Advisors' Sentiment Report* (*ADVSENTBULL*, *ADVSENTBEAR*). From the *Economic Policy Uncertainty* platform, their *News-Based Policy-Related Uncertainty* measure (*ECOPOLUNCERTINEWS*), the *Overall Policy-Related Economic Uncertainty* indicator (*ECOPOLUNCERTIOVER*) or *Equity Market-Related Economic Uncertainty* (*ECOUNCERT*) is used. For a full description of all variables, see the Table 4.7 in the Appendix. All data was obtained from the *Federal Reserve Bank of St. Louis* (www.fred.stlousfed.org) and *Thomson Reuters Datastream* (www.financial.thomsonreuters.com) on a monthly basis.

4.4 Methodology

4.4.1 Sentiment Extraction via Machine Learning

To extract sentiment from news headlines, this paper deploys a support vector machine as a supervised learning algorithm. Support vector machines or support vector networks are machine-learning techniques for two-group classification tasks proposed by Cortes and Vapnik (1995) during the nineties. Each headline is depicted as an input vector in some high-dimensional feature space via a non-linear mapping technique chosen a priori, where a linear decision surface is constructed to distinguish between different classes. As supervised learning technique, this requires a pre-classified set of training data, which are used to construct the decision surface described above. Our training set comprises about 4.500 pre-classified headlines. Knowing the position of the hyperplane, subsequently allows identifying the category of additional headlines, depending on their position in the feature space, relative to the surface.

Following Cortes and Vapnik (1995), a set of pre-classified training data $(y_1, \boldsymbol{x_1}), \dots, (y_l, \boldsymbol{x_l})$, $y_i \in \{-1,1\}$ is linearly separable, if the inequality $y_i(\boldsymbol{w x_i} + b) - 1 \geq 0, i = 1, \dots, l$ is fulfilled for all training elements. Hence, the optimal hyperplane $\boldsymbol{w_0 x} + b_0 = 0$ is the decision surface that separates the training data with the maximal margin i.e. maximizes the distance $\rho(\boldsymbol{w_0}, b_0) = \frac{2}{\|\boldsymbol{w}\|} = \frac{2}{\sqrt{\boldsymbol{ww}}}$ between data points on the edge of each class.[11] These training vectors $y_i(\boldsymbol{w x_i} + b) - 1 = 0$ are called support vectors. Because it is mathematically more convenient, the optimal hyperplane can be derived by minimizing $\frac{1}{2}\boldsymbol{w} * \boldsymbol{w}$ subject to $y_i(\boldsymbol{w x_i} + b) - 1 \geq 0, i = 1, \dots, l$.

Cortes and Vapnik (1995) show that the vector $\boldsymbol{w}_o$, which determines the optimal decision surface, is a linear combination of training vectors:

$$\boldsymbol{w}_o = \sum_{i=1}^{l} \alpha_i^0 y_i \boldsymbol{x}_i \tag{1}$$

where $\alpha_i^0 \geq 0$. Given that it can further be proven that $\alpha > 0$ is only valid for support vectors, $\boldsymbol{w}_o$ is a linear combination of those support ones.

To find the parameters of α_i, the algorithm has to solve the following quadratic programing problem:

$$W(\boldsymbol{\Lambda}) = \boldsymbol{\Lambda}^T \boldsymbol{1} - \frac{1}{2}\boldsymbol{\Lambda}^T \boldsymbol{D} \boldsymbol{\Lambda} \tag{2}$$

with respect to $\boldsymbol{\Lambda^T} = (\alpha_1, \dots, \alpha_l)$ subject to the constraints of $\boldsymbol{\Lambda^T Y} = 0$ and $\boldsymbol{\Lambda} \geq 0$, where ***1*** is a l-dimensional unit vector, $\boldsymbol{Y}^T = (y_1, \dots, y_l)$ the *l*-dimensional vector of labels and ***D*** the symmetric *l* x *l* - matrix $D_{ij} = y_i y_j \boldsymbol{x}_i \boldsymbol{x}_j$ with $i, j = 1, \dots, l$. Given $\boldsymbol{w_0}$, one can solve $\boldsymbol{w_0 x} + b_0 = 0$ for b_0, which provides us with all parameters required to state the optimal, maximal margin hyperplane. Hence, new data $\tilde{\boldsymbol{x}}$ can be classified applying a signum function:

[11] For ease of reading, we stick to the common notation of matrices using bold characters.

$$f(\tilde{\boldsymbol{x}}) = sign(\boldsymbol{w_o}\tilde{\boldsymbol{x}} + b_0). \tag{3}$$

Positive results indicate a class of '+1' and vice versa.

Due to the possibility that that training data may not be separable by a hyperplane without classification errors, we follow Cortes and Vapnik (1995) and use a so-called *soft-margin classifier* by introducing some non-negative 'slack' variable $\xi_i \geq 0, i = 1, \dots, l$ and minimize $\frac{1}{2}\boldsymbol{ww} + C\sum_{i=1}^{l}\xi_i$ subject to $y_i(\boldsymbol{wx_i} + b) \geq 1 - \xi_i$ and $\xi_i \geq 0$. The constant C is considered as a trade-off parameter between error and margin. Thus, one still has to solve (2) with respect to $\boldsymbol{\Lambda^T} = (\alpha_1, \dots, \alpha_l)$, but subject to slightly adjusted constraints of $\boldsymbol{\Lambda^T Y} = 0$ and $C * \mathbf{1} \geq \boldsymbol{\Lambda} \geq 0$.

To render the classification algorithm even more versatile, the data is not mapped into the input space, but some higher dimensional feature space using the so-called kernel trick. This enables separating data by a decision surface, even when they are not linearly separable in the input space. An N-dimensional vector function $\phi: \mathbb{R}^n \to \mathbb{R}^N$ transfers the n-dimensional input vector $\boldsymbol{x}$ into the N-dimensional space. One then constructs an N- and not an n-dimensional linear separator $\boldsymbol{w}$ and parameter *b,* using the transformed vectors $\phi(\boldsymbol{x_i}) = \phi_1(\mathbf{x}_i), \phi_2(\mathbf{x}_i), \dots, \phi_N(\mathbf{x}_i), i = 1, \dots, l$ in the same manner described above. 'New' data can be classified by transforming the 'data' vector into the feature space ($\tilde{\boldsymbol{x}} \to \phi(\tilde{\boldsymbol{x}})$) first, and then applying the sign function afterwards:

$$f(\tilde{\boldsymbol{x}}) = sign(\boldsymbol{w_o}\phi(\tilde{\boldsymbol{x}}) + b_0). \tag{4}$$

Additionally, in order to classify textual documents into three different sentiment categories, a few obstacles must be tackled. First, a support vector machine does not work without converting the textual documents into numeric vectors beforehand. Therefore, training headlines are split into single words or features. Combined with corresponding word frequencies, these features are then listed in a so-called document-term matrix, in which each training headline is represented by a numeric row vector. Hence, each feature of the training data set becomes one dimension of the input space. For new data, a vector is constructed by counting how often these training features are included in the headline, and using the respective frequencies as the coordinates of the corresponding dimension. Second, a support vector network just distinguishes between two classes. As we are using the categories 'positive', 'negative' and 'neutral', this requires us to run three different support vector machines with two categories each. At the end, a voting system assign headlines to the class with the highest number of votes.

