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The role of news-based uncertainty indices in predicting oil markets: a hybrid nonparametric quantile causality method

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Abstract A recent strand in the literature emphasizes the role of news-based economic policy uncertainty (EPU) and equity market uncertainty (EMU) as drivers of oil price movements. Against this backdrop, this paper uses a kth-order nonparametric quantile causality test, to analyse whether EPU and EMU predict stock returns and volatility. Based on daily data covering the period of 2 January 1986 to 8 December 2014, we find that, for oil returns, EPU and EMU have strong predictive power over the entire distribution barring regions around the median, but for volatility, the predictability virtually covers the entire distribution, with some exceptions in the tails. In other words, predictability based on measures of uncertainty is asymmetric over the distribution of oil returns and its volatility.

Keywords Uncertainty · Oil markets · Volatility · Quantile causality

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1 Introduction

Following the seminal work of Hamilton (1983), a large literature exists that connects oil price movements (shocks) with recessions and inflationary episodes in the US economy (e.g., see Kang and Ratti 2013a, b; Antonakakis et al. 2014 for detailed reviews). This, in turn, implies that it is of paramount importance to determine the variables that drives the oil market to properly model and forecast oil price. In this regard, a recently growing literature emphasizes the role of economic policy uncertainty on real activity (e.g., see Bloom 2009; Colombo 2013; Jones and Olson 2013 for detailed reviews), which, in turn, affects oil price movements (Kang and Ratti 2013a, b; Antonakakis et al. 2014). Equity market uncertainty also feeds into oil price movements because, as Bloom's (2009) firm-based theoretical framework notes, equity market uncertainty affects hiring and investment and, hence, production decisions of firms. In this regard, empirical evidence relating oil price movements and stock market volatility can be found in Kang et al. (2015).

Against this backdrop, the objective of this paper is to analyse whether recently developed news-based measures of economic policy uncertainty (EPU) and equity market uncertainty (EMU) by Baker et al. (2013) can predict returns and volatility of oil returns. For our purposes, we employ a modified bivariate quantile causality test that builds combines conditions of the causality-in-quantile test as in Jeong et al. (2012) and of the higher-moment kth-order nonparametric causality test as in Nishiyama et al. (2011). Our empirical analysis utilizes daily data of oil returns and of the EPU and EMU indices spanning the period 2 January 1986 to 8 December 2014.

While conditional mean-based evidence of EPU (mildly and negatively) affecting oil price from structural vector autoregressive (SVAR) models applied to monthly data can be found in Kang and Ratti (2013a,2013b) and Antonakakis et al. (2014), to the best of our knowledge, our paper is the first attempt to analyse the importance of both EPU and EMU in predicting within-sample oil returns and its volatility over the entire conditional distribution of oil returns and volatility. The causality-in-quantile approach has the following novelties: Firstly, it is robust to misspecification errors as it detects the underlying dependence structure between the examined time series; this could prove to be particularly important, as it is well known (and as we show below) that high-frequency data display nonlinear dynamics. Secondly, via this methodology, we are able to test for not only causality-in-mean (1st moment), but also causality that may exist in the tails of the joint distribution of the variables, which in turn, is particularly important if the dependent variable has fat tails—something we show below to hold for oil returns. Finally, we are also able to investigate causality-in-variance thereby volatility spillovers, as sometimes even when causality in the conditional mean might not exist, higher-order interdependencies cannot be ruled out. The remainder of the paper is organized as follows: Sect. 2 describes the mathematical context of quantile and higher-moment nonparametric causality, while Sect. 3 presents the empirical results. Finally, Sect. 4 concludes.

