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Rangan Gupta
University of Pretoria
Damien Moodley
University of Pretoria
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Department of Economics
University of Pretoria
0002, Pretoria
South Africa
Tel: +27 12 420 2413

Housing Search Activity and Quantiles-Based Predictability of Housing Price Movements in the United States

Rangan Gupta* and Damien Moodley**

Abstract

Recent evidence from a linear econometric framework, tend to suggest that housing search activity, as captured from Google Trends data, can predict housing returns of the overall United States (US), as well as at the regional-level for Metropolitan Statistical Areas (MSAs). Based on search-theory, we, however, postulate that search activity can also predict housing returns volatility. Given this, we use a *k*-th order nonparametric causality-in-quantiles test, which in turn, allows us to test for predictability in a robust manner over the entire conditional distribution of not only housing price returns, but also its volatility (i.e., squared returns), by controlling for nonlinearity and structural breaks that exists in the data. Using this model, over the monthly period of 2004:01 to 2021:01, we show that while housing search activity continues to predict aggregate US house price returns barring the extreme ends of the conditional distribution, volatility is relatively strongly predicted over the entire quantile range considered. Our results tend to carry over to an alternative (the Generalized Autoregressive Conditional Heteroskedasticity (GARCH)-based) metric of volatility, higher (weekly)-frequency data (over January, 2018-March, 2021), as well as to over 84% of the seventy-seven MSAs considered. Our findings have important implications for investors and policymakers, as well as academics.

Keywords: Housing Search Activity; Housing Returns and Volatility; Higher-Order Nonparametric Causality in Quantiles Test

JEL Codes: C22, R30

* Department of Economics, University of Pretoria, Private Bag X20, Hatfield, 0028, South Africa; Email: rangan.gupta@up.ac.za.

** Corresponding author. Department of Economics, University of Pretoria, Private Bag X20, Hatfield, 0028, South Africa; Email: u18037667@tuks.co.za.

1. Introduction

In a recent paper, Møller et al. (2023) provides statistical evidence in favour of the hypothesis that online housing search activity (measured by a Housing Search Index (HSI) obtained from Google Trends data),[1] which captures peoples' intentions of buying a house and hence, proxies for housing demand, contain predictive information for housing price returns for the overall United States (US), and its regions. This is not surprising since, an increase in search activity is propagated into future periods, which, given various frictions in the housing market, would imply sluggish price adjustment in response to an increase in demand, so that search activity should hold predictive power for future variation in house prices in line with the theoretical search-based models (see, for example, Berkovec and Goodman (1996), Genesove and Han (2012), and Carrillo et al. (2015)).

In this regard, Ngai and Sheedy (2022), extending the earlier works of Díaz and Jerez (2013), Ngai and Sheedy (2020), Smith (2020), used a calibrated search-and-matching model with both endogenous inflows (new listings) and outflows (sales), to show that a single persistent housing demand shock induces more moving and increases the supply of houses on the market, and hence, can quantitatively match the data on volatility of various housing-market variables, including housing price returns variability. In other words, we can postulate that the HSI of Møller et al. (2023), should not only contain predictive information for house price returns, but also its volatility.

To test our proposition, we use the *k*-th order nonparametric causality-in-quantiles framework of Balcilar et al. (2018). This econometric model allows us to test the predictability of the entire conditional distributions (capturing regimes) of both housing price returns and squared returns, i.e., volatility simultaneously, by controlling for misspecification due to uncaptured nonlinearity and regime changes with the HSI - both of which we show to exist in our dataset via formal statistical tests. As our focus is on volatility in this paper, being an extension to the work of Møller et al. (2023), to check for the robustness of our results, we also apply the first-order of the test to the conditional volatility as captured by the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model of Bollerslev (1986). While the primary focus is the aggregate US housing price returns and its volatility, just as in Møller et al. (2023), we also analyse the predictive impact of the HSI for the first and second moment of housing

[1] A recent report by the National Association of Realtors (NAR, 2023) shows that home buyers use the internet as their main source of information about the housing market, with as many as 96% of home buyers using the internet to search for a home.

prices of seventy-seven Metropolitan Statistical Areas (MSAs), as it is well-known that the US housing market is highly segmented (Gupta et al., 2023). Based on data availability, we conduct these predictive experiments over the monthly period of 2004:01 to 2021:01.

Statistically speaking, US residential real estate represents about 77.33% of total household non-financial assets, 37.30% of total household net worth, and 32.99% of household total assets (Financial Accounts of the US, Second Quarter, 2023).[2] Hence, it is not surprising that housing price movements have been historically associated with aggregate and regional business cycles (Balcilar et al. (2014), Apergis et al. (2015), Nyakabawo et al. (2015), Emirmahmutoglu et al., (2016), Payne and Sun (2023)). Naturally, predicting the future path of housing price returns and its volatility contingent on the information content of the HSI in our current context, is of immense value to not only real estate consumers and investors, but also to the policymaker. Understandably, information on the evolution of house price movements at a higher frequency would be immense value in making timely portfolio decisions (Bollerslev et al., 2016; Nyakabawo et al., 2018), and in particular to policy authorities from the perspective of nowcasting (Bańbura et al., 2011), which will assist in the designing of monetary and fiscal responses ahead-of-time to prevent possible recessions (Balcilar et al., 2020, 2021; Bouri et al., 2021). Hence, we also conduct our analysis at a weekly-frequency over the period of January, 2018 to March, 2021.

To the best of our knowledge, this is the first paper that evaluates the predictive power of HSI for overall and regional US housing price returns and volatility based on a nonparametric higher-order causality-in-quantiles framework. In the process, we add to the large existing literature on predicting the first and second moment of US house prices using various types of econometric models and predictors, the review of which is not only beyond the scope of this paper, but also not its objective, with the reader referred to the recent works of Bork and Møller (2015), Bork et al. (2020), Segnon et al. (2021), and Gupta et al. (2022) for this purpose.

The remainder of the paper is structured as follows: Section 2 describes the data used for our analysis, as well as outlines the methodology. Section 3 presents the findings, with Section 4 concluding the paper.

[2] https://www.federalreserve.gov/releases/z1/20230908/z1.pdf.

2. Data and Methodology

2.1. Datasets

This sub-section provides specific details concerning the dataset used in the main analysis. Furthermore, it presents an overview of the econometric methodology implemented to perform our investigation.

As mentioned above we make use of a newly developed housing search index (HSI) introduced by Møller et al. (2023) to test the possibility of using online search activity to predict housing returns and volatility of the aggregate US and that, for seventy-seven MSAs.[3] HSI is constructed using Google trends data, to quantify internet search activity related to housing demand. Google Trends data are available from 2004 onwards, resulting in a sample period of 2004:01 to 2021:01 at the monthly frequency. To obtain a measure of housing demand, Møller et al. (2023) initially used "buying a house" as their main search term, and subsequently utilized a list of 22 related terms, namely: "when buying a house", "buying a home", "buy a house", "mortgage", "buying a new house", "before buying a house", "how to buy a house", "real estate", "steps to buying a house", "buying a house calculator", "first time buying a house", "buying a house process", "house buying process", "homes for sale", "building a house", "buying a house with bad credit", "cost of buying a house", "buying a house to rent", "mortgage calculator", "houses for sale", "buying a house tips", and "buying a foreclosure house".

