High-Frequency Predictability of Housing Market Movements of the United States: The Role of Economic Sentiment

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Abstract

We analyse the ability of a newspaper-based economic sentiment index of the United States to predict housing market movements using daily data over the period 2nd August, 2007 to 19th June, 2020. For this purpose, we use a *k*-th order nonparametric causality-in-quantiles test, which allows us to test for predictability over the entire conditional distribution of not only housing returns, but also volatility, by controlling for misspecification due to nonlinearity and structural breaks – both of which we show to exist between housing returns and the economic sentiment index. Our results show that economic sentiment does indeed predict housing returns (unlike the conditional mean-based, i.e., linear, Granger causality test and volatility), barring the extreme upper ends of the respective conditional distributions. Our results have important implications for academics, policymakers, and investors.

Keywords: Economic Sentiment; Housing Returns and Volatility; Higher-Order Nonparametric Causality in Quantiles Test

JEL Codes: C22; C32; R30

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1. Introduction

Despite the large body of literature that associates investor sentiment with stock market movement (for a detailed review see Balcilar et al., 2018a), very few recent studies highlight the role of sentiment in predicting the aggregate and regional housing returns and volatility of the United States (see, for example, Soo, 2018; Cox and Ludvigson, 2019; Bork et al., 2020; Gupta et al., 2020).[1] While these studies are indeed insightful, they are conducted using low frequency (quarterly or annual) data and mostly use housing sentiment which reflects house buying conditions (e.g., Bork et al., 2020; Gupta et al., 2020). We aim to extend this growing body of literature by analysing, for the first time, the predictability of economic sentiment for daily housing returns and volatility of the CME-S&P/Case-Shiller House Price Index (HPI) Continuous Futures (CS CME). House price movements lead business cycles (Balcilar et al., 2014; Nyakabawo et al., 2015; Emirmahmutoglu et al., 2016), and information as to where they are headed on a daily basis would be valuable to policymakers for understanding the future path of monthly and quarterly real activity variables using mixed-frequency models (BańBura et al., 2011). Moreover, high frequency predictability of housing returns and volatility would assist investors in making timely portfolio allocation decisions (Nyakabawo et al., 2018; Segnon et al., 2020).

For our purpose, we use the *k*-th order nonparametric causality-in-quantiles framework of Balcilar et al. (2018b). This econometric model allows us to test the predictability of the entire conditional distributions of both housing returns and volatility simultaneously, by controlling for misspecification due to uncaptured nonlinearity and regime changes with economic sentiment - both of which we show to exist via formal statistical tests. The remainder of the paper is organized as follows: Section 2 outlines the methodology, Section 3 discusses the data and econometric results, and Section 4 concludes the paper.

2. Econometric Methodology

In this section, we briefly present the methodology for testing nonlinear Granger causality via a hybrid approach developed by Balcilar et al. (2018b), based on the frameworks of Nishiyama et al. (2011) and Jeong et al. (2012).

[1] The role of sentiment impacting overall and regional US home sales has also been studied by Dua and Smyth (1995), Baghestani et al. (2013), Baghestani (2017), and Gupta et al. (2019).

Let y_t denote housing returns and x_t the metric of economic sentiment, details of which we discuss below in the data segment. 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 q-th quantile hypotheses to be tested are:

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

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

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

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

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

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

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

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. (2018b) a rescaled version of $\hat{J}_T$ has the standard normal distribution. The 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 6 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. Data and Results

To measure economic sentiment (ES), we use a daily newspaper based index developed by Shapiro et al. (2020). The ES Index (ESI) is a high frequency measure of economic sentiment based on lexical analysis of economics-related news articles derived from 16 major US newspapers (with extensive regional and national coverage) compiled by the news aggregator service LexisNexis. Saphiro et al. (2020) selected articles with at least 200 words where LexisNexis identifies the article's topic as "economics" and the country subject as "United States". A sentiment-scoring model tailored specifically for newspaper articles has been developed by combining publicly available lexicons with a news-specific lexicon constructed by the authors. Saphiro et al. (2020) aggregate the individual article scores into a daily time-series measure of news sentiment, by relying on a statistical adjustment that accounts for changes over time in the composition of the sample across the newspapers. The daily ESI is based on a trailing weighted-average of time series, with the weights declining geometrically in terms of the length of time since the publication of the article. The data for the sentiment index is publicly available for download from: https://www.frbsf.org/economic-research/indicators-data/daily-news-sentiment-index/. For daily house prices, from which log-returns (HR) are computed,[2] we use the CME-S&P/Case-Shiller HPI Continuous Futures (CS-CME) derived from Datastream. Our sample ranges from 2nd August, 2007 to 19th June, 2020,

