THREE ESSAYS ON REAL ESTATE EQUITIES AND REAL ESTATE INVESTMENT TRUSTS

by

FAHAD ALMUDHAF

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ABSTRACT

THREE ESSAYS ON REAL ESTATE EQUITIES AND REAL ESTATE INVESTMENT TRUSTS

Fahad Almudhaf, Ph.D.

The University of Texas at Arlington, 2010

Supervising Professor: Salil K. Sarkar

This dissertation consists of three distinct essays. The first essay provides initial empirical evidence on the usefulness of consumer confidence index and investor optimism index in predicting REIT price movements. I find evidence of uni-directional Granger causality from REIT returns to the change in Michigan consumer sentiment index for the period 1978–2008. I find a negative and statistically significant relationship between the level of Michigan consumer sentiment index in one month and the FTSE/NAREIT US REIT returns in the next one, six, and twelve months. On the other hand, I find a positive and statistically significant relationship between Yale one-year confidence index of individuals and REIT returns.

In the second essay, both exploratory and confirmatory factor analytic techniques are applied to eighteen real estate equity markets using weekly FTSE EPRA/NAREIT

data during the period 1997-2009. Results from the common factor analysis with Direct Oblimin rotation suggest three distinct factors during 1997-2007. With a single exception, the national returns fall neatly into three geographical areas: Asia, Europe and North America. Interestingly, Australian returns were associated with Europe rather than the local geographical area of Asia. Results from confirmatory factor analysis to four different models show that the best model is the one with three pure continental factors (Asia, Europe, and North America) during the period 1997-2007. However, analysis for the period 2007-2009 shows that there are two factors only. It seems that the financial crisis has increased the integration of the European and North American real estate equity returns while Asian markets seem to be less related to markets of other continents.

The third essay investigates the relationship between media content (optimism/pessimism), REIT returns and REIT trading volume. Using computer-aided content analysis, I find that high media pessimism predicts downward pressure on REIT prices. There is a negative and significant relation between the percentage of negative words in the financial news and REIT returns. Also, there is a unidirectional Granger causality from pessimism to both REIT returns and volume. Moreover, I document that high media optimism predicts higher REIT volume. In addition, I analyze the relationship between search frequencies in Google (SVI) (a direct measure of investor attention), REIT returns and REIT trading volume. Results show that SVI Granger causes REIT volume.

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CHAPTER 1

INTRODUCTION

Real Estate Investment Trusts (REITs) are allowed to deduct dividends which are paid to shareholders from their corporate taxable income. According to the REIT Modernization Act of 1999, the required dividend distribution for REITs should not be less than 90% of their taxable income. Seventy five percent or more of the total investment assets of REITs should be in real estate related entities. These regulations differentiate REITs from other equity assets. Recently, a great amount of research has been devoted to REITs as an asset class. This increased attention has been fueled by the extreme growth in the market capitalization of REITs. According to the National Association of Real Estate Investment Trusts (NAREIT), the number of traded equity REITs has increased from 58 to 113 over the period 1990 to 2009. Over the same period, the market capitalization of REITs went from $8.7 billion to $227 billion.

Clayton and MacKinnon (2003) report that REITs went from being driven by the same economic factors as large caps in the 1970s and 1980s, to being more strongly related to both small caps and real estate related factors in the 1990s. Chan et al. (2005) document that REITs are becoming larger, more liquid, more focused in property type and have greater institutional ownerships and more analysts' coverage. Many financial economists exclude REITs from their sample and treat them differently. They do so because they believe that REITs are unique in their performance and are different from

common stocks. Ghosh et al. (1996) and Downs and Guner (1999) suggest that REITs are unique and support the fact that REITs differ than other traditional listed equities. "REITs have relatively more stable fixed income, are less sensitive to market information in the short term, and have slower market adjustment speeds than stocks" (Chang, 2006 p. 1). Recently, Lee et al. (2008) show that REITs are strongly related to the private real estate market. Therefore, my first and third essays focus on REITs in particular which could reveal different results and behavior of REITs as an investment asset compared to the general stock market. The choice of REITs in these studies is motivated by evidence in Ghosh et al. (1996) and Downs and Guner (1999) who find that REITs are unique.

Institutional investors are interested in real estate as an asset class in their mixed-asset portfolios to provide greater diversification benefits. However, the degree of integration between international property markets has been changing over time. Dynamic interrelationships among different global real estate markets affect the diversification benefits to investors, portfolio managers and institutions. Therefore, I evaluate the linkage among eighteen real estate markets in different geographical areas using more recent data which includes the more recent turmoil period (January 2008 to December 2009). Re-examination of the financial integration in the post-crisis environment deserves attention. I identify changes in the co-movement structure of international real estate markets in post global financial crisis era.

This dissertation consists of three distinct essays with one chapter per essay. In each chapter, I review the relevant literature, identify the contributions of my study, and

cover the data and methods used. Then, I present the results and conclude with a summary.

The first essay provides initial empirical evidence on the usefulness of consumer sentiment and investor optimism indices in explaining real estate investment trust (REIT) price movements. I find evidence of uni-directional causality from REIT returns to the change in Michigan Consumer Sentiment Index for the period 1978 to 2008. I find a negative and significant relationship between the level of Michigan Consumer Sentiment Index in one month and the FTSE/NAREIT US All REIT returns in the next one, six, and twelve months. However, the relationship is significant for the 1978-1992 period but not for the 1992-2008 period. Additionally, I find a positive and significant relationship between Yale One-Year Confidence Index of *Individuals* and REIT returns and no significant relationship was found between REIT returns and investor sentiment as measured by the UBS/Gallup Investor Optimism Index.

In the second essay, factor analytic techniques are applied to 18 real estate equity markets during the period 1997 to 2009. Results from the Exploratory Factor Analysis with Oblique Rotation suggest three distinct factors for the period 1997-2007. With the single exception of Australia, the national returns fall neatly into three geographical areas: Asia, Europe and North America. Interestingly, Australian returns were associated with Europe rather than the local geographical area of Asia. Results from confirmatory factor analysis models show that the best model is the one with three pure continental factors (Asia, Europe, and North America) during the period 1997 to 2007. However, the analysis for the period 2007 to 2009 showed that there are only two factors. The Liquidity Crisis

of 2007 had increased the integration of the European and North American real estate equity returns while Asian markets were less integrated with markets of other continents.

Finally, the third essay investigates the relationship between financial news content (optimism/pessimism), REIT returns and trading volume. I apply textual analysis and find that high media pessimism predicts downward pressure on REIT returns. Negative words in the financial press are significantly negatively related to REIT returns. I also show that high media optimism predicts higher REIT trading volume. In addition, I find that there is significant unidirectional Granger causality from both optimism and pessimism to REIT returns and volume. Results using Johansen cointegration suggest that there a long-run relationship between media content and REIT return and volume. Using EGARCH and TGARCH, I document significant asymmetry (leverage effects) in REIT returns. This indicates that negative shocks (bad news) have a greater impact than positive shocks (good news). Moreover, I analyze the relationship between search frequencies in Google, REIT returns and REIT trading volume.

CHAPTER 2

CONSUMER SENTIMENT, INVESTOR OPTIMISM AND REIT RETURNS

2.1 Introduction

Behavioral finance does not presume rationality and, therefore, investors may be influenced by market sentiment. Baker and Wurgler (2007, p. 129) define investor sentiment as "a belief about future cash flows and investment risks that is not justified by facts in hand." Shleifer and Vishny (1997) argue that betting against investor sentiment is risky and costly. Behavioral financial economists argue that asset pricing models should consider the role of investor sentiment. For example, Hirshleifer (2001) argues that expected equity returns are determined by both risk and misevaluation caused by cognitive biases and investors' psychology. Along the same lines, Daniel et al. (1998) developed a behavioral theory based on investor overconfidence and their trading mistakes related to misinterpreting new information. More recently, Ye (2009) developed the Sentiment Asset Pricing Model (SAPM).

Many proxies used to measure investor sentiment levels are evaluated in the financial economics literature. For example, Brown and Cliff (2005) use financial newsletter writers' predictions to explain equity market returns. Additionally, Baker and Wurgler (2007) list many other methods of measuring sentiment such as mood proxies, retail investor trades, trading volume, closed-end fund discounts, and option-implied volatility.

In this present study, I examine the relationship between real estate investment trust (REIT) returns and consumer sentiment to answer the following questions: Does *consumer sentiment* contain information about REIT returns or vice versa? Do *investor optimism* reports contain useful information about future REIT price movements?

Unlike previous work focusing on general equity market returns, this study represents the first examination of the relationship between survey-based sentiment measures and REIT returns. Ghosh et al. (1996, p. 46) find that "REITs look less and less like stocks, particularly small stocks, over time." The return pattern for REITs differs from other stocks due to local market fundamentals and less available information suggesting that equity REITs are somewhat unique. Therefore, the focus in this present study is REIT returns. I employ three indices: the University of Michigan Consumer Sentiment Index (referred to as UMCSI hereafter), the Yale One-Year Confidence Index (referred to as YOYCI hereafter), and UBS/Gallup Investor Optimism Index (referred to as GIOI hereafter) as survey-based sentiment measures to study the relationship between REIT returns and both investor optimism and consumer sentiment.

According to Baker and Wurgler (2006), the difficulty of determining the true value of some equities makes them more likely to be sensitive to the pressure of investor sentiment. Such stock returns are expected to be positively correlated with investor sentiment with inexperienced investors more likely to be influenced by sentiment. "REITs in the post-1990 period are more actively managed, which is likely to make them more difficult to value" (Chui et al. 2003, p. 452). Therefore, I expect

REITs to be more influenced by sentiment in the post-1990 period and the results of this study are useful to investors who pay close attention to survey-based sentiment indicators. Results should also be of interest for academicians in the area of behavioral finance and asset pricing.

In summary, I find a negative and significant relationship between the level of UMCSI in one month and the FTSE/NAREIT US All REITs returns in the next one, six, and twelve months. However, this relationship is not significant during the 1992-2008 period. In addition, I find evidence of uni-directional causality from REIT returns to the change in UMCSI for the period 1978 to 2008. On the other hand, I find a positive and significant relationship between YOYCI and REIT returns. However, all of the results between the GIOI and REIT returns are insignificant.

2.2 Literature Review

Many studies have evaluated sentiment in equity market returns. For example, Solt and Statman (1988) and Clarke and Statman (1998) use Investor Intelligence newsletters and find no statistically significant relationship between equity returns and the level of sentiment of newsletter writers. However, Fisher and Statman (2000) find a negative and statistically significant relationship between investor sentiment and future equity returns. They use a sentiment survey of the members of the American Association of Individual Investors. In another study, Lee et al. (1991) find that stock returns are lower (higher) when investors are irrationally pessimistic (optimistic). Chan et al. (1990) test the relationship of REIT returns and changes in the discount rate on

closed end stock funds, a proxy for investor sentiment. Measuring sentiment differently, Neal and Wheatley (1998) examine the forecast power of individual investor sentiment using the discounts on closed-end funds and ratio of net mutual fund redemptions to assets. They find that net redemptions and fund discounts predict the difference between small and large stock returns. In a study covering the German market, Honcoop and Lehnert (2007) find evidence that investor sentiment has predictive power in estimating future stock returns.

Using a composite sentiment index based on six technical factors, Baker and Wurgler (2006) find that sentiment affects equity returns of firms that are more difficult to arbitrage. They show that when investor sentiment is low, subsequent returns are relatively high for small and relatively new equities. In addition, they provide a review of the anecdotal evidence on investor sentiment since the early 1960s. Tetlock (2007) finds that high media pessimism, as measured by the **Wall Street Journal**'s "Abreast of the Market" column, predicts downward pressure on stock market prices. He also shows that low stock market returns lead to high media pessimism. More recently, Hengelbrock et al. (2009) find that investors can use survey-based sentiment indicators in Germany and United States to predict stock returns at intermediate horizons.

Studying the consumer confidence measures of the University of Michigan and The Conference Board, Fisher and Statman (2003) find that consumer confidence predicts stock returns. They document a negative and statistically significant relationship between consumer confidence and future stock returns. In contrast, Otoo (1999) finds that an increase in equity values enhances sentiment. The results of his

causality tests show that stock price movements affect changes in consumer sentiment. Using the same measures of consumer confidence, Lemmon and Portiniaguina (2006) study the relationship between investor sentiment and a size premium. They find that sentiment does not appear to forecast momentum and value premiums. However, they find that sentiment does forecast the size premium and that the consumer confidence measures correlate strongly with small stock returns. Covering Europe, Jansen and Nahuis (2003) find that stock returns and changes in sentiment are positively correlated in nine European countries. Over short time periods, they find that stock returns Granger-cause consumer confidence. Similarly, using data from France, United Kingdom and the United States, Asgary and Gu (2005) find that stock market performance positively affects consumer confidence.

Brown and Cliff (2005) find that sentiment as measured by Investor Intelligence market newsletters is positively related to changes in equity market valuations. High levels of sentiment result in lower returns over the preceding three years. They find that the market experiences below average subsequent returns when sentiment is bullish. Their results are consistent with the theoretical behavioral model of Barberis et al. (1998). Optimistic investors drive prices above fundamental values that then tend to mean revert over the long run. Likewise, Fisher and Statman (2002) find that individual investors are victims of cognitive biases and are unrealistically optimistic and overconfident. Using a large dataset of retail trades in the United States, Kumar and Lee (2006) find that changes in retail sentiment stimulate co-movement in stock returns.

Lashgari (2000) uses Barron's Confidence Index and reports a negative and significant relationship between confidence and stock returns.

Chan et al. (1990) test the relationship of REIT returns and changes in the discount on closed end stock funds, a proxy for investor sentiment. DeLong et al. (1990) and Lee et al. (1991) argue that noise traders overestimate changes in fundamental values of assets in general. This is a possible explanation of the fact that closed-end funds trade at a discount, on average. Barkham and Ward (1999) evaluate this hypothesis with respect to property companies and find evidence in favor of it in explaining the discount of closed-end funds. Using a questionnaire, Gallimore and Gray (2002) find that investor sentiment is an important factor in property decision-making in the United Kingdom.

More recently, Lin et al. (2009) find that REIT returns increase (decrease) when investors are optimistic (pessimistic) using the change in closed-end fund discounts as an investor sentiment proxy. However, Qiu and Welch (2006) highly recommend the use of a sentiment index, such as the UMCSI, over the use of a closed-end fund discount-based sentiment index. Therefore, I use the UMCSI, the YOYCI, and the GIOI indices in this present study.

Many measures of investor sentiment have been employed. However, my review of the literature suggests, Vissing-Jorgensen (2003) is the only study which has analyzed the GIOI, over the time period 1998 to 2002, and does not examine the usefulness of GIOI in predicting stock returns. To the best of my knowledge, the present study is the first examination of GIOI and its relationship to REIT returns. Ghosh et al.

(1996) show that REITs are less frequently traded than comparable size stocks and they conclude that REITs are less like stocks than the trade press would lead an investor to believe. Myer and Webb (1993, p. 106) state that "Intertemporally, REIT returns are much more strongly related to unsecuritized real estate than stock or closed end funds." Therefore, I aim to fill this literature gap and test the GIOI's ability to predict REIT returns. In addition, I examine the relationship between REIT returns and UMCSI and YOYCI for both individuals and institutions.

Rising real estate prices and rising sentiment tend to go hand in hand and higher real estate prices should result in greater wealth for investors and increasing optimism. Rising real estate markets give investors a more positive future outlook, boosting confidence. The direction of causality is not clear and I test this relationship empirically using the Granger causality test.

Models of investor sentiment predict low sentiment will produce downward price pressures. However, the results of Lin et al. (2009) show that REIT returns are negatively related to investor sentiment proxied by the change in closed-end fund discounts. In this present study, I complement the study of Lin et al. (2009) by using survey-based indices (UMCSI, YOYCI, and GIOI) to measure investor sentiment.

DeLong et al. (1990) suggested that investor sentiment plays a larger role in the pricing of small stocks. Therefore, I hypothesize that *investor* sentiment will have a significant role on REIT returns. In contrast, I expect *consumer* sentiment to have an insignificant relationship with REIT returns. "Due to significant changes in the organization, business plans and ownership structures after 1990, REITs became much

more difficult to value" (Chui et al. 2003, p. 476). Therefore, I expect to find a significant relationship between sentiment and REIT returns, as compared to equity returns in general.

