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Which Sentiment Indicators Matter? An Analysis of the European Commercial Real Estate Market

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Abstract

Property markets exhibit several classic market inefficiencies, which can lead to irrational behaviour and a better understanding of connections between yield modeling and the role of sentiment is of immense interest to property funds, pension funds, banks, insurance companies and other participants. While past studies have examined the role of sentiment in market performance, the conclusions have remained mixed. This paper compares established models against two new innovative methods, paying more attention towards the expectations of market participants to explain yield adjustments and swings in property values. Forecast evaluations reveal that models incorporating property-specific and google trend sentiment outperform the base model. The European market offers an interesting testing ground for our research questions as the interest of investors and banks in abrupt movements in yields and pricing and the role of market sentiment has grown in Europe post global financial crisis due to high level of non-performing loans.

Keywords

yield modelling, property lending, sentiment

JEL Classifications

C53, C82, E37, R31

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1 Introduction

A large number of studies in the last couple of decades have attempted to understand what roles the sentiment of economic agents play in shaping investment decisions and, subsequently, specific market movements through collective or individual actions. The second area is relatively under-researched. It is well understood that sentiment plays a key role in economic relationships, but its impact under various economic environments is not straightforward, as it may change for different types of agents at different times across different asset classes. Moreover, any causal analysis is fraught with endogenous feedback. In this paper, we choose commercial real estate as an asset class to examine several testable hypotheses on the relationships between sentiment and asset pricing. Real estate as an asset class offers several classic channels of inefficiencies (i.e., market imperfections and precautionary savings behind the rational expectations–permanent income hypothesis, Hall, 1978) due to (a) lumpy investment (b) infrequent transactions, and (c) information asymmetry. The related theoretical frameworks offer an explanation through the presence of "animal spirits," the possibility of "habit persistence," and forward-looking models. Moreover, if financial assets are informative because of public information being readily available, for some real assets such as property, responses may be asymmetric and should be even stronger as the information signaling and processing are more sensitive to new information in thin markets. Our findings support several hypotheses with statistical confidence.

1.1 Banking sector exposure to commercial real estate

Existing findings also indicate a significant bearing on bank lending practices and risk management strategies. The linkage of the banking sector to the residential real estate market through either loans or structured products is well known. Further, both systemic and local banks have exposure to commercial real estate, including office buildings and retail assets (e.g., shopping centers and retail warehouses). In 2015, commercial banks in Europe lent over €40billion to European commercial real estate (Cushman & Wakefield, 2016). The numbers are actually larger since these estimates are based on a subset of the whole commercial banking sector. Correctly mapping conditions in advance in the commercial real estate market is therefore important to credit risk management.

1.2 Risks to banks

The significant fall in commercial real estate prices during the global financial crisis was a reminder of the risks to servicing loans and to loan-to-value ratios, highlighting the greater need to study forthcoming risks to commercial real estate portfolios. A major factor underpinning severe changes in commercial real estate values is the discount rate or yield (cap rate) as it is known in real estate pricing models. A volatile component of yields is sentiment. Sentiment can change fast and hence the risk premia from taking exposure in commercial real estate. The time varying character of the risk premia has been documented by a number of studies (e.g., Hutchison et al., 2012).

Risk management of the real estate loan book requires assessment of risk premia changes and yield movements. This can help banks to price and structure commercial real estate loans appropriately and make provisions for severe downside risks.

1.3 Importance of signals and sentiment

Can banks hedge their risks? Lenders, valuers, and underwriters should be utilizing a range of signals to establish whether pricing is tight, i.e., whether pricing is too high perhaps being at a bubble state. The major risk in situations of high prices is that of a reversal in sentiment leading to jumps in risk premia and a fall in prices. The study of sentiment is under-researched in real estate pricing models. Lending decisions will benefit from pricing models in real estate that focus on sentiment more explicitly.

We have organized the paper as follows. In the next section, we review relevant literature and situate our hypotheses within the literature. Then, we proceed to discuss the underpinning theories behind our hypotheses. We then describe the data and our methodology. Finally, we present the empirical analysis and several robustness checks, and conclude with a summary of key findings in the last section.

2 Literature review

This literature review is divided into two parts. The first part summarizes the main approaches regarding the rent variable in a yield model; the second part describes the most recent developments concerning sentiment analysis.

2.1 Yield modeling

The topic of cap rates or yields have been widely discussed in the academic literature. Yields are a ratio of net operating income over the price of the property. An essential element in the yield modeling process is the expectation of the buyer about future income growth. This is commonly captured in the rent variable. The literature discusses all components of a standard yield model equally, while the risk premium and liquidity measures have been widely discussed by Chervachidze et al. (2009), Chervachidze and Wheaton (2013), and Duca and Ling (2015). Earlier DiPasquale and Wheaton (1992) established that asset prices are influenced by macroeconomic shocks. However, our focus is set on the rent component. The two methods introduced by Hendershott and MacGregor (2005a) and Chervachidze and Wheaton (2013) have been widely used in the literature. Both methods tried to capture the changes in the market, as well as the expectations of the market participants. Yet, we believe that a sole focus on the rent and its deviations is unable to mirror a more complex picture of factors which influence the expectations.

The importance of the rent variable during the yield modeling process becomes further apparent, by the fact that the rent is likely to be the only component that carries local fixed and time-invariant elements (Sivitanidou and Sivitanides, 1999), in comparison to the risk free rate and the risk premium. The latter two usually mirror macroeconomic developments. Sivitanides et al. (2001) point out that yields are likely to respond to new developments within the market sooner than rents, which are fixed over a longer period and are therefore unaffected by recent and current developments. The authors use panel data techniques on a National Council of Real Estate Investment Fiduciaries (NCREIF) dataset and introduce two components to measure the expected income growth: expected economy-wide inflation as well as expected real-rent growth. The latter component is computed as the change in real rents as a measure of rent differences. Due to this, the authors hope to capture all interactions across the different markets. As a result, it becomes clear that market-specific yields are influenced by local market behavior.

Hendershott and MacGregor (2005a) examine why property yields haven't dropped while rents increase in the UK market. Assuming that commercial real estate investors act in an irrational way, they develop a model that is centered on expected real rental growth. This new variable uses a four-quarter average of the deviation of the log of real rents. This method is able to capture the variation in the yields and should enable investors to anticipate yield movements in a more realistic way. Contradicting the previous research of Sivitanides et al. (2001), the newly constructed variable adjusts to the rolling changes and therefore does not have an irrational view on the developments of the market. What the authors describe as a mean reverting adjustment model, which seems to be present in the UK property market, could not be found in their other study for the US market (Hendershott and MacGregor, 2005b).

Shilling and Sing (2007) utilize the findings of Sivitanides et al. (2001) and Hendershott and MacGregor (2005a, b), and extend the research regarding the rationality of property investors. Chichernea et al. (2008) also identify that geographical differences among the examined MSAs

(Metropolitan statistical area) influence the property yields. The authors incorporate the supply side of the market into their model to have more reliable information from the market, instead of solely focusing on a growth component. Their model benefits from this approach. They identified that markets with a higher liquidity and markets with more stringent supply constraints experience lower yield levels. This knowledge would enable market participants to recognize markets that are out of equilibrium.

Later Chervachidze et al. (2009) extend this work. They introduce a risk premium and a liquidity measure. More recently, Chervachidze and Wheaton (2013) extend their analysis of macroeconomic factors. The risk premium and the growth rate of debt relative to the GDP incorporate information about liquidity, which significantly influences the yield. Duca and Ling (2015) examine the impact of the latest financial crisis on the commercial real estate market in the US. Picking up from the work of Chervachidze and Wheaton (2013), the authors do not focus on the rent element within their model but on the risk premium. They define the variable as the spread of the Baa corporate yield and the 10-year Treasury yield. Both elements capture the short- and the long-run changes of the market and therefore are able to bring this information into the model. Again the authors stress the importance of capturing market swings within the broader national economy, which will reflect back into the real estate market. Similar to Hendershott and MacGregor (2005a, b) the basic assumption of their model is based on the Gordon growth framework.

2.2 Sentiment analysis

A large body of sentiment-related literature is present in academia. Herding behavior that is caused by sentiment shifts is of particular interest. A deeper understanding of the underlying sentiment of investors could help to improve models and predictions about market movements. Sentiment analysis has its origin in the field of behavioral finance. The field is switching the focus from the rigid assumptions about rational and return-maximizing investors, who are able to process all available information immediately, towards the acceptance of irrational behavior of market participants.

The academic literature related to sentiment can be categorized into two types of sentiment measures, market-based (indirect) and survey-based (direct) measures. According to Hengelbrock et al. (2013) the market-based measures include, among others, closed-end fund discounts, liquidity figures, and trading volumes of the underlying asset. Other proxies are based on interest rates, labor income, or GDP figures. Survey-based measures instead extract the sentiment either with the help of interviews or surveys.

In the last decade a new form of sentiment measures has emerged. Due to the increasing use of computers and the dominant role of online search engines, a hybrid between direct and indirect measures can be used. Online search volume data provided by Google Trends (GT)[1] has been identified as a rich source of information about what people think and what they want. Scholars such as Choi and Varian (2009), Preis et al. (2010), Wu and Brynjolfsson (2013), and Loughlin and Harnisch (2013) have used Google Trends (GT) data in different fields and have shown that online search volume data is able to improve models. However, scholars are undecided whether GT data can predict the future or only predicts the current situation within the different markets.

Lee and Shleifer (1991) show that sentiment does play a role in the financial market. They analyze closed-end funds and their exposure to noise traders. These funds have been traded with discounts, which can be assumed to be an indicator of the expectations of the traders for future development of the asset. The larger the exposure of the fund, the more sensitive are the discounts to the investor sentiment. Baker and Wurgler (2006) reach a similar conclusion. They find that investor sentiment has a larger impact on the returns of small, young, and highly volatile stocks. The researchers are able to show that returns are higher (lower) when sentiment is weak (strong) at the beginning. This is understandable, since stocks with high prices usually enjoy more attention, which goes in hand with a higher sentiment. Kumar and Lee (2006) used a large dataset of retail investor transactions to prove that investors buy and sell stocks in concert. Noise traders focus on small, young, and highly volatile stocks, which underlines the observation of Baker & Wurgler (2006).