[2] The log-returns ensure that the house price data is mean-reverting, while the metric for the economic sentiment is stationary in levels, which in turn meets the data requirements of the test employed. The augmented Dickey-Fuller test (ADF; Dickey and Fuller, 1979) of stationarity is reported in Table A1, and shows the rejection of the null of unit root at the 1% level for both HR and ESI.

i.e., 3362 observations, based on data availability of these two variables of concern.[3] The HR and ESI data are summarized in Table A1, and plotted in Figure A1 in the Appendix to the paper. A Bayesian estimation of a Dynamic Conditional Correlation-Generalised Autoregressive Conditional Heteroskedasticity model of Engle (2002), as outlined in Balcilar et al. (2018c), indicates a positive time-varying correlation between HR and ESI (as can be seen from Figure A1(c)), i.e., a bullish (bearish) housing market is related to stronger (weaker) sentiment. 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.

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 6, as determined by the SIC. The resulting $\chi^2(6)$ statistic associated with the causality running from ESI to HR is 11.1067 with a *p*-value of 0.0851, i.e., the null hypothesis that sentiment does not Granger cause housing returns cannot be rejected at the conventional 5% level of significance (though weak evidence at the 10% level is indeed detected). Therefore, based on the standard linear test, we can conclude no significant impact of ESI on HR.

Given the insignificant results obtained from the linear causality tests, we statistically examine the presence of nonlinearity and structural breaks in the relationship between the ESI and HR. Nonlinearity and regime changes, if present, would motivate 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 apply the Brock et al. (1996) (BDS) test on the residual derived from the HR equation involving six lags each of HR and ESI. 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 economic sentiment and housing 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 ESI,

[3] Note that the ESI data actually goes as far back as 1st January, 1980.

allowing for heterogenous error distributions across the breaks. When we apply these tests to the HR equation involving six lags each of HR and ESI, we detect two breaks on 12th August, 2009, and 5th August, 2011, associated with the global financial and European sovereign debt crises.

Given the strong evidence of nonlinearity and structural breaks in the relationship between HR and ESI, we now turn our attention to the causality-in-quantiles test, which is robust to misspecification due to its nonparametric nature, besides allowing us to test for predictability over the entire conditional distributions of returns and volatility. In Table 1, we present the results for the *k*-th order causality-in-quantiles test for housing returns and squared housing returns, i.e., volatility, emanating from the ESI over the quantile range 0.05 to 0.95. As can be seen, unlike the linear causality test result, ESI causes HR at a 1% level of significance over all the quantiles of the conditional distribution considered, barring the extreme quantile of 0.95, with the strongest effect felt at the lowest quantile of 0.05.[4] For volatility, we draw a similar conclusion as for returns, with the slight difference that now, causality from ESI is absent at quantile 0.90 as well as 0.95. In other words, ESI causes both housing returns and volatility, barring the extreme upper ends of the conditional distributions corresponding to the highest possible conditional returns and variance. Understandably, this result originates from the ability of our approach to control for the presence of nonlinearity (as shown in Table A2) and structural breaks via the use of data-driven nonparametric functional forms defining the relationship between housing market movements and economic sentiment. The pattern in terms of the strength of causality also makes sense when one accounts for the evidence that investors are involved in herding in the housing market during bullish periods (Ngene et al., 2017) and high episodes of overall economic uncertainty (Babalos et al., 2015), which spills over to real estate-related uncertainty, i.e., volatility (Gabauer and Gupta, 2020). Given this, the strength of predictability for housing returns and volatility due to ESI declines at higher quantiles. In other words, economic agents tend to use the information content of economic sentiment

[4] When we use the DCC-Multivariate GARCH (DCC-MGARCH) approach of Lu et al., (2014) to capture the time-varying causality from ESI on to HR (based on 6 lags), we observe, as plotted in Figure A2(a) in the Appendix, that stronger evidence of sentiment-based predictability on housing returns is indeed observed during bearish phases of the housing market (as depicted via negative or low returns in Figure A1). Though we are unable to analyse the impact of ESI on volatility of HR in this framework, we can see the instantaneous spillover of sentiment on HR in Figure A2(b), which reveals a similar pattern to the causality test results in Figure A2(a). In examining Figures A2(a) and A2(b), the reader must keep in mind that the DCC-MGARCH Hong test is asymptotically normally distributed.

relatively strongly during bearish housing returns, and phases of lower volatility (risks) in the market resulting from lower trading,[5] to improve their investment position.[6]