2 Nonparametric quantile causality testing

We present thereafter a novel methodology for the detection on nonlinear causality via a hybrid approach based on the Nishiyama et al. (2011) and Jeong et al. (2012) framework. We denote oil returns as y_t and uncertainty index as x_t^n, where $n = 1, 2$ denoting EPU and EMU, respectively. The quantile-based causality is defined as follows: x_t^n does not cause y_t in the θth quantile with respect to the lag vector of $\{y_{t-1}, \ldots, y_{t-p}, x_{t-1}^n, \ldots, x_{t-p}^n\}$ if:

$$Q_\theta\left(y_t | y_{t-1}, \ldots, y_{t-p}, x_{t-1}^n, \ldots, x_{t-p}^n\right) = Q_\theta\left(y_t | y_{t-1}, \ldots, y_{t-p}\right) \tag{1}$$

x_t^n is a prima facie cause of y_t in the θth quantile with respect to $\{y_{t-1}, \ldots, y_{t-p}, x_{t-1}^n, \ldots, x_{t-p}^n$ if:

$$Q_\theta\left(y_t | y_{t-1}, \ldots, y_{t-p}, x_{t-1}^n, \ldots, x_{t-p}^n\right) \neq Q_\theta\left(y_t | y_{t-1}, \ldots, y_{t-p}\right) \tag{2}$$

where $Q_\theta\left(y_t|\cdot\right)$ is the θth quantile of y_t depending on t and $0 < \theta < 1$. Let $Y_{t-1} \equiv (y_{t-1}, \ldots, y_{t-p})$, $X_{t-1}^n \equiv (x_{t-1}^n, \ldots, x_{t-p}^n)$, $Z_t = (X_t^n, Y_t)$, and $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t|Y_{t-1})$ denote the conditional distribution functions of y_t given Z_{t-1} and Y_{t-1}, respectively. The conditional distribution $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ is assumed to be absolutely continuous in y_t for almost all Z_{t-1}. If we denote $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, we have $F_{y_t|Z_{t-1}}\left\{Q_\theta\left(Z_{t-1}\right)|Z_{t-1}\right\} = \theta$ with probability one. Consequently, the hypotheses to be tested based on definitions (1) and (2) are:

$$H_0 = P\left\{F_{y_t|Z_{t-1}}\left\{Q_\theta\left(Y_{t-1}\right)|Z_{t-1}\right\} = \theta\right\} = 1 \tag{3}$$

$$H_0 = P\left\{F_{y_t|Z_{t-1}}\left\{Q_\theta\left(Y_{t-1}\right)|Z_{t-1}\right\} = \theta\right\} < 1 \tag{4}$$

Jeong et al. (2012) employ the distance measure $J = \{\varepsilon_t E(\varepsilon_t|Z_{t-1}) f_Z(Z_{t-1})\}$ where ε_t is the regression error term and $f_Z(Z_{t-1})$ is the marginal density function of Z_{t-1}. The regression error ε_t emerges based on the null in (3), which can only be true if and only if $E\left[\mathbf{1}\left\{y_t \leq Q_\theta\left(Y_{t-1}\right)|Z_{t-1}\right\}\right] = \theta$ or equivalently $\mathbf{1}\left\{y_t \leq Q_\theta\left(Y_{t-1}\right)\right\} = \theta + \varepsilon_t$, where $\mathbf{1}\{\cdot\}$ is an indicator function. Jeong et al. (2012) specify the distance function as follows:

$$J = E\left[\left\{F_{y_t|Z_{t-1}}\left\{Q_\theta\left(Y_{t-1}\right)|Z_{t-1}\right\} - \theta\right\}^2 f_Z(Z_{t-1})\right] \tag{5}$$

In Eq. (3), it is important to note that $J \geq 0$, i.e., the equality holds if and only if H_0 in (5) is true, while $J > 0$ holds under the alternative H_1 in Eq. (4). Jeong et al. (2012) show that the feasible kernel-based test statistic for J has the following form:

$$\hat{J}_T = \frac{1}{T\left(T-1\right)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s \neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s \tag{6}$$

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

$$\hat{\varepsilon}_t = \mathbf{1}\left\{y_t \leq \hat{Q}_\theta\left(Y_{t-1}\right)\right\} - \theta \tag{7}$$