A range of studies such as Carroll et al. (1994), Bram and Ludvigson (1998), Howrey (2001), and Easaw and Heravi (2004) utilize different sentiment indices to improve their models. The studies show that the University of Michigan Consumer Sentiment Index can only explain current relationships rather than future developments. Non-US-focused studies have made scholars aware of the fact that cultural or economic factors also influence the power of predictions of those indices. Fan and Wong (1998) are unable to prove the findings of Carroll at al. (1994) for the Hong Kong market. In addition, Malgarini and Margani (2007) look at the Italian sentiment index and show that market models can benefit from the sentiment index.

Within real estate, studies largely focus on market activity data from the residential sector (Goodman, 1994; Weber and Devaney, 1996; Dua, 2008; Nanda, 2007; Croce and Haurin, 2009; Ling et al., 2014; Marcato and Nanda, 2016). Regarding the commercial real estate sector, Baker and Saltes (2005), Clayton et al. (2009), and Marcato and Nanda (2016) analyze the role of

[1] Google Trends Data 2016. Google, https://www.google.co.uk/trends/, accessed on 05.05.2016

sentiment data in explaining market dynamics and, more recently, Das et al. (2015) use the flight to liquidity and category/style investing theory to explain the sentiment-induced trading behavior of institutional investors (and subsequent impact on pricing) for publicly traded real estate investment trusts (REITs) throughout different market cycles.

On the real estate side, authors are motivated by the observation that prices follow a random path, rather than a rational or logical pattern. In general, studies are divided between sentiment analysis regarding the housing market, such as Case and Shiller (1989), Choi and Varian (2009), Jin et al. (2014), and the commercial real estate market, such as Barkham and Ward (1999). Focusing on the latter, the authors contribute to the question of noise traders in the real estate market. They pick up the analysis of closed-end funds from Lee et al. (1991) and look at real estate companies in the UK. They show that closed-end real estate funds are traded with a discount on average as well. This is caused by noise traders, who overestimate value changes in the underlying asset. The authors identified two groups of noise traders: stock investors and developers who are responsible for overbuilding.

Similar to the sentiment analysis described above, the general separation of the applied measures in the literature remains. Scholars use survey-based sentiment analysis and market-based analysis with the help of market proxies, for the examination of market sentiment. Tsolacos (2012) analyzes the application of sentiment indicators on the European real estate market. He points out that sentiment based on a survey can be seen as the beliefs of market participants of future developments, which makes sentiment an attractive feature in a forecasting framework. He uses the economic sentiment indicator (ESI) provided by the European Union for the three major markets: Germany, France, and the UK.

Clayton et al. (2009) examine lack of transparency, illiquidity, and strong segmentation of the market, which all go hand in hand with information inefficiency. Furthermore, investors are unable to short sell the asset, which leads to a sentiment-influenced market, with a strong bias to mispricing. Their analysis shows that the sentiment of investors influences the market even after controlling for changes in rental growth.

In a later study, Ling et al. (2014) focus on the short-sale constraints in private real estate markets. The resulting hypothesis is that sentiment has a much stronger influence on the private market than the public market, due to the fact that market- or price-correcting mechanisms do not work. The authors use both direct and indirect sentiment measures and apply the methodology introduced by Baker and Wurgler (2006, 2007). They use eight indirect sentiment measures, following the idea that all imperfect proxies contain, at least to a certain degree, some pure sentiment. Ling et al. (2014) show that prices and returns are affected by sentiment shocks for much longer in the private market.

Baker and Saltes (2005) contribute to the literature by looking at the investment side of the market, opting for the construction part of real estate. They use architecture billings in the US as a leading indicator for construction activity. Marcato and Nanda (2016) analyze a range of sentiment measures and confirm other results. They are able to show that sentiment measures help to forecast changes in real estate returns. Their results are more promising for the residential market than for the commercial real estate market. The authors assume that the latter does not react as strongly as the residential market to shocks in pure sentiment. The authors also apply the above-mentioned method of Baker and Wurgler (2006, 2007). Among others, Marcato and Nanda (2016) use the University of Michigan index, as well as the Architecture Billings Index (ABI) as introduced by Baker and Saltes, 2005, and the Housing Market Index (HMI).

Sentiment analysis has been further applied to REITs. Some of these studies, such as Chiang and Lee (2009), use the established understanding of closed-end fund discounts as a sentiment proxy. Lin et al (2009), on the other hand, draw a fine distinction and illustrate that REITs behave differently to closed-end funds; therefore a separate examination is needed. They develop a sentiment measure based on the ownership share of REITs. Among others, Das et al. (2015) investigate whether a sentiment component can improve a REIT trading strategy. Rather than using indirect sentiment proxies, such as the closed-end fund discount, the authors are able to use a survey-based measure for institutional investor sentiment. This is in line with the recommendation in the literature (Ling et al, 2014 and Lin et al., 2009) and their results suggest that a direct measure is superior in comparison. In Freybote and Seagraves (2016), the authors first pick up on the idea of disaggregated sentiments for different investor types. Unlike previous studies, they define their sentiment measure as the general attitude towards the office market, expressed in trading behavior. Following the idea of Kumar and Lee (2006) that noise traders trade in concert, the authors show that multi-asset property investors use the sentiment change of specialized property investors to adjust their trading strategy. Freybote (2016) further underlines the predictive power of forward-looking sentiment measures. Using credit ratings or real estate specific indices results in the fact that backward-looking elements dominate. A prediction of market movements is therefore limited.

Regarding the achievements of GT in combination with real estate research, the main direction of focusing on the US or the housing market seem to prevail (Choi et al., 2009 and Beracha et al., 2013). On the commercial real estate side, Dietzel, Braun and Schäfers (2014) construct three different sentiment proxies based on Google Search volume data. They use the CoStar Commercial Real Estate Repeat-Sales Index for a Granger causality test. Results reveal that Google Search volume data is able to predict the market. However, and this is consistent with other studies, the authors suggest that better results are achieved when researchers try to now-cast rather than forecast. Yet the authors criticize the lack of absolute search values and the data modification, in terms of scaling. Therefore, the use of this data leaves some questions unanswered.

It has become clear that sentiment does play a role in both the real estate and equity market. The real estate market, however, is much more influenced by its own characteristics.

3 Theory

3.1 Yield modeling – rent

In the first part of this section, we compare a set of five different approaches regarding the rent variable within a standard yield model. A standard yield model uses four components: the property yield as the dependent variable, the risk free rate, the expected rent, and the risk premium. The property yields are provided by Cushman & Wakefield (formerly DTZ). As a risk free rate, we use the 10-year government bond rate for each country. The risk premium has been widely used in the literature. Some studies have used the spread between the risk free rate and a Baa-rated corporate bond (Duca and Ling, 2015). Others calculated their risk premium based on the volatility of the equity market (Devaney et al., 2016). We follow this last idea and construct the risk premium based on the equity market volatility as an eight-quarter rolling standard deviation from the stock market return and subtract the national 10-year government bond rate (risk free rate) from it. In general, this approach is in line with the literature, which assumes that yields are more influenced by macroeconomic factors than regional factors (Sivitanides et al., 2001; Chervachidze and Wheaton, 2013).

$$Yield_{(office|retail)r,t} = \beta_o + \beta_1 Risk\ Free\ Rate_{j,t} + \beta_2 Risk\ Premium_{j,t} + \beta_3 Rent\ measure_{j,t} + \beta_4 regional\ fixed\ effect_r + \varepsilon_{j,t} \tag{1}$$

From the literature, we note that academia attaches some importance to the rent variable. Most of the scholars agree that the rent component should carry the expectations of landlords and investors (Sivitanidou and Sivitanides, 1999). Further, many studies base their rent component on a perpetual Gordon growth approach (Hendershott et al., 2005; Duca and Ling, 2015; Chichernea et al., 2007). Underlying the characteristics of the real estate market and given its heterogeneity, the rent variable carries regional information within the yield model (Hendershott and MacGregor, 2005). Our European-specific dataset differs at this point to the literature. A European-wide panel dataset has two layers of cross-sectional information. The rent variable carries the regional-specific cross-sectional information, whereas the remaining macroeconomic elements of our model carry country-specific information.

Regarding the rent component, the literature review has revealed that two methods are predominant (Hendershott and MacGregor, 2005a, 2005b; Chervachidze and Wheaton, 2013). In our opinion these methods lack complexity and, further, only rely on the rent series itself. That ignores macroeconomic influences and limits the expectations of landlords and investors to a one-sided view, which is only based on past developments. It is our belief that a more complex method that incorporates future expectations and forward-looking elements fulfils the requirements in a more suitable way.

In the following section we present the five different methods we constructed and compare.