2.3 Data

The data for the REIT returns comes from FTSE NAREIT US Real Estate Index Series for the period 1978 to 2009. I use the GIOI for the period from February 1999 to April 2009. I also use the UMCSI for the period January 1978 to September 2008. In addition, I use both the individual YOYCI and institutional YOYCI calculated by the International Center of Finance at the Yale School of Management. Both the YOYCI for individuals and the YOYCI for institutions are available monthly from July 2001 to March 2009.

UMCSI[1] is a monthly telephone survey of consumers on their expectations of general economic conditions. It relates measures of income expectations along with savings and spending. The more uncertain the consumer is, the more pessimistic he or she is. On the other hand, the more confident and certain the consumer is about the future, the more optimistic he or she is. Savings would increase when consumers are pessimistic about their future while spending would rise when people become optimistic. The index is computed from the answers of five questions; two of them on the outlook of the economy, two on personal finances, and one on buying conditions of major household items. The sample consists of adults living in United States households. The surveys incorporate both numeric probability scales measures and

[1] UMCSI is available at <http://www.sca.isr.umich.edu>.

verbal likelihood questions. Curtin (2008) provides an overview about this index. More information can be found on Qiu and Welch (2006, p. 8) and Baumohl (2007, p. 91).

The YOYCI[2] is the percentage of investors expecting an increase in the Dow Jones Industrial Average in the coming year. The decisions of people whether to save or not differs from their views about the stock market. This index is divided into a sample of wealthy individual investors with high income (YOYCI of individuals) and another sample of pension funds managers (YOYCI of institutions). The surveys report monthly six-month average of monthly surveys. For instance, the index level for December 2004 was the average result from surveys taken between July 2004 and December 2004. The index is measured as the percentage of respondents who report holding a particular view that expects an increase in the Dow Jones Industrial Index (DJII) during the following year. For more information, the reader can visit the YOYCI website. Qiu and Welch (2006, p. 12) include a brief discussion about this index which is discussed more recently in Samsell et al. (2009, p. 27).

The GIOI[3] index is developed from a survey that has been conducted since 1996. The GIOI became a monthly index in 1999. This index tracks investors' perceptions regarding the economy. It differs from other indices because it is distributed to investors only and not the general public. This is reasonable since the market moves by the actions of investors and not the public. They include persons with investments totaling $10,000 or more. They interview a random sample of 1000 investors. The index

[2] YOYCI is available at <http://icf.som.yale.edu/Confidence.Index>.

[3] GIOI is available at < http://www.ropercenter.uconn.edu/ubs.html>.

consists of seven questions measuring both the personal dimension and the economic dimension of optimism. The personal dimension covers questions related to meeting investment targets and goals for the next twelve months and five years. It also includes a question regarding maintaining and increasing the personal current income of the investor. The economic dimension covers the most effective factors affecting the investments during next year. The investor chooses among several factors such as unemployment rate, inflation and economic growth. The index is based on the total of economic and personal dimension scores. "This calculation differs in concept from the major measures of consumer confidence or sentiment" (Jacobe and Moore (2003, p. 36). More information can be found in Vissing-Jorgensen (2003, p. 6), Qiu and Welch (2006, p. 11) and Baumohl (2007, p. 97).

2.4 Method

The regression model is shown in equation 1 and the results are shown in tables A.1-A.3.

$$R_t = c + b(x_t) + \varepsilon \qquad (1)$$

Where R_t (the dependent variable) is the monthly rate of return on the FTSE/NAREIT US index, c is the intercept, x_t (the independent variable) is the level of sentiment index, and ε is a randomly distributed error term. The t-statistics are estimated using Newey-West heteroskedasticity and autocorrelation adjusted standard errors.

Different econometric techniques have been used in the literature to investigate short-run and long-run relationships. Engle and Granger (1987) developed a

cointegration theory that has been used in many studies to identify long-term relationships. Either an error correction model (ECM) or a vector autoregressive model (VAR) can be used to examine the relationship between the variables, taking data structure into account. If the series is stationary, a standard VAR is appropriate and this is applied in this study. The optimal number of lags is determined using the Akaike Information Criterion (AIC) by choosing the number of lags which minimizes AIC.

I first examine the time series on stationarity as a preliminary step. I use both Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979) and Phillips-Perron (PP) (Phillips and Perron, 1988) unit root tests. As the ADF test does not account for heteroskedasticity in the error term, I employ the PP tests that incorporate an automatic correction to the Dickey-Fuller procedure to allow for autocorrelated residuals. Please refer to Brooks (2002) for further information regarding the unit root tests.

Causality in this study refers to the ability of one variable to predict another. Based on Granger (1969), reports that variable y Granger causes variable x if variable x can be predicted better by including past values of variable y. “Bi-directional” causality exists when y Granger causes x and x Granger causes y. The test begins with estimating a VAR model as follows:

$$y_t = a_1 + \sum_{i=1}^{n} \beta_i x_{t-i} + \sum_{j=1}^{m} \gamma_j y_{t-j} + \varepsilon_t \tag{2}$$

$$x_t = a_2 + \sum_{i=1}^{n} \theta_i x_{t-i} + \sum_{j=1}^{m} \delta_j y_{t-j} + U_t \tag{3}$$

Where ε and U are randomly distributed error terms.

Significance of the coefficients, indicating that x Granger causes y or the reverse, does not imply that y is the effect or the result of x. Granger causality measures the information content of one variable on another and answers the question whether or not one variable precedes the other (Asteriou, 2006). REIT returns Granger-cause consumer confidence if lagged REIT returns contain information that is not already contained in past values of the confidence index.

2.4.1 Granger-Causality Hypothesis

I denote Y in equation (2) as the change in survey-based sentiment index and X in equation (3) as the change in REIT prices (REIT return). Here are the two null hypotheses:

$H_{0,\beta} : \beta_i = 0$ for i=1,2,…,n

$H_{0,\delta} : \delta_i = 0$ for j=1,2,…,m

F-statistics is used to evaluate both of the null hypotheses. There are four possible results from testing the hypotheses by comparing the F-statistics with the F-critical value. The cases are as follows.

- If both of the null hypotheses are rejected, then there exists a "bi-directional" or feedback Granger causal relationship between both variables (REIT return and change in survey-based sentiment index).
- If both of the null hypotheses are not rejected, then return and survey-based sentiment are independent and there is no causality which runs from one to the other.

- If $H_{0,\beta}$ is rejected and $H_{0,\delta}$ is not rejected, then x causes y or in this case the REIT returns cause the change in survey-based sentiment index.
- If $H_{0,\beta}$ is not rejected and $H_{0,\delta}$ is rejected, then y causes x or, in this case, the change in survey-based sentiment index causes the REIT returns.

In testing these hypotheses, I can determine whether REIT returns Granger cause change in survey-based sentiment index or changes in sentiment index Granger causes REIT returns.

2.5 Results

Results from table A.1 show that the level of UMCSI is a reliable contrary indicator of future REIT returns. There is a negative and significant relationship between the level of UMCSI in one month and the FTSE/NAREIT US All REIT returns in the next calendar month during the 1978 to 2008 period. However, I perform the Quandt-Andrews breakpoint test (Andrews 1993; Andrews and Ploberger 1994) to check for unknown structural breakpoints in our sample. Quandt-Andrews test results show that I fail to reject the null hypothesis of no structural breaks within our sample. The maximum statistic was in February 1992 which is the most likely breakpoint. I reconfirm this result using the Chow break point test which shows that there is a significant difference in the relationship before and after February 1992. Therefore, I test the stability of the relationship during both periods of January 1978 to February 1992 and February 1992 to September 2008.

I find that the relationship between UMCSI and REIT returns is significant during the earlier subsample (1978 to 1992). However, it is not statistically significant

for the more recent period after 1992. Moreover, there is a positive relationship between the GIOI and REIT returns. However, it is not statistically significant at the five percent level as shown in table A.1.

In addition, I test the relationship between the level of consumer sentiment in one month and ex ante FTSE/NAREIT US returns of six and twelve calendar months. The results are shown in tables A.2 and A.3. I find a negative and statistically significant relationship between the level of UMCSI in one month and ex ante returns in six and twelve months. The GIOI is negatively related to future REIT returns in six months, this relationship is not statistically significant at the ten percent level.

Chan et al. (1998) report that the REIT market expanded and became more dominated by institutions in the 1990s. Therefore, I test both individual and institutional survey-based confidence measures to test if there is a difference in the result. Results in tables A.1, A.2 and A.3 show that the relationship between the YOYCI and REIT returns is always positive. However, it is statistically significant for individuals only and not institutions. This is true and consistent in all of the cases (one month, six months, and twelve months). These results are expected since individuals are more influenced by sentiment. I note that the R-square is low in tables A.1, A.2 and A.3; however, this is consistent and similar with previous published work in this field [e.g., Clarke and Statman (1998), Fisher and Statman (2000, 2003), and Lashgari (2000)].

Unit root tests indicate that some of the indices are not stationary in the levels as shown in table A.4. Therefore, I take the first difference of these sentiment indices in order to transform them into stationary series. When testing with intercept only, I find

that the level of UMCSI does not have a unit root at the ten percent level. However, using a trend and intercept, I identify a unit root. The same is true for the level of the GIOI. In all series included in our study, the first difference is always stationary.

Continuing with the results of the pair-wise Granger-causality testing, table A.5 shows that REIT returns Granger-cause the change in UMCSI. However, the change in consumer sentiment index does not Granger-cause REIT returns. This means that the relationship is uni-directional running from REIT returns to the *change* in UMCSI. Thus, lagged REIT returns contain information that is not already contained in past values of the UMCSI.

Granger-causality tests of both the YOYCI and GIOI with REIT returns are not statistically significant. This means that the YOYCI and GIOI cannot be predicted better by including past values of REIT returns. Moreover, the YOYCI and GIOI cannot be used to better predict REIT returns. My results using the YOYCI are consistent with Samsell et al. (2009) who were the first to use this index and found no significant difference stock return forecasts with or without the YOYCI proxy for investor sentiment. They also rejected causality in all models of stock returns. Table A.6 compares the results of this study with the existing literature.

Differences in the results of the three survey-based indices of sentiment could be attributed to differences in the characteristics of these indices. The sample period covered is different in each of the three indices. Moreover, the subjects are different in each survey. For example, GIOI surveys investors with $10,000 or more while YOYCI for individuals surveys wealthy individuals with high income. However, UMCSI covers

households in general regardless of the fact that they invest in the stock market or not. In addition, the methodologies used in each survey and the way they are calculated differ. Moreover, each index covers different questions and dimensions. For instance, YOYCI asks only one question related to the expectations of the Dow Jones Industrials Index (DJII). On the other hand, GIOI asks investors both personal and economic questions. UMCSI asks a combination of five questions related to personal finance, the general economy and willingness and ability of buying conditions for major household items.

2.6 Conclusion

This study evaluates sentiment, as measured by three survey-based sentiment indices, in explaining REIT price movements. Granger causality tests show that REIT returns Granger causes the change of UMCSI during our sample period. Thus REIT returns add predictive power for future changes in the UMCSI. Over the sample period, consumer sentiment, as measured by the UMCSI, is a contrarian explanatory indicator of REIT returns as I find a negative and significant relationship between the level of UMCSI in one month and the FTSE/NAREIT US All REITs returns in the next one, six, and twelve months. However, this relationship has disappeared more recently as the sub-period 1992 to 2008 was statistically insignificant. For the YOYCI of individuals, only, I find a direct relationship with REIT price movements while the Granger-causality results are insignificant. All OLS regression and Granger-causality results between the GIOI and REIT returns were insignificant.

I extend the behavioral finance literature on survey-based measures of sentiment by specifically covering REITs. I complement the recent work of Lin et al. (2009) by using survey-based measures of sentiment. I show that sentiment, as proxied by UMCSI and YOYCI of individuals, contains information about future REIT returns. Financial economists could view these results as evidence against REIT market efficiency during certain time periods. Findings regarding the UMCSI are consistent with studies covering the general stock market [e.g., Fisher and Statman (2003), Otoo (1999), Lemmon and Portiniaguina (2006)]. My findings regarding the GIOI are consistent with Samsell et al. (2009) who also evaluated the stock market. Both REITs and stocks are similar in their relationship with the sentiment survey-based indices. The difficulty of determining REIT values is a possible reason for making it prone to sentiment. My results could be tied to the findings of Glascock et al. (2000) who show that REITs behave more like stocks after 1992. In addition, using the Quandt-Andrews break point test, I reconfirm the finding that there is a structural break for REITs in the year 1992.

CHAPTER 3

CO-MOVEMENTS IN INTERNATIONAL REAL ESTATE EQUITIES: EVIDENCE FROM FACTOR ANALYSIS

3.1 Introduction

Integration among financial markets of different countries has increased in recent years due to globalization, prompted by better telecommunications and fewer restrictions on capital flows. Investors are interested in international real estate markets as this alternative asset class has potential for portfolio diversification. International diversification reduces risk and is beneficial to investors as long as there is low correlation between domestic market and international markets (Harvey, 1991; Heston and Rouwenhorst, 1994; and Solnik, 1995). Academic literature has documented the diversification benefits of introducing international real estate to a mixed-asset portfolio [Conover et al. (2002) and Steinert and Crowe (2001)]. However, the presence of long-term relationships and integration among international real estate markets reduces diversification opportunities (Garvey et al., 2001; Myer et al., 1997, 1999; and Yang et al., 2005).

In this study, I use exploratory Factor Analysis (FA) as a basis for examining international integration between real estate equity returns. FA is a useful technique to describe, summarize and reduce data. Also, one can use FA to test hypotheses about the number of underlying factors (Norusis, 2003). Furthermore, I use Confirmatory Factor

Analysis (CFA) to test four different models and make comparisons and determine a best-fit model. The purpose of using CFA is to determine whether or not national real estate equity returns co-move with each other based on common continental geography. Hurley et al. (1997) explained that CFA requires an a priori hypothesis.

There is debate on the appropriate use of factor analysis. Hurley et al. (1997) explained that FA and CFA could provide complementary perspectives on data, but need to be cautious that the analysis is not reflecting random chance. Exploratory factor analytic methods have been employed as initial tests to confirm hypotheses about the latent structure underlying data. As a first pass, these methods are acceptable; however, more powerful confirmatory factor analytic procedures can address theory driven questions.

This present study contributes to the literature in three ways. First, a truly global perspective is taken as this sample includes eighteen international real estate equity markets. Second, no previous paper has used confirmatory factor analysis to study international property market integration. Third, this study includes the recent time period that includes the Liquidity Crisis of 2007.

Using both exploratory and confirmatory factor analysis, I found that there are three distinct continental factors (Asia, Europe, and North America) during the period 1997 to 2007. A notable exception was Australia, which was associated with Europe rather than Asia. These results suggested that real estate investors would have benefited from an inter-continental investment strategy to achieve benefits of international

diversification. During the 1997 to 2007 period, investing in countries from different continents was a better choice for real estate investors.

On the other hand, analysis of the turmoil period of 2007 to 2009 showed that there were two factors, as the North American and European markets merged into one factor. The financial crisis did indeed increase the interlinkages among these international real estate markets. Unfortunately for investors, some benefits from international diversification retreated in the face of a global economic crisis, just when the protection of diversification was most needed. Asian markets did continue to be related to markets of the same continent and Australia became part of the Asian factor during this period.

3.2 Literature Review

The dynamic interdependence and integration among international stock markets has been investigated heavily in the past literature.[4] However, to a lesser extent than the stock market, several researchers have examined the interlinkages among international real estate markets.[5] To date, most studies have used multivariate cointegration techniques to examine the extent and nature of integration among international real

[4] See, for example, Becker et al. (1990), Beine et al. (2009), Beine et al. (2010), Brocato (1994), Candelon et al. (2008),Chan et al. (1997), Chen et al. (2002), Cheung (1997), Christiansen and Ronaldo (2009), Darrat and Zhong (2005), De Jong and De Roon (2005), D'ecclesia and Costantini (2006), Elfakhani et al. (2008), Eun and Shim (1989), Fraser and Oyefeso (2005), Freimann (1998), Gilmore et al. (2008), Gultekin et al. (1989), Hardouvelis et al. (2006), Hunter (2006), Johnson and Soenen (2002), Kim et al. (2005), King et al. (1994), Masih and Masih (2001), Yang et al. (2003), and Yu and Hassan (2008).