$\hat{Q}_\theta\left(Y_{t-1}\right)$ is an estimate of the θth conditional quantile of y_t given Y_{t-1}. Below, we estimate $\hat{Q}_\theta\left(Y_{t-1}\right)$ using the nonparametric kernel method as:

$$\hat{Q}_\theta\left(Y_{t-1}\right) = \hat{F}^{-1}_{y_t|Y_{t-1}}\left(\theta|Y_{t-1}\right) \tag{8}$$

where $\hat{F}_{y_t|Y_{t-1}}\left(y_t|Y_{t-1}\right)$ is the *Nadaraya–Watson* kernel estimator given by:

$$\hat{F}_{y_t|Y_{t-1}}\left(y_t|Y_{t-1}\right) = \frac{\sum_{s=p+1,s\neq t}^{T} L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right)\mathbf{1}\left(y_s \leq y_t\right)}{\sum_{s=p+1,s\neq t}^{T} L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right)} \tag{9}$$

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

In an extension of the Jeong et al. (2012) framework, we develop a test for the 2nd moment. In particular, we want to test the causality running from EPU or EMU to the volatility of oil returns. Causality in the kth moment generally implies causality in the mth moment for $k < m$. Firstly, we employ the nonparametric Granger quantile causality approach by Nishiyama et al. (2011). In order to illustrate the causality in higher-order moments, consider the following process for y_t:

$$y_t = g\left(Y_{t-1}\right) + \sigma(X^n_{t-1})\varepsilon_t \tag{10}$$

where ε_t is a white noise process, and $g(\cdot)$ and $\sigma(\cdot)$ are unknown functions that satisfy certain conditions for stationarity. However, this specification does not allow for Granger-type causality testing from X^n_{t-1} to y_t, but could possibly detect the "predictive power" from X^n_{t-1} to y^2_t (i.e., volatility of the returns series under consideration, which in our case is oil returns volatility)[1] when $\sigma(\cdot)$ is a general nonlinear function. Hence, the Granger causality-in-variance definition does not require an explicit specification of squares for X^n_{t-1}. We re-formulate Eq. (8) into a null and alternative hypothesis for causality in variance as follows:

$$H_0 = P\left\{F_{y^2_t|Z_{t-1}}\left\{Q_\theta\left(Y_{t-1}\right)|Z_{t-1}\right\} = \theta\right\} = 1 \tag{11}$$

$$H_1 = P\left\{F_{y^2_t|Z_{t-1}}\left\{Q_\theta\left(Y_{t-1}\right)|Z_{t-1}\right\} = \theta\right\} < 1 \tag{12}$$

To obtain a feasible test statistic for testing the null in Eq. (8), we replace y_t in Eq. (6)–(9) with y^2_t. Incorporating the Jeong et al. (2012) approach, we overcome the problem that causality in the conditional 1st moment (mean) implies causality in the

[1] Measuring volatility of a series as squared returns, especially related to the oil markets has been discussed in detail by Lux et al., (*forthcoming*, 2016).

2nd moment (variance). In order to overcome this problem, we interpret the causality in higher-order moments using the following model:

$$y_t = g\left(X_{t-1}^n, Y_{t-1}\right) + \varepsilon_t \tag{13}$$

Thus, higher-order quantile causality can be specified as:

$$H_0 = P\left\{F_{y_t^k|Z_{t-1}}\left\{Q_\theta\left(Y_{t-1}\right)|Z_{t-1}\right\} = \theta\right\} = 1 \quad \text{for } k = 1, 2, \ldots, K \tag{14}$$

$$H_1 = P\left\{F_{y_t^k|Z_{t-1}}\left\{Q_\theta\left(Y_{t-1}\right)|Z_{t-1}\right\} = \theta\right\} < 1 \quad \text{for } k = 1, 2, \ldots, K \tag{15}$$

