

Oil Shocks and Volatility Jumps

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Abstract

In this paper, we analyse the role of oil price shocks, derived from expectations of consumers, economists, financial market, and policymakers, in predicting volatility jumps in the S&P500 over the monthly period of 1988:01 to 2015:02, with the jumps having been computed based on daily data over the same period. Standard linear Granger causality test fail to detect any evidence of oil shocks causing volatility jumps. But given strong evidence of nonlinearity and structural breaks between jumps and oil shocks, we next used a nonparametric causality-in-quantiles test, since the linear model is misspecified. Using this data-driven robust approach, we were able to detect overwhelming evidence of oil shocks predicting volatility jumps of the S&P500 over its entire conditional distribution, with the strongest effect observed at the lowest considered conditional quantile. Interestingly, the predictive ability of the four oil shocks on volatility jumps are found to be both qualitatively and quantitatively similar.

Keywords: S&P500, Volatility Jumps, Oil Shocks.

JEL Codes: C22, G10, Q02.

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1. Introduction

Theoretically, oil shocks are known to affect the stock market movements through, at least, five different channels: stock valuation, monetary, output, fiscal and uncertainty (see, Degiannakis et al., (2017) for a detailed discussion in this regard). To examine these channels empirically, one would need measures of oil shocks, which in turn, have been traditionally done using vector autoregressive models whereby the shocks is identified based on certain structural decomposition (Kilian and Park, 2009). More recently Baumeister and Kilian (2016), suggests the use of the gap between the price of oil that was expected and its eventual outcome as a measure of an oil price shock. More importantly, these authors illustrate that the same change in oil prices may be perceived quite differently by households, policymakers, financial markets, and economists, depending on how they form expectations. Given that this insight suggests different measures of oil shocks used by different agents in the economy to make their decisions, it is likely to have potentially important implications for understanding and modeling the transmission of oil price shocks to the economy, including financial markets.

Against this backdrop, the objective of this paper is to analyze the predictive ability of oil price shocks as perceived by households, policymakers, financial markets, and economists on volatility jumps of the S&P500 over the monthly period of 1988:03 to 2015:02, with the jumps having been computed based on daily data over the same period. Note that financial market volatility is used as an important input in investment decisions, option pricing and financial market regulation (Poon and Granger, 2003). In light of this, financial market participants care not only about the nature of volatility, but also about its level, with all traders making the distinction between good and bad volatilities (Giot et al., 2010). Good volatility is directional, persistent and relatively easy to predict, while, bad volatility is jumpy and comparatively difficult to foresee. Therefore, good volatility is generally associated with the continuous and persistent part, while bad volatility captures the discontinuous and jump component of volatility. Given this, it has been stressed that modeling jumps can improve the overall fit of volatility models (Duffie et al., 2000; Eraker et al., 2003; Broadie et al., 2007; Todorov and Tauchen, 2011). Understandably, a large literature has developed trying to not only model jumps, but also to try and explain the causes behind such jumps based on financial variables (Caporin et al., 2016), and news based on text-search (Cutler et al., 1989; Boudoukh et al., 2015; Baker et al., 2018; Gkillas et al., 2018).

With an already large number of studies investigating the the impact of oil shocks on

stock market returns and volatility (see, Gupta and Wohar (2017), and Smyth and Narayan (2018) for detailed reviews), our paper is a departure from this line of research, and aims to add to the literature on the drivers of volatility jumps by analysing for the first time, the predictive ability of oil price shocks as perceived by various agents in the economy. For our predictability analysis, we rely on the nonparametric causality-in-quantiles test of Jeong et al., (2012), and hence, in the process capturing various phases (sizes) of volatility jumps. Understandably, the causality-in-quantiles test used here is inherently a time-varying approach as various parts of the conditional distribution of volatility jumps would relate to various points in time associated with the evolution of jumps. The causality-in-quantile approach has the following two main novelties: First, it is robust to misspecification errors as it detects the underlying dependence structure between the examined time series. This is particularly important as we show that volatility jumps are nonlinearly associated with the oil shocks – a result that should not come as a surprise, that there is ample evidence of financial market variables being nonlinearly related to their predictors, including oil shocks (Jiménez-Rodríguez, 2015). And second, using this methodology, we are able to test not only for causality-in-mean (1st moment) (see for example, Heimstra and Jones, 1994; Diks and Panchenko, 2005, 2006), but also for causality that may exist in the tails of the joint distribution of the variables. This is again of tremendous importance since our dependent variable, i.e., volatility jumps is shown to have fat-tails – a feature also outlined in Bollerslev et al., (2013).

The remainder of the paper is organized as follows: Section 2 lays out the basics of the econometric methodologies involving volatility jumps and the causality-in-quantiles approach; Section 3 presents the data and results, with Section 4 concluding the paper.

2. Econometric Methodologies

2.1. Volatility Jumps

We employ daily log returns $R_{t,i}$ of the S&P500 to estimate the monthly median realized variance (MRV_t). In each month t , we retrieve a monthly point estimate of the MRV_t by employing all daily returns. We calculate monthly volatility by the median realized variance, MRV_t , which is the best alternative jump-robust estimator of realized variance, as introduced by Andersen et al. (2012), as follows:

$$MRV_t = \gamma \left(\frac{N}{N-2} \right) \sum_{i=1}^{N-1} med(|R_{t,i-1}|, |R_{t,i}|, |R_{t,i+1}|)^2 \quad (1)$$

where, $\gamma = \left(\frac{\pi}{6-4\sqrt{3}+\pi}\right)$, $R_{t,i}$ is the daily return for day i within month t and $i = 1, \dots, N$, where N is the total number of daily observations within a month.

Following, Bekaert and Hoerova (2014) we employ the threshold bipower variation ($TBPV_t$) as a jump-free volatility estimator as defined in Corsi et al. (2010), as follows:

$$TBPV_t = \sum_{i=2}^N |R_{t,i-1}|, |R_{t,i}| I_{\{|R_{t,i-1}|^2 \leq \theta_{i-1}\}} I_{\{|R_{t,i}|^2 \leq \theta_i\}} \quad (2)$$

where $I_{\{\cdot\}}$ is the indicator function and the threshold function, $R_{t,i}$ is the daily return series and t represents the time in months.

We calculate the jump statistic $\left(ZJ_t^{(TBPV)}\right)$ following Duong and Swanson (2015), as follows:

$$ZJ_t^{(TBPV)} = \sqrt{N} \frac{(MRV_t - TBPV_t)MRV_t^{-1}}{[(\xi_1^{-4} + 2\xi_1^{-2} - 5) \max\{1, TQ_t TBPV_t^{-2}\}]^{1/2}} \quad (3)$$

where TQ_t is the realized tripower quarticity which is $TQ_t = N\xi_{4/3}^{-3} \sum_{i=1}^N |R_{t,i}|^{4/3} |R_{t,i+1}|^{4/3} |R_{t,i+2}|^{4/3}$ and converges in probability to integrated quarticity. The $ZJ_t^{(TBPV)}$ statistic follow a normal gaussian distribution.

A jump is considered to be significant if the $ZJ_t^{(TBPV)}$ exceeds the appropriate critical value of the standard gaussian distribution, denoted by Φ_a , at a a significant level. The jump component of volatility in monthly frequency is:

$$JUMP_t^{(TBPV)} = |MRV_t - TBPV_t| I_{\{ZJ_t^{(TBPV)} > \Phi_a\}} \quad (4)$$

where $I_{\{\cdot\}}$ represents an indicator function of the $ZJ_t^{(TBPV)}$ exceeds of a given critical value of a Gaussian distribution.

2.2. Causality-in-Quantiles

This sub-section provides a brief description of the quantile based methodology based on the framework of Jeong *et al.* (2012). As mentioned earlier, this approach is robust to extreme values in the data and captures general nonlinear dynamic dependencies. Let y_t denote volatility jumps and x_t denote the predictor variable, in our case the various oil price shocks, considered in turn, as perceived by households, policymakers, financial markets, and economists (discussed in detail in the Data segment of the paper).