4.4.2 Creating Real Estate Sentiment Measures

After classifying each headline as either positive, negative or neutral, the respective sentiments for monthly observation periods are aggregated. Because this study explores the relationship between news-based sentiment and the real estate market comprehensively, we do not restrict our analysis to a single sentiment measure, but propose three different ones.

As in Tetlock (2007), the first measure is based on the idea of negativity bias*,* according to which individuals are affected more strongly by negative rather than positive influences – even when of equal intensity (Rozin and Royzman, 2001). The so-called 'Pessimism Indicator' (*PI*) is a measure of pessimism expressed in the news, which relates the number of negative headlines to the overall number of headlines for a given period. It is formally defined as follows:

Equation 4.1: Sentiment Measure 1 – Pessimism Indicator (*PI*)

$$PI_t = \frac{\sum_1^I negative\ headlines_{i,t}}{\sum total\ number\ of\ headlines_t} \tag{5}$$

where *i* is a headline classified as negative and *t* is the period in which all headlines must be published to be taken into account.

Similar to Antweiler and Frank (2004), we propose a second sentiment measure capturing optimism (bullishness) in news: an 'Optimism Indicator' (*OI*). As a contrary measure to the *PI,* it is defined as the number of positive headlines divided by the overall number of headlines for a given period. More formally:

Equation 4.2: Sentiment Measure 2 – Optimism Indicator (*OI*)

$$OI_t = \frac{\sum_1^I positive\ headlines_{i,t}}{\sum total\ number\ of\ headlines_t} \tag{6}$$

where *i* is a headline identified as positive and *t* the aggregation period.

Both *PI* and *OI* range from zero to one, whereby a higher value indicates a greater level of media-expressed pessimism or optimism, respectively. These measures can therefore be interpreted as percentages of pessimism and optimism in the news over the respective time period.

Thirdly, a relative measure is suggested, which accounts for both polarities, positivity as well as negativity expressed in news. The 'Sentiment Quotient' (*SQ*) indicates the degree of optimism and pessimism in the news, excluding all neutral headlines. This measure is inspired by *yukkalab*, a company offering commercial sentiment analysis (www.yukkalab.com). The *SQ* is defined as the number of positive headlines in relation to the number of positive and negative headlines for a given period *t*. If the SQ is greater than 0.5, the positive headlines exceed the negative ones, indicating overall optimism in the news, and vice versa.

In terms of computation, it can be stated as follows:

Equation 4.3: Sentiment Measure 3 – Sentiment Quotient (*SQ*)

$$SQ_t = \frac{\sum_1^I positive\ headlines_{i,t}}{\sum_1^I positive\ headlines_{i,t} + \sum_1^J negative\ headlines_{i,t}} \tag{7}$$

where *i* is a headline classified as positive, *j* is a headline identified as negative and *t* the time span used for aggregation.

Table 4.2 presents the descriptive statistics of all three sentiment measures. Mean, median, standard deviation, minimum and maximum are reported. During our sample period, the *PI* and *OI* range from 0.09 to 0.38 and 0.22 to 0.48, respectively. While the mean of the *PI* is 0.21, it is 0.35 for the

OI. The average SQ is 0.63, consistently indicating an (on average) higher amount of news classified as positive than such classified as negative by the support vector network.

Table 4.2: Descriptive Statistics – News-Based Sentiment Measures

	Mean	Median	SD	Min	Max
PI	0.21	0.20	0.06	0.09	0.38
OI	0.35	0.35	0.06	0.22	0.48
SQ	0.63	0.65	0.09	0.39	0.77

Notes: This table reports summary statistics of our monthly sentiment measures. *PI is* the pessimism indicator, *OI* the optimism indicator and *SQ* the sentiment quotient. The sample period is 2005:M1 to 2016:M12.

4.4.3 Vector Autoregression

To formalize the analysis, a vector autoregression framework is employed. Given that vector autoregression does not require any a priori assumptions on existing causalities, this technique offers an effective way to investigate the dynamic relationship between sentiment indicators extracted from newspaper headlines and real estate markets. Furthermore, VARs are more flexible than univariate models and offer a rich structure which allows them to capture more features of the data (Brooks and Tsolacos, 2010).

The simplest form of the well-known standard-form or conventional VAR is a bivariate model comprising of a system of two regression equations, where two endogenous variables (y_{1t} and y_{2t}) are expressed as linear functions of their own and each other's lagged values and error terms:

Equation 4.4: VAR Model

$$
\begin{aligned}
y_{1t} &= \beta_{10} + \beta_{11}\, y_{1t-1} + \cdots + \beta_{1k}\, y_{1t-k} + \alpha_{11}\, y_{2t-1} + \cdots + \alpha_{1k}\, y_{2t-k} + u_{1t} \\
y_{2t} &= \beta_{20} + \beta_{21}\, y_{2t-1} + \cdots + \beta_{2k}\, y_{2t-k} + \alpha_{21}\, y_{1t-1} + \cdots + \alpha_{2k}\, y_{1t-k} + u_{2t}
\end{aligned}
\qquad (8)
$$

where k is the number of lags and u_{it} a white noise disturbance term with $E(u_{it}) = 0$, (i = 1,2), $E(u_{1t}, u_{2t}) = 0$. In our case, y_{1t} are the return of the real estate market in period *t,* while y_{2t} is either the PI, the *OI* or the sentiment quotient for the respective month.

Note that, based on economic theory, further control variables are included in our VAR framework as additional exogenous variables on the right-hand side of Equation 4.4. This leads to the final model (9) which shows (8) in common matrix notation and uses **X** as a matrix of exogenous variables and **B** as a matrix of coefficients:

Equation 4.5: VAR in Matrix Notation

$$
\boldsymbol{y_t} = \boldsymbol{A_0} + \boldsymbol{A_1 y_{t-1}} + \cdots + \boldsymbol{A_k y_{t-k}} + \boldsymbol{BX} + \boldsymbol{u_t}. \qquad (9)
$$

During the regression analysis, components of the VAR are tested using an Augmented Dickey-Fuller Test (ADF) to check for the existence of a unit root. Whenever the null hypothesis and therefore the required stationarity is rejected, variables are differenced once or used as growth rates to ensure statistical appropriateness. Additionally, the optimal lag length has to be determined for a well-specified VAR by making use of an array of selection criteria. Our decision was based mainly on the three most popular ones, the Akaike (AIC), the Bayesian (BIC) and the Hannan-Quinn information criterion (HQIC). All three rest on the notion that including an extra term might increase the goodness of the model, but that the model should be penalized at the same time for the increasing number of parameters one needs to estimate. Whenever the rise in goodness of fit outweighs the penalty term, the information criteria decreases. Accordingly, the lag length which minimizes the value of the information criteria is chosen (Brooks and Tsolacos, 2010). Whenever results are inconclusive, the likelihood ratio test and the final prediction error are utilized to guide the decision on the appropriate lag length.

We further apply the Breusch-Godfrey Lagrange Multiplier test to ensure that the residual series from an estimated model are not serially correlated. Looking for any patterns in the plotted residuals is in some cases difficult to interpret and is therefore only for verification. In addition, several diagnostic tests are performed, for example, residuals are tested for normality and homoscedasticity.

As the main interest of this paper is to investigate whether the created media sentiment measures do indeed have predictive power when explaining returns of the direct and securitized real estate market in the US, for each VAR, Granger causalities are tested and reported. Furthermore, we always state the variance decomposition of forecast errors using a Cholesky factorization.