Integrating the entire framework, we define that x_t^n *Granger causes* y_t *in quantile* θ *up to* K*th moment* utilizing Eq. (14) to construct the test statistic of Eq. (6) for each k. However, it can be shown that it is not easy to combine the different statistics for each $k = 1, 2, \ldots, K$ into one statistic for the joint null in Eq. (14) because the statistics are mutually correlated (Nishiyama et al. 2011). To efficiently address this issue, we include a sequential testing method as described Nishiyama et al. (2011) with some modifications. Firstly, we test for the nonparametric Granger causality in the 1st moment ($k = 1$). Rejecting the null of non-causality means that we can stop and interpret this result as a strong indication of possible Granger quantile causality-in-variance. Nevertheless, failure to reject the null for $k = 1$ does not automatically lead to non-causality in the 2nd moment; thus, we can still construct the tests for $k = 2$. Finally, we can test the existence of causality-in-variance, or the causality-in-mean and variance successively. The empirical implementation of causality testing via quantiles entails specifying three important choices: the bandwidth h, the lag order p, and the kernel type for $K(\cdot)$ and $L(\cdot)$ in Eq. (6) and (9), respectively. In our study, the lag order (9 and 5, respectively) is determined using the Schwarz information criterion (SIC) under a VAR comprising oil returns and EPU or EMU, respectively. The SIC being parsimonious when it comes to choosing lags compared to other alternative lag length selection criterion helps us to prevent issues of overparametrization commonly associated with nonparametric approaches. The bandwidth value is selected using the least squares cross-validation method. Lastly, for $K(\cdot)$ and $L(\cdot)$ we employ Gaussian-type kernels.

3 Data analysis and empirical results

In this section, we empirically investigate the ability of EPU and EMU in predicting oil returns and volatility of oil returns over various quantiles, using data covering the period of 2 January 1986 to 8 December 2014, with the start and end dates being purely driven by data availability. We use the EMU and the EPU indices, developed by Baker et al. (2013), as two measures of the degree of uncertainty in the US economy. Data on these two measures of uncertainty come from the website: www.policyuncertainty.com. The daily news-based EPU index uses newspaper archives from Access World News Bank service. The primary measure for this index equals the number of articles that contain at least one term from each of 3 sets of terms, namely economic or economy, uncertain or uncertainty, and legislation or deficit or regulation or congress or Federal Reserve or White House.[2] Using the same news source, the EMU index searches for articles containing the terms uncertainty or uncertain, economic or economy, and one or more of the following terms: equity market, equity price, stock market, or stock price.[3] Note that we work with natural logarithmic values of EPU and EMU.

We use the daily spot price on West Texas Intermediate (WTI) crude to represent the oil market. These data come from the FRED database at the Federal Reserve Bank of St. Louis available at: http://research.stlouisfed.org/fred2/. We express oil prices as returns (i.e., the natural logarithmic difference expressed in percentage) to ensure stationarity.[4] Our effective sample therefore starts on 3 January 1986 and gives us a total of 7299 observations to work with. Note that, instead of using the VIX,[5] a popular measure of the implied volatility of S&P 500 index options, we use the news-based measure of EMU index to ensure that both our measures of uncertainty are derived in a similar method (i.e., news articles-based and, hence, the results, in terms of their relationship with oil, are comparable).[6]

The summary statistics of the variables have been reported in Table 1. As can be seen, oil returns and EPU are skewed to the left, and EMU skewed to the right, with all the variables having excess kurtosis. The Jarque–Bera test overwhelmingly rejects the null of normality, and this evidence of fat tails in the variables provides us the preliminary motivation to use causality-in-quantile test rather than standard linear Granger causality test based on the conditional mean. Note that EMU has higher volatility than EPU, which is understandable, given that it captures uncertainty in financial markets.

Though our primary objective is to analyse the predictability of EPU and EMU for oil returns and volatility, for the sake of comparison, we also investigated whether EPU and EMU can predict oil returns by conducting standard linear Granger causality tests based on VAR models with nine and five lags for EPU and EMU. As can be seen from Table 2, the null hypothesis of EPU (EMU) does not Granger cause oil returns was rejected at the 1 % (10 %) level of significance.[7]

Next, to motivate the use of the nonparametric quantile-in-causality approach, we statistically investigate the possibility of nonlinearity in the relationship between oil returns and EPU, and oil returns and EMU. To this end, we used the Brock et al. (BDS, 1996) test on the residuals of the oil returns equation of the VAR(9) and VAR(5) models comprising oil returns and EPU and EMU, respectively. As can be seen from Table 3,

[2] Further details are available at: http://www.policyuncertainty.com/us_daily.html.

[3] Further details are available at:http://www.policyuncertainty.com/equity_uncert.html.