Formally, 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 $F_{y_t|Z_{t-1}}(y_t, Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t, Y_{t-1})$ denote the conditional distribution functions of y_t given Z_{t-1} and Y_{t-1} , respectively. If we 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 $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1}) | Z_{t-1}\} = \theta$ with probability one. Consequently, the (non)causality in the q -th quantile hypotheses to be tested can be specified as:

$$H_0: P\{F_{y_t|Z_{t-1}}\{Q_q(Y_{t-1}) | Z_{t-1}\} = q\} = 1, \quad (5)$$

$$H_1: P\{F_{y_t|Z_{t-1}}\{Q_q(Y_{t-1}) | Z_{t-1}\} = q\} < 1. \quad (6)$$

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 hypothesis in (1), which can only be true if and only if $E[\mathbf{1}\{y_t \leq Q_\theta(Y_{t-1}) | Z_{t-1}\}] = \theta$ or, equivalently, $\mathbf{1}\{y_t \leq Q_\theta(Y_{t-1})\} = \theta + \varepsilon_t$, where $\mathbf{1}\{\cdot\}$ is an indicator function. Jeong *et al.* (2012) show that the feasible kernel-based sample analogue of J has the following form:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^T \sum_{s=p+1, s \neq t}^T K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s. \quad (7)$$

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:

$$\hat{\varepsilon}_t = \mathbf{1}\{y_t \leq Q_\theta(Y_{t-1})\} - \theta. \quad (8)$$

$\hat{Q}_\theta(Y_{t-1})$ is an estimate of the θ^{th} conditional quantile of y_t given Y_{t-1} , and we estimate $\hat{Q}_\theta(Y_{t-1})$ using the nonparametric kernel method as

$$\hat{Q}_\theta(Y_{t-1}) = \hat{F}_{y_t|Y_{t-1}}^{-1}(\theta | Y_{t-1}), \quad (9)$$

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

$$\hat{F}_{y_t|Y_{t-1}}(y_t | Y_{t-1}) = \frac{\hat{a}_{s=p+1, s^1 t}^T L((Y_{t-1} - Y_{s-1})/h) \mathbf{1}(y_s \leq y_t)}{\hat{a}_{s=p+1, s^1 t}^T L((Y_{t-1} - Y_{s-1})/h)}, \quad (10)$$

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

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 $L(\cdot)$ respectively. In this study, we use $p=1$ based on the Schwarz Information Criterion (SIC). Note that, when it comes to choosing lags, the SIC is considered to be parsimonious compared to other lag-length selection criteria. The SIC helps overcome the issue of over-parameterization usually arising with nonparametric frameworks. The bandwidth value is chosen by employing the least squares cross-validation techniques.¹ Finally, for $K(\cdot)$ and $L(\cdot)$ Gaussian-type kernels was employed.

3. Data and Results

3.1. Data

Monthly data on oil price shocks is based on the work of Baumeister and Kilian (2016) on oil price expectations of consumers, policymakers, financial market and consumers.² These authors employ a VAR model specification that includes the real price of oil, global crude oil production, global real economic activity, and changes in global crude oil stocks, and refer to the implied expectation of the price of oil as the economists' expectation. The most common approach to inferring the expected price of oil for immediate delivery in the physical market (also known as the spot price). The convention has been to treat the price of the oil futures contract with maturity h as the h -period ahead market expectation of the nominal price of crude oil, which in turn, is used as the measure of the policymakers' oil price expectation by Baumeister and Kilian (2016). Recently, Hamilton and Wu (2014) document that there is a large horizon-specific time-varying risk premium in the oil futures market. Further, this risk premium is shown to vary with the hedging demands of oil producers and refiners, and the willingness of financial investors to take the other side of hedging contracts. Baumeister and Kilian (2016) then recover the oil price expectation of financial market by subtracting Hamilton and Wu's (2014) estimates of the risk premium from the oil futures price for a given horizon. Finally, Baumeister and Kilian (2016) assume that consumers forecast the real and nominal prices of crude oil according to a simple no-change model such that the nominal price is expected to grow at the rate of inflation. This allows them to proxy consumer expectations about the nominal price of oil based on the current price of oil and an inflation forecast based on the Michigan Survey of Consumers about the price of gasoline (primarily determined by the price of crude oil) and inflation. Once these

¹ For each quantile, we determine the bandwidth h using the leave-one-out least-squares cross validation method of Racine and Li (2004) and Li and Racine (2004).

² We would like to thank Professor Christiane Baumeister for kindly providing us with this data.

expectations are derived, we, as in Baumeister and Kilian (2016), compute the corresponding perception of oil price shocks by subtracting these expectations from the realized (actual) West Texas Intermediate (WTI) spot price of that month, with the WTI oil data obtained from the FRED database of the Federal Reserve Bank of St. Louis.

As indicated above in Sub-section 2.1, we use daily returns of the S&P500 to arrive at the monthly volatility jump values. Stock returns are computed as the logarithmic first difference of the daily S&P500 stock price index, with data on the S&P500 stock index obtained from Datastream of Thomson Reuters. Note that our analysis covers the monthly period of 1988:03 to 2015:02 (i.e., 324 months), with the start and end date being purely driven by the availability of data on the oil price expectations. Figures A1(a) and A1(b) in the Appendix plot the volatility jump variable and the oil price shocks respectively, while Table A1 reports the summary statistics of the variables under consideration. The summary statistics highlight how different the various oil price shocks are from each other. While volatility in general is quite close to each other, with economists' oil price shocks having the highest volatility and consumers' version of the same the lowest, the mean values are quite different. The financial market and consumers' oil price shocks have positive means, but for the policymakers' and economists' oil price shocks, the means are negative. While excess kurtosis is observed for all the four oil shocks as well as for volatility jumps (*JUMPS*), negative skewness is observed for policymakers' and consumers' oil price shocks. More importantly, all the variables have non-normal distributions, as indicated by the overwhelming rejection (at 1 percent level of significance) of the null of normality under the Jarque-Bera test. The heavy-tail of the unconditional distribution of volatility jumps provide a preliminary justification for the causality-in-quantiles test used in the empirical analysis.

[INSERT FIGURE A1 and TABLE A1]

3.2. Empirical Findings

Before we discuss the findings from the causality-in-quantiles test, for the sake of completeness and comparability, we first conducted the standard linear Granger causality test, with a lag-length of one, as determined by the SIC. The resulting $\chi^2(1)$ statistics, as reported in Table 1, suggests that the null that the various oil price shocks (consumers', economists', financial market, and policymakers') does not Granger cause volatility jumps, cannot be rejected even at the 10 percent level of significance. Therefore, based on the standard linear test, one would conclude of no significant oil shocks-related effects on S&P500 volatility jumps.

[INSERT TABLE 1]

Given the insignificant results obtained from the linear causality tests, we next statistically examine the presence of nonlinearity and structural breaks in the relationship between *JUMPS* and the four oil shocks. Nonlinearity and regime changes, if present, would further motivate the use of the nonparametric quantiles-in-causality approach, as the quantiles-based test would formally address nonlinearity and structural breaks in the relationship between the two variables under investigation. For this purpose, we apply the Brock *et al.*, (1996, BDS) test on the residuals from the jump equation involving one lag of *JUMPS* and a specific oil shock. Table 2 presents the results of the BDS test of nonlinearity. As shown in this table, we find strong evidence, at highest level of significance, for the rejection of the null of *i.i.d.* residuals at various embedded dimensions (m), which in turn, is indicative of nonlinearity in the relationship between *JUMPS* and the four oil shocks, considered in turn. To further motivate the causality-in-quantiles approach, we next used the powerful *UDmax* and *WDmax* tests of Bai and Perron (2003), to detect 1 to M structural breaks in the relationship between *JUMPS* and the oil shocks, allowing for heterogenous error distributions across the breaks. When we applied these tests again to the jump equation involving one lag of *JUMP* and a particular oil shock under consideration GPR, we detected two breaks each for the economists', financial market's and policymakers' oil price shocks at months 2004:12 and 2008:12, while, only one break was found under the case of the consumers' oil price shock at 20018:11. Note that, while the early break date corresponds to sharp increases, the latter one is associated with a decline in the oil price, as well as a sharp increase in volatility jumps in the wake of the global financial crisis. These finding indicate that, the results based on the linear Granger causality test, cannot be deemed robust and reliable.

[INSERT TABLE 2]

Given the strong evidence of nonlinearity and structural break(s) in the relationship between volatility jumps and oil shocks, we now turn our attention to the causality-in-quantiles test, which is robust to linear misspecification due to its nonparametric (i.e., data-driven) approach. As can be seen from Figure 1, which reports this test for the quantile range of 0.05 to 0.95, the null that the four oil shocks (considered sequentially) does not Granger causes *JUMPS* is overwhelmingly rejected at the 5 percent level of significance (given the critical value of 1.96), with the strongest evidence of predictability observed at the lowest quantile of the conditional distribution of *JUMPS*. Note that, to study which of these oil shocks has a stronger impact on *JUMPS*, we standardized the oil shocks by dividing with their respective standard deviation.

Interestingly, the strength of causality is found to be quite similar across the four oil shocks considered. But more importantly, our results highlight that when we account for nonlinearity and structural breaks using a nonparametric approach, we are able to find strong evidence of predictability emanating from oil shocks onto volatility jumps of the S&P500, unlike what was observed under the linear framework. To put it alternatively, we observe that oil shocks can predict volatility jumps of the S&P500, irrespective of the magnitude of the jumps as captured by the various quantiles of the conditional distribution of *JUMPS*.