[INSERT TABLE 1]

Next, we carry out an additional analysis to ensure the robustness of our results. We reconduct our causality-in-quantiles test based on housing returns derived from a new set of daily housing price series constructed by Bollerslev et al. (2016). The daily housing price series covers ten US metropolitan statistical areas (MSAs). Following Wang (2014), we use the daily composite housing index ($P_{c,t} = \sum_{i=1}^{10} w_i P_{i,t}$) as a proxy for the aggregate US housing price, which is ,in turn, computed as a weighted average. The 10 MSAs and the specific values of the weights (w_i) used are: Boston (0.212), Chicago (0.074), Denver (0.089), Las Vegas (0.037), Los Angeles (0.050), Miami (0.015), New York (0.055), San Diego (0.118), San Francisco (0.272), and Washington D.C. (0.078), representing the total aggregate value of the housing stock in the 10 MSAs in the year 2000 (Wang, 2014). In Tables 2(a) and 2(b), we report the result of the *k*-th order causality-in-quantiles test from the ESI on housing returns and volatility of the aggregate US as well as the 10 MSAs.[7] In general, ESI is again found to be a predictor of not only national, but also regional housing returns and volatility, based on our higher-order nonparametric causality-in-quantiles test applied to an alternative data set, with again stronger evidence of predictability observed at lower quantiles in particular for the (aggregate and MSA-level) housing returns.

[INSERT TABLE 2]

[5] The statistically significant positive relationship between housing returns shocks and (conditional) volatility is confirmed using asymmetric GARCH frameworks, namely the exponential GARCH (EGARCH; Nelson, 1991), and GJR (Glosten et al., 1993) models. Complete details of the estimation results of the asymmetric GARCH models are available upon request from the authors.

[6] This line of reasoning is further vindicated by the similar pattern of results reported in Table A2 in the Appendix to the paper, wherein we analyse the impact of a daily newspaper-based index of equity market volatility originating from infectious diseases (as developed by Baker et al., 2020) on the CS-CME housing returns and volatility, using the causality-in-quantiles model (with p = 5, based on SIC) over the period 2nd August, 2007 to 24th June, 2020. The data of this index is freely available for download from: http://policyuncertainty.com/infectious_EMV.html, and helps us capture the negative influence of COVID-19 (among other pandemics such as swine flu, Middle East respiratory syndrome (MERS), Ebola, and bird flu that the world has witnessed since 2007) on economic sentiment (as observed from Figure A1 starting from January, 2000), and the resultant impact on housing market movements.

[7] The data coverage varies across the MSAs, and is as follows: Boston: 5th January, 1995 to 11th October, 2012; Chicago: 3rd September, 1999 to 12th October, 2012; Denver: 5th May, 1999 to 17th October, 2012; Las Vegas: 5th January, 1995 to 17th October, 2012; Los Angeles: 5th January, 1995 to 17th October, 2012; Miami: 3rd April, 1998 to 15th October, 2012; New York: 5th January, 1995 to 23rd October, 2012; San Diego: 4th January, 1996 to 23rd October, 2012; San Francisco: 5th January, 1995 to 18th October, 2012; Washington D.C.: 5th June, 2001 to 23rd October, 2012, and the Aggregate US: 5th June, 2001 to 11th October, 2012.

4. Conclusion

Recently, a growing number of studies relate sentiment with first- and second-moment movements of US housing returns. In this paper, we aim to extend these studies based on low frequency (i.e., quarterly and annual) data by carrying out a high frequency analysis using daily data on housing returns and economic sentiment over the period 2nd August, 2007 to 19th June, 2020. We use a recently developed *k*-th order nonparametric causality-in-quantiles test, which allows us to test for predictability over the entire conditional distributions of both housing returns and volatility, by controlling for misspecification due to uncaptured nonlinearity and structural changes – both of which we show to exist in the relationship between housing returns and economic sentiment. Our results point out that the newspaper-based index of economic sentiment does predict US housing returns and volatility, barring the extreme upper end of the respective conditional distributions.

Since our predictive analysis is performed at the highest possible frequency associated with housing returns, our results can be used by policymakers to obtain daily information about where the housing market is headed due to changes in economic sentiment, and predict the future path of low frequency economic activity variables at the daily frequency, given that house price movements are known to lead US business cycles. Moreover, daily predictions of housing returns and volatility contingent on economic sentiment would also help investors 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 sentiment, but this result is also contingent on the phase of the housing returns. Specifically, inefficiency is observed during bearish phases, but the market seems to be efficient during bullish regimes - an observation in line with the results Tiwari et al. (2020) obtain using the same dataset. In other words, our results have important implications for policy authorities, investors, and academics.

