FEAR AND THE HOUSING MARKET

by

SERGIY SAYDOMETOV

DISSERTATION

Submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy at
The University of Texas at Arlington
May, 2016

Arlington, Texas

Supervising Committee:

Sanjiv Sabherwal, Supervising Professor
John C. Adams
Ramya R. Aroul
William J. Crowder

ACKNOWLEDGEMENTS

My appreciation goes to several people, without whose support and encouragement, I would not have completed this degree, but above all I would like to acknowledge the work of my Creator, who enabled me to get this far. My first contact, as I considered UTA for the doctoral work, was Dr. Salil Sarkar. I would like to express my gratitude to him for accepting me into the program and being the first professor in my finance seminar courses. Next, I would like to acknowledge the contribution of Dr. Pei "Peter" Lung, whose investment seminar and a subsequent help in developing research ideas, helped to ignite a spark for future research.

I would not have completed this dissertation if it were not for Dr. Sanjiv Sabherwal, who is my dissertation chair. Dr. Sabherwal exemplifies academic excellence and professionalism, that is balanced with concern and respect of others. I spent many hours in his office discussing various research ideas, we exchanged numerous emails as we continued our discussion of results and the direction of future tests, and we Skyped for many hours as the dissertation completion date was drawing near. I am grateful to Dr. Sabherwal, who is a great mentor and an inspiration to me. I would like to acknowledge the contribution of Dr. Ramya Aroul, who is my dissertation committee member. She provided valuable feedback and joined our discussions with Dr. Sabherwal via Skype. I'm grateful to Dr. John C. Adams and Dr. William J. Crowder, who served on my dissertation committee and provided valuable comments and feedback.

I also appreciate the friendship and support of my cohort fellow students, especially of Keming Li and Riaz Uddin. Keming was always willing to study together for long hours and on the weekends and make difficult concepts seem clearer. Riaz helped to organize social gatherings, such as luncheons, birthday celebrations, and baby showers, which all contributed to developing deeper friendships outside of the academic setting.

DEDICATION

I dedicate this work to my dear wife, Mac, and my lovely children Victoria and Lucas. I would not be able to finish this dissertation if it were not for their encouragement and support. I appreciate the extra load that Mac had to endure while I was away working late hours or staying in the library during the weekends. Victoria and Lucas learned that daddy has to work late on his Ph.D., so it was a joy for me to learn that they were working on their "Ph.Ds." as they role played at home.

My gratitude goes to the chancellor, Dr. Gary Cook, at Dallas Baptist University, who encouraged me to pursue a Ph.D. and supported me throughout its completion. I also want to express my gratitude to my previous and current deans, Dr. Charlene Conner and Dr. Dale Sims, as they "lightened my load" while I was pursuing my doctoral studies. I want to thank my colleagues at Dallas Baptist University, in particular Dr. Dave Arnott, Dr. Andrew Schaffer, and Dr. John Jaeger, who helped to proof different parts of this manuscript.

This accomplishment would not be possible without my dear friend and mentor, Ravshan Kairbaev, who did not get to live to see this day. Ravshan taught me to trust in the power of invisible God and to trust in His Son, Jesus. Finally, I dedicate this work and any future to come to my Creator.

April 28, 2016

ABSTRACT

FEAR AND THE HOUSING MARKET

Sergiy Saydometov, Ph.D.

The University of Texas at Arlington, 2016

Supervising Professor: Sanjiv Sabherwal

In this dissertation, I use Google search frequency to construct a new measure of housing market-level sentiment and analyze its relation with housing prices. I term this measure as the *Home Price Fear Index,* or *Fear Index* or *Fear* for short. The *Fear Index* is based on Google Search volume for certain real estate and economic terms, such as foreclosure, recession, and market value.

In the first essay, I examine the relation between the *Fear Index* at the national level and the Case/Shiller National Home Price Index. I find this relation to be inverse, with an increase in *Fear* predicting a decrease in home prices. The relation is robust to controlling for a number of relevant economic variables. I also find that housing prices respond differently to increases versus decreases in *Fear*. Increases in *Fear* result in a significant negative response in housing prices, while decreases in *Fear* evoke little response. This asymmetric response can be attributed to the “negativity effect,” which is widely discussed in the psychology literature. I also find that home prices are more sensitive to *Fear* during recessionary periods.

In the second essay, I examine the relation between the *Fear Index* at the metropolitan statistical area (MSA) level and local home price changes. I construct 20 local *Fear Indexes* based on MSAs covered by Case/Shiller 20-City Composite Home Price Index. I find that forecasting ability of local *Fear* is comparable to those of other well-known predictors of housing price changes. Further, *Fear* in "cold" housing markets (cities with slow price appreciation) has a stronger effect than in "hot" markets (cities with rapid price appreciation). I also find that cities with high bankruptcy rates are more responsive to changes in *Fear* than low bankruptcy rate cities. Moreover, "cold" cities with high bankruptcy rates are the most responsive to negative sentiment.

In the third essay, I examine the impact of volatility on the relation between the *Fear Index* and home price changes. Using standard deviation and idiosyncratic volatility as alternative measures of volatility, I find that response to *Fear* across MSAs is stronger as volatility increases. Further, cities with low volatility exhibit a similar response to increases versus decreases in *Fear*, while high volatility cities display an asymmetric response, with a significant and negative reaction to an increase in *Fear* but little reaction to a decrease in *Fear*. I also differentiate between downside volatility and upside or "good" volatility, and find that *Fear* has a stronger impact on housing price changes as downside risk goes up relative to the upside volatility. Finally, I find that it is the downside and not the upside volatility that affects *Fear*.

TABLE OF CONTENTS

LIST OF ILLUSTRATIONS

LIST OF TABLES

CHAPTER 1

INTRODUCTION

In this study, I construct a market-level sentiment index with regard to the housing market and then analyze its relation with housing prices. I use web search data provided by *Google Trends* to assess relative popularity of terms related to real estate, such as foreclosure, recession, and market value. I select the 30 most important search terms that are negatively related to housing market returns and then combine them into a single measure of sentiment, that I call the *Fear Index* or *Fear*, for short.

In my first essay, I examine the relation between the *Fear Index* at the national level and the Case/Shiller National Home Price Index. I document the inverse association, with an increase in *Fear* predicting a decrease in home prices. This relation is robust to controlling for a number of relevant economic variables, such as CPI, real GDP, and unemployment rate. Moreover, the *Fear Index* is able to predict the change in the housing market returns up to three months into the future.

My results strongly suggest that housing market responds differently to increases versus decreases in the *Fear Index*. Increases in the *Fear Index* result in a significant negative response in housing market returns, while decreases in the *Fear Index* evoke little response. This asymmetric response can be accredited to the “negativity effect,” which is widely discussed in the psychology literature. In conclusion of my first essay, I analyze whether the housing market is more sensitive to *Fear* during either recessionary or expansionary periods of the business cycle and find that it is during the recessionary phase, the housing market returns are most responsive to *Fear*.

In my second essay, I examine the ability of local *Fear* to impact the national as well as local housing markets. In particular, I use the same methodology to construct negative sentiment indexes across the 20 largest Metropolitan Statistical Areas (MSAs) that correspond to the same MSAs included in the Case/Shiller 20-City Composite Home Price Indexes. First, I document that the forecasting ability of local *Fear* is comparable to those of other well-known predictors of housing price changes, such as the S&P 500 Index, HMI, unemployment rate, CPI, and real GDP. Further, the *Fear Index* in six cities is at least as important as *National Fear* and adds to the understanding of important metropolitan hubs in which negative sentiment helps in predicting the changes in the national housing market. I am also able to pinpoint to the broader geographic regions, which are relatively more important in spreading the negative sentiment across the country.

Next, I examine the impact of negative sentiment across cities grouped by price appreciation and bankruptcy rates. I find that the *Fear Index* in “cold” housing markets (cities with slow price appreciation) has a stronger effect than in “hot” markets (cities with rapid price appreciation). This finding is complementary to the one by Beracha and Wintoki (2013), who find that "hot" markets are more responsive to positive rather than negative sentiment. Further, using the data on bankruptcy filings compiled by the American Bankruptcy Institute, I find that cities with high bankruptcy rates are more responsive to changes in *Fear* than low bankruptcy rate cities. In addition, I examine the impact of local *Fear Index* on local home price index returns in two-by-two sorts of high and low bankruptcy markets and "hot" and "cold" markets. The evidence strongly suggests that “cold” cities with high bankruptcy rates are the most responsive to negative sentiment.

In my third essay, I examine the impact of volatility on the relation between the *Fear Index* and home price changes. Using standard deviation and idiosyncratic volatility as alternative measures of volatility, I document that response to the *Fear Index* across MSAs is stronger as volatility increases. Further, cities with low volatility exhibit a similar response to increases versus decreases in *Fear*, while high volatility cities display an asymmetric response, with a significant and negative reaction to an increase in *Fear* but little reaction to a decrease in *Fear*. One of the behavioral explanations of this result can be attributed to loss aversion. Loss aversion refers to people's heightened sensitivity to losses relative to gains of the same magnitude. High volatility in the value of someone's home can lead to substantial volatility in the overall level of households' wealth. Given that investors are more sensitive to losses than to gains, these fluctuations can cause a substantial discomfort and lead to higher sensitivity to changes in *Fear*. In this case, I posit that the *Fear Index* reflects the aggregate households' perception of risk.

I also differentiate between downside risk and upside or "good" volatility, and find that *Fear* has a stronger impact on housing price changes as downside risk goes up relative to the upside volatility. While Thaler and Johnson (1990) argue that losses after prior losses are more painful than usual, I find that negative sentiment is more informative with regard to future housing market returns after people experienced prior losses. Finally, I find that downside risk affects future changes in *Fear,* while upside volatility has no effect.

There is a growing body of literature that examines the impact of Google's web search data as a measure of attention, sentiment, information demand, or simply a predictor of another variable of interest. A landmark study to popularize web search query data is by Ginsberg *et al.*

(2009), which documents the ability of Google search data to predict the incidence of influenza-like diseases ahead of traditional influenza surveillance systems.

As a measure of unsophisticated investors' attention, Da, Engelberg, and Gao (2011) use search data to predict Russell 3000 stock returns and first day IPO returns. As a measure of information demand, Drake, Roulstone and Thornock (2012) examine the role of web search data around earnings announcements for the S&P 500 stocks. As a measure of sentiment, Da, Engelberg, and Gao (2015) construct a negative sentiment index using search data and find its ability to predict short-term return reversals, temporary increases in volatility, and mutual fund flows. Some other studies in the finance literature, such as Joseph, Wintoki, and Zhang (2011), Bank, Larch, and Peter (2011), Vlastakis and Markellos (2012), and Takeda and Wakao (2014), find Google search data to be positively associated with stock returns and trading volume.

A number of studies in the real estate literature, such as Wu and Brynjolfsson (2009), Hohenstatt, Käsbauer, and Schäfers (2011), Hohenstatt and Kaesbauer (2014), Beracha and Wintoki (2013), and Das, Ziobrowski, and Coulson (2015), argue that Google web searches offer a reasonable proxy for demand in real estate markets. Lee and Mori (2015) use Google web search data as a proxy for conspicuous demand in housing markets. Freybote and Fruits (2015) use web searches to analyze the effect of perceived risk on home values. Two recent studies document the relevance of web search data in the Chinese housing markets. The first study is by Wu and Deng (2015), which uses web searches as a measure of information flow, and the second study is by Zheng, Sun, Kahn (2015), which utilizes web searches as a measure of investor confidence.

A number of earlier studies examine Google's web search data as a predictor of various economic indicators. For example, Vosen and Schmidt (2011) use search data to forecast private consumption; McLaren and Shanbhogue (2011), Askitas and Zimmermann (2009), and D'Amuri and Marcucci (2010) use search data to predict changes in unemployment rates; Choi and Varian (2012) use Google data to predict unemployment claims and automobile demand; Della Penna and Huang (2009) and Schmidt and Vosen (2009) use search data as a measure of consumer sentiment; and Guzman (2011) investigates Google data as a predictor of inflation.

This study complements the existing literature on Google's web search data by providing strong evidence that web searches can be used as a good proxy for households' sentiment with regard to housing markets. My study is similar to Da, Engelberg, and Gao (2015) in that I combine multiple search terms into a single measure of negative sentiment, but it differs with respect to the terms I use to capture sentiment. I use the expanded set of terms, which are uniquely related to real estate, as I construct the measure of housing market sentiment. My study is similar to Beracha and Wintoki (2013), in that I also examine the relation between online search volumes and home price changes, but it differs since I use a more comprehensive measure of sentiment by aggregating multiple search terms, wherever they use only one search term as a measure of negative sentiment. In my study, I collect search volumes from the geographic areas contained within MSAs, while Beracha and Wintoki assign search volumes to MSAs that were generated across the whole United States. As such, the *Fear Index* is more robust in capturing aggregate household sentiment of local residents. Further research could examine the impact of negative sentiment in other markets, whether domestic or international.

CHAPTER 2

HOUSEHOLD SENTIMENT INDEX AND REAL ESTATE RETURNS

1. Introduction

The study of cognitive psychology sheds light on how people reason, make choices, and allocate their attention, among other things. A number of studies have applied advances in this field to the behavior of people in making economic and financial decisions. As a result, a new branch of finance has developed, exploiting human behavior as an important component in explaining market movements. Behavioral finance, as opposed to traditional finance, offers explanations as to the reasons people make irrational financial decisions and provides some guidance on how to avoid or minimize the impact of such errors. It acknowledges that the bounded rationality and psychological biases of investors fill a void in explaining the changes in asset prices where the changes in market fundamentals fall short. A number of studies explore the role of investor sentiment on stock returns.[1] Most of these studies agree that asset mispricing is a result of sentiment-driven investor demand and limits to arbitrage. In this study, I construct a new measure of market sentiment and then examine its impact on the residential real estate market, which in contrast to the stock market experiences more significant limits to arbitrage.

Residential real estate market plays an important role in the U.S. economy. The market value of residential real estate accounted for 56.7% of households' equity in the third quarter of

[1] See Neal and Wheatley (1998), Brown and Cliff (2004, 2005), Baker and Wurgler (2006, 2007), Kumar and Lee (2006), Han (2008), Baker, Wurgler, and Yuan (2012), and Stambaugh, Yu, and Yuan (2012).

2015 according to the Statistical Release by the Federal Reserve.[2] Sustainable home values are important for local governments as well, since about 30% of local government tax revenues come from residential real estate.[3] Homeowners have benefited from increasing home values over the last several decades but not without occasional slumps. The most pronounced drop in home values occurred at the time of subprime mortgage crisis during 2007 - 2009. As of July 2015, the national home price index was still below its peak in July 2006. Similar to other assets, housing prices are more volatile than the observable changes in fundamentals. Some argue that housing markets experience bubbles as in Abraham and Hendershott (1996), Case and Shiller (2003), Shiller (2007), Glaeser, Gyourko, and Saiz (2008), etc. Others question that conclusion and offer factors that can explain changes in housing prices as in Himmelberg, Mayer, and Sinai (2005), Smith and Smith (2006), and Goodman and Thibodeau (2008). While this study does not address the issue of bubbles in the housing market, I find evidence that market sentiment contributes to explaining the changes in housing prices. The demand side of the housing market is comprised of individuals whose decisions are impacted by their sentiment toward the current state of the real estate market. I use a proxy that captures that sentiment via search queries related to real estate.

For many families who own a home, the value of their residences comprises a significant portion of their overall wealth. In fact, Americans held a total of $10.1 trillion in their homes in 2011, which is about 25% of overall wealth.[4] It is second only to the share of overall wealth held in retirement accounts, which is close to 30%. A decade earlier, home equity accounted for even

[2] A full document is available at http://www.federalreserve.gov/releases/z1/Current/z1.pdf. See page 134 of the document for a complete balance sheet.
[3] Real Estate Roundtable's 2015 *Policy Agenda*. The report can be accessed at http://www.rer.org/PolAg15-entire-report/. Page 4 of the document contains all other categories that comprise the tax revenues raised by local governments.
[4] These values come from the U.S. Census Bureau's publication titled *Household Wealth in the U.S.: 2000 to 2011* prepared by Alfred Gottschalck, Marina Vornovytskyy, and Adam Smith. The report is located at https://www.census.gov/people/wealth/files/Wealth%20Highlights%202011.pdf.

a greater portion of overall wealth at 30%, while wealth held in retirement accounts was at 18%. Buying a home is one of the most important economic decisions people face in their lives. It is based on several factors, one of which has to do with people's attitudes toward current state of the economy and real estate market. Some prospective buyers may delay their home purchases if they expect the housing prices to decline in the near future. If there are enough potential buyers who share this belief, the demand for homes may temporarily decline and as a result cause housing prices to drop. In contrast, some may wait on selling a home if they believe the housing prices are going up in the near future. If this sentiment among sellers is prevailing, it may cause the supply of homes to decline, resulting in rising home prices. In both of these cases, the result of sentiment becomes a self-fulfilling prophecy. Beracha and Wintoki (2013) argue that search volume for real estate terms for a given city can be used as a proxy for buyer sentiment for that city. They posit that abnormal changes in search volume can signal a future change in demand for housing and result in a future abnormal price move. They find that abnormal change in housing sentiment helps to predict abnormal change in housing prices for a particular city. They also find that cities with inelastic land supply are more sensitive to changes in sentiment. This study is different from theirs in that I focus on aggregate search volume for the entire U.S., while they focus on search volumes for individual cities. I also construct an index measure that combines 30 of the most important search terms for the housing market, while their study uses only two query terms to gauge the search interest.

Finding an accurate measure of people's sentiment at the aggregate level is not an easy task. However, multiple measures have been created to gauge general public's level of optimism or pessimism, assess consumer attitudes, and provide guidance toward future economic activity. Some of these indicators are Consumer Confidence Index (CCI), University of Michigan

Consumer Sentiment Index (MCSI), Bloomberg Consumer Comfort Index, Consumer Confidence Average Index (CCAI), and Gallup Economic Confidence Index. The construction of these indexes relies heavily on conducting periodic surveys and then evaluating the feedback received from survey participants. Some of these measures have been proven to work well in some circumstances but each has its limitations. One of the weaknesses of survey-based indices is that there is little incentive to answer survey questions carefully or honestly, especially when questions inquire about sensitive personal information.[5]

Human interaction with the Internet has become an increasingly important part of daily life in the new millennium. Based on data provided by Statista (www.statista.com), an average American spent 159 minutes surfing the Internet via desktop and laptop devices each day in 2014. If I include the use of tablet devices and Smartphones, that number goes up to 456 minutes, which is equivalent to 32% of time spent per day. People use search engines to access information and, in doing so, they reveal their interests or provide insights on the things that grab their attention. *Google Trends* is a publicly available service that provides data on the volume of queries for different search terms at weekly or daily frequencies based on the length of the time period selected.

With greater access to aggregate search engine data such as *Google Trends* provides, professionals and academics are starting to use this data extensively and examine its usefulness in various contexts. In the context of financial markets, Da, Engelberg, and Gao (2011) use search data as a measure of retail investors' attention, Drake, Roulstone, and Thornock (2012) use it to investigate investor information demand around earnings announcements, and Da, Engelberg, and Gao (2015) use search data as a proxy for market-level sentiment. In the context of economic indicators, Vosen and Schmidt (2011) use *Google Trends* to forecast private

[5] See Singer (2002) for a complete list of weaknesses of a survey based approach.

consumption, McLaren and Shanbhogue (2011) use search data to predict changes in unemployment and house prices in the U.K., Choi and Varian (2012) use Google data to predict unemployment claims and automobile demand, and Guzman (2011) investigates Google data as a predictor of inflation. In the context of epidemiology, Polgreen *et al.* (2008) and Ginsberg *et al.* (2009) pioneered the research in that field by showing that Google search data could help predict the incidence of influenza-like diseases ahead of other well-known indicators. Outside of academic research, *Google Trends* data is used by business professionals who use it for market research, product development, etc.[6]

I use data on aggregate search frequencies to construct home price sentiment index and then examine the relation of this index to the Case/Shiller National Home Price Index. The Case/Shiller National Home Price Index is the leading measure of U.S. residential real estate prices, which tracks the total value of single-family housing within the U.S. It captures about 75% of U.S. residential housing stock by value and is based on nine monthly U.S. Census division repeat-sales indices.

To get a better understanding of my sentiment measure, I need to consider the reasons people search for information and the possible factors that drive people to search for certain terms but not others. People use web search engines for a number of reasons. It could be to access the news, learn definitions, inquire about certain subjects, access social media sites, watch a video, shop for some products or services, get directions, etc. Some of the factors that contribute to people's search for some terms but not the others are announcements on mass

[6] Google recently introduced a new tool called Shopping Insights that shows search volumes for the products in more than 16,000 U.S. cities and towns. Google intends this tool to be used by retailers to gauge geographical differences in demand for different products and then adjust marketing campaigns and better manage inventory of products in physical stores. Link to the article on *Wall Street Journal*: http://www.wsj.com/articles/google-discloses-more-search-data-to-woo-retailers-1445384100?cb=logged0.4088188075548398. Link to Shopping Insights: https://shopping.thinkwithgoogle.com.

media, interactions using social media outlets, work-related projects, personal interests, etc. While it is hard to quantify any of these factors in measurable terms and assess their impact on web search queries, it is safe to assume that people reveal their level of interest by their web search patterns and the aggregate search data contains information on prevailing sentiment.

Google Trends provides data on relative search interest over time that I call the Search Volume Index (SVI). SVI correlates well with an alternative measure of residential housing market sentiment. For example, Figure 1 plots monthly log SVI for “foreclosure listings” (with a minus sign since higher SVI on “foreclosure listings” signals pessimism) against the monthly Housing Market Index (HMI), which asks builders about their housing market outlook. During the time period from January 2005 to March 2015, the two time series are highly correlated with a correlation coefficient of 0.829. When I use the change in log SVI for “foreclosure listings” this month to predict next month’s HMI, I find that an increase in SVI helps to predicts a decrease in the HMI (t-value=23.47).

The purpose of this study is to examine the relation between the general public’s revealed sentiment and housing prices. In particular, I use search terms related to real estate, finance, and economics to form a sentiment index and then investigate the ability of this index to predict the changes in national home price index.

I find a negative and economically significant relation between the *Fear Index* and residential real estate returns. One standard deviation increase in the *Fear Index* corresponds with a decline of 16 basis points over the next month in the residential housing market returns. The effect of the sentiment index on housing market returns is robust to controls for key predictors of home index values. I also analyze whether the magnitude of the impact of changes in my sentiment index on housing prices differs for increases versus decreases in the index. I find that an increase in the *Fear Index* results in a stronger response in housing prices than a decrease in *Fear Index*. When market participants become more concerned about the real estate market, the housing prices decline over the next month. In contrast, when there is a decrease in fear, the housing prices do not show a significant increase. I attribute this finding to the "negativity effect" that suggests an asymmetric response to negative versus positive changes in sentiment. It implies a strong negative reaction to bad sentiment but a negligible reaction to positive sentiment. I also find that housing markets are more sensitive to negative sentiment during recessionary periods and that impact lasts up to three months.

The remainder of this paper proceeds as follows. In the next section I discuss related studies and how this study fits into the existing literature. The third section describes the data and methods used to construct the index that captures household sentiment in real estate market. In this section, I also describe other data that is used in this study. The fourth section reports my main empirical results for the regressions of home price index returns on the *Fear Index*. I discuss the asymmetric response to increases in *Fear* in the fifth section, along with the negativity effect. The sixth section presents robustness checks for my regression results across business cycles. Conclusions are presented in the last section.

2. Literature Review

There is a growing body of literature that uses Google's search volume data as a proxy for attention or sentiment. In this study, I use Google's search data to construct a proxy for household sentiment in the residential real estate market. Previous studies have shown that changes in query volumes for selected search terms are helpful in tracking current changes in financial, economic and health-related indicators.

Ginsberg *et al*. (2009) find that data on search queries are more accurate in tracking changes in current numbers of influenza cases than traditional surveillance systems employed by the U.S. Centers for Disease Control and Prevention (CDC). Choi and Varian (2012) analyze whether data from Google Trends can be linked to current values of various economic indicators, such as auto sales, unemployment claims, and consumer confidence. They find evidence that models that include *Google Trends* variables outperform those that do not by 5% to 20%.

Da, Engelberg, and Gao (2011) use search frequency in Google [the Search Volume Index (SVI)] as a proxy for attention of individual/retail investors. They find that it performs well in capturing the attention of retail investors, especially those that are less sophisticated. Further, the SVI captures investor attention in a more timely fashion than existing proxies for investor attention and it predicts higher stock prices in the next two weeks and an eventual price reversal within the year. Da, Engelberg, and Gao (2015) combine multiple Google search queries into a single measure that reveals market-level sentiment. They find that their new measure of investor sentiment helps to predict short-term return reversals, temporary increases in volatility, and mutual fund flows. In this study, I use a similar approach in combining multiple search queries into a single measure, but I start with an expanded list of terms that relate more to real estate.

A number of studies use survey-based indicators as a proxy for the sentiment in housing markets. Ling, Naranjo, and Scheick (2014) use surveys of home buyers, home builders, and mortgage lenders in the U.S. to construct their sentiment measure and examine its role in explaining housing price dynamics. They analyze the short- and long-run relation between investor sentiment and returns in private commercial real estate markets. They use vector autoregressive models and find a positive short-run effect of investor sentiment on subsequent private market returns. In contrast, they find a negative relation between investor sentiment and subsequent public real estate market returns, which they explain by a less significant role of limits to arbitrage in public markets. They also find that private real estate markets are subject to long-term sentiment-induced mispricing due to the inability of arbitrageurs to short-sell in periods of overvaluation and access credit in periods of undervaluation. Similarly to Ling *et al.*, I test directly the dynamic relation between the proxy for marketwide sentiment and house price movements. In contrast to their approach, I use a different measure of marketwide sentiment that is not survey based.

Jin, Soydemir, and Tidwell (2014) find evidence that consumer irrational sentiment impacts housing prices across 10 metropolitan areas. They suggest that real estate pricing models should include a variable capable of measuring irrational sentiment. Verma, Baklaci, and Soydemir (2008) also divide investor sentiment into rational and irrational components and find that irrational sentiment has a short-term impact on stock market returns. Marcato and Nanda (2015) use quarterly data over 1988-2010 to test whether survey-based sentiment indicators are important in explaining real estate price changes. They find that residential real estate prices respond significantly to changes in sentiment, but the non-residential prices do not show such effects.

Some studies find that behavioral biases play a role in price dynamics in the residential as well as commercial real estate markets. Genesove and Mayer (2001) find that loss aversion affects seller behavior in the residential real estate market in Boston in the 1990s. They find that condominium owners faced with a prospective loss, set a higher asking price and take a longer time to sell, but when they do sell, they do so at a higher price than other sellers. Ackert, Church, and Jayaraman (2011) explore the relation between money illusion and mispricing in the residential real estate market. They find evidence that individuals suffer from the money illusion, yet they have reasonable expectations of home prices. Bokhari and Geltner (2011) find that loss aversion and anchoring played a major role in the pricing of commercial real estate in the U.S. in the 2000s. They argue that more experienced investors exhibit as much loss aversion behavior as less experienced ones.

In the psychology literature, Kanouse and Hanson (1971), Czapinski (1988), and Peeters and Czapinski (1990) document and explain the behavioral bias known as the negativity effect. The negativity effect is characterized by a greater impact of negative versus equally intense positive stimuli on a subject. Taylor (1991) provides evidence that, all other things being equal, negative events will cause more physiological and behavioral activity than neutral or positive events. Baumeister *et al.* (2001) find that the negativity effect extends to everyday events, major life events, close relationship outcomes, social network patterns, interpersonal interactions, and learning processes.

There are two manifestations of this bias: (1) potential costs are more heavily weighted than potential gains in making decisions under risk, and (2) negative information is weighted more heavily than positive information in the formation of overall evaluations. The first manifestation became a cornerstone to the prospect theory of Kahneman and Tversky (1979). The second manifestation is of greater interest here since it suggests that households will react more to negative information than to positive information.

There are two studies of which I am aware that test the negativity effect in the context of financial markets. Akhtar *et al.* (2011) document a negativity effect in the Australian stock market. They find that upon the announcement of bad sentiment news, the equity market experiences a significant negative announcement day effect, while the announcement of good sentiment news generates no effect at all. Akhtar *et al.* (2012) document and explain the asymmetric response of stock and futures market returns to the preliminary announcement of the Michigan Consumer Sentiment Index. Similarly, they find that a negative market effect occurs upon the release of bad sentiment news, while there is no market reaction for the equivalent good news. They also document that the negativity effect is most evident in salient stocks.

Similarly to Akhtar *et al.* (2011, 2012) who find the presence of the negativity effect in the stock and futures markets, I find that negativity effect is present in the house price movements in its response to increases versus decreases in *Fear*. The negativity effect is likely to be even more pronounced in housing markets, since they exhibit more significant limits to arbitrage than stock and futures markets due to higher transaction costs and liquidity risks.

3. Data and Methodology

The data for this study comes from several sources, but I begin by discussing the construction of the main variable, the *Fear Index*.

3.1. Construction of *Fear Index*

I use search frequencies from *Google Trends* to construct a sentiment index. Google uses their proprietary methodology to measure the overall search interest over time. They do not report the total number of searches but rather the relative popularity of one term compared to other search terms. They explain:

> The numbers that appear show total searches for a term relative to the total number of searches done on Google over time. A line trending downward means that a search term's relative popularity is decreasing. But that doesn’t necessarily mean the total number of searches for that term is decreasing. It just means its popularity is decreasing compared to

other searches.[7]

Google Trends adjusts search data by dividing each data point by the number of total searches in the geographical area and time range it represents. The resulting data are then scaled to a range of 0 to 100. [8] I refer to the search interest over time as the Search Volume Index (SVI). Without having the total number of searches but only their adjusted numbers, it is difficult to compare the search frequencies across multiple terms. For example, the search interest of 100 for one term may be associated with a completely different number of searches than 100 for another term even when two queries share the same location and time period. This is the case since the highest number of searches is converted to 100 for each query term.

As a result, I make some adjustments to SVIs before I use them in constructing the index. I follow Da, Engelberg, and Gao (2015) as I construct the sentiment measure for real estate market. The steps I take in constructing the index can be summarized in the following steps:

1) Taking the log differences of each term's SVIs:

   $\Delta SVI_{i,t} = \ln\left(SVI_{i,t}\right) - \ln(SVI_{i,t-1})$

2) Winsorizing each series at the 5% level (2.5% in each tail).

3) Removing quarterly seasonality from $\Delta SVI_{i,t}$ by regressing $\Delta SVI_{i,t}$ on quarter dummies and keeping the residual.

4) Standardizing each series by scaling each by the time-series standard deviation. The final series are named as adjusted SVI or ΔASVI.

[7] The link is: https://support.google.com/trends/answer/4355164?hl=en&rd=1.

