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Jessica Ruscheinsky

Evaluating Sentiment in Real Estate Markets by Means of Textual Analysis

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1 Introduction

1.1 General Motivation and Theoretical Foundation

The real estate industry is the largest segment of most economies, comprising about 13% of total gross domestic product in the US and about 18% in Germany (Blue Water Credit, 2018; Just et al., 2017). Estimates of the global property value amounted to 2.7 times the world's GDP in 2015 (Savills, 2016). These figures highlight the important role of real estate to economies, companies and individual wealth. Property value changes can impact on the overall wellbeing of nations. Therefore, both the real estate industry, as well as academia, aim to understand market movements as precisely as possible. This is of particular importance to making the right assumptions within the process of individual property decision-making and in terms of entire economies, so as to avoid crises like the world economic crisis in 2007, which was in part caused by the real estate industry.

Since it has been confirmed that movements in real estate markets cannot be explained by fundamental value changes only, the focus has shifted to quantifying the other influencing factors. Mostly, these other impacts are subsumed by the concept of sentiment. As market shifts are thus caused by their participants, efforts are made to measure the sentiment impacting on individual decision-makers, who "[…] are motivated substantially by their own emotions, random attentions or conventional wisdom." according to Shiller (2015). Interestingly, Gallimore and Gray (2002) found that individuals are even well aware of the importance of sentiment in their property decisions. Gallimore and Gray (2002) conducted a questionnaire survey among individuals actively involved in the property investment process and discovered that they make almost the same use of a personal feel for the state of the market, as of hard market information, for their decision-making. Furthermore, they also take the views of others into account.

Traditional sentiment measures utilized in real estate include indirect measures such as closed-end fund discounts, buy-sell imbalances or mortgage flows, and direct measures, mostly survey-based proxies, such as the *Real Estate Research Corporation* sentiment measure, a quarterly survey of institutional investors, the *American Association of Institutional Investors Investor Sentiment Survey (AAII)* or the *U.S. Investor Intelligence sentiment indicator*. These sentiment measures have some disadvantages, as they are mostly backward-looking, data collection and evaluation take time, surveys can be biased, have a limited population and are expensive.

A new field of sentiment analysis offers considerable advantages, which has benefited from two current developments. On the one hand, all kinds of texts are now digitized and available online.

One the other hand, technical advances and increasing computational power enable to handling and analyzing large amounts of data. Together, these two advances present an opportunity for textual analysis-based sentiment measures. Innovative methodologies can be applied to investigate various sources such as news, earnings press releases, annual reports, 10 Ks, analyst reports, commentaries or IPO prospectuses. Textual analysis has the huge advantage, of not being restricted to any particular time restrictions, topic or people participating. As long as the text data is available, it can be analyzed within seconds, regarding any desired aspect.

Over the last decade, finance research has increasingly confirmed the value of textual analysis for identifying sentiment. According to Kearney and Liu (2014), textual sentiment can include facets of subjective judgment, behavioral characteristics of investors, as well as objective reflections of conditions within firms, institutions and markets. The application of textual analysis in financial literature presents promising results explaining market indices, company stock prices, trading volume or even market volatility.

Some initial research by Soo (2015), Walker (2014, 2016) and Nowak and Smith (2017) have assessed the relationship between textual sentiment measures and residential real estate markets in the US and UK, deploying sentiment-annotated word lists. However, little attention has generally been paid to applications in real estate. The value of these innovative methodologies has not yet been well identified for this sector. Therefore, this dissertation seeks to shed light on the opportunities arising through textual analysis. The three articles address different methodologies analyzing different text corpora and investigating the relationships between the created sentiment measures and different markets in different countries. Furthermore, it develops the groundwork for the first application in Germany. A variety of comparisons is made in order to understand the dynamics, always controlling for fundamental factors influencing the market. Beyond that, parts of news were analyzed individually, in order to discuss the trade-off between short "headline sentiment" and long "article sentiment". Overall, the extracted text-based sentiment measures constitute significant evidence explaining and even anticipating future real estate market movements. In short, this dissertation highlights the importance of paying attention to new media and digitalization, in order to gain new insights into real estate market movements.

1.2 Research Questions

This section provides an overview of the research questions investigated in this dissertation, presented separately in terms of the three articles.

Paper 1: Real Estate Media Sentiment Through Textual Analysis

- What methodologies in the literature can be used to conduct textual analysis?
- Which research attempts using textual analysis do exist so far in an economic context?
- Does media-expressed sentiment affect future REIT market movements?
- Is the dictionary-based approach appropriate for capturing sentiment from real estate-related newspaper articles?
- Does the mere number of newspaper articles published already constitute an indicator of real estate market sentiment?
- Is a domain-specific dictionary more efficient in creating sentiment scores than a general sentiment dictionary?
- Is there any difference in the explanatory power of positive or negative sentiment measures, or those incorporating both polarities?

Paper 2: News-Based Sentiment Analysis in Real Estate: A Machine-Learning Approach Via Support Vector Networks

- Which text documents have been analyzed so far using textual analysis?
- Can sentiment measures created via a machine learning approach, namely support vector networks, predict the securitized commercial real estate market?
- Is there a difference in predictive power for the direct commercial real estate market?
- How do the created text-based sentiment indicators perform in comparison to established sentiment measures?
- Are market participants maybe more influenced by negative than positive signals? Hence, is there evidence of a negativity bias on the part of market participants?

Paper 3: Predicting Real Estate Market Movements: the First Textual Analysis-Based-Sentiment Application in Germany

- Have any attempts been made in the past to apply textual analysis to German economic contexts?
- Is the application of the dictionary-based approach appropriate for the German language?
- Are there any issues deploying the dictionary-based approach for the German language in comparison to English?
- Do sentiment measures based on a newly developed German Real Estate Sentiment Dictionary have any predictive power with respect to the German residential real estate market?
- How crucial is the construction of the dictionary in terms of a threshold to including words?
- Is the analysis of the headline alone sufficient to capture sentiment, or does the inclusion of further text lead to better results?
- Is a discipline-specific German sentiment dictionary superior to a general German sentiment wordlist?

1.3 Course of Analysis

The following synopsis presents an overview of the three research papers with regard to the authors, the course of analysis, conference participations, as well as current publication status.

Paper 1: Real Estate Media Sentiment Through Textual Analysis

This is the first paper to capture media sentiment from news that is relevant to U.S. securitized real estate markets. For this purpose, 125,000 newspaper article headlines from four different sources, namely *Bloomberg, The Financial times, Forbes* and *The Wall Street Journal,* were collected. Subsequently applying the dictionary-based approach and aggregating the results, led to three different sentiment measures on a monthly level. In a vector autoregressive framework, the created sentiment measures yielded a significant relationship with future REIT market movements.

Authors: Jessica Roxanne Ruscheinsky, Marcel Lang, Wolfgang Schaefers

Submission to: Journal of Property Investment & Finance

Current Status: published in Volume 36 Number 5 (July 2018)

This paper was presented at the 2016 Annual Conference of the European Real Estate Society in Regensburg, Germany, and the 2017 Annual Conference of the American Rea Estate Society in San Diego, California, USA. Furthermore, this paper won the ERES Award for the Best Paper in the Ph.D. Session 2016.

Paper 2: News-Based Sentiment Analysis in Real Estate: A Machine-Learning Approach Via Support Vector Networks

This study applies a machine-learning approach, namely support vector networks, to capture sentiment from professional news headlines published by *S&P Global Market Intelligence* database (SNL). For the first time, sentiment measures based on a support vector machine as a classification algorithm, are investigated and compared regarding to their relationship with the U.S. securitized and direct commercial real estate market.

Authors: Jochen Hausler, Jessica Roxanne Ruscheinsky, Marcel Lang

Submission to: Journal of Property Research

Current Status: under Review

This paper was presented at the 2017 Annual Conference of the European Real Estate Society in Delft, Netherlands, and the 2017 Annual Conference of the American Rea Estate Society in San Diego, California, USA.

Paper 3: Predicting Real Estate Market Movements: the First Textual Analysis-Based-Sentiment Application in Germany

The major aim of this research paper is to lay the foundation for and test the applicability of text-based sentiment analysis in German real estate markets. First, the groundwork was accomplished by developing the first German Real Estate Sentiment Dictionary. The next steps yielded robust evidence of a significant relationship between the extracted negative sentiment measure and the residential real estate market in Germany.

Authors: Jessica Roxanne Ruscheinsky, Katrin Kandlbinder, Wolfgang Schaefers, Marian Alexander Dietzel, Karim Rochdi

Submission to: Journal of European Real Estate Research

Current Status: under Review

This paper was presented at the 2018 Annual Conference of the American Real Estate Society in Bonita-Springs, Florida, USA.

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 analyze 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.

2.1 Introduction

"A simple remark from him could cause the stock market and the dollar to rise or fall", commented Abe (2011), who analyzed 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 analyzing 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 analyses 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 reviews the relevant literature in the context of textual analysis, as well as sentiment analysis in REIT markets. Section 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 analyzed in Section 5. Afterwards, these results are tested regarding their robustness in Section 6. Finally, Section 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 behavioral 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. Behavioral 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 behavioral 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 home buyers, 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 indirect 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, 2002; Barkham and Ward, 1999), the buy-sell-imbalance (Freybote and Seagraves, 2017) 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. (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 (2016), 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 et al., 2009; Heston and Sinha, 2017). For example, Kothari et al. (2009) employed the Harvard GI word list to analyze firm-specific disclosures, discovering that positive disclosures are followed by declining firm risk measures and vice versa. Heston and Sinha (2017) made use of this dictionary, analyzing 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), Jegadeesh and Wu (2013) or lately, Heston and Sinha (2017). 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 analyzing 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 (2015) 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 analyzed 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 data-sets 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 analyze the impact of media-expressed sentiment not solely for a specific market phase, an eleven year time 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; Chatrath et al., 2014). 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 analyzed.

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

[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.

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 Peramunetilleke 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 data-set. On average, 945 headlines were published per month.

2.3.2 Time Series Variables

To analyze 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 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, 2003; Schätz and Sebastian, 2010; Hoesli and Oikarinen, 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 labor 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

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

(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 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.

Table 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.

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, before 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 analyzed. 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 analyzed manually regarding sentiment classification. Words appearing on 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

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

[4] See http://www.nd.edu/mcdonald/Word_Lists.html.

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 (2011) 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).*

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.

[5] RapidMiner Studio is a Data Science Software Platform available at: https://rapidminder.com/.

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

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.

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

Sentiment Measure 3: Positive Count (*PCount*)

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

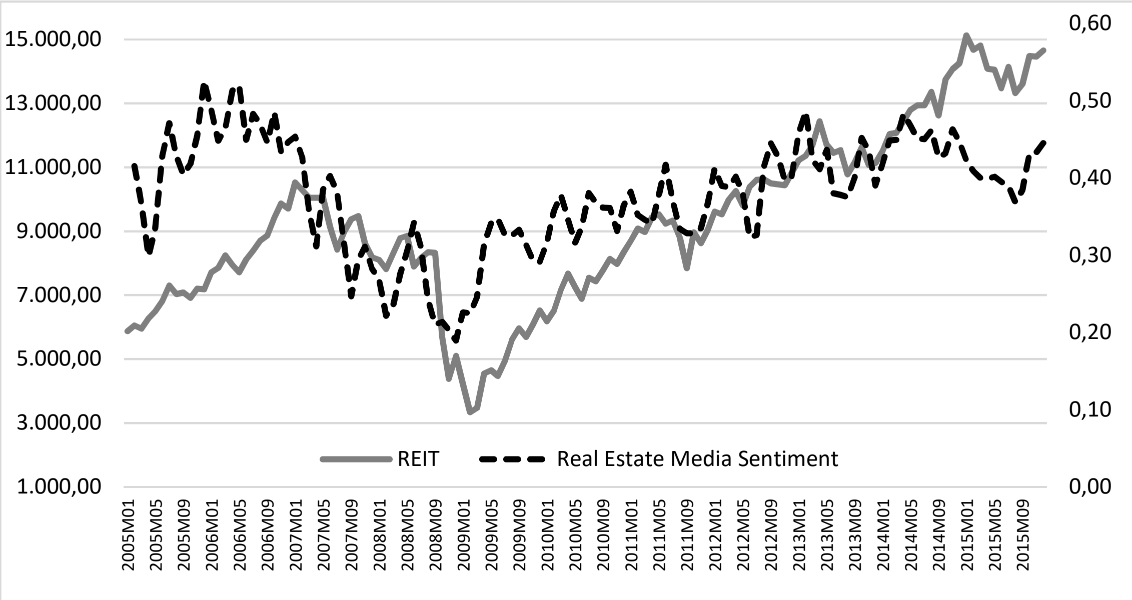
The *PCount* is defined as the number of positive headlines divided by the overall number of headlines for a given period t. It ranges from 0 to 1 and increases with a relative increase in positive headlines indicating increasing media optimism.

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 analyzed 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).

