Uncertainty and Daily Predictability of Housing Returns and Volatility of the United States: Evidence from a Higher-Order Nonparametric Causality-in-Quantiles Test[#]

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Highlights

- Predict US housing market movements using newspaper-based metric of US uncertainty.
- Consider daily data from 2nd August 2007 to 24th June 2020.
- Uncertainty predicts housing returns and volatility, barring the extreme upper quantiles
- Results are robust to various measures of uncertainty and alternative datasets.

Abstract

We analyse the ability of a newspaper-based metric of uncertainty of the United States in predicting housing market movements using daily data over the period 2nd August, 2007 to 24th June, 2020. For our 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 uncertainty index. Our results show that uncertainty does indeed predict housing returns and volatility, barring the extreme upper end of the respective conditional distributions. Our results are robust to eight other popular measures of uncertainty, as well as an alternative data set involving daily

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housing prices of the US and ten major metropolitan statistical areas (MSAs). Our findings have important implications for academics, investors, and policymakers.

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

JEL Codes: C22; C32; R30

1. Introduction

Borrowing from the academic literature that associates uncertainty with stock market movements (see Gupta et al., 2020, for detailed reviews), few recent studies (see for example, Antonakakis et al., 2015, 2016; André et al., 2017; Christou et al., 2017, 2019; Christidou and Fountas, 2018; Aye et al., 2019; Chien and Setyowati, 2020; Nguyen Thanh et al., 2020; Strobel et al., (2020), Gupta et al., 2021) have highlighted the role of the same in predicting (primarily) aggregate and regional housing returns and (to some extent) aggregate volatility of the United States (US). While these studies are indeed insightful, they are conducted using low frequency (monthly or quarterly) data[1]. We aim to extend this growing literature by analysing for the first time the predictive ability of a newspaper-based metric of economic uncertainty for daily housing returns and volatility of the CME-S&P/Case-Shiller House Price Index (HPI) Continuous Futures (CS CME). House price movements are known to lead US business cycles historically (Nyakabawo et al., 2015; Emirmahmutoglu et al., 2016), and information about where it is headed on a daily basis would be more 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), given that residential real estate represents about 83.98% of total household non-financial assets, 30.64% of total household net worth and 26.64% of household total assets (Financial Accounts of the US, First Quarter, 2020).[2]

[1] Recently, Balcilar et al., (2020a) consider higher frequency data on US housing prices but focus on the effect of mortgage default risks, while Balcilar et al., (2020b) investigate the role of economic sentiment.
[2] The reader is referred to: https://www.federalreserve.gov/releases/z1/20200611/z1.pdf for further details.

For our purpose, we use the *k*-th order nonparametric causality-in-quantiles framework of Balcilar et al. (2018). This econometric model allows us to test for 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 macroeconomic uncertainty - both of which we show to exist via formal statistical tests. Note that we also conduct thorough robustness checks based on a wide array of alternative measures of economic and financial uncertainties, and a different high-frequency data set on aggregate and metropolitan statistical areas (MSAs) of the US.

The remainder of the paper is organized as follows: Section 2 outlines the methodology, while Section 3 discusses the data and econometric results along with various robustness analyses, with Section 4 concluding 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. (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 metric of economic uncertainty, details of which we discuss below in the data segment. Furthermore, 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:

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

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

Jeong et al. (2012) show that the feasible kernel-based test statistics have 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. (2018) 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 uncertainty and housing returns 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 test can then be calculated by replacing y_t in Eqs. (3) and (4) with y_t^2. Balcilar et al. (2018) indicate that a rescaled version of the $\hat{J}_T$ 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 5 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

