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**ONLINE INFORMATION SEARCH, MARKET FUNDAMENTALS AND
APARTMENT REAL ESTATE**

BY

PRASHANT KUMAR DAS

A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree

Of

Doctor of Philosophy

In the Robinson College of Business

Of

Georgia State University

GEORGIA STATE UNIVERSITY

ROBINSON COLLEGE OF BUSINESS

2013

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ACCEPTANCE

This dissertation was prepared under the direction of the *PRASHANT DAS* Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctoral of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

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ABSTRACT

**ONLINE INFORMATION SEARCH, MARKET FUNDAMENTALS AND
APARTMENT REAL ESTATE**

BY

PRASHANT KUMAR DAS

OCTOBER 11 2013

Committee Chair: Dr. Alan Ziobrowski

Major Academic Unit: Department of Real Estate

Using a system of multi-step equations, I examine the association between online rental searches and fundamental apartment real estate market variables namely, vacancy rates, rental rates and real estate asset price returns. I find that consumer real estate searches are significantly associated with the market fundamentals after controlling for known determinants of these variables. In particular, I show that apartment rentals related online searches are endogenously and contemporaneously associated with reduced vacancy rate. However, the association between the searches and rental rates is not significantly detected. The searches are contemporaneously associated with positive return on the appraised values of multifamily assets. There is some evidence that the searches are fundamentally associated with REIT returns in the short run and that REIT investors watch the online search trends to inform their stock pricing decisions.

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CHAPTER ONE: INTRODUCTION

Overview

Information searches about products and securities play a critical role in pricing (Beatty and Smith, 1987, Pentland and Pentland, 2008, Han and Wild, 1991, Stigler, 1961, Da, Engleberg and Gao, 2011, Bloch, Sherrell and Ridgway, 1986). Before the advent of personal computers, it was challenging to track information searches by consumers or investors and traditional surveys were the only means of learning about people's buying intentions (Fishbein and Ajzen, 1975). However, in last two decades, internet search engines have emerged as an important means of gathering such information. Online searches dominate real estate searches, in particular (National Association of Realtors, 2008, Appleton-Young, 2008).

In 2008, Google started releasing online search data to the public through a feature named 'Insights for Search' (I4S). Historical I4S data is available on a weekly basis mitigating some issues related to most economic data such as low frequency and lagged release. The public availability of the I4S has led to several studies that examine models of social and economic variables using the I4S as a predictor. Central banks in Israel, Britain, Italy, Spain, Turkey and Chile use the I4S data in forecasting economic conditions¹. Moreover, there is substantial anecdotal evidence that investors watch the I4S for valuing assets and use the I4S in developing 'new algorithms to arbitrage'². Some hedge funds have started using the I4S data as

¹ See <http://www.businessweek.com/articles/2012-08-09/google-central-banks-new-economic-indicator>

² See '*Getting real-time: Internet economic indicator's*', June 14 2011 issue of The Economist

a tool for developing investment strategies³. A recent study by the New York Fed argues that the I4S can predict 'financial market data releases, as well as future price movements in some financial markets⁴.' Independent of whether the I4S represents market fundamentals, it may influence the investors' assessments of asset pricing. Kahneman (1973) and Merton (1987) observe that investors are fraught with cognitive limitations and may focus on factors other than market fundamentals⁵. For example, consider investors who regularly follow Jim Cramer, the host of popular nightly *Mad Money* on CNBC. Empirical studies report that his recommendations impact share prices of the companies being mentioned although the effects are short-lived⁶.

Da, Engelberg and Gao (2011) establish a predictive link between the I4S and earnings surprises in stocks whose ticker symbols are used as search keywords. Joseph, Wintoki and Zhang (2012) find that the I4S related to ticker symbols predicts abnormal stock returns and trading volume. Bank and Larch (2010) report historical and contemporaneous associations between the I4S based on the firm name and stock volatility or trading volume. However, despite the statistical significance, the relations between the I4S and the asset transactions reported in these studies are short-lived and reverse in the longer run.

Some recent studies provide evidence relating the I4S to real estate markets. Choi and Varian (2009) report a contemporaneous link between online real estate searches and the monthly single-family home price data released by the Housing and Urban Development (HUD). Wu

³ See <http://forbesindia.com/printcontent/22482>

⁴ See <http://libertystreeteconomics.newyorkfed.org/2012/01/forecasting-with-internet-search-data.html>

⁵ See Joseph, Wintoki and Zhang (2011) and Ghysels, Plazzi, Torous, & Valkanov (2012) for further details

⁶ See Bolster, Trahan and Venkateswaran (2012) and Neumann and Kenny (2007)

and Brynjolfsson (2009) show that the contemporaneous I4S and the lagged I4S from the previous quarter predict single-family housing sales volumes⁷ and price indexes⁸. They claim that the I4S reveals 'consumer interest' and helps to 'uncover sales trends before they appear in published data'. According to Hohenstatt, Kasbauer and Schafers (2011), the real estate I4S data reflects demand for housing and helps predict future housing transactions. They examine the predictive relationship between three lags of the I4S and home prices⁹ using monthly data. Similarly, Beracha and Wintoki (2012) examine the association between the quarterly OFHEO Home Price Index and up to four lags of the I4S. They argue that the real estate I4S provides information about the 'future demand' for housing. In their analysis of major cities in the United States, they find 'strong evidence that the search intensity Granger causes abnormal returns'. However, they also report that the price outperformance arguably related to the abnormal search activity holds only in the short-term and reverts in the long run.

Although the studies mentioned above (in particular, Wu and Brynjolfsson, 2009, Hohenstatt, Kasbauer and Schafers, 2011, and Beracha and Wintoki, 2012) argue that the real estate related I4S offers a proxy for real estate demand, their premise needs further examination. Unlike most consumption goods, real estate does not quickly depreciate in market value. Therefore, in addition to buyers, sellers must also constantly monitor the markets. In apartments, for example, for every lease that approaches expiration, both the tenant and the landlord have an incentive to search for rental-related information as both parties may be interested in comparing the rents across properties to gauge the market. Also, real estate enthusiasts with no

⁷ Data from National Association of Realtor

⁸ Data from Office of Federal Housing Enterprise Oversight (OFHEO)

⁹ Case-Shiller Index

intention to buy, sell or rent properties may be interested in rental information. If the market fundamentals truly drive the increase in internet traffic, we would expect the increase in prices to be long-lasting rather than short-term and rapidly dissipating .

Although the I4S has been studied in the context of for-sale real estate markets dominated by retail buyers and sellers, the association needs further examination in rental markets. Beyond the space market of renters and landlords, apartments also have active markets for real estate assets and stocks in which institutional investors participate among others. Compared to homes, apartment assets are thinly bought or sold and are 'big-ticket' transactions. The apartment asset market on 'Main Street' is dominated by sophisticated, large investors. However, the stock market on 'Wall Street' (i.e. the market for apartments REIT stocks) is composed of both individuals and institutions. Thus, apartments offer a multi-layered setting for examining the relationship between the I4S and asset returns.

This is the first study to examine the association between apartment markets and online searches. I also examine the link between the I4S and market fundamentals. I analyze whether the significance of the I4S in predicting the REIT returns is because the REIT investors watch the I4S, or because the I4S is related to the underlying apartment market fundamentals. I specifically examine the relationship between the I4S and decisions made by renters, landlords, investors in properties and REIT stock investors. The empirical testing is divided into the following tests:

Relating the I4S to Market Fundamentals

1. Vacancy Rates

If online searches represent apartment market fundamentals, then the I4S from the space market participants should be associated with changes in the vacancy rates. Based on the models proposed by Voith and Crone (1988), and Grenadier (1995), I use a quarterly panel data of 21 metropolitan statistical areas (MSAs) to model the vacancy rate as a function of its past values, the I4S, and polynomial time trends.

2. Rents

If the I4S is associated with increased demand for space, it should be reflected in rental rates. Operating expenses, vacancy rates and location-specific fixed effects are known determinants of rental rates (Rosen and Smith, 1983). To examine if the I4S is associated with rental rates after controlling for these factors, I analyze the quarterly panel data of 21 large MSAs. Contemporaneous models of the average rental rate as a function of operating expenses, vacancy rates and the I4S are examined on the quarterly panel data of 21 MSAs.

3. Capitalization Returns

If apartment investors incorporate the I4S into their decisions, then changes in the I4S should be associated with changes in capitalization rates or returns. Investors may perceive the I4S as an indicator of tenants' demand for apartments. In that case, the I4S should be associated with increases in apartment asset values. I examine the panel data of the 21 MSAs described above to test this. I examine a model of the capitalization returns using the I4S as an independent

variable controlling for factors such as rental growth, interest rate, credit-tightness and CMBS issuance based on Plazzi, Torous and Valkanov (2010) and An, Deng and Fisher (2011).

4. Short-run Abnormal Return in Apartment REITs

Given the unavailability of frequently updated data on apartment rental demand, short run changes in demand may only be reflected into stock prices if investors follow some frequently updated proxies for demand. The rental I4S could be such a proxy. If so, there should be a direct association between the I4S and short-run REIT returns. To test the short run abnormal returns associated with the I4S, I apply a vector autoregressive (VAR) predictive model to a weekly data set including the I4S, Fama-French factors and the CRSP/Ziman Apartment REIT Index return.

5. Long-run Persistence of Abnormal Returns in Apartment REITs

If the abnormal returns associated with the I4S are persistent over a longer term, it provides support for the argument that the I4S represents a fundamental variable. I apply an Impulse Response Function (IRF) to the system of equations in the VAR model discussed above. I examine the time-persistence of responses in the REIT returns of unit shocks in the independent variables such as the I4S. Finance and economics studies (such as Hasbrouck, 1991, Statman, Thorley and Vorkink, 2006, Sardosky, 1999, Glascock, Lu and So, 2002, Kim, Leatham and Bessler, 2007, Bernanke and Kuttner, 2005 and Miller and Peng, 2006) apply the IRF to examine how the dependent variable responds to shocks in the independent variables. I draw inferences about the longer term effects from the persistence of the response over time.

Robustness Tests

6. Availability of the I4S

Investors may only base the stock pricing on the I4S if this data is available to them. Although the data for the I4S is available going back as far as January 2004, it was first released only in July 2008. If the I4S is unrelated to fundamentals, it would logically follow that the I4S should not be statistically significant in modeling the REIT returns before it was available. On the other hand, if the I4S truly measures the underlying apartment market fundamentals, we would expect the I4S to be an equally significant predictor of real estate returns dating back to 2004. To test this hypothesis, I divide the sample into 'before' and 'after' time periods around July 2008. Across these time periods, I again test for the significance of the I4S in predicting the short-term returns as described in step 4. The insignificance of the I4S in the 'before' sub-sample coupled with the significance in the 'after' sub-sample would suggest that the significance of the I4S in predicting REIT returns is primarily due to investors watching this data.

7. Break-Point Analysis

The simple before-after analysis around July 2008 may potentially be confounded by the occurrence of the sub-prime real estate market crisis. The I4S was first released during the peak of the crisis. Moreover, substantial investor attention to the I4S may not necessarily begin exactly when it was first released. Rather, it would depend on when investors become aware

that the data is available. Therefore, I apply an algorithm developed by Bai and Perron¹⁰ (2003) to identify the structural breaks in the associations.

Contributions of this Dissertation

1. Relates the I4S to Apartment Market Fundamentals

Given the dominance of the internet in real estate searches, the link between the I4S and real estate fundamentals becomes a critical question of inquiry, especially if the I4S is suspected of significantly predicting real estate sales and prices. This is the first study to conduct an in-depth examination of how the I4S is linked to various aspects of apartment markets. In particular, the study separately examines the relationship between the I4S and respective apartment market variables associated with renters, landlords, real estate asset investors and stock (REIT) investors. The robust association between the I4S and market fundamentals would establish the I4S as a legitimate indicator of apartment market fundamentals.

2. Relates REIT Returns to Online Product Searches

Da et al. (2011) exclude REITs from their sample of stocks. Further, they focus on investor online searches about firms rather than public searches about products. The real estate studies such as Hohenstatt et al. (2011) and Beracha et al. (2012) study housing prices rather than stock returns. Moreover, they focus on relating the I4S to for-sale real estate. For-rent real

¹⁰ In particular, a software program offered by Zeileis, Kleiber, Kramer and Hornik (2003) is applied that is based on Bai and Perron (2003).

estate markets play a critical role in the real estate system¹¹. This is the first study that takes a fresh look at the link between the I4S and apartments REIT stock performance. After examining the relationship between the I4S and stock returns over a short-term horizon, this dissertation also examines the persistence of the price response. If the response is persistent, it provides evidence relating the I4S to market fundamentals. Dissipation of the response in the short run supports the hypothesis that the I4S is unrelated to fundamentals.

Organization

The dissertation is organized into several chapters. The first chapter introduces the topic and builds a case and an outline for this dissertation. The second chapter offers the literature survey. The third chapter discusses the data and methodology. The fourth chapter presents the results. The fifth chapter provides discussion and concludes.

¹¹ For example, the total market cap of the Homebuilder stocks is nearly \$3 Bi while that for Equity REITs is over \$500 Bi.

CHAPTER TWO: LITERATURE

The Role of the Internet in Society

There has been phenomenal growth in the number of people using the internet. According to World Bank,¹² the percentage of internet users in the United States multiplied 45 times from 1990 to 2000 and since 2004 the proportion of internet users has stabilized in a band of 65 to 74%. 87% of adult internet users in the United States use search engines to find information and about 78% of internet users seek online information about services or products¹³. According to USA Today¹⁴, 65% of online searches are captured by the Google search engine. Consumer searches are more intense when purchasing 'higher priced, more visible, and more complex products' (Beatty and Smith, 1987). Several studies note that a large proportion of real estate search activities happen on the internet. In particular, 90% of home buying search activities take place online¹⁵. Therefore, the role of online searches in the general economy and in real estate in particular deserves academic attention.

The I4S in Empirical Research

What is the I4S?

Studying online surfing and search behavior has traditionally been a challenging task as the data has not been readily available. Johnson, Moe, Fader and Bellman (2004) study the data collected by a private firm that tracks website usage data from volunteering families. They

¹² See <http://data.worldbank.org/indicator/IT.NET.USER.P2>

¹³ The Pew Research Center (May 2010)

¹⁴ May 2010

¹⁵ See www.realtor.org/reports/digital-house-hunt

point out the importance of observable online search data in empirical analyses of market behavior. Ettredge, Gerdes and Karuga (2005) apply online search data¹⁶ to forecast macroeconomic variables such as the unemployment rate and unemployment claims. Recently, the public availability of online search data made accessible by Google, Inc. (through 'Google Trends' in 2006 and 'Google Insights for Search' in 2008) has attracted substantial academic interest. 'Google Insights for Search (I4S),' in particular, provides the online search data cataloged in search categories and sub-categories based on geography (such as a country, a state or a metropolitan area). The time series I4S data is released as a weekly average. The search engine tracks the websites visited immediately before or after an internet user conducts an online search. This helps in identifying the 'category' in which a search can be placed. In 2011, Google searches were classified into 27 categories and 241 sub-categories¹⁷.

The search index (I4S) is a weekly time series. Each I4S series can be filtered based on search keywords (or categories/sub-categories), geographic location (e.g. country, state or metro area), and time line¹⁸. The underlying level (value) of the I4S index reflects how many searches have been done for a given set of keywords relative to the total number of searches done on Google over time. However, the index does not represent the absolute number of searches. Rather, the I4S reflects relative 'interest' in certain search key words. First the number of searches is normalized in cross-section. Searches on a keyword are shown as a fraction of all searches made on Google in a given week. If 100 million searches are conducted

¹⁶ They use the online search data provided by WordTracker Keyword Report. It was published by Rivergold Associates that tracks keywords submitted to the "web's largest meta-search engine"

¹⁷ Google changed its taxonomy in December 2011

¹⁸ For further details, see <http://support.google.com/insights/bin/answer.py?hl=en&answer=96693>

about 'apple' out of total 100 billion searches, then the index for that week is calculated as $1/1000$. This is the normalized index. Next, the normalized index is scaled on the timeline such that the maximum value equals 100. In the case of category-specific I4S, keywords need not be specified, as Google assumes the inclusion of all keywords in the category. However, category-specific I4S are only released as weekly changes (not as levels) reflecting the relative change in the 'interest' in certain key words and, thus, may vary beyond a range of -100%, and 100%.

The I4S in Socio-Economic Studies

The Center for Disease Control (CDC) is one of the earliest users of the I4S. The CDC collaborated with Google, Inc. to develop a model that detects flu outbreaks (Landau, 2008). Later, Ginsberg, Mohebbi, Patel, Brammer, Smolinski and Brilliant (2009) report that search queries could be used to detect influenza epidemics in areas with a large population of web search users. Kelly and Grant (2009) and Wilson, Mason, Tobias, Peacey, Huang and Baker (2009) find a significant relationship between Google flu trends and the official flu outbreak data of Australia and New Zealand respectively. McCarthy (2010) finds an association between relevant I4S and CDC statistics for suicide and self-injury. Penna and Huang (2009) suggest that the I4S can predict consumer sentiment and consumer confidence. They claim that six types of Google search indexes analyzed in their study are highly correlated with the University of Michigan's Index of Consumer Sentiments (ICS) and the Conference Board's Consumer Confidence Index (CCI). Askitas and Zimmermann (2009) report a strong correlation between specific online searches and unemployment data in Germany. Similarly, Suhoy (2009) reports a strong association between the I4S in the 'Human Resources (Recruitment and Staffing)' category and the unemployment rate in Israel. The I4S is reported

to be a leading indicator of the job openings ratio currently released at a monthly frequency by the Israeli government.

The I4S in Finance

Da et al. (2011) establish a relationship between online searches and returns on a sample of the Russell 3000 stocks. In particular, they utilize the I4S based on ticker symbols of firms as search keywords in predicting stock prices. They report that each standard deviation increase in the I4S is associated with nearly a 0.15% increase in the stock price in the second week that follows the increase in the I4S. However after the second week, the statistical significance of the I4S vanishes. Furthermore, Da et al. (2011) hypothesize that searches about a company's main products should be related to its stock price. The underlying argument for this hypothesis is that if the I4S contains fundamental information about a company's product-demand then it should have a positive relationship with the company's stock price. On the contrary, they detect a negative association between the online product searches and stock returns in the short run.

Unlike Da et al. (2011), who use ticker symbols as search keywords for the I4S, Bank and Larch (2011) use firm names arguing: 'it seems unlikely that the average Internet user searches for a firm on Google by ... "technical" stock symbols.' Their study focuses on the relationship between the I4S and stock liquidity¹⁹. Their model of monthly illiquidity is based on a panel data of companies and includes the lagged I4S and control variables such as market value and

¹⁹ They measure illiquidity as the ratio of the absolute daily return to trading volume summed over a month

interest rate. They report that the variation in search volume of a firm's name is significantly related to trading activity.

Vlastakis and Markellos (2012) examine the 30 largest stocks traded on the NYSE and NASDAQ. Similar to Bank and Larch (2011), they apply the firm names as search keywords. They reason that the firm name is better for extracting the I4S compared to ticker symbols because of its broader nature (as ticker symbols are primarily of interest to investors) and avoids problems associated with some tickers symbols having generic names²⁰. Their study focuses on examining if the I4S is related to stock volatility and trading volume. They demonstrate that variation in the I4S is significantly and positively associated, both at the individual stock and overall market levels, with volatility and trading volume.

Similar to Vlastakis and Markellos (2012), Drake, Roulstone and Thornock (2012) argue that the I4S is a measure of information demand. In particular, they extract the I4S related to the ticker symbols of the S&P 500 firms and employ a short-window event-study methodology around earnings announcements. They report that around earnings announcements the I4S is 13.2% greater than normal. They conclude that the I4S in the pre-disclosure period is associated with higher trading volume and earnings surprises.

The I4S in Real Estate

Some recent real estate studies suggest that the I4S could represent the underlying real estate fundamentals. Choi and Varian (2009) are the first to utilize the I4S in modeling real estate

²⁰ For example, "CAT", the ticker symbol of Caterpillar may be mixed with "cat" as an animal

variables. They point out that the I4S in the 'Real Estate' category has 6 sub-categories²¹: *Real Estate Agencies*, *Rental Listings and Referrals*, *Property Management*, *Home Inspections and Appraisal*, *Home Insurance*, and *Home Financing*. They examine the predictive ability of these sub-category-specific I4S on home sales as reported by the United States Census Bureau. They report a positive contemporaneous relationship of home sales with the I4S sub-category '*Real Estate Agencies*' and a negative relationship with the '*Rental Listing and Referrals*' sub-category.

