# Essays on the US Housing Market

Presented by

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## Abstract

The rapid decline in housing prices of the United States (US), following a prolonged boom, is generally associated with the global economic and financial crisis of 2008-2009. Naturally, from a policy perspective, understanding what shocks drive the housing market performance is now of paramount importance in order to avoid the repeat of the catastrophic effects observed under the "Great Recession". This research is motivated by the important effect changes in the housing market has on both households and the overall economy

The housing market plays an important role in the economy of the US, since it constitutes a significant share of many households' asset holding and net worth. Various hypothesis and theories have been considered in literature to investigate the impact of different determinants that affect the housing market. We apply a variety of quantitative modeling methods to investigate the impact of various economic determinants such as inflation, monetary policy and macroeconomic shocks and housing sentiment on the US housing market. The thesis consists of five independent papers which are compiled into five chapters.

The first paper analyses the long-run relationship between U.S house prices and non-housing Consumer Price Index (CPI) over the monthly period 1953 to 2016 using a quantile cointegration analysis. The possibility of instability in standard cointegration models, suggesting the possible existence of structural breaks and nonlinearity in the relationship between house prices and non-housing CPI motivates the use of a time-varying approach, namely, a quantile cointegration analysis, which allows the cointegrating coefficient to vary over the conditional distribution of house prices and simultaneously test for the existence of cointegration at each quantile. Our results suggest that the U.S

non-housing CPI and house price index series are cointegrated at lower quantiles only, with house prices over-hedging inflation at these quantiles. In addition, we also show that this result holds for higher price levels only. Using these two sets of results, we conclude that house prices act as an inflation hedge when the latter is relatively higher and the former is lower.

The second paper explores the impact of monetary policy and macroeconomic surprises on the U.S market returns and volatility at the Metropolitan Statistical Area (MSA) and aggregate level using a GJR (Glosten–Jagannathan-Runkle) generalized autoregressive conditional heteroscedasticity (GARCH) model. Using daily data and sampling periods which cover both the conventional and unconventional monetary policy periods, empirical results show that monetary policy surprises have a greater impact on the volatility of housing market returns across time with particularly pronounced effect during the conventional monetary policy period. We also show that macroeconomic surprises do not have a significant impact on housing returns for most MSAs for the full sample, conventional and unconventional monetary policy periods.

The third paper examines the predictive ability of housing-related sentiment on housing market volatility for 50 states, District of Columbia, and the aggregate US economy, based on quarterly data covering 1975:3 and 2014:3. Given that existing studies have already shown housing sentiment to predict movements in aggregate and state-level housing returns, we will use a k-th order causality-in-quantiles test for our purpose, since this methodology allows us to test for predictability for both housing returns and volatility simultaneously. In addition, this test being a data-driven approach accommodates the existing nonlinearity (as detected by formal tests) between volatility and sentiment, besides providing causality over the entire conditional distribution of (returns and) volatility. Our results show that barring 5 states (Connecticut, Georgia, Indiana, Iowa, and Nebraska), housing sentiment is observed to predict volatility barring the extreme ends of the conditional distribution. As far as returns are concerned, except for California, predictability is observed for all of the remaining 51 cases.

In the fourth paper we investigate the impact of uncertainty shocks on the United States housing market using the time-varying parameter vector autoregression (TVP-VAR) following Mumtaz and Theodoris (2018). We will use quarterly time-series data on real economic activity, price, financial and housing market variables, covering the period 1975:Q3 to 2014:Q3. Besides housing prices, we also consider variables related to home sales, permits, starts, as well as housing market sentiment. In general, the results of the cumulative response of housing variables to a 1 standard deviation positive uncertainty shock at the one-, four- and eight quarter horizon tends to change over time, both in terms of sign and magnitude, with the uncertainty shock primarily affecting home sales, permits and starts over short-, medium and long-runs, and housing sentiment in the medium-term. Interestingly, the impact on housing prices is statistically insignificant.

Our final paper applies Bayesian Additive Regression Trees (BART) to study the comovement of REIT returns with expected and unexpected inflation using U.S. monthly data covering the sample period 1979 2016 and survey data to decompose inflation into an expected and unexpected component. Our findings show that the two inflation components are not among the leading predictors of REIT returns in terms of their relative importance, but also that the marginal effects of the two inflation components for REIT returns changed over time. REIT returns exhibit an asymmetric response to unexpected inflation, a phenomenon mainly concentrated in the Greenspan era.

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# Chapter 1
# General Introduction

This dissertation is motivated by the important effect changes in the housing market has on households and the overall economy. The global economic and financial crisis of 2008-2009 is generally associated with the rapid decline in housing prices of the US, following a prolonged boom (Leamer, 2015; Nyakabawo et al., 2015). It is therefore important from a policy perspective, to understand what factors drive the housing market in order to avoid the catastrophic effects experienced during the "Great Recession" from happening again.

The objectives of this PhD are to: (1) explore the long run impact of inflation on homeowner equity; (2) analyse the high-frequency impact of the surprise component of monetary policy (Federal funds rate) as well as macroeconomic surprises on 10 U.S Metropolitan Statistical Areas (MSAs) housing market returns and volatility; (3) extend the literature on housing market volatility by analysing whether housing market sentiment drives variation in housing returns; (4) determine the time-varying response of not only house prices, but home sales, permits and starts, as well as sentiment associated with the housing market to uncertainty shocks; and (5) investigate how returns on real-estate investments in general and REIT returns in particular are linked to (un-)expected inflation using Bayesian Additive Regression Trees (BART). The dissertation therefore consists of five independent papers.

The relationship between real estate returns and inflation has been a subject of interest particularly for investors since perceived inflation-hedging ability of real estate is often used to justify its inclusion in mixed-asset investment portfolios (Simpson, Ramchander, & Webb, 2007). Empirical studies show mixed evidence on whether real estate provides a good inflation hedge. This mixed evidence could possibly be because of the time-varying relationship between house prices and its predictors, including inflation, as suggested by Anari and Kolari (2002), Bork and Møller (2015), and Pierdzioch, Risse, Gupta, and Nyakabawo (2016). In addition, this empirical relationship should be tested regularly based on updated data, given the dynamic nature of the housing market and the transformations it has gone and going through continuously post the recent financial crisis.

Given this, the objective of the first paper, “Do house prices hedge inflation in the US? A quantile cointegration approach” is to explore within the context that cointegration coefficients may vary over time, the long-run impact of inflation on homeowner equity by analysing the relationship between house prices and prices of non-housing goods and services, which is Consumer Price Index (CPI) excluding housing costs, across various quantiles of house prices using monthly data from 1953 to 2016.

There is a general consensus that housing prices are a good indicator of economic recovery as they reflect the level of consumers’ confidence (Wang, 2014). As such, timely measures of housing price movements contain important information concerning the current state of the economy. This highlights the need to fully understand the house price movements and the factors that drive the housing markets. Housing, being a consumption as well as an investment asset, intuitively is driven by interest rates and the news reflecting macroeconomic fundaments (Kishor and Marfatia, 2017). The second paper, “High Frequency Impact of Monetary Policy and Macroeconomic Surprises on US MSAs and Aggregate US Housing Returns and Asymmetric Volatility” will analyse the high-frequency impact of the surprise component of monetary policy (Federal funds rate) as well as macroeconomic surprises on 10 U.S Metropolitan Statistical Areas (MSAs) housing market returns and volatility. The study will further investigate this impact on an aggregate level, and analyse how the results compare to the impact on stocks using the Standard & Poor’s 500 (S&P500), and also aggregate Real Estate Investment Trusts (REITs) market. One of the main contributions of this paper is that it uses new high-frequency daily data of the housing market, which is not easily available.

In light of a growing number of studies which have attempted to model and predict volatility (using univariate models and also with econometric frameworks including wide array of factors) at the aggregate and regional (state and metropolitan statistical areas (MSAs)-levels) of the US, the third paper, “Predicting Aggregate and State-Level US House Price Volatility: The Role of Sentiment” aims to extend the literature on housing market volatility by analysing whether housing market sentiment drives variation in housing returns. We do this by drawing on the findings of recent studies related to the equity markets, which tend to show that investor and corporate manager sentiments predicts volatility (over and above returns) of stock markets (Bekiros et al., 2016; Balcilar et al., 2018a, b; Gupta, 2018) in line with "noise traders" theory, whereby market agents tend to make overly optimistic or pessimistic judgments and choices. In this regard, we use the housing sentiment index developed by Bork et al., (2017), which is constructed based on household responses to questions regarding house buying conditions from the consumer survey of the University of Michigan, to predict volatility of the aggregate US housing market, the 50 states, as well as that of the District of Colombia. We apply the recently developed *k*-th order causality-in-quantiles test of Balcilar et al., (2017), which in turn, allows us to test for predictability for both housing returns and volatility simultaneously.

More recently, in the wake of the Great Recession, a growing number of studies have started relating real estate (housing and Real Estate Investment Trusts (REITs)) market-related variables to measures of macroeconomic uncertainty, which in turn, was at unprecedented levels during the crisis. But majority of these studies have analysed movements in real estate market prices to uncertainty in constant parameter models, and even if time-variation (which have been shown to be of paramount importance for the US housing market by Simo-Kengne et al., 2015) was allowed based on either dynamic conditional correlation or rolling estimations, the models in general were restricted to only few macroeconomic variables. Given the well-known fact that the US real estate market is affected by large number of variables the fourth paper, "Time-varying impact of uncertainty shocks on the United States Housing Market", uses an extended factor augmented vector autoregressive (FAVAR) model (as proposed by Mumtaz and Theodoridis (2018)), based on a dataset of 45 variables for the US, that allows the estimation of a measure of macroeconomic uncertainty which encompasses volatility of the real and financial sectors. In addition, we allow for time-varying parameters (TVP) in the proposed FAVAR model (TVP-FAVAR), which in turn allows us to estimate time-varying response of not only house prices, but home sales, permits and starts, as well as sentiment associated with the housing market to uncertainty shocks, thus allowing the investigation of temporal shifts in the overall housing market in a coherent manner.

Building on the pioneering research by Fama and Schwert (1977), much research has been done to recover how returns on real-estate investments in general and REIT returns in particular are linked to (un-)expected inflation (Gyourko and Linneman 1988, Park et al. 1990, Yobaccio et al. 1995, among others). Some researchers find that REIT returns exhibit a positive comovement with expected inflation. Other researchers report that REIT returns do not comove or even are negatively linked to (un-)expected inflation. The final paper, "On REIT Returns and (Un-)Expected Inflation: Empirical Evidence Based on Bayesian Additive Regression Trees" contributes to this large body of research by using Bayesian Additive Regression Trees (BART) (Chipman et al. 1998, 2010) to re-examine the REIT returns-inflation nexus.

In terms of empirical analysis, various quantitative modelling methods are applied to investigate the effects of housing market on households and the economy as whole. In the first paper, we apply a quantile cointegration method due to the mixed evidence on the cointegration relation between non-housing CPI and house price index and the existence of parameter instability. By applying Kuriyama's (2016) quantile cointegration method, we are able to examine the equilibrium relationship across different quantiles of the distribution of the response variable (house price), as it allows for the long run relationship among time series which contain unit root to be non-uniform across the various quantiles of the dependent variable.

The second paper employs the GJR (or threshold GARCH) by Glosten et al., 1993 in analysing the impact of monetary policy and macroeconomic surprises as it allows us to capture an important phenomenon in the conditional variance of assets, which is the leverage effect captured by the asymmetric terms.

We attempt to analyse the role of sentiment on predicting the volatility of house prices in the third paper by using the *k*-th order causality-in-quantiles test proposed by Balcilar et al., (2017) as it allows for the simultaneous testing for both housing returns and volatility. The main advantages of using this non-parametric causality-in-quantiles framework are that: it is robust to misspecification errors as it able to detect the underlying dependence structure between the analysed variables; it allows for the testing of causality-in-mean which is the 1st moment as well as causality that may exist in the tails of the distribution of the variable; and it makes it possible to investigate causality-in-variance, therefore are able to analyse higher-order dependency.

The fourth paper applies an extended factor augmented vector autoregressive (FAVAR) model by Mumtaz and Theodoridis (2018) by allowing for time-varying parameters, which enables us to estimate the time-varying response of house prices, home sales, permits and starts as well as sentiment associated with the housing market to uncertainty shocks.

In the fifth paper, we use the Bayesian Additive Regression Trees (BART; Chipman et al. 1998, 2010) to examine the relationship between REIT returns and inflation because it allows for us to model the complex nonlinearities in the links between the two variables. Additionally, by using the BART modelling, we are able to evaluate the importance of (un)expected inflation for REIT returns relative to other macroeconomic variables.

Overall, this study contributes to the growing literature on understanding the effects of the housing market on households and the general economy by applying a variety of quantitative modelling methods and new datasets to investigate the impact various economic determinants such as inflation, monetary policy and macroeconomic shocks and housing sentiment have on the housing market. The aim is for our results to facilitate policy makers better understand the impact the various shocks may have on the housing market in order to avoid a recurrence of the 2008-2009 global economic crisis.

# Chapter 2
# Do House Prices Hedge Inflation in the US? A Quantile Cointegration Approach[1]

## 2.1 Introduction

Price stability plays an important role in the economy, since price levels affect economic activities, financial sector and investment decisions (Chang, 2016). A rise in price levels can reduce the real value of holding money, and since the main objective for investors is to obtain a positive real rate of return on their investment portfolio (Rubens, Bond and Webb, 1989), they aim to increase the portfolio positions of inflation-hedging assets. The relationship between real estate returns and inflation has been a subject of interest particularly for investors since perceived inflation-hedging ability of real estate is often used to justify its inclusion in mixed-asset investment portfolios (Simpson, Ramchander and Webb, 2007).

The importance of the relationship between house prices and inflation is highlighted in that, in the United States and other countries, residential real estate is the principal asset held in most private portfolios (Hong, Khill and Lee, 2013). In the United States, two thirds of the nation's households are homeowners and homeowner equity constitutes approximately one third of all households (Iacoviello, 2012, pp.673 – 678; Tracy, Schneider and Chan, 1999). Corporate equity has recently surpassed homeowner equity to become the largest asset in the household sector but it is important to note that over half of all households do not hold corporate equity. In this context, homeowner equity constitutes the larger portion of most households' investment portfolio and its ability to protect the investor against

[1] Published in International Review of Economics & Finance, Volume 54, March 2018, Pages 15-26.

price level changes has important implications for personal wealth and the economy as a whole (Anari and Kolari, 2002).

Empirical studies show mixed evidence on whether real estate provides a good inflation hedge.[2] Using residential property indexes for the period 1975 to 2008, Hong et al (2013) find that house prices are a relatively good hedge over the long term against inflation in the US and UK. Anari and Kolari (2002) using new and existing house prices and CPI excluding housing costs for the US from 1968 to 2000 also supports the evidence that house prices provide a stable inflation hedge in the lAong run. In contrast, Hoesli, Lizieri and MacGregor (2007), using UK data, conclude that real estate provides little hedging ability when the inflation rate is low, which actually disappears when inflation is high. Barber, Robertson and Scott (1997) support the findings that the UK real estate provides weak hedge against changes in underlying inflation, and no hedge against shocks that change price levels. Furthermore, there is also evidence that real estate assets are not a good hedge against inflation both in the shorter- and longer-terms (Glascock, Feng, Fan and Bao, 2008). Mixed evidence can also be found in earlier studies of Fama and Schwert, (1977); Fogler, Granito and Smith (1985); Hartzell, Heckman and Miles (1987); Rubens et al. (1989).[3]

In addition to the studies that consider the relationship between house prices and inflation, other studies focus on securitized real estate in the form of real estate investment trust (REITs) (Chang, 2016; Glascock, Lu and So, 2002; Gyourko and Linneman, 1988; Hardin III et al, 2012; Glascock et al, 2002; Gyourko and Linneman, 1988; Park, Mullineaux and Chew, 1990). This literature shows that the role of REITs as inflation hedge is also ambiguous, with some evidence supporting REITs as a good inflation hedge, while others show evidence that they provide a perverse inflation hedge.

So clearly, there is mixed evidence on whether real estate provides a good inflation hedge, and this mixed evidence could possibly be because of the time-varying relationship between house prices and its predictors, including inflation, as suggested by Anari and Kolari (2002), Bork and Møller (2015),

[2] See also Fama and Schwert, (1977); Fogler et al. (1985); Hartzell et al. (1987); Rubens et al. (1989).

[3] For a detailed review of the international literature on housing acting as an inflation hedge, the readers are referred to Inglesi-Lotz and Gupta (2013).

and Pierdzioch, Risse, Gupta and Nyakabawo (2016). In addition, this empirical relationship should be tested regularly based on updated data, given the dynamic nature of the housing market and the transformations it has gone and going through continuously post the recent financial crisis. Given this, the objective of the study is to explore within the context that cointegration coefficients may vary over time, the long-run impact of inflation on homeowner equity by analyzing the relationship between house prices and prices of non-housing goods and services, which is Consumer Price Index (CPI) excluding housing costs[4], across various quantiles of house prices using monthly data from 1953 to 2016. Note that, we decided to work with house prices instead of REITs, given the role played by the housing market in the recent financial crisis, and its influence on US business cycles (Ghysels, Plazzi, Torous and Valkanor, 2013; Leamer, 2007;), thus making it of paramount importance to determine the predictors, in this case, inflation in driving the US housing market. In addition, the size of investment in owner-occupied homes are also larger compared to that of REITs (Iacoviello, 2012, pp.673-678) Following Anari and Kolari (2002), non-housing CPI is used instead of return series and inflation rate as in previous studies because of two important reasons. Firstly, return on housing cannot be accurately measured as they strongly depend on the underlying assumptions about imputed values of rent and services performed by the owner, house prices can therefore be used since they fully reflect total return on housing. Secondly, by using returns series, the time series is differenced and this is likely to lead to loss of long-run information contained in the time series.

Note that, since the quantile cointegration approach of Kuriyama (2016), which we follow in this paper allows us to test for the existence of cointegration and also estimate the cointegrating parameters, at each point of the conditional distribution of the dependent variable, it is inherently a time-varying approach to detecting and estimating long-run relationships (Xiao, 2009). This is because each point of the conditional distribution of the dependent variable captures the phase in which the dependent variable, in our case, the housing market is, with lower quantiles suggesting bear market, the median capturing the normal phase of the market, while the upper quantiles depicting the bull-phase of the market. Clearly, this approach is preferable over Markov-Switching methods (see, Jochmann and

[4] Housing costs historically range from 20% to 30% of the consumer price index (Anari and Kolari, 2002).

Koop (2015) for a detailed discussion of regime-switching cointegration), as we do not explicitly need to pre-specify and test for the number of regimes in the housing market. Of course, there are pure time-varying parameter cointegration approaches of Park and Hahn (1999), and Bierens and Martins (2010).

However, it is well known that in the presence of structural breaks, standard unit root tests are biased towards the non-rejection of the unit root hypothesis. We, however, decided to work with the quantile cointegration test, since unlike the time-varying cointegration, the former test allows us to detect cointegration at specific parts of the conditional distribution, and hence specific points of housing market phases. Time-varying cointegration tests for whether there is overall time-varying cointegration to fixed-parameter based cointegration, and thus is of little value to the question we are asking, which is to determine cointegration at specific market phases. In addition, in time varying cointegration, testing for parameter restriction is not necessarily straight-forward and requires understanding of cointegrating spaces (Martins, forthcoming). An alternative approach could have been the interrupted cointegration method of Martins and Gabriel (2014), which would have allowed us to detect cointegration at specific points in time, but this again would have required us to use extraneous information to categorize the market phase the housing prices were in. So overall, for our purpose of detecting time varying inflation hedging at specific phases of the housing market, the quantile cointegration approach is the most-suited, with it being also preferable over recursive or rolling test of cointegration as pursued in Anari and Kolari (2002) in relation to housing and inflation. This is because results in such approaches are sensitive to the size of the estimation window (sub-samples) with no clear-cut statistical approach in determining the length of the window to be used (Nyakabawo, Miller, Balcilar, Das and Gupta, 2015).

To the best of our knowledge, this is the first attempt to test for inflation hedging characteristic of house prices using a quantile cointegration method. Prior to that, we take the following standard steps: First we test the variables for unit root using standard unit root tests as a starting point for cointegration analysis. Since house price series and inflation are characterized by the presence of potential structural breaks (Canarella, Miller and Pollard, 2012; Caporin and Gupta, 2017) which can significantly reduce the power of unit root tests, we apply the Zivot and Andrews (1992) unit root test which allows for an endogenous structural break. Furthermore, we employ Lumsdaine and Papell (1997) and Lee and Strazicich (2003) unit root test which allows for two shifts in the deterministic trend at two distinct unknown dates, with the main difference between the two being that the latter test allows for breaks under both the null and alternative hypotheses. To accommodate the possibility of a non-linear dynamics of house prices and inflation (Canarella et al., 2012; Álvarez-Díaz and Gupta 2016), we perform Kapetanios, Shin and Snell (2003) nonlinear unit root test. All the tests suggested that both house prices and non-hoisng CPI are I(1) processes, so we proceeded to testing for cointegration using various standard cointegration tests (for example, Engle and Granger (1987), Phillips and Ouliaris (1990), Park (1992) and Johansen (1988, 1991)). However, these tests provided mixed evidence in favour of cointegration, which was not surprising given that we detected instability in the cointegrating vector using Hansen's (1992) parameter instability test. This statistical result in turn, justified the implementation of the quantile cointegration methodology proposed by Kuriyama (2016), which test for the existence of a long-run relationship across the conditional quantiles of the dependent variable, which is house price. The remainder of the paper is organized as follows: Section 2.2 presents the theoretical model that defines our econometric testing framework, while Section 2.3 outlines the basics of the quantile cointegration approach. Section 2.4 discusses the data and empirical results, with Section 2.5 concluding the paper.

## 2.2 Theoretical Framework

Economic theory identifies housing expenditure as possessing both investment and consumption effects. Survey findings of Case and Shiller (1988), and Case, Shiller and Thompson (2012) tend to show that 44% to 64% of responding households purchase houses for investment benefits, while only 10% considered potential investment benefits as unimportant.

Since houses are considered as both investment and consumption goods, it is important to understand their relationship with inflation. There exist two transmission channels through which higher prices of goods and services can be transmitted to higher house prices (Anari and Kolari, 2002). Through the consumer good channel, inflation causes an increase in construction costs through higher costs of not only building materials, but also construction wages. These higher construction costs of new houses will result in higher new house prices. This further affects replacement costs of existing houses which also increase since they are close substitutes for new houses.

The second channel is through a house being an investment good. House prices in the investment context are equivalent to the present value of actual or imputed net rents. Without taking into account taxes on income and capital gains, the present value model can be defined as:

$$HP = PV = \sum_{k=1}^{n} \frac{E_t(R_{t+k})}{(1+r)^k} \tag{1}$$

where $PV$ denotes present value (equivalent to house price or $HP$), $n$ is the life span of the house, $E_t(R_{t+k})$ is the net annual rent in period $t + k$ that is expected in period $t$, and $r$ is the discount rate. Anari and Kolari (2002) further define net annual rent as gross rent less depreciation and other charges, and depreciation charges accumulated at the end of the lifespan of the house are used to develop another house on the land. Flow of net rent is therefore permanent, meaning that $n \to \infty$. When rent and discounting are presented in real terms, it means that the present value is also in real terms. Imposing the assumption that annual rent is constant, Equation 1 can be represented as:

$$HP = PV = \frac{R}{r} \tag{2}$$

Fisher (1930) proposes that a 1% increase in expected inflation will increase interest rates by 1% because of constant real rate of interest. Applying this proposition to Equation (2) means that it can be expressed in nominal terms, to show the link between nominal house prices and goods and services prices adjusted for housing costs. Since landlords aim to maintain purchasing power of rental income in real terms, expected inflation is incorporated in rent agreements by taking into account consumer price index. Therefore Equation (2) can be expressed as:

$$HP_t = PV_t = \frac{R\left[\frac{E_t\left(NH_{CPI_{t+1}}\right)}{NH_{CPI_b}}\right]}{r} \tag{3}$$

where $E_t$ $(NH_{CPI_{t+1}})$ is the expected nonhousing price index of goods and services for period $t + 1$ based on all available information in period $t$, and $NH\_CPI_b$ is the nonhousing price index in the base period. Assuming that $R$ and $r$ are constants and that $NH\_CPI_b = 1$, and taking the log of both sides of Equation (3), we obtain

$$ln\, HP_t \;=\; \alpha \;+\; \beta\, ln\, E_t\, (NH\_CPI_t\,) \tag{4}$$

where the coefficient of the goods price index $\beta\; = 1$, and the constant term $\alpha\; = ln\, R\; - ln\, r$ . Equation (4) is consistent with the Fisher effect as it proposes that in the absence of taxes, there is inflation elasticity of unity for house prices with respect to goods and services prices adjusted for housing costs (Anari and Kolari, 2002).

But, accounting for taxes complicates the relationship between house prices and inflation. Taxes applying to landlords include income tax on rents and capital gains from selling property, and deductions for depreciation and maintenance costs from rental income are included. However, by living in a home for two of the previous five years, homeowner can be exempt from capital gains tax and are permitted to subtract mortgage interest payments from their income but not depreciation and maintenance expenses (Anari and Kolari, 2002). But, there are data limitations in analysing the impact of taxes and exemptions on housing prices or returns.

Darby (1975) and Carrington and Crouch (1987) suggest that the effects of all these taxes and exemptions are reflected in the $\beta$ coefficient. They further suggest that if $NIR_t, RIR_t,$ and $INR_t$ represent nominal interest rate, real interest and inflation rate respectively, and $T$ is the tax rate, then the Fisher relationship can be written as

$$NIR_t = (1-T)^{-1} RIR_t^e + (1-T)^{-1} INR_t^e \tag{5}$$

According to Crowder and Wohar (1999) and Anari and Kolari (2001), the tax version of the Fisher relationship will hold for the relationship between asset price and CPI indexes, such that the $\beta$ coefficient in Equation (4) can be written as $\beta\; = (1-T)^{-1}$.

## 2.3 Methodology

Let $z_t = (y_t, x_t)'$ be (k+1)x1 process, where $y_t$ is a scalar. We further assume that $z_t$ is an $I(1)$ process and the elements of $x_t$ are not cointegrated. Consider the following model:

$$y_t = \alpha' d_t + \beta' x_t + u_t, \;\; t = 1,2,\dots,T, \tag{6}$$

$$z_t = z_{t-1} + v_t, \tag{7}$$

where $d_t$ is the vector of deterministic components like constant and a linear trend. If the error terms $u_t$ and $v_t$ are $(0)$ , then $y_t$ and $x_t$ are cointegrated.

Xiao and Phillips (2002) suggest a cumulated sum (CUMSUM) statistic for testing the null of cointegration. The authors argue that if $y_t$ and $x_t$ are cointegrated, then the residual process $\hat{u}_t$ of regression (6) should be stable and reflect only equilibrium errors. Thus, the null of cointegration can be tested directly by looking at the fluctuation of the residual process $\hat{u}_t$ through the following statistic:

$$\underbrace{max}_{\tau=1,2,\dots,T} \frac{1}{\sqrt{T}} \sum_{t=1}^{\tau} |\hat{u}_t|. \tag{8}$$

It is the well-known (Park and Phillips (1988); Phillips and Hansen (1990)) that under the null of cointegration, the least squares estimator of the cointegration vector, $\hat{\beta}_{LS}$ , is super-consistent (T-consistent). Unfortunately, the asymptotic distribution of $\hat{\beta}_{LS}$ is miscentered and depends on nuisance parameters. As a consequence, the statistic (8) cannot be used directly for valid inference.

Xiao and Phillips (2002) show that the conventional CUMSUM statistic can be applied to test the null of cointegration. To construct a CUMSUM statistic with a limiting distribution free from nuisance parameters, Xiao and Phillips (2002) construct fully modified (FM) residuals in the spirit of the fully modified least squares (FMLS) method of Phillips and Hansen (1990).

Kuriyama (2016) extends the CUSUM type fully modified analysis of Xiao and Phillips (2002) to the case of conditional quantiles. Specifically, the proposed statistic examines the equilibrium relationships across different quantiles of the distribution of the response variables. To introduce the statistic for quantile cointegration, Kuriyama (2016) introduces the quantile analog of eq. (6):

$$y_t = \alpha'(\tau) d_t + \beta'(\tau) x_t + u_t(\tau) = \theta'(\tau) z_t + u_t(\tau), \;\; t = 1,2,\dots,T, \tag{9}$$

where $\theta(\tau) = (\alpha'(\tau), \beta'(\tau))', \tau \epsilon [0,1]$.

This suggests that $\hat{u}_t = y_t - \hat{\theta}'(\tau) z_t$ and the estimator $\hat{\theta}(\tau)$ of the parameters of interest $\theta(\tau)$ is the solution to:

$$\min_{\theta} \sum_{t=1}^{T} \rho_\tau\left(y_t - z_t{}'\theta(\tau)\right), \tag{10}$$

where $\rho_\tau(u) = u(\tau - I(u < 0))$ , the check function (Koenker and Basset, 1978). Define $\varphi_\tau(u) = \tau - I(u < 0)$. Kuriyama (2016) shows that although $\hat{\beta}(\tau)$ is consistent, its asymptotic distribution shares the same undesirable properties with the least squares estimator of the cointegration vector $\beta$, $\hat{\beta}_{LS}$. Specifically the asymptotic distribution of $\hat{\beta}(\tau)$ contains nuisance parameters and second order bias terms. These effects make $\hat{\beta}(\tau)$ a poor candidate for inference. The author following Xiao and Phillips (2002) adopts the FM corrections initially suggested by Phillips and Hansen (1990). The resulting FM estimator $\hat{\beta}^{+}(\tau)$ of $\beta(\tau)$ takes the following form:

$$\hat{\beta}^{+}(\tau) = \hat{\beta}(\tau) - \left[f\left(\widehat{F^{-1}(\tau)}\right) \sum_{t=1}^{T} x_t^d x_t^{d\prime}\right]^{-1} \left[\sum_{t=1}^{T} x_t^d \, \hat{\Omega}_{\psi x} \hat{\Omega}_{xx}^{-1} \Delta x_t + \hat{\Delta}_{x\psi}^{+}\right], \tag{11}$$

where $x_t^d$ denotes demeaned or detrended regressors, and $f\left(\widehat{F^{-1}(\tau)}\right)$ is a nonparametric consistent estimator of the density function $f\left(F^{-1}(\tau)\right)$. $\hat{\Omega}_{\psi x}$ and $\hat{\Omega}_{xx}$ are semiparametric kernel estimators of the long run covariance matrices: $\Omega_{\psi x} = \Omega_{x\psi}' = \sum_{t=-\infty}^{\infty} E\left(v_t \psi_\tau(u_0(\tau))\right)$, and $\Omega_{xx} = \sum_{t=-\infty}^{\infty} E(v_t v_0{}')$, where $\psi_\tau(u(\tau)) = \tau - I(u < 0)$. Analogously, $\hat{\Delta}_{x\psi}^{+}$ is semiparametric kernel estimators of the modified one-sided long run covariance matrix $\Delta_{x\psi}^{+} = \Delta_{x\psi} - \Omega_{\psi x}\Omega_{xx}^{-1}\Delta_{xx}$, where $\Delta_{x\psi} = \sum_{t=0}^{\infty} E\left(v_t \psi_\tau(u_0(\tau))\right)$, $\Delta_{xx} = \sum_{t=0}^{\infty} E(v_t v_0{}')$. Kuriyama (2016) shows that the fully modified estimator $\hat{\beta}^{+}(\tau)$ follows asymptotically a mixed normal distribution:

$$T\left(\hat{\beta}^{+}(\tau) - \beta(\tau)\right) \Rightarrow MN\left(0, \frac{\omega_{\psi.x}^2}{f\left(F^{-1}(\tau)\right)} \left[\int B_{xd} B'{}_{xd}\right]^{-1}\right), \tag{12}$$

where $B_{xd} = B_x - (\int B_x d')(\int B_d{}')^{-1} B_d$ is a demeaned or detrended Brownian motion (for more details see Kuriyama (2016)), $B_x$ is a Brownian motion with covariance matrix $\Omega_{xx}$ , $\omega_{\psi.x}^2 = \omega_\psi^2 - \Omega_{\psi x}\Omega_{xx}^{-1}\Omega_{x\psi}$ , and $\omega_\psi^2$ the long run variance of $\psi_\tau(u(\tau))$. Again, all long run variances are estimated nonparametrically using kernel methods. Next, the author uses the residuals $\hat{u}^{+}(\tau) = y_t^{+} - \hat{\theta}^{+\prime}(\tau) z_t$ , from the fully modified regression to build the CUSUM test statistic in the spirit of eq. 8, as follows:

$$CS_T(\tau) = \max_{n=1,..,T} \frac{1}{\hat{\omega}_{\psi.x}\sqrt{T}} \left|\sum_{t=1}^{n} \psi_\tau(\hat{u}_t^{+}(\tau))\right|, \tag{13}$$

where $\hat{\theta}^{+}(\tau) = \hat{\theta}(\tau) - \left[f\left(\widehat{F^{-1}(\tau)}\right)\sum_{t=1}^{T} z_t z_t{}'\right]^{-1} \left[\sum_{t=1}^{T} z_t\, \hat{\Omega}_{\psi x}\hat{\Omega}_{xx}^{-1}\Delta x_t + \bar{\hat{\Delta}}_{x\psi}^{+}\right]$,

$\bar{\hat{\Delta}}_{x\psi}^{+} = \left(0, \hat{\Delta}_{x\psi}^{+}{}'\right)'$ , and $y_t^{+} = y_t - \hat{\Omega}_{\psi x}\hat{\Omega}_{xx}^{-1}\Delta x_t$. Kuriyama (2016) shows that under certain assumptions and for a certain quantile τ, the asymptotic represantaion of the $CS_T(\tau)$ statistic is as follows:

$$CS_T(\tau) \Rightarrow \underbrace{sup}_{0 \le r \le 1} |W(r)|, \tag{14}$$

Where $W(r) = W_1 - [\int dW_1 S'][\int SS']^{-1} \int_0^r S$, $S = (B_d', W_2{}')$, and $W_1$ and $W_2$ are one and k-dimensional independent standard Brownian motions. Critical values of the $CS_T(\tau)$ statistic can be obtained by Monte Carlo simulation (see Table 1, Xiao and Phillips (2002), among others).

Note that, we preferred the Kuriyama (2016) methodology over that developed earlier by Xiao (2009), since in the latter case, detection of cointegration is contingent on the correct choice of leads and lags in the model, as it is based on the Dynamic Ordinary Least Squares (DOLS)-type approach of Saikkonen (1991). The CUSUM test statistic developed by Kuriyama (2016) corrects for endogeneity by using fully-modified residuals.

## 2.4 Empirical Analysis

### 2.4.1 Data description

For the empirical estimation, we use monthly US data covering the monthly time period from 1953:M1 to 2016:M2 for non-housing CPI and nominal house price index. The data span ensures that we cover the longest possible known economic expansions and recessions, as well as housing market innovations that may imply different responses during different periods (Nyakabawo et al., 2015). Non-housing CPI is obtained from the United States Department of Labor, Bureau of Labor Statistics, and the nominal house price index is obtained from the data segment of the website of Professor Robert J. Shiller: http://www.econ.yale.edu/~shiller/data.htm. We process the data by first seasonally adjusting it, and then transform it into logarithms denoted as $LNHCPI$ and $LNHPI$ for non-housing CPI and house price index, respectively. Figure 2.1 shows the comovement between the housing price index and the non-housing CPI.

### 2.4.2 Preliminary analysis

We perform standard unit root tests to determine whether the non-housing CPI and house price index series are stationary and results are reported in Table 2.1.[5] According to results in Table 2.1, the Augmented Dickey and Fuller (ADF, 1981), Elliott et al.'s (1996) Dickey-Fuller Generalized Least Squares (DF-GLS), Phillips and Perron (PP, 1988) (PP), and Ng and Perron (2001) tests fail to reject the null hypothesis of non-stationarity for the non-housing CPI and house price index series at conventional levels of significance. The tests further indicate that the first differences of non-housing CPI and house price index series reject the null of a unit root. Therefore, the unit root test results indicate that the non-housing CPI and house price index series of the U.S both conform to $I(1)$ processes.

However, a major shortcoming with the standard unit root tests is that they do not allow for the possibility of structural breaks. Perron (1989) shows that the power to reject a false unit root null hypothesis decreases and therefore a structural break can be ignored. While Perron (1989) treats the structural break as being exogenous, we follow Zivot and Andrews (1992) by implementing a unit root test to determine a break point endogenously, allowing for a break in both trend and intercept. Results of Zivot and Andrews (1992) unit root test are reported in Table 2.2 and show that we cannot reject null hypothesis implying that both series contain unit root. It is also expected that there is a loss of power when two or more breaks are not accommodated when employing a test that only accommodates a one-time structural break. Therefore, we also implement Lumsdaine and Papell's (1997) unit root test that

[5] For all the unit root and cointegration tests, the choice of lag-length was based on the Schwarz Information Criterion. However, alternative choice of lag-length based on other criteria, like the Akaike Information Criterion and the Hannan-Quinn Criterion, yielded qualitatively the same results. Complete details of these results are available upon request from the authors.

allows for two breaks in the trend at two distinct unknown dates. Table 2.3 reports the results of the Lumsdaine and Papell (1997) test allowing for breaks in both intercept and trend. According to the results, we cannot reject the null hypothesis, implying that non-housing CPI and house price index contain unit root with two breaks. In this regard, we further apply the powerful Lee and Strazicich (2003) LM unit root tests, which takes into account two structural breaks and the alternative hypothesis unambiguously implies the series to be trend stationary. Results are reported in Table 2.4, and indicate that we cannot reject null hypothesis of unit root again.[6]

To accommodate the possibility of a non-linear dynamics of house price and non-housing CPI, we perform Kapetanios et al., (KSS, 2003) nonlinear unit root test on the de-meaned and detrended data, which shows further evidence of non-stationarity in these two variables, as reported in Table 2.5.

Therefore, based on the unit roots tests which incorporate the possibility of one or two structural breaks and nonlinearity, the null hypothesis of unit root cannot be rejected, and hence, we can move ahead to the test of cointegration having met its pre-requisite of both variables being *I(1)*.

We start off the cointegration analysis with the standard Engle and Granger (1987) cointegration test (reported in Table 2.6) which tests the null hypothesis that series are not cointegrated.[7] Based on the results, we reject the null hypothesis of no cointegration indicating that non-housing CPI and the house price index series are cointegrated.[8] The Phillips and Ouliaris (1990) test (Table 2.7) tests the null hypothesis that series are not cointegrated. We do not reject the null hypothesis of no

[6] We also applied the Residual Augmented Least Squares–Lagrange Multiplier (RALS–LM) unit root test with structural breaks in the mean and trend as recently proposed by Meng et al., (forthcoming); however, our results still indicated that both the house price index and the non-housing CPI index are I(1) processes. Complete details of these results are available upon request from the authors.

[7] In cases where cointegration holds, for instance in the case of the Engle and Granger (1987) and Kuriyama (2016) tests, we normalize the cointegrating vector on the house price index, since we are interested in the inflation-hedging property of house price. But, standard Granger causality tests (available upon request from the authors) also indicated that house prices are caused by non-housing CPI, but not the other way round, hence, we can treat non-housing CPI as the exogenous variables and normalize the cointegrating vector on the house price index. Note however, for the single-equation based cointegration tests, our results were unaffected irrespective of which variable was used as the dependent variable. Again complete details of these results are available upon request from the authors.

[8] The inflation hedging coefficient in this case was 1.20 (p-value=0.00), suggesting that house prices act as an overhedge of inflation. This result was statistically vindicated when we found that this coefficient is significantly different from 1, with the coefficient restriction of equal to 1 being rejected at one percent level of significance. Complete details of these results are available upon request from the authors.

cointegration suggesting that the non-housing CPI and house price index series are not cointegrated. Further analysis using Park (1992) added variable test (Table 2.8), leads us to reject the null hypothesis of cointegration at one percent level suggesting that series are not cointegrated. We also perform the Johansen (1988; 1991) cointegration tests to determine whether non-housing CPI and house price index cointegrate with each other. The result reported in Table 2.9 reports show evidence of no cointegration between non-housing CPI and house price index, implying that the two series do not maintain a long-run relationship in log-levels. So, based on the cointegration results, the Engle and Granger (1987) test imply possible cointegration between non-housing CPI and house price index, while the Phillips and Ouliaris (1990), Park (1992), and Johansen (1988; 1991) cointegration test results show evidence of no cointegration between the two series. Therefore, these conflicting conclusions caused us to apply the parameter stability test of Hansen (1992) based on the Fully Modified Ordinary Least Squares (FM-OLS) estimation of the cointegrating vector. As shown in Table 2.10, the null of parameter stability is overwhelmingly rejected, which implies that the long-run relationship between the two variables of concern are unstable. This result differs from the findings of Anari and Kolari (2002), who find evidence of a stable long-run relationship between these data series, though over a different sample period (1968:M1-2000:M6), which does not of course include the recent financial crisis. The existence of instability was further vindicated when we applied the powerful WDmax test of 1 to M globally determined breaks proposed by Bai and Perron (2003) to the FM-OLS estimated regression, and obtain five breaks at: 1968:M2, 1977:M7, 1986:M12, 1997:M4, and 2006M:10.

### 2.4.3 Quantile regression analysis

The mixed evidence on the cointegration relationship between non-housing CPI and house price index and that of parameter instability motivates us to continue with quantile regression analysis. Specifically, we apply the Kuriyama's (2016) quantile cointegration analysis which examines the equilibrium relationships across different quantiles of the distribution of the response variable, namely the house price in our case. The methodology allows the long-run relationship among time series which contains unit root to be non-uniform across the various conditional quantiles of the dependent variable.