[4] Not surprisingly, standard unit root tests reveal that oil price is a unit root process, while oil returns is stationary. On the other hand, EMU and EPU are found to be stationary. Complete details on the unit root tests are available upon request from the authors.

[5] Often referred to as the fear index or the fear gauge, it represents one measure of the Market's expectation of stock market volatility over the next 30-day period.

[6] As indicated at: http://www.policyuncertainty.com/equity_uncert.html, the EMU exhibits a contemporaneous daily correlation with the VIX of over 0.3.

[7] There was no evidence of predictability running from oil returns to either EPU or EMU even at 10 % level of significance. Complete details of these results are available upon request from the authors.

Table 1 Summary statistics

	Oil returns	Natural log of EPU	Natural log of EMU
Mean	0.0124	4.3682	3.8552
Median	0.0572	4.3913	3.8259
Maximum	19.1507	6.5780	7.8655
Minimum	−40.6396	1.5572	1.5688
Std. Dev.	2.5106	0.6773	1.0523
Skewness	−0.7701	−0.2726	0.2743
Kurtosis	18.1602	3.2468	2.7419
Jarque–Bera	70618.7200***	108.9293***	111.7629***
Observations	7299	7299	7299

SD Standard deviation
*** The rejection of the null of normality of the Jarque–Bera test at 1 % level of significance

Table 2 Linear Granger causality test

Null hypothesis	χ^2 test statistic	p value
EPU does not Granger cause oil returns	26.0263	0.0020
EMU does not Granger cause oil returns	9.9797	0.0758

VAR(9) and VAR (5) are, respectively, used for oil returns and EPU, and oil returns and EMU

Table 3 BDS test

m	Residual_OilReturns_EPU		Residual_OilReturns_EMU	
	z statistic	p value	z statistic	p value
2	17.8988	0.0000	18.1228	0.0000
3	22.9663	0.0000	23.1243	0.0000
4	26.5541	0.0000	26.5874	0.0000
5	29.2632	0.0000	29.2943	0.0000
6	32.1287	0.0000	32.1917	0.0000

Residual_OilReturns_EPU (Residual_OilReturns_EPU): residual series derived from the oil returns' equation in the VAR(9) (VAR(5)) for the case of EPU (EMU); The Null hypothesis tests whether residuals are *iid*; *m* stands for the embedded dimension

the null hypothesis of *iid* residuals is strongly rejected at 1 % level of significance across various dimensions. Those results provide evidence of nonlinearities in the data. Next we employed parameter (in)stability testing developed by Andrews (1993) and Andrews and Ploberger (1994) for the oil returns equations in the two VAR models. As can be seen from Table 4, the null of stability was rejected at 1 % level of significance by all test-stats, i.e., *Sup-F*, *Exp-F* and *Ave-F*. The results were also corroborated by Bai and Perron (2003) test of multiple structural breaks, which detected four breaks each in the oil returns equation for the EPU- and EMU-based VARs. The break dates are based on the *WDMAX* test under 1 to *M* globally determined breaks. As suggested

Table 4 Parameter stability testing

Test statistic	Oil returns VAR equations with EPU		Oil returns VAR equations with EMU	
Maximum LR F statistic	3.2173	0.0002	5.30660	0.0000
Exp LR F statistic	1.2440	0.0008	1.8360	0.0000
Ave LR F statistic	2.4528	0.0000	3.4398	0.0000

Parameter stability tests by Andrews (1993) and Andrews and Ploberger (1994) with the null of parameter stability

by Bai and Perron (2003), we used a maximum of 5 breaks and trimming of 15 %, which resulted in the break dates of 8 August 1990; 20 May 1996; 26 March 2003; and 10 December 2008 for the oil returns equation in the VAR with EPU, and 24 October 1990; 2 October 1998; 13 March 2003; and 26 November 2008 for the same in the VAR with EMU. So as under the BDS test which detected nonlinearity, existence of structural breaks in the association between oil returns with EPU and EMU implies that the Granger causality tests based on a linear framework are likely to suffer from misspecification. Given the strong evidence of both nonlinearity and regime changes in the relationships between oil returns and the two measures of uncertainty, we now turn our attention to the causality-in-quantile test.