3.1.1 Naïve approach

The first method we apply is a naïve approach. The data provided by Cushman & Wakefield (formerly DTZ) includes an in-house estimation of the rent for the following quarter. These forecasts are performed on a quarterly basis from 2009 onwards. However, both datasets do not fully match in terms of regions for the property types, especially on the retail side, for which this forecast dataset is much shorter. Due to these two facts, the available data only covers 20 quarters. On the other side, only 50 regions for office and 35 regions for retail are covered. Little is known about the model used by the agency to forecast these rents. Besides the dataset, there is little known about the estimation process.

$$\exp\_rent_{Naive} = Cushman \,\&\, Wakefield\ 'inhouse'\ forecast \quad (2)$$

3.1.2 Adaptive expectations (I)

In this approach, we reproduce one of the recommended methods in the literature. Hendershott and Macgregor (2005b), who have examined yield models via focusing on the rent component, have used a four-quarter moving average of the long-run deviation of the log of real rent. Hoping to capture the market cycle and introducing mean reverting mechanisms to the model, the authors generated some promising results.

$$\exp\_rent_{HMG} = \log(long\ run\ average\ of\ RR) - four\ quarter\ MA\ of\ the\ deviation\ of\ the \log of\ real\ rent \quad (3)$$

3.1.3 Adaptive expectations (II)

Another well-known method also solely focusing on the rent component can be found in Chervachidze and Wheaton (2013). The authors use a real rent ratio, which is defined as the ratio of real rent in a given quarter to the historic average from the real rent. Different to the previous method, the authors do not include any recent developments and rely on the current picture, which is mirrored in the real rent. The authors further point out that the relationship of their ratio with the yield depends on the behavior of the investors, whether they are forward or backward looking. If they are forward (backward) looking, and rents are at high levels, then investors will be informed that an adjustment is likely to happen in the future, so the influence will be positive (negative) on the yield.

$$RRR_{CW_t} = \frac{real\ rent_t}{historic\ average\ of\ RR} \quad (4)$$

3.1.4 Rent expectation

The fourth approach is based on our assumption that landlords and investors do not solely base their decision on the past developments of commercial rents. Their expectations are influenced by micro- and macroeconomic developments as well. One good indicator of what investors can expect of the future is based on the development of the GDP. The national GDP summarizes all economic developments within the country. We use the expected changes of annual real GDP. Those expected values have been extracted partly form the semi-annual/quarterly published economic forecasts from the European Commission and partly from the annual World Economic Outlook published by the International Monetary Fund (IMF). The economic forecasts only cover European Union members and candidate states. Norway, Switzerland, Russia, and Ukraine have therefore been covered by the IMF document. Each year the European Commission publishes at least two main documents under the title "European Economic Forecast." The two main periods that have been used for the data generation are spring and autumn. Over the 11-year period from 2004 until 2014, the publication has barely changed. Between 2007 and 2010, two interim forecast documents were added. In contrast to the main documents, these are much briefer and only include a quarterly forecast for some of the 27 European countries. Since 2013, the Commission has included a winter document, in addition to the spring and autumn forecast.

We use these forecasts to calculate a forecast error, where we calculate the difference between the forecasted and the actual value. We than add the forecast error to the change of the current rent to consider investors' expectations ($\exp\_rent_{FE}$). The forecast error summarizes the unexpected market development and should have an impact on the expected rent.

$Rent\ expectation$:

$$\exp\_rent_{FE} = change\ of\ current\ RR + GDP\ forecast\ error \quad (5)$$

3.1.5 Adaptive rational approach

Our last approach extends both the critique on the mainstream models and the idea of mirroring a clearer picture of investors' expectations. As pointed out earlier, we assume that the expectations about future developments of commercial real estate rents cannot be fully mirrored by the rent series itself. Also the previous method combines both backward- and forward- looking elements, we therefore propose a more complex method to mirror the expectations. We use the GDP from the previous period, the current GDP, as well as the GDP of the following period, the interest rate spread (long run – short run), as well as the Economic sentiment indicator. Both the three GDP variables and the interest rate spread will capture macroeconomic developments, which will shape the expectations of investors. The ESI on the other side introduces a forward-looking element to the rent variable. We obtain the fitted values from this regression, as the expected rent.

$Adaptive\ rational$:

$$\exp\_rent_{AR} = GDP_{t-1} + GDP_t + GDP_{t+1} + interest\ rate\ spread_t + ESI_t + \varepsilon \quad (6)$$

3.2 Sentiment analysis

The second part of our paper applies a behavioral finance approach to the yield modelling process. Even though the literature review has revealed a relative depth in the field of sentiment analysis, it seems that yield or cap rate models have been widely excluded from the inclusion of sentiment indices, with the exception of Clayton et al. (2009). As shown in various studies, such as Tsolacos (2012), the European commercial real estate market is subject to sentiment. We are therefore certain that an irrational or human element within the yield model will enable us to improve our model.

$$Yield = Risk\ Premium + Risk\ Free\ Rate + Expected\ Rent + Sentiment \quad (7)$$

In addition, the literature review has shown that the distinction between direct and indirect sentiment proxies has been applied in both equity and real estate markets. Since our study covers 24 European countries, we face a data issue when it comes to direct real estate specific sentiment indicators. For the UK, for instance, the Royal Institute of Chartered Surveyors (RICS) publishes a property survey, where RICS members are asked about their opinions of future developments in the English real estate market. However, to our knowledge many European countries do not offer an equivalent.

Given that, studies have to employ indirect sentiment proxies to mirror market perceptions. Yet, the quantification of sentiment, based on indirect sentiment proxies remains a crucial process. Following the basic idea of Baker and Wurgler (2006, 2007) and its application by Ling et al. (2014) on the real estate market that each imperfect sentiment proxy, at least to a certain degree, carries some pure sentiment, we are confident to extract the sentiment from indirect measures.

However, we do not follow the literature when it comes to the selection of sentiment proxies (Lee et al., 1991; Clayton et al., 2009; or Ling et al., 2014). Ling et al. (2014), for instance used one survey-based measure from the Real Estate Research Corporation (RERC) and eight different indirect sentiment proxies (REIT stock price premium to the Net Asset Value (NAV), percentage of properties sold each quarter from the NCREIF index, REIT share turnover, number of REIT Initial Public Offerings (IPOs), average first day returns, share of net REIT equity issues relative to total net REIT debt issues, net commercial mortgage flow as a percentage of GDP, and net capital flows to dedicated REIT mutual funds). These proxies share a relative focus on the REIT market in the US. More mature western European countries such as the UK, Germany, and France are able to show a healthy REIT market. However, eastern European countries do not have similar markets and especially not at the same depth. We have therefore decided not to follow the above-described approach.

Before we describe the intention of our four different sentiment indicators in more detail, we need to point out two things. First, we assume that the measured sentiment should have a negative impact on property yields. A positive sentiment indicates a rise in property prices and, vice versa, a decrease in yields. We are aware of the fact that different groups of investors follow different goals and hence should use different sentiment types.

Second, we follow the overall belief that direct real estate markets, given short-selling constraints and limits to arbitrage, incorporate mispricing of their properties. Nevertheless, the literature review has left the impression that scholars in the real estate market, even though they emphasize that they measure the sentiment of investors, do not follow a fully behavioral approach. Their definition of irrationality is, instead, based on the incompleteness of classical financial theories, which is caused by the real estate market structure. However, this violates the basic definition of behavioral finance, where the individual rather than the market is the focus of interest. Following Baker and Wurgler (2007), sentiment is the belief of investors about future cash flows and investment risk that is not justified by the facts at hand. This belief is easily quantified with direct sentiment measures, which are based on the opinions of market participants and incorporate forward-looking elements (Freybote, 2016). Using indirect measures (e.g. REIT share turnover), on the other hand, the aggregated belief of investors should be equal to the unexplainable part. This is why orthogonalization in combination with principal component analysis (PCA) should provide a good indication about the actual irrationality.

3.3 Macroeconomic sentiment indicator

With regards to the yield modeling process and the influence of the economy on the real estate market, we assume that macroeconomic sentiment proxies are able to give information about the market sentiment. Therefore, the first sentiment indicator we construct is based on pure macroeconomic factors. The factor combines two direct sentiment proxies and four indirect sentiment proxies.

Similar to Tsolacos (2012), we use the ESI. It is published by the European Commission and summarizes five sector-specific confidence indicators by means of a weighted aggregation of standardized input series. Since the indicator covers construction, retail, industrial, service, and consumer confidence we are able to get a good indication about the European market and economic developments.

The second direct proxy is the business climate indicator (BCI) also published by the European Commission, which provides a timely composite indicator for the manufacturing sector in the Euro area. This indicator is based on five opinions from an industry survey: production trends in recent months, order books, export order books, stocks, and production expectations. These questions aim to retrieve the forward-looking opinions of market participants.

The choice of the four indirect sentiment proxies is motivated by two things. First, as pointed out earlier, we face some data issues given the range of European countries within our panel dataset. Second, we focus on macroeconomic factors that are likely to be influenced by sentiment changes in the general economy. The stock market and corresponding national index have always been seen as a health indicator of the national economy. Among others, Baker and Wurgler (2006, 2007), Tetlock (2007), and Kurov (2010) have shown that investor sentiment influences the stock markets. For each of the 24 countries, we have used the quarterly return from the stock market. The values have been provided by Thomson Reuters Datastream. Similar to the stock index, the government bond rate can be used as an indicator of national health and represents the public side of the market. This indicator is less likely to change as rapidly as the stock markets return; however, the government bond gives information about several country-specific risks, such as inflation, interest rate risk and state of public finances.

Consumer confidence has been at the center of interest since Katona (1968). Markets and governments are interested in which direction consumer confidence is heading. Therefore, consumer confidence has been identified as a suitable sentiment proxy. We have taken most of the values from the OECD. We assume that this indicator can pick up some developments from consumer behavior, which translates back into the market itself.

In addition, the credit rating can be seen as an indicator, showing how a country is valued based on a range of macroeconomic factors. The credit rating is likely to be one of the main indicators foreign investors focus on before they make an investment decision. The credit rating figures are provided by Oxford Economics and range between 0 and 20, where 20 equals an AAA rating.

3.4 Sentiment construction

To derive at a suitable sentiment indicator we apply an orthogonalization process to the sentiment proxies and try to remove known macroeconomic influences. We focus on the main factors such as the change of GDP, the forecasted change of GDP, the interest rate, the logarithm of the consumer price indicator, the logarithm of consumer spending, the unemployment rate, as well as the percentage change of the industry production of the country ($c\_gdp, fc\_gdp, intr, logcpi,\ logcsp, unemp, indpropc$). All these factors influence the development of our proxies.

The process requires each of the proxies to be regressed against those factors without an intercept. The residuals of these six orthogonalization regressions should be equal to the irrational and unexplainable part. Following Baker and Wurgler (2006), we standardize the residuals and, due to the fact that some variables may react to changes in sentiment more rapidly than others, it is recommended to use both the standardized variables and a lagged version of them in a PCA. We obtain the first principal component with the highest eigenvalue.[2] Then we verify the correlation of the factor loadings with the first stage index from the PCA. Factor loadings with a small correlation are removed from the final sentiment calculation. We check the correlation between the first stage index and the constructed sentiment indicator,

[2] In unreported tests, we construct the sentiment indicators following the Kaiser criterion. Here all principal components with an eigenvalue greater than 1 are used. We than construct a weighted average of the number of recommended components based on their explanation power. However, the results do not suggest that this method is superior in any way.

whether there is any severe loss of information by removing the weak factors. This combines the six proxies to our macroeconomic sentiment indicator.