3.1. Data

Uncertainty is latent, and hence one requires a way to measure it. In this regard, besides the various alternative metrics of uncertainty associated with financial markets (such as the Chicago Board Options Exchange (CBOE) implied-volatility index (popularly called the VIX)), there are primarily three broad approaches to quantifying uncertainty (Gupta et al., 2018): (1) a newspaper-based approach, where searches of major newspapers are conducted for terms related to economic and policy uncertainty (EPU), and the results are used to construct indexes of uncertainty; (2) measures of uncertainty derived from stochastic-volatility estimates of various types of small and large-scale structural models related to macroeconomics and finance; and (3) uncertainty obtained from dispersion of professional forecaster disagreements. As far as our metric of uncertainty is concerned, we rely on the EPU index of Baker et al. (2016), i.e., EPU, for several reasons. Firstly, EPU is a wider measure associated with overall macroeconomic uncertainty, which is also likely to include the multi-dimensional negative influence that has resulted from the recent outbreak of the COVID-19 pandemic (Baker et al., 2020)[3]. Secondly, EPU is model-free and available at high-frequency. Thirdly, the literature relating uncertainty and housing price movements have primarily used the low-frequency versions of the same, which makes our study to uncover high frequency predictability of housing returns and volatility a nice extension to previous studies that often used monthly and quarterly data. Note though, in the robustness segment we do use various other daily estimates of uncertainty, mainly derived from high-frequency financial market-related variables.

Specifically, to measure the EPU index, Baker et al. (2016) use 1,000 newspapers from the archives of Access World News' NewsBank service. The daily EPU index is the number of articles that contain at least one term from each of 3 sets: economic or economy; uncertain or uncertainty; and legislation or deficit or regulation or congress or Federal Reserve or White House. The number of newspapers that NewsBank covers increased drastically over the sample period, and, to correct for this growth, the authors normalize the index of the number of economic policy uncertainty articles using the daily counts of the total number of newspaper articles. The EPU index is updated daily at 8:00pm Pacific Time. The data is publicly available for download from: http://policyuncertainty.com/us_monthly.html.

For daily house prices, from which log-returns (HR) are computed,[4] we use the CME-S&P/Case-Shiller HPI Continuous Futures (CS-CME) derived from Datastream. Our sample is from 2nd August, 2007 to 24th June, 2020, i.e., 3,221 observations, based on data availability

[3] Francke and Korevaar (2021) indicate the uncertainty surrounding pandemics and its impact on urban housing markets, whereas Ling et al., (2020) argue that that firms involving in retail and residential properties react more negatively to the COVID-19 outbreak than firms from other sectors.
[4] The log-returns ensure that the house price data is mean-reverting, while the metric for the economic sentiment is stationary in levels, which 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 EPU.

of these two variables of concern.[5] The HR and the EPU data are summarized in Table A1, and plotted in Figure A1 in the Appendix to the paper. 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 a preliminary justification for using a quantiles-based approach to predictability.

3.2. Empirical results

For a preliminary test and for the sake of completeness and comparability, we conduct the standard linear Granger causality test, with a lag-length of 5, as determined by the SIC. The resulting $\chi^2(5)$ statistics associated with the causality running from EPU to HR is found to be 15.4665 with a *p*-value of 0.0085, i.e., the null hypothesis that sentiment does not Granger cause housing returns can be rejected at the 1% level of significance. Therefore, based on the standard linear test, we can conclude the significant impact of EPU on HR. However, this preliminary evidence is derived from a conditional mean-based test, which does not provide any information on causality at various quantiles of the conditional distribution, i.e., states, of housing returns, besides the fact that the standard causality framework is also silent about the predictability of the variance of HR.

Although we obtain significant results from the linear causality test, it could be misspecified due to the presence of nonlinearity and structural breaks in the relationship between the EPU and HR, which are general observations when dealing with high-frequency data. Moreover, 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 five lags each of HR and EPU. Table A2 in the Appendix presents the results of the BDS test of nonlinearity. As shown in this table, 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 uncertainty and housing returns. To further motivate the causality-

[5] Note that the EPU data actually goes as far back as 1st January, 1985.

in-quantiles approach, we 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 EPU, allowing for heterogenous error distributions across the breaks with 5% trimming. When we apply these tests again to the HR equation involving five lags each of HR and EPU, we detect three breaks at 24th of March, 2008, 5th August, 2009, and 25th September, 2019, associated with the global financial crisis and heightened uncertainty due to the intensifying of the US-China trade war.

