Sentiment-Based Commercial Real Estate Forecasting with Google Search Volume Data

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Abstract

Purpose – This article examines internet search query data provided by 'Google Trends', with respect to its ability to serve as a sentiment indicator and improve commercial real estate forecasting models for transactions and price indices.

Methodology – The study uses data from CoStar the largest data providers of US commercial real estate repeat sales indices. We design three groups of models: baseline models including fundamental macro data only, those including Google data only and models combining both sets of data.
One-month-ahead forecasts based on VAR models are conducted to compare the forecast accuracy of the models.

Findings – The empirical results show that **all** models augmented with Google data, combining both macro and search data, significantly outperform baseline models which **abandon** internet search data.
Models based on Google data alone, outperform the baseline models in all cases.
The models achieve a reduction over the baseline models of the mean squared forecasting error (MSE) for transactions and prices of up to 35% and 54% respectively.

Practical Implications – The results suggest that Google data can serve as an early market indicator. The findings of this study suggest that the inclusion of Google search data in forecasting models can improve forecast accuracy significantly. This implies that commercial real estate forecasters should consider incorporating this free and timely data set into their market forecasts or when performing plausibility checks for future investment decisions.

Originality – This is the first paper applying Google search query data to the commercial real estate sector.

Keywords Forecasting, Commercial Real Estate, Investment Process, Google Trends, Search Query Data, Sentiment, Prices, Transactions

Paper type Research paper

1. Introduction

Among others, Brooks and Tsolacos (2010) emphasise the importance of good forecasts for the commercial real estate industry. There are fewer commercial properties than residential buildings, but the former are usually of much higher value per unit. They form a heterogeneous asset class, as they differ significantly in size, value and across sectors (retail, office, industrial etc.), which makes them more difficult to compare among each other. As opposed to the typical house buyer, commercial real estate buyers and sellers are predominately professionals aiming to maximise their income.

Baum (2009) stresses the importance of forecasts, as real estate investors are interested in what property type/market develops better than others, when it comes to selecting future investments. Institutional investors, like insurance companies or property funds, usually have a specific investment horizon in mind when allocating their funds. Hence, they produce implicit and explicit forecasts about the performance of property markets across different regions and sectors. Real estate consultancies publish market reports, in which they give an outlook of market activity and movement. Property developers are particularly interested in the future development of rents and prices, when setting up feasibility studies. When making credit-approval decisions, banks and other real estate financers are interested in which direction a market moves.

While homes serve either as self-owned accommodation or income-producing assets, commercial properties usually serve only as the latter. This is particularly evident in periods where, for example, sale-and-lease-back deals are fashionable, which leads to a reduction in the share of users owning their own commercial property.

These unique attributes of commercial property cause the market to behave differently from the housing market, which makes commercial real estate markets a special case in terms of forecasting.

Although the literature on commercial real estate forecasting is not as comprehensive as for housing, there are nonetheless many studies investigating the prediction of market behaviour.

Wheaton (1987) and Malizia (1991) focus on long-term relationships between the demand and supply sides of commercial real estate markets and relate this to fundamental market factors. MacKinnon and Al Zaman (2009) also take a closer look at the long-term effects of return predictability and long-horizon asset allocations. Ghysels et al. (2007), on the other hand, conclude that fundamental economic indicators “[…] cannot fully account for future movements in returns”. This implies that there are unobservable factors influencing the market, which are not captured by fundamentals.

Clayton et al. (2009) claim that since the property market is inefficient due to its heterogeneity, a sentiment factor could describe the part of market variation that cannot be explained by widely recognised fundamentals. They find that, while real estate fundamentals are the main driver of markets, sentiment also plays a role in pricing.

Krystalogianni et al., (2004) are one of the first to deploy leading economic indicators to make short-term predictions of commercial real estate market turning points. In a very similar approach, Tsolacos (2012) finds that sentiment data derived from business tendency surveys employed in a probit methodology produce acceptable early signals of rent-growth turning points in three major European office markets. Both pieces of research use either survey-based sentiment indicators or common leading economic indicators (e.g. export orders, retail sales, car registrations etc.).

Although the application of sentiment/leading indicators is very promising for the forecasting profession, there are some drawbacks that should be mentioned. First of all, most of these indicators are published with a delay of up to two months. In the case of survey-based indicators, the data collection is expensive and time-consuming. Furthermore, it is questionable whether the designated respondent is always the one actually answering the questionnaire, and if so, whether she always answers truthfully. The latter could also be related to a fear of revealing sensitive information, given the lack of anonymity standards. Leading indicators such as export orders, car registrations or retail sales are not affected by these problems, but are totally detached from the real estate market in terms of its underlying. In our opinion it seems somewhat unsatisfactory to use such indicators to produce monthly forecasts of the highly complex commercial real estate market.

Google search volume data, on the other hand, overcome many of these issues. As the uncontested search engine market leader[1], Google provides publicly accessible search-query data by means of their tool 'Google Trends 2.0'[2], which evolved from 'Google Insights for Search'. Unlike other sentiment data sets, the time delay can virtually be neglected, as Google data are available only two days after the day of collection. Needless to say, that the data collection takes significantly less effort than, for example, survey-based indicators. Furthermore, the sample size is relatively large and problems like the abovementioned questionnaire bias can be avoided. Search volume indices (SVI) can be filtered for certain categories or key words, in order to make the index case-specific (here: real estate). If used correctly, SVI should reveal the information required by the searcher, and without distortion. To the authors' best knowledge, this is the first study that utilises Google Trends search volume indices (SVI) as a sentiment indicator for the commercial real estate market. Google Trends users are able to retrieve and download historical logs of online search queries on a weekly basis from January 2004 until now.

A growing number of academic studies employing Google search query data for research purposes in various economic sectors, and especially the field of property research, reveal Google's potential as a sentiment indicator, as the users' desire for information on specific fields of interest is well catered for. This helps researchers to make inferences about the near future.

In order to show the role internet research plays during an investment process, we augment a transaction model designed by Roberts and Henneberry (2007), to highlight the phases during which an investor makes use of the internet (Google) and thereby reveals his specific interests. Critics may now claim that especially a (large) professional institutional investor would hardly go on the internet to simply 'google' for a property he would like to purchase. This is surely true, as a large investor would most probably get in touch directly with real estate agents. However, by conducting online research, as typically done by investment /research departments when gathering information for a future investment decision, an investor does reveal his interest after all. We posit that the more searchers display such interest, the greater the demand for real estate.

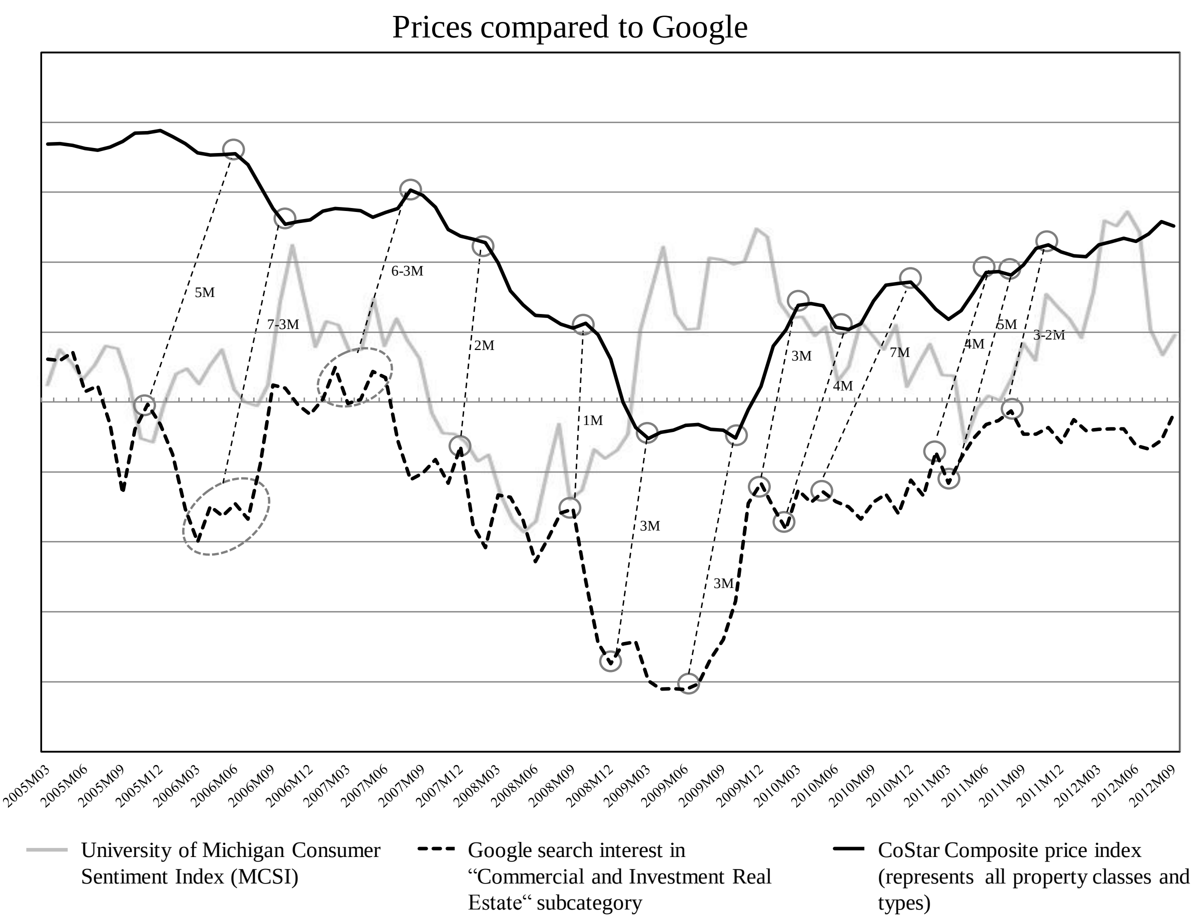
Thus, we differentiate between 'object-related' and 'market-related' interest, which we discuss in further detail in Section 2.

