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

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Abstract: This 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 2017:3. Given that existing studies have already shown housing sentiment to predict movements in aggregate and state-level housing returns, we 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.

Keywords: Housing sentiment, housing market returns and volatility, higher-order nonparametric causality-in-quantiles test, overall and regional US economy.

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.[1] 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).[2] 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 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.

We aim 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[3], whereby market agents tend to

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JEL Codes: C22, C32, C53, E7, R3.

[#]We would like to thank three anonymous referees for many helpful comments. However, any remaining errors are solely ours.

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

[2]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.

[3]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 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.

E-ISSN: 1929-7092/20

make overly optimistic or pessimistic judgments and choices. In this regard, we use the housing sentiment index developed by Bork *et al*., (forthcoming), 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*., (forthcoming) has been shown to predict movements in aggregate and state-level housing returns (even after controlling for other predictors),[4] 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 to nonlinearity, they are restricted to the conditional mean of the first-moment of the dependent variable only. In addition, 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. In sum, this framework allows us to test the predictability of the returns and volatility of the overall and state-level housing market due to housing market sentiment, over the entire conditional distributions of returns and volatility by simultaneously controlling for misspecification due to nonlinearity, since the *k*-th order causality-in-quantiles approach is a nonparametric data-driven framework. The remainder of the paper is organized as follows: Section 2 outlines the methodology, while Section 3 discusses the data and econometric results, with Section 4 concluding the paper.

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 $\theta - th$ quantile hypotheses to be tested are:

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

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

Jeong *et al*. (2012) use the distance measure $J = \{\varepsilon_t E(\varepsilon_t \mid Z_{t-1}) f_z(Z_{t-1})\}$, where ε_t is the regression error term and $f_z(Z_{t-1})$ is the marginal density function of Z_{t-1}. The regression error ε_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 h $\hat{\varepsilon}_t$ is the

[4]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*., (forthcoming) 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.

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 θ^{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

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

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

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:

$$H_0: \ P\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1}) \mid Z_{t-1}\} = \theta\} = 1 \ \text{ for } \ k = 1,2,...,K \tag{7}$$

$$H_1: \ P\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1}) \mid Z_{t-1}\} = \theta\} < 1 \ \text{ for } \ k = 1,2,...,K \tag{8}$$

We can integrate the entire framework and test whether x_t Granger causes y_t in quantile θ 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. Note that squared values of returns are used traditionally in the literature when comparing with model-generated estimates of the latent variable, i.e., volatility (Granger and Poon, 2003). Squared returns is the benchmark measure of volatility, with which estimates derived from econometric models, like from the GARCH-family, are compared to. In addition, the advantage of using squared-returns rather than a model-based estimate, is that the squared returns as a measure of volatility follows directly from the k-th order sequential test of returns and volatility. This natural extension of the test, ensure that our underlying measure of volatility is not model sensitive, if generated from the GARCH-family, but is based directly from the data and is in line with the traditional benchmark measure of volatility. Alternatively, we could have used the absolute returns, but then it would not follow automatically from the k-th order test.

However, one can show that it is difficult to combine the different statistics for each $k = 1,2,...,K$ 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.

3. DATA AND EMPIRICAL RESULTS

Our data set covers the quarterly period of 1975:3 to 2017:3, with the start and end date being purely driven by the availability of the housing sentiment index developed by Bork *et al*., (forthcoming). 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*., (forthcoming) 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*., (forthcoming) 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.[5]

For house prices, following Bork *et al*., (forthcoming), 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).[6] The FHFA house price indexes are broad measures of the movement of single-family 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.[7] Tables **1** and **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.[8]

Evidence from Table **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.[9] 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 to be stronger, given higher values of the statistic - as shown in Table **A2**) at the upper end of the conditional distribution.[10]

Table **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.[11] Further, as can be seen from the results, predictability is mostly located (and is also the strongest as seen from Table **A3**) 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.[12]

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

[5]The data can be downloaded from: https://www.dropbox.com/s/al3sddq1026xci2/Online%20data.xlsx?dl=0.

[6] The data is downloadable from: https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx#qpo.

[7]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 Table **A1**, 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.

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

[9]This result is in contradiction with Bork *et al*., (forthcoming), 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*., (forthcoming) conducts out-of-sample forecasting based on a linear model, whereas, we are relying on in-sample predictability based on a nonparametric model.

[10]Bork *et al*., (forthcoming) 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.

[11]In Table **A4** in the Appendix 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 Table **A1**, 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 Table **A1**.

[12]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 Table **A5** and are qualitatively similar, in the sense of strongest predictability around the median, to those derived from the squared quarterly returns obtained using the FHFA data in Table **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.

Table 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
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

(Table 1). Continued.

States	Quantile
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 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
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

(Table 2). Continued.

States	Quantile
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.

market-related sentiment plays negligible role in the process.

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

Table A1: 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.

Table A2: 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.

Table A3: 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.

Table A4: 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.

Table A5: 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.

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Received on 18-12-2019 Accepted on 03-01-2020 Published on 29-01-2020

DOI: https://doi.org/10.6000/1929-7092.2020.09.05