We start our analysis by testing the unit root hypothesis in quantiles. Koenker and Xiao (2004) propose quantile regression-based inference for the unit root hypothesis. The quantile unit root tests are based on the quantile autoregression (QAR) approach. The authors introduce the so-called QAR model as follows:

$$y_t = Q_\tau(y_t|\mathcal{J}_{t-1}) + \varepsilon_t = a_0(\tau) + a_1(\tau)y_{t-1} + \sum_{i=1}^{k}\gamma_i(\tau)\Delta y_{t-k} + \varepsilon_t, \tag{15}$$

where $Q_\tau(y_t|\mathcal{J}_{t-1})$ is the τ-th conditional quantile and $\mathcal{J}_{t-1}$ is the σ-field generated by $\{\varepsilon_s, s \leq t-1\}$. If $a_1(\tau) = 1$, then $y_t$ is persistent and contains a unit root at quantile $\tau$. Koenker and Xiao (2004) suggest testing the unit root hypothesis $H_0: a_1(\tau) = 1$, using the following t-ratio statistic:

$$t(\tau) = \frac{f\widehat{(F^{-1}(\tau))}}{\sqrt{\tau(1-\tau)}}(Y_{-1}'P_X Y_{-1})^{\frac{1}{2}}(\hat{a}_1(\tau) - 1), \tag{16}$$

where $f\left(\widehat{F^{-1}(\tau)}\right)$ is a consistent estimator of $f\left(F^{-1}(\tau)\right)$, $f(\cdot)$ and $F(\cdot)$ are the density and the distribution function of $\{\varepsilon_t\}$, respectively, $Y_{-1}$ is the vector of lagged dependent variables, and $P_X$ is the projection matrix onto the space orthogonal to $X = (1, \Delta y_{t-1}, \dots, \Delta y_{t-k})$. Like the augmented Dickey-Fuller statistic, the limiting distribution of $t(\tau)$ is not standard and depends on nuisance parameters. Xiao and Koenker (2004) suggest calculating critical values using resampling methods. In addition to the t-ratio statistic $t(\tau)$ which focuses on a single selected quantile, the authors also introduce a Kolmogorov-Smirnov (KS) type statistic which tests the unit root property over a range quantiles $\boldsymbol{\tau} \in \mathcal{T}$:

$$QKS = \underbrace{sup}_{\boldsymbol{\tau}\in\mathcal{T}}|t(\tau)|. \tag{17}$$

We apply the QAR-based tests, $t(\tau)$ and $QKS$, to the non-housing CPI ($LNHCPI$) and house price index ($LNHPI$). Table 2.11 reports the quantile unit root test results for $LNHCPI$ (Panel A) and $LNHPI$ (Panel B) and the bootstrapped critical values. We first apply the quantile unit root test $t(\tau)$ for a sequence of quantiles. Results indicate that the unit root hypothesis cannot be rejected at the 5% significance level, at each one of the selected quantiles. Next, we apply the KS-type test, QKS, over the range of quantiles $\boldsymbol{\tau} \in \mathcal{T} \coloneqq \{0.5, 0.10, 0.20, \dots, 0.90, 0.95\}$. QKS results also support the unit root hypothesis.

However, it is well known that in the presence of structural breaks, standard unit root tests are biased towards the non-rejection of the unit root hypothesis. In order to examine the robustness of the quantile unit root results reported in Table 2.12, we test for the presence of breaks in regression quantiles. Specifically, we test for structural stability and estimate the break dates (if breaks are present) across a range of quantiles $\tau \in \{0.5, 0.10, 0.20, \dots, 0.90, 0.95\}$, using the *DQ-test* introduced by Qu (2008) and Oka and Qu (2011). Oka and Qu (2011) argue that it can be more informative to consider a range of quantiles as opposed to a single one. *DQ*-test results reported in Table 2.12 suggest the existence of two and one breaks in the LNHCPI and LNHPI time series, respectively. Following Wolters and Tillman (2014), we further investigate whether LNHCPI and LNHPI time series follow a unit root process by repeating the analysis of persistence in different subsamples, which are chosen based on the break points suggested by the *DQ-test.* The results and the 5% critical values are reported in Table 2.12. In the case of the LNHCPI time series, $t(\tau)$ and $QKS$ tests results support the unit root hypothesis in the first two subsamples (1953:M1-1968:M9 and 1968:M10-1982:M5). In the third subsample covering the period 1982:M6 – 2016:M2, the ratio t-test $t(\tau)$ rejects the unit root hypothesis at three quantiles, 0.20, 0.30 and 0.40. The QKS test marginally rejects the unit root null over the range of quantiles $\mathcal{T} \coloneqq \{0.5, 0.10, 0.20, \dots, 0.90, 0.95\}$. In the case of the LNHPI time series, $t(\tau)$ and $QKS$ tests results support the unit root hypothesis in the first subsample (1953:M1-1977:M6). In the second subsample (1977:M7 – 2016:M2) the ratio t-test $t(\tau)$ rejects the unit root hypothesis only at $\tau = 0.2$. Contrary, the QKS test accepts the unit root null over the range of quantiles $\mathcal{T} \coloneqq \{0.5, 0.10, 0.20, \dots, 0.90, 0.95\}$.

Having examined the persistence of our time series, we proceed with the quantile cointegration analysis, given that we establish that the two series are indeed I(1). Note that, the break dates in the conditional distribution of LNHPI and the sub-samples created in the process, already includes the break dates and the sub-samples of the conditional distribution of LNHCPI. And given that, the quantile cointegration approach of Kuriyama (2016) allows us to test for the existence of cointegration and also estimate the cointegrating parameters, at each point of the conditional distribution of the dependent variable, it is inherently a time-varying approach to detecting and estimating long-run relationships, we do not need to conduct sub-sample analysis of quantile cointegration based on the breaks in the distributions of the two variables of concern identified in Table 3G. Test results are reported in Table 2.13, Panel A. For each quantile the intercept term ($\alpha$), the fully modified coefficient estimate ($\beta$) and the CUSUM test statistic ($CS_T(\tau)$) are reported. We also report the *t*-test statistics for testing whether $\beta$ is significantly different from zero and one. While the former allows us to test whether, the relationship between house price and non-housing CPI is significant, the latter tells us if housing under-hedges, serves as a perfect hedge or over-hedges inflation. The results provide evidence that non-housing CPI and house price index are cointegrated at the lower quantiles of 0.05 to 0.20 at 5 percent significance level. However, there is no evidence of a cointegration relationship over the quantile range of 0.30 to 0.90 even at the 10 percent level of significance. The response of house price to non-housing CPI is always positive and statistically significant over the entire conditional distribution of house price. In addition, $\beta$ is also statistically greater than one over the entire conditional distribution, suggesting that house prices over-hedges inflation. But given that the cointegration exists only over the quantile range of 0.05 to 0.20, we need to restrict our discussion of the overhedging characteristic of house prices to only these quantiles, over which one percent increases in inflation, leads to between 1.11 to 1.16 percent increases in nominal housing returns. As pointed out by Anari and Kolari (2002), the fact that the coefficients are greater than one is indicative of the fact that they may be incorporating the impact of tax (see also, Darby (1975), Carrington and Crouch (1987), and Crowder and Wohar (1999)). The fact that majority of the conditional mean based cointegration fail to pick up cointegration is possibly due to the fact that cointegration does not hold over the majority of the conditional distribution of house prices. But at the same time, our results highlight the importance of using the quantile-based approach, since if we would have just relied on the conditional-mean based tests, we would have wrongly concluded that house price does not hedge inflation, when in fact it overhedges inflation, but only at certain lower quantiles.[9] Understandably, overhedging suggests that the real value of the investment in housing is retained in the presence of inflation, as it ensures a positive real rate of return.

In order to further qualify our results, and the fact that the hedging ability of asset prices depends on the level of inflation rate (Hong and Lee, 2013), we categorize lower and higher inflationary situations by looking at lower and upper quantiles of the distribution of LNHCPI, and re-conducting the quantile cointegration test.[10] Specifically speaking, we look at the part of the distribution of the LNHCPI below 0.10 and above 0.90 categorizing relatively lower and higher general price levels. The results are reported in Panels B and C of Table 2.13. We can draw two main observations[11]: (a) The overall results which considers the entire distribution of LNHCPI, as reported in Panel A of Table 4, is basically driven by the upper quantiles-based results obtained under the LNHCPI. In other words, housing acts as an overhedge of inflation, when LNHPI is relatively lower given that LNHCPI is comparatively higher, and; (b) Secondly, while there is no evidence of quantile cointegration when we look at the part of the distribution of LNHCPI that is below 0.10, we do find that the response of LNHPI to LNHCPI is stronger when the latter is restricted to its upper quantiles, i.e., part of the distribution above 0.90 relative to the case of the distribution of LNHCPI being below the quantile of 0.10.

## 2.5 Conclusion

In this paper, we analyse whether house prices provide a good hedge against inflation in the US by investigating the long run relationship between non-housing CPI and houses prices using quantile

[9] We also tested for quantile cointegration using Xiao’s (2009) methodology and detected evidence of quantile cointegration and over-hedging, but we prefer the Kuriyama (2016) approach for reasons already discussed in the methodology segment. Similar results in terms of overhedging were also obtained under the quantile Autoregressive Distributed Lag (QARDL) approach of Cho et al., (2015). Note that, Anari and Kolari (2002) had used an ARDL model, which in turn, is also a conditional mean-based model with existence or non-existence of cointegration being often sensitive to the appropriate choice of lag-lengths like many of the cointegration tests discussed in the main text. But, for the sake completeness and comparability, we also applied the test to our dataset, but failed to detect cointegration at conventional levels of significance, which should not be surprising given the evidence of parameter instability discussed in the main text. Complete details of all these results are available upon request from the authors.

[10] We would like to thank an anonymous referee for guiding us in this direction.

[11] When we look at other possible break-ups of the distribution of LNHCPI, i.e., below 0.25 and above 0.75, and below 0.50 and above 0.50, we obtained similar results, complete details of which are available upon request from the authors.

cointegration analysis. Monthly data covering the period 1953:M1 to 2016:M2 is used. Before proceeding with the quantile cointegration analysis, standard and quantiles-based unit root tests were performed, and our results conclude that both non-housing CPI and house price index are $I(1)$ series. Allowing for the possibility of structural breaks, we perform unit root test with both one and two structural breaks, and also with breaks of the conditional distribution, and find evidence that we cannot reject the null hypothesis of unit root. Evidence from non-linear unit root test also concludes that the series are non-stationary. Next, when we conduct standard cointegration tests, we find mixed evidence of a cointegration relationship between non-housing CPI and house price index, which motivates us to perform a stability test on the cointegrating vector. Results from the stability test conclude that the cointegration relationship is unstable, therefore we use a time-varying approach by applying Kuriyama's (2016) quantile cointegration which test for the existences of a long-run relationship across the conditional quantiles of the dependent variable, thus capturing various phases of the US housing market. Empirical results using quantile cointegration suggest that the U.S non-housing CPI and house price index series are cointegrated at lower quantiles, but show evidence of no long-run relationship at the middle and upper quantiles. Our results also imply that at lower levels, house prices over-hedge against inflation. In addition, when we categorize lower and higher inflationary situations by looking at lower and upper quantiles of the distribution of non-housing CPI, and re-conduct the quantile cointegration test, we find that the above result only holds at the upper quantiles of the non-housing CPI. In other words, housing acts as an overhedge for inflation when the former is relatively lower and the latter is comparatively higher. But given that there is no long-run relationship at moderate to high levels, our results are possibly indicative of bubbles that exists in an overheated housing market, captured by housing prices deviating from a fundamental, namely non-housing CPI in our case. As part of future research, it would be interesting to extend our analysis to REITs.

**Figure 2.1. Data plots**

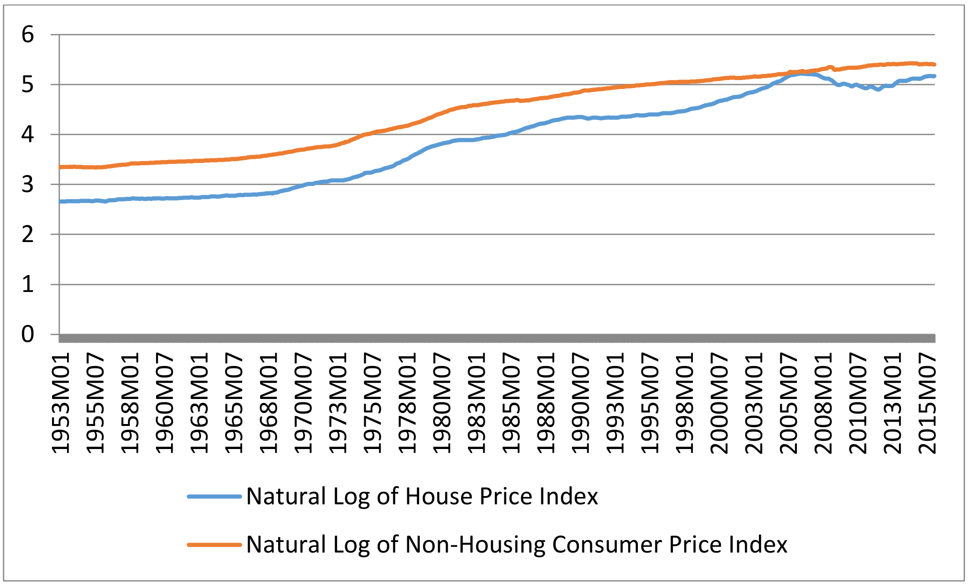


**Table 2.1. Unit root Tests**

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Levels** | | | | | | | | |
| | ADF | | DF-GLS | | PP | | Ng-Perron | |
| | C | C+T | C | C+T | C | C+T | C (MZa) | C+T (MZa) |
| House prices | -0.526 | -3.938 | -1.053 | -2.984 | -0.003 | -1.712 | 1.377 | -2.238 |
| Inflation | -1.140 | 0.522 | 1.268 | -0.956 | -0.810 | -0.189 | 1.237 | -0.761 |
| **First difference** | | | | | | | | |
| | ADF | | DF-GLS | | PP | | Ng-Perron | |
| | C | C+T | C | C+T | C | C+T | C (MZa) | C+T (MZa) |
| House prices | -3.515*** | -3.506** | -2.451** | -3.246** | -9.679*** | -9.643*** | -128.295*** | -156.670*** |
| Inflation | -4.028*** | -4.120*** | -1.514 | -2.265 | -18.441*** | -18.471*** | -138.036*** | -270.351*** |

Notes: *** indicates significance at a 1% level;
ADF and PP: a constant is included in the test equation; one-sided test of the null hypothesis that a unit root exists; 1, 5 and 10% significance critical value equals -3.439, -2.865,-2.569, respectively.

ADF and PP: a constant and a linear trend are included in the test equation; one-sided test of the null hypothesis that a unit root exists; 1, 5 and 10% critical values equals -3.970, -3.416, -3.130, respectively.

Ng-Perron: a constant is included in the test equation; one-sided test of the null hypothesis that a unit root exists; 1, 5 and 10% significance critical value equals -13.800, -8.100, -5.700, respectively.

Ng-Perron: constant and a linear trend are included in the test equation; one-sided test of the null hypothesis that a unit root exists; 1, 5 and 10% critical values equals -23.800, -17.300, -14.200, respectively.

DF-GLS: a constant is included in the test equation; one-sided test of the null hypothesis that a unit root exists; 1, 5 and 10% significance critical value equals -2.568, -1.941, -1.616, respectively.

DF-GLS: constant and a linear trend are included in the test equation; one-sided test of the null hypothesis that a unit root exists; 1, 5 and 10% critical values equals -3.480, -2.890, -2.57, respectively.

## Table 2.2. Zivot and Andrews (1992) one break unit root test

| Series | Test statistic | Breakpoint |
|---|---|---|
| **LNHPI** | **-5.57** | **2002:01** |
| **LNHCPI** | **-3.71** | **1973:08** |

Notes: Allowing for Break in both Intercept and Trend Breaks Tested for 1962:10 to 2006:10. Including 5 Lags of Difference selected by user. The critical values for the Zivot and Andrews (1992) test are -5.57 per cent, -5.08 per cent and -4.82 per cent at the 1 per cent, 5 per cent and 10 per cent levels of significance respectively (Zivot and Andrews, 1992).

## Table 2.3. Lumsdaine and Papell (1997) two breaks unit root test

| Series | Test statistic | Breakpoint 1 | Breakpoint 2 |
|---|---|---|---|
| **LNHPI** | **-3.69** | **1976:06** | **2002:02** |
| **LNHCPI** | **-5.15** | **1966:04** | **1978:12** |

Notes: Regression period 1953:07 to 2016:02. The critical values for the Lumsdaine and Papell (1997) two break test are -7.19 per cent, -6.75 per cent and -6.48 per cent at the 1 per cent, 5 per cent and 10 per cent levels of significance respectively.

## Table 2.4. Lee and Strazicich (2003) LM two breaks unit root test

| Series | Test statistic | Breakpoint 1 | Breakpoint 2 |
|---|---|---|---|
| **LNHPI** | **-0.79** | **1965:12** | **1978:11** |
| **LNHCPI** | **-1.57** | **1969:08** | **1981:05** |

Notes: Regression period 1953:02 to 2016:02. The critical values for the Lee and Strazicich (2003) two break test are -6.32 per cent, -5.71 per cent and -5.33 per cent at the 1 per cent, 5 per cent and 10 per cent levels of significance respectively.

## Table 2.5. Kapetanios, Shin and Snell (2003) nonlinear unit root test

| Series | Test statistic |
|---|---|
| **LNHPI** | **-1.91** |
| **LNHCPI** | **2.38** |

Notes: *** indicates significance at a 1% level; ** indicate significance at a 5% level; * indicate significance at a 10% level
The critical values for the Kapetanios, Shin and Snell (2003) KSS test are: -3.93 (1-percnt level); -3.40 (5-percent level); and -3.13 (10-percent level) (Kapetanios, et al., 2003, Table 1).

## Table 2.6. Engle and Granger (1987) cointegration test

| Statistic | Value | Prob |
|---|---|---|
| **Engle-Granger tau-statistic** | **-3.777438** | **0.0151** |
| **Engle-Granger z-statistic** | **-40.02597** | **0.0006** |

Notes: Tests null hypothesis of no cointegration against the alternative of cointegration.

## Table 2.7. Phillips and Ouliaris (1990) cointegration test

| Statistic | Value | Prob* |
|---|---|---|
| **Phillips-Ouliaris tau-statistic** | **-1.215704** | **0.8546** |
| **Phillips-Ouliaris z-statistic** | **-3.257794** | **0.8614** |

Notes: Tests null hypothesis of no cointegration against the alternative of cointegration.

### Table 2.8. Park (1992) added variables test

| | Value | df | Probability |
|---|---|---|---|
| **Chi-square** | **60.38389** | **2** | **0.0000** |

Notes: Tests null hypothesis of cointegration against the alternative of no cointegration.

### Table 2.9. Johansen'Cointegration Test

| Series | $H_0$[a] | $H_1$ | Trace Statistic | Maximum-Eigen Value Statistic |
|---|---|---|---|---|
| **LHCPI and LNHPI** | $r = 0$ | $r > 0$ | 7.75 | 5.74 |
| | $r \leq 1$ | $r > 1$ | 0.49 | 0.65 |

Notes: [a]One-sided test of the null hypothesis ($H_0$) that the variables are not cointegrated against the alternative ($H_1$) of at least one cointegrating relationship. The critical values are taken from MacKinnon et al., (1999) with 5-percent critical values equal to 15.49 for testing $r = 0$ and 3.84 for testing $r \leq 1$ for the Trace test. The corresponding values for the Maximum Eigenvalue tests are 14.26 and 3.84.

### Table 2.10. Hansen Parameter Instability Test

| $L_c$ Statistic | Stochastic Trends(m) | Deterministic Trends (k) | Excluded Trends (p2) | Prob* |
|---|---|---|---|---|
| **3.047** | **1** | **0** | **0** | **<0.01** |

Notes:Hansen (1992b) Lc(m2=1, k=0) p-values, where m2=m-p2 is the number of stochastic trends in the asymptotic distribution. Test null hypothesis of parameter stability against the alternative of instability.

**Table 2.11. Quantile Unit Root Test**

| T | 0.05 | 0.10 | 0.20 | 0.30 | 0.40 | 0.50 | 0.60 | 0.70 | 0.80 | 0.90 | 0.95 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: LNHCPI (1953:M1 – 2016:M2) | | | | | | | | | | | |
| $\hat{a}_1(\tau)$ | 0.9990 | 0.9995 | 0.9999 | 1.0001 | 1.0002 | 1.0001 | 1.0000 | 0.9998 | 0.9999 | 1.0003 | 1.0003 |
| t(τ) | -1.7230** | -1.3660** | -0.4056** | 0.7668** | 1.2113** | 0.9785** | -0.0932** | -0.9163** | -0.3156** | 1.1149** | 0.5271** |
| critical value | -2.3560 | -2.3481 | -2.4604 | -2.5149 | -2.5359 | -2.5633 | -2.5718 | -2.5787 | -2.4404 | -2.1903 | -2.1954 |
| KS test | QKS = 1.7230** | | critical value =2.8434 | | | | | | | | |
| **DQ**-test | 1st break: 1968:M9 | | 2nd break: 1982:M6 | | | | | | | | |
| Panel B: LNHPI (1953:M1 – 2016:M2) | | | | | | | | | | | |
| $\hat{a}_1(\tau)$ | 1.0007 | 1.0006 | 1.0004 | 1.0003 | 1.0001 | 1.0000 | 0.9997 | 1.9995 | 0.9992 | 0.9989 | 0.9990 |
| t(τ) | 2.3036** | 2.0121** | 2.2878** | 2.1682** | 0.5680** | -0.4690** | -2.5755** | -2.5416** | -2.4736** | -2.2681** | -2.4746** |
| critical value | -2.4305 | -2.6038 | -2.7456 | -2.7834 | -2.7838 | -2.8093 | -2.8299 | -2.7391 | -2.8477 | -2.6241 | -2.5891 |
| KS-test | QKS = 2.5755 ** | | critical value = 2.7565 | | | | | | | | |
| **DQ**-test | 1977:M7 | | | | | | | | | | |

Notes: ** indicates acceptance of the unit root hypothesis at the 5% significance level. $\hat{a}_1(\tau)$ is the point estimate of the coefficient $a_1(\tau)$ *in* QAR: $y_t = a_0(\tau) + a_1(\tau)y_{t-1} + \sum_{i=1}^{k} \gamma_i(\tau)\Delta y_{t-k} + \varepsilon_t$. *t(τ) and* QKS stand for the t-ratio and Kolmogorov-Smirnov (KS) Koenker and Xiao (2004) statistics, respectively. Breaks dates are estimated using the DQ-test (Qu; 2008, Oka and Qu; 2011). Critical values correspond to the 5% significance level and are calculated using resampling methods.

**Table 2.12. Quantile Breaks and Subsample Unit Root Test**

| T | 0.05 | 0.10 | 0.20 | 0.30 | 0.40 | 0.50 | 0.60 | 0.70 | 0.80 | 0.90 | 0.95 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: LNHCPI | | | | | | | | | | | |
| Subsample: 1953:M1 – 1968:M9 | | | | | | | | | | | |
| $\hat{a}_1(\tau)$ | 1.0041 | 1.0081 | 1.0000 | 1.0000 | 1.0063 | 1.0000 | 1.0032 | 1.0047 | 1.0038 | 1.0022 | 0.9957 |
| t(τ) | 1.4121** | 1.7193** | 0.0018** | 0.0001** | 2.2942** | 0.0092** | 0.7380** | 1.0211** | 0.7981** | 0.3586** | -0.9923** |
| critical value | -2.1200 | -2.3070 | -2.5177 | -2.5344 | -2.3966 | -2.6463 | -2.6387 | -2.6401 | -2.5863 | -2.5596 | -2.5743 |
| KS-test | QKS = 2.2942** | | critical value =2.8328 | | | | | | | | |
| Subsample: 1968:M10 – 1982:M5 | | | | | | | | | | | |
| $\hat{a}_1(\tau)$ | 1.0002 | 1.0010 | 1.0001 | 1.0000 | 0.9997 | 0.9999 | 0.9999 | 1.0007 | 1.0006 | 0.9983 | 0.9976 |
| t(τ) | 0.2275** | 0.6369** | 0.0914** | 0.0185** | -0.2538** | -0.0897** | -0.0615** | 0.4056** | 0.3333** | -0.6179** | -1.6179** |
| critical value | -2.2034 | -2.4791 | -2.5139 | -2.6092 | -2.7540 | -2.7363 | -2.7538 | -2.7257 | -2.6354 | -2.6115 | -2.4196 |
| KS-test | QKS = 1.1591** | | critical value =2.8348 | | | | | | | | |
| Subsample: 1982:M6 – 2016:M2 | | | | | | | | | | | |
| $\hat{a}_1(\tau)$ | 0.9949 | 0.9950 | 0.9968 | 0.9972 | 0.9978 | 0.9987 | 0.9990 | 0.9993 | 1.0010 | 1.0033 | 1.0026 |
| t(τ) | -1.6743** | 0.6369** | -2.8201 | -2.8664 | -2.5436 | -2.2453** | -0.15504** | -0.8185** | 0.9669** | 2.2223** | 0.8831** |
| critical value | -2.4771 | -2.2488 | -2.4060 | -2.4384 | -2.4178 | -2.3503 | -2.2645 | -2.2887 | -2.1949 | -2.1200 | -2.1200 |
| KS-test | QKS = 2.8664 | | critical value =2.8662 | | | | | | | | |
| Panel B: LNHPI | | | | | | | | | | | |
| Subsample: 1953:M1 – 1977:M6 | | | | | | | | | | | |
| $\hat{a}_1(\tau)$ | 1.0067 | 1.0055 | 1.0044 | 1.0027 | 1.0026 | 1.0014 | 1.0028 | 1.0065 | 1.0071 | 1.0075 | 1.0092 |
| t(τ) | 2.2988** | 1.6868** | 1.8427** | 1.2458** | 1.4165** | 0.6487** | 1.2438** | 2.5880** | 2.2036** | 1.9393** | 2.5303** |
| critical value | -2.1468 | -2.3384 | -2.4203 | -2.5657 | -2.5967 | -2.6064 | -2.6187 | -2.5491 | -2.4420 | -2.1993 | -2.1200 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| KS-test | QKS = 2.5880** | | critical value = 2.8625 | | | | | | | | |
| Subsample: 1977:M7 – 2016:M2 | | | | | | | | | | | |
| $\hat{a}_1(\tau)$ | 0.9994 | 0.9992 | 0.9992 | 0.9996 | 0.9997 | 0.9997 | 0.9999 | 0.9999 | 1.0001 | 1.0008 | 1.0016 |
| t(τ) | -1.5279** | -1.9323** | -2.6508 | -2.4960** | -1.6252** | -1.7454** | -0.4931** | -0.3377** | 0.3904** | 1.7054** | 2.0276** |
| critical value | -2.3207 | -2.5832 | -2.5557 | -2.7208 | -2.8076 | -2.7787 | -2.7395 | -2.7231 | -2.7164 | -2.6188 | -2.4545 |
| KS-test | QKS = 2.6508** | | critical value = 2.8142 | | | | | | | | |

Notes: ** indicates acceptance of the unit root hypothesis at the 5% significance level. $\hat{a}_1(\tau)$ is the point estimate of the coefficient $a_1(\tau)$ *in* QAR: $y_t = a_0(\tau) + a_1(\tau)y_{t-1} + \sum_{i=1}^{k}\gamma_i(\tau)\Delta y_{t-k} + \varepsilon_t$. *t(τ) and* QKS stand for the t-ratio and Kolmogorov-Smirnov (KS) Koenker and Xiao (2004) statistics, respectively. Critical values correspond to the 5% significance level and are calculated using resampling methods.

**Table 2.13. Kuriyama's (2016) Quantile Cointegration Test**

| | $\tau$=0.05 | $\tau$=0.10 | $\tau$=0.20 | $\tau$=0.30 | $\tau$=0.40 | $\tau$=0.50 | $\tau$=0.60 | $\tau$=0.70 | $\tau$=0.80 | $\tau$=0.90 | $\tau$=0.95 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A:** Full sample | | | | | | | | | | | |
| $\hat{\boldsymbol{\alpha}}$ | -1.40*** | -1.37*** | -1.17*** | -1.19*** | -1.26*** | -1.30*** | -1.37*** | -1.42*** | -1.47*** | -1.61*** | -1.74 |
| $\hat{\boldsymbol{\beta}}$ | 1.16*** | 1.15*** | 1.11*** | 1.12*** | 1.15*** | 1.16*** | 1.18*** | 1.20*** | 1.23*** | 1.28*** | 1.31*** |
| *p*-value $H_0$: $\beta$=1 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| $CS_T(\tau)$ $H_0$:cointegration | 0.74 | 0.82 | 1.02 | 1.48*** | 1.76*** | 1.65*** | 1.84*** | 1.74*** | 1.83*** | 1.30** | 2.82*** |
| **Panel B:** Sample below the quantile 0.10 of LNHCPI | | | | | | | | | | | |
| $\hat{\boldsymbol{\alpha}}$ | 0.20 | 0.27 | 0.21 | 0.21 | 0.37 | 0.34 | 0.45 | 0.61 | 0.66 | 0.61 | 0.68 |
| $\hat{\boldsymbol{\beta}}$ | 0.71*** | 0.70*** | 0.72*** | 0.72*** | 0.68*** | 0.69*** | 0.66*** | 0.61*** | 0.60*** | 0.61*** | 0.60*** |
| *p*-value $H_0$: $\beta$=1 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| $CS_T(\tau)$ $H_0$:cointegration | 1.26** | 2.41*** | 3.03*** | 3.11*** | 4.54*** | 4.18*** | 3.73*** | 3.78*** | 3.14*** | 8.32*** | 1.29** |
| **Panel C:** Sample above the quantile 0.90 of LNHCPI | | | | | | | | | | | |
| $\hat{\boldsymbol{\alpha}}$ | -1.37*** | -1.28*** | -1.14*** | -1.11*** | -1.13*** | -1.21*** | -1.92*** | -1.37*** | -1.48*** | -1.67*** | -1.76 |
| $\hat{\boldsymbol{\beta}}$ | 1.15*** | 1.13*** | 1.10*** | 1.10*** | 1.11*** | 1.13*** | 1.17*** | 1.18*** | 1.23*** | 1.29*** | 1.31*** |
| *p*-value $H_0$: $\beta$=1 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| $CS_T(\tau)$ $H_0$:cointegration | 0.79 | 0.86 | 0.92 | 1.38** | 1.82*** | 1.84*** | 1.86*** | 1.89*** | 1.95*** | 1.39** | 2.91*** |

Notes: *** and ** denote statistical significance (rejection of the null hypothesis) at the 1% and 5% levels respectively. $\hat{\boldsymbol{\alpha}}$ and $\hat{\boldsymbol{\beta}}$ are the estimates of the parameters of the regression $LNHPI_t = \alpha(\tau) + \beta(\tau)LNHCPI_t + u_t(\tau)$, where $LNHPI$ and $LNHCPI$ are the logarithms of house price index and non-housing CPI, respectively.

# Chapter 3
# High Frequency Impact of Monetary Policy and Macroeconomic Surprises on US MSAs, Aggregate US Housing Returns and Asymmetric Volatility[12]

## 3.1 Introduction

Residential homes are the largest financial asset holding in the portfolios of most U.S households (specifically, about half of total household net worth), hence changes in homeowner equity can impact the individual's wealth and the overall economy (Iacoviello, 2012). The housing market has an impact on the consumers through the wealth effect, and on the financial sector through the mortgage market and activities from the management of investor portfolios. Thus, house price movements are vital in driving the broader macroeconomic outcomes. There is a general consensus that housing prices are a good indicator of economic recovery as they reflect the level of consumers' confidence (Wang, 2014). As such, timely measures of housing price movements contain important information concerning the current state of the economy.

This highlights the need to fully understand the house price movements and the factors that drive the housing markets. Housing, being a consumption as well as an investment asset, intuitively is driven by interest rates and the news reflecting macroeconomic fundaments (Kishor and Marfatia, 2017). Moreover, the arrival of new information about the factors that drive house prices and the timing of measuring the house price data is mostly non-synchronous. This makes it necessary to undertake a high-frequency analysis of house price responses to macroeconomic and policy announcements. This paper investigates the high-frequency impact of the surprise component of monetary policy (Federal funds rate) as well as macroeconomic surprises on 10 U.S Metropolitan Statistical Areas (MSAs) housing market returns and volatility. The study further investigates this impact on an aggregate level, and analyzes how the results compare to the impact on stocks using the Standard & Poor's 500 (S&P500), and also aggregate Real Estate Investment Trusts (REITs) market. Given the typical nature

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of volatility clustering of high-frequency asset returns, we apply the GJR (Glosten-Jagannathan-Runkle or threshold generalized autoregressive conditional heteroscedasticity (GARCH)) model of Glosten et al., (1993) to examine the impact of monetary policy and macroeconomic surprises on the returns and volatility in the housing market at both individual MSA and aggregate level, using daily data of the housing market.

The study considers MSAs because of the variation in the house price cycle across the US housing market. Evidence from Mayer (2011) suggests that as house prices boomed globally, there were significant differences in the extent of house price appreciation across the different US MSAs. While coastal and a few inland markets such as Las Vegas boomed and then crashed, in other areas such the Southern markets house prices were less volatile. It is therefore interesting to understand the impact monetary policy and macroeconomic surprise have on the different MSAs as well as on an aggregate level. One of the main contributions of this paper is that it uses new high-frequency daily data of the housing market, which is not easily available. Apart from this dataset, Wang (2014) notes that housing market data is mostly available in relatively low monthly and quarterly frequencies, compared to other financial assets. Such low-frequency data tends to underestimate housing market risk as it ignores the information in the within variations in housing prices due to aggregation bias (Wang, 2014). In addition, the use of high-frequency daily housing data allows us to estimate a more accurate measure of not only housing returns but also of the volatility in the housing markets. Understanding the dynamics of housing volatilities and its response to the surprise component of monetary policy and macroeconomic surprises is important since housing asset plays a significant role in the investor's optimal portfolio decision (Yao and Zhang, 2005).

Wang (2014) further demonstrates the informational advantage of using high frequency daily data series through forecasting performance comparison with lower frequency data. He finds that out-of-sample forecasts of monthly housing returns produced using daily housing returns together with daily return model are more superior in comparison to other forecast procedures based on lower frequency data.

In the present study, the sample period varies for the different MSAs, mostly starting in 1995 - 2012 for most MSAs and the aggregate sample period starting in 2001 – 2012. This sample period allows us to cover the period when the Federal Reserve applied conventional monetary policy as well as the period when the short-term nominal interest rates were at or near the zero lower bound and unconventional monetary policy tools were implemented. In order to fully uncover how these changes in policy tools impact housing markets, we undertake the analysis for the full sample period, the conventional monetary policy period which constitutes the start of the dataset to December 2008, and the sample period from 2009-2012 representing the period the Federal Reserve started to use unconventional methods of monetary policy.

In efficient markets, asset prices respond to new information, therefore it is important to measure the surprise component of that information and the uncertainty that results from it (Scotti, 2016). According to Kroencke et al., (2016), there exist two transmission channels through which asset markets can be affected by macroeconomic information risk. Firstly, news on macroeconomic data is sometimes published randomly and secondly, the arrival of news announcements of macroeconomic variables and policy actions occurs on a pre-scheduled date, therefore the exact value of these factors can only be predicted. In light of this, it is essential to measure expectations contained in the macroeconomic and policy announcements.

One of the reliable and trusted sources of the predicted values macroeconomic announcements is the consensus estimations of professionals (Marfatia et al., 2017). Based on the semi-strong form of the efficient market hypothesis, the pricing of an asset already includes forecasted values after the publication of consensus data, but not the unanticipated difference between the predicted and the announced, which is the surprise component. To measure the monetary policy surprise, it is found that the Federal (Fed) funds futures rate is a natural market-based proxy of the otherwise unobserved market expectations of the Federal Reserve policy actions (Kuttner 2001; Kishor and Marfatia, 2013). All the expectations of the future changes in the interest are expected to be captured by the Fed funds futures rate. Therefore, any change in this futures rate after the Federal Open Market Committee (FOMC) meeting is because the announcement rate change (or no change) measures the unexpected (surprise) changes in the monetary policy. These monetary policy surprises are found to have a statistically significant impact on the returns on financial assets (Marfatia et al., 2017).

It is not surprising that several studies focus on analyzing the impact of domestic and U.S monetary policy and macroeconomic news surprises on bonds, commodity, currency, equity markets, and REITs market (see for example, Kishor and Marfatia, 2013; Cakan et al., 2015; Caporale et al., 2017; Scotti, 2016). However, in spite of the central role of housing markets, there is almost no literature on the study of the high-frequency impact of both monetary policy and macroeconomic surprises on the general housing market. However, there is a relatively sparse literature focusing on the real estate investment trusts (REITs) market returns (see for example, Bredin et al., 2011; Xu and Yang, 2011; Claus et al., 2014; Kroencke et al., 2016; Marfatia et al., 2017)[13], which to some extent, is understandable, given that daily data on house prices was not available until recently.[14] REITs market is indeed associated with the real estate market, but characteristically different from it, and is much similar to standard equity markets like S&P500 with REIT market capturing partial[15] movements in primarily non-residential (commercial) properties which include apartments, industrial properties, offices, and retail properties (Ghysels et al., 2013). Institutions and individuals can take positions in the commercial real estate market by investing in publicly-traded REIT companies. Market-based indices can be obtained from the trading of individual REIT stocks. These indices are usually constructed as value-weighted averages of firm-specific REIT returns. Residential house prices movements tend to capture housing wealth, with REITs associated with the financial wealth variability, but the former is the dominant part in household's net worth. Also, as pointed out by Iacoviello (2012), 80 percent of housing wealth is made up by the stock of owner-occupied homes, with the remaining 20 percent of the residential real estate held by nonfarm noncorporate businesses, which is made up by the rental housing stock. Hence, by looking at housing price reactions to monetary policy and macroeconomic surprises,

[13] Gabriel and Lutz (2017) analysed the impact of unconventional monetary policy surprises on mortgage default risks.

[14] Of course there is a large literature that has analysed the impact of macroeconomic and monetary policy shocks on the US housing market at monthly, quarterly and annual frequencies using Vector Autoregressive (VAR) models (see for example, Simo-Kengne et al., (2014), Rahal (2016), Plakandaras et al., (2017) and Gupta and Marfatia (forthcoming) for detailed reviews in this regard).

[15] Note that REITs represent quite a small fraction of estimated value of non-residential real estate market. Hence, REITs may not constitute a representative sample of the U.S. commercial real estate market as a whole.

we are essentially concentrating on owner-occupied homes used mainly for residential purposes (i.e., consumption), and also to a limited degree for investment.

To the best of our knowledge, this is the first paper to analyze monetary policy (both conventional and unconventional) and macroeconomic surprises on high-frequency movements (returns and volatility) of the housing markets of 10 US MSAs, besides the aggregate market. The remainder of the paper is organized as follows: Section 3.2 presents the data, while Section 3.3 discusses the model and empirical results, with Section 3.4 concluding the paper.

## 3.2 Data

This study uses daily housing returns based on a new set daily housing price series constructed by Bollerslev et al., (2016) using the repeat sales method[16] (Shiller, 1991) and comprehensive housing transaction data from DataQuick. The daily housing price series covers the all of the 10 MSAs. Following Wang (2014), we use the daily Composite 10 Housing Index ($P_{c,t} = \sum_{i=1}^{10} w_i \, P_{i,t}$) as a proxy for the aggregate housing price computed as a weighted average. The 10 MSAs and the specific values of the weights ($w_i$) are Boston (0.212), Chicago (0.074), Denver (0.089), Las Vegas (0.037), Los Angeles (0.050), Miami (0.015), New York (0.055), San Diego (0.118), San Francisco (0.272), and Washington D.C. (0.078), representing the total aggregate value of the housing stock in the 10 MSAs in the year 2000 (see Wang (2014)). The S&P500 equity and S&P REIT indices data are obtained from Datastream of Thomson Reuters.

For the macroeconomic surprises, we follow the daily macroeconomic index by Scotti (2016) which is constructed using a dynamic factor model and business condition indexes to estimate the weights of the contribution of the economic indicator, which include: quarterly Gross Domestic Product

[16] Repeat sales methodology is used to estimate house price changes by evaluating repeat transactions of the same house, assuming that the quality of the same house remains the same over time unless there are records of significant renovations and reconstruction. The advantages of this method is that it controls for the heterogeneity in characteristics of houses and the estimation only requires data transaction prices and sales dates for properties (Wang, 2014).

(GDP), monthly industrial production (IP), employees on non-agriculture payroll, monthly retail sales and the monthly Institute of Supply Management (ISM) manufacturing index to these business condition indexes. The weights are then used to average surprises to construct the macroeconomic surprise index (see Scotti, 2016 for details on the construction of the index).

For the monetary policy surprise, we use the monetary policy shock measure by Nakamura and Steinsson (2018). They construct a monetary policy shock dataset using data on changes in the prices of federal funds futures rate over a 30-minute window around FOMC announcements (see Appendix A in Nakamura and Steinsson (2018)).

Summary statistics of the housing log returns, S&P500 log returns, monetary policy and macroeconomic surprises for the 10 MSA and aggregate daily data are presented in Appendix 3.1, along with the respective length of data availability. Appendix 3.3 shows plots of the data used. Note that, our data heterogeneously covers the period of June, 1995 to October, 2012, with the endpoint being a month after the third phase of the Quantitative Easing was announced by the Federal Reserve on 13th September of 2012, and with tapering talks starting in the June of the following year. The sample period of the daily housing indices is understandably determined by its availability based on the work of Bollerslev et al., (2016), who purchased the data from DataQuick.[17] The sample mean for the daily housing returns as well as the mean macroeconomic surprise is generally positive, while the mean of monetary policy surprise and S&P500 returns are negative, with all the variables being non-normal as suggested by the Jarque-Bera test. Interestingly, the REITs return is more volatile than equity and aggregate housing market returns over the common sample period.

[17] One of the limitations of our analysis is that our sample period ends in 2012. However, the endpoint corresponds to the paper by Bollerslev et al., (2016), from where we obtained the data set. The authors of this paper confirmed that they do not have access to an updated version of this data, and we could not obtain updated data from the primary source due to the tremendously high expense involved in securing the daily housing transaction data from the primary source. Having said this, we believe that we do cover the sample period associated with the most turbulent episodes of the US housing market and the corresponding policies implemented to calm the real estate sector.

## 3.3 Methodology and Empirical Results

In this paper, we use the GJR (or threshold GARCH) proposed by Glosten et al., (1993) to examine the impact of monetary policy and macroeconomic surprises on housing market returns and volatility at the daily frequency for both individual MSA and aggregate levels. The GJR model is preferred for this analysis because it is designed to capture an important phenomenon in the conditional variance of assets, which is the leverage effect captured by the asymmetric terms. Since future increases in the volatility of returns are associated with present falls in asset prices, in order to capture the statistical leverage effect, which is the propensity for the volatility to rise more subsequent to large negative shocks than to large positive shocks, we use the following GJR specification following Wang (2014):

$$R_t = \mu + \rho R_{t-1} + \gamma_0 MP_{t-1} + \gamma_1 MS_{t-1} + \varepsilon_t \qquad (1)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-1}^2 d_{t-1} + \beta_0 h_{t-1} + d_1 MP_{t-1} + d_2 MS_{t-1} \qquad (2)$$

$R_t$ represents the U.S housing return series, $MP$ is the federal funds rate monetary policy surprise, $MS$ represents the macroeconomic news surprise and $\varepsilon_t$ is the stochastic disturbance term that is assumed to be normally distributed with zero mean. The conditional variance $h_t$ depends on the mean volatility level ($\alpha_0$), the lagged error ($\varepsilon_{t-1}^2$) and the lagged conditional variance ($h_{t-1}$). The asymmetric effect is captured by the $\varepsilon_{t-1}^2 d_{t-1}$ term, where $d_t = 1$ if $\varepsilon_t^2 < 0$; and $d_t = 0$ otherwise. The shocks have an asymmetric impact on conditional variance if $\alpha_2$ is statistically significant. Note that, the GJR model requires $\alpha_0$, $\alpha_1$, and $\alpha_2$ should be positive (McAleer, 2014).