[1] According to ComScore (2014) Google's market share in the USA was 67.5% in March, 2014

[2] http://www.google.com/trends/

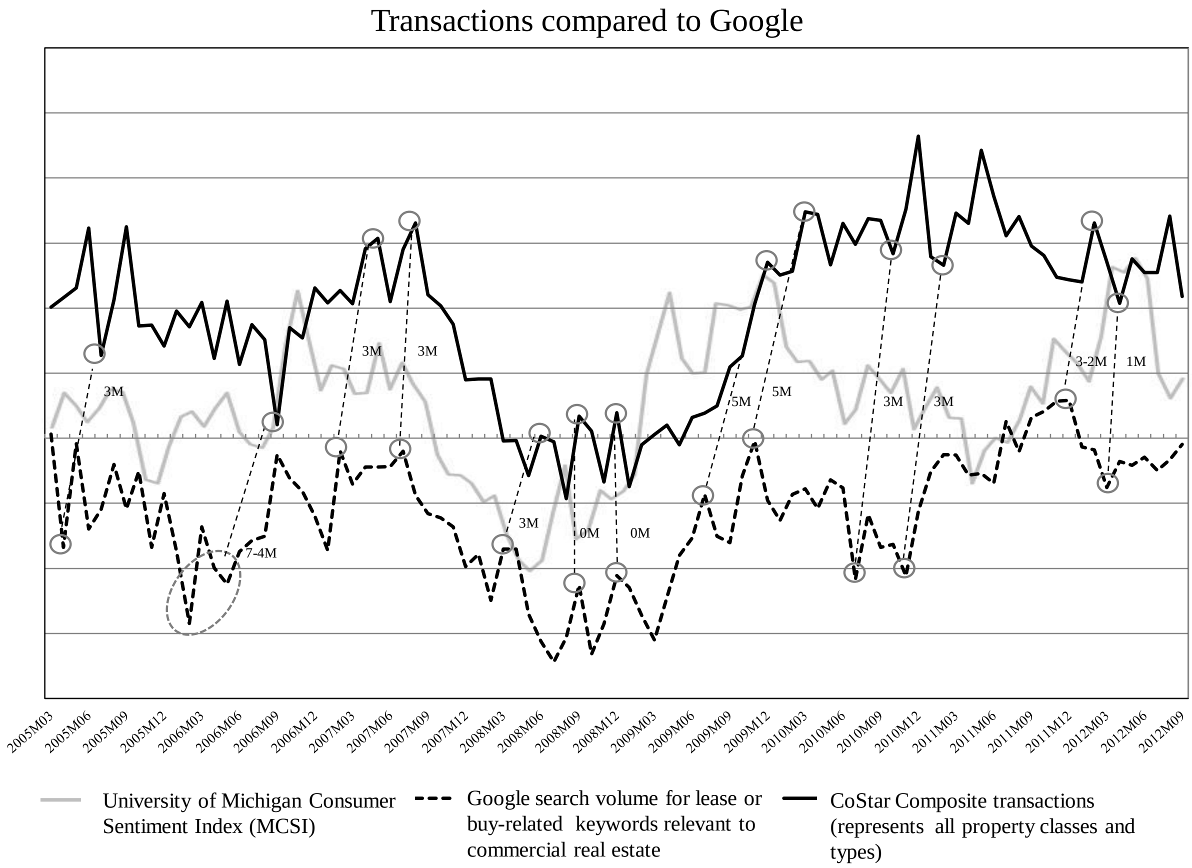
For illustrative purposes, Figures 1 and 2 respectively display a monthly commercial real estate price index (CoStar composite index) and the transactions count of its underlying portfolio. The time series are expressed in rolling year-on-year growth rates against two real-estate-related Google search indices. The SVI, depicted against the price index, is the Google Trends subcategory “Commercial & Investment Real Estate”, the SVI depicted against the transactions is a combined index for the search terms “commercial property”, commercial property sale”, “commercial real estate”, “property for sale”, “lease commercial property”, “commercial lease”. The latter index is extracted from within the Commercial & Investment Real Estate subcategory, in order to ensure that all captured searches are strictly related to commercial real estate[3].

Figure 1: CoStar composite price index and Google “Commercial and Investment Real Estate” subcategory SVI



[3] The SVI are described in more detail in Section Three of this article.

Figure 2: CoStar composite transaction count and Google SVI, based on general commercial-real-estate-related search terms



Both graphs convey the leading character in the sense of a temporal advantage of Google search volume indices. For clarification, prominent peaks and lows have been highlighted. As one can see, especially for prices, Google seems to have a quite significant leading character. Over the whole time period, this lead averages about 3-4 months for prices and about 3 months for transactions.

However, the fact that Google loses its leading character to a certain extent in downturns should be mentioned. Mere graphical inspection is not sufficient to accurately determine the leading properties of Google SVI. Hence, we take a closer econometric look at the seemingly leading character of Google's SVI and test whether search data can improve the accuracy of one-month-ahead forecasting models.
Section 2 contains a summary of recent Google-data-related literature and the commercial real estate transaction process. Section 3 explains the extraction and transformation of the data. Furthermore, we describe how specific real-estate-related key words were chosen for the construction of seven different Google search-volume indices. This is followed by a general description of the real world data used in this study.
Section 4 explains the development of the econometric models used for this research. In Section 5, we present the results of the one-month-ahead forecasts. Section 6 shows that the models are robust across different commercial real estate sectors and we test our results for significance. Section 7 concludes.

2. Literature Review

2.1. Research with Google Search Volume Data

A large variety of social/economic activities now take place online. In our developed world, everyday-life without the internet seems unimaginable for private and business consumers alike. According to www.forrester.com, the internet penetration rate for the United States was 79% in December 2012[4], and for businesses the proportion is probably greater. Therefore, Google search data can be regarded as largely representative.

Academic research on internet search activity has been around for about a decade, although mainly in the field of computer science. With the launch of Google Trends in 2006, researchers from various fields started recognising the potential of this very extensive dataset made available by Google. Various factors suggest the suitability of Google data for our purposes as outlined in the introduction. The collection of Google data is much cheaper than traditional market sentiment measures like survey or interview-based indicators, and are presented in real-time. This enables the forecasting of short-term trends. The first to make use of these particular features in a scientific article were Ginsberg et al. (2009), who identify flu hotspots by collecting searches related to symptoms across the United States. They find a high correlation between internet searches and data from surveillance reports of "influenza-like illness physician visits". As mentioned above, Google data are publicly accessible just two days after the search activity, whereas traditional influenza surveillance systems are typically published with a 1-2 week delay. This time advantage makes SVI a very efficient indicator of the flu virus spread and led to the development of an epidemic tracking tool called Google Flu Trends[5].