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Table 1. *k*-th Order Causality-in-Quantiles Test Results due to Economic Sentiment Index (ESI)

Quantile	Housing Returns	Squared Housing Returns (Volatility)
0.05	8404.4211***	7836.8810***
0.10	5401.5888***	5041.4440***
0.15	3999.7032***	3721.3500***
0.20	3126.7289***	2892.6110***
0.25	2509.0658***	2302.9160***
0.30	2039.6634***	1853.1590***
0.35	1666.6286***	1495.1420***
0.40	1361.2633***	1202.1470***
0.45	1106.2142***	957.9986***
0.50	890.3012***	752.2868***
0.55	705.9853***	578.0249***
0.60	548.0253***	430.4139***
0.65	412.7220***	306.1591***
0.70	297.4856***	203.1018***
0.75	200.6045***	120.0710***
0.80	121.1778***	57.6376***
0.85	59.2715***	15.6615***
0.90	16.6506***	0.0019
0.95	0.2602	0.0120

Note: *** indicates rejection of the null hypothesis of no Granger causality at 1% level of significance (critical value of 2.575) from the ESI to housing returns and volatility for a particular quantile.

Table 2(a). *k*-th Order Causality-in-Quantiles Test Results for Housing Returns

Quantile	Boston	Chicago	Denver	Las Vegas	Los Angeles	Miami	New York	San Diego	San Francisco	Washington D.C.	US
0.05	1.6892*	6.3991***	1.7403*	1.0319	1.7933*	2.7755***	0.7503	1.1563	4.3143***	2.1202**	5.0084***
0.10	2.4573**	8.4140***	2.5687**	1.8872*	3.2894***	5.5010***	1.2369	2.8959***	7.3286***	4.4308***	9.0810***
0.15	2.9712***	10.3125***	4.3425***	3.9211***	3.8918***	6.4916***	2.3423**	2.7892***	8.3596***	5.6826***	10.8068***
0.20	2.7370***	10.8174***	4.6992***	4.7030***	4.3338***	7.5691***	3.0944***	3.5586***	6.2613***	6.7855***	11.8063***
0.25	3.0367***	9.3740***	4.5599***	6.5610***	4.9294***	8.0065***	3.4011***	3.2035***	5.3194***	6.4594***	10.8822***
0.30	3.3841***	6.9919***	5.0732***	6.3412***	5.0967***	7.8966***	3.0073***	3.7856***	4.8759***	5.9829***	9.1341***
0.35	3.5731***	5.3824***	5.7548***	7.3543***	5.5446***	7.0374***	3.3642***	2.8856***	4.0637***	4.8687***	7.9181***
0.40	3.591***	3.4783***	5.1303***	6.7087***	5.6112***	7.1390***	3.4271***	2.8645***	2.9048***	4.1781***	6.3364***
0.45	3.636***	2.1065**	4.4591***	6.2726***	5.7864***	5.8717***	2.8081***	2.9420***	2.3694**	2.4737**	5.5194***
0.50	3.809***	1.0789	3.9859***	5.4169***	5.1030***	5.5794***	2.0196***	2.3837***	1.1537	1.8274*	4.1083***
0.55	3.965***	0.4709	3.6757***	4.0573***	4.4088***	5.2688***	2.0094***	1.5471	1.3760	1.2237	2.6647***
0.60	3.9403***	0.4578	3.2797***	4.0790***	3.5799***	4.5120***	1.6128	1.0203	1.3796	0.9592	2.5288**
0.65	3.8076***	1.6204	3.5710***	3.6607***	3.3833***	4.3823***	1.4752	0.8754	0.9573	1.0557	2.2587**
0.70	3.984***	3.5044***	2.9884***	3.4120***	3.1920***	3.9874***	1.3861	0.8136	0.7333	1.1953	1.7272*
0.75	3.7043***	4.8465***	2.6167***	3.1963***	3.0146***	4.1170***	1.5264	0.5301	0.7136	1.3440	1.2690
0.80	3.3152***	5.8111***	2.7163***	3.9996***	2.7778***	4.0072***	1.2398	0.4576	0.6811	1.9245	1.3148
0.85	2.5594**	5.8861***	2.2289**	2.9582***	2.7701***	3.0498***	1.0889	0.3008	0.9835	3.0129***	1.3447
0.90	2.0669**	6.2840***	1.8535*	2.5131**	2.3011**	2.9563***	0.9739	0.4233	0.9128	2.2205**	0.7154
0.95	1.4139	2.9758***	1.4025	1.9479*	1.4320	1.9218*	0.7183	0.6266	0.7498	1.3496	0.7669

Note: ***, **, and * indicate rejection of the null hypothesis of no Granger causality at 1%, 5% and 10% levels of significance (i.e., critical values of 2.575, 1.96 and 1.645) respectively from economic sentiment index (ESI) to housing returns for a particular quantile.