To filter out the noise and more accurately estimate latent demand, Møller et al. (2023) use the elastic net estimator to select the ten most relevant search indexes and then apply Principal Component Analysis (PCA) to summarize the most important information from these indices into one common component, which is interpreted as a summary measure for housing search, and referred to as the HSI.[4] Note that the same approach is followed for the overall US, but by now explicitly specifying the MSA for which the search is conducted.[5]

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[3] The data is available for download from the research segment of the website of Professor Christian Montes Schütte at: https://sites.google.com/view/christian-montes-schutte/research?authuser=0.

[4] Before extracting the first principal component, the indexes are used in their logarithms, a sequential testing strategy is used to account for the possibility that the individual Google Trends series could follow different trends, and seasonality is removed by regressing each series on monthly dummy variables to study the residuals from this regression.

[5] While search activity for individuals residing in a given MSA counts in the overall search volume for that particular MSA, some individuals may also be interested in buying a home in one of the neighboring MSAs. To allow for such potential moves across MSA borders, Møller et al. (2023) also include search activity in the state in which the MSA is located.

We use the log growth rate (HR) in the seasonally adjusted monthly Federal Housing Finance Agency (FHFA) purchase-only house price index for the US and the MSAs to capture housing price returns, with the corresponding squared values measuring volatility.[6] As indicated earlier, a GARCH model was estimated on the log-returns to also provide an alternative conditional estimate of volatility. As part of our high-frequency analysis, we also construct housing log-returns at weekly frequency using the smoothed, seasonally adjusted weekly median sale prices from Zillow[7] for the overall US over the 1st week of January, 2018 to the 4th week of March, 2021.

Table A1 and Figure A1 in the Appendix of the paper summarizes the HR and HSI variables for the overall US over 2004:01 to 2021:01. As can be seen from Table A1, HR is negatively skewed and has excess kurtosis, resulting in a non-normal distribution as indicated by the overwhelming rejection of the null of normality under the Jarque-Bera test. This provides preliminary justification for using a quantiles-based approach to predictability.

2.2. Econometric Model

In this sub-section, we briefly present the methodology for testing nonlinear causality via a hybrid approach as developed by Balcilar et al. (2018), which is based on the frameworks of Nishiyama et al. (2011) and Jeong et al. (2012). Let y_t denote housing returns and x_t the HSI. Further, let $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$, $Z_t = (X_t, Y_t)$, and $F_{y_t|\cdot}(y_t| \bullet)$ denote the conditional distribution of y_t given $\bullet$. Defining $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, we have $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$ with probability one. The (non)causality in the θ-th quantile hypotheses to be tested are:

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

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

Jeong et al. (2012) show that the feasible kernel-based test statistics has the following format:

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

where $K(\bullet)$ is the kernel function with bandwidth h, T is the sample size, p is the lag order, and $\hat{\varepsilon}_t = \mathbf{1}\{y_t \leq \hat{Q}_\theta(Y_{t-1})\} - \theta$ is the regression error, where $\hat{Q}_\theta(Y_{t-1})$ is an estimate of the

[6] The data is available for download at: https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index.aspx.
[7] The data can be accessed at: https://www.zillow.com/research/data/

θ-th conditional quantile and $\mathbf{1}\{\bullet\}$ is the indicator function. The *Nadarya-Watson* kernel estimator of $\hat{Q}_\theta(Y_{t-1})$ is given by

$$\hat{Q}_\theta(Y_{t-1}) = \frac{\sum_{s=p+1,s\neq t}^{T} L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right) \mathbf{1}\{y_s \leq y_t\}}{\sum_{s=p+1,s\neq t}^{T} L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right)} \tag{4}$$

with $L(\bullet)$ denoting the kernel function.

Balcilar et al. (2018) extend the model of Jeong et al. (2012) framework, based on the work of Nishiyama et al. (2011), to the *second* (or higher) moment which allows us to test the causality between the HSI and housing returns volatility. In this case, the null and alternative hypotheses are given by:

$$H_0\colon\ P\left\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1, \quad k = 1,2,\dots,K \tag{5}$$

$$H_1\colon\ P\left\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1, \quad k = 1,2,\dots,K \tag{6}$$

The causality-in-variance test can then be calculated by replacing y_t in Eqs. (3) and (4) with y_t^2. As pointed out by Balcilar et al. (2018) a rescaled version of the $\hat{J}_T$ has the standard normal distribution. Testing approach is sequential and failing to reject the test for $k = 1$ does not automatically lead to no-causality in the *second* moment; one can still construct the test for $k = 2$.

The empirical implementation of causality testing via quantiles entails specifying three key parameters: the bandwidth (h), the lag order (p), and the kernel types for $K(\cdot)$ and $L(\cdot)$. We use a lag order of one based on the Schwarz Information Criterion (SIC). We determine h by the leave-one-out least-squares cross validation. Finally, for $K(\cdot)$ and $L(\cdot)$, we use Gaussian kernels.

3. Empirical Findings

Before we discuss the findings from the causality-in-quantiles test, for the sake of completeness and comparability we conduct the standard linear Granger causality test, with a lag-length of 1, as determined by the SIC. The resulting $\chi^2(1)$ test statistic associated with the causality running from HSI to HR is 61.5012 with a p-value of 0.0000, i.e., the null hypothesis that housing search activity does not Granger cause housing returns, in line with Møller et al. (2023), is strongly rejected at 1% level of significance. However, the linear framework is unable to provide information on regime-specific, i.e., quantiles-based, predictability, besides being silent about the causal influence on volatility, i.e., squared returns. Naturally, we turn to the *k*-th order nonparametric causality-in-quantiles test next. But to econometrically motivate this framework, we statistically examine the presence of nonlinearity and structural breaks in the relationship between the HSI and HR. Nonlinearity and regime changes, if present, would warrant the use of the nonparametric quantiles-in-causality approach, since this data-driven test would formally address the issues of nonlinearity and structural breaks in the relationship between the variables under investigation.

For this purpose, we first apply the Brock et al. (1996, BDS) test on the residual derived from the HR equation involving one lag each of HR and HSI. Table A2 in the Appendix presents the results of the BDS test of nonlinearity. As the table shows, we find strong evidence, at the highest level of significance, for the rejection of the null hypothesis of *i.i.d.* residuals at various embedded dimensions (m), which, in turn, is indicative of nonlinearity in the relationship between housing search activity and housing price returns. To further motivate the causality-in-quantiles approach, we next use the powerful *UDmax* and *WDmax* tests of Bai and Perron (2003), to detect 1 to M structural breaks in the relationship between HR and HSI, allowing for heterogeneous error distributions across the breaks. When we apply these tests to the HR equation involving one lag each of HR and HSI, we detect four breaks on: 2008:12, 2012:03, 2014:09, and 2017:03 associated with the downturns and weak sentiment during the global financial and the European sovereign debt crises, but then sustained economic recovery and improved sentiment since 2014 (see, Figure A1).