Later the same year, Google's chief economist Hal Varian and his colleague Hyunyoung Choi published a seminal article on how Google search data could be used for research (Choi and Varian, 2009). By employing simple seasonal autoregressive models, they show how the inclusion of search data reduces the mean absolute error of one-month-ahead forecasts of retail, automotive and home sales, as well as travel to foreign countries. In an updated version of their first article, they demonstrate similar results for the prediction of vehicles and motor parts sales, initial claims for unemployment benefits, travel and consumer confidence (Choi and Varian, 2012). Chamberlin (2010) replicates Choi and Varian's research on UK data and confirms the leading characteristics and forecasting abilities of Google search indices. He points to the problem that the large overall rise in total searches over the last few years has led to a falling share of specific searches, which possibly stunts the upward growth of search indices, but reinforces downward movements. These opinions on the advantages and disadvantages of Google data are also shared by Tierney and Pan (2012).

Askitas and Zimmermann (2009) utilise Google search data to construct an index based on search words that job-seekers would use to find employment. Evidence shows that the index is highly predictive of the monthly German unemployment rate.

More recently, researchers have discovered the usefulness of search data for stock markets and investor sentiment. Dzielinski (2012) uses search data to create a novel *ex ante* indicator of economic uncertainty, based on the notion that in times of uncertainty, the demand for information increases. As a measure of uncertainty, he uses the SVI for the term "economy".

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[4] http://www.forrester.com/Online+Penetration+Rate+In+The+US+Has+Stabilized+At+79/-/E-PRE4464

[5] http://www.google.org/flutrends/

His findings suggest a negative correlation between the Google index and commonly used measures of investor confidence. Based on an analogous concept, Preis et al. (2013) identify 98 stock-market-related search terms and find a connection between an increase in Google search volume before stock market declines. They show that trading strategies based on these early warning signs significantly outperform random investment strategies. Furthermore, they conclude that national as opposed to international search volume indices explain market movements more effectively, which is probably because the proportion of (private) traders among internet users is higher in the U.S. than it is globally. Beer et al. (2013) construct a Google sentiment indicator for the French market and find a correlation with commonly used alternative sentiment indicators. Empirical tests based on a VAR-model show that investor sentiment is predictive of short-term market returns, where a negative relationship between investor sentiment and stock returns during the first two weeks is prevalent. Da et al. (2011) make use of Google Trends to construct a new measure of investor attention by which they predict trading volume. Examining search indices derived from Russell 3000 stock tickers in a VAR-framework, they come to the conclusion that the internet-based indices lead alternative commonly used attention measures. Moreover, they find that a rise in Google searches predicts an increase in stock prices over the next two weeks and a reversal of the prices within the year. Drake et al. (2012) use a SVI to measure investor demand for information. Similar to Da et al. (2011), they obtain Google search indices for the tickers of S&P 500 stocks. Their main findings are that investor demand increases in a period of 1-2 weeks around corporate announcements and is positively related to media attention and news, while being negatively associated with investor distraction[6]. Bank et al. (2011) use Google search data as an indicator of stock markets activity for the German and European stock markets and find supporting evidence that internet searches are correlated with a rise in stock trading volume and liquidity.

Wu and Brynjolfsson (2009) conducted one of the first research projects on Google data that is solely related to real estate. They examine the influence of Google search indices on house prices and transaction volume for 50 US states on a quarterly basis. They conclude that an increase in the search index is positively correlated with higher transaction volumes and prices. They find no significant connection between the "real estate" category and house prices, which may be because of its broad and unspecified nature in terms of the searches it captures (e.g. property management, property development). The subcategory "real estate agencies", on the other hand, seems robust and positively correlated with sales. By testing forecast accuracy, they show that Google search index augmented models outperform those without Google by a significant margin. Kulkarni et al. (2009) derive Google search indices based on real-estate-related keywords at the city level and test their predictive power for the Case Shiller Index for the 20 largest MSAs. By carrying out two-way regressions, they provide evidence that Google search indices Granger-cause house prices, but not the other way around. Also testing for causal relationships at city levels, Beracha and Wintoki (2012) use panel vector autoregressions for 245 MSAs to demonstrate that housing-related search data Granger-cause abnormal price movements.

Hohenstatt et al. (2011) confirm these results at a national level for the 20 largest MSAs. Testing whether Google search data add explanatory power to housing market models, they find that search data significantly improve the goodness-of-fit, especially where the

[6] Investors conduct less internet research when distracted by more important competing earning news.

subcategory “Real Estate Agency” serves as a very robust indicator for transactions. In addition, they confirm empirically the time setting for the home buying process derived from the existing literature and the National Association of Realtors’ “Profile of Home Buyers and Sellers 2009”. Building on their first article, Hohenstatt and Kaesbauer (2013) confirm their results for the UK housing market. By splitting their sample into downturn and upturn phases, they provide evidence that the relatively robust subcategory “Real Estate Agencies” works particularly well during upswings. Also, they propose a potential stress indicator for market soundness by filtering the “Home Financing” subcategory for mortgage approvals and find that the transaction volume reacts much more sensitively to a change in the indicator than house prices. McLaren and Shanbhogue (2011) also focus on UK data using SVI to construct indicators for house prices and unemployment rates. In line with previous studies, they find that search data help in forecasting unemployment rates and perform about equally to other more common early indicators. The results for house prices are even more convincing, as SVI outperform existing indicators in terms of forecasting accuracy. They also mention the limitations of the data in that they are scaled and rehashed and that two users with different intentions might use similar key terms to carry out their search, which may distort the index marginally.