[5] See, for example, Bond et al. (2003), Eichholtz et al. (1998), Gallo and Zhang (2010), Garvey et al. (2001), Liow et al. (2005), Liow et al. (2009), Liow and Webb (2007, 2008 and 2009), Lizieri et al. (2003), Mcallister and Lizieri (2006), Myer et al. (1997 and 1999), Wilson and Okunev (1996), Wilson et al. (2007), Wilson and Zurbruegg (2001), Worzala and Bernasek (1995), Worzala and Sirmans (2003), Yang et al. (2005), Yunus (2009), and Yunus and Swanson (2007).

estate markets. In one of the earliest published studies, Eichholtz et al. (1998) investigated the influence of continental factors on real estate returns. They found a strong continental factor in North America where country returns depend significantly on the returns of the home continent. Their results suggested that European and United States investors should invest in other continents for diversification benefits. Covering Pacific-Asian markets, Garvey et al. (2001) used co-integration and Granger-causality to investigate linkage between real estate equity markets in Australia, Hong Kong, Japan, and Singapore. Testing for cointegration, Wilson and Zurbruegg (2001) find that the property markets of Australia, Japan, United Kingdom, and United States were interrelated.

Kleiman et al. (2002) used co-integration analysis to find that real estate prices of Asia, Europe and North America are co-integrated and shared a common long-run trend. Covering the European property markets exclusively, Bond and Glascock (2006) and Newell (2003) showed that diversification benefits were gained investing in listed real estate equities. Yang et al. (2005) showed that European Monetary Union countries have become more integrated with countries of the same continent after the founding of the European Monetary Union.

Using GARCH and co-integration techniques, Liow et al. (2005) investigated short-term linkages and long-run relationships among Asian and European real estate equity markets. Their results supported the diversification benefits to investors from including these international real estate equity portfolios. Similarly, Yunus and Swanson (2007) find that United States investors benefited from investing in the

international property markets of Asia-Pacific. They did not find any significant long-term relationships between United States and Asia-Pacific real estate markets.

Recently, Liow and Webb (2009) examined the existence of common factors in the securitized real estate markets of Hong Kong, Singapore, United Kingdom, and United States. They used canonical correlation analysis and exploratory factor analysis to study the period 1993 to 2003. Using monthly returns, they found that there was at least one risk factor that was moderately correlated with the global real estate market. Their results showed the diversification benefits of international real estate markets. Similarly, Yunus (2009) investigated the interdependence of securitized real estate markets of Australia, France, Hong Kong, Japan, Netherlands, United Kingdom, and United States for the period 1990 to 2007. Using cointegration tests and common trends analysis, she found that the real estate markets of Australia, Hong Kong, Japan, United Kingdom and United States were tied together over the long-run. Using cointegration methodology, Gallo and Zhang (2010) investigated the long-term relationships among S&P/Citigroup global property markets over the period 1992 to 2007.

Financial economists have employed FA techniques. For example, White and Woodbury (1980) applied Principal Components Analysis (PCA) to study three different asset classes (money market, bonds and stock markets) for five industrial countries to measure capital market integration. They argued that factor analysis could be used to simultaneously examine yield movements across large numbers of countries. Nellis (1982) employed PCA to determine the extent of international financial integration. He studied levels and changes in interest rates across various countries to

determine the extent of co-movement. Nellis found a high degree of money and capital market integration since 1973 when countries started to maintain floating exchange rate regimes. Using PCA, Meric and Meric (1997) studied co-movements in twelve large European equity markets. They demonstrated that co-movements of European equity markets were harmonious in the period 1987 to 1992. They revealed that the level of co-movements between European and United States equity markets were strong. Using factor analysis, Hui (2005) studied the co-movement and interdependence between United States and Asia-Pacific stock markets.

Ostermark (1999) modeled global arbitrage pricing models using factors attributable to geographical continents. Using data from thirteen stock exchanges and a method of PCA with a VARIMAX orthogonal rotation, Ostermark discovered that the countries fell neatly into geographical areas according to the three return generating factors: Western Europe, Far East, and North America. Subsequently, CFA confirmed these findings.

Worzala and Bernasek (1995) find evidence of convergence in European countries. They argued that real estate markets had converged as a result of economic integration. However, their results showed that real estate markets were different from other financial markets and concluded that one should not expect to see a single market for European real estate. Lizieri et al. (2003) investigated the behavior of stock returns in European real estate companies to understand the effect of European monetary integration. Using PCA, Lizieri et al. tested returns for both the pre-1997 and the post-1997 period with a research objective to detect a single factor influencing performance.

They found evidence of a common European stock factor, however, they did not find a strong common factor in the Euro-zone public real estate markets. McAllister and Lizieri (2006) investigated the impact of global equity integration. They showed that global market movements influenced the national equity indices. Again, this factor did not explain movements in real estate stocks suggesting other important national drivers.

Lizieri et al. (2003) covered eight Eurozone countries for the period 1991 to 2001. This present study extends Lizieri et al. (2003) by including eighteen international real estate equity markets for the period 1997 to 2009 to provide additional insight into the interdependence among international real estate equity markets. Furthermore, I use Confirmatory Factor Analysis (CFA) as our method while Lizieri et al. (2003) used correlations, PCA, Granger causality tests and VAR to study real estate equity market co-movements. Because the extent literature does not present a convincing a priori hypothesis or confirmed theory, I start with FA and will test developed models using CFA.

This study builds upon the existing literature as follows. First, I evaluate eighteen international real estate equity markets while most published studies cover a subset. Second, no previous study has used confirmatory factor analysis to study the integration of international real estate markets. Third, to my knowledge, the study periods of extent literature stops at December 2007 (e.g., Gallo and Zhang, 2010; Liow et al., 2009; Liow and Webb, 2009; and Yunus, 2009). I include the recent and important time period of January 2008 to December 2009. This recent period is

classified as a turmoil period due to the Liquidity Crisis of 2007, a crisis that profoundly impacted and changed global financial and real estate markets.

3.3 Data

The sample covers the time period January 1997 to December 2009 and consists of weekly returns from eighteen real estate equities markets: Australia, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Italy, Japan, Netherlands, Norway, Singapore, Spain, Sweden, Swiss, United Kingdom, and United States. This FTSE EPRA/NAREIT was obtained from DataStream. Data for Belgium and Denmark is not available for 2009. Therefore, I exclude them from my analysis of the 2007-2009 period.

The FTSE EPRA/NAREIT indices are comprised of large publicly-traded real estate companies. In a guide to REIT indices, Frost et al. (2005) rate the major REIT indices according to their acceptance by investors, accuracy, completeness, transparency and liquidity and conclude that the FTSE EPRA/NAREIT is a premier global real estate index. For more information on this index, see Bond and Glascock (2006), Bond et al. (2003), Lenkkeri et al. (2006), Newell (2003), Yang et al. (2005), Yunus (2009), and Yunus and Swanson (2007).

Sample size is a concern when using factor analysis. Ford et al. (1986) suggested at least ten observations per variable. Costello and Osborne (2005) suggested a subject to item ratio of 10:1 as a rule-of-thumb for factor analysis. This study's sample of 678 observations is of an appropriate size.

3.4 Method

3.4.1 Exploratory Factor Analysis

As previously discussed, FA is appropriate in hypothesis development and CFA is used in hypothesis testing. FA and CFA are both tools used in identifying common ground upon which the data rest. The appropriateness of each depends on the purpose of the study and the nature of the data.

Several exploratory factor analysis techniques are used for extracting factor loadings. The most common method is Principal Components Analysis (PCA). However, it is not considered the best method. Conway and Huffcutt (2003) argued that the use of common factor model such as principal axis or maximum likelihood factoring represents a high-quality decision. They demonstrated that both theory and empirical evidence favor common factor analysis as an appropriate technique. Also, they explained that PCA is not technically factor analysis. Instead, PCA is intended to simply summarize many variables into fewer components, and the latent constructs or factors are not the true focus of the analysis (Henson and Roberts 2006). True factor analysis offers a more realistic model of measurement than principal components analysis by admitting the presence of random and systematic error.

Factor rotating makes analysis interpretation easier. There is debate among social scientists, whether the use of an orthogonal rotation is appropriate since the assumption of no correlation between variables rarely holds in real life. Relaxation of the orthogonal assumption and using oblique factors results in a more realistic model.

As a result, my study employs common factor analysis (principal axis factoring) with Direct Oblimin Oblique rotations.

Using SPSS, exploratory common factor analysis was used on eighteen items, with the goals of identifying underlying relationships and reducing the data structure. After exploring various methods of extraction and rotation, FA (Principal Axis Factors) with direct Oblimin Oblique rotation was selected as the optimal model. List-wise deletion was used to address missing values and delta was set to zero (default).

3.4.2 Confirmatory Factor Analysis

Next, CFA was used to test four different measurement models with the objective of finding the best fit among alternative models. AMOS software was used to develop the CFA analysis and testing.

3.5 Results

3.5.1 Exploratory Factor Analysis Results

The Kaiser-Meyer-Olkin (KMO) procedure was used to test for linearity. My results show a KMO measure of 0.909 which is close to one and confirms that there is sufficient multicollinearity to warrant further analysis. Also noteworthy is the significance of Bartlett's Test of Sphericity indicating a significant difference from the identity matrix (Bartlett 1950, 1951). This again demonstrates that common factor analysis is appropriate and the sample can be reduced.

Three methods are used to determine the number of components to include in the FA. First a scree plot (Cattell 1966), which is a plot of total variance associated with each component. The scree test involves examining the graph of the eigenvalues for a

flattening inflection in the curve that indicates a natural bend or break point in the data. Figure A.1 shows the scree plot which indicates that three factors may be appropriate for the 1997-2007 period. However, it shows two factors only for the 2007-2009 period.

I also considered an eigenvalue-greater-than-one criterion where components that account for variances greater than one are included. As shown in table A.7, this metric also indicated using 3 factors for the 1997-2007 period. Finally, I considered parallel analysis (Horn, 1965; Turner, 1998). Henson and Roberts (2006) consider parallel analysis the most accurate procedure. SPSS syntax provided by O'Connor (2000) was used to generate the parallel analysis. Results from parallel analyses also suggested three factors for the 1997-2007 period. From table A.7, please note that 44.09% of the total variance was explained by three factors for the 1997-2007 period.

From table A.8, it is apparent that certain factors influence specific variables. Tabachnick and Fidell (2001) cite 0.32 as an appropriate benchmark for a minimum loading. Therefore, I suppressed coefficients of less than 0.32 in absolute value. Three factors remain: Asia, Europe and North America. I note that the first factor (Europe) includes twelve countries: Australia, Belgium, Finland, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, Swiss and United Kingdom. This factor included all European countries in my sample except Denmark and also includes Australia (with a loading 0.395 in the first factor). The second factor (Asia) included all three Asian countries: Hong Kong, Japan and Singapore. The third factor (North America) included two countries: Canada and the United States. Using Principal Axis Factoring (PAF)

with Direct Oblimin oblique rotation and the 0.32 benchmark as a cutoff point, there are no cross loadings on more than one of the three factors.

On the other hand, my results for the recent 2007-2009 period show two factors only as shown in tables A.7 and A.8. The first factor included all European and North American countries while the second part included all Asian countries. Australia is more related to Asian markets during the 2007-2009 period. This indicates that the financial crisis has increased co-movement of European and North American real estate markets.

3.5.2 Confirmatory Factor Analysis Results

Thompson and Daniel (1996) note that CFA can readily be used to test rival models and quantify the fit of each model. Testing rival models is usually essential because multiple models commonly fit a single sample. Of course, finding that a single model provides the best fit, does not "prove" the model, since untested models may fit even better. This process does improve model validity (Thomson and Daniel, 1996).

In Figure A.2, the hypothesized measurement model was compared to the three alternative measurement models (found in figures A.3, A.4, and A.5). The hypothesized model had three latent variables (Asia, Europe and North America) with each country linked to the latent variable based on geography. Australia was related to Europe, based on the initial FA results (0.395 loading in factor 1). Alternative model 1 assumes a single global factor and had a single latent variable consisting of all countries (global). Alternative model 2 had two factors. The first latent variable (Europe) included all European countries. The second latent variable (Asia/North America) included the

remaining countries and Australia. Alternative model 3 considered two factors with countries randomly linked to one of the two latent variables as shown in figure A.5.

Absolute fit measures, chi-square, GFI, RMSEA, an incremental fit measure, AGFI, parsimonious fit measures, PGFI and PNFI were reported. Absolute fit measures provided overall model fit without adjusting for "over fitting." Incremental fit measures compared the proposed model fit to an alternative specification. Parsimonious fit measures adjust the model to provide comparison between models with differing numbers of estimated coefficients.

Table A.9 summarized the goodness of fit indices for the hypothesized model and the three alternative measurement models. The Goodness of Fit Index (GFI) was 0.924 for the hypothesized model and GFI values of greater than 0.9 were considered good by Hair et al. (2006, p. 747). With a GFI greater than 0.90, the hypothesized model is significantly better than the null model. The Root Mean Square Error Approximation (RMSEA) was 0.059 for the hypothesized model. Evidence of good fit would include an RMSEA of 0.08 or lower according to Hair et al. (2006, p. 753). Based on these criteria, the hypothesized model has a good fit. The AGFI of the hypothesized model of 0.902 also indicated a good fit. The parsimonious normed fit index (PNFI) and parsimony goodness of fit index (PGFI) both compare the null and theoretical models. Index values larger than 0.60 are considered generally acceptable according to Blunch (2008, p. 115). Both PNFI and PGFI for the hypothesized model are above 0.60.

The chi-square of the hypothesized model is statistically significant at the five percent probability level. Similarly, the three alternative models had statistically significant chi-square. These results indicated that the observed data was different from the reproduced data for the hypothesized and three alternative models. Comparing the PGFI of the hypothesized model with the other alternative models, the PGFI was largest for the hypothesized model, which means the hypothesized model was superior according to this criterion. The hypothesized model had the largest GFI, AGFI and PNFI when compared to the alternative models. Also, it had the lowest RMSEA value. All these indicators of the goodness of fit select the hypothesized model to all other alternative models.

In addition, I conducted chi-square difference tests comparing the fit of the hypothesized measurement model to the fit of each of the alternative measurement models. From table A.10, the hypothesized model again fits significantly better than all other alternative models. Ling and Naranjio (2002) showed that there exists a strong worldwide factor in international real estate returns. However, results from confirmatory factor analysis indicated that the best-fit model was a three-factor model. My findings were consistent with McAllister and Lizieri (2006) who found that the European factor is more significant than the global factor for European real estate stocks. These results are also consistent with Ostermark (1999) who identified three continental factors in thirteen general international equity exchange markets.

On the other hand, results of our confirmatory factor analysis for the 2007 to 2009 period reconfirmed our exploratory factor analysis results for the same period. I

found that the hypothesized model, which has two factors, only has the best fit compared to the other three alternative models. The hypothesized model for this period had a factor including all Asian countries (Japan, Singapore and Hong Kong) including Australia. The other factor had European and North American countries exclusively. This finding was consistent with Butler and Joaquin (2002) and Campbell et al. (2002) who discovered that markets' co-movement increased during bear markets. It was also consistent with Michayluk et al. (2006) who revealed that the correlation structure between real estate markets was not constant over time. In addition, Wilson and Zurbruegg (2004) reported that correlations between property markets increased in crisis periods. Similarly, diversification benefits in real estate were lower during the Asian financial crisis (Bond et al., 2006; and Gerlach et al., 2006).

3.6 Conclusion

The objective of this study was to investigate the relationship between eighteen global real estate equity markets using factor analysis. Results from the common factor analysis with Direct Oblimin rotation during 1997 to 2007 indicated three distinct factors. With the single exception of Australia, the eighteen countries fell neatly into three geographical areas of Asia, Europe and North America. It was found that Australia was associated with the European factor rather than the Asian local factor. Confirmatory factor analysis was used to test four different models. Results indicated that the best model was the pure three continental factors of Asia, Europe and North America. My results during 1997 to 2007 were similar to the results of Gallo and Zhang (2010) who document that property markets were inter-regionally independent and there

was no cointegration among the regional indices of Asia Pacific, Europe and North America.