Table 2(b). *k*-th Order Causality-in-Quantiles Test Results for Squared Housing Returns (Volatility)

Quantile	Boston	Chicago	Denver	Las Vegas	Los Angeles	Miami	New York	San Diego	San Francisco	Washington D.C.	US
0.05	0.5114	0.8017	0.9056	0.6883	1.0616	1.7340*	0.8761	0.4342	0.4303	0.5911	0.6065
0.10	0.9672	2.2192**	1.9411*	1.3422	1.3764	1.8267*	1.6131	0.6781	1.1368	1.2877	1.4721
0.15	1.6021	3.8686***	3.8054***	1.4082	2.0121**	2.9891***	1.9510*	0.9042	2.6257***	2.5033**	2.4278**
0.20	1.7477*	5.6536***	3.2750***	2.5744**	2.2510**	4.8732***	2.1334**	0.7106	2.3641**	3.7719***	3.4906***
0.25	1.5415	7.3352***	4.2769***	3.4196***	2.2120**	5.9511***	2.8061***	1.4170	3.0122***	5.0012***	3.9241***
0.30	1.5488	10.7968***	5.9827***	3.7052***	2.3332**	7.5017***	3.4294***	2.1370**	3.3481***	6.1239***	4.8665***
0.35	1.9526*	13.7573***	4.9130***	3.3464***	2.1563**	8.8929***	4.5330***	1.8881*	3.5590***	6.8543***	5.9420***
0.40	1.8777*	16.8870***	4.4996***	4.0739***	2.3331**	9.7334***	6.2399***	2.0553**	4.5686***	7.3423***	6.7878***
0.45	1.9419*	18.6115***	4.8959***	4.6726***	2.6597***	11.3775***	6.2609***	2.0770**	4.3013***	8.6005***	8.3330***
0.50	1.9619**	21.1580***	5.2789***	6.3129***	2.9747***	14.2201***	5.7677***	2.2779**	5.6673***	8.2612***	9.6183***
0.55	2.1942**	22.2422***	6.5907***	5.4942***	2.9745***	16.3506***	5.4343***	2.6999***	6.7088***	9.0567***	10.0696***
0.60	2.0606**	22.7794***	8.0441***	5.7889***	3.1449***	15.8579***	4.5034***	2.4729**	6.9930***	10.7597***	8.9959***
0.65	1.8962*	22.6174***	8.2236***	6.5948***	3.1196***	12.7288***	4.0410***	1.9642**	9.1958***	9.9933***	10.6197***
0.70	1.5123	20.5727***	6.3536***	7.2115***	3.9782***	12.489***	4.7588***	2.6282***	9.2807***	11.3379***	10.5325***
0.75	1.6813*	17.9621***	5.0042***	5.4747***	3.7233***	11.1730***	4.0029***	3.4881***	8.6279***	11.2117***	10.7504***
0.80	1.4049	18.1447***	4.7911***	5.3374***	4.0957***	12.3008***	3.8306***	3.7605***	7.7397***	8.5702***	7.6228***
0.85	1.4207	16.9356***	3.5050***	5.2527***	3.7321***	8.5546***	2.9084***	3.0931***	7.3070***	7.4321***	6.5563***
0.90	1.0081	12.9072***	2.4907**	3.6603***	1.9700**	5.0353***	2.5398**	2.4279**	5.9857***	4.2223***	5.9014***
0.95	0.5506	5.6102***	0.5192	1.6025	1.0572	1.3434	1.6234	1.5298	2.5059**	2.3588**	3.1762***

Note: ***, **, and * indicate rejection of the null hypothesis of no Granger causality at 1%, 5% and 10% levels of significance (i.e., critical values of 2.575, 1.96 and 1.645) respectively from economic sentiment index (ESI) to housing returns volatility for a particular quantile.