4.5 Results

A quick recap: our analysis follows the theoretical premise that real estate market participants base their decisions on available information, as well as their own personal beliefs, which are not fully reflected in fundamental economic data. While researchers like Marcato and Nanda (2016) use readily available sentiment indices such as the *Architecture Billings Index* and the *National Association of Homebuilders/Wells Fargo Housing Market Index* to capture an aggregate of individual expectations in non-residential as well as residential real estate markets, respectively, we pursue another direction. Corresponding with Akerlof and Shiller (2010), we argue that '[a]ll of … processes are driven by stories. The stories that people tell to themselves, about themselves, about how others behave, and even about how the economy as a whole behaves all influence what they do' (p. 173). Thus, our approach makes use of a trained support vector machine to measure market sentiments based on 'published' news stories, which arguably bear the potential to influence the decision-making of informed commercial real estate market participants in the United States. As we do not know whether media simply reflects or causes market movements of the direct as well as securitized real estate markets, or whether there is a bi-directional relationship, all the following results aim to shed light on the dynamic as well as temporal dimension between these two possibly linked aspects. The analysis starts by looking at the securitized real estate market and proceeds by comparing the results to the findings from the direct real estate market.

4.5.1 Securitized Real Estate Market

Table 4.3 shows the endogenous dynamics between the *FTSE/NAREIT All Equity REIT Total Return Index* (*NAREIT*) and our three different sentiment indicators, using a VAR framework. All three models control for the same set of macroeconomic variables i.e. term, spread, inflation and the returns of the S&P 500, all models are robust in terms of diagnostic tests and show an optimal lag length of two. The regressions are conducted on a monthly basis, as we are able to benefit from our manually constructed sentiment measures. As long as there are enough news stories provided, our indicators can be computed for any desired period. Thus, when analyzing the securitized real estate market, we are only limited by the frequency at which control variables are available. This differs from the work of other researchers such as Ling et al. (2014) and Das et al. (2015), in which the frequency of the sentiment measure e.g. the quarterly published *Real Estate Research Corporation* (RERC) survey is the limiting factor.

The regression equations of Models 1 to 3 show the expected statistical significance at the first and second lag of the autoregressive *NAREIT* component and similar levels of goodness of fit around 62% to 64%. With regard to sentiment measures, all coefficients have the expected sign. While a rising pessimism indicator negatively affects market returns, the opposite is true for the optimism indicator and sentiment quotient. This corresponds to the way the indicators are created. *PI* and *SQ* facilitate the number of positive headlines, *NI* the number of negative headlines as the numerator. However, only the first lag of the *PI* and *SQ* are statistically significant at the 5% level. The optimism indicator has no significant impact at all on market returns. Granger causalities confirm these findings. In contrast to the *OI* of Model 2, the *PI* has predictive power at the 5% level. The sentiment quotient slightly misses the 10% level of significance. Note that for none of the three models *NAREIT* does Granger-cause the sentiment measures. Hence, the sentiment indicators are not affected by past market performance, but provide additional information that is relevant to the securitized real estate market. This indicates a non-existing endogenous dynamic between the securitized real estate market and the sentiment indicators in Model 2 and Model 3 and a one-sided relationship from the *PI* to market returns in Model 1. Variance decomposition figures up to 12 months, using the Cholesky decomposition, yield a contribution of 6.12% for the PI, 0.46% for the *OI* and 3.56% for the *SQ*, which is consistent with previous findings.

Overall, based on Table 4.3, the pessimism indicator shows the highest predictive power in explaining the growth of returns in the United States securitized real estate market. This is the case despite the fact that we used the same SNL dataset for all three indicators, as well as an identical trained support vector machine when classifying news items beforehand. A more pronounced market sensitivity to negative news was also found by Tetlock (2007), when analyzing the interactions between media and the general stock market. As his mathematically derived dictionary-based sentiment measure consisted primarily of negatively annotated word categories, he referred to it as pessimism factor. Furthermore, Loughran and McDonald (2011) also focus primarily on negative word lists in their seminal paper.

According to research question 3, the question remains as to whether our sentiment measures and especially the *PI,* retain their predictive power when including other sentiment measures. To check for robustness, and hence include a broad spectrum of other sentiment indicators at the same time, Table 4.4 contrasts the base Model 1 from Table 4.3 with two augmented regression models i.e. Models 4 and 5. Facilitating other available sentiment measures, we run two principal component analyses – one for bearish and one for bullish market indicators – and include the extracted principal components as endogenous variables in our Model 1. This allows us to consider the opinion of individual investors (*AAIIBULL* and *AAIIBEAR*), as well as sentiment expressed by stock market newsletter editors (*ADVSENTBULL*, *ADVSENTBEAR*). At the same time, we include further policy (*ECOPOLUNCERTINEWS*, *ECOPOLUNCERTIOVER*) as well as equity–market-related economic uncertainty (*ECOUNCERT*) – expressed by news coverage, disagreement among economic forecasters and federal tax code provisions – and consumer sentiment (*CONSUESENTI*). Again, all models yield an optimal lag length of 2 months.

Despite including additional sentiment components, the pessimism indicator retains sign, coefficient size and significance of the first lag at the 5% level. Changes in the *PI* still Granger-cause NAREIT market returns, while the reverse causation further on cannot be stated. Considering the coefficient estimations of the bearish and bullish sentiment components, one can observe a similar dynamic. Except for the second lag of the bullish component, all second-lag principal components (PCs) are statistically significant at the 10% or 5% levels and show the expected coefficient signs. However, while the first component of the bullish sentiment measure Granger-cause *NAREIT* returns at the 5% level, the results are slightly weaker for the first bearish component, which fails to reach the 5% level. In both cases, the second component does not Granger-cause *NAREIT* returns and *NAREIT* returns do not Granger-cause the sentiment PCs at all.

The variance decomposition figures show a contribution of 3.42% - 4.62% for the *PI,* while the first and second components of the bearish (bullish) indicator range up to 8.66% (7.54%) and 3.20% (2.65%), respectively. Overall, these results confirm that our pessimism indicator has some return-signaling effect in the securitized real estate market in the United States, besides the more general sentiment expressed by the principal components.

It is worth noting that the sentiment indicators constructed via support vector machine usually have a more timely impact on *NAREIT* returns than the general sentiment components. Usually, the first lag of the *PI* is the significant one, as opposed to the second of the sentiment PCs in Models 4 and 5. Provided one can adopt the presumption that investors require some time to gather information and subsequently form their own personal beliefs about the market, one could argue that this is induced by the temporal nature of the perception-building process. As survey-based indicators aggregate sentiment from market participants which should be at least partly influenced by news items, our news-based sentiment measures are positioned one step ahead, directly capturing sentiment from the information source. Thus, they should have a more timely impact on market returns. This theory would also explain why the news specific *PI*, as well as the general sentiment principal components, have predictive power on *NAREIT* returns in the same model. The PCs not only incorporate sentiment from news items, but also from other sources such as the abovementioned federal tax code provisions, which differentiates them from our purely news-based sentiment indicators.