Given that the model used here is multivariate, a natural question to ask is: why a multivariate asymmetric conditional volatility model, such as an extension of GJR to VARMA-GARCH as in McAleer, et al., (2009), was not considered? This is because, the monetary policy and macroeconomic news surprise variables are shocks, and hence, are considered to be exogenous to the movements in the housing markets. Therefore, we do not need to set-up a system-based model with all variables as endogenous to each other. In our case, the GJR model with the monetary policy and macroeconomic news shocks treated as right-hand side exogenous variables serves our purpose without concerns of endogeneity (see, for example, Cakan et al., (2015)).

Table 3.1 present the summary of estimation results revealing the positive and negative impact of monetary policy and macroeconomic surprises on housing returns and volatility. The full set of GJR estimation results of the impact of monetary policy and macroeconomic surprises on housing returns and volatility is presented in Appendix 3.2. The results show that for the full sample, monetary policy shocks do not statistically impact housing returns for all U.S MSAs. Similarly, for the period when the conventional monetary policy was implemented, evidence suggests that monetary policy shocks do not statistically impact housing returns for all U.S MSAs, except Miami, which has a positive and statistically significant relationship. For the unconventional monetary policy period, monetary policy shocks also do not statistically impact most of the U.S MSAs, except for Washington which shows a significant relationship.

The full sample results for the impact of macroeconomic surprises on housing returns at the MSA level shows that macroeconomic surprises do not statistically impact housing returns for most of the MSAs, with the exception of Los Angeles and New York which show a positive and significant impact at a 10 percent level of significance. For the conventional monetary policy period, macroeconomic surprises have a negative and statistically significant (10% level) impact on housing returns for Washington, and a positive and statistically significant at a 5% level for Denver, while the rest are insignificant. The results show that macroeconomic surprises do not statistically impact housing returns for all MSAs, for the period of the unconventional monetary policy.

The estimated parameter of the lagged conditional variance ($\alpha_2$) is positive and statistically significant for Los Angeles, Miami, New York, San Francisco and Washington for the full sample period, Boston during the conventional and unconventional monetary policy period and aggregate returns as well as S&P500 returns for all three periods. The positive coefficient $\alpha_2$ implies that bad news increases volatility more than good news ($\alpha_1$). This means that policy shocks have an asymmetric impact on conditional variance for these MSAs. The results show that monetary policy surprises have a negative and statistically significant impact on housing returns volatility at a 5 percent level of significance for Boston, Miami and Washington for the full sample period, while it has a positive and statistically significant impact for Denver and New York. For the conventional monetary policy period, the policy surprises have a negative and statistically significant impact on housing return volatility for Boston, Los Angeles and Washington, with Miami, New York, San Diego showing a positive and statistically significant impact. In the unconventional monetary policy period, monetary policy surprises have a mostly positive but insignificant impact on housing returns volatility.

With regards to the effect of macroeconomic surprises on the volatility of housing returns, the results show a positive and statistically significant impact at a 1% level for Denver, but negative and statistically significant for Miami and New York for the full sample. For the conventional monetary policy period, macroeconomic surprises have a positive and statistically significant effect on housing returns volatility for Denver and Miami at a 1% level of significance. In the case of New York, the macroeconomic surprises have a negative impact on housing returns volatility, but only at a 10% level of significance.

For the aggregate housing market, results indicate that monetary policy surprises have a positive and statistically significant impact on housing returns for the full sample period and conventional monetary policy period. For the unconventional monetary policy period, monetary policy surprises have an insignificant impact on housing returns. Macroeconomic surprises have no significant impact on aggregate housing returns across all sample periods.

The estimated parameter of the lagged conditional variance is positive and statistically significant, which suggests that volatility will increase more following a negative return shock and confirms volatility asymmetry for daily aggregate housing returns. This is in line with results Wang (2014). At an aggregate level, monetary policy surprises have a negative and statistically impact (10% level of significance) on daily aggregate housing returns during the conventional monetary policy period only.

For comparison, we also evaluate the impact of monetary policy and macroeconomic surprises on REIT and S&P500 returns and volatility. Results show that monetary policy surprises negatively impact REIT returns for the full sample and unconventional monetary policy period, but does not impact the volatility of REIT returns for all the periods. However, during the conventional monetary policy period, monetary policy surprises have an insignificant impact on REIT. This corroborates the findings of Claus et al., (2014) who show that REIT prices have an insignificant response to monetary policy shocks during normal monetary policy settings, but significant during the zero lower bound period. Macroeconomic surprises have a positive and statistically significant impact on REIT returns during the full sample and conventional monetary policy period, but a negative and significant impact on REIT volatility during the full sample period. Volatility asymmetry exists, similar to the aggregate housing market. Wang (2014) obtains similar results. In terms of the S&P500 returns, results show that monetary policy surprises have a negative and statistically significant (5% level) impact on stock returns during the full sample and conventional monetary policy period. However, macroeconomic surprises show a positive and statistically significant impact on stock returns during the conventional and unconventional monetary policy periods. Similar to the aggregate housing market, the stock market also shows evidence of volatility asymmetry. The results show that monetary policy surprises have a positive and significant impact on stock returns volatility during the conventional monetary policy period. However, the macroeconomic surprise has a negative and statistically significant impact on stock returns volatility for all the sample periods.

Overall, evidence suggests that monetary policy surprises, rather than macroeconomic news surprises, generally have a more significant impact on housing returns, especially volatility. In some MSAs, the volatility is increasing as in the case of Chicago, Denver, Miami (full sample period), New York and San Diego and in some cases decreasing as in the case of Boston, Las Vegas, Los Angeles, Miami (unconventional monetary policy period) and Washington. The results show that mostly coastal MSAs exhibit lower return volatility compared to the most inland MSAs which showed an increase in volatility. Although there are a few exceptions, in general, monetary policy surprises affect housing returns volatility more during the conventional monetary policy period. The fact that monetary policy surprises are more important at higher frequency than macroeconomic news surprises is an indication that agents put more weight on monetary policy movements at the shorter-run. This is possibly also a reason we see more impact on volatility, i.e., the risk-profile of the housing market, than returns, which are likely to be affected by such decisions in the longer-term. Finally, the increase in volatility of the inland MSAs could be due to them being global cities and tends to behave just like equities.

## 3.4 Conclusion

In this paper, we employ a GJR model to analyse the impact of monetary policy and macroeconomic surprises on daily housing returns and volatility for 10 U.S MSAs and on aggregate housing returns. We further compare the results with the impact on the aggregate stock market using S&P500 returns. We use a set of newly constructed daily housing price series, which allows us to investigate the volatility asymmetries and volatility relationship of the housing market and monetary policy and macroeconomic surprises.

The evidence suggests that at the MSAs level, monetary policy surprises have a positive and significant impact on housing returns for Denver and Miami during the period of conventional monetary policy and for Washington during the unconventional monetary policy period. Furthermore, monetary policy surprises have a positive and significant impact on housing volatility for the full sample period for Denver, New York and San Francisco, and then for Chicago, Miami and New York and San Diego as well during the conventional monetary policy period. During the unconventional monetary policy period, the policy surprises have a positive impact on Washington only. At an aggregate level, monetary policy surprises have a positive impact on housing returns during the full sample and conventional monetary policy period. This is in contrast to the aggregate stock market where we find a significant response of market returns in all three periods and the volatility response only in and the conventional monetary policy period.

In terms of macroeconomic surprises, the results suggest that they have a positive and significant impact on housing returns during the full sample period for Los Angeles and New York. Macroeconomic surprises have a positive impact on housing volatility in Las Vegas and Miami during the conventional monetary policy period and unconventional monetary policy period for Las Vegas only.

The results show that monetary policy has a negative and significant impact mostly on housing volatility across the various periods for Boston, Las Vegas, Los Angeles, Miami, New York and Washington. On aggregate, results show that monetary policy surprises have a negative and statistically significant impact on housing returns volatility during the conventional monetary policy period compared to the stock market where it shows an impact on stock returns during the full sample and conventional.

The evidence suggests that macroeconomic surprises do not have a negative and statistically significant impact on housing returns both at the MSA and aggregate level. However, in terms of volatility, macroeconomic surprises have a negative and statistically significant impact for Miami only during the full sample period. At the aggregate level, macroeconomic surprises show a negative and significant impact on the stock market during the full sample, unconventional and conventional monetary policy period.

Overall, at the MSA level monetary policy and macroeconomic surprises do not have a significant impact on housing returns for most MSAs for the full sample, conventional and unconventional monetary policy period. However, the results show that in relation to volatility, monetary policy surprises have a significant impact on housing returns volatility for 5 MSAs in the full sample, 5 in the conventional monetary policy period, but a mostly positive and insignificant impact in the unconventional monetary policy period. Macroeconomic surprises largely have an insignificant impact on housing returns volatility across all sample periods and most MSAs.

**Table 3.1. GJR model estimation summary results of significant results of the impact of monetary and macroeconomic surprises on housing returns and volatility**

**Panel A: Positive Effects**

| Metropolitan Area | Sample period | Monetary policy surprise | | Macroeconomic surprise | |
|---|---|---|---|---|---|
| | | *Returns* | *Volatility* | *Returns* | *Volatility* |
| Chicago | $P_2$ | ____ | 2.500** (0.012) | ____ | ____ |
| Denver | $P_1$ | ____ | 16.023*** (0.000) | ____ | ____ |
| | $P_2$ | 2.589** (0.010) | ____ | ____ | ____ |
| Las Vegas | $P_2$ | ____ | ____ | ____ | 1.777* (0.076) |
| | $P_3$ | ____ | ____ | ____ | 3.336*** (0.001) |
| Los Angeles | $P_1$ | ____ | ____ | 1.683* (0.092) | ____ |
| Miami | $P_2$ | 2.278** (0.023) | 22.676*** (0.000) | ____ | 2.905*** (0.004) |
| New York | $P_1$ | ____ | 85.501*** (0.000) | 2.472** (0.013) | 3.238*** (0.001) |
| | $P_2$ | ____ | 6.238*** (0.000) | ____ | ____ |
| San Diego | $P_1$ | ____ | 6.490*** (0.000) | ____ | ____ |
| | $P_2$ | ____ | 4.719*** (0.000) | ____ | ____ |
| Washington | $P_3$ | 1.717* (0.090) | ____ | ____ | ____ |
| Aggregate housing returns | $P_1$ | 4.041*** (0.000) | ____ | ____ | ____ |
| | $P_2$ | 3.333*** (0.000) | ____ | ____ | ____ |
| REIT Returns | $P_1$ | ____ | ____ | 3.178*** (0.002) | ____ |
| | $P_3$ | ____ | ____ | 3.664*** (0.000) | ____ |
| S&P500 returns | $P_1$ | ____ | ____ | 6.027*** (0.000) | ____ |
| | $P_2$ | ____ | 2.157** (0.031) | 2.272** (0.023) | ____ |
| | $P_3$ | ____ | ____ | 3.211*** (0.001) | ____ |

Notes: $P_1$ = full sample period; $P_2$ = conventional monetary policy period and $P_3$ =unconventional monetary policy period.

GJR(1,1) specification used: *Mean equation:* $R_t = \mu + \rho R_{t-1} + \gamma_0 MP_{t-1} + \gamma_1 MS_{t-1} + \varepsilon_t$. *Volatility equation:* $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-1}^2 d_{t-1} + \beta_0 h_{t-1} + d_1 MP_{t-1} + d_2 MS_{t-1}$. $R_t$ represents the U.S housing return series, $MP$ is the federal funds rate monetary policy surprise, $MS$ represents the macroeconomic surprise and $\varepsilon_t$ is the stochastic disturbance term that is assumed to be normally distributed with zero mean. The conditional variance $h_t$ depends on the mean volatility level $(\alpha_0)$, the lagged error $(\varepsilon_{t-1}^2)$ and the lagged conditional variance $(h_{t-1})$. The asymmetric effect is captured by the $\varepsilon_{t-1}^2 d_{t-1}$ term, where $d_t = 1$ if $\varepsilon_t^2 < 0$; and $d_t = 0$ otherwise. The standard errors are given in parenthesis. Level of significance: ***1 percent; ** 5 percent, *10 percent.

**Panel B: Negative Effects**

| Metropolitan Area | Sample period | Monetary policy surprise | | Macroeconomic surprise | |
|---|---|---|---|---|---|
| | | *Returns* | *Volatility* | *Returns* | *Volatility* |
| Boston | $P_1$ | ______ | -3.676*** (0.000) | ______ | ______ |
| | $P_2$ | ______ | -3.973*** (0.000) | ______ | ______ |
| Las Vegas | $P_1$ | ______ | -3.331*** (0.000) | ______ | ______ |
| | $P_2$ | ______ | -2.063** (0.039) | ______ | ______ |
| | $P_3$ | ______ | -1.650* (0.099) | ______ | ______ |
| Los Angeles | $P_2$ | ______ | -1.721* (0.085) | ______ | ______ |
| Miami | $P_1$ | ______ | -2.018** (0.044) | ______ | -3.218*** (0.001) |
| New York | $P_1$ | ______ | -1.993** (0.046) | ______ | ______ |
| | $P_2$ | ______ | -1.925* (0.054) | ______ | ______ |
| Washington | $P_2$ | ______ | -5.368*** (0.000) | -1.908* (0.056) | ______ |
| | $P_1$ | ______ | -5.221*** (0.000) | ______ | ______ |
| Aggregate Returns | $P_2$ | ______ | -1.828* (0.068) | ______ | ______ |
| REIT Returns | $P_1$ | -1.747* (0.081) | | | -13.763*** (0.000) |
| | $P_3$ | -2.186** (0.029) | | | |
| S&P500 Returns | $P_1$ | -3.435*** (0.001) | ______ | ______ | -2928.55*** (0.000) |
| | $P_2$ | -2.243** (0.025) | ______ | ______ | -5.810*** (0.000) |
| | $P_3$ | ______ | ______ | ______ | -1.983** (0.047) |

Notes: $P_1$ = full sample period; $P_2$ = conventional monetary policy period and $P_3$ =unconventional monetary policy period.

GJR(1,1) specification used: *Mean equation:* $R_t = \mu + \rho R_{t-1} + \gamma_0 MP_{t-1} + \gamma_1 MS_{t-1} + \varepsilon_t$. *Volatility equation:* $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-1}^2 d_{t-1} + \beta_0 h_{t-1} + d_1 MP_{t-1} + d_2 MS_{t-1}$. $R_t$ represents the U.S housing return series, $MP$ is the federal funds rate monetary policy surprise, $MS$ represents the macroeconomic surprise and $\varepsilon_t$ is the stochastic disturbance term that is assumed to be normally distributed with zero mean. The conditional variance $h_t$ depends on the mean volatility level $(\alpha_0)$, the lagged error $(\varepsilon_{t-1}^2)$ and the lagged conditional variance $(h_{t-1})$. The asymmetric effect is captured by the $\varepsilon_{t-1}^2 d_{t-1}$ term, where $d_t = 1$ if $\varepsilon_t^2 < 0$; and $d_t = 0$ otherwise. The standard errors are given in parenthesis. Level of significance: ***1 percent; ** 5 percent, *10 percent.

## Appendix 3.1. Table of Summary statistics for the 10 U.S MSA and aggregate housing returns

| Housing returns | Sample Period | Observations | Minimum | Maximum | Average | Standard Deviation | Skewness | Kurtosis | Jarque-Bera (*p*-value) |
|---|---|---|---|---|---|---|---|---|---|
| Boston | 1/6/1995 - 10/11/2012 | 4424 | -5.419 | 2.947 | 0.017 | 0.400 | -1.119 | 18.344 | 0.000 |
| Chicago | 9/7/1999- 10/12/2012 | 3265 | -5.300 | 7.081 | 0.001 | 0.593 | 0.131 | 13.417 | 0.000 |
| Denver | 5/6/1999 – 10/17/2012 | 3344 | -4.434 | 2.930 | 0.010 | 0.330 | -0.823 | 20.027 | 0.000 |
| Las Vegas | 1/6/1995 – 10/17/2912 | 4399 | -8.667 | 5.425 | 0.001 | 0.569 | -1.613 | 28.151 | 0.000 |
| Los Angeles | 1/6/1995– 10/23/2012 | 4425 | -3.030 | 1.602 | 0.017 | 0.381 | -0.510 | 6.015 | 0.000 |
| Miami | 4/6/1998- 10/15/2012 | 3587 | -3.073 | 4.261 | 0.013 | 0.505 | 0.085 | 6.950 | 0.000 |
| New York | 1/6/1995- 10/23/2012 | 4442 | -5.162 | 3.988 | 0.017 | 0.380 | -0.041 | 19.232 | 0.000 |
| San Diego | 1/5/1996- 10/23/2012 | 4163 | -2.478 | 2.082 | 0.022 | 0.411 | -0.179 | 4.916 | 0.000 |
| San Francisco | 1/6/1995- 10/18/2012 | 4422 | -4.403 | 3.855 | 0.016 | 0.530 | -0.955 | 9.036 | 0.000 |
| Washington | 6/6/2001- 10/23/2012 | 2816 | -4.477 | 2.650 | 0.015 | 0.506 | -0.192 | 6.825 | 0.000 |
| Aggregate housing returns | 6/6/2001- 10/11/2012 | 2806 | -0.627 | 0.663 | 0.010 | 0.163 | -0.211 | 3.770 | 0.000 |
| REITs returns | 6/6/2001- 10/11/2012 | 2806 | -21.945 | 17.124 | 0.019 | 2.222 | -0.185 | 17.863 | 0.000 |
| S&P500 returns | 6/6/2001- 10/11/2012 | 2806 | -9.470 | 10.246 | 0.004 | 1.331 | -0.360 | 10.148 | 0.000 |
| Monetary policy surprise | 1/6/1995- 10/11/2012 | 4424 | -0.413 | 0.125 | -0.000 | 0.013 | -18.355 | 510.165 | 0.000 |
| Macroeconomic surprise | 1/6/1995- 10/11/2012 | 4424 | -1.649 | 2.451 | 0.000 | 0.139 | 0.373 | 52.795 | 0.000 |

**Note:** The Jarque-Bera test has the null hypothesis of normality

## Appendix 3.2. Table of GJR model estimation results of the impact of monetary policy and macroeconomic surprises on housing returns and volatility for 10 US metropolitan statistical areas and the aggregate housing returns

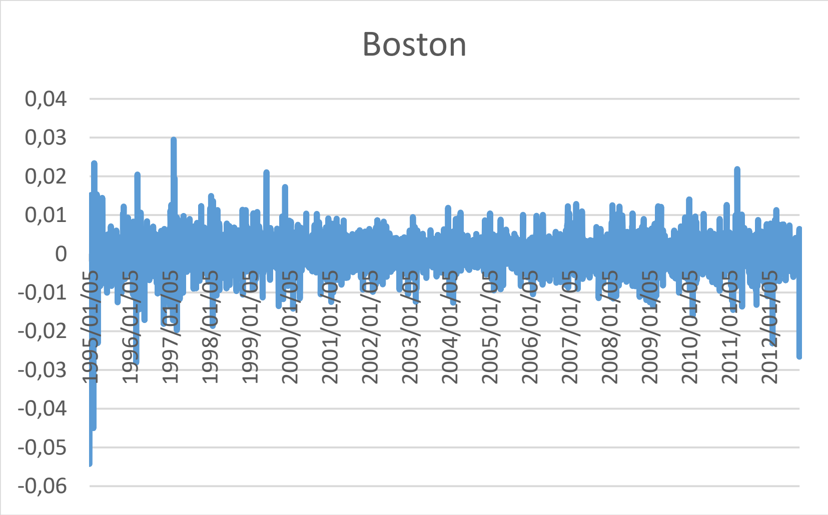
| *Metropolitan Area* | | | **Full sample** | | | **Conventional monetary policy period** | | | **Unconventional monetary policy period** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | *Coefficient* | *z-Statistic* | *p-value* | *Coefficient* | *z-Statistic* | *p-value* | *Coefficient* | *z-Statistic* | *p-value* |
| Boston | *Mean* | $\gamma_0$ | -0.105 | -0.197 | 0.844 | -0.164 | -0.315 | 0.753 | 3.796 | 0.399 | 0.690 |
| | | $\gamma_1$ | 0.038 | 0.819 | 0.413 | 0.034 | 0.652 | 0.514 | 0.054 | 0.516 | 0.606 |
| | *Volatility* | $\alpha_0$ | 0.000 | 6.973*** | 0.000 | 0.002 | 7.675*** | 0.000 | 0.007 | 5.099*** | 0.000 |
| | | $\alpha_1$ | 0.148 | 3.558*** | 0.000 | 0.012 | 3.043*** | 0.002 | 0.055 | 2.463** | 0.014 |
| | | $\alpha_2$ | 0.049 | 1.183 | 0.237 | 0.035 | 5.733*** | 0.000 | 0.080 | 2.496** | 0.013 |
| | | $\beta_0$ | 0.949 | 276.741*** | 0.000 | 0.955 | 279.981*** | 0.000 | 0.871 | 45.828*** | 0.000 |
| | | $d_1$ | -0.254 | -3.676*** | 0.000 | -0.250 | -3.937*** | 0.000 | -0.020 | -0.019 | 0.985 |
| | | $d_2$ | 0.002 | 0.313 | 0.754 | 0.005 | 1.080 | 0.280 | 0.007 | 0.408 | 0.684 |
| Chicago | *Mean* | $\gamma_0$ | -0.365 | -0.433 | 0.665 | -0.503 | -0.911 | 0.362 | 6.434 | 0.228 | 0.820 |
| | | $\gamma_1$ | -0.092 | -1.553 | 0.120 | -0.080 | -0.564 | 0.573 | 0.052 | 0.182 | 0.855 |
| | *Volatility* | $\alpha_0$ | 0.000 | 4.311*** | 0.000 | 0.171 | 3.297*** | 0.001 | 0.447 | 1.070 | 0.285 |
| | | $\alpha_1$ | 0.139 | 2.536** | 0.011 | 0.057 | 2.650*** | 0.008 | -0.009 | -0.443 | 0.658 |
| | | $\alpha_2$ | 0.046 | 0.910 | 0.363 | -0.045 | -1.600 | 0.110 | 0.034 | 0.796 | 0.426 |
| | | $\beta_0$ | 0.948 | 254.890*** | 0.000 | 0.508 | 3.529*** | 0.000 | 0.465 | 0.928 | 0.354 |
| | | $d_1$ | -0.021 | -0.224 | 0.823 | 0.844 | 2.500** | 0.012 | 5.184 | 1.626 | 0.104 |
| | | $d_2$ | -0.003 | -0.306 | 0.759 | -0.009 | -0.116 | 0.908 | -0.198 | -0.481 | 0.631 |
| Denver | *Mean* | $\gamma_0$ | -0.006 | -0.056 | 0.956 | -0.135 | -0.190 | 0.849 | 0.822 | 0.028 | 0.977 |
| | | $\gamma_1$ | 0.028 | 0.474 | 0.635 | 0.088 | 2.589** | 0.010 | -0.020 | -0.151 | 0.880 |
| | *Volatility* | $\alpha_0$ | 0.000 | 3.714*** | 0.000 | 0.003 | 7.999*** | 0.000 | 0.111 | 1.462 | 0.144 |
| | | $\alpha_1$ | 0.150 | 3.038*** | 0.002 | 0.072 | 9.978*** | 0.000 | 0.041 | 0.436 | 0.663 |
| | | $\alpha_2$ | 0.050 | 0.703 | 0.482 | -0.031 | -4.418*** | 0.000 | -0.027 | -0.286 | 0.775 |
| | | $\beta_0$ | 0.528 | 3.906*** | 0.000 | 0.916 | 114.012*** | 0.000 | 0.528 | 1.657* | 0.098 |
| | | $d_1$ | 0.502 | 16.023*** | 0.000 | -0.058 | -1.046 | 0.296 | 2.311 | 1.212 | 0.225 |
| | | $d_2$ | 0.082 | 5.125*** | 0.000 | 0.013 | 4.025*** | 0.000 | 0.175 | 2.745*** | 0.006 |
| Las Vegas | *Mean* | $\gamma_0$ | 0.435 | 0.621 | 0.534 | 0.525 | 0.796 | 0.426 | 0.836 | 0.078 | 0.938 |
| | | $\gamma_1$ | -0.027 | -0.600 | 0.549 | -0.015 | -0.314 | 0.754 | -0.013 | -0.136 | 0.892 |
| | *Volatility* | $\alpha_0$ | 0.000 | 4.204*** | 0.000 | 0.000 | 3.344*** | 0.001 | 0.201 | 4.543*** | 0.000 |
| | | $\alpha_1$ | 0.012 | 6.661*** | 0.000 | 0.013 | 5.646*** | 0.000 | -0.024 | -0.907 | 0.364 |
| | | $\alpha_2$ | 0.001 | 1.049 | 0.294 | 0.001 | 0.861 | 0.389 | 0.018 | 0.504 | 0.614 |
| | | $\beta_0$ | 0.986 | 964.517*** | 0.000 | 0.985 | 803.190*** | 0.000 | -0.085 | -0.374 | 0.709 |
| | | $d_1$ | -0.148 | -3.331*** | 0.000 | -0.100 | -2.063** | 0.039 | -8.078 | -1.650* | 0.099 |
| | | $d_2$ | 0.007 | 1.277 | 0.202 | 0.011 | 1.777* | 0.076 | 0.158 | 3.336*** | 0.001 |
| Los Angeles | *Mean* | $\gamma_0$ | 0.159 | 0.456 | 0.648 | 0.046 | 0.121 | 0.904 | 5.581 | 0.545 | 0.585 |
| | | $\gamma_1$ | 0.056 | 1.683* | 0.092 | 0.055 | 1.598 | 0.110 | 0.108 | 0.811 | 0.417 |
| | *Volatility* | $\alpha_0$ | 0.000 | 4.731*** | 0.000 | 0.001 | 4.855*** | 0.000 | 0.114 | 0.915 | 0.360 |
| | | $\alpha_1$ | 0.013 | 3.150*** | 0.002 | 0.010 | 2.509** | 0.012 | 0.002 | 0.030 | 0.976 |
| | | $\alpha_2$ | 0.027 | 5.200*** | 0.000 | 0.023 | 4.112*** | 0.000 | 0.076 | 1.297 | 0.195 |
| | | $\beta_0$ | 0.966 | 308.731*** | 0.000 | 0.969 | 265.843*** | 0.000 | 0.432 | 0.729 | 0.466 |
| | | $d_1$ | -0.069 | -1.223 | 0.221 | -0.094 | -1.721* | 0.085 | 1.270 | 0.431 | 0.667 |
| | | $d_2$ | 0.006 | 1.267 | 0.205 | 0.007 | 1.480 | 0.139 | -0.041 | -0.473 | 0.636 |
| Miami | *Mean* | $\gamma_0$ | 0.466 | 0.939 | 0.347 | 0.547 | 2.278** | 0.023 | 4.835 | 0.782 | 0.434 |
| | | $\gamma_1$ | 0.015 | 0.279 | 0.780 | 0.012 | 0.150 | 0.881 | -0.007 | -0.045 | 0.965 |
| | *Volatility* | $\alpha_0$ | 0.000 | 6.317*** | 0.000 | 0.127 | 22.525*** | 0.000 | 0.187 | 0.745 | 0.456 |
| | | $\alpha_1$ | 0.144 | 0.498 | 0.618 | 0.155 | 5.198*** | 0.000 | 0.021 | 0.403 | 0.687 |
| | | $\alpha_2$ | 0.047 | 6.332*** | 0.000 | -0.014 | -0.357 | 0.721 | -0.02 | -0.436 | 0.663 |
| | | $\beta_0$ | 0.985 | 488.550*** | 0.000 | 0.455 | 213.733*** | 0.000 | 0.364 | 0.434 | 0.665 |
| | | $d_1$ | -0.091 | -2.018** | 0.044 | 0.617 | 22.676*** | 0.000 | 1.885 | 0.267 | 0.789 |

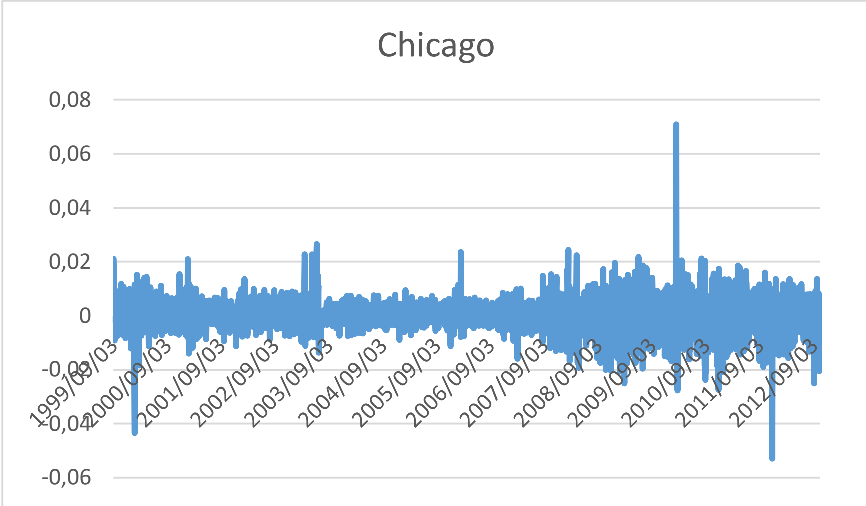
| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | $d_2$ | -0.018 | -3.218*** | 0.001 | 0.157 | 2.905*** | 0.004 | -0.087 | -0.740 | 0.459 |
| New York | *Mean* | $\gamma_0$ | -0.506 | -0.638 | 0.523 | -0.165 | -0.247 | 0.805 | 0.768 | 0.185 | 0.853 |
| | | $\gamma_1$ | 0.113 | 1.651* | 0.099 | 0.078 | 0.929 | 0.353 | 0.052 | 0.486 | 0.627 |
| | *Volatility* | $\alpha_0$ | 0.000 | 14.041*** | 0.000 | 0.112 | 9.212*** | 0.000 | 0.081 | 1.587 | 0.113 |
| | | $\alpha_1$ | 0.148 | 5.448*** | 0.000 | 0.097 | 3.445*** | 0.001 | 0.021 | 0.470 | 0.638 |
| | | $\alpha_2$ | 0.049 | 1.853* | 0.064 | -0.005 | -0.191 | 0.848 | -0.094 | -2.129** | 0.033 |
| | | $\beta_0$ | 0.533 | 10.327*** | 0.000 | 0.539 | 12.681*** | 0.000 | 0.479 | 1.395 | 0.163 |
| | | $d_1$ | 0.512 | 14.382*** | 0.000 | 0.556 | 6.238*** | 0.000 | 1.062 | 0.263 | 0.793 |
| | | $d_2$ | -0.068 | -1.993** | 0.046 | -0.082 | -1.925* | 0.054 | 0.017 | 0.351 | 0.726 |
| San Diego | *Mean* | $\gamma_0$ | -0.308 | -0.603 | 0.546 | -0.301 | -0.578 | 0.563 | 2.760 | 0.136 | 0.892 |
| | | $\gamma_1$ | 0.042 | 0.598 | 0.549 | 0.023 | 0.293 | 0.769 | 0.016 | 0.078 | 0.937 |
| | *Volatility* | $\alpha_0$ | 0.000 | 4.232*** | 0.000 | 0.114 | 4.377*** | 0.000 | 0.144 | 2.076** | 0.038 |
| | | $\alpha_1$ | 0.145 | 2.835*** | 0.005 | 0.028 | 0.817 | 0.414 | 0.017 | 0.341 | 0.733 |
| | | $\alpha_2$ | 0.046 | 0.775 | 0.438 | -0.039 | -1.104 | 0.270 | -0.087 | -1.629 | 0.103 |
| | | $\beta_0$ | 0.496 | 4.509*** | 0.000 | 0.472 | 3.706*** | 0.000 | 0.460 | 1.683* | 0.092 |
| | | $d_1$ | 0.608 | 6.490*** | 0.000 | 0.524 | 4.719*** | 0.000 | 1.771 | 0.482 | 0.630 |
| | | $d_2$ | -0.009 | -0.243 | 0.808 | -0.004 | -0.105 | 0.917 | -0.011 | -0.088 | 0.930 |
| San Francisco | *Mean* | $\gamma_0$ | -0.635 | -1.471 | 0.141 | -0.628 | -1.229 | 0.219 | -6.044 | -0.120 | 0.905 |
| | | $\gamma_1$ | -0.020 | -0.169 | 0.866 | -0.006 | -0.045 | 0.964 | -0.050 | -0.178 | 0.859 |
| | *Volatility* | $\alpha_0$ | 0.000 | 6.149*** | 0.000 | 0.197 | 39.966*** | 0.000 | 0.344 | 2.171** | 0.030 |
| | | $\alpha_1$ | 0.012 | 5.446*** | 0.000 | 0.049 | 1.474 | 0.141 | 0.006 | 0.068 | 0.945 |
| | | $\alpha_2$ | 0.013 | 4.185*** | 0.000 | -0.057 | -1.697 | 0.090 | -0.113 | -1.406 | 0.160 |
| | | $\beta_0$ | 0.512 | 557.713*** | 0.000 | 0.530 | 173.892*** | 0.000 | 0.530 | 2.256** | 0.024 |
| | | $d_1$ | 1.094 | 1.525 | 0.127 | 1.008 | 1.487 | 0.137 | 2.772 | 0.532 | 0.595 |
| | | $d_2$ | -0.028 | -0.406 | 0.685 | -0.026 | -0.373 | 0.709 | -0.054 | -0.189 | 0.850 |
| Washington | *Mean* | $\gamma_0$ | 0.003 | 0.002 | 0.998 | -0.235 | -0.166 | 0.869 | 0.983 | 1.717* | 0.09 |
| | | $\gamma_1$ | -0.062 | -0.998 | 0.318 | -0.136 | -1.908* | 0.056 | 0.195 | 1.445 | 0.149 |
| | *Volatility* | $\alpha_0$ | 0.000 | 5.275*** | 0.000 | 0.001 | 4.179*** | 0.000 | 0.101 | 1.638 | 0.102 |
| | | $\alpha_1$ | 0.033 | 0.895 | 0.371 | 0.030 | 3.836*** | 0.000 | 0.084 | 2.127** | 0.034 |
| | | $\alpha_2$ | 0.007 | 203.129*** | 0.000 | 0.016 | 1.613 | 0.107 | -0.026 | -0.582 | 0.560 |
| | | $\beta_0$ | 0.958 | 203.181*** | 0.000 | 0.955 | 162.503*** | 0.000 | 0.579 | 2.506** | 0.012 |
| | | $d_1$ | -0.684 | -5.221*** | 0.000 | -0.691 | -5.368*** | 0.000 | 1.691 | 0.743 | 0.458 |
| | | $d_2$ | 0.006 | 0.557 | 0.577 | 0.005 | 0.418 | 0.676 | -0.067 | -0.719 | 0.472 |
| Aggregate housing returns | *Mean* | $\gamma_0$ | 0.937 | 4.041*** | 0.000 | 0.791 | 3.333*** | 0.001 | 4.197 | 0.868 | 0.385 |
| | | $\gamma_1$ | -0.006 | -0.256 | 0.798 | -0.023 | -0.896 | 0.370 | 0.057 | 1.094 | 0.274 |
| | *Volatility* | $\alpha_0$ | 0.000 | 4.630*** | 0.000 | 0.000 | 2.317** | 0.021 | 0.000 | 2.852*** | 0.004 |
| | | $\alpha_1$ | 0.000 | 0.000 | 0.999 | -0.000 | -0.350 | 0.726 | -0.023 | -9.167*** | 0.000 |
| | | $\alpha_2$ | 0.016 | 4.899*** | 0.000 | 0.012 | 3.679*** | 0.000 | 0.029 | 5.248*** | 0.000 |
| | | $\beta_0$ | 0.985 | 275.219*** | 0.000 | 0.991 | 242.318*** | 0.000 | 0.999 | 289.440*** | 0.000 |
| | | $d_1$ | -0.020 | -1.578 | 0.115 | -0.019 | -1.828 | 0.068* | 0.019 | 0.272 | 0.786 |
| | | $d_2$ | 0.002 | 1.536 | 0.125 | 0.001 | 1.205 | 0.228 | 0.003 | 0.741 | 0.459 |
| REITs Returns | *Mean* | $\gamma_0$ | -0.060 | -1.747** | 0.081 | -3.653 | -1.399 | 0.162 | -57.822 | -2.186** | 0.029 |
| | | $\gamma_1$ | 0.005 | 3.178*** | 0.002 | -0.031 | -0.201 | 0.841 | 1.086 | 3.664*** | 0.000 |
| | *Volatility* | $\alpha_0$ | 0.000 | 16.311*** | 0.000 | 0.021 | 3.988*** | 0.000 | 0.028 | 2.295** | 0.022 |
| | | $\alpha_1$ | 0.237 | 9.380*** | 0.000 | 0.079 | 4.478*** | 0.000 | 0.091 | 3.448*** | 0.001 |
| | | $\alpha_2$ | 0.154 | 4.002*** | 0.000 | 0.106 | 4.414*** | 0.000 | 0.051 | 1.850* | 0.064 |
| | | $\beta_0$ | 0.442 | 20.043*** | 0.000 | 0.862 | 60.002*** | 0.000 | 0.875 | 51.032*** | 0.000 |
| | | $d_1$ | 0.000 | 0.347 | 0.729 | 1.477 | 0.638 | 0.524 | 24.824 | 1.299 | 0.194 |
| | | $d_2$ | -0.000 | -13.373*** | 0.000 | 0.084 | 1.102 | 0.270 | 0.046 | 0.200 | 0.842 |
| S&P500 | *Mean* | $\gamma_0$ | -6.465 | -2.540** | 0.011 | -5.999 | -2.243** | 0.025 | -24.576 | -1.494 | 0.135 |
| | | $\gamma_1$ | 0.520 | 3.641*** | 0.000 | 0.412 | 2.272** | 0.023 | 0.729 | 3.211*** | 0.001 |
| | | $\alpha_0$ | 0.000 | 14.959*** | 0.000 | 0.008 | 5.749*** | 0.000 | 0.024 | 5.020*** | 0.000 |
| | | $\alpha_1$ | 0.178 | 6.949*** | 0.000 | -0.022 | -2.779*** | 0.005 | -0.033 | -2.214** | 0.027 |
| | | $\alpha_2$ | 0.159 | 4.869*** | 0.000 | 0.117 | 9.525*** | 0.000 | 0.196 | 7.762*** | 0.000 |

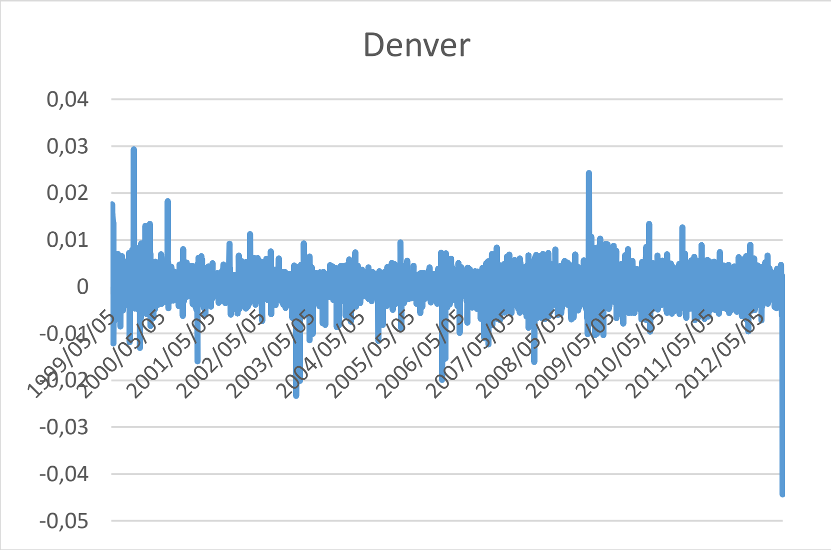
| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *Volatility* | $\beta_0$ | 0.934 | 121.592*** | 0.000 | 0.956 | 114.092*** | 0.000 | 0.916 | 62.959*** | 0.000 |
| | | $d_1$ | 1.910 | 1.647 | 0.100 | 2.439 | 2.157** | 0.031 | 5.948 | 0.793 | 0.428 |
| | | $d_2$ | -0.222 | -5.804*** | 0.000 | -0.187 | -5.810*** | 0.000 | -0.207 | -1.983** | 0.047 |

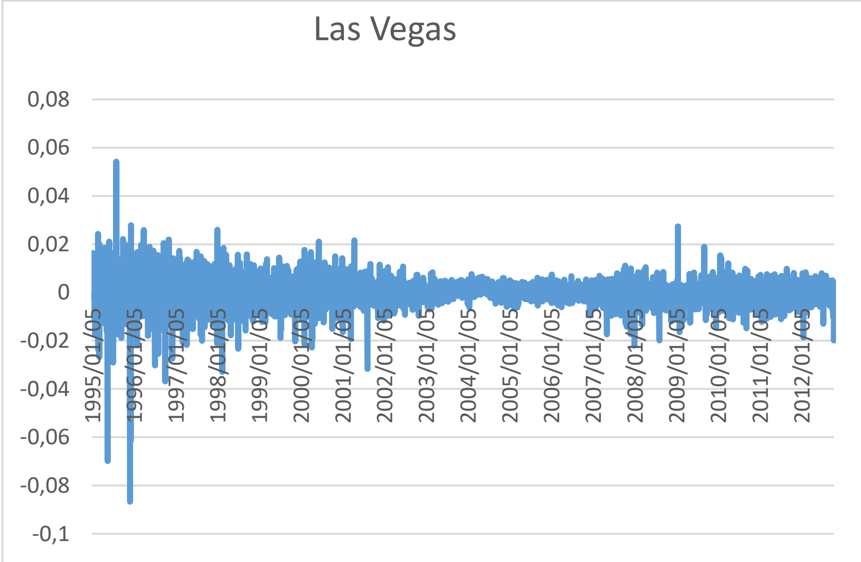
**Note**: GJR(1,1) specification used: *Mean equation:* $R_t = \mu + \rho R_{t-1} + \gamma_0 MP_{t-1} + \gamma_1 MS_{t-1} + \varepsilon_t$.*Volatility equation:* $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-1}^2 d_{t-1} + \beta_0 h_{t-1} + d_1 MP_{t-1} + d_2 MS_{t-1}$. $R_t$ represents the U.S housing return series, $MP$ is the federal funds rate monetary policy surprise, $MS$ represents the macroeconomic surprise and $\varepsilon_t$ is the stochastic disturbance term that is assumed to be normally distributed with zero mean. The conditional variance $h_t$ depends on the mean volatility level ($\alpha_0$), the lagged error ($\varepsilon_{t-1}^2$) and the lagged conditional variance ($h_{t-1}$). The asymmetric effect is captured by the $\varepsilon_{t-1}^2 d_{t-1}$ term, where $d_t = 1$ if $\varepsilon_t^2 < 0$; and $d_t = 0$ otherwise. Level of significance: ***1 percent; ** 5 percent, *10 percent.