3.5 Real estate specific sentiment indicators

The second and third indicators are designed to give an approximation about the commercial real estate specific sentiment. We assume that a sentiment indicator based on property-specific elements, which are linked to the specific market, will be superior to a solely macroeconomic sentiment indicator, since the latter also covers other industries. As pointed out earlier, Europe suffers from data differences especially with regards to the real estate side. To retrieve a sentiment proxy that covers most European countries, we obtain the property-specific total return series from the MSCI Investment Property Databank (IPD). This performance measure mirrors the development of the commercial property market and therefore responds to sentiment swings.

Other property-specific factors, such as demand and supply, also contribute to market swings. On the office side, Cushman & Wakefield (formerly DTZ) provides, in addition to the rent series, office supply, office availability, office take-up, office availability ratio, and office new supply. Since these are the observable factors, we follow the same process as above and orthogonalize the IPD total return for office against these factors to obtain the residual. Since we are only using one proxy, there is no need for a PCA to retrieve a common sentiment component. However, we standardize the residuals for a better comparison.

On the retail side, our dataset is limited and we are only provided with the retail-specific rent series, which we use in the orthogonalization process. We are aware that this results in a less informative sentiment indicator, since we are unable to remove more obvious factors.

3.6 Google Trends

The last sentiment indicator utilizes online search volume data. Studies, such as Dietzel et al. (2014), show that online search volume data is able to give information about the thoughts of millions of people and about their intensions. Still, we need to question the motivation of online searches. Probably the majority of those searches are motivated by information gathering. However, a proportion could be triggered by “hot topics” within the market. In that scenario, these searches would not reveal the actual interest in the search term, which we assume precedes a later action. Nevertheless, using the Google categorization should filter out those reactional searches. The searches related to a specific category, such as “property”, are only counted by the Google algorithm in the category, if a series of property-related searches is performed. We assume that the volume of online searches within the specific category reflects the sentiment of the market and represents a suitable way of measuring the mood. Similar to Dietzel et al. (2014), we address critics who would question the actual Google activity of professional real estate investors, such as pension funds, REITs, or other institutional investors. Undoubtedly, these kinds of investors might have in-house information-providing services and, additionally, are able to rely on a network and experience. Given this, our contribution to the literature using Google data is twofold. First, we apply the analysis to the European commercial real estate market. This market is characterized by a variety of different national languages, which forces us to translate our search terms to generate specific results. And second, unlike Dietzel et al. (2014), we do not solely rely on the broad search volume index (SVI), which is an aggregation of all category-specific (property) searches. This broad SVI also incorporates other searches regarding the housing market and is therefore assumed to carry noise. We run a set of 90 specific search words for each region within our dataset. These search words are partly focused on the office and retail property category, and partly focused on the market players, such as service agencies and banks. The intention is, and here we come back to the critics, that institutional investors might not search online for an office property but search for a telephone number or a market report from a service agency, which could result in an actual transaction. Therefore, we are able to capture these motivations as well. As pointed out earlier, this new measure can be seen as a hybrid between direct and indirect sentiment measures.

4 Data description

This paper analysis the European commercial real estate market from 2004q1 until 2014q4 (44 quarters), for 80 different regions spread out over 24 countries. The majority of countries are located in Europe, with the exception of Russia and Turkey. Some regions do match entire cities, however, other cities such as London or Paris are present multiple times in the dataset, since some regions are specific economic regions, such as the Central Business District (CBD). The dataset consists of real estate data for the office and retail markets, and a range of macroeconomic variables. Cushman & Wakefield (formerly DTZ) provided the real estate data. The macroeconomic data was collected via Thomson Reuters Datastream, the OECD, and the IMF, and through the European Commission. We construct a panel dataset with 3,520 possible observations.

Unfortunately we are unable to collect observations for all variables at all times. On the real estate side, the data is much more consistent for western European countries than for former

Eastern Bloc countries. The real estate variables include, among others, rents and yield values. For office, Cushman & Wakefield (formerly DTZ) also provides take-up, stock, new supply, availability and the availability ratio.

The macroeconomic variables include, among others: GDP, consumer price indices, interest rates and unemployment rates. Due to the incompleteness of the individual variables the number of observations per variable ranges between 3,520 observations (for interest rates) to 220 observations (for change of GDP forecasted by the IMF). For some regions, individual variables are not available, either because the property type is not documented by the agency or because the data providers do not cover those specific markets. For instance, the consumer confidence indicator from the OECD is not available for all countries; in such cases we construct a combined variable that fills the OECD values with national-specific consumer confidence values.

Due to friction in both datasets, we modify the variables in advance. First, we harmonize the property variables in terms of measures, frequency, and currency towards monthly square-meter EUR values. Those monetary values recorded in their national currency have been recalculated into EUR, which was done with the help of historic exchange rates. On the macroeconomic side, GDP values have been recorded in different scales and have been harmonized to multiples of millions. The Appendix reports all acronyms in Table 11

4.1 Google Trends data

We additionally collect data from Google Trends, which is worth describing in more detail. The search volume data is available from 2004 onwards. Google Trends allows a detailed look at searches within different regions ranging from an international search down to a regional search. According to the provider, the data is based on the analysis of Google web searches over a certain period of time. However, the provided values are only given as normalized values of all searches for the specific search word within the same location at the same time. Search words with a low volume and repeated searches from single individuals are excluded. The provided data is adjusted for a better comparison between different terms. These results are scaled to a range from 0 to 100. Nevertheless, the manipulation of the data has been criticized before by scholars, who would prefer actual search volumes and the possibility of accessing the subsequent searches and clicks of individuals to get a clearer picture of their behavior.

Besides the possibility of analyzing different search terms in different regions and at different points in time, the application offers the chance to search within different categories. One of these categories is ‘Property’ (0–29).[3] The categorical filter function eliminates different meanings of words, for better and clearer results. However, Google does not explain how it knows that certain words have been searched within this category, since the “normal” Google Search does not offer such a pre-filtered option. Dietzel et al. (2014) explain that the categorization is based on the individual search behavior. Each search is placed into a framework of searches before and after the specific search. According to this, a series of searches with real estate related search terms, would force the underlying algorithm to place searches within the property category.[4] The property category comprises further sub-categories: apartments & residential rentals, commercial & investment real property, property development, property inspections & appraisals, property management, real estate agencies, real estate listings and timeshares & vacation properties.

In comparison to other parts of the world, Europe is characterized by a variety of different languages in a relatively small area. Bearing this in mind, we performed simple searches in advanced to identify an optimal way of extracting the data from the online tool. For instance, the term “office” can be used for the UK and will produce results for this country. It can further be used for other countries within Europe and will produce results as well, since English is a universal language. However, a German person is more likely to use the German term “Büro.” This leads to the fact that the words we use for the sentiment extraction need to be translated into the country-specific language. A list of all words used is provided in Table 13a of the Appendix.

Besides this language issue, the online tool is limited in the way the data is provided. Since we assume that location-specific data is more suitable in a real estate context, the best solution is to collect the data on a city level. Nevertheless, Google Trends does not offer this option. It is possible to filter for regions within a country, such as the federal states in Germany (e.g., Berlin, Bavaria, and Saxony) or the constituent countries of the UK (England, Scotland, Northern Ireland, and Wales). From there the options are limited. The tool offers a list of cities with the corresponding proportion of searches as part of the regional searches. However, this proportion is related to the highest search volume among the cities. Unfortunately, there is no way of extending the given list to see all cities within the region. Therefore, some cities are not displayed and data collection is impossible.

[3] The source code of the Google Trends webpage uses those codes for each of the categories.
[4] Unfortunately, the authors do not explain where they get this information. Up to this point, we have not been able to get in contact with Google about this and other questions. Google does not offer any service line for GT and emails remain unanswered.

Another issue that needs to be addressed is the focus on the city or region. This might not show the actual search behavior. It further excludes the impact of other national and international investors. Cities such as London, Paris, or Frankfurt are probably driven to a significant share by international investors. We have to incorporate national and international interests within the city-specific data.

This leads to the question how people use the online tool for information mining. Investors or tenants who search for new opportunities or spaces may search in general at first, but as soon as they have decided on where they want to go, they are more likely to add a specific city name to their search. Test searches, however, have shown that including the name of the location does not provide a worldwide overview. One possible explanation would be that the market is not attractive to international or national investors. This, however, does not mirror the reality. Another explanation could be the dense network of real estate service firms. It is unlikely that any investor in person starts to search for an office property on their own. It is more likely that sellers and buyers rely on professionals and their networks. These professionals are based in those cities and they may generate such search results. The assumption that Google might not be used for these specific searches can be denied, based on the given market share of desktop search engines on a global scale.

To summarize, the online tool offers the potential to extract the thoughts of millions of people and the sentiment of the markets. However, the data extraction needs to be done with some care, since the data is not straightforward and the sole focus on regions or cities may lead to the exclusion of other people's intention to enter certain markets.

The displayed graph on the Google Trends page is always shown in monthly figures. However, after downloading the data as a comma-separated values (CSV) file, the results are sometimes shown in weekly figures. It is possible that both data series do not match. Google does not offer an explanation for this. We tried collecting monthly data and converting it into quarterly data. For the data collection, we have used a modified version of the "R package googletrend" by okugami79.

Since Google only displays results on a regional level, we use the "list of top cities". According to Google: "the number represents search volume relative to the highest point on the map which is always 100." We have used these numbers as a percentage share for the specific cities.