[8] Google Trends describes the adjustment of raw data in the section titled *How Trends data is adjusted* located at https://support.google.com/trends/answer/4365533?hl=en&ref_topic=4365599&vid=1-635784374679226867-2748185092.

5) Running expanding window backward rolling regressions of $\Delta ASVI_i$ on housing market index returns every January to identify the 30 most important terms in each time period. I use these terms to compute *Fear Index* in the following year.
6) Computing the average $\Delta ASVI$ of these thirty terms in month *t*:

$$Fears\ Index_{\ t} = \frac{\sum_{\mathrm{j}=1}^{30}(\Delta ASVI_{j,t})}{30}$$

One of my primary objectives is to select a list of search terms that reveal sentiment towards the real estate market. I compile the list of 604 terms pertaining to real estate taken from two online sources.[9] Some of these words are "bankruptcy," "foreclosure," "fha," and "market value."

Once I have identified the list of real estate terms, my next objective is to examine how households may search for these terms using Google. With each query *Google Trends* provides a list of "Related searches," which includes the terms that are most frequently searched with the entered term.[10] For example, a search for "closing" results in the related searches "closing costs," "school closing," "closing time," "closing ceremony" because this is how the term "closing" is usually searched in Google. I examine the list of such related "top searches" for each real estate term and then weed out duplicates or those terms that are not clearly related to real estate. I am left with 1,000 related searches in addition to my original list of 604 terms. However, not all of these terms have search data available from *Google Trends*. If the search interest was relatively low, no search data will be generated. If the search interest was low for a part of the time period entered, *Google Trends* will generate zeros for those data points. After I download the search

[9] The first list I use has been compiled by the Columbia University, accessible at http://worklife.columbia.edu/real-estate-terminology#section1. To supplement my first list, I use another source for real estate terms accessible at http://www.realestateabc.com/glossary/.
[10] According to Google Trends Help, "Top searches are terms that are most frequently searched with the term you entered in the same search session, within the chosen category, country, or region."

data and eliminate those terms that do not generate at least 40 monthly observations,[11] I am left with 721 terms related to real estate and their related searches.

The SVI data for each of these 721 terms over the sample period of January 2004 to December 2014 comes from *Google Trends*. I restrict the search interest data to the U.S., since most of the variables of interest in this study are related to the U.S. As a result, my measure gauges the sentiment of American households towards the real estate market in the United States.

I collect weekly SVI series for each query term from *Google Trends.* Since the *Home Index*, which is the main dependent variable in this study, is computed at monthly frequency I compute monthly search interest by averaging weekly SVI data. Each week's SVI starts on Sunday and goes through Saturday, but each calendar month can start on any day of the week. To adjust for the fact that weekly SVI can include search interest for some portion of the new month, I apply a simple rule of thumb. If four or more days in a given week fall into a new month, I assign that week's SVI to that month. For example, if Saturday falls on October 4, I assign that week's SVI to October. However, if it falls on October 3, I assign that week's SVI to September. I define the monthly change in search term *i* as:

$$\Delta SVI_{i,t} = \ln\left(SVI_{i,t}\right) - \ln(SVI_{i,t-1}) \qquad (1)$$

Figure 2 plots the monthly log changes for two terms, "Foreclosure Listings" and "Lease," over a 3-year period from 2012 to 2014. I can observe several features of the search data from these figures. The first feature is seasonality: SVI change falls during October and November and rises during January and February generating a hump-shaped pattern. The second feature is heteroscedasticity, the difference in variances across terms. The standard deviation of

[11] Since I sample period is from 2004 to 2014, it includes 132 monthly observations for each term. My objective is to have non-zero search volume data for at least 40 months or about 30% of the time.

SVI change for “Foreclosure Listings” is 3.5 times greater than that of “Lease.” The third feature is the presence of some extreme values.

To eliminate some of these issues, I apply a similar adjustment to the monthly change in search volume as in Da, Engelberg, and Gao (2015). I follow the steps that are mentioned above by first winsorizing, then deseasonalizing, and finally standardizing each series. First, I winsorize each series at the 5% level (2.5% in each tail) to address the issue of outliers. Then, I regress $\Delta SVI_{i,t}$ on quarter dummies and keep the residual to eliminate seasonality from the series. Finally, I standardize each of the time series by subtracting the mean and dividing by the standard deviation to address heteroscedasticity and make each times series easier to compare. I term the resulting series as abnormal ΔSVI or $\Delta ASVI$.

Next, I identify the terms that are most important for the real estate market. To achieve this, I run expanding backward rolling window regressions of $\Delta ASVI$ on housing market index returns every twelve months (every January). This helps determine the historical relation between search queries and contemporaneous housing market returns for each of 721 search terms. I also notice that most terms that have a strong relation with the real estate market are negatively related to it. For example, only one term in the full sample (January 2004 – December 2014) has a *t*-statistic on $\Delta ASVI$ above 1.95, but fifteen terms have a *t*-statistic below -1.95. These negatively-related terms include "loan modification," "homepath," "fha," and "foreclosure listings," among others. As in Da, Engelberg, and Gao (2015), and Tetlock (2007), I find that negative terms are most helpful in identifying the sentiment. As a result, I use only the terms with the largest negative *t*-statistic to construct the *Fear Index*.

The *Fear Index* in month *t* is defined as:

$$Fears\ Index_{\ t} = \frac{\sum_{j=1}^{30}(\Delta ASVI_{j,t})}{30} \tag{2}$$

where $\Delta ASVI_{j,t}$ is $\Delta ASVI_t$ for one of the 30 terms with most negatively ranked *t*-statistic from the period January 2004 through the most recent twelve-month period. For example, at the end of December 2012, I run a regression of Δ*ASVI* on contemporaneous home price index returns during the period of January 2004-December 2012, for each of 721 query terms. Then I sort the terms based on their *t*-statistic on Δ*ASVI* in ascending order and select the 30 most negative terms to be used in forming the *Fear Index* for the period from January 2013 to December 2013. The *Fear Index* in month *t* over this period is simply the average Δ*ASVI* of these 30 terms in that month. Using expanding rolling window regressions helps to increase the statistical power of the selected terms. The above approach follows Kogan *et al.* (2009) and Da, Engelberg, and Gao (2015), who use historical regression approach to identify relevant terms and to select these terms in an objective manner.

Table 1 shows the top 30 terms over the entire sample period from January 2004 to December 2014. Some of the terms that have the largest historical correlation with housing market include "loan modification" (*t*-statistic = -3.03), "processing" (*t*-statistic = -2.62), "modification" (*t*-statistic = -2.61), "homepath" (*t*-statistic = -2.48), and "assessment" (*t*-statistic = -2.42).

3.2. Other Data

Table 2 provides a description of each variable that I use in this study. I present the description and if applicable the source from which each variable is collected. Two main variables for my study are *Fear Index* and *Home Index*. The *Fear Index* is a measure of negative sentiment captured by web search volumes and the *Home Index* is a measure of returns in the residential housing market proxied by the Case/Shiller National Home Price Index. The control variables that I use throughout the study are *Home Index Momentum*, *Real GDP*, *CPI*, *Unemployment Rate*, *HMI*, and *S&P 500 Index*. *Home Index Momentum* is computed on a rolling basis with each value representing the average housing market return over the previous 12 months. The *Home Index Momentum* controls for the autocorrelation of the home index returns, *Real GDP*, *CPI*, and *Unemployment Rate* control for the macroeconomic factors that affect the housing market, the *HMI* controls for an alternative measure of sentiment in the housing market, and the *S&P 500 Index* controls for the stock market returns. The reason for including these control variables comes from prior literature and adds to the robustness of my results.

Table 3 presents summary statistics for the main variables in this study and correlation coefficients across these variables. Panel A of this table presents descriptive sample statistics and Panel B shows correlation coefficients and their significance. In Panel A, I present summary statistics for the levels of each variable, but in Panel B and the subsequent tables I use log changes of *Home Index*, *Real GDP*, *CPI*, *Unemployment Rate*, and *HMI* to account for non-stationary qualities of these series. The *Fear Index* and the *S&P 500 Index* have not been transformed, since these variables are stationary by construction.

As shown in Panel A, the *Fear Index* ranges from -1.18 to 1.23, with a mean value of -0.04 and a median of 0.00. The units are percentage changes in sentiment from one month to the next. The positive *Fear Index* values imply that negative sentiment is growing, while the negative values imply the decrease in the negative sentiment, i.e., an increase in the positive sentiment. The mean monthly return for the *S&P 500 Index* is 0.01 or 1% during my period. The lowest monthly return during the period happened in October of 2008, which was

-16.94%, and the highest in October of 2011 with 10.77%.[12] The average unemployment rate over the sample period is 6.95%, which hit its highest level in October of 2009 at 10%.

From Panel B, I can see that the *Fear Index* and the Case/Shiller National Home Price Index are negatively correlated, as I would expect, with the correlation coefficient at -0.17. When households become more concerned about the housing market and as their concerns are revealed by their search queries, the housing market experiences declines. The other variables that are negatively but not significantly correlated with the *Fear Index* are the *S&P 500 Index*, the *Real GDP*, the *HMI*, and the *Home Index Momentum*. The strongest negative correlation is among the following pairs: *Home Index Momentum* and *Unemployment Rate* (-0.48), *Home Index* and *Unemployment Rate* (-0.32), and *S&P 500 Index* and *Unemployment Rate* (-0.21). The strongest positive correlation is between the following pairs: *Home Index Momentum* and *Home Index* (0.58), *S&P 500 Index* and *HMI* (0.26), and *Real GDP* and *Home Index* (0.20). The signs of these coefficients emphasize the established relation between each pair of these series and are consistent with my expectations.

4. *Fear Index* and Housing Prices

In this section, my main objective is to investigate whether the *Fear Index* helps to predict the housing market returns. To see whether this sentiment index is helpful in predicting the housing market returns, I estimate the following regression:

$$Home\ Index_t = \beta_0 + \beta_1 Fear\ Index_{t-1} + \sum_m \gamma_m Control_t^m + \varepsilon_t \tag{3}$$

[12] A quote from Mark Twain comes to mind, “October: This is one of the particularly dangerous months to invest in stocks. Other dangerous months are July, January, September, April, November, May, March, June, December, August and February.”

where $Home\ Index_t$ stands for the returns on the Case/Shiller National Home Price Index in month *t*, *Fear Index*$_{t-1}$ is the value of *Fear* in month *t-1*, and $Control_t^m$ is a set of control variables at time *t*. Control variables include *Home Index Momentum*, *Real GDP*, *CPI*, *Unemployment Rate*, *HMI*, *S&P 500 Index*.

Table 4 presents the results of Equation (3), which assesses the impact of *Fear Index* on home price index returns. This table includes results from four regression models with each having a different set of control variables. The sample period starts with January 2005 and continues through December 2014. I lose one year of search data since I use 2004 data to identify the terms to be included in the *Fear Index* in 2005.

Results from regression specification (1) suggest that lagged *Fear Index* is statistically significant in determining the change in home price index at the 5% level. One standard deviation increase in *Fear Index* (standard deviation is 0.42 from Table 3) corresponds with a decline of 18 basis points in the returns of the *Home Price Index* over the following month. After adding a number of controls, the *Fear Index* is still statistically significant at explaining the changes in the residential real estate market. In regressions specifications (2) through (4), I add more control variables to establish the predictive ability of the *Fear Index*. First, I add macroeconomic variables such as *Real GDP*, *CPI*, and *Unemployment rate* in regression (2). Next, I add *HMI* to control for the sentiment regarding the single-family housing market in regression (3). Finally, in regression (4) I add returns on the S&P 500 Index to control for the impact of stock market returns on housing market returns. The results are consistent across all four models and imply that the *Fear Index* is an important factor in predicting the changes in the housing market. The *Fear Index* coefficient in model (4) is statistically significant at the 5% level and implies that one standard deviation increase in *Fear* corresponds with a decline of 16 basis points in the *National Home Price Index*' returns over the next month. In all of these regressions, the negative and significant coefficient on *Fear Index* suggests that increases in *Fear Index* predict lower housing market returns over the next month.

5. Asymmetric Response to Increases in *Fear Index*

In this section, I test whether home index returns respond differently to increases in pessimism versus decreases in pessimism (increasing optimism) toward real estate market.

Based on the "negativity effect" discussed in an earlier section, individuals respond more significantly to bad news than good ones. One potential channel through which the negative sentiment information impacts households relates to selective media coverage. I often notice that media coverage is more skewed on emphasizing the negative sentiment information than the positive one, which is consistent with the psychology literature's assertion. Hearing negative news grabs people's attention more than hearing equally good news. It incentivizes media avenues to focus on such news in order to sustain a larger following, which also helps to attract advertisers, whose payments comprise a large portion of media's profits. Consequently, negative sentiment news widely conveyed by the popular press affects households' sentiment toward the housing market, which triggers selling behavior. Since positive sentiment news do not receive the same attention and coverage as negative sentiment ones, there is no counterpart media-driven force to spark the buying behavior.

As households respond more to negative sentiment than to positive one, increases in the *Fear Index* are likely to cause households to sell homes or delay purchasing decisions in the belief that the housing market is going to fall in the (near) future. On the other hand, the decreases in the *Fear Index* would not create a significant upward pressure on the housing prices. The negativity hypothesis can be formally stated:

The increases (decreases) in negative sentiment will induce a negative (negligible) housing market reaction.

To assess the empirical validity of the negativity effect, I estimate the model similar to the one in Akhtar *et al*. (2011 and 2012). In particular, I run the following regression:

$$Home\ Index_t = \beta_0 + \beta_1(Fear\ Index \times Decrease)_{t-1} + \beta_2(Fear\ Index \times Increase)_{t-1}$$
$$+ \beta_3 Increase_{t-1} + \sum_m \gamma_m Control_t^m + \varepsilon_t \quad (4)$$

where the $Home\ Index_t$ is the return on the Case/Shiller National Home Price Index in month *t*. *Decrease (Increase)* is a binary variable that takes on a value of 1 if the *Fear Index* is less (greater) than zero, and 0 otherwise. $(Fear\ Index \times Decrease)_{t-1}$ is the interaction term of the *Fear Index* and *Decrease* at time *t-1*. $(Fear\ Index \times Increase)_{t-1}$ is the interaction term of the *Fear Index* and *Increase* at time *t-1*. I use the same control variables as in the previous model. They are *Home Index Momentum*, *Real GDP*, *CPI*, *Unemployment Rate*, *HMI*, and *S&P 500 Index*.

My main focus is on the coefficients β_1 and β_2 of the interaction terms. The coefficient β_1 measures the response of housing index returns to decreases in *Fear Index* and β_2 to increases in it. I expect that β_2 is negative and significant while β_1 is not statistically significant. This result would indicate that the real estate market experiences a strong negative response to increases in *Fear* but a negligible response to its decreases.

Table 5 presents the results of testing for the asymmetric response to increases versus decreases in negative sentiment. In model specifications (1) – (3), I present the results from the regression shown above as equation (4). In model specifications (4) and (5), I run separate regressions for either increases or decreases in *Fear*.

In regressions (1) – (3), the coefficient of the $(Fear\ Index \times Increase)_{t-1}$ interaction term is negative and significant in each of the first three regressions. In Model 3 of Table 5, one standard deviation increase in the *Fear Index* corresponds with a decline of 29 basis points in the *Home Index* over the next month, after controlling for all the other variables in the model. The coefficient on $(Fear\ Index \times Decrease)_{t-1}$ is not statistically significant in any of the models, which implies that decreases in bad sentiment do not result in future changes of housing market returns. The negative coefficient on $(Fear\ Index \times Decrease)_{t-1}$ is in the expected direction since increasingly negative values of *Fear* (i.e. rising positive sentiment) are expected to correspond with the rising housing market.

In regressions (4) and (5), the same pattern emerges with lagged *Fear*'s coefficient being negative and significant when the sample includes only positive values of *Fear* and statistically insignificant when the sample includes only negative values of *Fear*. Positive values of *Fear* imply increases in web search activity over the previous month and negative values of *Fear* imply the opposite effect. This result provides further evidence that market participants strongly respond to increases in bad sentiment but overlook the increases in good sentiment.

Results in Table 5 are robust even with inclusion of all the controls. *Home Index Momentum* is highly and significantly correlated with the *Home Index* at a 1% level. The sign of this coefficient is what I would expect. In regressions (4) and (5), *HMI* is also statistically significant at the 10% and 5% levels, respectively.

Overall, the results I find support the negativity hypothesis with the increases in negative sentiment resulting in a negative housing market reaction, while the decreases in negative sentiment leading to a negligible reaction of the housing market.

6. *Fear Index* at different lags and during expansionary versus recessionary periods of the Business Cycle

In this section, I focus my attention on the impact of the *Fear Index* on housing prices at different lags and during expansionary versus recessionary periods of the U.S. business cycle. I use up to four lags of the *Fear Index* to assess the longevity of the impact of sentiment on housing market returns. I use the U.S. Business Cycle Expansions and Contractions data provided by the National Bureau of Economic Research (NBER).[13] The recessionary period goes from peak to trough, while the expansionary period from trough to peak. The indicator variable for recession takes on a value of one starting on the first day of the period following a peak and ends on the last day of the period of the trough.[14] Assigning each month of the sample period to either recessionary or expansionary portion of the business cycle helps to analyze whether good versus bad economic climate changes the role of sentiment on housing prices.

Ling, Ooi, and Le (2015) find that the changing sentiment in the current quarter helps to predict house price appreciation in subsequent quarters. They also compare sentiment's effect in two subperiods, which they term as a prehousing boom (or normal) market and a boom and bust market. They find evidence that sentiment is highly predictive of future price changes in both a "normal" period as well as in the boom and bust period. In this study, I focus on boom and bust cycles separately, unlike Ling, Ooi, and Le (2015), who treat them as part of a single subperiod.

I set up the following regression model for multiple lags of the *Fear Index*, which is similar to the model given in (3):

[13] Further information on the business cycles is located at http://www.nber.org/cycles/cyclesmain.html.
[14] NBER based recession indicators are taken from the Federal Reserve Bank of St. Louis, available at https://research.stlouisfed.org/fred2/series/USREC.

$$Home\ Index_t = \beta_0 + \sum_{i=1}^{n=4} \beta_i Fear\ Index_{t-i} + \sum_m \gamma_m Control_t^m + \varepsilon_t \qquad (5)$$

I present the results from this regression in Panel A, model specification (4). Model specifications (1) – (3) use the previous, the previous two, and the previous three lags, respectively. The coefficient on the *Fear Index* is negative and significant up to three lags, which implies that the housing market has a memory of the negative sentiment that lasts up to three months. I can interpret the coefficients on the lagged *Fear Index* as I did before and using the results from regression (4); one standard deviation increase in the *Fear Index* (standard deviation is 0.42 from Table 3) corresponds with a decline of 25 basis points in the returns of the Home Price Index in the following month, 23 basis points in the second month, and 21 basis points in the third month. The results are robust after controlling for a number of relevant variables that I used in prior tests.

In Panel B, I present the results from expansionary versus recessionary periods using the following regression in model specification (1):

$$Home\ Index_t = \beta_0 + \beta_1 (Fear\ Index \times Expansion)_{t-1} + \beta_2 (Fear\ Index \times Recession)_{t-1}$$
$$+ \beta_3 Recession_{t-1} + \sum_{i=2}^{n=3} \delta_i Fear\ Index_{t-i} + \sum_m \gamma_m Control_t^m + \varepsilon_t \qquad (6)$$

in which *Recession* (*Expansion*) is a binary variable that takes on a value of 1 during recessionary (expansionary) portion of the business cycle, and 0 otherwise. The interaction term $(Fear\ Index * Expansion)_{t-1}$ is the product of the *Fear Index* and *Expansion* during time *t-1*. Similarly, the interaction term $(Fear\ Index * Recession)_{t-1}$ is the product of the *Fear Index* and *Recession* during time *t-1*. Control variables are the same as those I used in the previous models.

Model specification (1) from Table 6 highlights the marginal impact of *Fear* across expansionary versus recessionary periods. The main focus is on the coefficients of the interaction terms ($Fear\ Index*Expansion)_{t-1}$ and ($Fear\ Index*Recession)_{t-1}$. Both coefficients are negative and significant as expected, but the absolute value of the coefficient during recessionary periods is greater than the one during expansionary period. I posit that sentiment has a greater impact on the housing market during bad times. Model specifications (2) and (3) support my conclusion as I add the second and third lags of the interaction terms, respectively. They confirm my results and additionally show that *Fear* has a more lasting impact on the housing market during recessionary periods. The coefficient of the interaction term ($Fear\ Index*Recession)_{t-3}$ is statistically significant, while the coefficient on ($Fear\ Index*Expansion)_{t-3}$ is not.

Findings in this section confirm that negative sentiment has an impact on housing market returns that lasts up to three months and the strength of this relation varies based on whether the U.S. economy goes through bad versus good times. I find strong and consistent evidence that sentiment during recessionary periods has a greater impact on the housing market and helps to predict house price changes up to three months in advance.

7. Conclusion

As households weigh different factors that go into a decision of a home purchase or sale, an important factor is sentiment toward the current state of the housing market. I examine the role of negative sentiment revealed by Google searches on the national residential housing prices. I find that the sentiment measure and housing prices are inversely related. Increases in the *Fear Index* help to predict decreases in housing index returns over the next month controlling for other relevant factors. I find evidence that the impact of negative sentiment lasts up to three months in helping to predict changes in the home price index.

In addition, I examine the impact of sentiment on housing prices during increases versus decreases in *Fear*. I find that housing market returns are more sensitive to increases than to decreases in *Fear*. I attribute this finding to the negativity effect, which asserts that individuals respond greater to the negative events than the positive ones. In the context of this study, the negativity impact can be seen by decreasing housing market returns after *Fear* goes up but negligible positive response as negative sentiment subsides. My finding is consistent with Akhtar *et.al.* (2011, 2012), who find evidence for the negativity effect in the stock market. In contrast to the stock market, the housing market is subject to greater short-sale constraints and limits to arbitrage. As a result, I test for and document the negativity effect to be prevalent in the housing market, just as it was documented in the stock and futures markets.

Finally, I examine the response of housing market returns to changes in sentiment during recessionary versus expansionary periods. I find that sentiment has a more lasting impact on housing market during recessionary periods than during expansionary ones. Housing market returns respond negatively and significantly for up to three months following the changes in sentiment during recessions but only up to two months during expansions. I suggest that sentiment is an increasingly important factor in determining the future direction of the housing market returns and the importance of the sentiment increases during economic downturns. There are multiple avenues for future research using web search volumes. Future studies on this topic could investigate the role of sentiment in different geographic regions across the U.S. and internationally. In addition, future studies could examine the impact of negative sentiment on the price dynamics of tradeable securities, such as REITs, futures, and options.

References

Abraham, J.M. and P.H. Hendershott. 1996. Bubbles in Metropolitan Housing Markets. *Journal of Housing Research* 7(2): 191–207.

Ackert, L.F., B.K. Church and N. Jayaraman. 2011. Is There a Link Between Money Illusion and Homeowners' Expectations of Housing Prices? *Real Estate Economics* 39(2): 251–275.

Akhtar, S., R. Faff, B. Oliver and A. Subrahmanyam. 2011. The Power of Bad: The Negativity Bias in Australian Consumer Sentiment Announcements on Stock Returns. *Journal of Banking and Finance* 35(5): 1239–1249.

Akhtar, S., R. Faff, B. Oliver and A. Subrahmanyam. 2012. Stock Salience and the Asymmetric Market Effect of Consumer Sentiment News. *Journal of Banking and Finance* 36(12): 3289–3301.

Baker, M. and J. Wurgler. 2006. Investor Sentiment and the Cross-Section of Stock Returns. *Journal of Finance* 61(4): 1645–1680.

Baker, M. and J. Wurgler. 2007. Investor Sentiment in the Stock Market. *The Journal of Economic Perspectives* 21(2): 129–151.

Baker, M., J. Wurgler and Y. Yuan. 2012. Global, Local, and Contagious Investor Sentiment. *Journal of Financial Economics* 104: 272–287.

Baumeister, R., E. Bratslavsky, C. Finkenauer and K. Vohs. 2001. Bad is Stronger than Good. *Review of General Psychology* 5: 323–370.

Beracha, E. and M.B. Wintoki. 2013. Forecasting Residential Real Estate Price Changes from Online Search Activity. *Journal of Real Estate Research* 35(3): 283–312.

Bokhari, S. and D. Geltner. 2011. Loss Aversion and Anchoring in Commercial Real EstatePricing: Empirical Evidence and Price Index Implications. *Real Estate Economics* 39(4): 635–670.

Brown, G.W. and M.T. Cliff. 2004. Investor Sentiment and the Near Term Stock Market. *Journal of Empirical Finance* 11: 1–27.

Brown, G.W. and M.T. Cliff. 2005. Investor Sentiment and Asset Valuation. *Journal of Business* 78(2): 405–440.

Case, K.E. and R.J. Shiller. 2003. Is There a Bubble in the Housing Market? *Brookings Papers on Economic Activity* 2: 299–362.

Choi, H. and H. Varian. 2012. Predicting the Present with Google Trends. *Economic Record* 88(1): 2–9.

Czapinski, J. 1985. Negativity Bias in Psychology: an Analysis of Polish Publications. *Polish Psychological Bulletin* 17: 155–164.

Da, Z., J. Engelberg and P. Gao. 2011. In Search of Attention. *Journal of Finance* 66: 1461–1499.

Da, Z., J. Engelberg and P. Gao. 2015. The Sum of All FEARS Investor Sentiment and Asset Prices. *Review of Financial Studies* 28(1): 1–32.

Drake, M.S., D.T. Roulstone and J.R. Thornock. 2012. Investor Information Demand: Evidence from Google Searches Around Earnings Announcements. *Journal of Accounting Research* 50(4): 1001–1040.

Genesove, D. and C. Mayer. 2001. Loss Aversion and Seller Behavior: Evidence from the Housing Market. *Quarterly Journal of Economics* 166: 1233–1260.

Ginsberg, J., M.H. Mohebb, R.S. Patel, L. Brammer, M.S. Smolinsky and L. Brilliant. 2009. Detecting Influence Epidemics Using Search Engine Query Data. *Nature* 457: 1012–1014.

Glaeser, E., J. Gyourko and A. Saiz. 2008. Housing Supply and Housing Bubbles. *Journal of Urban Economics* 64: 198–217.

Goodman, A.C. and T.G. Thibodeau. 2008. Where are the Speculative Bubbles in US Housing Markets? *Journal of Housing Economics* 17(2): 117–137.

Guzman, G. 2011. Internet Search Behavior as an Economic Forecasting Tool: The Case of Inflation Expectations. *The Journal of Economic and Social Measurement* 36(3): 119–167.

Han, B. 2008. Investor Sentiment and Option Prices. *The Review of Financial Studies* 21(1): 387–414.

Himmelberg, C., C. Mayer and T. Sinai. 2005. Assessing High House Prices: Bubbles, Fundamentals and Misperceptions. *Journal of Economic Perspectives* 19(4): 67–92.

Jin, C., G. Soydemir and A. Tidwell. 2014. The US Housing Market and the Pricing of Risk: Fundamental Analysis and Market Sentiment. *Journal of Real Estate Research* 36(2): 187–219.

Kahneman, D. and A. Tversky. 1979. Prospect Theory: An Analysis of Decision under Risk. *Econometrica* 47: 263–291.

Kanouse, D. and L. Hanson. 1971. Negativity in Evaluations. In: Jones, E.E., Kanouse, D.E., Kelley, H.H., Nisbett, R.E., Valins, S., Weiner, B. (Eds.), Attribution: Perceiving the Causes of Behaviour. *General Learning Press*, Morristown.

Kogan, S., D. Levin, B. Routledge, J. Sagi and N. Smith. 2009. Predicting Risk from Financial Reports with Regression. Proceedings of the North American Association for Computational Linguistics Human Language Technologies Conference.

Kumar, A. and C. Lee. 2006. Retail Investor Sentiment and Return Comovements. *The Journal of Finance* 61(5): 2451–2486.

Ling, D.C., A. Naranjo and B. Scheick. 2014. Investor Sentiment, Limits to Arbitrage and Private Market Returns. *Real Estate Economics* 42(3): 531–577.

Ling, D.C., J.T. Ooi and T.T. Le. 2015. Explaining House Price Dynamics: Isolating the Role of Nonfundamentals. *Journal of Money, Credit and Banking* 47(1): 87-125.

Marcato, G. and A. Nanda. 2014. Information Content and Forecasting Ability of Sentiment Indicators: Case of Real Estate Market. *Journal of Real Estate Research,* forthcoming.

McLaren, N. and R. Shanbhogue. 2011. Using Internet Search Data as Economic Indicators. *Bank of England Quarterly Bulletin* Q2: 134–140.

Neal, R. and S. Wheatley. 1998. Do Measures of Investor Sentiment Predict Returns? *Journal of Financial and Quantitative Analysis* 33: 523–547.

Peeters, G., J. Czapinski. 1990. Positive–Negative Asymmetry in Evaluations: The Distinction Between Affective and Informational Negativity Effects. *European Review of Social Psychology* 1: 33–60.

Polgreen, P.M., Y. Chen, D.M. Pennock, F.D. Nelson and R.A. Weinstein. 2008. Using Internet Searches for Influenza Surveillance. *Clinical infectious diseases* 47(11): 1443–1448.

Shiller, R.J. 2007. Understanding Recent Trends in House Prices and Home Ownership. NBER Working Paper No. 13553, Cambridge, MA.

Singer, E. 2002. The Use of Incentives to Reduce Nonresponse in Household Surveys. *Survey Nonresponse* 51: 163–177.

Smith, M.H. and G. Smith. 2006. Bubble, Bubble, Where's the Housing Bubble? *Brookings Papers on Economic Activity* 1: 1–67.

Stambaugh, R.F., J. Yu and Y. Yuan. 2012. The Short of It: Investor Sentiment and Anomalies. *Journal of Financial Economics* 104: 695–732.

Taylor, S. 1991. Asymmetrical Effects of Positive and Negative Events: the Mobilization–Minimization Hypothesis. *Psychological Bulletin* 110: 67–85.

Tetlock, P.C. 2007. Giving Content to Investor Sentiment: The Role of Media in the Stock Market. *Journal of Finance* 62: 1139–1168.

Verma, R., H. Baklaci and G. Soydemir. The Impact of Rational and Irrational Sentiments of Individual and Institutional Investors on DIJA and S&P 500 Index Returns. *Applied Financial Economics* 18(16): 1303–1317.

Vosen, S. and T. Schmidt. 2011. Forecasting Private Consumption: Survey-Based Indicators vs. Google Trends. *Journal of Forecasting* 30(6): 565–578.