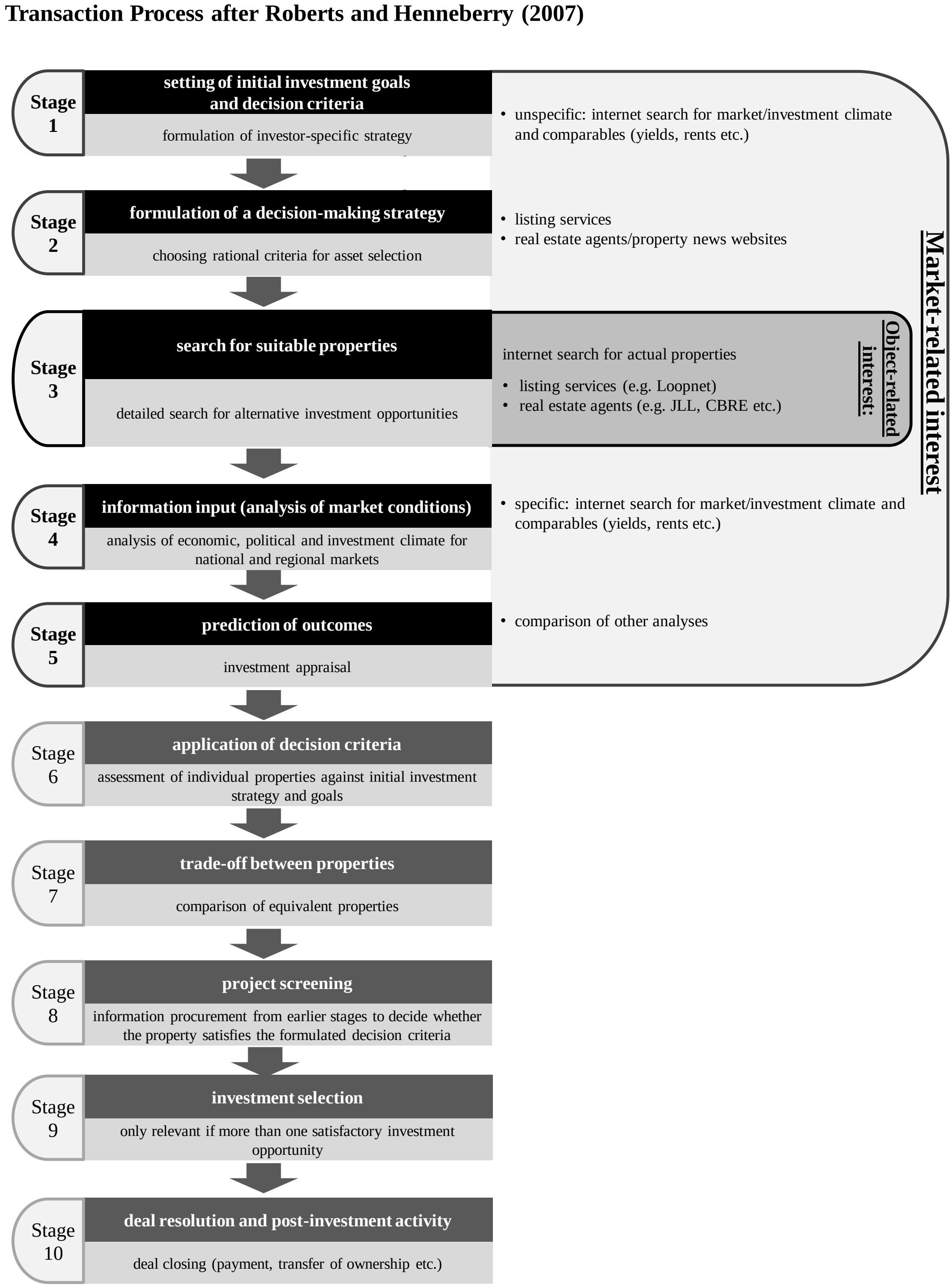
2.2. Investment Process

Nedleman (1999) realised early on that firms are able to improve their information procurement and target their investment objects more precisely by making use of the internet. Stravroski (2004) stated that the use of the internet could facilitate the access to services even for complex products like real estate or legal services. By designing an e-business model for commercial real estate, he shows that tenants and investors can potentially conduct an entire real estate transaction via the internet without even leaving their desk. Of course this does not correspond to the practice for the investment process as a whole, but it suggests that especially during early phases of the investment decision process, internet research does play a major role.

Henderson and Cowart (2002) show that visitors of residential and commercial real estate brokerage websites make extensive use of the internet for their preliminary research before making a purchase.

The body of literature of models describing the real estate investment process is large. Among others, Pyhrr et al. (1989), , , , Baum (2009), , Farragher and Savage (2008), Farragher and Kleiman (1996) define the decision-making/transaction process for commercial real estate. Roberts and Henneberry (2007) analyse existing literature about the normative decision-making process to design a composite investment process combined from various models. Based on this process, we reveal during which phases of the investment process Google research plays a part. It seems intuitive that the moment an investor starts an internet research is the same point in time at which he reveals his interest in real estate to Google. Figure 3 depicts the process and points out the relevant phases for internet research.

Figure 3: Investment process and impact of internet search



In terms of investor interest captured by Google, we differentiate between ‘object-related’ and ‘market-related’ interest.

Object-related interest is the effort an investor makes to find a property he would like to buy. Investors might either search for very general terms (e.g. “office property for sale”) or for listing services/real estate agents (e.g. “Loopnet”[7], “CBRE”, “JLL”) in order to access property information online. Such interest will most probably come from investors who are predominately interested in non-investment grade properties (e.g. private equity funds, family offices, private investors). According to our transaction process, an investor would very likely reveal this kind of interest during stage three.

Market-related interest is that which virtually every investor reveals during the first five stages, and refers specifically to the analysis of market information and real estate specific input variables (e.g. market rent, cap rate) needed for the internal investment appraisal process. In this context investors are not interested in finding a potential investment opportunity on the internet, but rather in gathering enough market information to make a decision about whether or not to make a potential investment. Typically, during this phase, research departments will look at market reports published by large real estate agents or at commercial-property-related news websites to obtain information on rent and yield development, the direction of movement of national and local markets and other market activities. Furthermore, they might browse listing services or brokerage websites to find properties comparable to the currently appraised investment opportunity, as well as potential competition in the market.

3. Data

3.1. Data Extraction from Google Trends

Google offers search query data through its tool Google Trends 2.0, which has existed since 2012 as a merging of Google Insights and Google Trends[8]. Users are able to download search volume indices that show the level of interest in certain search terms over time. These search indices can be aggregated at international, national, state and MSA levels. Instead of absolute numbers, the search data are normalized and scaled from 0 to 100, the latter representing the highest search volume within the viewed time period. Thus, the trend/chart for the same keywords can change over time, as soon as a new maximum has been reached. This has been criticised by Tierney and Pan (2012), among others, because the aggregation of data, and the scaling process, can lead to a loss of data.

In order to filter certain topics, Google provides categories and subcategories for specific searches. In this respect, the search engine not only monitors a single search query at a time, but also those a user conducts before and after. If, for example, a user had been searching for “office” followed by “lease contract”, Google Trends would probably put this search into the ‘Real Estate’ category. If, however, he searched for “office” then “stapler”, he would most probably be placed in the retail category.

Following the existing literature, we apply two methods to construct our search volume indices. Similar to Askitas and Zimmermann (2009) we use popular single search terms, combine them into one search and build an index. In addition, we make use of the

[7] “LoopNet.com is the most heavily trafficked commercial real estate website, with an average of nearly four million monthly unique visitors according to Google Analytics” Loopnet (2013)

[8] https://support.google.com/trends/answer/2423202?hl=en&ref_topic=13973

subcategories already provided by Google Trends analogous to Choi and Varian (2012) or Hohenstatt et al. (2011).
While subcategory indices were used as provided by Google, the following approach was employed to construct indices based on search words.
The specific search terms were chosen by starting with logical keywords like "commercial property" or "commercial real estate", then adding the top "related [search] terms" suggested by Google Trends. In order to ensure that all search interest is related to commercial real estate only, all indices were extracted from within the "Commercial & Investment Real Estate" subcategory provided by Google. Therefore, all single search indices form a subset of the "Commercial & Investment Real Estate" subcategory.
Based on the above, seven different search indices were extracted from Google Trends. Each index is based on either a different set of search keywords or a real estate subcategory. Therefore, each index differs in its progression over time, as attempts were made to capture various interests.
We split the seven indices into two groups, in order to generate (general) market, as well as sector-specific search indices. While the first three indices are intended to capture general interest in commercial real estate, the remaining four indices are aimed at finding out about interest in specific real estate sectors (office, retail, industrial, multifamily). The latter kind serves to show the robustness of Google Trends data in our forecasting models in section 6.
As Table I depicts, the first index is the "Commercial & Investment Real Estate" subcategory provided by Google. The second is constructed from general search terms for commercial real estate. The third contains search terms for large commercial real estate service providers, as well as commercial real estate listing services such as "Jones Lang Lasalle" or "Loopnet". Critics might now argue that investors will not google for well-known agents. However, googling e.g. "market report office New York" and being forwarded to a direct link to the report is much faster and more practical than to first call up an agent's website, look for the research section, choose the desired property class (for example office) and finally select the required market. If one fails to find a suitable report, then the procedure has to start from square one, but with a different real estate service provider. Hence, searchers would very likely first use Google to find a desired market report simply for the sake of convenience and brevity.
Of the remaining four indices, three are linked to specific search terms related to office, retail and industrial properties respectively. In order to capture the interest in multifamily properties, the subcategory "Apartments & Residential Rentals" was chosen. This stems simply from the fact that Google Trends are very unlikely to place any searches related to apartments in the "Investment & Commercial Real Estate" subcategory.

Table I: Overview of extracted Google search volume indices

	Code	Search Interest	Search Terms	Category	Subcategory
general interest	g_inv_subcat	"Commercial and Investment Real Estate" subcategory	*Google does not report the exact search terms that were aggregated in the subcategory*	Real Estate	Commercial and Investment Real Estate
	g_comm	General search terms for commercial real estate	commercial property+commercial real estate+commercial property sale+property for sale+lease commercial property+commercial lease	Real Estate	Commercial and Investment Real Estate
	g_agents+list	Commercial real estate service providers and listing services	jll+cbre+jones lang lasalle+ colliers+dtz+ cushman and wakefield +knight frank+savills+grubb ellis+newmark grubb+cb richard ellis+marcus millichap+cimls+loopnet+xceligent+ "propertyline"+catylist	Real Estate	Commercial and Investment Real Estate
specific interest	g_off	Office property related search terms	office for sale+office space+office space rent+commercial office space+office rental+office lease	Real Estate	Commercial and Investment Real Estate
	g_ret	Retail property related search terms	retail space+commercial retail+retail lease+retail sale space+retail property+rent retail space+retail space for sale	Real Estate	Commercial and Investment Real Estate
	g_indus	Industrial-property-related search terms	industrial property+industrial for sale+industrial leases+commercial industrial property+industrial building+warehouse for sale+industrial property for sale	Real Estate	Commercial and Investment Real Estate
	g_apart	"Apartments & Residential Rentals" subcategory	*Google does not report the exact search terms that were aggregated in the subcategory*	Real Estate	Apartments & Residential Rentals

Notes: All indices have been extracted from Google Trends (http://www.google.com/trends/) for an observation period from January 2004 to January 2013.