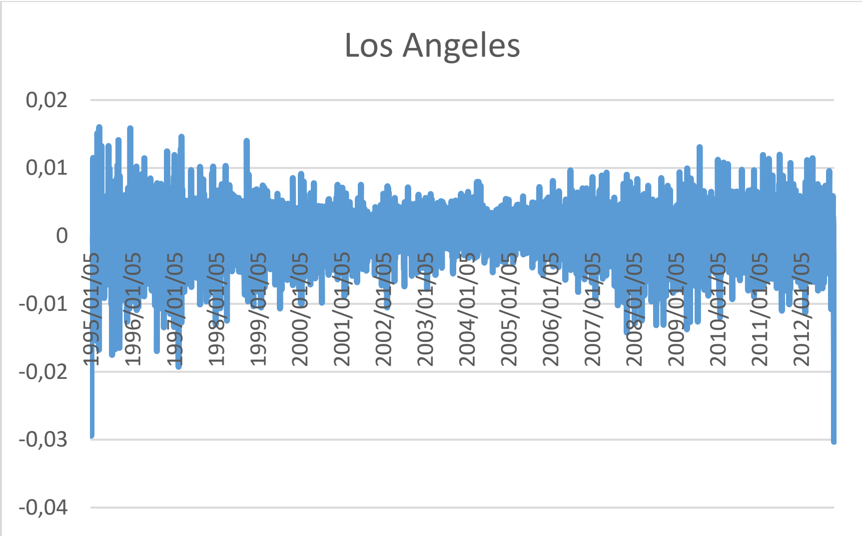
**Appendix 3.3. Figure of Daily housing returns for 10 U.S MSAs**

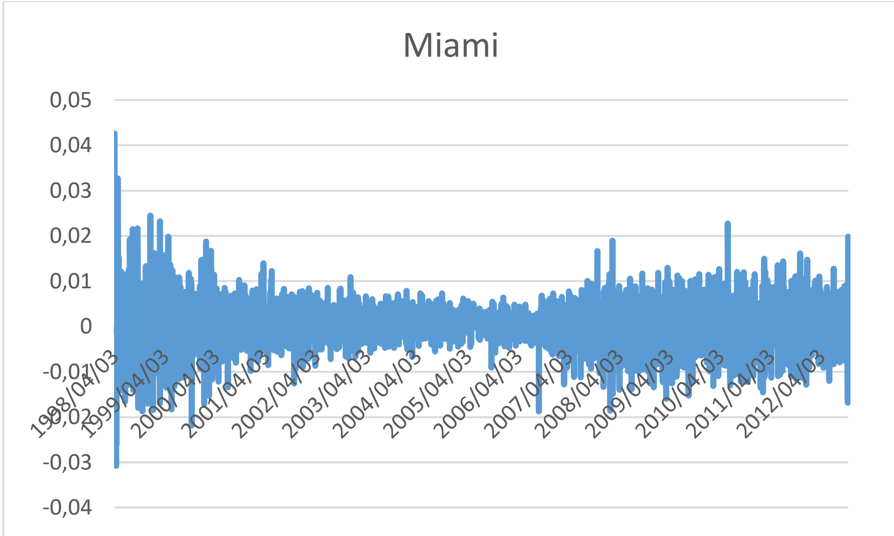



Los Angeles
0,02
0,01
0
-0,01
-0,02
-0,03
-0,04
1995/01/05
1996/01/05
1997/01/05
1998/01/05
1999/01/05
2000/01/05
2001/01/05
2002/01/05
2003/01/05
2004/01/05
2005/01/05
2006/01/05
2007/01/05
2008/01/05
2009/01/05
2010/01/05
2011/01/05
2012/01/05


Miami
0,05
0,04
0,03
0,02
0,01
0
-0,01
-0,02
-0,03
-0,04
1998/04/03
1999/04/03
2000/04/03
2001/04/03
2002/04/03
2003/04/03
2004/04/03
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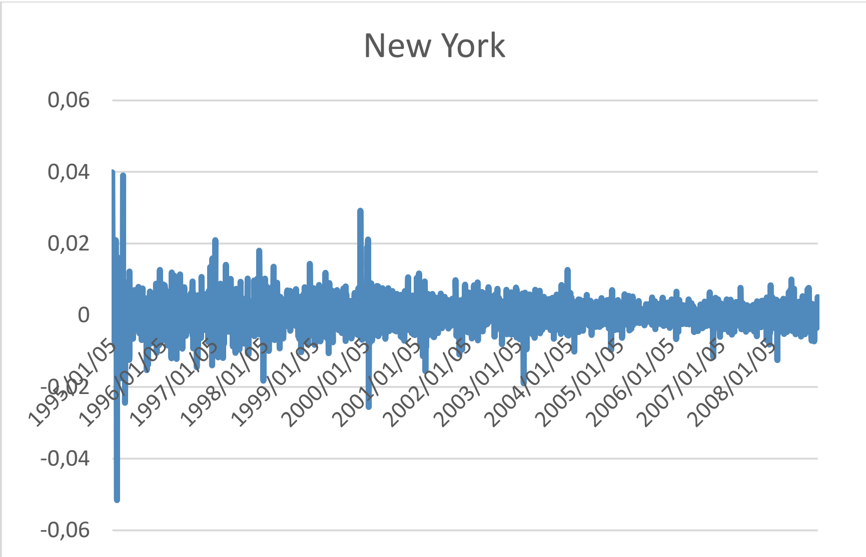
2011/04/03
2012/04/03


New York
0,06
0,04
0,02
0
-0,02
-0,04
-0,06
1995/01/05
1996/01/05
1997/01/05
1998/01/05
1999/01/05
2000/01/05
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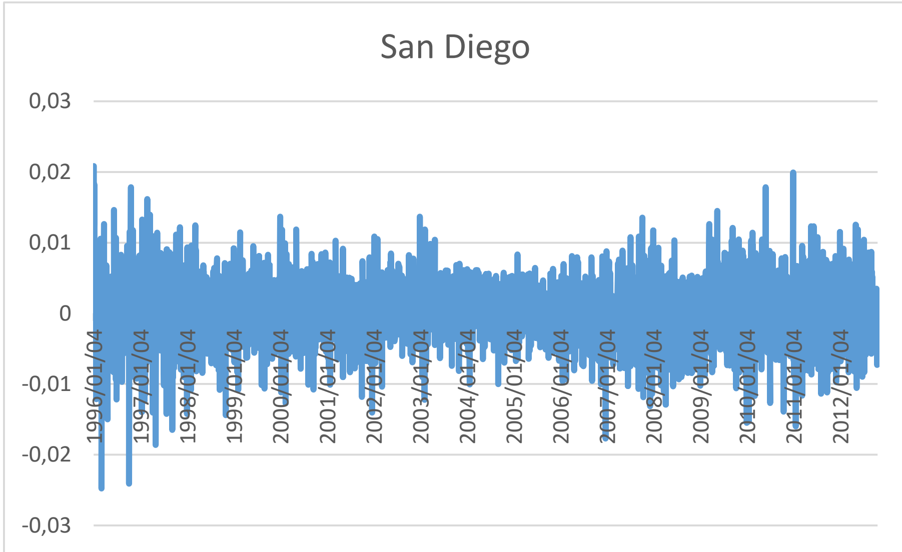
2007/01/05
2008/01/05


San Diego
0,03
0,02
0,01
0
-0,01
-0,02
-0,03
1996/01/04
1997/01/04
1998/01/04
1999/01/04
2000/01/04
2001/01/04
2002/01/04
2003/01/04
2004/01/04
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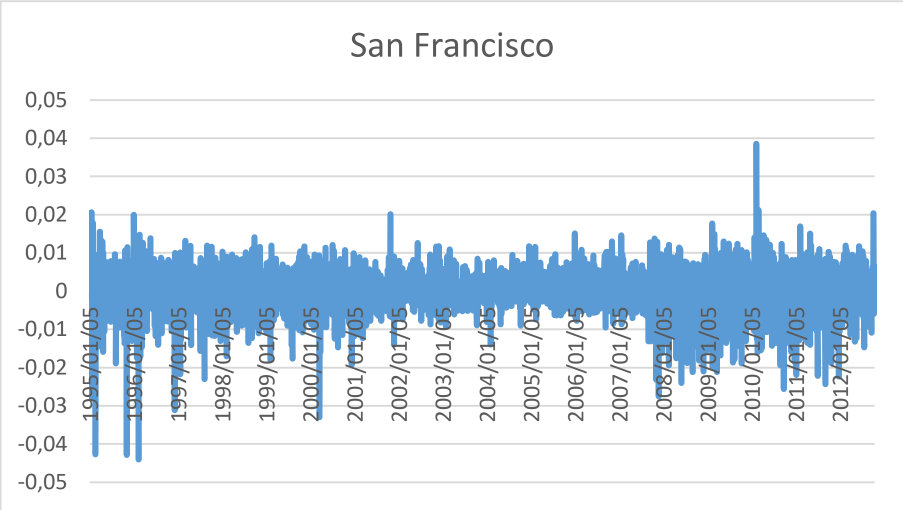
2011/01/04
2012/01/04


San Francisco
0,05
0,04
0,03
0,02
0,01
0
-0,01
-0,02
-0,03
-0,04
-0,05
1995/01/05
1996/01/05
1997/01/05
1998/01/05
1999/01/05
2000/01/05
2001/01/05
2002/01/05
2003/01/05
2004/01/05
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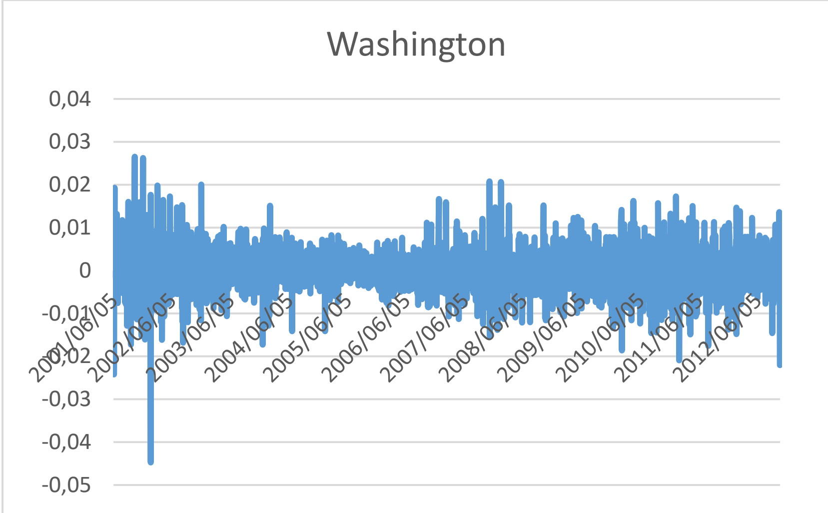
2011/01/05
2012/01/05


Washington
0,04
0,03
0,02
0,01
0
-0,01
-0,02
-0,03
-0,04
-0,05
2001/06/05
2002/06/05
2003/06/05
2004/06/05
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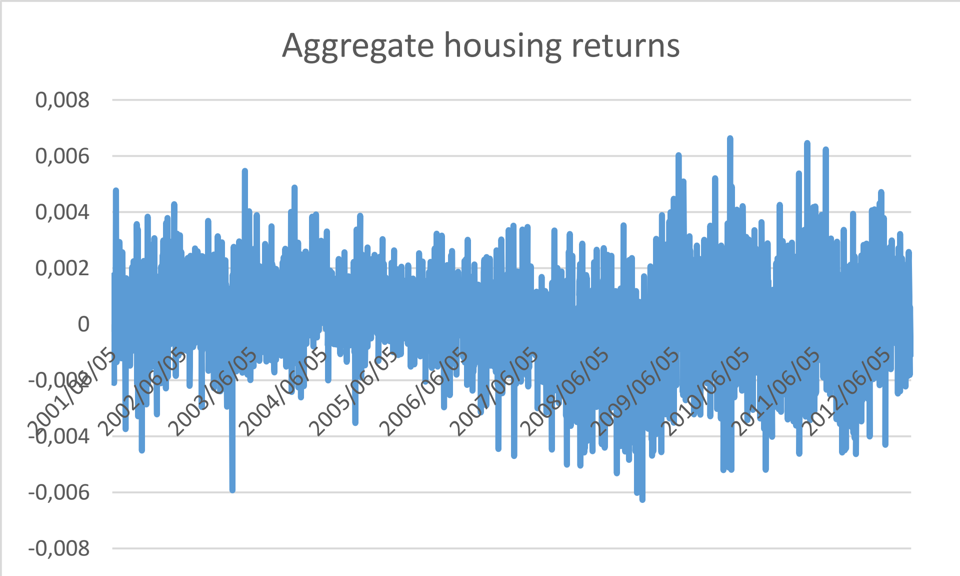
2011/06/05
2012/06/05


Aggregate housing returns
0,008
0,006
0,004
0,002
0
-0,002
-0,004
-0,006
-0,008
2001/06/05
2002/06/05
2003/06/05
2004/06/05
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2008/06/05
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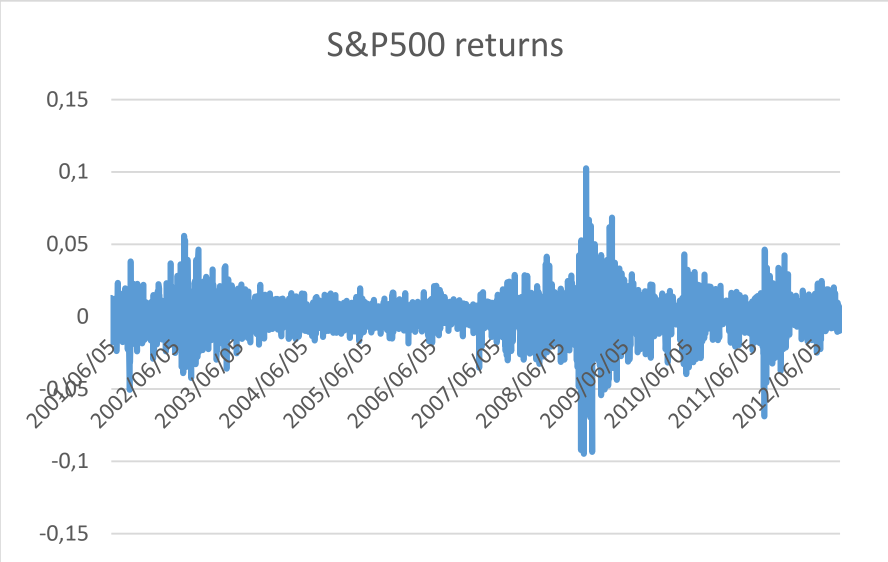
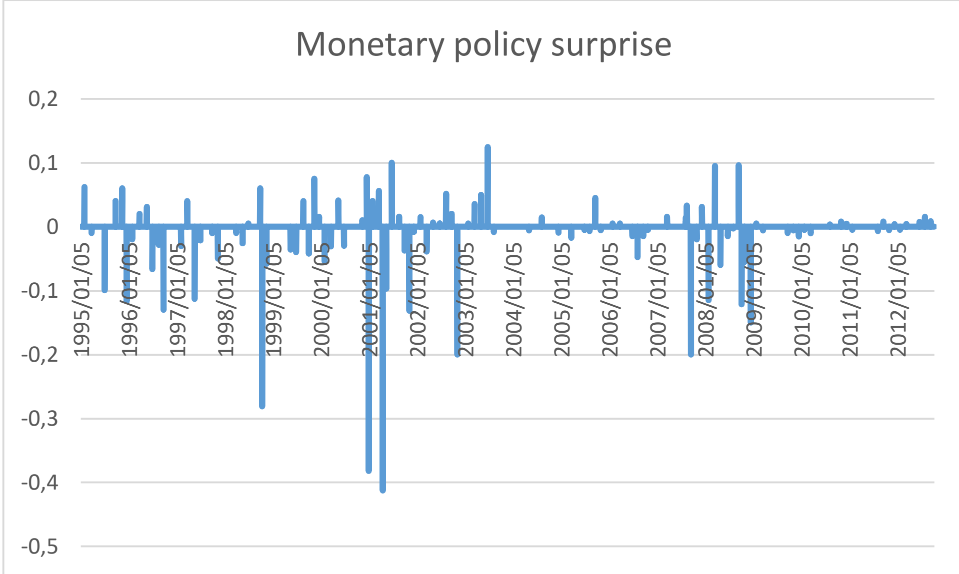
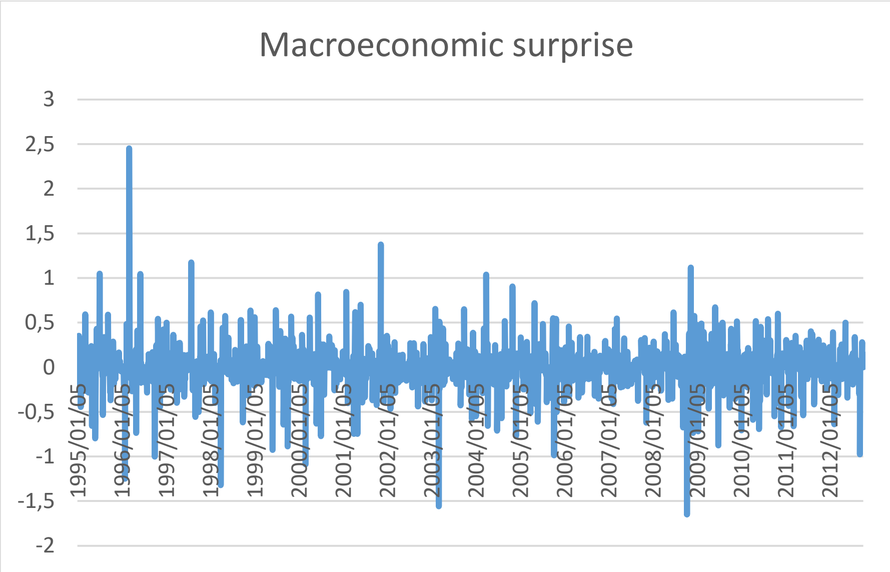
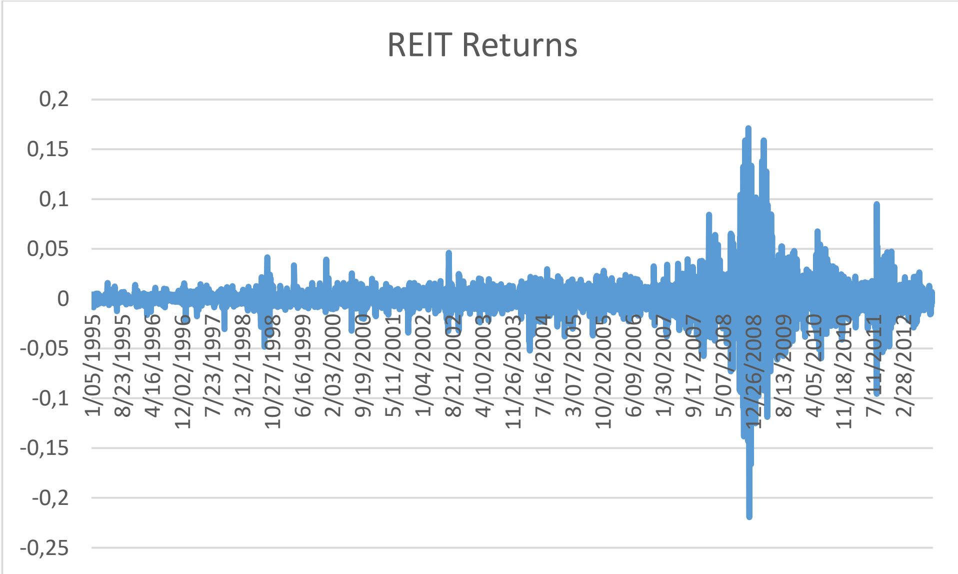
2011/06/05
2012/06/05


S&P500 returns
0,15
0,1
0,05
0
-0,05
-0,1
-0,15


Monetary policy surprise
0,2
0,1
0
-0,1
-0,2
-0,3
-0,4
-0,5


Macroeconomic surprise
3
2,5
2
1,5
1
0,5
0
-0,5
-1
-1,5
-2


REIT Returns
0,2
0,15
0,1
0,05
0
-0,05
-0,1
-0,15
-0,2
-0,25

# Chapter 4
# Predicting Aggregate and State-Level US House Price Volatility: The Role of Sentiment

## 4.1 Introduction

The housing market plays an important role in the economy of the United States (US), since it constitutes a significant share of many households' asset holding and net worth. According to the Financial Accounts data of the US corresponding to the fourth quarter of 2017, residential estate represents about 71.2% of total household non-financial assets, 24.8% of total household net worth and 21.4% of household total asset.[18] Therefore, the risk of the housing market is among the largest personal economic risks faced by individuals (Shiller, 1998). Housing assets differ from financial assets, such as stocks, in that they serve the dual role of investment and consumption (Henderson and Ioannides, 1987). Thus, the effects of housing on savings and portfolio choices are extremely important questions, and hence, understanding the source of the housing market price volatility has individual portfolio implications, as it affects households' investment decisions regarding tenure choice and housing quantity (Miles, 2008). Furthermore, the housing market affects the economy through not only wealth effects (Case et al., 2013), but also through influences on other markets such as the mortgage market, mortgage insurance and mortgage backed bonds, as well as consumer durables (Miller and Peng, 2006). Finally, knowledge about house price volatility is also an important input to housing policy (Zhou and Haurin, 2010).[19] Consequently, the variations in the housing market are important to key components of the overall economy and the welfare of the society.

In light of this, a growing number of studies have attempted to model and predict volatility (using univariate models and also with econometric frameworks including wide array of factors) at the

[18] See, https://www.federalreserve.gov/releases/z1/current/default.htm.

[19] For example, consider the following case: if low-valued houses' values are relatively volatile, then policies that encourage low-income renter households to become homeowners should be evaluated in light of the house price risk that they would bear.

aggregate and regional (state and metropolitan statistical areas (MSAs)-levels) of the US (see for example, Dolde and Tirtiroglu (2002), Miller and Peng (2006), Miles (2008), Zhou and Haurin (2010), Li (2012), Barros et al., (2015), Ajmi et al., (2014), Engsted and Pedersen (2014), Bork and Møller (2015), Fairchild et al., (2015), André et al., (2017), Chen (2017), Nyakabawo et al., (forthcoming)). In general, these studies highlight the role of information in macroeconomic, financial, and economic uncertainty related variables in predicting US housing market volatility.

With growing evidence suggesting that the collapse of the housing market was one of the main driving factors of the "Great Recession", Gupta, Lv, and Wong (2019) and Case, Shiller, and Thompson (2012, 2014) highlight the importance of taking into account people's opinions about buying conditions, that is housing sentiment, in analyzing housing decisions. Housing sentiment can possibly predict house price volatility since it captures the expectations of economic agents concerning how the housing market is going to behave in the future. From a behavioral point of view, housing sentiments can determine home purchase decisions either for consumption or as investment by renting it out (Gupta, Lau, Plakandaras and Wong, 2019). Unlike the financial markets, the housing market features high percentage of individual traders, market segmentation and asymmetry of information, making it highly susceptible to sentiment-mispricing. It is therefore important to understand the relationship between housing sentiment and housing returns.

Therefore, the aim of this study is to extend the literature on housing market volatility by analyzing whether housing market sentiment drives variation in housing returns by drawing on the findings of recent studies related to the equity markets, which tend to show that investor and corporate manager sentiments predicts volatility (over and above returns) of stock markets (Bekiros et al., 2016; Balcilar et al., 2018a, b; Gupta, 2018) in line with "noise traders" theory[20], whereby market agents tend

[20] Noise traders are defined as investors whose trading decisions are based on what they perceive to be an informative signal but which, to a rational agent, does not convey any information (Black, 1986). Studies by De Long et al. (1990, 1991), Campbell and Kyle (1993), Shefrin and Statman (1994) develop models to demonstrate that even a small group of noise traders, driven by joint unpredictable sentiment rather than by information, and acting in a correlated manner, can create long-lasting inefficient market outcomes. This is because their actions

to make overly optimistic or pessimistic judgments and choices. In this regard, we use the housing sentiment index developed by Bork et al., (2017), which is constructed based on household responses to questions regarding house buying conditions from the consumer survey of the University of Michigan, to predict volatility of the aggregate US housing market, the 50 states, as well as that of the District of Colombia.

Given that the housing sentiment Bork et al., (2017) has been shown to predict movements in aggregate and state-level housing returns (even after controlling for other predictors),[21] we use the recently developed *k*-th order causality-in-quantiles test of Balcilar et al., (2017), which in turn, allows us to test for predictability for both housing returns and volatility simultaneously. As indicated by Balcilar et al., (2017), the causality-in-quantiles approach has the following novelties: Firstly, it is robust to misspecification errors as it detects the underlying dependence structure between the examined time series. Secondly, via this methodology, we are able to test for not only causality-in-mean (1st moment), but also causality that may exist in the tails of the distribution of the variables. Finally, we are also able to investigate causality-in-variance and, thus, study higher-order dependency. Understandably, this test is comparatively superior to the conditional mean-based standard linear Granger causality test, as it not only studies the entire conditional distribution of both returns and volatility, but, being a data-driven nonparametric approach, also controls for misspecification due to nonlinearity – a widely observed characteristic in the US housing market (Balcilar et al., 2015; Plakandaras et al., 2015; André et al., forthcoming). In this regard, while nonlinear causality tests of Hiemstra and Jones. (1994), and Diks and Panchenko (2005, 2006) can control for misspecification due

introduce a new type of risk faced by rational investors and limit their ability to fully arbitrage away the emerging price inefficiencies. In these models, the noise traders are also shown, to be able to survive in the long run under certain conditions; thus, making their ever-changing sentiment a persistent determinant of asset market movements.

[21] Note that Soo (2018) develops annual measures of housing market sentiment for 34 US cities, and also find strong evidence of predictability for housing returns based on these indices. We however, rely on the national-level index developed by Bork et al., (2017) for our analysis due to three reasons: (a) The index is publicly available; (b) The index is at quarterly frequency, and hence is likely to be related more to volatility of the housing market than at the lower annual frequency, where volatility of housing returns are more subdued, and; (c) Given that housing market movements are considered to be a leading indicator of the economy (growth and inflation), prediction of volatility at a higher frequency is likely to be more informative to a policy-maker (in terms of designing appropriate policies based on the future paths of the macroeconomic variables) than at the annual frequency.

to nonlinearity, they are restricted to the conditional mean of the first-moment of the dependent variable only. Finally, the causality-in-quantiles test is also superior to the standard GARCH models (as primarily used in the studies cited above), since the latter specifies a linear relationship between returns and volatility with the predictors being studied, besides being restricted to the analysis of the conditional mean.

To the best of our knowledge, this is the first paper that evaluates the predictive power of housing market sentiment for US aggregate and state-levels housing returns and volatility based on a nonparametric causality-in-quantiles framework. The remainder of the paper is organized as follows: Section 4.2 outlines the methodology, while Section 4.3 discusses the data and econometric results, with Section 4.4 concluding the paper.

## 4.2 Methodology

In this section, we briefly present the methodology for the detection of nonlinear causality via a hybrid approach as developed by Balcilar et al. (2017), which in turn is based on the frameworks of Nishiyama et al., (2011) and Jeong et al., (2012). We start by denoting housing returns by $y_t$ and the predictor variable (in our case, the housing market sentiment index, as discussed in detail in the data segment) as $x_t$. We further let $Y_{t-1} \equiv (y_{t-1},...,y_{t-p})$, $X_{t-1} \equiv (x_{t-1},...,x_{t-p})$, $Z_t = (X_t, Y_t)$ and $F_{y_t|Z_{t-1}}(y_t, Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t, Y_{t-1})$ denote the conditional distribution functions of $y_t$ given $Z_{t-1}$ and $Y_{t-1}$, respectively. If we let denote $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t \mid Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t \mid Y_{t-1})$, we have $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1}) \mid Z_{t-1}\} = \theta$ with probability one. As a result, the (non)causality in the $q$-th quantile hypotheses to be tested are:

$$H_0: \quad P\{F_{y_t|Z_{t-1}}\{Q_q(Y_{t-1}) \mid Z_{t-1}\} = q\} = 1, \tag{1}$$

$$H_1: \quad P\{F_{y_t|Z_{t-1}}\{Q_q(Y_{t-1}) \mid Z_{t-1}\} = q\} < 1. \tag{2}$$

Jeong et al. (2012) use the distance measure $J = \{\varepsilon_t E(\varepsilon_t \mid Z_{t-1}) f_z(Z_{t-1})\}$, where $\varepsilon_t$ is the regression error term and $f_z(Z_{t-1})$ is the marginal density function of $Z_{t-1}$. The regression error $\varepsilon_t$ emerges based on the null hypothesis in (1), which can only be true if and only if $E[1\{y_t \le Q_\theta(Y_{t-1}) \mid Z_{t-1}\}] = \theta$ or, expressed in a different way, $1\{y_t \le Q_\theta(Y_{t-1})\} = \theta + \varepsilon_t$, where $\mathbf{1}\{\cdot\}$ is the indicator function. Jeong et al., (2012) show that the feasible kernel-based sample analogue of $J$ has the following format:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right)\hat{\varepsilon}_t \hat{\varepsilon}_s. \tag{3}$$

where $K(\cdot)$ is the kernel function with bandwidth $h$, $T$ is the sample size, $p$ is the lag order, and $\hat{\varepsilon}_t$ is the estimate of the unknown regression error, which is given by

$$\hat{\varepsilon}_t = 1\{y_t \le Q_\theta(Y_{t-1})\} - \theta. \tag{4}$$

$\hat{Q}_\theta(Y_{t-1})$ is an estimate of the $\theta^{\text{th}}$ conditional quantile of $y_t$ given $Y_{t-1}$, and we estimate $\hat{Q}_\theta(Y_{t-1})$ using the nonparametric kernel method as

$$\hat{Q}_\theta(Y_{t-1}) = \hat{F}^{-1}_{y_t|Y_{t-1}}(\theta \mid Y_{t-1}), \tag{5}$$

where $\hat{F}_{y_t|Y_{t-1}}(y_t \mid Y_{t-1})$ is the *Nadarya-Watson* kernel estimator given by

$$\hat{F}_{y_t|Y_{t-1}}(y_t \mid Y_{t-1}) = \frac{\sum_{s=p+1, s\neq t}^{T} L\left((Y_{t-1} - Y_{s-1})/h\right) 1(y_s \le y_t)}{\sum_{s=p+1, s\neq t}^{T} L\left((Y_{t-1} - Y_{s-1})/h\right)}, \tag{6}$$

with $L(\cdot)$ denoting the kernel function and $h$ the bandwidth.

As an extension of Jeong et al., (2012)'s framework, Balcilar et al., (2017) develop a test for the *second* moment which allows us to test the causality between the housing sentiment index and housing returns volatility. Adapting the approach in Nishiyama et al., (2011), higher order quantile causality can be specified in terms of the following hypotheses as:

$$H_0: \quad P\{F_{y_t^k|Z_{t-1}}\{Q_q(Y_{t-1})|Z_{t-1}\}=q\}=1 \qquad \text{for } k=1,2,\ldots,K \tag{7}$$

$$H_1: \quad P\{F_{y_t^k|Z_{t-1}}\{Q_q(Y_{t-1})|Z_{t-1}\}=q\}<1 \qquad \text{for } k=1,2,\ldots,K \tag{8}$$

We can integrate the entire framework and test whether $x_t$ *Granger causes* $y_t$ *in quantile* $\theta$ *up to the* $k^{th}$ *moment* using Eq. (7) to construct the test statistic in Eq. (6) for each $k$. The causality-in-variance test can then be calculated by replacing $y_t$ in Eqs. (3) and (4) with $y_t^2$ - measuring the volatility of housing returns (as used traditionally in the literature when comparing with model-generated estimates of the latent variable). However, one can show that it is difficult to combine the different statistics for each $k=1,2,\ldots,K$ into one statistic for the joint null in Eq. (7) because the statistics are mutually correlated (Nishiyama et al., 2011). Balcilar et al., (2017), thus, propose a sequential-testing method as described in Nishiyama et al., (2011). First, as in Balcilar et al., (2017), we test for the nonparametric Granger causality in the *first* moment (i.e., $k$=1). Nevertheless, failure to reject the null for $k=1$ does not automatically lead to no-causality in the *second* moment. Thus, we can still construct the test for $k=2$, as discussed in detail in Balcilar et al., (2017).

The empirical implementation of causality testing via quantiles entails specifying three key parameters: the bandwidth ($h$), the lag order ($p$), and the kernel type for $K(\cdot)$ and $L(\cdot)$. We use a lag order based on the Schwarz information criterion (SIC), which is known to select a parsimonious model as compared with other lag-length selection criteria, and hence, help us to overcome the issue of the over-parameterization that typically arises in studies using nonparametric frameworks. For each quantile, we determine the bandwidth parameter ($h$) by using the leave-one-out least-squares cross validation method. Finally, for $K(\cdot)$ and $L(\cdot)$, we use Gaussian kernels.

## 4.3 Data and Empirical results

Our data set covers the quarterly period of 1975:3 to 2014:3, with the start and end date being purely driven by the availability of the housing sentiment index developed by Bork et al., (2017). The authors use time series data from the consumer surveys of the University of Michigan to generate the housing sentiment index, with housing sentiment defined based on the general attitude of households about house buying conditions. In particular, Bork et al. (2017) consider the underlying reasons households to provide their views about all the house buying conditions. The part of University of Michigan's consumer survey related to house buying conditions starts with the question: "Generally speaking, do you think now is a good time or a bad time to buy a house?", with the follow-up question: "Why do you say so?". In constructing the index, Bork et al., (2017) focuses on the responses to the follow-up question as the idea is to draw on the information in the underlying reasons why households believe that it is a bad or good time to buy a house. Specifically, the housing sentiment index is based on the following ten time series: good time to buy ; prices are low, good time to buy ; prices are going higher, good time to buy; interest rates are low, good time to buy; borrow-in-advance of rising interest rates, good time to buy; good investment, good time to buy; times are good, bad time to buy; prices are high, bad time to buy; interest rates are high, bad time to buy; cannot afford, and bad time to buy; uncertain future. Then Bork et al., (2017) used partial least squares (PLS) to aggregate the information contained in each of the ten time series into an easy-to-interpret index of housing sentiment, with PLS filtering out idiosyncratic noise from the individual time series and summarizing the most important information in a single index.[22]

For house prices, following Bork et al., (2017), we use the seasonally-adjusted data for the aggregate US, the 50 states and that of District of Columbia obtained from the Federal Housing Finance Agency (FHFA), and correspond to the All-Transactions Indexes (estimated using sales prices and appraisal data).[23] The FHFA house price indexes are broad measures of the movement of single-family

[22]The data can be downloaded from: https://www.dropbox.com/s/al3sddq1026xci2/Online%20data.xlsx?dl=0.
[23]The data is downloadable from: https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx#qpo.

house prices. The indexes are weighted, repeat-sales indexes, meaning that it measures average price changes in repeat sales or refinancings on the same properties. This information is obtained by reviewing repeat mortgage transactions on single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac since January 1975.

Having discussed the data, we now turn our attention to the results from the k-th order nonparametric causality-in-quantiles test of Balcilar et al., (2017), which produces predictability results for housing returns and volatility simultaneously by controlling for possible nonlinearity.[24] Tables 4.1 and 4.2 report the results of states showing causality at the specific quantiles (i.e., where the test statistic is greater than the 5 percent critical value of 1.96, given that the statistic follows a standard normal distribution) for returns and squared returns due to the sentiment index.[25]

Evidence from Table 4.1 indicates that using the nonparametric causality-in-quantiles to test for causality between housing returns and housing sentiment index, California is the only state which shows no causality over the entire conditional distribution of returns.[26] For Georgia, Idaho, Indiana, Mississippi, New Mexico, North Carolina, and South Carolina, the results show that housing sentiment predicts housing returns over the entire conditional distribution. While housing sentiment predicts returns both towards the lower (bearish/bust regime)- and upper (bullish/boom regime)- ends of the conditional distribution, the causality is generally observed in relatively more instances (and also found

[24] We checked whether the estimated residuals from a linear model relating squared returns (volatility) with sentiment, are independent and identically distributed (*i.i.d.*), i.e., whether a linear model is correctly specified in capturing the relationship between volatility and sentiment. In this regard, we performed the Brock *et al.* (1996, BDS) test on the residuals recovered from models involving squared returns as the dependent variable, and lagged squared returns and the sentiment index used as regressors, with the lags determined by the SIC. Results presented in Appendix 4.1, overwhelmingly reject the null of *i.i.d.* errors, and hence, provide evidence of omitted nonlinear structure in the relationship between volatility and sentiment for the 50 states, the aggregate US and also for District of Columbia. Since the BDS test indicates existence of nonlinear interdependencies, the testing of predictability using the nonparametric causality-in-quantiles test proposed by Balcilar *et al.* (2017) is warranted, which in turn, being a data-driven approach accommodates for nonlinearity in the relationship between volatility and housing sentiment, and also produces predictability results for housing returns.

[25]Complete corresponding results have been presented in Tables A2 and A3 respectively of returns and volatility in the Appendix of the paper.

[26] This result is in contradiction with Bork et al., (2017), who detects predictability for California, but not Texas, Oklahoma, and North Dakota. The differences between the findings could be attributed to the fact that Bork et al., (2017) conducts out-of-sample forecasting based on a linear model, whereas, we are relying on in-sample predictability based on a nonparametric model.

to be stronger, given higher values of the statistic - as shown in Appendix 4.2) at the upper end of the conditional distribution.[27]

**Table 4.1. Summary of states showing causality from housing sentiment index on nominal housing returns**

| States | Quantile |
|---|---|
| ALABAMA | 0.05 – 0.95 |
| ALASKA | 0.05-0.10, 0.60 - 0.95 |
| ARIZONA | 0.05 - 0.20; 0.30 – 0.45; 0.55; 0.65 – 0.95 |
| ARKANSAS | 0.15 - 0.95 |
| COLORADO | 0.05 – 0.15; 0.80 - 0.95 |
| CONNECTICUT | 0.25 – 0.30; 0.65 – 0.70; 0.80 – 0.85; 0.95 |
| DELAWARE | 0.15 – 0.30; 0.40 – 0.95 |
| DISTRICT OF COLUMBIA | 0.10 – 0.15; 0.25 – 0.95 |
| FLORIDA | 0.05; 0.35 – 0.45; 0.70 – 0.95 |
| GEORGIA | 0.05 -0.95 |
| HAWAII | 0.20; 0.35 – 0.95 |
| IDAHO | 0.05 - 0.95 |
| ILLINOIS | 0.15 – 0.30; 0.65 – 0.95 |
| INDIANA | 0.05 – 0.95 |
| IOWA | 0.25 – 0.95 |
| KANSAS | 0.10 – 0.95 |
| KENTUCKY | 0.15 – 0.95 |
| LOUISIANA | 0.40 – 0.95 |
| MAINE | 0.45 – 0.95 |
| MARYLAND | 0.05 – 0.60; 0.75 – 0.95 |
| MASSACHUSETTS | 0.75; 0.85 – 0.95 |
| MICHIGAN | 0.05; 0.70 – 0.80; 0.95 |
| MINNESOTA | 0.05 – 0.15; 0.25 – 0.40; 0.50 – 0.95 |
| MISSISSIPPI | 0.05 – 0.95 |
| MISSOURI | 0.20 – 0.95 |
| MONTANA | 0.25 – 0.95 |
| NEBRASKA | 0.60 – 0.95 |
| NEVADA | 0.05 – 0.20; 0.85 – 0.90 |
| NEW HAMPSHIRE | 0.40 - 0.55; 0.75 – 0.95 |
| NEW JERSEY | 0.80 – 0.95 |
| NEW MEXICO | 0.05 – 0.95 |
| NEW YORK | 0.20 – 0.30; 0.45 - 0.75; 0.85 – 0.95 |
| NORTH CAROLINA | 0.05 – 0.95 |
| NORTH DAKOTA | 0.05-0.1; 0.70 – 0.95 |
| OHIO | 0.05; 0.25 – 0.55; 0.80 – 0.95 |

[27] Bork et al., (2017) observed predictability of the aggregate US housing returns for both busts and booms – a result we find as well, given that we observe causality of sentiment to housing returns at the extreme ends of the conditional distribution.

| | |
|---|---|
| OKLAHOMA | 0.25 – 0.95 |
| OREGON | 0.10 – 0.20; 0.60 – 0.95 |
| PENNSYLVANIA | 0.10; 0.65 – 0.95 |
| RHODE ISLAND | 0.25 – 0.70; 0.85 – 0.95 |
| SOUTH CAROLINA | 0.05 – 0.95 |
| SOUTH DAKOTA | 0.40 – 0.95 |
| TENNESSEE | 0.10 – 0.95 |
| TEXAS | 0.25; 0.35 – 0.75; 0.85 – 0.95 |
| UTAH | 0.05 – 0.1; 0.2 – 0.25; 0.35 – 0.60; 0.75 – 0.95 |
| VERMONT | 0.05; 0.30 – 0.95 |
| VIRGINIA | 0.10 – 0.90 |
| WASHINGTON | 0.10 – 0.40; 0.55 – 0.95 |
| WEST VIRGINIA | 0.05; 0.35 – 0.95 |
| WISCONSIN | 0.10 – 0.85 |
| WYOMING | 0.35 - 0.95 |
| USA | 0.05 – 0.75; 0.95 |

**Note:** State which show no causality – California.

Table 4.2 summarizes the results of housing returns volatility due to housing sentiment, which hold for all cases barring the states of Connecticut, Georgia, Indiana, Iowa, and Nebraska.[28] Further, as can be seen from the results, predictability is mostly located (and is also the strongest as seen from Appendix 4.3) around the median of the conditional distribution of squared returns and spans the moderately low and high quantiles as well. The exceptions are the quantiles at the extreme ends, i.e., the phases of the market corresponding to exceptionally low and high volatilities.[29]

[28] In Appendix 4.4 of the paper, we report the standard linear Granger causality test for squared nominal housing returns due to sentiment, for the sake of comparability and complementarity reasons, even though the main focus of the paper is the prediction of volatility based on the causality-in-quantiles test. As can be seen from Appendix 4.1, the null hypothesis that housing sentiment does not Granger cause volatility is rejected for 28 out of the 49 U.S states, as well as on an aggregate level and for the District of Columbia, i.e., in a total of 30 out of 52 cases. In other words, when compared to the causality-in-quantiles test, results based on the standard Granger causality test is weaker, which however should not be surprising, given the strong evidence of nonlinearity in the relationship between volatility and housing sentiment as reported in Appendix 4.1.