Table 4.3: VAR Results – News-Based Sentiment and Securitized RE Market

	FTSE/NAREIT All Equity REIT Total Return Index (NAREIT)					
	Model 1		**Model 2**		**Model 3**	
NAREIT (-1)	-0.168	*	-0.193	**	-0.185	**
	[-1.88658]		[-2.17359]		[-2.09171]	
NAREIT (-2)	-0.200	**	-0.200	**	-0.193	**
	[-2.31786]		[-2.26888]		[-2.21658]	
Pessimism Indicator (-1)	-0.254	**				
	[-2.54932]					
Pessimism Indicator (-2)	-0.056					
	[-0.55530]					
Optimism Indicator (-1)			0.057			
			[0.69979]			
Optimism Indicator (-2)			0.053			
			[0.64730]			
Sentiment Quotient (-1)					0.128	**
					[2.00084]	
Sentiment Quotient (-2)					0.049	
					[0.75974]	
Constant	0.005		0.004		0.004	
	[1.11839]		[0.89662]		[0.98906]	
Macroeconomic variables	**YES**		**YES**		**YES**	
Adj. R-squared	0.64		0.62		0.63	
F-statistic	16.37		15.21		15.83	
Log likelihood	256.82		253.32		255.22	
Akaike AIC	-3.40		-3.35		-3.38	
Schwarz SC	-3.05		-3.00		-3.02	
Granger causality						
Sentiment measure	**0.03**		0.74		0.13	
NAREIT	0.54		0.69		0.91	

Notes: This table reports results for the estimated VAR models with monthly NAREIT returns and news-based sentiment as endogenous variables. The set of macroeconomic control variables includes the difference between BAA- and AAA-rated corporate bonds yields (*SPREAD*), the difference between the 10-year U.S. Treasury bond and the 3-Month Treasury bill yields (*TERM*), the percentage change of the CPI (*INFL*) and the total return of the S&P 500 Composite Index (*SP500*). For brevity, we only report the results of the real estate return equations for each sentiment indicator. T-statistics are reported in brackets underneath the coefficient estimates. In terms of Granger causality, p-values are reported for both directions. P-values in bold show a significance up to 5%. * denotes significance at 90%, ** significance at 95%, *** significance at 99%. The sample period is 2005:M4 to 2016:M12.

Table 4.4: VAR Results – News-Based Sentiment and Securitized RE Market – Controlling for Other Sentiment Indicators

	FTSE/NAREIT All Equity REIT Total Return Index (NAREIT)					
	Model 1		Model 4		Model 5	
NAREIT (-1)	-0.168	*	-0.142		-0.140	
	[-1.88658]		[-1.56605]		[-1.55211]	
NAREIT (-2)	-0.200	**	-0.110		-0.124	
	[-2.31786]		[-1.22274]		[-1.39038]	
Pessimism Indicator (-1)	-0.254	**	-0.249	**	-0.250	**
	[-2.54932]		[-2.52610]		[-2.52191]	
Pessimism Indicator (-2)	-0.056		-0.093		-0.081	
	[-0.55530]		[-0.93056]		[-0.80736]	
First component (bearish) (-1)			0.000			
			[0.03499]			
First component (bearish) (-2)			-0.011	**		
			[-2.05542]			
Second component (bearish) (-1)			-0.002			
			[-0.55066]			
Second component (bearish) (-2)			-0.007	*		
			[-1.74007]			
First component (bullish) (-1)					0.000	
					[0.05343]	
First component (bullish) (-2)					0.015	**
					[2.52453]	
Second component (bullish) (-1)					-0.001	
					[-0.33726]	
Second component (bullish) (-2)					-0.004	
					[-1.18864]	
Constant	0.005		0.005		0.005	
	[1.11839]		[1.26585]		[1.20840]	
Macroeconomic variables	**YES**		**YES**		**YES**	
Adj. R-squared	0.64		0.66		0.65	
F-statistic	16.37		14.32		14.12	
Log likelihood	256.82		262.77		262.07	
Akaike AIC	-3.40		-3.43		-3.42	
Schwarz SC	-3.05		-3.00		-2.98	
Granger causality (PI ~ NAREIT)						
Pessimism indicator	**0.03**		**0.04**		**0.04**	
NAREIT	0.54		0.36		0.38	
Granger causality (Sentiment PCA ~ NAREIT)						
First component			0.08		**0.02**	
Second component			0.22		0.49	
NAREIT on first component			0.26		0.54	
NAREIT on second component			0.77		0.76	

Notes: This table reports results for the estimated VAR models with monthly NAREIT returns, news-based sentiment and further sentiment proxies as endogenous variables. The set of macroeconomic control variables includes the difference between BAA- and AAA-rated corporate bonds yields (*SPREAD*), the difference between the 10-year U.S. Treasury bond and the 3-Month Treasury bill yields (*TERM*), the percentage change of the CPI (*INFL*) and the total return of the S&P 500 Composite Index (*SP500*). Principal components are constructed as described in the text. For brevity, we only report the results of the real estate return equations for each sentiment measure. T-statistics are reported in brackets underneath the coefficient estimates. In terms of Granger causality, p-values are reported for both directions. P-values in bold show a significance up to 5%. * denotes significance at 90%, ** significance at 95%, *** significance at 99%. The sample period is 2005:M4 to 2016:M12.

4.5.2 Direct Real Estate Market

This and the following paragraphs repeat the entire process for the direct real estate market, further assessing the predictive power and robustness of our sentiment indicators according to research question 2. Thus, the VAR framework of Table 4.5 analyses the potentially endogenous relations between the three machine-learning sentiment indicators and the *CoStar Commercial Repeat Sales Index* (*CCRSI*), as a measure of direct market performance. Once again, all models control for economic default risk, expectations about future economic and labor market developments, as well as real estate supply, by including spread, term, initial unemployment claims and construction-spending variables. The analysis uses an optimal lag length of 8 months following the joint recommendations of several lag-length indicators such as Akaike, Schwarz and Hannan-Quinn Information Criteria, final prediction error as well as the sequential modified LR-test statistic. For ease of reading, sentiment measure means pessimism indicator in Model 6, optimism indicator in Model 7 and sentiment quotient in Model 8. Again, Table 4.5 states Granger causalities for both directions at the bottom of each column.

Models 6 to 8 show a very pronounced autoregressive component; except for the second lag, all other lagged values of the *CCRSI* are highly significant when explaining future market returns. Considering the pronounced cyclical behavior of the CoStar Index over the observation period with a boom phase until 2007, the bust of 2008/2009 and subsequent market recovery, this has to be expected. In terms of sentiment measures, Table 4.3 and Table 4.5 yield similar results for the securitized and direct commercial real estate markets. Once more, *PI* and *SQ* show the expected sign of significant lags, while the *OI* does not significantly predict direct market returns. However, the *CCRSI* reacts later to the sentiment indicators than the *NAREIT*. While the first lag appeared to be relevant in the REIT market, the second, third and – in terms of magnitude less pronounced than – the eighth lag are now the three important ones.

Overall, the pessimism indicator predicts the direct real estate market best. Its changes Granger-cause market returns at the 1% level of significance. However, in contrast to previous results, the sentiment quotient now reaches similar levels of predictive power. This can also be seen when comparing the goodness of fit measures for Models 6 and 8 that are very similar in terms of magnitude. The variance decomposition up to 36 months corroborates these findings, as the *PI's*, *OI's* and *SQ's* contribution to forecast errors reach 20.94%, 3.50% and 15.47%, respectively.

Again, with a non-significant *OI*, one could argue that there is evidence of a negativity bias of market participants. Nevertheless, the results in the direct real estate market are slightly less pronounced than in the securitized one. Note that CoStar returns do not Granger-cause any of the three sentiment indicators in Table 4.6. All existing endogenous relationships extend from changes in the indicators to market returns and not vice versa, or in a bi-directional manner. Hence, the indicators are again able to extract additional information from news that is relevant in explaining direct market movements.