However, during the period 2007 to 2009, I found only two factors, as North America and Europe had emerged into a single factor. This indicated that the financial crisis increased linkages between North American and European markets. Asia remained as a separate factor as Asian real estate equity markets were still strongly related to one another, exclusively. This was consistent with results of Gallo and Zhang (2010) who find most diversification benefits in the Asia-Pacific region. My results for increasing co-movements in Europe and North America during the turmoil period were consistent with Bond et al. (2006), and Gerlach et al. (2006) who found that diversification opportunities in real estate were reduced during the Asian financial crisis. Also, the results of this present study were along the same lines of Liow et al. (2010) who demonstrated that volatility co-movement was different under various market regimes, especially during crisis conditions. The results of this present study build upon the academic literature concerned with international real estate returns and integration. These results would be beneficial to investors and portfolio managers interested in international diversification.

CHAPTER 4

MEDIA CONTENT, ATTENTION AND REIT RETURNS

4.1 Introduction

Kahneman (2003) argues that an individual's reasoning depends on his perceptions and intuition. According to Merton's (1987) framework, the market value of a firm increases when the visibility of a firm and the awareness among investors increases. The exposure of a stock can increase through many ways. Advertising, analyst coverage and appearance in the media are among these ways which increase the awareness of the stock investors. Schuster (2003) argues that the media generates positive feedback where it focuses attention on current prices and reinforces investors to project them into the future which causes overreaction. Good news lead to greater optimism and bad news reinforce future pessimism. The efficient market hypothesis states that asset prices should reflect all available information (Fama, 1970). Do media play a role in price formation? Is it just a transmission channel where news is passed on to investors?

The purpose of this study is to provide initial empirical evidence on the usefulness of media content in predicting REIT price movements and REIT trading volume. Unlike previous work that focuses on the general stock market, my study represents the first examination of the relationship between media content and real estate investment trusts (REIT) returns. Ghosh et al. (1996, p. 48) state that "REITs

become less comparable to the average stock in the market." They show that REITs are less frequently traded than comparable size stocks. The return pattern for REITs differs from other stocks due to fundamentals of local markets and less available information. They suggest that equity REITs are unique. They conclude that REITs are less like stocks than the trade press would lead an investor to believe. Myer and Webb (1993) and Downs and Guner (1999) support the fact that REITs differ from other traditional listed firms. Therefore, I aim to fill this gap in the literature and test whether or not media pessimism can be used to predict REIT returns and /or REIT trading volume.

DeLong et al. (1990) argue that sentiment is essential in pricing smaller stocks. Since REITs are viewed to be strongly related and comparable to small stocks, I expect REITs to be affected by sentiment and therefore media pessimism. Therefore, I study the nature of the relationship between the content of REIT news and the performance of listed REITs. I expect investors to be affected by the overall tone of the message contained in the news. The usage and frequency of optimistic words and pessimistic words in the media will potentially affect readers and their perceptions about the overall REIT market.

In addition, I provide initial empirical evidence on the usefulness of the aggregate search frequency in Google (SVI) in predicting REIT price movements and REIT trading volume.

I measure the degree of pessimism in the financial news according to the relative frequency of negative words suggested by Loughran and McDonald (2010). Using Factiva database as the source for news stories, I find that media pessimism is

significantly associated with future REIT returns. There is a negative influence between media pessimism and future REIT returns.

4.2 Literature Review

"The media select, they interpret, they emotionalize and they create facts" (Schuster, 2003 p. 5). Fang and Peress (2009) find that stocks with high media coverage earn lower returns than those with no media coverage. Their findings supports the fact that media affects security prices. According to the "investor recognition hypothesis" of Merton (1987), investors are not aware of all securities and, therefore, require higher returns for stocks with less information in the media. Chemannur and Yan (2009) study the relationship between advertising and find that it increases attention of investors and, therefore, affects the return of stocks. These results are consistent with Barber and Odean (2008) who find that investors buy attention-grabbing stocks which appear frequently in the media.

Public information plays a role in informing individual investors. Tetlock (2009a) finds that news resolves more asymmetric information in less liquid stocks. Soroka (2006) finds that the response of an individual to negative and positive news is asymmetric. He relates his findings to the prospect theory of Kahneman and the loss aversion theory. Covering listed companies at the London Stock Exchange, Ryan and Taffler (2004) find that corporate news significantly affects companies' returns and trading volume.

Tetlock (2007) links the content of daily news related to the stock market which appears in the **Wall Street Journal** and the performance of the stock market. He uses a

quantitative software for content analysis called the General Inquirer. This software counts the number of negative and positive words which appear in the news using built-in dictionaries. He finds that “high values of media pessimism induce downward pressure on market prices; unusually high or low values of pessimism lead to temporarily high market trading volume“(p. 1166). His results are consistent with the models of noise and liquidity traders [Delong et al. (1990) and Campbell et al. (1993)].

Tetlock et al. (2008) quantify the language used in financial news stories and relate them to firms’ earnings and stock returns. They measure the negativity of a story through the frequency of negative words in the news. They use the Harvard-IV-4 dictionary to find positive and negative words. This psychological dictionary is built in a software called General Inquirer which is popular in computer-aided text analysis. They find that negative words forecast low earnings. Moreover, these negative words which appear in stories that focus on firm fundamentals are useful in predicting both earnings and stock returns. Tetlock (2009b) shows that investors overreact to stale information which appears in stories about S&P 500 firms. He finds that reactions to redundant and repeated information reverse in the next week.

Engelberg (2009) shows that the content of the financial media can predict asset prices in the medium term. Henry (2008) finds that the tone of press releases influence investors’ reactions to earnings. He uses the prospect theory (Tversky and Kahneman, 1981) to explain his results. Using DICTION software, Davis et al. (2008) find a statistically significant relation between the linguistic style in earnings press releases (optimistic/pessimistic) and future return on assets. Using textual analysis, Brockman

and Cicon (2009) find that soft (qualitative) information in equity earnings announcements by management has positive and significant effects. They study certainty and optimism in the tone of management announcement.

Gurun and Butler (2009) argue that newspapers influence the publics' perceptions of events. They use text analysis to show that the media could be biased when covering the news related to some companies because of advertising expenditures or proximity to a firm's headquarters. Using content analysis, Kothari et al. (2009) show that positive (negative) news disclosures decreases (increases) return volatility, cost of capital and analyst forecast dispersion. Loughran and McDonald (2010) show that researchers who analyze financial texts with content analysis should not be using word lists developed by other disciplines. They develop an alternative negative words list to be used for financial text analysis studies. Recently, Garcia (2010) uses the financial dictionaries which are created by Loughran and McDonald (2010) to study the financial news which appeared in the **New York Times** during the 1905-1958 period.

Two related studies use the method of content analysis to study REIT-related questions. First, Diaz and Jin (2009) use content analysis to examine the relationship between activities in the real estate market in the state of Georgia and the content of local real estate news. They find that there is a downward pressure in the residential real estate market when media coverage is pessimistic. In addition, they find that the use of pessimistic words have a much greater effect on home prices when compared to the use of optimistic words. In another study, covering earnings conference calls in REITs,

Doran et al. (2009) use content analysis with the help of General Inquirer software to find that the tone has a significant explanatory power for the abnormal returns.

4.3 Research Questions and Hypotheses

4.3.1 Research Questions

- What is the relationship between media content (pessimism/optimism), REIT returns, and REIT trading volume?

- Does the search frequency in Google (a direct measure of investor attention) affect real estate investment trust (REIT) returns and trading volume?

4.3.2 Hypotheses

The theoretical investor sentiment model of DeLong et al. (1990) predicts that high sentiment generates high trading volume while low sentiment generates downward pressure on stock prices. If high media pessimism predicts low stock returns, then this indicates that media pessimism forecasts investor sentiment. On the other hand, if high media pessimism follows low stock returns, then one can argue that media pessimism reflects past investor sentiment. Finding a significant and negative relationship between stock returns and media pessimism could be interpreted as media pessimism reflecting negative information about cash flows and fundamental values (Tetlock, 2007).

The following hypotheses are based on the results of Tetlock (2007) who studies the stock market in general. However, my paper studies REITs specifically.

H1: High media pessimism predicts downward pressure on REIT prices.

H2: Abnormally High or low media pessimism predicts higher REITs trading volume.

H3: Low REIT returns lead to high media pessimism.

Kahneman (1973) shows that attention is a scarce cognitive resource. Individual investors will select certain information only when they have lots of new information flow and just limited attention. “Attention has a strong impact on the trading behavior of individual investors” (Yuan, 2008 p. 5). Advertising helps the firm attract public attention. For example, Chemmanur and Yan (2009) find that more advertising is associated with higher stock returns. Peng and Xiong (2006) show that investors allocate more attention to market- and sector-level factors than to firm-level factors. Therefore, I expect individual investors to give more weight to the overall REITs market. Gervais et al. (2001) document high volume return premium in stock prices. Recently, Hou et al. (2009) investigate the relation between investor attention and asset prices. Using trading volume as a proxy for attention, they find that high volume stocks have higher price momentum profits.

In the field of medicine, Ginsberg et al. (2009) use the relative frequency of Google-search queries to detect influenza activity in several regions of the United States. In the field of finance, Da et al. (2009) use the search frequency in Google (SVI) as a direct measure of investor attention. They find that the increase in SVI increases stock prices. The following hypotheses are based on the results of Da, Engleberg and Gao (2009) who study the stock market in general. However, my paper is devoted to the study of REITs, specifically.

H4: Search frequency in Google (SVI) is related to REIT returns. Increases in SVI push up REIT prices.

H5: Search frequency in Google (SVI) is related to REIT trading volume.

Increases in SVI push up REIT trading volume.

4.4 Data

I obtain both weekly and monthly REIT return and volume data through DataStream.[6] I use Factiva to search for news related to REITs during the period of January 2001 to March 2010. I search the free text REIT in Factiva filtering the industry to "Real Estate Investment Trust", the region is "United States" and the subject "Performance". I collect news from major news and business publications and Dow Jones newswire. This includes news appearing in the **Wall Street Journal**, **New York Times**, Reuters news, and Associated Press as well as other sources. Figure A.6 shows a screen shot of a Factiva search. I start with raw data of 1,136 articles. However, after excluding duplicates, I end up analyzing 1,105 articles. Figure A.7 shows the distribution of news during the sample period.

I also use the search frequency in Google (SVI) which is available for free through their website[7] and used in Choi and Varian (2009) and Da et al. (2009). Figure A.8 shows a screen shot of Google Trend. SVI is available on a weekly basis starting from January 2004. My analysis for SVI covers the period from January 2004 to April

[6] The name of the index as it appears in DataStream is US DS-REITs. This index is calculated by DataStream.

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

2010 using weekly data. I use both forms of scaling (fixed and relative) which are available for Google search frequency.[8]

4.5 Method

4.5.1 Content Analysis

Content analysis is a "research method that uses a set of procedures to make valid inferences from text" (Weber, 1990, p. 9). I employ a computer-aided text analysis technique. My analysis of these texts is designed to explore whether I could find a statistically significant relation between the performance of REITs and the content (optimism/ pessimism) of news related to REITs. There are many computer programs available for quantitative text analysis to choose from. The General Inquirer (GI) is a textual analysis software used by Tetlock (2007), Tetlock et al. (2008). This software classifies texts' words into content categories according to the list of words within the categories of Harvard IV 4 psychological dictionary. It produces a file with the frequency of the occurrence of each category.

The General Inquirer is designed to:

> (a) identify systematically, within text, instances of words and phrases that belong to categories specified by the investigator; (b) count occurrences and specified co-occurrences of these categories; (c) print and graph tabulations;(d) perform statistical tests; and(e) sort and regroup sentences according to whether they contain instances of a particular category or combination of categories (Stone et al., 1966, p. 68).

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[8] See http://www.google.com/intl/en/trends/about.html#7.

"The data is scaled based on the average search traffic of the term. There are two modes of scaling – relative and fixed – and the only difference between them is the time frame that's used to calculate the average. In relative mode, the data is scaled to the average search traffic for your term (represented as 1.0) during the time period you've selected. In fixed mode, the data is scaled to the average traffic for your term during a fixed point in time."

While GI is used by earlier studies in the field of finance, more recent research by Loughran and McDonald (2010) show that GI is not the best choice to analyze financial news. They create their own list of words which is available from the website of Professor McDonald.[9] Therefore, I use their lists of positive and negative words to classify the content in this current study. Then I also create a variable named "LM_OPT" which is the difference between positive and negative words. I combine all articles each month into one article and then analyze it. I divide the frequency of both positive and negative by the total number of words for all relevant articles during the month.

In this study, I use the textual analysis software DICTION 5.0. This software uses thirty one built-in dictionaries in searching texts. It automatically creates an OPTIMISM score which is defined as "language endorsing some person, group, concept or event or highlighting their positive entailments."[10] The software uses the following formula to create the OPTIMISM scores (Praise + Satisfaction + Inspiration) – (Blame + Hardship + Denial).

DICTION 5.0 allows users to employ ten custom dictionaries of 200 words each. I take advantage of this option and use the custom dictionaries suggested by both Henry (2008) and Loughran and McDonald (2010). Henry (2008) includes 85 negative

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

[10] DICTION 5.0 the text analysis program user's manual (pg. 43) available at <http://www.dictionsoftware.com/>.

words and 105 positive words while Loughran and McDonald (2010) include 2,337 negative words and 353 positive words.

4.5.2 VAR, VEC and Unit Root Tests

I employ a Vector Auto Regressive (VAR). Also, I conduct unit root tests for the variables used in this study (Dickey and Fuller (1979), Phillips and Perron (1988), and Kwiatkowski et al. (1992)). Then I use Granger causality tests (Granger (1969)). In addition, I apply Johansen cointegration test and a Vector Error Correction model (VEC).

4.5.3 Models with Asymmetry (TGARCH and EGARCH)

Bollerslev (1986) proposed the Generalized Autoregressive Conditional Heteroscedasticity model (GARCH). Researchers began to develop several extensions of the GARCH model. One of the most popular asymmetric GARCH models is the Threshold GARCH (TGARCH) [Zakoian (1994); Rabemananjara and Zakoian (1993); and Glosten et al. (1993)]. Another popular asymmetric GARCH model is the Exponential GARCH (EGARCH) proposed by Nelson (1991). Hentschel (1995) reviews several models of the GARCH family. Several researchers applied GARCH to Real Estate Investment Trusts data [see for example, Jirasakuldech et al. (2009); Lee (2009); and Stevenson (2002)].

Since good news (positive shocks) are expected to have smaller impact on volatility of equities than bad news (negative shocks), I use a TGARCH. By using this type of a GARCH model, I can capture asymmetries and determine if there is a

significant difference when shocks to the REIT market are negative. The specification of TGARCH (1, 1) is as follows:

$$h_t = \gamma_0 + \gamma u_{t-1}^2 + \vartheta u_{t-1}^2 d_{t-1} + \delta h_{t-1} \qquad (1)$$

where negative shocks have an impact of γ +θ and positive shocks have an impact of γ only. The impact is symmetric if θ is zero. However, if θ is greater than zero, one may conclude that there is asymmetry (Asteriou, 2006).

The variance equation of the EGARCH model is as follows:

$$\log(h_t) = \gamma + \sum_{j=1}^{q} \zeta_j \left| \frac{u_{t-j}}{\sqrt{h_{t-j}}} \right| + \sum_{j=1}^{q} \xi_j \frac{u_{t-j}}{\sqrt{h_{t-j}}} + \sum_{i=1}^{p} \delta_i h_{t-i} \qquad (2)$$

where the non-negativity of the estimates of conditional variance is guaranteed through taking the log of the variance series in the left-hand side. The model is symmetric if $\xi_1 = \xi_2 = \ldots = 0$. However, if ξ_j is less than zero, then bad news (negative shocks) generate greater volatility than good news (positive shocks) (Asteriou, 2006).

4.6 Results

Table A.11 presents the results of an OLS regression where the monthly REIT returns is the dependent variable and financial news content variable is the independent variable. The t-statistics are estimated using Newey-West heteroskedasticity and autocorrelation adjusted standard errors. From table A.11, I find that there is a negative and significant relationship between the variable (FIN_NEG) and REIT returns. FIN_NEG is the negative list of words suggested by Loughran and McDonald (2010). The number of negative words is divided by the total number of words which appear in

the articles during that month. On the other hand, I find a positive and significant relationship between REIT returns and LM_OPT, which is the difference between positive and negative words suggested by Loughran and McDonald (2010). These results are expected since negative words (pessimism) should be inversely related to returns while positive words (optimism) would be directly related to returns. All other OLS regression results in this table are statistically insignificant.