[29] As a robustness check, we also computed a measure of variation in house prices using the classical estimator of realized volatility (*RV*) derived from the sum of squared monthly returns over a quarter (as suggested by Andersen and Bollerslev, 1998), based on the seasonally adjusted monthly house prices indexes of the Freddie Mac (http://www.freddiemac.com/research/indices/house-price-index.html). The Freddie Mac indexes are constructed using a repeat transactions methodology, which has become a common practice in housing research. The indexes are estimated with data including transactions on single-family detached and town-home properties serving as collateral on loans originated between January 1, 1975, and the end of the most recent index month, where the loan has been purchased by Freddie Mac or Fannie Mae. The results based on the *RV* have been reported in Appendix 4.5 and are qualitatively similar, in the sense of strongest predictability around the median, to those

In general, the lack of predictability of housing market volatility based on sentiment at the extreme ends of the conditional distribution does seem intuitively correct. Understandably, when volatility is low (i.e., markets are calm), agents do not require information from the predictor (in our case, sentiment) to predict the path of future volatility, and when volatility is already at its upper end, information from sentiment is possibly of no value given that agents are likely to be herding (Ngene et al., 2017). In other words, when volatility is exceptionally low or high, to predict the future path of this variable, all that agents need are information on past volatility, and housing market-related sentiment plays negligible role in the process.

In terms of whether we should expect any feedback from volatility on the sentiment, evidence from Ling et al, 2015 suggest that the dynamic relation between sentiment and house prices can create feedback effects which contribute to the persistence typically observed in house price movements during boom and bust cycles, therefore one can expect feedback. Case and Shilling (2003) also find evidence of a positive feedback loop from prices to buyer and lender sentiment which explains the increased persistence and volatility of house price changes during boom and bust periods.

**Table 4.2. Summary of states showing causality from housing sentiment index on squared nominal housing returns, i.e., volatility**

| States | Quantile |
|---|---|
| ALABAMA | 0.15 – 0.70 |
| ALASKA | 0.05 – 0.85 |
| ARIZONA | 0.20 – 0.80 |
| ARKANSAS | 0.05 – 0.85 |
| CALIFORNIA | 0.20 – 0.85 |
| COLORADO | 0.10 – 0.70 |
| DELAWARE | 0.05 – 0.85 |
| DISTRICT OF COLUMBIA | 0.30 – 0.75 |
| FLORIDA | 0.10 -0.85 |
| HAWAII | 0.05 – 0.85 |
| IDAHO | 0.05 – 0.85 |
| ILLINOIS | 0.15 – 0.75 |

derived from the squared quarterly returns obtained using the FHFA data in Table 4.2. However, in this case, there is lack of predictability in seven states (Alaska, Arizona, Florida, Nebraska, Nevada, North Dakota and South Dakota) compared to five (Connecticut, Georgia, Indiana, Iowa, and Nebraska) under squared returns, with one common state being Nebraska. But as suggested by Balcilar et al., (2018c), that since squared returns as a measure of volatility follows directly from the *k*-th order test and is independent of a model-based estimate of volatility (which could vary depending on what estimate of *RV* we choose), the use of squared returns is more appropriate in our context, and the results based on it should be deemed as more reliable.

| | |
|---|---|
| KANSAS | 0.40; 0.50 – 0.60 |
| KENTUCKY | 0.20 -0.55 |
| LOUISIANA | 0.50; 0.75 |
| MAINE | 0.35; 0.65 – 0.70 |
| MARYLAND | 0.20 – 0.80 |
| MASSACHUSETTS | 0.20 – 0.80 |
| MICHIGAN | 0.05 – 0.75 |
| MINNESOTA | 0.30 – 0.80 |
| MISSISSIPPI | 0.30 – 0.55 |
| MISSOURI | 0.10 – 0.85 |
| MONTANA | 0.05 – 0.85 |
| NEVADA | 0.05 – 0.85 |
| NEW HAMPSHIRE | 0.05 – 0.90 |
| NEW JERSEY | 0.20 - 0.80 |
| NEW MEXICO | 0.15 – 0.75 |
| NEW YORK | 0.25 – 0.80 |
| NORTH CAROLINA | 0.15 – 0.65 ; 0.75 – 0.80 |
| NORTH DAKOTA | 0.25 – 0.75 |
| OHIO | 0.55 – 0.60 ; 0.70 ; 0.80 |
| OKLAHOMA | 0.20 ; 0.45 – 0.55 ; 0.65 |
| OREGON | 0.25 – 0.85 |
| PENNSYLVANIA | 0.05 – 0.80 |
| RHODE ISLAND | 0.40 – 0.50 ; 0.60 – 0.65 |
| SOUTH CAROLINA | 0.25 – 0.35 ; 0.45 – 0.55 ; 0.65 – 0.80 |
| SOUTH DAKOTA | 0.05 – 0.90 |
| TENNESSEE | 0.05 - 0.90 |
| TEXAS | 0.45 – 0.60 |
| UTAH | 0.15 – 0.30 ; 0.40 – 0.70 |
| VERMONT | 0.05 – 0.85 |
| VIRGINIA | 0.20 – 0.70 |
| WASHINGTON | 0.25 – 0.80 |
| WEST VIRGINIA | 0.05 – 0.85 |
| WISCONSIN | 0.05 – 0.85 |
| WYOMING | 0.15 – 0.70 |
| USA | 0.20-0.65 |

**Note**: States which show no causality – Connecticut; Georgia; Indiana; Iowa; and Nebraska.

## 4.4 Conclusion

Housing returns volatility is vital for portfolio management, and is also an important determinant of both mortgage default and prepayment, besides having policy implications. Hence, accurate prediction of volatility is of paramount importance. Borrowing from the literature on the ability of sentiment in predicting equity market volatility, we in this paper analyze whether a recently developed measure of housing-market sentiment (constructed based on household responses to questions regarding house buying conditions) leads housing market volatility at the aggregate and regional-levels of the US economy. Given the existing evidence that housing sentiment can predict returns, we use the *k*-th order causality-in-quantiles test of Balcilar et al., (2017) for our purpose, since this methodology allows us to test for predictability for both housing returns and volatility simultaneously. Being a nonparametric approach, the test also controls for possible misspecification due to nonlinearity between housing market movements and sentiment. In addition, being a quantiles-based model, we are able to analyze predictability over the entire conditional distribution of both returns and volatility, rather than just at the conditional mean. Based on this test, which is able to guard against misspecification due to the existing nonlinearity between volatility and sentiment, as detected by formal statistical tests, we find that housing sentiment predicts squared housing returns, i.e., volatility for 45 of the 50 states, District of Columbia and the overall US market. The exceptions are the states of Connecticut, Georgia, Indiana, Iowa, and Nebraska. In general, predictability of volatility is found to be the strongest around the median of the conditional distribution and also tends cover moderately low and high quantiles. As far as returns is concerned, barring California, sentiment is found to predict housing returns for 51 out of the 52 cases especially towards the upper end of the conditional distribution.

Our results have implications from different perspectives. From the viewpoint of an academic, our results tend to suggest that the semi-strong version of the efficient market hypothesis (EMH), which in turn implies lack of predictability emanating from housing sentiment, tends to hold only for certain parts of the conditional distribution of returns and volatility. In other words, EMH is regime-dependent, and primarily holds for extreme returns and volatility, i.e., based on our results, adaptive market hypothesis (AMH as suggested by Lo (2004)) seems to be holding for the housing market. Given this, investors can design strategies to make profits out of their portfolios including housing, barring the excessive booms and bust phases of the market. Finally, from the perspective of a policy maker, the information that housing market is generally predictable based on sentiment, except at its extreme ends, can provide valuable information as to where the macroeconomy is possibly headed, especially when the housing market is functioning at its normal mode (i.e., around the median of the conditional distribution).

As part of future research, it would be interesting to extend our study, as in Bonaccolto et al., (2018), to examine if our results for both returns and volatility continue to hold over an out-of-sample, as in-sample predictability does not guarantee favourable forecasting results (Rapach and Zhou, 2013).

## Appendix 4.1. Table of BDS test

| | Dimension | | | | |
|---|---|---|---|---|---|
| | 2 | 3 | 4 | 5 | 6 |
| ALABAMA | 0.063* | 0.133* | 0.183* | 0.216* | 0.238* |
| ALASKA | 0.100* | 0.165* | 0.229* | 0.272* | 0.292* |
| ARIZONA | 0.067* | 0.142* | 0.191* | 0.215* | 0.225* |
| ARKANSAS | 0.045* | 0.093* | 0.128* | 0.149* | 0.160* |
| CALIFORNIA | 0.090* | 0.151* | 0.192* | 0.208* | 0.209* |
| COLORADO | 0.062* | 0.125* | 0.176* | 0.210* | 0.224* |
| CONNECTICUT | 0.090* | 0.165* | 0.227* | 0.263* | 0.280* |
| DELAWARE | 0.071* | 0.136* | 0.185* | 0.223* | 0.242* |
| DISTRICT OF COLUMBIA | 0.059* | 0.110* | 0.145* | 0.174* | 0.189* |
| FLORIDA | 0.069* | 0.146* | 0.193* | 0.232* | 0.253* |
| GEORGIA | 0.045* | 0.073* | 0.105* | 0.136* | 0.167* |
| HAWAII | 0.092* | 0.173* | 0.228* | 0.259* | 0.274* |
| IDAHO | 0.084* | 0.146* | 0.174* | 0.190* | 0.199* |
| ILLINOIS | 0.047* | 0.088* | 0.136* | 0.167* | 0.181* |
| INDIANA | 0.055* | 0.119* | 0.175* | 0.208* | 0.224* |
| IOWA | 0.105* | 0.198* | 0.268* | 0.312* | 0.336* |
| KANSAS | 0.076* | 0.127* | 0.171* | 0.193* | 0.202* |
| KENTUCKY | 0.063* | 0.110* | 0.146* | 0.164* | 0.171* |
| LOUISIANA | 0.095* | 0.181* | 0.239* | 0.269* | 0.282* |
| MAINE | 0.134* | 0.237* | 0.314* | 0.372* | 0.410* |
| MARYLAND | 0.078* | 0.134* | 0.168* | 0.177* | 0.176* |
| MASSACHUSETTS | 0.050* | 0.117* | 0.164* | 0.200* | 0.218* |
| MICHIGAN | 0.057* | 0.085* | 0.113* | 0.146* | 0.161* |
| MINNESOTA | 0.043* | 0.067* | 0.087* | 0.103* | 0.109* |
| MISSISSIPPI | 0.065* | 0.121* | 0.157* | 0.179* | 0.191* |
| MISSOURI | 0.103* | 0.187* | 0.248* | 0.285* | 0.303* |
| MONTANA | 0.090* | 0.180* | 0.256* | 0.311* | 0.343* |
| NEBRASKA | 0.074* | 0.139* | 0.190* | 0.226* | 0.249* |
| NEVADA | 0.079* | 0.141* | 0.180* | 0.200* | 0.202* |
| NEW HAMPSHIRE | 0.107* | 0.183* | 0.235* | 0.267* | 0.288* |
| NEW JERSEY | 0.066* | 0.141* | 0.190* | 0.225* | 0.244* |
| NEW MEXICO | 0.074* | 0.135* | 0.191* | 0.221* | 0.234* |
| NEW YORK | 0.065* | 0.139* | 0.197* | 0.242* | 0.268* |
| NORTH CAROLINA | 0.060* | 0.109* | 0.154* | 0.179* | 0.191* |
| NORTH DAKOTA | 0.139* | 0.237* | 0.305* | 0.363* | 0.403* |
| OHIO | 0.065* | 0.122* | 0.161* | 0.180* | 0.186* |
| OKLAHOMA | 0.051* | 0.102* | 0.149* | 0.178* | 0.196* |
| OREGON | 0.090* | 0.155* | 0.197* | 0.220* | 0.233* |
| PENNSYLVANIA | 0.087* | 0.157* | 0.204* | 0.234* | 0.250* |
| RHODE ISLAND | 0.050* | 0.096* | 0.131* | 0.153* | 0.173* |
| SOUTH CAROLINA | 0.049* | 0.102* | 0.151* | 0.177* | 0.188* |
| SOUTH DAKOTA | 0.131* | 0.228* | 0.290* | 0.339* | 0.368* |
| TENNESSEE | 0.088* | 0.167* | 0.219* | 0.251* | 0.266* |
| TEXAS | 0.094* | 0.158* | 0.212* | 0.251* | 0.271* |
| UTAH | 0.043* | 0.074* | 0.094* | 0.096* | 0.089* |
| VERMONT | 0.142* | 0.252* | 0.328* | 0.375* | 0.401* |
| VIRGINIA | 0.066* | 0.123* | 0.160* | 0.184* | 0.193* |
| WASHINGTON | 0.061* | 0.110* | 0.151* | 0.178* | 0.193* |
| WEST VIRGINIA | 0.066* | 0.128* | 0.190* | 0.242* | 0.284* |
| WISCONSIN | 0.066* | 0.131* | 0.175* | 0.205* | 0.218* |
| WYOMING | 0.066* | 0.130* | 0.180* | 0.215* | 0.246 |
| USA | 0.064* | 0.124* | 0.167* | 0.192* | 0.204 |

**Note:** Entries are the BDS test statistic for the null of serial independence in the error for the residuals recovered from squared nominal housing returns equation with the independent variables being the lags of volatility and housing sentiment, where the lag-length is determined optimally by the SIC.* indicates the rejection of the null hypothesis at 5 percent level of significance.

## Appendix 4.2. Table of Causality-in-Quantiles of Nominal Housing Returns

| | Quantile | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| STATES | 0.05 | 0.10 | 0.15 | 0.20 | 0.25 | 0.30 | 0.35 | 0.40 | 0.45 | 0.50 | 0.55 | 0.60 | 0.65 | 0.70 | 0.75 | 0.80 | 0.85 | 0.90 | 0.95 |
| ALABAMA | 2.35* | 2.10* | 1.99* | 2.79* | 2.74* | 3.16* | 3.45* | 3.34* | 4.75* | 5.38* | 5.34* | 5.62* | 5.81* | 5.60* | 4.37* | 4.87* | 5.42* | 5.41* | 5.72* |
| ALASKA | 3.21* | 2.20* | 1.56 | 0.92 | 0.41 | 0.03 | 1.00 | 1.33 | 1.32 | 1.45 | 1.15 | 2.10* | 2.64* | 3.12* | 3.40* | 2.47* | 2.01* | 3.38* | 2.64* |
| ARIZONA | 4.49* | 2.90* | 3.21* | 2.90* | 1.93 | 2.53* | 2.52* | 2.54* | 2.33* | 1.93 | 1.96* | 1.86 | 2.38* | 3.25* | 3.43* | 3.22* | 2.62* | 2.53* | 2.69* |
| ARKANSAS | 0.87 | 1.64 | 2.98* | 3.01* | 2.82* | 2.57* | 2.67* | 3.10* | 3.27* | 3.56* | 3.93* | 3.88* | 4.27* | 5.05* | 5.16* | 5.34* | 4.67* | 3.41* | 2.45* |
| CALIFORNIA | 1.84 | 1.28 | 0.59 | 0.55 | 0.50 | 0.76 | 0.63 | 0.86 | 0.87 | 0.64 | 0.08 | 0.11 | 0.00 | 0.16 | 0.38 | 0.08 | 0.12 | 0.21 | 1.25 |
| COLORADO | 3.45* | 3.16* | 2.14* | 0.88 | 1.39 | 1.25 | 1.12 | 1.22 | 1.49 | 1.19 | 1.44 | 1.68 | 1.78 | 1.85 | 1.93 | 2.27* | 2.72* | 4.92* | 3.78* |
| CONNECTICUT | 1.09 | 0.63 | 1.45 | 1.23 | 2.97* | 2.23* | 1.88 | 1.20 | 1.51 | 1.87 | 1.51 | 1.76 | 2.26* | 2.13* | 1.95 | 2.09* | 2.03* | 1.58 | 3.33* |
| DELAWARE | 0.79 | 1.32 | 3.48* | 3.28* | 3.95* | 4.55* | 1.50 | 5.08* | 5.04* | 4.78* | 5.15* | 5.54* | 5.80* | 6.28* | 5.45* | 9.74* | 10.96* | 10.23* | 5.27* |
| DISTRICT OF COLUMBIA | 1.92 | 2.07* | 2.84* | 1.89 | 2.69* | 2.92* | 2.83* | 2.94* | 3.39* | 4.03* | 3.69* | 4.06* | 3.66* | 4.06* | 4.78* | 5.17* | 5.35* | 5.41* | 8.17* |
| FLORIDA | 2.55* | 1.91 | 1.46 | 1.95 | 1.59 | 1.83 | 2.07* | 2.28* | 2.08* | 1.66 | 1.68 | 1.89 | 1.78 | 2.05* | 2.76* | 3.46* | 4.38* | 3.84* | 5.95* |
| GEORGIA | 2.43* | 6.16* | 3.89* | 3.75* | 4.16* | 4.10* | 3.94* | 3.60* | 3.41* | 2.73* | 2.20* | 2.16* | 2.24* | 3.53* | 3.82* | 3.91* | 3.86* | 5.00* | 3.18* |
| HAWAII | 0.58 | 1.54 | 1.45 | 2.00* | 1.67 | 1.62 | 1.97* | 2.31* | 2.71* | 3.28* | 3.09* | 3.33* | 3.23* | 3.09* | 2.71* | 2.29* | 7.87* | 8.56* | 9.15* |
| IDAHO | 3.02* | 4.29* | 5.62* | 4.55* | 3.62* | 3.00* | 2.72* | 2.79* | 2.97* | 3.19* | 3.43* | 3.61* | 3.62* | 3.98* | 3.60* | 3.60* | 4.53* | 4.38* | 5.53* |
| ILLONOIS | 0.84 | 1.64 | 4.06* | 2.28* | 2.17* | 2.16* | 1.83 | 1.87 | 1.79 | 1.65 | 1.79 | 1.53 | 2.35* | 2.70* | 3.73* | 5.20* | 2.22* | 4.87* | 6.81* |
| INDIANA | 2.53* | 2.14* | 3.56* | 2.94* | 2.92* | 2.95* | 2.96* | 2.94* | 3.00* | 2.82* | 2.99* | 3.31* | 3.54* | 3.76* | 3.92* | 4.07* | 5.21* | 5.41* | 6.78* |
| IOWA | 0.73 | 0.43 | 1.04 | 1.81 | 2.50* | 2.74* | 2.75* | 2.78* | 2.62* | 2.74* | 3.04* | 3.21* | 3.74* | 4.75* | 4.71* | 5.31* | 5.42* | 6.61* | 7.54* |
| KANSAS | 1.85 | 2.93* | 3.11* | 3.84* | 4.08* | 3.87* | 4.49* | 4.85* | 4.63* | 4.49* | 5.09* | 5.48* | 4.31* | 5.02* | 4.69* | 3.19* | 3.52* | 3.94* | 6.70* |
| KENTUCKY | 1.50 | 1.26 | 2.32* | 2.67* | 3.17* | 3.28* | 3.10* | 3.41* | 3.31* | 4.06* | 5.19* | 5.51* | 5.74* | 5.41* | 5.73* | 5.25* | 3.67* | 4.83* | 5.29* |
| LOUISIANA | 0.73 | 0.42 | 1.29 | 1.17 | 1.47 | 1.65 | 1.58 | 1.98* | 2.12* | 3.28* | 4.14* | 3.93* | 3.99* | 4.18* | 4.42* | 4.78* | 3.43* | 4.04* | 8.09* |
| MAINE | 0.79 | 1.02 | 1.58 | 1.82 | 1.80 | 1.76 | 1.45 | 1.42 | 2.37* | 3.43* | 3.46* | 2.79* | 2.61* | 2.86* | 2.73* | 4.86* | 5.72* | 5.64* | 3.15* |
| MARYLAND | 3.09* | 2.33* | 3.51* | 4.43* | 4.31* | 3.80* | 3.10* | 3.06* | 2.81* | 2.46* | 2.42* | 2.86* | 1.73 | 1.64 | 2.22* | 2.22* | 2.82* | 2.66* | 4.60* |
| MASSACHUSETTS | 0.88 | 0.38 | 0.38 | 0.25 | 0.59 | 0.34 | 0.15 | 0.31 | 0.28 | 0.69 | 1.09 | 1.56 | 1.59 | 1.95 | 2.17* | 1.60 | 3.12* | 4.89* | 6.37* |
| MICHIGAN | 6.51* | 1.70 | 1.85 | 1.33 | 1.54 | 1.12 | 1.41 | 1.38 | 1.25 | 1.04 | 0.70 | 0.84 | 1.77 | 2.18* | 2.27* | 2.05* | 1.42 | 1.44 | 2.57* |

| | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| MINNESOTA | 4.37* | 3.87* | 2.14* | 1.63 | 1.96* | 2.29* | 2.55* | 2.99* | 1.65 | 2.41* | 2.80* | 2.59* | 2.84* | 3.64* | 3.38* | 2.56* | 2.48* | 2.43* | 2.65* |
| MISSISSIPPI | 3.12* | 3.96* | 5.64* | 2.42* | 2.68* | 2.62* | 2.40* | 2.81* | 3.02* | 3.12* | 3.38* | 4.37* | 4.57* | 4.55* | 4.12* | 3.71* | 3.77* | 3.30* | 4.42* |
| MISSOURI | 0.90 | 0.64 | 1.62 | 3.15* | 3.96* | 4.67* | 5.09* | 5.17* | 5.28* | 5.35* | 5.61* | 5.59* | 5.89* | 6.11* | 6.13* | 5.28* | 4.82* | 8.18* | 2.75* |
| MONTANA | 0.53 | 0.15 | 1.27 | 1.91 | 3.08* | 3.16* | 2.41* | 3.09* | 3.41* | 3.12* | 3.01* | 3.35* | 3.88* | 3.87* | 4.25* | 4.41* | 6.65* | 6.45* | 4.95* |
| NEBRASKA | 0.59 | 1.47 | 1.62 | 1.02 | 1.39 | 1.74 | 1.88 | 1.86 | 1.81 | 1.89 | 1.75 | 2.13* | 2.20* | 2.64* | 2.98* | 2.71* | 2.33* | 6.98* | 7.52* |
| NEVADA | 4.36* | 4.48* | 3.35* | 2.85* | 1.33 | 1.25 | 1.22 | 1.43 | 1.52 | 1.34 | 1.27 | 1.48 | 1.82 | 1.31 | 0.93 | 0.95 | 2.04* | 3.03* | 1.11 |
| NEW HEMPSHIRE | 0.36 | 0.87 | 1.67 | 1.44 | 1.53 | 1.48 | 1.57 | 1.99* | 2.15* | 2.02* | 1.96* | 1.93 | 1.76 | 1.60 | 7.11* | 7.27* | 4.12* | 3.98* | 4.55* |
| NEW JERSEY | 1.06 | 1.30 | 1.40 | 1.01 | 1.00 | 1.11 | 0.59 | 1.00 | 0.98 | 1.35 | 1.36 | 1.76 | 1.73 | 0.92 | 1.70 | 2.37* | 2.87* | 3.30* | 2.86* |
| NEW MEXICO | 3.13* | 3.34* | 3.70* | 3.46* | 3.75* | 3.31* | 2.51* | 2.56* | 2.39* | 3.21* | 3.12* | 3.41* | 3.77* | 4.30* | 5.23* | 4.89* | 4.58* | 4.03* | 2.87* |
| NEW YORK | 1.13 | 0.44 | 1.68 | 2.49* | 2.67* | 2.31* | 1.93 | 1.92 | 2.35* | 2.04* | 2.75* | 2.97* | 2.84* | 3.18* | 3.00* | 1.51 | 3.96* | 4.22* | 4.09* |
| NORTH CAROLINA | 2.60* | 3.33* | 4.70* | 4.57* | 3.35* | 4.21* | 3.75* | 4.06* | 3.62* | 4.13* | 5.03* | 5.73* | 5.23* | 7.15* | 7.93* | 8.46* | 8.21* | 5.50* | 4.38* |
| NORTH DAKOTA | 3.08* | 2.08* | 0.56 | 0.52 | 0.22 | 0.02 | 0.15 | 0.09 | 0.45 | 0.67 | 1.10 | 1.69 | 1.95 | 2.85* | 3.07* | 4.22* | 4.03* | 3.65* | 4.12* |
| OHIO | 2.12* | 1.79 | 1.75 | 1.86 | 2.46* | 2.10* | 2.71* | 2.62* | 2.53* | 2.67* | 2.15* | 1.44 | 1.15 | 1.71 | 1.85 | 2.50* | 3.30* | 2.92* | 2.48* |
| OKLAHOMA | 1.24 | 0.35 | 1.34 | 1.31 | 2.26* | 2.19* | 2.53* | 2.77* | 3.32* | 3.65* | 3.80* | 3.80* | 3.53* | 3.56* | 3.72* | 4.21* | 4.97* | 7.38* | 8.42* |
| OREGON | 1.72 | 3.80* | 2.15* | 2.00* | 1.67 | 1.74 | 1.59 | 1.65 | 1.29 | 1.59 | 1.61 | 2.11* | 2.25* | 2.69* | 2.98* | 3.12* | 3.85* | 4.73* | 3.39* |
| PENNSYLVANIA | 1.83 | 2.10* | 1.59 | 1.47 | 1.32 | 1.44 | 1.20 | 1.22 | 1.30 | 1.44 | 1.71 | 1.94 | 2.80* | 3.37* | 4.18* | 4.13* | 3.71* | 2.46* | 3.56* |
| RHODE ISLAND | 0.32 | 0.72 | 0.75 | 1.69 | 2.02* | 1.97* | 2.28* | 2.74* | 2.05* | 2.51* | 2.19* | 2.68* | 2.78* | 1.99* | 1.51 | 1.63 | 2.04* | 1.97* | 2.45* |
| SOUTH CAROLINA | 3.78* | 4.52* | 4.82* | 4.83* | 6.13* | 6.23* | 6.28* | 6.51* | 6.65* | 6.73* | 6.59* | 6.52* | 6.75* | 6.50* | 5.86* | 5.94* | 5.62* | 6.16* | 5.36* |
| SOUTH DAKOTA | 1.83 | 1.58 | 0.76 | 0.06 | 0.86 | 1.39 | 1.74 | 2.00* | 2.08* | 2.21* | 2.82* | 3.01* | 2.61* | 2.36* | 3.19* | 3.12* | 2.09* | 2.72* | 5.03* |
| TENNESSEE | 1.90 | 3.50* | 4.02* | 3.91* | 3.73* | 3.21* | 3.73* | 3.94* | 3.64* | 4.03* | 4.25* | 4.58* | 4.33* | 4.18* | 4.00* | 5.85* | 7.00* | 6.68* | 4.28* |
| TEXAS | 0.57 | 0.21 | 0.42 | 0.96 | 2.14* | 1.92 | 2.51* | 2.57* | 2.83* | 2.78* | 2.49* | 2.83* | 2.78* | 3.13* | 2.79* | 1.57 | 3.48* | 3.34* | 5.99* |
| UTAH | 3.68* | 2.90* | 1.83 | 2.16* | 1.97* | 1.91 | 2.12* | 2.69* | 2.73* | 2.91* | 2.52* | 1.97* | 1.68 | 1.71 | 2.13* | 3.45* | 2.95* | 2.46* | 2.84* |
| VERMONT | 4.38* | 1.04 | 0.22 | 1.00 | 1.54 | 2.04* | 3.17* | 4.12* | 4.84* | 5.12* | 5.46* | 5.31* | 6.66* | 6.99* | 6.61* | 4.86* | 4.00* | 4.17* | 7.38* |
| VIRGINIA | 1.66 | 3.80* | 4.75* | 4.85* | 3.02* | 3.14* | 2.63* | 2.79* | 2.82* | 3.36* | 3.63* | 3.45* | 2.70* | 2.98* | 3.23* | 3.16* | 3.11* | 3.33* | 1.87 |
| WASHINGTON | 1.05 | 2.44* | 2.80* | 3.09* | 2.58* | 2.22* | 2.28* | 2.03* | 1.67 | 1.72 | 2.09* | 2.17* | 2.44* | 2.55* | 2.37* | 2.78* | 2.43* | 3.61* | 3.21* |
| WEST VIRGINIA | 3.44* | 0.05 | 1.85 | 1.48 | 1.47 | 1.92 | 2.26* | 2.65* | 2.68* | 3.88* | 4.52* | 4.80* | 4.82* | 3.75* | 3.94* | 6.43* | 6.04* | 3.53* | 7.87* |
| WISCONSIN | 0.09 | 2.14* | 2.62* | 3.16* | 3.30* | 3.32* | 3.49* | 3.68* | 3.76* | 3.78* | 3.94* | 4.26* | 4.03* | 3.93* | 4.35* | 3.96* | 2.62* | 1.93 | 1.73 |
| WYOMING | 1.15 | 0.88 | 0.27 | 0.62 | 1.48 | 1.51 | 2.26* | 1.97* | 2.42* | 2.80* | 3.28* | 3.20* | 3.17* | 3.28* | 4.49* | 3.87* | 6.04* | 8.06* | 8.40* |

| | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| USA | 4.91* | 3.02* | 1.97* | 2.56* | 2.76* | 2.87* | 2.80* | 2.90* | 2.89* | 2.61* | 2.72* | 2.85* | 2.79* | 2.55* | 2.25* | 1.54 | 1.80 | 1.91 | 4.18* |

**Note:** * indicates rejection of the null hypothesis of no Granger causality from housing sentiment to housing returns at the 5 percent level of significance (critical value of 1.96) at a specific quantile.

## Appendix 4.3. Table of Causality in Quantiles of Squared Nominal Housing Returns (Volatility)

| | Quantile | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| STATES | 0.05 | 0.10 | 0.15 | 0.20 | 0.25 | 0.30 | 0.35 | 0.40 | 0.45 | 0.50 | 0.55 | 0.60 | 0.65 | 0.70 | 0.75 | 0.80 | 0.85 | 0.90 | 0.95 |
| ALABAMA | 1.16 | 1.57 | 2.03* | 1.97* | 2.25* | 2.69* | 3.23* | 2.80* | 2.48* | 2.61* | 2.48* | 2.38* | 2.31* | 2.30* | 1.92 | 1.56 | 1.46 | 1.05 | 0.93 |
| ALASKA | 3.80* | 4.11* | 4.62* | 4.85* | 5.11* | 5.10* | 4.96* | 4.74* | 4.55* | 4.34* | 4.20* | 3.87* | 3.61* | 3.38* | 3.24* | 2.82* | 2.19* | 1.72 | 1.17 |
| ARIZONA | 1.41 | 1.67 | 1.63 | 2.62* | 2.60* | 3.26* | 3.31* | 3.17* | 3.45* | 3.89* | 3.73* | 3.12* | 3.26* | 2.86* | 3.14* | 2.20* | 1.60 | 1.35 | 0.66 |
| ARKANSAS | 3.02* | 3.25* | 3.01* | 3.26* | 3.68* | 3.83* | 3.63* | 3.82* | 3.65* | 3.49* | 3.73* | 3.92* | 3.66* | 3.26* | 2.85* | 2.41* | 2.13* | 1.40 | 0.83 |
| CALIFORNIA | 0.58 | 1.05 | 1.02 | 2.22* | 2.67* | 2.47* | 2.49* | 3.41* | 4.49* | 5.78* | 5.67* | 5.76* | 4.39* | 3.42* | 3.46* | 2.77* | 2.16* | 1.22 | 0.69 |
| COLORADO | 0.74 | 2.22* | 2.12* | 3.35* | 3.33* | 2.65* | 3.36* | 3.06* | 3.22* | 3.17* | 3.05* | 2.31* | 2.59* | 2.66* | 1.79 | 1.68 | 1.59 | 1.05 | 0.75 |
| CONNECTICUT | 0.25 | 0.35 | 0.62 | 1.12 | 1.39 | 1.28 | 1.43 | 1.50 | 1.54 | 1.78 | 1.47 | 1.19 | 1.70 | 1.82 | 1.72 | 1.14 | 0.90 | 0.56 | 0.53 |
| DELAWARE | 2.60* | 2.80* | 3.22* | 3.51* | 3.68* | 3.71* | 3.83* | 3.47* | 3.37* | 3.13* | 2.97* | 2.93* | 3.37* | 3.14* | 2.95* | 2.69* | 2.18* | 1.59 | 1.14 |
| DISTRICT OF COLUMBIA | 0.39 | 0.81 | 1.20 | 1.81 | 1.40 | 2.13* | 2.00* | 2.78* | 2.24* | 2.80* | 2.50* | 2.81* | 2.29* | 2.13* | 2.13* | 1.78 | 1.60 | 1.31 | 0.86 |
| FLORIDA | 0.65 | 2.28* | 2.71* | 2.93* | 3.06* | 3.05* | 3.74* | 3.42* | 4.18* | 4.00* | 4.95* | 4.38* | 4.31* | 3.83* | 3.53* | 3.10* | 2.43* | 1.56 | 0.82 |
| GEORGIA | 0.23 | 0.76 | 0.88 | 0.98 | 1.08 | 0.99 | 1.65 | 1.73 | 1.18 | 1.36 | 1.31 | 0.88 | 1.04 | 0.84 | 1.03 | 1.25 | 1.36 | 0.71 | 0.61 |
| HAWAII | 2.61* | 2.99* | 3.34* | 3.13* | 3.27* | 3.22* | 3.71* | 4.19* | 3.90* | 3.63* | 3.52* | 3.36* | 3.24* | 3.05* | 2.65* | 2.48* | 1.97* | 1.37 | 1.46 |
| IDAHO | 3.85* | 3.65* | 4.24* | 4.27* | 4.18* | 4.24* | 4.39* | 4.40* | 4.41* | 4.26* | 3.97* | 3.88* | 3.74* | 3.69* | 3.37* | 3.01* | 2.69* | 1.89 | 0.99 |
| ILLONOIS | 1.64 | 1.84 | 2.62* | 3.22* | 3.11* | 3.60* | 3.46* | 2.94* | 3.00* | 2.79* | 2.72* | 2.75* | 2.71* | 2.43* | 2.48* | 1.92 | 1.65 | 1.13 | 0.73 |
| INDIANA | 1.08 | 1.14 | 1.47 | 1.27 | 1.45 | 1.21 | 1.30 | 0.95 | 1.00 | 1.12 | 1.41 | 1.25 | 1.56 | 1.48 | 1.09 | 0.90 | 1.12 | 0.87 | 0.56 |
| IOWA | 0.71 | 0.40 | 0.84 | 0.67 | 0.87 | 0.85 | 1.01 | 1.21 | 1.20 | 1.17 | 1.18 | 1.38 | 1.12 | 1.49 | 1.20 | 0.89 | 0.60 | 0.77 | 0.17 |
| KANSAS | 0.53 | 0.89 | 1.25 | 1.04 | 1.30 | 1.95 | 1.87 | 2.02* | 1.68 | 2.05* | 2.36* | 2.35* | 1.92 | 1.50 | 1.23 | 1.24 | 1.00 | 1.02 | 0.47 |
| KENTUCKY | 0.38 | 0.59 | 1.58 | 2.33* | 2.68* | 3.10* | 2.94* | 2.77* | 2.66* | 2.14* | 2.00* | 1.14 | 1.22 | 1.01 | 0.89 | 0.76 | 0.68 | 0.70 | 0.36 |
| LOUISIANA | 0.34 | 0.87 | 0.60 | 1.26 | 1.69 | 1.27 | 1.44 | 1.16 | 1.09 | 2.00* | 1.80 | 1.84 | 1.92 | 1.64 | 2.01* | 1.68 | 1.23 | 0.90 | 0.77 |

| | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| MAINE | 0.49 | 0.72 | 0.62 | 1.33 | 1.71 | 1.90 | 2.02* | 1.93 | 1.52 | 1.50 | 1.67 | 1.76 | 2.02* | 2.34* | 1.75 | 1.39 | 1.02 | 1.05 | 0.74 |
| MARYLAND | 0.64 | 1.20 | 1.70 | 3.21* | 3.21* | 3.52* | 3.42* | 3.15* | 2.77* | 3.34* | 3.51* | 3.22* | 2.90* | 2.70* | 2.32* | 2.03* | 1.51 | 1.21 | 0.82 |
| MASSACHUSETTS | 0.77 | 1.27 | 1.64 | 2.80* | 2.72* | 3.32* | 3.18* | 3.16* | 3.17* | 3.01* | 3.44* | 3.43* | 3.62* | 3.46* | 2.53* | 2.11* | 1.75 | 1.52 | 0.69 |
| MICHIGAN | 1.99* | 2.73* | 3.14* | 3.32* | 3.20* | 2.83* | 2.88* | 2.83* | 3.08* | 2.91* | 3.00* | 2.75* | 2.58* | 2.52* | 2.28* | 1.95 | 1.80 | 1.36 | 0.93 |
| MINNESOTA | 1.20 | 1.31 | 1.46 | 1.78 | 1.61 | 2.26* | 2.11* | 2.14* | 2.20* | 2.11* | 2.03* | 2.85* | 2.57* | 2.18* | 2.14* | 1.96* | 1.69 | 0.80 | 0.64 |
| MISSISSIPPI | 0.97 | 1.30 | 1.54 | 1.51 | 1.36 | 2.32* | 2.38* | 3.01* | 2.62* | 2.15* | 2.09* | 1.86 | 1.88 | 1.68 | 1.28 | 1.51 | 1.48 | 1.15 | 0.88 |
| MISSOURI | 1.64 | 2.16* | 2.44* | 2.83* | 3.08* | 3.18* | 3.13* | 2.69* | 2.59* | 3.20* | 3.09* | 3.34* | 2.68* | 2.50* | 2.69* | 2.47* | 2.07* | 1.45 | 0.92 |
| MONTANA | 4.28* | 3.78* | 4.14* | 3.81* | 4.19* | 4.39* | 4.25* | 4.31* | 4.23* | 4.24* | 4.15* | 3.98* | 3.69* | 3.48* | 3.09* | 2.66* | 2.10* | 1.65 | 1.33 |
| NEBRASKA | 0.64 | 0.88 | 0.47 | 0.57 | 0.70 | 0.55 | 0.44 | 0.46 | 0.06 | 0.69 | 0.61 | 0.54 | 0.47 | 0.23 | 0.18 | 0.24 | 0.37 | 0.32 | 0.06 |
| NEVADA | 6.35* | 4.78* | 4.87* | 4.74* | 4.82* | 4.73* | 4.66* | 4.63* | 4.45* | 4.33* | 4.03* | 3.86* | 3.61* | 3.31* | 2.85* | 2.51* | 2.11* | 1.42 | 0.78 |
| NEW HEMPSHIRE | 3.11* | 3.55* | 3.47* | 3.33* | 3.47* | 3.42* | 3.65* | 3.48* | 3.74* | 3.57* | 3.63* | 3.57* | 3.24* | 3.20* | 2.98* | 2.66* | 2.52* | 1.98* | 1.41 |
| NEW JERSEY | 1.23 | 1.94 | 1.72 | 2.05* | 2.70* | 2.44* | 2.72* | 2.41* | 2.74* | 3.20* | 3.21* | 2.64* | 2.58* | 3.16* | 2.39* | 2.14* | 1.76 | 1.17 | 0.56 |
| NEW MEXICO | 1.15 | 1.78 | 2.99* | 2.51* | 3.06* | 2.35* | 2.38* | 2.67* | 3.25* | 3.09* | 2.43* | 3.01* | 2.62* | 2.93* | 2.12* | 1.65 | 1.02 | 0.85 | 0.39 |
| NEW YORK | 1.02 | 1.14 | 1.71 | 1.84 | 2.39* | 2.25* | 2.37* | 2.91* | 3.19* | 3.53* | 3.67* | 3.33* | 3.03* | 3.29* | 2.89* | 1.99* | 1.94 | 1.63 | 0.95 |
| NORTH CAROLINA | 1.36 | 1.66 | 2.48* | 2.10* | 2.38* | 2.35* | 2.36* | 2.69* | 2.60* | 2.42* | 2.24* | 2.34* | 1.99* | 1.95 | 2.32* | 2.05* | 1.63 | 1.39 | 0.77 |
| NORTH DAKOTA | 0.64 | 1.27 | 1.54 | 1.60 | 2.31* | 2.81* | 3.02* | 3.38* | 3.01* | 2.76* | 3.08* | 2.76* | 2.89* | 2.40* | 2.39* | 1.93 | 1.77 | 1.27 | 0.59 |
| OHIO | 0.76 | 0.88 | 0.89 | 0.70 | 0.79 | 0.90 | 0.89 | 0.76 | 1.19 | 1.17 | 2.00* | 2.05* | 1.69 | 2.00* | 1.85 | 2.08* | 1.31 | 1.10 | 0.62 |
| OKLAHOMA | 0.58 | 0.94 | 1.54 | 2.07* | 1.81 | 1.85 | 1.94 | 1.67 | 2.23* | 2.13* | 2.01* | 1.56 | 2.06* | 1.72 | 1.57 | 1.47 | 1.30 | 0.74 | 0.74 |
| OREGON | 0.26 | 0.95 | 1.23 | 1.69 | 2.12* | 2.95* | 3.53* | 2.90* | 3.05* | 3.85* | 3.24* | 3.33* | 2.97* | 3.04* | 3.12* | 3.24* | 2.11* | 1.52 | 0.45 |
| PENNSYLVANIA | 3.41* | 3.51* | 3.54* | 3.47* | 4.06* | 3.83* | 3.74* | 3.88* | 3.99* | 3.64* | 3.64* | 3.47* | 3.29* | 3.14* | 2.61* | 2.14* | 1.92 | 1.44 | 1.12 |
| RHODE ISLAND | 0.77 | 1.03 | 0.98 | 1.01 | 1.61 | 1.57 | 1.90 | 2.16* | 2.67* | 2.14* | 1.95 | 2.21* | 2.19* | 1.63 | 1.46 | 1.48 | 1.16 | 0.70 | 0.38 |
| SOUTH CAROLINA | 0.36 | 1.02 | 1.09 | 1.49 | 2.30* | 2.52* | 2.26* | 1.88 | 2.15* | 2.56* | 2.14* | 1.81 | 2.02* | 2.71* | 2.84* | 2.53* | 1.85 | 1.48 | 0.88 |
| SOUTH DAKOTA | 5.77* | 4.64* | 5.31* | 4.86* | 4.44* | 4.58* | 4.50* | 4.40* | 4.58* | 4.50* | 4.32* | 4.12* | 3.94* | 3.61* | 3.18* | 2.82* | 2.42* | 2.07* | 0.55 |
| TENNESSEE | 6.91* | 5.62* | 5.21* | 5.14* | 5.04* | 4.80* | 4.83* | 4.62* | 4.36* | 4.25* | 3.99* | 3.77* | 3.70* | 3.42* | 2.91* | 2.65* | 2.19* | 2.20* | 1.46 |
| TEXAS | 0.21 | 0.48 | 0.73 | 0.72 | 1.03 | 1.68 | 1.49 | 1.57 | 2.11* | 2.13* | 2.00* | 1.96* | 1.47 | 1.59 | 1.44 | 1.35 | 1.58 | 1.55 | 0.93 |
| UTAH | 0.75 | 0.77 | 2.05* | 2.44* | 1.99* | 2.06* | 1.68 | 2.59* | 2.43* | 3.25* | 3.48* | 3.35* | 3.41* | 2.62* | 1.73 | 1.12 | 1.21 | 1.40 | 0.70 |
| VERMONT | 4.09* | 4.16* | 4.16* | 4.48* | 4.33* | 4.30* | 4.45* | 4.38* | 4.37* | 4.21* | 4.15* | 3.98* | 3.58* | 3.32* | 2.98* | 2.93* | 2.62* | 1.89 | 1.46 |
| VIRGINIA | 1.37 | 1.85 | 1.92 | 2.38* | 2.29* | 3.16* | 3.28* | 2.72* | 2.90* | 3.21* | 2.89* | 3.37* | 2.96* | 2.44* | 1.94 | 1.80 | 1.38 | 1.17 | 0.80 |

| | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| WASHINGTON | 0.48 | 1.40 | 1.21 | 1.51 | 2.58* | 3.30* | 4.26* | 3.56* | 2.84* | 3.32* | 2.61* | 3.54* | 3.48* | 2.45* | 2.45* | 2.02* | 1.67 | 1.54 | 0.61 |
| WEST VIRGINIA | 4.51* | 4.55* | 4.22* | 4.33* | 4.33* | 4.57* | 4.69* | 4.50* | 4.46* | 4.49* | 4.27* | 4.01* | 3.78* | 3.51* | 2.97* | 2.68* | 2.29* | 1.71 | 1.67 |
| WISCONSIN | 5.46* | 4.58* | 4.67* | 4.82* | 4.44* | 4.62* | 4.49* | 4.33* | 4.27* | 4.43* | 4.29* | 4.03* | 3.88* | 3.39* | 3.21* | 2.50* | 2.21* | 1.57 | 1.01 |
| WYOMING | 1.57 | 1.71 | 2.25* | 2.45* | 2.58* | 2.45* | 2.33* | 2.12* | 2.32* | 3.00* | 2.64* | 2.77* | 3.12* | 2.19* | 1.82 | 1.57 | 1.68 | 1.03 | 0.60 |
| USA | 1.28 | 1.04 | 1.48 | 2.52* | 2.81* | 2.58* | 2.77* | 2.76* | 2.50* | 2.15* | 2.00* | 2.36* | 2.25* | 1.90 | 1.55 | 1.64 | 1.39 | 0.99 | 0.61 |

**Note:** * indicates rejection of the null hypothesis of no Granger causality from housing sentiment to housing volatility at the 5 percent level of significance (critical value of 1.96) at a specific quantile.