APPENDIX:

Table A1. Summary Statistics

Statistic	Housing Returns (HR)	Economic Sentiment Index (ESI)
	Variable	
Mean	2.90E-05	-0.0448
Median	0.0000	-0.0321
Maximum	0.0457	0.4523
Minimum	-0.0593	-0.7281
Std. Dev.	0.0034	0.2098
Skewness	-0.3090	-0.2177
Kurtosis	115.3949	2.7662
Jarque-Bera	1769671.0000***	34.2170***
ADF-Test Statistic	-56.6266***	-3.9112***
Observations	3362	

Note: Std. Dev: stands for standard deviation; The null hypotheses of the Jarque-Bera and ADF tests correspond to the null of normality and unit root respectively; *** 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
ESI	17.1241***	17.3268***	18.3631***	19.5829***	21.2393***

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 return equation with six lags each of housing returns and economic sentiment index (ESI); *** indicates rejection of the null hypothesis at 1% level of significance.

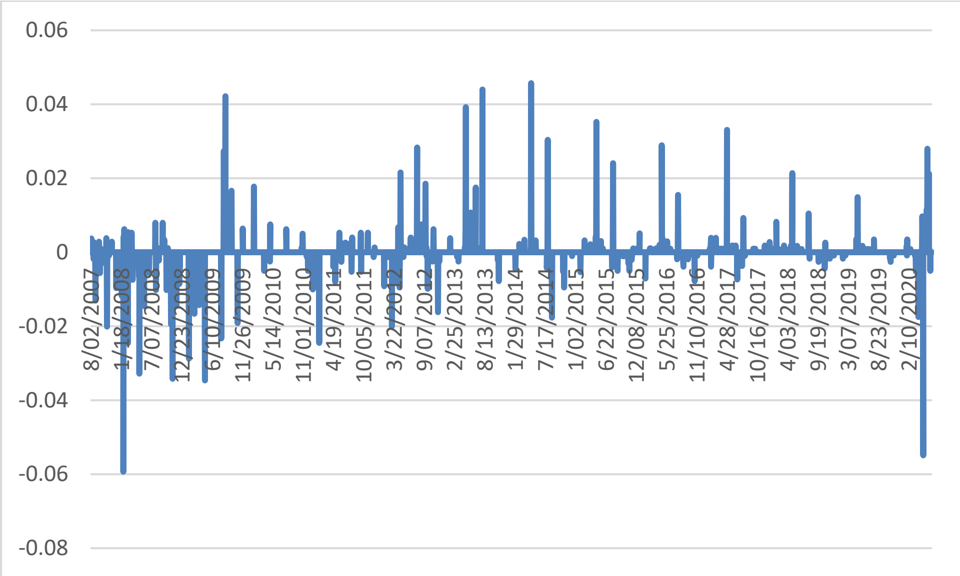
Table A3. *k*-th Order Causality-in-Quantiles Test Results due to Pandemic-Related Stock Market Volatility

Quantile	Housing Returns	Squared Housing Returns (Volatility)
0.05	8462.4935***	7841.0100***
0.10	5470.9955***	5044.0160***
0.15	4065.8788***	3723.1910***
0.20	3186.4468***	2894.0040***
0.25	2561.5877***	2303.9970***
0.30	2085.0510***	1854.0080***
0.35	1705.2481***	1495.8100***
0.40	1393.6044***	1202.6690***
0.45	1132.8167***	958.4017***
0.50	911.7222***	752.5900***
0.55	722.7859***	578.2441***
0.60	560.7645***	430.5624***
0.65	421.9561***	306.2486***
0.70	303.7696***	203.1435***
0.75	204.4945***	120.0763***
0.80	123.2342***	57.6230***
0.85	60.0606***	15.6419***
0.90	16.7368***	0.0074
0.95	0.1708	0.0115

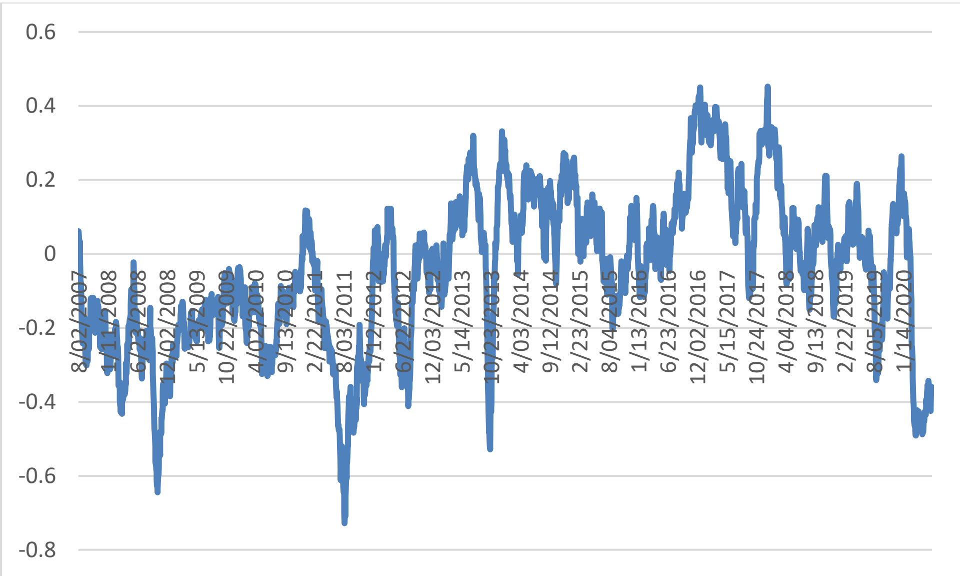
Note: *** indicates rejection of the null hypothesis of no Granger causality at 1% level of significance (critical value of 2.575) from economic sentiment index (ESI) to housing returns and volatility for a particular quantile.