Figure 1a, b reports the predictive ability of EPU for oil returns and volatility of oil returns, while Fig. 2a, b does the same based on EMU. As far as predicting oil returns is concerned, the results are quite similar for EPU and EMU across the various quantiles, with the null hypothesis of no causality being rejected for quantiles below 0.40 and above 0.55, and below 0.45 and above 0.55, respectively. As far as predicting the volatility is concerned, the situation is quite similar again, barring a slight difference at the higher end of the distribution. While for EPU, the null is rejected for all quantiles above 0.15, for EMU the null is rejected between quantiles 0.20 and 0.85. Overall, our results show that, as far as oil returns are concerned, EPU and EMU have predictability except around a region close to the median, but for volatility, the predictability virtually covers the entire distribution, with some exceptions in the tails.[8, 9]

The results tend to suggest that uncertainties related to economic policy and the equity market have predictive information content except around the median of the conditional distribution of oil returns. In other words, uncertainty matters only when the oil market is performing below or above its normal (average) mode, i.e., either in bullish or bearish scenarios. In case of the volatility of oil returns, uncertainty in general

[8] We obtained qualitatively similar results when we used oil returns and volatility based on the Brent crude price covering the period of 21 May 1987 to 8 December 2014. These results are available upon request from the authors.

[9] Oil returns are found to cause the mean of EPU from quantiles 0.25 and above, while its volatility is predicted over the entire conditional distribution. For EMU, oil returns predict the mean over the entire conditional distribution. As far as volatility of EMU is concerned, oil returns predict it adequately except around the median and upper quantiles, i.e., beyond 0.80. Note that as it is difficult to interpret economically what part of the variance of the uncertainty is implied, we keep these results restricted only to this footnote. Complete details of these results are available upon request from the authors.

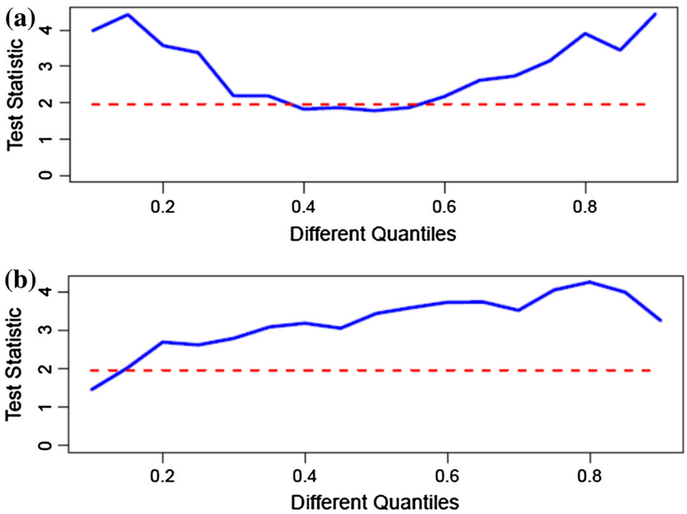

Fig. 1 **a** Quantile causality results for the H_0: *EPU does not Granger cause oil returns*. **b** Quantile causality results for the H_0: *EPU does not Granger cause oil return volatility*

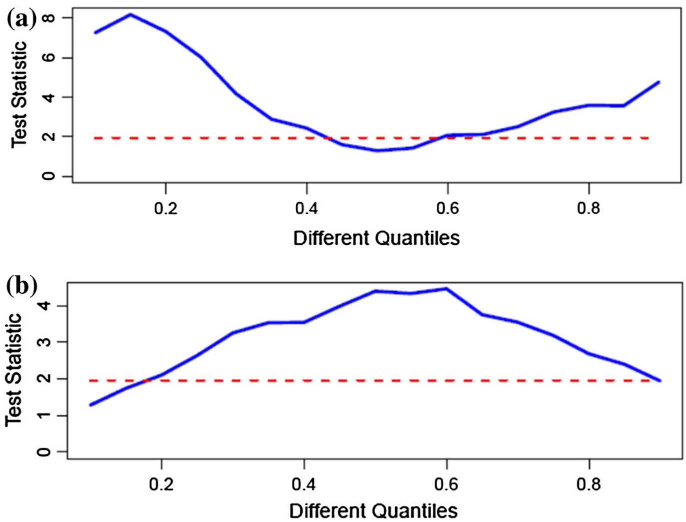

Fig. 2 **a** Quantile causality results for the H_0: *EMU does not Granger cause oil returns*. **b** Quantile causality results for the H_0: *EMU does not Granger cause oil return volatility*