## Appendix 4.4. Table of Linear Granger causality test

| | $H_0$: Sentiment does not Granger cause Volatility | |
|---|---|---|
| | **Statistics** | ***p*-value** |
| ALABAMA | 5.276* | 0.023 |
| ALASKA | 4.736* | 0.031 |
| ARIZONA | 0.364 | 0.547 |
| ARKANSAS | 8.886* | 0.003 |
| CALIFORNIA | 1.244 | 0.266 |
| COLORADO | 12.226* | 0.001 |
| CONNECTICUT | 3.297 | 0.071 |
| DELAWARE | 11.332* | 0.001 |
| DISTRICT OF COLUMBIA | 9.726* | 0.002 |
| FLORIDA | 0.363 | 0.548 |
| GEORGIA | 5.066* | 0.026 |
| HAWAII | 0.1462 | 0.703 |
| IDAHO | 0.568 | 0.452 |
| ILLINOIS | 7.132* | 0.008 |
| INDIANA | 15.194* | 0.000 |
| IOWA | 1.685 | 0.196 |
| KANSAS | 10.054* | 0.002 |
| KENTUCKY | 9.833* | 0.002 |
| LOUISIANA | 18.833* | 0.000 |
| MAINE | 1.250 | 0.265 |
| MARYLAND | 6.215* | 0.014 |
| MASSACHUSETTS | 2.306 | 0.131 |
| MICHIGAN | 0.150 | 0.699 |
| MINNESOTA | 5.835* | 0.017 |
| MISSISSIPPI | 18.049* | 0.000 |
| MISSOURI | 2.890 | 0.091 |
| MONTANA | 1.206 | 0.274 |
| NEBRASKA | 16.261* | 0.000 |
| NEVADA | 0.535 | 0.465 |
| NEW HAMPSHIRE | 1.707 | 0.193 |
| NEW JERSEY | 4.185* | 0.043 |

| | | |
|---|---|---|
| NEW MEXICO | 5.298* | 0.023 |
| NEW YORK | 7.721* | 0.006 |
| NORTH CAROLINA | 18.805* | 0.000 |
| NORTH DAKOTA | 0.063 | 0.802 |
| OHIO | 5.707* | 0.018 |
| OKLAHOMA | 12.733* | 0.001 |
| OREGON | 1.861 | 0.175 |
| PENNSYLVANIA | 7.327* | 0.008 |
| RHODE ISLAND | 2.033 | 0.156 |
| SOUTH CAROLINA | 14.320* | 0.000 |
| SOUTH DAKOTA | 0.001 | 0.975 |
| TENNESSEE | 5.535* | 0.020 |
| TEXAS | 21.379* | 0.000 |
| UTAH | 8.980* | 0.003 |
| VERMONT | 0.985 | 0.323 |
| VIRGINIA | 2.432 | 0.121 |
| WASHINGTON | 5.046* | 0.026 |
| WEST VIRGINIA | 1.343 | 0.248 |
| WISCONSIN | 1.810 | 0.181 |
| WYOMING | 6.283* | 0.013 |
| USA | 8.354* | 0.004 |

**Note:** * indicates rejection of the null hypothesis of no linear Granger causality from housing sentiment to housing volatility at the 5 percent level of significance.

## Appendix 4.5. Table of Causality in Quantiles of Realized Volatility

| | Quantile | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| STATES | 0.05 | 0.10 | 0.15 | 0.20 | 0.25 | 0.30 | 0.35 | 0.40 | 0.45 | 0.50 | 0.55 | 0.60 | 0.65 | 0.70 | 0.75 | 0.80 | 0.85 | 0.90 | 0.95 |
| ALABAMA | 0.93 | 1.09 | 1.42 | 1.53 | 1.71 | 1.81 | 1.75 | 1.98 | 1.73 | 1.50 | 1.62 | 1.73 | 1.51 | 2.06* | 1.87 | 2.19* | 1.84 | 0.83 | 0.44 |
| ALASKA | 0.38 | 0.52 | 0.73 | 1.03 | 1.24 | 0.97 | 0.70 | 0.78 | 0.95 | 1.00 | 0.93 | 1.10 | 1.61 | 1.64 | 1.70 | 1.74 | 1.37 | 0.81 | 0.53 |
| ARIZONA | 0.08 | 0.30 | 0.50 | 0.56 | 0.65 | 0.80 | 1.02 | 1.19 | 1.07 | 0.81 | 0.58 | 0.83 | 0.66 | 0.72 | 0.63 | 0.82 | 0.57 | 0.36 | 0.20 |
| ARKANSAS | 1.05 | 1.20 | 1.24 | 1.95 | 2.59* | 2.80* | 2.30* | 2.40* | 2.73* | 3.23* | 2.96* | 2.93* | 2.78* | 2.51* | 2.43* | 1.84 | 0.93 | 0.74 | 0.38 |
| CALIFORNIA | 0.30 | 0.37 | 0.87 | 1.26 | 2.29* | 2.29* | 3.21* | 3.66* | 3.77* | 3.47* | 3.36* | 3.29* | 3.16* | 2.77* | 2.08* | 1.41 | 0.89 | 0.55 | 0.31 |
| COLORADO | 1.29 | 1.80 | 1.64 | 1.95 | 2.26* | 3.17* | 3.02* | 3.25* | 3.21* | 3.48* | 3.09* | 2.60* | 2.29* | 2.19* | 1.79 | 1.55 | 1.07 | 0.87 | 0.35 |
| CONNECTICUT | 1.02 | 1.63 | 1.90 | 1.65 | 1.64 | 1.47 | 1.94 | 1.82 | 2.10* | 2.29* | 2.45* | 2.39* | 2.29* | 2.34* | 2.16* | 1.92 | 1.61 | 1.47 | 0.41 |
| DELAWARE | 1.33 | 1.94 | 1.63 | 1.83 | 2.21* | 2.02* | 2.22* | 2.79* | 2.58* | 2.92* | 2.66* | 2.65* | 2.48* | 2.52* | 2.11* | 2.14* | 1.75 | 1.17 | 0.60 |
| DISTRICT OF COLUMBIA | 1.17 | 2.21* | 2.04* | 1.78 | 2.02* | 1.97* | 2.41* | 2.65* | 2.80* | 2.55* | 2.40* | 2.37* | 2.56* | 2.27* | 1.91 | 1.74 | 1.37 | 0.89 | 0.59 |
| FLORIDA | 0.10 | 0.35 | 0.58 | 0.97 | 0.79 | 0.96 | 0.77 | 0.55 | 0.62 | 0.83 | 1.12 | 1.06 | 1.15 | 0.94 | 1.11 | 0.91 | 0.77 | 0.50 | 0.20 |
| GEORGIA | 0.90 | 1.04 | 1.95 | 3.12* | 4.12* | 4.02* | 3.64* | 3.29* | 3.32* | 3.44* | 3.25* | 3.13* | 2.63* | 2.10* | 1.27 | 1.10 | 0.63 | 0.40 | 0.33 |
| HAWAII | 1.11 | 1.76 | 2.13* | 3.04* | 2.88* | 3.22* | 3.35* | 3.92* | 3.23* | 3.25* | 3.28* | 2.90* | 2.48* | 2.51* | 1.95 | 1.68 | 1.74 | 1.26 | 0.41 |
| IDAHO | 0.40 | 0.86 | 1.03 | 1.15 | 1.35 | 1.63 | 1.35 | 1.53 | 1.35 | 1.25 | 1.51 | 1.65 | 1.86 | 2.18* | 1.98* | 1.33 | 1.26 | 0.80 | 0.35 |
| ILLONOIS | 0.45 | 1.05 | 1.72 | 2.07* | 2.46* | 3.23* | 3.77* | 3.95* | 4.14* | 3.72* | 3.36* | 3.10* | 2.88* | 3.06* | 2.60* | 1.89 | 1.55 | 1.07 | 0.48 |
| INDIANA | 0.69 | 1.25 | 2.16* | 2.37* | 2.80* | 2.68* | 2.27* | 2.86* | 2.87* | 2.48* | 2.35* | 2.23* | 2.13* | 1.65 | 1.48 | 1.39 | 1.55 | 1.09 | 0.45 |
| IOWA | 3.00* | 2.25* | 2.32* | 2.76* | 2.91* | 3.02* | 3.15* | 2.79* | 2.84* | 2.62* | 2.43* | 2.32* | 2.26* | 1.79 | 1.61 | 1.32 | 1.08 | 0.76 | 0.48 |
| KANSAS | 0.87 | 1.49 | 2.03* | 2.94* | 3.00* | 3.25* | 3.21* | 2.73* | 2.97* | 2.93* | 2.74* | 2.32* | 2.13* | 1.90 | 1.71 | 1.42 | 1.08 | 0.76 | 0.45 |
| KENTUCKY | 1.35 | 1.73 | 2.29* | 2.18* | 2.09* | 2.12* | 1.95 | 2.14* | 2.21* | 2.46* | 2.02* | 1.77 | 1.48 | 1.38 | 1.42 | 1.54 | 1.35 | 0.92 | 0.38 |
| LOUISIANA | 1.62 | 1.27 | 1.92 | 2.54* | 2.95* | 2.62* | 2.40* | 3.30* | 3.42* | 3.60* | 3.50* | 3.16* | 2.66* | 1.86 | 1.54 | 1.02 | 1.17 | 0.90 | 0.61 |
| MAINE | 1.58 | 1.71 | 1.98* | 2.21* | 2.44* | 2.47* | 2.63* | 2.28* | 2.10* | 2.14* | 2.22* | 2.02* | 2.23* | 2.04* | 2.17* | 1.88 | 1.42 | 1.03 | 0.62 |
| MARYLAND | 0.66 | 1.10 | 1.14 | 0.96 | 1.67 | 2.27* | 1.98* | 2.70* | 2.79* | 2.72* | 3.09* | 2.86* | 2.58* | 2.71* | 3.10* | 2.84* | 1.95 | 1.26 | 0.40 |
| MASSACHUSETTS | 1.04 | 1.22 | 1.30 | 1.53 | 1.85 | 2.75* | 3.07* | 3.13* | 3.50* | 3.72* | 3.36* | 3.68* | 3.42* | 3.19* | 3.00* | 2.49* | 1.80 | 0.95 | 0.61 |
| MICHIGAN | 1.36 | 1.37 | 2.05* | 3.30* | 3.87* | 4.81* | 4.83* | 4.34* | 4.35* | 4.36* | 3.90* | 3.15* | 3.11* | 2.06* | 1.85 | 0.94 | 0.78 | 0.53 | 0.53 |
| MINNESOTA | 0.73 | 1.64 | 1.68 | 2.58* | 2.98* | 2.88* | 2.52* | 2.83* | 2.62* | 3.05* | 2.67* | 2.02* | 2.02* | 1.44 | 1.29 | 1.08 | 0.75 | 0.81 | 0.63 |
| MISSISSIPPI | 2.25* | 2.60* | 2.56* | 3.04* | 3.41* | 3.56* | 3.57* | 3.13* | 3.17* | 2.88* | 2.45* | 2.61* | 2.35* | 2.17* | 2.34* | 1.99* | 1.75 | 1.05 | 0.35 |

| | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| MISSOURI | 0.57 | 0.95 | 1.90 | 1.91 | 2.44* | 3.09* | 3.32* | 3.29* | 2.95* | 2.76* | 2.62* | 2.14* | 2.35* | 2.63* | 2.32* | 2.16* | 1.64 | 1.29 | 0.63 |
| MONTANA | 1.01 | 2.00* | 1.73 | 2.20* | 2.57* | 2.71* | 3.38* | 3.18* | 2.93* | 2.98* | 2.98* | 3.10* | 3.50* | 3.03* | 2.21* | 1.86 | 1.57 | 1.09 | 0.47 |
| NEBRASKA | 0.50 | 1.21 | 1.60 | 1.66 | 1.61 | 1.76 | 1.53 | 1.32 | 1.24 | 1.05 | 0.94 | 0.95 | 0.96 | 1.40 | 1.16 | 1.44 | 1.13 | 0.88 | 0.54 |
| NEVADA | 0.00 | 0.03 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.02 | 0.01 | 0.01 | 0.01 | 0.00 | 0.00 | 0.01 | 0.01 | 0.02 | 0.02 | 0.00 | 0.01 |
| NEW HEMPSHIRE | 1.83 | 1.51 | 2.01* | 1.92 | 2.15* | 2.42* | 2.82* | 3.13* | 3.32* | 3.08* | 3.26* | 3.05* | 2.97* | 2.76* | 2.71* | 2.18* | 2.07* | 1.35 | 0.97 |
| NEW JERSEY | 1.14 | 1.28 | 1.92 | 1.58 | 1.56 | 2.19* | 2.43* | 2.36* | 2.22* | 2.23* | 2.61* | 2.92* | 3.02* | 3.05* | 2.46* | 2.12* | 1.73 | 1.28 | 0.64 |
| NEW MEXICO | 1.43 | 1.45 | 1.65 | 1.72 | 1.42 | 1.68 | 2.30* | 2.22* | 2.40* | 2.75* | 2.51* | 2.27* | 2.40* | 2.47* | 2.38* | 2.22* | 1.84 | 1.03 | 0.48 |
| NEW YORK | 0.79 | 1.44 | 1.78 | 1.81 | 1.99* | 2.69* | 3.06* | 2.92* | 2.67* | 2.61* | 2.42* | 2.10* | 1.79 | 1.64 | 1.85 | 1.88 | 1.53 | 1.37 | 0.63 |
| NORTH CAROLINA | 0.56 | 1.21 | 1.62 | 1.65 | 1.99* | 2.92* | 2.97* | 3.25* | 3.43* | 3.26* | 3.58* | 3.37* | 2.53* | 2.87* | 2.16* | 2.33* | 1.93 | 1.36 | 0.58 |
| NORTH DAKOTA | 0.67 | 0.77 | 0.85 | 1.15 | 1.27 | 1.42 | 1.63 | 1.92 | 1.73 | 1.26 | 1.57 | 1.16 | 1.12 | 1.25 | 0.95 | 1.06 | 0.85 | 0.73 | 0.45 |
| OHIO | 1.30 | 1.97* | 2.16* | 2.53* | 3.01* | 3.29* | 3.51* | 3.57* | 3.61* | 3.60* | 2.98* | 2.61* | 2.28* | 2.01* | 1.74 | 1.30 | 1.19 | 1.03 | 0.43 |
| OKLAHOMA | 1.55 | 1.28 | 1.72 | 1.69 | 2.31* | 2.80* | 3.20* | 2.85* | 2.80* | 2.55* | 2.32* | 1.95 | 1.83 | 1.71 | 1.41 | 1.20 | 1.06 | 0.84 | 0.45 |
| OREGON | 0.42 | 0.97 | 1.13 | 1.59 | 2.10* | 2.17* | 2.19* | 2.62* | 2.07* | 2.48* | 2.09* | 1.78 | 1.47 | 1.83 | 1.36 | 1.78 | 1.27 | 0.82 | 0.31 |
| PENNSYLVANIA | 1.28 | 1.62 | 3.28* | 2.93* | 3.71* | 3.10* | 3.21* | 3.07* | 3.08* | 2.83* | 2.78* | 2.73* | 2.25* | 1.84 | 2.06* | 1.42 | 1.43 | 0.90 | 0.56 |
| RHODE ISLAND | 1.47 | 1.70 | 2.00* | 2.39* | 2.06* | 2.48* | 2.25* | 2.44* | 2.39* | 2.58* | 2.60* | 2.84* | 2.98* | 2.33* | 2.95* | 2.19* | 1.35 | 0.98 | 0.41 |
| SOUTH CAROLINA | 0.69 | 1.23 | 1.26 | 1.82 | 2.29* | 2.51* | 2.04* | 2.47* | 1.77 | 1.87 | 2.03* | 2.42* | 2.18* | 2.37* | 2.49* | 2.72* | 2.50* | 1.07 | 0.43 |
| SOUTH DAKOTA | 0.53 | 0.68 | 1.10 | 1.00 | 1.13 | 0.94 | 0.87 | 0.87 | 1.53 | 1.17 | 1.18 | 1.14 | 1.37 | 1.49 | 1.94 | 1.36 | 0.96 | 0.48 | 0.54 |
| TENNESSEE | 1.00 | 1.62 | 1.47 | 2.15* | 2.48* | 3.63* | 4.11* | 3.60* | 2.94* | 2.85* | 2.90* | 2.63* | 2.67* | 2.09* | 1.86 | 1.31 | 1.23 | 0.81 | 0.53 |
| TEXAS | 0.90 | 1.26 | 1.90 | 1.77 | 1.91 | 2.23* | 2.45* | 2.41* | 2.88* | 2.39* | 1.88 | 1.90 | 1.87 | 1.65 | 1.18 | 0.99 | 0.83 | 0.72 | 0.44 |
| UTAH | 0.37 | 0.78 | 1.67 | 1.78 | 1.92 | 2.31* | 2.91* | 3.15* | 3.08* | 3.63* | 4.20* | 3.70* | 3.58* | 2.98* | 2.63* | 2.28* | 1.45 | 1.01 | 0.83 |
| VERMONT | 0.34 | 0.67 | 1.06 | 1.25 | 1.75 | 2.45* | 2.33* | 2.48* | 2.35* | 3.09* | 2.85* | 3.08* | 2.92* | 2.26* | 1.68 | 1.33 | 1.42 | 0.91 | 0.54 |
| VIRGINIA | 1.34 | 1.55 | 1.92 | 1.79 | 2.18* | 2.33* | 2.91* | 2.79* | 3.60* | 3.02* | 2.82* | 2.88* | 2.69* | 2.41* | 2.44* | 2.23* | 2.17* | 1.17 | 0.59 |
| WASHINGTON | 0.53 | 0.67 | 1.43 | 1.80 | 2.31* | 2.46* | 3.33* | 3.92* | 4.00* | 4.13* | 3.64* | 3.47* | 3.45* | 3.39* | 2.72* | 2.16* | 1.77 | 0.89 | 0.29 |
| WEST VIRGINIA | 0.38 | 0.62 | 0.78 | 1.10 | 1.56 | 1.85 | 2.04* | 2.23* | 2.17* | 2.60* | 2.07* | 2.59* | 2.57* | 1.87 | 2.04* | 1.40 | 1.24 | 0.51 | 0.42 |
| WISCONSIN | 1.10 | 1.93 | 2.06* | 1.70 | 1.79 | 1.93 | 2.41* | 2.28* | 2.09* | 2.07* | 2.15* | 2.90* | 2.76* | 2.52* | 2.76* | 2.52* | 1.76 | 1.37 | 0.40 |
| WYOMING | 0.91 | 1.14 | 1.53 | 2.00* | 2.98* | 2.78* | 3.02* | 3.60* | 3.94* | 3.17* | 2.97* | 2.86* | 3.38* | 2.75* | 2.55* | 2.15* | 1.91 | 1.51 | 0.86 |
| USA | 0.76 | 1.07 | 1.47 | 1.84 | 2.41* | 2.97* | 3.50* | 3.89* | 4.25* | 4.53* | 4.15* | 4.16* | 3.76* | 3.29* | 3.27* | 2.47* | 1.89 | 1.18 | 0.83 |

**Note:** * indicates rejection of the null hypothesis of no Granger causality from housing sentiment to housing volatility at the 5 percent level of significance (critical value of 1.96) at a specific quantile.

# Chapter 5
# Time-Varying Impact of Uncertainty Shocks on the US Housing Market[30]

## 5.1 Introduction

The rapid decline in housing prices of the United States (US), following a prolonged boom, is generally associated with the global economic and financial crisis of 2008-2009 (Leamer, 2015; Nyakabawo et al., 2015). Naturally, from a policy perspective, understanding what shocks drive the housing market performance is now of paramount importance in order to avoid the repeat of the catastrophic effects observed under the "Great Recession". In this regard, there exists a large number of studies that have analyzed the role of both conventional and unconventional (in the wake of the zero lower bound (ZLB) scenario) monetary policies (see for example, Claus et al., (2016), Rahal (2016), Simo-Kengne et al., (2016), Huber and Punzi (forthcoming), Nyakabawo et al., (forthcoming) and the papers cited therein), as well as, more recently fiscal policy (see for example, El Montasser et al., (forthcoming) and Gupta et al., (forthcoming) for exhaustive reviews of earlier studies), besides the role of aggregate demand and supply shocks (Marfatia et al., 2017; Gupta et al., 2018a; Plakandaras et al., forthcoming).

More recently, in the wake of the Great Recession, a growing number of studies (see for example, Miles (2009), Sum and Brown (2012), Ajmi et al., (2014), Antonakakis et al., (2015, 2016), El Montasser et al., (2016), André et al., (2017), Christou et al., (2017), Aye and Gupta (2018); Christidou and Fountas (2018), Strobel et al., 2018, Aye et al., (forthcoming)), have also started relating real estate (housing and Real Estate Investment Trusts (REITs)) market-related variables to measures of macroeconomic uncertainty, which in turn, was at unprecedented levels during the crisis.[31] Majority of these studies have analyzed movements in real estate market prices to uncertainty in constant parameter models, and even if time-variation (which have been shown to be of paramount importance for the US housing market by Simo-Kengne et al., 2015) was allowed based on either dynamic conditional correlation or rolling estimations, the models in general were restricted to only

[30] Published in Economic Letters, Volume 180, July 2019, Pages 15-20.
[31] Understandably, there also exists a large literature analysing the impact of uncertainty shocks on macroeconomic and financial market variables (see Chuliá et al., (2017), and Gupta et al., (2018b) for detailed reviews in this regard).

few macroeconomic variables. Given the well-known fact that the US real estate market is affected by large number of variables (see, Gupta et al., (2011), Gupta et al., (2012a, b), and Akinsomi et al., 2016 for detailed discussions in this regard), we use an extended factor augmented vector autoregressive (FAVAR) model (as proposed by Mumtaz and Theodoridis (2018)), based on a dataset of 45 variables for the US, that allows the estimation of a measure of macroeconomic uncertainty which encompasses volatility of the real and financial sectors. In addition, we allow for time-varying parameters (TVP) in the proposed FAVAR model (TVP-FAVAR), which in turn allows us to estimate time-varying response of not only house prices, but home sales, permits and starts, as well as sentiment associated with the housing market to uncertainty shocks, thus allowing the investigation of temporal shifts in the overall housing market in a coherent manner.

The recent growth in the literature of uncertainty has been centered around the popularity of the financial crisis. Policy attention on the subject has increased over time firstly due to the fact that uncertainty was identified as one of the key driver of the Great Recession and secondly because of the increase in the availability of empirical proxies for uncertainty, prompting several empirical investigations on the subject.

The modern definition of uncertainty follows Knight (1921) and defines uncertainty as the peoples' inability to forecast the likelihood of events happening. Since uncertainty is not directly observable, it is hard to measure. It is viewed as a broad concept that reflects the uncertainty in the mind of consumers, managers and policymakers about possible futures (Bloom, 2009). Therefore, it is not surprising that there is not one perfect measure of uncertainty, but several proxies with commonly cited ones such as macroeconomic uncertainty by Juardo et al (2015), stock market and GDP volatility (Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012), and a survey-based measure of disaggregated and economic policy uncertainty index by Baker et al. (2016).

Theoretically, uncertainty can affect the housing market activity either negatively or positively. Housing is an irreversible form of investment. Due to the irreversible nature of housing investment which causes agents to delay their decisions (Bernanke, 1983), uncertainty should be decreasing housing investment. Further, under risk-aversion and incomplete markets, uncertainty and investment is likely to be negatively related (Craine, 1989). But when risk aversion or incomplete markets do not apply, the effect of uncertainty may be positive on investment (Hartman, 1972). Moreover, Caballero (1991) presents a model of asymmetric adjustment costs to show that the effect of uncertainty on investment is not always negative, as it depends also on the degree of competition. In this regard, Abel and Eberly (1999) also show that depending on the relative size of parameters, uncertainty may increase or decrease the long-run capital stock (investment) under irreversibility relative to the case of reversible investment. Given this, whether the impact of uncertainty is negative or positive on housing market activity is an empirical question, and is likely to vary over time based on which of the theoretical channels are in place.

To the best of our knowledge this is the first attempt to use a TVP-FAVAR model provide a comprehensive time-varying analysis of uncertainty shocks on several important housing market variables of the US by controlling for a large number of other macroeconomic and financial variables that affect the housing market. The remainder of the paper is organized as follows: Section 5.2 presents the methodology, while Section 5.3 discusses the data and results, with Section 5.4 concluding the paper.

## 5.2 Methodology

We use the following TVP-FAVAR model as in Mumtaz and Theodoridis (2018):

$$Z_t = c_t + \sum_{j=1}^{P} \beta_{tj} Z_{t-j} + \sum_{j=0}^{J} \gamma_{tj} ln\lambda_{t-j} + \Omega_t^{\frac{1}{2}} e_t, \qquad (1)$$

where $Z_t$ represents a matrix of endogenous variables. The covariance matrix is defined as:

$$\Omega_t = A_t^{-1} H_t A_t^{-1'}, \qquad (2)$$

where $A_t$ denotes a lower triangular matrix whose non-zero elements follow a random walk process

$$a_t = a_{t-1} + g_t, \qquad VAR(g_t) = G, \qquad (3)$$

where G is block diagonal.[32] The coefficients of model (1) evolve as follows:

$$B_t = B_{t-1} + \eta_t, \; VAR(\eta_t) = Q_B, \qquad (4)$$

[32] See Primiceri (2005).

where $B = vec([c;\ \beta;\ \lambda])$.

The volatility process of the shocks is defined as[33]

$$= \lambda_t S, \qquad S = diag\ (s_1, \dots, s_N). \tag{5}$$

The overall volatility follows an AR(1) process given by

$$ln\lambda_t = \alpha + Fln\lambda_{t-1} + \overline{\eta_t}, VAR(\overline{\eta_t}) = Q_\lambda. \tag{6}$$

The matrix $Z_t$ consists of a large number of macroeconomic and financial variables so as to account for possibly omitted variables. As such, the estimate of $\lambda_t$ represents wide-ranging economic and financial uncertainty. However, it is difficult to achieve the VAR coefficients stability at each point in time when there are more than 4 endogenous variables[34]. Mumtaz and Theodoridis (2018) suggest dealing with this issue by including a factor structure into the model. The observation equation is defined as:

$$X_{it} = \Lambda_t Z_t + R^{1/2}\varepsilon_{it}, \tag{7}$$

where $\varepsilon_{it}$ denotes the idiosyncratic elements with a diagonal covariance matrix *R*, $Z_t$ a set of *K* unobserved factors, $\Lambda_t$ is the time-varying factor loading matrix defined as:[35]

$$\Lambda_t = \Lambda_{t-1} + \overline{\eta_t}, VAR(\overline{\eta_t}) = Q_\Lambda. \tag{8}$$

The underlying dataset $X_{it}$ regroups main real activity and nominal variables, financial variables as well as housing variables. As such, the measure of uncertainty $\lambda_t$ captures the volatility across the main sectors of the U.S. economy.

Following Mumtaz and Theodoridis (2018), the model defined by Equations (1) and (7) are estimated using a Markov chain Monte Carlo (MCMC) algorithm.

[33] See Carriero *et al.* (2015).
[34] See Koop and Potter (2011).
[35] See Del Negro and Otrok (2005).

## 5.3 Data and Empirical Findings

The study uses quarterly data covering the main sectors of the U.S. economy over the period 1975Q3-2014Q3. Following Mumtaz and Theodoridis (2018), the dataset includes real activity variables (consumption, investment, GDP, taxes, government spending, employment, unemployment, hours, and surveys of economic activity), price variables (CPI, consumption and GDP deflator, and the producer price index) as well as financial variables (short-term and long-term interest rates, various corporate bond spreads, money and credit growth, stock prices, commodity prices, and exchange rates).[36] In addition, given that we investigate the time-varying impact of uncertainty shocks on US housing market, we include the following housing market variables: new and single-family houses for sale and houses sold, median sales price of new and single-family houses, new private housing units authorized by building permits, and new privately owned housing units started, and housing market sentiment. Barring the sentiment index, all data are from the US Census Bureau. The start and end dates of our sample depend on the availability of the housing sentiment index developed by Bork *et al*., (2017), which in turn, is constructed based on household responses to questions regarding house buying conditions from the consumer survey of the University of Michigan.[37] The sales and price variables are in their growth rate forms to ensure mean-reversion as required by the TVP-FAVAR model.

Having discussed the data, we now turn our attention to the results. Figures 5.1, 5.2 and 5.3 display the cumulated response of six housing variables, namely "houses for sale", houses sold", "housing prices", "housing sentiment", housing starts" and "permit", at one-, four- and eight-quarters, respectively. The uncertainty shock is calibrated to be equal to one-standard-deviation. Figure 5.1 plots the cumulated response of housing variables along with the error bands to a shock to uncertainty at the one-quarter horizon. The response of "houses for sale", "housing starts" and "permit" is estimated to be negative and statistically significant on impact. Furthermore, the response seems to decline over time. Specifically, the responses of "houses for sale" and "housing starts" are statistically significant until 1995 and 1993, respectively. The response of "permit" is more pronounced, and remains

[36] The reader is referred to Table 1 of Mumtaz and Theodoridis (2018) for further details on the 39 macroeconomic and financial variables used along with their sources and transformations.

[37] Complete details on how the sentiment index is constructed can be found in Bork *et al*., (2017).

statistically significant until 2000. Contrary, our results suggest that the response of “houses sold”, “housing prices” and “housing sentiment” is not statistically significant.

Figure 5.2 shows the cumulated response of housing variables along with the error bands to a shock to uncertainty at the four-quarter horizon. Time varying response is not statistically significant in the cases of “housing prices” and “housing starts”. The responses of “houses for sale” and “permit” are negative and statistically significant only for the periods 1996-1998 and 1995-1998, respectively, while they are relatively stable over these periods of time. The response of “houses sold” demonstrates similar behavior, although it remains statistically significant for a longer period of time (1993-2000). Lastly, “housing sentiment” responses negatively to an uncertainty shock. The time varying response is statistically significant until 2006 while it declines over time.

Figure 5.3 reports the cumulated response of housing variables along with the error bands to a shock to uncertainty at the eight-quarter horizon. It is evident that time varying response is not statistically significant at impact in all the cases.

In sum, at the shortest horizon, uncertainty shocks is shown to have a negative and significant impact on houses for sale, permits and starts till the late 1990s. At the one-year-ahead horizon, the strongest negative and statistically significant influence is observed for housing market sentiment, with some negative impact also observed for houses for sale, permits and starts during the mid-1990s, and for homes sold over the entire decade of 1990. Post 2010, we also observe a positive and significant impact on houses for sale, permits and starts. At the longest horizon of two-year-ahead, there is some initial negative impact on houses for sale and permit, but the effect on these variables, along with homes sold and housing start tends to become positive and significant from the mid-2000s and onwards. What is most interesting is the statistically insignificant impact on house prices – a result in contradiction with the existing literature, and is possibly an indication of misspecification due to omitted variable bias in the earlier studies which tended to rely on small-scale models.

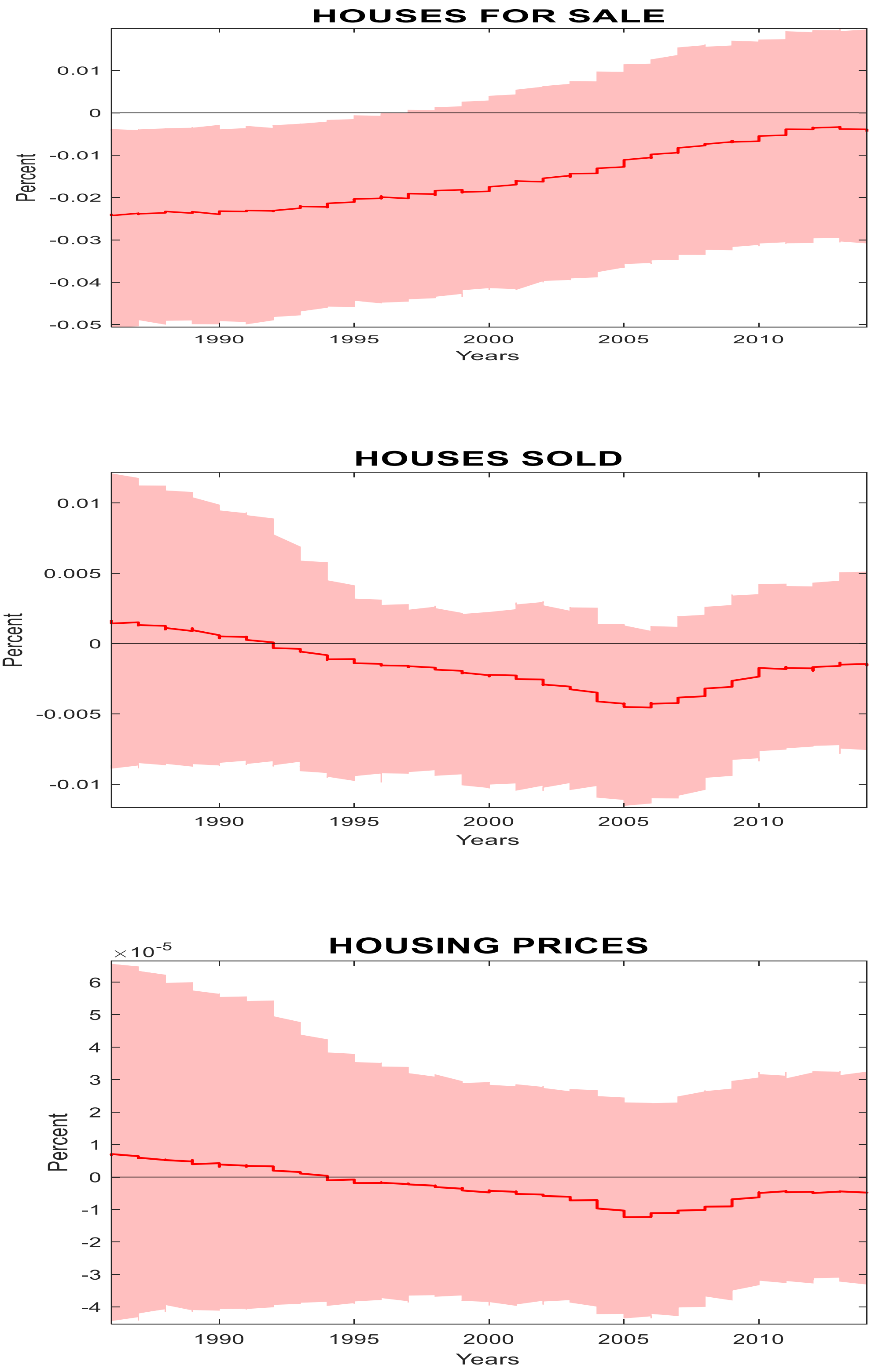
Our results tend to suggest either risk neutrality or complete markets were driving the positive effects of uncertainty on housing market activity towards the end of the period of analysis, especially in the longer-run. While the irreversible nature of housing investment, was playing a role in negatively affecting the housing sector, in the early part of the sample. As pointed out by Mumtaz and Theodoridis

(2018), increases in uncertainty around the recent global financial crisis, which in turn led to the ZLB and pursuing of unconventional monetary and real-estate market related policies is likely to have neutralized the impact of uncertainty shocks towards the end of the sample, to the extent that we observed positive impact on sales, permits and starts.

## 5.4 Conclusion

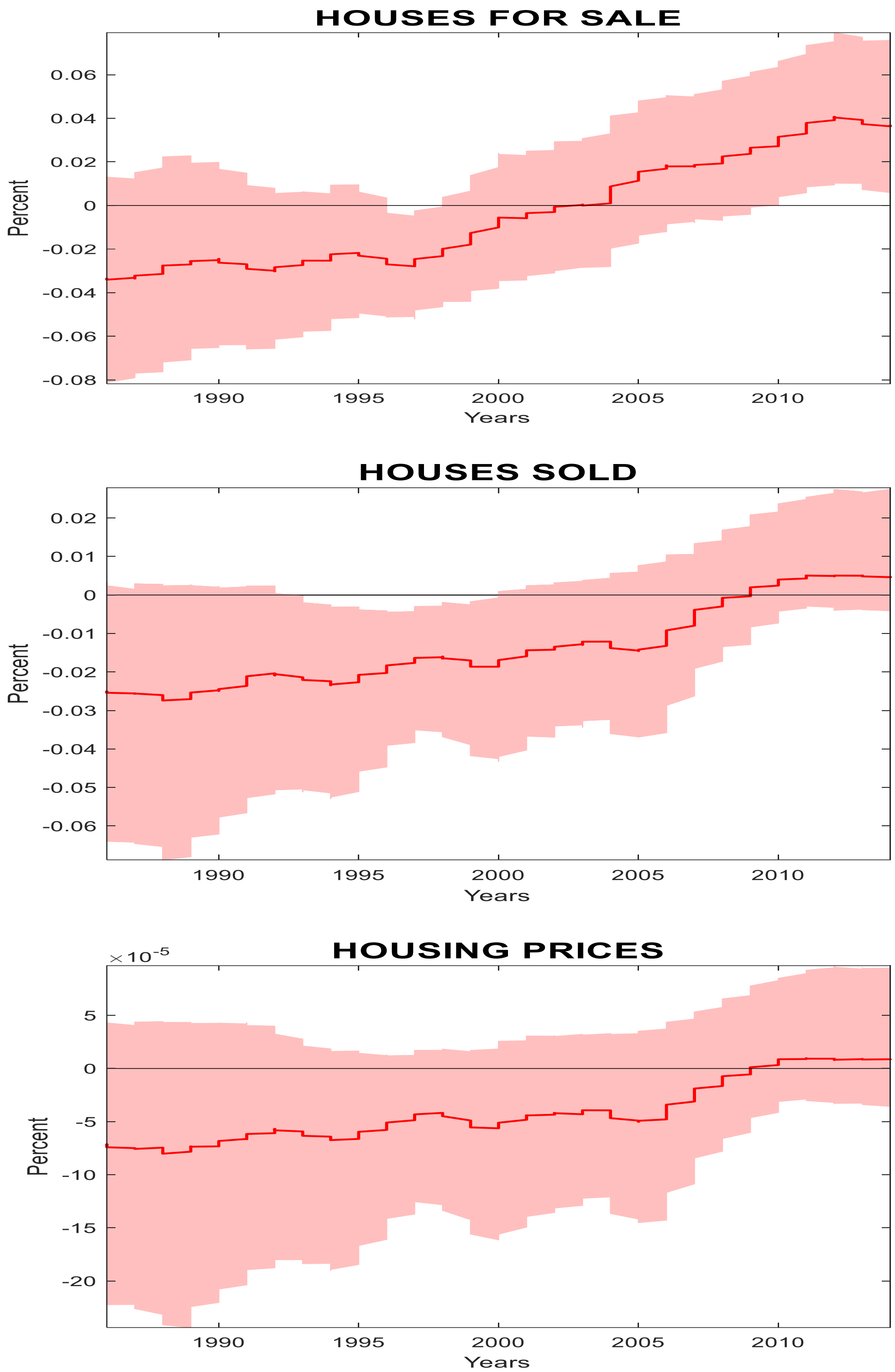
This study empirically investigates the impact of macroeconomic uncertainty shocks on US housing market variables (sales, prices, permits, starts, and sentiment), using a TVP-FAVAR model comprising of a comprehensive dataset of other macroeconomic and financial variables. Overall, the results of the cumulative response of housing variables to a 1 standard deviation positive uncertainty shock at the one-, four- and eight-quarter horizon tends to change over time, both in terms of sign and magnitude. The uncertainty shock is shown to affect primarily home sales, permits and starts over short-, medium and long-runs, and housing sentiment in the medium-term. Interestingly, the impact on housing prices is statistically insignificant.