In addition, I test the relationship between the tone of the financial media content and REITs index volume and the results are presented in table A.12. Very high or very low media pessimism is expected to be related with higher trading volume. Divergence of opinion caused by new information is associated with increases in trading volume. I find a positive and statistically significant relationship between the first difference of REIT volume and each of the variables LM_OPT and OPTIMISM. The later variable is the change in the optimism score which is automatically generated by textual analysis software (DICTION 5.0) using its built-in dictionaries. The negative word list of Henry (2008) and the negative word lists of Loughran and McDonald (2010) are negatively related to REIT volume. However, this relationship is statistically insignificant.

This is consistent with the findings of Tetlock (2007) who shows that financial news content significantly predicts movements of the general stock market. He reports that media pessimism predicts downward pressure on the general equity market. Also, Tetlock finds that pessimism forecasts high trading volume for the stock market. My results regarding the significant relationship with trading volume of REITs are

consistent with the model of Campbell et al. (1993) who predict that higher values of media pessimism increases volume. Higher trading volume could be caused by the disagreement between rational traders and noise traders in the REIT market. Moreover, these results are along the same lines of Diaz and Jin (2009) who find a negative and significant association between media pessimism and residential home prices in the state of Georgia.

Unit root tests indicate that all of the financial news content variables are stationary as shown in table A.13. I reject the null hypothesis that there is a unit root using both the Augmented Dickey Fuller test (ADF) and the Phillips Perron test (PP). In addition, I use KPSS test and find that most of the variables are stationary. Using KPSS with constant only, provides us with statistical evidence at the ten percent level to reject the null hypothesis that LM_OPT and H_NEG are stationary. However, when using KPSS with trend, I find that both variables are stationary. Since the KPSS unit root test results for SVI_REIT_F and SVI_REIT_REL indicate that these variables are not stationary, I take the first difference of both variables in the analysis.

After examining the time series on stationarity as a preliminary step, I continue with the Vector Autoregressive (VAR) pair-wise Granger-causality testing. The optimal number of lags is determined using Akaike Information Criterion (AIC) by choosing the number of lags which minimizes the AIC. Table A.14 shows that the first difference of both LM_OPT and FIN_NEG Granger-cause REIT returns. This relationship is unidirectional from LM_OPT and FIN_NEG to REIT returns. This indicates that lagged

financial news content as proxied by these variables contain information that is not already contained in past values of REIT returns.

In addition, table A.14 shows that the first difference of LM_OPT and FIN_NEG Granger causes the REIT volume turnover. Moreover, results related to the Google search frequency for the term 'REIT' show that there is a unidirectional Granger causality from SVI_REIT_F and SVI_REIT_REL to the weekly volume of REIT index.

REITs seem to be similar to the general stock market in terms of its reaction to financial media content. Pessimism plays an important role in both the equity market in general and REITs in particular. The fraction of negative words in the news about REIT market is significantly associated to both volume and return in the future. The REIT market responds to the information conveyed by the negative words in the financial press.

When the linear combination of two or more variables is stationary, then these variables are cointegrated. This indicates that the two variables have some relationship in the long-run. This long run relationship will return even if the cointegrating variables deviate in the relationship in the short run. Table A.15 shows the results of Johansen cointegration tests. It shows that most of the variables which proxy for optimism and pessimism in the financial news for REITs are cointegrated with the level of REIT return index and the level of volume for the index. Trace test indicates that the level of REIT index is cointegrated with all variables which measure the tone (optimism/pessimism) of financial news content. The only exception is H_NEG which

is the negative word lists suggested in Henry (2008). In addition, trace test results at the five percent level show that the level of volume for REITs index is cointegrated with all variables which measure the tone of financial news content. The single exception is H_OPT to the previous relationship between volume and media content variables. This means that there exists a long-run relationship between tone of financial news content and the level of both the price index and the volume turnover of REITs.

Since most of the series are cointegrated, I use Vector Error Correction (VEC) to test for Granger causality among the variables. From table A.16, one can note that there is significant unidirectional Granger causality from LM_OPT and FIN_NEG to the REIT returns. This was true even when using the VAR model and not the VEC model as shown in table A.14. However, a new finding when using VEC is that there is another unidirectional Granger causality from OPTIMISM to REIT returns. FIN_NEG Granger causes volume still holds even after using VEC. This means that volume can be better predicted by including past values of variable FIN_NEG. Lagged Google search frequency as proxied by SVI_REIT_F and SVI_REIT_REL contain information that is not already contained in past values of the weekly volume turnover of REITs. The other results of statistically insignificant Granger causality tests indicates that these variables cannot be predicted better by including past values of the other variables.

Results from the threshold GARCH (TGARCH) which are presented in table A.17 show significant evidence of asymmetries (leverage effects). This means that negative shocks for REITs (bad news) have greater impact than positive shocks (good

news). The coefficient of RESID(-1)^2*(RESID(-1)<0) is positive and significant which indicates that there are asymmetries in the news of REITs.

Table A.18 presents the results of the exponential GARCH (EGARCH) model and reconfirms the findings of table A.17. I find that there is asymmetry where bad news and good news have different impact. The coefficient of RESID(-1)/@SQRT(GARCH(-1)) is negative and significant which indicates that there are asymmetries in the news of REITs. Overall, these results show statistically significant difference when shocks are negative.

Differences in the results of the different measures of optimism and pessimism could be attributed to difference in the number of words which is included in each dictionary. Also, the fact that some dictionaries are written for other fields such as political science, mass communication and psychology could affect the results. The negative and positive word lists of Loughran and McDonald (2010) are the most comprehensive list which is related to the field of finance. The results of my study are important to investors, pension funds and portfolio managers who are interested in REITs as an asset class. It is also important to academicians who are interested in the market efficiency of REITs.

4.7 Conclusion

This article is the first to examine the information content of the tone of REIT-specific financial news using computer-aided textual analysis. As expected, investors are affected by the overall tone message contained in the news. The usage and

frequency of optimistic and pessimistic words in the media do, indeed, affect readers and their perception about the overall REIT market.

My results show that REIT returns is negatively related to media pessimism as proxied by the percentage of negative words in the news using the financial dictionaries suggested by Loughran and McDonald (2010). Moreover, there is a positive and significant relation between media optimism and REIT volume. Both pessimism and optimism does Granger cause REIT return and volume. However, I note that the results of textual analysis studies are sensitive to the dictionary of words used to capture the tone of the financial news content. It seems that the word lists of Loughran and McDonald (2010) best fits financial news. In general, my results are consistent with the model of noise traders (DeLong et al., 1990) and the model of liquidity traders (Campbell et al., 1993).

The results of the Johansen cointegration tests show that most of the variables which proxy for optimism and pessimism in the financial news for REITs are cointegrated with the REIT return index and the volume of the index. This suggests that there is a long-run relationship between these variables since they are cointegrated. In addition, I analyze the relationship between search frequencies in Google (SVI), REIT returns and REIT trading volume. I find that SVI is not significantly related to REIT returns. However, SVI does Granger cause REIT volume.

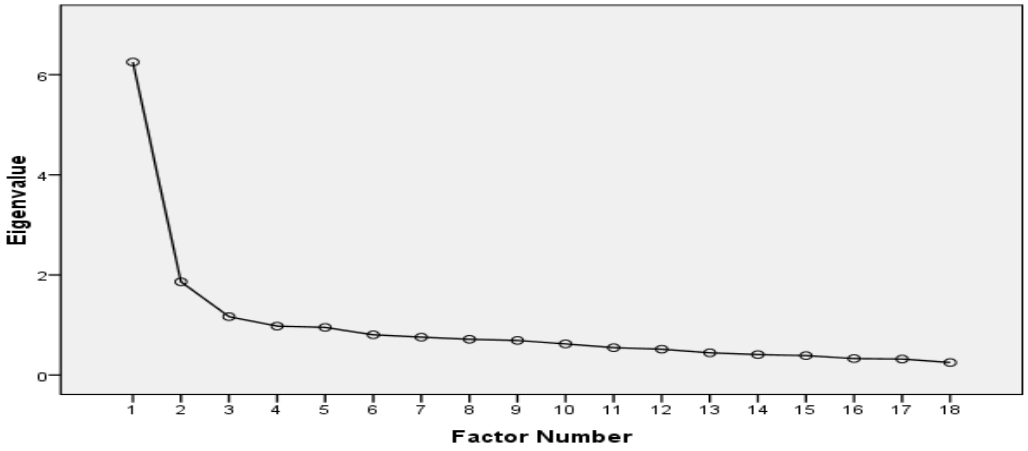
Using asymmetric models (TGARCH and EGARCH), I find that negative shocks on REITs (bad news) have a greater impact than positive shocks on REITs (good news). The overall results of this current study can be linked to investor psychology.

These findings are along the same lines of the psychology literature which suggests that positive information has less impact than negative information (e.g. Rozin and Royzman (2001) and Baumeister et al. (2001)). It is also consistent with the prospect theory from the behavioral economy discipline. My findings of asymmetrical response in REIT prices echo the findings of Diaz and Jin (2009) who document that optimistic words have less impact on home prices when compared to the impact of pessimistic words in the media.

Results of this study could be viewed as some evidence against the efficient market hypothesis and the argument that the REIT market follows a random walk. Investors who are always searching for profitable trading strategies could try to use the monthly variation in media pessimism to better forecast REIT returns. However, high transaction costs and low liquidity could prevent investors from generating abnormal returns.

APPENDIX A

FIGURES AND TABLES



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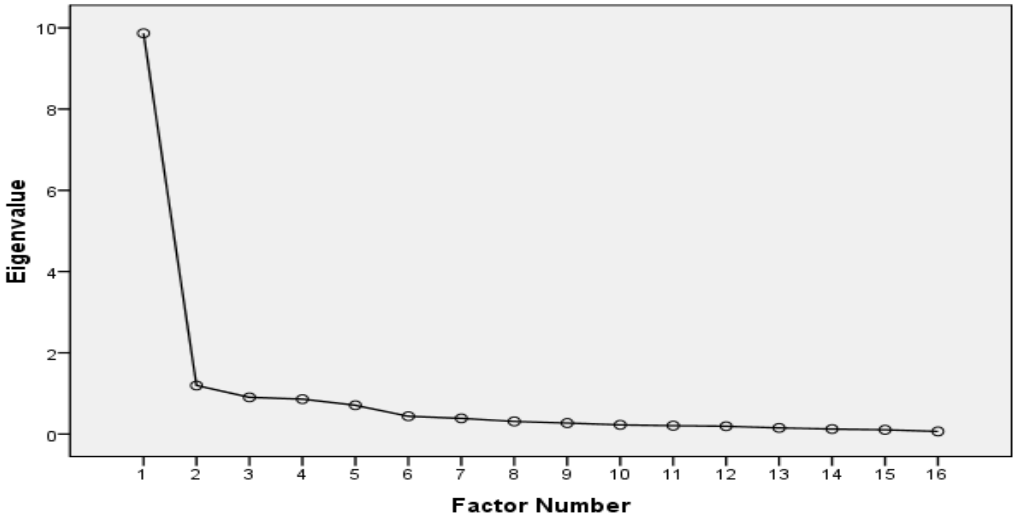
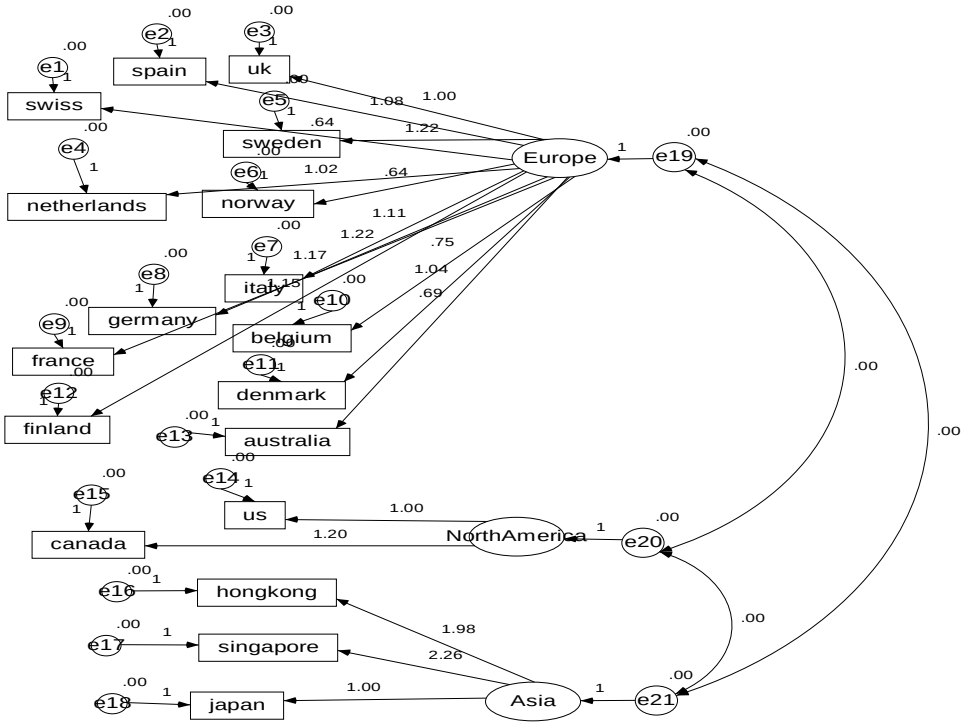


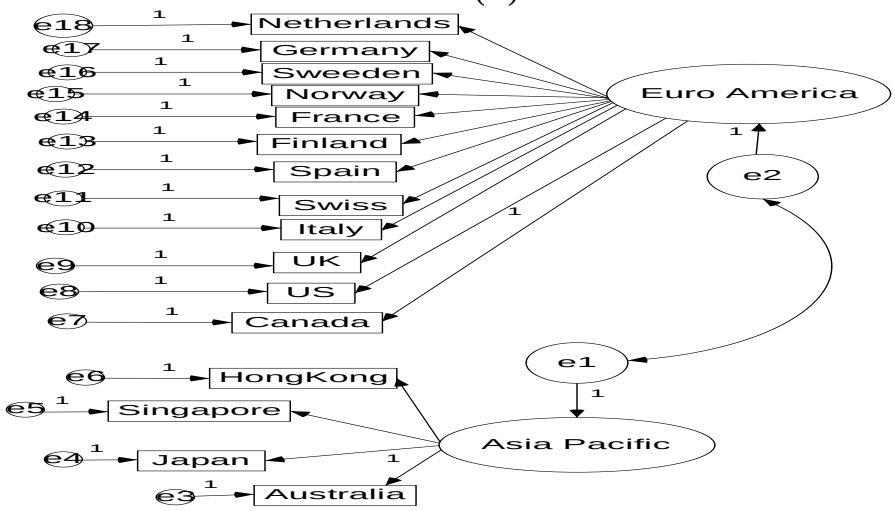
(B)

Figure A.1
Scree Plot

A scree plot (Cattell, 1966) is a plot of total variance associated with each component. The scree test involves examining the graph of the Eigenvalues for a flattening inflection in the curve that indicates a natural bend or break point in the data. Part (A) covers the period 1997-2007 and part (B) covers the period 2007-2009