GRAPHS AND TABLES

Figure 2-1: Search Volume for "foreclosure listings" and the Housing Market Index

I plot the monthly log Search Volume Index (SVI) for "foreclosure listings" (with a negative sign) against the monthly Housing Market Index. The data are from January 2005 to March 2015. The correlation between the two series is 0.829.

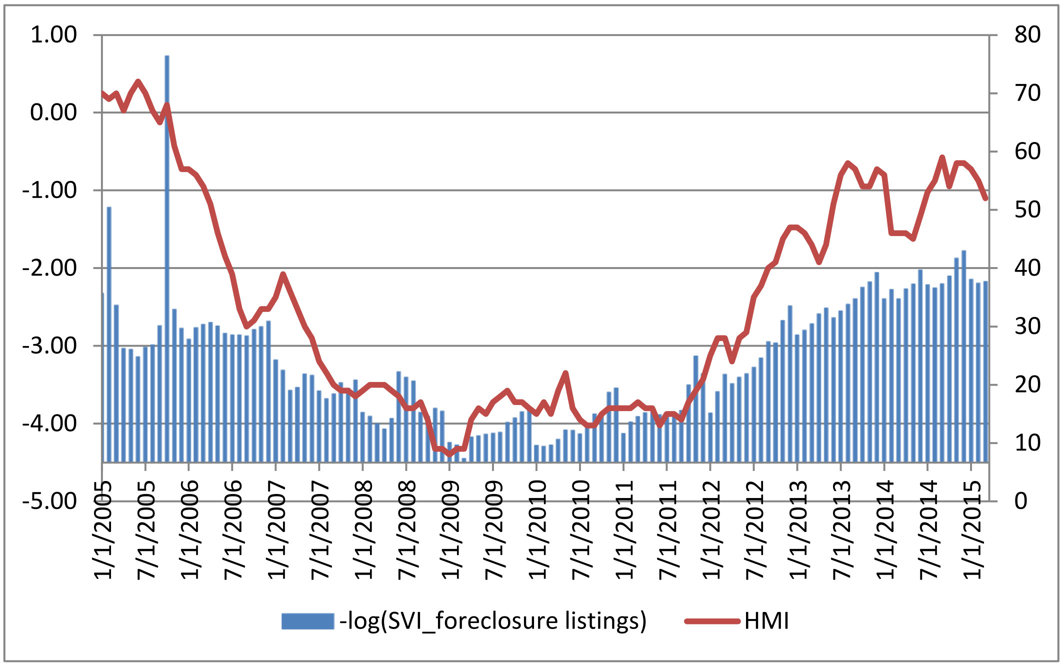
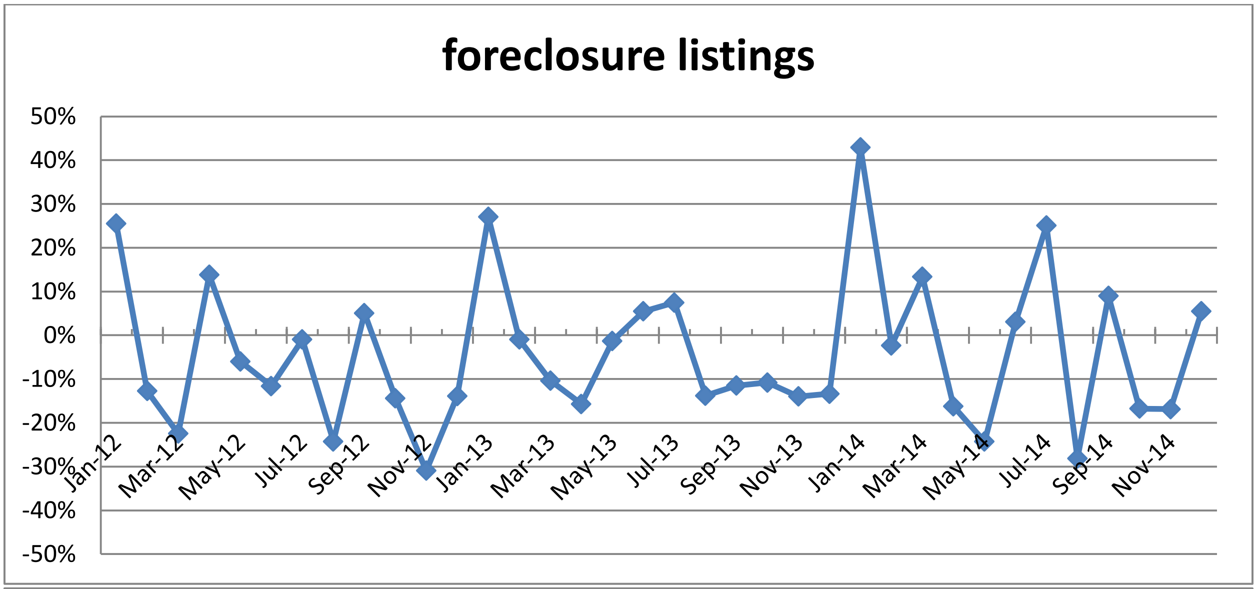


Figure 2-2: SVI Log Changes for "foreclosure listings" and "lease"

I plot two examples of monthly changes in SVI over the period January 2012-December 2014.



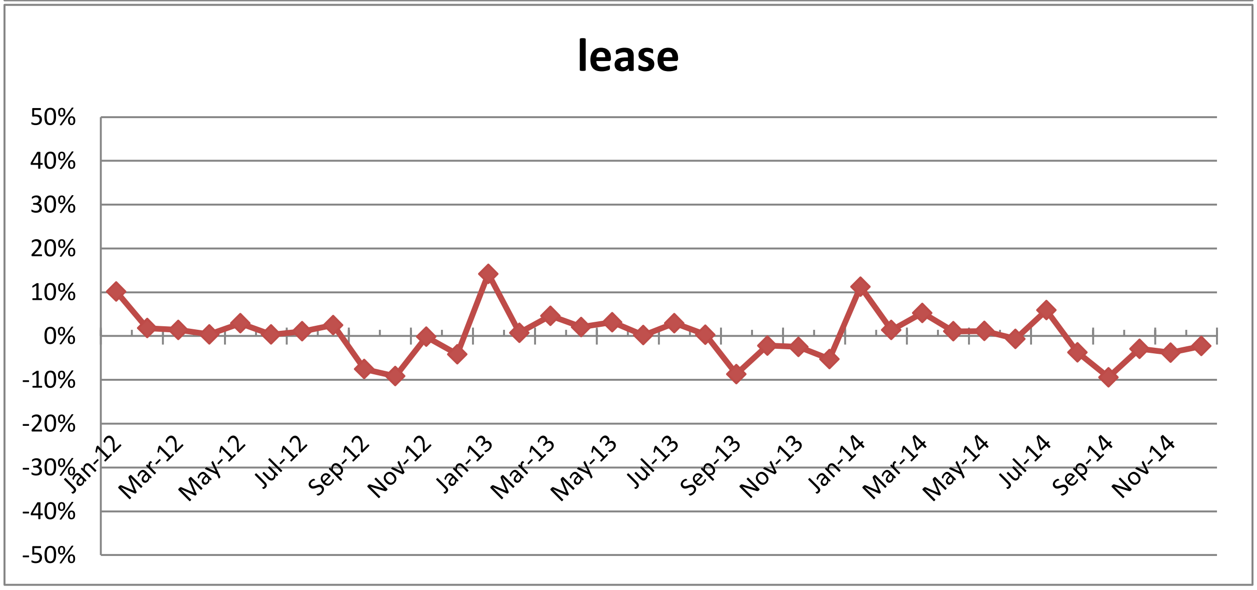


Table 2-1: *Fear* Terms from the Full Sample (2004 to 2014)

This table reports the 30 search terms derived from **real estate** glossary terms that have the largest negative correlation with the S&P/Case-Shiller housing price index. The terms are ordered from most negative to least negative.

Term Number	Search Term	*t*-Statistic
1	loan modification	-3.03
2	processing	-2.62
3	modification	-2.61
4	homepath	-2.48
5	assessment	-2.42
6	fha	-2.40
7	liability	-2.38
8	asset	-2.35
9	loan servicing	-2.23
10	foreclosure listings	-2.21
11	points	-2.15
12	assignment	-2.14
13	deposit	-2.04
14	amortization	-2.02
15	servicing	-1.98
16	mortgage insurance	-1.95
17	price index	-1.95
18	consumer price index	-1.95
19	fha loan	-1.92
20	effective interest rate	-1.86
21	direct loan	-1.86
22	fee simple	-1.85
23	pmi	-1.84
24	money market account	-1.82
25	gross domestic product	-1.82
26	cpi	-1.79
27	equity	-1.77
28	lease purchase	-1.76
29	ratios	-1.75
30	bankruptcy	-1.75

Table 2-2: Description of Variables

This table describes the variables included in this study. I present the description and if applicable the source from which each variable is collected.

Variable	Description
SVI	Search Volume Index for a given term represents its relative popularity over time by analyzing data from Google web searches. For example, if you search for coffee in Texas in March 2015, *Google Trends* examines a percentage of all searches for coffee within the same time and location parameters. To make search data comparable, each data point is divided by the total searches of the geography and time range it represents. The resulting numbers are then scaled so the values range from 0 to 100. Weekly SVI is available via the product *Google Trends* from 2004 to 2014 <https://www.google.com/trends/explore> and <https://support.google.com/trends/answer/4355213?hl=en&ref_topic=4365599>.
ΔASVI	*ΔASVI* is an adjusted (winsorized, deseasonalized, and standardized) monthly change in search volume.
Fear Index	The Fear Index is a measure of people's sentiment toward housing prices. This Fear Index is constructed using the search volume for real estate terms. These terms include an initial pool of 604 Real Estate glossary terms plus 1,000 related terms that are coined as Top Searches by *Google Trends*. First, I calculate monthly log differences and then to make terms comparable I winsorize, remove intra-quarter seasonality, and standardize each time series to get ΔASVI. Next, I run expanding-window backward rolling regressions of ΔASVI on log differences of housing prices every 12 months to determine the historical relation between search and contemporaneous housing index changes for all search terms. 30 terms with highest *t*-statistics from the regressions ending in a given year are chosen to construct the following year's Fear Index. For example, the top 30 terms from the regressions from 2004 to 2010 were used to build Fear Index for 2011. Monthly ΔASVIs for these top 30 terms are averaged to build the Fear index.
Home Index	The S&P/Case-Shiller U.S. National Home Price Index ("the U.S. national index"). It tracks the value of single-family housing within the United States. The data is from the S&P Dow Jones Indices <http://us.spindices.com/index-family/real-estate/sp-case-shiller>.
Home Index Momentum	This variable is computed as a 12-month average of *Home Index* returns. For example, *Home Index Momentum* for January 2011 stands for the average of monthly returns over the previous 12 months from January to December 2010.
Expansion	*Expansion* is a binary variable that assumes a value of 1 during the expansionary portion of the business cycle, and 0 during the recessionary portion. The period between a trough and a peak represents a period of expansion. Business cycles follow the dates from the NBER. The data has been retrieved from <https://research.stlouisfed.org/fred2/series/USREC>.

Recession	*Recession* is a binary variable that assumes a value of 1 during the recessionary portion of the business cycle, and 0 otherwise. Recession begins on the first day of the period following a peak and ends on the last day of the period of the trough. Business cycles follow the dates from the NBER. The data has been retrieved from <https://research.stlouisfed.org/fred2/series/USREC>.
Real GDP	Monthly Real GDP in trillions. Data was retrieved from <http://ycharts.com/indicators/real_gdp>.
CPI	Monthly Consumer Price Index (seasonally adjusted). The data is provided by Sentier Research, LLC, which compiles monthly CPI from the U.S. Bureau of Labor Statistics. Web page: <http://www.sentierresearch.com/>.
Unemployment Rate	Monthly Unemployment Rate (seasonally adjusted). The data is provided by Sentier Research, LLC, which estimates monthly unemployment data from the U.S. Bureau of Labor Statistics. Web page: <http://www.sentierresearch.com/>.
HMI	The Housing Market Index (HMI) measures builder sentiment regarding the demand side of the single-family housing market in the U.S. HMI ranges from 0 to 100, with any number over 50 indicating that more builders view sales conditions as good rather than poor. The National Association of Home Builders (NAHB) computes HMI as a weighted average of responses to survey questions asking builders to rate three aspects of their local market conditions: current sales of single-family detached new homes, expected sales of single-family detached new homes over the next six months, and traffic of prospective buyers in new homes. The data was retrieved from: <http://www.nahb.org/en/research/housing-economics/housing-indexes/housing-market-index.aspx>.
S&P 500 Index	Monthly returns on S&P 500 Index drawn from CRSP Monthly stock files.

Table 2-3: Sample Characteristics

This table presents summary statistics (Panel A) and correlation coefficients (Panel B) for *Fear Index*, *Home Price Index*, and control variables. The sample consists of 120 monthly observations over the period from January 2005 to December 2014. Panel A reports summary statistics for the main variables in the study. Panel B reports the correlation coefficients across log changes of these variables at monthly frequency. The *Fear Index*, *S&P 500 Index*, and *Home Index Momentum* were kept at levels since these variables already represent the rate of change. I use log changes of the variables throughout the study. In Panel B, significance level of each correlation coefficient is indicated with $***$, $**$, and $*$ and corresponds with 1%, 5%, and 10% significance level, respectively. Variable descriptions are provided in Table 2.

Panel A: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.	5%	Median	95%
Fear Index	120	-0.04	0.42	-1.18	1.23	-0.70	0.00	0.63
Home Index	120	159.23	15.76	134.03	184.62	137.77	159.50	183.86
H.I. Momentum (%)	120	0.08	0.65	-1.14	1.13	-0.98	-0.05	1.11
Real GDP	120	15.00	0.57	14.07	16.34	14.26	14.88	16.12
CPI	120	217.63	13.13	191.60	237.75	194.30	217.38	237.01
Unemployment Rate	120	6.95	1.90	4.40	10.00	4.50	6.90	9.80
HMI	120	33.61	18.71	8.00	72.00	13.00	28.50	68.50
S&P 500 Index	120	0.01	0.04	-0.17	0.11	-0.08	0.01	0.07

Panel B: Correlation Coefficients

Variable	*Fear Index*	*Home Index*	*H.I. Mom.*	*Real GDP*	*CPI*	*Unemp. rate*	*HMI*
Home Index	-0.17*						
H.I. Momentum	-0.02	0.58***					
Real GDP	-0.12	0.20**	0.18**				
CPI	0.02	0.15	0.07	0.05			
Unemployment Rate	0.10	-0.32***	-0.48***	-0.15	-0.10		
HMI	-0.09	0.11	-0.07	0.12	0.15*	-0.15	
S&P 500 Index	-0.14	0.18**	0.12	0.19**	0.08	-0.21**	0.26***

Table 2-4: *Fear Index* and Future *Home Price Index Returns*

This table assesses the impact of the lagged *Fear Index* on *Home Index* returns controlling for a number of key variables. It shows the results of regressions of *Home Index* returns on the *Fear Index* in the previous period and other control variables. *Fear Index* coefficients have been multiplied by 100 to reduce the number of decimals. The interpretation of these coefficients has been adjusted accordingly. The table includes results from four regression models with each having a different set of control variables. The sample period is from January 2005 to December 2014. All variables are included at a monthly frequency. Variable descriptions are provided in Table 2. *t*-statistics are included below the coefficient estimates in parentheses, and 1%, 5%, and 10% statistical significance are indicated with ∗∗∗,∗∗, and ∗, respectively.

	(1)	(2)	(3)	(4)
Fear Index$_{t-1}$	-0.42**	-0.38**	-0.38**	-0.37**
	(-2.53)	(-2.28)	(-2.27)	(-2.21)
Home Index Momentum	0.84***	0.78***	0.82***	0.81***
	(7.74)	(6.31)	(6.54)	(6.48)
Real GDP		0.11	0.09	0.08
		(0.94)	(0.76)	(0.65)
CPI		0.21	0.17	0.16
		(1.07)	(0.84)	(0.83)
Unemployment Rate		-0.01	-0.00	-0.00
		(-0.48)	(-0.17)	(-0.08)
HMI			0.01	0.01
			(1.59)	(1.39)
S&P 500 Index				0.01
				(0.72)
Constant	-0.00	-0.00	-0.00	-0.00
	(-0.64)	(-1.14)	(-1.02)	(-1.08)
Observations	119	119	119	119
Adj. *R*-squared	0.36	0.35	0.36	0.36

Table 2-5: Asymmetric Response Model to Increases versus Decreases in Sentiment

This table presents results of increases versus decreases in sentiment on the residential real estate returns. Models (1)-(3) use interaction terms of increases versus decreases in sentiment and *Fear Index* to assess the asymmetric response of residential real estate returns to downside sentiment. *Increase (Decrease)* is a binary variable that takes on value of 1 if *Fear Index* is greater (less) than zero, and 0 otherwise. *Fear Index * Decrease* is the interaction term of *Fear Index* and *Decrease* binary variable. *Fear Index * Increase* is the interaction term of *Fear Index* and *Increase* binary variable. Models (4) and (5) use separate regressions for increases versus decreases in *Fear* to measure the asymmetric response to downside sentiment. Model specifications (4) tests for increases in *Fear* while (5) for decreases in *Fear*. *Fear Index* coefficients have been multiplied by 100 to reduce the number of decimals. The interpretation of these coefficients has been adjusted accordingly. The sample period is from January 2005 to December 2014. All variables are presented at a monthly frequency. Variable descriptions are provided in Table 2. *t*-statistics are included below the coefficient estimates in parentheses, and 1%, 5%, and 10% statistical significance are indicated with ***, **, and *, respectively.

	(1)	(2)	(3)	(4) Increases in *Fear*	(5) Decreases in *Fear*
Fear Index$_{t-1}$				-0.45*	-0.37
				(-1.99)	(-1.39)
*(Fear Index * Decrease)*$_{t-1}$	-0.58	-0.61	-0.59		
	(-1.56)	(-1.65)	(-1.58)		
*(Fear Index * Increase)*$_{t-1}$	-0.79**	-0.71*	-0.70*		
	(-2.14)	(-1.92)	(-1.90)		
Increase$_{t-1}$	0.00	0.00	0.00		
	(1.49)	(1.41)	(1.38)		
Home Index Momentum	0.75***	0.78***	0.78***	0.91***	0.75***
	(5.99)	(6.18)	(6.13)	(5.46)	(3.67)
Real GDP	0.09	0.08	0.06	0.18	0.06
	(0.72)	(0.61)	(0.51)	(1.16)	(0.26)
CPI	0.23	0.19	0.19	0.29	0.02
	(1.19)	(0.98)	(0.97)	(1.09)	(0.05)
Unemployment Rate	-0.02	-0.01	-0.01	-0.02	-0.00
	(-0.63)	(-0.32)	(-0.24)	(-0.37)	(-0.01)
HMI		0.01	0.01	-0.02*	0.02**
		(1.45)	(1.26)	(-1.75)	(2.60)
S&P 500 Index			0.01	0.02	0.01
			(0.67)	(0.75)	(0.50)
Constant	-0.00	-0.00	-0.00	-0.00**	-0.00
	(-1.32)	(-1.33)	(-1.31)	(-2.19)	(-0.24)
Observations	119	119	119	58	61
Adjusted *R*-squared	0.36	0.36	0.36	0.49	0.26

Table 2-6: Response to *Fear* at Different Lags and during Recessionary versus Expansionary Periods

This table presents the results of regressions of *Home Index* returns on *Fear Index* at different lags in Panel A, and during recessionary versus expansionary periods in Panel B. In Panel A, I present results from four regression specifications with each successive model having an additional lag of *Fear Index*. In Panel B, *Recession (Expansion)* is a binary variable that assumes a value of 1 during recessionary (expansionary) portion of the business cycle, and 0 otherwise. *Fear Index * Expansion* is the interaction term of *Fear Index* and *Expansion* binary variable. *Fear Index * Recession* is the interaction term of the *Fear Index* and *Recession* binary variable. The recession begins on the first day of the period following a peak and ends on the last day of the period of the trough. Business cycles follow the dates from the NBER. For brevity, the coefficients and their statistical significance for the control variables are not reported. Each model includes the following control variables: *Home Index Momentum, Real GDP, CPI, Unemployment rate, HMI,* and *S&P 500 Index*. Variable descriptions are provided in Table 2. The *Fear Index* coefficients have been multiplied by 100 to reduce the number of decimals. The interpretation of these coefficients has been adjusted accordingly. The sample period is from January 2005 to December 2014. All variables are presented at a monthly frequency. *t*-statistics are included below the coefficient estimates in parentheses, and 1%, 5%, and 10% statistical significance are indicated with ∗∗∗,∗∗, and ∗, respectively.

Panel A: Response of Housing Index to *Fear* at Different Lags

	(1)	(2)	(3)	(4)
Fear Index$_{t-1}$	-0.37**	-0.46***	-0.58***	-0.59***
	(-2.21)	(-2.68)	(-3.27)	(-3.14)
Fear Index$_{t-2}$		-0.35**	-0.47**	-0.54***
		(-2.03)	(-2.58)	(-2.86)
Fear Index$_{t-3}$			-0.40**	-0.51***
			(-2.26)	(-2.62)
Fear Index$_{t-4}$				-0.27
				(-1.49)
Controls	Yes	Yes	Yes	Yes
Observations	119	118	117	116
Adjusted *R*-squared	0.36	0.37	0.38	0.37

Table 2-6: Continued

Panel B: Response to *Fear* during Recessionary versus Expansionary Periods

	(1) i=1	(2) i=2	(3) i=3
*(Fear Index * Expansion)*$_{t-i}$	-0.55***	-0.40**	-0.30
	(-2.84)	(-2.03)	(-1.56)
*(Fear Index * Recession)*$_{t-i}$	-0.81*	-0.88**	-0.83**
	(-1.96)	(-2.23)	(-2.17)
Recession$_{t-i}$	0.00	0.00	0.00
	(1.28)	(1.38)	(1.33)
Fear Index$_{t-1}$		-0.57***	-0.56***
		(-3.23)	(-3.18)
Fear Index$_{t-2}$	-0.49***		-0.46**
	(-2.70)		(-2.51)
Fear Index$_{t-3}$	-0.41**	-0.41**	
	(-2.31)	(-2.32)	
Controls	Yes	Yes	Yes
Observations	117	117	117

CHAPTER 3

LOCAL FEAR AND ITS EFFECT ON NATIONAL AND LOCAL HOUSING MARKETS.

1. Introduction

I examine the variation in housing market-level sentiment across the major cities in the U.S. and measure its effect on housing market returns. Housing markets in the U.S. are quite diverse and go through their own cycles of rising and falling sentiment. I capture this variation in Figure 1, which plots Google search volume for the word "foreclosure" in Dallas, Boston, Las Vegas, and Tampa. A clear pattern emerges between two city pairs, Dallas and Boston versus Las Vegas and Tampa. In Dallas and Boston, search interest for "foreclosure" is not as high and shares a similar pattern, while it is much higher in Las Vegas and Tampa. A similar pattern emerges when I examine the relation between Case-Shiller Home Price Indexes in those four MSAs, which I depict in Figure 2. Figures 1 and 2 provide a major motivation for this study. My main objective is to examine further the relation between sentiment and home price indexes in 20 major MSAs. I also divide these cities into groups based on common characteristics and analyze whether they respond differently to changes in negative sentiment.

This study has been primarily inspired by two articles that use Google's web searches as a measure of sentiment. The first is by Da, Engelberg, and Gao (2015), who combine multiple Google search queries into a single measure of market-level sentiment. The second is by Beracha and Wintoki (2013), who argue that search volumes reveal buyers' sentiment at the MSA level. This study is similar to Da, Engelberg, and Gao (2015) in that I build on their method of combining multiple search terms into a single measure of sentiment. I am different in that I use an expanded set of terms, which are uniquely related to real estate, as I construct my measure of housing market sentiment. This study is similar to Beracha and Wintoki (2013), in that I also examine the relation between online search volumes and home price changes. I differ since they use only one search term as a measure of negative sentiment, while I use a combined measure of the 30 most important terms in relation to home price indexes as the measure of negative sentiment. This measure of negative sentiment is also more contained within each MSA. In particular, when I collect data from *Google Trends*, I limit search volumes to be generated within the same geographic areas as those represented by home price indexes, while Beracha and Wintoki (2013) collect search volumes that were generated across the whole United States. In addition to the two studies I referenced above, a number of other studies use data on web search volumes to gauge the sentiment applied to different contexts.

The purpose of this study is to investigate the relation between negative sentiment captured by Google search volumes for real estate and economics terms on housing market returns in 20 of the largest metropolitan areas (MSAs) across the U.S. In particular, I construct *Fear Indexes* for each of the 20 housing markets included in the Case-Shiller 20-City Composite Home Price Index and examine their ability to predict changes in the national home price index and city home price indexes. I assess economic significance of local *Fear* as a predictor of national housing market returns relative to other well-known predictors. I also divide 20 local housing markets into different groups based on their price appreciation and bankruptcy rates and analyze the varying response to *Fear* in each of these groups. Finally, I evaluate the interaction of *Fear* and bankruptcy rates as two continuous variables, which helps better to understand the response to *Fear* at varying levels of bankruptcy filings. Overall, my study contributes to previous research on real estate market sentiment and extends the importance of aggregate sentiment captured by web search volumes on predicting changes in national as well as local housing markets.

I find negative and economically significant relation between *City Fear Indexes* and residential real estate returns at the national as well as metropolitan area levels. For example, one standard deviation increase in *Fear* in Boston corresponds with a decline of 20 basis points in the *National Home Index* over the next month. *Fear Indexes* in other cities evoke a similar response. The effect of negative sentiment index is robust to controls for key predictors of housing market returns. Next, I compare the ability of *City Fear Indexes* to predict the *National Home Index* to well-known predictors such as real GDP, unemployment rate, CPI, or the stock market returns and find comparable forecasting power. In my next analysis, I show that *Local Fear* in "cold" housing markets (cities with slow price appreciation) has a stronger effect than in "hot" markets (cities with rapid price appreciation) and high bankruptcy rates cities are more responsive to changes in *Fear* than low bankruptcy rate cities. Finally, I find that *Fear* has a stronger impact on housing price changes at higher levels of bankruptcy filings and that effect is stronger for cold cities.

The remainder of this study proceeds as follows: In the next section, I discuss related literature and discuss the extension of my study and its contribution to the existing literature. The third section describes the data and methods used to construct the *Fear Index.* In this section, I also describe other variables that I used in this study. The fourth section reports the results for the regressions of national home price index returns on lagged *National* and *Local Fear*. I also discuss economic significance of my results compared to other well-known predictors. Next, I discuss the response to *Fear* in hot versus cold markets, high bankruptcy rate versus low bankruptcy rate cities, and then the combination of both of these sorts in the fifth section. The sixth section presents the results of an analysis of interacting *local* Fear with bankruptcy rates. Conclusions are described in the last section.

2. Literature Review

There is a growing number of studies that use Google's search frequencies as a predictor of various market indicators. In this article, I use Google's search data to construct a proxy for household sentiment and examine its ability to predict future changes in the local residential real estate markets. Previous studies have shown that search volumes are helpful in predicting current and future changes in financial and real estate markets.[15]

The study by Da, Engelberg, and Gao (2011) is one of the first major articles in the finance literature to explore the ability of Google's web searches to predict individual stock returns. They posit that search volumes capture attention of retail investors, especially those who are less sophisticated. Their sample includes Russell 3000 stocks, for which they collect time series of online search intensity using ticker symbols of these stocks. They find that rising search volumes are able to predict rising stock prices over the following two weeks and any price gains are reversed within the year. They also find that abnormal search intensity prior to the first day of trading for an IPO leads to a large first day return. In sum, their study establishes the importance of Google's web searches as a measure of revealed attention.

Drake, Roulstone and Thornock (2012) is the first major study in the accounting field that explores the role of web search volumes around earnings announcements for the S&P 500 stocks. They also explore the changes in web search volumes around management forecast days,

[15] See Da, Engelberg and Gao (2015), Beracha and Wintoki (2013), Hohenstatt and Kaesbauer (2014), Wu and Brynjolfsson (2009), and Hohenstatt, Kaesbauer, and Schaefers (2011).

analyst forecast days, dividend announcements, acquisition announcements, and numbers of articles appearing in popular press. They find that the highest abnormal search volumes occur during acquisition and earnings announcement dates. They suggest that investors express their demand for public information via web searches and abnormal search volumes imply increases in information already in the public domain that has not yet been fully impounded into prices. They find that high search volumes in the pre-earnings-announcement period, which may reflect differences of opinion among investors, result in higher trading volumes but not significant changes in price. They also suggest that higher information demand prior to the earnings announcement reduces the information content of the announcement itself when it is released. Vlastakis and Markellos (2012) also suggest that Google search volume is a measure of information demand and find that it is significantly related to stock return volatility, trading volume, return, and risk.

This study is similar to Da, Engelberg, and Gao (2015) since they are the first to combine multiple web queries collected from *Google Trends* into a single measure of negative market-level sentiment. They find evidence that their measure helps to predict short-term return reversals, temporary increases in volatility, and mutual fund flows.

A number of studies in real estate, such as Choi and Varian (2009), Wu and Brynjolfsson (2009), Hohenstatt, Käsbauer, and Schäfers (2011), Beracha and Wintoki (2013), and Das, Ziobrowski, and Coulson (2015), argue that Google web searches related to real estate offer a reasonable proxy for demand in real estate markets.

Choi and Varian (2009) examine the link between search volumes of certain subcategories within real estate and the number of home sales and median home prices. They find a significant contemporaneous relation. Wu and Brynjolfsson (2009) examine the predictive power of Google's search volumes for quarterly housing market sales and prices across 50 U.S. states. They find that search volumes of specific subcategories within real estate strongly predict housing market prices and sales the following quarter. For example, they find that "Real Estate Agencies," which is one of the subcategories within real estate helps to predict housing market sales in the next quarter. They report that "each percentage point increase in the housing search index is correlated with additional sales of 67,220 houses in the next quarter."

Hohenstatt, Kaesbauer, and Schaefers (2011) argue that Google search volumes can be used to assess consumer sentiment, predict housing market changes, and possibly explain the driving force of housing prices. They use a vector autoregressive (VAR) framework to address the issue of endogeneity and find that specific searches are able to provide information about prices and transactions in the near future. Hohenstatt and Kaesbauer (2014) extend their research by applying Google search data to the U.K. housing market using a similar VAR approach. They find that "Real Estate Agency," which is one of the Google subcategories, is the strongest indicator of transaction volume, especially during upturns. They posit that during market downturns, the "Home Financing" subcategory works as a potential stress indicator and evokes twice as strong a response in transaction volumes as it does in house prices.

Beracha and Wintoki (2013) generate single search queries for ''real estate *i*'' and ''rent *i*,'' where *i* stands for one of 314 MSAs and find that search intensities provide information about the "future demand" for housing and that they "Granger cause abnormal returns." However, they demonstrate that this link holds well in the short-term only but reverses in the long run. They also suggest a higher sensitivity of prices to search volume in cities with rapid price appreciation due to a return-chasing behavior as compared to cities with slow price appreciation.