Given the strong evidence of nonlinearity and structural breaks in the relationship between HR and HSI, we now turn our attention to the causality-in-quantiles test, which is robust to misspecification in the linear model due to its nonparametric nature, besides allowing us to test for predictability over the entire conditional distributions of both returns and volatility. The results are reported in Figure 1, whereby we test the regime-specific null hypothesis of no – Granger causality running from HSI to HR and HR^2 over the quantile range of 0.10 to 0.90 based on the standard normal test statistic. As can be seen from the figure, predictability for housing returns from HSI holds over the range of 0.20 to 0.80 at least at the 5% level of significance, with the strongest causal influence observed at the median. Interestingly, there is no evidence of predictability at the extreme quantiles of 0.10 and 0.90. In other words, allowing for a quantiles-based model, we provide a more nuanced evidence of predictability as detected by Møller et al. (2023) from a linear (conditional mean-based) predictive regression framework, as we are able to detect varied strength of causality conditional on the regimes of the market. Put alternatively, we can now say that the impact of HSI on HR increases as we move from a bearish regime to a bullish regime, with a peak at the median, but there is no evidence of causal influence at the two extreme-ends of the market. These findings tend to support the idea that for exceptionally weak and strong phases of the real estate market, i.e., at the quantiles of 0.10 and 0.90, participants tend to herd (Babalos, 2015; Ngene et al., 2017), and hence does not require information of a predictor like HSI to gauge the future path of HR. Note that, the lack of predictability at the upper quantiles could also be signalling market efficiency related to HSI in line with the quantiles-based test of efficiency of Tiwari et al. (2020) for the overall US, as well as at the MSA-level.

Interestingly however, the predictability of HSI for squared returns, i.e., volatility is observed over its entire conditional distribution at least at the 5% level of significance for majority of the quantiles (barring the 90^{th} quantile, where causality holds at the 10% level), with a peak at the quantile of 0.40. In other words, we provide strong evidence in favour of our hypothesis that housing search activity can lead house price volatility over and above housing returns, with the effect holding irrespective of the size this price variability, unlike returns.

[INSERT FIGURE 1]

Although robust predictive inference is derived based on the nonparametric causality-in-quantiles test, it is also interesting to estimate the sign of the effect of the HSI on HR and HR^2 at various quantiles, especially to validate the theoretical positive relationship outlined in the introduction. But, in a nonparametric framework, this is not straightforward, as we need to employ the first-order partial derivatives. Estimation of the partial derivatives for nonparametric models can give rise to complications, because nonparametric methods exhibit slow convergence rates, due to the dimensionality and smoothness of the underlying conditional expectation function. However, one can look at a statistic that summarizes the overall effect or the global curvature (i.e., the global sign and magnitude), but not the entire derivative curve. In this regard, a natural measure of the global curvature is the average derivative (AD) using the conditional pivotal quantile, based on approximation or the coupling approach of Belloni et al. (2019), which allows us to estimate the partial ADs. Based on the ADs reported in Table 1, we find consistent evidence of a positive predictive effect of HSI on housing price returns and its volatility.

[INSERT TABLE 1]

When we rely on a GARCH-based metric of volatility,[8] our findings, as reported in Figure 2, continue to be robust in the sense that predictability is again observed over the entire conditional distribution, with a peak at the median, in a quite strong manner at the 1% level of significance, except at the two ends where the same holds at the 10% level. Barring the highest quantile of 0.90, a similar result is also obtained for weekly squared returns, as seen from Figure 3. At the same time from the Figure 3, it must be noted that causality of HSI on HR is restricted now over the quantile range of 0.30-0.70, i.e., compared to the monthly data, though sample periods are different, the lack of predictability at the two ends of the conditional distribution of house price returns gets extended.

[INSERT FIGURES 2 AND 3]

At the regional-level, as can be seen from Table 2 (Panel A), 65 of the 77 MSAs considered, i.e., in 84.42% of the cases considered, there is evidence of predictability running from HSI to HR (for at least one quantile of the conditional distribution at the 1% to 10% level of significance). In line with the results for the overall US, for these instances, predictability peaks at quantiles closer to the median, and fades away at the extreme ends. Furthermore, as reported in Table 2 (Panel B), predictability for housing price returns volatility is detected for 68 of the 77 MSAs, i.e., in 88.31% of instances, again with an inverted u-shaped pattern of the test statistic registering its highest value close to the median. But in this case, just as for the aggregate US, the coverage of causality over the conditional distribution of volatility is relatively higher compared to that of HR, in terms of the number of quantiles for which predictability is observed.

[INSERT TABLE 2]

In sum, we tend to conclude that the predictability of HSI for house price volatility, unlike housing returns is, in general, not regime-specific, and tends to be stronger in the sense of its coverage of the entire conditional distribution of the former, with these observations tending to hold both at the aggregate and MSA-level of the US housing market.

[8] Complete details of the parameter estimates of the GARCH model are available upon request from the authors.

4. Conclusions

In a recent study, Møller et al. (2023), developed a Google-based online search volume index of housing activity as a measure of underlying housing demand to show that the metric can predict housing price returns of the US and its MSAs. Based on recent models of housing search theory, we can also postulate that this housing search index (HSI) should also be able to predict volatility in house prices. To test our hypothesis, we use the *k*-th order nonparametric causality-in-quantiles framework of Balcilar et al. (2018), which is capable of capturing predictability of the entire conditional distributions of both housing price returns and squared returns, i.e., volatility simultaneously, by controlling for misspecification due to uncaptured nonlinearity and regime changes with the HSI, which we statistically show to exist in our dataset over the monthly period of 2004:01 to 2021:01.

We show that while housing search activity continues to predict aggregate US house price returns under the misspecified linear Granger causality model, as in Møller et al. (2023), the same, in general, also holds true for the quantiles-causality framework, barring at the extreme ends of the conditional distribution of returns. Our results thus provide a more nuanced evidence of causality running from HSI to housing price returns, with an inverted u-shape of the strength of the underlying standard normal test statistic, which reached its peak at the median. Comparatively, volatility is found to relatively strongly predicted over the entire quantile range considered of squared returns, with the highest value test statistic again registered close to the median. Our results tend to carry over to an alternative (the Generalized Autoregressive Conditional Heteroskedasticity (GARCH)-based) metric of volatility, as well as for higher-frequency, i.e., weekly data over January, 2018 to March, 2021. When we take a regional perspective by delving into 77 MSAs, we find that the predictive impact of HSI is detected for 65 and 67 of the cases for the first and second moment of house prices, respectively. In other words, the causal influence of HSI is dominant not only for the overall US, but also at the local-level, with strong evidence in favour of our hypothesis that housing search activity tends to predict housing returns volatility, over and above returns.

Since our predictive analysis is performed at the monthly as well as weekly frequencies associated with housing returns, our results can be used by policymakers to obtain high-frequency information about where the housing market is headed due to changes in housing search activity, and predict the future path of low-frequency, i.e., quarterly, economic activity variables, such as growth of Gross Domestic Product (GDP), at monthly and weekly-levels, given that house price movements are known to lead US business cycles. Moreover, monthly and weekly predictions of housing returns and volatility contingent on online housing search activity, capturing latent demand, would also help investors to make optimal portfolio allocation decisions in a timely-manner. Finally, from the perspective of a researcher, our results suggest that the housing market is in fact inefficient in the semi-strong sense, given the predictive role of search activity, but this result is also contingent on the phase of the housing returns, which excludes bearish- and bullish-regimes. In other words, our results have important implications for policy authorities, investors, and academics.

Since in-sample predictability does not necessarily translate into out-of-sample gains, as part of future research, it would be interesting to extend our analysis to a full-fledged forecasting exercise using the k-th order nonparametric causality-in-quantiles test, as outlined in Bonaccolto et al. (2018).