Figure 1: RE Media Sentiment vs. REIT Total Return, 2005 – 2015



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

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 1 plots the 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 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:

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

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. ut 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 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.

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 Models (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.

Table 2: VAR Results for Sentiment Quotient

Model	(1)		(2)		(3)		(4)	
	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	-0.007		0.0018		0.0062		0.0086	
Adj R^2	0.6518		0.7186		0.7237		0.7415	
AIC	-3.326		-3.507		-3.5100		-3.5608	
Loglikelihood	222.2010		222.2853		222.2974		223.5561	

Notes: The 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 monthly observations: January 2005 to December 2015. * 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.

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 Schätz and Sebastian (2010), Hoesli and Moreno (2006) 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 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.

Table 3: VAR Results with Different Sentiment Measures

Model	(4)		(5)		(6)		(7)		(8)		(9)	
	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.

Furthermore, the relationship is bi-directional similarly to the results in Model (4) with the *SQ_RE*. As can be seen in Table 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 focusing 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 focusing on one polarity.

Moreover, this paper examines the importance of choosing an adequate dictionary to extract sentiment from real estate specific newspaper articles, formulated in Hypothesis 2. As 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 ($Ncount\_HAV_{t-4}$ & $Pcount\_HAV_{t-1}$) 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 (2017), 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.

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 analyze 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 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 4: REIT Sector Specific VAR Results

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 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 & Gas Index *(DJ OIL)* was chosen as a representation of a different market / asset class. As Table 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 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
Model with 5 lags	0.1135	0.1177	0.2287***	0.2475***	0.0924				11.9846**
Model with 6 lags	0.0884	0.0937	0.2325**	0.2527***	0.1051	0.0296			11.2841*
Model with 7 lags	0.1029	0.1231	0.2786***	0.2825***	0.1304	0.0528	0.0272		12.4307*
Model with 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

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
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 & 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). *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 2007 with new insights into market behavior.

The findings of this paper are in accordance with current behavioral 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 private 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 time 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 and hence, another time reference might be ascertained.

Considering the bigger picture, this study highlights the importance of paying sufficient attention to new media and digitalization. The information behavior 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. 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 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 indirect 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.

3.1 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 private 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 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 pessimism indicator 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 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 presents the machine-learning approach, as well as the methods of aggregating the sentiment measures. Furthermore, the VAR framework is derived. Chapter 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.

3.2 Literature Review

3.2.1 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).

3.2.2 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 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 Nassirtoussi 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).

3.2.3 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?*

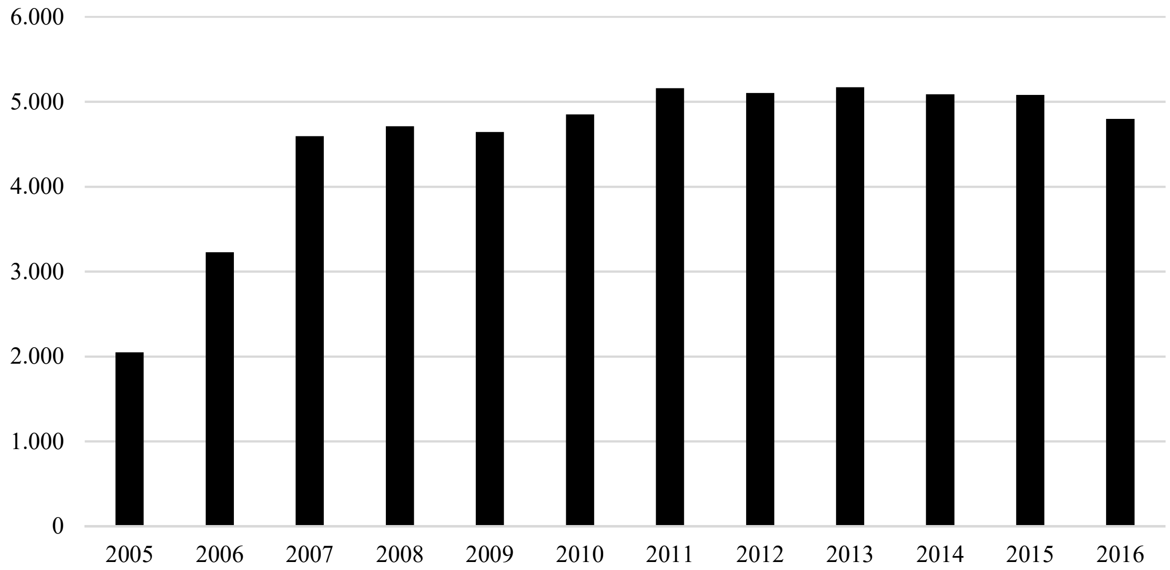
3.3 Data

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.

3.3.1 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 1: SNL Real Estate News Coverage, 2005 – 2016



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'.

Figure 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.

3.3.2 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.

3.3.3 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. Schätz 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 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 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 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.

3.4 Methodology

3.4.1 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 $(y_1, \boldsymbol{x_1}), \ldots, (y_l, \boldsymbol{x_l})$, $y_i \in \{-1,1\}$ is linearly separable, if the inequality $y_i(\boldsymbol{w}\boldsymbol{x_i} + b) - 1 \geq 0, i = 1, \ldots, l$ is fulfilled for all training elements. Hence, the optimal hyperplane $\boldsymbol{w_0}\boldsymbol{x} + b_0 = 0$ 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.[6] These training vectors $y_i(\boldsymbol{w}\boldsymbol{x_i} + b) - 1 = 0$ 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 $y_i(\boldsymbol{w}\boldsymbol{x_i} + b) - 1 \geq 0, i = 1, \ldots, l$.

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 $\boldsymbol{\Lambda^T} = (\alpha_1, \ldots, \alpha_l)$ subject to the constraints of $\boldsymbol{\Lambda^T Y} = 0$ and $\boldsymbol{\Lambda} \geq 0$, where ***1*** is a l-dimensional unit vector, $\boldsymbol{Y}^T = (y_1, \ldots, y_l)$ 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 $i, j = 1, \ldots, l$. Given $\boldsymbol{w_0}$, one can solve $\boldsymbol{w_0}\boldsymbol{x} + b_0 = 0$ 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:

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

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

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 $\xi_i \geq 0, i = 1, \ldots, l$ 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 $\boldsymbol{\Lambda^T} = (\alpha_1, \ldots, \alpha_l)$, but subject to slightly adjusted constraints of $\boldsymbol{\Lambda^T Y} = 0$ and $C * \boldsymbol{1} \geq \boldsymbol{\Lambda} \geq 0$.

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 $\phi: \mathbb{R}^n \rightarrow \mathbb{R}^N$ 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 $\phi(\boldsymbol{x_i}) = \phi_1(\mathbf{x}_i), \phi_2(\mathbf{x}_i), \ldots, \phi_N(\mathbf{x}_i), i = 1, \ldots, l$ in the same manner described above. “New” data can be classified by transforming the “data” vector into the feature space ($\widetilde{\boldsymbol{x}} \rightarrow \phi(\widetilde{\boldsymbol{x}})$) first, and then applying the sign function afterwards:

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

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.

3.4.2 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:

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

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:

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

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:

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

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

Table 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 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.

3.4.3 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:

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

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 (8). 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:

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

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 indirect 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.

3.5 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 indirect 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.

3.5.1 Securitized Real Estate Market

Table 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.

Table 3: VAR Estimation 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.

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 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 contrasts the base Model 1 from Table 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.

Table 4: VAR Estimation 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.

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.

3.5.2 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 Reasearch Question 2. Thus, the VAR framework of Table 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 5 states Granger causalities for both directions at the bottom of each column.

Table 5: VAR Estimation 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 5: VAR Estimation 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.

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 3 and Table 5 yield similar results for the indirect 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 – 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 5. 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 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 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 indirect but also for the direct real estate market.

Table 6: VAR Estimation 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 6: VAR Estimation 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.

3.5.3 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 deal with whether the readily constructed sentiment indicators are able to predict direct and indirect 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 indirect one.

In Tables 3 and 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.

3.6 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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3.9 Appendix

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

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

4 Predicting Real Estate Market Movements: the First Textual Analysis-Based-Sentiment Application in Germany

Abstract

Purpose

The purpose of this study is to examine the value of text-based sentiment analysis for German real estate markets. By developing the first *German Real Estate Sentiment Dictionary,* this paper lays the foundation for future real estate-related textual-analysis applications in Germany.

Design / Methodology / Approach

Conducting a large survey of about 1,700 real estate professionals, enables generating the *German Real Estate Sentiment Dictionary* with objective sentiment scores for real estate-related German words. Accordingly, this paper examines 125,462 newspaper articles published in the *Immobilien Zeitung,* the major real estate news provider in Germany, applying the dictionary-based approach. A vector autoregressive framework and out-of-sample forecasts are utilized to analyze the dynamic relationship between the created news-based sentiment measures and the German residential market from 2007 to 2017.

Findings

Overall, the results yield strong and robust evidence of a significant relationship between the extracted sentiment and the housing market. More precisely, the negative sentiment indicator Granger-causes one-month-ahead *IMX* returns, even when controlling for macroeconomic fundamentals and an indirect sentiment measure. Furthermore, this paper finds that the analysis of German newspaper headlines alone, and analyzing the complete article, both constitute significant real estate sentiment measures.

Originality/Value

Most notably, in this paper, an objectively validated *German Real Estate Sentiment Dictionary* with 14,137 real estate-related words is developed. This exceptional resource will enable future researchers, as well as industry participants, to analyze all kinds of German text documents with regard to their inherent real estate sentiment. For the first time, sentiment measures from German real estate-related news items were extracted, and subsequently applied to the market.

4.1 Introduction

Germany is Europe's strongest and largest economy and ranks fourth in the world after the United States, China and Japan in terms of nominal GDP (International Monetary Fund, 2017). Within the German economy, real estate is one of the largest industries, at about 18% gross value added. Furthermore, real estate comprises 80% of gross invested assets and is hence the most important asset class (Just et al., 2017). Although Germany is one of the world's leading real estate markets, the market still lags behind global players like the UK and the US in terms of data availability, market transparency and academic research (Maurer et al., 2004; Schulte et al., 2005). According to Schulte et al. (2005), academic and general research institutions play an important role in improving real estate market transparency in Germany. Comparing global real estate market transparency levels, JLL (2016) reports that Germany has improved remarkably over the last decade. Nevertheless, in the field of national real estate research, Germany still has a need to catch up, in order to gain deeper insights into real estate market dynamics. Especially such contemporary approaches as sentiment analysis have not yet found their way into German real estate research.

Until now, international research has consistently confirmed the value of sentiment for explaining real estate market movements (Clayton et al., 2009; Ling et al., 2014; Marcato and Nanda, 2016; Freybote and Seagraves, 2017). Within this field, textual analysis has recently attracted much attention from academia. The digitization of all kinds of text corpora and technical advances have opened up a potential new field of sentiment analysis, namely textual analysis. Various information- and sentiment-bearing texts such as news, earnings press releases, annual reports, 10 Ks, analyst reports, commentaries or IPO prospectuses are now available online and can be analyzed with innovative textual analysis methodologies.

The first economically relevant textual-analysis studies were conducted in the field of finance. They demonstrate that the "tone" extracted from various text documents contains information relevant to future stock market returns (Tetlock, 2007; Tetlock et al., 2008; Bollen et al., 2011) or trading volumes (Tetlock, 2007; Price et al., 2012). Some initial attempts to apply this methodology to the real estate sector were conducted by Walker (2014), who found that the media Granger-caused real house-price changes between 1993 and 2008 in the UK. Thereafter, Soo (2015) analyzed 34 cities across the US and confirmed earlier findings by showing that measures of housing sentiment predict future house prices. Investigating about 125,000 real-estate-related newspaper article headlines, Ruscheinsky et al. (2018) provide evidence of a leading relationship between media tone and future US REIT market movements.

However, these innovative textual analysis approaches have not yet been applied to German real estate markets. Reasons for this might include difficulties in accessing data and language barriers.

Among other things, the dictionary-based approach cannot be applied without a sentiment dictionary in the local language. Until now, there have been no efforts – to the authors' best knowledge – to establish a German sentiment dictionary for economic contexts.

Hence, the purpose of this paper is to develop the first *German Real Estate Sentiment Dictionary*, which makes it possible to apply the dictionary-based approach to German real estate-related news. Following Loughran and McDonald (2011, 2015), who found that discipline-specific pre-annotated word lists lead to better classification results than general ones, the aim is to include words with regard to their meaning in a real estate context only. Conducting a large survey among about 1,700 real estate professionals, enables generating a *German Real Estate Sentiment Dictionary* with objective sentiment scores for 14,137 real estate-related German words. Having this exceptional resource available, enables analyzing all kinds of text documents with regard to their inherent real estate sentiment.