A recent study by Das, Ziobrowski, and Coulson (2015) finds that online apartment rental searches are significantly correlated with market fundamentals such as vacancy rates, rental rates, and real estate returns. They show that online searches are endogenously and contemporaneously associated with decreased vacancy rates but not rental rates. The linkage between online rental searches and future REIT returns suggests that REIT investors scrutinize the online search data as they make investment decisions. Some other recent studies include Lee and Mori (2015), who examine the association between conspicuous demand measured by Google searches and housing price dynamics and Wu and Deng (2015) and Zheng, Sun, Kahn (2015), who use Google data as a measure of information flow or investor confidence in Chinese housing markets.

It is important to note that Google web searches are extensively used in other contexts as well. Ginsberg et al. (2009) has become a landmark study to popularize Google search data. The authors use Google search queries to identify influenza hotspots across the U.S. in a more timely manner than traditional influenza surveillance systems. Their article led to the development of an epidemic tracking tool called Google Flu Trends. Google data is also used in several other areas of research: including employment[16], inflation[17], consumer sentiment[18], etc.

3. Data and Methodology

[16] See Askitas and Zimmermann (2009), D'Amuri (2009), D'Amuri and Marcucci (2009), Choi and Varian (2009b), and McLaren and Shanbhogue (2011).
[17] Guzman (2011)
[18] See Della Penna and Huang (2009) and Schmidt and Vosen (2009).

The data for this study comes from several sources, but the main data source used in constructing the *Fear Indexes* comes from *Google Trends.*[19] This section starts with the discussion of the methodology I use in constructing my measure of housing market-level sentiment and then continues with the description of other variables that I use in this study.

3.1. Construction of local *Fear Indexes*

I follow similar methodology as I did in the previous chapter in constructing local *Fear Indexes*. I use *Fear Indexes* at two levels in this study, first–the national and second–the MSA levels. I use exactly the same methodology in constructing the national *Fear Index* as I did in the previous chapter, however I made some slight adjustments in constructing local *Fear Indexes* due to some data restraints.

Google Trends provides aggregate data on relative popularity of the terms people search for using Google's web search engine. It allows to select up to five terms that can be compared in their relative popularity in a specific geographic location over a desired period of time. *Google Trends* was officially released in May of 2006 to help visualize the popularity of searches over time.[20] The data goes back to 2004 and extends to the current period. Google uses proprietary methodology to adjust the raw number of searches into the time series, which I refer to as the Search Volume Index (SVI). SVI captures relative popularity of a desired term over time and is reported on a scale from 0 to 100. *Google Trends* allows to compare the popularity of searches over time for up to five terms at a time. However, if the same five terms are entered separately,

[19] The link to this service is: www.google.com/trends/explore. *Google Trends* reports aggregate data on relative popularity of various query terms in various locations starting with 2004. *Google Trends* collects the data that people search for using Google's web search engine.
[20] The webpage link to Google's "Our history in depth" timeline can be found at: www.google.com/about/company/history/

they generate slightly different SVI series. Furthermore, if terms are entered separately, which is what I do since I have many terms for which I am collecting SVIs, I am unable to assess relative popularity by comparing their SVIs, since each series of unadjusted search volumes are standardized by a different factor before they are scaled to fit on a range from 0 to 100. As a result, I use changes of SVI series instead of their levels.

My first objective is to identify a list of search terms that reveal sentiment toward the housing market. To compile such a list, I use terms related to real estate and supplement it with another list that relates to the economy as a whole. The first list of terms includes the glossary of real estate terms compiled by Colombia University, which I supplement with another list of real estate terms from an online source.[21] My compiled list includes 604 terms related to real estate. The second list includes economic terms that were used by Da, Engelberg, and Gao (2015). This list comes from the Harvard IV-4 Dictionary and the Lasswell Value Dictionary, which were used in the context of text analytics by Tetlock (2007), and Tetlock, Saar-Tsechansky, and Macskassy (2008). The list of economic terms includes 150 words that carry either "positive" or "negative" sentiment. In addition to the joined list of real estate and economic terms, I include those terms that are most frequently searched along with these terms.[22] I inspect the list of such related "top searches" and then weed out duplicates or those terms that are not clearly related to real estate or the economy. I am left with 1,400 related searches in addition to the original list of 754 terms, which makes a total of 2,154 terms. Next, I collect SVIs for each of these terms from *Google Trends* for each MSA in my sample.

---

[21] The first list I use has been compiled by the Columbia University, accessible at http://worklife.columbia.edu/real-estate-terminology#section1. To supplement the first list, I use another source for real estate terms accessible at http://www.realestateabc.com/glossary/.

[22] According to Google Trends Help, "Top searches are terms that are most frequently searched with the term you entered in the same search session, within the chosen category, country, or region."

I find that *Google Trends* does not provide any data for some terms at some locations, while other terms that generate enough web search interest have many zeros in their SVI series, especially at earlier years, between 2004 to 2008. A value of zero does not mean there were no searches for a given term but that the search volume for that week was less than 100 times the volume during the most popular week over the whole period. I realize that having a limited range from 0 to 100 hides the variation that is present in the actual search volumes. This is the drawback in the SVI data provided by *Google Trends*, which all researchers face who use these series.

After I collect weekly SVI series for each term, I convert them to a monthly frequency by averaging search volumes within a month. Next, I remove those SVI series that generate less than 40 non-zero monthly observations to ensure that each series that I keep for further analysis is adequate in capturing the variation and providing meaningful data.[23] The final number of terms per each MSA is reported in Figure 1, which fluctuates from the lowest number of 148 in Las Vegas to the highest of 548 in New York. As I proceed further, I identify 30 terms from each MSA to be used in constructing a *Fear Index* in that city.

The SVI data for each term in each MSA is over a sample period from January 2004 to December 2014. SVI series across terms are not easily comparable for the reasons stated above, so I transform each series of SVIs by taking their log changes as follows:

$$\Delta SVI_t = \ln(SVI_t) - \ln(SVI_{t-1}) \tag{1}$$

Next, I apply a similar adjustment process to *ΔSVI* as in Da, Engelberg, and Gao (2015). First, I winsorize, then remove annual trend, and finally standardize each series. I winsorize each series at the 5% level (2.5% in each tail) to address the issue of outliers. Then, I regress *ΔSVI* on

[23] Since my sample period is from 2004 to 2014, it includes 132 monthly observations for each term in each location. The objective is to have non-zero search volume data for at least 40 months or about 30% of the time.

annual dummies and keep the residual to eliminate seasonality from the series. Finally, I standardize each series by subtracting the mean and dividing by standard deviation to address the issue of heteroscedasticity. I refer to the resulting series as abnormal *ΔSVI* or *ΔASVI*.

Next, I identify the terms that are most important to each housing market in my sample of MSAs. To achieve this, I run expanding rolling window regressions of $\Delta ASVI_i$ on housing market index returns in city *i* every twelve months (every December) starting with 2004. For example, at the end of December 2010, I run a regression of $\Delta ASVI_i$ on contemporaneous home price index returns in city *i* for the period of January 2004-December 2010. Overall, I run 10 regressions with the last including the period from 2004-2013 for each MSA. Next, I rank all terms from each regression by their *t*-statistics and keep 30 terms with the largest negative *t*-statistics to capture the negative sentiment. To address the issues of endogeneity, I use the terms identified by each regression in the construction of *Fear Index* in the following year. For example, the terms identified by 2004-2013 regression are used to build the *Fear Index* in 2014. Formally, *Fear Index* in month *t* in MSA *i* is defined as:

$$Fears\ Index_{\ t} = \frac{\sum_{j=1}^{30}(\Delta ASVI_{j,t})}{30} \tag{2}$$

where $\Delta ASVI_{i,j,t}$ is *ΔASVI* at time *t* in MSA *i* for one of 30 terms with the most negatively ranked *t*-statistic from the period of 2004 through the most recent year that ends prior to *t*. For example, at the end of December 2013, I run a regression of *ΔASVI* on contemporaneous home price index returns during the period of January 2004-December 2013 for each query term in that MSA. Then, I sort the terms based on their *t*-statistic on *ΔASVI* in ascending order and select the 30 most negative terms to be used in forming the *Fear Index* for the period from January, 2014 to December, 2014 in that MSA. The *Fear Index* in month *t* over this period is simply the average *ΔASVI* of these 30 terms in that month. Using expanding rolling window regressions helps to increase the statistical power of the selected terms as it was done by Kogan *et al.* (2009) and Da, Engelberg, and Gao (2015). In sum, I create the *Fear Index* for each of 20 MSAs that captures negative sentiment related to the housing market.

3.2. Sample Characteristics and Other Data

Table 1 presents descriptions of the variables used in this study. Two main variables used in this study are the *Fear Index* and the *Home Index*. Each variable contains national-level and 20 city-level series over the sample period from January 2005 to December 2014. Cities chosen for this study come from those included in the individual S&P/Case-Shiller Home Price Indexes computed for 20 MSAs. City-level home indexes measure the value of residential real estate in the following U.S. metropolitan areas: Atlanta, Boston, Charlotte, Chicago, Cleveland, Dallas, Denver, Detroit, Las Vegas, Los Angeles, Miami, Minneapolis, New York, Phoenix, Portland, San Diego, San Francisco, Seattle, Tampa, and Washington, D.C.

City Fear Indexes are constructed using the Google search volume for a range of real estate and economics terms gathered in the same metropolitan areas (MSAs) as those used for home price indexes. Both *National* and *City Fear Indexes* are measures of people's sentiment toward housing prices, particularly negative sentiment. A number of words that I chose can be classified as having either positive or negative sentiment. However, those terms that have a strong negative relationship with the housing market are almost always negative sentiment words. I select 30 terms that are most negatively related with the local housing market to form a single measure of sentiment in that location by averaging the adjusted search volumes for those terms. Thus, city-level *Fear Indexes* represent the aggregate housing market sentiment in that location. The total number of unique terms across 20 cities is 162, but 15 out of the 30 highly negative terms appear in at least half of the cities. That ensures that cities in my sample share a number of homogeneous triggers of fear but at the same time include the terms that capture unique city characteristics.

I use *Bankruptcy filings* to differentiate local housing markets by their relative levels of financial distress. I expect that cities with higher numbers of bankruptcy filings will respond differently to changes in *Fear* than those that are more financially stable. Bankruptcy filings are grouped by the Federal Court jurisdictions and are available at a monthly frequency from 2006 through the end of the sample in 2014. The data does not provide the number of bankruptcy filings at the city level since each jurisdiction covers either the whole state or a portion of a more populous state. Bigger states such as Texas or California have up to four jurisdictions, while smaller states such as Nevada or Oregon only one. I assign each city to its appropriate jurisdiction and then compute its bankruptcy rate by adding the number of bankruptcy filings across jurisdictions in a given state and dividing by state population. Thus, bankruptcy rate assumes that bankruptcy filings are uniformly distributed across the state. This approach has merit since each metropolitan area in this study represents one of the most populous areas of that state, which would adequately reflect economic health of the whole state.

One of the other variables form Table 1 is *Home Index Momentum*, which controls for the autocorrelation of home index returns. It is computed at a monthly frequency with each value representing the average housing market return over the previous 12 months. *Home Index Momentum* is calculated for each metropolitan area as well as for the U.S. as a whole. I term metropolitan areas momentum as *City H.I. Momentum* and national level momentum as *National H.I. Momentum*. The other control variables are *Real GDP*, *CPI*, and *Unemployment Rate*, which control for the macroeconomic factors that affect the housing market. Housing Market Index

(*HMI)* controls for an alternative measure of sentiment in the housing market. And *S&P 500 Index* controls for the stock market returns. Intuition for the inclusion of these control variables comes from prior literature and adds to the robustness of my results.

Table 2 presents summary statistics in Panel A and correlation coefficients in Panel B. Positive *Fear Index* values imply that negative sentiment is growing, while negative values imply that negative sentiment is decreasing, i.e. fear subsides. *Fear Index* is presented at both levels, as the *National Fear Index* and *City Fear Indexes*. *Fear Index* at both levels represents the rate of change in the adjusted search volume for 30 terms related to real estate and economics. *National Fear Index* has been constructed using the methodology described in Chapter 2 and captures negative sentiment for the whole U.S., while *City Fear Indexes* capture negative sentiment across 20 metropolitan areas. From Panel A, I observe that the means and the medians for *City Fear Indexes* and *National Fear Index* are about the same, but standard deviation of *City Fear Indexes* is nearly 24% lower than it is for the *National Fear Index.* It implies that negative sentiment fluctuates more at the national level than it does across 20 MSAs. It can be partially explained by the fact that summary statistics for *City Fear Indexes* are the averages of these statistics across 20 cities. Averaging these statistics across 20 cities has a moderating effect, i.e. high variation in some cities is being subdued by lower variation in the others.

The *National Home Index* is the S&P/Case-Shiller U.S. National Home Price Index that captures the value of single-family housing within the United States. *City Home Indexes* are the S&P/Case-Shiller Home Price Indexes for 20 individual cities. Summary statistics for *City Home Indexes* are first computed for each city separately and then averaged across all twenty cities. Comparing the means for both levels of home price indexes, I see that nationwide home prices fared slightly better than they did across 20 metropolitan areas. Standard deviation for *City Home*

Indexes reflects greater variation in home values within 20 major cities compared with the national home values. *City Fear Indexes* and *City Home Indexes* include 2,400 observations with each of the 20 cities having monthly observations over the period from January 2005 to December 2014.

Summary statistics for the *Bankruptcy filings* are first computed for each city and then averaged across all 20 cities. The mean of 0.02% represents the average monthly number of bankruptcy filings per capita across 20 cities. The mean monthly return for the *S&P 500 Index* is 0.01 or 1% during the sample period. The lowest monthly return happened in October of 2008 which was -16.94%, and the highest in October of 2011, with 10.77%.

In Panel A, I present summary statistics for the levels of each variable, but in Panel B and the subsequent tables, I use log changes of the *National Home Index*, *City Home Indexes*, *Real GDP*, *CPI*, *Unemployment Rate*, and *HMI* to account for non-stationary qualities of these series. *Fear Indexes* and *S&P 500 Index* have not been transformed, since these variables are stationary by construction.

In Panel B of Table 2, I show correlation coefficients for *City Fear Indexes*. Most of these coefficients are statistically significant, so to enhance the readability of the table I omit showing their significance with asterisks. All the coefficients above 0.15 are significant at a 10% level, above 0.18 at a 5% level, and above 0.26 at a 1% level. The following pairs of *City Fear Indexes* exhibit the strongest positive correlation, New York and Boston, Chicago and Atlanta, and New York and Los Angeles. The following pairs show the strongest negative correlation, San Francisco and Chicago, Washington DC and Portland, and Los Angeles and Chicago. I notice that negatively correlated pairs are geographically dispersed, while positively correlated ones may or may not be. For example, New York and Boston are located relatively near to each other, while New York and Los Angeles are located on East versus West Coasts. In sum, my measure of negative sentiment is not conditioned by proximity of two cities, but captures other sentiment driven city specific characteristics that correlate with each other over time.

4. The effect of *Fear Indexes* on the Future National *Home Price Index Returns*

In this section, I examine the relationship between *Fear* and national housing market returns. In aggregate, I expect the relationship to be negative with increases in *Fear* corresponding to decreases in housing market returns. I also assess whether changes in *Fear* this month are able to predict the changes in housing market returns over the following month. *Fear Index* is measured at two levels, national-level *Fear* and metropolitan-level *Fear*. One captures negative sentiment across the nation, while the other narrows it down to a specific metropolitan area. *Local Fear* is the main variable of interest, but I also present the results for national *Fear* and use it as one of the control variables. I expect that some cities play a more important role in spreading the sentiment and my objective is to identify these cities and determine any common characteristics or special ties among these cities.

Table 3, Model (1) assesses the effect of the *National Fear Index* on future home index returns. I deploy the following regression:

$$National\ Home\ Index_t = \beta_0 + \beta_1 National\ Fear\ Index_{t-1} + \sum_m \gamma_m Control_t^m + \varepsilon_t \qquad (1)$$

where *National Home Index*$_t$ stands for returns of the S&P/Case-Shiller U.S. National Home Price Index at time *t*, and *National Fear Index*$_{t-1}$ is the measure of negative sentiment across the U.S. at time *t-1*. *Control* variables are as follows: *Home Index Momentum, Real GDP, CPI, Unemployment Rate*, *HMI*, and *S&P 500 Index*. My focus in this regression is on the estimated coefficient β_1, which I expect to be negative and statistically significant. Results presented in

Table 3 confirm the prediction with the coefficient being negative and statistically significant at a 1% level. These results suggest that one standard deviation increase in *National Fear Index* corresponds with a decline of 16 basis points in the returns of National Home Price Index over the next month.

In Models (2) – (4) of Table 3, I employ a single regression framework to assess the effect of *Local Fear* on national home index returns. I create twenty binary variables with each representing a city, i.e. *City Dummy*$_i$ takes on the value of unity for *Local Fear* in city *i*, and zero otherwise. Next, I create twenty interaction terms of *Local Fear* and its binary variable. I use these interaction terms in a single regression to assess the marginal contribution of each city's *Fear Index* in explaining the variation in national home price returns. I set up the following regression model:

$$National\ Home\ Index_t = \beta_0 + \sum_{i=1}^{n=20} \beta_i\,(Local\ Fear \times City\ Dummy)_{i,t-1} + \sum_m \gamma_m Control_t^m + \varepsilon_t \qquad (2)$$

where *National Home Index*$_t$ is the return on the Case/Shiller National Home Price Index in month *t*. *City Dummy* takes on the value of 1 if *Local Fear* and *City Dummy* are both for city *i*, and 0 otherwise. $(Local\ Fear \times City\ Dummy)_{i,t-1}$ is the interaction term of *Local Fear* and *City Dummy* for city *i* in month *t-1*. I include the following *Control* variables in Model (3): *Home Index Momentum*, *Real GDP*, *CPI*, *Unemployment Rate*, *HMI*, *S&P 500 Index*. In Model (2), I exclude all controls except *Home Index Momentum*, and in Model (4) I include all controls plus *National Fear Index*$_{t-1}$. Descriptions of these variables are provided in Table 1.

The results of model specification (2) include ten estimated coefficients on local *Fear* that are negative and statistically significant. The top five estimated coefficients are -0.57 (*t* = -

2.89), -0.57 (*t* = -2.31), -0.55 (*t* = -2.61), -0.52 (*t* = -2.44), and -0.50 (*t* = -2.19) for Boston, Seattle, Dallas, Los Angeles, and Denver, respectively. One standard deviation increase in the *Fear Index* in Boston (standard deviation of *Fear* in Boston is 0.35) corresponds with a decline of 20 basis points in *National Home Index* over the next month. I can similarly interpret the coefficients of other interaction terms. Once I add the other controls in model specification (3), the number of cities with negative and significant coefficients goes down from 10 to 9 with the coefficient for Detroit being no longer statistically significant. It is interesting that significant *Fear* coefficients are spread out across the U.S. without any single region dominating the others. Two cities are located in the Northeast (Boston and Washington D.C.), three in the Pacific (Los Angeles, San Francisco, and Seattle), two in the South (Dallas and Atlanta), one in the Midwest (Chicago), and one in the Mountain region (Denver).

In the last model specification (Model 4) from Table 3, I observe that *National Fear* subdues the significance of estimated coefficients of *Local Fear* in four cities. The remaining significant coefficients in descending order of magnitude are in Boston, Los Angeles, Washington D.C., Seattle, Denver, and San Francisco. A clear pattern emerges that the Pacific and the Northeast are two of the most important regions in which *Fear* affects the changes in the housing market. The rankings of the top five cities from Model (2) to Model (4) somewhat change, but four of the five cities are still the same and only Dallas has been replaced by Washington D.C.

In sum, *Local Fear* is marginally significant in predicting the changes of national home index returns over the following month. *Local Fear* in six cities is at least as important as *National Fear* and adds to our understanding of important metropolitan hubs in which negative sentiment helps in predicting the changes in the national housing market. I am also able to pinpoint to the broader geographic regions, which are relatively more important in spreading the negative sentiment across the country.

5. Economic Significance of local Fear Indexes on the National Home Price Index Returns

In Table 4, I take a closer look at the statistical and economic significance of local *Fear* to forecast home price changes over the next month. My objective is to compare the forecasting power of local *Fear* to those of well-known predictors such as real GDP, inflation, unemployment, HMI, and stock market returns as a gauge of the economic significance of my results. I follow a similar methodology in computing economic significance and absolute relative significance as in Hong, Torous, and Valkanov (2007). They apply these measures to estimate the ability of industry returns to predict stock market movements.

To accomplish this goal, I first run separate regressions of the *National Home Index* on each of the 20 lagged city *Fear Indexes* along with other controls to estimate the coefficients. I find that estimated *Fear* coefficients are most negative for the following cities: Boston (β = -0.0049, *t*-stat = -2.44), Washington DC (β = -0.0043, *t*-stat = -2.31), Los Angeles (β = -0.0044, *t*-stat = -2.13), San Francisco (β = -0.0031, *t*-stat = -1.97), Dallas (β = -0.0038, *t*-stat = -1.67), Denver (β = -0.0039, *t*-stat = -1.69), and Seattle (β = -0.0038, *t*-stat = -1.45).

Next, I compute the effect of a two-standard deviation shock to the lagged local *Fear* on the next month's housing market returns and call this value "Economic Significance." I also report economic significance of each control variable that I include in the regressions. In Panel A, I present the results on economic significance for seven cities. To reduce the number of decimal points in Panel A, I report economic significance times 100. In addition to economic significance, I also report its lower and upper bounds by adding and subtracting the standard errors from the coefficient estimates. In Panel B, I present the absolute value of economic significance as a fraction of volatility in *National Home Index*. This value is termed as "Absolute Relative Significance" or ARS for short.

For example, a two-standard deviation shock to a monthly *Fear* in Los Angeles is (2*0.33). A 0.33 is the standard deviation of monthly *Fear* in Los Angeles over the sample period. This shock leads to a change in next month's *National Home Index* of -0.0029 (-0.0044*2*0.33), which is roughly 31% of home index returns' volatility. The volatility of the *National Home Index* over the sample period is 0.0094.

In Panel A of Table 4, the economic significance of *Fear* for the reported metropolitan areas are comparable to other predictors of Home Index returns. For example, economic significance of a two-standard deviation shock to the estimate coefficient on *Fear* in Boston is -0.35, which is only second in its relative magnitude following after *Home Index Momentum*. The same pattern emerges in Panel B, as I report the absolute relative significance. The ARS of *Fear Indexes* ranges from 23% to 37% for the top seven cities. Economic significance of *Fear* in Boston is very high, with a two standard deviation shock in *Fear* resulting in a movement of *National Home Index* that is 37% of house market returns volatility.

I also compute ARS and present the results in Panel A for the other housing market predictors. The coefficients of these market predictors do not fluctuate much across the separate regressions of national housing market returns on local *Fear*. For brevity, I only discuss the coefficient estimates from the Los Angeles regression to gauge the relative significance of *Fear Index* compared to other predictors of housing market returns. *Home Index Momentum* is economically the strongest predictor with a two-standard deviation shock in *Home Index Momentum* leading to a 0.011 (-0.0065 *2*0.8445) movement in the housing market, which is roughly 116% of the housing market returns' volatility. The *Fear Index* for Los Angeles is the second strongest predictor of *National Home Index* with ARS of 31%. From Panel B, the ARS values of other predictors of the housing market changes in Los Angeles are at 30%, 25%, 24%, 17%, 17%, and 10% for *National Fear Index*, *S&P 500 Index*, *HMI*, *Unemployment rate*, *CPI*, and *Real GDP*, respectively.

The results that I discuss in this section strongly confirm that *Local Fear* is an economically significant predictor of housing market returns and does a comparable job when assessed in the same regression with some other well-known predictors of the housing market returns.

6. Fear Index and Local Housing Market Returns in "Hot" and "Cold" Markets

In this section, I examine the impact of *Fear* on housing markets in 20 metropolitan areas. I switch to individual home price indexes to understand better the variation in city characteristics and their response to changes in negative sentiment. I use 20 Case/Shiller Home Price Indexes to capture the variation in values of local housing markets. As I discussed in the previous section, local *Fear Indexes* are constructed using the Google search volume in the same 20 metropolitan areas (MSAs) for which I have home price indexes available. This ensures that local *Fear* is capturing the sentiment of those individuals who are using Google's search engine in the same cities for which I am tracking home price changes.

Beracha and Wintoki (2013) examine the role of sentiment on housing market returns across 245 MSAs and find that abnormal search volume helps to predict abnormal changes in housing prices. They also find evidence that housing price changes in "hot" cities, those with rapid price appreciation, are more sensitive to search intensity compared to "cold" cities, those with slow price appreciation. I use a similar approach for classifying cities into "hot" and "cold" markets but, in contrast use a more dynamic method into assigning cities into "hot" versus "cold" markets. Beracha and Wintoki (2013) assign MSAs into "hot" and "cold" markets based on whether their returns are above or below the median returns during the out-of-sample period from 2001 to 2004. I use a more dynamic approach of classifying the cities into "hot" versus "cold" markets monthly by using the average returns over the previous six months. Moreover, if the average return for city *i* over the previous six months is above (below) the median return from the cross section of 20 cities, I classify that city as a hot (cold) market. Using this dynamic approach, a city that is "hot" this month can turn into a "cold" city in the following month.

In Table 5, I present the results of an analysis of the impact of local *Fear Index* on local home price changes in "Hot" versus "Cold" markets. I set up the following regression model:

$$City\ Home\ Index_{i,t} = \beta_0 + \beta_1 (Local\ Fear \times Hot)_{i,t-1}$$
$$+\beta_2 (Local\ Fear \times Cold)_{i,t-1} + \beta_3 Cold_{i,t-1} + \sum_m \gamma_m Control_t^m + \varepsilon_t \qquad (3)$$

where *City Home Index*$_{i,t}$ stands for returns of the S&P/Case-Shiller U.S. Home Price Index in city *i* at time *t*. $Hot_{i,t-1}$ ($Cold_{i,t-1}$) is set to unity if the average housing market return over the previous six months in city *i* at time *t-1* is above (below) the median return in the cross section of 20 cities, and to zero otherwise. This classification helps to differentiate between cities with slow price appreciation and cities with rapid price appreciation and determine whether each city group has a different response to *Fear*. $(Local\ Fear * Hot)_{i,t-1}$ is the interaction term of *Fear* and *Hot* dummy in city *i* at time *t-1*. Likewise, $(Local\ Fear * Cold)_{i,t-1}$ is the interaction term of *Fear* and *Cold* dummy in city *i* at time *t-1*. *Control* variables are as follows: *Home Index Momentum*, *Real GDP*, *CPI*, *Unemployment Rate*, *HMI*, and *S&P 500 Index*. My focus in this regression is on the relative significance of the estimated coefficients β_1 and β_2. I expect $\beta_2 > \beta_1$, since cold markets are more susceptible to negative sentiment than hot markets. Results presented in Table 5 confirm the prediction with the coefficient on *(Local Fear * Hot)*$_{i,t-1}$ being less negative than the coefficient on *(Local Fear * Cold)*$_{i,t-1}$. These results suggest that one standard deviation increase in local *Fear* in cold (hot) markets corresponds with a decline of 28 (21) basis points in the returns of National Home Price Index over the next month.

In model specifications (2) and (3), I run the following regression for either hot or cold markets separately.

$$City\ Home\ Index_{i,t} = \beta_0 + \beta_1 Local\ Fear_{i,t-1} + \sum_m \gamma_m Control_t^m + \varepsilon_t \tag{4}$$

where all the variables are defined as before. I present the results of classifying the cities into hot and cold markets using the geometric average returns from the previous six months.[24] The point of interest is on the estimated coefficients on *Local Fear* for hot versus cold markets. As I can see from Table 5, both coefficients are significant at a 1% level but the coefficient for cold markets is more negative. These results are consistent with those from the full sample, signifying that *Fear* has a greater impact on housing market returns in cold markets.

In sum, the results from Table 5 suggest that local *Fear* is an important predictor of local home price index returns over the next month and impact of *Fear* is more pronounced in cities with slow price appreciation (cold markets). These results are not surprising, since the same factors that keep housing prices from rapid appreciation are indicative of home buying behavior that is more susceptible to negative sentiment.

7. Fear Index and Local Housing Market Returns in High and Low Bankruptcy Markets

[24] When using different periods like three years instead of six months or arithmetic average instead of geometric average as I classify the cities into "hot" versus "cold" markets yield qualitatively and statistically similar results.

In this section, I analyze whether cities that have experienced relatively greater economic or financial distress respond to negative sentiment differently than those that are relatively stable. I use monthly bankruptcy rates to gauge the magnitude of economic and financial distress across 20 metropolitan areas that I cover in my sample.

There is a growing literature that examines the relation between bankruptcy and housing prices. Springer and Waller (1993), Carroll and Li (2008), Ambrose, Buttimer, and Capone (1997), and Capozza and Thomson (2006) find that consumers who file for bankruptcy prolong their stay in the home before it eventually goes to a foreclosure sale. Campbell, Giglio, and Pathak (2010) find that houses sold after foreclosure, or close in time to the death or bankruptcy of at least one seller, are sold at lower prices than other houses. They find that bankruptcy-related sales offer the lowest discounts and foreclosure-related sales the highest. They also find that bankruptcy-related discounts appear more closely related to the urgency of sale immediately after bankruptcy. Dick and Lehnert (2007) find that following deregulation a greater number of consumers became eligible for new credit and that followed with the increase in the rate of consumer bankruptcy. They suggest that credit market liberalization, as opposed to changes in bankruptcy law, plays an important role in explaining the increase in the number of bankruptcies. Liu and Sengupta (2013) show that home price changes have a strong association with the bankruptcy rates. They find that MSAs with the lowest bankruptcy filing rates experience the greatest housing price increases. Fay, Hurst, and White (2002) find support that households are more likely to file for bankruptcy when their financial benefit from filing is higher. In contrast, they do not find support that households file for bankruptcy when adverse events occur, which reduce their ability to repay. They also find support that households are more likely to file for bankruptcy if they live in areas with relatively higher bankruptcy rates.

Previous studies have examined the relation between bankruptcy rates and housing prices, while I examine the relation between local *Fear* and local home price changes in high and low bankruptcy markets. I retrieve the data for monthly bankruptcy filings by court jurisdiction from the American Bankruptcy Institute. These series are available starting with 2006 and include Chapters 7, 11, and 13 bankruptcies, which capture both individual and business bankruptcies. Since the number of filings can vary due to the population size each jurisdiction covers, I aggregate bankruptcy filings across jurisdictions in a given state and then standardize these numbers by state population. I term the resulting series as bankruptcy filings or bankruptcy rates.