Wu and Brynjolfsson (2009) apply AR(1) autoregressive models to a panel of state-specific quarterly data with sales volume, the I4S and the home price index controlling for states and quarters of the year in which the sales take place. In particular, they use the I4S data in the '*Real Estate*' and '*Real Estate Agencies*' sub-categories. They report that the I4S ('*Real Estate*' category and '*Real Estate Agencies*' sub-category) strongly predict the housing market sales and prices in the following quarter. They argue that 'by identifying correlations with prices and quantities we can draw inferences about changes in the underlying supply and demand.'

Hohenstatt, Kasbauer and Shaefer (2011) build further on Choi and Varian (2009) using a richer data set. They use the S&P Case Shiller Composite home price index for 20 metropolitan areas as a proxy for home prices. Other variables in their VAR framework include the I4S (sub-categories such as '*Real Estate Agency*', '*Homes for Sale*' and '*Rental Listings and Referrals*'), mortgage rates, the S&P 500 stock index, and the employment rate. They report that the I4S sub-categories ('*Real Estate Agency*', '*Homes for Sale*' and '*Rental*

²¹ According to Google, the taxonomy of the I4S was updated in December 2011. For example, '*Rental Listings & Referrals*' was replaced by '*Apartments & Residential Rentals*'.

Listings and Referrals’) provide information about prices and transactions in the near future. However, they also report some associations among the variables that are not intuitive. For example, the I4S in the ‘*Home Financing*’ sub-category has a negative relationship with home prices. They attribute this puzzling link to the environment of ‘high foreclosure’ that characterizes their sample period (2004-2010). Similarly, in their study, the I4S in the ‘*Real Estate*’ category has a negative contemporaneous relationship with home prices. They argue that the I4S is a measure of consumer sentiment and, in combination with the ‘real world data,’ may help to improve the efficiency of real estate markets.

Beracha and Wintoki (2012) analyze a panel of 245 Metropolitan Statistical Areas (MSAs) of the United States, on a quarterly frequency between January 2004 and June 2011. They collect home price index data from the Federal Housing Finance Agency (FHFA) and population data from the U.S. Census. For generating the I4S, they utilize specific keywords in the format of ‘keyword <name of city>’ such as ‘*real estate Miami*’ and ‘*rent New York*’. They conclude that the I4S ‘Granger causes’ the abnormal return in home prices.

Information Search Behavior

As discussed in the earlier section, information search about products and securities is an important economic phenomenon associated with prices and returns. Information search is considered to be a proxy for attention. For example, Da et al. (2011) argue that when you are searching for something on internet, you are paying attention to it. Investor attention is often focused on profiting from predictability (Seasholes and Wu 2004). Odean (1999) adds: ‘Investors do not buy all stocks that catch their attention, however, for the most part, they only

buy stocks that do so'. Therefore, events that signify information search from investors are associated with significant changes in short-run market prices and trading volume (Yuan, 2008). In other word, information seeking is a precursor to asset-price movements. Barber and Odean (2001) add: 'investors... now make decisions in a very different environment than investors in the past. They have access to far more data (and) can conduct extensive searches and comparisons on a wide variety of criteria.'

However, any new information regarding the overall market, a firm or its products must be comprehended by the investors in order to impact the stock price. Thus, the importance of investor attention is not so much an object of inquiry as is what information they are seeking.

Yuan (2008), Da et al. (2011), Drake et al. (2010) and Vlastakis et al. (2012) focus on information about firms or securities in general. They show that investor information search is related to variables such as return, volatility or trading volume.

Barber and Odean (2008) argue that retail investors are net buyers of the stocks about which they seek information. When buying a stock, investors have to choose from a very large set of options for which they have to search information. However, when selling, they are limited to the information of the usually fewer stocks they own. Because retail investors rarely short stocks (Da et al., 2011), their information search is dominated by buying decisions of the assets that they do not own. Therefore, the net effect of the retail investor attention implies the demand for the stock.

Studies including Da et al. (2011), Grullon, Kantatas and Weston (2004), Hohenstatt et al. (2011), Choi and Varian (2009), Wu and Brynjolfsson (2009) and Beracha and Wintoki (2012)

also show that consumer search about products are associated with product prices and trading, beyond investor searches.

The Nature of Online Information Search

Information search behavior, that generates the I4S series, may be driven by several factors other than demand or supply fundamentals. According to Bloch, Sherrell and Ridgway (1986), consumers gather product information on a regular basis from a variety of sources with two general objectives: to augment stores of product knowledge and to experience pleasure.

Kahneman (1973) suggests that humans possess a limited capacity for new information and attention is a cognitive resource in short supply. Therefore, the 'bounded rationality' in consumers leads to their limited capacity of collecting or interpreting information (Martín-Herráa, Rubel and Zaccour, 2008). Further, beyond personal preferences, public attention that leads to information searches is substantially influenced by external agents unrelated to fundamentals. For example, advertisers may be involved in 'bartering and stealing' the information availability to consumers (Sagarin, Britt, Heider, Wood and Lynch, 2005), and may even mislead the consumer to wrong information (McKean, 1973). Similarly, in addition to fundamental variables, consumer information searches about products may be attributed completely to media coverage such as television advertisements and newspapers as Thoenes and Gores (2012) report in their study about automobile consumers. In short, consumer information seeking behavior is not necessarily associated with the fundamental movements in the market and can not be inferred to be a proxy for the fundamentals, unless their association

with the fundamentals is directly established. If investment decisions are based on the I4S, it does not establish the I4S as an indicator of market fundamentals.

Nevertheless, public information searches have far-reaching implications for investments. For example, consumer attention is known to be associated with the stock returns of firms, above its impact on earnings and profits (Joshi and Hanssens, 2010). According to Luo (2006), increased consumer attention improves the overall firm value.

So long as the public information search is not driven by fundamental shifts in the market, its response to the stock price must be temporary. Therefore, information search-driven events can produce significant changes in short-run market prices and trading volume that often revert in the long run (Yuan, 2008, and Da, Engelberg and Gao, 2011).

Fundamentals of the Apartment Markets

Players in the apartment markets may be divided into three separate categories: space markets, asset markets and development industry (Geltner, 2001). According to Archer and Ling (1997) the three markets that 'play a role in determining commercial real estate prices' are space markets, capital markets and property markets. Rents and vacancy rates are among the fundamental variables that define space markets. Capitalization return is fundamental to asset (real property) markets. Capitalization return and stock return are fundamental to capital markets.

In this dissertation, I examine how the I4S is linked to the space and property markets and explain its association with REIT stock returns. In the space markets landlords and renters

represent the supply and demand sides of real estate space and determine the rents and the vacancy rates. Rosen and Smith (1983) posit that the vacancy rate reflects the difference between the demand and supply of rental units. Rent adjustment is a function of the excess demand or supply. The excess demand or supply is measured by the deviation in the vacancy rate from its natural state, also known as natural vacancy. Rosen and Smith (1983) also argue that similar to labor markets; housing markets maintain an inventory of vacant units to facilitate the search process. The natural vacancy rate implies a market with no excess demand or supply of apartments. However, the landlords need to optimize between the vacancy rates and the net rental rates. Thus, operating expense becomes an important determinant of the rent. While Rosen and Smith (1983) assume that the natural vacancy is a constant for a market, Grenadier (1995) argues that the natural vacancy rate is time varying and that the natural vacancy rate in a market could be fitted to a fourth-degree polynomial curve.

In the property (multifamily asset) markets, investors transact apartment real estate assets expecting asset value appreciation. Investors' asset valuation is based on the growth in expected income (rent) from the asset. Clayton, Ling and Naranjo (2007) argue that the asset price is a function of the income generated by an asset and the discount rate. Capitalization (cap) rate and, thus, the capitalization return on the asset relate its income to the value. The discount rate is determined by Treasury yields. Thus, empirically the capitalization rate is a function of income growth and Treasury Bond yield. Plazzi, Torous and Valkanov (2010) suggest that the cap rates follow an autoregressive process. An, Deng and Fisher (2011) further report that the cap rate is determined by expected future rent growth. They further argue that the expectations for future growth are based on the current rent growth. Thus, cap rates could

be modeled with the current rent growth. Moreover, they suggest that the cap rates are sensitive to investors' perception about credit tightness and the availability of debt capital reflected in CMBS issuances. Sivitanides, Southard and Wheaton (2001) suggest that the inflation rate is also a determinant of the capitalization rate among other variables.

Based on the discussions provided above, there are several ways the online consumer information search related to apartment rentals can be associated with prices and returns. If the searches are reflective of market fundamentals, their association with prices and returns is obvious. There is a possibility that the online searches may contain additional fundamental information not captured by the traditionally known indicators of the fundamentals. If so, the searches should be associated with prices and returns even after controlling for the known fundamentals. Additionally, if the searches are perceived to be related to fundamentals, then irrespective of whether they indeed are reflective of the fundamentals or not, they should be associated with the variables that characterize multifamily real estate markets.

Predictability in Asset Prices

Predictability and Market Efficiency

In efficient markets, investors react to the new information quickly in order to maximize returns. Thus, the new information is instantly priced into assets. The residual price movements are assumed to be random events that may not be predicted. However, the existence of predictability in asset returns, stocks in particular, has been debated in academia for over a century. Ling, Naranjo and Ryngaert (2000) and Ling (2005) summarize the progress of research on the predictability of stock prices and returns. Early studies based on the Efficient

Market and Random Walk hypotheses strongly rejected the possibility of predictions. However, predictability of stock prices and returns has been reported over time with the advances in asset pricing theory, behavioral finance and computational sophistication.

In theory, predictability in stock prices is an anomaly to the efficient market hypothesis. Yet, applying the knowledge of such anomalies to investment strategies may lead to abnormal returns. According to Merton (1987), the opportunity to achieve abnormal returns from the knowledge of an anomaly may persist for a long time. He suggests that even if the anomaly is published in a scientific journal, the diffusion rate of the knowledge is likely to be significantly slower and the predictive abilities of the anomaly may continue adding to the inefficiency of the market. Merton argues that ‘...an anomaly must in fact exist for a long enough period of time to permit sufficient statistical documentation.’ Therefore, wider recognition of an anomaly may lead to predictability in asset returns.

Predictability in Real Estate Returns

Real estate markets are known for their lack of efficiency and are relatively more predictable. Chung, Fung, Shilling and Simmons-Mosley (2005) report that hedge funds have superior returns forecasting capability when it comes to real estate investments. Several other studies have also reported the presence of predictability in various real estate asset returns. Mei and Liu (1994) find that the expected excess return on real estate investments is a linear function of past economic state variables known to investors after controlling for currently available information. Nellling and Gyourko (1998) adopt an autoregressive modeling approach to model the excess return of a REIT on monthly returns data. They report that equity REITs became

more predictable since the 'new era' of REITs that started in 1992. Finance studies such as Petkova (2006) and real estate studies such as MacKinnon and Zaman (2009), Clayton and MacKinnon (2007) and Serrano and Hoesli (2007) argue that lagged Fama-French factors are good predictors of stock returns in general and REIT returns in particular.

Predictability and Real Estate Market Fundamentals

It may be argued that the I4S series (in '*Real Estate*' category and its sub-categories) are merely the representation of information searches that investors may be wrongly interpreting as a proxy for demand from the end-users of the real estate assets. Whether the information search behavior is truly associated with market fundamentals is an open question. Rajgopal, Venkatachalam and Kotha (2001) demonstrate that investors in the stock market watch web traffic (on firms' websites) although it 'contains no predictive information about future revenues once past revenues are accounted for'. Even if a relationship could be established between search activity and prices, the relationship does not provide evidence that searches offer a proxy for demand. Fama and French (1988) argue that 'predictive regressions ... cannot identify the economic reasons' underlying forecasting ability. Joseph, Wintoki, and Zhang (2011), who relate the I4S to stock returns, argue that individual investors 'may be prone to invest for a wide variety of reasons unrelated to fundamentals.' Similarly, Ghysels, Plazzi, Torous, and Valkanov (2012) suggest that real estate markets, in particular, may be driven by factors other than fundamentals.

Synthesis of the Literature

Despite the efficient market premise inherent in the widely accepted random walk hypothesis, in the pursuit of wealth maximization, investors watch certain new information that may help in predicting future stock prices. To some extent, real estate prices are predictable, REIT stock prices in particular. Public attention or information seeking behavior related to products is one of the trends that investors watch in order to predict asset returns. Many challenges inherent in traditional methods of measuring public information seeking behavior are overcome by the public availability of online search trends data released by the Google Insights for Search. Several studies have reported predictive capabilities of the I4S in modeling socio-economic and financial variables, such as unemployment rate, suicide rate, flu trends, stock prices, stock trading volume and stock volatility among others. Some studies also report the predictive capabilities of the I4S as far as real estate sales and prices are concerned. Based on the statistical significance of the I4S as a predictor, some real estate studies argue that the I4S (related to real estate searches) is a proxy for real estate demand. However, the I4S may be driven by supplier-side searches and even by factors such as recreational information searches that have no clear relationship with either supply or demand. Thus, the fact that the I4S may be statistically significant, does not confirm that it is a legitimate indicator of market fundamentals.

CHAPTER THREE: DATA AND METHODOLOGY

This section starts with a discussion on data summary and sources. The data summary includes results from econometric due diligence tests. Finally, explanations for the proposed empirical models and the expectations with respect to the results are presented.

Keyword Selection for I4S

A potential issue with empirical studies based on the I4S series is related to the sensitivity of the I4S to the selection of keywords. To assess housing markets, Beracha et al. (2012) select 'real estate' and 'rent' suffixed by the market name arguing the generality of these keywords. However, the subjectivity involved in the selection of keywords cannot be ignored. Subtle variation across the keywords such as 'home' and 'homes' provides noticeably different I4S series. Hohenstatt et al. (2011) point out that the I4S for 'homes for sale' exceeds the I4S for 'home for sale' by a factor of six.

Another issue with the keyword selection is related to the intention of the internet user. A person searching for 'real estate' may be a prospective buyer, renter, or even a window shopper. Rangaswamy, Giles and Seres (2009) argue: 'Some of the searches conducted on search engines are purely for learning, enjoyment, or entertainment'. Such searches may add substantial noise to the I4S data creating further challenges to establishing the I4S as a proxy for market fundamentals.

Some studies²² avoid the subjectivity related to keyword selection by resorting to the ticker symbols of firms arguing that ticker symbols are unique and more popular among informed investors. However, an argument can be made that ticker symbols may not comprehensively represent the searches made by investors who may use other keywords (such as variations in firm names). Also, as Rangaswamy et al. (2009) argue, searches on ticker symbols are not necessarily related to investment decisions.

Instead of the keyword-specific I4S, applying a combined index of the I4S for a category of keywords addresses these issues. Google's website specifies that an I4S category 'determines the context' for the search term²³. Search categories are assigned based on the website navigation pattern of the internet user immediately before and after a search is executed. An internet user may search for 'apple' for many different purposes: for example, buying fruits or smart phones. The I4S categories would distinguish between a search on 'apple followed by a visit to, say, a grocery store website from another search with the same keyword, but followed by a visit to, say, an electronics shop website. Thus, search categories mitigate the issue of search intention to a large extent. Moreover, in the case of apartment rental searches, the '*Apartments and Residential Rentals*' sub-category includes all variations in the keywords (such as 'apartment', 'rent apartment', 'apartment rentals', etc.) and, thus, addresses the issue of the I4S's sensitivity to the selection of keywords.

In this dissertation, I focus on the online consumer searches in residential apartment markets. I argue that investors consider this attention as new information that represents apartment market

²² Such as Da et al. (2011) and Joseph et al. (2012)

²³ See <http://support.google.com/insights/bin/answer.py?hl=en&answer=94792>

fundamentals and factor it into pricing the apartment REIT stocks. Theory suggests that although investors are sensitive to new information, the degree of response to new information may vary. Some new information may require ‘a greater effort of processing’ and their complexity may reduce the degree of comprehension (Kahneman, 1973, Barber and Odean, 2008). Peng and Xiong (2006) report that in such situations, investors resort to ‘category learning’ behavior. Thus, investors may ignore specific information and rather focus on market and sector (‘category’) level information. In other words, apartment REIT investors are more likely to focus on the I4S in a broader category of ‘*Apartment and Rental Listings*’ than examining a virtually unlimited set of the I4S based on individual keywords related to rental searches. Indeed, Bucklin (2007) reports that category-specific (‘unbranded’) keywords (such as ‘cheap hotels’) have stronger impact on the conversions (of online searches into sales) compared to specific (‘branded’) keywords such as ‘Hilton Hotels’.

Based on the arguments discussed above, I utilize the I4S based on search categories rather than keyword-specific I4S. The sub-category that I use combines all searches that, according to the search engine’s algorithm, relate to apartment rentals searches. The typical search terms in this sub-category are: ‘apartment’, ‘apartments’, ‘rent’, ‘for rent’ and ‘rentals’.

I4S and the Apartment Rental Markets

Some MSAs are dominated by renters while some others by homeowners. For example, residential apartment markets in New York have been resilient and witnessed a relatively shorter downturn and very low vacancy rates during the recent crisis. Due to excessive rental

demand, Forbes ranks New York among the worst cities for renters²⁴. On the other extreme are markets such as Houston, TX that are dominated by homebuyers. Due to lower regulation, new homes are easily built and are more affordable in Houston. This leads to lower demand pressure for apartment rentals. For a preliminary indication of whether the I4S in the '*Apartments and Residential Rentals*' sub-category truly reflects rental searches by tenants, I present graphical comparisons to compare respective I4S in extreme market scenarios, both over time and across locations. **Figure 1** compares the online rental searches in these two markets during the period between 2004 and 2011. Except during the period of economic crisis (2007 Q3 to 2010 Q1), when the I4S across the two markets overlap, rental searches in New York are significantly higher compared to Houston. This supports the argument that the rental I4S reflects rental demand.

Figure 2 compares real rental rates to the online rental search interest in four MSAs included in the study. Dotted curves depict polynomial trends fitted to the online search data. Apparently, the search trends co-move with rental rates. These figures provide some preliminary evidence that in a bi-variate relationship, the rental I4S may be reflective of net rental space demand.

Stationarity and Seasonality in Time Series Data

By definition, the statistical properties of a stationary time series process, such as mean, variance and autocorrelation remain constant over time. Predictive time-series models are based on the assumption that these properties shall not change over time. However, several

²⁴ <http://www.forbes.com/sites/morganbrennan/2012/06/14/the-best-and-worst-cities-for-renters-2/>

financial time series such as stock prices are non-stationary. I test all time series data for stationarity. In particular, I apply the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (null hypothesis: the process is stationary), the Phillips-Perron (PP) test (null hypothesis: the process has a unit root) and the Augmented Dickey-Fuller (ADF) test (null hypothesis: the process has a unit root) to the data. To understand the nature of the error term, I apply the Von-Mises (MN) type white-noise test statistic for each model that is based on the null hypothesis of white noise.

When analyzing quarterly data (e.g. panel data analyses), I calculate the I4S as the mean of all weekly I4S in a quarter. The variable reflects the average level of the I4S during all weeks in a quarter²⁵. However, for stock modeling, in addition to the I4S I also examine ‘abnormal I4S’ (abI4S) models following Da et. al (2011). The *abI4S* at time t is defined as the deviation in I4S from the median of its recent values:

$$abI4S_t = I4S_t - (\text{Median of the I4S in recent } k \text{ weeks}) \quad \text{--Eq(1)}$$

In the analysis I examine many values of k to establish the robustness of the test starting from $k=3$ up to $k=26$.

For the panel data, I apply two stationarity tests (the Im-Pesaran-Shin (IPS) and Maddala-Wu tests (MW) for each variable recorded across the 21 MSAs. The null hypotheses for both tests are the presence of unit root. All variables are stationary.

²⁵ See Appendix Note 1 for further discussion

Beyond unit roots (i.e. absence of stationarity), confounds may stem from the presence of seasonality in the process. Therefore, I include appropriate indicators (3 quarter dummies in analyses with quarterly data and 52 week dummies for weekly data analyses) to control for seasonality.