Given the strong evidence of nonlinearity and structural breaks in the relationship between HR and EPU, we 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 both housing returns and its 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 EPU over the quantile range of 0.05 to 0.95. As can be seen, EPU causes HR at 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. We make a similar observation for volatility as for return, with the slight difference that causality from ESI is absent at quantile 0.90 as well as 0.95. In other words, EPU causes both housing returns and volatility, barring the extreme upper ends of the conditional distributions corresponding to the highest possible conditional returns and variance. The pattern, in terms of the strength of causality, 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). Given this, the strength of the predictability of housing returns and volatility (as captured by squared returns) due to EPU declines at higher quantiles. This result implies that economic agents tend to use the information content of uncertainty relatively strongly during bearish housing returns, and phases of lower volatility (risk) [6] in the market resulting from lower trading, to improve their investment positions.

[6] 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 from the asymmetric GARCH models are available upon request from the authors.

Table 1. *k*-th Order Causality-in-Quantiles Test Results due to Economic Policy Uncertainty (EPU) Index

Quantile	Housing Returns	Squared Housing Returns (Volatility)
0.05	6177.6141***	5566.2991***
0.10	3936.9116***	3486.0968***
0.15	2891.2058***	2538.1348***
0.20	2247.4293***	1956.7926***
0.25	1795.8042***	1550.1632***
0.30	1455.5070***	1244.0394***
0.35	1186.8671***	1002.7755***
0.40	968.1075***	806.8157***
0.45	786.1436***	644.4172***
0.50	632.5861***	508.0706***
0.55	501.8039***	392.7596***
0.60	389.8919***	295.0437***
0.65	294.0997***	212.5522***
0.70	212.4990***	143.7076***
0.75	143.8084***	87.6100***
0.80	87.3388***	44.1446***
0.85	43.1565***	14.0748***
0.90	12.5789***	0.4719
0.95	0.1784	0.4097

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

Next, we carry out two additional analyses to ensure the robustness of our results. Firstly, we repeat our *k*-th order causality-in-quantiles test by substituting the EPU index with multiple alternative publicly available daily measures of financial market uncertainties, namely the newspaper-based equity market uncertainty index (EMU) of Baker et al. (2016), VIX, Volatility of VIX (VVIX) (the role of which for the US stock market is highlighted by Bu et al. (2019)), measures of time-varying risk aversion (RA_BEX) and uncertainty (UNC_BEX) calculated from observable financial information at high frequencies by Bekaert et al. (2019), an uncertainty index (UNC_SCOTTI) based on weighted averages of the squared surprises from a set of macroeconomic data releases developed by Scotti (2016), and Twitter-based economic uncertainty (TEU) and equity market uncertainty (TMU) indexes.[7] As can be seen

[7] The sources are as follows: EMU: http://policyuncertainty.com/equity_uncert.html; VIX: FRED database of the Federal Reserve Bank of St. Louis; VVIX: http://www.cboe.com/products/vix-index-volatility/volatility-on-stock-indexes/the-cboe-vvix-index; RA_BEX and UNC_BEX: https://www.nancyxu.net/risk-aversion-index; UNC_SCOTTI: https://sites.google.com/site/chiarascottifrb/research?authuser=0; TEU and TMU: http://policyuncertainty.com/twitter_uncert.html. The analyses involving EMU, VIX, VVIX, RA_BEX, and

Table 2(a). *k*-th Order Causality-in-Quantiles Test Results for Housing Returns Using Alternative Metrics of Uncertainty