The adjustment process assumes that the bankruptcy rate is evenly distributed across the state, which I understand has its limitations. However, given bankruptcy filing data are available only at the court jurisdictions level, I have to make certain assumptions in capturing differences in bankruptcy rates across metropolitan areas. This approach seems reasonable since court jurisdictions are spread among multiple cities but always stay within state boundaries. Also, there is no clear standard in terms of the population that each court jurisdiction overseas but there are reliable data sources on population at the state level. Also, the number of court jurisdictions per state varies from one to four but it is a clearly identifiable number, which makes it easy to find the aggregate number of bankruptcy filings at the state level.

I use a similar approach of classifying cities into high versus low bankruptcy markets as the one I used for classifying cities into "hot" versus "cold" markets. I classify a city into a high (low) bankruptcy group if the geometric average bankruptcy rate over the previous 6 months in that city is above (below) the median bankruptcy rate in the cross section of 20 cities.[25] Table 6

[25] These results are robust to classifying the high versus low bankruptcy markets using different periods like three years instead of six months or arithmetic average instead of geometric average.

presents the results of local home price changes regressed on local *Fear Index* in high versus low bankruptcy markets. I use the following regression model:

$$City\ Home\ Index_{i,t} = \beta_0 + \beta_1(Local\ Fear \times Low)_{i,t-1}$$
$$+\beta_2(Local\ Fear \times High)_{i,t-1} + \beta_3 High_{i,t-1} + \sum_m \gamma_m Control_t^m + \varepsilon_t \tag{5}$$

where *Local Fear* and *Controls* are used as previously defined and $High_{i,t-1}$ ($Low_{i,t-1}$) is set to unity if the average bankruptcy rate over the previous 6 months in city *i* at time *t-1* is above (below) the median bankruptcy rate in the cross section of 20 cities, and to zero otherwise. Table 6 includes results from three regression models with the first one including the full sample and the other two including either high or low bankruptcy market. My main focus in Model (1) is on the relative magnitude of the interaction terms. The coefficient of local *Fear* and *Low* is -0.59, while it is -0.87 for local *Fear* and *High*. They are both statistically significant at the 1% level but the estimated coefficient on the interaction term of local *Fear* and *High* is more negative. Estimated coefficients on the interaction terms are significantly different at a 10% level. These results suggest that *Fear* has a greater impact on home price changes in high bankruptcy markets. The same conclusion can be drawn from the results of model specifications (2) and (3), which assess the effect of local *Fear* on *City Home Index* in either "Low Bankruptcy Markets" (Model 2) or "High Bankruptcy Markets" (Model 3). The results provide evidence that high bankruptcy markets are more responsive to changes in *Fear* than low bankruptcy markets. This finding is consistent with the previous literature on bankruptcy rates and housing prices that affirms the inverse relationship.

In sum, the results I present in Table 6 suggest that negative sentiment is an increasingly important factor in explaining house price movements especially in those areas which are more prone to economic and financial distress. I find that increases in *Fear* help to predict future housing market declines and this effect is more pronounced in high bankruptcy markets. When running regressions for each group separately, the same pattern emerges.

8. *Fear Index* and Local Housing Market Returns in two-by-two sorts of High and Low Bankruptcy Markets and "Hot" and "Cold" Markets

In this section, I examine how the interactions of high versus low bankruptcy markets and “hot” versus “cold” markets impact the relation between *Fear* and housing market returns. Based on the results from above, I expect *Fear* to have the greatest impact on cold markets with high bankruptcy rates and the least on hot markets with low bankruptcy rates. In Table 5, I find evidence that *Fear* in cold markets has more impact on housing market returns than in hot markets. In Table 6, I find support that *Fear* in high bankruptcy rate cities has a stronger effect on housing market returns than in low bankruptcy rate cities. To further investigate the impact of two-way sorts, I first examine two-way interactions of *Fear* with dummies for hot versus cold markets and high versus low bankruptcy rate cities for the full sample. Next, I run individual regressions for four types of markets: cold markets with high bankruptcy; hot markets with high bankruptcy; hot markets with low bankruptcy; and cold markets with low bankruptcy. The results of this analysis are presented in Table 7. Regression in Model (1) is as follows:

$$\begin{aligned} City\ Home\ Index_{i,t} &= \beta_0 + \beta_1(Local\ Fear \times High \times Cold)_{i,t-1} + \\ &\beta_2(Local\ Fear \times High \times Hot)_{i,t-1} + \beta_3(Local\ Fear \times Low \times Hot)_{i,t-1} + \\ &\beta_4(Local\ Fear \times Low \times Cold)_{i,t-1} + \beta_5 High_{i,t-1} + \beta_6 Cold_{i,t-1} + \sum_m \gamma_m Control_t^m + \varepsilon_t \end{aligned} \quad (3)$$

where all the variables are defined as before. My main focus in the table is on the relative significance of interaction terms. Based on the previous results, I expect that $\beta_1 > \beta_2$, β_3, or β_4 and $\beta_3 < \beta_1$, β_2, or β_4. Results presented for model specification (1) of Table 7 are consistent with the first prediction and the estimated coefficient on the interaction term of *(Local Fear*High*Cold)*$_{i,t-1}$ is the most negative and significant. It implies that changes in *Fear* have the most explanatory power on housing market returns in cities with slow price appreciation ("cold" markets) and those that experience relative economic distress (high bankruptcy rates). My second prediction does not exactly hold, since the magnitude of the estimated coefficient on the interaction term of *(Local Fear*Low*Hot)*$_{i,t-1}$ is not the smallest, but at the same time it is not significantly different from the other two coefficients.

In model specifications (2) – (5) of Table 7, I examine the impact of two-way city sorts on the relationship of *Fear* and housing market returns in separate regressions. Results in these regressions are similar to those I find for the whole sample. The estimated coefficient on *Fear* in "Cold Markets with High Bankruptcy" (Model 2) is the most negative and significant but the coefficient in "Hot Markets with Low Bankruptcy" (Model 4) is not the smallest relative to the other two (Models 3 and 5).

In sum, I gain better understanding of the relation between local *Fear* and local housing market returns in four different types of housing market environments. Particularly, I find that housing market that is "cold" with high bankruptcy rates is the most susceptible to *Fear*. This finding makes sense since housing markets that undergo a slow price appreciation and experience high bankruptcy rates are indicative of the worsening economic conditions, which contribute to the responsiveness of market participants to changes in negative sentiment.

9. *Fear Index* and the Effect of Bankruptcy on Local Housing Market Returns

In this section, I assess the impact of *Fear* interacted with bankruptcy rates on local housing markets. The main contribution of this analysis is that I use bankruptcy rates as a continuous variable when I interact it with *Fear*. From Panel A, I find that the interaction term of *Local Fear* and *Bankruptcy filings* is negative and statistically significant at a 1% level. This coefficient implies that as *Bankruptcy filings* increases, the impact of *Fear* on home price changes increases as well. When comparing the magnitude of the interaction term in cold (Model 2) versus hot (Model 3) markets, I find that in cold markets as bankruptcy rate goes up *Fear* has a greater effect on housing market returns. This analysis is more robust and supports main findings from Tables 5-7. In addition, I perform two supplementary tests and present the results in Panels B and C.

In Panel B, I center *Bankruptcy filings* at two different values: one standard deviation above and one standard deviation below the mean. Then, I compute the coefficient for *Local Fear* corresponding to each of those values. These coefficients can be interpreted as the slopes of housing price changes on *Local Fear* when *Bankruptcy filings* equals mean *Bankruptcy filings* + one standard deviation and mean *Bankruptcy filings* - one standard deviation. Panel B reports those coefficients.

The results show that the coefficient of *Local Fear* is greater when *Bankruptcy filings* is centered one standard deviation above the mean than when its centered one standard deviation below the mean. There is no need to test for statistical significance of the difference in the coefficients as that test is already reflected in the significance of the interaction term in the corresponding models in Panel A.

In Panel C, I examine the slopes of home price changes on *Local Fear* when *Bankruptcy filings* is held constant at different combinations of values from low (0.007%) to high (0.081%). The results show that in each model, the slope increases as *Bankruptcy filings* increases as well.

These results further confirm that the effect of *Fear* is stronger in those cities with high bankruptcy rates.

10. Conclusion

Recent studies have shown that sentiment is well captured by web search intensity for certain words or categories of related searches.[26] These studies focus on the ability of sentiment captured by Google searches in predicting changes in real estate and stock markets. This study complements previous research on sentiment literature related to residential real estate markets. I use Search Index Volumes (SVI) from *Google Trends* to construct a new measure of housing market-level sentiment and analyze its relation with housing prices. I term this measure as the *Fear Indexes*, *Local Fear*, or *Fear* for short. The *Fear Indexes* are based on SVIs for certain real estate and economic terms, such as foreclosure, recession, market value, etc.

I uncover the relation between the *Local Fear* at the metropolitan statistical area (MSA) level and local home price changes. I construct 20 local *Fear Indexes* based on MSAs covered by Case/Shiller 20-City Composite Home Price Index and find that the forecasting ability of local *Fear* is comparable to those of other well-known predictors of housing price changes. Further, *Fear* in "cold" housing markets (cities with slow price appreciation) has a stronger effect than in "hot" markets (cities with rapid price appreciation). I also find that cities with high bankruptcy rates are more responsive to changes in *Fear* than low bankruptcy rate cities. Moreover, "cold" cities with high bankruptcy rates are the most responsive to negative sentiment.

This study provides evidence that local sentiment is an economically important predictor of national housing market returns over the next month. I find that local markets that share

[26] See Da, Engelberg and Gao (2015), Beracha and Wintoki (2013), Hohenstatt and Kaesbauer (2014), and Wu and Brynjolfsson (2009), among others.

certain traits are more prone to respond to sentiment. Current study is the starting point for further investigation into the ability of local sentiment to predict changes of other well-known local as well as national economic and financial indicators. Further studies may also investigate factors driving local sentiment and examine spill overs of sentiment from one market to the next.

References

Ambrose, B.W., R.J. Buttimer Jr and C.A. Capone. 1997. Pricing Mortgage Default and Foreclosure Delay. *Journal of Money, Credit, and Banking* 29(3): 314–325.

Askitas, N. and K.F. Zimmermann. 2009. Google Econometrics and Unemployment Forecasting. *German Council for Social and Economic Data (RatSWD) Research Notes*, (41).

Beracha, E. and M.B. Wintoki. 2013. Forecasting Residential Real Estate Price Changes from Online Search Activity. *Journal of Real Estate Research* 35(3): 283–312.

Campbell, J.Y., S. Giglio and P. Pathak. 2011. Forced Sales and House Prices. *American Economic Review* 101(5): 2108–2131.

Capozza, D.R. and T.A. Thomson. 2006. Subprime Transitions: Lingering or Malingering in Default? *The Journal of Real Estate Finance and Economics* 33(3): 241–258.

Carroll, S.W. and W. Li. 2011. The Homeownership Experience of Households in Bankruptcy. *Cityscape* 1: 113–134.

Choi, H. and H. Varian. 2009. Predicting the Present with Google Trends. Retrieved April 10, 2016, from Google, Inc.: http://static.googleusercontent.com/external_content/untrusted_dlcp/www.google.com/en/us/googleblogs/pdfs/google_predicting_the_present.pdf.

Choi, H. and H. Varian. 2009. Predicting Initial Claims for Unemployment Benefits. *Google Research* (Google Inc.).

D’Amuri, F. 2009. Predicting Unemployment in Short Samples with Internet Job Search Query Data. Munich Personal RePEc Archive (MPRA), No. 18403.

D'Amuri, F. and J. Marcucci. 2009. 'Google it!' Forecasting the US Unemployment Rate with a Google Job Search Index (No. 2009–32). *Institute for Social and Economic Research.*

Da, Z., J. Engelberg and P. Gao. 2011. In Search of Attention. *Journal of Finance* 66: 1461–1499.

Da, Z., J. Engelberg and P. Gao. 2015. The Sum of All FEARS Investor Sentiment and Asset Prices. *Review of Financial Studies* 28(1): 1–32.

Das, P., A. Ziobrowski and N.E. Coulson. 2015. Online Information Search, Market Fundamentals and Apartment Real Estate. *The Journal of Real Estate Finance and Economics* 51(4): 480–502.

Della Penna, N. and H. Huang. 2009. Constructing Consumer Sentiment Index for U.S. Using Google Searches. Working Paper No. 2009–2026, University of Alberta.

Dick, A.A. and A. Lehnert. 2010. Personal Bankruptcy and Credit Market Competition. *The Journal of Finance* 65(2): 655–686.

Drake, M.S., D.T. Roulstone and J.R. Thornock. 2012. Investor Information Demand: Evidence from Google Searches Around Earnings Announcements. *Journal of Accounting Research* 50(4): 1001–1040.

Fay, S., E. Hurst and M.J. White. 2002. The Household Bankruptcy Decision. *The American Economic Review* 92(3): 706–718.

Ginsberg, J., M.H. Mohebb, R.S. Patel, L. Brammer, M.S. Smolinsky and L. Brilliant. 2009. Detecting Influence Epidemics Using Search Engine Query Data. *Nature* 457: 1012–1014.

Guzman, G. 2011. Internet Search Behavior as an Economic Forecasting Tool: The Case of Inflation Expectations. *The Journal of Economic and Social Measurement* 36(3): 119–167.

Hohenstatt, R. and M. Kaesbauer. 2014. GECO's Weather Forecast for the UK Housing Market: To What Extent Can We Rely on Google Econometrics? *Journal of Real Estate Research* 36(2): 253–281.

Hohenstatt, R., M. Käsbauer and W. Schäfers. 2011. "Geco" and its Potential for Real Estate Research: Evidence from the US Housing Market. *Journal of Real Estate Research* 33(4): 471–506.

Hong, H., W. Torous and R. Valkanov. 2007. Do Industries Lead Stock Markets? *Journal of Financial Economics* 83(2): 367–396.

Kogan, S., D. Levin, B. Routledge, J. Sagi and N. Smith. 2009. Predicting Risk from Financial Reports with Regression. Proceedings of the North American Association for Computational Linguistics Human Language Technologies Conference.

Lee, K.O. and M. Mori. 2015. Do Conspicuous Consumers Pay Higher Housing Premiums? Spatial and Temporal Variation in the United States. *Real Estate Economics,* forthcoming.

Liu, Y. and R. Sengupta. 2012. Household Financial Stress Declines in the Eighth District. *The Federal Reserve Bank of St. Louis' The Regional Economist* 20(4): 20–21.

McLaren, N. and R. Shanbhogue. 2011. Using Internet Search Data as Economic Indicators. *Bank of England Quarterly Bulletin* Q2: 134–140.

Schmidt, T. and S. Vosen. 2009. Forecasting Private Consumption: Survey-Based Indicators vs. Google Trends. *Ruhr Economic Papers* No. 155.

Springer, T.M. and N.G. Waller. 1993. Lender Forbearance: Evidence from Mortgage Delinquency Patterns. *Real Estate Economics* 21(1): 27–46.

Tetlock, P.C. 2007. Giving Content to Investor Sentiment: The Role of Media in the Stock Market. *Journal of Finance* 62: 1139–1168.

Tetlock, P.C., M. Saar-Tsechansky and S. Macskassy. 2008. More than Words: Quantifying Language to Measure Firms' Fundamentals. *The Journal of Finance* 63(3): 1437–1467.

Vlastakis, N. and R.N. Markellos. 2012. Information Demand and Stock Market Volatility. *Journal of Banking and Finance* 36(6): 1808–1821.

Wu, L. and E. Brynjolfsson. 2009. The Future of Prediction: How Google Searches Foreshadow Housing Prices and Quantities. Working Paper, NBER.

Wu, J. and Y. Deng. 2015. Intercity Information Diffusion and Price Discovery in Housing Markets: Evidence from Google Searches. *The Journal of Real Estate Finance and Economics* 50(3): 289–306.

Zheng, S., W. Sun and M.E. Kahn. 2015. Investor Confidence as a Determinant of China's Urban Housing Market Dynamics. *Real Estate Economics*, forthcoming.

GRAPHS AND TABLES

Figure 3-1: Illustrations of Google Search Volume across Four MSAs

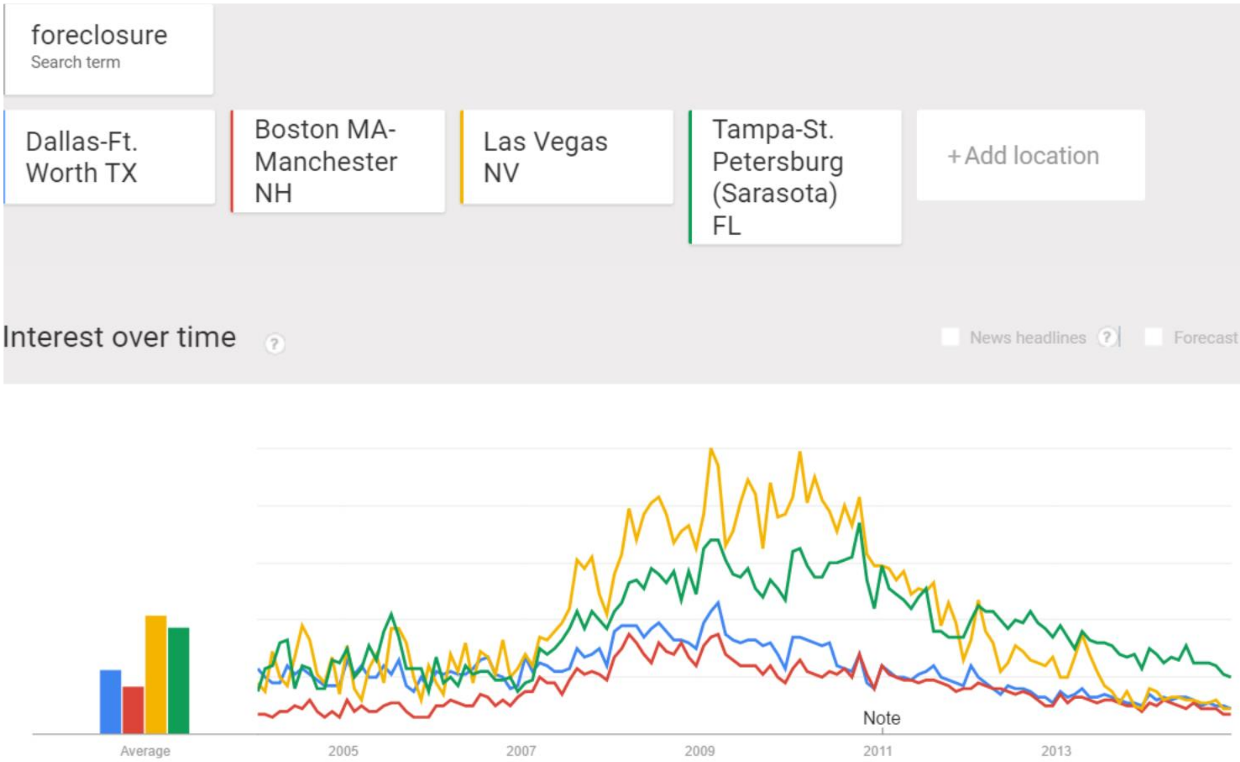


Figure 3-2: Case-Shiller Home Price Indexes in Four MSAs.

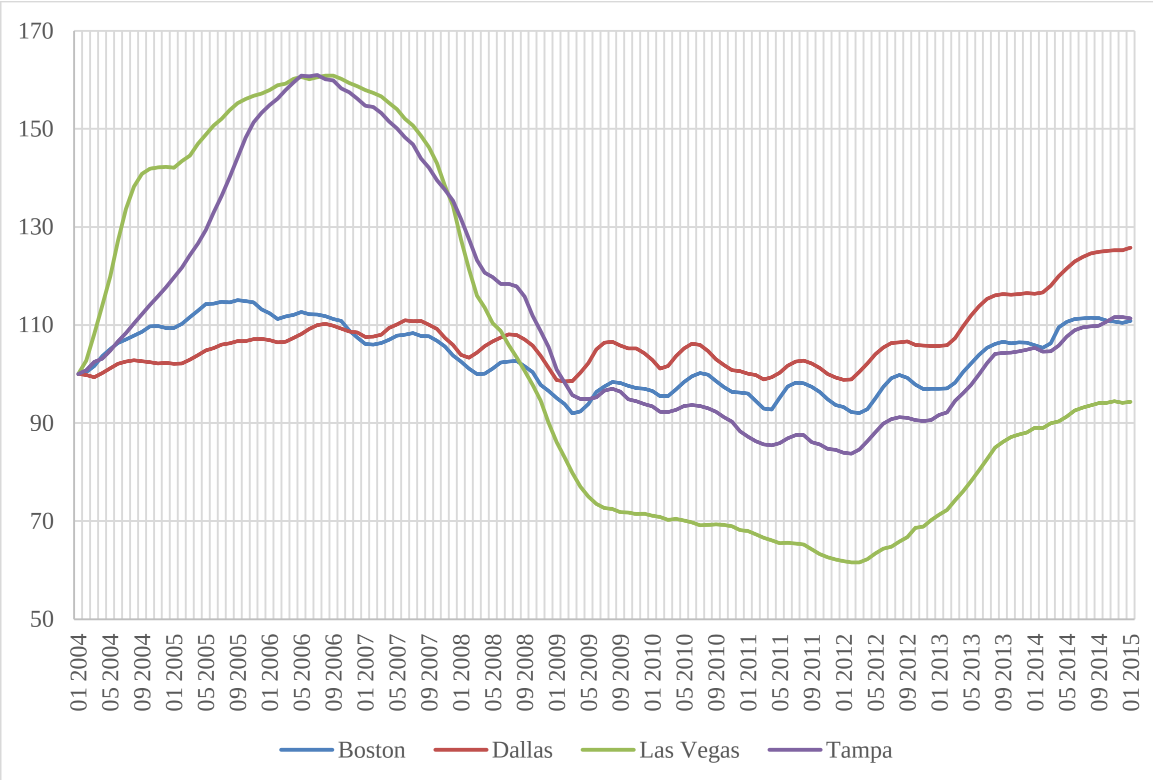


Figure 3-3: Number of Terms per MSA

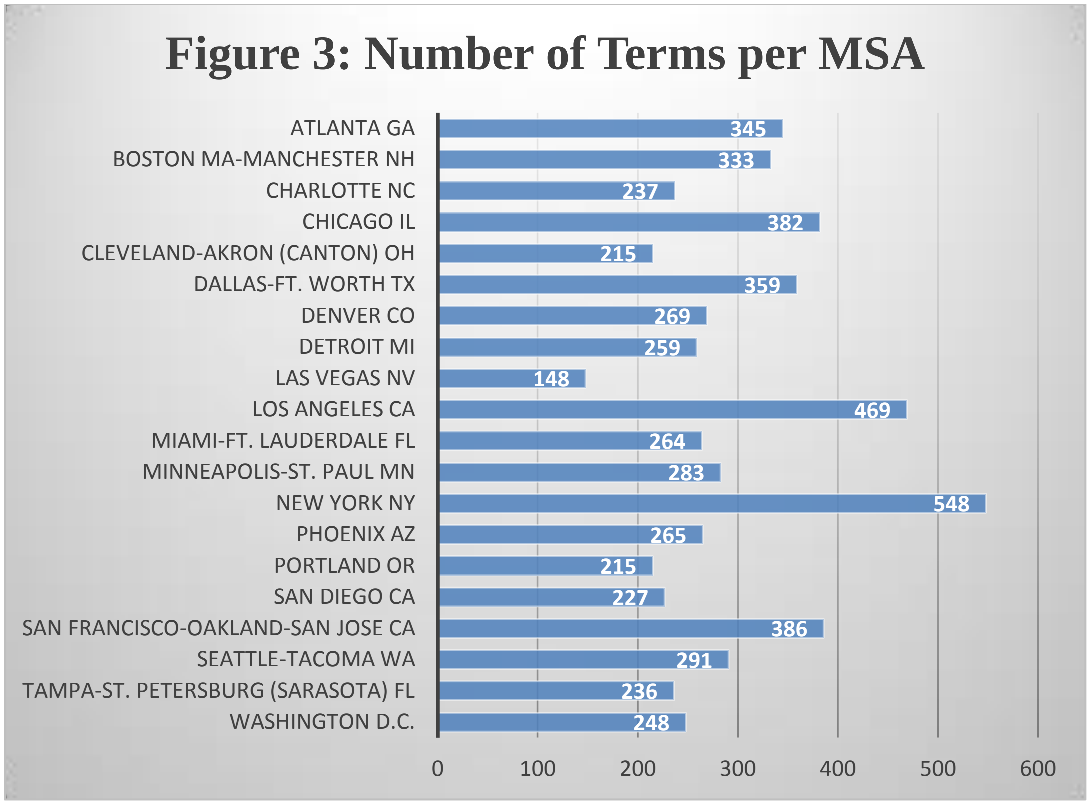


Table 3-1: Description of Variables

This table includes descriptions for each variable I use in this study. I first present the description and then, if applicable, the source from which each variable is collected.

Variable	Description
National Fear Index and *City Fear Indexes (Local Fear)*	The *Fear Index* is a monthly measure of people's sentiment toward housing prices in the U.S. (*National Fear Index*) and 20 major U.S. cities (*City Fear Indexes* or *Local Fear*) over the period from January of 2005 to December 2014. Both national and city *Fear Indexes* are constructed using the search volume for real estate and economic terms. I also include Top Searches that relate to each real estate and economic term in my sample. I adjust search volume data by taking monthly log differences, winsorizing, removing intra-annual seasonality, and then standardizing each time series. Next, I run expanding window backward rolling regressions of adjusted search volume queries on log differences of housing prices every 12 months to determine the historical relationship between search and contemporaneous housing index changes for all search terms for each city. The 30 terms with the highest *t*-statistics from the regressions ending in a particular year were chosen to construct the following year's *Fear Index* in that location. For example, the top 30 terms from the regressions from 2004 to 2010 in Dallas were used to build Dallas' *Fear Index* for 2011. Fear Index is the average of top 30 adjusted search volume queries in a given housing market. Search volume data that was used in constructing the index comes from Google Trends.
National Home Index and *City Home Indexes*	*National Home Index* tracks the value of single-family housing within the United States using the S&P/Case-Shiller U.S. National Home Price Index. It measures changes in the total value of all existing single-family housing stock within nine U.S. Census divisions. *City Home Indexes* are computed using Case-Shiller home price indexes for 20 major housing markets in the U.S. Individual home price indexes are computed for the following metropolitan areas: Atlanta, Boston, Charlotte, Chicago, Cleveland, Dallas, Denver, Detroit, Las Vegas, Los Angeles, Miami, Minneapolis, New York, Phoenix, Portland, San Diego, San Francisco, Seattle, Tampa and Washington, D.C. Before using the home price series I adjust them by taking monthly log differences. These series are collected at the S&P Dow Jones Indices' webpage <http://us.spindices.com/index-family/real-estate/sp-case-shiller>.
Bankruptcy filings	It represents the number of bankruptcy filings by jurisdiction standardized by state population. Each metropolitan area is assigned to the appropriate jurisdiction so that bankruptcy filings could be assigned to it. The filings include Chapters 7, 11, and 13 bankruptcies. The series is monthly and ranges from 2006 through 2014. The data was retrieved from the American Bankruptcy Institute at the following webpage <http://www.abi.org/newsroom/bankruptcy-statistics>.
Home Index Momentum	This variable is computed as a 12-month average of *Home Index* returns. For example, *Home Index Momentum* for January 2011 stands for the average of monthly returns over the previous 12 months from January to December of 2010. *Home Index Momentum* is computed at both national and city levels. I term metropolitan areas momentum as *City HI Momentum* and national level momentum as *National HI Momentum*.

Real GDP	Monthly Real GDP in trillions. Data was retrieved from <http://ycharts.com/indicators/real_gdp>.
CPI	Monthly Consumer Price Index (seasonally adjusted). The data is provided by Sentier Research, LLC, which compiles monthly CPI from the U.S. Bureau of Labor Statistics. Web page: <http://www.sentierresearch.com/>.
Unemployment rate	Monthly Unemployment Rate (seasonally adjusted). The data is provided by Sentier Research, LLC, which estimates monthly unemployment data from the U.S. Bureau of Labor Statistics. Web page: <http://www.sentierresearch.com/>.
HMI	The Housing Market Index (HMI) measures builder sentiment regarding the demand side of the single-family housing market in the U.S. HMI ranges from 0 to 100, with any number over 50 indicating that more builders view sales conditions as good rather than poor. The National Association of Home Builders (NAHB) computes HMI as a weighted average of responses to survey questions asking builders to rate three aspects of their local market conditions: current sales of single-family detached new homes, expected sales of single-family detached new homes over the next 6 months, and traffic of prospective buyers in new homes. The data was retrieved from: <http://www.nahb.org/en/research/housing-economics/housing-indexes/housing-market-index.aspx>.
S&P 500 Index	Monthly returns on S&P 500 Index taken from CRSP Monthly stock files.

Table 3-2: Sample Characteristics

This table presents summary statistics for key variables used in this study. Fear indexes and home price indexes are constructed at the national as well as city levels. Statistics for *City Fear Indexes, City Home Indexes*, and *Bankruptcy filings* were first computed at a city level and then averaged across 20 cities. Variable descriptions are provided in Table 1.The sample consists of 2,400 observations in total with each of the twenty cities having monthly observations over the period from January 2005 to December 2014. *Bankruptcy filings* are not available prior to 2006, and as a result these series start from January 2006. In Panel B, I present correlation coefficients for *City Fear Indexes*. All the coefficients above 0.15 are significant at the 10% level, above 0.18 at the 5% level, and above 0.26 at the 1% level.