The total amount of search results per city region ranges between 4 (Triangle Area (Denmark), Malmö (Sweden) and Geneva (Switzerland)) and 57 (London (UK)) (see Appendix Table 13b). The individual search words for each region score between 0 times and 51 times (see Appendix

Table 13a). The Google Trends index for 20 city/regions is built out of less than 10 search terms. Besides this, some countries are not covered by the property category at all. We use the general search in all categories for the Czech Republic, Finland, Latvia, Luxembourg, Norway, and Romania. We are aware that this will incorporate noise, since not all searches can be linked to real estate. Another reason for the low number of results can be found in translation errors. We use Google Translate for all languages.

Finally we aggregate the search volume results for each region as a time series.

5 Results

In this section, we present our results for the different methods regarding the rent estimation and the yield models with and without the different sentiment indicators.

5.1 Basic yield model

Our results for the basic yield models differ for the two property types (see Tables 1 and 2). For the office yield model, all but the naïve approach produce highly significant results with the expected sign. For the retail yield model, only the adaptive rational approach produces satisfying results. These results are highly significant and carry the expected negative signs. For both property types all the remaining yield components are significant and they carry the expected sign.

Table 1 – Comparison of five different basic office yield models

Dependent Variable Office Yield						
VARIABLE	LABEL	Naïve approach	Adaptive Expectations (I)	Adaptive Expectations (II)	Rent expectations	Adaptive rational expectations
f_gofr	Forecasted change of office rents by C&W	–0.138 [0.098]				
ofr4qma	Office rent 4 quarter moving average		–0.019*** [0.005]			
ofrrr	Office real rent ratio			–0.128*** [0.015]		
log_xofr_fe	Estimated office rent with GDP forecast error				–0.000*** [0.000]	
xofr_ar	Estimated office rent					–0.026*** [0.002]
gbondr	Government bond	0.008*** [0.001]	0.007*** [0.002]	0.008*** [0.001]	0.008*** [0.002]	0.005*** [0.002]
rprem	Risk premium	0.004*** [0.000]	0.004*** [0.000]	0.004*** [0.000]	0.004*** [0.000]	0.004*** [0.000]
Constant	Constant	1.747*** [0.019]	1.757*** [0.023]	1.882*** [0.027]	1.750*** [0.020]	1.769*** [0.019]
cid	Regional fixed effects	omitted from this output				
Observations		919	2802	2802	2802	2599
Number of cross sections		46	69	69	69	65
χ^2		5495	1876	2030	2312	2135
df		48	71	71	71	67

Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1

Note: This table illustrates the five different rent approaches within a standard yield model. The estimation period is 2004q1 to 2014q4. The naïve approach is based on the in-house forecast by Cushman & Wakefield (formerly DTZ). The adaptive expectation (I) approach reproduces the rent variable as discussed in Hendershott and MacGregor (2005b). The adaptive expectation (II) approach reproduces Chervachidze and Wheaton's (2013) real rent ratio. The fourth approach uses an expected rent based on the GDP forecast error. The fifth approach is an adaptive rational approach, where the expected rent is estimated with a simple economic model.

Table 2 – Comparison of five different basic retail yield models

Dependent Variable Retail Yield						
VARIABLE	LABEL	Naïve approach	Adaptive Expectations (I)	Adaptive Expectations (II)	Rent expectations	Adaptive rational expectations
f_gretr	Forecasted change of retail rents by C&W	–0.007 [0.083]				
retr4qma	Retail rent 4 quarter moving average		0.003 [0.004]			
retrrr	Retail real rent ratio			0.000 [0.001]		
log_xretr_fe	Estimated retail rent with GDP forecast error				0.000 [0.000]	
xretr_ar	Estimated retail rent					–0.009*** [0.001]
gbondr	Government bond	0.008*** [0.001]	0.008*** [0.002]	0.008*** [0.002]	0.008*** [0.002]	0.005*** [0.002]
rprem	Risk premium	0.003*** [0.000]	0.003*** [0.000]	0.003*** [0.000]	0.003*** [0.000]	0.003*** [0.000]
Constant	Constant	1.374*** [0.014]	1.480*** [0.049]	1.480*** [0.048]	1.482*** [0.050]	1.491*** [0.046]
cid	Regional fixed effects	omitted from this output				
Observations		639	1975	2063	2063	1893
Number of cross sections		32	51	53	53	49
χ^2		10467	1120	1141	1069	1057
df		34	53	55	55	51

Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1

Note: This table illustrates the five different rent approaches within a standard yield model. The estimation period is 2004q1 to 2014q4. The naïve approach is based on the in-house forecast by Cushman & Wakefield (formerly DTZ). The adaptive expectation (I) approach reproduces the rent variable as discussed in Hendershott and MacGregor (2005b). The adaptive expectation (II) approach reproduces Chervachidze and Wheaton's (2013) real rent ratio. The fourth approach uses an expected rent based on the GDP forecast error. The fifth approach is an adaptive rational approach, where the expected rent is estimated with a simple economic model.

Unfortunately, this result is not explicit, since the “classical” methods, at least for the office yield model, produce significant results. However, due to the fact that the new rational adaptive approach generates good results for both property types, we assume that an expected rent based on macroeconomic factors is a suitable alternative. It is our belief that market participants base their expectations on more than just the recent development of the market rent. The adaptive rational approach captures the wider market development and further captures forward-looking elements.

We proceed the remaining analysis with a yield model based on the adaptive rational approach.

5.2 Sentiment comparison

Unlike the literature, we deviate from conventional sentiment proxies. Motivated by the fact that many European countries lack a direct real estate specific sentiment measure, we need to make sure that our constructed sentiment proxies are able to capture, at least to a certain degree, some market sentiment. We run a simple statistical comparison between our constructed sentiment measures and the RICS survey measures. The comparison is based on the correlation between the measures for the London West End office and retail market,[5] as well as the macroeconomic measure against their counterparts from RICS.

The first comparison uses our macroeconomic sentiment measure and the Google Trends measure against the UK RICS Property Survey: Sales & Rental Levels – London for the next quarter. The correlation table (Table 3) shows that both of our indirect measures reveal a correlation of more than 0.30, which equals a low positive correlation. Looking at the correlation between the two constructed measures, we see that it is negligible. This means that both measures are able to capture some sentiment for the London West End property market on a low level.

Table 3 – Correlation table: London West End all properties

	UK RICS PROPERTY SURVEY	Google Trends	ME sentiment
UK RICS PROPERTY SURVEY	1.0000		
Google Trends	0.3252	1.0000	
ME sentiment	0.3472	0.0701	1.0000

[5] We have chosen the London West End market, since the market provides both the office and the retail market. Other London regions lack one or other of the markets.

Comparing the three office specific measures we can see that the correlation between the direct measure[6] and the GT measure remains low. However, our constructed measure shows a high positive correlation (0.7662), which shows that the indicator is able to capture the market sentiment nearly as well as the direct sentiment proxy (Table 4).

Table 4 – Correlation table: London West End office market

	UK RICS PROPERTY SURVEY	Google Trends	Office sentiment
UK RICS PROPERTY SURVEY	1.0000		
Google Trends	0.3109	1.0000	
Office sentiment	0.7662	0.0866	1.0000

This picture changes slightly for the retail market (Table 5). The constructed and the direct RICS measure[7] share a moderate positive correlation. This drop can be explained by the fact that the retail sentiment measure is based on fewer variables in comparison. The GT measure instead drops below 0.30 and therefore has a negligible correlation. Interestingly, however, is the fact that, in comparing the three categories, the correlation between the GT measure and the constructed retail measure is now moderate and above 0.50. This may be caused by the fact that the retail market is strongly influenced by consumer behavior. Online search volume data possibly mirrors this consumer behavior, instead of mirroring property investor searches.

Table 5 – Correlation table: London West End retail market

	UK RICS PROPERTY SURVEY	Google Trends	Retail sentiment
UK RICS PROPERTY SURVEY	1.0000		
Google Trends	0.2697	1.0000	
Retail sentiment	0.6219	0.5525	1.0000

5.3 Yield models induced with sentiment

The results for the office market (Table 6) show that both the base model and the set of the three sentiment yield models produce very satisfying results. Our theoretical assumption that the sentiment has a negative impact on the property yield has been confirmed within all three

[6] UK RICS Survey: Office Sales & Rent Levels-London, Next Quarter not adjusted
[7] UK RICS Survey: Retail Sales & Rent Levels-London, Next Quarter not adjusted

models (the macroeconomic, the office and the Google Trends sentiment models). All sentiment coefficients are highly significant. The GT measure offers the lowest standard error (standard error GT: 0.002) in comparison. Further, all standard yield model components are highly significant and show the expected sign.

Table 6 – Yield models with different sentiment measures for the office market

Dependent Variable Office Yield					
VARIABLE	LABEL	Base model	ME sentiment	Office sentiment	GT
macroeconomic_sentiment	ME sentiment		–0.018***		
			[0.004]		
office_sentiment	Office sentiment			–0.010***	
				[0.003]	
zgt	Standardized values of (GT)				–0.007***
					[0.002]
xofr_ar	Estimated office rent (AR)	–0.026***	–0.025***	–0.042***	–0.029***
		[0.002]	[0.002]	[0.002]	[0.002]
gbondr	Government bind	0.005***	0.004***	0.007***	0.006***
		[0.002]	[0.002]	[0.002]	[0.002]
rprem	Risk premium	0.004***	0.003***	0.005***	0.004***
		[0.000]	[0.000]	[0.000]	[0.000]
cid	Regional fixed effects	omitted from this output			
Constant	Constant	1.769***	1.780***	1.758***	1.769***
		[0.019]	[0.017]	[0.046]	[0.015]
Observations		2599	2522	1453	2599
Number of cross sections		65	65	57	65
$\chi 2$		2135	2515	2645	3256
df		67	68	60	68

Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1

Note: This table shows the comparison between the base model and the three different sentiment yield models. The dependent variable is the logarithm of office yield for the estimation period from 2004q1 to 2014q4. The country fixed effects have been omitted from this report. Amsterdam is the reference region for the output presented above.

The base model and the GT measure have the same number of observations and the same number of regions (2599 observations; 65 regions). This number slightly drops for the macroeconomic sentiment measure (2522 observations; 65 regions). Only the office-specific sentiment measure has a more severe drop (1453 observations; 57 regions), which is caused by data availability of the sentiment proxy (IPD total return for office).