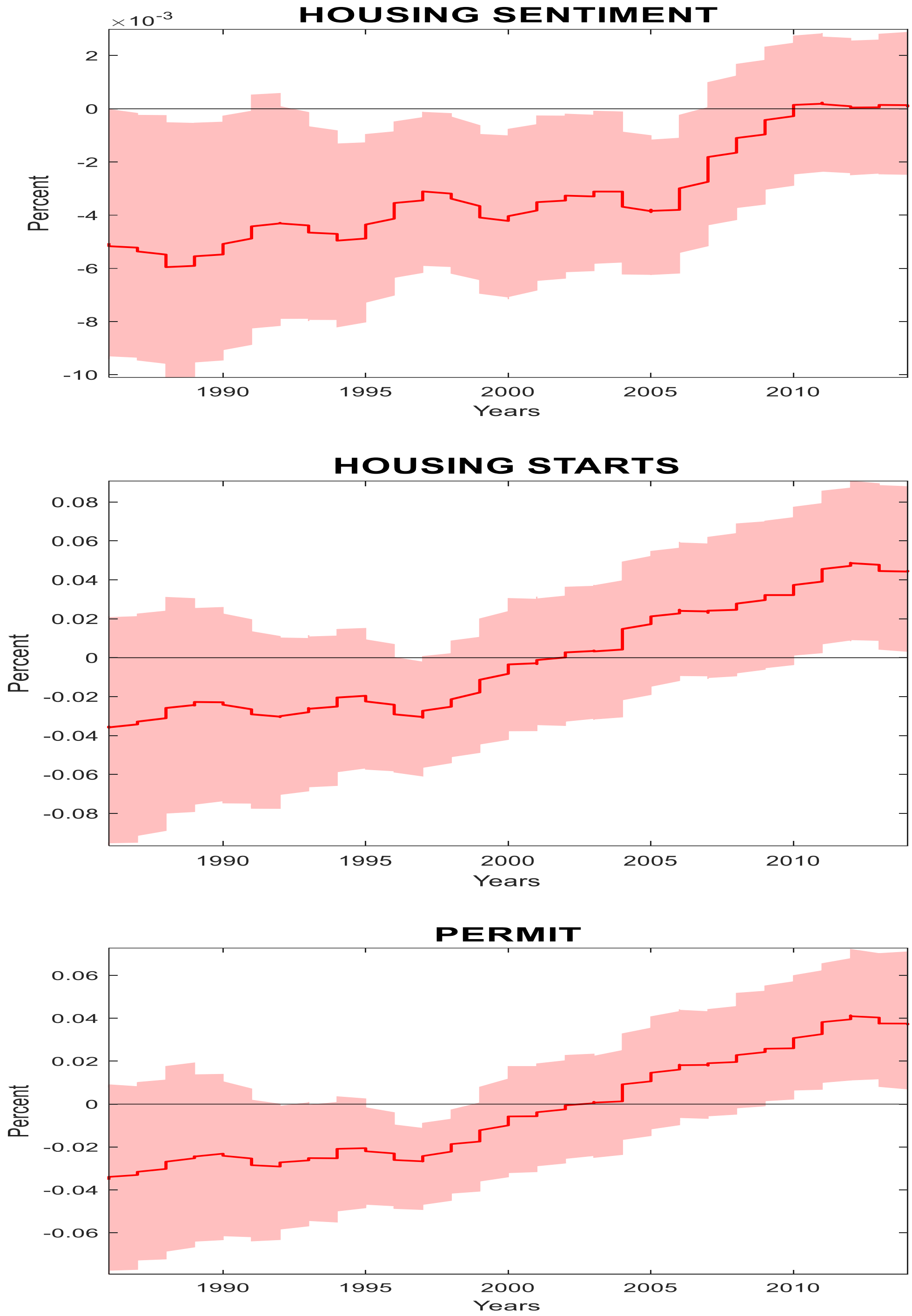
**Figure 5.1. Cumulative responses at the one-quarter horizon**




**Note:** Impulse response of housing variables to a one standard deviation positive uncertainty shock.

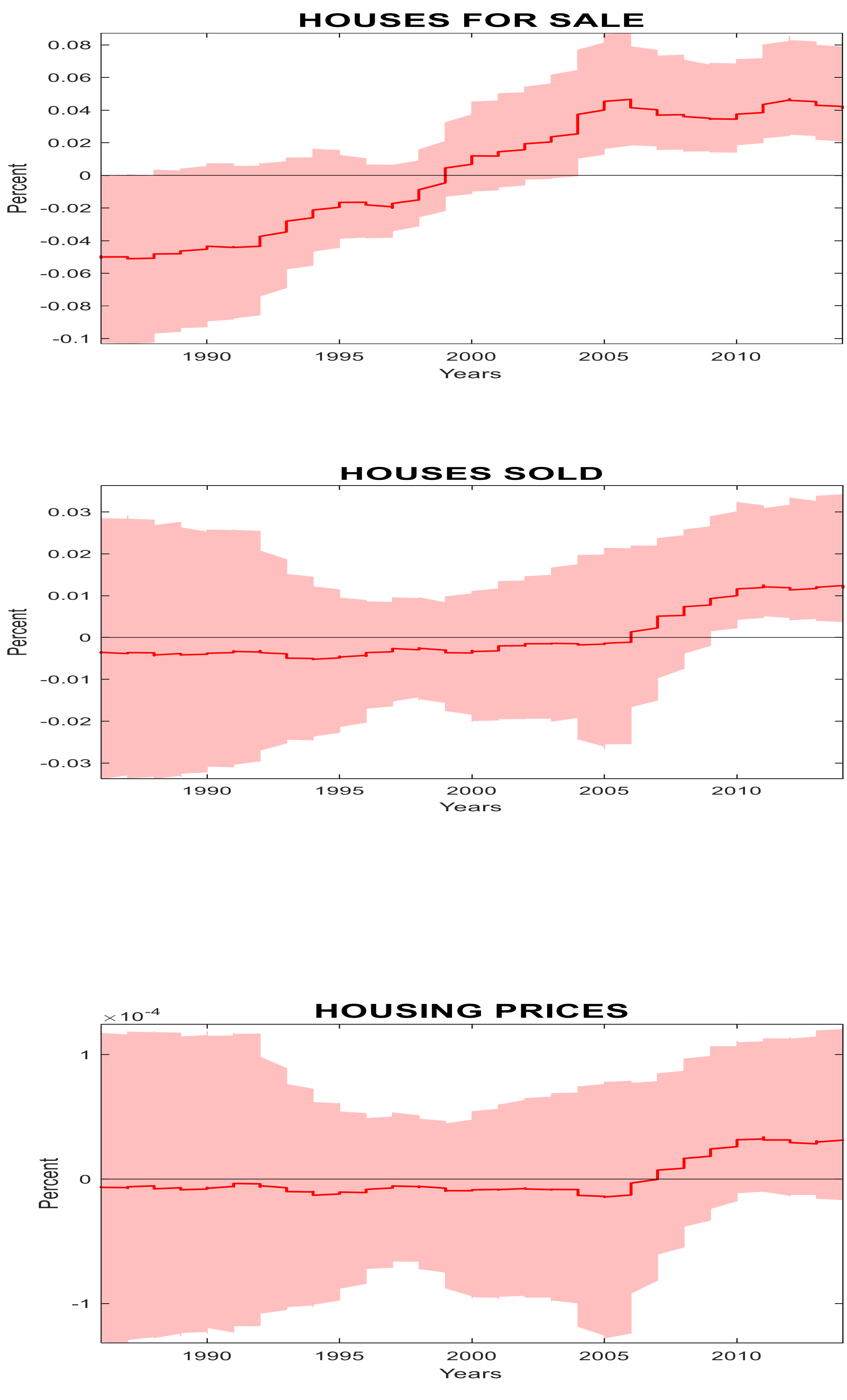
**Figure 5.2. Cumulative responses at the four-quarter horizon**

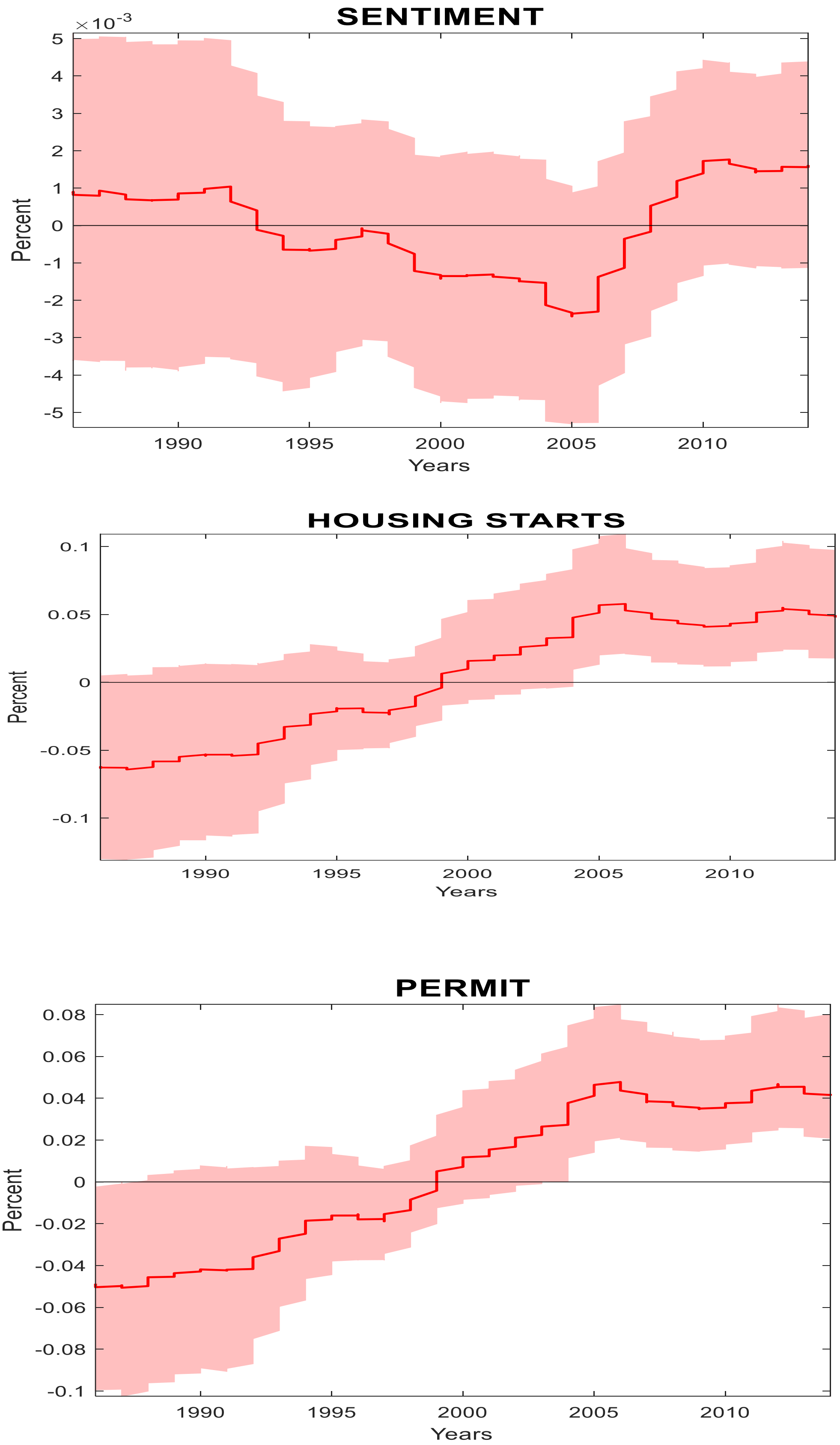





**Note:** see note to Figure 1.

**Figure 5.3. Cumulative responses at the eight-quarter horizon**






**Note:** see note to Figure 1.

# Chapter 6
# On REIT Returns and (Un-)Expected Inflation:Empirical Evidence Based on Bayesian Additive Regression Trees[38]

## 6.1 Introduction

Building on the pioneering research by Fama and Schwert (1977), much research has been done to recover how returns on real-estate investments in general and REIT returns in particular are linked to (un-)expected inflation (Gyourko and Linneman 1988, Park et al. 1990, Yobaccio et al. 1995, among others). Some researchers find that REIT returns exhibit a positive comovement with expected inflation. Other researchers report that REIT returns do not comove or even are negatively linked to (un-)expected inflation.[39] Our contribution to this large body of research is that we use Bayesian Additive Regression Trees (BART; Chipman et al. 1998, 2010) to reexamine the REIT returns-inflation nexus. Apart from the (un)expected inflation, the following predictors are included in this study: dividend yield of the REIT index; commodity index; industrial production; house price growth; stock market, that is the year-on-year rate of change of the log S&P500 composite index; the exchange rate; CB spread; and term spread.[40]

BART modeling is a natural candidate for studying how REIT returns comove with inflation because it has two advantages in comparison to other modeling techniques studied in earlier research.[41] First, BART modeling allows even complex nonlinearities in the links between REIT returns and inflation to be modeled. Modeling nonlinearities is important given that evidence has mounted that REIT returns are linked to macroeconomic variables in a nonlinear way (Chang 2011, Chang et al. 2011, Chang 2017). Second, BART modeling informs about the importance of (un-)expected inflation for REIT returns relative to other macroeconomic variables. Controlling for the

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[38] Published in Finance Research Letters, available online 28 September 2018.
https://doi.org/10.1016/j.frl.2018.09.010

[39] The list of hypotheses to explain the comovement between asset returns and inflation includes the inflation-illusion hypothesis (Modigliani and Cohn 1979) and the proxy hypothesis (Fama 1981). See Hong and Lee (2013) for a useful review of the literature.

[40] Full definition of predictor variables are presented in table 6.1.
[41] For recent applications of BART modeling in economics, see Pierdzioch et al. (2016) and Gupta et al. (2016).

impact of other macroeconomic variables is important because researchers have extensively studied the links between REIT returns and various macroeconomic variables (Ewing and Payne 2005, Chang et al. 2011).

We study U.S. monthly data covering the sample period 1979 2016 and, like Park et al. (1990) and Yobaccio et al. (1995), we use survey data to decompose inflation into an expected and unexpected component. Our findings show that expected and unexpected inflation are not among the leading determinants of REIT returns in terms of their relative importance. While expected inflation hardly affects REIT returns, marginal effects show that REIT returns significantly increase when unexpected inflation is positive. In contrast, REIT returns are insensitive to negative unexpected inflation, revealing an asymmetry in the link between REIT returns and unexpected inflation (Simpson et al. 2007). The asymmetric link between REIT returns and unexpected inflation is mainly concentrated during the period of time when Alan Greenspan served as Chairman of the Federal Reserve. The changing sensitivity of REIT returns with respect to unexpected inflation mirrors results in other recent contributions to the REIT literature demonstrating the importance of monetary policy for REIT returns (e.g., Chang et al. 2011). We further document the impact of the financial crisis of 2008/2009.

## 6.2 Bayesian Additive Regression Trees

Bayesian regression trees are defined as a sum-of-tree ensemble that uses binary hierarchical recursive splits to partition the space of predictors into a set of rectangles. A single regression tree, $T$, consists of a root, interior nodes, and terminal nodes. Interior nodes are characterized by a decision rule taking the form $x_j < c$, where $x_j$ is the splitting variable and $c$ is the splitting value. Terminal nodes are synonymous with the leaves of a tree. Every leaf, $i$, is then dedicated to a real-valued parameter $\mu_i \epsilon M = \{\mu_i, \dots, \mu_b\}$ with $b$ being the total number of leaves. After running through all decision rules, every $x_j$ of the predictor space is assigned to a leave parameter $\mu_i$. For a single tree, the model can be expressed as

$$y_t = f(x|T, M) + \epsilon_t \qquad \epsilon \sim N(0, \sigma^2 \qquad (1)$$

where $y_t$ is the response variable, $\epsilon$ is a normally distributed disturbance term, and $f$ equals the function that links $x_j$ with $\mu_i$ .

Using a sum of trees rather than a single tree increases model flexibility and is expected to generally increase model performance because a single tree model may end up in too many leaves once the data structure is getting too complex. BART combines an ensemble of trees in an additive way:

$$y_t = \sum_{j=1}^{m} f\left(x \middle| T_j, M_j\right) + \epsilon_t \tag{2}$$

The subscript $j$ now denotes the leaf parameters of the $j$-th regression tree that links the leave parameters to the predictor space.

To prevent large influences of a single trees, prior knowledge on the tree structure itself, the leaf parameters, and the residual error variance has to be specified to maintain regularization.

The prior is of the form

$$p\left(\{T_j, M_j\}, (\sigma^2|x)\right) = p(\sigma^2) \prod_{j=1}^{m} p\left(\mu_{ij} \middle| T_j\right) p\left(T_j \middle| x\right) \tag{3}$$

which controls for the location of the interior nodes in a tree, and the residual variance $\sigma^2$. Upon letting $\alpha\, \epsilon (0,1)$ and $\beta\, \epsilon\, [0, \infty)$; the absolute size of interior nodes (i.e., the dept of the tree, $d$) is controlled by $\alpha(1+d)^{-\beta}$ . A larger leads to a deeper structure of the single tree, while a larger $\beta$ reduces the number of interior nodes and makes the tree more shallow. We follow Chipman et al. (2010) and set $\alpha(\beta)$ to 0.95 (2).[42]

In order to sample from the posterior distribution, we assume $\mu_j$ to be normally and identically distributed with $\mu \sim N(\mu_\mu/m, \sigma_\mu^2)$; where $\mu_\mu$ is the mean of $y_{max}$ and $y_{min}$ and $\sigma^2$ follow an Inverse Gamma (IG) distribution with $\sigma^2 \sim IG(v/2\,, v\lambda/2)$. The parameter $\lambda$ is determined to achieve a $q$-percentage chance to reduce the root mean squared error. The IG distribution prevents $\sigma^2$ from becoming too small and reduces the probability of overfitting. $\sigma_\mu^2$ is then chosen such that $y_{min} =$

[42]In this case, a regression tree with 2 or 3 interior nodes reaches the highest likelihood.

$m\mu_\mu - k\sqrt{m\sigma_\mu}$ and $y_{max} = m\mu_\mu - k\sqrt{m\sigma_\mu}$ . The tightness of the prior is controlled by $k$, where a larger $k$ leads to a stronger regularization of $\mu_\mu$ .[43]

After setting up the priors, Chipman et. al. (2010) recommend an iterative Bayesian MCMC backfitting algorithm[44] to sample from the posterior distribution

$$p\left(f\{T_j, \mu_j\}_{j=1}^{m}, \sigma^2 \middle| y, x\right) \propto \ell(y|\{T_j, \mu_j\}_{j=1}^{m}, \sigma^2, x) p(\{T_j, \mu_j\}_{j=1}^{m}, \sigma^2 | \, x), \tag{4}$$

where $\ell$ denotes the likelihood for the entire training data, with

$$\ell\left(y \middle| \left(\{T_j, \mu_j\}_{j=1}^{m}, \sigma^2, x\right) = \prod_n \ell(y_n|\{T_j, \mu_j\}_{j=1}^{m}, \sigma^2, x_n\right). \tag{5}$$

## 6.3 Empirical Analysis

We study monthly data from January 1979 to March 2016. We consider monthly index returns on the following three REIT indexes: the FTSE NAREIT All Equity REITs index (an equity index), the FTSE NAREIT Mortgage REITs Index (a mortgage index), and the FTSE NAREIT Composite REIT Index (a composite index).[45] Earlier researchers have analyzed the sensitivities of REIT returns to a large number of macroeconomic variables (Allen et al. 2000, Clayton and MacKinnon 2003, Ewing and Payne 2003, Bredin et al. 2007, Glascock et al. 2002, Simpson et al. 2007; for a study of spillover effects, see Damian and Elsayed 2018). Accordingly, we consider various macroeconomic variables as predictors of REIT returns (Table 6.1). We measure the expected rate of inflation as the median expected price change for the next 12 months published by the Surveys of Consumers, University of Michigan. We extract the unexpected component of the inflation rate by subtracting the expected inflation rate as of period t 12 from the actual inflation rate in period t. Figure 6.1 shows both components.

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[43] As in Gupta et al. (2016), we choose k = 5, q = 0:75, and v = 10, which equals a conservative setup (see Chipman et al. 2010). The number of trees, m, is set to 50.

[44] For details, see Kapelner and Bleich (2016). We use 7,000 simulation runs and discard the first 2,000 as burns-in runs.

[45] Datasource: https://www.reit.com/investing/index-data/monthly-index-values-returns. Results for the FTSE NAREIT All REITs Index are similar to the results for the FTSE NAREIT Composite REIT Index, and results for the FTSE NAREIT Equity Index resemble those for the FTSE NAREIT All Equity REITs Index. Results for these two other indexes are not reported, but are available from the authors upon request.

The results that we summarize in Table 6.2 demonstrate that the BART model is superior to a standard linear model. The standard linear model included all predictors and is estimated by the ordinary-least-squares technique. While the result of an F-test show that the predictors are jointly significant in the linear model for all three of categories of REIT returns, the results of a RESET test for nonlinearity clearly indicate a misspecification of two out of the three linear models. A BART-based linearity test confirms the results of the RESET test. We implement the BART-based linearity test by estimating a BART model on the residuals of the linear model. We then use permutation tests to assess the explanatory power of the BART model. The null hypothesis is that the BART model does not have explanatory power for the residuals of the linear model. The results of the permutation tests clearly show that we can reject the null hypothesis for two REIT indexes.

Figure 6.2 illustrates the convergence properties of the BART model.[46] The top-left subplot shows the dynamics of the error variance, the top-right subplot shows the acceptance rate given prior information, the lower-left subplot shows the number of leaves, and the lower-right subplot shows tree depth. The two upper subplots further show results for the burn-in period. The message to take home from Figure 6.2 is that the BART model produces a stable evolution of the three parameters and the acceptance rate across iterations. The relatively small size of individual trees (lower plots) is a result of our choice of hyperparameters.

Figure 6.3 shows the relative importance (in percent) of the predictors for REIT returns. Relative importance of a predictor informs about its average use as a splitting variable defined as the mean of the average use calculated across all posterior samples (Chipman et al. 2010, Bleich et al. 2014). For the returns on the equity and composite indexes, the returns on the S&P500 index clearly are the most important predictor. For the mortgage index, the S&P500 index is also the leading predictor, but to a lesser extent than for the other two REIT indexes. Expected and unexpected inflation are not among the leading predictors, with both having a relative importance below 10% for all three indexes.

[46]Convergence results for the Mortgage REIT and the Composite REIT index are similar and are not reported (but available from the authors upon request).

Table 6.3 summarize the results of permutation tests (full sample period). The null hypothesis is that the predictors have no explanatory power for REIT returns. A joint permutation test for all predictors yields highly significant results. Individual permutation tests show that lagged REIT returns are a significant predictor in cases of the equity and the composite indexes. The returns on the S&P500 index have predictive power for the returns of all three REIT indexes. The dividend yield has predictive power mainly in case of the mortgage index. Unexpected inflation is weakly significant only in case of the mortgage index. The Pseudo-$R^2$ shows that the overall fit of the fitted BART model is better for the equity and composite indexes than for the mortgage index.

Table 6.4 summarizes results of additional permutation tests for expected/unexpected inflation, where we use an AR(12) model rather than survey data to decompose the inflation rate into its expected/unexpected components. Results are similar to those reported in Table 6.3.

Table 6.5 summarizes results of permutation tests for the Volcker (1979/09 1987/08), Greenspan (1987/09 2006/01), and Bernanke (2006/02 2014/01) eras. The test results for expected inflation are insignificant in all three subsample periods. While the test results for unexpected inflation are significant at the 10% for the mortgage index during all three subsample periods, the test results are strongest for the Greenspan era. The joint permutation tests for all predictors are highly significant for all three subsample periods.

Figure 6.4 plots the marginal effect of (un-)expected inflation on REIT returns holding all other predictors fixed (the grey areas are the posterior 90% and 95% confidence intervals). We report marginal effects for the full sample period and for the Volcker, Greenspan, and Bernanke eras. As for the full sample period, the marginal effects for expected inflation is more or less a flat function that slightly increases in expected inflation in case of the equity and the composite index. In contrast, REIT returns significantly increase when unexpected inflation is positive. A negative unexpected inflation, in contrast, hardly affects REIT returns. We observe the asymmetric response of REIT returns to unexpected inflation for all three REIT indexes. The strength of the asymmetric response is stronger in terms of significance for the equity and composite indexes than for the mortgage index. Turning to the subsample periods, we observe that the asymmetric response of REIT returns to unexpected inflation mainly was a phenomenon of the Greenspan era, especially for the equity and composite indexes.

Results on the relationship between REITs and both expected and unexpected inflation rates reported in earlier research are in general mixed. In other words, the evidence provided in favor or against whether REITs act as an inflation hedge is ambiguous, with results depending on model specification, variables under consideration, and also sample periods. Our BART-based analysis can be considered as an extension of earlier studies since we consider a more general model which allows for many possible predictors of REIT returns besides expected or unexpected inflation. Hence, our framework is a more robust one, unlike standard bivariate frameworks often used in earlier research to analyze the inflation-hedging properties of REITs, involving inflation rates and REITs returns only. In addition, our approach also controls for nonlinearities and, hence, avoids model misspecification in a linear framework. Given the superiority of our framework, our results are more reliable than those reported in earlier research using linear models and suffering from an omitted variable bias.

In sum, while (un-)expected inflation is not among the top predictors of REIT returns, the marginal effects show that the markets tend to act as an inflation hedge primarily for unexpected increases of the inflation rate rather than expected ones. To put it differently, the markets tend to price risks associated with expected movements of the inflation rate (so that REIT returns are largely invariant to changes in expected inflation), but REITs can indeed serve as a hedge, albeit an incomplete one, against unexpected inflation risks, especially if the latter are associated with an increase in the inflation rate. This result is in line with those reported by Chang (2017), whose results are based on a bivariate Markov-switching copula model. Hence, by using a modeling framework that avoids the misspecification of linear models, omitted variable bias, and also based on an extended data sample that includes the pre-, during- and post- financial-crisis periods (which, in the first place, originated from the U.S. real estate sector), we conclude that unexpected inflation (especially increases of the same) matter more than expected inflation for predicting REIT returns, where monetary policy evidently matters a lot for the strength of this effect.

The positive relationship between increases in unexpected inflation rates and REIT returns provides support to the Gordon (1962) growth model (and not necessarily the models postulating a negative relationship as in Modigliani and Cohn 1979, Feldstein 1980, and Fama 1981), which shows that asset prices are directly related to current and expected growth rates of dividend returns and inversely related to the required rate of return on the equity. Given this, unexpected inflation has a positive impact on REITs prices through two channels: First, a monetary easing that stimulates the economy along with inflation would have a positive impact on the growth rate of dividends. Second, a monetary expansion that depresses bond returns would result in an increased demand for equities, including REITS, which in turn, would cause the average investor to lower expected rate of returns of REITs. Whether it is increased dividend returns or decreased expected returns on investment, both serve to raise REITs prices.

Figure 6.5 shows that the wider confidence bands of the marginal effects that we observe for the Bernanke era transmit onto a more dispersed density of expected REIT returns. We compute the density estimates using a scaled Gaussian kernel and quantile predictions of the posterior sampling distribution averaged over all observations for the three different subsample periods. The estimated mean expected returns are larger for the Volcker than for the Greenspan era.

For the Bernanke era, mean returns shrink further, and they become even negative in the case of the mortgage index. It is also evident that the estimated standard deviation is larger for the Bernanke era than for the other two subsample periods.

Figure 6.6 summarizes the effects of the financial crisis. The figure plots the mean width (computed across quantiles) of the confidence bands around the marginal effects of (un-)expected inflation for a BART model that we recursively estimated (beginning in September 1997) for every third month. The width of the confidence bands sharply increases for the equity and the composite indexes in September 2008 when Lehman Brothers collapsed, implying that the link between (un-)expected inflation and REIT returns can be estimated with less precision after the financial crisis than before. The confidence bands estimated for the mortgage index are relatively wide before the financial crisis, implying that the financial crisis had a comparatively small impact. Interestingly, in the case of the mortgage index, the width of the confidence band started increasing gradually several months before Lehman Brothers collapsed.

## 6.4 Conclusion

Our findings show that (un-)expected inflation is not among the top predictors in terms of relative importance. REIT returns exhibit an asymmetric response in terms of marginal effects to unexpected inflation, but this asymmetry was mainly a phenomenon of the Greenspan era. The asymmetric and time-varying sensitivity of REIT returns with respect to unexpected inflation implies that investors may find it difficult to use REIT investments to protect against inflation risk. Our findings further shed light on the effect of the financial crisis of 2008/2009 on the link between (un-)expected inflation and REIT returns. In future research, it is interesting to trace out in more detail how the financial crisis affected the REIT returns-inflation nexus. Moreover, given that our findings show that monetary policy matters for the comovement of REIT returns with (un-)expected inflation, it is interesting to study more closely the dynamics of REIT returns in an era of very low interest rates.

**Figure 6.1. Components of Inflation**

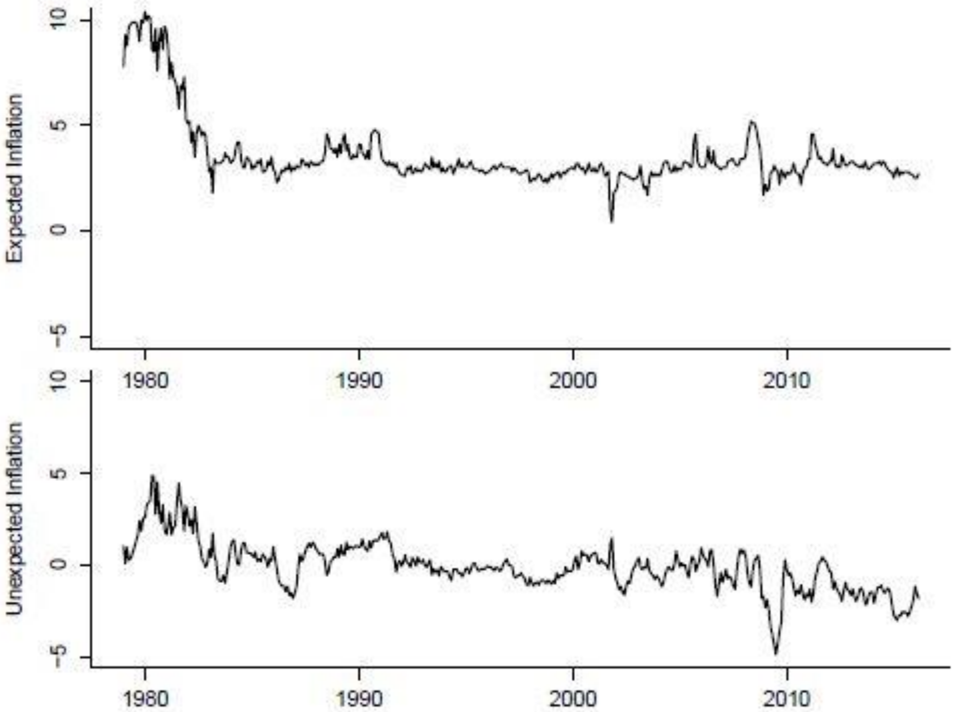
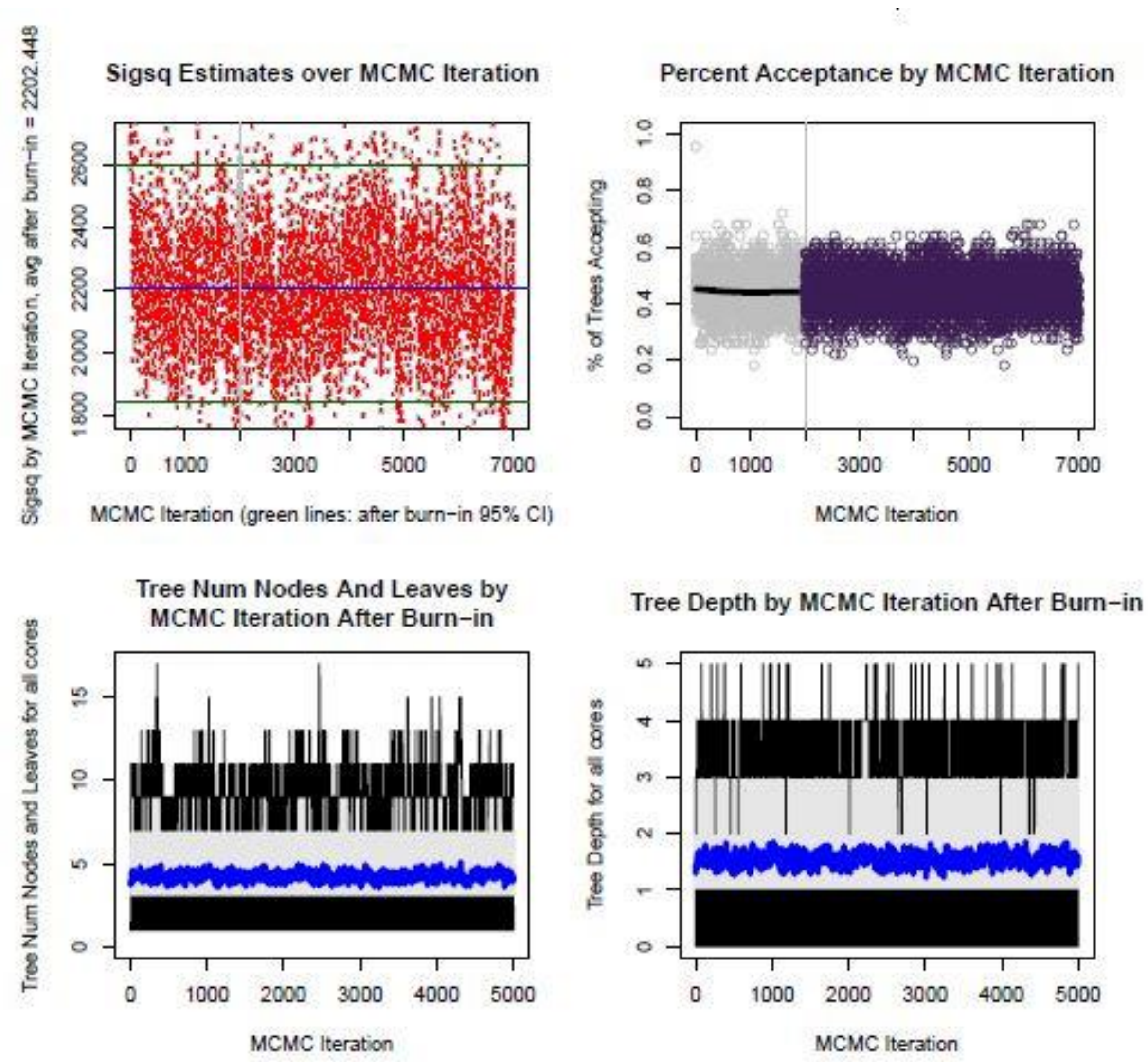
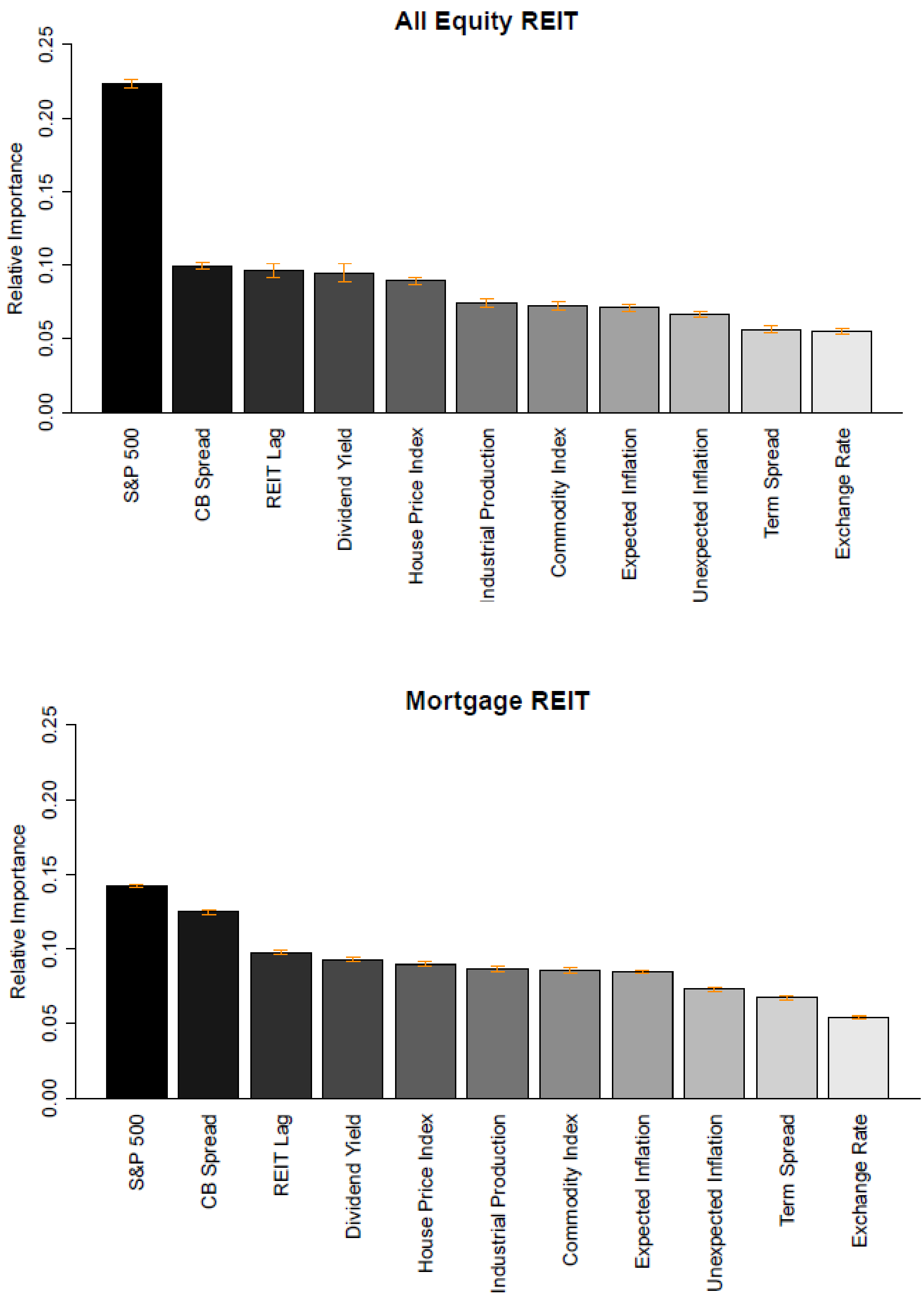


**Figure 6.2. Convergence Statistics (All Equity REIT)**




**Note:** Upper-left subplot: Sigsq denotes the error variance, $\boldsymbol{\sigma}^2$. Burn-in results are shown in the region on the left-hand side of the vertical line. Upper-right subplot: Acceptance (in %) of the proposals across the $\boldsymbol{m}$ trees. Burn-in results are shown in the same region on the left-had side of the left vertical line. Lower-left subplot: Mean after-burn-in number of leaves across the $\boldsymbol{m}$ trees. Lower-right subplot: Mean after-burn-in tree depth across the $\boldsymbol{m}$ trees.