Figure A1. Data Plots:

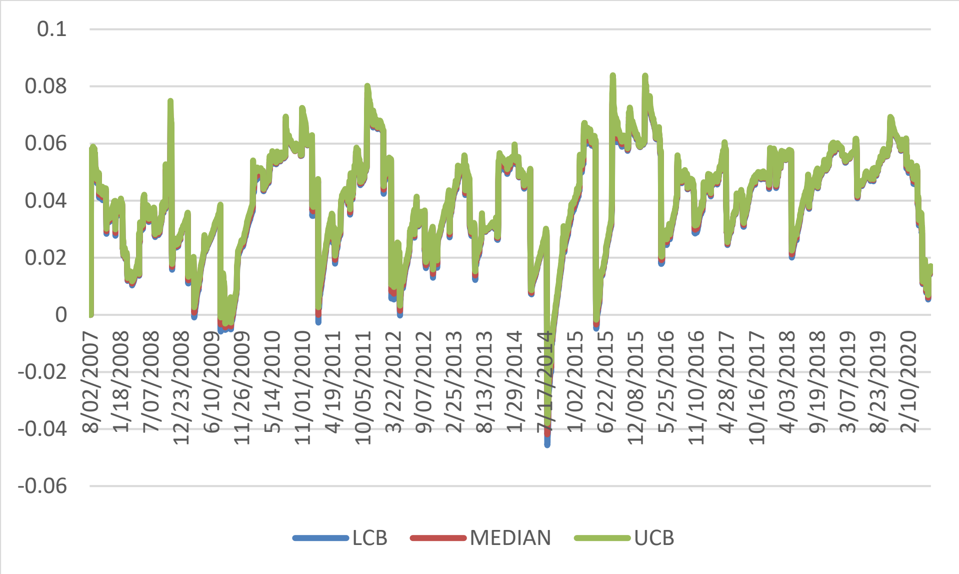
A1(a). Housing Returns (HR)



A1(b). Economic Sentiment Index (ESI)



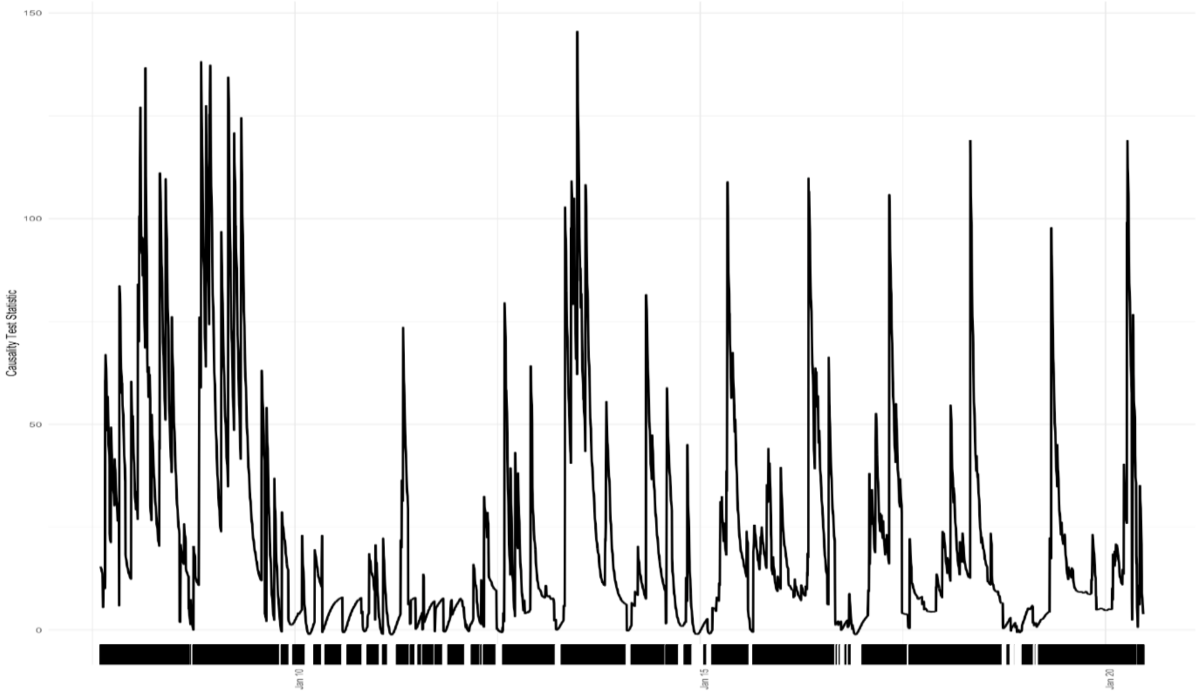
A1(c). Dynamic Conditional Correlation (DCC) between HR and ESI