Table 4.6 depicts the relative performance of our sentiment indicators created via machine learning, in contrast to other more general sentiment measures. Models 7 and 8 augment Model 6 of Table 4.5 with the same first and second bullish and bearish components of the principal component analysis. Because the optimal lag length remains 8 months, we refrain from an extended VAR approach and incorporate the components only as additional exogenous controls. This is because the addition as endogenous variables would lead to a massive loss of degrees of freedom, due to two additional equations and two additional variables with eight lags each, for which coefficients have to be estimated. Although still significantly explaining direct markets returns with the second, third and eighth lag, the results of Models 9 and 10 are slightly weaker in terms of significance, as well as coefficient magnitude in comparison to Model 6. Once again, a reverse causation cannot be stated.

The variance decomposition shows a contribution of the *PI* up to 14.66% (19.63%) in the case of Model 9 (10). This leads us to the conclusion that there is indeed evidence of the pessimism indicator's return-signaling effect not only for the securitized but also for the direct real estate market.

Table 4.5: VAR Results – News-Based Sentiment and Direct RE Market

	CoStar Commercial Repeat-Sales Index (CCRSI)					
	Model 6		**Model 7**		**Model 8**	
	Pessimism Indicator		*Optimism Indicator*		*Sentiment Quotient*	
CCRSI (-1)	1.081	***	1.126	***	1.097	***
	[12.2066]		[12.2800]		[12.1386]	
CCRSI (-2)	-0.071		-0.097		-0.116	
	[-0.62895]		[-0.79707]		[-0.56192]	
CCRSI (-3)	-1.072	***	-1.069	***	-1.108	***
	[-10.0662]		[-9.22729]		[-9.98168]	
CCRSI (-4)	1.304	***	1.305	***	1.307	***
	[9.49656]		[8.90372]		[9.30795]	
CCRSI (-5)	-0.364	***	-0.313	**	-0.320	**
	[-2.63687]		[-2.10608]		[-2.25577]	
CCRSI (-6)	-0.494	***	-0.535	***	-0.549	***
	[-4.68369]		[-4.55049]		[-4.97542]	
CCRSI (-7)	0.831	***	0.818	***	0.840	***
	[7.42224]		[6.69008]		[7.36439]	
CCRSI (-8)	-0.395	***	-0.397	***	-0.386	***
	[-4.76615]		[-4.50364]		[-4.58881]	
Sentiment measure (-1)	-0.026		-0.011		0.004	
	[-1.29342]		[-0.57983]		[0.29472]	
Sentiment measure (-2)	-0.060	**	0.014		0.028	
	[-2.32027]		[0.62850]		[1.59966]	
Sentiment measure (-3)	-0.087	***	0.019		0.045	**
	[-3.00079]		[0.83651]		[2.29096]	
Sentiment measure (-4)	-0.031		0.016		0.024	
	[-1.03654]		[0.72929]		[1.16132]	
Sentiment measure (-5)	0.010		-0.016		-0.005	
	[0.33006]		[-0.75305]		[-0.25187]	
Sentiment measure (-6)	0.038		-0.011		-0.008	
	[1.34760]		[-0.49419]		[-0.40430]	
Sentiment measure (-7)	-0.006		-0.004		0.008	
	[-0.23158]		[-0.17419]		[0.46902]	
Sentiment measure (-8)	-0.049	**	0.018		0.040	***
	[-2.39110]		[1.09460]		[2.82321]	
Constant	0.001		0.000		0.001	
	[0.85106]		[0.62156]		[0.78543]	

Table continues on the following page.

Table 4.5: VAR Results – News-Based Sentiment and Direct RE Market (continued)

Macroeconomic variables	**YES**	**YES**	**YES**
Adj. R-squared	0.81	0.78	0.81
F-statistic	21.88	18.13	21.04
Log likelihood	494.88	484.22	492.64
Akaike AIC	-6.90	-6.74	-6.87
Schwarz SC	-6.28	-6.12	-6.24
Granger causality			
Sentiment measure	**0.00**	0.65	**0.01**
CCRSI	0.99	0.74	0.92

Notes*:* This table reports results for the estimated VAR models with monthly CCRSI returns and news-based sentiment as endogenous variables. The set of macroeconomic control variables includes the difference between BAA- and AAA-rated corporate bond yields (*SPREAD*), the difference between the 10-year U.S. Treasury bond and 3-Month Treasury bill yields (*TERM)*, the amount of unemployment initial claims (*UNEMPL*) and the amount of construction spending (*CONSTR*). For the sake of brevity, we only report the results of the real estate return equations for each sentiment measure. T-statistics are reported in brackets underneath the coefficient estimates. In terms of Granger causality, values are reported for both directions. P-values in bold show a level of significance up to 5%. * denotes significance at 90%, ** significance at 95%, *** significance at 99%. The sample period is 2005:M10 to 2016:M12.

Table 4.6: VAR Results – News-Based Sentiment and Direct RE Market – Controlling for Other Sentiment Indicators

	CoStar Commercial Repeat-Sales Index (CCRSI)					
	Model 6		**Model 9**		**Model 10**	
	Pessimism Indicator		Sentiment Indices (bearish)		Sentiment Indices (bullish)	
CCRSI (-1)	1.081	***	1.103	***	1.120	***
	[12.2066]		[12.2347]		[12.5269]	
CCRSI (-2)	-0.071		-0.099		-0.091	
	[-0.62895]		[-0.87003]		[-0.81061]	
CCRSI (-3)	-1.072	***	-1.041	***	-1.062	***
	[-10.0662]		[-9.58587]		[-10.2399]	
CCRSI (-4)	1.304	***	1.302	***	1.298	***
	[9.49656]		[9.25507]		[9.47375]	
CCRSI (-5)	-0.364	***	-0.378	***	-0.369	***
	[-2.63687]		[-2.72855]		[-2.76909]	
CCRSI (-6)	-0.494	***	-0.468	***	-0.468	***
	[-4.68369]		[-4.38024]		[-4.56236]	
CCRSI (-7)	0.831	***	0.828	***	0.835	***
	[7.42224]		[7.24651]		[7.69898]	
CCRSI (-8)	-0.395	***	-0.426	***	-0.428	***
	[-4.76615]		[-5.04040]		[-5.34518]	
Sentiment measure (-1)	-0.026		-0.025		-0.019	
	[-1.29342]		[-1.20390]		[-0.88914]	
Sentiment measure (-2)	-0.060	**	-0.058	**	-0.055	**
	[-2.32027]		[-2.20412]		[-2.14026]	
Sentiment measure (-3)	-0.087	***	-0.063	**	-0.057	*
	[-3.00079]		[-2.05561]		[-1.95132]	
Sentiment measure (-4)	-0.031		-0.006		-0.001	
	[-1.03654]		[-0.19909]		[-0.03824]	
Sentiment measure (-5)	0.010		0.021		0.028	
	[0.33006]		[0.69597]		[0.97256]	
Sentiment measure (-6)	0.038		0.032		0.038	
	[1.34760]		[1.10973]		[1.37261]	
Sentiment measure (-7)	-0.006		-0.007		-0.003	
	[-0.23158]		[-0.27399]		[-0.13043]	
Sentiment measure (-8)	-0.049	**	-0.039	*	-0.036	*
	[-2.39110]		[-1.81901]		[-1.79544]	

Table continues on the following page.