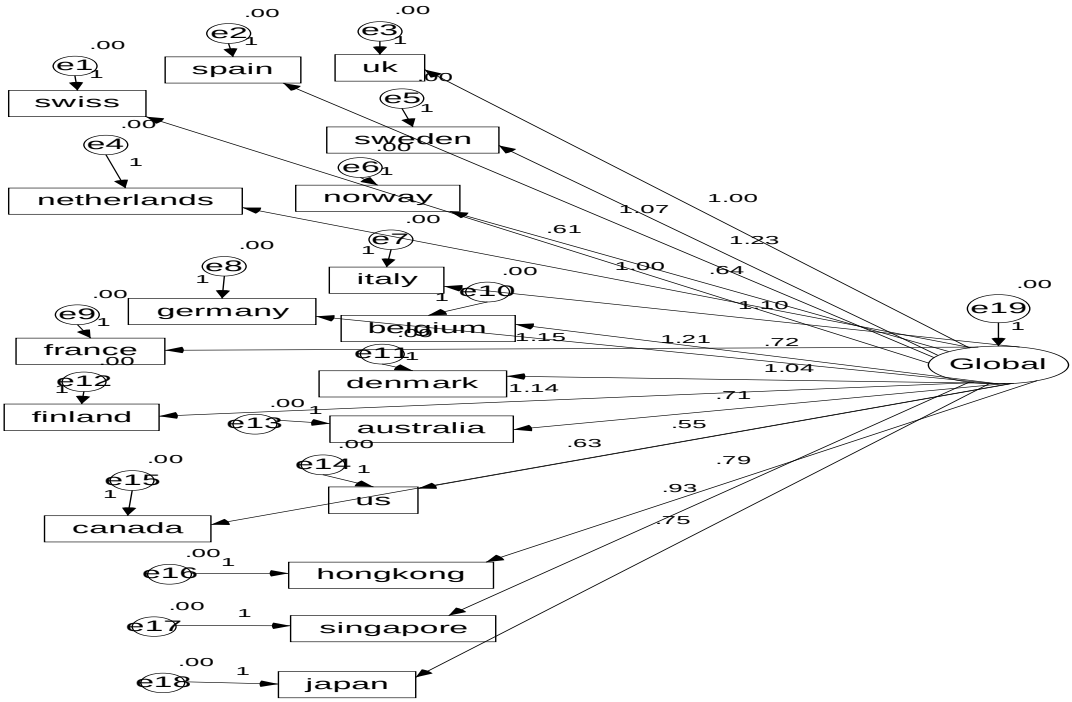


(A)

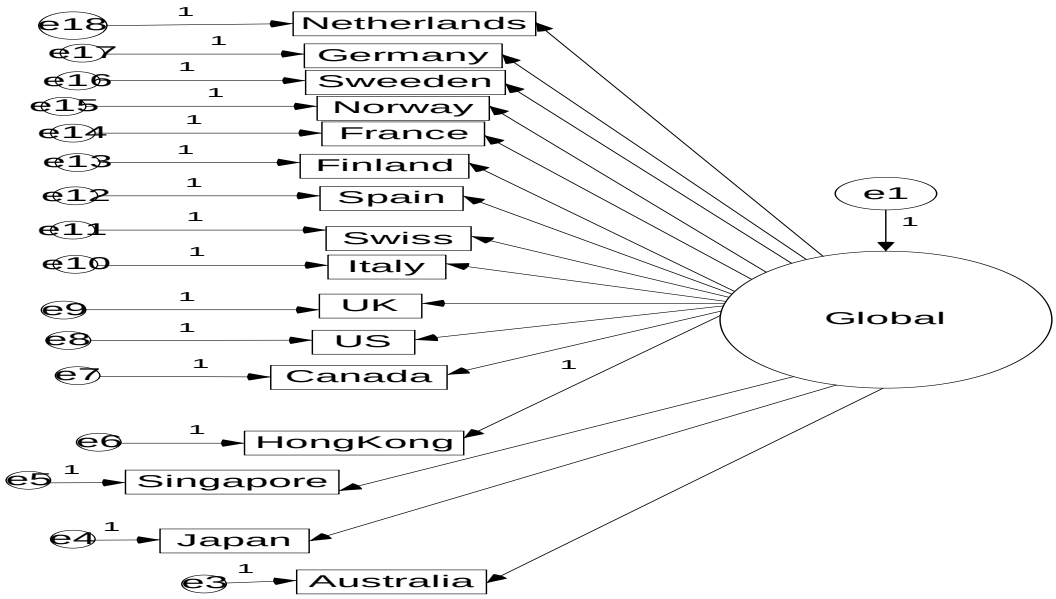


(B)

Figure A.2
Hypothetical Model
Part (A) covers the period 1997-2007 and part (B) covers the period 2007-2009

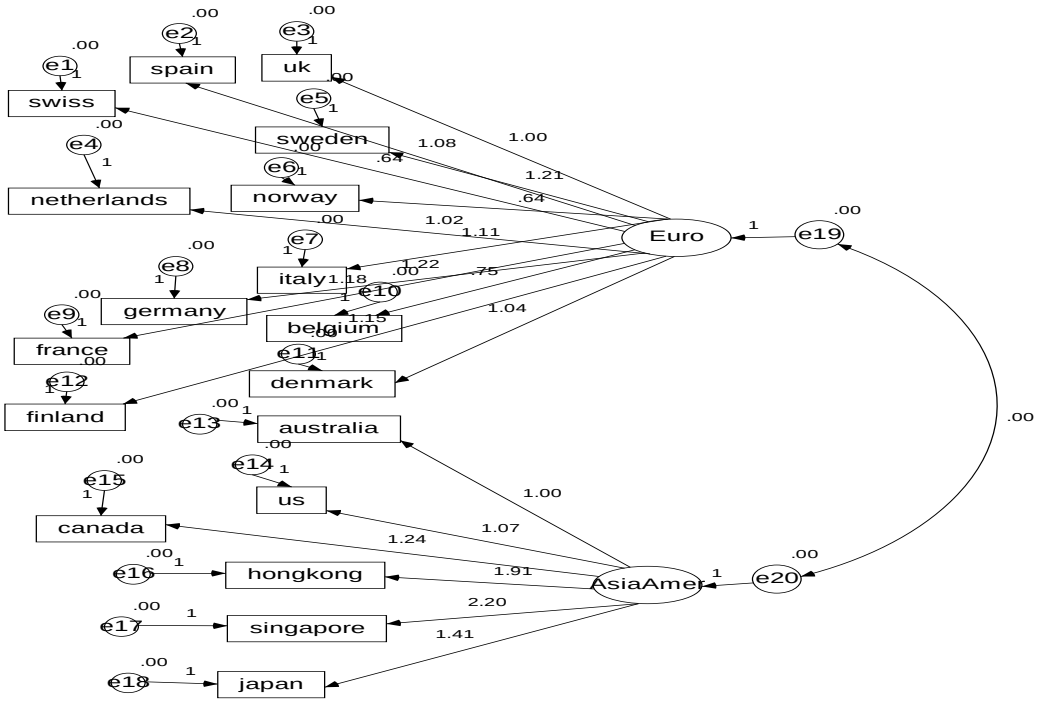


(A)

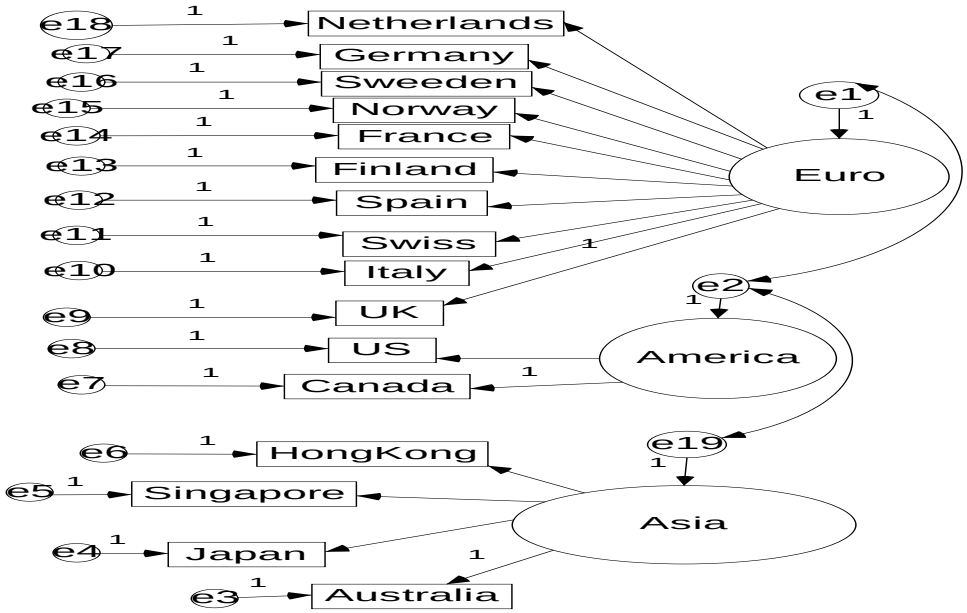


(B)

Figure A.3
Alternative Model 1
Part (A) covers the period 1997-2007 and part (B) covers the period 2007-2009.

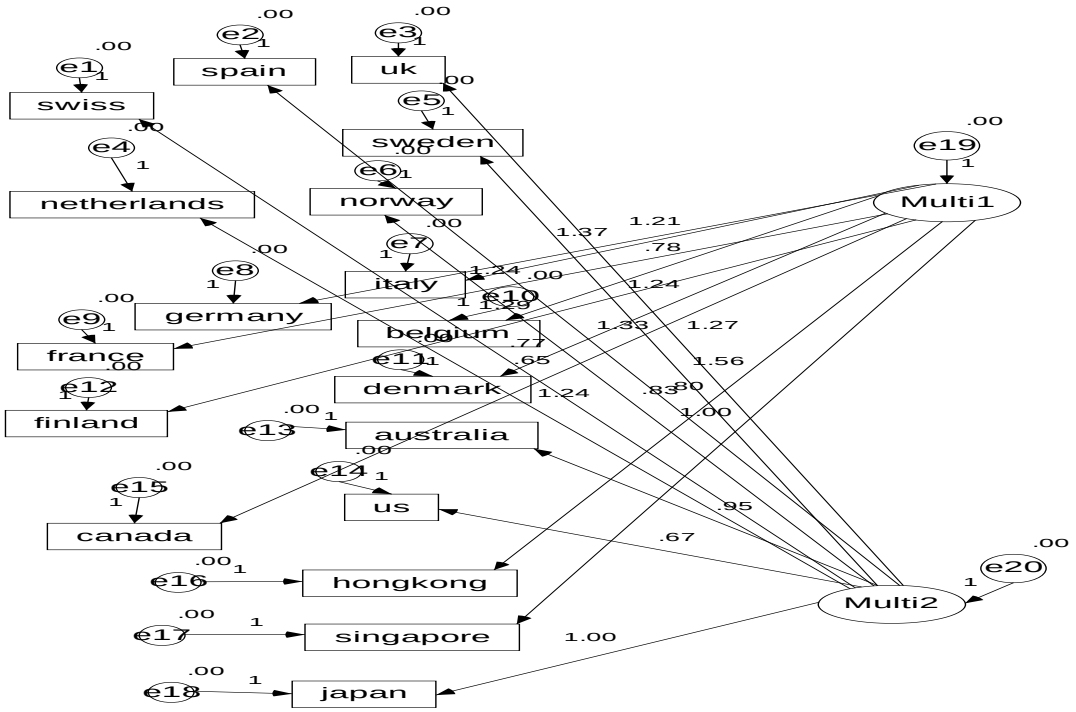


(A)

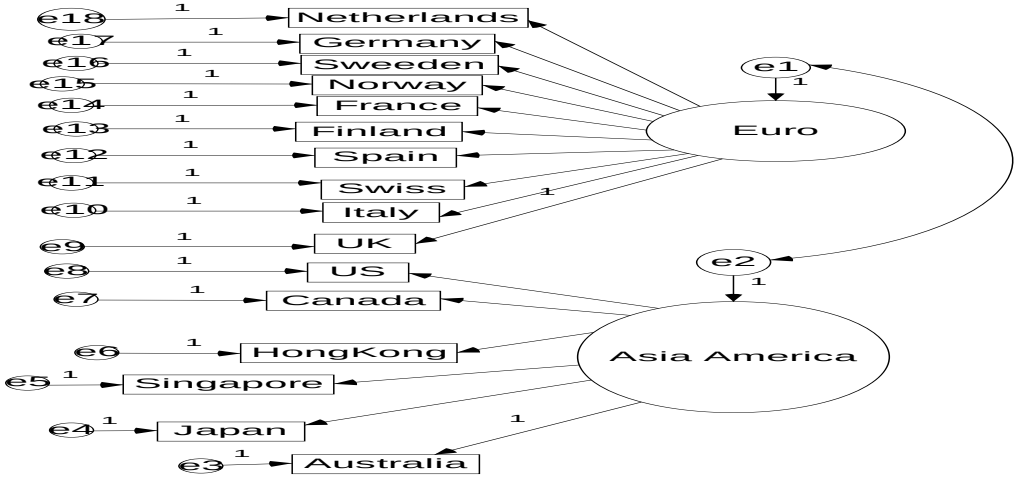


(B)

Figure A.4
Alternative Model 2
Part (A) covers the period 1997-2007 and part (B) covers the period 2007-2009.

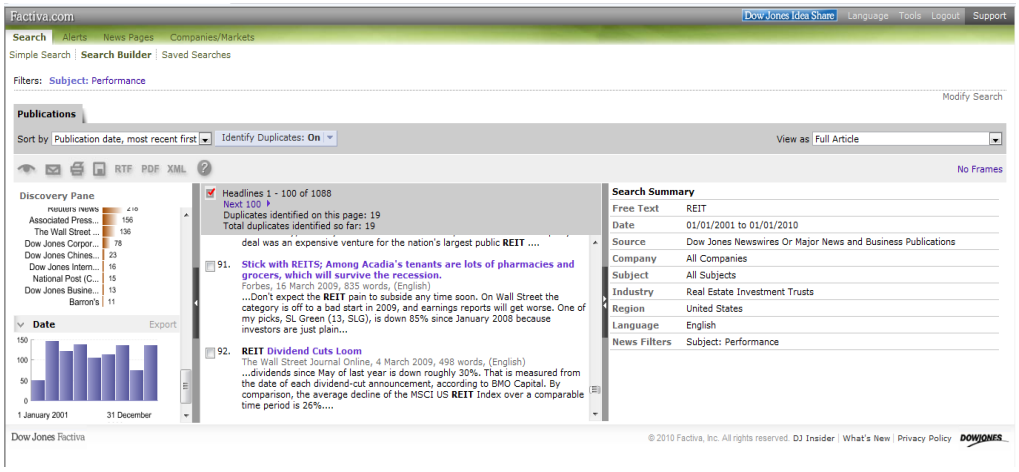


(A)



(B)

Figure A.5
Alternative Model 3
Part (A) covers the period 1997-2007 and part (B) covers the period 2007-2009.



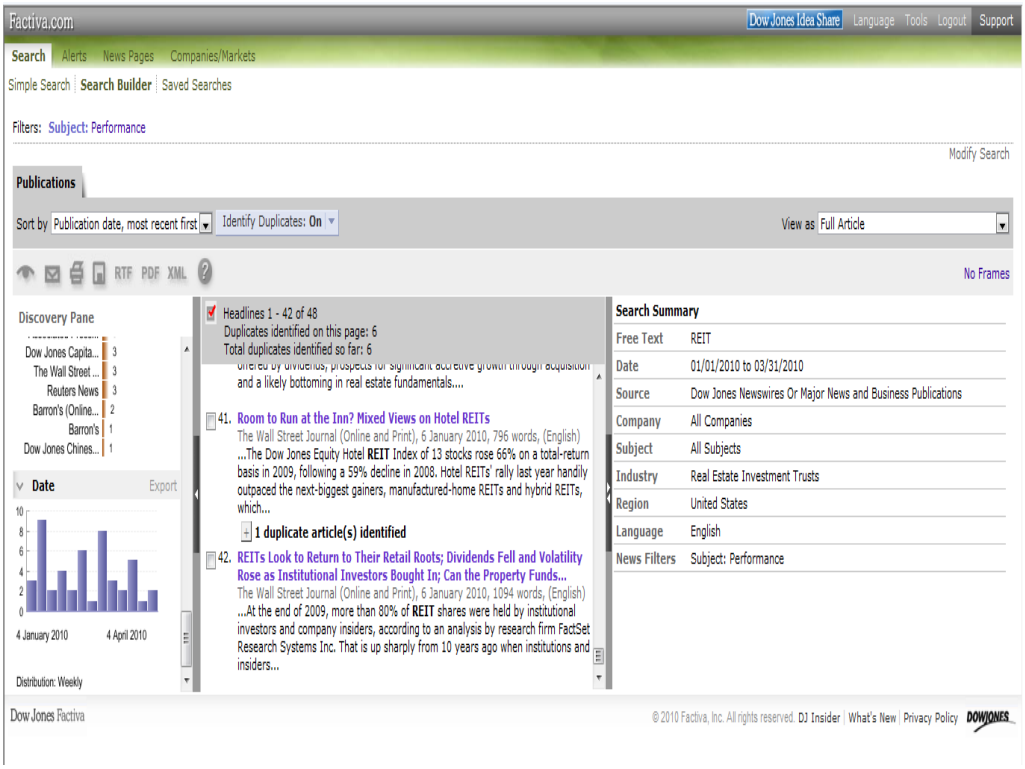


Figure A.6
A Screenshot of Factiva Search of the Word "REIT" in the United States for the Period 2001 to 2010.