Accordingly, this paper examines 125,462 newspaper articles from 2007 to 2017, published in the *Immobilien Zeitung,* the major real estate news provider in Germany (Edelmann.ergo, 2017), by applying the dictionary-based approach. Aggregating the thus gained sentiment classifications enables us to calculate monthly positive and negative sentiment measures. As residential property represents the largest share in the property industry, with approximately 60% of total net fixed assets (Just and Maennig, 2012), the *IMX* apartment price index from *ImmobilienScout24* is selected. Due to the fact that direct real estate markets tend to be less transparent, one could expect sentiment to be even more relevant. Accordingly, the dynamic relationship between the created news-based sentiment measures and the residential real estate market is investigated in a vector autoregressive framework. Out-of-sample forecasts of direct real estate market returns complete the analysis.

The results yield strong and robust evidence of a significant relationship between the news-based sentiment measures and housing market movements. More precisely, the negative sentiment indicator has predictive power over future *IMX* returns, even when controlling for macroeconomic fundamentals. This is even the case when controlling for another sentiment measure in the vector autoregressive model. Sentiment measures generated using the *German Real Estate Sentiment Dictionary* reveal superior results, compared to ones constructed with generic dictionaries such as *SentiWS* or *German Polarity Clues*. Furthermore, this paper found that the analysis of newspaper headlines alone, and analyzing the complete article, both constitute significant real estate sentiment measures. Constructing and utilizing different scopes for design of the *German Real Estate Sentiment Dictionary* confirmed earlier research findings regarding the supreme importance of having an appropriate sentiment dictionary. The comparison of forecasting accuracy further supports the added value of taking sentiment measures into consideration.

The findings provide insights that enable a better understanding of influences on German residential market movements that are not based solely on fundamental value changes. Most notably, an objectively validated *German Real Estate Sentiment Dictionary* is developed, which lays the foundation for future textual analysis in the German real estate market. Furthermore, this paper is the first to compare various dictionary designs in order to identify which yields the highest predictive power. Novel insights are ascertained by investigating the parts of newspaper articles. Accordingly, this paper makes a valuable contribution to the emerging literature on textual analysis and takes the first step for future applications in the German real estate market.

The remainder of the paper is structured as follows. The second section reviews the relevant literature in the field of sentiment extraction from textual data, and its so far limited application to real estate markets. The third section describes the creation of the *German Real Estate Sentiment Dictionary*, which comprises three sequential steps. Data description and summary statistics are presented in the fourth section, while the fifth contains the methodology for the dictionary-based approach, the sentiment measure creation, and the vector autoregressive framework. The Results are presented and discussed in the sixth section, together with an evaluation of the forecasting accuracy. The seventh section provides a number of robustness tests. Conclusions and practical implications of the developed *German Real Estate Sentiment Dictionary* are drawn in the eighth section.

4.2 Literature Review

Winson (2017) provides a good definition of studies on market sentiment: they "[…] analyze different sources of information to assess the prevailing attitude or mood of investors towards a given market or asset class, making qualitative judgements that are used to predict directionality." The notion underlying this definition is that decision-making processes are often not based purely on information about fundamentals, but are also influenced by further factors causing market movements. One current stream of research focuses on developing and testing ways to quantify sentiment extracted from textual data and accordingly evaluates the value added for traditional asset pricing models.

Over the last few years, academic research has increasingly confirmed the value of textual analysis to gain insights into market sentiment. The ongoing rise of the internet, accompanied by the digitization of all kinds of text corpora, and technical advances, have created various possibilities for a new field of sentiment analysis. Innovative methodologies have been developed, focusing on the evaluation of text data. There are two common streams of content analysis methods: machine learning and the dictionary-based approach.

The first was pioneered by computer scientists and mathematicians based on statistical techniques (Li, 2010). Algorithms such as Naïve Bayes classifiers or support-vector machines are trained in, with a pre-classified data set a first step. The training data set can, for example, be annotated manually (Li, 2010) or using an existing sentiment lexicon, as by Das and Chen (2007). In a second step, the algorithm applies the "learned" classification rules to annotate each text entity with one of the pre-defined sentiment categories. One of the earliest works by Antweiler and Frank (2004) conducted textual analysis with both the Naïve Bayes and the Support Vector Machine algorithm and found that bullishness indices extracted from stock message postings on *Yahoo! Finance* and *Raging Bull* have a relationship with future stock trading volume.

Secondly, the dictionary-based approach is well-established in the literature. The methodology is based on word lists, in which each word is pre-annotated with a sentiment category. These word lists are often referred to as "sentiment dictionary" or "sentiment lexicon". In order to measure the sentiment of a text corpus, the researcher counts the occurrence of words from the pre-annotated word list, scaled by the total number of words in the text document. Tetlock (2007) popularized this methodology in the finance literature by demonstrating that high media pessimism extracted from *Wall Street Journal* newspaper articles, predicts downward pressure on stock market prices. Furthermore, he found that unusually high or low values of his pessimism measure lead to higher market trading volume. In 2008, Tetlock et al. again used the *Harvard IV-4* psychosocial dictionary to extract the fractions of negative words from financial news stories between 1980 and 2004. This paper confirms earlier findings of a negative relationship between media pessimism and stock prices, this time at the firm level. These studies were the starting point for future research. Applying the *Harvard IV-4 dictionary,* Engelberg (2008) found evidence of a significant linkage between *Dow Jones News Service* stories about firms' earnings announcements and subsequent asset prices. Following the same example, Frankel et al. (2010) quantified the linguistic tone of quarterly earnings conference call transcripts.

Another milestone in the evolution of the dictionary-based approach was the work of Loughran and McDonald in 2011. They investigated the notion that words have different meanings in different contexts – hence, a general dictionary might lead to misclassifications in a specific context. Loughran and McDonald (2011) analyzed 10-Ks from 1994 to 2008, and found that the application of the general *Harvard IV-4 dictionary* resulted in a misclassification of almost three-quarters of the words identified as negative. Consequently, they developed word lists which aimed to capture the meaning of words specifically in a financial context. Loughran and McDonald (2011) created six word lists, which are publicly available: negative, positive, uncertainty, litigious, strong modal, and weak modal annotated words. Over the following years, they improved and extended their word lists continuously. Similarly, Loughran and McDonald (2015) discovered that the use of Diction, a platform that enables tabulating words into pre-defined functional categories, so as to gauge sentiment in a financial context, is inappropriate. Many researchers, such as Doran et al. (2012), Engelberg et al. (2012), Price et al. (2012), Ferris et al. (2013) or Heston and Sinha (2017) adapted this notion and compared the applicability of different dictionaries in various contexts. Price et al. (2012), for example, found that using the finance-specific Loughran and McDonald (2011) sentiment dictionary leads to a better detection of the tone of relevant quarterly earning conference calls, than using the general psychological *Harvard IV-4 dictionary*. Ferris et al. (2013) further confirms these results by analyzing IPO prospectuses. Examining over 900,000 news stories among others, with the dictionary-based approach, Heston and Sinha (2017) extracted sentiment with the help of the Harvard psychological dictionary and the financial dictionary of Loughran and McDonald (2011). They found that the specialized financial dictionary is superior to the general dictionary for extracting sentiment that is relevant to future stock returns. This evidence from the literature further confirms the importance of an appropriate sentiment-annotated word list, either for each dictionary-based approach, or for some machine learning approaches.

Some first attempts at applying the dictionary-based approach in the real estate literature, include Doran et al. (2012), Walker (2014,, 2016), Soo (2015) and Ruscheinsky et al. (2018). Doran et al. (2012) examined the tone of quarterly earnings conference calls from Real Estate Investment Trusts. Their results yield robust evidence of the predictive power of sentiment measures on contemporaneous stock price reactions. Walker (2014, 2016) twice tested the relationship between news media and the UK housing market. Applying the dictionary-based approach to housing-related news led to valuable sentiment measures. Likewise, Soo (2015) quantified the tone of housing news and found a leading linkage from sentiment on future house prices in the US. Ruscheinsky et al. (2018) contributed to this stream of literature by analyzing 125,000 news-media article headlines from four different source, namely *Bloomberg*, *The Financial Times*, *Forbes* and *The Wall Street Journal.* In a vector autoregressive framework, they found significant evidence of a positive relationship between media-expressed sentiment and three- and four-month-ahead REIT market movements.

However, no research has been found so far that concentrates on the German real estate market. Accordingly, this paper pioneers textual analysis-based sentiment extraction for German real estate text corpora. As mentioned above, the first step is to choose an appropriate sentiment-annotated word list. Until now, there have been some first attempts to summarize presumably sentiment-bearing words. *German Polarity Clues* is a publicly available sentiment-annotated word list, developed by a semi-automatic translation approach from existing English resources into German (Waltinger, 2010). Similarly, the *SentiWS* dictionary uses translations from the General Inquirer by *Google Translate* and was subsequently revised manually (Remus et al., 2010). Both pre-annotated sentiment word lists are constructed for a broad, general usage and relatively error-prone due to translation difficulties. The textual analysis literature generally agrees that discipline-specific dictionaries lead to fewer misclassified results, but no appropriate dictionary for an application in the German real estate market is available so far. Therefore, this paper provides a foundation by developing a *German Real Estate Sentiment Dictionary*.

Applying this dictionary to German real estate newspaper articles enables to create sentiment indices and therefore leads to the first research question (1): *Do sentiment measures based on the German Real Estate Sentiment Dictionary have predictive power with respect to the German residential real estate market returns?*

Another main objective of this study is to gain deeper a understanding of the decisive configuration of a sentiment dictionary. Hence, the paper tests different compilations by parsing the second research question (2): *How crucial is the construction of the dictionary in terms of a threshold to included words?*

In order to gain further insights into the relevance of the data structure, research question three is developed (3): *Is the analysis of the headline alone sufficient to capture sentiment or does the inclusion of further text raise sentiment predictability?*

Following the abovementioned notion in the literature, the fourth research question reads as follows (4): *Is a discipline-specific dictionary superior to a general one?*

4.3 Creation of the German Real Estate Sentiment Dictionary

Dictionary-based textual analysis stands or falls with the quality and relevance of the dictionary. A commonly used source for word classifications is the Harvard psychological dictionary, especially the *Harvard IV-4* negative word list (Tetlock, 2007; Engelberg, 2008; Tetlock et al., 2008). Among others, Loughran and McDonald (2011) claim that discipline-specific dictionaries can reduce measurement errors. Each discipline has its own word meanings, which may not translate and apply effectively across different disciplines. As neither well-established general dictionaries like the *Harvard IV-4* word list for the German language, nor a real estate-specific word list are available, one objective of this paper is to develop a discipline-specific sentiment dictionary for the German real estate industry. This dictionary is intended to comprise real estate-related words with a clear positive or negative connotation in a real estate context.

By conducting an online survey of 1,686 respondents, relative objectivity in terms of the word classification can be achieved. The development of the *German Real Estate Sentiment Dictionary (GRESD)* is structured in the following three main steps:

Step 1: Creation of an extensive word list of real estate-related words, which are assumed to have a positive or negative tone in real estate contexts

Step 2: Classification of word list by survey participants into one of three categories: positive, neutral or negative

Step 3: Evaluation of the survey and creation of the *German Real Estate Sentiment Dictionary*

4.3.1 Step 1: Creation of Word List

The basis of the survey is a list of real estate-related words, which presumably bear sentiment. Nouns, verbs, adjectives, adverbs and prepositions are extracted from existing general German sentiment dictionaries, namely from the *German Polarity Clues* of Waltinger (2010) and the *SentiWS* of Remus et al. (2010). Furthermore, words that are likely to capture sentiment from the German real estate dictionary *Wörterbuch Immobilienwirtschaft* of Schulte et al. (2011) are included. Words with ambiguous meanings, swear words or colloquial vocabulary, and expressions with more than one word, are all excluded. In order to ensure that each word is indeed used in a real estate context, the word list is verified by checking the occurrence of each word in the *Immobilien Zeitung* between 1995 and 2017. This ensures that only words constituting real estate jargon are included in the final *GRESD*. Next, the large collection of words is reduced to their basic forms (lemmas), in order to obtain a reasonable number of words, which is feasible for survey use. The result is a word list comprising 2,245 lemmas.