Table 4.6: VAR Results – News-Based Sentiment and Direct RE Market – Controlling for Other Sentiment Indicators (continued)

First component (bearish)		0.001	
		[1.46930]	
First component (bearish) (-1)		0.001	
		[1.15635]	
First component (bearish) (-2)		-0.001	
		[-1.63152]	
Second component (bearish)		-0.001	
		[-0.84100]	
Second component (bearish) (-1)		-0.001	
		[-0.84360]	
Second component (bearish) (-2)		-0.001	
		[-1.43150]	
First component (bullish)			-0.001
			[-1.76414]
First component (bullish) (-1)			-0.001
			[-1.43729]
First component (bullish) (-2)			0.002 **
			[2.08032]
Second component (bullish)			-0.001
			[-1.67842]
Second component (bullish) (-1)			-0.001
			[-0.77426]
Second component (bullish) (-2)			-0.001 *
			[-1.85649]
Constant	0.001	0.001	0.001
	[0.85106]	[1.06344]	[1.08778]
Macroeconomic variables	**YES**	**YES**	**YES**
Adj. R-squared	0.81	0.82	0.83
F-statistic	21.88	18.80	20.29
Log likelihood	494.88	500.72	505.20
Akaike AIC	-6.90	-6.90	-6.97
Schwarz SC	-6.28	-6.15	-6.21
Granger causality			
Pessimism indicator	**0.00**	0.07	**0.03**
CCRSI	0.99	0.99	1.00

***Notes**:* This table reports results for the estimated VAR models with monthly CCRSI returns and news-based sentiment as endogenous variables. The set of macroeconomic control variables includes the difference between BAA- and AAA-rated corporate bonds yields (*SPREAD*), the difference between the 10-year U.S. Treasury bond and the 3-Month Treasury bill yields (*TERM)*, the amount of unemployment initial claims (*UNEMPL*), the amount of construction spending (*CONST R*) and further sentiment proxies per PCA. Principal components are constructed as described in the text. For brevity, we only report the results of the real estate return equations for each sentiment measure. T-statistics are reported in brackets underneath the coefficient estimates. In terms of Granger causality, values are reported for both directions. P-values in bold show a significance up to 5%. * denotes significance at 90%, ** significance at 95%, *** significance at 99%. The sample period is 2005:M10 to 2016:M12.

4.5.3 Synopsis

Based on the notion of the general importance of news for the decision-making process of market participants, our research aimed to investigate the potential of sentiment indicators created via machine learning and a dataset of news items. Research questions 1 and 2 address with whether the readily constructed sentiment indicators are able to predict direct and securitized commercial real estate market returns and whether there are differences with respect to the markets. Our results indeed indicate predictive power for both markets, and the results are comparable with respect to the quality of individual sentiment measures. Furthermore, for neither of the two markets a reverse causation could be found. However, the results deviate in market reaction times to changes in the sentiment indicators. During the 12-year sample period, returns in the securitized market respond to news-based sentiment one month earlier than CoStar returns. This might the case because of the typical characteristics of the two markets; the direct real estate market is known to move slower than the securitized one.

In Table 4.3 and Table 4.5, not all sentiment indicators have the same prediction potential. While the optimism indicator – concentrating on positive news – showed no explanatory power, the *SQ* and *PI* measures – based on positive and negative news or negative news only – were both successful in explaining market movements. The *PI* worked very well for both markets, the *SQ* better in the direct than in the securitized one. Overall, this can be interpreted as negativity bias of the market. Additionally, the *PI* retained its impact and significance when controlling for other more general sentiment measures in both markets. Even more so, *NAREIT* returns reacted earlier to changes in our sentiment indicator, in contrast to changes in more general sentiment, further showing the capability of ‘new’ sentiment measures created via textual analysis and a machine-learning approach.

4.6 Conclusion

Due to the specific characteristics of real estate markets such as low transparency, information asymmetry, illiquidity as well as long transaction periods, one could argue that real estate is by nature more prone to sentiment than stock markets, for example. A number of articles have indeed dealt with the role of market sentiment measured by different proxies and found evidence of significance for real estate asset pricing. One area of research extracts sentiment by investigating text corpora. However, for real estate, related research focuses mainly on a dictionary-based approach. The ongoing digitalization of news and technical advances enables us to contribute to the literature on text-based sentiment analysis in the realm of real estate, by creating and testing sentiment measures constructed via a machine-learning approach. Hence, this paper examines the relationship between news-based sentiment, captured through support vector networks, and the U.S. securitized and direct commercial real estate markets.

In order to extract sentiment from about 54,500 news items, provided by *S&P Global Market Intelligence* Platform (SNL), we train a support vector machine as a classification algorithm. Subsequently, the classification scores thus gained are aggregated into three different monthly sentiment measures, i.e. a pessimism and optimism indicator, as well as a 'neutral' sentiment quotient. Applying a VAR framework and monthly real estate return data provided by *NAREIT* and *CoStar*, we analyze the dynamic relationship between our created sentiment measures and direct as well as securitized market returns.

The results indeed show evidence of a significant relationship between our sentiment indicators and real estate market movements. More precisely, the *PI* Granger-causes *NAREIT* returns and leads the market by one month, even when controlling for macroeconomic fundamentals. Furthermore, the text-based indicator provides information in explaining securitized market returns beyond more general market sentiment. Our results do not indicate a significant influence of past market performance on any of the three constructed sentiment measures.

The direct real estate market yields similar findings. The pessimism indicator, as well as the sentiment quotient, drive total returns by two, three and eight months. For both measures, Granger causality remains significant when including macroeconomic and general sentiment controls. In equal measure to the REIT market, there is no bi-directional relationship. Overall, the findings are consistent with the notion of a slower-moving direct market, in contrast to the securitized one. Furthermore, empirical evidence suggests that the measure based on the idea of a negativity bias delivers the most significant and consistent results. This is in accordance with the psychology literature, which proposes market participants as more sensitive to negative, rather than positive news. In general, these findings highlight the importance of real estate news analytics as an innovative source of sentiment, and indicate that news-based sentiment can be deployed as a leading market indicator. Additionally, the findings make a contribution to real estate research and industry participants, as we show the successful application of a sentiment-measuring method that allows short and flexible aggregation periods.

However, in order to create sentiment indicators for even smaller aggregation periods, a more extensive news dataset than the one we used would be required. Future research could therefore combine professional news with other sources such as news directed to the public, such as from *The Wall Street Journal* or *Financial Times*. Nevertheless, at higher frequency levels, efficiently controlling for macroeconomic fundamentals becomes progressively more complicated. In addition, a comparison to the established dictionary-based approach would be worthwhile. Due to different levels of transparency in other real estate markets, one could expect sentiment to be even more relevant in countries with a less advanced real estate industry, an issue that is also worth investigating.