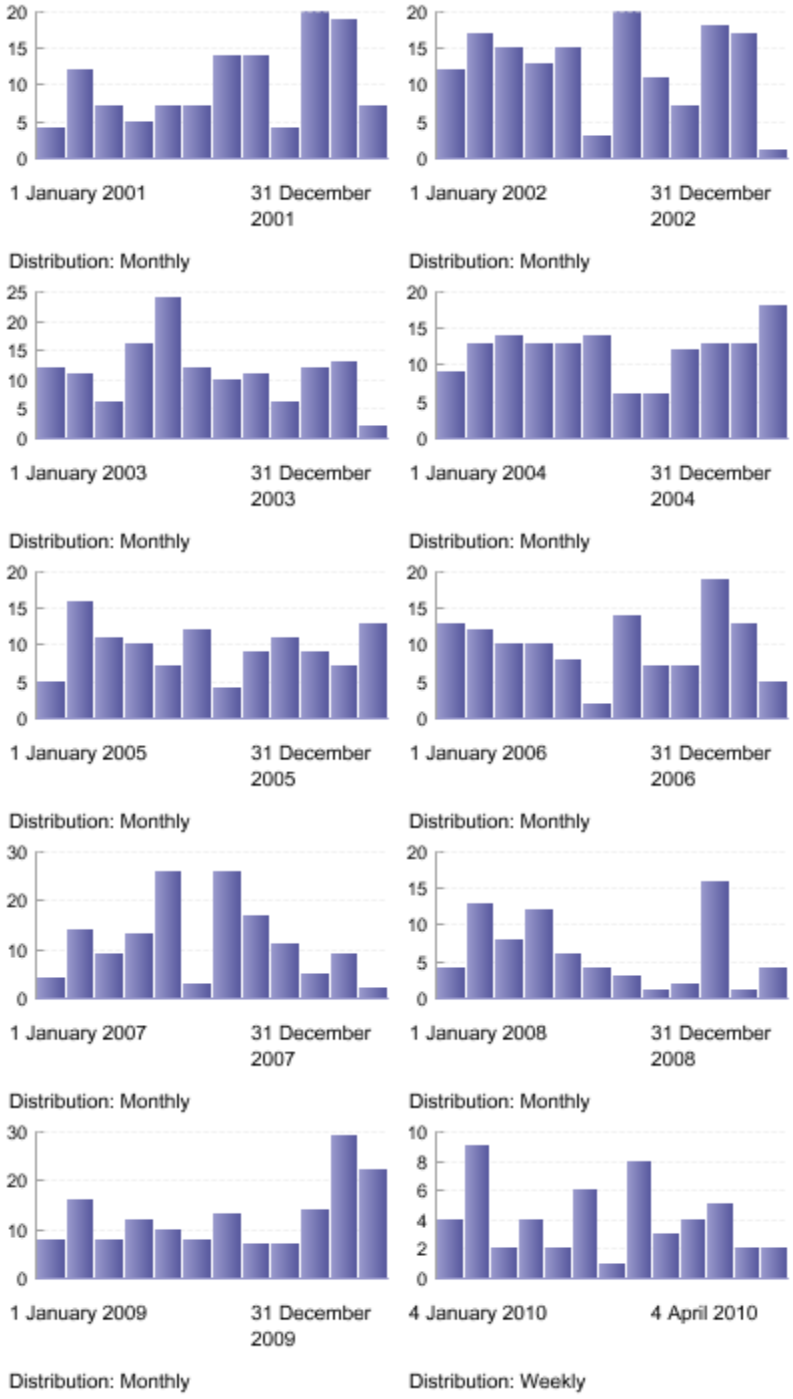


Figure A.7
Distribution of Articles from Factiva search for the Word "REIT" in the United States for the Period 2001 to 2010.

Figure A.8
A Screenshot of the Average Traffic Search Frequency of the Word "REIT" in the United States through Google Trends for the Period 2004 to 2010.

Table A.1
Relationship between the Level of Consumer Sentiment in One Month and the FTSE/NAREIT US All REIT Index Return in the Next Calendar Month

	Independent Variable			
Dependent Variable REIT Returns		Slope		Adjusted R^2
	Constant	Coefficient	t-stat	
UMCSI (1978:01 – 2008:09)	4.40**	-0.039**	-2.054	0.012
UMCSI (1978:01 – 1992:02)	7.71**	-0.081**	-3.307	0.061
UMCSI (1992:02 – 2008:09)	0.765	0.002	0.091	-0.005
YOYCI – individuals (2001:07 – 2009:03)	-27.19**	0.326**	2.585	0.076
YOYCI – institutions (2001:07 – 2009:03)	0.274	0.000	0.002	-0.011
GIOI (1999:02 – 2009:04)	-0.584	0.017	0.891	0.009

*, ** denotes significance at the 0.1 and 0.05 level, respectively.
The t-statistics are created according to the Newey–West adjusted standard errors.
UMCSI is the Michigan consumer sentiment index, YOYCI is the Yale One-year confidence index, and GIOI is the UBS/Gallup optimism index. The break point of UMCSI is chosen based on Quandt-Andrews Breakpoint test and Chow's Breakpoint test. In general, I do not find any significant differences in our results when using Equity REITs or Mortgage REITs instead of All REITs index during our sample period.

Table A.2
Relationship between the Level of Consumer Sentiment in One Month and the FTSE/NAREIT US All REIT Index Return in the Next Six Calendar Months

	Independent Variable			
Dependent variable - REIT Returns		Slope		Adjusted R^2
	Constant	Coefficient	t-stat	
UMCSI (1978:01 – 2008:09)	4.170**	-0.036*	-1.954	0.009
UMCSI (1978:01 – 1992:02)	5.010**	-0.048*	-1.897	0.017
UMCSI (1992:02 – 2008:09)	3.748	-0.030	-1.073	0.000
YOYCI – individuals (2001:07 – 2009:03)	-33.786**	0.401**	2.611	0.102
YOYCI – institutions (2001:07 – 2009:03)	-10.718	0.136	1.471	-0.001
GIOI (1999:02 – 2009:04)	0.252	0.005	0.235	-0.007

*, ** denotes significance at the 0.1 and 0.05 level, respectively.
The t-statistics are created according to the Newey–West adjusted standard errors.
UMCSI is the Michigan consumer sentiment index, YOYCI is the Yale One-year confidence index, and GIOI is the UBS/Gallup optimism index. The break point of UMCSI is chosen based on Quandt Andrews Breakpoint test and Chow's Breakpoint test. In general, I do not find any significant differences in our results when using Equity REITs or Mortgage REITs instead of All REITs index during our sample period.

Table A.3
Relationship between the Level of Consumer Sentiment in One Month and the FTSE/NAREIT US All REITs Index Return in the Next Twelve Calendar Months

	Independent Variable			
Dependent variable - REIT Returns		Slope		Adjusted R^2
	Constant	Coefficient	t-stat	
UMCSI (1978:01 – 2008:09)	4.08**	-0.035*	-1.910	0.008
UMCSI (1978:01 – 1992:02)	5.20**	-0.049*	-1.907	0.020
UMCSI (1992:02 – 2008:09)	2.769	-0.019	-0.678	-0.002
YOYCI – individuals (2001:07 – 2009:03)	-29.93*	0.350*	1.867	0.047
YOYCI – institutions (2001:07 – 2009:03)	-5.661	0.072	0.557	-0.010
GIOI (1999:02 – 2009:04)	0.614	0.002	0.124	-0.009

*, ** denotes significance at the 0.1 and 0.05 level, respectively.
The t-statistics are created according to the Newey–West adjusted standard errors.
UMCSI is the Michigan consumer sentiment index, YOYCI is the Yale One-year confidence index, and GIOI is the UBS/Gallup optimism index. The break point of UMCSI is chosen based on Quandt-Andrews Breakpoint test and Chow's Breakpoint test. In general, I do not find any significant differences in our results when using Equity REITs or Mortgage REITs instead of All REITs index during our sample period.

Table A.4
Unit Root Test Results

	ADF with Intercept	ADF with Intercept and Trend	PP with Intercept	PP with Intercept and Trend
UMCSI (level)	-2.90**	-2.93	-2.71*	-2.76
UMCSI (1st difference)	-19.57***	-19.56***	-20.70***	-20.84***
YOYCI Individual (level)	-1.03	-2.67	-1.04	-2.78
YOYCI Individual (1st difference)	-6.34***	-6.39***	-9.49***	-9.49***
YOYCI Institution (level)	-3.26**	-3.31*	-3.02**	-3.06
YOYCI Institution (1st difference)	-7.16***	-7.12***	-7.12***	-7.08***
GIOI (level)	-1.76	-2.78	-1.59	-2.65
GIOI (1st difference)	-13.95***	-13.89***	-14.11***	-14.07***

*, **, and *** denotes statistical significance at the 10%, 5%, and 1% level.
UMCSI is the Michigan consumer sentiment index, YOYCI is the Yale One-year confidence index, and GIOI is the UBS/Gallup optimism index. ADF is the Augmented Dickey Fuller test and PP is the Phillips-Perron test.

Table A.5
Granger Causality Test Results

Sample: 1978M01 2008M09
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
UMCSIC does not Granger Cause RALLREIT	366	0.78424	0.4572
RALLREIT does not Granger Cause UMCSIC		6.61428	**0.0015**

Sample: 2001M07 2009M03
Lags: 6

Null Hypothesis:	Obs	F-Statistic	Prob.
YOYCIC does not Granger Cause RALLREIT	86	1.81609	0.1077
RALLREIT does not Granger Cause YOYCIC		1.29890	0.2686

Sample: 2001M07 2009M03
Lags: 6

Null Hypothesis:	Obs	F-Statistic	Prob.
YOYCI does not Granger Cause RALLREIT	86	0.50111	0.8056
RALLREIT does not Granger Cause YOYCI		1.17486	0.3292

Sample: 1999M02 2009M04
Lags: 6

Null Hypothesis:	Obs	F-Statistic	Prob.
GIOIC does not Granger Cause RALLREIT	106	0.75250	0.6090
RALLREIT does not Granger Cause GIOIC		1.77175	0.1134

*The lag length of each VAR was chosen based on lag order selected by Akaike information criterion (AIC). UMCSIC is the change in the Michigan sentiment index, YOYCI is the change in the Yale One-year confidence index of institutions, YOYCIC is the change in the Yale One-year confidence index of individuals, GIOIC is the change in the UBS/Gallup optimism index. In general, I do not find any significant differences in our results when using Equity REITs or Mortgage REITs instead of All REITs.

Table A.6
Comparison between This Study and the Existing Literature

Index	Findings of This Study	Previous Literature	Comparison
UMCSI	REIT returns → UMCSIC	Fisher and Statman (2003), Otoo (1999), Lemmon and Portiniaguina (2006)	Consistent
YOYCI - individuals	No causality	Samsell et al. (2009)	Consistent
YOYCI - institutions	No causality	Samsell et al. (2009)	Consistent
GIOI	No causality	Vissing-Jorgensen (2003)	N/A

* To the best of our knowledge, there are no studies previously published that cover these indices with REIT returns. a→b means uni-directional Granger-Causality from a to b and not the opposite direction. UMCSI is the Michigan consumer sentiment index, UMCSIC is the change in the Michigan sentiment index, YOYCI is the Yale One-year confidence index, and GIOI is the UBS/Gallup optimism index.

Table A.7
Total Variance Explained

(A)

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	6.252	34.736	34.736	5.753	31.959	31.959	5.425
2	1.863	10.349	45.085	1.445	8.030	39.989	2.659
3	1.166	6.479	51.564	.738	4.101	44.090	2.633
4	.978	5.432	56.995				
5	.952	5.287	62.282				
6	.804	4.466	66.749				
7	.756	4.200	70.949				
8	.714	3.968	74.917				
9	.691	3.838	78.755				
10	.622	3.454	82.209				
11	.548	3.042	85.251				
12	.516	2.868	88.119				
13	.444	2.466	90.585				
14	.409	2.273	92.858				
15	.388	2.157	95.016				
16	.328	1.824	96.840				
17	.320	1.775	98.615				
18	.249	1.385	100.000				

Extraction Method: Principal Axis Factoring.

a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

Table A.7 continued

(B)

Factor	Initial Eigenvalues			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total
1	9.867	61.666	61.666	9.326
2	1.195	7.467	69.134	7.107
3	.903	5.641	74.775	
4	.859	5.371	80.146	
5	.708	4.427	84.572	
6	.437	2.731	87.304	
7	.387	2.416	89.719	
8	.311	1.944	91.663	
9	.270	1.686	93.350	
10	.226	1.410	94.760	
11	.205	1.281	96.041	
12	.192	1.198	97.239	
13	.150	.939	98.178	
14	.124	.773	98.951	
15	.104	.649	99.600	
16	.064	.400	100.000	

Extraction Method: Principal Axis Factoring.

a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance. Part (A) covers the period 1997-2007 while part (B) covers the period 2007-2009.

Table A.8

Pattern Matrix [a]

(A)

	Factor		
	1	2	3
France	.848		
Netherlands	.832		
Swiss	.788		
Belgium	.771		
Sweden	.594		
United Kingdom	.592		
Germany	.545		
Italy	.512		
Spain	.510		
Finland	.405		
Australia	.395		
Norway	.362		
Denmark			
Hong Kong		.897	
Singapore		.761	
Japan		.329	
United States			-.769
Canada			-.671

Extraction Method: Principal Axis Factoring. Rotation Method: Oblimin with Kaiser Normalization.

Rotation converged in six iterations. This table presents the results of Principal Axis Factoring with Direct Oblimin rotation. I suppress factor loadings below 0.32 in absolute value.

Table A.8 continued

(B)

	Factor	
	1	2
United Kingdom	.819	
Swiss	.750	
Sweden	1.033	
Norway	.483	
Netherlands	.991	
Italy	.820	
Germany	.821	
France	.909	
Finland	.787	
Spain	.481	
United States	.650	
Canada	.651	
Hong Kong		.842
Singapore		.962
Australia		.670
Japan		.553

Extraction Method: Principal Axis Factoring. Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 4 iterations.

Part (A) covers the period 1997-2007
Part (B) covers the period 2007-2009.

Table A.9
Model Comparisons in Terms of Goodness of Fit Indices

(A)

	Hypothesized	Alternative 1	Alternative 2	Alternative 3
Chi-square	391.2 (df =132)	900.8 (df=135)	654.527(df=134)	1656 (df=135)
GFI	0.924	0.831	0.88	0.785
RMSEA	0.059	0.100	0.082	0.14
AGFI	0.902	0.786	0.847	0.727
PNFI	0.775	0.675	0.726	0.501
PGFI	0.714	0.656	0.69	0.619

(B)

	Hypothesized	Alternative 1	Alternative 2	Alternative 3
Chi-square	288.5 (df=103)	418.1 (df=104)	368.7(df=102)	327.3(df=104)
GFI	0.816	0.733	0.796	0.782
RMSEA	0.107	0.139	0.129	0.118
AGFI	0.757	0.651	0.728	0.712
PNFI	0.76	0.723	0.725	0.747
PGFI	0.618	0.560	0.597	0.592

This table presents the results from Confirmatory Factor Analysis. It compares the hypothesized model created through exploratory Factor Analysis to the three alternative models. It presents the results of Goodness of Fit Index (GFI), Root Mean Square Error Approximate (RMSEA), Adjusted Goodness of Fit Index (AGFI), Parsimony Normed Fit Index (PNFI), and Parsimonious Goodness of Fit Index (PGFI). Part (A) covers the period 1997-2007 and part (B) covers the period 2007-2009

Table A.10
Chi-square Difference Results

(A)

	Alt1- Hyp	Alt 2-Hyp	Alt3-Hyp
Chi-square diff.	509.6 (df=3) P = 0.0	263.33 (df=2) P = 0.0	1265.32 (df=3) P = 0.0

(B)

	Alt1- Hyp	Alt 2-Hyp	Alt3-Hyp
Chi-square diff.	129.6(df=1) P = 0.0	80.2 (df=1) P = 0.0	38.8 (df=1) P = 0.0

This table compares the hypothesized measurement model to each of the three alternative models using Chi-square difference test where df is the degrees of freedom.
Part (A) covers the period 1997-2007 and part (B) covers the period 2007-2009.