Data Sources

Online search data is available from the Google search engine's Insights for Search ('I4S') tool. I focus on the I4S index in 'Apartment and Residential Rentals' sub-category from the 'Real Estate' category of the I4S tool. In the remaining parts of this dissertation, 'the I4S' refers to this particular Google search index unless stated otherwise. In a robustness analysis, I also extract a keyword ('REIT') specific online search index data aggregated at the national level. The weekly data is converted to lower frequencies (e.g. monthly or quarterly) by averaging the weekly data across the appropriate time-windows. The analysis uses the I4S data extracted for a specific time-period (i.e. January 2004 to December 2011). I filter the I4S data for specific geographies (e.g. nationally aggregated for the U.S. or at MSA levels). I4SL refers to the average weekly I4S during the last four weeks of a quarter. The I4SF is the average weekly I4S during earlier weeks in a quarter.

Quarterly NOI, operating expenses (OPEX), vacancy rates (VAC) and capitalization return (CR) data for each MSA are extracted from the Custom Query Tool of the *NCREIF Property Data-Research* database. **Table 1** provides the summary of balanced panel data set aggregating quarterly information for 21 metropolitan statistical areas (MSA) of the United States during 27 quarters (2005 Q2 to 2011 Q4). From the NCREIF database, all MSAs for which complete

data was available for this analysis²⁶ are included. The list of the MSAs included in the study is provided in Appendix **Table 10**.

NCREIF reports property-level data in an MSA averaged over a quarter. However, for several MSA-quarters, the sample size is small (e.g. 4 properties). To address this issue, the number of properties from which the NCREIF statistic has been calculated is included in the models. In particular, I introduce a low observation indicator variable (LOBS) that assumes a value of 1 if the sample size is less than 30, 0 otherwise. 47% of the vacancy rate and 60% of rental rate observations fall in the LOBS=1 category.

NCREIF calculates per-square foot net rental rate by adding the Operating Expenses to the NOI and dividing the sum by the total area. Dividing the net rental rate by occupancy rate provides gross rental rates. I further standardize the gross rental rates at the 2004 Q1 consumer price level to calculate the real rental rate (RENT). In particular, the consumer price indexes (CPI) for the following quarters are shown in multiples of the CPI during 2004 Q1 and used as denominators for the standardization. Thus, RENT and OPEX refer to inflation adjusted quantities at per square foot level. '*Percent Leased by Quarter*' query of the *NCREIF Property Data-Research* database provides the vacancy rate (VAC) data. The NOI, OPEX and the corresponding property count data come from '*Expense Details*' query. I extract the capitalization return (CR) and the corresponding property count data from '*Leveraged Return*'

²⁶ Rental rate and operating expense data for San Francisco for the 2010 Q3 was imputed by straight-lining the adjacent quarter values. The I4S data from Miami was applied to Fort Lauderdale, FL. The Washington DC I4S data was applied to Bethesda, MD. Also, the same I4S data was repeated for Dallas, TX and Fort Worth, TX metros.

query of the *NCREIF Property Data-Research* database. Also, I calculate the quarterly percent rental growth rate (RGROWTH) for each MSA from the RENT data.

The Federal Reserve Senior Loan Officer Survey provides quarterly data on the respondent's perception of credit-tightness (CREDIT). CREDIT is the net percentage of respondents claiming tightened credit. The CRE Finance Council (CREFC) offers quarterly aggregated data on the total dollar value of CMBS issuances. The Federal Reserve provides the monthly averages of the 10-year Constant Maturity Treasury Bond and 1-month Constant Maturity Treasury Bill. I convert them to quarterly data by averaging. TBILL is the quarterly average of the yield on the latter. SPREAD is the yield-spread across these two security types.

RGROWTHQ is the quarterly average of the monthly percent change in the Consumer Price Index of residential rents reported at the nationally aggregated level available from the Bureau of Labor Statistics (BLS). American Housing Survey (AHS) provides the quarterly vacancy rates reported in primary rental residences (VACN). I apply RGROWTHQ and VACN that are aggregated nationally to model the quarterly REIT Index returns²⁷.

The Apartment REIT stocks data is available from the CRSP/Ziman Multifamily REIT index. The daily REIT index is averaged each week to calculate the weekly returns. I extract the systematic risk factors (e.g. excess returns on the market portfolio, the Fama-French factors and the Carhart's momentum factor) from Kenneth-French's website.

²⁷ See Appendix Table 22.

Data Summary

Table 1 provides the summary of the panel data. The weekly I4S across the MSAs and quarters averages at 6.25 %. The I4S tends to be higher during the initial weeks in a quarter (average: 7.5%) compared to the last four weeks (average: 3.6%). The average vacancy rate is 6.6%. The average real rental rate and operating expenses are \$3.4 and \$1.4 respectively on per square foot basis. Real rents exhibit a quarterly average growth of 2.3%. The quarterly rental growth across MSA-quarters averages at 2.3%. However, the data is fraught with extreme values ranging between -71% and 421%. Very small sample sizes characterize several of such extreme statistics. For example, with a small sample of 4 properties, the average real rental rates increase from \$3/SF to over \$15/SF between 2010Q1 to 2010Q3 in San Francisco. To address this issue, I Winsorize the data. In particular, I cap (and floor) the rental growth rates within three standard deviations of the original data, based on Harrison, Panasian and Seiler (2011). After the Winsorization, the mean and standard deviation of rental growth reduce to 1.4% and 9.0% respectively.

On average, the appraised asset values appreciate by 0.7% per quarter. During the period of analysis (2004 to 2011), \$59 billion worth of CMBS were issued per quarter, on average. In the Federal Reserve's survey, the proportion of people who believed that the credit was tight exceeded those who had an opposite view by 27%. Average quarterly inflation was nearly 0.6%. Most variables in the panel data set are stationary based on both Im-Pesaran-Shin and Maddala-Wu tests. These tests are based on the null hypothesis of unit root in panel data. The I4SL passes only one of the two stationarity tests (i.e. Maddala-Wu).

I present the correlations between the panel data variables in **Table 2**. The various I4S measures are highly correlated with each other. Also, the correlation between RENT and OPEX is nearly 0.9. The perception of credit tightness (CREDIT) has high, yet negative correlation (-0.7) with the capitalization return (CR). The CMBS issuances exhibit a high correlation (0.7) with the interest rate (BOND).

More detailed MSA specific data summaries on selected variables are provided in **Appendix Tables 12-16**. It is evident from the **Appendix Table 12** that during the period of analysis, the average online rental search interest (the I4S) increased substantially in some markets such as Portland (OR), Baltimore (MD) and Tampa (FL) while it decreased noticeably in some others such as West Palm Beach (FL), Houston (TX) and Los Angeles (CA). The average vacancy rate (**Appendix Table 13**) is the highest in Phoenix- AZ (9%) and Charlotte-NC (8%) and the lowest in MSAs such as Bethesda-MD (5%) and Fort Lauderdale-FL (6%). During 2006Q2, the vacancy rate²⁸ reported in San Francisco was 18.8%. However, around the same time in 2006Q1, the average vacancy rate in Fort Lauderdale²⁹ was 1.6%. **Appendix Table 14** suggests that the average real rental rates³⁰ are the highest in New York and San Francisco (\$6.9/SF, \$5.3/SF respectively) and the lowest in Charlotte (\$2.0/SF) and Atlanta (\$2.3/SF). During 2010Q4, San Francisco reported an average real rental rate³¹ of \$15.2/SF while Portland-OR reported a small rental rate³² of \$1.7/SF. During the period of analysis (**Appendix Table 15**), average real operating expenses per square foot are \$3.0 in New York and \$1.0 in

²⁸ Sample size = 10

²⁹ Sample size = 24

³⁰ At 2004 Q1 levels. Not shown in the table. Detailed tables available upon request.

³¹ Sample size = 4. Not shown in the table. Detailed tables available upon request.

³² Sample size = 49. Not shown in the table. Detailed tables available upon request.

Phoenix (AZ). The highest real operating expenses³³ per square foot were recorded in San Francisco (\$5.4) during 2010Q4 and the lowest³⁴ in Dallas (\$0.42) during 2008Q2. Between 2004 and 2011, the quarterly appreciation in appraised values of multifamily assets was the highest in New York (7.0%) and the lowest in Dallas-TX (3.0%, **Appendix Table 16**). During 2005 Q2, West Palm Beach-FL witnessed a quarterly capitalization return³⁵ of 22.8% while Charlotte-NC witnessed a fall of -0.1% in the appraised asset values.

In summary, the 21 MSAs included in the study offer a heterogeneous sample. The contrasts in the variables across these markets allow detailed statistical documentation of the significant associations among them.

Table 3 describes the data used in the REIT Index modeling. The REIT index yields an average of 0.3% weekly return ranging between -19% and 23% and has a standard deviation of 3%. The risk-adjusted market return (MKT) has a relatively lower weekly return of 0.1% and a standard deviation of 3%. The portfolio of Small minus Big market-cap stocks yields an even smaller weekly return of 0.03% with a lower standard deviation of 1%. The portfolio of High minus Low book-to-market ratio stocks has a similar profile of weekly yields with an average return of 0.03% and a 1% standard deviation. The Carhart's momentum factor has nearly a zero mean and varies in the range of -17% to 12% with a standard deviation of nearly 3%. The weekly I4S in the '*Apartment and Residential Rentals*' sub-category averages at 6% during

³³ At 2004 Q1 levels. Sample size = 4. Not shown in the table. Detailed tables available upon request.

³⁴ Sample size = 49. Not shown in the table. Detailed tables available upon request.

³⁵ Sample size = 11. Not shown in the table. Detailed tables available upon request.

2004 to 2011 and varies between -28% and 39% with a standard deviation of 14%. All variables are stationary. The abnormal I4S (i.e. I4S in excess of the median of recent 6 observations) averages at 7% and has a lower standard deviation of 8% compared to the I4S. **Figure 3** compares the I4S with the abnormal I4S (abI4S) for the period of analysis. The abI4S series exhibits lower-dispersion around its mean. Although less pronounced in the abI4S, seasonal variations can be seen in both the I4S measures. **Table 4** presents the correlations between the stock modeling variables. The I4S exhibits low correlation with all stock portfolio returns. However, the REIT portfolio return is positively correlated with the Market (correlation = 0.6) and Fama-French portfolio returns (correlations 0.2, 0.5 and 0.5) and negatively correlated with the Carhart’s momentum factor (correlation = -0.5).

Models

I4S and Market Fundamentals

Vacancy Rate

Grenadier (1995) and Voith and Crone (1988) detail the association between vacancy rate and natural vacancy rate. The current deviation of vacancy rates from the natural vacancy rate determines the degree to which a real estate market is out of equilibrium. The observed vacancy rate (VAC) in a market i during quarter t is the sum of the natural vacancy rate (V_n) and the deviation from it:

$$VAC_{i,t} = V_{n,i,t} + \varepsilon_{i,t} \quad \text{EQ(2)}$$

Local fixed effects and time-varying macroeconomic factors determine the natural vacancy rate as follows:

$$V_{n,i,t} = \alpha_0 + f(t) \quad \text{EQ(3)}$$

For estimation purposes, the macroeconomic factors are shown as a polynomial of time:

$$f(t) = \sum_{j=1}^k \alpha_{1,j} \cdot t^j \quad \text{EQ(4)}$$

Grenadier proposes a fourth degree polynomial (i.e. $k=4$). The deviation $\varepsilon_{i,t}$ exhibits persistence (ρ) such that it is an MA(1) process:

$$\varepsilon_{i,t} = \rho_i \cdot \varepsilon_{i,t-1} + u_{i,t} \quad \text{EQ(5)}$$

Cause-Effect Relationship between the I4S and VAC

The direction of causality between the I4S and the vacancy rate (VAC) is unclear. Moreover, if they share a cause-effect relationship, whether they granger cause each other or the causality is instantaneous needs to be tested empirically. According to Granger (1969), if the current value of X_t (the effect) is better “predicted” when the present value of Y_t (the cause) is included in the “prediction” model than it is not, then Y and X cause each other in instantaneously.

Appendix Table 11 lays out the causal relationship between the two variables for each MSA. The results of the causality analyses are mixed. Moreover, there is some evidence that in several markets, there is a two-way instantaneous causality between the two variables. Because vacancy rates are ‘state’ variables and likely reported during the end of each quarter, to model

the vacancy rates, I calculate a specific I4S as the average of the search interest during the last four weeks³⁶ of a quarter (specified as ‘I4SL’).

Empirical Models for the I4SL and VAC

The full specifications of the endogenous variables (I4SL and VAC) are as follows:

$$I4SL_{i,t} = \omega_{0,i} + \omega_1 \cdot VAC_{i,t} + \sum_{k=1}^4 \omega_{1+k} \cdot I4S_{t-k} + \omega_6 \cdot I4SF_{i,t} + \omega_7 \cdot LOBS_{i,t} + W_8 \cdot Q_t + W_9 \cdot I_{i,t} + \varepsilon_{i,t} \quad \text{EQ(6)}$$

$$VAC_{i,t} = \gamma_{0,i} + \sum_{j=1}^4 \gamma_{1,j} \cdot t^j + \gamma_5 \cdot I4SL_{i,t} + \sum_{j=1}^4 \gamma_{5+j} \cdot VAC_{i,t-j} + \gamma_{10} \cdot LOBS_{i,t} + Y_{11} \cdot I + \varepsilon v_{i,t} \quad \text{EQ(7)}$$

In all equations, i indexes MSAs and t indexes time in quarters. From **EQ(6)**, the mean I4S during the last four weeks of a quarter (I4SL) is contemporaneously determined by the vacancy rate (VAC), the mean I4S during the earlier weeks of a quarter (I4SF), quarterly seasonality (Q), low-observation indicator (LOBS) and MSA fixed effects (I). In addition, the I4SL is also influenced by its own lagged values during the past year. LOBS is an indicator specifying whether the sample from that the vacancy rate data is collected has substantial number of observations. For observations less than 30, LOBS =1, 0 otherwise. W_8 and W_9 are respectively 1x3 and 1x20 matrices of regression coefficients. Q is a 3x1 vector of quarterly seasonality indicators. I is a 20x1 vector of indicators specifying the MSA fixed effects. ε_i is the error term. If the I4S is a proxy for net demand, ω_1 should have a positive sign. Also, I expect that ω_6 has a positive sign.

³⁶ I also examine the model that replaces the average of the last 4 quarters of the I4S by the quarterly averaged I4S. The results are similar.

The model for VAC (**EQ(7)**) is developed from further simplification of equations 2-5 and including the I4SL as an additional determinant. Thus, the vacancy rate (VAC) is determined by the polynomial time trends (t to t^4), the I4SL, lagged VAC, low-observation indicators (LOBS) and the MSA fixed-effects (I). Similar to **EQ(6)**, for observations less than 30 of an MSA-quarter, LOBS =1, 0 otherwise. Y_{11} is a 1x20 matrix of regression coefficients and I is a 20x1 vector of indicators specifying the MSA fixed effects. εv is the error term. In an alternate specification, I also include seasonality controls in the vacancy rate model.

As a robustness check, I also run the same set of analysis by replacing the I4SL by the I4S. As argued earlier, I expect a positive sign for γ_5 . Because the vacancy rate is known to show persistence (Voith and Crone, 1998), in the short run the autoregressive component should have a positive coefficient. However, because the deviation from a natural state is considered disequilibrium, the vacancy rate will have a tendency to offset its changes in the longer run. Thus, different earlier lags of the AR components may have different signs.

Two-Stage Least Square (2SLS) Models

To address the potential endogeneity issue, I apply the two-stage least square (2SLS) method to the models of the I4SL and VAC. In the first stage, only reduced-form models are run that exclude the VAC and I4SL from the respective sets of independent variables in the two models. Also, all exogenous variables from the system (i.e. from the two proposed models: EQ 8 and EQ 9) are included in both the “reduced-form” models. The reduced form model for I4SL is as follows:

$$\begin{aligned} I\hat{4}SL_{i,t} = & \omega'_0 + \sum_{k=1}^4 \omega'_{1+k} \cdot I4S_{t-k} + \omega'_6 \cdot I4SF_{i,t} + \sum_{j=1}^4 \omega'_{6+j} \cdot t^j + \sum_{j=11}^{14} \omega'_j \cdot VAC_{i,t-j} + \\ & \omega'_{15} \cdot LOBS_{i,t} + W'_{16} \cdot Q_{i,t} + W'_{17} \cdot I_{i,t} \end{aligned} \quad \text{EQ(8)}$$

The reduced form model for $I\hat{4}S_{i,t}$ is similar except that the RHS does not include I4SF.

Similarly, the reduced-form model for VAC is as follows:

$$\begin{aligned} V\hat{A}C_{i,t} = & \gamma'_0 + \sum_{k=1}^4 \gamma'_{1+k} \cdot I4S_{t-k} + \gamma'_6 \cdot I4SF_{i,t} + \sum_{j=1}^4 \gamma'_{6+j} \cdot t^j + \sum_{j=11}^{14} \gamma'_j \cdot VAC_{i,t-j} + \\ & \gamma'_{15} \cdot LOBS_{i,t} + Y'_{16} \cdot Q_{i,t} + Y'_{17} \cdot I_{i,t} \end{aligned} \quad \text{EQ(9)}$$

The fitted values of the endogenous variables from the reduced form models (e.g. EQ 8) are applied to the full model specifications (e.g. EQ 7).

Rental Rate

According to Rosen and Smith (1983), the real rental rate (RENT) is a function of excess demand or supply for rental housing and the real operating expenses (OPEX). Assuming it to be linear, the relationship is:

$$RENT_t = \pi + \pi_1 \cdot OPEX_t + \pi_2 \cdot VAC_t \quad \text{EQ(10)}$$

To examine if the I4S contains additional information that determine the rental rates, the I4S could be included as an additional variable in the model:

$$RENT_t = \pi + \pi_1 \cdot OPEX_t + \pi_2 \cdot VAC_t + \pi_3 \cdot I4S_t \quad \text{EQ(11)}$$

To allow for the autoregressive nature of the rental rates, I develop the empirical model of the panel data corresponding to EQ (11) as follows:

$$\begin{aligned}
 RENT_{i,t} = & \pi_0 + \pi_1 \cdot I4S_{i,t} + \sum_{j=1}^4 \pi_{1+j} \cdot RENT_{i,t-j} + \pi_6 \cdot OPEX_{i,t} + \pi_7 \cdot VAC_{i,t} + \\
 & \pi_8 \cdot LOBS_{i,t} + \pi_9 \cdot Q_{i,t} + \pi_{10} \cdot I_{i,t} + \varepsilon_{i,t}
 \end{aligned}
 \tag{EQ(12)}$$

RENT is the average potential gross rental rate in real terms³⁷, OPEX equals the average operating expenses in real terms³⁸, VAC is the apartment vacancy rate. The last three terms have similar meanings as discussed earlier. If the rental prices are informed by online searches after controlling for the association between the I4S and the vacancy rate, π_1 should be positive. Because the landlords adjust the rent to offset the operating expense (Rosen and Smith, 1983), OPEX should also have a positive association with RENT. Increased vacancy rates reflect reduced net demand. Therefore, I expect that π_7 will have a negative sign.

Capitalization Return

Capitalization rate is a ratio used to value an income-producing asset based on income returns. Capitalization return in such assets is the return attributed to value-appreciation. Therefore, the determinants of the capitalization returns should be similar to the determinants of the capitalization rate. While the capitalization rate data is not available from NCREIF, the dataset does provide details on capitalization returns. The capitalization rate is a function of rent growth (Clayton, Ling and Naranjo, 2007, Plazzi, Torous and Valkanov, 2010, An Deng and Fisher, 2011), Long-term Treasury Bond Yield (Clayton, Ling and Naranjo, 2007, An, Deng and Fisher, 2011, Sivitanides, Southard and Wheaton, 2001), inflation rate (Sivitanides, Southard and Wheaton, 2001), CMBS issuance and the perception about credit tightness (An,

³⁷ Calculated by dividing the per square foot rental rate by occupancy rate and the consumer Price Index(CPI)

³⁸ Per square foot rate adjusted by the CPI

Deng and Fisher, 2011). Most studies also claim that capitalization rates are localized across markets. Based on these studies that focus on real estate capitalization rates, to examine the relationship between the apartment cap rates and the I4S, I develop the following model:

Empirical Model for Capitalization Return

$$CR_{i,t} = \vartheta_0 + \vartheta_1 \cdot I4S_{i,t} + \vartheta_2 \cdot RGROWTH_{i,t} + \vartheta_3 \cdot CREDIT_t + \vartheta_4 \cdot CMBS_t + \sum_{j=1}^4 \vartheta_{4+j} \cdot CR_{i,t-j} + \vartheta_9 \cdot TBILL_{i,t} + \vartheta_{10} \cdot SPREAD_{i,t} + \vartheta_{11} \cdot LOBS_{i,t} + V_{12} \cdot Q_t + V_{13} \cdot I_t + \varepsilon_{C_{i,t}} \quad \text{EQ(13)}$$

CR is the average quarterly MSA capitalization return on apartments and RGROWTH refers to quarterly percent growth in the rental rate. CREDIT equals the net percentage of survey respondents claiming tightened credit for commercial real estate from the Federal Reserve Senior Loan Officer Survey. CMBS denotes the quarterly issuance of CMBS reported by CRE Finance Council. SPREAD reflects how expensive long term debt instruments (such as multifamily mortgages) are compared to the risk-free rates. TBILL is directly associated with the inflation rates.