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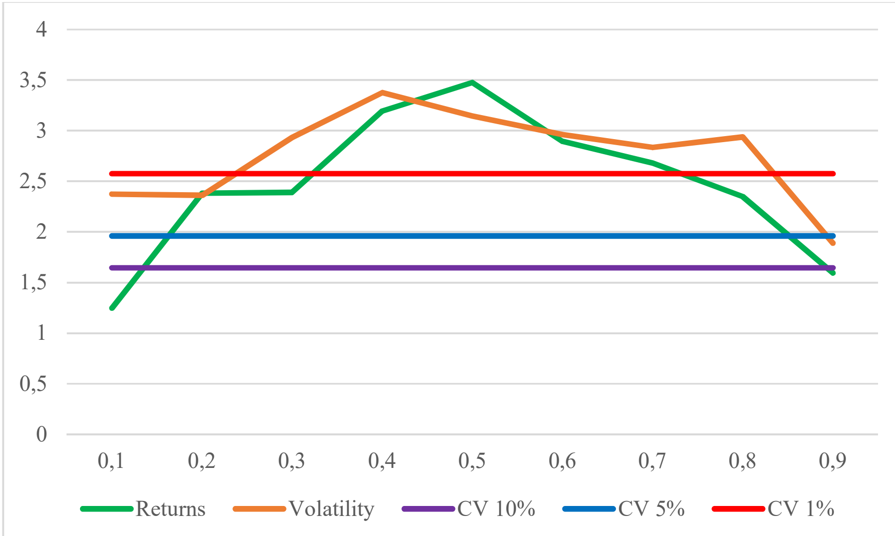
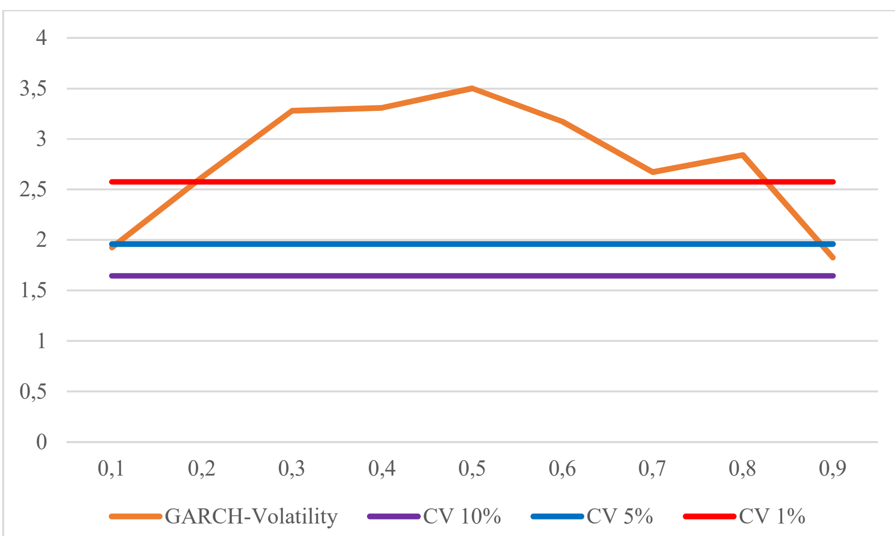
Figure 1. *k*-th order causality-in-quantiles test results for housing price returns and volatility for the US using monthly data: 2004:01-2021:01



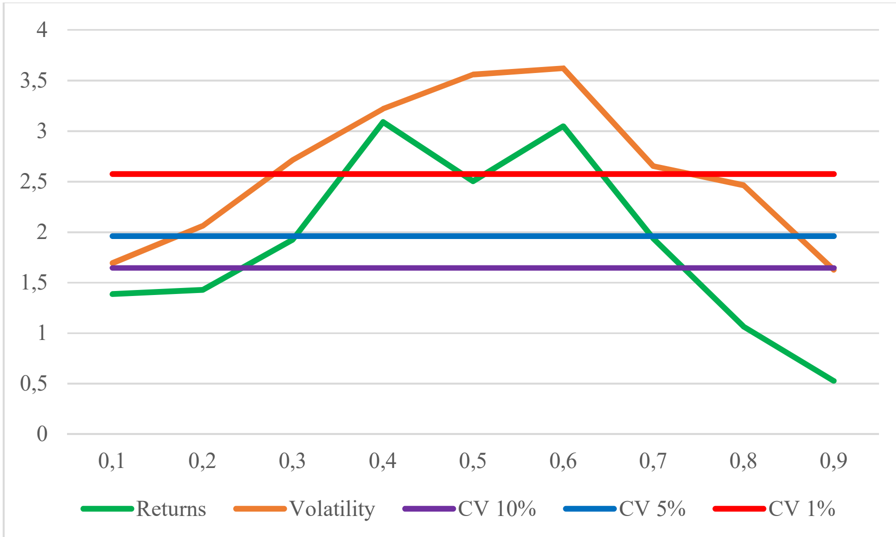
Note: Vertical axis reports the standard normal test statistic for the hypothesis that there is no Granger causality for a particular quantile on the horizontal axis running from housing search activity index (HSI) to housing price returns (HR) and squared returns (volatility; HR^2); CV 10%, CV 5% and CV 1 % correspond to the critical values of 1.645, 1.96 and 2.575 respectively.

Figure 2. *k*-th order causality-in-quantiles test results for GARCH-based housing price returns volatility for the US using monthly data: 2004:01-2021:01



Note: Vertical axis reports the standard normal test statistic for the hypothesis that there is no Granger causality for a particular quantile on the horizontal axis running from housing search activity index (HSI) to GARCH-based housing price returns volatility; CV 10%, CV 5% and CV 1 % correspond to the critical values of 1.645, 1.96 and 2.575 respectively.

Figure 3. *k*-th order causality-in-quantiles test results for housing price returns and volatility for the US using weekly data: 2018:01-2021:03



Note: Vertical axis reports the standard normal test statistic for the hypothesis that there is no Granger causality for a particular quantile on the horizontal axis running from housing search activity index (HSI) to housing price returns (HR) and squared returns (volatility; HR^2); CV 10%, CV 5% and CV 1 % correspond to the critical values of 1.645, 1.96 and 2.575 respectively.

Table 1. Average Derivative Estimates for the Effect of HSI on housing price returns and volatility for the US using monthly data: 2004:01-2021:01

Quantile	HR	HR^2
0.10	0.8934	0.0637
0.20	0.8667	0.1696
0.30	0.7906	0.1680
0.40	0.7151	0.2372
0.50	0.7775	0.2351
0.60	0.7213	0.2635
0.70	0.6685	0.2758
0.80	0.6361	0.2767
0.90	0.5778	0.2175

Note: Entries correspond to average derivative (AD) estimates of the sign of the effect of HSI on to housing price returns (HR) and its volatility (HR^2) at a particular quantile.