4.3.2 Step 2: Online Survey and Respondent Profiles

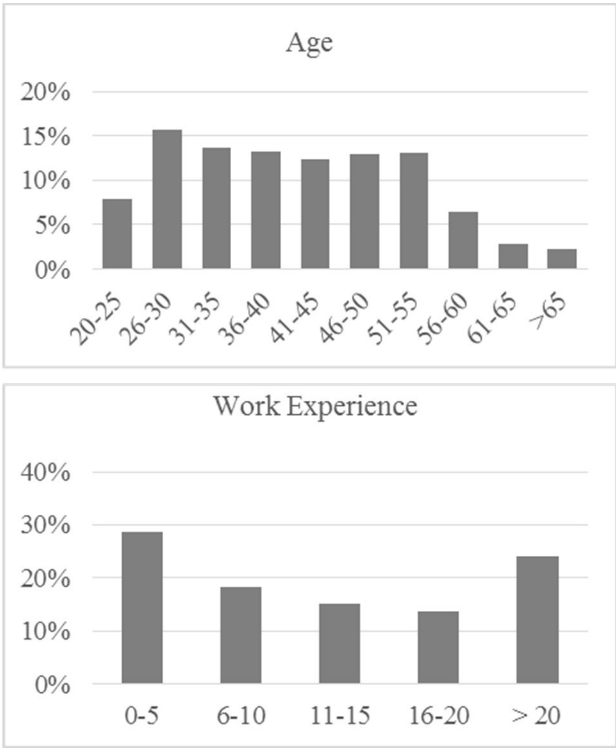
For the survey, an email-based questionnaire divided into two parts, was developed. In order to determine whether the respondents constitute a representative sample of real estate professionals, the first part contains personal questions about the respondents' gender, age, work experience, company size, qualifications, etc. Closed questions with specified response options are employed to reduce the answering effort for respondents and to facilitate the questionnaire analysis (Krosnick and Presser, 2009).

In the second part of the survey, each participant is asked to classify 30 randomly selected words as positive, neutral or negative. To increase the response rate and to shorten the survey duration, the number of words was limited to 30 per respondent. The participants were asked to spend no longer than five seconds on each word classification in order to identify their spontaneous feeling when reading a specific word. The layout of the questionnaire is shown in Appendix 1. The survey was sent exclusively to German real estate professionals.

The results of the personal questions provide insights into whether the respondent sample is representative or not. The respondents comprised 34% females and 66% males, with the relatively high proportion of male participants being inevitable, due to the distribution of human resources in the real estate industry in general. Respondents’ age and work

The age distribution comprises a very well-balanced sample, with the highest proportion of 16% in the age group 26-30 years. Overall, the age groups (from 26-55 years) are all well represented, with more than 12% per group. Furthermore, the sample is dominated by respondents with work experience of either 0-5 years (29%) or over 20 years (24%). Other groups are well distributed between 6 and 20 years of work experience. Furthermore, the respondents were asked to indicate their qualifications, their current position and the company size. 33% of the participants have a diploma (German “Diplom”) followed by 23% with a master’s and 14% with a bachelor’s degree. The majority of participants work as employees without management or operational responsibility (41%) in a company with 51-250 staff members (27%). The participants were also asked in which field of the real estate industry they are working. The highest proportions are employed in Asset-, Property- & Facility Management (13%) and Real Estate Development (11%). Overall, the respondents work in more than 20 different sectors of the industry. A detailed respondent profile description is shown in Appendix 2.

Figure 1: Respondents' age and work experience in years



Notes: The figure depicts the distribution of age and wok experience in years.

In summary, the respondent profiles represent a well-diversified sample of the German real estate industry, as no question delivered a biased distribution. Hence, the survey is representative of the entire German real estate industry and thus yields reliable sentiment-classification results.

4.3.3 Step 3: Development of the German Real Estate Sentiment Dictionary

In the course of sentiment classification, each word was classified by at least 21 different respondents as negative, neutral or positive. This means, that all words were classified 21 times, some words already 22 times, but the round 22 was not completed for all words. As a threshold for a word being included in the *German Real Estate Sentiment Dictionary*, it has to be classified as positive or negative by more than 50% of the respondents. Neutral words are not included in the *GRESD,* as they do not have any explanatory power for textual analysis.

The lemma word list is subsequently expanded by their inflections. Finally, the *GRESD* comprises 8,330 (59%) negative and 5,807 (41%) positive words, which results in a list of 14,137 sentiment-bearing German words. Table 1 provides a comprehensive overview of the dictionary composition.

Table 1: The German Real Estate Sentiment Dictionary

	Lemmas			Inflections included		
	Negative lemmas	*Positive lemmas*	*Total*	*Negative words*	*Positive words*	*Total*
Nouns	695	341	1,036 *(55%)*	2,158	1,024	3,182 *(23%)*
Verbs	157	77	234 *(12%)*	1,569	744	2,313 *(16%)*
Adjectives	325	279	604 *(32%)*	4,597	4,034	8,631 *(61%)*
Adverbs	4	5	9 *(0%)*	5	5	10 *(0%)*
Prepositions	1	0	1 *(0%)*	1	0	1 *(0%)*
Total	1,182 *(63%)*	702 *(37%)*	1,884	8,330 *(59%)*	5,807 *(41%)*	14,137

Notes: The *GRESD* comprises 1,182 (63%) negative and 702 (37%) positive lemmas. Including all inflections for each word. The dictionary results in 14,137 words with 8,330 (59%) negative and 5,807 (41%) positive ones. The numbers in italics state the breakdown of the total number of words.

In comparison to the *GRESD*, the *Harvard IV-4* word list consists of 2,291 (54%) negative and 1,915 (46%) positive lemmas, and the discipline-specific dictionary of Loughran and McDonald (2011), 2,355 (87%) negative and 354 (13%) positive words. Hence, regarding these numbers, the *German Real Estate Sentiment Dictionary* represents a comprehensive word list with a well-balanced proportion of negative and positive words, thus preventing biased results. The *German Real Estate Sentiment Dictionary* is freely accessible online at www.irebs.de (Link will be activated, once the paper is accepted for publication).

4.4 Data

The data used in this paper consists of two different sets. The first is a text corpus comprising newspaper articles, and the second, a direct real estate price index, as well as macroeconomic variables. The sample period extends from February 2007 to October 2017. The data frequency is monthly, which results in 129 observations in total.

4.4.1 Text Corpus

The text data includes all newspaper articles of the *Immobilien Zeitung (IZ)* published between 2007 and 2017. There are several reasons for choosing the news provider *Immobilien Zeitung* to quantify German real estate-related sentiment. Firstly, the *IZ* is one of the leading and most well-established newspapers in the real estate industry in Germany. Secondly, it covers current events in the real estate market and provides background information, market data, as well as people and company news. Thirdly, in terms of data availability, electronic texts are available from 1995 onwards. The original sample covers 125,462 print and online articles with about 27 Million words in total. With an average article length of 222 words, the articles of the *Immobilien Zeitung* are relatively short compared to other international newspapers like the *New York Times* (1,021 words per article) or the *Huffington Post* (641 words per article) (Newswhip, 2017). Therefore, the *IZ* constitutes a real estate news portal, which provides compact industry-related news.

All texts are tokenized to decompose text into single words, and punctuation characters were removed. Pictures, graphs tables, English articles, and editorial shortcuts were excluded. The average number of articles per month was about 345 in 1995 and increased up to 1,131 in 2017.

4.4.2 Real Estate and Macroeconomic Data

To replicate the German residential real estate market, the *IMX Immobilienindex* is used. This is a real estate price index based on over 12 million real estate residential offers on Germany's most popular home search website *ImmobilienScout24*. This website is shown to be the market leader amongst residential real estate portals in Germany as 63% of all home-seekers use this website in order to find their new home (comScore, 2016). In this paper, the price index for new apartments is employed as a measure of the direct German real estate market. The *IMX* has been publicly available since the beginning of March 2007 (end of February 2007) on a monthly basis.

Based on previous empirical evidence from the German and US housing market, this paper includes macroeconomic control variables thought to influence real estate returns (Cieleback, 2012; Walker, 2016; Freybote and Seagraves, 2017). Given that several housing studies highlight the impact of labor market variables on housing demand (Nakajima, 2011; Soo, 2015), the number of unemployed people (*UNEMP*), and the average wages and salaries in the overall economy (*WAGES*) are incorporated. To replicate the current economic situation, the industry turnover of capital goods (*INDTURN*) is included. Furthermore, building permits (*BUILDPER*) and construction turnover (*CONSTURN*) are considered as two proxies for the housing supply. In addition, the home loan interest rate (*INT*), which has been shown to influence housing demand and prices (Mayer and Sinai, 2009; Taylor, 2013), is used.

Table 2: Descriptive Statistics

	Mean	Median	Max	Min	SD	Datasource
IMX	0.45%	0.40%	1.78%	-0.76%	0.35%	ImmobilienScout24
UNEMP	-0.38%	-1.20%	12.48%	-5.07%	3.66%	Destatis
WAGES	2.47%	0.05%	55.49%	-34.07%	20.66%	Datastream
INDTURN	1.16%	-0.45%	37.01%	-28.75%	14.61%	Datastream
BUILDPER	0.74%	0.02%	34.95%	-34.87%	11.36%	Destatis
CONSTURN	3.51%	4.92%	92.99%	-63.78%	21.09%	Destatis
INT	-0.61%	-0.72%	1.06%	-2.74%	0.65%	Deutsche Bundesbank

Notes: This table reports descriptive statistics of monthly variables between 2007 and 2017. *IMX* is the growth rate of the German real estate price index for new apartments. *UNEMP* is the growth rate of the number of unemployed people. *WAGES* is the growth rate of wages and salary for the overall economy. *INDTURN* is the growth rate of whole industry turnover. *BUILDPER* is the growth rate of construction permits. *CONTURN* is the growth rate of construction turnover and *INT* is the growth rate of residential loan interest rate. The sources of the variables are named accordingly in the last column of the table.

Table 2 provides descriptive statistics of *IMX* returns and control variables. Mean, median, maximum, minimum and standard deviation of growth rates are reported in decimal form. The residential real estate market for new apartments averages a monthly growth rate of 0.45%. The monthly growth rate of unemployed people (*UNEMP*) is very stable, with a low standard deviation of 3.66% due to seasonal employment, whereas the salary (*WAGES*) and turnover of the construction industry (*INDTURN*) show a higher standard deviation of about 20%. As expected, the average growth rate of home loan interest rates (*INT*) is negative at -0.61%, because of decreasing interest rates over the last years. The *IMX* prices, as well as all control variables, were transformed into growth rates to address non-stationarity issues.

4.5 Methodology

4.5.1 Dictionary-based Approach

In order to extract sentiment from newspaper articles, the dictionary-based approach is applied. This methodology belongs to the “bag-of-words” approaches (Loughran and McDonald, 2016), because it separates each word from a text corpus and treats it as an individual entity. Consequently, the order and co-occurrence of words are ignored. With a pre-annotated sentiment dictionary, the number of words belonging to one of the sentiment categories can be counted. Referring to Loughran and McDonald (2016), this methodology has three main advantages. First, the subjectivity of researcher decisions is largely avoided, because the classification is based solely on the dictionary. Second, the methodology is easily scalable with an appropriate computer program and with publicly available dictionaries, and thirdly, the analysis process is more straightforward to replicate than most others.

To meet the crucial challenge of negation in textual analysis, this is treated similarly as in Soo (2015), by switching the sentiment around if one of the predetermined 20 negation terms is present five words before the occurrence of the sentiment-bearing word. The number of positive and negative words is added up separately for each text entity. As the dataset is quite large, RapidMiner is utilized to conduct the counting task. RapidMiner is a software platform for data science applications, such as data preparation, machine learning, deep learning, text mining, or predictive analysis (https://rapidminer.com/). The final process constructed to perform the dictionary-based approach on textual data is replicable and can be seen in Appendix 3.

4.5.2 Real Estate Sentiment Measures

The results from the dictionary-based approach give the amount of positive and negative words for each text entity. Depending on the time period of interest, the sentiment measures can be aggregated at different frequencies. This is a major advantage, compared to traditional sentiment measures which are usually based on surveys, because sentiment indicators can be constructed for any desired frequency – quarterly, monthly, weekly, daily or even hourly – the only restrictive factor being the number of text entities available for analysis. Due to the limited availability of the *IMX* and the macroeconomic variables, a monthly analysis is chosen. Hence, the sentiment extracted from each text entity is aggregated to a monthly level. Two different sentiment measures are introduced; one focusing on negative text entities and one on positive texts, scaled by the total number of newspaper articles taken into account for the time period. The *Negative Indicator* is calculated by:

$$NI_{t}\_D = \frac{\sum_{1}^{I} negative\ text\ entity_{i,t}}{\sum total\ number\ of\ text\ entities_{t}} \tag{1}$$

and the *Positive Indicator* accordingly as:

$$PI_{t}\_D = \frac{\sum_{1}^{I} positive\ text\ entity_{i,t}}{\sum total\ number\ of\ text\ entities_{t}} \tag{2}$$

where *i* is a text entity classified as negative or positive and *t* is the period in which all text entities must be published in order to be taken into account. *D* relates to the dictionary threshold used to assign words to positive or negative sentiment categories. As the *GRESD* is constructed by conducting a survey, each word has a percentage score, showing how often it was classified positive or negative in relation to the total amount of responses. For example, the word "Verlust" (translation: loss) was classified negative by 18 and neutral by 4 respondents, resulting in a negativity score of 82%. “Flexibilität” (translation: flexibility), for example, was classified positive by 17, neutral by 4, and negative by 1 respondent(s), which yields a positivity score of 77%. This sentiment scoring for each word enables constructing sentiment dictionaries with different thresholds. Meaning the *GRESD* with the threshold of 50% (*GRESD_50*) includes all words which are classified positive or negative by at least 50% of the respondents, *GRESD_60* by at least 60% and so on.