[INSERT FIGURE 1]

To get additional insights into the results obtained, we conducted three additional analyses, and report them in the Appendix of the paper. First, we repeat our analysis using the cross-quantilogram approach of Han et al., (2016). The cross-quantilogram measures quantile dependence and tests for directional predictability between two time series.³ Using this approach, as reported in Figure A2(i)-(viii), we observe that oil shocks do positively and significantly affect volatility jumps, with this effect being particularly strong at higher quantiles, i.e., for higher magnitude of the various oil price shocks. In other words, in line with the extant literature on the asymmetric effect of oil shocks on stock markets (see for example the discussion in Alsalman and Herrera (2015)), larger shocks tend to cause bigger volatility jumps. Second, just as there is a large literature on the size of the oil shock, there are also many studies that have looked into the effect of the sign of shock, i.e., whether an oil shock is positive or negative (see for example, Narayan and Gupta (2015) for a detailed review). Given this, we decompose the various oil shocks into their positive and negative components by first defining two dummy variables, which takes a value of 1 when the shock is positive and 0 otherwise, and vice-versa (i.e., 1 when the shock is negative and 0 otherwise), and then we multiply these two dummy variables with the oil price shocks separately to obtain the positive and negative oil shocks for each of the four agents. As can be seen from Table A2, while the strongest predictability is observed at the lowest conditional quantile of *JUMPS*, there is hardly any evidence in favour of causality beyond the conditional median. This result tends to suggest that, disaggregating the oil shocks into its positive and negative components is not necessarily of value when it comes to predicting volatility jumps of the S&P500, as unlike the overall shocks, the predictability gets restricted to smaller volatility jumps only. Finally, we revisit our analysis by computing oil shocks at various horizons based on the financial market expectations of oil price at various horizons (3-, 6-, 9-,

³ The reader is referred to Han et al., (2016) for further details on the technical details of the cross-quantilogram methodology.

and 12-month-ahead), as recently developed Baumeister and Kilian (2017).⁴ Our results derived in the main text carries over to this measure of financial market's oil price shock, as we observe from Table A3 that, irrespective of the horizon considered, the effect is strongest at the lower quantiles of *JUMPS*. One interesting observation is that at the longest-horizon of 12-month-ahead, oil price shocks, unlike at horizons of 3-, 6- and 9-month ahead, fail to predict volatility jumps beyond the conditional quantile of 0.40, i.e., the predictive content of the oil price shock at the horizon considered is absent when it comes to explaining large volatility jumps. However, just in the case positive financial market's oil shocks based on the Baumeister and Kilian's (2016) data discussed above in the second point, the effect is restricted only at the lower quantiles of the conditional distribution of *JUMPS*. But unlike as discussed earlier under the second issue above, for the negative version of these financial market oil price shocks at various horizons, predictability is observed at certain moderately high quantiles excluding the region around the median, even for the 12-month-ahead horizon. This result tends to hint towards the fact that larger volatility jumps are likely to be driven by negative oil price shocks perceived by the financial the market.

[INSERT FIGURE A2 and TABLES A2 AND A3]

4. Conclusions

In the recent volatility-related literature, it has been stressed that jumps in volatility can improve the overall fit of volatility models. Therefore, a large literature has developed trying to not only model volatility jumps, but also attempting to explain the causes behind such jumps based on financial variables, and more recently, news. Given this, in this paper we analyse the role of oil price shocks, derived from expectations of consumers, economists, financial market, and policymakers, in predicting volatility jumps in the S&P500 over the monthly period of 1988:01 to 2015:02, with the jumps having been computed based on daily data over the same period. For our predictability analysis, we rely on a nonparametric causality-in-quantiles test, which in turn, is robust to misspecification due to nonlinearity and structural breaks being a data-driven procedure.

Starting off with the standard linear causality test, we were unable to detect any evidence of oil shocks causing volatility jumps. But, we indicate that linear Granger causality test results cannot be relied upon because formal tests reveal strong evidence of nonlinearity and structural breaks between volatility jumps and the four different oil shocks. Hence, linear Granger causality tests are misspecified. When we use the nonparametric causality-in-quantiles test instead, we

⁴ The data is available for download from the website of Professor Christiane Baumeister at: <https://sites.google.com/site/cjsbaumeister/research>, and covers the monthly period of 1992:01 to 2017:06

were able to detect overwhelming evidence rejecting the null hypothesis that oil shocks does not Granger causes jumps over the entire conditional distribution of the latter, with the strongest effect observed at the lowest considered conditional quantile. Interestingly however, even though the underlying nature of the oil shocks are quite different, the effect of the four oil shocks considered are found to be both qualitatively and quantitatively similar in predicting the S&P500 volatility jumps. Thus, our results indicated that when we control for misspecification due to nonlinearity and regime changes, it is indeed true that oil shocks can predict movements in volatility jumps of the S&P500, irrespective of the size of such jumps. Interestingly however, the strength of causality is found to be quite similar across the four oil shocks considered. Though there exists a large literature on the effect of oil shocks on returns and volatility of equity markets, which caused us to concentrate only on volatility jumps, as part of future research it would be interesting to revisit the effect of these newly identified shocks as perceived by various agents on stock returns and volatility. In addition, one could also analyze the role of these oil shocks on volatility jumps of equity markets of other developed and developing countries, besides alternative asset classes like, currencies, bonds and commodities.

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Table 1. Linear Granger Causality Test

Dependent Variable	Independent Variable	$\chi^2(1)$	p -value
<i>JUMPS</i>	Consumers' Oil Price Shocks	0.0007	0.9783
	Economists' Oil Price Shocks	2.6810	0.1025
	Financial Market Oil Price Shocks	1.0236	0.3124
	Policymakers' Oil Price Shocks	2.0110	0.1571

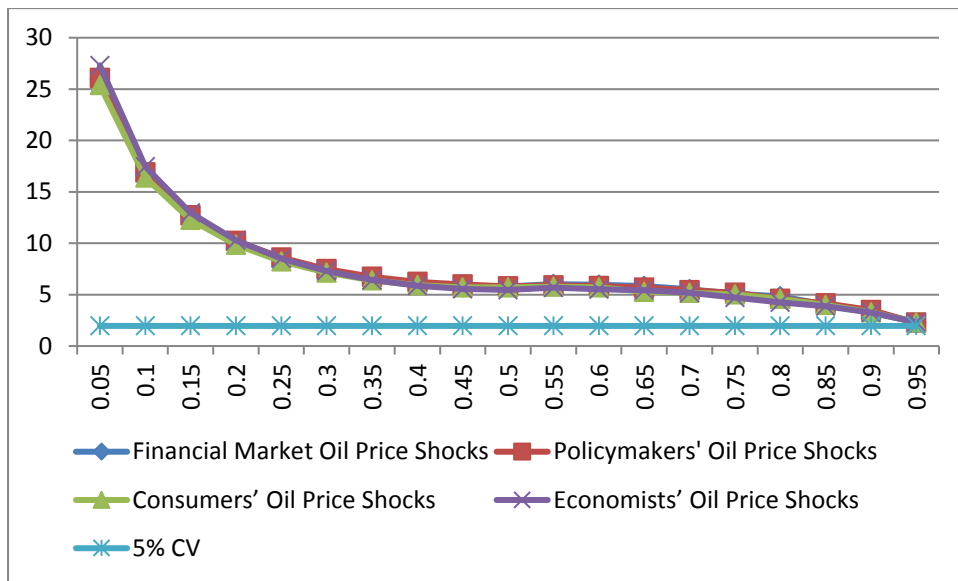
Note: The null hypothesis tests that the independent variable does not Granger cause *JUMPS*.

Table 2. Brock et al., (1996, BDS) Test of Nonlinearity

Independent Variable	m				
	2	3	4	5	6
Consumers' Oil Price Shocks	3.1950*	3.2720*	3.7610*	3.8310*	4.4140*
Economists' Oil Price Shocks	4.2950*	4.5490*	5.0070*	5.4830*	6.2360*
Financial Market Oil Price Shocks	3.725*	3.826*	4.237*	4.533*	5.243*
Policymakers' Oil Price Shocks	3.918*	4.030*	4.448*	4.868*	5.551*

Note: Entries correspond to the $\hat{\alpha}$ -statistic of the BDS test with the null of *i.i.d.* residuals, with the test applied to the residuals recovered from the jump equation with one lag each of *JUMPS* and the four different oil shocks considered in turn; * indicates rejection of the null hypothesis at 1 percent level of significance.

Figure 1. Causality-in-Quantiles Test Results for S&P500 Volatility Jumps due to Oil Shocks



Notes: CV(5%) is the 5 percent critical value of 1.96. The horizontal axis measures the various quantiles while the vertical axis captures the tests statistic. The lines corresponding to consumers', economists', financial market's, and policymakers' oil price shocks show the rejection (non-rejection) of the null of no Granger causality from the various oil shocks to volatility jumps at the 5 percent level, if the lines are above (below) 1.96 for a specific quantile.