3.2. Commercial Real Estate Data

In order to find out about Google's ability to enhance the prediction of commercial real estate markets, the CoStar CCRSI indices (CoStar Commercial Repeat-Sale Indices) are used to analyse Google data on prices and transactions.

Later in the robustness section we test our models across different sectors with Moody's/RCA CPPI (Commercial Property Price Indices) dataset.

Both providers use the repeat-sales methodology for constructing their indices. While the CCRSI set enters the analysis as equal-weighted indices, the CPPI indices are value-weighted. Moody's/RCA use a two-stage annual-to-monthly frequency conversion on top of the repeat-sales approach, which smoothes the index. Both providers release their reports with a two-month delay, meaning that the latest report refers to data from two months ago. We specifically use two slightly differently constructed index families with differing underlying portfolios in order to substantiate the robustness of our results.

3.3.Macroeconomic Data

In order to account for overall market conditions, US unemployment initial claims (Unemp), US construction expenditures (Const), the National Financial Conditions Index (NFCI) and the Chicago Fed National Activity Index (CFNAI) are included into the analysis section of this research. Initial claims are a widely accepted leading indicator for the national employment situation.

Construction expenditures are, partly because of their very nature, an early indicator of upcoming supply (e.g. Brooks and Tsolacos, 2010).

The NFCI, published by the Federal Reserve Bank of Chicago, is a weighted index of 105 financial indicators representing U.S. financial conditions in money markets, debt and equity

markets and banking systems. Treasury yield-, cmbs-, fixed rate mortgage- and corporate bond yield-spreads are among the ten highest weighted subindicators [9]. For this research, the NFCI is intended to account for the general financing conditions of market participants.
The CFNAI is a weighted average of 85 economic indicators drawn from four broad categories also published by the Federal Reserve Bank of Chicago. Among others, it includes data on production and income, personal consumption and housing, as well as sales, orders and inventories[10]. For this study, the CFNAI is used to account for the overall US economy.
Table II provides an overview of the abbreviations of all variables used for further analysis.
Appendices I and II present the summary statistics and correlations of all data used for this research.

Table II: Abbreviations and sources of input parameters

	Code	Data	Source	Type
Price Indices	co_comp	**CoStar Composite** - represents the whole CoStar portfolio across all property classes and types	CoStar	price index
	co_gen	**CoStar General Commercial** - represents all properties apart from investment grade properties	CoStar	price index
	co_inv	**CoStar Investment Grade** - represents the proportion of properties regarded as investment grade *	CoStar	price index
	mo_off	**Moody's/RCA Tier 4 Office** comprising offices located in the CBD as well as in suburban markets	Moody's/RCA	price index
	mo_ret	**Moody's/RCA Tier 4 Retail** representing all properties related to retail activities	Moody's/RCA	price index
	mo_indus	**Moody's/RCA Tier 4 Industrial** representing all properties related to industrial activities	Moody's/RCA	price index
	mo_apart	**Moody's/RCA Tier 2 Apartment** representing all residential properties	Moody's/RCA	price index
Transactions	co_comp_tra	Transactions underlying CoStar Composite	CoStar	transactions
	co_gen_tra	Transactions underlying CoStar General Commercial	CoStar	transactions
	co_inv_tra	Transactions underlying CoStar Investment Grade	CoStar	transactions
	mo_off_tra	Transactions underlying Moody's/RCA Tier 4 Office	Moody's/RCA	transactions
	mo_ret_tra	Transactions underlying Moody's/RCA Tier 4 Retail	Moody's/RCA	transactions
	mo_indus_tra	Transactions underlying Moody's/RCA Tier 4 Industrial	Moody's/RCA	transactions
	mo_apart_tra	Transactions underlying Moody's/RCA Tier 2 Apartment	Moody's/RCA	transactions
Macro Data	mcr_const	Construction Expenditures	US Census Bureau	macroeconomic data
	mcr_unemp	U.S Labor Department report of initial state jobless benefit claims	US Department of Labor	macroeconomic data
	mcr_nfci	National Financial Conditions Index (NFCI)**	Federal Reserve Bank of Chicago	macroeconomic data
	mcr_cfnai	Chicago Fed National Activity Index (CFNAI), a monthly index designed to gauge overall economic activity and related inflationary pressure ***	Federal Reserve Bank of Chicago	macroeconomic data
Consumer Confidence	mhu_consumer	Survey of Consumers	University of Michigan/ Thomson Reuters	consumer sentiment data

Notes:
*CoStar defines investment grade properties as class A and B offices, industrial properties built in the last 20 years, multifamily properties with 30 units or more, and retail properties with 20,000 square feet or more (CoStar, 2013).
** https://www.chicagofed.org/webpages/publications/nfci/index.cfm
*** https://www.chicagofed.org/webpages/publications/cfnai/index.cfm

[9] http://chicagofed.org/webpages/research/data/index.cfm
[10] http://chicagofed.org/webpages/research/data/cfnai/current_data.cfm

4. Analysis

4.1. Preliminary Steps

All data used for this research were retrieved as seasonally unadjusted series. In order to account for seasonality, we put them into rolling year-on-year differences. Since Google search data can only be downloaded on a weekly basis, they first have to be transformed into monthly series. Weeks extending into the next month were therefore split up, weighted by days and counted into the month to which they belong. The sample used for this study runs from January 2004 to January 2013. Transforming the time series into year-on-year differences implies a loss of 12 months, leaving 97 observations in total.

In order to ensure that the time series are I(0) processes, common unit root tests (Dickey and Fuller, 1979; Phillips and Perron, 1988; Kwiatkowski et al., 1992) were employed. The tests suggest a need for first differencing to ensure stationarity. As an additional positive effect, first differencing resolves the issue of the downward trending of Google search indices, which is due to the rapid increase in total search volumes over recent years and has already been criticised, for example, by Carrière-Swallow and Labbé (2013). Due to the very volatile nature of the year-on-year transaction counts, we put them into log form to account for outliers.

4.2. Granger-causality

In order to study the relationship between Google SVI, real estate indices and transactions, we perform pairwise Granger-causality tests (Granger, 1969). As a specification, we assume a lag-order of 12 which, as a period of one year, is adequate for the analysis. Additionally, we perform the tests with six lags to check our results for consistency.

Basic model for testing Granger-causality:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \dots + \alpha_l y_{t-l} + \beta_1 x_{t-1} + \dots + \beta_l x_{-l} + \varepsilon_t \tag{1}$$

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + \dots + \alpha_l x_{t-l} + \beta_1 y_{t-1} + \dots + \beta_l y_{-l} + \varepsilon_t \tag{2}$$

where l is either 6 or 12 lags as described above; y represents prices/transactions and x stands for the Google SVI.

As depicted in Table III, the Granger-causality tests suggest that the search volume indices have higher power in explaining past values of real world data than the other way round. This result is stronger for six lag Granger-causality tests than for 12. Despite the presence of bi-directional causality in some cases, the results point towards a leading character of the search volume indices.

Table III: Granger-causality tests between prices/transactions and Google SVI

		Prices			Transactions		
		g_agents_list	g_comm	g_inv_subcat	g_agents_list	g_comm	g_inv_subcat
co_gen	dependent	**	***	**	**/+	**	***/++
	independent	**/++	*/++			***/+++	**
co_comp	dependent	*	**	***	***/++	*/++	**/++
	independent	+	++	*/++		**/+++	*
co_inv	dependent		**	***/++	***	**/++	
	independent	**		++			

Notes: Performance of pairwise Granger-causality tests, where **d** and **i** represent the dependent and independent variable respectively. The test is performed for 6 lags (indicated by "*") and 12 lags (indicated by "+"). Significant at: */+ $p < 0.10$, **/++ $p < 0.05$ and ***/+++ $p < 0.01$.

Generally, bi-directional relationships are present as shown in Table III.
For time series with interdependencies, Sims (1980) suggests the use of vector-autoregressive (VAR) models to avoid endogeneity problems. As no clear one-side causal direction can be determined, VAR-models seem appropriate for further analysis.