Table 1 (Panel A). *k*-th order causality-in-quantiles test results for housing price returns at local (MSA) level using monthly data: 2004:01-2021:01

	Quantiles								
MSA	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Miami, FL	1.0315	1.4009	1.4803	1.1712	0.7886	0.8352	1.1120	1.0232	0.9610
Los Angeles–Long Beach	1.6172	2.4281**	3.1131***	2.6601***	2.9570***	2.4529**	2.5215**	1.8816*	1.7244*
San Francisco, CA	0.3846	0.5856	0.5890	0.7001	0.8839	0.6040	0.9766	0.8529	0.8039
San Diego, CA	0.0297	0.0125	0.0049	0.0011	0.0069	0.0026	0.0049	0.0056	0.0019
Salt Lake City–Ogden, UT	0.8457	1.1103	1.6508*	2.1129**	1.6261	1.4383	1.0168	0.7117	0.4247
New York, NY	0.5398	0.6002	0.9871	0.8503	1.0702	0.6045	0.7042	0.4508	0.1450
New Orleans, LA	0.2549	0.9730	0.9229	0.8069	0.4172	0.4403	0.4563	0.1943	0.0415
Chicago, IL	0.0783	0.0204	0.0424	0.0151	0.0150	0.0142	0.0296	0.0314	0.0470
West Palm Beach–Boca Raton, FL	0.7922	0.5847	0.5895	0.4146	0.5078	1.1368	1.1028	1.0023	0.1704
Boston–Worcester–Lawrence–Lowell–MA-NH	0.5223	0.7183	1.1918	1.2904	1.1493	1.5974	2.0438**	1.1216	0.6838
Seattle–Bellevue–Everett, WA	1.3265	2.1514**	1.3000	2.2435**	2.0830**	1.7651*	0.9728	0.9178	0.6126
Sarasota–Bradenton, FL	0.5239	0.7290	0.8896	1.3928	1.3280	0.9660	0.9136	0.8324	0.4598
Milwaukee–Waukesha, WI	0.9720	1.5021	1.2144	1.7936*	1.9767**	1.9644**	1.5705	1.1497	0.8825

Quantiles									
MSA	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Jacksonville, FL	1.0741	1.8793*	2.1737**	1.4697	1.4369	1.5129	1.4428	1.1978	1.0618
Portland–Vancouver, OR–WA	1.5964	1.5876	3.2543***	3.1052***	2.8820***	2.6871***	3.1567***	2.1055**	1.2170
Orlando, FL	0.2242	0.1142	0.1436	0.1765	0.2541	0.2259	0.1878	0.1155	0.0102
Charleston–North Charleston, SC	1.1628	1.4145	1.3444	1.5315	1.8511*	2.4513**	1.6873*	1.6276	0.7773
Pittsburgh, PA	0.0297	0.0125	0.0109	0.0011	0.0069	0.0026	0.0003	0.0003	0.0227
Baltimore, MD	0.8807	1.5390	1.7551*	1.1636	1.5181	1.7940*	1.7453*	1.4437	0.8052
Detroit, MI	1.3360	1.9523*	2.9844***	3.2718***	2.4783**	1.2232	0.8939	1.1375	0.5979
Las Vegas, NV–AZ	1.2482	2.4415**	1.8425*	2.4518**	1.8768*	1.1186	1.0021	0.8975	0.7407
Rochester, NY	1.2886	0.9997	1.5033	2.1694**	2.3091**	3.0241***	2.1271**	1.2446	0.8146
Tucson, AZ	1.3234	1.0723	2.1754**	2.1017**	1.8669*	2.0634**	1.5311	1.5100	0.9449
Knoxville, TN	0.9294	1.3284	1.1705	1.4031	1.8139*	2.0568**	2.2482**	2.2348**	1.1416
Minneapolis–St. Paul, MN–WI	0.8279	1.4193	1.1155	1.4068	1.7771*	2.5054**	2.6168***	2.8726***	1.9257*
Hartford, CT	0.9639	2.0299**	2.4521**	2.3619**	1.5036	1.1521	1.4457	1.1273	0.6974
Springfield, MA	1.7069*	2.1698**	1.8684*	2.0740**	2.1631**	1.2705	0.8792	1.0704	1.1143

Quantiles									
MSA	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Denver, CO	1.2080	2.4052**	3.1959***	2.6348***	1.7198*	1.5048	1.0974	1.3067	0.8487
Providence–Warwick–Pawtucket, RI	1.1515	1.4914	1.9584*	1.9702**	1.9663**	2.5125**	2.7372***	1.6985*	1.2235
Washington, DC–MD–VA–WV	1.1079	1.8825*	2.0805**	1.9628**	2.3268**	2.6011***	3.1993***	2.5861***	1.6609*
Phoenix–Mesa, AZ	1.0222	1.6476*	2.6507***	2.5610**	2.0493**	2.2587**	2.1026**	1.7802*	0.5833
Scranton–Wilkes-Barre–Hazleton, PA	0.7570	1.1224	1.3310	2.3950**	2.4429**	2.9612***	2.3274**	2.4546**	1.6816*
Harrisburg–Lebanon–Carlisle, PA	0.9990	1.5114	1.7468*	1.9619**	2.8813***	1.8169*	1.7417*	1.6672*	0.9664
Bakersfield, CA	1.0639	0.8970	2.5892***	2.2546**	1.8009*	1.7610*	2.5116**	1.4811	0.7470
Philadelphia, PA–NJ	1.3665	1.8516*	1.7397*	2.2293**	3.0995***	2.2630**	1.4608	1.4072	0.7484
Colorado Springs, CO	1.2947	1.9661**	2.7020***	2.4998**	2.7360***	2.1308**	1.9941**	1.7832*	1.2118
Albany–Schenectady–Troy, NY	1.4288	1.8400*	1.6962*	1.8392*	2.0853**	2.9321***	2.2955**	1.9511*	1.0322
Baton Rouge, LA	1.5405	1.8065*	1.9067*	1.7699*	2.2405**	2.0414**	1.5779	1.5663	0.7470
Memphis, TN–AR–MS	1.9584*	2.8592***	3.8258***	3.9451***	3.4101***	2.1399**	1.9956**	2.2495**	1.6166
Buffalo–Niagara Falls, NY	1.7342*	2.8795***	3.0687***	3.4654***	2.7187***	1.8934*	2.0187**	1.8165*	1.2763
Fresno, CA	1.5792	1.5859	2.0167**	2.5058**	3.1755***	3.7592***	2.9497***	1.9863**	1.3931

Quantiles									
MSA	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Mobile, AL	1.5873	2.0574**	2.5170**	2.6588***	2.7147***	2.4968**	3.0013***	2.2005**	1.6771*
Stockton–Lodi, CA	1.2421	1.7719*	2.3989**	3.0228***	2.4810**	1.9310*	2.2088**	2.0231**	1.1430
Raleigh–Durham–Chapel Hill, NC	1.7304*	1.7121*	1.5564	1.9191*	1.9940**	1.7604*	2.0654**	2.4008**	1.7610*
Albuquerque, NM	1.1578	1.7769*	2.3672**	2.7646***	3.8512***	2.3503**	2.1771**	1.8785*	1.1242
Birmingham, AL	0.9247	1.7948*	1.9787**	2.3515**	2.5025**	3.3346***	2.5357**	2.2238**	1.3168
Dallas, TX	2.1536**	3.2999***	4.0244***	3.6804***	2.8397***	2.6609***	2.4549**	2.3625**	1.7889*
Syracuse, NY	1.4190	1.8243*	2.2039**	2.2401**	2.3091**	2.7562***	2.8785***	1.9178*	1.4464
Toledo, OH	1.2193	2.0333**	2.2469**	2.0911**	2.5175**	2.7884***	3.3375***	2.7302***	1.7709*
Nashville, TN	1.8309*	2.7301***	3.4952***	3.4010***	2.9874***	2.3399**	2.6290***	2.9454***	2.0077**
Houston, TX	1.4731	1.5189	2.0764**	2.2869**	2.6411***	2.7310***	2.9190***	2.4201**	1.2746
Louisville, KY–IN	1.7590*	2.0245**	2.2745**	2.1711**	1.9693**	1.6940*	1.4193	1.2770	1.1261
El Paso, TX	1.6071	1.6035	3.2674***	3.1187***	2.9011***	2.7018***	3.1655***	2.1168**	1.2268
St. Louis, MO–IL	1.6979*	2.1327**	2.0580**	2.3715**	3.1767***	2.5749**	1.6855*	1.6462*	0.9160
Grand Rapids–Muskegon–Holland, MI	1.3830	2.1189**	2.8493***	2.6240***	2.8924***	2.2741**	2.1277**	1.8781*	1.2852