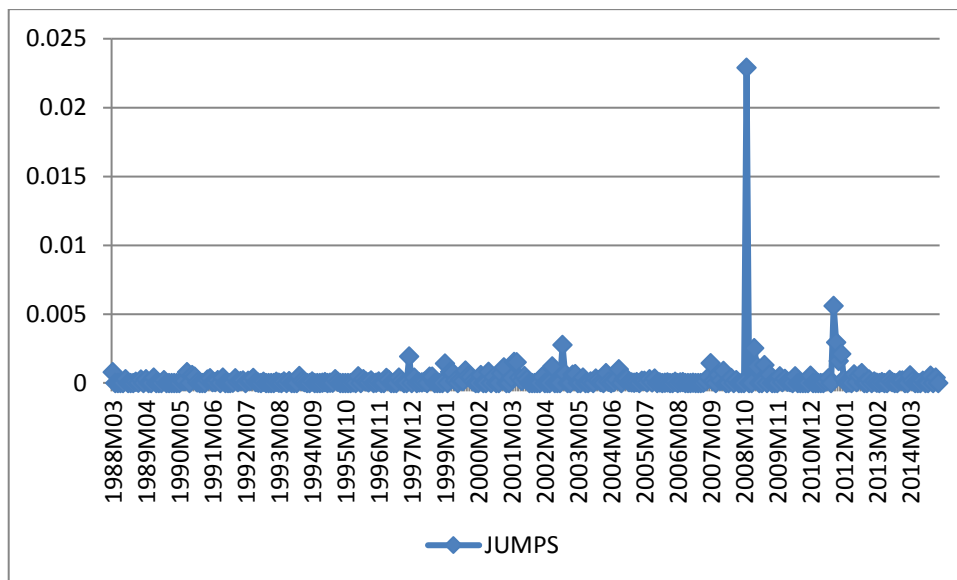
APPENDIX:

Table A1. Summary Statistics

	Variable				
Statistic	Financial Market Oil Price Shocks	Policymakers' Oil Price Shocks	Consumers' Oil Price Shocks	Economists' Oil Price Shocks	<i>JUMPS</i>
Mean	0.9183	-0.4323	0.4415	-0.0016	0.0003
Median	-0.3333	-0.7942	0.3827	-0.9797	0.0000
Maximum	36.1833	27.8137	16.6832	39.6887	0.0229
Minimum	-30.0989	-46.6125	-31.4363	-31.7466	0.0000
Std. Dev.	8.3352	8.2878	6.9725	8.4571	0.0014
Skewness	0.8050	-0.2617	-0.3629	0.8581	14.6105
Kurtosis	5.7207	6.1447	3.7549	6.0802	240.2552
Jarque-Bera	134.9217	137.2027	14.8059	167.8413	771442.9000
<i>p</i> -value	0.0000	0.0000	0.0006	0.0000	0.0000
Observations	324				

Note: Std. Dev: stands for standard deviation; *p*-value corresponds to the Jarque-Bera test with the null of normality.

Figure A1. Data Plots
A1(a). S&P500 Volatility Jumps



A1(b). Oil Price Shocks

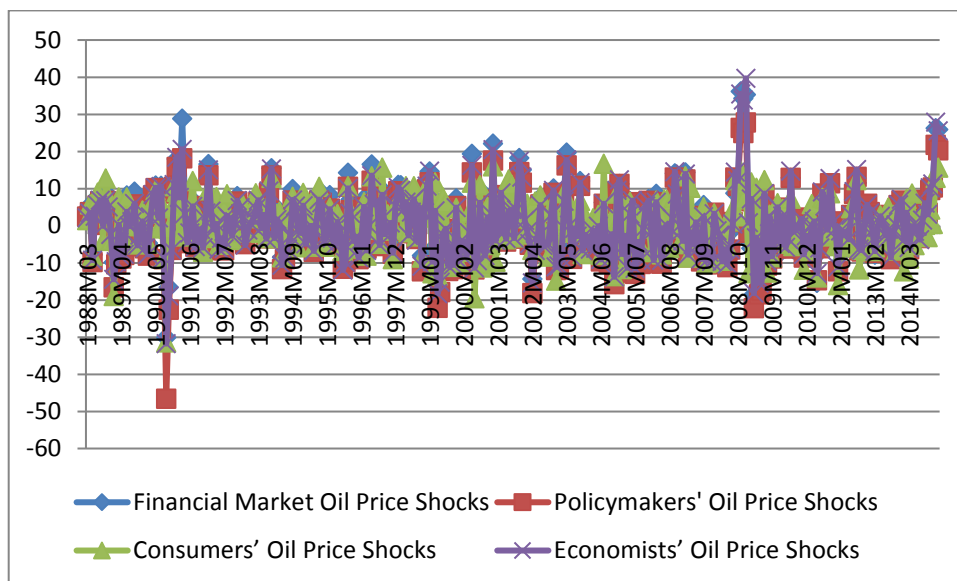
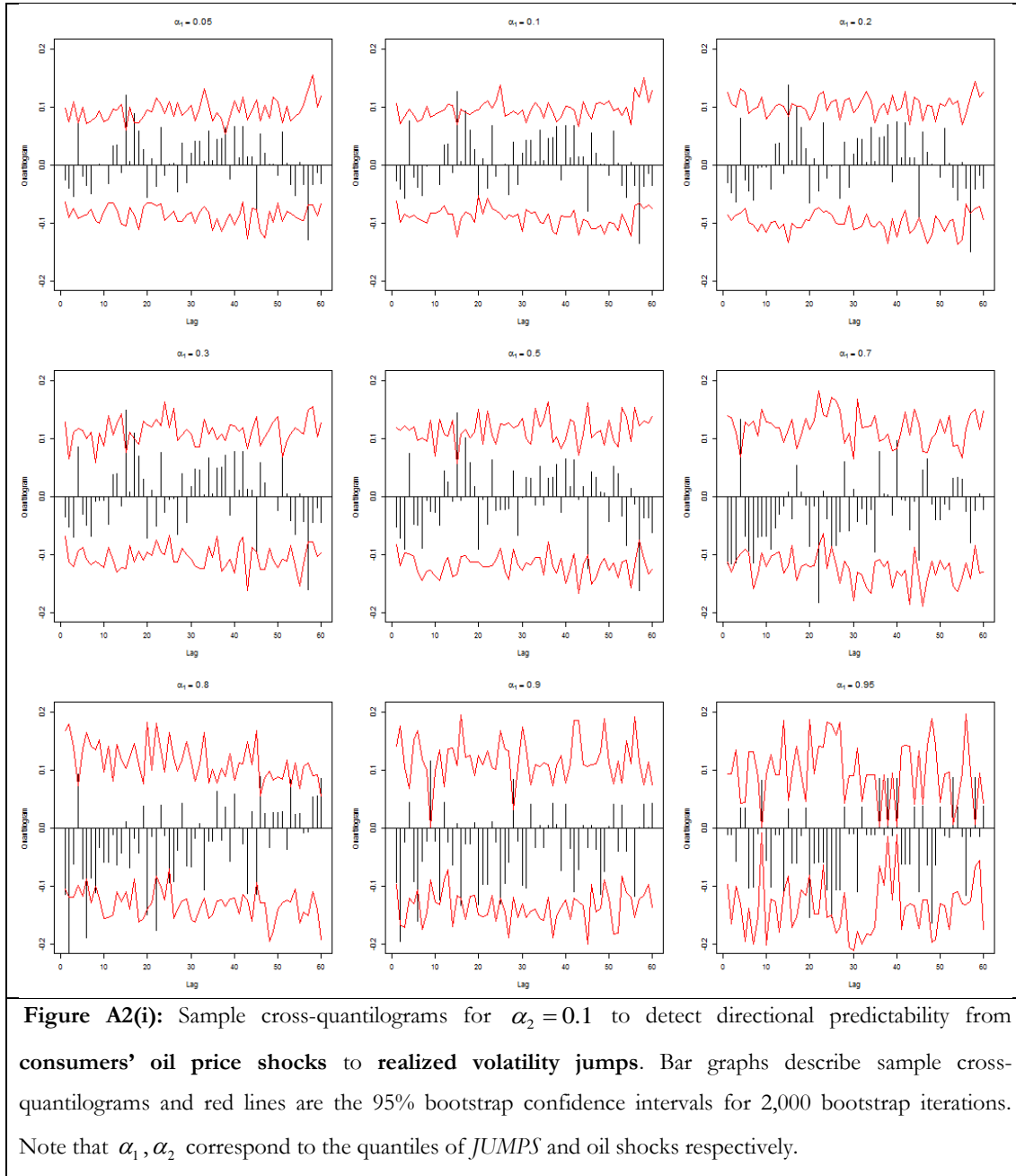
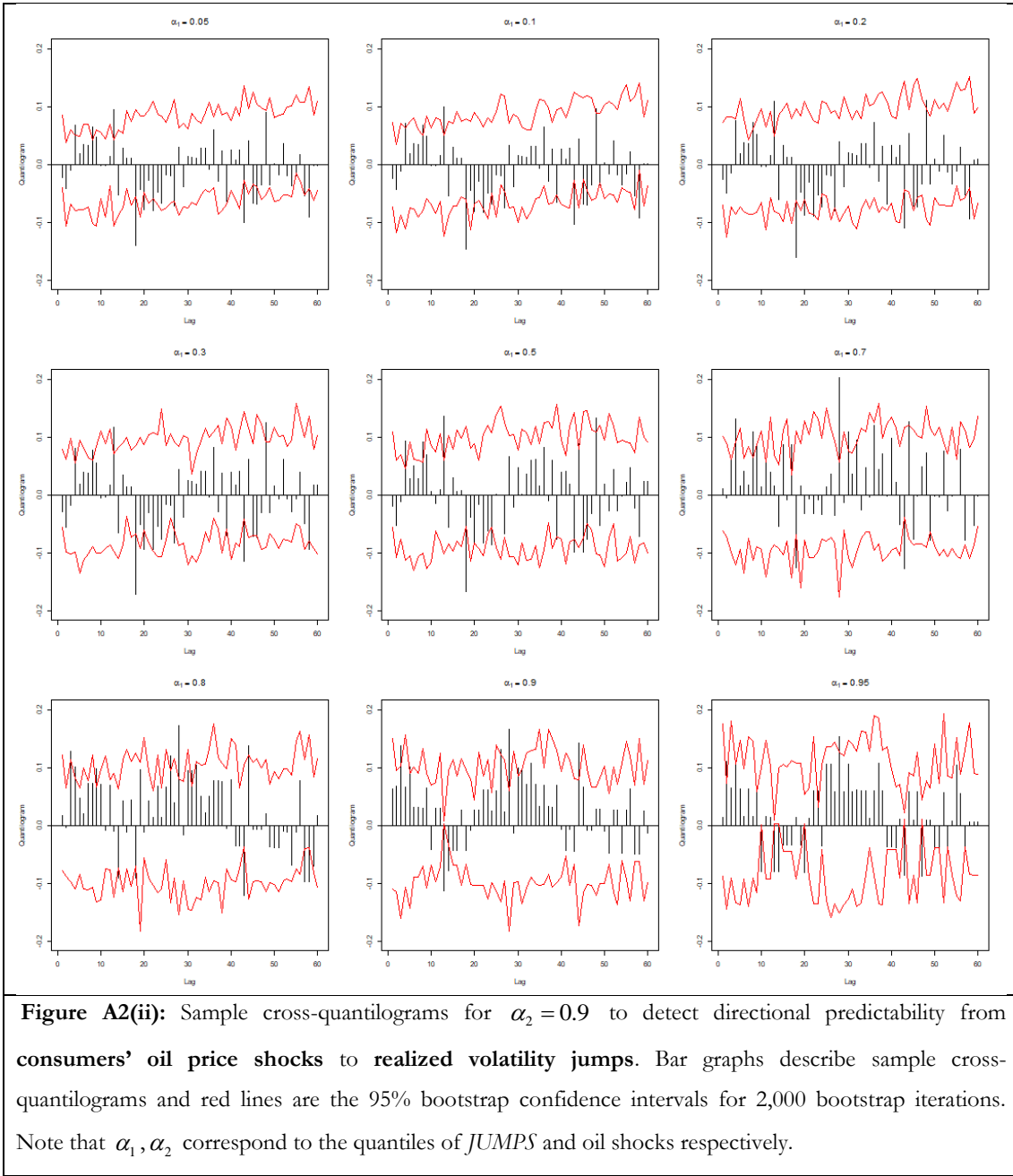