4.3. Lag Order

In VAR-models, variable adjustments responding to changes in another variable are often inert, so that over a one-period horizon, only part of the overall effect of the change is observable. Therefore, it is necessary to determine the optimal lag-structure before specifying the models. One way of doing this is to pairwise estimate all Google and real estate variables in VAR Models.
Table IV reports the optimal lag lengths based on the Akaike Information Criterion (AIC) for all clusters.

Table IV: Optimal lag-lengths based on Akaike Information Criterion (AIC)

	Prices			Transactions		
	g_agents_list	g_comm	g_inv_subcat	g_agents_list	g_comm	g_inv_subcat
co_gen	7	7	7	4	5	3
co_comp	7	7	7	4	4	3
co_inv	7	7	7	4	3	2

Notes: In order to determine the optimal lag-structure between Google and real estate indices pairwise estimations of VAR models are carried out. The optimal lag-lengths are then chosen by the smallest Akaike Information Criterion (AIC).

We wish to mention that a possible theoretical explanation for part of the lead effect could be due to the way the repeat-sales-indices are constructed. The index averages the absolute value growth (loss) of a property over the months between the first and the second transaction pair. Therefore, especially sales-pairs which lie farther apart can, to some extent, be problematic, since the actual (non-measurable) monthly value appreciation cannot be determined precisely. This issue could become somewhat more relevant during extreme market phases, in which vast numbers of transactions take place within a short time frame. However, even then, a definite lead (lag) effect cannot be determined, since the first sales-pairs still differ from transaction to transaction in terms of which cycle phase they were transacted in. Further research could investigate this issue. There are some reasons, however, why we believe that this problem is more theoretical than practical. Firstly, it is mitigated by a growing number of transactions feeding into the index. CoStar provides the largest commercial real estate database ranging back more than twenty years and including more than 1.3 million property sale records. Consequently, many of these transactions overlap with each other in both the past and the future. This automatically eliminates a substantial proportion of the theoretical systematic lead/lag effect of the index. Moreover, according to CoStar most transactions occur after a 12-month holding period, which is fairly short for commercial real estate. This means that the value de- or appreciation of the building can be ascribed quite precisely to the respective month for the largest part of the underlying portfolio.

We believe that at least part of the leading effect of the Google indicators stems from the fact that they incorporate information from the early phases of the transaction process (see Section 2.2). However, not all Google research necessarily takes place during a transaction or due diligence process, but could also be conducted at an even earlier point of time. The commercial real estate indices on the other hand, receive their data from deal closings, which by their very nature, occur at the end of the transaction process.

4.4.Models

We believe that at least part of the leading effect of the Google indicators stems from the fact that they incorporate information from the early phases of the transaction process (see Section 2.2). However, not all Google research necessarily takes place during a transaction or due diligence process, but could also be conducted at an even earlier point of time. The commercial real estate indices on the other hand, receive their data from deal closings, which by their very nature, occur at the end of the transaction process.

For prices, the test reveals an average of seven lags as the optimum lag length. For transactions, a slightly shorter lag structure of four lags is, on average, suggested by the AIC. Therefore, it can be assumed that transactions lead prices. The results are broadly in line with the graphical analysis from Section 1 as they support the proposition that Google has a stronger leading effect on prices than it does on transactions. From our preliminary analysis, we find interdependencies between prices, transactions and search indices, which lead us to use vector autoregressive (VAR) models. Based on the lag-length-tests from above, we use a lag-order specification of six for the models.

In order to test forecast accuracy, we construct four different general models, separated into two baseline and two Google models. As a result, we obtain a total of 24 models.[11] As shown in Table V, the b1 model carries macro data and prices or transactions; b2 contains prices and transactions as well as macro data; g1 contains prices or transactions and Google data; g2 contains all mentioned variables.

[11] Twelve models for price and transaction forecasts each.

Table V: Model input variables

			forecasted variable	included variables		
				Macro Data	Transactions	Google Data
Prices	baseline	b1	Prices	x		
		b2	Prices	x	x	
	google	g1	Prices			x
		g2	Prices	x	x	x
				Macro Data	Prices	Google Data
Transactions	baseline	b1	Transactions	x		
		b2	Transactions	x	x	
	google	g1	Transactions			x
		g2	Transactions	x	x	x

Notes: The baseline models b1 and b2 contain macro data only and macro data in combination with transactions respectively. The Google model g1 contains Google data only. The G2 model combines macro data, transactions/prices and Google data.

Since the two baseline models ("b1" and "b2") and the first Google model ("g1") are all nested within the second Google model ("g2")[12], we start by describing the basic functional form of the latter:

$$g2_{(\mathrm{Pr/Tr})}: \begin{pmatrix} Equation\ 1: \\ Equation\ 2: \\ Equation\ 3: \\ Equation\ 4: \\ Equation\ 5: \end{pmatrix} \begin{pmatrix} P_t \\ T_t \\ G1_t \\ G2_t \\ G3_t \end{pmatrix} = \begin{pmatrix} \beta_{01} \\ \beta_{02} \\ \beta_{03} \\ \beta_{04} \\ \beta_{05} \end{pmatrix} + A \begin{pmatrix} P_{t-i} \\ T_{t-i} \\ G1_{t-i} \\ G2_{t-i} \\ G3_{t-i} \end{pmatrix} + B \begin{pmatrix} CFNAI_t \\ Const_t \\ NFCI_t \\ Unemp_t \end{pmatrix} + \begin{pmatrix} u_{Pt} \\ u_{Tt} \\ u_{G1t} \\ u_{G2t} \\ u_{G3t} \end{pmatrix} \quad (3)$$

P_t refers to the price indices, T_t to the transaction volume underlying the price indices, $G1_t$ to the g_agents+list-SVI, $G2_t$ to g_subcat, $G3_t$ to g_comm. All endogenous variables enter the equation with six lags: $i = \{1, \dots, 6\}$.

$CFNAI_t$, $Const_t$, $NFCI_t$ and $Unemp_t$ enter the model as exogenous variables and represent the macro data described in Section 3.

A is the coefficient matrix of the endogenous variables, B stands for the exogenous variables.

u represents the errors in each equation.

Models b1, b2[13] and g1 for prices and transactions are designed analogously and formulated as follows:

[12] The "g2"-models are identical for prices and transactions.

[13] The "b2"-models are identical for prices and transactions.

$$\text{b1}_{(\text{Pr})}: (Equation\ 1{:})\ (P_t) = (\beta_{01}) + A\ (P_{t-i}) + B \begin{pmatrix} CFNAI_t \\ Const_t \\ NFCI_t \\ Unemp_t \end{pmatrix} + (u_{Pt})$$

$$\text{b1}_{(\text{Tr})}: (Equation\ 1{:})\ (T_t) = (\beta_{01}) + A\ (T_{t-i}) + B \begin{pmatrix} CFNAI_t \\ Const_t \\ NFCI_t \\ Unemp_t \end{pmatrix} + (u_{Tt}) \tag{4}$$

$$\text{b2}_{(\text{Pr/Tr})}: \begin{pmatrix} Equation\ 1{:} \\ Equation\ 2{:} \end{pmatrix} \begin{pmatrix} P_t \\ T_t \end{pmatrix} = \begin{pmatrix} \beta_{01} \\ \beta_{02} \end{pmatrix} + A \begin{pmatrix} P_{t-i} \\ T_{t-i} \end{pmatrix} + B \begin{pmatrix} CFNAI_t \\ Const_t \\ NFCI_t \\ Unemp_t \end{pmatrix} + \begin{pmatrix} u_{Pt} \\ u_{Tt} \end{pmatrix} \tag{5}$$

$$\text{g1}_{(\text{Pr})}: \begin{pmatrix} Equation\ 1{:} \\ Equation\ 2{:} \\ Equation\ 3{:} \\ Equation\ 4{:} \end{pmatrix} \begin{pmatrix} P_t \\ G1_t \\ G2_t \\ G3_t \end{pmatrix} = \begin{pmatrix} \beta_{01} \\ \beta_{02} \\ \beta_{03} \\ \beta_{04} \end{pmatrix} + A \begin{pmatrix} P_{t-i} \\ G1_{t-i} \\ G2_{t-i} \\ G3_{t-i} \end{pmatrix} + B \begin{pmatrix} CFNAI_t \\ Const_t \\ NFCI_t \\ Unemp_t \end{pmatrix} + \begin{pmatrix} u_{Pt} \\ u_{G1t} \\ u_{G2t} \\ u_{G3t} \end{pmatrix}$$

$$\text{g1}_{(\text{Tr})}: \begin{pmatrix} Equation\ 1{:} \\ Equation\ 2{:} \\ Equation\ 3{:} \\ Equation\ 4{:} \end{pmatrix} \begin{pmatrix} T_t \\ G1_t \\ G2_t \\ G3_t \end{pmatrix} = \begin{pmatrix} \beta_{01} \\ \beta_{02} \\ \beta_{03} \\ \beta_{04} \end{pmatrix} + A \begin{pmatrix} T_{t-i} \\ G1_{t-i} \\ G2_{t-i} \\ G3_{t-i} \end{pmatrix} + B \begin{pmatrix} CFNAI_t \\ Const_t \\ NFCI_t \\ Unemp_t \end{pmatrix} + \begin{pmatrix} u_{Tt} \\ u_{G1t} \\ u_{G2t} \\ u_{G3t} \end{pmatrix} \tag{6}$$

Section 5 compares the baseline model forecasting accuracy against that of the Google models and investigates whether an inclusion of Google data adds explanatory power and thereby improves forecasting results. The forecast improvements are examined for significance in section 6.