Quantile	EMU	VIX	VVIX	RA_BEX	UNC_BEX	UNC_SCOTTI	TEU	TMU
0.05	6638.2748***	6100.1486***	5690.3150***	7233.2730***	5911.6852***	5672.9538***	6134.8210***	6141.4870***
0.10	4269.7899***	3888.7392***	3598.5310***	4691.5070***	3749.8656***	3569.6424***	3954.2020***	3961.1090***
0.15	3151.7339***	2857.2073***	2633.1510***	3478.1140***	2746.1606***	2614.0124***	2931.4490***	2937.5670***
0.20	2457.1283***	2220.4964***	2041.6440***	2719.0030***	2129.8853***	2032.1653***	2292.1620***	2297.3940***
0.25	1966.8698***	1773.3719***	1628.2890***	2180.3530***	1698.6289***	1621.4798***	1838.4770***	1842.8710***
0.30	1595.7752***	1436.3268***	1317.8010***	1771.0730***	1374.4149***	1312.9348***	1492.8820***	1496.5140***
0.35	1301.7844***	1170.1872***	1073.2960***	1445.8610***	1118.9475***	1069.9119***	1217.7570***	1220.7070***
0.40	1061.7253***	953.4427***	874.5843***	1179.6830***	911.2440***	872.3671***	992.2741***	994.6194***
0.45	861.6338***	773.1647***	709.5602***	957.4114***	738.7147***	708.2749***	803.8304***	805.6415***
0.50	692.5364***	621.0672***	570.4795***	769.3086***	593.3026***	569.9458***	644.3005***	645.6441***
0.55	548.3978***	491.5860***	452.1539***	608.8130***	469.6058***	452.2230***	508.2070***	509.1459***
0.60	425.0299***	380.8659***	350.9892***	471.3656***	363.8850***	351.5339***	391.7467***	392.3412***
0.65	319.4828***	286.1966***	264.4585***	353.7558***	273.5120***	265.3641***	292.2453***	292.5543***
0.70	229.6951***	205.6846***	190.7915***	253.7436***	196.6513***	191.9504***	207.8478***	207.9301***
0.75	154.3093***	138.0834***	128.8139***	169.8599***	132.0960***	130.1197***	137.3558***	137.2720***
0.80	92.6186***	82.7488***	77.9024***	101.3550***	79.2138***	79.2389***	80.2019***	80.0167***
0.85	44.7657***	39.8236***	38.1377***	48.4218***	38.1402***	39.3247***	36.5844***	36.3723***
0.90	12.2515***	10.7136***	10.7352***	12.7638***	10.2708***	11.5918***	8.1496***	8.0067***
0.95	0.2197	0.1825	0.0758	0.0372	0.2315	0.2158	0.0332	0.0295

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 alternative measures of economic uncertainty to housing returns for a particular quantile.

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

Quantile	EMU	VIX	VVIX	RA_BEX	UNC_BEX	UNC_SCOTTI	TEU	TMU
0.05	6027.7872***	5514.1906***	5098.2872***	6599.5475***	5311.7587***	5485.8637***	5144.4042***	5206.3733***
0.10	3812.1808***	3456.4107***	3169.3827***	4208.2707***	3308.6076***	3424.3476***	3265.6018***	3307.1782***
0.15	2789.4091***	2517.1777***	2298.5561***	3092.3760***	2401.2944***	2488.7309***	2393.7522***	2424.8248***
0.20	2156.8795***	1940.5731***	1767.5536***	2397.3872***	1847.0582***	1916.4739***	1852.9771***	1877.2136***
0.25	1711.7176***	1536.9418***	1397.6264***	1905.7604***	1460.5018***	1516.9577***	1471.6413***	1490.9281***
0.30	1375.0184***	1232.9019***	1119.9754***	1532.4699***	1170.1446***	1216.6263***	1182.8079***	1198.2873***
0.35	1108.7092***	993.1905***	901.6699***	1236.3322***	941.7338***	980.1996***	954.1133***	966.5502***
0.40	891.8206***	798.4477***	724.6932***	994.5911***	756.5085***	788.3423***	767.7056***	777.6498***
0.45	711.7241***	637.0477***	578.2524***	793.5076***	603.2243***	629.4587***	612.8172***	620.6852***
0.50	560.3263***	501.5574***	455.4599***	624.2587***	474.7052***	496.1400***	482.5435***	488.6649***
0.55	432.2077***	387.0092***	351.7204***	480.9305***	366.1614***	383.4411***	372.2602***	376.9056***
0.60	323.6524***	289.9985***	263.8885***	359.4606***	274.3164***	287.9711***	278.7890***	282.1888***
0.65	232.1018***	208.1846***	189.7997***	257.0582***	196.9209***	207.3941***	199.9448***	202.3016***
0.70	155.8625***	140.0168***	128.0170***	171.8838***	132.4889***	140.1587***	134.2808***	135.7801***
0.75	93.9847***	84.6236***	77.7220***	102.9212***	80.1938***	85.3884***	80.9866***	81.8065***
0.80	46.3909***	41.9269***	38.8264***	50.1206***	39.9718***	42.9722***	40.0234***	40.3570***
0.85	13.9674***	12.7647***	12.0437***	14.5392***	12.6784***	13.6329***	12.1212***	12.1623***
0.90	0.1770	0.3115	0.2761	0.1148	1.6065	0.3619	0.2003	0.1983
0.95	0.2589	0.8050	0.2174	0.3337	0.8218	0.4214	0.1835	0.3029

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 alternative measures of economic uncertainty to housing returns volatility for a particular quantile.

from Tables 2(a) and 2(b), compared to the results for EPU, a similar pattern and strength of predictability is observed for housing returns and volatility emanating from these eight alternative uncertainty indicators.