Figure A2. Cross-Quantilogram Results





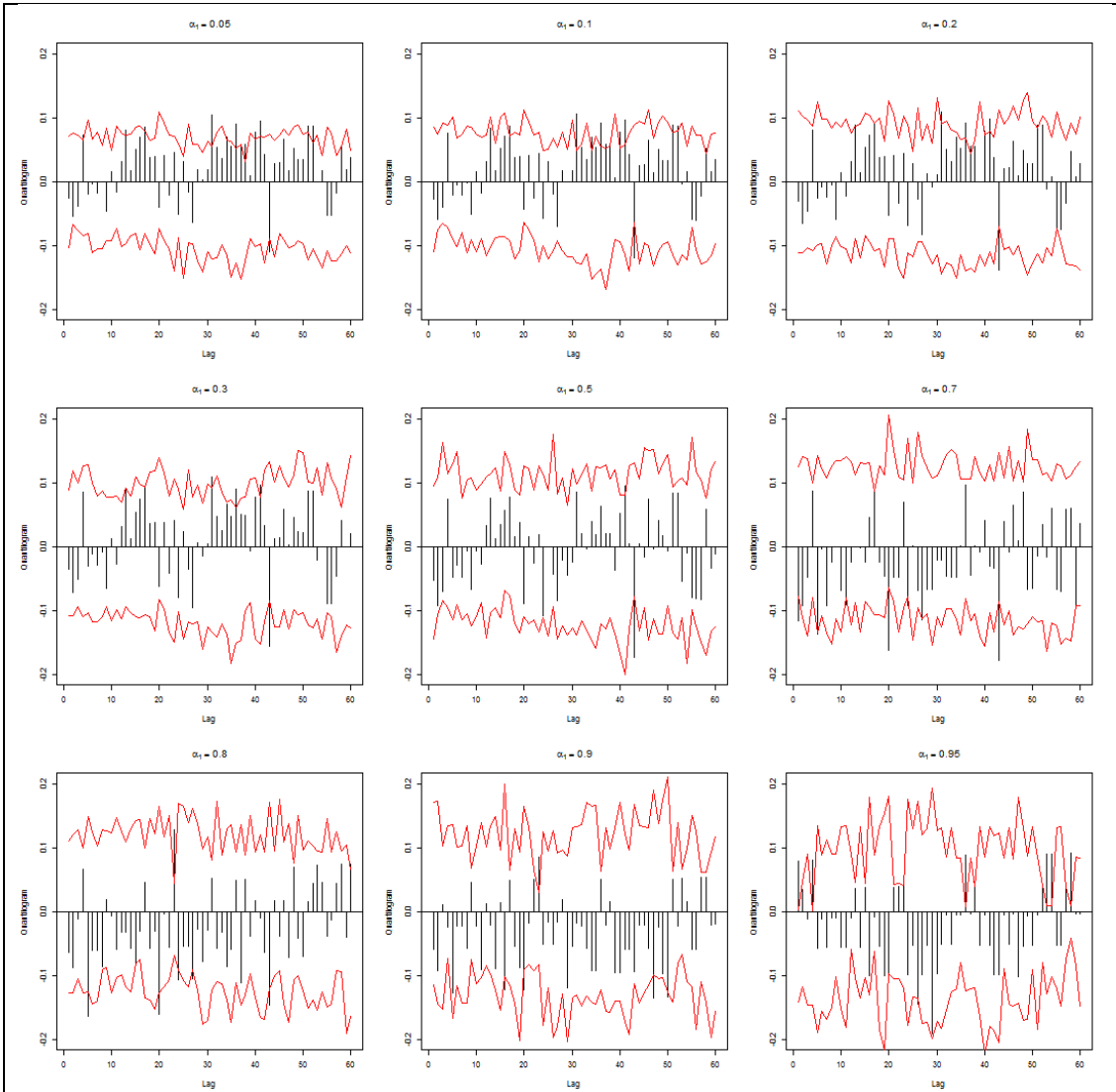


Figure A2(iii): Sample cross-quantilograms for $\alpha_2 = 0.1$ to detect directional predictability from **economists' oil price shocks** to **realized volatility jumps**. Bar graphs describe sample cross-quantilograms and red lines are the 95% bootstrap confidence intervals for 2,000 bootstrap iterations. Note that α_1, α_2 correspond to the quantiles of *JUMPS* and oil shocks respectively.