Panel A: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	5%	Median	95%
National Fear Index	-0.04	0.42	-1.18	1.23	-0.70	0.00	0.63
City Fear Indexes	0.00	0.32	-0.92	0.96	-0.54	0.00	0.52
National Home Index	159.23	15.76	134.03	184.62	137.77	159.50	183.86
National HI Momentum (%)	0.08	0.65	-1.14	1.13	-0.98	-0.05	1.11
City Home Indexes	152.55	24.61	119.50	195.78	122.90	146.88	193.91
City HI Momentum (%)	0.02	0.93	-1.91	1.60	-1.69	0.09	1.41
Bankruptcy filings (%)	0.02	0.01	0.00	0.04	0.01	0.02	0.03
Real GDP	15.00	0.57	14.07	16.34	14.26	14.88	16.12
CPI	217.63	13.13	191.60	237.75	194.30	217.38	237.01
Unemployment rate	6.95	1.90	4.40	10.00	4.50	6.90	9.80
HMI	33.61	18.71	8.00	72.00	13.00	28.50	68.50
S&P 500 Index	0.01	0.04	-0.17	0.11	-0.08	0.01	0.07

Table 3-2: Continued

Panel B: Correlation Coefficients of *City Fear Indexes*

City Fear Indexes:	*Atl*	*Bos*	*Cha*	*Chi*	*Cle*	*Dal*	*Den*	*Det*	*LasV*	*LosA*	*Mia*	*Min*	*NewY*	*Pho*	*Por*	*SanD*	*SanF*	*Sea*	*Tam*
Boston MA	0.61																		
Charlotte NC	0.24	0.13																	
Chicago IL	0.66	0.63	0.14																
Cleveland OH	0.39	0.39	0.33	0.48															
Dallas TX	0.57	0.41	0.31	0.44	0.37														
Denver CO	0.57	0.48	0.21	0.48	0.34	0.50													
Detroit MI	0.34	0.42	0.25	0.40	0.41	0.29	0.20												
Las Vegas NV	0.20	0.01	0.30	0.31	0.29	0.17	0.05	0.32											
Los Angeles CA	0.61	0.59	-0.03	0.62	0.32	0.34	0.37	0.31	0.10										
Miami FL	0.42	0.44	0.33	0.50	0.34	0.28	0.29	0.22	0.20	0.37									
Minneapolis MN	0.51	0.46	0.14	0.63	0.31	0.33	0.35	0.34	0.22	0.44	0.31								
New York NY	0.51	0.66	0.07	0.65	0.41	0.27	0.39	0.28	0.08	0.66	0.37	0.42							
Phoenix AZ	0.37	0.18	0.33	0.46	0.29	0.20	0.18	0.22	0.32	0.18	0.37	0.38	0.14						
Portland OR	0.31	0.16	0.19	0.32	0.18	0.24	0.13	0.25	0.30	0.31	0.25	0.28	0.23	0.24					
San Diego CA	0.33	0.44	0.00	0.43	0.04	0.03	0.09	0.16	0.01	0.50	0.26	0.29	0.39	0.19	0.14				
San Francisco CA	0.45	0.45	-0.18	0.43	0.19	0.30	0.29	0.21	0.18	0.41	0.28	0.33	0.27	0.21	0.11	0.33			
Seattle WA	0.53	0.40	0.21	0.55	0.32	0.39	0.41	0.15	0.28	0.38	0.44	0.36	0.26	0.47	0.21	0.26	0.44		
Tampa FL	0.24	0.25	0.29	0.41	0.28	0.32	0.15	0.32	0.23	0.19	0.33	0.37	0.20	0.56	0.23	0.03	0.12	0.23	
Washington DC	0.22	0.22	0.02	0.23	0.05	0.16	0.15	0.07	0.06	0.19	0.13	0.16	0.01	0.26	-0.18	0.16	0.42	0.28	0.23

Table 3-3: The Effect of *City Fear Indexes* on the Future *National Home Price Index Returns*

This table presents the results from regressions of *National Home Index* returns on national as well as local *Fear*. Model specification (1) tests the impact of *National* $Fear_{t-1}$ on *National Home* $Index_t$ returns. Models (2), (3), and (4) use lagged local *Fear Indexes* and different combinations of control variables to assess the impact of local $Fear_{t-1}$ on *National Home Price* $Index_t$ returns. In models (2) - (4), I use interaction terms of local *Fear* and city binary variables to capture the marginal effect of each local *Fear* on national housing market. For example, Atlanta GA is the interaction term of *City Fear* $Index_{t-1}$ and a dummy variable that assumes a value of 1 for Atlanta GA observations and 0 otherwise. I include the following control variables: *National HI Momentum*, *Real GDP*, *CPI*, *Unemployment rate*, *HMI,* and *S&P 500 Index.* Variable descriptions are provided in Table 1. *Fear Index* coefficients have been multiplied by 100 to reduce the number of decimals. The interpretation of these coefficients has been adjusted accordingly. The sample period is from January 2005 to December 2014. All variables are included at a monthly frequency. *t*-statistics are included below the coefficient estimates in parentheses, and 1%, 5%, and 10% statistical significance are indicated with ***, **, and *, respectively.

Metropolitan Area /	(1)		(2)		(3)		(4)	
Controls	Coeff.	*t*-stat	Coeff.	*t*-stat	Coeff.	*t*-stat	Coeff.	*t*-stat
Atlanta GA			-0.38**	(-2.01)	-0.33*	(-1.81)	-0.27	(-1.47)
Boston MA			-0.57***	(-2.89)	-0.57***	(-2.94)	-0.48**	(-2.54)
Charlotte NC			-0.03	(-0.10)	-0.03	(-0.09)	0.02	(0.06)
Chicago IL			-0.39**	(-2.04)	-0.35*	(-1.89)	-0.25	(-1.35)
Cleveland OH			-0.22	(-0.79)	-0.24	(-0.89)	-0.10	(-0.37)
Dallas TX			-0.55***	(-2.61)	-0.50**	(-2.45)	-0.33	(-1.64)
Denver CO			-0.50**	(-2.19)	-0.48**	(-2.18)	-0.37*	(-1.68)
Detroit MI			-0.35*	(-1.72)	-0.30	(-1.54)	-0.24	(-1.21)
Las Vegas NV			0.25	(1.06)	0.27	(1.19)	0.36	(1.60)
Los Angeles CA			-0.52**	(-2.44)	-0.51**	(-2.47)	-0.48**	(-2.37)
Miami FL			-0.05	(-0.24)	-0.04	(-0.21)	0.04	(0.23)
Minneapolis MN			-0.36	(-1.45)	-0.32	(-1.32)	-0.16	(-0.66)
New York NY			-0.15	(-0.78)	-0.14	(-0.76)	-0.10	(-0.58)
Phoenix AZ			0.20	(0.71)	0.21	(0.79)	0.23	(0.88)
Portland OR			-0.17	(-0.92)	-0.15	(-0.80)	-0.07	(-0.39)
San Diego CA			-0.06	(-0.22)	0.04	(0.15)	0.01	(0.05)
San Francisco CA			-0.39**	(-2.47)	-0.37**	(-2.41)	-0.30**	(-1.98)
Seattle WA			-0.57**	(-2.31)	-0.51**	(-2.10)	-0.40*	(-1.70)
Tampa FL			-0.15	(-0.62)	-0.15	(-0.65)	-0.06	(-0.27)
Washington DC			-0.40**	(-2.07)	-0.46**	(-2.44)	-0.44**	(-2.40)
Nat. Fear $Index_{t-1}$	-0.37***	(-10.20)					-0.34***	(-9.26)
H.I. Momentum	0.81***	(29.96)	0.84***	(34.69)	0.82***	(29.67)	0.82***	(30.14)
Real GDP	0.08***	(3.00)			0.10***	(3.76)	0.08***	(3.03)
CPI	0.16***	(3.85)			0.20***	(4.59)	0.16***	(3.83)
Unemployment rate	-0.00	(-0.36)			0.00	(0.23)	-0.00	(-0.01)
HMI	0.01***	(6.42)			0.01***	(5.80)	0.01***	(6.06)
S&P 500 Index	0.01***	(3.31)			0.02***	(4.61)	0.01***	(3.80)
Constant	-0.00***	(-4.98)	-0.00***	(-1.80)	-0.00***	(-4.73)	-0.00***	(-5.00)
Observations	2,380		2,380		2,380		2,380	
Adjusted R-squared	0.40		0.34		0.38		0.40	

Table 3-4: Economic Significance of the Effect of *Local Fear Indexes* on the *National Home Price Index Returns*

This table presents the results on economic significance in Panel A and absolute relative significance in Panel B. In Panel A, Economic Significance reports the response of the housing market return to a two-standard deviation shock of the corresponding *City Fear Index* using the point estimates from running separate regressions of *National Home Index* returns on each of the local *Fear Indexes*. In all regressions, *City Fear Indexes* and the control variables are lagged at 1 month. Lower and upper bounds are presented in parentheses. Same calculations are done for the other control variables and their economic significance is presented. For brevity, the results are presented for the top seven cities ranked by Economic Significance. In Panel B, the column "Absolute relative significance" or ARS computes the absolute value from dividing "Economic significance" by the standard deviation of the national housing market returns. ARS is computed for *City Fear Indexes* along with the other control variables.

Panel A: Economic Significance and the lower and upper bounds

	Boston	DC	Los Angeles	San Francisco	Dallas	Denver	Seattle
Fear Index	-0.35	-0.31	-0.29	-0.27	-0.26	-0.24	-0.22
	(-0.49, -0.21)	(-0.45, -0.18)	(-0.43, -0.16)	(-0.41, -0.14)	(-0.41, -0.10)	(-0.38, -0.10)	(-0.37, -0.07)
Home Index Momentum	1.08	1.10	1.09	1.09	1.08	1.09	1.07
	(0.92, 1.24)	(0.95, 1.26)	(0.94, 1.25)	(0.93, 1.25)	(0.92, 1.24)	(0.93, 1.25)	(0.91, 1.23)
National Fear Index	-0.23	-0.29	-0.29	-0.24	-0.19	-0.24	-0.25
	(-0.37, -0.09)	(-0.43, -0.16)	(-0.42, -0.15)	(-0.38, -0.10)	(-0.35, -0.04)	(-0.38, -0.10)	(-0.39, -0.11)
Real GDP	0.08	0.10	0.10	0.06	0.07	0.09	0.11
	(-0.06, 0.22)	(-0.04, 0.23)	(-0.04, 0.24)	(-0.08, 0.20)	(-0.07, 0.21)	(-0.05, 0.24)	(-0.03, 0.26)
CPI	0.16	0.14	0.16	0.14	0.17	0.18	0.16
	(0.03, 0.30)	(0.00, 0.27)	(0.02, 0.29)	(0.00, 0.28)	(0.04, 0.31)	(0.04, 0.32)	(0.02, 0.30)
Unemp. rate	0.12	0.14	0.16	0.13	0.06	0.12	0.08
	(-0.03, 0.28)	(-0.01, 0.30)	(0.00, 0.32)	(-0.03, 0.29)	(-0.10, 0.23)	(-0.04, 0.28)	(-0.09, 0.24)
HMI	0.17	0.27	0.22	0.26	0.26	0.24	0.23
	(0.03, 0.32)	(0.13, 0.41)	(0.08, 0.37)	(0.12, 0.40)	(0.12, 0.40)	(0.10, 0.38)	(0.08, 0.37)
S&P 500 Index	0.30	0.26	0.24	0.26	0.22	0.25	0.22
	(0.16, 0.45)	(0.12, 0.41)	(0.10, 0.38)	(0.11, 0.40)	(0.08, 0.36)	(0.10, 0.39)	(0.08, 0.37)

Table 3-4: Continued

Panel B: Absolute Relative Significance

	Boston	DC	Los Angeles	San Francisco	Dallas	Denver	Seattle
Fear Index	0.37	0.33	0.31	0.29	0.27	0.25	0.23
Home Index Momentum	1.14	1.17	1.16	1.15	1.14	1.16	1.13
National Fear Index	0.24	0.31	0.30	0.25	0.21	0.25	0.27
Real GDP	0.08	0.10	0.10	0.06	0.08	0.10	0.12
CPI	0.17	0.14	0.17	0.15	0.18	0.19	0.17
Unemp. rate	0.13	0.15	0.17	0.14	0.07	0.13	0.08
HMI	0.18	0.28	0.24	0.28	0.28	0.25	0.24
S&P 500 Index	0.32	0.28	0.25	0.27	0.23	0.26	0.24

Table 3-5: *Fear Index* and Local *Housing Market Returns* in "Hot" and "Cold" Markets

This table presents the results of an analysis of the impact of local *Fear* on local home price index returns in "Hot" versus "Cold" markets. The table includes results from three regression models with the first including the full sample and the remaining two including either "Hot" or "Cold" Market. $Hot_{i,t-1}$ ($Cold_{i,t-1}$) is set to unity if housing market performance over the previous 6 months in city *i* at time *t-1* is above (below) the median return in the cross section of 20 cities, and to zero otherwise. For the purpose of this table, the reported *Local Fear* coefficients are hundred times their estimated coefficients. Variable descriptions are provided in Table 1. The sample period is from January 2005 to December 2014. All variables are presented at a monthly frequency. *t*-statistics are included below the coefficient estimates in parentheses, and 1%, 5%, and 10% statistical significance are indicated with ***,**, and *, respectively.

Sample:	Full Sample (1)	"Hot" Markets (2)	"Cold" Markets (3)
Local Fear$_{i,t-1}$		-0.54***	-0.64***
		(-5.27)	(-5.63)
*(Local Fear * Hot)*$_{i,t-1}$	-0.51***		
	(-4.72)		
*(Local Fear * Cold)*$_{i,t-1}$	-0.67***		
	(-6.31)		
Cold$_{i,t-1}$	0.00**		
	(2.49)		
Home Index Momentum	0.78***	0.74***	0.75***
	(26.02)	(18.10)	(16.79)
Real GDP	0.13***	0.11**	0.17**
	(3.03)	(1.97)	(2.50)
CPI	0.15**	0.30***	0.01
	(2.15)	(3.18)	(0.11)
Unemployment rate	-0.01	-0.01	-0.02
	(-0.94)	(-0.78)	(-1.30)
HMI	0.01***	0.01**	0.01*
	(3.19)	(2.55)	(1.76)
S&P 500 Index	0.02***	0.02***	0.02**
	(3.39)	(2.72)	(2.19)
Constant	-0.00***	-0.00**	-0.00*
	(-3.93)	(-2.35)	(-1.67)
Observations	2,380	1,190	1,190
Adj. *R*-squared	0.34	0.30	0.32

Table 3-6: *Fear Index* and Local *Housing Market Returns* in High and Low Bankruptcy Markets

This table presents the results of an analysis of the impact of *Local Fear Index* on local home price index returns in high and low bankruptcy markets. The table includes results from three regression models with the first one including the full sample and the other two including either low or high bankruptcy market. $High_{i,t-1}$ ($Low_{i,t-1}$) is set to unity if the average bankruptcy rate over the previous 6 months in city *i* at time *t-1* is above (below) the median rate in the cross section of 20 cities, and to zero otherwise. For the purpose of this table, the reported *Local Fear* coefficients are hundred times their estimated coefficients. Variable descriptions are provided in Table 1. Bankruptcy rates are not available prior to 2006, and as a result these series start from January 2006. All variables are presented at a monthly frequency. *t*-statistics are included below the coefficient estimates in parentheses, and 1%, 5%, and 10% statistical significance are indicated with ∗∗∗,∗∗, and ∗, respectively.

Sample:	Full Sample	Low Bankruptcy Markets	High Bankruptcy Markets
	(1)	(2)	(3)
Local Fear$_{i,t-1}$		-0.58***	-0.85***
		(-5.07)	(-6.33)
*(Local Fear * Low)*$_{i,t-1}$	-0.59***		
	(-4.77)		
*(Local Fear * High)*$_{i,t-1}$	-0.87***		
	(-7.12)		
High$_{i,t-1}$	0.00**		
	(1.99)		
Home Index Momentum	0.72***	0.73***	0.71***
	(21.08)	(13.72)	(14.16)
Real GDP	0.16***	0.16**	0.15*
	(3.23)	(2.47)	(1.91)
CPI	0.10	0.16	0.06
	(1.14)	(1.39)	(0.45)
Unemployment rate	-0.02	-0.02	-0.01
	(-1.59)	(-1.44)	(-0.80)
HMI	0.01**	0.01**	0.01
	(2.54)	(2.10)	(1.27)
S&P 500 Index	0.02***	0.01	0.03***
	(3.56)	(1.55)	(2.80)
Constant	-0.00***	-0.00***	-0.00
	(-3.68)	(-4.16)	(-0.61)
Observations	2,020	975	971
Adj. *R*-squared	0.30	0.26	0.28

Table 3-7: *Fear Index* and Local *Housing Market Returns* in Two-by-Two Sorts of High and Low Bankruptcy Markets and "Hot" and "Cold" Markets

This table presents the results of an analysis of the impact of *Local Fear Index* on local home price index returns in two-by-two sorts of high and low bankruptcy markets and "hot" and "cold" markets. The table includes results from five regression models, the first includes the full sample while the other four are run separately for each respective market. $Hot_{i,t-1}$ ($Cold_{i,t-1}$) is set to unity if housing market performance over the previous 6 months in city *i* at time *t-1* is above (below) the median return in the cross section of 20 cities, and to zero otherwise. $High_{i,t-1}$ ($Low_{i,t-1}$) is set to unity if the average bankruptcy rate over the previous 6 months in city *i* at time *t-1* is above (below) the median rate in the cross section of 20 cities, and to zero otherwise. For the purpose of this table, the reported *Local Fear* coefficients are hundred times their estimated coefficients. Variable descriptions are provided in Table 1. All variables are presented at a monthly frequency. *t*-statistics are included below the coefficient estimates in parentheses, and 1%, 5%, and 10% statistical significance are indicated with ∗∗∗,∗∗, and ∗, respectively.

Sample:	Full Sample	Cold Markets with High Bankruptcy	Hot Markets with High Bankruptcy	Hot Markets with Low Bankruptcy	Cold Markets with Low Bankruptcy
	(1)	(2)	(3)	(4)	(5)
Local Fear$_{i,t-1}$		-1.04***	-0.68***	-0.69***	-0.48***
		(-4.69)	(-4.14)	(-4.31)	(-2.93)
*(Local Fear * High * Cold)*$_{i,t-1}$	-1.06***				
	(-5.97)				
*(Local Fear * High * Hot)*$_{i,t-1}$	-0.69***				
	(-4.10)				
*(Local Fear * Low * Hot)*$_{i,t-1}$	-0.64***				
	(-3.53)				
*(Local Fear * Low * Cold)*$_{i,t-1}$	-0.55***				
	(-3.35)				
High$_{i,t-1}$	0.00**				
	(2.28)				
Cold$_{i,t-1}$	0.00***				
	(2.79)				
Home Index Momentum	0.76***	0.79***	0.63***	0.62***	0.77***
	(20.54)	(9.33)	(8.43)	(7.05)	(10.38)
Real GDP	0.15***	0.17	0.12	0.12	0.20**
	(3.04)	(1.33)	(1.25)	(1.35)	(2.05)
CPI	0.10	0.04	0.07	0.39***	-0.08
	(1.25)	(0.18)	(0.46)	(2.64)	(-0.45)
Unemployment rate	-0.01	-0.01	-0.02	-0.02	-0.04
	(-0.99)	(-0.20)	(-0.74)	(-0.73)	(-1.48)
HMI	0.01***	0.00	0.01	0.01	0.01
	(2.66)	(0.68)	(1.18)	(1.48)	(1.20)
S&P 500 Index	0.02***	0.02	0.04***	0.02	0.01
	(3.46)	(0.92)	(3.13)	(1.29)	(1.05)
Constant	-0.00***	0.00	-0.00	-0.00***	-0.00**
	(-4.64)	(0.43)	(-0.61)	(-3.43)	(-2.18)
Observations	2,020	422	549	437	538
Adj. *R*-squared	0.30	0.30	0.19	0.21	0.28

Table 3-8: *Fear Index* and the Effect of Bankruptcy on Local *Housing Market Returns* in "Hot" and "Cold" Markets

This table presents the results of an analysis of the impact of *Local Fear Index* interacted with bankruptcy rates on local housing market returns. In Panel A, the interaction term (*Local Fear *Bankruptcy filings)*$_{i,t-1}$ is a product of *Local Fear* and *Bankruptcy filings* in metropolitan area *i* at time *t-1*. Model specification (1) shows the results for a full sample and model specifications (2) and (3) show the results for "Cold" and "Hot" markets, respectively. Metropolitan area is classified as Cold (Hot) market if the previous 6 months average return was below (hot) the median return in my sample of 20 MSAs. Each model includes the following control variables: *Home Index Momentum*, *Real GDP*, *CPI*, *Unemployment rate*, *HMI*, and *S&P 500 Index*. Variable descriptions are provided in Table 1. In Panel B, *Bankruptcy filings* is centered at two different values: one standard deviation above and one standard deviation below the mean. Then the coefficient for *Local Fear* corresponding to each of those values is computed and reported. The *t*-statistics are included in parentheses below. The coefficients for the control variables are the same as those included in the corresponding models in Panel A. In Panel C, I report slopes of local housing market returns on *Local Fear* when *Bankruptcy filings* is held constant at different combinations of values from low (0.007%) to high (0.081%). The sample period is from January 2006 to December 2014. *t*-statistics are included below the coefficient estimates in parentheses, and 1%, 5%, and 10% statistical significance are indicated with ***,**, and *, respectively.

Panel A: Interaction between *Local Fear* and *Bankruptcy filings*

	Full Sample (1)	"Cold" Markets (2)	"Hot" Markets (3)
*(Local Fear * Bankruptcy filings)*$_{i,t-1}$	-19.03***	-20.08***	-14.97**
	(-3.81)	(-2.96)	(-2.04)
Main Effects and Controls	Yes	Yes	Yes
Observations	2,140	1,070	1,070
Adj. *R*-squared	0.34	0.32	0.17

Panel B: Interaction between *Local Fear* and recentered *Bankruptcy filings*

Model:	Full Sample (1)	"Cold" Markets (2)	"Hot" Markets (3)
Recentered *Bankruptcy filings (Low)*:			
Local Fear	-0.46***	-0.50***	-0.41***
	(-4.44)	(-3.25)	(-2.94)
Recentered *Bankruptcy filings (High)*:			
Local Fear	-1.06***	-1.09***	-0.90***
	(-9.90)	(-7.10)	(-6.06)
Controls	Yes	Yes	Yes
Observations	2,140	1,070	1,070

Table 3-8: Continued

Panel C: Interaction between *Local Fear* and constant *Bankruptcy filings* values

Model:	Full Sample (1)	"Cold" Markets (2)	"Hot" Markets (3)
Bankruptcy filings at:	Slope: (*z*-stat)	Slope: (*z*-stat)	Slope: (*z*-stat)
0.00007 (1%)	-0.24*	-0.25	-0.25
	(-1.67)	(-1.26)	(-1.24)
0.00010 (5%)	-0.29**	-0.31*	-0.30
	(-2.26)	(-1.70)	(-1.60)
0.00013 (10%)	-0.35***	-0.37**	-0.34**
	(-2.96)	(-2.21)	(-2.04)
0.00018 (25%)	-0.45***	-0.47***	-0.42***
	(-4.40)	(-3.23)	(-2.96)
0.00029 (50%)	-0.66***	-0.69***	-0.58***
	(-8.21)	(-5.83)	(-5.49)
0.00042 (75%)	-0.90***	-0.95***	-0.77***
	(-9.25)	(-6.76)	(-5.79)
0.00053 (90%)	-1.11***	-1.17***	-0.94***
	(-8.11)	(-6.11)	(-4.83)
0.00060 (95%)	-1.25***	-1.31***	-1.04***
	(-7.46)	(-5.68)	(-4.36)
0.00081 (99%)	-1.65***	-1.74***	-1.36***
	(-6.23)	(-4.81)	(-3.54)
Controls	Yes	Yes	Yes
Observations	2,140	1,070	1,070

CHAPTER 4

VOLATILITY IMPACT ON HOUSEHOLD SENTIMENT INDEX AND REAL ESTATE RETURNS

1. Introduction and Literature Review

A growing body of literature has emerged that examines the role of Google web searches as a predictor of various economic, financial, and socio-economic series. This study extends this literature by examining the impact of search-based sentiment measure on the residential housing markets in 20 major metropolitan statistical areas (MSAs). In particular, the main focus of this study is to examine the interaction of volatility with my measure of negative sentiment. I construct the sentiment index using search data provided by *Google Trends*. A landmark study to popularize Google search data is by Ginsberg et al. (2009), which documents the ability of Google search data to predict the incidence of influenza-like diseases in a more timely manner than traditional influenza surveillance systems.

In the context of financial markets, Da, Engelberg, and Gao (2011) use search data as a measure of retail investors' attention and examine its ability to predict short-term stock returns. Drake, Roulstone and Thornock (2012) use search data as a proxy of investor information demand around earnings announcements. Da, Engelberg, and Gao (2015) construct a negative sentiment index using search data and find its ability to predict short-term return reversals, temporary increases in volatility, and mutual fund flows. Some other studies that find Google search data to be positively associated with stock returns and trading volume are Joseph, Wintoki, and Zhang (2011), Bank, Larch, and Peter (2011), Vlastakis and Markellos (2012), and Takeda and Wakao (2014).

In the context of economic indicators, Vosen and Schmidt (2011) use search data to forecast private consumption; McLaren and Shanbhogue (2011), Askitas and Zimmermann (2009), and D'Amuri and Marcucci (2010) use search data to predict changes in unemployment rates; Choi and Varian (2012) use Google data to predict unemployment claims and automobile demand; Della Penna and Huang (2009) and Schmidt and Vosen (2009) use search data as a measure of consumer sentiment; and Guzman (2011) investigates Google data as a predictor of inflation.

In the context of housing markets, Wu and Brynjolfsson (2009), Hohenstatt, Käsbauer, and Schäfers (2011), Hohenstatt and Kaesbauer (2014), Beracha and Wintoki (2013), and Das, Ziobrowski, and Coulson (2015) argue that Google web searches related to real estate offer a reasonable proxy for demand in real estate markets. Two recent studies examine the impact of search data on Chinese housing markets, Wu and Deng (2015) use it as a measure of information flow while Zheng, Sun, Kahn (2015) use it as a measure of investor confidence. Lee and Mori (2015) use Google web search data to measure conspicuous demand in housing markets. Freybote and Fruits (2015) use Google web searches in examining the effect of perceived risk on home values.

In this essay, I focus my attention on the interaction of the *Fear Index* and volatility in the housing markets. I choose the S&P/Case-Shiller Home Price Indices in 20 MSAs to capture the differences in residential housing market volatilities across the United States. The fluctuations in real estate markets are quite different from city to city and over time, hence the importance of measuring the impact of volatility on the relation between sentiment and housing market returns.

I document that volatility impacts the relation between the *Fear Index* and home price index returns. I find as volatility increases, the housing markets become more sensitive to *Fear*, and as volatility declines, they become more immune to *Fear*. I also document the asymmetric response of housing markets to increases versus decreases in *Fear*. I attribute this finding to the negativity effect, widely explored in psychology literature. Furthermore, high volatility housing markets are more prone to this effect, while low volatility markets are less so. I also find that housing markets are more sensitive to *Fear* in times of falling prices, i.e. downside volatility increases more than upside volatility. I explain this phenomenon by the behavioral bias known as the "house money" effect, whereby prior gains and losses affect current sensitivity to losses. As housing markets are falling, households become more risk averse, which increases their sensitivity to negative sentiment. On the contrary, when housing markets are rising, households discount the effect of negative sentiment on future housing prices. Finally, I find a positive and significant relation between the *Fear Index* and downside volatility, but no significant link between *Fear* and upside volatility.

In Figure 1, I plot home price indexes for Las Vegas, NV and Dallas, TX to exemplify the differences in home price volatilities across different parts of the U.S. The historical standard deviation of home prices in Las Vegas is 47.85 and in Dallas it is 8.45. The median volatility across 20 regional areas is 25.29. The top three cities ranked by their overall volatility are San Diego, Los Angeles, and Miami, while the bottom three are Dallas, Cleveland, and Denver. Another interesting pattern is that high volatility MSAs include mostly the coastal cities, while the low volatility ones are primarily inland cities. Abraham and Hendershott (1996) examine cross-sectional annual variation in real house price movements in 30 U.S. cities between 1977 and 1992 and find that factors, which account for the deviations from the equilibrium price, are more pronounced in the coastal cities and are representative of speculative pressures that lead to price bubbles.

2. Data and Methodology

I use the same methodology in constructing the *Fear Index* for each MSA as I did in the previous chapter of this dissertation. I start with a broad list of terms relating to real estate and the economy.[27] Then, I obtain web search data from *Google Trends*[28] on all these terms for each MSA in the sample. Next, I narrow down the list to 30 terms in constructing the *Fear Index* for each MSA. I follow Da, Engelberg and Gao (2015) as I adjust search volume series termed the Search Volume Index (SVI) in constructing a negative sentiment index.

The method can be described in the following steps:

1) Take the log differences of each term's SVIs:

   $\Delta SVI_{i,t} = \ln\left(SVI_{i,t}\right) - \ln(SVI_{i,t-1})$

2) Winsorize each series at the 5% level (2.5% in each tail).

3) Remove annual seasonality from $\Delta SVI_{i,t}$ by regressing $\Delta SVI_{i,t}$ on annual dummies and keeping the residual.

4) Standardize each series by scaling each by the time-series standard deviation. The final series are named as adjusted SVI or ΔASVI.

5) Running expanding window backward rolling regressions of $\Delta ASVI_i$ on housing market index returns every January to identify 30 most important terms in each time period. I use these terms to compute *Fear Index* in the following year.

[27] The first list includes real estate terms retrieved from: http://worklife.columbia.edu/real-estate-terminology#section1. To supplement the first list, I use another source for real estate terms accessible at http://www.realestateabc.com/glossary/. The third list includes economic terms from the Harvard IV-4 Dictionary and the Lasswell Value Dictionary retrieved from: http://www.wjh.harvard.edu/~inquirer/homecat.htm

[28] The link to *Googel Trends* is: https://www.google.com/trends/explore

6) Computing the average $\Delta ASVI$ of these 30 terms in month *t*:

$$Fears\ Index_{\ t} = \frac{\sum_{\mathrm{j=1}}^{30}(\Delta ASVI_{j,t})}{30}$$

For example, at the end of December 2013, I run a regression of Δ*ASVI* on contemporaneous home price index returns during the period of January 2004-December 2013, for each query term in every MSA. Next, I sort the terms based on their *t*-statistic on Δ*ASVI* in ascending order and select 30 most negative terms to be used in forming the *Fear Index* for the period from January 2014 to December 2014. The *Fear Index* in month *t* over this period is simply the average Δ*ASVI* of these 30 terms in that month. Thus, I construct the *Fear Index* for each of 20 MSAs that includes web search terms that are most related to home index returns in that city. Combining the search interest for 30 terms provides an aggregate measure of revealed sentiment uniquely capturing local housing market characteristics.

I describe all the variables used in this study in Table 1. The key variables of interest are *Fear Index* or *Local Fear*, *Home Index*, *Volatility*, and *ssdGAP*. *Local Fear* is a measure of negative household sentiment in the housing markets that is constructed for each of the 20 largest MSAs. The *Home Index* is the main dependent variable in this study that measures the change in the Case-Shiller Home Price Index in each of the 20 local markets. *Volatility* is a dynamic measure that captures the variation in the local housing market conditions. I use standard deviation and idiosyncratic volatility as alternative measures of volatility. Standard deviation of monthly housing market returns is computed on a rolling 36-month basis for each MSA in the sample. Idiosyncratic volatility assess risk after I remove the systematic component from housing returns. I use a two-factor model similar to the one in Miller and Pandher (2008), who estimate submarket idiosyncratic volatility at the zip code level. Explicitly, this model assumes only two sources of systematic risk affecting local housing returns. The first factor represents the risk exposure and sensitivity of local housing market returns to the stock market, while the second factor reflects the risk and sensitivity to changes in the national housing market. As such, idiosyncratic volatility captures the local drivers of housing market returns that are unrelated to systematic economy-wide drivers. As it rises, systematic factors explain less of the observed variation in the local housing returns.