4.5.3 Vector Autoregressive Framework

To test the relationship between the created sentiment measures based on the developed *German Real Estate Sentiment Dictionary* and the German residential real estate market, a vector autoregressive framework is deployed. Before conducting any regression analysis, all variables of the vector autoregressive model are tested using an *Augmented Dickey-Fuller Test* to check for the existence of a unit root. Whenever the required stationarity was rejected, variables are differenced or used as growth rates to ensure statistical appropriateness.

A vector autoregressive regression (VAR) is able to capture the dynamic relationship between endogenous variables, is flexible and compact in expressing the notation. In its simplest form, it just contains two variables, y_{1t} and y_{2t}, depending on different combinations of the previous k values of each other and error terms, the so-called bivariate VAR:

$$y_{1t} = \beta_{10} + \beta_{11}\, y_{1t-1} + \dots + \beta_{1k}\, y_{1t-k} + \alpha_{11}\, y_{2t-1} + \dots + \alpha_{1k}\, y_{2t-k} + u_{1t} \quad (3)$$

$$y_{2t} = \beta_{20} + \beta_{21}\, y_{2t-1} + \dots + \beta_{2k}\, y_{2t-k} + \alpha_{21}\, y_{1t-1} + \dots + \alpha_{2k}\, y_{1t-k} + u_{2t} \quad (4)$$

where u_{it} is a white noise disturbance term with $E(u_{it}) = 0$, ($i = 1, 2$), $E(u_{1t}, u_{2t}) = 0$ (Brooks and Tsolacos, 2010).

As this paper investigates the value of media sentiment on direct real estate market movements, further influencing factors have to be included as well. Hence, the final model denoted in a short matrix notation includes X as a matrix of further exogenous model variables, and B as a matrix of corresponding coefficients:

$$y_t = A_0 + A_1 y_{t-1} + \dots + A_k y_{t-k} + BX + u_t \quad (5)$$

Vector autoregressive models are highly sensitive to the lag length. Hence, determining the optimal lag length is crucial. One method recommended by Brooks and Tsolacos (2010), is to use information criteria such as Aikaike’s information criterion (AIC), Schwarz’s Bayesian information criterion (SC) or the Hannan-Quinn information criterion (HQIC). These criteria contain two factors with different characteristics, one factor is a function of the residual sum of squares (RSS) and the other factor penalizes for the loss of degrees of freedom by adding further parameters to the model. Hence, including an additional lag will cause the RSS to fall, but at the same time, the penalty term will increase. From this scenario, it follows that the lag length that minimizes the value of the information criteria should be chosen.

To test whether changes in y_2 – here the created sentiment measures – cause changes in y_1 – here the direct real estate market – and vice versa, the Granger Causality test is applied to each model. Furthermore, the Breusch-Godfrey Lagrange Multiplier test is conducted for each model, so as to ensure that the residual series are not serially correlated.

4.6 Results

4.6.1 Relationship between Sentiment Measures and the IMX Price Index

Based on economic theory, a vector autoregressive model is derived to explain the residential real estate market returns between 2007 and 2017. The regressions are conducted on a monthly basis and control for the same set of macroeconomic variables each time, namely unemployment, building permits, construction turnover, industry turnover, wages and home loan interest rate. The *IMX* returns and the calculated sentiment measures are included in the vector autoregressive framework as endogenous variables and the controls as exogenous variables. All models are stable regarding the common robustness tests and indicate an optimal lag length of three. The analysis starts with the *Negative* and *Positive Indicators*, which are calculated by applying the *German Real Estate Sentiment Dictionary* with the threshold of 70 percent, in order to analyze the complete sample of newspaper articles.

Model 1, hereinafter referred to as *Base Model*, shows the dynamic relationship between the *IMX* price index returns and the *Negative Indicator (NI)*. The *NI_70* exerts a statistically significant influence on one-month-ahead *IMX* returns. The first lag of the *Negative Indicator* shows the expected negative sign and is significant at the 5% level. This result is backed by the associated Granger Causality, which demonstrates that the sentiment measure *NI_70* influences the *IMX* movements beyond all control variables and past returns of the *IMX* itself. One explanation for the relatively quick impact of sentiment on prices, might be that less informed investors are more prone to sentiment than informed investors (Garcia, 2013). Most residential investors are supposedly less informed than institutional investors for example. Furthermore, compared to other real estate markets, the amount of transactions in the residential market is higher, whereas the transaction volumes are lower. Hence, sentiment changes might be incorporated into housing prices faster.

Compared to the VAR with no sentiment measure, the *Comparison Model*, the inclusion of the *Negative Indicator* enhances the R-squared by 6.9% from 53.1% to 57.1% and the adjusted R-squared by 5.8% from 49% to 52.1%. As the Log likelihood increases and the information criteria decreasing, the whole model improves in terms of goodness of fit, by including the *sentiment measure*.

An interesting aspect worth mentioning is that the *IMX* does not Granger-cause the *Negative Indicator*, so that this causality is unidirectional. However, the *Positive Indicator*, based solely on text corpora classified as positive, does not show any significance in explaining future *IMX* movements. Moreover, the *PI_70* presents negative coefficients. This entails the Granger Causality of the *PI_70* also not being statistically significant.

These findings indicate a negativity bias of German real estate market participants. The bias refers to the notion that humans accord greater relevance to negative entities and results than to positive ones, even when both are of the same magnitude. This phenomenon has already been discovered and discussed in the psychological literature (Rozin and Royzman, (2001). Furthermore, Tetlock (2007) developed this idea by creating pessimism indicators only. He found a significant relationship between media pessimism and subsequent stock market prices.

Table 3: VAR estimation results with Negative and Positive Indicator

	IMX					
	Model 1		Model 2		Comparison Model	
	Negative Indicator		*Positive Indicator*		-	
IMX (-1)	0.485	***	0.443	***	0.462	***
	[5.87851]		[5.19546]		[5.51991]	
IMX (-2)	-0.170	*	-0.137		-0.160	*
	[-1.78406]		[-1.39351]		[-1.66332]	
IMX (-3)	-0.210	**	-0.164	*	-0.204	**
	[-2.53134]		[-1.84989]		[-2.42480]	
Sentiment (-1)	-0.039	**	-0.013			
	[-2.53628]		[-1.25516]			
Sentiment (-2)	0.001		-0.014			
	[0.04977]		[-1.25201]			
Sentiment (-3)	0.020		-0.003			
	[1.24851]		[-0.26684]			
Constant	-0.004	**	-0.004	**	-0.004	**
	[-2.39240]		[-2.49936]		[-2.51878]	
Macroeconomic Controls	YES		YES		YES	
R^2	0.571		0.542		0.531	
Adj. R^2	0.521		0.488		0.490	
Log likelihood	580.948		576.843		575.451	
Akaike AIC	-9.071		-9.005		-9.031	
Schwarz SC	-8.754		-8.689		-8.782	
Granger Causality						
Sentiment indicator	10.205	**	2.501			
IMX	0.072		6.863	*		

Notes: This table reports results for the estimated VAR models with 3 lags, monthly *IMX* returns, and news-based sentiment as endogenous variables. The set of macroeconomic control variables includes the following: unemployment growth rate with a seventh lag, building permits and construction turnover growth rates with no lag, industry turnover growth rate with a fourth lag, wages with a first lag and home loan interest rate with a second lag. For brevity, the table reports the results of the real estate return equations. T-statistics are reported in square brackets below each coefficient estimate. Granger Causality values are reported for both directions. The regression is based on 129 observations from 2007M02 to 2017M10. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level

4.6.2 Importance of Sentiment Dictionary Compilation

Several studies emphasize the importance of choosing an appropriate sentiment dictionary, because it is the basis for at least the dictionary-based approach, and in some cases for machine learning approaches as well. Due to the classification of the world list by survey participants, it is possible to test different design scopes for the *German Real Estate Sentiment Dictionary*. As the survey yielded percentage amounts for each word, referring to how often it was classified by the respondents as neutral, positive and negative, it is possible to construct dictionaries with different thresholds. For example, the adjective "wertvoll" (translation: valuable) was classified positive by 19 respondents and neutral by 3, resulting in a positivity score of 86%. In Table 4, *Negative Indicators* constructed with different dictionary manifestations are included in the VAR framework.

The results yield a significant predictability of the *Negative Indicator_60* and the *Negative Indicator_70* on future residential real estate market movements. As mentioned above in the *Base Model*, the *NI_70* Granger-causes *IMX* returns at the 5% significance level. The *NI_60* presents similar findings, with a Granger Causality at the 10% significance level. Equally to the *Base Model*, the first lag of the *NI_60* is statistically significant and has the expected negative sign. However, no other negative indicators based on the thresholds of 50%, 80% and 90% (Models 3, 5, 6) show any predictive power with respect to subsequent *IMX* returns. This seems reasonable, especially for the threshold of 90% classification accordance, as here, 3,219 words are left in the *GRESD* only. This amount might be too low to identify enough sentiment bearing words. Looking at the other extreme, a possible explanation of the non-existent relationship between the *NI_50* and *IMX* returns is, that too many words are used for the sentiment-extraction process, which might have ambiguous meanings. The *NI_70* yields the strongest results in terms of both statistical significance, and regarding the overall goodness of fit of the model. By containing different classification accordance levels, the *GRESD* empowers future researchers to individually determine which threshold is suitable for investigating their research questions.

Table 4: VAR estimation results for sentiment measures based on dictionaries with different thresholds

	IMX									
	Model 3		Model 4		*Base Model*		Model 5		Model 6	
	NI_ 50		*NI_60*		*NI_70*		*NI_80*		*NI_90*	
IMX (-1)	0.478	***	0.488	***	0.485	***	0.475	***	0.461	***
	[5.68780]		[5.83799]		[5.87852]		[5.65732]		[5.48456]	
IMX (-2)	-0.189	*	-0.180	*	-0.170	*	-0.171	*	-0.150	
	[-1.92399]		[-1.85897]		[-1.78403]		[-1.76201]		[-1.54554]	
IMX (-3)	-0.200	**	-0.211	**	-0.210	**	-0.193	**	-0.205	**
	[-2.33829]		[-2.50007]		[-2.53136]		[-2.27758]		[-2.38338]	
Sentiment (-1)	-0.021		-0.031	**	-0.039	**	-0.020		-0.009	
	[-1.34626]		[-2.11146]		[-2.53629]		[-1.20633]		[-0.42879]	
Sentiment (-2)	-0.013		-0.023		0.001		-0.006		0.009	
	[-0.78515]		[-1.37487]		[0.04977]		[-0.30632]		[0.42333]	
Sentiment (-3)	0.014		0.011		0.020		0.017		0.029	
	[0.91114]		[0.74186]		[1.24850]		[1.05069]		[1.44340]	
Constant	-0.004	**	-0.004	**	-0.004	**	-0.004	**	-0.004	**
	[-2.53645]		[-2.46744]		[-2.39240]		[-2.44515]		[-2.51074]	
Macroeconomic controls	YES		YES		YES		YES		YES	
R^2	0.548		0.559		0.571		0.545		0.543	
Adj. R^2	0.495		0.508		0.521		0.491		0.489	
Log likelihood	577.683		579.283		580.948		577.270		576.989	
Akaike AIC	-9.019		-9.045		-9.071		-9.012		-9.008	
Schwarz SC	-8.702		-8.728		-8.754		-8.696		-8.691	
Granger Causality										
Sentiment indicator	4.035		7.019	*	10.205	**	3.278		2.765	
IMX	2.481		1.109		0.072		3.122		8.725	
Number of words in dictionary	14,137		12,851		10,563		7,363		3,219	

Notes: This table reports results for the estimated VAR models with 3 lags, monthly *IMX* returns, and news-based sentiment, using different thresholds of the *GRESD* as endogenous variables. The set of macroeconomic control variables includes: unemployment growth rate with a seventh lag, building permits and construction turnover growth rates with no lag, industry turnover growth rate with a fourth lag, wages with a first and home loan interest rate with a second lag. For brevity, the table reports the results of the real estate return equations. T-statistics are reported in square brackets below each coefficient estimate. Granger Causality values are reported for both directions. The regression is based on 129 observations from 2007M02 to 2017M10. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.

4.6.3 Investigating Different Parts of the Newspaper Article

Besides the choice of an appropriate dictionary, another decision to make is which text data to analyze. This decision is equally important in order to capture relevant market sentiment. First, the data source and hence, the news quality is decisive. Second, it must be decided which parts of a newspaper and in greater detail, which parts of a particular newspaper article should be selected.

Different notions about which part of newspaper articles should be investigated can be found in the literature. Strapparava and Mihalcea (2008) describe headlines of news articles as especially suitable for textual sentiment analysis, as they are short, written to attract reader attention and are often provocative. As the dataset of this present paper is clearly-structured, it is possible to distinguish and make comparisons between the predictive power of the sentiment measures extracted from different parts of a newspaper article. The question arises, whether the analysis of the headline alone is already enough to capture market sentiment?