This positive picture only changes slightly for the retail yield models (Table 7). The sentiment measures show the same expected negative impact on the property yield, which is highly significant. Yet, for the macroeconomic sentiment measure and the retail-specific measure the risk free rate becomes insignificant and for the latter, even negative. Only the online search volume measure produces overall satisfying results.

Table 7 – Yield models with different sentiment measures for the retail market

Dependent variable retail yield					
VARIABLE	LABEL	Base model	ME sentiment	Retail sentiment	GT
macroeconomic_sentiment	ME sentiment		–0.026***		
			[0.004]		
retail_sentiment	Retail sentiment			–0.131***	
				[0.014]	
zgt	Standardized values of (GT)				–0.009***
					[0.002]
xretr_ar	Estimated retail rent	–0.009***	–0.008***	–0.013***	–0.010***
		[0.001]	[0.001]	[0.002]	[0.002]
gbondr	Government bond	0.005***	0.003	–0.002	0.006***
		[0.002]	[0.002]	[0.002]	[0.002]
rprem	Risk premium	0.003***	0.003***	0.002***	0.004***
		[0.000]	[0.000]	[0.000]	[0.000]
cid	Regional fixed effects	omitted from this output			
Constant	Constant	1.491***	1.513***	1.412***	1.488***
		[0.046]	[0.047]	[0.044]	[0.036]
Observations		1893	1858	1517	1893
Number of cross sections		49	49	42	49
χ^2		1057	1032	828.2	1584
df		51	52	45	52

Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1

Note: This table shows the comparison between the base model and the three different sentiment yield models. The dependent variable is the logarithm of retail yield for the estimation period from 2004q1 to

2014q4. The country fixed effects have been omitted from this report. Amsterdam is the reference region for the output presented above.

Regarding the number of observations and regions within the different models, we see that only 49 regions are included (42 regions for the property-specific model). Again this is caused by data availability for the retail market.

5.4 Forecast

The results presented above show that the inclusion of sentiment indicators in a yield model can produce significant results. It is in our interest to evaluate the quality of the different indicators, in order to determine which indicator is best. We perform a four-quarter forecast for the period 2013q1 to 2013q4. We estimate each model until 2012q4 and forecast the subsequent four quarters for both the office and the retail yield (Table 8 & 9).

Table 8 illustrates the results for the office yield model. We compare the base model (adaptive rational approach) and the three models, including one of the constructed sentiment indicators. All four models have a negative mean forecast error. Therefore, the forecasts tend to be higher than the actual values. Each of the models over-predicts the development of the office yield. For both the mean absolute error and the mean squared error, the office-specific sentiment indicator (office sentiment) produces the lowest value in comparison. The sentiment indicator based on online search volume data (Google Trends) ranks second in this comparison. All but the solely macroeconomic sentiment indicator (ME sentiment) are able to outperform the base model. The same conclusion accounts for the root mean square error. Theil's inequality measure for all four models reaches a value of below 0.2. To check whether our models are able to produce better results than a naïve forecast, we use the yield values of 2012q4 for the next four quarters. Unfortunately all models have a higher value than 1 and therefore no model produces better results than a naïve forecast. The same accounts for the last calculated measure, the c-statistic. All five values are above zero, which indicates that the models are unable to outperform a naïve forecast. However, looking at the regional performance, we see that there are some regions which outperform the naive forecast within all the different models.

Table 8 – Log of office yield model (forecast)

	Mean forecast error	Mean absolute error	Mean squared error	Root mean squared error	Theil's U1	Theil's U2	C-statistic
Base model	–0.1977	0.2244	0.2998	0.5475	0.1578	2.6375	5.9563
Google Trends	–0.1867	0.2202	0.2971	0.5451	0.1576	2.6256	5.8938
ME sentiment	–0.1990	0.2254	0.3071	0.5542	0.1597	2.6696	6.1267
Office sentiment	–0.0577	0.0760	0.0083	0.0910	0.0275	2.0100	3.0400

Note: This table shows the forecast evaluation for the office yield model based on the adaptive rational approach with the three corresponding sentiment indicators. The columns show the different evaluation measures for the periodic forecast from 2013q1 to 2013q4 on a panel-wide basis.

In general, the picture is similar for the retail models (Table 9). All four models produce a negative mean forecast error, indicating that the models over-predict the yield development. Similar to the office models, again the property-specific sentiment indicator (retail sentiment) produces the lowest mean absolute and mean squared error. In both cases, the online search volume indicator (Google Trends) ranks second again. Also the macroeconomic sentiment indicator (ME sentiment) produces the weakest result, in comparison. The other models jointly outperform the base model. Regarding Theil's U1, only the retail specific sentiment is able to produce a lower value than 0.2, which suggests a good forecast performance. For the last two measures all but the retail-specific measure are unable to produce good results. This indicates that the model outperforms a naïve forecast. Looking again at the regional evaluation, we see that for some regions the sentiment models are able to produce good results for Theil's U2 and the c-statistic.

Table 9 – Log of retail yield model (forecast)

	Mean forecast error	Mean absolute error	Mean squared error	Root mean squared error	Theil's U1	Theil's U2	C-statistic
Base model	–0.5048	0.5277	0.7298	0.8543	0.2813	3.4423	10.8495
Google Trends	–0.4943	0.5210	0.7203	0.8487	0.2804	3.4196	10.6939
ME sentiment	–0.5154	0.5393	0.7556	0.8692	0.2853	3.5025	11.2672
Retail sentiment	–0.0566	0.1273	0.0735	0.2711	0.0845	0.8202	–0.3272

Note: This table shows the forecast evaluation for the office yield model based on the adaptive rational approach with the three corresponding sentiment indicators. The columns show the different evaluation measures for the periodic forecast from 2013q1 to 2013q4 on a panel-wide basis.

5.5 Robustness check

Next, we perform some robustness checks. On the methodological side, we construct the macroeconomic sentiment indicator following the Kaiser criterion. Even though the first principal component carries the largest share of information during the principal component analysis, the Kaiser criterion as well as the scree test usually recommend the use of more than one component. We use all the recommended components (with an eigenvalue above 1) and construct a weighted average of them. The newly constructed sentiment indicator is inserted into the yield models to check whether it produces better results than the one recommended by Baker and Wurgler (2006). In general, we can say that the weighted sentiment indicator shows an inferior result. We conclude that both methods produce significant results to a certain point. However, there is no additional benefit from changing the recommended method.

We also use two other approaches to capture an all-property sentiment indicator. Following the assumption that the office and retail sentiment within the market only represent shares of a wider commercial real estate sentiment, we first develop an index based on the average of the two property-specific ones (property_sentiment), and second we apply PCA to the two indicators to extract a common trend (pca_property_sentiment). In both cases, a significant increase in the correlation towards the RICS all-property measure is observed. Using the new indicators in the log of office yield model, the results are mixed. The property_sentiment indicator is not significant, the pca_property_sentiment indicator, however, produces good results. Evaluating the forecast quality of the new measures for the office model (see Appendix Table 16), we see that improvements regarding the Mean Squared Error (MSE) are achieved for both measures, especially for the property sentiment (PCA) measure. However, both new indicators fail to outperform the naïve forecast as well. For the log of retail yield model, the picture is slightly different. The property sentiment indicator remains insignificant and, for the model using the pca_property_sentiment indicator, the risk free rate becomes insignificant; however, the coefficient of the indicator is highly significant with the expected sign. Using the two new indicators to forecast the log of retail yield (see Appendix Table 17), we can see that both outperform the base model. However, the property sentiment indicator provides only a small improvement. The property sentiment (PCA) indicator instead reveals the lowest MSE, yet fails to outperform the naïve forecast. We conclude that the improvement within the MSE is caused by the low number of considered regions and not by the indicator itself.

Following the observation that the retail specific indicator is able to outperform the naïve approach, we revisit the sentiment construction and devise a second office sentiment measure (Office Sentiment2), using the same method as for the retail indicator, where we only orthogonalize the total IPD return index for office against the office rent. The question arises as to whether this observation is data caused or whether the orthogonalization of the retail rent from the proxy leaves a good sentiment proxy.

The results reported in the Appendix (Table 15), show that the correlation of office sentiment 2 with the direct sentiment measure from the RICS has slightly increased. Nevertheless, running the office yield model we observe that the risk free rate becomes insignificant (Table 14). Analyzing the forecast performance of the model we observe a decrease in accuracy in comparison to the office sentiment indicator for the MSE and Root Mean Squared Error (RMSE). We therefore conclude that the orthogonalization process should include more observable economic indicators rather than less.

5.6 Slicing

Finally, we run another set of analyses on a sliced dataset. As pointed out earlier, our dataset is a mixture of economically stronger and weaker countries. Some countries are represented with more regions in the dataset than other. This could lead to a blurring effect, where stronger countries contribute more than their weaker counterparts. To clarify whether the results are robust we have sliced the dataset. The first part includes Germany, the UK, and France (GUF); the second part incorporates the remaining countries (rEUR). We run the analysis described above for the yield models and construct a new set of sentiment indicators based on the smaller datasets.

Starting with the GUF dataset, the results for the office market are much more distinct. The model using the adaptive rational rent component is the only model that produces overall satisfying results. Both the rent component and the remaining model variables remain highly significant and show the right sign. For the other approaches, either the rent component (naïve approach) or the risk free rate becomes insignificant (all other models). Applying the sentiment measures to the office yield model, we still produce the same quality of results, as for the whole dataset.

On the retail side, the picture slightly changes. The only model that comes out with satisfying results is the yield model, which uses the rent expectations based on the GDP forecast error, even though the risk free rate is only significant at a 5% level. Despite this, the sentiment measures prevail in their significance and in showing the expected sign.