In particular, I estimate it as a root-mean-square deviation of residuals from a two-factor model, which regresses excess local housing market returns on excess national housing market returns and excess returns on the S&P 500 Index. I run the following rolling regression each month over the previous 36 periods for each MSA:

$$Home\ Index\ PR_t = \alpha_0 + \beta_1 Stock\ Market\ PR_t + \beta_2 National\ Home\ Index\ PR_t + \varepsilon_t \qquad (1)$$

where *Home Index* PR_t is the excess return of the local home index over the 3-month T-bill rate in month t. *Stock Market* PR_t is the excess return of the S&P 500 Index over the 3-month T-bill rate in month t. *National Home Index* PR_t is the excess return of the Case-Shiller National Home Price Index over the 3-month T-bill in month t. β_1 and β_2 are the local housing market's sensitivity to the stock market (stock market beta) and the overall housing market (housing market beta), respectively. Idiosyncratic volatility is the root-mean-square deviation (RMSD) of the estimated residuals:

$$Idiosyncratic\ Volatility = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\varepsilon_t - \bar{\varepsilon})^2} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\varepsilon_t)^2} \qquad (2)$$

I posit that this measure of volatility captures the fluctuations of the unsystematic component driving local housing returns. Standard deviation and idiosyncratic volatility in month t both capture the deviation over the previous 36 months (from t-36 to t-1). The last variable of interest in Table 1 is *ssdGAP*, which captures the difference between downside volatility and upside volatility. I follow Low (2004) in computing downside and upside volatilities. More formally, *ssdGAP* and upside (*ssdUpside*) and downside (*ssdDownside*) standard semideviations of the housing market returns are defined as:

$$ssdGAP = ssdUpside - ssdDownside$$

$$ssdUpside = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \max(Home\ Index_{t-i}\,, 0)^2} \tag{3}$$

$$ssdDownside = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \min(Home\ Index_{t-i}\,, 0)^2}$$

where *Home Index* is a series of housing market returns in each local market and *n* equals to 36, since the standard semideviations are computed in rolling 36-month windows. The rolling windows offer an *ex post* look at the upside-downside orientation of the housing market. A negative *ssdGAP* indicates stronger downside than upside housing market return volatility in the 36-month window period. The other variables in Table 1 are used as controls in the regressions, which are *Home Index Momentum*, *Real GDP*, *CPI*, *Unemployment rate*, *HMI*, and *S&P 500 Index*.

Table 2 presents sample characteristics in Panel A and Pearson correlation coefficients in Panel B. The reported values in Panel A for the *Fear Index*, *Home Index*, *Home Index Momentum*, *Standard Deviation*, *Idiosyncratic Volatility*, and *ssdGAP* are first computed at the MSA level and then averaged across 20 cities. The shown statistics for the *Home Index*, *Real GDP*, *CPI*, *Unemployment Rate*, and *HMI* are computed using the levels of these variables. For example, the mean value of 152.55 for *Home Index* is calculated in two steps. First, I find the average value of the Home Price Index in each MSA, and then compute the average across MSAs over the sample period from 2005 to 2014. I should note that there is quite a variation in the average index values across my sample of MSAs. However, I cannot just compare these averages to assess the relative performance, since initial index values are not the same. For example, the average in Detroit is 92.31, while it is 206.45 in Los Angeles. This difference can be partially explained by the initial index values in January 2005 of 123.06 and 219.41, respectively. In panel B and throughout the rest of this study, I use log differences of the home price indexes to mitigate the issue on non-stationarity. For the same reason, I use log changes of *Real GDP*, *CPI*, *Unemployment Rate*, and *HMI.* I do not transform the *S&P 500 Index* since the series already represent monthly returns and are stationary. The mean monthly return of the *S&P 500 Index* is at 1% during the sample period, but it fluctuates widely with the lowest taking place in October 2008 at -16.94%, and the highest in October 2011 at 10.77%.

From Panel B of Table 2, I gain some understanding on the direction and strength of association between various pairs of variables. I report Person correlation coefficients followed by asterisks to denote statistical significance. The main focus of these results is on the correlation between the *Fear Index* and the *Home Index*, which I expect to be negatively and significantly related. I find that they are, with the correlation coefficient at -0.15 and significance at a 1% level. *Fear Index* is also negatively and significantly associated with *ssdGAP*, which implies that fear goes up as downside volatility increases relative to upside volatility.

From Panel B, the strongest positive correlation pairs are *Standard Deviation* and *Idiosyncratic Volatility* (ρ=0.88), *Home Index Momentum* and *ssdGAP* (ρ=0.72), and *Home Index* and *Home Index Momentum* (ρ=0.55). Strong positive correlation between these pairs is not surprising given they are all related to home price index returns in a systematic way. The strongest negative correlation is between the following pairs: *Home Index Momentum* and *Unemployment Rate* (ρ=-0.45), *Idiosyncratic Volatility* and *ssdGAP* (ρ=-0.38), and *Standard Deviation* and *ssdGAP* (ρ=-0.36). The first pair reveals that unemployment drops when housing market returns over the last year are increasing. This is not surprising since improving conditions in the labor market and increased demand for single-family homes are strongly associated with an economic expansion. Negative correlation between both measures of volatility and *ssdGAP* reveals that risk tends to increase when downside volatility increases more than upside volatility.

3. *Fear Index* and the Effect of Volatility on Housing Market Returns

In this section, I examine the interaction of *Fear* and volatility on housing market returns using a panel data regression framework. My focus is on the local markets since *Fear*, housing market returns, and its associated volatility are all capturing housing market conditions at the MSA level. A key objective is to investigate whether there is a systematic relation between *Fear* and volatility as they both help to predict future changes of the housing market returns.

Table 3 presents the results for two model specifications. The first includes standard deviation and the second idiosyncratic volatility as an alternative measure of volatility. Both measures of volatility are continuous variables, the construction of which I discussed in the previous section. I run the following panel data regression with city fixed effects in Panel A:

$$\begin{aligned} Home\ Index_{it} &= \beta_0 + \beta_1 (Fear\ Index \times Volatility)_{i,t-1} \\ &+ \beta_2 Fear\ Index_{i,t-1} + \beta_3 Volatility_{i,t-1} + \sum_m \gamma_m Control_{it}^m + \varepsilon_{it} \end{aligned} \tag{4}$$

where *Home Index*$_{it}$ stands for the Case-Shiller Home Price Index returns in MSA *i* at time *t*. *Volatility* stands for either *Standard Deviation* in Model (1) or *Idiosyncratic Volatility* in Model (2). *Fear Index* is the measure of negative sentiment estimated for each housing market at the

MSA level. $(Fear\ Index * Volatility)_{i,t-1}$ is the interaction term of *Fear* and *Volatility* in city *i* at time *t-1*. I use the following set of *Control* variables: *Home Index Momentum, Real GDP*, *CPI*, *Unemployment Rate*, *HMI*, and *S&P 500 Index*. Their full descriptions are provided in Table 1.

It is important to note that there are some difficulties in interpreting the coefficients β_2 and β_3, since they reflect conditional relationship. β_2 is the effect of *Fear Index* on *Home Index* when *Volatility* equals zero. Similarly, β_3 is the effect of *Volatility* on *Home Index* when *Fear Index* equals zero. To help in interpreting the main effects I use the method of recentering in Panels B and C. First, I report results on the interaction term of *Fear Index* and *Volatility* in Panel A of Table 3. The estimated coefficient is negative and significant which signifies that the slope of *Fear Index* on the response variable changes as the values on *Volatility* change. This finding supports the assertion that response to negative sentiment is subject to the level of housing market volatility.

In Panel B, I center *Volatility* at two different values: one standard deviation above (High) and one standard deviation below the mean (Low). Then, I compute the coefficient on *Fear Index* corresponding to each of those values. These coefficients can be interpreted as the slopes of housing price changes on *Local Fear* when *Volatility* equals mean *Volatility* plus one standard deviation and mean *Volatility* minus one standard deviation. Panel B reports those coefficients.

The results show that coefficient on *Fear Index* is greater when *Standard Deviation* is centered one standard deviation above the mean than when it is centered one standard deviation below the mean. I observe the same pattern when using *Idiosyncratic Volatility* in Model (2). There is no need to test for statistical significance of the difference in the coefficients for high versus low as that test is already reflected in the significance of the interaction term in the corresponding models in Panel A. I posit that housing markets characterized by high uncertainty are more sensitive to changes in *Fear*, while housing markets that do not experience much fluctuation are less responsive to changes in *Fear*. One of the behavioral explanations of this result can be loosely attributed to loss aversion. Loss aversion refers to people's heightened sensitivity to losses relative to gains of the same magnitude. High volatility in the housing markets can lead to substantial volatility in the overall level of households' wealth. Given that investors are more sensitive to losses than to gains, these fluctuations can cause a substantial discomfort and lead to higher sensitivity to changes in *Fear*.

In Panel C, I provide further evidence on the interpretation of the interaction term from Panel A. I examine the slopes of home price changes on *Fear Index* when *Volatility* is held constant at different combinations of values from low (1%) to high (99%). The results show that in each model, the slope increases as *Volatility* increases as well. The results are similar for both specifications of *Volatility*, i.e. *Standard Deviation* and *Idiosyncratic Volatility*. In sum, I find evidence that *Fear Index* helps to predict local housing market returns and this association strengthens as volatility increases.

4. Asymmetric Response to Increases versus Decreases in *Fear* by Volatility Group

In this section, I examine whether local housing markets respond differently to increases versus decreases in *Fear* and whether this response is subject to the relative volatility found in the sample of MSAs. My objective is of twofold: first I analyze whether increases in *Fear* evoke a greater response, and second I investigate whether this response depends on volatility.

Tetlock *et al.* (2008) find that negative words in the financial press help to forecast low firm earnings. They also find that market prices consistently underreact to negative words in firm-specific news stories, especially those that relate to fundamentals. Garcia (2013) constructs a sentiment measure based on financial news from the *New York Times* and finds that investor sentiment has a more prominent effect on stock returns during bad times. Akhtar *et al.* (2011, 2012) find the asymmetric response in the U.S. and Australian stock markets at the release of positive versus negative consumer sentiment news. They term this as the "negativity effect" named as such in the psychology literature. As a behavioral concept, it suggests that individuals are more prone to respond to a negative rather than positive stimuli.

I test whether the negativity effect is present in the response to *Fear* in the housing markets. I first divide the *Fear Index* up into two parts, one capturing increases and the other decreases in *Fear*. I accomplish that by creating two binary variables. *Increase* (*Decrease*) dummy takes on the value of one (zero) if *Fear* in that month is a positive value, and zero (one) if it is a negative one. By construction, *Fear* represents the change in the search volume interest from one month to the next, so positive values imply increases in *Fear* while negative values imply decreases to it. I use the following regression to capture the asymmetric response to increases versus decreases in *Fear*:

$$Home\ Index_{it} = \beta_0 + \beta_1 (Fear\ Index \times Decrease)_{i,t-1}$$

$$+\beta_2 (Fear\ Index \times Increase)_{i,t-1} + \beta_3 Increase_{i,t-1} + \sum_m \gamma_m Control_{it}^m + \varepsilon_{it} \qquad (5)$$

where $Home\ Index_{it}$ is the return on the Case/Shiller Home Price Index in MSA *i* in month *t*. *Decrease (Increase)* is a binary variable that takes on the value of 1 if *Fear Index* is less (greater) than zero, and 0 otherwise. $(Fear\ Index \times Decrease)_{i,t-1}$ is the interaction term of *Fear Index* and *Decrease* in MSA *i* at time *t-1*. $(Fear\ Index \times Increase)_{i,t-1}$ is the interaction term of *Fear Index* and *Increase* in MSA *i* at time *t-1*. I use the same controls, which are *Home Index Momentum*, *Real GDP*, *CPI*, *Unemployment Rate*, *HMI*, and *S&P 500 Index*. Model specification (1) includes the full sample of 20 MSAs, while Models (2) and (3) include observations for high versus low volatility groups, respectively. High (low) volatility group includes those cities that have experienced above (below) the median volatility in the cross section of 20 cities. Volatility is computed monthly for each MSA as the standard deviation of home index returns over the previous 36 months. The main focus is on the relative significance of estimated coefficients β_1 and β_2 in each model specification. Results from these regressions are presented in Table 4.

In Model (1), the absolute value of estimated coefficient β_2 is greater than that for β_1. They are significantly different as well at a 5% level. This asymmetric response implies that housing market returns are more sensitive to increases in *Fear* than to decreases in it. This result is consistent with the negativity effect found in the equity and futures markets.[29] A negative sign of the β_1 coefficient is harder to interpret, but it indicates the expected relation. As *Fear* decreases, i.e. its values become more negative, housing markets rise. In all three models, I observe a highly positive and significant coefficient on the *Home Index Momentum*. It reveals that housing market returns are highly autocorrelated and it is important to control for it.

In Model (2), I observe a similar pattern that the absolute value of β_2 is greater than β_1, but the difference between them is no longer statistically significant. This finding suggests that cities with lower fluctuations in their housing prices respond to decreases and increases in *Fear* in a similar fashion, i.e. when *Fear* goes up, housing markets decline over the next month and when *Fear* goes down, housing markets tend to go up. The negativity effect previously found in the full sample is not observed in low volatility cities. I reason that low volatility MSAs are characterized by relative price stability, and that works to reduce their sensitivity to negative sentiment, but increase their response to positive sentiment.

[29] See Akhtat *et al.* (2011 and 2012).

For example, the housing market in Dallas would fall more often into a low volatility group as can be seen from Figure 1. This market did not experience any major losses even during the Great Recession (2007-2009), which falls within my sample period. In this MSA, market participants may not react as strongly to increases in *Fear*, since they place a low probability of big losses to occur. On the contrary, market participants are more prone to respond to positive news that reassure their expectations of rising demand for homes. Decreases in *Fear* would be one of such conduits of carrying positive news.

In Model (3), the estimated coefficient on β_1 is not significant, while β_2 is negative and statistically significant at a 1% level. This result supports the finding from the full sample on the negativity effect. The negativity hypothesis can be formally stated as follows:

The increases (decreases) in negative sentiment will induce a negative (negligible) housing market reaction.

High volatility housing markets exhibit the strongest evidence of this effect, with the negative and significant response to increases in *Fear*, but negligible response to decreases in *Fear*. I posit that these markets experience a heightened sensitivity to negative news, because of potential losses. It may also be attributed to higher demand for negative news in highly volatile housing markets. Figure 2 provides some support of this view. It depicts Google search interest for the word "bad" under the subcategory of Economic News for Las Vegas, Tampa, and Dallas over the period from January 2005 to December 2014. I notice that there is a greater interest over time for "bad" news in Las Vegas and Tampa, than it is in Dallas. Specifically, volatility in Las Vegas is 53.4 and average search interest of 22, in Tampa it is 37.11 with average search interest of 13, and in Dallas the volatility is 7.34 and average search interest of 8 over the sample period. A general pattern is observed as volatility rises, the search for "bad" news goes up.

The psychology literature argues that people's emotions affect information procession and decision making.[30] In particular, negative mood states affect people's decision making abilities. This evidence suggests that market participants may use different decision-making rules in times of high uncertainty or risk and exhibit greater sensitivity to rising *Fear*.

A number of factors contribute to the negativity effect, but the more important ones are selective media coverage and skewed demand for bad news. These two factors are related, with one reinforcing the other. Watching news, regardless whether it is the Fox News, MSNBC, or CNN, can be emotionally disturbing and draining at times. It is not surprising, since mass media regularly give more coverage to bad news rather than good news.[31] Hearing negative news grabs people's attention more than hearing equally good news. It incentivizes mass media to focus on bad news in order to sustain a larger following, which also helps to attract advertisers, whose payments comprise a large portion of media's profits.

Some other studies argue that mass media's emphasis on negative news can be explained by a greater demand for such news. A study by McCluskey *et al.* (2015) builds on the Law of Diminishing Marginal Utility to show that people generally have more to lose from neglecting negative news than to gain from awareness of a positive one. In an interview, Jill McCluskey explains: "People will always want bad news because they don't want those bad situations to happen to them."[32] Trussler and Soroka (2014) also argue for the importance of demand-side

[30] Lerner and Keltner (2001) show how fear and anger trigger different perceptions of risk; Tiedens and Linton (2001) show that emotions evoke either reliance on heuristic or systematic processing of information; Smith and Ellsworth (1985) and Ortony, Clore, and Collins (1988) observe that anxiety, hope, and sadness are linked with a greater sense of uncertainty; Forgas (1998) find that transient moods affect people's tendency to commit the fundamental attribution errors (FAE); and Gino, Wood, and Schweitzer (2009) show that anxiety makes individuals more receptive to advice.

[31] Numerous studies find that news tends to be more negative than positive. For example, mass media exaggerate the prevalence of violent crime (e.g., Altheide 1997; Davie and Lee 1995; Smith 1984), more attention is given to events involving conflict or crisis (Bagdikian 1987; Herman and Chomsky 2010; Paraschos 1988; Patterson 1997; Shoemaker, Danielian, and Brendlinger 1991), and more coverage is given to bad economic trends (Harrington 1989).

explanations of news content. They conduct an experiment and find that participants spend more time on reading negative content than on content more neutral or positive. Stuart Soroka voices another argument in favor of greater demand for bad news: “We are living, and always have lived, in a very information-rich environment. We can’t pay attention to everything. We need some heuristic that helps us select the information that’s important and the information that’s not—or at least the information that requires us to change our behavior versus the information that doesn’t.”[32]

In this context, excessive media coverage of negative news in conjunction with higher demand for such news work to sustain the negativity effect, especially in high volatility markets. As individuals are drawn to negative news, which are abundant during highly volatile market environments, their sentiment affects buying and selling decisions in the housing market. In particular, increases in the *Fear Index* are likely to cause households to sell homes or delay purchasing decisions in the belief that the housing market is going to fall in the (near) future. On the contrary, positive sentiment news do not receive the same attention and media coverage to generate counterpart media-driven force to spread the positive outlook and spark the buying behavior.

In sum, these results reveal that housing markets exhibit the asymmetric response to increases versus decreases in *Fear*. I attribute this finding to the negativity effect, which seems to be more pronounced in high volatility markets. I also offer some alternative explanations of this finding. In the next section, I dissect volatility into good and bad components to further understand housing markets’ reaction to changes in *Fear*.

5. Semidimensions of the *Fear Index*

[32] A full article featuring this quote has been published by Pacific Standard and can be retrieved at: https://psmag.com/why-bad-news-is-good-news-57c9ecd4ee5e#.lgwrh7x4s.

In this section, I am interested to extract bad and good components of volatility to examine their interaction with the *Fear Index*. As I described above, I follow Low (2004) to compute the downside volatility (*ssdDownside*), upside volatility (*ssdUpside*), and the difference between them (*ssdGAP*). A negative *ssdGAP* indicates a stronger downside than upside housing market return volatility. Low (2004) argues that risk perception, using the implied Volatility Index (VIX) as a proxy, is semidimensional in nature, i.e., it tends to increase when downside volatility increases more than upside volatility. His findings provide evidence to support the common perception that financial markets are volatile only when prices are dropping. In addition, he finds that extreme price drops are strongly associated with rapid increases in risk, while extreme price rises are weakly associated with decreases in risk.

I construct two regression models to perform the tests. In the first test, I analyze whether housing market's response to the lagged *Fear Index* is semidimensional in nature, i.e., response is subject to the relative magnitudes of downside versus upside volatilities. In the second test, I examine whether falling prices are strongly and negatively correlated with the *Fear Index.* A negative correlation between the *Fear Index* and *ssdGAP* indicates that *Fear* tends to increase when downside volatility increases more than upside volatility.

For the first test, I use the following regression with city fixed effects:

$$Home\ Index_{it} = \beta_0 + \beta_1(Fear\ Index \times ssdGAP)_{i,t-1}$$
$$+\beta_2 Fear\ Index_{i,t-1} + \beta_3 ssdGAP_{i,t-1} + \sum_m \gamma_m Control_{it}^m + \varepsilon_{it} \quad (6)$$

where the *Home Index*, *Fear Index*, *ssdGAP*, and *Controls* are defined as before. The only exception is the *Home Index Momentum*, which I adjust to account for its high correlation with the *ssdGAP*. In its place, I use the residual after regressing *Home Index Momentum* on *ssdGAP*. $(Fear\ Index \times ssdGAP)_{i,t-1}$ is the interaction term of the *Fear Index* and *ssdGAP* in MSA *i* at time *t-1*. The results are presented in Table 5. In Panel A, I run three model specifications to improve the robustness of my results. Model (1) excludes the interaction term, $(Fear\ Index \times ssdGAP)_{i,t-1}$; Model (2) excludes the following controls: *Real GDP*, *CPI*, *Unemployment rate*, *HMI*, and *S&P 500 Index*; and Model (3) presents the results from a complete model given in equation (6).

In Model (1), estimated coefficients on $Fear\ Index_{i,t-1}$ and $ssdGAP_{i,t-1}$ are significant at a 1% level. Housing market returns decrease as *Fear* goes up, and increase as upside volatility rises more than downside volatility. In Models (2) and (3) the interaction term is positive and significant, which implies that *Fear*'s impact on the *Home Index* is subject to the level of *ssdGAP*. To help interpret this result, I use the same method of recentering as I did in Table 3. In Panels B, I compute the estimated coefficient on the *Fear Index* corresponding to high and low *ssdGAP* values. These coefficients can be interpreted as the slopes of *Home Index* on *Local Fear* when *ssdGAP* equals mean *ssdGAP* plus one standard deviation and mean *ssdGAP* minus one standard deviation. The absolute value of estimated coefficient on *Fear Index* is greater at low value of *ssdGAP* than it is at high. The same pattern in observed from Panel C. This result implies that the effect of *Fear* on the *Home Index* is stronger when downside volatility increases more than upside volatility. There is no need to test for statistical significance of the difference in the coefficients for high versus low *ssdGAP* values as that test is already reflected in the significance of the interaction term in Panel A. The results suggest that housing market's response to *Fear* is asymmetric; the *Home Index* is more sensitive to negative sentiment in times of escalating downside risk.

For the second test, I use the following regression:

$$Fear\ Index_{it} = \beta_0 + \beta_1 ssdGAP_{i,t-1} + \beta_2 Fear\ Index_{i,t-1} + \sum_m \gamma_m Control_{it}^m + \varepsilon_{it} \qquad (7)$$

where all the variables are defined as before. Table 6 Model (1) presents the results from running this regression. These results show that lagged *ssdGAP* is negatively and significantly related to *Fear Index*. It shows that negative sentiment rises when downside volatility increases more than upside volatility. In Model (2), I replace *ssdGAP* with *ssdDownside* to examine the relation directly between downside volatility and future *Fear Index*. The coefficient on *ssdDownside* is positive and significant, which implies that *Fear Index* goes up following increases in downside volatility. In Model (3), I do not observe a significant association between lagged upside volatility and negative sentiment. I posit that people become more fearful when bad risk is rising, but do not respond in a systematic way to changes in good risk.

There are several possible behavioral explanations of my results in this section, but the two that dominate are loss aversion and "house money" effect. Thaler and Johnson (1990) argue that the degree of loss aversion is not constant over time, but depends on prior gains and losses. In particular, they present evidence that after a gain, people are more risk seeking than usual, while after a prior loss, they become more risk averse. The "house money" effect asserts that prior gains and losses affect current sensitivity to losses, which is consistent with Thaler and Johnson's (1990) finding even though they do not call it as such. Benartzi and Thaler (1995), Barberis and Huang (2001) suggest that loss aversion is helpful in explaining a high equity premium. Barberis, Huang, and Santos (2001) expand on their prior model to show that it captures not only loss aversion, but also its dynamic version sometimes known as the "house money" effect. Panel C of Table 5 shows that at high levels of *ssdGAP*, i.e. high prior gains, housing market returns are no longer sensitive to changes in *Fear*. On the other hand, at low levels of *ssdGAP*, i.e. high prior losses, housing market returns are very sensitive to changes in *Fear*. Supporting evidence in Table 6 shows that *Fear* goes up as downside risk goes up, but

Fear shows no response to changes in upside risk. As Thaler and Johnson (1990) argue that losses after prior losses are more painful than usual, perhaps because individuals have only limited capacity for handling bad news. I find that negative sentiment is more informative with regard to future housing market returns after people experienced prior losses.

6. Conclusion

I examine the role of negative sentiment revealed by Google searches on housing market returns controlling for volatility. I use Case–Shiller individual metro area indices to track changes in housing prices. Using standard deviation and idiosyncratic volatility as alternative measures of volatility, I find that response to *Fear* across MSAs is stronger as volatility increases.

Further, cities with low volatility exhibit a similar response to increases versus decreases in *Fear*, while high volatility cities display an asymmetric response, with a significant and negative reaction to an increase in *Fear* but little reaction to a decrease in *Fear*. I also differentiate between downside volatility and upside volatility, and find that *Fear* has a stronger impact on housing price changes as downside risk goes up relative to the upside volatility. Finally, I find that it is the downside and not the upside volatility that affects changes in *Fear*. I offer some possible behavioral explanations of key results, expanding on loss aversion and the “house money” effect.

References

Abraham, J.M. and P.H. Hendershott. 1996. Bubbles in Metropolitan Housing Markets. *Journal of Housing Research* 7(2): 191–207.

Akhtar, S., R. Faff, B. Oliver and A. Subrahmanyam. 2011. The Power of Bad: The Negativity Bias in Australian Consumer Sentiment Announcements on Stock Returns. *Journal of Banking and Finance* 35(5): 1239–1249.

Akhtar, S., R. Faff, B. Oliver and A. Subrahmanyam. 2012. Stock Salience and the Asymmetric Market Effect of Consumer Sentiment News. *Journal of Banking and Finance* 36(12): 3289–3301.

Altheide, D.L. 1997. The News Media, the Problem Frame, and the Production of Fear. *The Sociological Quarterly* 38(4): 647–668.

Askitas, N. and K.F. Zimmermann. 2009. Google Econometrics and Unemployment Forecasting. *German Council for Social and Economic Data (RatSWD) Research Notes*, (41).

Bagdikian, B. 1987. *The Media Monopoly.* 2nd ed. Boston: Beacon Press.

Bank, M., M. Larch and G. Peter. 2011. Google Search Volume and its Influence on Liquidity and Returns of German Stocks. *Financial markets and portfolio management* 25(3): 239–264.

Barberis, N. and M. Huang. 2001. Mental Accounting, Loss Aversion, and Individual Stock Returns. *The Journal of Finance* 56(4): 1247–1292.

Barberis, N., M. Huang and T. Santos. 2001. Prospect Theory and Asset Prices. *Quarterly Journal of Economics* 116(1): 1–53.

Benartzi, S. and R.H. Thaler. 1995. Myopic Loss Aversion and the Equity Premium Puzzle. *The Quarterly Journal of Economics* 110(1): 73–92.

Beracha, E. and M.B. Wintoki. 2013. Forecasting Residential Real Estate Price Changes from Online Search Activity. *Journal of Real Estate Research* 35(3): 283–312.

Choi, H. and H. Varian. 2012. Predicting the Present with Google Trends. *Economic Record* 88(1): 2–9.

D'Amuri, F. and J. Marcucci. 2009. 'Google it!' Forecasting the US Unemployment Rate with a Google Job Search Index (No. 2009–32). *Institute for Social and Economic Research.*

Da, Z., J. Engelberg and P. Gao. 2011. In Search of Attention. *Journal of Finance* 66: 1461–1499.

Da, Z., J. Engelberg and P. Gao. 2015. The Sum of All FEARS Investor Sentiment and Asset Prices. *Review of Financial Studies* 28(1): 1–32.

Das, P., A. Ziobrowski and N.E. Coulson. 2015. Online Information Search, Market Fundamentals and Apartment Real Estate. *The Journal of Real Estate Finance and Economics* 51(4): 480–502.

Davie, W.R. and J.S. Lee. 1995. Sex, Violence, and Consonance/Differentiation: An Analysis of Local TV News Values. *Journalism and Mass Communication Quarterly* 72(1): 128–138.

Della Penna, N. and H. Huang. 2009. Constructing Consumer Sentiment Index for U.S. Using Google Searches. Working Paper No. 2009–2026, University of Alberta.

Drake, M.S., D.T. Roulstone and J.R. Thornock. 2012. Investor Information Demand: Evidence from Google Searches Around Earnings Announcements. *Journal of Accounting Research* 50(4): 1001–1040.

Forgas, J.P. 1998. On Being Happy and Mistaken: Mood Effects on the Fundamental Attribution Error. *Journal of Personality and Social Psychology* 75(2): 318–331.

Freybote, J. and E. Fruits. 2015. Perceived Environmental Risk, Media, and Residential Sales Prices. *Journal of Real Estate Research* 37(2): 217–244.

Garcia, D., 2013. Sentiment During Recessions. *The Journal of Finance* 68(3): 1267–1300.

Gino, F., A. Wood and M.E. Schweitzer. 2009. How Anxiety Increases Advice-Taking (Even When the Advice is Bad). Working paper, Wharton School of the University of Pennsylvania.

Ginsberg, J., M.H. Mohebb, R.S. Patel, L. Brammer, M.S. Smolinsky and L. Brilliant. 2009. Detecting Influence Epidemics Using Search Engine Query Data. *Nature* 457: 1012–1014.

Guzman, G. 2011. Internet Search Behavior as an Economic Forecasting Tool: The Case of Inflation Expectations. *The Journal of Economic and Social Measurement* 36(3): 119–167.

Harrington, D.E. 1989. Economic News on Television: The Determinants of Coverage. *Public Opinion Quarterly* 53(1): 17–40.

Herman, E.S. and N. Chomsky. 2010. *Manufacturing Consent: The Political Economy of the Mass Media.* Random House.

Hohenstatt, R. and M. Kaesbauer. 2014. GECO's Weather Forecast for the UK Housing Market: To What Extent Can We Rely on Google Econometrics? *Journal of Real Estate Research* 36(2): 253–281.

Hohenstatt, R., M. Käsbauer and W. Schäfers. 2011. "Geco" and its Potential for Real Estate Research: Evidence from the US Housing Market. *Journal of Real Estate Research* 33(4): 471–506.

Joseph, K., M.B. Wintoki and Z. Zhang. 2011. Forecasting Abnormal Stock Returns and Trading Volume Using Investor Sentiment: Evidence from Online Search. *International Journal of Forecasting* 27(4): 1116–1127.

Lee, K.O. and M. Mori. 2015. Do Conspicuous Consumers Pay Higher Housing Premiums? Spatial and Temporal Variation in the United States. *Real Estate Economics,* forthcoming.