Table 5 shows the results of the *Negative Indicators* based on the *GRESD_60* and *GRESD_70* analyzing headlines alone (H) in the first step, and the full text of all newspaper articles in the second step (HT). The results show that the analysis of newspaper headlines alone, is indeed already sufficient to determine predictive power with respect to future residential real estate market movements. In both Models 7 and 8, the *Negative Indicator* Granger-causes *IMX* price changes significantly at the 5% level, even when controlling for various macroeconomic fundamentals. As comparison, both models analyzing the headlines of all newspaper articles with the *GRESD_60* and *_70* are reported again. As mentioned earlier, they both have statistically significant explanatory power with respect to the *IMX* return changes. The results further indicate the robustness of the relationship found.

Overall, both variations lead to statistically significant results, but it is worth mentioning the trade-off choosing parts of the newspaper article. On the one hand, as headlines are short and generally summarize the article, it should be easy to capture the sentiment. On the other hand, the headline might have too few words to identify any sentiment. Regarding complete texts, there are normally enough words to capture sentiment, but articles often contain conflicting views and balance various reasons and factors in the end. Therefore, the dictionary-based approach might not be able to capture this assessment adequately.

Table 5: VAR estimation results for sentiment measures based on different parts of a newspaper article

	IMX							
	NI_ 60				*NI_70*			
	Model 7		Model 4		Model 8		*Base Model*	
	H		*HT*		*H*		*HT*	
IMX (-1)	0.477	***	0.488	***	0.475	***	0.485	***
	[5.74123]		[5.83799]		[5.71930]		[5.87852]	
IMX (-2)	-0.164	*	-0.180	*	-0.161	*	-0.170	*
	[-1.72773]		[-1.85897]		[-1.69659]		[-1.78403]	
IMX (-3)	-0.190	**	-0.211	**	-0.181	**	-0.210	**
	[-2.28047]		[-2.50007]		[-2.17973]		[-2.53136]	
Sentiment (-1)	-0.049	*	-0.031	**	-0.076	**	-0.039	**
	[-1.86226]		[-2.11146]		[-2.31578]		[-2.53629]	
Sentiment (-2)	-0.017		-0.023		-0.012		0.001	
	[-0.58718]		[-1.37487]		[-0.36106]		[0.04977]	
Sentiment (-3)	0.031		0.011		0.030		0.020	
	[1.18864]		[0.74186]		[0.91364]		[1.24850]	
Constant	-0.004	**	-0.004	**	-0.004	**	-0.004	**
	[-2.47530]		[-2.46744]		[-2.51260]		[-2.39240]	
Macroeconomic variables	YES		YES		YES		YES	
R^2	0.564		0.559		0.570		0.571	
Adj. R^2	0.513		0.508		0.520		0.521	
Log likelihood	579.928		579.283		580.832		580.948	
Akaike AIC	-9.055		-9.045		-9.069		-9.071	
Schwarz SC	-8.738		-8.728		-8.753		-8.754	
Granger Causality								
Sentiment indicator	8.242	**	7.019	*	9.980	**	10.205	**
IMX	3.624		1.109		4.333		0.072	

Notes: This table reports results for the estimated VAR models with 3 lags, monthly *IMX* returns, and sentiment measures based on different parts of the newspaper article. The set of macroeconomic control variables includes: Unemployment growth rate with a seventh lag, Building Permits and Construction Turnover growth rates with no lag, Industry Turnover growth rate with a fourth lag, Wages with a first and Home Loan Interest Rate with a second lag. For brevity, the table reports the results of the real estate return equations. T-statistics are reported in square brackets below each coefficient estimate. Granger Causality values are reported for both directions. The regression is based on 129 observations from 2007M02 to 2017M10. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.

4.6.4 Comparison with General German Sentiment Dictionaries

Following the findings of Loughran and McDonald (2011), Price et al. (2012) and Heston and Sinha (2017), a comparison with two generic German linguistic sentiment dictionaries is performed in order to determine whether the created discipline-specific *German Real Estate Sentiment Dictionary* leads to superior sentiment measures.

Positive and *Negative Indicators* are constructed employing two general dictionaries, namely *SentiWS* and *German Polarity Clues* (*GPC*). The dictionary-based approach is applied to the complete newspaper articles accordingly. The descriptive statistics of the developed sentiment measures for each dictionary and their correlations are shown in Table 6. The *Negative Indicators* of all three variations are around 10% on average, whereas the *Positive Indicator* lies between 46% and 82% looking at the means. However, standard deviations are similarly low for all sentiment measures. As expected, *Positive* and *Negative Indicators* are in all three cases negatively correlated with a similar altitude.

Table 6: Descriptive stats of constructed sentiment measures

	NI_70	*PI_70*	*GPC_NI*	*GPC_PI*	*SENTIWS_NI*	*SENTIWS_PI*
Mean	10.63%	46.15%	16.16%	73.64%	6.96%	82.24%
Median	10.35%	46.46%	16.09%	73.55%	6.67%	82.67%
Max	16.65%	56.30%	22.59%	80.07%	12.33%	89.39%
Min	5.64%	36.03%	11.11%	66.34%	3.83%	73.58%
Std. Dev.	2.48%	4.50%	1.89%	2.52%	1.61%	3.22%
Number of words in dictionary	6,282	4,281	19,962	17,627	10,155	10,103
Correlations						
NI_70	1.00					
PI_70	-0.51	1.00				
GPC_NI	0.60	-0.45	1.00			
GPC_PI	-0.53	0.76	-0.78	1.00		
SENTIWS_NI	0.78	-0.61	0.67	-0.68	1.00	
SENTIWS_PI	-0.57	0.81	-0.58	0.84	-0.77	1.00

Notes: This table provides descriptive statistics and correlations for the sample between 2007 and 2017. The number of words indicates how many positive or negative words are included in each dictionary.

The VAR results in Table 7 indicate no significant relationship between the sentiment measures based on the general dictionaries *SentiWS* (Models 9 and 10) or *GPC* (Models 11 and 12) and future residential real estate market returns. The negative and positive sentiment indicators do not yield any statistically significant coefficients, neither sentiment measures based on *SentiWS,* nor on *GPC* Granger-cause *IMX* returns. These findings support the argument of Loughran and McDonald (2011) among others, who state that a domain-specific dictionary is much more powerful in detecting sentiment. This confirms the quality and appropriateness of the (self-established) *German Real Estate Sentiment Dictionary*.

Table 7: Comparison with general German sentiment dictionaries

	IMX					
	Model 1	Model 2	Model 9	Model 10	Model 11	Model 12
	GRESD NI_70	*GRESD PI_70*	*SentiWS Negative Indicator*	*SentiWS Positive Indicator*	*GPC Negative Indicator*	*GPC Positive Indicator*
IMX (-1)	0.485 ***	0.443 ***	0.472 ***	0.488 ***	0.477 ***	0.482 ***
	[5.87851]	[5.19546]	[5.56973]	[5.74793]	[5.59574]	[5.66972]
IMX (-2)	-0.170 *	-0.137	-0.169 *	-0.197 **	-0.179 *	-0.186 *
	[-1.78406]	[-1.39351]	[-1.72919]	[-2.02228]	[-1.81725]	[-1.88276]
IMX (-3)	-0.210 **	-0.164 *	-0.205 **	-0.197 **	-0.196 **	-0.201 **
	[-2.53134]	[-1.84989]	[-2.41070]	[-2.33441]	[-2.29030]	[-2.34859]
Sentiment (-1)	-0.039 **	-0.013	-0.013	0.013	-0.011	0.015
	[-2.53628]	[-1.25516]	[-0.62667]	[1.09638]	[-0.91067]	[1.34956]
Sentiment (-2)	0.001	-0.014	-0.007	0.000	0.005	0.005
	[0.04977]	[-1.25201]	[-0.27041]	[0.01292]	[0.37384]	[0.37316]
Sentiment (-3)	0.020	-0.003	-0.019	0.015	0.000	0.010
	[1.24851]	[-0.26684]	[-0.93553]	[1.30698]	[-0.00401]	[0.92906]
Constant	-0.004 **	-0.004 **	-0.004 **	-0.004 **	-0.004 **	-0.004 **
	[-2.39240]	[-2.49936]	[-2.44060]	[-2.47865]	[-2.43835]	[-2.42567]
Macroeconomic Variables	YES	YES	YES	YES	YES	YES
R^2	0.571	0.542	0.537	0.549	0.538	0.542
Adj. R^2	0.521	0.488	0.483	0.496	0.484	0.488
Log likelihood	580.948	576.843	576.261	577.826	576.406	576.841
Akaike AIC	-9.071	-9.005	-8.996	-9.021	-8.999	-9.005
Schwarz SC	-8.754	-8.689	-8.679	-8.704	-8.682	-8.689
Granger Causality						
Sentiment indicator	10.205 **	2.501	1.447	4.299	1.710	2.496
IMX	0.072	6.863 *	0.846	3.655	0.741	2.203

Notes: This table reports results for the estimated VAR models with 3 lags, monthly *IMX* returns, and news-based sentiment as endogenous variables. The set of macroeconomic control variables includes: unemployment growth rate with a seventh lag, building permits and construction turnover growth rates with no lag, industry turnover growth rate with a fourth lag, wages with a first and home loan interest rate with a second lag. For brevity, the table reports the results of the real estate return equations. T-statistics are reported in square brackets below each coefficient estimate. Granger Causality values are reported for both directions. The regression is based on 129 observations from 2007M02 to 2017M10. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level

4.6.5 Out-of-sample Forecasting

By comparing the forecasts from alternative models, the aim is to determine whether sentiment-augmented models achieve better results than models without any sentiment. Researchers agree that forecasting methods should be assessed using out-of-sample rather than in-sample tests, because in-sample errors are likely to understate forecasting errors (Tashman, 2000). The number of forecasting periods should not exceed the number of estimation periods. A sensible approach evaluating the forecasting accuracy is not to use all the observations in the estimation period, but rather to hold some back. Hence, in this paper, the estimation period is defined from June 2007 to December 2016, and the forecasting period is from January 2017 to October 2017.

In order to compare the forecasting accuracy, this paper follows (Brooks and Tsolacos, 2010) and focuses on the forecast error $\hat{e}_{t+n,t}$, defined as the difference between the actual value of real estate returns (A_{t+n}) and the value of the forecast ($F_{t+n,t}$). This analysis concentrates on the variance-based forecasting error, namely the Root Mean Squared Error (RMSE), which is measured on the same scale as the data. Furthermore, the Theil's U1 coefficient constitutes an appropriate scalar for comparing forecasting accuracy of two different models (Theil, 1966,, 1971). This coefficient ranges between zero and one, whereas coefficients closer to zero represent better predictions.

Table 8: Forecast results

Model	Macro	Sentiment	Adj. *R2*	RMSE	RMSE Reduction	MSE	U1 Theil	U1 Theil Reduction
Model 7	x		0.486	0.00150		2.253E-06	0.110	
	x	*NI_60 H*	0.503	0.00119	20.5%	1.426E-06	0.088	19.8%
Model 4	x		0.486	0.00150		2.253E-06	0.110	
	x	*NI_60 HT*	0.497	0.00117	22.2%	1.364E-06	0.087	21.3%
Model 8	x		0.486	0.00150		2.253E-06	0.110	
	x	*NI_70 H*	0.508	0.00104	30.5%	1.088E-06	0.077	29.9%
Base Model	x		0.486	0.00150		2.253E-06	0.110	
	x	*NI_70 HT*	0.507	0.00098	34.7%	9.604E-07	0.073	33.3%

Notes: The reduction of the RMSE and of the U1 Theil coefficient is always measured in relation to the model without any sentiment measure. A positive value stands for an improvement in forecasting, in comparison to the no-sentiment-model.

Table 8 reports the dynamic forecasting accuracy results, namely the RMSE, MSE, U1 Theil statistic and the RMSE and U1 Theil reduction of sentiment augmented models against models which include only macroeconomic control variables. The adjusted *R*-squared serves as a goodness of fit measure for the estimated model from 2007 to 2016 for all VAR models which have already been tested in Table 5.

The most important finding is that models enriched with a sentiment measure have lower RMSE and U1 coefficients and thereby score better in terms of forecasting accuracy than the models without sentiment. For *NI_70* models, the RMSE reduction ranges between 30% and 35%, whereas for *NI_60* models, it lies between 20% and 22%. Theil's U1 coefficients of the sentiment-augmented models indicate that return forecasts for real estate residential prices come very close to their actual values, as U1 ranges from 0.10 to 0.07. The best forecasting accuracy measured by the U1 coefficient is achieved by the model that is augmented by *NI_70,* which is constructed from full texts.