If the I4S is perceived as a measure of apartment demand by the multifamily asset investors beyond the already known determinants of the capitalization return, we should expect a positive coefficient for the I4S. Rent growth should be positively associated with asset value returns. Tightening credit makes asset financing tougher, thus reducing the demand for such assets. Therefore, I expect that CREDIT has a negative coefficient. High interest rates reflect increased cost of capital that should diminish asset value appreciation controlling for other factors. Being associated with the inflation rate, TBILL is expected to be positively associated

with the capitalization return. Increased CMBS issuance reflects a heated market for asset transactions that should be positively associated with the capitalization return. However, if the CMBS issuance is reflective of excessive supply for new space, it could also have a negative association with the capitalization return.

I4S and REIT Returns

Short-Run Abnormal Returns in Apartment REITs

Previous studies such as Ling and Naranjo (2003) and Serrano and Hoesli (2007) have applied the vector auto regressive (VAR) method to Fama-French factors in forecasting REIT returns. To test the short-run relationship between the apartment REIT returns and the I4S, I run variations of the VAR models in which the I4S and REIT are endogenous to the system whereas the systematic risk factors (MKT, SMB, HML and MOM) are determined externally in a contemporaneous fashion.

REIT = return on CSRP/Ziman Multifamily REIT index in excess of the risk-free rate

MKT = Excess return on the CAPM 'Market' factor

SMB = 'Small-Minus-Big' Fama-French factor

HML = 'High-Minus-Low' Fama-French factor

MOM = Carhart's Momentum factor

In particular, I run the following VAR model:

Empirical Model for REIT Returns

$$\begin{bmatrix} REIT_t \\ abI4S_t \end{bmatrix} = \begin{bmatrix} \alpha & 1 \\ \alpha & 2 \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix} \begin{bmatrix} REIT_{t-1} \\ abI4S_{t-1} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} \\ \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} \end{bmatrix} \begin{bmatrix} MKT_t \\ SMB_t \\ HML_t \\ UMD_t \end{bmatrix} \quad \text{EQ(14)}$$

Response of REIT returns to Impulse in the I4S

Several studies in stock returns literature (Hasbrouck, 1991, Statman, Thorley and Vorkink, 2006, Sardosky, 1999) in general and REIT literature (Glascok, Lu and So, 2002, Kim, Leatham and Bessler, 2007) in particular have examined the persistence of the response of a dependent variable to shocks in an independent variable using impulse response function (IRF). According to Garratt, Lee, Pesaran, and Shin (2000), the IRF ‘relies exclusively on time-series observations to identify long-run relationships if they exist’. Pesaran and Shin (1998) argue, ‘an impulse response function measures the time profile of the effect of shocks at a given point in time on the (expected) future values of variables in a dynamical system’. In other words, the IRF describes the outcome of a conceptual experiment in which the effect of a hypothetical vector of shocks hitting the economy at time t is compared with a base-line profile at time $t+h$, given the system’s history. The shape of the impulse and the consistency in the signs of its confidence intervals over the following weeks provides insights about the persistence of the response over time.

I focus on the sensitivity defined as $\frac{\delta REIT_{t+h}}{\delta \varepsilon_{I4S,t}}$ that describes the marginal response of h step-ahead $REIT$ to a one-time impulse in the $I4S$ introduced at time t . In theory, a unit shock is applied, at time t to the error term of the equation with $I4S$ as a dependent variable. $REIT_t$ can

be estimated from the actual values of lagged determinants as specified in the VAR model. A one-step ahead expected value of $REIT_{t+1}$ (i.e. $E[REIT_{t+1}]$) can be estimated by substituting the $REIT_t$ in the equation and assuming zero error terms. Similarly, the process chain may be generated for up to h steps. If the h -step ahead value of $E[REIT_{t+h}]$ is $\widetilde{REIT}_{t+h}$, the IRF is defined as: $IRF(h) = \widetilde{REIT}_{t+h} - REIT_{t+h}$. Statistical programs estimate the confidence intervals of the IRF by using a bootstrapping methodology. By orthogonalizing the impulse response coefficients, the system can be split into distinct components that are independent of each other. Thus, an orthogonalized IRF describes the response to an impulse that is solely attributed to the variable in question.

Robustness Tests

Availability of the I4S

To examine if the availability of the I4S is associated with any change to its significance in predicting the abnormal REIT returns, I divide the data into two sub-samples based on time-intervals. The division is around the public release of the I4S data (July 2008). On both the sub-samples I run models similar to EQ(12). Specifically, I examine if the statistical significance of the I4S variable changes during the 'before' and 'after' periods.

Breakpoint Analysis

Structural relationships between economic variables are known to change over time, especially in a system defined by multiple variables. Within a given time frame of observations, one may reasonably assume that there are some breakpoints around which the coefficients shift. I apply

an algorithm to identify the break-point as a robustness check. Bai and Perron (2003) offer an algorithm to compute the optimal breakpoints. Their method minimizes the residual sum of squares from the sample calculated across different sets of time-period specific coefficients. In this dissertation, I apply an R-package³⁹ (a software program) developed by Zeileis, Kleiber, Kramer, and Hornik (2003) that is based on Bai and Perron (2003). I use the breakpoints suggested by the approach to validate the before-after sub-sample break up.

³⁹ “strucchange”

CHAPTER FOUR: RESULTS AND DISCUSSION

Association between the I4S and Fundamental Apartment Market Variables

If the I4S in the ‘*Apartment and Rental Listings*’ sub-category contains information about any net increase in the demand for residential rental space, it should be associated with the vacancy rate. However, as presented earlier, the evidence regarding the direction of causality between the I4S and vacancy rates is mixed. To address this issue, I apply two-stage least square models. **Table 5** presents the 2SLS, second stage result of vacancy rate analysis across the panel of 21 MSAs. Because vacancy rates are released during the final weeks of a quarter, the I4SL should be significantly associated with it. Therefore, I examine the association of VAC with the I4SL.

The statistical packages⁴⁰ provide results of the second stage analysis. The first column in the upper panel of Table 5 presents the second stage results for vacancy rate modeling using the fitted values of the I4SL. Each percent increase in the quarterly averaged I4SL is associated with a 0.02 percent reduction in the vacancy rate. The second column includes seasonality controls for the vacancy rates. All seasonality indicators are statistically insignificant and their inclusion in the model leads to a statistically insignificant I4SL in the model. The lower panel presents the second stage model for the I4SL. This model shows that each percent increase in the vacancy rate is associated with 0.4 percent reduction in the I4SL after controlling for its other determinants. In short, Table 5 presents some evidence that online rental searches are

⁴⁰ For example, a package named “systemfit” in R

associated with reduced vacancy rate and, by inference, with increased net demand for rental space.

Because **Table 5** provides evidence that the I4S is reflective of increased net demand, it is inherent that the I4S could be used to draw inferences about rental rates based on Rosen and Smith (1983). Such an inference is based on the argument that the I4S reflects fundamental changes in the rental markets. Controlling for the fundamental information, however, it is possible that the players in the rental pricing markets also watch the I4S to educate their rental pricing decisions. If so, the I4S should be significant in modeling the rental rates after controlling for its association with vacancy rates that is one of the determinants of the I4S.

In the models presented in **Table 6**, the I4S is included as a determinant of various measures of the rental rate after controlling for its known determinants such as operating expenses (OPEX) and vacancy rates (VAC). **Model 6.1** has per square foot real rental rate (RENT) as the dependent variable. The known determinants such as operating expenses and vacancy rates have expected coefficients. In particular, each dollar increase in the real operating expenses leads to nearly double increase in the real rental rate. The vacancy rate is negatively associated with the real rent per square foot. The I4S is significant at 10% level and has a positive coefficient suggesting that search activities are positively associated with the rental rates⁴¹.

I also examine first-difference models presented in the columns two to four of **Table 6**. **Model 6.2** excludes the MSA fixed effects as is standard in first-difference models. However, I include the dummy variables and the I4S in levels for empirical interpretability. To address the

⁴¹ Excluding the vacancy rate from this model improves the statistical significance of the I4S.

heterogeneity in the error terms across MSAs, I report the coefficients robust to MSA-clustered standard errors. VAC and OPEX have expected coefficient signs and significance. In this model, the I4S is statistically insignificant.

To allow for variations across the MSAs, the **Model 6.3** adds the MSA fixed effects in the **Model 6.2**. The results are similar. Finally, **Model 6.4** uses the percent growth in rental rates as the dependent variable. The model controls for the MSA fixed effects and has similar coefficients for OPEX and VAC. However, this model has a lower adjusted R-squared (0.79). None of the four models reported in **Table 6** provide any strong evidence that the I4S measures are directly associated with the rental rate after controlling for their association with vacancy rates. The Von-Mises type test in all four models suggests that the error terms are not white noise. Also, the I4S is significant in only one of the specifications. The evidence in **Table 6** suggests that the I4S is directly associated with vacancy rates however the empirical support for the association between the I4S and rental rates is weak.

An explanation for the lack of significance of the I4S in modeling rental rates lies in the nature of the rental rate data. Apartment leases tend to be of longer term (e.g. 1 year) compared to the frequency of the vacancy rate data. Thus, changes in the vacancy rate would only be reflected in the newly signed lease contracts. This may blur the overall impact of changes in the vacancy rate observed on the rental rates. A more accurate data on new rental rate contracts may add to the significance of the association. This is a limitation of this dissertation.

In the next set of analyses, I examine if the multifamily asset market incorporates the I4S information in pricing the apartment properties. Online rental searches may be associated with

the capitalization returns indirectly, through vacancy rates or rental growth. Yet, if the searches are associated with the capitalization return after controlling for these and other determinants, it supports the argument that the multifamily asset valuations are directly influenced by the online rental searches. Results of four different models (7.1 to 7.4) are reported in **Table 7** with gradually increasing number of independent variables. Because earlier I find evidence that the vacancy rates are determined by the I4S, I also include the vacancy rate (VAC) data in the model.

Table 7 provides the results of these analyses. Each one percent increase in the average weekly online rental interest is associated with nearly 0.06 to 0.1 percent additional return in the appraised value of the multifamily assets. The I4S is significantly and positively associated with capitalization return, as expected. The finding is robust to all model specifications with varying set of determinants. Other variable coefficients have expected signs and significances. The autoregressive terms suggest that up to two lags, the multifamily asset value appreciation exhibits persistence and shows a sign of some disciplining in the third quarter.

The significance of SPREAD in determining capitalization return is sensitive to model specification. The perception of credit-tightness (CREDIT) is negatively associated with the capitalization return. As expected, higher inflation is reflective of an overall appreciation in asset prices and, thus, is positively associated with capitalization return. The amount of CMBS issuances is negatively associated with the capitalization. This is potentially indicative of over-supplied space markets during the period of analysis supported by excessive access to debt capital. Unlike some earlier studies, I find is no evidence that the rental growth is significantly associated with the capitalization return. In general, this analysis provides evidence that after

controlling for the known determinants of capital appreciation, the I4S information is incorporated into asset value returns.s

Modeling REIT Returns with the I4S

Due to a limited number of quarterly observations on the nationally aggregated I4S, the sample size for quarterly CRSP/Ziman Multifamily REIT Index return modeling is limited. **Appendix Tables 18 and 19** present the summary and correlation matrices respectively for the quarterly data for stock modeling. All variables pass at least two of the three stationarity/unit root tests. **Appendix Table 20** presents the results of the analysis. I run four different models. Despite a small sample size (N=32), the models have high adjusted R-squared (0.53 to 0.70). The I4S has a positive and statistically significant coefficient. The finding is robust to introducing vacancy rates and rental inflation in the models. The statistical significance of the I4S after controlling for market fundamentals suggests that investors potentially watch the I4S to inform their REIT stock pricing decisions.

However, the inferences drawn from the **Appendix Table 20** are limited by some data-validity issues. Because the data set (including variables such as VACN, CPI etc.) is drawn from different sources the inter-applicability of such data sets may be questionable. For example, the I4S sub-category “Apartment and Residential Rentals” may not truly represent the searches made specifically for REIT-owned assets. The Consumer Price Index of residential rents reported by the BLS is not specific to institutionally owned multifamily properties. Also, the vacancy rate reported by the American Housing Survey includes all primary rental units and not the ones specifically owned by REITs/ Institutions.

To further analyze the significance of the I4S in REIT stock modeling, I run several models using weekly data series as follows. First, I examine the contemporaneous association between the I4S and REIT returns. The results are presented in **Appendix Table 21**. The $abI4S$ is insignificant⁴² in absence of the systematic risk factors. Inclusion of the Fama-French factors and Carhart's momentum factors makes the $abI4S$ statistically significant. Each one percent increase in abnormal search activity is associated with a contemporaneous 0.1 percent additional REIT return.

To examine if the I4S contains information about future REIT returns in the short run, I apply VAR models to the same data set. I introduce lagged REIT returns and the $abI4S$ to the models contemporaneously controlling for the exogenously determined systematic risk factors. **Table 8** provides the results of the REIT index modeling. I run three different models using the abnormal I4S ($abI4S$) as a determinant. The results are based on the $abI4S$ calculated from recent six observations of the I4S. All models control for weekly seasonality.

The first model includes lagged excess REIT returns and the abnormal I4S, but no systematic risk factors. The intercept is insignificant, as expected. The lagged dependent variable is also insignificant. However, the $abI4S$ is statistically significant. A one percent increase in the abnormal search activity is associated with nearly 0.1 percent addition return on REITs. This weak-form efficient ('Naïve', hereafter) model fails to explain the changes in the dependent variable having a negative adjusted R-squared. However, the null hypothesis of white noise cannot be rejected for the residuals.

⁴² $k=6$

The second ('CAPM', hereafter) model includes the exogenous market factor that is known to be contemporaneously associated with the stock returns. This model is a modified version of the capital asset pricing model as it also includes lagged values of the dependent variable and the abI4S. The abI4S is statistically significant. One percent increase in the abnormal search activity is associated with a five basis points additional return in REITs. Compared to the Naïve model, this model has a substantially higher R-squared of 0.34. The systematic risk (Market-beta) is 0.7 and the returns show persistence (with a statistically significant autocorrelation of 0.1). The residuals pass the white-noise test.

The third ('Four-factor', hereafter) model is a further modification on the CAPM model. It includes the exogenous Fama-French three factors and Carhart's momentum factor. All systematic risk factors have expected signs and significance⁴³. REIT returns exhibit persistence as reflected in the coefficient of the lagged dependent variable. Similar to the CAPM model, REIT returns exhibit persistence and are significantly associated with the lagged I4S. Inclusion of additional risk factors improves the adjusted R-squared to 0.44. However, the null hypothesis of white-noise residuals is rejected.

A concern with the model presented in **Table 8** is that it provides results only for a specific rolling window (i.e. $k=6$) for the I4S median (and, hence, the abI4S) calculation. To address this concern, I also run the same set of models adopting different rolling windows for the abI4S calculations (i.e. $k=3$ to $k=26$). Thus, I run each of the three models (Naïve, CAPM and Four-factor) 24 times, once for each value of k . The results for these analyses are presented in

⁴³ See Derwall, Huji, Brounen and Maquering (2009) for the expected coefficient signs.

Appendix Tables 23-25. It can be observed that the significance of the I4S is sensitive to the selection of the rolling window (k). There is only one rolling window (i.e. $k=6$) for which all the three models specifications lead to significant abI4S coefficients. For the CAPM model, the abI4S is significant only for one rolling window ($k=6$). For the Naïve and Four-factor models, the abI4S is significant for specific rolling windows ($k= 4$ to 7 and $k = 22$ to 26). For all rolling windows, the adjusted R-squared for the Naïve model are negative. In the four-factor models, the abI4S coefficient and the model adjusted R-squared vary around the values of 0.10 and 0.44 respectively.

The sensitivity of the results to the rolling window of the I4S may reflect the time-frame of past observations over which the investors build their expectations for the current value of the I4S. **Figure 1** shows the typical time-series profile of the I4S used in this dissertation. The sinusoidal I4S trend completes a full cycle in one year experiencing a crest and a trough each year. It is theoretically challenging to explain why only a specific rolling window ($k=6$) for the abnormal I4S calculation leads to statistically significant results in the CAPM model. Therefore, the role of chance in this significant finding cannot be ruled out. The rolling windows for the Naïve and Four-factor models reflect that expectations for the I4S are built over past 1 to 2 months or 5-6 months of observations. 1-2 months of observation reflects sensitivity towards a short-run trend in searches where as 5-6 months reflects a medium horizon of searches capturing half the annual cycle. Thus, sensitivity towards these two specific rolling windows reflect that investors carefully observe short as well as medium term trends in the online rental search patterns.

Before-After Analysis: REIT Returns

To test whether the I4S is significant in the REIT return models before the data was publicly released, I break the sample into time periods before and after July 2008 (when the I4S was first released). **Table 9** presents the results of the before-after analysis. Similar to **Table 8**, the before-after analysis is applied to all the three different types of models (Naïve, CAPM and four-factor). The upper panel provides results for the sub-sample in the 'before' sub-period. I present the results of the analysis on the 'after' sub-period in the lower panel. Despite a smaller sample size of the 'after' sub-sample (N=161) compared to the 'before' sub-sample (N= 249), the abI4S is consistently insignificant in the 'before' sub-samples, but significant in the 'after' sub-samples. This provides some support to the argument that investors utilize the I4S in informing their stock pricing decisions.

To examine multivariate breakpoint in the association between various variables included in the models, I apply a structural breakpoint approach. Suggested breakpoints for various models are presented in **Appendix Table 27**. The breakpoint for the CAPM and Four-factor models coincide in October 2008. The breakpoint occurs three months after the first public release of the I4S data. The breakpoint for the Naïve model falls a year earlier in October 2007. An analysis similar to the before-analysis described above, however, based on the empirically arrived at structural breaks (rather than the point of the first public release of the I4S data) is presented in **Appendix Table 30**. The results are similar to those presented in Appendix Table 27.

Continuously Expanding Re-sampling of REIT Returns

The 'after' sub-sample ignores the fact that during this sub-period, the data for the 'before' sub-sample is also available. If the significance of the abI4S is argued to be a function of the I4S data availability, continually expanding time series offers a more appropriate re-sampling technique. To explore the evolution in statistical significance of the abI4S over time, I run the Four-factor model on a continuously expanding 'before' sample. The Four-factor regression model is run with the first 52 observations (all observations from the first year of observations). I record the p-value of the I4S and the R-squared of the model after each iteration in the sampling. In the following iteration, the sample increases by a week and I repeat the process until all available observations are exhausted.

Figure 4 depicts how the p-value⁴⁴ of the abI4S and R-squared of the model evolve over time. The R-squared of the model exhibits an upward trend following September 2008. The abI4S become statistically significant for the first time during December 2009, several months after the first public release of the I4S in 2008. This is reflective of Merton's (1987) arguments that the recognition of anomalies in stocks markets, that are considered to be efficient, could be a time-taking process. Before the launch of the 'Google Insights for Search', Google Inc. introduced a relatively less structured tool named 'Google Trends'⁴⁵ in May 2006. However, the data release during 2006 and 2008 had not been administered regularly⁴⁶. As a result, a fall in the p-value of the I4S may also be observed in latter parts of 2006. Despite such changes in

⁴⁴ $k = 6$

⁴⁵ See <http://www.skyhorse.org/2006/10/google-trends-what-the-world-is-searching-for>

⁴⁶ See <http://joseph.randomnetworks.com/2007/03/08/google-trends-died-back-in-november-2006/>

the p-value, the I4S remains statistically insignificant for most time periods during the analysis except during the final year of the analysis.