Secondly, we re-conduct 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 computed as a weighted average. The 10 MSAs and specific values of the weights (w_i) are: Boston (0.212), Chicago (0.074), Denver (0.089), Las Vegas (0.037), Los Angeles (0.050), Miami (0.015), New York (0.055), San Diego (0.118), San Francisco (0.272), and Washington D.C. (0.078), representing the total aggregate value of the housing stock in the 10 MSAs in the year 2000 (Wang, 2014). In Tables 3(a) and 3(b), we report the results of the k-th order causality-in-quantiles test from the EPU on housing returns and volatility of the aggregate US as well as the 10 MSAs.[8] Generally, EPU is 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, again with stronger evidence of predictability observed at lower quantiles, particularly for the (aggregate and MSA-level) housing returns.

In summary, our results are robust to alternative data on not only (regional and aggregate) house prices, but also metrics of uncertainty, with strong evidence of predictability in both the first and second moments of housing returns.

UNC_BEX have the same data coverage as EPU, while the UNC_SCOTTI and TEU, and TMU results are based on data covering 2nd August, 2007 to 29th November, 2019, and 3rd January, 2011 to 24th June, 2020, respectively.

[8] The data coverage varies across the MSAs 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.

Table 3(a). *k*-th Order Causality-in-Quantiles Test Results for Housing Returns Using Alternative House Price Data

Quantile	Boston	Chicago	Denver	Las Vegas	Los Angeles	Miami	New York	San Diego	San Francisco	Washington DC	Aggregate
0.05	1.2370	3.3361***	1.2254	0.4835	0.9688	1.4185	0.7474	1.1540	1.7734*	1.1848	2.0104**
0.10	1.8113*	3.0381***	1.6881*	1.0785	1.6756*	2.5547***	1.3805	2.0337**	2.2834**	1.9742**	3.5129***
0.15	2.3534**	2.3159**	1.7657*	1.9605**	2.0013**	2.2520**	1.7773*	2.3733**	2.6988***	2.4347**	3.2742***
0.20	2.5907***	2.2295**	2.0977**	2.5064**	2.1364**	2.6202***	1.5166	2.2776**	3.0316***	3.3900***	3.6496***
0.25	3.0811***	1.6668*	2.1434**	2.5677***	2.2253**	2.8794***	1.3736	2.8281***	2.9280***	3.8717***	3.8887***
0.30	2.8466***	1.5731	1.9158*	2.4254**	2.4045**	3.1149***	1.1231	3.0340***	2.7231***	3.2853***	3.3048***
0.35	3.0239***	1.7534*	2.3290**	2.1881**	2.2266**	3.5949***	1.1365	3.0270***	2.7329***	2.9714***	3.0512***
0.40	3.2409***	1.4003	2.4423**	1.9606**	2.1381**	3.4462***	0.8413	3.2599***	2.8499***	2.9445***	2.8291***
0.45	2.8991***	1.0045	2.2097**	1.5577	2.2265**	3.0247***	0.7202	2.8751***	3.3186***	2.9023***	2.5320**
0.50	2.7289***	1.2053	2.0170**	1.1976	2.3838**	2.9931***	0.5363	2.6247***	3.3275***	2.8878***	2.8031***
0.55	3.0746***	1.4675	2.0753**	0.7909	2.3465**	2.5170**	0.4131	2.1772**	3.8160***	2.6427***	2.7434***
0.60	3.0246***	1.1327	2.3171**	0.5696	2.1382**	2.4634**	0.4253	2.5629***	3.2857***	3.0845***	2.8689***
0.65	3.0285***	1.5344	2.3839**	0.3894	2.2307**	2.5272**	0.5444	2.3276**	3.1531***	2.9655***	2.5077**
0.70	3.1068***	1.7146*	1.9279*	0.2414	2.1471**	2.1602**	0.7420	1.9863**	3.1332***	2.6449***	2.3547**
0.75	2.6061***	2.5030**	1.6588*	0.2926	2.0136**	1.7601*	0.8869	2.1726**	3.1247***	2.7925***	1.9695**
0.80	2.3437**	2.1094**	2.3656**	0.7399	2.2749**	1.7364*	0.9826	1.9492*	2.9876***	2.5299**	1.8380*
0.85	1.9022*	2.1719**	1.5860	0.7290	2.2033**	1.6062	0.6911	1.5261	2.5503***	2.6786***	1.7316*
0.90	1.8402*	1.9276*	1.2599	0.5451	1.6558*	2.0091**	0.3761	1.0981	1.7056*	2.1606**	1.4146
0.95	1.0712	0.8553	0.7796	0.4792	1.0136	0.9044	0.2569	0.7611	0.8754	1.4924	1.2256