Quantiles									
MSA	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Cincinnati, OH–KY–IN	1.4276	1.7081*	1.6916*	3.2130***	2.6618***	2.7388***	2.0568**	1.7322*	1.0176
Atlanta, GA	1.1597	2.0861**	2.2544**	1.9151*	2.1358**	2.5020**	2.5864***	2.0286**	1.2088
Akron, OH	1.3681	1.4483	1.5130	1.9876**	2.0251**	1.8975*	1.7117*	1.9233*	1.1918
Richmond–Petersburg, VA	1.1380	1.6732*	2.5305**	2.9522***	2.1733**	1.0307	0.7218	0.8730	0.3825
Youngstown–Warren, OH	1.0673	0.8120	1.2339	1.8985*	1.9496*	2.5551**	1.7199*	0.9278	0.5679
Columbia, SC	1.0899	0.8096	1.7444*	1.6330	1.4198	1.7113*	1.3049	1.2619	0.7193
Columbus, OH	0.5767	1.1656	1.4594	2.0776**	1.4285	1.4978	1.0568	0.9371	0.6818
Greenville–Spartanburg–Anderson, SC	1.3893	2.0681**	2.5085**	2.6938***	2.3514**	2.0502**	1.7485*	1.2987	0.7215
Little Rock–North Little Rock, AR	0.4724	0.6745	1.0939	0.7762	1.1838	0.6972	0.8240	0.8068	0.3496
San Antonio, TX	0.5114	1.0929	1.2055	1.2786	1.6673*	2.7928***	1.8211*	1.5456	0.7899
Austin–San Marcos, TX	1.0708	1.5119	1.1402	1.2476	1.3066	0.5248	0.2587	0.4986	0.7598
Charlotte–Gastonia–Rock Hill, NC–SC	0.6165	0.8297	1.3283	1.4147	1.2774	1.7696*	2.1862**	1.2142	0.7585
Greensboro–Winston–Salem–High Point, NC	0.4463	1.0402	1.1558	1.3421	0.9448	1.3012	2.0395**	1.7061*	1.0543
Kansas City, MO–KS	1.7648*	2.5646**	1.9925**	2.8205***	2.7256***	1.9966**	1.3909	1.4963	1.0217

Quantiles									
MSA	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Oklahoma City, OK	2.4923**	3.1768***	3.9544***	4.4959***	4.2997***	4.0092***	3.6874***	3.0245***	2.1822**
Tulsa, OK	1.2549	1.8172*	2.1911**	2.2828**	3.1208***	2.0177**	2.0014**	2.0320**	1.1488
Omaha, NE–IA	1.0514	1.8565*	2.1434**	1.4386	1.3987	1.4674	1.4104	1.1597	1.0404
McAllen–Edinburg–Mission, TX	1.5781	1.5605	3.2318***	3.0817***	2.8491***	2.6618***	3.1415***	2.0862**	1.2003
Dayton–Springfield, OH	0.7699	0.9734	1.5553	1.6369	1.8718*	1.3761	1.3163	1.2357	0.7780
Indianapolis, IN	1.2560	1.5460	1.4584	1.6395	1.9304*	2.6180***	1.8842*	1.7453*	0.8653
Fort Wayne, IN	0.4695	0.7598	1.0543	1.1525	0.9726	1.7609*	1.5190	0.9813	0.7564
Wichita, KS	0.7452	0.7934	0.9622	1.5843	1.6864*	1.4958	1.0378	1.4877	0.8458

Note: ***, ** and *** indicate rejection of the null hypothesis of no Granger causality running from the housing search activity index (HSI) to housing price returns (HR) for a particular quantile at 1%, 5% and 10% levels of significance (i.e., critical values of 2.575, 1.96 and 1.645 of the standard normal test statistic) respectively.

Table 1 (Panel B). *k*-th order causality-in-quantiles test results for squared housing returns (volatility) at local (MSA) level using monthly data: 2004:01-2021:01

	Quantiles								
MSA	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Miami, FL	0.8703	0.8950	1.3486	1.8427*	2.2876**	2.2929**	2.1602**	1.9359*	1.2383
Los Angeles–Long Beach, CA	0.7213	1.2580	1.1667	1.2354	1.2994	0.8677	0.8762	1.0332	0.3263
San Francisco, CA	0.7275	1.2885	1.5128	1.5848	1.8735*	2.4123**	2.8068***	1.8178*	1.3707
San Diego, CA	0.0747	0.3316	0.4756	0.5282	0.2470	0.4307	0.3147	0.1035	0.1510
Salt Lake City–Ogden, UT	0.5626	0.7968	0.8965	0.6792	1.8796*	1.4745	1.7500*	2.0929**	0.7326
New York, NY	1.9700**	2.5368**	3.0200***	2.8922***	2.8510***	2.6424***	2.5665**	2.8133***	2.0357**
New Orleans, LA	2.0347**	2.8877***	3.1719***	3.7951***	3.4485***	3.3966***	3.1575***	2.7593***	1.8943*
Chicago, IL	2.5074**	3.0688***	3.2208***	3.0966***	3.3560***	3.3225***	3.3806***	2.5228**	1.8023*
West Palm Beach–Boca Raton, FL	2.3858**	3.5280***	3.6042***	3.2835***	3.2161***	3.1981***	3.0464***	2.9806***	1.9629**
Boston–Worcester–Lawrence–Lowell–MA-NH	2.3321**	3.6856***	3.8455***	3.7483***	3.7849***	3.9532***	4.0359***	3.4730***	2.4074**
Seattle–Bellevue–Everett, WA	1.7174*	3.2167***	3.4201***	4.0392***	3.5926***	3.3423***	3.0351***	2.9114***	1.3935
Sarasota–Bradenton, FL	0.0042	0.0125	0.0049	0.0026	0.0069	0.0011	0.0003	0.0056	0.0019