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4.8 Appendix

Table 4.7: Data Description

Variable label	Description	Unit	Mnemonic	Source	RE Market
10Y	10-Year Treasury Constant Maturity Rate	Percent	GS10	FRED	Direct, Securitized
3M	3-Month Treasury Constant Maturity Rate	Percent	GS3M	FRED	Direct, Securitized
AAA	Moody's Seasoned Aaa Corporate Bond Yield	Percent	AAA	FRED	Direct, Securitized
AAIIBEAR	US Sentiment Survey: AAII % Bearish	Percent	USAAIIN	TR Datastream	Direct, Securitized
AAIIBULL	US Sentiment Survey: AAII % Bullish	Percent	USAAIIP	TR Datastream	Direct, Securitized
ADVSENTBEAR	Advisors' Sentiment Bearish	Percent	USIIBER	TR Datastream	Direct, Securitized
ADVSENTBULL	Advisors' Sentiment Bullish	Percent	USIIBUL	TR Datastream	Direct, Securitized
BAA	Moody's Seasoned Baa Corporate Bond Yield	Percent	BAA	FRED	Direct, Securitized
CONSTR	Total Construction Spending	Million USD	TTLCON	FRED	Direct
CONSUSENTI	University of Michigan: Consumer Sentiment	Index	UMCSENT	FRED	Direct, Securitized
CPI	Consumer Price Index for All Urban Consumers	Price Index	CPIAUCNS	FRED	Direct, Securitized
ECOPOLUNCERTINEWS	US Economic Policy Uncertainty Index – News-Based	Index	USEPUNEWR	TR Datastream	Direct, Securitized
ECOPOLUNCERTOVER	US Economic Policy Uncertainty Index – Overall	Index	USEPUPOLR	TR Datastream	Direct, Securitized
S_P500	S&P 500 Composite	Price Index	S&PCOMP	TR Datastream	Securitized
UNEMPL	Civilian Unemployment Rate	Percent	UNRATENSA	FRED	Direct
ECOUNCERT	US Equity Related Economic Uncertainty	Index	USEPUEQ	TR Datastream	Direct, Securitized

Notes: Series were taken from Federal Reserve Bank of St. Louis (FRED) and Thomson Reuters Datastream (TR). The data span for all series is 2005:M1 – 2016:M12.

5. Conclusion

The following section contains the executive summaries for the respective paper of the dissertation, which addresses the research objective and design, as well as the main findings and their practical implications. In Section 5.2, the dissertation concludes with some final remarks on text-based sentiment analysis in real estate, and directions for future research.

5.1 Executive Summaries

Paper 1: Real Estate Media Sentiment Through Textual Analysis

A variety of studies shows that economic fundamentals do not account for all observed prices movements in securitized real estate markets (e.g. Lin et al., 2009; Ling et al., 2014; Das et al, 2015). In addition, research in mainstream finance provides promising results augmenting fundamental market-prediction models with text-based sentiment measures (e.g. Tetlock, 2007; Loughran and McDonald, 2011; Heston and Sinha, 2016). That said, no prior research addresses the role of text-based sentiment measures in the U.S. securitized real estate market. Hence, the first paper of this dissertation examines the relationship between news-based sentiment, captured by textual analysis, and the securitized real estate market in the United States.

Consequently, more than 125,000 real-estate-related news headlines from U.S. newspapers (*Bloomberg*, *The Financial Times*, *Forbes* and *The Wall Street Journal*) were analyzed concerning their sentiment. For this purpose, textual analysis using a dictionary-based approach was performed and various sentiment measures were created. Subsequently, in a vector autoregressive framework, the relationship between news-based sentiment and monthly price movements of the FTSE/NAREIT All Equity U.S. Total Return Index from 2005 to 2015 was investigated.

The empirical results show that news-based sentiment, reflected in real estate news headlines, helps predict returns from the securitized real estate market three to four months in advance. The results are statistically significant and robust, even when controlling for other influencing factors. Interestingly, when the purely fundamental prediction model was augmented with the created sentiment measures, the explanatory power, as well as the goodness of fit of the model improved. This indicates that news-based sentiment exerts a persistent influence on securitized real estate market returns. Furthermore, it is an innovative sentiment measure, which can serve as a leading market indicator. The results were confirmed by performing pairwise Granger causality analysis. However, there is also evidence suggesting that REIT returns Granger-cause news-based sentiment. This suggests that information flows from the news-based sentiment measures to the REIT market, but also provides evidence that news contains information on past REIT market performance.

Additionally, the results reveal that both optimism and pessimism expressed in news have a significant relationship with REIT market returns. However, the sentiment measure, which considers media optimism as well as pessimism, is more successful in predicting REIT returns than measures which solely consider negative or positive media-expressed sentiment. Lastly, the findings in this paper are in accordance with Loughran and McDonald (2011) and highlight the importance of choosing a domain-specific dictionary when performing domain-specific sentiment analysis. Evidently, none of the sentiment measures based on the general dictionary significantly Granger-cause REIT market returns.

To sum up, the findings in this paper contribute to the recently emerging literature on text-based sentiment analysis and further improve the understanding of REIT market movements. Finally, the results underline the importance for real estate professionals of monitoring real-estate-related news as a measure of investor sentiment and/or as a leading indicator.

Paper 2: On the Relationship Between Market Sentiment and Commercial Real Estate Performance – A Textual Analysis Examination

The existing literature shows that sentiment plays a role in the pricing of direct real estate markets (Clayton et al., 2009; Ling et al., 2014). However, only limited research directly investigates the role of sentiment in commercial real estate markets. In fact, no prior research has explored the role of text-based sentiment in the direct CRE markets. Therefore, the second paper of this dissertation investigates the bi-directional relationship between text-based sentiment and the performance of the U.S. direct commercial real estate market.

For this purpose, more than 65,000 real-estate-related news abstracts from the *The Wall Street Journal* were analyzed to detect real-estate-related sentiment. Following Loughran and McDonald (2011) and Ruscheinsky et al. (2017), the textual analysis was performed with a dictionary-based approach using a word list adjusted to real estate terminology. The sentiment was quantified via a measure that accounts for the occurrence of media optimism and pessimism, as well as the respective intensity thereof. Afterwards, the intertemporal links between news-based sentiment and quarterly direct CRE market movements from 2001 to 2016 were examined in various regression frameworks. Furthermore, to help understand the lead-lag relationship between sentiment in real estate-related news and the direct CRE market, Granger causality tests were conducted. Here, the performance of the U.S. direct CRE market is derived from total returns from a transaction-based total return index provided by the *National Council of Real Estate Investment Fiduciaries* (*NCREIF*).

Overall, the findings suggest that sentiment reflected in news can indeed help predict returns from the CRE market by two to three quarters in advance. The findings are statistically significant and persist even when controlling for other related factors. This suggests that news-based sentiment can serve as an early market indicator. Furthermore, the findings in this paper illustrate the importance of adequately quantifying text-based sentiment. Specifically, the findings reveal that the news-based measure not only accounts for the occurrence of optimism and pessimism in the news, but also its respective intensity has the highest and most significant predictive power regarding CRE market returns. Furthermore, the results of the Granger-causality tests reveal that information and sentiment in news affects direct CRE returns, and the news reflect, at least partially, sentiment driven by past market performance. Interestingly, in accordance with the literature (e.g. Beracha and Wintoki, 2013), the findings suggest that commercial real estate prices are more susceptible to news-based sentiment when markets are slowing down and/or declining.

In conclusion, the findings in this paper underpin the importance and potential of sentiment expressed in real estate news with regard to predicting movements in the direct CRE market. Moreover, this paper lays the foundation for future research on text-based sentiment analysis and direct CRE.