Persistence of REIT's Response to Shocks in the I4S

At a quarterly frequency, it is established that the I4S is reflective of some fundamental rental market variables, namely vacancy rates and capitalization returns. The previous set of analysis provides some evidence from the stock data that investors potentially watch the I4S. However, due to the limitations in the frequency of data on fundamental variables, an alternate test: impulse response function (IRF) is applied to establish if the association between the I4S and REIT returns on a weekly basis reflects a fundamental relationship between the two variables. **Figure 5** presents the results of the IRF applied to the three types of REIT index models: Naïve, CAPM and Four-factor. All corresponding vector autoregressive models include lagged values of REIT returns and the abI4S and contemporaneous systematic risk factors depending on the model definition. The impulse responses are orthogonalized. **Figure 5** suggests that the IRF is insignificant in the Naïve and the CAPM models, because the upper and lower limits are of different signs throughout the horizon of responses. However, the Four-factor model suggests that the IRF is significant during several following weeks after the introduction of the impulse in the system. In other words, the response of the REIT index to the unit shock in the abI4S is significant during the following weeks. Also, the response does not revert quickly. Rather, it persists over several weeks, although with declining effect. Therefore, the information provided by the I4S is priced persistently. This supports the findings of the quarterly panel data analyses that the I4S is associated with apartment market fundamentals.

CHAPTER FIVE: CONCLUSIONS

A stream of research has examined the association between consumer information searches and product prices. Investor information searches about securities are considered to be a signal for net demand for investments. Several studies report that although the information search may be generated from both the demand and supply side of the pricing equation, increased information searches about an asset by investors is reflective of a net increase in demand. This creates a price pressure on assets that leads to abnormal future returns.

Abnormal future returns and predictability in asset returns are anomalous to the theory of market efficiency. Early studies on asset pricing were based on the random walk hypothesis and argued against the possibility of predictability in stock returns. Over time, in some asset classes such as real estate some degree of predictability has been reported. The lead-lag association is attributed to information inefficiencies in the market. In the pursuit of abnormal asset returns, investors chase certain information that they believe is associated with future movement in stock prices.

In recent years, the internet has become an effective means of searching and collecting information. Several studies have shown that internet searches conducted on the Google search engine about a firm is directly associated with increased trading activity, increased returns and increased volatility in stocks. However, most of these studies are focused on the association with investor searches about securities and the corresponding returns. Some real estate studies have shown that real estate related online searches are associated with future real estate sales activity and housing prices in a predictive fashion as well as contemporaneously.

These studies argue that because the searches are significantly associated with the sales volumes and prices, they are proxies for real estate demand.

In this dissertation, I examine the claim that online real estate rental searches are a proxy for net increases in real estate demand. Unlike several other products, real estate product searches are popular among both the sellers and the buyers that may have offsetting effects on the net demand. In addition, some online real estate searches may be conducted for purely recreational purposes. Thus, despite a significant relationship between real estate sales and online searches, it is necessary to empirically examine the direct relationship between the online searches and market fundamentals. In the absence of such evidence, the statistical significance of online searches in predicting variables such as asset prices may simply be attributed to investors watching the search trends. If investors believe that the product search trends are proxies for product demand, it may bias their valuation of the asset and hence the association between searches and prices. Real estate offers a good laboratory to answer this research question due to the unique nature of inefficient real estate markets. This study addresses these issues in the context of multifamily commercial real estate assets. For real estate assets, there is an active space market on the 'Main Street' and a substantially large stock market on the 'Wall Street'.

Online searches may be fundamental indicators of net demand. Net demand should be reflected in reduced vacancy rates. However, the ex-ante direction of causality between the I4S and vacancy rates is unclear. Therefore, I examine Granger and instantaneous causality between the two variables across 21 MSAs. The results are mixed. For some markets, both the variables Granger cause or instantaneously cause each other. To address the endogeneity issue, I apply a two-stage least square model. The first stage, reduced-form models for both variables include

all exogenous variables in the system as regressors. Fitted values of the endogenous variables from the reduced form models are applied as regressors in the second stage models. I show that beyond the known determinants of vacancy rates such as trends, recent vacancy rates and MSA fixed effects, online searches are significantly indicative of reducing vacancy rates. Each percent increase in the abnormal search activity is associated with 0.01 to 0.02 percent decrease in the vacancy rate. This provides support to earlier studies that posit online real estate searches as a proxy for net product demand. Increased net demand should lead to higher prices (higher rents in the case of apartments).

However, whether the searches are directly associated with the prices or the association exists indirectly through vacancy rates is a matter of empirical inquiry. In the next step of analysis, I model rental rate with its known determinants such as vacancy rates and operating expenditure as well as the online searches. After controlling for the association between searches and adjustments to the net demand (i.e. vacancy rate), the association between the searches and additional price pressure is statistically less significant. Excluding the vacancy rate (which are partially determined by online searches), the statistical significance of the online searches improves. However, the association is not robust to alternate model specifications. The I4S should be reflected primarily in the newly signed leases. However, the rental rate is a cash flow measure which also includes existing leases. This is a limitation of the study.

Further, if the searches are associated with increased demand for investment then the searches should be associated with apartment asset price returns. After controlling for other known determinants of the capitalization return such as interest rates and credit tightness online searches are significantly and positively associated with the capitalization return on

multifamily assets. The findings are robust to several model specifications. This implies that online searches are incorporated into asset pricing decisions.

I show that each percent increase in the I4S is associated with a 0.02% decrease in vacancy rates and approximately 0.06% decrease in rental rates⁴⁷. Thus, at the mean RENT (\$3.43/SF) and mean VAC (6.56%), the effective rental rate is⁴⁸ \$3.205/SF. A percent increase in the I4S will raise the RENT to⁴⁹ \$3.4321/SF and reduce the VAC to 6.54%⁵⁰. Therefore, the new effective rent will be⁵¹ \$3.208/SF. The NOI is a function of rental rate, vacancy rate and operating expenditure. Being a proxy for demand for rental space, the sensitivity of the operating expenditure to online searches may be assumed to be zero. Thus, a percent increase in the I4S increases the NOI by approximately⁵² 0.09%.

In the dissertation, the capitalization return proxies for cap rate. Cap rate is defined as the ratio of net operating income (NOI, the numerator) to the asset value (the denominator). As shown above, a theoretically derived sensitivity of the numerator (NOI) to the I4S is 0.09%. In table 7 I show that the sensitivity of the ratio (cap rate) to a percent increase in the I4S is approximately 0.06%. Thus, the difference of 0.03% potentially comes from the denominator. In other words, the sensitivity⁵³ of the asset value to a one percent increase in the I4S is 0.03%.

⁴⁷ The coefficient for the I4S in model 6.1 is \$0.002/SF i.e. 0.06% of the mean RENT i.e. \$3.43/SF from Table 1.

⁴⁸ $3.43 \times (1 - 6.46\%) = 3.205$

⁴⁹ $3.43 \times (1 + 0.06\%) = 3.4321$

⁵⁰ $6.56 - 0.02 = 6.54$

⁵¹ $3.4321 \times (1 - 6.54\%) = 3.208$

⁵² $(3.208 - 3.205) / 3.205 = 0.09\%$.

⁵³ $(1 + 0.09\%) / (1 + 0.06\%) - 1 = 0.03\%$

The sensitivity of REIT stocks to changes in the I4S should incorporate the rental market's sensitivity to the I4S in terms of both income return (0.09%) and value return (0.03%). Thus, if the markets are not perfectly informed about the availability of the I4S data, and if the I4S has a perfectly fundamental association with the REIT returns, we should expect the coefficient of the I4S to be around 0.12% in stock pricing equations. However, in this dissertation, I find this sensitivity (Table 8) to vary between 0.07% and 0.09%. This may imply that the association between the I4S and REIT returns is fundamental in nature. Also, the stock market is only partially inefficient when it comes to the awareness about the association between the I4S and future REIT returns still leaving an opportunity to detect such an association potentially anomalous to the efficient market hypothesis.

In the previous set of analysis, I provide evidence that online rental searches are associated with fundamental apartment market variables such as vacancy rates and capitalization return. If so, fundamental shifts in the product markets should be reflected in the corresponding stock returns. To examine this, I run several specifications of standard stock pricing models including contemporaneous risk factors and lagged online search among other variables. I find mixed evidence regarding the association between online rental searches and future REIT returns. Although the findings are valid for specific transformations of the I4S, in presence of contemporaneous exogenous controls, abnormal online rental searches are associated with additional REIT returns in the short run.

In the next set of analysis, I focus on examining what drives the statistical significance of the online searches in modeling REIT stock returns. First, I break the observations on time line around the first public release of the online search data. If the apartment REIT stock investors

watch the online rental searches, then the association of the searches should be influenced by the availability of the online search data. I find that in all model specifications, online searches were insignificant before the data availability; but significant afterwards. This provides some evidence that investors watch the online search data.

To further examine whether the online searches fundamentally shift the stock returns, I apply impulse response function to the stock return models. The response of REIT returns to shocks in abnormal search activities is gradually fading, although persistent over several weeks further supporting the argument that online rental searches reflect fundamental shifts in the apartment real estate markets.

The findings of this dissertation have theoretical implications as well as business applications. Evidences suggest that online searches offer an instantaneous and frequent indicator of net demand for real estate. Observing a carefully selected and filtered set of online search trends may offer useful insights about the current as well as future real estate markets. However, the online search patterns need to be utilized carefully in modeling variables. Based on Merton (1987), the phenomenon of price predictability using new information may be a temporary phenomenon. However, its association with fundamental variables adds to the efficacy of online search data.

This study has several limitations. Availability and inclusion of online search data from other search engines beyond Google such as Bing and Yahoo could provide a more complete picture of the phenomenon. Moreover, postings related to supply or demand of rental space on listing sites such as Craigslist could also provide additional insights. Not all online rental searches are

associated with REIT owned multifamily assets. REIT-owned rental units may be systemically different from other rental units and may be subject to different types of search patterns by prospective tenants. Also, the online search volume by investors about REITs is thin. Yet, being the single largest search engine, the online search data provided by Google offers a fairly good representation of the online search universe.

Future research could focus on detailed studies specific to investor searches about REITs and the variations across MSAs.

APPENDIX

Note 1: Weekly and Quarterly I4S

Suppose that the average I4S in the ‘Apartment and Residential Rentals’ sub-category across all weeks in a quarter is $k\%$. As discussed earlier, category-specific I4S are only available as the percent change in the interest in that category. Suppose, the ‘levels’ of the interest rate during the beginning and the end of a quarter are x and y respectively. Then, logically, y can be estimated as:

$$y = x \cdot (1 + k\%)^{13} ; \text{ given that there are, on average, 13 weeks in a quarter.}$$

From binomial expansion:

$$\begin{aligned} (1 + k\%)^{13} &= \sum_{k=0}^{13} \binom{13}{0} * \left(\frac{k}{100}\right)^{13} \\ &= \binom{13}{0} \left(\frac{k}{100}\right)^0 + \binom{13}{1} \left(\frac{k}{100}\right)^1 + \binom{13}{2} \left(\frac{k}{100}\right)^2 + \dots + \binom{13}{13} \left(\frac{k}{100}\right)^{13} \approx 1 + 13 * \left(\frac{k}{100}\right) \end{aligned}$$

(Latter terms are neglected for practical purposes due to diminished sizes). Thus, the equivalent quarterly I4S may be estimated as $13 * k\%$.

Note 2: Controlling for Investor Searches about ‘REIT’

Da et al. (2011) focus on investor online searches (I4S) specific to specific stocks (i.e., based on stock tickers). This study, however, focuses on consumer online searches. The evidence

presented above suggests that consumer searches are associated with REIT stock returns. Therefore, a pertinent question to ask is whether the results are robust to the inclusion of investor searches in the model. Unlike in Da et al. (20011) study that is based on non-REIT stocks, the I4S related to ticker symbols of individual REITs are not available due to their smaller online search volumes. **Appendix Table 26** presents the results of this analysis. $abRI4S$ is the abnormal I4S for a specific keyword: “REIT”. The $abI4S$ is not included in the first model. As expected, the investment search is significantly associated with REIT returns. However, the coefficient has a negative sign. In Barber and Odean (2008), it is argued that investor searches related to a particular stock reflects a net demand for the security. However, the $abRI4S$ is not based on an individual security, rather than on a class of securities. A plausible explanation for the negative coefficient is that abnormal search about REITs may be a signal of perceived distress in REIT stocks during the period of analysis such that the net effect is that the investors shall either sell or short REIT stocks. Similar to Da et al. (2011) who fail to explain a negative association of stock returns with product-related consumer searches, such a negative association in REITs needs further attention. In the second model the $abI4S$ variable is also introduced. It has a positive and statistically significant coefficient. This finding further supports the argument that the consumer rental searches are associated with REIT returns even after controlling for investor searches about REITs.

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EXHIBITS

Tables

Table 1. Panel Data Summary for Apartment Market Fundamentals

	<i>I4S</i>	<i>I4SL</i>	<i>I4SF</i>	<i>VAC</i>	<i>RENT</i>	<i>RGROWTH</i> (Winsorized)	<i>OPEX</i>	<i>CR</i>	<i>CREDIT</i>	<i>CMBS</i>	<i>SPREAD</i>	<i>TBILL</i>
Units	%	%	%	%	\$/SF	%	\$/SF	%	%	%	%	%
Descriptive Statistics												
Mean	6.25	3.56	7.45	6.56	3.43	2.314 (1.40)	1.4	0.67	27.0	58.89	1.84	1.94
Min	-47.5	-49.5	-46.6	1.58	0.84	-70.7 (-53.5)	0.4	-24.8	-22.2	0.000	-0.43	0.01
Max	69.1	68.5	76.1	18.8	15.2	420.5 (72.5)	5.4	22.8	87.0	230.5	3.65	5.11
St. dev.	20.7	21.3	21.3	2.11	1.45	23.41 (9.04)	0.60	0.20	32.7	71.37	1.33	2.00
Stationarity Tests												
IPS	-3.5***	-0.876	-3.13***	-2.67***	-3.52***	-2.972***	-3.65***	-1.6799*	-2.252**	-5.17***	3.17***	-6.73***
MW	-277***	197***	262***	198.5***	223.6***	212.7***	223***	167***	176***	256.6***	42.03	232.6***
N	567	567	567	567	567	567	567	567	567	567	567	567

Notes: All data recorded at quarterly frequency between 2005 Q2 and 2011 Q4 and reported as an average of 21 metropolitan statistical areas (MSA) included in this study (for the list of MSAs, refer to Appendix Table 10). *I4S* = quarterly average of weekly online Google Insights for Search Index in 'Apartment and Residential Rentals' sub-category. *I4SL* = Average *I4S* during the last four weeks of a quarter. *I4SF* = Average of all the *I4S* in a quarter except the last four weeks. *VAC* = vacancy rate. *RENT* = Inflation adjusted (at 2004 Q1 level) average rental rate. *RGROWTH* = quarterly percent growth in *RENT*. Data in parentheses signify Winsorized data (i.e. enforcing a cap and floor of 3-times the standard deviation). *OPEX* = Inflation adjusted average operating expenses. *CR* = capitalization return on appraised asset values. *VAC*, *RENT*, *RGROWTH*, *OPEX* and *CR* data extracted from NCREIF database. *CREDIT* = the net percentage of survey respondents claiming tightened credit for commercial real estate from the Federal Reserve Senior Loan Officer Survey. *CMBS* = Quarterly Issuance of CMBS reported by CRE Finance Council, in billion dollars. *SPREAD* = yield spread between 10-Year Constant Maturity Treasury Bond and 1-Month Constant Maturity Treasury Bill. *TBILL* = Yield on 1-Month Constant Maturity Treasury Bill. *IPS* = Test statistic for Im-Pesaran-Shin test with a null hypothesis that the panel data has a unit root. *MW* = test statistic for Maddala-Wu test with a null hypothesis that the panel data has a unit root. All unit-root tests consider trend-stationarity for four lags. ***, ** and * reflect statistical significance at 1%, 5% and 10% levels respectively.

Table 2. Panel Data Correlation Matrix for Apartment Market Fundamentals

	<i>I4S</i>	<i>I4S.L</i>	<i>I4S.F</i>	<i>VAC</i>	<i>RENT</i>	<i>RGROWTH</i>	<i>OPEX</i>	<i>CR</i>	<i>CREDIT</i>	<i>CMBS</i>	<i>SPREAD</i>	<i>TBILL</i>
<i>I4S</i>	1	0.935	0.987	-0.113	-0.267	-0.098	-0.273	0.264	-0.293	0.059	-0.173	0.215
<i>I4S.L</i>		1	0.867	-0.091	-0.271	-0.109	-0.279	0.233	-0.250	-0.013	-0.139	0.192
<i>I4S.F</i>			1	-0.118	-0.254	-0.090	-0.259	0.266	-0.301	0.089	-0.181	0.217
<i>VAC</i>				1	-0.019	-0.063	-0.010	-0.333	0.398	0.015	-0.002	0.025
<i>RENT</i>					1	0.344	0.934	0.038	-0.026	0.025	-0.036	0.018
<i>RGROWTH</i>						1	0.308	0.041	-0.046	-0.022	0.017	-0.029
<i>OPEX</i>							1	-0.027	0.024	-0.014	0.015	-0.029
<i>CR</i>								1	-0.662	0.310	-0.358	0.323
<i>CREDIT</i>									1	-0.194	0.202	-0.162
<i>CMBS</i>										1	-0.778	0.785
<i>SPREAD</i>											1	-0.965
<i>TBILL</i>												1
<i>N</i> = 567												

Notes: The table reports bivariate Pearson-Correlation coefficient between variables. All data recorded at quarterly frequency between 2005 Q2 and 2011 Q4 and reported as an average of 21 metropolitan statistical areas (MSA) included in this study (for the list of MSAs, refer to Appendix Table 10). *I4S* = quarterly average of weekly online Google Insights for Search Index in 'Apartment and Residential Rentals' sub-category. *I4S.L* = Average *I4S* during the last four weeks of a quarter. *I4S.F* = Average of all the *I4S* in a quarter except the last four. *VAC* = vacancy rate. *RENT* = Inflation adjusted (at 2004 Q1 level) average rental rate. *RGROWTH* = quarterly percent growth in *RENT*. Data in parentheses signify Winsorized data (i.e. enforcing a cap and floor of 3-times the standard deviation). *OPEX* = Inflation adjusted average operating expenses. *CR* = capitalization return on appraised asset values. *VAC*, *RENT*, *RGROWTH*, *OPEX* and *CR* data extracted from NCREIF database. *CREDIT* = the net percentage of survey respondents claiming tightened credit for commercial real estate from the Federal Reserve Senior Loan Officer Survey. *CMBS* = Quarterly Issuance of CMBS reported by CRE Finance Council. *SPREAD* = yield spread between 10-Year Constant Maturity Treasury Bond and 1-Month Constant Maturity Treasury Bill. *TBILL* = Yield on 1-Month Constant Maturity Treasury Bill.

Table 3. Data Summary for Stock Modeling

	<i>REIT</i>	<i>MKT</i>	<i>SMB</i>	<i>HML</i>	<i>MOM</i>	<i>I4S</i>	<i>abI4S (k=6)</i>
Descriptive Statistics							
<i>Mean</i>	0.282	0.086	0.033	0.033	0.001	5.913	6.873
<i>Min</i>	-18.48	-19.29	-3.770	-7.760	-16.68	-28.00	-19.00
<i>Max</i>	22.82	12.15	4.480	7.090	12.00	39.00	36.00
<i>St. Dev.</i>	3.477	2.783	1.180	1.399	2.671	13.72	7.633
Unit Root/ Stationarity Tests							
<i>KPSS</i>	0.1321	0.0843	0.0784	0.1724	0.1161	0.1324	0.0401
<i>PP</i>	-387.2***	-431.9***	-457.9***	-496.6***	-487.4***	-34.8***	-119.0***
<i>ADF</i>	-6.7***	-6.8***	-7.4***	-6.9***	-7.4***	-4.3***	-6.0***
<i>N</i>	416	416	416	416	416	416	410

Notes: All data expressed in percentage and reported at weekly frequency. Data collected for the period of January 2004 to December 2011. REIT= Weekly return on CRSP/Ziman Multifamily REIT Index. MKT= CAPM Market factor. SMB = Small-Minus-Big Fama-French factor. HML = High-Minus-Low Fama-French Factor. MOM = Carhart's Momentum factor. I4S = Weekly Google Insights for Search Index in 'Apartments and Residential Rentals' sub-category in the 'Real Estate' category. abI4S = I4S in a week in excess of the median of recent 6 weeks. KPSS = Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test statistic for the null hypothesis of trend stationarity. PP = Phillips-Perron test statistic for the null hypothesis of a unit root. ADF = Augmented Dickie-Fuller test statistic for the null hypothesis of a unit root. *** denote statistical significance at 1% level.