4.5. Impulse-Response-Function

Since an ordinary interpretation of VAR-models can be vague, due to various interactions between the equations, we employ an impulse response function (IRF) to determine the reaction of the price/transaction variables to a shock from the Google variables.

The IRF describes the reaction of the process in $t+1, t+2, \dots t+n$, when, at point of time t, a single shock hits the i^{th} variable in the system (Lütkepohl et al., 2004).

In order to remain consistent, we set the observation period to six months $(\mathrm{t}+1, \mathrm{t}+2, \dots, \mathrm{t}+6)$. The accumulated impulse response shows the total reaction over the observation period for all possible six month-periods over the entire sample.

Table VI demonstrates that 14 out of 18 price indices and transactions yield a positive reaction to the IFR of the Google variable over a following six-month period. This suggests that an upward movement of the real estate indices and transactions is very likely to be connected to an early upward movement of the Google indicators.

Table VI: Accumulated impulse response of prices/transactions to Google SVI

	Prices			Transactions		
Dependent Variable	g_agents_list	g_inv_subcat	g_comm	g_agents_list	g_inv_subcat	g_comm
co_gen	0.061936	0.176108	1.64041	0.006833	0.008523	0.005798
co_comp	0.246844	-0.439046	2.019921	0.009521	0.009725	0.002869
co_inv	4.822633	-0.580048	-2.831145	0.000393	0.014699	-0.001062

Notes: With the impulse response function (IRF) the reaction of the price/transaction variables to a shock from the Google variables is measured. As the observation period is six months, the accumulated impulse responses describe the total reaction over the observation period for all possible six month-periods over the entire sample. Positive responses are highlighted in grey.

5. Forecast Tests

For our purposes, we split the sample into price- and transactions-subsets in order to conduct one-month-ahead forecasts.

The procedure for the one-month-ahead forecasts is the following. The first sub-period from January 2005 to December 2006 serves to estimate the parameters of our models. Based on this, we perform an out-of-sample forecast for January 2007. In the next step, we extend the estimation sample by one month and make a forecast for February 2007. This process is repeated over the whole sample until January 2013. Hence, the estimation period becomes larger over time, causing parameters to be re-estimated with each further step. This approach ensures that the out-of-sample prediction abilities of our models are tested thoroughly over the observation period.

In order to determine whether the models augmented with Google data achieve an improvement over the baseline models, we measure their forecasting accuracy based on out-of-sample criteria. To do so, we introduce the "loss function" or forecast error $\hat{e}$ (see Brooks and Tsolacos, 2010):

$$\hat{e}_{t+1,t} = A_{t+1} - F_{t+1,t} \tag{7}$$

where A_{t+1} are the realisations (actuals) at time $t + 1$ and $F_{t+1,t}$ is the one-month-ahead forecast made at time t. We have 73 observations (n) from January 2007 to January 2013. Based on this loss function, we compute the mean squared error (MSE) for all forecasts.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \hat{e}_i^2 \tag{8}$$

Theil (1966, 1971) introduced the U1 coefficient which ranges between 0 and 1, with the basic rule being that the closer the coefficient is to zero, the better the forecast accuracy. We utilise the U1 coefficient in order to render the measurement of forecast accuracy of all models comparable.

$$U1 = \frac{\sqrt{MSE}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n} A_i^2} + \sqrt{\frac{1}{n}\sum_{i=1}^{n} F_i^2}} \tag{9}$$

We report the MSE, the MSE reduction in Google data augmented models, against the best baseline model and Theil's U1 statistic. In addition, the adjusted-R^2 serves as a goodness-of-fit measure and in-sample criterion. Table VII gives an overview of the results of all (24) tested models. The best performing models are highlighted in grey.

Table VII: Forecast results

Dependent Variable			Macro	Transactions / Prices	Google	Prices: Adj. R²	Prices: MSE	Prices: MSE Reduction *	Prices: U1 Theil *	Transactions: Adj. R²	Transactions: MSE	Transactions: MSE Reduction *	Transactions: U1 Theil *
co_gen	baseline	b1	x			0.461	4.1108	-12%	0.062	0.276	0.0024	-31%	0.210
		b2	x	x		0.473	3.6868	0%	0.059	0.392	0.0018	0%	0.188
	google	g1			x	0.515	2.7364	26%	0.051	0.386	0.0016	10%	0.170
		g2	x	x	x	0.484	2.4670	33%	0.048	0.448	0.0013	29%	0.155
co_comp	baseline	b1	x			0.498	3.7666	-15%	0.059	0.304	0.0021	-23%	0.177
		b2	x	x		0.526	3.2691	0%	0.055	0.386	0.0017	0%	0.164
	google	g1			x	0.568	2.3054	29%	0.046	0.421	0.0014	16%	0.143
		g2	x	x	x	0.561	1.9800	39%	0.043	0.474	0.0011	33%	0.132
co_inv	baseline	b1	x			0.538	10.8856	-13%	0.080	0.343	0.0074	-4%	0.191
		b2	x	x		0.559	9.5989	0%	0.076	0.306	0.0072	0%	0.188
	google	g1			x	0.641	6.1344	36%	0.060	0.451	0.0052	28%	0.155
		g2	x	x	x	0.665	4.4380	54%	0.052	0.466	0.0047	35%	0.149

Notes: * The reduction of the MSE and U1 Theil statistic is always measured in relation to the best baseline model (b2). A positive value represents an improvement in forecasting accuracy in comparison to the baseline model. The best performing models are highlighted in grey.

The strongest finding is that the g2 models have the lowest MSE and U1 statistic, and thereby outperform the baseline models across all groups. For prices, the reduction in the MSEs ranges between 33% and 54%, when comparing the best Google models (g2) to the best baseline models (b2). The comparison of the b2 and g1 models indicates that models based only on Google search indices, and the lags of the dependent variable, outperform the baseline models every time.

For transactions, the reduction in the MSEs lies between 29% and 35%. As for prices both Google models outperform the baseline models across all groups at all times. This provides strong evidence that the models augmented with internet search data outperform by a large margin the baseline models that only include fundamental market data. The results verify existing research which is stating that the best forecasting results are achieved by combining real world and internet data.

The in-sample criterion adjusted-R^2 largely supports the above findings. In all cases, the adjusted-R^2 of either one of the Google models is higher than for the baseline models.

A few additional findings are worth mentioning.

Firstly, Theil’s U1 statistic suggests that price forecasts generally come closer to their actual values than transaction forecasts. A possible explanation could be that prices are generally less prone to large shifts, which makes them easier to predict in one-month-ahead forecasts. The generally much lower MSE level for transactions stems from the fact that they are put into log transformations.

Secondly, it should be mentioned that the implementation of Google data appears to work very successfully in the prediction of investment grade property prices. This appears somewhat puzzling at first sight. It seems intuitive, however, that larger, more expensive and better located properties draw much more searcher attention. Hence, analogously to residential properties, we expect the user-side interest to be well covered by Google Trends, especially in an era in which internet presence and individually created websites play a large role in the marketing of larger properties. Furthermore, a closer look at the MSE reveals that the forecasting error for investment grade properties was significantly larger from the start (in the baseline models), compared, for instance, against the ‘general’ properties index. Hence, the clearly sharper MSE-reduction could partly stem from a mathematical background. All in all, the results paint a clear picture. Forecasting models augmented with Google search data are able to reduce the forecasting errors about one third.