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 policy uncertainty (EPU) index to housing returns for a particular quantile.

Table 3(b). *k*-th Order Causality-in-Quantiles Test Results for Squared Housing Returns (Volatility) Using Alternative House Price Data

Quantile	Boston	Chicago	Denver	Las Vegas	Los Angeles	Miami	New York	San Diego	San Francisco	Washington DC	Aggregate
0.05	0.3438	0.3834	0.6592	0.9009	0.6339	0.9102	0.9215	0.1973	0.1477	0.4989	0.4139
0.10	0.7919	0.7483	1.4915	1.3895	0.8779	1.1242	1.2931	0.6818	0.3434	0.7092	0.6316
0.15	0.6380	1.1880	1.8210*	1.4893	1.3408	1.3218	1.2240	0.7685	0.4662	1.5844	0.8841
0.20	0.8942	1.9116*	1.6533*	2.0986**	1.3839	1.8340*	1.2742	0.8418	0.5467	2.4382**	1.3391
0.25	1.0327	2.8884***	2.2094**	2.6062***	1.3979	1.7074*	1.7679*	0.9426	0.9365	2.6311***	0.9946
0.30	1.2008	3.0411***	3.1050***	2.3777**	1.3803	2.1285**	1.7670*	1.1235	0.5976	3.3973***	1.6089
0.35	1.7430*	4.0839***	2.3542**	2.3666**	1.1834	2.2212**	2.5422**	0.8534	0.8284	3.4965***	1.7610*
0.40	1.8918*	4.3198***	2.2659**	2.6279***	1.3815	2.4103**	3.8716***	0.9020	0.8602	3.9143***	1.9985**
0.45	2.2277**	4.5947***	2.1430**	3.4529***	1.4529	2.8905***	3.3891***	1.0093	0.9609	3.9872***	2.6860***
0.50	2.3317**	5.2695***	2.0527**	3.4478***	1.9313*	3.1802***	3.6969***	1.5810	0.9473	4.5100***	3.4232***
0.55	2.6138***	6.0163***	2.1966**	3.6100***	2.0082**	3.2748***	3.7386***	1.7314*	1.4347	4.2634***	4.0798***
0.60	2.3431**	5.3987***	3.2036***	3.7053***	1.6875*	3.0391***	3.5953***	1.5556	1.2510	4.8705***	4.2128***
0.65	2.0891**	5.3564***	3.0878***	3.6946***	1.9497*	2.7637***	3.6587***	1.5224	1.8722*	3.6032***	4.6545***
0.70	2.3152**	5.2633***	2.2686**	3.2893***	2.1946**	2.9964***	3.0911***	1.3372	2.5875**	3.8280***	5.5938***
0.75	2.3103**	5.9566***	1.9840**	2.7112***	2.2223**	2.7424***	2.7306***	1.3569	1.8668*	4.1627***	5.3069***
0.80	2.3032**	6.8756***	1.6594*	2.3087**	2.1998**	3.6541***	2.0510**	1.3794	1.8213*	3.5874***	3.7091***
0.85	1.7814*	6.7074***	1.4249	1.9977**	1.9650**	2.9511***	1.1488	0.7974	1.7114*	3.0308***	3.0754***
0.90	1.1602	5.1590***	0.9200	1.7503*	1.1993	1.2686	0.7734	0.6343	1.3965	2.0062**	2.1251**
0.95	0.4238	2.5995***	0.4793	1.6596*	0.7082	0.4809	0.3286	0.5632	0.5770	1.3928	1.5620

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 policy uncertainty (EPU) index to housing returns volatility for a particular quantile.