Quantiles									
MSA	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Milwaukee–Waukesha, WI	0.4985	0.5995	0.5232	1.2423	1.2790	1.3837	1.5230	0.7894	0.3720
Jacksonville, FL	1.2901	3.1035***	3.2118***	2.8427***	2.5329**	2.2116**	1.4379	0.7276	0.5150
Portland–Vancouver, OR–WA	0.4586	0.6138	0.9899	1.3995	1.2190	1.2726	2.0073**	0.8690	0.3902
Orlando, FL	2.4296**	3.9410***	3.4785***	3.6268***	3.7040***	3.4718***	3.0547***	2.9759***	1.8225*
Charleston–North Charleston, SC	0.3375	0.3577	0.7429	0.7065	1.2109	1.2095	0.7105	1.0772	0.5840
Pittsburgh, PA	2.5278**	3.0941***	3.3136***	3.6568***	4.0745***	3.9911***	3.3000***	2.2853**	1.7135*
Baltimore, MD	1.9005*	3.0557***	4.1613***	4.3945***	4.3343***	4.7444***	5.2918***	4.2823***	2.2293**
Detroit, MI	0.9201	0.9385	1.4495	1.9332*	2.3648**	2.3560**	2.2123**	1.9660**	1.2604
Las Vegas, NV–AZ	1.4486	1.6593*	1.4347	1.6429	2.2149**	2.0583**	1.7868*	1.5392	0.8722
Rochester, NY	0.6384	1.1238	1.3760	1.4089	1.7111*	2.2279**	2.5964***	1.5997	1.1879
Tucson, AZ	0.9062	1.9164*	2.5067**	2.1125**	2.1777**	2.0804**	1.4190	1.2101	1.2126
Knoxville, TN	0.9554	1.8263*	2.0436**	1.7790*	2.4685**	2.2650**	2.3140**	2.5703**	1.2816
Minneapolis–St. Paul, MN–WI	1.3702	1.8024*	2.2160**	1.8775*	1.8316*	1.6450*	1.8495*	2.2751**	1.6257
Hartford, CT	1.7256*	2.5832***	3.0645***	2.6259***	1.7448*	1.4598	1.8168*	1.5229	0.8309

Quantiles									
MSA	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Springfield, MA	0.7719	1.2192	1.2653	1.3262	1.4975	1.6951*	2.4270**	1.6050	0.6698
Denver, CO	2.0919**	2.5273**	2.6077***	2.9588***	3.0687***	3.2438***	2.7256***	2.1361**	1.7162*
Providence–Warwick–Pawtucket, RI	1.1044	2.3733**	2.0048**	1.8707*	2.2137**	2.0510**	1.7915*	2.0273**	1.3533
Washington, DC–MD–VA–WV	1.2803	2.2880**	2.5206**	2.1444**	2.0815**	2.4187**	2.6160***	2.3878**	1.7671*
Phoenix–Mesa, AZ	1.3113	3.0041***	2.8881***	3.5670***	3.0388***	2.1941**	2.0342**	1.9509*	0.7595
Scranton–Wilkes-Barre–Hazleton, PA	1.0561	1.2866	1.1985	1.8976*	2.0250**	2.4707**	2.6621***	1.7903*	0.9243
Harrisburg–Lebanon–Carlisle, PA	1.2589	3.0361***	3.1269***	2.7738***	2.4950**	2.1588**	1.3991	0.6818	0.5005
Bakersfield, CA	1.1184	1.8107*	2.1036**	2.6435***	2.6641***	2.0956**	2.6565***	1.6240	1.1635
Philadelphia, PA–NJ	1.3496	1.9497*	2.1062**	2.3734**	2.5730**	2.9948***	3.7178***	2.5190**	1.7351*
Colorado Springs, CO	1.0634	1.8171*	1.9610**	2.5025**	2.7436***	2.4228**	2.2589**	2.5706**	1.2080
Albany–Schenectady–Troy, NY	0.9097	1.5745	3.0043***	3.9817***	3.7736***	3.0433***	3.3014***	1.5944	0.8832
Baton Rouge, LA	0.9090	2.0467**	2.8309***	2.6395***	2.6998***	3.1491***	3.5969***	2.7533***	1.3631
Memphis, TN–AR–MS	1.7452*	2.9557***	3.0763***	3.8195***	3.3128***	2.8290***	2.7686***	2.7780***	1.9302*
Buffalo–Niagara Falls, NY	2.5312**	2.8628***	3.1145***	3.3351***	3.7601***	3.5848***	3.6605***	2.9605***	2.2033**

Quantiles									
MSA	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Fresno, CA	2.1116**	2.5803***	3.0367***	2.8128***	3.1856***	2.9397***	2.9705***	2.2250**	1.9952**
Mobile, AL	2.0718**	2.9141***	2.9610***	3.0311***	3.0133***	3.1211***	2.6828***	2.7084***	1.9030*
Stockton–Lodi, CA	2.3866**	3.5564***	3.9375***	3.8241***	4.1971***	4.1110***	3.8094***	3.2976***	2.3427**
Raleigh–Durham–Chapel Hill, NC	2.5448**	3.3876***	4.1297***	4.0599***	4.0583***	3.9497***	3.5219***	3.2509***	2.4664**
Albuquerque, NM	2.6521***	3.6986***	3.8698***	4.4678***	4.3920***	4.2729***	3.9686***	3.4709***	2.5719**
Birmingham, AL	2.3044**	3.0809***	3.3656***	3.4531***	3.5504***	3.2768***	2.9780***	2.8053***	2.1962**
Dallas, TX	2.9449***	4.0323***	4.6233***	4.8084***	4.5618***	4.5782***	4.2095***	3.6711***	2.9286***
Syracuse, NY	3.0918***	4.0467***	4.6168***	4.8342***	4.3974***	3.7560***	3.6350***	3.1527***	2.5518**
Toledo, OH	2.3007**	3.6586***	3.8203***	3.7104***	3.7419***	3.9179***	4.0102***	3.4479***	2.3914**
Nashville, TN	2.2370**	3.0924***	3.2461***	3.8869***	3.7642***	3.5127***	3.2286***	3.3857***	2.1694**
Houston, TX	2.7515***	3.9438***	4.4109***	4.2427***	4.3691***	4.2894***	3.9229***	3.5593***	2.5118**
Louisville, KY–IN	2.5604**	3.5874***	4.3698***	3.6192***	4.0795***	3.9993***	3.6115***	3.1413***	2.0755**
El Paso, TX	2.2442**	3.0897***	3.0920***	3.3278***	3.1480***	3.1096***	2.9105***	2.9025***	2.1632**
St. Louis, MO–IL	2.2421**	2.9522***	3.3401***	3.2736***	3.5053***	3.5653***	3.8323***	3.2400***	2.3885**