6. Robustness

6.1. Robustness across different commercial real estate sectors

In order to test our Google data augmented forecasting models for robustness we use a different set of commercial real estate data (RCA/Moody’s CPPI) and test them on different sectors (office, retail, industrial, multifamily). We exchange the “G3” index g_comm by the respective sector related search indices described in Section 3 to account for specific interest.

As illustrated in table VIII the results confirm the results from above. In all cases Google augmented models outperform non-Google models.

Table VIII: Forecast results across different commercial real estate sectors

							Prices				Transactions			
	Dependent Variable			Macro	Transactions / Prices	Google	Adj. R^2	MSE	MSE Reduction *	U1 Theil *	Adj. R^2	MSE	MSE Reduction *	U1 Theil *
office	mo_off	baseline	b1	x			0.852	2.5167	-23%	0.027	0.290	0.0242	-17%	0.287
			b2	x	x		0.844	2.0522	0%	0.025	0.340	0.0206	0%	0.260
		google	g1			x	0.880	1.9803	4%	0.024	0.304	0.0188	9%	0.246
			g2	x	x	x	0.864	1.3859	32%	0.020	0.387	0.0152	26%	0.220
retail	mo_ret	baseline	b1	x			0.204	8.7869	-31%	0.071	0.355	0.0365	-23%	0.378
			b2	x	x		0.314	6.7246	0%	0.062	0.408	0.0296	0%	0.335
		google	g1			x	0.196	7.2237	-7%	0.065	0.424	0.0265	10%	0.305
			g2	x	x	x	0.380	4.5788	32%	0.051	0.451	0.0223	25%	0.279
industrial	mo_indus	baseline	b1	x			0.766	1.1233	-34%	0.028	0.357	0.0253	-20%	0.313
			b2	x	x		0.796	0.8397	0%	0.024	0.407	0.0211	0%	0.277
		google	g1			x	0.754	0.9747	-16%	0.026	0.368	0.0202	4%	0.267
			g2	x	x	x	0.816	0.6001	29%	0.020	0.416	0.0168	20%	0.242
multifamily	mo_apart	baseline	b1	x			0.891	0.9711	-16%	0.019	0.397	0.0071	-25%	0.188
			b2	x	x		0.894	0.8375	0%	0.018	0.452	0.0057	0%	0.165
		google	g1			x	0.902	0.7271	13%	0.016	0.456	0.0048	16%	0.151
			g2	x	x	x	0.914	0.4731	44%	0.013	0.485	0.0040	31%	0.136

Notes: * The reduction of the MSE and U1 Theil statistic is always measured in relation to the best baseline model (b2). A positive value represents an improvement in forecasting accuracy in comparison to the baseline model. The best performing models are highlighted in grey.

The case of multifamily properties stands out to some degree. The fact that Google works very well for residential properties seems straightforward, however, as the internet has become one of the most important media for finding a residence. We assume that forecasting models benefit perticularly from the well-displayed consumer demand information provided by Google search queries. This result is in line with existing research such as Hohenstatt et al. (2011, 2013); Wu and Brynjolfsson (2009) and Beracha and Wintoki (2012). The evidence provided in Tables VII and VIII indicates quite clearly that the inclusion of Google Trends data is robust in improving the in- and out-of-sample accuracy of price and transaction forecast models for US commercial real estate markets.

6.2.Forecast Significance Tests

To test whether the improvements in forecast accuracy are not only due to chance, we calculate Clark & West's MSE-adjusted test statistic for all models, in order to determine whether the improvement in the best Google model (g2), compared to the best performing baseline (b2) model, is significant.

Since the b2-models are nested in the g2-models, their residuals are identical and therefore dependent, under the null of equal forecasts. As a result, the commonly used test statistic introduced by Diebold and Mariano (1995) does not follow a normal distribution under the null hypothesis. We therefore apply Clark & West's MSE-adjusted test statistic (Clark and West, 2007), which works with nested models and is robust with respect to a wide variety of estimation methods.

We find strong evidence that the improvement in the Google augmented models over the baseline models is indeed significant. Test statistics and p-values are presented in Table IX.

Table IX: Clark-West forecast-improvement significance test

		Prices			**Transactions**		
		t-stat	p-value		t-stat	p-value	
all property	co_comp	5.031109	0.0000	***	4.566811	0.0000	***
	co_gen	5.161966	0.0000	***	4.946523	0.0000	***
	co_inv	4.512639	0.0000	***	4.299512	0.0001	***
office	mo_off	3.838397	0.0003	***	3.030389	0.0034	***
retail	mo_ret	4.35522	0.0000	***	4.247521	0.0001	***
industrial	mo_indus	5.114553	0.0000	***	3.311156	0.0015	***
multifamily	mo_apart	3.2297	0.0019	***	3.926208	0.0002	***

Notes: H=0: improvement of g2 over b2 model is insignificant.
Sample: 2007m01 2013m01; 73 observations
Significant at: * p < 0.10, ** p < 0.05 and *** p < 0.01.

7. Conclusion

Existing research shows that internet data offer considerable potential for 'nowcasting' (real-time estimation of indicators/indices that are released with a time lag) and forecasting purposes. Google's search volume indices are freely available and easily accessible, and feature certain advantages over survey-based sentiment indicators, in terms of their rapid delivery and avoidance of common interviewer effects. Combined with the fact that Google is the unchallenged leading search engine provider with a U.S. market share of 67.5 % in March 2014[14], this renders the corresponding share of searchers sufficiently representative. However, correct and precise measurement of sentiment/interest constitutes a much greater challenge. Especially Google's intelligent categorisation helps researchers to capture a great chunk of search interest for specific areas. However, particularly the absence of absolute search counts and the way the data are scaled and rehashed, creates something of a black box in some respects.

To the authors' best knowledge, this is the first study examining the role of internet search data in the commercial real estate sector. Based on a theoretical framework, we construct various forecast models and find that the inclusion of Google data significantly improves the one-month-ahead forecasts of commercial real estate prices and transactions for the US market. These results are robust for the whole sample of prices and transactions supplied by the two largest US repeat-sales index providers, whether smoothed or unsmoothed, value- or equal-weighted, aggregated or sector-specific. In line with existing research, we come to the conclusion that models containing both macro and Google data deliver the best forecasting results.

The results imply that Google search data are suitable for measuring sentiment in commercial real estate markets. Despite the fact that the commercial real estate market is dominated by professional investors who make use of various information sources, we find that Google does indeed often play a role during the search process before deal closing. This raises the questions of whether this additional set of information could help to make commercial real estate markets more efficient. Fama (1970) gives a definition of efficient market prices, which "fully reflect" available information. Fu and Ng (2001) state that real estate markets are less efficient than stock markets, which Clayton et al. (2009) ascribe to their highly segmented and heterogeneous underlying assets. This causes commercial real estate markets to be inefficient in terms of information availability. We demonstrate that Google search volume indicators can be applied effectively to commercial real estate and thereby improve market transparency. This allows market participants to adapt faster to changes in market climate, which could consequently improve the market efficiency.

The apparent leading character of Google data in commercial real estate markets could make this tool an indispensable instrument for the forecasting profession in the industry. This corresponds to Wu and Brynjolfsson (2009), who claim that especially real estate, with its long, research-intensive buying processes compared to stocks for example, is very suitable for being forecasted by internet-search-data-based models. Real estate forecasters are thus advised to make use of this dataset to improve or substantiate their forecasting results.

As a whole our findings suggest that search volume data can serve as leading indicators for short-term trends or even turning-points in the market. In general, we believe that there is great potential for multiple-month-ahead market forecasts, for which Google's search index forecasting tool could create further advantages for estimating market sentiment and as a

[14] Comscore (2014)

consequence, market movement. This kind of information could certainly contribute to real estate investors’ investment decisions and selection processes.

Further research should also examine Google’s explanatory power with respect to rent trends. This includes focussing on the demand for space by the user side. If successful, price bubbles or market turnarounds could potentially be detected at an early stage.

More generally, research in this area should be extended to MSA/city level and the specific behaviour of Google search volume indices during downturns and upswings, and to the performance predictability of indirect real estate investment vehicles and other financial market products, such as REITs, CMBS or MBS.

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