affects the variance over the entire conditional distribution, i.e., at various phases of the oil market. There are, however, some exceptions, with the economic policy-related uncertainty unable to predict volatility of oil returns when the market is in extreme bearish regime. The same structure of predictability of oil returns volatility carries over for the case of equity market-related uncertainty, in addition to the fact that EMU also cannot predict oil market volatility under extreme bullish situations. So, while there is evidence of lack of predictability emanating from measures of uncertainty around the median for oil returns, the same is true for volatility around the tails.

Providing an explanation of why we observe these results by looking closely at the data structure and the relationship amongst the variables is of utmost importance. Firstly, we point out that the non-rejection ranges of the quantiles for causality in mean correspond to quantiles between 0.40 and 0.55 for EPU, and between 0.45 and 0.55 for EMU. These quantile ranges correspond to quantiles around the median, i.e., the centre of the conditional distribution of the oil returns. Most of the observations also fall into these quantile ranges. From Table 1, we see that the mean oil return is approximately zero; therefore, the non-causality in mean occurs around the zero return ranges, which in turn correspond to low volatility periods, where markets are optimistic and quite. The changes in both EPU and EMU are also relatively small during the low volatility periods, implying that the information flow is low during those periods. Therefore, during periods where the markets are tranquil and returns are not high, a low level of information flow is observed which does not have any significant impact on the average market return. This happens because, when the volatility is low, the response of the average returns will also be low and not significant.

However, during the high volatility periods where market returns are extreme (negative or positive) the same level of change in EPU and EMU has a significant impact on oil returns. Secondly, when we consider the causality in variance, we observe that EPU and EMU both have significant impact on the entire distribution of the conditional variance above the 0.15th quantile for EPU and between 0.20th and 0.85th quantiles for EMU. By noting that the low quantiles of the variance correspond to zero return ranges of the level of the oil returns, we corroborate this consistent outcome with the causality in mean results. Therefore, changes in the EPU and EMU do not also significantly affect the volatility when the markets are moderate and volatility is low, i.e., in periods of low average returns. Non-significant causality results in variance observed above 0.85th quantiles for EMU are probably due to very high variance estimates of the tests statistics, as not many observations (squared returns) fall into these very extreme ranges for the EMU.

4 Conclusions

There exists a large literature that connects oil price movements (shocks) with recessions and inflationary episodes in the US economy. Given this, it is important to determine the variables that drive the oil market to. In this regard, a recently growing literature emphasizes the role of uncertainties (economic policy and equity market) as drivers of oil price movements. Against this backdrop, the objective of this paper is to analyse whether recently developed news-based measures of economic policy uncertainty (EPU) and equity market uncertainty (EMU) can predict returns and volatility of oil returns. For our purpose, we use a bivariate quantile causality test, which combines causality in quantiles, with a kth-order nonparametric Granger causality.

Based on daily data on WTI oil price returns, EPU and EMU, and covering the period of 2 January 1986 to 8 December 2014, we find that as far as oil returns are concerned, the EPU and EMU measures present strong predictability over the entire distribution barring regions around the median. However, for volatility the predictability virtually covers the entire distribution, with some exceptions in the tails. In other words, uncertainty variables are likely to predict oil returns under extreme situations in the oil market, while volatility is likely to be predicted when the market is relatively calm, i.e., predictability is asymmetric over the distribution of oil returns and its volatility. As part of future research and according to the work by Bekiros et al. (2015), it would be interesting to extend our study to forecasting, since it is well accepted that in-sample outperformance does not guarantee high out-of-sample predictability.

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