Table 4. Correlation Matrix for Stock Modeling Data

	<i>REIT</i>	<i>abI4S</i>	<i>MKT</i>	<i>SMB</i>	<i>HML</i>	<i>MOM</i>
<i>REIT</i>	1.000	-0.008	0.565	0.188	0.493	-0.526
<i>abI4S</i>		1.000	-0.079	-0.016	-0.021	-0.036
<i>MKT</i>			1.000	0.027	0.036	-0.052
<i>SMB</i>				1.000	0.118	-0.145
<i>HML</i>					1.000	-0.159
<i>MOM</i>						1.000
<i>N</i>	410					

Notes: The table presents bivariate Pearson Correlation coefficient. All data expressed in percentage and reported at weekly frequency. Data collected for the period of January 2004 to December 2011. REIT= Weekly return on CRSP/Ziman Multifamily REIT Index. MKT= CAPM Market factor. SMB = Small-Minus-Big Fama-French factor. HML = High-Minus-Low Fama-French Factor. MOM = Carhart's Momentum factor. I4S = Weekly Google Insights for Search Index in 'Apartments and Residential Rentals' sub-category in the 'Real Estate' category. abI4S = the I4S in excess of the median of recent 6 weeks.

Table 5. 2SLS Modeling of the Vacancy Rate

Dependent Variable: Vacancy Rate						
Intercept	3.40	(1.64)		4.58	(2.10)	**
$I\hat{4}SL_t$	-0.015	(-3.59)	***	-0.002	(-0.23)	
VAC_{t-1}	0.76	(17.82)	***	0.76	(17.6)	***
VAC_{t-2}	-0.12	(-2.29)	**	-0.12	(-2.22)	**
VAC_{t-3}	0.07	(1.40)		0.09	(1.81)	*
VAC_{t-4}	-0.06	(-1.38)		-0.09	(-2.06)	**
LOBS	-0.50	(-1.91)	**	-0.49	(-1.89)	*
Q2				-0.19	(-1.04)	
Q3				-0.16	(-0.93)	
Q4				0.43	(1.93)	
Polynomial trends	Included			Included		
MSA Fixed effects	Included			Included		
R-squared	0.66			0.67		
Adj. R-Squared	0.64			0.65		
Dependent Variable: Online Search						
Intercept	5.48	(2.71)	***			
$V\hat{A}C_t$	-0.36	(-2.24)	**			
$I4SF_t$	0.86	(22.8)	***			
$I4SL_{t-1}$	-0.07	(-1.62)				
$I4SL_{t-2}$	0.007	(0.19)				
$I4SL_{t-3}$	-0.002	(-0.07)				
$I4SL_{t-4}$	0.06	(2.08)	**			
Q2	4.53	(3.30)	***			
Q3	-17.01	(-10.7)	***			
Q4	-5.18	(-3.56)	***			
MSA Fixed effects	Included					
N	567					
R-squared	0.94					
Adj. R-Squared	0.93					

Notes: The table reports the results of second-stage panel data modeling of vacancy rates in a two-stage least square (2SLS) set up. The first stage, reduced-form models for both variables include all exogenous variables in the system as regressors. Fitted values of the endogenous variables from the reduced form models are applied as regressors in the second stage models that are reported in this table. Stage 1 (reduced form) model specifies $I4SL$ (or VAC) as a function of 4 lags of VAC , 4 lags of $I4SL$, $I4SFW$, polynomial time trends, LOBS, seasonality and MSA fixed effects. Stage-2 models are specified as above. The data is spread across 21 Metropolitan Statistical Areas (MSAs), and 27 quarters between 2005Q2 and 2011Q4 (for the list of MSAs, refer to Appendix Table 10). Subscripts t and i signify time and MSA respectively. $I4S$ = quarterly average of the weekly Google Insights for Search Index in 'Apartments and Residential Rentals' sub-category. $I4SL$ = Average weekly $I4S$ during the last four weeks of a quarter. $I4SF$ = Average weekly $I4S$ in a quarter excluding the last four weeks. VAC = average vacancy rate in a MSA reported by NCREIF. LOBS = Low Observation Indicator that assumes a value of 1 when the number of properties in the sample is less than 30, 0 otherwise. 47% of the observations fall in the 'Low Observation' category for the data applied above. The polynomial trend term includes up to the fourth degree terms of t . A hat ($\hat{X}$) above a variable name signifies the fitted value of the variable derived from the first-stage model. The error term is the 'Unexpected' component of the $I4S$. Quantities in the parentheses signify t-statistics. ***, ** and * denote statistical significance at 1%, 5% and 10% levels respectively.

Table 6. Rent Modeling

6.1				6.2			6.3			6.4		
Dependent <i>RENT</i>				$\Delta RENT$			$\Delta RENT$			<i>RGROWTH</i>		
				(All independent variables except the I4S and Dummy variables are first-differenced)								
Coeff. T-Stat				Coeff. T-Stat			Coeff. T-Stat			Coeff. T-Stat		
				(Robust to MSA clustering)								
<i>Intercept</i>	-0.13	(-1.1)		-0.003	(-0.08)		-0.06	(-0.77)		-1.14	(-0.61)	
<i>I4S_{i,t}</i>	0.002	(1.71)	*	6E-5	(0.18)		0.001	(0.68)		0.03	(0.98)	
<i>OPEX_{i,t}</i>	2.07	(36.0)	***	2.17	(23.4)	***	2.17	(41.3)	***	25.2	(19.0)	***
<i>VAC_{i,t}</i>	-0.02	(-2.35)	**	0.03	(3.75)	***	0.03	(3.57)	***	0.76	(3.59)	***
<i>Dependent_{i,t-1}</i>	0.19	(6.99)	***	-0.05	(-3.5)	***	-0.06	(-2.68)	***	0.01	(0.79)	
<i>Dependent_{i,t-2}</i>	-0.09	(-3.23)	***	-0.11	(-7.9)	***	-0.12	(-5.38)	***	-0.01	(-0.48)	
<i>Dependent_{i,t-3}</i>	0.06	(2.27)	**	-0.01	(-1.0)		-0.02	(-0.72)		-0.01	(-0.58)	
<i>Dependent_{i,t-4}</i>	-0.03	(-1.27)		-0.06	(-3.5)	**	-0.07	(-2.46)	**	0.001	(0.09)	
<i>LOBS</i>	0.25	(4.70)	***	-0.0001	(-0.42)		0.001	(0.47)		0.02	(0.41)	
<i>Quarter Dummies</i>	<i>Included</i>			<i>Included</i>			<i>Included</i>			<i>Included</i>		
<i>MSA Fixed effects</i>	<i>Included</i>			<i>Excluded</i>			<i>Included</i>			<i>Included</i>		
N	567			567			567			567		
<i>R</i> ²	0.96			0.80			0.80			0.46		
<i>Adj. R</i> ²	0.96			0.79			0.79			0.42		
MN	18.0***			4.41**			4.70**			-3.28		

Notes: The table reports the coefficients of panel-data OLS models of the dependent variable. RENT = Inflation adjusted (at 2004 Q1 level) apartment rental rate per square foot. OPEX = Inflation adjusted average operating expenses per square foot. The table reports panel data modeling of vacancy rates across 21 Metropolitan Statistical Areas (MSAs), and 27 quarters between 2005 Q2 and 2011Q4 (for the list of MSAs, refer to Appendix Table 10). RENT and OPEX data is provided by NCREIF. Subscripts *t* and *i* signify time and MSA respectively. I4S = quarterly average of the weekly Google Insights for Search Index in 'Apartments and Residential Rentals' sub-category. VAC = vacancy rate. LOBS = Low Observation Indicator that assumes a value of 1 when the number of properties in the sample is less than 30, 0 otherwise. 60% of the observations fall in the 'Low Observation' category for the data applied above. Quantities in the parentheses signify t-statistics. MN = Von Mises test statistic for the error term with the null hypothesis that the residuals are white noise. ***, ** and * denote statistical significance at 1%, 5% and 10% levels respectively.

Table 7. Capitalization Return Modeling

	7.1			7.2			7.3			7.4		
	Coeff.	T-Stat		Coeff.	T-Stat		Coeff.	T-Stat		Coeff.	T-Stat	
Intercept	-1.78	(-1.91)	*	0.44	(0.48)		-2.22	(-1.29)		-0.22	(-0.12)	
$I4S_{i,t}$	0.10	(6.1)	***	0.06	(3.90)	***	0.06	(3.35)	***	0.06	(3.31)	***
$RGROWTH_{i,t}$	0.02	(1.57)		0.02	(1.51)		0.02	(1.54)		0.02	(1.51)	
$CREDIT_{i,t-4}$				-0.02	(-2.04)	**	-0.02	(-2.07)	**	-0.02	(-2.02)	**
$CMBS_{i,t-4}$				-0.02	(-8.83)	***	-0.02	(-8.32)	***	-0.02	(-7.26)	***
$SPREAD_t$	-0.21	(-1.47)		-0.46	(-2.56)	**	0.47	(0.86)		0.29	(0.54)	
$TBILL_t$							0.64	(1.83)	*	0.55	(1.56)	
$VAC_{i,t}$										-0.17	(-2.32)	***
$Dependent_{i,t-1}$	0.46	(10.8)	***	0.39	(9.07)	***	0.39	(9.02)	***	0.38	(8.82)	***
$Dependent_{i,t-2}$	0.17	(3.55)	***	0.15	(3.25)	***	0.15	(3.37)	***	0.14	(3.05)	***
$Dependent_{i,t-3}$	-0.10	(-2.08)	**	-0.10	(-2.02)	**	-0.07	(-1.54)		-0.08	(-1.77)	**
$Dependent_{i,t-4}$	-0.03	(-0.72)		-0.02	(-0.41)		0.002	(0.06)		-0.002	(-0.06)	
$LOBS_{i,t}$	0.72	(1.18)		0.53	(0.95)		0.35	(0.61)		0.36	(0.62)	
Quarter Dummies	Included			Included			Included			Included		
MSA Fixed effects	Included			Included			Included			Included		
N	567			567			567			567		
R^2	0.51			0.58			0.59			0.60		
$Adj. R^2$	0.48			0.56			0.56			0.56		
MN	55.5***			38.2***			41.7***			46.3***		

Notes: The table reports coefficients from panel-data OLS models with CR as the dependent variable. CR = Capitalization Return on the appraised values. The data covers 21 Metropolitan Statistical Areas (MSAs), and 27 quarters between 2005Q2 and 2011Q4. Subscripts t and i signify time and MSA respectively. I4S = weekly Google Insights for Search (I4S) Index in 'Apartments and Residential Rentals' sub-category. CREDIT = the net percentage of survey respondents claiming tightened credit for commercial real estate from the Federal Reserve Senior Loan Officer Survey. CMBS = Quarterly Issuance of CMBS reported by CRE Finance Council. SPREAD = yield spread between 10-Year Constant Maturity Treasury Bond and 1-Month Constant Maturity Treasury Bill. TBILL = Yield on 1-Month Constant Maturity Treasury Bill. VAC = vacancy rate. LOBS = Low Observation Indicator that assumes a value of 1 when the number of properties in any of the samples from that the NCREIF data is collected is smaller than 30, 0 otherwise. 60% of the observations fall in the 'Low Observation' category for the data applied above. MN = Von Mises test statistic for the error term with the null hypothesis that the residuals are white noise. Quantities in the parentheses signify t-statistics. ***, and ** denote statistical significance at 1% and 5% levels respectively.

Table 8. Weekly REIT Returns and Abnormal Search Activities

	Model 1			Model 2			Model 3		
<i>Intercept</i>	0.233	(0.17)		0.225	(0.20)		-0.048	(-0.05)	
<i>Lagged Variables</i>									
<i>abI4S_{t-1}</i>	0.087	(1.77)	*	0.074	(1.85)	*	0.077	(2.11)	**
<i>REIT_{t-1}</i>	0.063	(1.20)		0.109	(2.52)	**	0.081	(2.02)	**
<i>Exogenous Variables</i>									
<i>MKT_t</i>				0.725	(13.4)	***	0.430	(7.02)	***
<i>SMB_t</i>							0.390	(3.02)	***
<i>HML_t</i>							0.421	(3.43)	***
<i>MOM_t</i>							-0.381	(-5.9)	***
<i>Week Dummies</i>	Included			Included			Included		
<i>N</i>	410			410			410		
<i>R²</i>	0.111			0.410			0.518		
<i>Adj. R²</i>	-0.024			0.318			0.438		
<i>MN</i>	0.969			1.103			3.72		*

Notes: Dependent Variable: REIT. REIT = Weekly return on CRSP/Ziman Multifamily REIT returns in excess of the risk-free rate. Variable subscripts denote time. All data expressed in percentage and reported at weekly frequency. Data analyzed for the period of January 2004 to December 2011. *abI4S* = the *I4S* in excess of the median of recent 6 weeks (*I4S* = Weekly Google Insights for Search Index in 'Apartments and Residential Rentals' sub-category in the 'Real Estate' category). *MKT* = CAPM Market factor. *SMB* = Small-Minus-Big Fama-French factor. *HML* = High-Minus-Low Fama-French Factor. *MOM* = Carhart's Momentum factor. *MN* = Von Mises test statistic for the error term with the null hypothesis that the residuals are white noise. *, ** and *** denote statistical significance at 10%, 5% and 1% levels respectively.

Table 9. Modeling Weekly CRSP/Ziman Multifamily REIT Index Returns Around the Point of First Data Release

Before								
	Panel-1a: Naive			Panel-1b: CAPM			Panel-1c: Four-factor	
	Coeff	T-Stat		Coeff	T-Stat		Coeff	T-Stat
<i>Intercept</i>	2.13	(1.11)		1.14	(0.72)		1.26	(0.78)
<i>Lagged Variables</i>								
<i>abI4S_{t-1}</i>	0.08	(1.40)		0.04	(0.85)		0.04	(0.78)
<i>REIT_{t-1}</i>	0.23	(3.26)	***	0.26	(4.34)	***	0.24	(4.03) ***
<i>Exogenous Variables</i>								
<i>MKT_t</i>				0.58	(8.76)	***	0.51	(7.03) ***
<i>SMB_t</i>							0.19	(1.35)
<i>HML_t</i>							0.01	(0.07)
<i>MOM_t</i>							-0.26	(-2.83) ***
<i>Week Dummies</i>	<i>Included</i>			<i>Included</i>			<i>Included</i>	
<i>N</i>	249			249			249	
<i>R²</i>	0.25			0.46			0.49	
<i>Adj. R²</i>	0.03			0.30			0.33	
<i>MN</i>	1.97			0.88			1.61	
After								
	Panel-2a: Naive			Panel-2b: CAPM			Panel-2c: Four-factor	
	Coeff	T-Stat		Coeff	T-Stat		Coeff	T-Stat
<i>Intercept</i>	0.53	(0.19)		0.07	(0.03)		-1.9	(-1.0)
<i>Lagged Variables</i>								
<i>abI4S_{t-1}</i>	0.29	(2.44)	**	0.25	(2.58)	**	0.20	(2.4) **
<i>REIT_{t-1}</i>	-0.05	(-0.56)		0.03	(0.51)		0.01	(0.18)
<i>Exogenous Variables</i>								
<i>MKT_t</i>				0.79	(8.12)	***	0.23	(1.7) *
<i>SMB_t</i>							0.64	(2.07) **
<i>HML_t</i>							0.65	(2.85) ***
<i>MOM_t</i>							-0.42	(-3.64) ***
<i>Week Dummies</i>	<i>Included</i>			<i>Included</i>			<i>Included</i>	
<i>N</i>	161			161			161	
<i>R²</i>	0.29			0.55			0.67	
<i>Adj. R²</i>	-0.05			0.33			0.50	
<i>MN</i>	0.24			3.48	*		3.89	*

Notes: Dependent variable: REIT. REIT = Weekly return on CRSP/Ziman Multifamily REIT Index. All data expressed in percentage and is reported at weekly frequency. Subscript signifies time. Data collected for the period of January 2004 to December 2011. MKT= CAPM Market factor. SMB = Small-Minus-Big Fama-French factor. HML = High-Minus-Low Fama-French Factor. MOM = Carhart's Momentum factor. abI4S = abnormal Google Insights for Search in 'Apartments and Residential Rentals' sub-category in the 'Real Estate' category in excess of the median of the trailing 4 weeks. MN = Von Mises test statistic for the error term with the null hypothesis that the residuals are white noise. ***, ** and * denoted statistical significance at 1%, 5% and 10% levels respectively.

Appendix Table 10: List of Metropolitan Statistical
Areas included in the Panel Data Analyses

1	AZ - Phoenix
2	CA - Los Angeles
3	CA - San Diego
4	CA - San Francisco
5	CO - Denver
6	DC - Washington
7	FL - Fort Lauderdale
8	FL - Orlando
9	FL - Tampa
10	FL - West Palm Beach
11	GA - Atlanta
12	IL - Chicago
13	MD - Baltimore
14	MD - Bethesda
15	NC - Charlotte
16	NY - New York
17	OR - Portland
18	TX - Austin
19	TX - Dallas
20	TX - Fort Worth
21	TX - Houston

Appendix Table 11. Direction of Causation between the I4S and VAC

	Granger Cause = I4S	Instantaneous Causation	Granger Cause = VAC
AZ - Phoenix	0.009 ***	0.154	0.755
CA - Los Angeles	0.593	0.068 *	0.074
CA - San Diego	0.238	0.010 **	0.625
CA - San Francisco	0.272	0.138	0.804
CO - Denver	0.167	0.264	0.638
DC - Washington	0.418	0.212	0.137
FL - Fort Lauderdale	0.587	0.983	0.035 **
FL - Orlando	0.449	0.027 **	0.441
FL - Tampa	0.044 **	0.142	0.005 ***
FL - West Palm Beach	0.006 ***	0.976	0.318
GA - Atlanta	0.545	0.104	0.779
IL - Chicago	0.476	0.361	0.124
MD - Baltimore	0.131	0.365	0.003 ***
MD - Bethesda	0.140	0.595	0.976
NC - Charlotte	0.588	0.835	0.312
NY - New York	0.511	0.871	0.243
OR - Portland	0.337	0.242	0.824
TX - Austin	0.099 *	0.264	0.030 **
TX - Dallas	0.338	0.552	0.155
TX - Fort Worth	0.821	0.474	0.211
TX - Houston	0.398	0.137	0.037 **

Notes: This table reports the p-value of causality tests between VAC and the I4S. Null hypothesis: no causality. A vector autoregressive model using quarterly data for each MSA is run including four lags of the cause and effect variables and a fourth-degree polynomial in time as exogenous to the system. The Instantaneous causation model also includes a contemporaneous term of the cause. I4S = quarterly average of weekly online Google Insights for Search Index in 'Apartment and Residential Rentals' sub-category. VAC = apartment vacancy rate in a metropolitan statistical area (MSA) reported during a quarter in the NCREIF database. *, ** and *** denote statistical significance at 10%, 5% and 1% respectively.

Appendix Table 12. Summary of the I4S across MSAs

MSA	Mean	Min	Max	St. Dev.
AZ - Phoenix	8.95	-15.8	40.4	13.3
CA - Los Angeles	-8.49	-27.9	8.62	10.1
CA - San Diego	8.22	-20.6	32.8	14.0
CA - San Francisco	-18.1	-47.5	7.62	16.5
CO - Denver	-1.23	-28.-	20.2	12.4
DC - Washington	7.14	-24.2	31.3	14.9
FL - Fort Lauderdale	-7.01	-28.2	12.1	9.77
FL - Orlando	19.3	-7.54	41.2	13.2
FL - Tampa	20.0	-5.69	51.3	15.1
FL - West Palm Beach	-28.9	-44.5	-8.77	7.81
GA - Atlanta	-0.94	-21.3	18.9	10.5
IL - Chicago	2.92	-23.5	25.2	11.9
MD - Baltimore	20.2	-9.31	51.1	14.6
MD - Bethesda	7.14	-24.2	31.3	14.9
NC - Charlotte	18.7	-14.5	51.8	15.7
NY - New York	0.77	-29.0	24.2	14.2
OR - Portland	33.8	-1.85	69.1	17.8
TX - Austin	17.8	-10.0	47.2	15.1
TX - Dallas	13.8	-24.7	47.4	16.4
TX - Fort Worth	13.8	-24.7	47.4	16.4
TX - Houston	-11.8	-33.7	6.93	10.3

Notes: All data recorded at quarterly frequency between 2004 Q1 and 2011 Q4. I4S = quarterly average of weekly online Google Insights for Search Index (%) in 'Apartment and Residential Rentals' sub-category.