Table A.11
Relationship between Financial News Content and US REITs Index Return

	Independent Variable			
Dependent variable - REIT Returns		Slope		R^2
	Constant	Coefficient	t-stat	
Fin_NEG	0.080 **	-5.246 *	-1.970	0.110
LM_OPT	0.024 ***	3.353 *	1.661	0.066
OPTIMISM	0.007	0.218	0.822	0.009
H_NEG	0.014	-0.596	-0.957	0.004
H_POS	0.006	0.061	0.246	0.000
H_OPT	0.000	0.563	0.891	0.006

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level.
The t-statistics are created according to the Newey–West adjusted standard errors. Fin_NEG is the negative list of words suggested by Loughran and McDonald (2010). LM_OPT is the difference between positive and negative words suggested by Loughran and McDonald (2010). OPTIMISM is the change in a score automatically generated by DICTION 5.0 software using its built in dictionaries. H_NEG and H_POS is the negativity and positivity word lists suggested by Henry (2008). H_OPT is the difference between positive and negative words of Henry (2008). The frequency of each variable is divided by the total number of words which appear in the relative articles during that month.

Table A.12
Relationship between Financial News Content and Volume of US REITs Index

	Independent Variable			
Dependent variable - REIT Volume (1st difference)		Slope		R^2
	Constant	Coefficient	t-stat	
Fin_NEG	18259.97	-88748.55	-1.468	0.015
LM_OPT	17528.65	9457297.00 **	2.318	0.049
OPTIMISM	19034.93	2093052.00 ***	2.899	0.045
H_NEG	18632.16	-2249945.00	-1.055	0.006
H_POS	18681.99	-503693.10	-0.627	0.001
H_OPT	18629.24	470597.20	0.341	0.000

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level.
The t-statistics are created according to the Newey–West adjusted standard errors. Fin_NEG is the change in the negative list of words suggested by Loughran and McDonald (2010). LM_OPT is the first difference between the difference of positive and negative words suggested by Loughran and McDonald (2010). OPTIMISM is the change in a score automatically generated by DICTION 5.0 software using its built in dictionaries. H_NEG and H_POS is change in the negativity and positivity word lists suggested by Henry (2008). H_OPT is the first difference in difference between positive and negative words of Henry (2008). The frequency of each variable is divided by the total number of words which appear in the relative articles during that month.

Table A.13
Unit Root Test Results

	ADF with Intercept	ADF with Intercept and Trend	PP with Intercept	PP with Intercept and Trend	KPSS with Constant
Fin_NEG	-8.01 ***	-8.13 ***	-8.348 ***	-8.347 ***	0.319
LM_OPT	-8.943 ***	-9.26 ***	-9.15 ***	-9.37 ***	0.398 *
OPTIMISM	-9.64 ***	-9.60 ***	-9.66 ***	-9.62 ***	0.157
H_NEG	-9.19 ***	-9.51 ***	-9.39 ***	-9.66 ***	0.349 *
H_POS	-8.37 ***	-8.40 ***	-8.49 ***	-8.52 ***	0.117
H_OPT	-7.30 ***	-7.26 ***	-7.36 ***	-7.32 ***	0.137
SVI_REIT_F	-3.72 ***	-6.99 ***	-4.94 ***	-10.58 ***	1.880 ***
SVI_REIT_REL	-2.65 *	-7.036 ***	-4.90 ***	-10.63 ***	1.881 ***

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level.
ADF is the Augmented Dickey Fuller test, PP is the Phillips-Perron test, and KPSS is the Kwiatkowski et al. (1992) unit root test. The null hypothesis for KPSS is that the variable is stationary. Fin_NEG is the negative list of words suggested by Loughran and McDonald (2010). LM_OPT is the difference between positive and negative words suggested by Loughran and McDonald (2010). OPTIMISM is a score automatically generated by DICTION 5.0 software using its built in dictionaries. H_NEG and H_POS is the negativity and positivity word lists suggested by Henry (2008). H_OPT is the difference between positive and negative words of Henry (2008). SVI_REIT_F is the Google search frequency for the term 'REIT' scaled by fixed mode. SVI_REIT_REL is the Google search frequency for the term 'REIT' scaled by relative mode.

Table A.14
VAR Granger Causality Results

Null Hypothesis	Obs	Lags	F-Statistic	Prob.
D(LM_OPT) does not Granger Cause RET_RI	102	8	1.78040	0.0921
RET_RI does not Granger Cause D(LM_OPT)	102	8	0.68746	0.7014
D(Fin_NEG) does not Granger Cause RET_RI	104	6	1.96316	0.0791
RET_RI does not Granger Cause D(Fin_NEG)	104	6	1.00356	0.4280
D(H_NEG) does not Granger Cause RET_RI	106	4	0.76892	0.5480
RET_RI does not Granger Cause D(H_NEG)	106	4	0.67315	0.6122
D(H_POS) does not Granger Cause RET_RI	106	4	1.02243	0.3997
RET_RI does not Granger Cause D(H_POS)	106	4	0.30524	0.8738
D(H_OPT) does not Granger Cause RET_RI	106	4	1.15529	0.3354
RET_RI does not Granger Cause D(H_OPT)	106	4	0.49827	0.7370
D(OPTIMISM) does not Granger Cause RET_RI	105	5	0.81891	0.5392
RET_RI does not Granger Cause D(OPTIMISM)	105	5	0.83941	0.5251
D(Fin_NEG) does not Granger Cause D(VO)	103	7	3.90715	0.0009
D(VO) does not Granger Cause D(Fin_NEG)	103	7	0.30166	0.9514
D(LM_OPT) does not Granger Cause D(VO)	103	7	2.80199	0.0111
D(VO) does not Granger Cause D(LM_OPT)	103	7	0.38400	0.9095
D(H_NEG) does not Granger Cause D(VO)	103	7	1.49990	0.1778
D(VO) does not Granger Cause D(H_NEG)	103	7	1.18418	0.3201
D(H_POS) does not Granger Cause D(VO)	105	5	0.37154	0.8670
D(VO) does not Granger Cause D(H_POS)	105	5	1.94577	0.0940
D(H_OPT) does not Granger Cause D(VO)	105	5	0.21930	0.9534
D(VO) does not Granger Cause D(H_OPT)	105	5	1.34413	0.2527
D(OPTIMISM) does not Granger Cause D(VO)	105	5	1.61199	0.1644
D(VO) does not Granger Cause D(OPTIMISM)	105	5	0.27040	0.9283
D(SVI_REIT_F) does not Granger Cause RET_RI	321	4	0.82443	0.5104
RET_RI does not Granger Cause D(SVI_REIT_F)	321	4	1.40333	0.2327
D(SVI_REIT_REL) does not Granger Cause RET_RI	321	4	0.85549	0.4910
RET_RI does not Granger Cause D(SVI_REIT_REL)	321	4	1.29918	0.2703
D(SVI_REIT_F) does not Granger Cause D(VO)	322	3	16.6615	0.0000
D(VO) does not Granger Cause D(SVI_REIT_F)	322	3	1.41743	0.2376
D(SVI_REIT_REL) does not Granger Cause D(VO)	322	3	16.6948	0.0000
D(VO) does not Granger Cause D(SVI_REIT_REL)	322	3	1.22692	0.3000

*The lag length of each VAR was chosen based on lag order selected by Akaike information criterion (AIC). Fin_NEG is the negative list of words suggested by Loughran and McDonald (2010). LM_OPT is the difference between positive and negative words suggested by Loughran and McDonald (2010). OPTIMISM is a score automatically generated by DICTION 5.0 software using its built in dictionaries. H_NEG and H_POS is the negativity and positivity word lists suggested by Henry (2008). H_OPT is the difference between positive and negative words of Henry (2008). SVI_REIT_F is the Google search frequency for the term 'REIT' scaled by fixed mode. SVI_REIT_REL is the Google search frequency for the term 'REIT' scaled by relative mode.

Table A.15
Johansen Cointegration Rank (Trace) Results

Test for Cointegration between	Hypothesized Number of Cointegrated Vectors	
	r = 0	r ≤ 1
RI and Fin_NEG	28.653 *	4.210 *
RI and LM_OPT	31.072 *	4.001 *
RI and H_NEG	13.152	3.306
RI and H_POS	18.559 *	3.610
RI and H_OPT	17.247 *	4.043 *
RI and OPTIMISM	30.531 *	3.431
RI and SVI_REIT_F	9.064	1.563
RI and SVI_REIT_REL	9.132	1.559
VO and Fin_NEG	20.665 *	1.875
VO and LM_OPT	27.449 *	2.092
VO and H_NEG	17.172 *	2.603
VO and H_POS	14.671 *	2.334
VO and H_OPT	11.675	2.265
VO and OPTIMISM	21.291 *	1.875
VO and SVI_REIT_F	21.433 *	2.229
VO and SVI_REIT_REL	21.529 *	2.265
Critical values at 0.05	15.4947	3.8415

*denotes rejection of the hypothesis at the 0.05 level by comparing the Trace statistics with the Critical values. RI is the level of the REIT return index (US DS-REIT) from DataStream. VO is the level of volume turnover of the REIT index. Fin_NEG is the negative list of words suggested by Loughran and McDonald (2010). LM_OPT is the difference between positive and negative words suggested by Loughran and McDonald (2010). OPTIMISM is a score automatically generated by DICTION 5.0 software using its built in dictionaries. H_NEG and H_POS is the negativity and positivity word lists suggested by Henry (2008). H_OPT is the difference between positive and negative words of Henry (2008). SVI_REIT_F is the Google search frequency for the term 'REIT' scaled by fixed mode. SVI_REIT_REL is the Google search frequency for the term 'REIT' scaled by relative mode.

Table A.16
VEC Granger Causality Results

Null Hypothesis	Number of Lags	p-value
D(LM_OPT) → D(RI)	8	**0.0275**
D(RI) → D(LM_OPT)	8	0.3471
D(FIN_NEG) → D(RI)	6	**0.0957**
D(RI) → D (FIN_NEG)	6	0.1814
D(H_NEG) → D(RI)	4	0.3456
D(RI) → D(H_NEG)	4	0.4448
D(H_POS) → D(RI)	4	0.1100
D(RI) → D(H_POS)	4	0.6232
D(H_OPT) → D(RI)	4	0.1394
D(RI) → D(H_OPT)	4	0.4277
D(OPTIMISM) → D(RI)	5	**0.0440**
D(RI) → D(OPTIMISM)	5	0.7597
D(LM_OPT) → D(VO)	7	0.4181
D(VO) → D(LM_OPT)	7	0.8989
D(FIN_NEG) → D(VO)	7	**0.0229**
D(VO) → D (FIN_NEG)	7	0.9759
D(H_NEG) → D(VO)	7	0.2531
D(VO) → D(H_NEG)	7	**0.0102**
D(H_POS) → D(VO)	5	0.8782
D(VO) → D(H_POS)	5	**0.0203**
D(H_OPT) → D(VO)	5	0.9587
D(VO) → D(H_OPT)	5	0.1325
D(OPTIMISM) → D(VO)	5	0.5691
D(VO) → D(OPTIMISM)	5	0.9533
D(SVI_REIT_F) → D(RI)	4	0.4183
D(RI) → D(SVI_REIT_F)	4	0.2549
D(SVI_REIT_REL) → D(RI)	4	0.4044
D(RI) → D(SVI_REIT_REL)	4	0.2948
D(SVI_REIT_F) → D(VO)	3	**0.0000**
D(VO) → D(SVI_REIT_F)	3	0.8718
D(SVI_REIT_REL) → D(VO)	3	**0.0000**
D(VO) → D(SVI_REIT_REL)	3	0.8861

a→b indicates that "a" does not Granger cause "b" using a Vector Error Correction (VEC). Rejection of this null hypothesis indicates that there is Granger causality from a to b. D(a) is the first difference of "a". RI is the level of REIT return index and VO is the volume of this index.

Table A.17
Threshold GARCH (TGARCH) Results
(A)

Dependent Variable: RET_RI
Method: ML - ARCH (Marquardt) - Normal distribution
Bollerslev-Wooldridge robust standard errors & covariance
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1)^2*(RESID(-1)<0) + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.067986	0.010233	6.643573	0.0000
FIN_NEG	-4.825463	0.598935	-8.056741	0.0000
Variance Equation				
C	0.001675	0.000430	3.899160	0.0001
RESID(-1)^2	-0.281547	0.084822	-3.319274	0.0009
RESID(-1)^2*(RESID(-1)<0)	0.646281	0.154638	4.179328	**0.0000**
GARCH(-1)	0.675079	0.153265	4.404655	0.0000

R-squared	0.104550	F-statistic	2.521958
Adjusted R-squared	0.096259	Prob(F-statistic)	0.033581
Durbin-Watson stat	1.981569		

(B)

Dependent Variable: RET_RI
Bollerslev-Wooldridge robust standard errors & covariance
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*RESID(-1)^2*(RESID(-1)<0) + C(7)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.044490	0.009402	4.732077	0.0000
RET_RI(-1)	-0.021030	0.103712	-0.202773	0.8393
FIN_NEG	-3.141333	0.585515	-5.365074	0.0000
Variance Equation				
C	0.001169	0.000366	3.194992	0.0014
RESID(-1)^2	-0.318834	0.156856	-2.032652	0.0421
RESID(-1)^2*(RESID(-1)<0)	0.675435	0.219853	3.072214	**0.0021**
GARCH(-1)	0.750680	0.157741	4.758930	0.0000

R-squared	0.086682	F-statistic	1.676729
Adjusted R-squared	0.069450	Prob(F-statistic)	0.133778
Durbin-Watson stat	1.947306		

Table A.18
Exponential GARCH (EGARCH) Results

(A)

Dependent Variable: RET_RI
Method: ML - ARCH (Marquardt) - Normal distribution
Bollerslev-Wooldridge robust standard errors & covariance
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)
*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.019045	0.017959	1.060456	0.2889
FIN_NEG	-1.054273	1.133432	-0.930160	0.3523
Variance Equation				
C(3)	-0.187821	0.310759	-0.604396	0.5456
C(4)	-0.214967	0.186699	-1.151409	0.2496
C(5)	-0.349235	0.123627	-2.824901	**0.0047**
C(6)	0.931959	0.027781	33.54625	0.0000

R-squared	0.038775	F-statistic	0.871327
Adjusted R-squared	0.029875	Prob(F-statistic)	0.502964
Durbin-Watson stat	1.963729		

(B)

Dependent Variable: RET_RI
Bollerslev-Wooldridge robust standard errors & covariance
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.017659	0.015965	1.106096	0.2687
RET_RI(-1)	-0.032600	0.108768	-0.299725	0.7644
FIN_NEG	-1.066161	0.934054	-1.141434	0.2537
Variance Equation				
C(4)	-0.205629	0.320764	-0.641060	0.5215
C(5)	-0.242903	0.171192	-1.418891	0.1559
C(6)	-0.370231	0.144879	-2.555459	**0.0106**
C(7)	0.922125	0.032609	28.27854	0.0000

R-squared	0.035312	F-statistic	0.646683
Adjusted R-squared	0.017110	Prob(F-statistic)	0.692639
Durbin-Watson stat	1.914136		

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BIOGRAPHICAL INFORMATION

Fahad Waleed Almudhaf was born on March 16, 1982, in Kuwait. In 2003, he received a Bachelor of Science degree majoring in Electrical Engineering with a minor in Mathematics from California State University at Fresno. In 2007, he received his Masters in Business Administration degree with a concentration in Finance from the University of Nebraska at Lincoln. He enrolled in the Ph.D program in Finance at The University of Texas at Arlington in 2007. His current research interests include international real estate, REITs, behavioral finance, investments and international finance. As of fall 2010, he will be an Assistant Professor of Finance at Kuwait University.