In the wake of RMSE and U1 reduction, it shows that for *NI_60* and *NI_70,* the sentiment measures extracted from full texts (HT) show the better forecasting accuracies. All in all, the inclusion of any kind of news-based sentiment measures apparently reduces forecasting errors for the residential real estate market in Germany. These results confirm that sentiment extracted from real estate-related newspaper articles contains relevant information which helps to explain and forecast residential real estate return movements.

4.7 Robustness

The results section already tests, in a variety of ways, the robustness of the relationship between the dictionary-derived news-based sentiment measures and the German residential real estate market. Nevertheless, this paper aims at conducting some final robustness tests in the following analysis. As the vector autoregressive framework is highly sensitive to the lag-length specification, the *Base Model* is run again with varying lag lengths. From Panel A in Table 9, it can be seen that the first lag of the *NI_70* is robust at least at the 5% significance level, regardless of the total number of lags included. Models between one and five lags do result in a significant Granger Causality of the *Negative Indicator* on the *IMX*. All models are run with the same set of control variables as introduced in the *Base Model*. Choosing a lag length of six, still presents a significant first lag of the *NI_70*, but jointly, the Granger Causality becomes insignificant for the first time.

Winsorizing the *IMX*, shows whether or not the results are dependent on the extreme values of the times series. In a first step, the default is set to the 1% and 99% quantiles of the *IMX* and in a second step, to the 5% and 95% quantiles. Panel B shows that the results still hold. The *NI_70* significantly explains the winsorized *IMX* returns beyond their own past values and even when controlling for the set of macroeconomic variables. The Granger Causality is significant for both variations at the 5% significance level.

In addition, this paper tests three German sentiment measures regarding their relationship with the housing market. *IFO* is the business climate index for the overall economy and *CONCLIMATE* is the that for the total construction industry, both published by the *Institute for Economic Research*. *KONBAR* refers to the business climate index published by the *DIW*. All three measures are tested in the vector autoregressive framework with the same set of control variables and lags as in the *Base Model*. As shown in Panel C of Table 9, *IFO* and *KONBAR* do not have any significant relationship at all with the residential market returns. However, *CONCLIMATE* significantly explains the *IMX,* with the first and second lag showing statistical significance. Overall, *CONCLIMATE* Granger-causes *IMX* returns at the 1% significance level. In order to test whether the news-based sentiment measure *NI_70* contains similar information as *CONCLIMATE*, a VAR model is estimated with both measures. The two sentiment measures might explain different effects. Hence, the *Base Model* is augmented by the significant lags *CONCLIMATE(-1)* and *CONCLIMATE (-2)*.

Table 10 confirms the robustness of the *Negative Indicator* created with the *GRESD_70*. The first lag of *NI_70* still has significant predictive power. Nonetheless, one lag of *CONCLIMATE* or two lags are included in the vector autoregressive framework. For both variations, a significant Granger Causality supports the findings. This means that the news-based sentiment measure seems to capture another form of sentiment, which is not already explained by *CONCLIMATE*. In conclusion, it is definitely worth considering sentiment measures extracted from newspaper articles by means of the dictionary-based approach, in order to improve direct German real estate market models.

Table 9: Robustness tests

Panel A: Robustness of Granger Causality with Varying Lag Length								
	NI_70 $_{t-1}$	*NI_70* $_{t-2}$	*NI_70* $_{t-3}$	*NI_70* $_{t-4}$	*NI_70* $_{t-5}$	*NI_70* $_{t-6}$	Macro	$\chi 2$
Model with 1 lag	-0.035**						x	6.246**
Model with 2 lags	-0.042***	-0.005					x	8.664**
Model with 3 lags	-0.039**	0.001	0.020				x	10.205**
Model with 4 lags	-0.040**	-0.002	0.014	-0.014			x	10.558**
Model with 5 lags	-0.041**	-0.003	0.013	-0.015	-0.004		x	10.320*
Model with 6 lags	-0.038**	0.000	0.013	-0.015	-0.006	0.001	x	9.466
Panel B: Winsorizing *IMX*								
	NI_70 $_{t-1}$	*NI_70* $_{t-2}$	*NI_70* $_{t-3}$					$\chi 2$
IMX WIN 99	-0.032405**	0.006822	0.018784				x	9.924**
IMX WIN 95	-0.025086**	0.006243	0.010306				x	8.138**
Panel C: Testing the *Base Model* with different Market Sentiment Indices								
	Sentiment $_{t-1}$	*Sentiment* $_{t-2}$	*Sentiment* $_{t-3}$					$\chi 2$
IFO	0.000	0.000	0.000				x	1.238
KONBAR	0.001	0.001	-0.002753*				x	3.788
CONCLIMATE	0.026**	0.023*	-0.017				x	14.288***

Notes: This table reports results for the estimated VAR models with different variations, so as to test the robustness of Panels A-C. All regressions were run with the same set of macroeconomic control variables: The set of macroeconomic control variables includes: unemployment growth rate with a seventh lag, building permits and construction turnover growth rates without any lag, industry turnover growth rate with a fourth lag, wages with a first and home loan interest rate with a second lag. For brevity, the table reports the results of the real estate return equations. For brevity, the table reports the results of the real estate return equations. T-statistics are reported in square brackets below each coefficient estimate. Granger Causality values are reported for both directions. The regression is based on 129 observations from 2007M02 to 2017M10. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.

Table 10: Robustness test with CONCLIMATE

	IMX			
	Model 13		Model 14	
	NI_70		*NI_70*	
IMX (-1)	0.353	***	0.380	***
	[3.86942]		[4.34213]	
IMX (-2)	-0.175	*	-0.160	*
	[-1.87650]		[-1.73492]	
IMX (-3)	-0.175	**	-0.165	**
	[-2.12899]		[-2.01639]	
Sentiment (-1)	-0.034	**	-0.036	**
	[-2.28309]		[-2.41368]	
Sentiment (-2)	0.000		-0.001	
	[0.01488]		[-0.04915]	
Sentiment (-3)	0.018		0.020	
	[1.15220]		[1.25231]	
Constant	-0.004	***	-0.004	**
	[-2.73347]		[-2.59893]	
Macroeconomic Controls	YES		YES	
CONCLIMATE (-1)	0.025	**	0.030	***
	[2.30190]		[2.93010]	
CONCLIMATE (-2)	0.013	*		
	[1.07751]			
R^2	0.606		0.602	
Adj. R^2	0.552		0.551	
Log likelihood	586.307		585.645	
Akaike AIC	-9.125		-9.130	
Schwarz SC	-8.763		-8.791	
Granger Causality				
Sentiment indicator	8.199	**	9.213	**
IMX	0.636		0.170	

Notes: This table reports results for the estimated VAR models with 3 lags, monthly IMX returns, and news-based sentiment as endogenous variables. The set of macroeconomic control variables includes: unemployment growth rate with a seventh lag, building permits and construction turnover growth rates without any lag, industry turnover growth rate with a fourth lag, wages with a first and home loan interest rate with a second lag. For brevity, the table reports the results of the real estate return equations. For brevity, the table reports the results of the real estate return equations. T-statistics are reported in square brackets below each coefficient estimate. Granger Causality values are reported for both directions. The regression is based on 129 observations from 2007M02 to 2017M10. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.

4.8 Conclusion

In recent years, there has been increasing interest in quantifying sentiment and accordingly investigating its influence on market movements. This topic attracts ever-growing attention, due to findings consistently approving that investor decision-making processes can be influenced by whether they feel optimistic or pessimistic about current market conditions (Bollen et al., 2011). Thanks to the internet revolution, huge amounts of information are now available online. This has paved the way for a new field of sentiment analysis, namely textual analysis, which attempts to extract sentiment from all kinds of text documents. However, there have so far been few quantitative textual analysis applications in real estate. Some initial attempts have analyzed the inherent sentiment of housing news in the US and UK (Walker, 2014, 2016; Soo, 2015). Referring to Germany, research lags far behind, as no previous study has ever investigated real estate-related German text entities.

Therefore, this study was designed to determine the relationship between news-based sentiment measures extracted by means of textual analysis and the direct residential real estate market in Germany. A fundamental prerequisite to performing the dictionary-based approach is an appropriate sentiment pre-annotated word list. As no such dictionary exists for an economic context in German, one aim of this paper was to construct the first *German Real Estate Sentiment Dictionary*. The results of the survey of about 1,700 real estate professionals resulted in a real estate-related word list with objective sentiment scores. The final *GRESD* comprises 14,137 sentiment-annotated words. Having this exceptional resource on hand, 125,462 newspaper articles published by the *Immobilien Zeitung* were analyzed with the help of the dictionary-based approach. Subsequently, the generated monthly positive and negative sentiment indicators were used to augment fundamental-based vector autoregressive models for the residential real estate market.

Most importantly, the results reveal a significant relationship between the created news-based sentiment measures and the direct real estate market. The *Negative Indicator* influences one-month ahead *IMX* returns, even when controlling for a set of macroeconomic variables such as unemployment, building permits, construction turnover, industry turnover, wages, the home loan interest rate and another indirect sentiment measure. However, no significant evidence can be reported for the *Positive Indicator*. This supports the notion that individuals are affected more strongly by negative rather than positive news. In order to gain deeper knowledge about the construction of suitable sentiment annotated word lists, different scopes for design were examined. It turned out that the number of words included and the sentiment intensity play a central role. Furthermore, this paper confirms that the consideration of headlines alone already generates robust sentiment measures. Comparing the domain-specific *GRESD* to general sentiment dictionaries reinforces the value and quality of the self-developed *German Real Estate Sentiment Dictionary.* Several robustness-checks confirmed the strength of the findings.

These results are not only valuable for academia, but also for decision-making processes in the real estate industry. Like the forecasting results suggest, news-based sentiment measures can help anticipate of future market movements. The created *German Real Estate Sentiment Dictionary* does not claim to be exhaustive. Rather, it should be seen as the groundwork for future German text-based sentiment analysis. As with Loughran and McDonald (2011), the development of a sentiment dictionary takes time and several revisions. Therefore, future work could extend the current list of words containing sentiment with regard to a real estate context. Furthermore, the *GRESD* could be applied to various text documents such as earnings press releases, annual reports, 10 Ks, analyst reports, commentaries or IPO prospectuses and other real estate markets as well. As this approach is scalable, an even shorter aggregation frequency – weekly or even daily – could be tested if enough text entities are available.

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4.11 Appendix

1) Layout Questionnaire

IRE|BS
International Real Estate Business School
Universität Regensburg

Umfrage IRE|BS Forschungsprojekt

Herzlich willkommen!

Vielen Dank, dass Sie sich **3 - 4 Minuten Zeit** nehmen, um an unserer Umfrage teilzunehmen.

Die Umfrage dient dazu, Ihr persönliches, spontanes Empfinden zu erfassen, wenn Sie bestimmte Wörter lesen – ein richtig oder falsch gibt es folglich nicht. Mit Hilfe dieser Einschätzungen werden wir im nächsten Schritt Nachrichten über den deutschen Immobilienmarkt, die freundlicherweise von der Immobilien Zeitung zur Verfügung gestellt werden, auswerten.

Die Umfrage ist intuitiv und verständlich aufgebaut und dauert nicht länger als 4 Minuten.

Sämtliche Umfrageergebnisse werden selbstverständlich komplett anonymisiert behandelt.

Wir freuen uns über Rückmeldung und Anregung per E-Mail unter:
jessica.ruscheinsky@irebs.de
katrin.kandlbinder@irebs.de
oder telefonisch unter 0941 943 5025

Mit freundlichen Grüßen,

Jessica Ruscheinsky & Katrin Kandlbinder

Umfrage starten

Mit freundlicher Unterstützung von IMMOBILIEN ZEITUNG
FACHZEITUNG FÜR DIE IMMOBILIENWIRTSCHAFT
Impressum

IRE|BS
International Real Estate Business School
Universität Regensburg

Umfrage IRE|BS Forschungsprojekt

Diese Daten werden anonymisiert gespeichert und dienen lediglich zur Verfizierung der Umfrageteilnehmer.