Using the remaining regions as a comparable (rEUR), we see that for the office yield model the naïve and the Hendershott approach fail to produce significant results. The Wheaton model and the two new approaches remain highly significant and show the expected sign. Proceeding with the adaptive rational approach, we apply the different sentiment measures. The results show the expected negative sign, yet the significance has dropped for the online search volume indicator to 10%. The office sentiment indicator, on the other hand, reveals an insignificant risk free rate. Analyzing the retail side, the overall results remain consistent with full-panel analysis.

Re-running the forecasts for the two models for each of the sliced parts of the dataset, we observe that the GUF dataset for both property yields produces worse forecasting results on a panel-wide scale. Nevertheless, in all cases it becomes clear that the property-specific indicator outperforms the base and the other models. For the remaining European regions (rEUR), however, the results remain consistent with the overall panel dataset and do not vary in such a large scale. For the office yield, however, the office-specific indicator does not outperform the other models. Yet, the base model is outperformed by the other two indicators. On the retail side, we see that the property-specific indicator is able to produce excellent results, which even outperform a naïve forecast. However, we need to mention, that the total number of regions has dropped dramatically to seven.

6 Conclusion

Lenders and investors in real estate are subject to irrationality in price determination in real estate markets. This irrationality can be observed in the relationship of net income from real estate assets (known as NOI - net operating income) and market price that define property yields. Market prices and yields may not reflect fundamentals in the market as pricing and yields are driven by sentiment.

Yield modeling and the role of sentiment that can induce irrationality in property pricing is of interest to property funds, pension funds, banks, insurance companies and other participants. The present paper outlines the key properties and premises of standard models existing studies have developed to explain yield adjustments and swings in property values. Scholars stress the importance of the rent component in these models, since they carry both the regional fixed effects (and hence market idiosyncracies) as well as the income expectations of market participants. In addition, the widespread view is that shifts in property yields are caused by shifts in underlying market sentiment. Except for the study of Ling et al. (2014), who applies a set of different sentiment measures to the yield model, the field is widely under-researched.

In this paper, we contribute to the existing literature in three ways. First, we advance extant methodologies to calculate the rent expectations component with two new methods which, in our view, are closer to capture how such expectations are formed in practice. Unlike established methods, we extend the view to other macroeconomic components, rather than solely using the rent series on its own. This is underlined by the assumption that market participants base their expectations on more than just past rent developments and expectations of rents reverting to some sustainable path. Our results suggest that this more diversified approach and, especially the adaptive rational approach, produce satisfactory results.

The second contribution relates to the sentiment measures we construct and use. Unlike the measures found in Ling et al. (2014), we focus on a different set of sentiment proxies. This is motivated both by the underlying idea of Baker and Wurgler (2006) that each imperfect sentiment proxy carries, at least to a certain extent, some pure sentiment and by data availability. Forecast evaluations reveal that models incorporating property-specific and google trend sentiment outperform the base model. We are further able to report that the property-specific measure produces better results in comparison for both office and retail sectors. More specifically, regarding the online search volume measure, our initial hypothesis is not confirmed. Even though we believe that the measure produces more reliable results for the retail market, the google trend models for both office and retail sectors outperform the base model.

Finally, we extend the research area of sentiment-induced yield modeling to the European commercial real estate market. A number of studies focus on the US market, partially triggered by data availability. However, the interest of investors and banks in abrupt movements in yields and pricing and the role of market sentiment has grown in Europe post global financial crisis. With the level of non-performing loans in Europe remaining at high levels according to the European Banking Authority, research on property yields and sentiment will remain to be of significance relevance.

The ultimate objective of the present study is to add to existing knowledge with new tools that lenders can use in property risk management. In particular changes in sentiment, sometimes irrational due to market over-reaction, can trigger long lasting price adjustments in real estate. Risk management requires constant monitoring of expectations and sentiment in the market to identify exuberant pricing and market behaviour. It is then when risks are heightened and lending institutions should tighten credit standards. We propose additional, measurable expectations and sentiment metrics for monitoring risks in real estate lending.

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Appendix A

Table 10 – Variable definition for the yield models

Variable name	Variable definition	Source	Expected sign
logofy	Log of the quarterly office yield	Cushman & Wakefield (formerly DTZ)	
logrety	Log of the quarterly retail yield	Cushman & Wakefield (formerly DTZ)	
gbondr	10-year national government bond rate	Datastream	+
rprem	The risk premium is calculated as an 8-quarter rolling standard deviation from the national stock market return, minus the national 10-year government bond rate (risk free rate).	Constructed	+
f_gofr	The forecasted change of office rent.	Cushman & Wakefield (formerly DTZ)	–
f_gretr	The forecasted change of retail rent.	Cushman & Wakefield (formerly DTZ)	–
ofr4qma	Four-quarter moving average of the deviation of the log of real office rent.	Constructed based on Cushman and Wakefield (forermerly DTZ) rent data	–
retr4qma	Four-quarter moving average of the deviation of the log of real retail rent.	Constructed based on Cushman and Wakefield (forermerly DTZ) rent data	–
ofrrr	Real rent ratio, defined as the current real rent divided by the historic average of the real office rent.	Constructed based on Cushman and Wakefield (forermerly DTZ) rent data	–
retrrr	Real rent ratio, defined as the current real rent divided by the historic average of the real retail rent.	Constructed based on Cushman and Wakefield (forermerly DTZ) rent data	–
log_xofr_fe	Logarithm of the current real office rent plus the GDP forecast error.	Constructed based on Cushman and Wakefield (forermerly DTZ) rent data, European Commission, IMF	–
log_xretr_fe	Logarithm of the current real retail rent plus the GDP forecast error.	Constructed based on Cushman and Wakefield (forermerly DTZ) rent data, European Commission, IMF	–

xofr_ar	Fitted values of the rent estimation, using the growth rate of the real office rent as the dependent variable and the economic sentiment indicator, the interest rate spread (LT-ST), the current GDP, GDP (t+1) and GDP (t-1) as the independent variables.	Constructed based on Cushman and Wakefield (forermerly DTZ) rent data, Datastream	–
xretr_ar	Fitted values of the rent estimation, using the growth rate of the real retail rent as the dependent variable and the economic sentiment indicator, the interest rate spread (long term - short term), the current GDP, GDP (t+1) and GDP (t-1) as the independent variables.	Constructed based on Cushman and Wakefield (forermerly DTZ) rent data, Datastream	–

Table 11 – Data description

Variable name	Variable label
ofy	Office yield
rety	Retail yield
ofr	Office rent
retr	Retail rent
f_gofr	Forecast of office rent changes by Cushman & Wakefield
f_gretr	Forecast of retail rent changes by Cushman & Wakefield
ofr4qma	Office rent 4 quarter moving average
retr4qma	Retail rent 4 quarter moving average
ofrrr	Real rent ratio office rent
retrrr	Real rent ratio retail rent
xofr_fe	Expected office rent based on the GDP forecast error
xretr_fe	Expected retail rent based on the GDP forecast error
xofr_ar	Expected office rent based on a ME estimation
xretr_ar	Expected retail rent based on a ME estimation
gdp	GDP
fc_gdp	Forecasted change of GDP by the EU and IMF
c_gdp	Change of GDP
cpi	Consumer price index
unemp	Unemployment rate
cred	Credit rating
ipdtroff	IPD Total return office
ipdtrret	IPD Total return retail
stoind	Stock index
gbondr	Government bond
rprem	Risk premium
intr	Intrest rate
csp	Consumer spending
indpropc	Industry production percentage change
esi	Economic sentiment index by the European Union
bci	Business cycle index by the European Union
hcpi	Harmonised consumer price index (EU)

Note: This table reports all the used variables within this panel dataset and the corresponding acronyms.

Table 12a – Descriptive statistics

Variable		Mean	Std. dev.	Min	Max	Observations
ofy	overall	6.151	1.577	3.500	20.000	N = 3014
	between		1.471	3.951	13.066	n = 74
	within		0.740	2.285	13.085	T-bar = 40.7297
rety	overall	5.856	1.857	2.500	19.000	N = 2272
	between		1.724	3.531	12.327	n = 58
	within		0.853	2.877	13.377	T-bar = 39.1724
ofr	overall	33.389	21.110	9.000	185.486	N = 3170
	between		20.443	10.138	142.826	n = 77
	within		5.709	−14.678	78.626	T-bar = 41.1688
retr	overall	227.629	214.44	14.48	1666.67	N = 2222
	between		205.44	14.48	993.69	n = 57
	within		63.93	−76.25	923.76	T-bar = 38.9825
f_gofr	overall	0.003	0.012	−0.087	0.096	N = 1000
	between		0.006	−0.008	0.021	n = 50
	within		0.010	−0.089	0.092	T = 20
f_gretr	overall	0.002	0.012	−0.117	0.083	N = 700
	between		0.004	−0.012	0.011	n = 35
	within		0.011	−0.111	0.075	T = 20
ofr4qma	overall	−0.189	0.636	−3.475	0.875	N = 3380
	between		0.512	−2.670	0.007	n = 77
	within		0.381	−3.022	2.923	T-bar = 43.8961
ret4qma	overall	−0.359	0.981	−4.504	0.744	N = 2508
	between		0.810	−3.428	0.004	n = 57
	within		0.564	−4.226	3.466	T = 44
ofrrr	overall	1.000	0.499	0.000	6.629	N = 3388
	between		0.000	1.000	1.000	n = 77
	within		0.499	0.000	6.629	T = 44
retrrr	overall	1.000	0.499	0.000	6.629	N = 3388
	between		0.000	1.000	1.000	n = 77
	within		0.499	0.000	6.629	T = 44
xofr_fe	overall	25.996	20.345	0.000	172.168	N = 3480
	between		19.813	0.000	126.042	n = 80
	within		4.824	−3.288	72.122	T-bar = 43.5
xretr_fe	overall	203.917	195.4	6.0	1306.3	N = 2192
	between		188.6	9.8	874.2	n = 57
	within		55.5	−109.0	708.7	T-bar = 38.4561
xofr_ar	overall	−0.059	1.004	−4.810	3.854	N = 3041
	between		0.642	−1.668	1.934	n = 75
	within		0.779	−3.333	2.457	T = 40.5467
xretr_ar	overall	0.345	1.519	−10.169	4.871	N = 3041
	between		1.331	−7.471	2.813	n = 75
	within		0.718	−3.609	4.203	T = 40.5467
gdp	overall	307332.100	230489.8	3258.9	685900.0	N = 3484
	between		231146.6	3989.5	644427.0	n = 80
	within		25620.1	223646.8	395064.8	T-bar = 43.55
fc_gdp	overall	0.005	0.006	−0.072	0.109	N = 3520
	between		0.002	0.003	0.013	n = 80
	within		0.006	−0.073	0.102	T = 44