Lerner, J.S. and D. Keltner. 2001. Fear, Anger, and Risk. *Journal of Personality and Social Psychology* 81(1): 146–159.

Low, C. 2004. The Fear and Exuberance from Implied Volatility of S&P 100 Index Options. *The Journal of Business* 77(3): 527–546.

McCluskey, J.J., J. Swinnen and T. Vandemoortele. 2015. You Get What You Want: A Note on the Economics of Bad News. *Information Economics and Policy* 30: 1–5.

McLaren, N. and R. Shanbhogue. 2011. Using Internet Search Data as Economic Indicators. *Bank of England Quarterly Bulletin* Q2: 134–140.

Miller, N. and G. Pandher. 2008. Idiosyncratic Volatility and the Housing Market. *Journal of Housing Research* 17(1): 13–32.

Ortony, A., G.L. Clore and A. Collins. 1990. *The Cognitive Structure of Emotions.* Cambridge University Press.

Paraschos, M. 1988. News Coverage of Cyprus: A Case Study in Press Treatment of Foreign Policy Issues. *Journal of Political and Military Sociology* 16(2): 201–213.

Patterson, T.E. 1997. The News Media: An Effective Political Actor? *Political Communication* 14(4): 445–455.

Schmidt, T. and S. Vosen. 2009. Forecasting Private Consumption: Survey-Based Indicators vs. Google Trends. *Ruhr Economic Papers* No. 155.

Shoemaker, P.J., L.H. Danielian and N. Brendlinger. 1991. Deviant Acts, Risky Business and US Interests: The Newsworthiness of World Events. *Journalism and Mass Communication Quarterly* 68(4): 781–795.

Smith, S.J. 1984. Crime in the News. *The British Journal of Criminology* 24(3): 289–295.

Smith, C.A. and P.C. Ellsworth. 1985. Patterns of Cognitive Appraisal in Emotion. *Journal of Personality and Social Psychology* 48(4): 813-838.

Takeda, F. and T. Wakao. 2014. Google Search Intensity and Its Relationship with Returns and Trading Volume of Japanese Stocks. *Pacific–Basin Finance Journal* 27: 1–18.

Tetlock, P.C., M. Saar-Tsechansky and S. Macskassy. 2008. More than Words: Quantifying Language to Measure Firms' Fundamentals. *The Journal of Finance* 63(3): 1437–1467.

Thaler, R.H. and E.J. Johnson. 1990. Gambling with the House Money and Trying to Break Even: The Effects of Prior Outcomes on Risky Choice. *Management Science* 36(6): 643–660.

Tiedens, L.Z. and S. Linton. 2001. Judgment under Emotional Certainty and Uncertainty: The Effects of Specific Emotions on Information Processing. *Journal of Personality and Social Psychology* 81(6): 973-988.

Trussler, M. and S. Soroka. 2014. Consumer Demand for Cynical and Negative News Frames. *The International Journal of Press/Politics* 19(3): 360–379.

Vlastakis, N. and R.N. Markellos. 2012. Information Demand and Stock Market Volatility. *Journal of Banking and Finance* 36(6): 1808–1821.

Vosen, S. and T. Schmidt. 2011. Forecasting Private Consumption: Survey-Based Indicators vs. Google Trends. *Journal of Forecasting* 30(6): 565–578.

Wu, L. and E. Brynjolfsson. 2009. The Future of Prediction: How Google Searches Foreshadow Housing Prices and Quantities. Working Paper, NBER.

Wu, J. and Y. Deng. 2015. Intercity Information Diffusion and Price Discovery in Housing Markets: Evidence from Google Searches. *The Journal of Real Estate Finance and Economics* 50(3): 289–306.

Zheng, S., W. Sun and M.E. Kahn. 2015. Investor Confidence as a Determinant of China's Urban Housing Market Dynamics. *Real Estate Economics*, forthcoming.

GRAPHS AND TABLES

Figure 4-1: S&P/Case-Shiller Home Price Indexes for Las Vegas, NV and Dallas, TX

I plot two individual home price indexes for Las Vegas, NV and Dallas, TX over the period January 2000-May 2015. The index values are retrieved from http://us.spindices.com/indices/real-estate/sp-case-shiller-us-national-home-price-index.

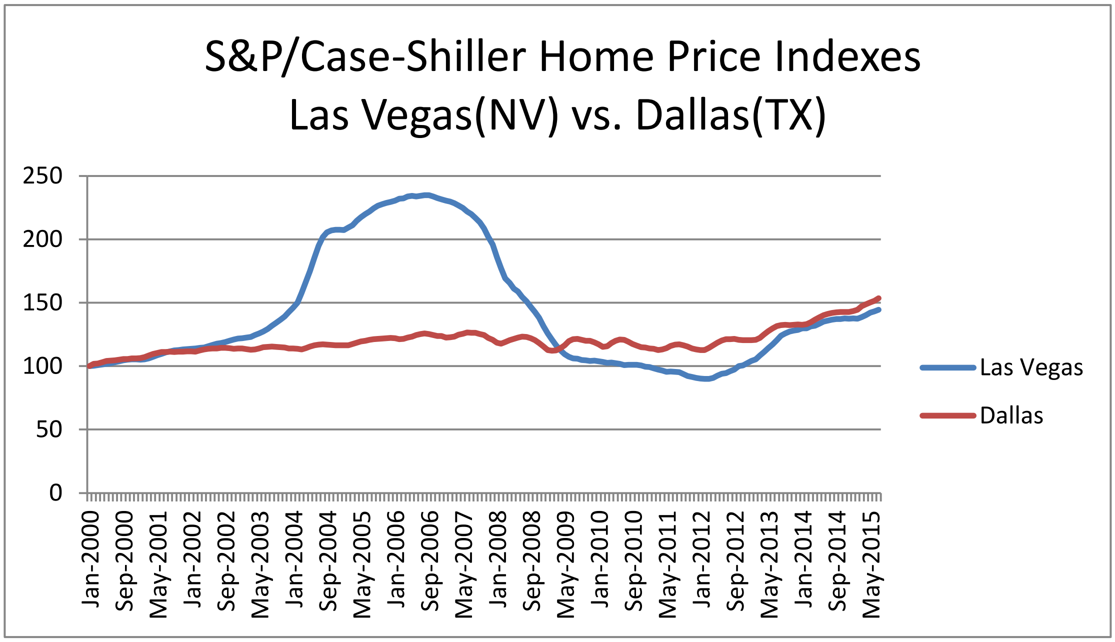


Figure 4-2: Web Search Interest for “bad” Economic News in Las Vegas, Tampa, and Dallas

This figure represents the graphical output of aggregate search interest from *Google Trends* (https://www.google.com/trends/explore). It depicts the search interest for the word “bad” under the subcategory of Economic News for three MSAs (Las Vegas, Tampa, and Dallas) over the period from January 2005 to December 2014.

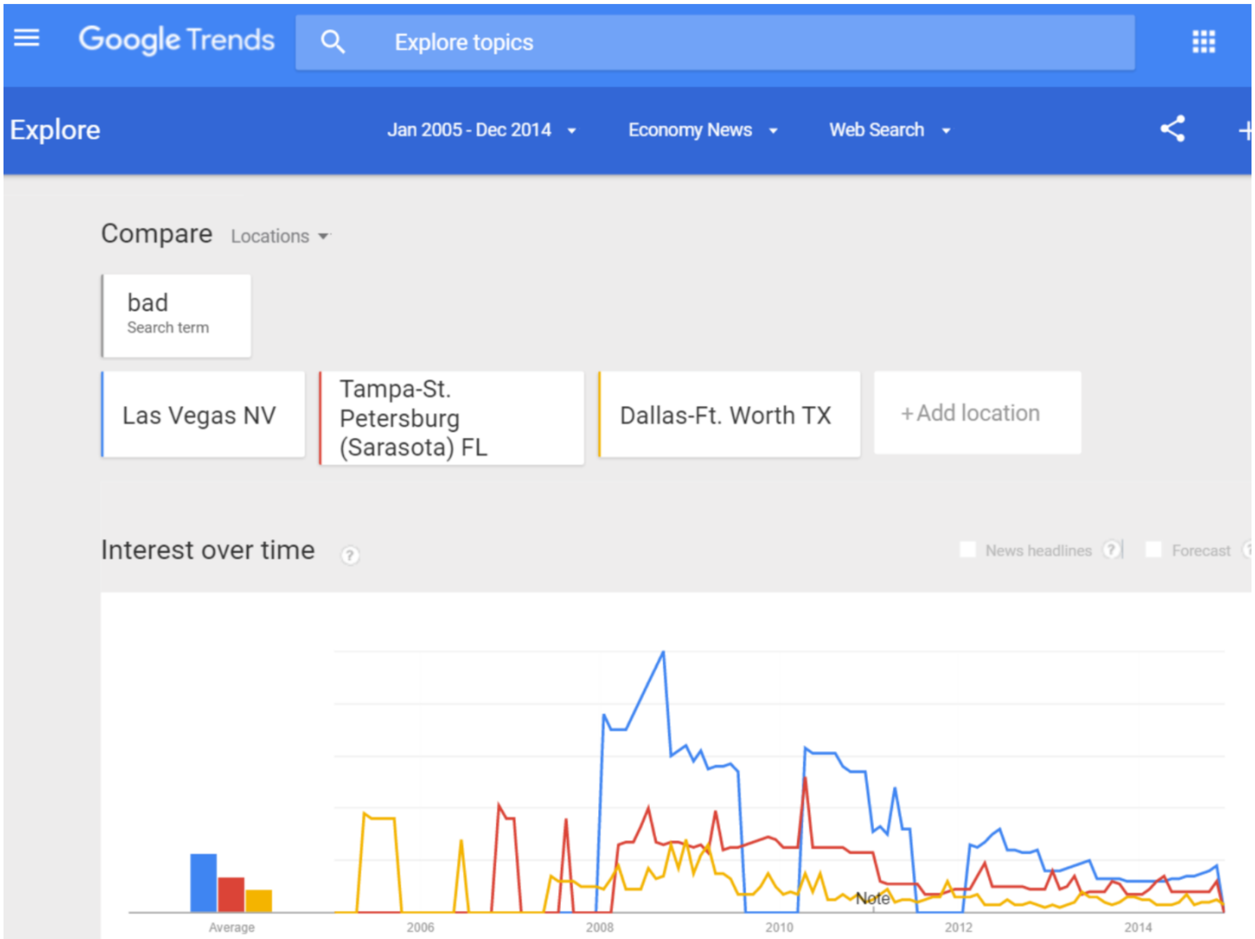


Table 4-1: Description of Variables

This table includes descriptions for each variable I use in this study. I first present the description and then, if applicable, the source from which each variable is collected.

Variable	Description
Fear Index (Local Fear)	The *Fear Index* is a monthly measure of people's sentiment toward housing prices in 20 major U.S. cities over the period from January of 2005 to December 2014. Local *Fear Indexes* are constructed using the search volume for real estate and economic terms. I also include Top Searches that relate to each real estate and economic term in the sample. I adjust search volume data by taking monthly log differences, winsorizing, removing intra-annual seasonality, and then standardizing each time series. Next, I run expanding window backward rolling regressions of adjusted search volume queries on log differences of housing prices every 12 months to determine the historical relationship between search and contemporaneous housing index changes for all search terms for each city. The 30 terms with the highest *t*-statistics from the regressions ending in a particular year were chosen to construct the following year's *Fear Index* in that location. For example, the top 30 terms from the regressions from 2004 to 2010 in Denver were used to build Denver's *Fear Index* for 2011. Fear Index is the average of top 30 adjusted search volume queries in a given housing market. Search volume data that was used in constructing the index comes from *Google Trends*.
Home Index	The *Home Index* tracks the value of single-family housing in 20 major U.S. housing markets. I use Case-Shiller home price indexes for the following metropolitan areas: Atlanta, Boston, Charlotte, Chicago, Cleveland, Dallas, Denver, Detroit, Las Vegas, Los Angeles, Miami, Minneapolis, New York, Phoenix, Portland, San Diego, San Francisco, Seattle, Tampa and Washington, D.C. Before using the home price series I adjust them by taking monthly log differences. These series are collected at the S&P Dow Jones Indices' webpage <http://us.spindices.com/index-family/real-estate/sp-case-shiller>.
Volatility	I use two measures of volatility, which are standard deviation and idiosyncratic volatility. Standard deviation of monthly housing market returns is computed on a rolling 36-month basis. Idiosyncratic volatility is computed as root-mean-square deviation of residuals from a 2-factor model, which regresses excess local housing market returns on excess national housing market returns and excess returns on the S&P 500 Index. Standard deviation and idiosyncratic volatility in month t both capture deviation from month t-36 to month t-1. I compute both of these measures for each metropolitan area.

Table 4-1: Continued

Variable	Description
ssdGAP	*ssdGAP* is computed as the difference between upside and downside standard semideviations of the housing market returns. Downside volatility (*ssdDownside*) is computed as the volatility of negative returns over the previous 36 monhts while replacing the positive returns by zeros. Upside volatility (*ssdUpside*) is computed as the volatility of positive returns over the previous 36 months while replacing the negative returns by zeros. Downside and upside volatilities are dynamic measures and computed monthly for each metropolitan area in this study.
Home Index Momentum	This variable is computed at a monthly frequency as an average return of home price index over the previous 12 months. For example, *Home Index Momentum* for January 2011 stands for the average of monthly returns over the previous 12 months from January to December of 2010. *Home Index Momentum* is computed for each metropolitan area used in this study.
Real GDP	Monthly Real GDP in trillions. Data was retrieved from <http://ycharts.com/indicators/real_gdp>.
CPI	Monthly Consumer Price Index (seasonally adjusted). The data is provided by Sentier Research, LLC, which compiles monthly CPI from the U.S. Bureau of Labor Statistics. Web page: <http://www.sentierresearch.com/>.
Unemployment rate	Monthly Unemployment Rate (seasonally adjusted). The data is provided by Sentier Research, LLC, which estimates monthly unemployment data from the U.S. Bureau of Labor Statistics. Web page: <http://www.sentierresearch.com/>.
HMI	The Housing Market Index (HMI) measures builder sentiment regarding the demand side of the single-family housing market in the U.S. HMI ranges from 0 to 100, with any number over 50 indicating that more builders view sales conditions as good rather than poor. The National Association of Home Builders (NAHB) computes HMI as a weighted average of responses to survey questions asking builders to rate three aspects of their local market conditions: current sales of single-family detached new homes, expected sales of single-family detached new homes over the next 6 months, and traffic of prospective buyers in new homes. The data was retrieved from: <http://www.nahb.org/en/research/housing-economics/housing-indexes/housing-market-index.aspx>.
S&P 500 Index	Monthly returns on S&P 500 Index taken from CRSP Monthly stock files.

Table 4-2: Sample Characteristics

This table presents summary statistics in Panel A and correlation coefficients in Panle B for main variables used in this study. In Panel A, I first compute statistics for the *Fear Index, Home Index*, *Home Index Momentum*, *Standard Deviation*, *Idiosyncratic Volatility*, and *ssdGAP* at the metropolitan level and then report the average across 20 cities. In Panel A, statistics for *Home Index*, *Real GDP*, *CPI*, *Unemployment Rate*, and *HMI* are computed using the levels of these variables. However, in Panel B and throughout the rest of the study I use log changes of these variables. To reduce the number of decimal points, I present statistics for *Home Index Momentum*, *Standard Deviation*, *Idiosyncratic Volatility*, and *ssdGAP* in percent. Variable descriptions are provided in Table 1.The sample consists of 2,400 observations in total with each of the twenty cities having monthly observations over the period from January 2005 to December 2014.

Panel A: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	5%	Median	95%
Fear Index	0.00	0.32	-0.92	0.96	-0.54	0.00	0.52
Home Index	152.55	24.61	119.50	195.78	122.90	146.88	193.91
Home Index Momentum (%)	0.02	0.93	-1.91	1.60	-1.69	0.09	1.41
Standard Deviation (%)	1.17	0.41	0.48	1.82	0.55	1.24	1.74
Idiosyncratic Volatility (%)	0.75	0.27	0.33	1.21	0.38	0.75	1.15
ssdGAP (%)	0.04	0.86	-1.42	1.33	-1.24	0.15	1.24
Real GDP	15.00	0.57	14.07	16.34	14.26	14.88	16.12
CPI	217.63	13.13	191.60	237.75	194.30	217.38	237.01
Unemployment rate	6.95	1.90	4.40	10.00	4.50	6.90	9.80
HMI	33.61	18.71	8.00	72.00	13.00	28.50	68.50
S&P 500 Index	0.01	0.04	-0.17	0.11	-0.08	0.01	0.07

Table 4-2: Continued

Panel B: Correlation Coefficients

Variable	*Fear Index*	*Home I.*	*H.I.Mom.*	*Std.Dev.*	*iVol*	*ssdGAP*	*Real GDP*	*CPI*	*U-rate*	*HMI*
Home Index	-0.15***									
Home Index Momentum	-0.02	0.55***								
Standard Deviation	0.00	-0.08***	-0.20***							
Idiosyncratic Volatility	0.01	-0.02	-0.15***	0.88***						
ssdGAP	-0.04*	0.29***	0.72***	-0.36***	-0.38***					
Real GDP	0.04**	0.17***	0.17***	-0.01	0.01	0.09***				
CPI	-0.06***	0.09***	0.06***	-0.06***	-0.04*	0.08***	0.05***			
Unemployment rate	-0.01	-0.30***	-0.45***	-0.01	-0.03	-0.25***	-0.15***	-0.10***		
HMI	-0.12***	0.08***	-0.03	0.14***	0.11***	-0.11***	0.12***	0.15***	-0.15***	
S&P 500 Index	0.01	0.15***	0.13***	0.05**	0.05**	0.02	0.19***	0.08***	-0.21***	0.26***

Table 4-3: *Fear Index* and the Effect of Volatility on *Housing Market Returns*

This table presents the results of an analysis of the impact of *Local Fear* interacted with *Volatility* on local housing market returns. I use two measures of volatility, which are standard deviation (Model 1) and idiosyncratic volatility (Model 2). In Panel A, the interaction term ($Local\ Fear * Volatility)_{i,t-1}$ is a product of *Local Fear* and *Volatility* in a metropolitan area *i* at time *t-1*. Model specifications (1) and (2) include the following control variables: *Home Index Momentum*, *Real GDP*, *CPI*, *Unemployment rate*, *HMI*, and *S&P 500 Index*. Variable descriptions are provided in Table 1. In Panel B, *Volatility* is centered at two different values: one standard deviation above and one standard deviation below the mean. Then the coefficient for *Local Fear* corresponding to each of those values is computed and reported. The *t*-statistics are included in parentheses below. The coefficients for the control variables are the same as those included in the corresponding models in Panel A. In Panel C, I report slopes of local housing market returns on *Local Fear* when *Volatility* is held constant at different combinations of values from low (1%) to high (99%). The sample period is from January 2005 to December 2014. *t*-statistics are included below the coefficient estimates in parentheses, and 1%, 5%, and 10% statistical significance are indicated with ***,**, and *, respectively.

Panel A: Interaction between *Fear* and *Volatility*

Volatility measure:	*Standard Deviation*	*Idiosyncratic Vol.*
Model:	(1)	(2)
$(Local\ Fear * Volatility)_{i,t-1}$	-70.00***	-96.82***
	(-4.99)	(-5.22)
Main Effects and Controls	Yes	Yes
Observations	2,380	2,380
Adj. R-squared	0.33	0.34

Panel B: Interaction between *Fear* and recentered *Volatility*

Volatility measure:	*Standard Deviation*	*Idiosyncratic Vol.*
Model:	(1)	(2)
Recentered *Volatility* (Low):		
Local Fear	-0.13	-0.20**
	(-1.23)	(-2.03)
Recentered *Volatility* (High):		
Local Fear	-0.78***	-0.79***
	(-8.31)	(-8.52)
Controls	Yes	Yes
Observations	2,380	2,380

Table 4-3: Continued

Panel C: Interaction between *Fear* and constant *Volatility* values

Volatility measure:	*Standard Deviation*	*Idiosyncratic Vol.*
Model	(1)	(2)
Volatility at:	Slope: (*z*-stat)	Slope: (*z*-stat)
1%	0.09	-0.07
	(0.56)	(-0.52)
5%	0.02	-0.15
	(0.12)	(-1.34)
10%	-0.05	-0.19*
	(-0.40)	(-1.76)
25%	-0.26***	-0.29***
	(-2.59)	(-2.99)
50%	-0.47***	-0.46***
	(-5.89)	(-5.76)
75%	-0.75***	-0.73***
	(-9.11)	(-9.12)
90%	-1.03***	-1.16***
	(-8.88)	(-8.86)
95%	-1.24***	-1.32***
	(-8.25)	(-8.43)
99%	-1.38***	-1.68***
	(-7.89)	(-7.64)
Controls	Yes	Yes
Observations	2,380	2,380

Table 4-4: Asymmetric Response Model to Increases vs Decreases in *Fear* by Volatility Group

This table presents results of increases versus decreases in sentiment on home index returns by volatility groups. Models (1)-(3) use interaction terms of increases versus decreases in sentiment and *Fear Index* to assess the asymmetric response of residential real estate returns to downside sentiment. *Increase (Decrease)* is a binary variable that takes on value of 1 if *Fear Index* is greater (less) than zero, and 0 otherwise. *Fear Index * Decrease* is the interaction term of *Fear Index* and *Decrease* binary variable. *Fear Index * Increase* is the interaction term of *Fear Index* and *Increase* binary variable. Model (1) uses the full sample, while Models (2) and (3) use above versus below the median volatility groups to measure the asymmetric response to downside sentiment. Volatility is a monthly variable that is computed as standard deviation of home index returns over the previous 36 months. Each month I compute the median standard deviation across 20 cities and then divide each metropolitan area into one of two groups, below the median volatility group and above the median volatility group. Model specification (2) includes the results for "Below the Median Volatility" group, while Model (3) presents the results for "Above the Median Volatility" group. *Fear Index* coefficients have been multiplied by 100 to reduce the number of decimals. The interpretation of these coefficients has been adjusted accordingly. The sample period is from January 2005 to December 2014. All variables are presented at a monthly frequency. Variable descriptions are provided in Table 1. *t*-statistics are included below the coefficient estimates in parentheses, and 1%, 5%, and 10% statistical significance are indicated with ***, **, and *, respectively.

Sample:	Full Sample	Below the Median Volatility	Above the Median Volatility
	(1)	(2)	(3)
*(Local Fear * Decrease)*$_{i,t-1}$	-0.34**	-0.41**	-0.28
	(-2.07)	(-2.12)	(-1.09)
*(Local Fear * Increase)*$_{i,t-1}$	-0.81***	-0.57***	-1.00***
	(-4.86)	(-2.92)	(-3.72)
Increase$_{i,t-1}$	-0.00	0.00	-0.00
	(-0.19)	(0.09)	(-0.40)
Home Index Momentum	0.76***	0.75***	0.75***
	(27.34)	(16.78)	(19.49)
Real GDP	0.14***	0.13***	0.14*
	(3.09)	(2.70)	(1.95)
CPI	0.15**	0.26***	0.03
	(2.09)	(3.41)	(0.27)
Unemployment rate	-0.01	-0.01	-0.02
	(-1.43)	(-0.72)	(-1.35)
HMI	0.01***	0.01**	0.01**
	(3.15)	(2.13)	(2.29)
S&P 500 Index	0.02***	0.02***	0.02**
	(3.37)	(3.03)	(2.11)
Constant	-0.00	-0.00	-0.00
	(-0.33)	(-0.57)	(-0.03)
Observations	2,380	1,190	1,190
Adjusted *R*-squared	0.34	0.28	0.36

Table 4-5: *Fear Index* and the Effect of Gap between Upside and Downside Semideviations on *Housing Market Returns*

In this table, I examine the effect of *Local Fear* interacted with *ssdGAP* on the residential real estate returns. *ssdGAP* is the difference between upside (*ssdUpside*) and downside (*ssdDownside*) semideviations. *ssdDownside (ssdUpside)* is computed at a monthly frequency as the volatility of negative (positive) home price index returns over the past 36 months. Model (1) of Panel A includes *Local Fear* and *ssdGAP* as two explanatory variables but Models (2) and (3) include the interaction term *(Local Fear*ssdGAP)*$_{i,t-1}$ as well, which is the product of *Local Fear* and *ssdGAP* in metropolitan area *i* at time *t-1*. Model (2) does not include the main control variables while Model (3) does. *Home Index Momentum*$_{res}$ is the residual from regressing *ssdGAP* on *Home Index Momentum*. I used orthogonal values of *Home Index Momentum* since it is highly correlated with *ssdGAP* as can be seen from Panel B of Table 2. All other variable descriptions are provided in Table 1. In Panel B, *ssdGAP* is centered at two different values: one standard deviation above and one standard deviation below the mean. Then the coefficient for *Local Fear* corresponding to each of those values is computed and reported. The *t*-statistics are included in parentheses below. The coefficients for the control variables are the same as those included in the corresponding models in Panel A. In Panel C, I report slopes of local housing market returns on *Local Fear* when *ssdGAP* is held constant at different combinations of values from low (-0.022 – bottom 1%) to high (0.022 - top 1%). The sample period is from January 2005 to December 2014. *t*-statistics are included below the coefficient estimates in parentheses, and 1%, 5%, and 10% statistical significance are indicated with ***,**, and *, respectively.

Panel A: Interaction between *Fear* and *ssdGAP*

Model:	(1)	(2)	(3)
Local Fear$_{i,t-1}$	-0.63***	-0.66***	-0.64***
	(-8.25)	(-8.64)	(-8.38)
ssdGAP$_{i,t-1}$	0.38***	0.39***	0.38***
	(13.82)	(15.10)	(13.95)
*(Local Fear * ssdGAP)*$_{i,t-1}$		41.93***	41.41***
		(5.07)	(5.02)
Home Index Momentum$_{res}$	0.97***	1.04***	0.97***
	(25.27)	(29.63)	(25.38)
Real GDP	0.14***		0.13***
	(3.11)		(3.00)
CPI	0.21***		0.17**
	(2.93)		(2.48)
Unemployment rate	-0.01		-0.01
	(-1.39)		(-1.24)
HMI	0.00*		0.01**
	(1.90)		(2.35)
S&P 500 Index	0.02***		0.02***
	(3.15)		(3.20)
Constant	-0.00***	-0.00	-0.00***
	(-3.31)	(-1.07)	(-2.93)
Observations	2,380	2,380	2,380
Adj. *R*-squared	0.33	0.32	0.34

Table 4-5: Continued

Panel B: Interaction between *Fear* and recentered *ssdGAP*

Model:	(2)	(3)
Recentered *ssdGAP* (Low):		
Local Fear	-1.03***	-1.01***
	(-10.39)	(-10.20)
Recentered *ssdGAP* (High):		
Local Fear	-0.47***	-0.46***
	(-4.66)	(-4.53)
Controls	No	Yes
Observations	2,380	2,380

Panel C: Interaction between *Fear* and constant *ssdGAP* values

Model:	(2)	(3)
ssdGAP at:	Slope: (*z*-stat)	Slope: (*z*-stat)
-0.022 (1%)	-1.59***	-1.56***
	(-7.93)	(-7.80)
-0.016 (5%)	-1.32***	-1.29***
	(-8.65)	(-8.49)
-0.011 (10%)	-1.13***	-1.11***
	(-9.29)	(-9.10)
-0.005 (25%)	-0.86***	-0.84***
	(-9.92)	(-9.68)
0.002 (50%)	-0.59***	-0.57***
	(-7.66)	(-7.41)
0.006 (75%)	-0.41***	-0.40***
	(-4.61)	(-4.43)
0.01 (90%)	-0.24**	-0.23**
	(-2.17)	(-2.04)
0.012 (95%)	-0.16	-0.14
	(-1.27)	(-1.17)
0.022 (99%)	0.25	0.26
	(1.31)	(1.35)
Controls	No	Yes
Observations	2,380	2,380

Table 4-6: The Effect of Semideviations on *Fear Index*

In this table, I present the results of examining the effect of *ssdGAP*, *ssdDownside,* and *ssdUpside* on *Local Fear*. *ssdGAP* is the difference between upside (*ssdUpside*) and downside (*ssdDownside*) semideviations. *ssdDownside (ssdUpside)* is computed at a monthly frequency as the volatility of negative (positive) home price index returns over the past 36 months. In Model (1), I assess the effect of *ssdGAP* on *Local Fear*. In Model (2), I examine the effect of *ssdDownside* on *Local Fear*. And in Model (3), I analyze the effect of *ssdUpside* on *Local Fear*. All other variables are defined as before and presented in Table 1. The sample period is from January 2005 to December 2014. All variables are presented at a monthly frequency. *t*-statistics are included below the coefficient estimates in parentheses, and 1%, 5%, and 10% statistical significance are indicated with ***, **, and *, respectively.

Model:	(1)	(2)	(3)
$ssdGAP_{i,t-1}$	-0.02**		
	(-2.48)		
$ssdDownside_{i,t-1}$		0.02**	
		(2.44)	
$ssdUpside_{i,t-1}$			-0.02
			(-1.40)
$Local\ Fear_{i,t-1}$	0.02	0.02	0.03
	(1.14)	(1.16)	(1.23)
$Real\ GDP_{t-1}$	-0.01	-0.01	-0.02
	(-1.24)	(-1.29)	(-1.34)
CPI_{t-1}	-0.05***	-0.05***	-0.06***
	(-2.81)	(-2.79)	(-2.98)
$Unemployment\ rate_{t-1}$	-0.01***	-0.01***	-0.01***
	(-2.96)	(-2.80)	(-2.69)
HMI_{t-1}	-0.00**	-0.00**	-0.00*
	(-2.17)	(-2.19)	(-1.86)
$S\&P\ 500\ Index_{t-1}$	-0.00**	-0.00**	-0.00**
	(-2.26)	(-2.31)	(-2.20)
Constant	0.00*	-0.00	0.00**
	(1.82)	(-0.65)	(2.17)
Observations	2,380	2,380	2,380
Adjusted *R*-squared	0.01	0.01	0.01

BIOGRAPHICAL INFORMATION

Sergiy Saydometov was born in Ukraine and raised in a family of educators. He arrived to Dallas, Texas in 2001 to study at the Christ for the Nations Institute. In 2004, Mr. Saydometov earned a bachelor's degree in Business Studies from Dallas Baptist University. In 2007, he graduated with the MBA in Finance from the University of Texas at Arlington. In 2009, Mr. Saydometov joined Dallas Baptist University as an Associate Professor of Finance, and later that year started on the Ph.D. in Finance from the University of Texas at Arlington. In 2012, Sergiy was appointed as an Associate Dean in the College of Business at Dallas Baptist University. Mr. Saydometov plans to continue his service at the university for the foreseeable future. His current research interests include residential real estate, behavioral finance, and asset pricing.