4. Conclusion

Recently, a growing number of studies have related uncertainty to first- and second-moment movements of US housing returns based on low frequency (i.e., monthly or quarterly) data. In this paper, we aim to extend these studies by carrying out a high frequency analysis using daily data on housing returns and economic sentiment over the period 2nd August, 2007 to 24th June, 2020. Methodologically, 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 show that a newspaper-based index of economic sentiment does predict US housing returns and volatility, barring the extreme upper end of the respective conditional distributions. Notably, our results, in terms of predictability of housing returns and volatility, continue to hold when we look at alternative metrics of the latent variable of uncertainty, and aggregate and regional housing prices.

Our results have important implications for policymakers, investors and academicians. Since our predictive analysis is performed at the highest frequency possible associated with housing returns, our results can be used by policy authorities to obtain daily information about where the housing market is headed due to changes in economic uncertainty, and, in turn, use this knowledge to predict the future path of low frequency economic activity variables at a 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 uncertainty would 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 uncertainty, but this finding is also contingent on the phase of the housing returns. Specifically, inefficiency is observed during bearish phases, though the market seems to be efficient during bullish regimes - an observation in line with Tiwari et al. (2020), obtained using the same housing returns dataset.

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APPENDIX:

Table A1. Summary Statistics

	Variable	
Statistic	Housing Returns (HR)	Economic Policy Uncertainty Index (EPU)
Mean	3.15E-05	116.0743
Median	0.0000	93.1100
Maximum	0.0457	807.6600
Minimum	-0.0593	3.3200
Std. Dev.	0.0035	83.4753
Skewness	-0.3031	2.7241
Kurtosis	109.4689	14.0490
Jarque-Bera	1506271.0000***	20165.6800***
ADF-Test Statistic	-54.58904***	-5.3884***
Observations	3221	

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.

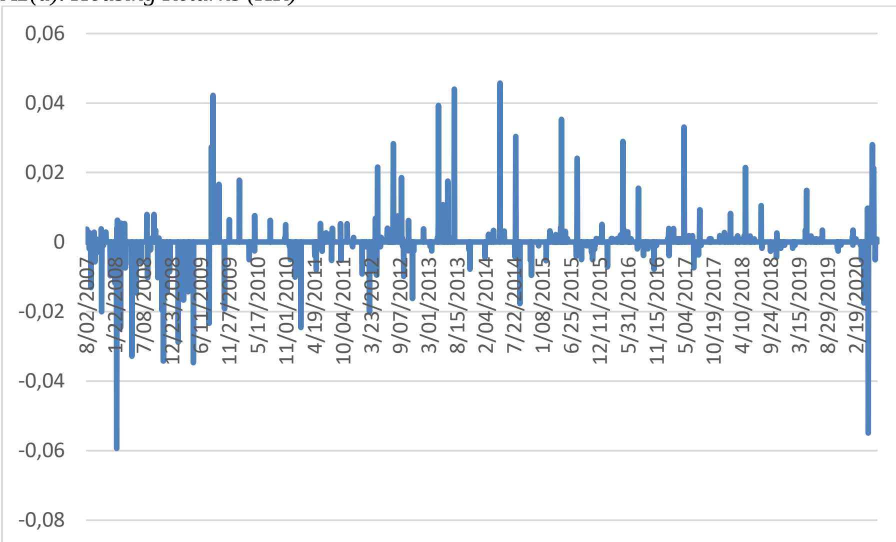
Table A2. Brock et al. (1996, BDS) Test of Nonlinearity

Independent Variable	Dimension (*m*)				
	2	3	4	5	6
EPU	12.3002***	13.1532***	15.3440***	16.8119***	18.0349***

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 five lags each of housing returns and economic policy uncertainty index (EPU); *** indicates rejection of the null hypothesis at 1% level of significance.

Figure A1. Data Plots:

A1(a). Housing Returns (HR)



A1(b). Economic Policy Uncertainty (EPU) Index