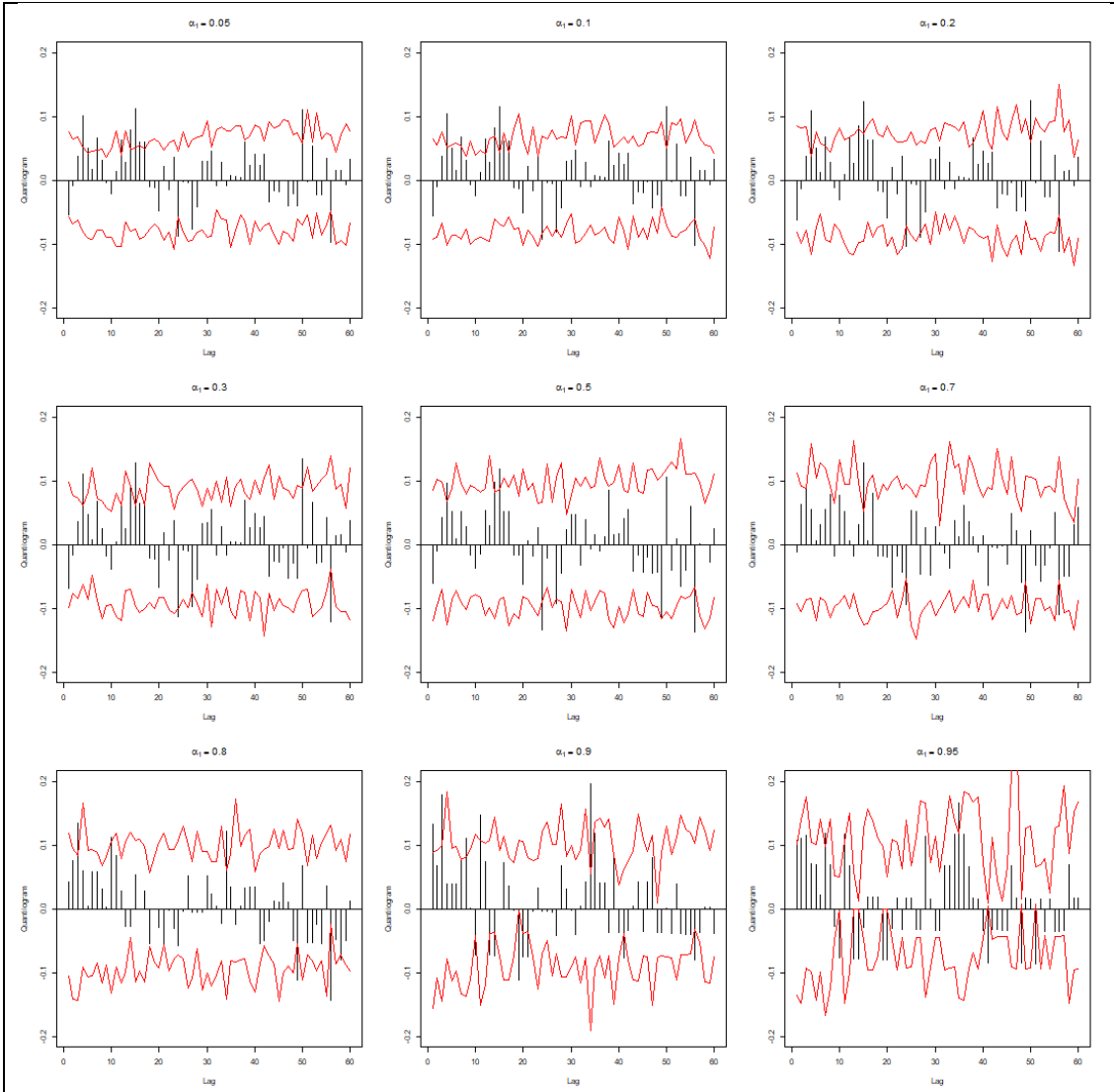


Figure A2(iv): Sample cross-quantilograms for $\alpha_2 = 0.9$ to detect directional predictability from **economists' oil price shocks** to **realized volatility jumps**. Bar graphs describe sample cross-quantilograms and red lines are the 95% bootstrap confidence intervals for 2,000 bootstrap iterations. Note that α_1, α_2 correspond to the quantiles of *JUMPS* and oil shocks respectively.

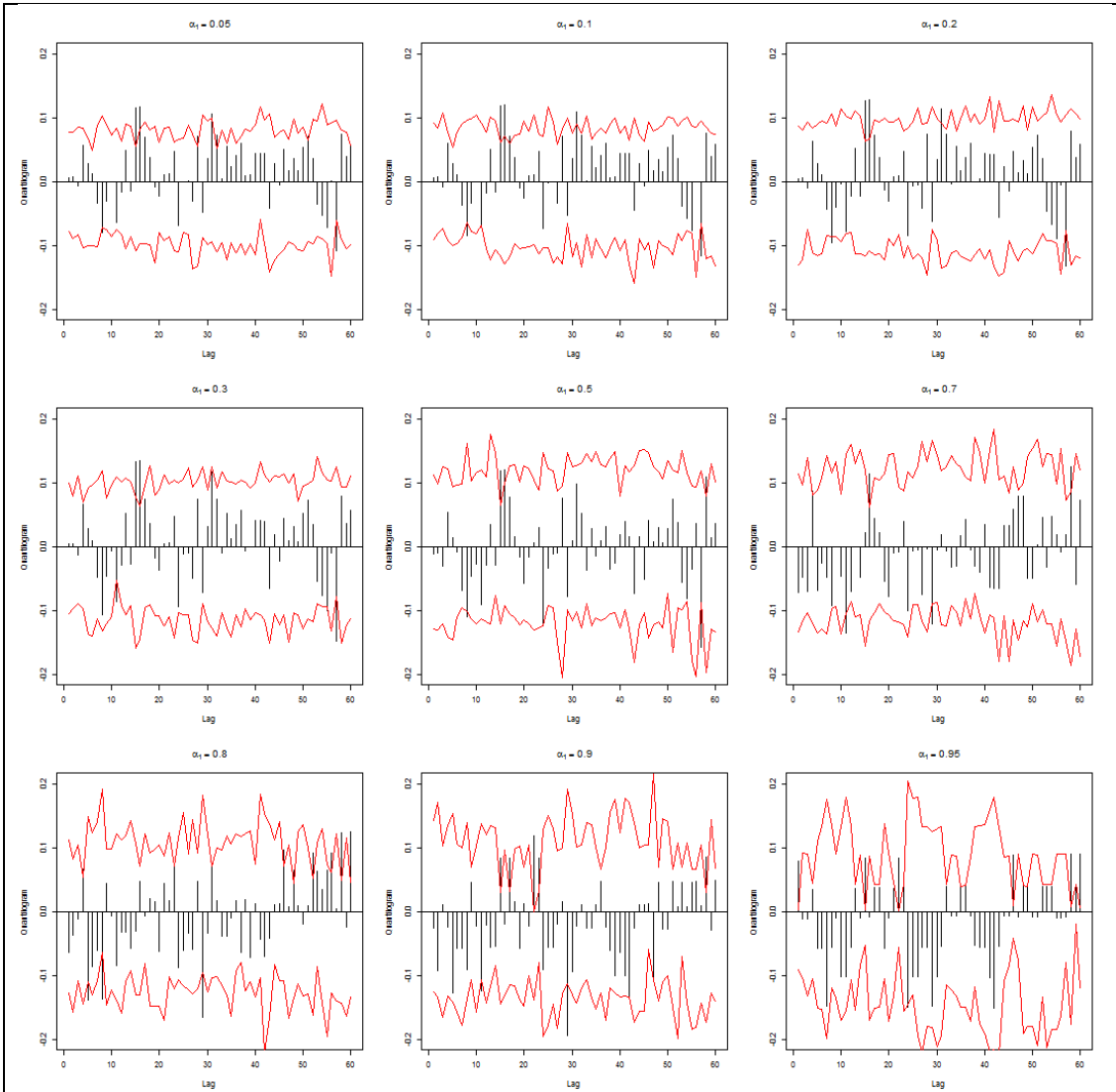


Figure A2(v): Sample cross-quantilograms for $\alpha_2 = 0.1$ to detect directional predictability from **financial market's oil price shocks** to **realized volatility jumps**. Bar graphs describe sample cross-quantilograms and red lines are the 95% bootstrap confidence intervals for 2,000 bootstrap iterations. Note that α_1, α_2 correspond to the quantiles of *JUMPS* and oil shocks respectively.