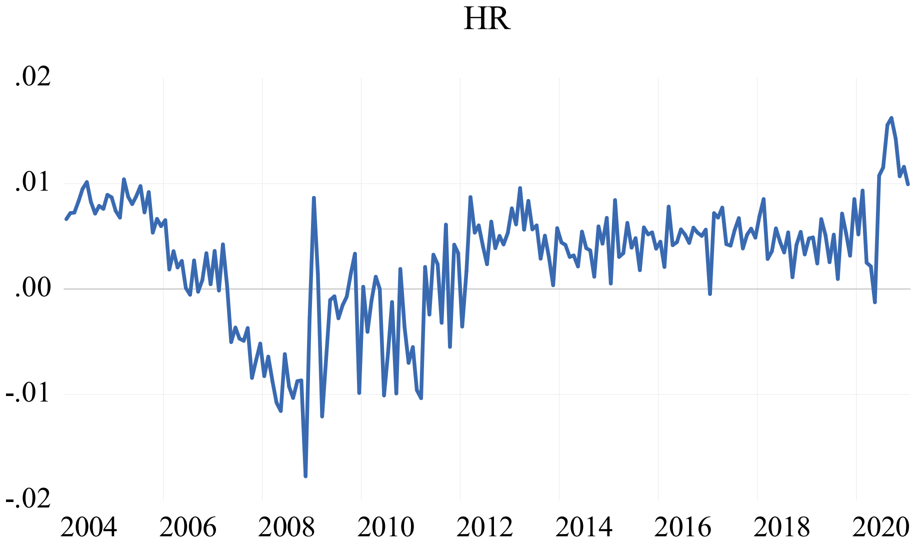
Quantiles									
MSA	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Grand Rapids–Muskegon–Holland, MI	2.5279^{**}	4.0167^{***}	3.6860^{***}	3.9030^{***}	3.9668^{***}	3.7672^{***}	3.3539^{***}	3.2432^{***}	2.0050^{**}
Cincinnati, OH–KY–IN	2.2388^{**}	2.9998^{***}	3.4880^{***}	3.7923^{***}	4.1827^{***}	4.3543^{***}	3.7351^{***}	3.4423^{***}	2.5692^{**}
Atlanta, GA	2.5835^{***}	3.1895^{***}	3.4345^{***}	3.7882^{***}	4.1923^{***}	4.1291^{***}	3.4081^{***}	2.4040^{**}	1.8084^{*}
Akron, OH	2.2533^{**}	3.4198^{***}	3.9638^{***}	3.8596^{***}	3.6327^{***}	3.7273^{***}	3.7135^{***}	3.2775^{***}	2.3498^{**}
Richmond–Petersburg, VA	0.7017	0.7832	1.0523	1.5680	2.0568^{**}	2.1281^{**}	1.9971^{**}	1.7976^{*}	1.1402
Youngstown–Warren, OH	1.9397^{*}	2.8534^{***}	3.1442^{***}	2.9138^{***}	2.8365^{***}	2.5522^{**}	2.6584^{***}	2.5106^{**}	1.7579^{*}
Columbia, SC	0.2409	0.8537	1.2956	0.9853	0.6724	0.8433	0.5656	0.3082	0.3845
Columbus, OH	0.5614	0.7676	1.3391	1.1282	1.6215	1.4030	1.5389	1.2441	1.1088
Greenville–Spartanburg–Anderson, SC	0.7214	1.2265	1.6382	1.6722^{*}	1.2023	0.7185	0.8307	1.4257	0.5427
Little Rock–North Little Rock, AR	0.5026	0.6365	0.8494	1.6220	1.3867	0.8672	1.1021	0.8013	0.4811
San Antonio, TX	0.9044	0.8797	0.6511	0.7969	0.7757	0.6941	1.2459	0.7842	0.3383
Austin–San Marcos, TX	0.7190	0.9101	1.2932	1.1730	1.7133^{*}	2.4632^{**}	2.1453^{**}	1.3625	0.8940
Charlotte–Gastonia–Rock Hill, NC–SC	1.5769	2.4250^{**}	1.6712^{*}	1.6665^{*}	2.0390^{**}	2.0765^{**}	0.9206	0.8035	0.8019
Greensboro–Winston–Salem–High Point, NC	1.8372^{*}	0.8819	0.6037	0.7192	0.7967	0.8120	0.8495	1.0102	0.4916

Quantiles									
MSA	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Kansas City, MO–KS	1.6603*	3.1778***	3.3138***	3.9360***	3.4434***	3.1102***	2.8301***	2.7626***	1.2862
Oklahoma City, OK	0.7622	0.8718	0.8250	1.5776	1.7039*	2.0880**	2.2510**	1.3679	0.6632
Tulsa, OK	0.7513	0.9374	1.3036	1.3077	1.7797*	2.0324**	1.7535*	1.1327	0.4420
Omaha, NE–IA	1.2067	2.9158***	2.9786***	2.6564***	2.4341**	2.0698**	1.3378	0.6098	0.4794
McAllen–Edinburg–Mission, TX	0.6717	1.2159	1.7774*	0.7030	1.0303	0.9283	0.7171	0.6253	0.3363
Dayton–Springfield, OH	1.0504	1.7978*	1.9333*	2.4781**	2.7191***	2.4009**	2.2392**	2.5539**	1.1952
Indianapolis, IN	1.2693	1.5350	1.5973	2.2893**	2.3702**	2.0141**	1.4383	1.1400	0.7896
Fort Wayne, IN	0.5610	1.0066	1.5165	1.9027*	1.7622*	1.5717	0.8940	0.8619	0.6646
Wichita, KS	0.3596	1.0858	0.7555	1.5275	1.3643	0.9991	0.8174	0.7549	0.4577

Note: ***, ** and * indicate rejection of the null hypothesis of no Granger causality running from the housing search activity index (HSI) to squared housing price returns (HR^2) for a particular quantile at 1%, 5% and 10% levels of significance (i.e., critical values of 2.575, 1.96 and 1.645 of the standard normal test statistic) respectively.

Appendix

Figure A1. Data Plots of Housing Price Returns (HR) and Housing Search Activity Index (HSI)



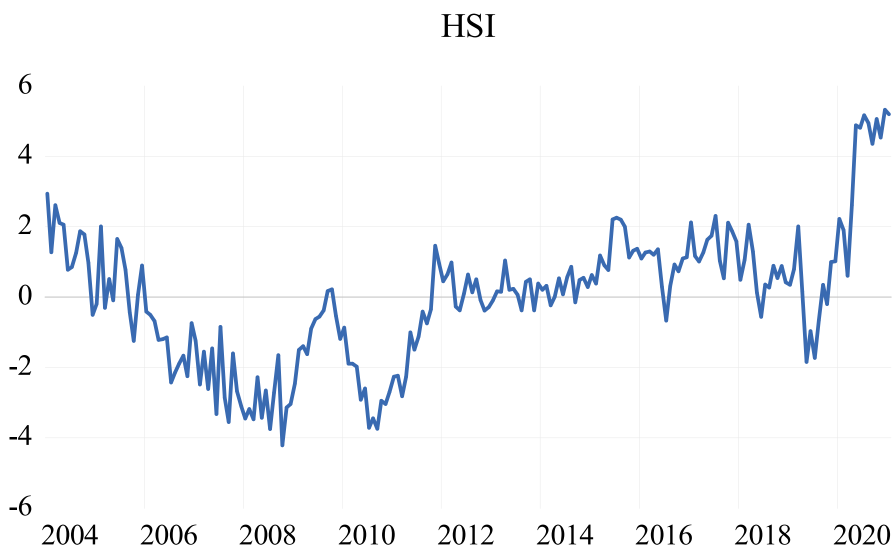


Table A1. Summary Statistics

Statistic	Variable	
	Housing Price Returns (HR)	Housing Search Activity Index (HSI)
Mean	0.0027	0.0000
Median	0.0041	0.2032
Maximum	0.0162	5.3304
Minimum	-0.0178	-4.2176
Std. Dev.	0.0057	1.9094
Skewness	-0.8805	0.2334
Kurtosis	3.7467	3.4026
Jarque-Bera	31.2536^{***}	3.2452
Observations	205	

Note: Std. Dev: stands for standard deviation; The null hypotheses of the Jarque-Bera test correspond to the null of normality; *** indicates rejection of the null hypothesis at the 1% level of significance.

Table A2. Brock *et al*. (1996, BDS) Test of Nonlinearity

Independent Variable	Dimension (*m*)				
	2	3	4	5	6
HSI	2.0535^{**}	4.1866^{***}	4.5429^{***}	5.1949^{***}	5.6212^{***}

Note: Entries correspond to the *z*-statistic of the BDS test with the null of *i.i.d.* residuals, with the test applied to the residuals recovered from the housing returns equation with one lag each of housing price returns and housing search activity index (HSI); ** and *** indicates rejection of the null hypothesis at 5% and 1% levels of significance, respectively.