Geschlecht
--Geschlecht--

Alter
--Alter--

Höchster Abschluss
--Höchster Abschluss--

Tätigkeitsfeld
--Tätigkeitsfeld--

Jahre Berufserfahrung in der Immobilienbranche allgemein
--Jahre Berufserfahrung in der Immobilienbranche allgemein--

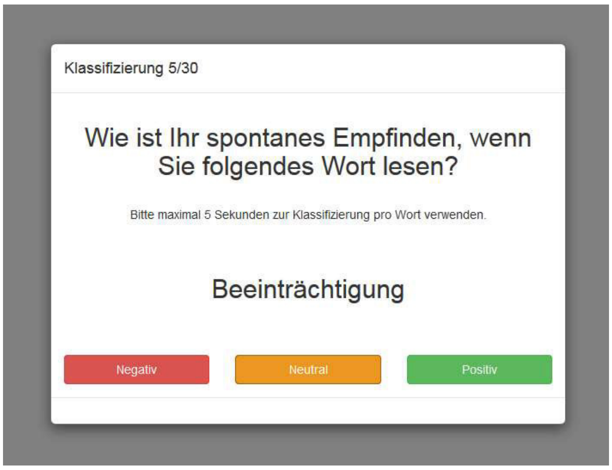
Aktuelle Position
--Aktuelle Position--

Unternehmensgröße (Anzahl Mitarbeiter)
--Unternehmensgröße (Anzahl Mitarbeiter)--

Bundesland (Unternehmenssitz)
--Bundesland (Unternehmenssitz)--

Weiter

Mit freundlicher Unterstützung von IMMOBILIEN ZEITUNG
FACHZEITUNG FÜR DIE IMMOBILIENWIRTSCHAFT
Impressum


Klassifizierung 5/30
Wie ist Ihr spontanes Empfinden, wenn Sie folgendes Wort lesen?
Bitte maximal 5 Sekunden zur Klassifizierung pro Wort verwenden.
Beeinträchtigung
Negativ
Neutral
Positiv


Klassifizierung 8/30
Wie ist Ihr spontanes Empfinden, wenn Sie folgendes Wort lesen?
Bitte maximal 5 Sekunden zur Klassifizierung pro Wort verwenden.
beste
Negativ
Neutral
Positiv

2) Respondent Profiles

Participants	**#**	**#/total**
female	566	34%
male	1120	66%
Total	**1686**	**100%**

Age (years)	**#**	**#/total**
20-25	132	8%
26-30	264	16%
31-35	230	14%
36-40	223	13%
41-45	208	12%
46-50	218	13%
51-55	219	13%
56-60	109	6%
61-65	46	3%
>65	37	2%
Total	**1686**	**100%**

Work experience (years)	**#**	**#/total**
0-5	485	29%
6-10	307	18%
11-15	254	15%
16-20	233	14%
> 20	407	24%
Total	**1686**	**100%**

Company Size (number of employees)	**#**	**#/total**
0-5	210	12%
6-20	207	12%
21-50	180	11%
51-250	450	27%
251-500	228	14%
>500	411	24%
Total	**1686**	**100%**

Qualification	#	#/total
Diploma	557	33%
Master's degree	383	23%
Bachelor's degree	228	14%
A level (Abitur)	140	8%
Doctorate	109	6%
Advanced technical certificate (Fachhochschulreife)	79	5%
State examination	76	5%
Middle School Education (Realschule)	71	4%
Professor	34	2%
Lower Secondary Education (Hauptschulabschluss)	9	1%
Total	**1686**	**100%**

Real Estate Sector	#	#/total
Asset-, Property- & Facility Management	220	13%
Real Estate Development	181	11%
Real Estate Valuation or Consulting	173	10%
Real Estate Transactions / Acquisition	137	8%
Real Estate Finance	118	7%
Fund Management	112	7%
Real Estate Service Provider	111	7%
Real Estate Research	78	5%
Property Management	76	5%
Construction Company	66	4%
Project Management	59	3%
Human Resources	55	3%
Portfolio Management	54	3%
Architecture and Planning	49	3%
Real Estate Leasing	44	3%
Real Estate Marketing	43	3%
Real Estate Research and Teaching	39	2%
Real Estate Law	35	2%
Urban Planning	19	1%
Real Estate Tax	17	1%
Real Estate Controlling	0	0%
Total	**1686**	**100%**

Position	#	#/total
Employee without management or operation responsibility	689	41%
Head of department	231	14%
Director	155	9%
Division Manager	146	9%
Self-employed	115	7%
Other	106	6%
Trainee / Working Student	93	6%
Partner	59	3%
Official	59	3%
Board Member	33	2%
Total	**1686**	**100%**

5 Conclusion

The aim of this dissertation is to assess the opportunities for extracting real estate-related sentiment from text documents and its possible applications to real estate markets in the US and Germany. Accordingly, the dictionary-based approach and a neural network, namely support vector machines, were utilized to investigate different text sources and manifestations with regard to any sentiment expressed. The gained sentiment scores could subsequently be aggregated to form various sentiment measures according to the desired time frequency and the sentiment of interest, that is, a positive or negative focus. Consequently, the relationship between the text-based sentiment measures and both direct and indirect real estate markets was investigated.

The main result of this dissertation is that sentiment extracted from real estate-related text does indeed help explain future real estate return movements. This is true when applying different methodologies, investigating different text sources and looking at different real estate markets, although always controlling for other influencing factors such as macroeconomic fundamentals. The results hold even when including other sentiment measures, which have been established in the real estate literature.

In Articles 2 and 3, especially the negative sentiment measures lead to promising results. One possible explanation could be a negativity bias of real estate market participants, according to which individuals allocate attention, and are hence affected more strongly by negative rather than positive stimuli – even when of equal intensity (Smith et al., 2003). The negativity bias is strongly linked to risk-aversion, which is known to be widespread among real estate investors. Another explanation for this phenomenon is the concept of negation. Positive words are frequently used to express something negative, thus applying negation. For example, if a company has to declare negative news, they will nevertheless try to sound as positive about it as possible. This might lead to incorrect positive signals and hence, incorrect positive measures. In contrast something positive is rarely expressed by negating negative words.

Overall, the findings suggest that the extraction of sentiment by deploying textual analysis captures something incorporated neither in fundamentals nor in traditional measures used to capture sentiment. The results of all component articles of this dissertation support the considerations of Kearney and Liu (2014), who define investor sentiment and textual sentiment differently. They state that investor sentiment "(…) captures the subjective judgements and behavioral characteristics of investors (…)", but argue that textual sentiment can account for more, as it "(..) can include the former, but also includes the more objective reflection of conditions with firms, institutions and market."

The following chapter gives an overview and presents the main findings of the three articles comprising the main body of this dissertation. The work rounds off with general remarks and recommendations for further research.

5.1 Executive Summary

Paper 1: Real Estate Media Sentiment Through Textual Analysis

The first article of this thesis is designed to systematically determine the relationship between news media sentiment, extracted through textual analysis from newspaper articles, and the securitized real estate market. The extensive text dataset comprises 125,000 U.S. news-media article headlines from *Bloomberg*, *The Financial Times*, *Forbes* and *The Wall Street Journal* from 2005 until 2015. The results contribute to the contemporary literature on textual analysis and furthermore, add insights to the growing research on sentiment analysis in the context of REIT models.

Applying the dictionary-based approach enables counting the positive and negative words within each text entity, specifically news headlines. As the basis, two different dictionaries are compared, one general psychology dictionary, the Harvard General Inquirer Word list, and the financial dictionary of Loughran and McDonald (2011), adjusted for real estate specifics. With the resulting sentiment scores, different sentiment measures can be aggregated, focusing on one polarity (*Positive Count, Negative Count*) or on both polarities at the same time (*Sentiment Quotient*). These sentiment measures are tested separately in vector autoregressive models for their linkage to the REIT market, always controlling for known influence factors. All sentiment measures created with the help of the financial dictionary do indeed display a significant relationship with future REIT returns. Especially the sentiment measure considering both polarities, the *Sentiment Quotient*, has a robust leading relationship by three to four months with a highly significant Granger-Causality. The *Positive* and *Negative Count* present significant lags as well, but with a smaller Granger-Causality significance.

Interestingly, none of the created sentiment measures based on the general Harvard Dictionary significantly Granger-causes future REIT market movements. These results confirm the notion already present in the textual analysis literature, of the importance of adapting the methodologies to the context under consideration. The results are robust for the established REIT subcategories, namely residential, office and retail. Overall, the findings suggest that both positive and negative changes in real estate media sentiment induces both upward and downward pressure on REIT returns three to four months later.

Paper 2: News-Based Sentiment Analysis in Real Estate: A Machine-Learning Approach Via Support Vector Networks

Until recently, extracting real estate sentiment has been limited to dictionary-based approaches. Hence, the second article of this dissertation is the first to use a sentiment classification algorithm to extract sentiment from qualified news items and to quantify the performance in relation to both the securitized and direct commercial real estate markets. A support vector machine is trained in order to measure market sentiment from 54,530 real estate-related news stories from the *S&P Global Market Intelligence* database (SNL), which arguably have the potential to influence the decision-making of informed commercial real estate market participants in the United States. Belonging to supervised learning techniques, this methodology requires a pre-classified set of training data. The training set contains about 4.500 pre-classified positive, negative and neutral headlines, which are used to construct the so-called decision surface. In the next step, the algorithm is able to determine the classification of a new headline with regard to where it is mapped in the decision surface.

With monthly real estate return data provided by *NAREIT* and *CoStar*, this paper analyses the dynamic relationship between the created sentiment measures and direct as well as securitized market returns from the beginning of 2005 until the end of 2016. Overall, the results yield predictive power for both markets. Furthermore, for neither of the two markets could a significant impact of past market performance on current sentiment measures be found, so that, a bi-directional relationship cannot be claimed.

However, the results differ concerning the market reaction time periods to changes in the text-based sentiment indicators. During the 12-year sample period, returns in the securitized market respond to news-based sentiment one month earlier than direct commercial real estate market returns. A possible explanation emerges from considering the characteristics of the two markets; the indirect real estate market is claimed to move faster on average than the direct one.

Concluding for both markets, the pessimism indicator provides the strongest additional information to supplement macroeconomic fundamentals in explaining market returns.

Paper 3: Predicting Real Estate Market Movements: the First Textual Analysis-Based-Sentiment Application in Germany

The aim of this article is to lay the foundation for text-based sentiment analysis applications of German real estate markets, as no related research attempts have been found so far. For a start, the first German Real Estate Sentiment Dictionary is developed by means of a large-scale survey among real estate professionals. Subsequently, the value of the created news-based sentiment measures for predicting the German real estate market is demonstrated.

Following the findings of Loughran and McDonald (2011), the first objective is to derive a discipline-specific sentiment wordlist, containing words used in a real estate context, and with regard to the meaning in this context only. Therefore, words presumably expressing a positive or a negative tone were collected, and assessed by about 1700 survey participants. Having this resource available, the dictionary-based approach can be applied to analyze 125,462 newspaper articles published in the *Immobilien Zeitung*, the major real estate news provider in Germany. With a vector autoregressive framework and out-of-sample forecasts, the relationship between the created news-based sentiment measures and the direct German residential market from 2007 to 2017 is investigated explicitly.

Overall, the findings yield strong and robust evidence of predictive power of the sentiment measures over future residential market movements. More specifically, even when controlling for macroeconomic fundamentals and another sentiment measure, the news-based negative indicator Granger-causes one-month-ahead IMX returns. Possible explanations of more efficient negative sentiment measure rather than positive ones, may be a negativity bias of real estate market participants or the use of negation. That is, positive words are frequently used to express something that is really negative, applying negation. This might lead to incorrect positive signals and hence, incorrect positive measures. By contrast something positive is rarely expressed in negating negative words. Furthermore, this paper found evidence that the analysis of German newspaper article headlines alone is already appropriate for creating a significant real estate media sentiment measure. Last but not least, the paper contains evidence that the mode of compilation of the dictionary is absolutely crucial. Even apparently small changes can lead to insignificance. The findings of this research surely confirm the value of text-based sentiment analysis for the German real estate industry, as well as for academia.

5.2 Final Remarks and Further Research

Together, the results of the three research articles provide an overall consistent picture. Most importantly, this dissertation highlights the importance of real estate-related textual analysis as an innovative way to capture market sentiment. Text-based sentiment measures can be deployed as a leading market indicator and enhance the explanatory power of fundamental market models. Not only the immediate availability and objectivity of results is a key aspect, but also the option of scaling the methodology to large data sets. As more and more information and processes are available online, all kind of digital texts will increase in volume over time. Simultaneously, better technology and rising computational power to handle and analyze large sets of data emerges perpetually. These developments strengthen the future value of textual analysis for the real estate industry, as well as for academia.

Given that this dissertation reveals, how and why real estate-specific applications lead to superior results, future research might augment and improve sentiment dictionaries in English and German, focusing especially on meanings of words in a real estate context. To improve machine learning, a database for objectively classified real estate-specific text corpora is worthwhile.

It would be interesting to compare the sentiment extracted from different forms of articles or text documents, as some categories might include more sentiment than others. The investigation of earnings press releases, annual reports, 10 Ks, analyst reports, commentaries or IPO prospectuses may lead to different results. Furthermore, there will be texts which are written specifically to influence readers on purpose. For example, press releases from companies normally influence other market participants to think more positively about the company's future. Does the sentiment extracted from such news impact differently on market participants?

As there are different levels of transparency in real estate markets across the world, it would be worthwhile to assess the effects of text-based sentiment cross-nationally. Furthermore, once larger datasets of text documents are available, the methodologies could be scaled in order to investigate even shorter aggregation frequencies – weekly or even daily. This would be of considerable interest for real estate stock forecasting.

5.3 References from Introduction and Conclusion

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Universität Regensburg
IRE|BS Institut für Immobilienwirtschaft
Fakultät für Wirtschaftswissenschaften