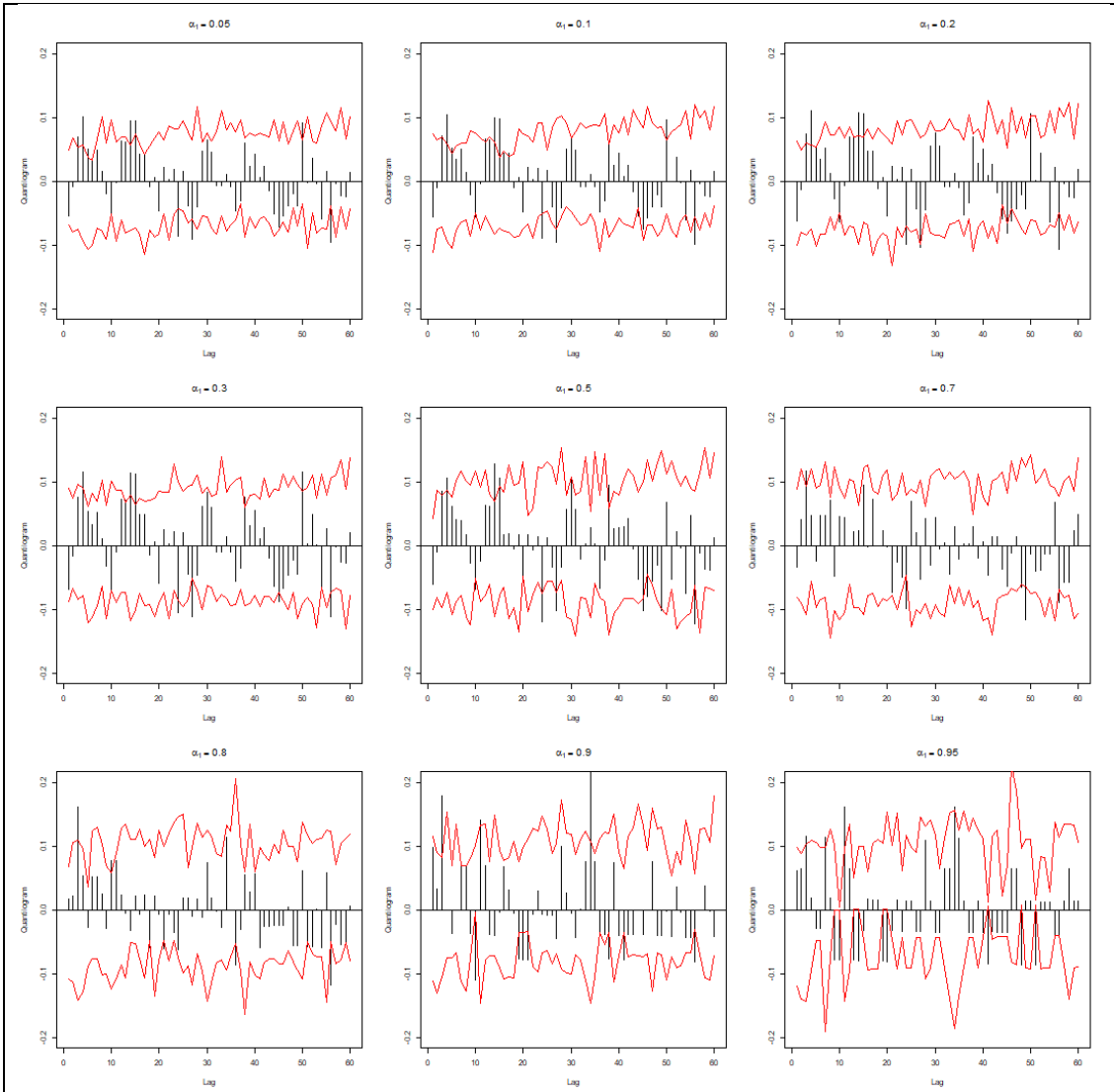


Figure A2(vi): Sample cross-quantilograms for $\alpha_2 = 0.9$ to detect directional predictability from **financial market's oil price shocks to realized volatility jumps**. Bar graphs describe sample cross-quantilograms and red lines are the 95% bootstrap confidence intervals for 2,000 bootstrap iterations. Note that α_1, α_2 correspond to the quantiles of *JUMPS* and oil shocks respectively.

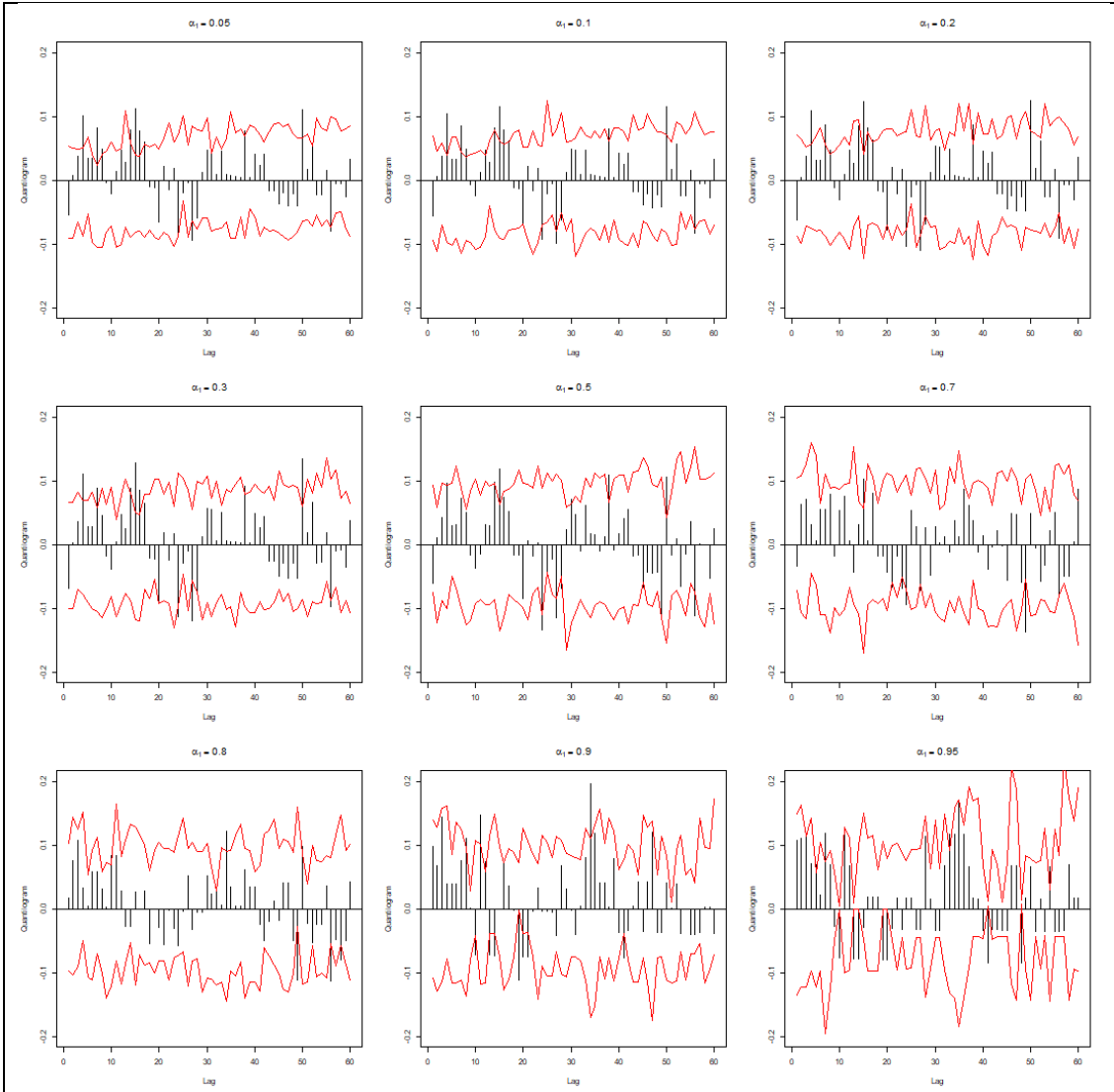


Figure A2(vii): Sample cross-quantilograms for $\alpha_2 = 0.1$ to detect directional predictability from **policymakers' oil price shocks** to **realized volatility jumps**. Bar graphs describe sample cross-quantilograms and red lines are the 95% bootstrap confidence intervals for 2,000 bootstrap iterations. Note that α_1, α_2 correspond to the quantiles of *JUMPS* and oil shocks respectively.