**Figure 6.3. Relative Importance of Predictors**



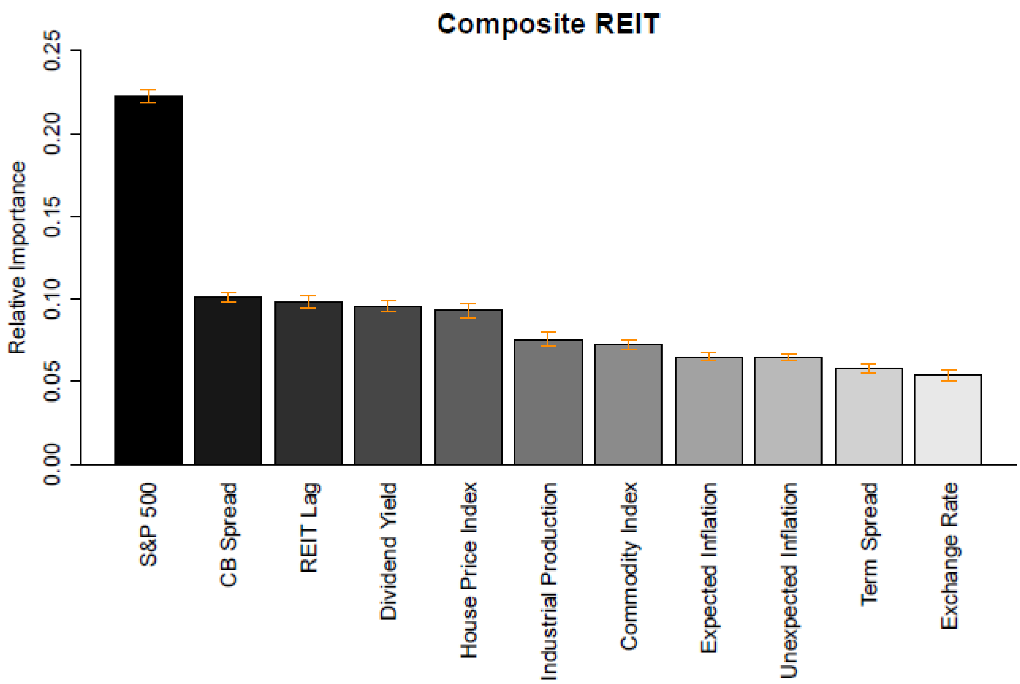
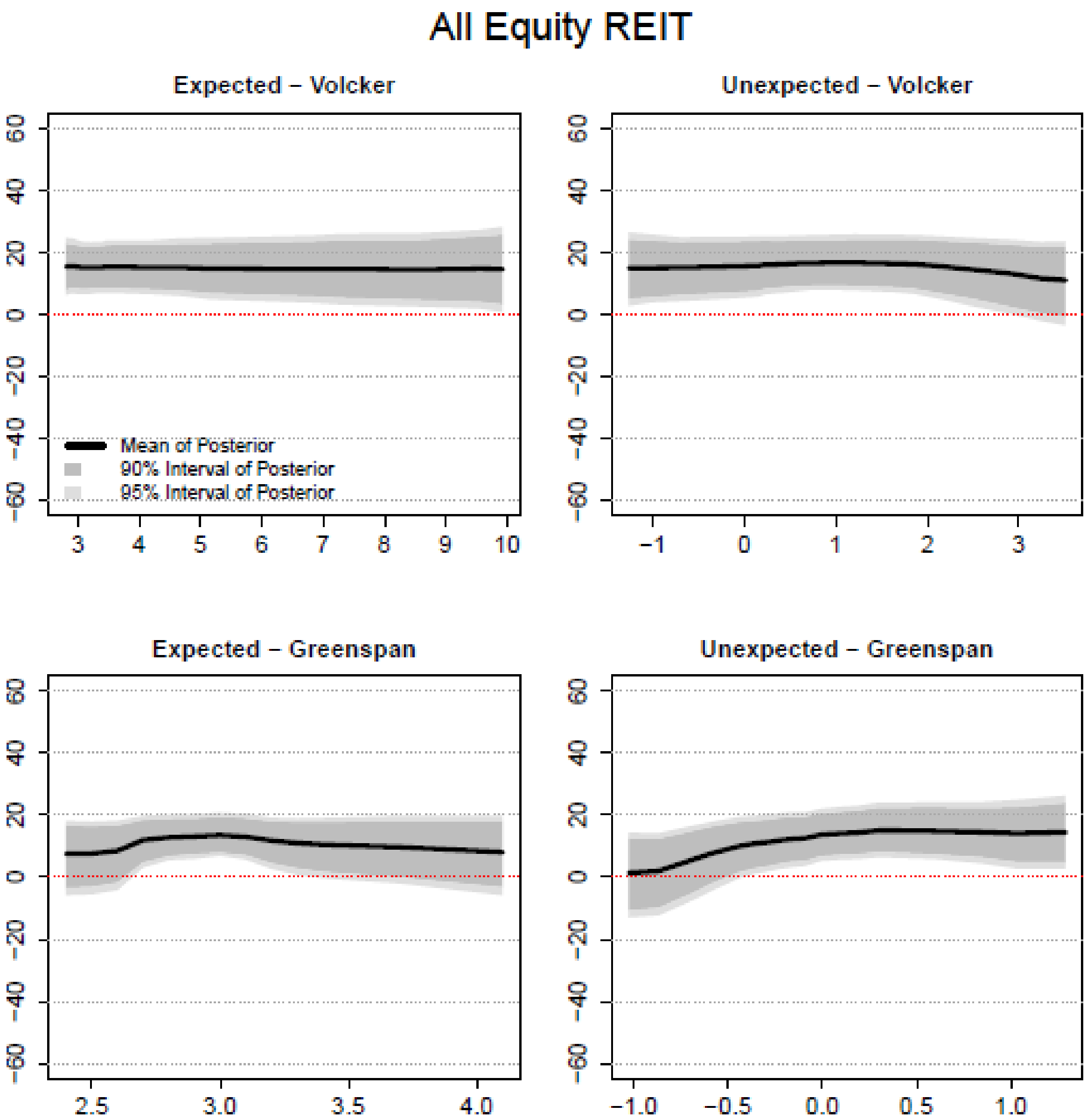
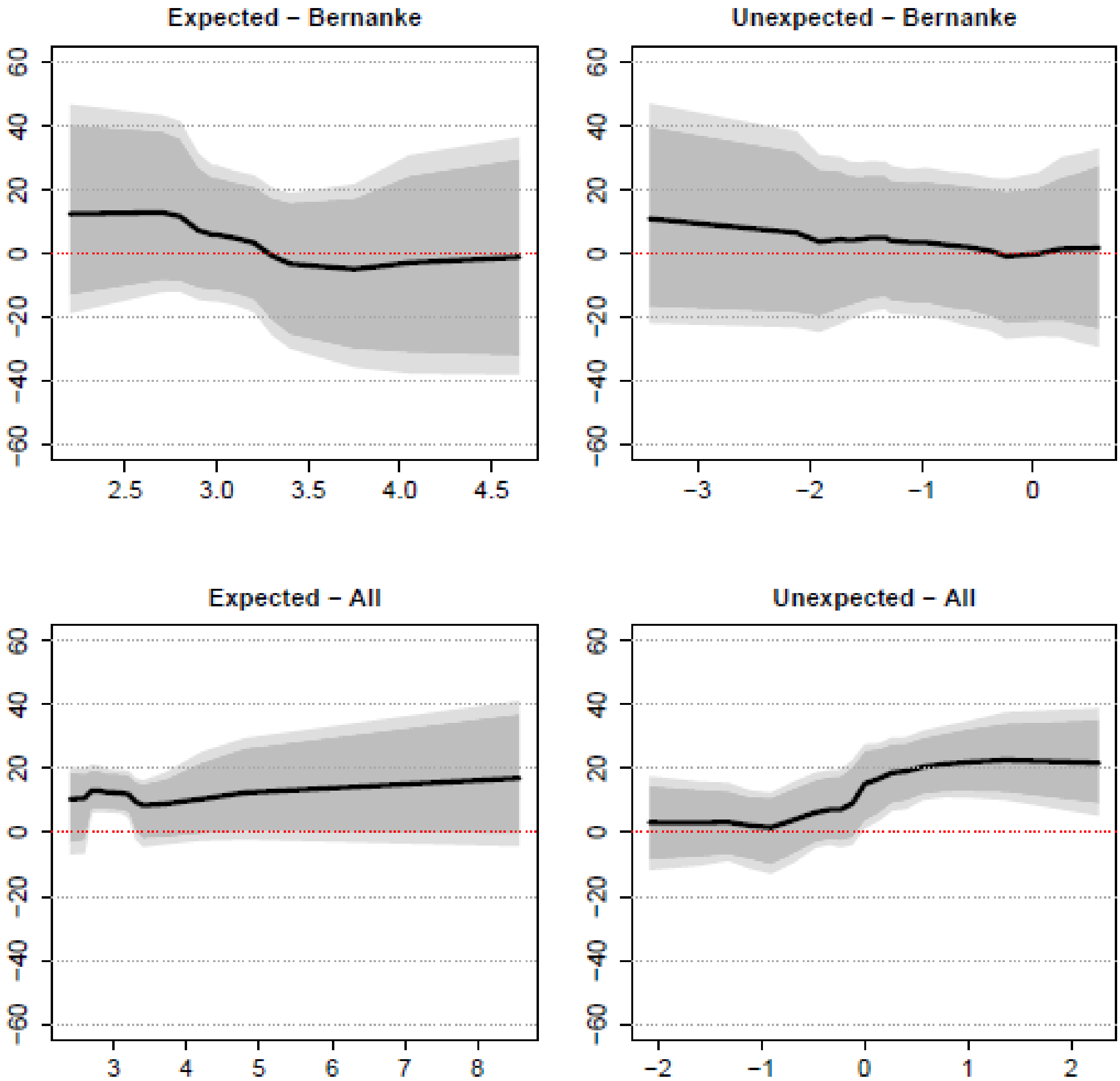
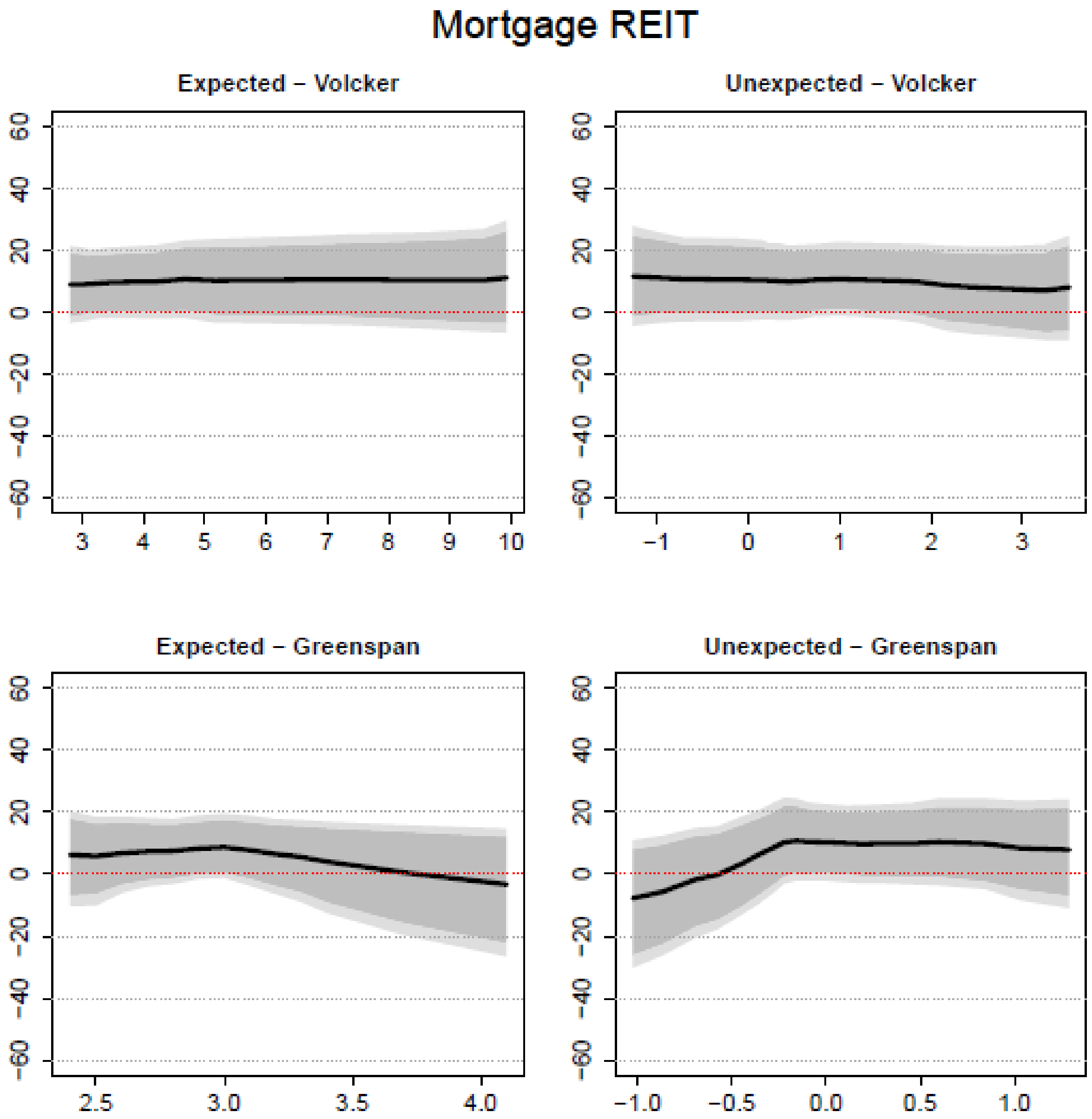

Composite REIT
Relative Importance
0.00
0.05
0.10
0.15
0.20
0.25
S&P 500
CB Spread
REIT Lag
Dividend Yield
House Price Index
Industrial Production
Commodity Index
Expected Inflation
Unexpected Inflation
Term Spread
Exchange Rate

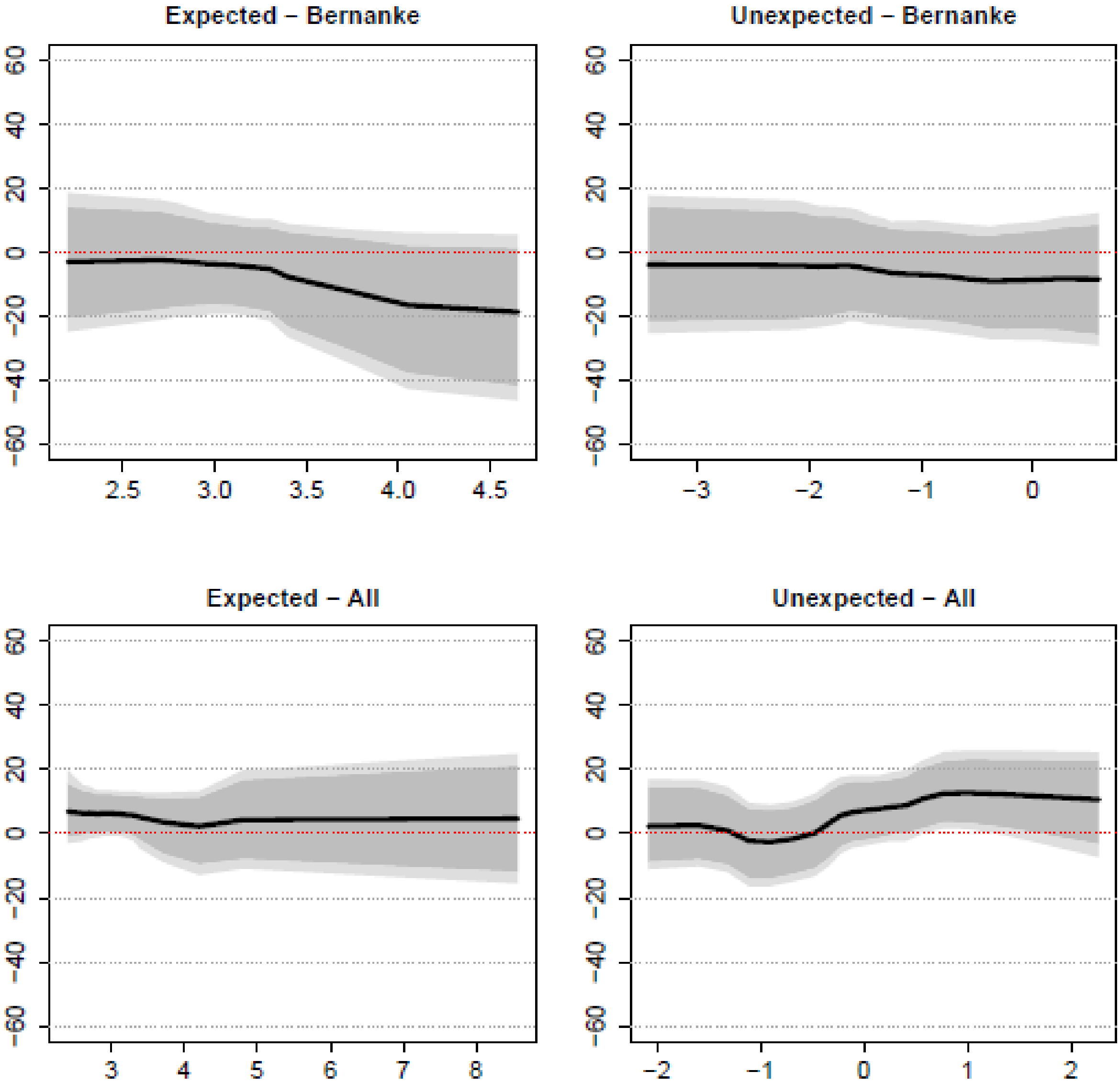
**Figure 6.4 Marginal Effects**

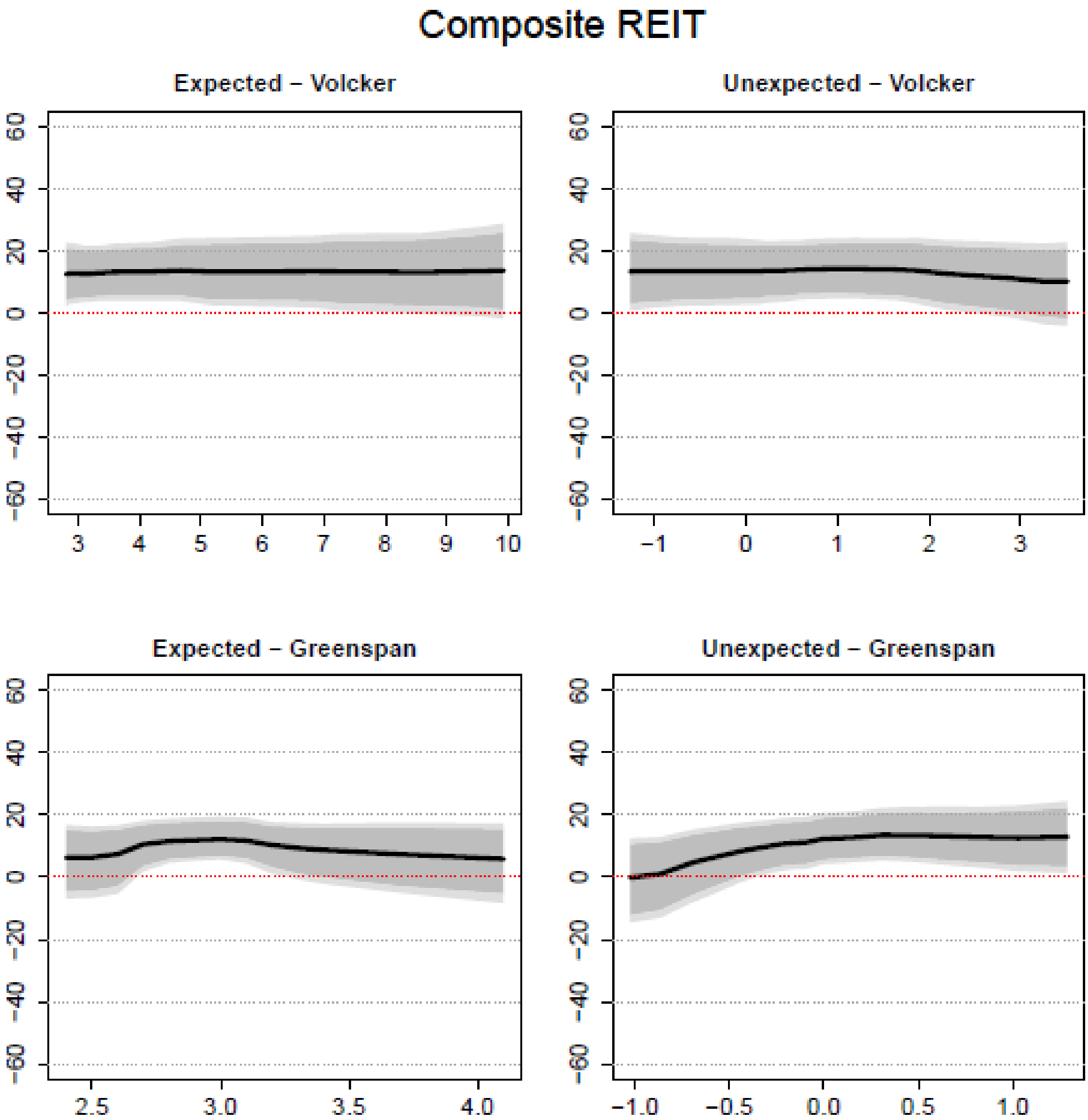




Expected – Bernanke
Unexpected – Bernanke
Expected – All
Unexpected – All
60
40
20
0
−20
−40
−60
2.5
3.0
3.5
4.0
4.5
−3
−2
−1
0
3
4
5
6
7
8
−2
−1
0
1
2


Mortgage REIT
Expected – Volcker
Unexpected – Volcker
Expected – Greenspan
Unexpected – Greenspan


Expected – Bernanke
Unexpected – Bernanke
Expected – All
Unexpected – All
60
40
20
0
-20
-40
-60
2.5
3.0
3.5
4.0
4.5
-3
-2
-1
0
3
4
5
6
7
8
-2
-1
0
1
2


Composite REIT
Expected – Volcker
Unexpected – Volcker
Expected – Greenspan
Unexpected – Greenspan
60
40
20
0
−20
−40
−60
3
4
5
6
7
8
9
10
−1
0
1
2
3
2.5
3.0
3.5
4.0
−1.0
−0.5
0.0
0.5
1.0

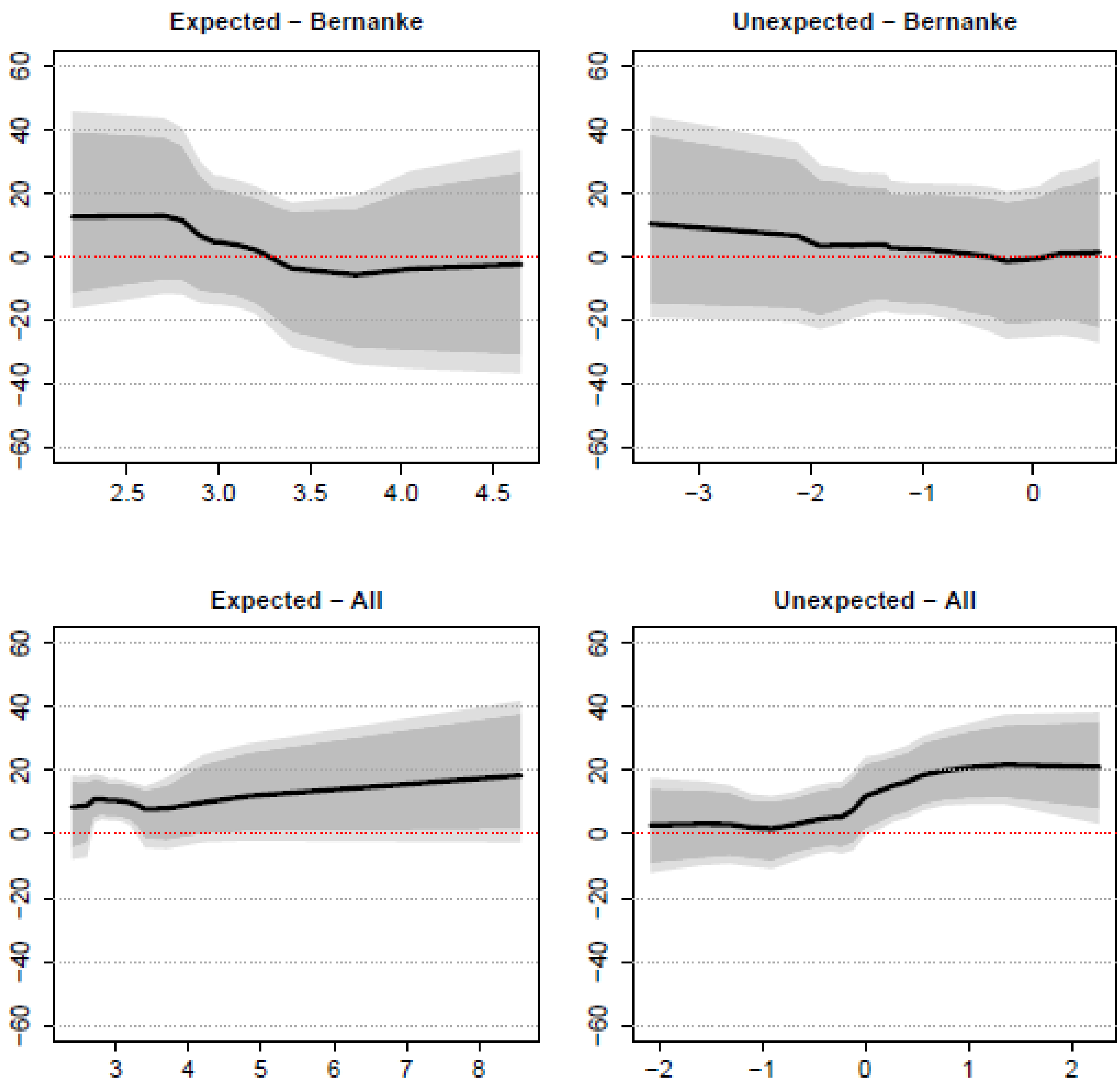
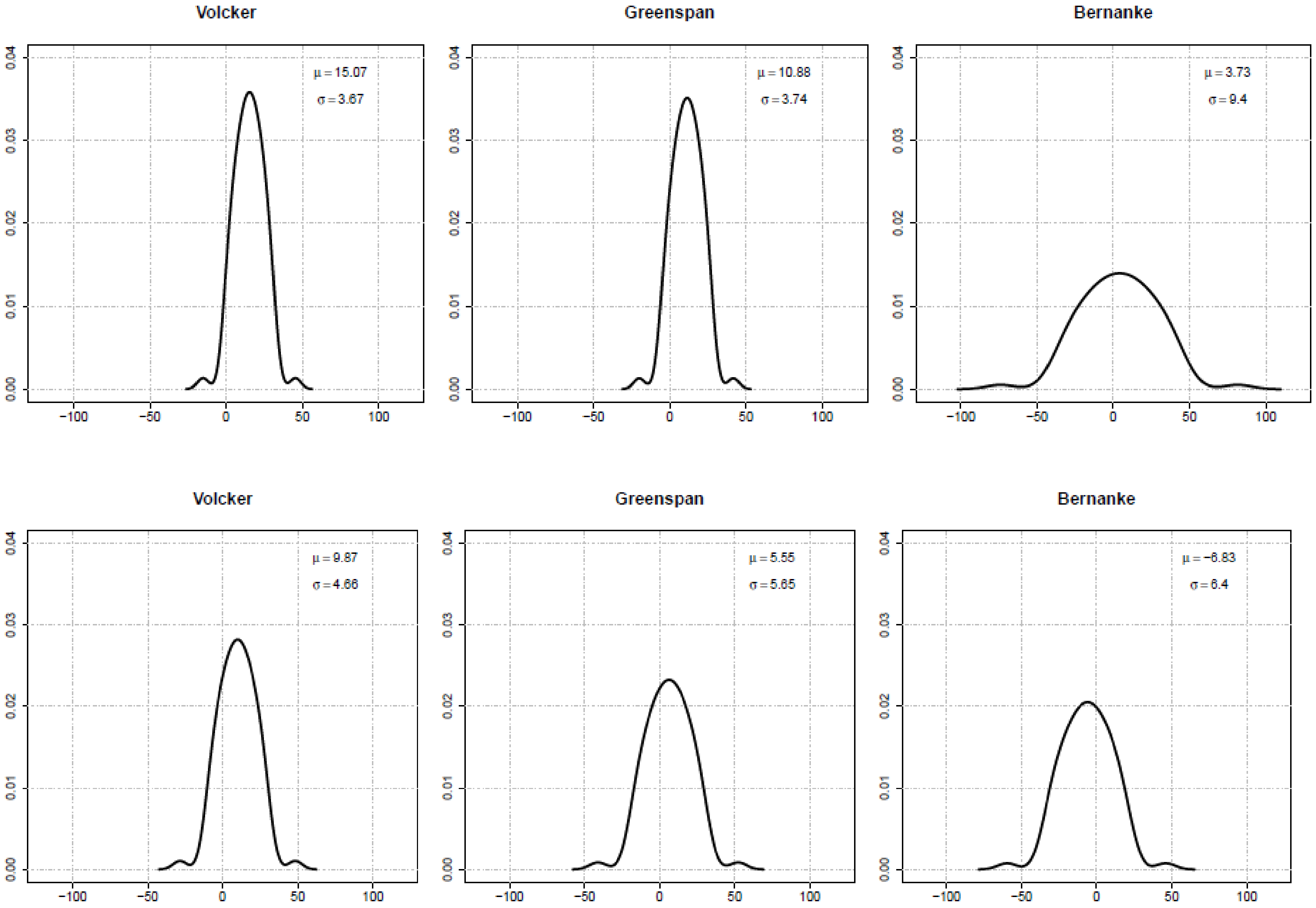
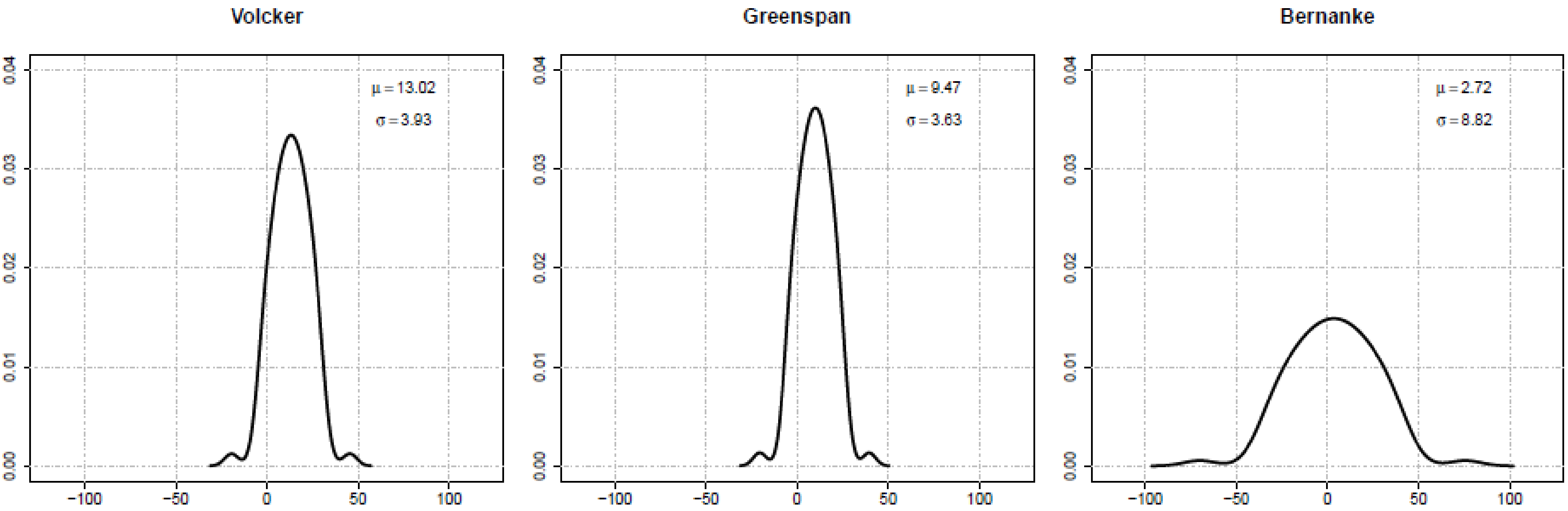

Expected – Bernanke
Unexpected – Bernanke
Expected – All
Unexpected – All

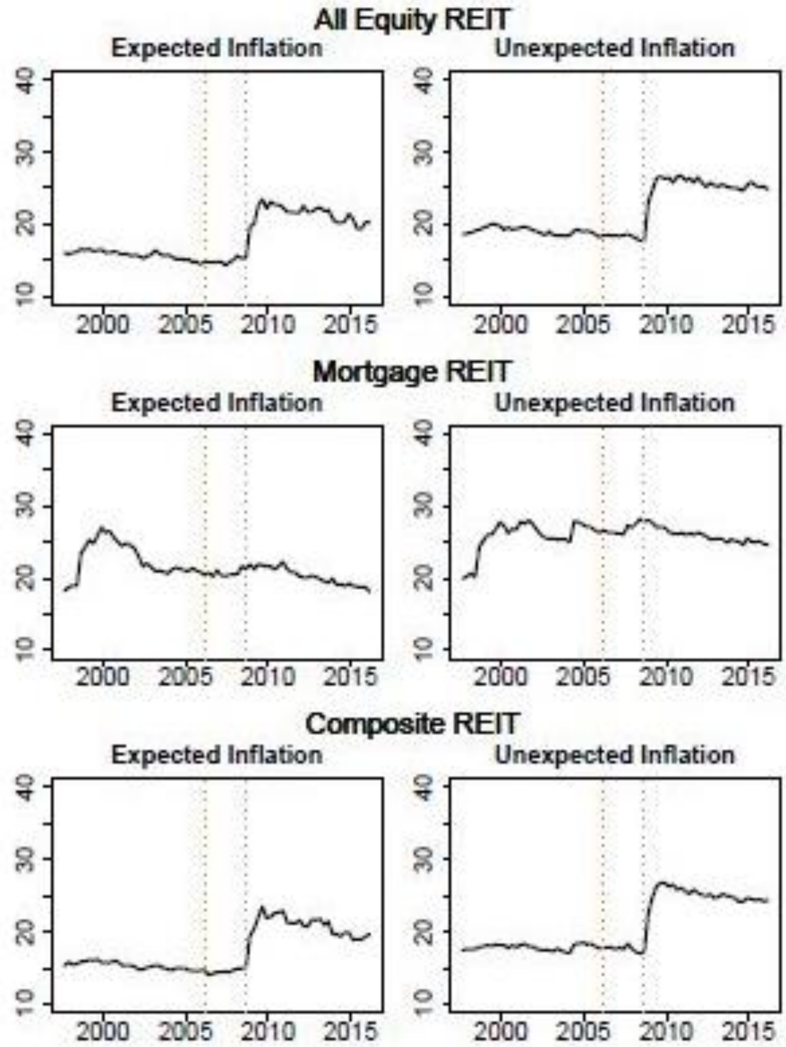
**Figure 6.5. Time-Varying Density of Expected Returns**






**Note:** This figure shows the density plots of expected returns for the All Equity index (top panel), the Mortgage REIT index (middle panel), and the Composite REIT index (lower panel) for the sub-sample periods when Volcker, Greenspan, and Bernanke served as chairman of the Federal Reserve. Density estimates are computed using a scaled Gaussian kernel and quantile predictions of the posterior sampling distribution averaged over all observations for the three different subsample periods $\boldsymbol{\mu}$ :density mean, $\boldsymbol{\sigma}$: kernel standard deviation (bandwidth).

**Figure 6.6. Stability of Confidence Bands**




**Note:** This figure shows the mean of the distance between the 0.975 quantiles and the 0.025 quantile over time. The red dotted vertical line marks the beginning of Bernanke's first term as chairman of the Federal Reserve. The grey dotted line marks the collapse of Lehman Brothers in September 2008.

## Table 6.1 The Data

| Predictors | Explanations | Sources |
|---|---|---|
| Dividend yield | Dividend yield of the REIT index. | www.reit.com |
| Commodity Index | Month-on-month rate of change of the log GSCI commodity index (spot). | DATASTREAM |
| Industrial Production | Year-on-year rate of change of the log industrial production index. | FRED |
| House-price growth | Year-on-year rate of change of Robert Shiller's log House Price index. | SHILLER |
| Stock Market | Month-on-month rate of change of the log S&P500 Composite index. | SHILLER |
| Exchange Rate | Year-on-year rate of change of the BIS log trade weighted exchange rate (broad). | FRED |
| CB spread | BAA corporate bond yield minus AAA corporate bond yield. | FRED |
| Term spread | Three-month treasury bill minus ten-year treasury bond. | FRED |
| Expected inflation | Expected inflation rate for period *t*, measured in *t*-12. | FRED |
| Unexpected inflation | Actual inflation in *t* minus expected inflation for *t*. | - |

**Note:** FRED – Federal Reserve Bank of St Louis, http://fred.stlouisfed.org/; SHILLER - http://www.econ.yale.edu/shiller/

## Table 6.2. Specification Tests for a Linear Model

| ***Dependent Variable*** | **F-test** | $\mathbf{R^2_{OLS}}$ | **RESET** | **BART-LT** | $\mathbf{R^2}_{\mathrm{BART}}$ |
|---|---|---|---|---|---|
| All Equity REIT | 0.0000 | 0.2953 | 0.0000 | 0.0014 | 0.1989 |
| Mortgage REIT | 0.0000 | 0.1692 | 0.5875 | 0.2196 | 0.1536 |
| Composite REIT | 0.0000 | 0.3023 | 0.0000 | 0.0579 | 0.1800 |

**Note:** This table reports diagnostic tests for a standard linear model estimated by the ordinary-least-squares technique. The linear model includes all predictors. The column entitled F-test reports by the p-value of an F-test for the joint significance of the predictors. The column entitled $R^2_{OLS}$ reports the unadjusted coefficient of determination for the linear model. The column RESET reports p-values of a RESET test that uses the second and third powers of the fitted values of the linear model. The column entitled BART-LT reports the p-values of a BART-based linearity test. The test is implemented by estimating a BART model on the residuals of the linear model and then using permutation test (500 simulation runs) to assess the explanatory power of the BART model. The column entitled $R^2_{BART}$ reports the explanatory power of the BART model for the residuals of the linear model.

**Table 6.3. Significance of Predictors and Model Fit (*p*-values)**

| Regressor | All Equity REIT | Mortgage REIT | Composite REIT |
|---|---|---|---|
| Lagged REIT | 0.0204 | 0.8898 | 0.0076 |
| House price index | 0.0870 | 0.2659 | 0.1118 |
| S&P500 index | 0.0000 | 0.0004 | 0.0000 |
| Industrial production | 0.5206 | 0.5752 | 0.5293 |
| Exchange rate | 0.5150 | 0.1070 | 0.6603 |
| Commodities index | 0.2762 | 0.6263 | 0.4124 |
| Dividend yield | 0.1082 | 0.0000 | 0.0834 |
| CB spread | 0.3529 | 0.1054 | 0.3749 |
| Term spread | 0.6100 | 0.0587 | 0.6890 |
| Expected inflation | 0.5497 | 0.8128 | 0.6467 |
| Unexpected inflation | 0.3489 | 0.0842 | 0.4571 |
| Expected + unexpected inflation | 0.5086 | 0.1309 | 0.3864 |
| Overall significance | 0.0000 | 0.0000 | 0.0000 |
| Pseudo $R^2$ | 0.5202 | 0.2815 | 0.5201 |

**Notes:** For the BART algorithm, *p*-values are computed by averaging over the results from permuting the data five times using different seeds 500 times. Overall significance summarizes the result of a joint permutation test for all predictors. The pseudo-$R^2$ is computed as $\mathbf{1} - \sum_{t=1}^{T}(\boldsymbol{y_t} - \widehat{\boldsymbol{y_t}})^{\mathbf{2}} / \sum_{t=1}^{T}(\boldsymbol{y_t} - \overline{\boldsymbol{y_t}})^{\mathbf{2}},$ where $\hat{\boldsymbol{y}}_{\boldsymbol{t}}$ is the predicted response and $\bar{\boldsymbol{y}}_{\boldsymbol{t}}$ the historical mean.

**Table 6.4. Results Based on an Alternative Inflation Model**

| Period | Expected | Unexpected | Both | All | Pseudo-$R^2$ |
|---|---|---|---|---|---|
| All Equity REIT | 0.3210 | 0.4555 | 0.3353 | 0.0000 | 0.5333 |
| Mortgage REIT | 0.1756 | 0.0902 | 0.0559 | 0.0000 | 0.2914 |
| Composite REIT | 0.3796 | 0.4583 | 0.3453 | 0.0000 | 0.5275 |

**Notes:** For the BART algorithm, *p*-values are computed by averaging over the results from permuting the data five times using different seeds 500 times. The pseudo-$R^2$ is computed as $1 - \sum_{t=1}^{T}(y_t - \widehat{y_t})^2 / \sum_{t=1}^{T}(y_t - \overline{y_t})^2$, where $\hat{y}_t$ is the predicted response and $\bar{y}_t$ the historical mean. The BART models used to set up the permutation tests for expected/unexpected inflation also include all other (not permuted) predictors. The column entitled "All" summarizes the result of permutation tests for all predictors. An AR(12) model is used to decompose inflation into its expected/unexpected components.

**Table 6.5. Expected vs. Unexpected Inflation Rate**

| Period | Expected | Unexpected | Both | All | Pseudo-$R^2$ |
|---|---|---|---|---|---|
| | | **All Equity** | **REIT** | | |
| Volcker | 0.5457 | 0.3733 | 0.4559 | 0.0000 | 0.5216 |
| Greenspan | 0.5792 | 0.4116 | 0.5086 | 0.0000 | 0.5202 |
| Bernanke | 0.7018 | 0.5078 | 0.5681 | 0.0000 | 0.5175 |
| | | **Mortgage** | **REIT** | | |
| Volcker | 0.7110 | 0.0527 | 0.1637 | 0.0000 | 0.2802 |
| Greenspan | 0.5848 | 0.0395 | 0.1309 | 0.0000 | 0.2815 |
| Bernanke | 0.7872 | 0.0651 | 0.1772 | 0.0000 | 0.2794 |
| | | **Composite** | **REIT** | | |
| Volcker | 0.5780 | 0.4200 | 0.4531 | 0.0000 | 0.5177 |
| Greenspan | 0.4914 | 0.3421 | 0.3864 | 0.0000 | 0.5201 |
| Bernanke | 0.7409 | 0.5613 | 0.5916 | 0.0000 | 0.5135 |

**Note:** For the BART algorithm, *p*-values are computed by averaging over the results from permuting the data five times using different seeds 500 times. The pseudo-$R^2$ is computed as $\mathbf{1 - \sum_{t=1}^{T}(y_t - \widehat{y_t})^2 / \sum_{t=1}^{T}(y_t - \overline{y_t})^2}$, where $\widehat{y_t}$ is the predicted response and $\overline{y}_t$ the historical mean. The BART models used to set up the permutation tests for expected/unexpected inflation also include all other (not permuted) predictors. The column entitled "All" summarizes the result of permutation tests for all predictors.

# Chapter 7
# General Conclusion

The objectives of this study are to: (1) explore the long run impact of inflation on homeowner equity; (2) analyse the high-frequency impact of the surprise component of monetary policy (Federal funds rate) as well as macroeconomic surprises on 10 U.S Metropolitan Statistical Areas (MSAs) housing market returns and volatility; (3) extend the literature on housing market volatility by analysing whether housing market sentiment drives variation in housing returns; (4) determine the time-varying response of not only house prices, but home sales, permits and starts, as well as sentiment associated with the housing market to uncertainty shocks; and (5) investigate how returns on real-estate investments in general and REIT returns in particular are linked to (un-)expected inflation using Bayesian Additive Regression Trees (BART).

We begin by analysing the long-run relationship between U.S house price and non-housing Consumer Price Index (CPI) using monthly data for the period 1953 to 2016 in Chapter 2. Quantile cointegration analysis results indicate cointegration at lower quantiles only between non-housing CPI and house price index series. At these lower quantiles, the results show that house prices over-hedge inflation. Our results further show that this result also holds for higher price levels only. Overall, to answer the question of whether house price hedge against inflation, our results suggest that house prices act as an inflation hedge when the latter is relatively higher and the former is lower.

Chapter 3 examines the impact of monetary policy and macroeconomic surprises on the U.S market returns and volatility at the MSA and aggregate level using daily data covering both the conventional and unconventional monetary policy periods. Using the GJR (Glosten-Jagannathan-Runkle) generalized autoregressive conditional heteroscedasticity (GARCH) model, we find that monetary policy surprises have a greater impact on the volatility of housing market returns, showing pronounced effects during the conventional monetary policy period. In terms of macroeconomic surprises, our results indicate an insignificant impact on housing returns for most MSAs for the full sample, conventional and unconventional monetary policy periods.

In Chapter 4 we investigate whether housing market sentiment drives variation in housing returns by using a k-th order causality-in-quantiles test, which permits us to test for predictability for both housing returns and volatility. We use quarterly data for the period 1975:3 to 2014:3. We find that barring 5 states (Connecticut, Georgia, Indiana, Iowa, and Nebraska), housing sentiment is observed to predict volatility barring the extreme ends of the conditional distribution. As far as returns are concerned, except for California, predictability is observed for all of the remaining 51 cases.

Chapter 5 employs a time-varying parameter vector autoregression (TVP-VAR) following Mumtaz and Theodoris (2018) to examine the impact of uncertainty shocks on the U.S housing market. Using quarterly data covering the period 1975:Q3 to 2014:Q3, we consider the following variables: real economic activity; price; financial and housing market variables; home sales; permits; starts; and housing market sentiment. Overall, the results of the cumulative response of housing variables to a 1 standard deviation positive uncertainty shock at the one-, four- and eight quarter horizon tends to change over time, both in terms of sign and magnitude, with the uncertainty shock primarily affecting home sales, permits and starts over short-, medium and long-runs, and housing sentiment in the medium-term. Interestingly, the impact on housing prices is statistically insignificant.

In Chapter 6, we apply Bayesian Additive Regression Trees (BART) to study the comovement of REIT returns with expected and unexpected inflation using U.S. monthly data covering the sample period 1979 to 2016 and survey data to decompose inflation into an expected and unexpected component. We find that the two inflation components are not among the leading predictors of REIT returns in terms of their relative importance, but also that the marginal effects of the two inflation components for REIT returns changed over time. REIT returns exhibit an asymmetric response to unexpected inflation, a phenomenon mainly concentrated in the Greenspan era.

In conclusion our study contributes to the growing literature on understanding the effects of the housing market on both households and the overall economy by employing a variety of quantitative modeling methods and new datasets in order to unpack the impact various economic determinants have on the housing market. In Chapter 2, our analysis of using a quantile cointegration method to test for inflation hedging characteristics is the first attempt to the best of our knowledge. Given the interesting results obtained in this analysis, we suggest extending this analysis to REITs as part of future research.

One of the main contributions of Chapter 3 is that it uses new high-frequency daily data of the housing market, which is not easily available. However, the limitations of our analysis is that our sample period ends in 2012. For the purposes of our analysis, the dataset does covers the sample period associated with the most turbulent episodes of the U.S housing market and the corresponding policies implemented to calm the real estate sector. With access to an updated version of this data, it is worth extending the analysis to cover a more recent sample period. In Chapter 4 our results from using a *k*-th order causality-in-quantiles test to examines the predictive ability of housing-related sentiment on housing market volatility show that with the exception of 5 states (Connecticut, Georgia, Indiana, Iowa, and Nebraska), housing sentiment is observed to predict volatility excluding the extreme ends of the conditional distribution. As far as returns are concerned, except for California, predictability is observed for all of the remaining 51 cases. As part of future research, it would be interesting to extend our study, as in Bonaccolto et al., (2018), to examine if our results for both returns and volatility continue to hold over an out-of-sample, as in-sample predictability does not guarantee favourable forecasting results (Rapach and Zhou, 2013).

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