Paper 3: News-Based Sentiment Analysis in Real Estate: A Machine-Learning Approach Via Support Vector Networks

Building upon Paper 1 and 2, which clearly demonstrated the relevancy of text-based real estate sentiment analysis, this paper applies a more advanced method of textual analysis. Specifically, the third and final paper of this dissertation is the first to assess the potential of a supervised machine-learning approach for conducting text-based real estate sentiment analysis. Moreover, it investigates the relationship between news-based sentiment, captured through support vector networks (SVM), and the securitized and direct commercial real estate markets in the United States.

Approximately 54,500 real-estate-related news headlines from *S&P Global Market Intelligence* were analyzed concerning their inherent sentiment, via the pre-trained machine-learning algorithm. In a vector autoregressive framework, the dynamic relationship between different news-based sentiment measures and monthly total returns of the U.S. securitized and direct real estate markets was investigated. The return data from the securitized and direct real estate market is based on the *CoStar Commercial Repeat Sales Index* (*CCRSI*) and the *FTSE/NAREIT All Equity REIT Total Return Index* (*NAREIT*), respectively. The data collected in this paper spans from 01/2005 to 12/2016.

The findings reveal a significant relationship between news-based sentiment measures and commercial real estate market movements. On average, news-based sentiment leads total returns from the securitized and direct real market by one to two, and two, three and eight months, respectively. This is consistent with the notion that the securitized market, compared to the direct one, is more efficient and reacts more quickly to new information and sentiment expressed in news. Interestingly, the sentiment measure concentrating on pessimism in the news has the most significant and robust results in terms of its predictive power for both markets. This is in accordance with the findings of Tetlock (2007), and indicates the existence of a negativity bias (Rozin and Royzman, 2001) on the part of real estate professionals. Surprisingly, the findings do not reveal any significant evidence of past market performance impacting on current news based sentiment. Hence, a bi-directional relationship and/or potential feedback loop cannot be claimed. The findings in this paper remain robust – even when controlling for other potential influencing factors and established sentiment proxies.

Overall, the results contribute to the literature on text-based sentiment analysis research in real estate. For the first time, a machine-learning approach has successfully captured text-based sentiment relevant to the U.S. real estate markets. Once more, this paper provides evidence on the importance of real estate news analytics and its potential to provide valuable leading market indicators.

5.2 Final Remarks and Further Research

Selected studies have demonstrated that sentiment plays a role in real estate asset pricing and real estate investors' decision-making processes, independent of economic fundamentals (Clayton et al., 2009; Seiler et al., 2012; Ling et al., 2014; Das et al., 2015). However, traditional measures that are used to directly capture investor sentiment in the real estate sector suffer from several disadvantages. Therefore, the dissertation in hand proposes an innovative approach to capturing real estate-relevant sentiment by employing textual analysis. Specifically, this dissertation investigates *whether* and *to what extent* sentiment in real estate news can help predict movements of the securitized and direct CRE market in the United States. To address this empirical research gap, two methods of textual analysis (dictionary-based and machine-learning approach) were deployed to capture sentiment expressed in real-estate related news items, from various established and authoritative news outlets. Subsequently, the optimism and pessimism expressed in the news was quantified via various sentiment measures.

Interestingly, despite the different news sources, methods and levels of textual analysis, the findings in this dissertation yield a consistent picture. The main findings are as follows: (i) It was demonstrated that textual analysis, could in fact be applied to capture sentiment in news that is relevant to U.S. CRE markets. (ii) On average, the created news-based sentiment measures lead securitized and direct commercial real estate market returns. However, the direct CRE market adjusts more slowly to sentiment expressed in news, due to its inherent inefficiencies. (iii) The statistical significance of the captured news-based sentiment also persists when controlling for other economic fundamentals, as well as established sentiment measures. In fact, the inclusion of news-based sentiment in CRE prediction models improved the goodness of fit of the model and its predictive power. This suggests that the text-based measures capture additional information, which macroeconomic fundamentals and traditional sentiment indicators do not already reflect. (iv) CRE prices were found to be more vulnerable to news-based sentiment during decelerating markets and/or times of downward price pressure. The study by Beracha and Wintoki (2013) also points to the role of sentiment during up versus down markets of residential properties. (v) When analyzing the bi-directional relationship between news-based sentiment and CRE markets, the results clearly show that information and sentiment in news affects CRE movements. However, the results also reveal that news, at least partially, reflects sentiment driven by past market performance, thus indicating a feedback effect. (vi) Consistent with the findings of Loughran and McDonald (2011), this dissertation underpins the importance of choosing a real-estate-specific word list when performing text-based sentiment analysis in the realm of real estate.

In summary, the present dissertation lays the foundation for text-based sentiment analysis applications for the U.S. direct and securitized CRE markets. Furthermore, the text-based sentiment measures can be clearly differentiated from traditional sentiment measures, as the former can be constructed readily for higher and more flexible aggregation periods with a practically unlimited amount of text corpora and topics. By contributing knowledge about the role of news in CRE markets, the findings in this dissertation underpin the importance of real-estate news analytics. This topic has obvious practical relevance, as tracking the mood expressed in real-estate related news, can guide management *by* and the investment decisions *of* real estate professionals. In practice, complementing fundamental forecasting models with news-based sentiment as a leading market indicator is advisable, as this could help improve forecasts, rebalance real estate asset portfolios and control risk.

Due to the early stage of text-based sentiment analysis in real estate, the opportunities for further research are manifold. For example, the research conducted in this dissertation was limited to aggregate market-level analysis. Hence, for textual sentiment researchers in real estate, it would be worth investigating the impact of text-based sentiment on firm-level performance. In this context, firm-specific news, public corporate disclosures and analyst reports are information sources that might affect the risk-return-characteristics of individual REITs. Daily or weekly text-based sentiment measures are also worth investigating when performing firm-level analysis. Nevertheless, this comes with a caveat, as it is becoming increasingly difficult to control for other influencing factors and/or to collect the required number of news stories. In addition, the inability to differentiate between news stories represents a limitation in the research conducted for this dissertation. Specifically, when performing news analytics, it could be worth differentiating between expected and unexpected news as these might affect investor sentiment differently and hence influence real estate prices with varying intensity. It may also be advantageous to differentiate between certain news categories as they might vary in the degree of relevance and/or attention attracted. In this context, focusing primarily on breaking news could be a worthwhile experiment, as this type of news is highly relevant and current, thus helping to avoid noise. Also, in the text mining literature (e.g. Nassirtoussi et al., 2015), shorter texts are argued to be naturally more concise and to contain fewer repetitions and irrelevant words. Therefore, the sentiment in this dissertation was captured from real estate news headlines and news abstracts, i.e. shorter texts. Yet, future studies should compare the sentiment captured from news headlines versus the sentiment in the full text of news with regard to its predictive power over future real estate market movements. Moreover, this dissertation focused exclusively on the role of news-based sentiment in CRE markets in the United States. However, it would be worth performing similar analysis in other countries with varying degrees of transparency and/or to conduct cross-national comparisons. One could assume that less transparent markets, i.e. those with more friction and higher information asymmetries are more susceptible to the impact of sentiment. In this regard, the *Global Real Estate Transparency Index* from Jones Lang LaSalle could be helpful as it provides a comprehensive country comparison in terms of market transparency levels. Finally, from a technical perspective, some of the main issues involved in performing textual analysis are the approach deployed and the type of text corpus at hand. Hence, it would be interesting to contrast and compliment the performances of different machine learning algorithms (e.g. SVM, Naïve Bayes or Neural Networks) with the dictionary-based approach by analyzing a uniform text corpus.

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