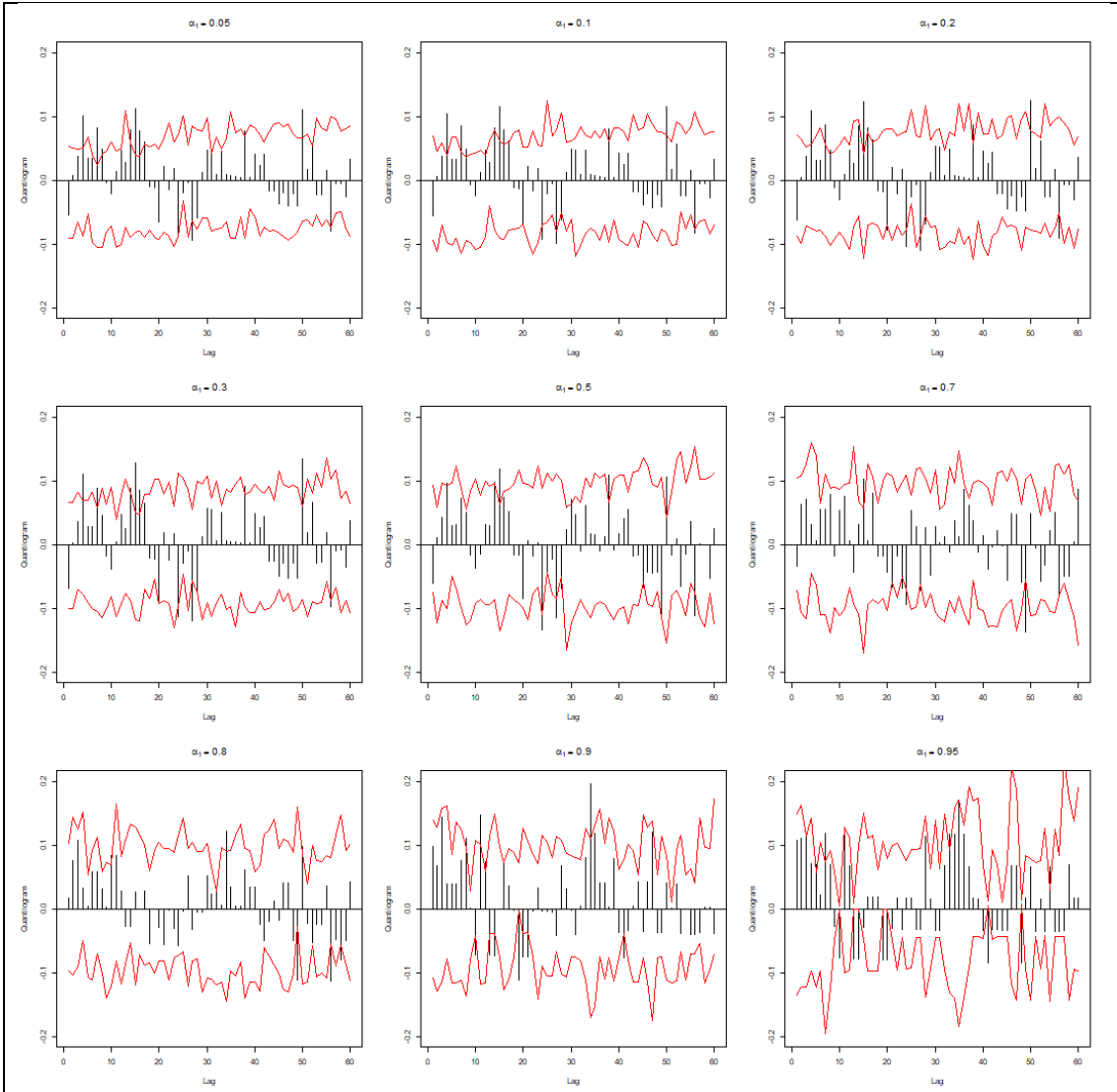


Figure A2(viii): Sample cross-quantilograms for $\alpha_2 = 0.9$ to detect directional predictability from **policymakers' oil price shocks** to **realized volatility jumps**. Bar graphs describe sample cross-quantilograms and red lines are the 95% bootstrap confidence intervals for 2,000 bootstrap iterations. Note that α_1, α_2 correspond to the quantiles of *JUMPS* and oil shocks respectively.

Table A2. Causality-in-Quantiles Test Results for S&P500 Volatility Jumps due to Positive and Negative Oil Shocks

Variable	Quantile																		
	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9	0.95
Cons.(+)	50.15*	28.52*	18.21*	11.89*	7.65*	4.74*	2.79*	1.61	1.09	1.15	1.18	1.10	1.44	1.36	1.70	1.45	1.18	1.13	0.38
Cons.(-)	65.53*	38.42*	25.51*	17.50*	12.00*	8.05*	5.19*	3.18*	1.87	1.38	1.36	1.11	1.09	1.07	1.05	1.16	1.22	0.62	0.46
Econ.(+)	51.33*	28.71*	17.97*	11.43*	7.09*	4.18*	2.30*	1.27	0.97	1.00	0.97	1.18	1.60	1.47	1.75	1.40	1.11	0.96	0.32
Econ.(-)	66.89*	39.94*	27.15*	19.19*	13.68*	9.66*	6.68*	4.49*	2.95*	1.92	1.92	1.40	1.41	1.15	1.10	1.19	1.34	0.73	0.54
FM(+)	48.34*	27.22*	17.17*	11.04*	6.97*	4.22*	2.44*	1.45	1.13	1.27	1.20	1.54	2.00*	1.73	1.70	1.48	1.05	1.00	0.37
FM(-)	67.67*	40.06*	26.90*	18.73*	13.09*	9.01*	6.03*	3.88*	2.44*	1.84	1.95	1.32	1.33	1.10	1.00	1.12	1.34	0.63	0.45
PM(+)	47.48*	26.42*	16.42*	10.36*	6.36*	3.71*	2.04*	1.17	1.02	1.13	1.02	1.37	1.82	1.65	1.98*	1.57	1.22	1.06	0.34
PM(-)	69.97*	41.85*	28.46*	20.13*	14.35*	10.14*	7.01*	4.71*	3.08*	2.07*	2.01*	1.43	1.47	1.20	1.14	1.11	1.23	0.74	0.49

Note: Cons. is consumers' oil price shock; Econ. is economists' oil price shock; FM is financial market's oil price shock; PM is policymakers' oil price shock; (+) or (-) indicate whether the shock is positive or negative; * indicates significance at the 5 percent level.

Table A3. Causality-in-Quantiles Test Results for S&P500 Volatility Jumps due to Financial Market's Oil Shocks at Various Forecast Horizons

Variable	Quantile																		
	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9	0.95
3M	23.86*	15.41*	11.58*	9.31*	7.81*	6.80*	6.13*	5.71*	5.52*	5.68*	5.72*	5.46*	5.48*	5.14*	4.95*	4.47*	3.83*	3.23*	2.22*
3M(+)	52.05*	29.86*	19.34*	12.88*	8.51*	5.46*	3.35*	1.97*	1.24	1.33	1.59	1.21	1.16	1.05	0.92	0.97	0.68	0.64	0.41
3M(-)	33.07*	18.16*	11.13*	6.92*	4.22*	2.49*	1.51	1.13	1.29	1.50	1.52	2.12*	2.31*	2.44*	2.25*	1.58	1.97*	1.76	0.44
6M	23.78*	15.68*	12.00*	9.81*	8.38*	7.41*	6.75*	6.34*	6.14*	6.13*	6.09*	5.99*	5.83*	5.59*	5.26*	4.85*	4.30*	3.68*	2.50*
6M(+)	52.95*	30.72*	20.08*	13.49*	9.00*	5.83*	3.60*	2.13*	1.29	1.32	1.52	1.12	0.98	1.01	0.91	0.85	0.71	0.61	0.42
6M(-)	29.14*	16.17*	10.02*	6.34*	3.98*	2.49*	1.65	1.36	1.55	1.74	1.75	2.59*	2.29*	2.66*	2.72*	2.39*	2.07*	1.79	0.53
9M	24.88*	16.04*	12.04*	9.66*	8.09*	7.02*	6.30*	5.85*	5.62*	5.62*	5.72*	5.68*	5.44*	5.21*	5.11*	4.66*	4.05*	3.14*	2.24*
9M(+)	53.46*	30.52*	19.67*	13.02*	8.54*	5.42*	3.27*	1.90	1.19	1.12	1.26	1.10	1.05	0.95	0.89	1.08	0.76	0.60	0.42
9M(-)	35.89*	20.06*	12.57*	8.04*	5.06*	3.09*	1.86	1.23	1.13	1.20	1.30	1.68	2.23*	2.30*	2.03*	1.53	1.52	1.57	0.50
12M	54.98*	31.85*	20.87*	14.10*	9.48*	6.22*	3.91*	2.35*	1.43	1.30	1.37	1.11	1.03	1.00	0.93	1.03	0.79	0.61	0.45
12M(+)	54.98*	31.85*	20.87*	14.10*	9.48*	6.22*	3.91*	2.35*	1.43	1.30	1.37	1.11	1.03	1.00	0.93	1.03	0.79	0.61	0.45
12M(-)	32.27*	17.78*	10.93*	6.83*	4.19*	2.52*	1.56	1.19	1.36	1.32	1.42	1.90	1.97*	2.34*	2.04*	1.67	1.41	1.46	0.50

Note: 3M, 6M, 9M and 12M stands for financial market's oil price shock at horizon of 3-month, 6-month, 9-month, and 12-month-ahead respectively; (+) or (-) indicate whether the shock is positive or negative; * indicates significance at the 5 percent level.