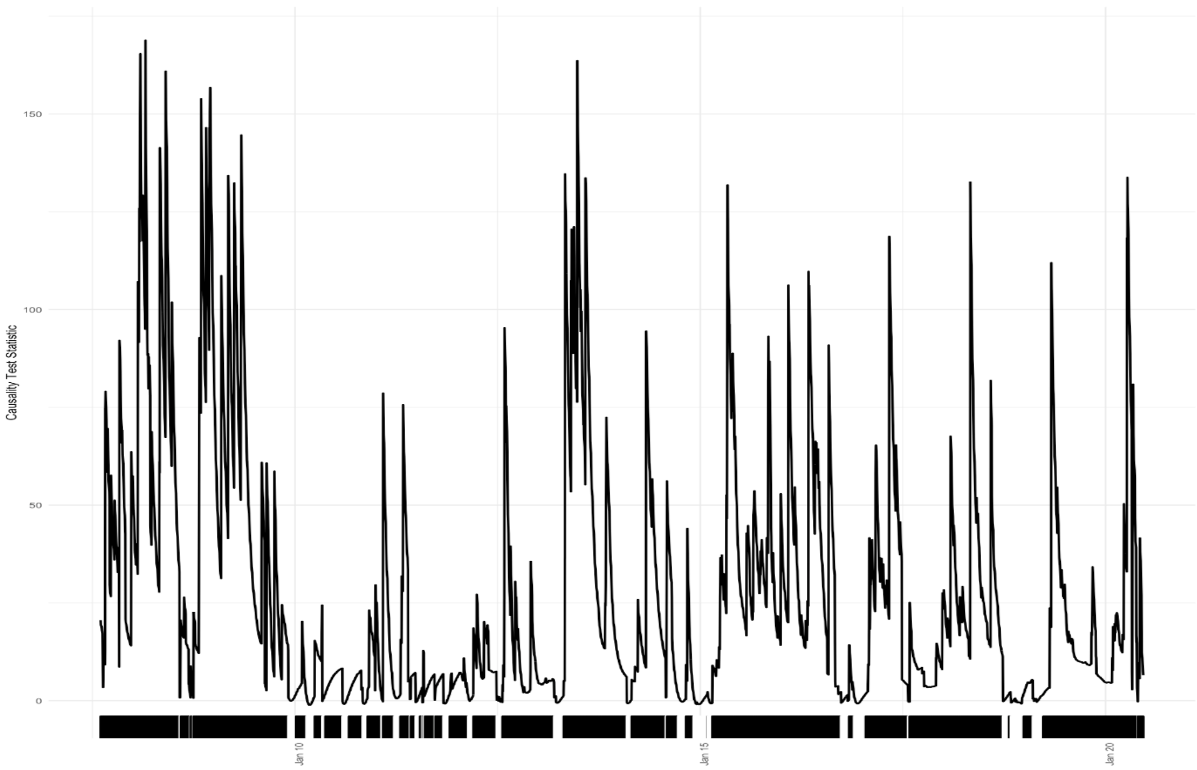
Note: LCB and UCB are lower and upper 95% confidence bands; Median is the median DCC between HR and ESI.

Figure A2. Results of the DCC-MGARCH Hong Tests between Housing Returns (HR) and Economic Sentiment Index (ESI):

A2(a). Unidirectional Causality Test from ESI to HR



A2(b). Instantaneous Causality Test from ESI to HR



Note: The top panel in Figures A2(a)-A2(b) shows the time-varying DCC-MGARCH Hong causality test statistic; the shaded region below shows the period during which the test is statistically significant at the 5% level.