Table 12b – Descriptive statistics

Variable		Mean	Std. dev.	Min	Max	Observations
c_gdp	overall	0.004	0.042	−0.273	0.246	N = 3480
	between		0.005	−0.011	0.023	n = 80
	within		0.042	−0.291	0.261	T-bar = 43.5
cpi	overall	88.827	128.247	−6.090	1209.600	N = 3520
	between		127.537	1.539	1022.309	n = 80
	within		19.506	−142.915	276.118	T = 44
unemp	overall	7.131	3.635	1.100	26.940	N = 3497
	between		3.006	2.027	16.589	n = 80
	within		2.065	−1.528	17.482	T-bar = 43.7125
cred	overall	17.853	4.001	0.001	20.000	N = 3494
	between		3.629	4.901	20.000	n = 80
	within		1.818	1.425	22.293	T = 43.675
ipdtroff	overall	438.217	558.043	−2.748	1985.860	N = 2785
	between		540.433	3.648	1290.901	n = 68
	within		138.749	50.761	1133.176	T-bar = 40.9559
ipdtrret	overall	578.334	755.645	−3.225	2376.150	N = 2780
	between		741.602	7.696	1795.432	n = 68
	within		142.607	63.359	1159.052	T-bar = 40.8824
stoind	overall	135988.400	227689.6	14.6	680292.0	N = 3334
	between		226091.0	32.7	562017.9	n = 76
	within		35867.5	−30468.5	254262.5	T-bar = 43.8684
gbondr	overall	3.816	1.763	0.310	14.020	N = 3378
	between		1.507	0.537	9.066	n = 79
	within		1.197	−0.105	12.655	T-bar = 42.7595
rprem	overall	5.199	4.433	−4.091	23.047	N = 3202
	between		1.608	2.954	11.035	n = 75
	within		4.148	−4.003	19.412	T-bar = 42.6933
intr	overall	2.812	3.086	−0.750	22.000	N = 3520
	between		2.332	0.744	11.016	n = 80
	within		2.037	−6.350	15.835	T = 44
csp	overall	182993.600	137934.6	1661.0	407413.0	N = 3482
	between		137900.1	2103.0	364750.0	n = 80
	within		18566.1	125797.7	242844.6	T-bar = 43.525
indpropc	overall	0.097	2.531	−18.700	13.300	N = 3505
	between		0.488	−0.552	1.286	n = 80
	within		2.484	−18.571	12.681	T-bar = 43.8125
esi	overall	98.858	16.419	−58.200	118.800	N = 3308
	between		12.894	−11.323	104.011	n = 76
	within		10.182	51.980	128.180	T-bar = 43.5263
bci	overall	100.116	1.533	85.100	108.633	N = 3412
	between		0.360	98.668	101.197	n = 80
	within		1.490	85.477	108.977	T = 42.65
hcpi	overall	111.064	12.162	89.827	210.867	N = 3426
	between		6.550	102.812	143.086	n = 78
	within		10.276	57.805	178.845	T-bar = 43.9231

Table 13a – GT indicator construction

Search words	Total Frequency per word	Search words	Total Frequency per word	Search words	Total Frequency per word
REIT	7	Cushman and Wakefield	2	Royal Bank of Scotland	1
rent	51	Knight Frank	10	Societe Generale	6
real estate	49	office lease	5	Banco Santander	2
debt	11	office rent	12	Lloyds Bank	7
sale	50	office for sale	4	ING	22
investment	23	office rental	9	UBS	8
investor	8	commercial office space	1	UniCredit	5
credit	30	office	41	Credit Suisse	2
boom	4	office space	8	Rabobank	4
bust	5	retail	12	Nordea	7
raise	10	retail space	6	BBVA	6
increase	7	retail rent	2	Commerzbank	7
decrease	3	retail for sale	1	Credit Mutuel	4
shopping centre	18	commercial retail	3	KfW	5
high street	11	retail lease	1	Danske Bank	4
finance	23	retail property	6	Sberbank of Russia	0
mortgage	25	Newmark Grubb Knight Frank	0	CaixaBank	0
loan	16	BNP	10	Handelsbanken	3
commercial real estate	6	BNP real estate	2	Dexia	1
commercial property	15	CoStar	0	KBC	3
commercial property sale	10	Blackstone	2	Nationwide	8
property for sale	26	RE/MAX	0	Bankia	2
lease commercial property	3	Prudential	8	Swedbank	5
commercial lease	9	Voit Real Estate Services	0	La Banque Postale	4
JLL	6	Century 21 Real Estate LLC	0	VTB	2
CBRE	11	HSBC	16	Banco Sabadell	4
Jones Lang LaSalle	12	BNP Paribas	7	Bank of Ireland	0
Colliers	4	Credit Agricole	7	Deka	1
Savills	11	Barclays	15	CB Richard Ellis	2
DTZ	15	Deutsche Bank	9	City name	51

Note: This table lists the search words used to construct the GT indicator and the frequency with which they have generated a result.

Table 13b – GT indicator construction

Region	Sum of words
Antwerp	7
Brussels	12
Liège	5
Prague*	27
Aarhus	5
Copenhagen	7
Triangle Area	4
Helsinki*	25
Paris	31
Lyon	19
Marseille	19
Berlin (region)	3
Berlin (city share)	25
Düsseldorf	14
Frankfurt	24
Hamburg (Region)	3
Hamburg (city share)	24
Munich	22
Budapest	8
Cork	10
Dublin	22
Galway	6
Limerick	6
Milan	18
Rome	17
Riga	15
Luxembourg City*	31
Amsterdam	11

Region	Sum of words
Rotterdam	11
The Hague	9
Utrecht	9
Oslo*	30
Kraków	9
Warsaw	13
Bucharest	23
Moscow	12
Barcelona	14
Madrid	20
Gothenburg	5
Malmö	4
Stockholm	7
Geneva	4
Zürich	8
Istanbul	13
Birmingham	32
Bristol	17
Leeds	14
London	57
Manchester	36
Newcastle	6
Nottingham	8
Sheffield	18
Cardiff	16
Edinburgh	24
Glasgow	23

* National wide search

Note: This table illustrates the regions within the panel and how many search words out of the 90 have contributed to the regional indicator.

Table 14 – Log of office yield with the different sentiment indicators (incl. office sentiment 2)

Dependent Variable Office Yield						
VARIABLE	LABEL	Base model	ME sentiment	Office sentiment	Office sentiment2	GT
macroeconomic_ sentiment	ME sentiment		–0.018***			
			[0.004]			
office_sentiment	Office sentiment			–0.010***		
				[0.003]		
office_sentiment2	Office sentiment 2				–0.077***	
					[0.008]	
zgt	Standardized values of GT					–0.007***
						[0.002]
xofr_ar	Estimated office rent	–0.026***	–0.025***	–0.042***	–0.027***	–0.029***
		[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
gbondr	Government bond	0.005***	0.004***	0.007***	0.001	0.006***
		[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
rprem	Risk premium	0.004***	0.003***	0.005***	0.003***	0.004***
		[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
cid	Regional fixed effects	omitted from this output				
Constant	Constant	1.769***	1.780***	1.758***	1.724***	1.769***
		[0.019]	[0.017]	[0.046]	[0.020]	[0.015]
Observations		2599	2522	1453	2309	2599
Number of cross sections		65	65	57	60	65
chi2		2135	2515	2645	2127	3256
df		67	68	60	63	68

Standard errors in brackets;

*** p<0.01, ** p<0.05, * p<0.1

Note: This table illustrates the comparison of the different sentiment measures for the log of office yield for the period from 2004q1 to 2014q4. The comparison includes the newly constructed office sentiment 2. This measure replicates the method used for the retail sentiment measure.

Table 15 – Correlation table between the direct and indirect measures

	UK RICS property survey	Google Trends	ME sentiment	Property sentiment	Property sentiment (PCA)
UK RICS property survey	1.0000				
Google Trends	0.3252	1.0000			
ME sentiment	0.3472	0.0701	1.0000		
Property sentiment	0.5267	0.1321	0.1735	1.0000	
Property sentiment (PCA)	0.8281	0.2275	0.3258	0.9935	1.0000

Note: This table compares the direct RICS measure, the GT measure, as well as the ME sentiment measure and the two newly property sentiment measures. The property sentiment is an average of the office- and retail-specific measure, where the latter is based on a PCA of the property-specific ones.

Table 16 – Forecast evaluation for the log of office yield model

	Mean forecast error	Mean absolute error	Mean squared error	Root mean squared error	Theil's U1	Theil's U2	C–statistic
Office sentiment2	–0.0483	0.1027	0.0486	0.2205	0.0641	4.9787	23.7877
Property sentiment	–0.1973	0.2245	0.2991	0.5469	0.1577	2.6345	5.9404
Property sentiment (PCA)	–0.0370	0.0648	0.0059	0.0768	0.0232	2.7215	6.4065

Note: This table illustrates the forecast evaluation for the newly constructed office sentiment indicator and the two new property sentiment indicators on an overall panel basis.

Table 17 – Forecast evaluation for the log of retail yield model

	Mean forecast error	Mean absolute error	Mean squared error	Root mean squared error	Theil's U1	Theil's U2	C–statistic
Property sentiment	–0.5039	0.5275	0.7282	0.8533	0.2811	3.4384	10.8224
Property sentiment (PCA)	–0.0716	0.0836	0.0102	0.1010	0.0317	2.5704	5.6072

Note: This table illustrates the forecast evaluation for the two new property sentiment indicators on an overall panel basis for the log of retail yield model.