Appendix Table 13. Summary of Quarterly Vacancy Rates across MSAs

MSA	Mean	Min	Max	St. Dev.
AZ - Phoenix	8.50	4.79	12.1	2.07
CA - Los Angeles	7.26	4.90	10.4	1.30
CA - San Diego	6.40	3.27	9.75	1.53
CA - San Francisco	7.17	1.99	18.8	4.18
CO - Denver	7.00	3.90	10.9	1.78
DC - Washington	6.96	3.52	11.9	2.32
FL - Fort Lauderdale	5.77	1.93	9.06	1.81
FL - Orlando	7.27	2.86	11.8	2.77
FL - Tampa	6.67	3.10	9.94	1.72
FL - West Palm Beach	6.04	1.58	9.52	1.86
GA - Atlanta	7.01	4.94	9.33	1.12
IL - Chicago	6.66	4.22	9.58	1.34
MD - Baltimore	6.76	3.77	10.4	1.87
MD - Bethesda	5.32	3.20	9.47	1.48
NC - Charlotte	7.70	4.63	12.6	1.96
NY - New York	5.82	2.75	9.94	2.04
OR - Portland	5.80	4.07	9.90	1.25
TX - Austin	6.21	3.58	8.91	1.23
TX - Dallas	6.46	3.96	7.74	1.01
TX - Fort Worth	6.50	3.52	11.4	2.02
TX - Houston	6.91	4.43	12.3	1.90

Notes: All data recorded at quarterly frequency between 2004 Q1 and 2011 Q4. Vacancy rate measured in % as an average of all properties included in a sample from a metropolitan statistical area (MSA) in the NCREIF database.

Appendix Table 14. Summary of Quarterly Apartment Real Rental Rates across MSAs

MSA	Mean	Min	Max	St. Dev.
AZ - Phoenix	2.39	1.92	2.86	0.28
CA - Los Angeles	5.38	4.78	6.80	0.56
CA - San Diego	4.75	4.09	5.54	0.36
CA - San Francisco	5.53	2.94	15.2	2.44
CO - Denver	2.78	2.42	3.81	0.34
DC - Washington	4.62	4.09	4.99	0.24
FL - Fort Lauderdale	3.02	2.66	3.50	0.19
FL - Orlando	2.40	2.14	2.75	0.15
FL - Tampa	2.51	2.30	2.79	0.13
FL - West Palm Beach	2.85	2.61	3.12	0.14
GA - Atlanta	2.34	2.22	2.44	0.06
IL - Chicago	3.81	3.46	4.32	0.23
MD - Baltimore	3.44	3.27	3.58	0.08
MD - Bethesda	3.70	3.20	4.07	0.26
NC - Charlotte	1.95	1.47	2.24	0.20
NY - New York	6.87	5.54	8.35	0.77
OR - Portland	2.53	1.72	2.96	0.28
TX - Austin	2.79	2.48	3.17	0.18
TX - Dallas	2.69	0.84	2.97	0.38
TX - Fort Worth	2.29	2.14	2.58	0.12
TX - Houston	2.78	2.64	2.99	0.08

Notes: All data recorded at quarterly frequency between 2004 Q1 and 2011 Q4. Rental rate is measured as the sum of net operating income and operating expenses on per square foot basis divided by occupancy rate after adjusting for inflation at 2004 Q1 level. The data is averaged across properties in a sample from a metropolitan statistical area (MSA) during a quarter as recorded in the NCREIF database.

Appendix Table 15. Summary of Apartment Operating Expenses across MSAs

MSA	Mean	Min	Max	St. Dev.
AZ - Phoenix	0.99	0.84	1.33	0.09
CA - Los Angeles	2.11	1.75	2.80	0.29
CA - San Diego	1.68	1.42	1.94	0.13
CA - San Francisco	2.16	0.98	5.42	0.89
CO - Denver	1.05	0.81	1.42	0.13
DC - Washington	1.57	1.32	1.79	0.14
FL - Fort Lauderdale	1.35	1.15	1.54	0.11
FL - Orlando	1.03	0.85	1.23	0.09
FL - Tampa	1.15	0.96	1.24	0.06
FL - West Palm Beach	1.24	1.03	1.37	0.09
GA - Atlanta	1.07	0.99	1.18	0.05
IL - Chicago	1.67	1.54	1.82	0.08
MD - Baltimore	1.32	1.15	1.54	0.10
MD - Bethesda	1.32	1.14	1.52	0.11
NC - Charlotte	0.87	0.53	1.12	0.13
NY - New York	2.99	2.27	3.83	0.41
OR - Portland	1.09	0.68	1.35	0.15
TX - Austin	1.37	1.18	1.54	0.09
TX - Dallas	1.39	0.42	1.61	0.19
TX - Fort Worth	1.25	1.13	1.41	0.06
TX - Houston	1.31	1.22	1.40	0.05

Notes: All data recorded at quarterly frequency between 2004 Q1 and 2011 Q4. Operating Expenditure is measured per square foot after adjusting for inflation at 2004 Q1 level. The data is averaged across properties in a sample from a metropolitan statistical area (MSA) during a quarter as recorded in the NCREIF database.

Appendix Table 16. Summary of Return on Appraised Values of Apartments across MSAs

MSA	Mean	Min	Max	St. Dev.
AZ - Phoenix	0.74	-14.2	14.9	5.72
CA - Los Angeles	0.91	-13.6	11.9	4.72
CA - San Diego	1.25	-8.57	6.65	3.45
CA - San Francisco	1.50	-10.8	9.60	4.53
CO - Denver	0.46	-8.75	5.38	3.31
DC - Washington	1.63	-9.55	8.44	3.77
FL - Fort Lauderdale	1.62	-11.8	9.37	4.50
FL - Orlando	1.01	-10.4	19.5	5.35
FL - Tampa	0.80	-11.7	12.7	4.52
FL - West Palm Beach	1.44	-14.9	22.8	6.53
GA - Atlanta	0.08	-8.05	3.33	3.27
IL - Chicago	0.74	-7.65	4.76	3.00
MD - Baltimore	0.70	-13.0	11.9	4.28
MD - Bethesda	1.19	-8.12	10.5	3.43
NC - Charlotte	-0.07	-10.6	4.95	3.51
NY - New York	-0.09	-24.8	13.6	6.73
OR - Portland	1.13	-9.16	8.99	4.38
TX - Austin	0.84	-8.21	8.28	3.32
TX - Dallas	0.62	-5.85	5.41	2.78
TX - Fort Worth	0.79	-6.45	6.15	2.83
TX - Houston	0.21	-5.56	4.86	2.38

Notes: All data recorded at quarterly frequency between 2004 Q1 and 2011 Q4. Returns measured in percentage and reported as an average of all properties in the sample collected during a quarter from a metropolitan statistical area (MSA) during a quarter in the NCREIF database.

Appendix Table 17. Correlation Matrix: Vacancy Rates, I4S and Fitted Vacancy Rates

	VAC	$I4S$	$I4SL$	$I4SF$	$I\hat{4}S.L$	$I\hat{4}S.F$	$I^{4SL}V\hat{A}C$	$I^{4SF}V\hat{A}C$
VAC	1	-0.11	-0.09	-0.12	-0.09	-0.11	0.82	-0.15
$I4S$		1	0.94	0.99	0.95	0.96	-0.14	0.99
$I4SL$			1	0.87	0.97	0.90	-0.11	0.93
$I4SF$				1	0.89	0.95	-0.14	0.99
$I\hat{4}S.L$					1	0.92	-0.11	0.94
$I\hat{4}S.F$						1	-0.13	0.96
$I^{4SL}V\hat{A}C$							1	-0.15
$I^{4SF}V\hat{A}C$								1

I4S = quarterly average of the weekly Google Insights for Search Index in 'Apartments and Residential Rentals' sub-category. I4SL = The I4S during the last four weeks of a quarter. I4SF = The I4S in a quarter excluding the last four weeks. VAC = vacancy rate reported in the NCREIF data base averaged across the sample properties from a metropolitan statistical area (MSA) during a quarter. A hat ($\hat{X}$) above a variable name signifies the fitted value of the variable derived from the first-stage model. $I^{4SL}V\hat{A}C_t$ = Fitted value of the vacancy rate derived from the second stage of a two-stage least square model that uses I4S as an endogenous variable. I4SL = Average weekly I4S during the last four weeks of a quarter. $I^{4SF}V\hat{A}C_t$ = Fitted value of the vacancy rate derived from the second stage of a two-stage least square model that uses I4SL as an endogenous variable.

Stage 1 (Reduced form) models

Set 1: I4SL (or VAC) = function of (4 lags of VAC, 4 lags of I4SL, I4SFW, polynomial time trends, LOBS, seasonality, MSA fixed effects)

Set 2: I4S (or VAC) = function of (4 lags of VAC, 4 lags of I4S, polynomial time trends, LOBS, seasonality, MSA fixed effects)

Stage-2 Model

Set1: $I^{4SL}V\hat{A}C_t$ = function of ($I\hat{4}S.L_t$, 4 lags of VAC, LOBS, polynomial trend and MSA fixed effects.

Set 2: $I^{4SF}V\hat{A}C_t$ = function of ($I\hat{4}S.L_t$, 4 lags of VAC, LOBS, polynomial trend and MSA fixed effects.

Appendix Table 18. Data Summary for Quarterly REIT Return Modeling

	<i>REITQ</i>	<i>MKTQ</i>	<i>SMBQ</i>	<i>HMLQ</i>	<i>MOMQ</i>	<i>I4SNQ</i>	<i>RGROWTHQ</i>	<i>VACN</i>
Descriptive Statistics								
Mean	3.83	0.87	0.60	0.32	-0.06	6.79	0.53	9.98
Min	-38.3	-23.43	-8.44	-14.1	-41.9	-15.5	-0.62	9.20
Max	33.9	15.83	8.55	13.7	15.5	25.9	1.37	11.1
St. Dev.	13.8	8.67	3.73	5.40	9.84	11.8	0.49	0.42
Stationarity/ Unit Root Tests								
KPSS	0.1	0.08	0.08	0.21	0.10	0.06	0.71	0.16
PP	25.8***	-23.9***	-30.6***	-28.6***	-21.3***	-25.4***	-23.7***	-10.4***
ADF	-2.52	-2.71	-2.7	-4.1**	-2.8	-0.61	-1.13	-2.0

Notes: All data expressed in percentage and reported at quarterly frequency. Data collected for the period of 2004 Q1 to 2011 Q4. REITQ= Quarterly return on CRSP/Ziman Multifamily REIT Index in excess of the risk-free rate. MKTQ= CAPM Market factor. SMBQ = Small-Minus-Big Fama-French factor. HMLQ = High-Minus-Low Fama-French Factor. MOMQ = Carhart's Momentum factor. I4SNQ = Quarterly average of weekly Google Insights for Search Index in 'Apartments and Residential Rentals' sub-category aggregated at national level. RGROWTHQ = quarterly inflation in Consumer Price Index in the Primary Residence Rental category reported by the Bureau of Labor Statistics (BLS). VACN = Nationally aggregated vacancy rate in renter-occupied residential assets reported by the American Housing Survey (AHS). KPSS = Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test statistic for the null hypothesis of trend stationarity. PP = Phillips-Perron test statistic for the null hypothesis of a unit root. ADF = Augmented Dickie-Fuller test statistic for the null hypothesis of a unit root. *** and ** denote statistical significance at 1% and 5% levels respectively.

Appendix Table 19. Correlation Matrix for Quarterly REIT Return Modeling

	<i>REITQ</i>	<i>MKTQ</i>	<i>SMBQ</i>	<i>HMLQ</i>	<i>MOMQ</i>	<i>I4SNQ</i>	<i>RGROWTHQ</i>	<i>VACN</i>
<i>REITQ</i>	1.00	0.74	0.54	0.63	-0.44	0.09	-0.06	0.23
<i>MKTQ</i>		1.00	0.47	0.36	-0.34	-0.11	-0.15	0.10
<i>SMBQ</i>			1.00	0.31	-0.28	-0.30	-0.21	0.17
<i>HMLQ</i>				1.00	-0.31	0.09	0.18	0.24
<i>MOMQ</i>					1.00	-0.10	-0.03	-0.37
<i>I4SNQ</i>						1.00	0.63	-0.19
<i>RGROWTHQ</i>							1.00	-0.32
<i>VACN</i>								1.00

Notes: All data expressed in percentage and reported at quarterly frequency. Data collected for the period of 2004 Q1 to 2011 Q4. *REITQ*= Quarterly return on CRSP/Ziman Multifamily REIT Index in excess of the risk-free rate. *MKTQ*= CAPM Market factor. *SMBQ* = Small-Minus-Big Fama-French factor. *HMLQ* = High-Minus-Low Fama-French Factor. *MOMQ* = Carhart's Momentum factor. *I4SNQ* = Quarterly average of weekly Google Insights for Search Index in 'Apartments and Residential Rentals' sub-category aggregated at national level. *RGROWTHQ* = quarterly inflation in Consumer Price Index in the Primary Residence Rental category reported by the Bureau of Labor Statistics (BLS). *VACN* = Nationally aggregated vacancy rate in renter-occupied residential assets reported by the American Housing Survey (AHS).

Appendix Table 20. Quarterly REIT Returns and Fundamentals

	Model-1			Model-2			Model-3			Model-4		
<i>Intercept</i>	2.32	(1.4)		1.98	(1.4)		2.75	(1.3)		-29.1	(-0.8)	
<i>MKTQ</i>	1.17	(6.0)	***	0.78	(4.1)	***	0.75	(4.1)	***	0.81	(4.3)	***
<i>SMBQ</i>				0.66	(1.5)		0.87	(2.0)	*	0.90	(2.0)	*
<i>HMLQ</i>				0.90	(3.1)	***	0.93	(3.3)	***	0.77	(2.7)	**
<i>MOMQ</i>				-0.17	(-1.1)		-0.12	(-0.8)		-0.08	(-0.5)	
<i>I4SNQ</i>							0.35	(2.4)	**	0.23	(1.8)	*
<i>VACN</i>										2.94	(0.8)	
<i>RGROWTHQ</i>							-6.14	(-1.7)	*			
<i>N</i>	32			32			32			32		
<i>R²</i>	0.55			0.73			0.78			0.76		
<i>Adj. R²</i>	0.53			0.69			0.73			0.70		
<i>MN</i>	-2.4			-2.3			0.33			-1.6		

Notes: All data expressed in percentage and reported at quarterly frequency. Data collected for the period of 2004 Q1 to 2011 Q4. Dependent variable = REITQ. REITQ= Quarterly return on CRSP/Ziman Multifamily REIT Index in excess of the risk-free rate. MKTQ= CAPM Market factor. SMBQ = Small-Minus-Big Fama-French factor. HMLQ = High-Minus-Low Fama-French Factor. MOMQ = Carhart's Momentum factor. I4SNQ = Quarterly average of weekly Google Insights for Search in 'Apartments and Residential Rentals' sub-category in the 'Real Estate' category aggregated at national level. RGROWTHQ = quarterly inflation in Consumer Price Index in the Primary Residence Rental category reported by the Bureau of Labor Statistics (BLS). VACN = Nationally aggregated vacancy rate in renter-occupied residential assets reported by the American Housing Survey (AHS). MN = Von Mises test statistic for the error term with the null hypothesis that the residuals are white noise. *, ** and *** denote statistical significance at 10%, 5% and 1% levels respectively.

Appendix Table 21. Contemporaneous Model for REIT Returns

	Coeff.	T-Stat.	Coeff.	T-Stat.		Coeff.	T-Stat.	
<i>Intercept</i>	1.72	(0.67)	0.88	(0.41)		1.62	(8.85)	
<i>abI4S</i>	0.05	(1.35)	0.04	(1.38)		0.06	(1.97)	*
<i>MKT</i>			0.71	(12.7)	***	0.41	(6.57)	***
<i>SMB</i>						0.38	(2.87)	***
<i>HML</i>						0.40	(3.16)	***
<i>MOM</i>						-0.41	(-6.10)	***
<i>Week Dummies</i>	<i>Included</i>		<i>Included</i>			<i>Included</i>		
<i>N</i>	416		416			416		
<i>R²</i>	0.11		0.41			0.52		
<i>Adj. R²</i>	-0.02		0.31			0.44		
<i>MN</i>	2.04		0.12			3.34	*	

Notes: Dependent variable: REIT. REIT = weekly return on CRSP/Ziman Multifamily REIT index return in excess of the risk-free rate. Data analyzed between January 2004 and December 2011. Subscripts signify time. MKT= CAPM Market factor. SMB = Small-Minus-Big Fama-French factor. HML = High-Minus-Low Fama-French Factor. MOM = Carhart's Momentum factor. abI4S = I4S in excess of the median of recent 6 weeks (I4S = Weekly Google Insights for Search Index in 'Apartments and Residential Rentals' sub-category). MN = Von Mises White Noise test statistic for the error term with the null hypothesis of white noise. *, and *** signify statistical significance at 10 % and 1 % levels respectively.

Appendix Table 22. REIT Returns Modeled with LaggedI4S

	Model 1		Model 2		Model 3	
	Coeff.	T-Stat.	Coeff.	T-Stat.	Coeff.	T-Stat.
<i>Intercept</i>	-0.13	(-0.09)	-0.18	(-0.01)	-0.09	(-0.08)
<i>Lagged Variables</i>						
<i>I4S_{t-1}</i>	-0.001	(-0.03)	0.003	(0.16)	0.02	(0.82)
<i>REIT_{t-1}</i>	0.06	(1.19)	0.11	(2.50) **	0.08	(2.03) **
<i>Exogenous Variables</i>						
<i>MKT_t</i>			0.73	***	0.06	(7.08) ***
<i>SMB_t</i>					0.13	(2.84) ***
<i>HML_t</i>					0.12	(3.23) ***
<i>MOM_t</i>					-0.07	(-6.04) ***
<i>Week Dummies</i>	<i>Included</i>		<i>Included</i>		<i>Included</i>	
<i>N</i>	410		410		410	
<i>R²</i>	0.10		0.40		0.51	
<i>Adj. R²</i>	-0.03		0.31		0.43	
<i>MN</i>	0.91		-0.09		1.76	

Notes: Dependent variable: REIT. REIT = weekly return on CRSP/Ziman Multifamily REIT index return in excess of the risk-free rate. Period of analysis: January 2004 to December 2011. Subscripts signify time. MKT= CAPM Market factor. SMB = Small-Minus-Big Fama-French factor. HML = High-Minus-Low Fama-French Factor. MOM = Carhart's Momentum factor. I4S = Weekly Google Insights for Search Index in 'Apartments and Residential Rentals' sub-category. MN =Von Mises White Noise test statistic for the error term with the null hypothesis of white noise. **, and *** signify statistical significance at 5% and 1 % levels respectively.

Appendix Table 23. Sensitivity of REIT Returns to the Selection of Rolling Window (k) for Abnormal I4S Calculation: The Naïve Modeling Approach

k	Coefficients			Adj. R^2
	Intercept	$abI4S_{t-1}$	$REIT_{t-1}$	
3	0.006	0.052	0.064	-0.031
4	0.024	0.060	0.063	-0.031
5	0.160	0.082	0.063	-0.027
6	0.233	0.087 *	0.063	-0.024
7	0.187	0.068	0.060	-0.026
8	0.131	0.050	0.063	-0.025
9	0.129	0.046	0.062	-0.026
10	0.066	0.031	0.063	-0.028
11	0.090	0.034	0.063	-0.028
12	0.115	0.036	0.064	-0.027
13	0.229	0.049	0.058	-0.023
14	0.316	0.057	0.058	-0.021
15	0.270	0.048	0.057	-0.023
16	0.242	0.042	0.056	-0.025
17	0.418	0.058	0.056	-0.023
18	0.521	0.065	0.059	-0.020
19	0.574	0.066	0.056	-0.022
20	0.579	0.062	0.055	-0.023
21	0.677	0.066 *	0.054	-0.022
22	0.781	0.070 *	0.054	-0.021
23	0.850	0.073 *	0.053	-0.018
24	0.899	0.073 **	0.051	-0.018
25	0.922	0.071 *	0.051	-0.019
26	0.874	0.064 *	0.051	-0.021

Notes: Each row represents a unique regression model using a particular $abI4S(k)$ as an independent variable. Dependent variable: REIT. REIT= Weekly return on CRSP/Ziman Multifamily REIT Index in excess of the risk-free rate. $abI4S$ = I4S in a week in excess of the median of recent k weeks (I4S = Weekly Google Insights for Search Index in 'Apartments and Residential Rentals' sub-category). Columns 2 to 4 provide regression coefficients of the respective variables included in the model. The last column provides the corresponding Adjusted R-squared. Dependent variable: REIT. Subscripts denote time. Data analyzed for the period of January 2004 to December 2011. * and ** denote statistical significance at 10%, and 5% levels respectively.

Appendix Table 24. Sensitivity of REIT Returns to the Selection of Rolling Window (k) for Abnormal I4S Calculation: The CAPM Modeling Approach

k	Coefficients						Adj. R ²
	Intercept	$abI4S_{t-1}$	$REIT_{t-1}$		MKT_t		
3	0.078	0.065	0.111 **		0.729 ***		0.314
4	0.088	0.070	0.109 **		0.729 ***		0.316
5	0.176	0.074	0.109 **		0.727 ***		0.317
6	0.225	0.074 *	0.109 **		0.725 ***		0.318
7	0.210	0.064	0.107 **		0.725 ***		0.317
8	0.170	0.049	0.107 **		0.724 ***		0.315
9	0.148	0.041	0.107 **		0.724 ***		0.313
10	0.074	0.026	0.108 **		0.724 ***		0.312
11	0.069	0.023	0.108 **		0.724 ***		0.311
12	0.061	0.021	0.109 **		0.724 ***		0.313
13	0.099	0.024	0.104 **		0.720 ***		0.314
14	0.129	0.027	0.105 **		0.719 ***		0.314
15	0.110	0.023	0.105 **		0.722 ***		0.314
16	0.119	0.022	0.104 **		0.723 ***		0.314
17	0.229	0.033	0.104 **		0.721 ***		0.314
18	0.281	0.036	0.106 **		0.720 ***		0.316
19	0.289	0.034	0.104 **		0.720 ***		0.314
20	0.309	0.034	0.104 **		0.721 ***		0.314
21	0.417	0.041	0.103 **		0.720 ***		0.315
22	0.524	0.047	0.103 **		0.719 ***		0.316
23	0.573	0.049	0.102 **		0.718 ***		0.317
24	0.571	0.047	0.101 **		0.717 ***		0.317
25	0.614	0.047	0.100 **		0.719 ***		0.317
26	0.598	0.044	0.101 **		0.720 ***		0.317

Notes: Each row represents a unique regression model using a particular $abI4S(k)$ as an independent variable. Dependent variable: REIT. REIT= Weekly return on CRSP/Ziman Multifamily REIT Index in excess of the risk-free rate. $abI4S$ = I4S in a week in excess of the median of recent k weeks (I4S = Weekly Google Insights for Search Index in 'Apartments and Residential Rentals' sub-category). Columns 2 to 5 provide regression coefficients of the respective variables included in the model. The last column provides the corresponding Adjusted R-squared. Subscripts denote time. Data analyzed for the period of January 2004 to December 2011. MKT= CAPM Market factor. *, ** and *** denote statistical significance at 10%, 5% and 1% levels respectively.

Appendix Table 25. Sensitivity of REIT Returns to the Rolling Window (k): The Four-Factor Modeling Approach

k	Coefficients											Adj. R ²	
	Intercep t	abI4S _{t-1}		REIT _{t-1}	MKT _t		SMB _t		HML _t		MOM _t		
3	-0.19	0.069		0.082 **	0.434 ***		0.394 ***		0.419 ***		-0.381 ***		0.434
4	-0.17	0.079 *		0.080 **	0.433 ***		0.399 ***		0.417 ***		-0.383 ***		0.436
5	-0.09	0.079 *		0.081 **	0.431 ***		0.392 ***		0.417 ***		-0.384 ***		0.437
6	-0.05	0.077 **		0.080 **	0.430 ***		0.390 ***		0.421 ***		-0.382 ***		0.438
7	-0.07	0.067 *		0.078 **	0.431 ***		0.384 ***		0.416 ***		-0.383 ***		0.436
8	-0.11	0.051		0.079 **	0.430 ***		0.381 ***		0.409 ***		-0.387 ***		0.435
9	-0.13	0.044		0.080 **	0.429 ***		0.381 ***		0.408 ***		-0.388 ***		0.434
10	-0.20	0.028		0.081 **	0.430 ***		0.377 ***		0.408 ***		-0.389 ***		0.432
11	-0.20	0.027		0.081 **	0.429 ***		0.379 ***		0.408 ***		-0.389 ***		0.432
12	-0.19	0.026		0.082 **	0.430 ***		0.378 ***		0.404 ***		-0.388 ***		0.433
13	-0.17	0.027		0.078 *	0.427 ***		0.367 ***		0.396 ***		-0.394 ***		0.435
14	-0.15	0.029		0.078 *	0.427 ***		0.367 ***		0.394 ***		-0.394 ***		0.435
15	-0.19	0.023		0.078 *	0.429 ***		0.368 ***		0.395 ***		-0.393 ***		0.435
16	-0.19	0.021		0.078 *	0.428 ***		0.366 ***		0.400 ***		-0.393 ***		0.435
17	-0.10	0.030		0.078 *	0.427 ***		0.363 ***		0.401 ***		-0.394 ***		0.436
18	-0.05	0.033		0.079 *	0.426 ***		0.360 ***		0.396 ***		-0.396 ***		0.437
19	0.02	0.038		0.078 *	0.424 ***		0.363 ***		0.397 ***		-0.398 ***		0.437
20	0.07	0.040		0.077 *	0.424 ***		0.363 ***		0.397 ***		-0.399 ***		0.437
21	0.17	0.046		0.076 *	0.424 ***		0.363 ***		0.396 ***		-0.399 ***		0.437
22	0.28	0.052 *		0.076 *	0.423 ***		0.363 ***		0.394 ***		-0.400 ***		0.439
23	0.34	0.054 *		0.075 *	0.423 ***		0.355 ***		0.387 ***		-0.404 ***		0.441
24	0.37	0.055 **		0.075 *	0.421 ***		0.358 ***		0.387 ***		-0.405 ***		0.441
25	0.41	0.054 *		0.074 *	0.422 ***		0.358 ***		0.389 ***		-0.403 ***		0.440
26	0.39	0.050 *		0.074 *	0.424 ***		0.357 ***		0.389 ***		-0.403 ***		0.439

Notes: Each row represents a unique regression model using a particular abI4S(k) as an independent variable. Dependent variable: REIT. REIT= Weekly return on CRSP/Ziman Multifamily REIT Index in excess of the risk-free rate. abI4S = I4S in a week in excess of the median of recent k weeks (I4S = Weekly Google Insights for Search Index in 'Apartments and Residential Rentals' sub-category). Columns 2 to 8 provide regression coefficients. The last column provides the corresponding Adjusted R-squared. Subscripts denote time. Data analyzed for the period of January 2004 to December 2011. SMB = Small-Minus-Big Fama-French factor. HML = High-Minus-Low Fama-French Factor. MOM = Carhart's Momentum factor. *, ** and *** denote statistical significance at 10%, 5% and 1% levels respectively.

Appendix Table 26. Modeling REIT Returns with the I4S based on “REIT” as the Search Term

	Model 1			Model 2		
	Coeff	T-Stat.		Coeff.	T-Stat.	
<i>Intercept</i>	-0.63	(-0.62)		-0.32	(-0.31)	
<i>Lagged Variables</i>						
<i>abI4S_{t-1}</i>				0.07	(1.95)	*
<i>abRI4S_{t-1}</i>	-2.26	(-2.38)	**	-2.12	(2.23)	**
<i>REIT_{t-1}</i>	0.09	(2.17)	**	0.08	(2.15)	**
<i>Exogenous Variables</i>						
<i>MKT_t</i>	0.44	(7.23)	***	0.44	(7.16)	**
<i>SMB_t</i>	0.35	(2.75)	***	0.37	(2.91)	***
<i>HML_t</i>	0.40	(3.24)	***	0.41	(3.33)	***
<i>MOM_t</i>	-0.38	(-5.91)	***	-0.38	(-5.87)	***
<i>Week Dummies</i>	<i>Included</i>			<i>Included</i>		
<i>N</i>	410			410		
<i>R²</i>	0.52			0.54		
<i>Adj. R²</i>	0.44			0.44		
<i>MN</i>	4.59	**		5.08	**	

Notes: Dependent Variable: REIT. REIT = Weekly return on CRSP/Ziman Multifamily REIT returns in excess of the risk-free rate. Variable subscripts denote time. All data expressed in percentage and reported at weekly frequency. Data analyzed for the period of January 2004 to December 2011. *abI4S* = the I4S in a week in excess of the median of recent 6 weeks (I4S = Weekly Google Insights for Search in Index ‘Apartments and Residential Rentals’ sub-category). *abRI4S* = the RI4S in a week in excess of the median of recent 6 weeks (RI4S = Weekly Google Insights for Search Index with “REIT” as the search term). *MKT* = CAPM Market factor. *SMB* = Small-Minus-Big Fama-French factor. *HML* = High-Minus-Low Fama-French Factor. *MOM* = Carhart’s Momentum factor. *MN* = Von Mises White Noise test statistic for the error term with the null hypothesis of white noise. *, ** and *** denote statistical significance at 10%, 5% and 1% levels respectively.

Appendix Table 27. Empirically Determined Break Points

Model	Week	Month	Year
Naive	4	October	2007
CAPM	3	October	2008
Four-factor	3	October	2008

Notes: Each row in this table reports structural break-points in the corresponding multivariate model that has REIT as the dependent variable. REIT = weekly return on CRSP/Ziman Multifamily REIT index in excess of the risk free rate. All models include the first lag of REIT and $abI4S$ in the model. CAPM and Four-factor models also include contemporaneous systematic risk factors. The CAPM model includes MKT. The Four-factor model includes MKT, SMB, HML and MOM. Additionally, all models control for weekly seasonality in the $abI4S$. Data analyzed for the period of January 2004 to December 2011. $abI4S$ = the $I4S$ in a week in excess of the median of recent 6 weeks ($I4S$ = Weekly Google Insights for Search in Index 'Apartments and Residential Rentals' sub-category). MKT= CAPM Market factor. SMB = Small-Minus-Big Fama-French factor. HML = High-Minus-Low Fama-French Factor. MOM = Carhart's Momentum factor. Breakpoints are derived by applying the programming developed by Zeileis, Kleiber, Kramer, and Hornik (2003) to these models that is based on Bai and Perron (2003).

Appendix Table 28. Univariate Structural Breakpoints

Variable	AR-order	Structural Breakpoint
I4S	1	August 2008: week 1
REIT	0	
MKT	0	
SMB	1	March 2008: week 4
HML	1	September 2008: week 3
MOM	3	March 2009: week 2

Notes: This table presents structural breakpoints in the univariate autoregressive OLS models of the variables specified in the first column. The order of the autoregressive (AR) process for each univariate series is determined based on an automatic AR algorithm (Hyndman and Khandekar, 2008) that returns the best AR model according to either AIC, AIC or BIC value. The function conducts a search over possible model within the order constraints provided.

Appendix Table 29. Modeling Δ Vacancy Rates and I4S

Stage-1						
<i>Dependent</i>	<i>I4S_{i,t}</i>					
	Coeff.	T-Stat		Coeff.	T-Stat	
<i>Intercept</i>	17.4	(10.4)	***	20.8	(10.8)	***
$\Delta VAC_{i,t}$				-0.37	(-3.41)	***
<i>Dependent_{i,t-1}</i>	0.86	(19.9)	***	0.83	(19.5)	***
<i>Dependent_{i,t-2}</i>	-0.16	(-2.79)	***	-0.15	(-2.75)	***
<i>Dependent_{i,t-3}</i>	0.03	(0.57)		0.03	(0.70)	
<i>Dependent_{i,t-4}</i>	-0.02	(-0.36)		-0.01	(-0.33)	
<i>LOBS</i>				-0.10	(-3.58)	***
<i>Quarter Dummies</i>	<i>Included</i>			<i>Included</i>		
<i>MSA Fixed effects</i>	<i>Included</i>			<i>Included</i>		
<i>N</i>	567			567		
<i>R²</i>	0.90			0.91		
<i>Adj. R²</i>	0.90			0.90		

Stage-2						
<i>Dependent</i>	<i>VAC_{i,t}</i>					
	Coeff.	T-Stat		Coeff.	T-Stat	
<i>Intercept</i>	-4.85	(-2.41)	**	-4.11	(-1.93)	*
$\widehat{I4S}_{i,t}$	-0.02	(-3.71)	***	-0.02	(-4.86)	***
<i>Unexpected.I4S_{i,t}</i>	-0.02	(-1.74)	*			
<i>Dependent_{i,t-1}</i>	-0.11	(-2.66)	***	-0.10	(-2.41)	**
<i>Dependent_{i,t-2}</i>	-0.20	(-4.87)	***	-0.19	(-4.63)	***
<i>Dependent_{i,t-3}</i>	-0.06	(-1.48)		-0.06	(-1.36)	
<i>Dependent_{i,t-4}</i>	-0.07	(-1.71)	*	-0.08	(-2.01)	**
<i>LOBS</i>	0.007	(0.95)		0.006	(0.83)	
<i>Polynomial Time Terms</i>	<i>Included</i>			<i>Included</i>		
<i>MSA Fixed effects</i>	<i>Included</i>			<i>Included</i>		
<i>N</i>	567			567		
<i>R²</i>	0.12			0.14		
<i>Adj. R²</i>	0.07			0.08		

Notes: The table reports the results of two-stage panel data modeling of quarterly change in vacancy rates across 21 Metropolitan Statistical Areas (MSAs), and 27 quarters between 2005Q2 and 2011Q4 (for the list of MSAs, refer to Appendix Table 10). Subscripts t and i signify time and MSA respectively. I4S = quarterly average of the weekly Google Insights for Search Index in 'Apartments and Residential Rentals' sub-category. VAC = average vacancy rate in a metropolitan statistical area (MSA) reported by NCREIF. LOBS = Low Observation Indicator that assumes a value of 1 when the number of properties in the sample is less than 30, 0 otherwise. 47% of the observations fall in the 'Low Observation' category for the data applied above. The polynomial time term includes up to the fourth degree terms of t . A hat ($\hat{X}$) above a variable name signifies the fitted value of the variable derived from the first-stage model. The error term is the 'Unexpected' component of the I4S. Quantities in the parentheses signify t-statistics. ***, ** and * denote statistical significance at 1%, 5% and 10% levels respectively.

Stage-1: $I4S = f(\text{Independent variables}) + \text{error}$

Stage-2: $VAC = g(\text{independent variables}', \text{fitted and residual values from the first stage})$.

The fitted values from stage-1 i.e. $f(\text{independent variables})$ and the residuals i.e. error term from the first stage are utilized in the second stage.

Appendix Table 30. Modeling Weekly CRSP/Ziman Multifamily REIT Index Returns Around the Structural Breakpoint

Before the Point of Structural Break									
	Panel-1a: Naive		Panel-1b: CAPM			Panel-1c: Four-factor			
	Coeff	T-Stat	Coeff	T-Stat		Coeff	T-Stat		
Intercept	2.08	(1.32)	1.14	(0.72)		1.26	(0.78)		
Lagged Variables									
$abI4S_{t-1}$	0.07	(1.40)	0.04	(0.85)		0.04	(0.78)		
$REIT_{t-1}$	0.15	(1.76)	*	0.26	(4.34)	***	0.24	(4.03)	***
Exogenous Variables									
MKT_t			0.58	(8.76)	***	0.51	(7.03)		***
SMB_t						0.19	(1.35)		
HML_t						0.01	(0.07)		
MOM_t						-0.26	(-2.83)		***
Week Dummies	Included		Included			Included			
N	194		244			244			
R^2	0.33		0.46			0.49			
$Adj. R^2$	0.06		0.31			0.33			
MN	0.25		0.88			1.61			
After the Point of Structural Break									
	Panel-2a: Naive		Panel-2b: CAPM			Panel-2c: Four-factor			
	Coeff	T-Stat	Coeff	T-Stat		Coeff	T-Stat		
Intercept	-1.59	(-0.71)	0.07	(0.03)		-1.9	(-1.0)		
Lagged Variables									
$abI4S_{t-1}$	0.12	(1.30)	0.25	(2.58)	**	0.20	(2.4)		**
$REIT_{t-1}$	0.02	(0.19)	0.04	(0.51)		0.01	(0.18)		
Exogenous Variables									
MKT_t			0.79	(8.12)	***	0.23	(1.7)		*
SMB_t						0.64	(2.07)		**
HML_t						0.65	(2.85)		***
MOM_t						-0.42	(-3.64)		***
Week Dummies	Included		Included			Included			
N	216		166			166			
R^2	0.24		0.55			0.67			
$Adj. R^2$	-0.02		0.33			0.50			
MN	1.32		3.48	*		3.88	*		

Notes: Dependent variable: REIT. REIT = Weekly return on CRSP/Ziman Multifamily REIT Index. All data expressed in percentage and is reported at weekly frequency. Subscript signifies time. Data collected for the period of January 2004 to December 2011. MKT= CAPM Market factor. SMB = Small-Minus-Big Fama-French factor. HML = High-Minus-Low Fama-French Factor. MOM = Carhart's Momentum factor. $abI4S$ = abnormal Google Insights for Search in 'Apartments and Residential Rentals' sub-category in the 'Real Estate' category in excess of the median of the trailing 4 weeks. ***, ** and * denoted statistical significance at 1%, 5% and 10% levels respectively.

Figures**Figure 1. Online Rental Searches in Owners versus Renters Markets**

Notes: Weekly Google Insights for Search (I4S) Index in 'Apartments and Residential Rentals' sub-category in the 'Real Estate' category is averaged for each quarter between 2004 Q1 and 2011 Q4 and plotted on time line for two different Metros.

Figure 2. Comparing Trends in Rental Searches and Rental Rates across the Markets

Notes: All I4S reflects the weekly I4S in 'Apartment and Residential Rentals' sub-category averaged on a quarterly basis. RENT depicts quarterly Potential Gross Rental rate per square foot adjusted for inflation at 2004 Q1 level. The trend curves are derived from respective polynomial fitted curves.

Figure 3. I4S versus abI4s (k=6)

Notes: I4S = Weekly Google Insights for Search in 'Apartments and Residential Rentals' sub-category in the 'Real Estate' category. abI4S = I4S in a week in excess of the median of recent 6 weeks.

Figure 4. Evolution of the Significance (p-value) of the abI4S in Modeling REIT Returns

Notes: The solid line depicts the p-value of the abI4S in the Four-factor VAR model. The X- axis depicts the last observation in the continually increasing sample used for the VAR model. For the corresponding vector auto-regressive (VAR) models, refer to Table 9. Dependent variable = REIT (Weekly excess return in CRSP/Ziman Multifamily REIT Index).

REIT = f(lagged REIT and I4S, Contemporaneous Market, Fama-French and Carhart's factors)

Figure 5. Impulse Response Function
Naïve Model

CAPM Model

Four-Factor Model

Notes: For the corresponding vector auto-regressive (VAR) models, refer to Table 9. In all the models shown above, REIT is the dependent variable and lagged abI4S is one of the independent variables. REIT = Weekly excess return on CRSP/Ziman Multifamily REIT index. Period of analysis: 2004 to 2011. abI4S = the I4S in a week in excess of the median of recent 6 weeks (I4S = Weekly Google Insights for Search Index in 'Apartments and Residential Rentals' sub-category in the 'Real Estate' category). LL and UL signify the lower and upper confidence intervals of the impulse response function (IRF) at 95% level. Impulse = abI4S. Response = REIT.