Working Paper

Causality-in-quantiles between crude oil and stock markets: Evidence from emerging economies

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Note: This version is one of the earlier drafts of the paper. To access the final version please visit https://doi.org/10.1016/j.frl.2020.101736

Abstract
This study investigates the asymmetric effect of crude oil shocks on emerging sectoral stock indices using a non-parametric causality-in-quantiles approach. This study considers the origin of the oil shock i.e. demand shock or supply shock to investigate its impact on various sectors in mean and volatility. We find that the impact of crude oil is heterogeneous across shocks (demand or supply), market states (bullish, bearish and normal) and to a limited extent across sectors. Observing similar pattern of crude oil's impact on emerging sectors, we argue that the influence of crude oil shocks extends beyond energy intensive sectors.

Keywords
Crude oil; Stock markets; Demand shock; Supply shock; Causality-in-quantiles.
JEL Classification
G120, G190, Q020, Q430

1. Introduction

Crude oil contributes significantly in meeting world's energy needs and any fluctuation in its prices can have a sizable influence on economic activities like: employment, real economic activity, investment and stock market returns (Papapetrou, 2001; Rafiq, Salim, & Bloch, 2009). Of numerous implications of crude oil (CO) price fluctuations, its impact on stock markets (SMs) becomes an important variable to investigate since SMs can indicate and anticipate the impending economic developments (Fama, 1990). Thus, numerous studies focus on the association between CO and SMs (Apergis & Miller, 2009; Arouri, 2011; Syed Abul Basher, Haug, & Sadorsky, 2018; Syed Abul Basher & Sadorsky, 2016; Bhatia & Mitra, 2018; Kilian, 2009; Kilian & Park, 2009; Miller & Ratti, 2009; Naifar & Al Dohaiman, 2013; Ready, 2017; Zhang & Wang, 2019).

Literature recognize several modes of association between CO and SMs. CO is an essential commodity required during the production processes of numerous goods and services. Any positive shock to CO prices translates into higher production costs, which can result in reduced earnings and can also have a negative impact on stock prices (Apergis & Miller, 2009; Syed A. Basher & Sadorsky, 2006; Sadorsky, 1999). CO can also impact SMs through inflationary channels. Central banks typically increase interest rates as a counter mechanism to fight high inflation. However, higher interest rates usually result in higher discount rates, which may exert downward pressure on stock prices (Jammazi, Ferrer, Jareño, & Shahzad, 2017; Miller & Ratti, 2009).

Recently, it has also been argued that the origin of a shock i.e. demand driven or supply driven, to CO prices can also play an important role in determining the extent of impact CO has on stock prices (Hamilton, 2009; Kilian, 2009; Ready, 2017). For instance, positive demand shocks can indicate an optimistic economic outlook, as higher demand suggests an economy to be on a growth trajectory. Therefore, an increase in CO prices could have a positive impact on stock prices. Such positive association is more prominent in case of CO dependent manufacturing industries (Ready, 2017). On the contrary, demand side shocks can also have a negative impact on stock prices. The increase in oil prices can prompt consumers to moderate their consumption expenditure and elicit precautionary savings behavior. Such events can force stock prices on a descending course (Kilian & Park, 2009; Xu, 2015). Whereas, supply side shocks tend to have a nil to a strong negative effect on stock prices.

In this study, we investigated the causality-in-quantiles of demand and supply shocks of CO on emerging sectoral stock indices. We followed the framework suggested by Ready (2017) to segregate the origin of CO shock, i.e. into demand or supply driven and then investigated its causal impact on emerging sectoral SMs. To investigate the causal relationship, we employed the non-parametric causality-in-quantiles approach proposed by Balcilar, Bekiros, & Gupta (2017). This approach takes care of the misspecification errors that may arise due to the nonlinear dynamics of time-series under investigation.

This study contributes to the extant literature in many ways. *First*, CO shocks on a whole may not appear to influence SM returns, as the impact of demand side and supply side shocks may cancel out each other in empirical settings. This may result into diminished to no impact of CO shocks on SMs. Segregating CO shocks into demand and supply shocks could overcome such limitations and therefore, may provide additional insights into CO and SM relationship. *Second*, we examine the causal impact of demand and supply shocks on sectoral SM indices. Such analysis could provide additional details on the dynamics between CO shocks on SMs, which could be overlooked while studying a representative stock market index. Considering different sectors could reveal the influence of CO shocks on the industries which are less dependent on CO. *Third*, we investigate the higher order interdependency between CO and SMs, i.e. we investigate causality between the selected series not only in first moment but also in second moment. *Fourth*, we examine the causal relationship not only around mean, but also for the entire distribution (bullish, normal and bearish time periods).

Remaining paper is organized as follows: Section 2 describes the empirical methodology used in this paper. Section 3 presents the data and preliminary analysis followed by empirical results in section 4. Section 5 provides the discussion and conclusion.

2. Empirical methodology

2.1

To segregate oil shocks into demand shocks and supply shocks using the framework proposed by Ready (2017), the three series necessary to consider are: the series representing the index of energy (oil and gas) firms, the series measuring oil price changes and the series measuring changes in expected return. The index of energy firms was regressed with the innovations in VIX (volatility index) and the resultant residuals were defined as demand shocks. Similarly, supply shocks were defined using the residue of changes in the series representing change in oil prices that is orthogonal to both demand shocks and innovations in VIX. Therefore, the entire variation in oil prices (X_t) is segregated into demand shocks (D_t), supply shocks (S_t), and risk shocks (R_t), which are orthogonal and defined as follows.

$$X_t = \begin{bmatrix} \Delta price_t \\ R_t^{index} \\ \xi VIX_t \end{bmatrix}, Z_t = \begin{bmatrix} S_t \\ D_t \\ R_t \end{bmatrix}, A \equiv \begin{bmatrix} 1 & 1 & 1 \\ 0 & a_{22} & a_{23} \\ 0 & 0 & a_{33} \end{bmatrix} \tag{1}$$

Change in oil prices is depicted by $\Delta price_t$, R_t^{index} is the index returns, and ξVIX_t represents innovation in VIX. Further, X_t is defined as:

$$X_t = AZ_t \tag{2}$$

To impose orthogonality, the following condition is satisfied:

$$A^{-1} \textstyle\sum_x (A^{-1})^T = \begin{bmatrix} \sigma_S^2 & 0 & 0 \\ 0 & \sigma_D^2 & 0 \\ 0 & 0 & \sigma_R^2 \end{bmatrix} \tag{3}$$

Equation 3 shows the covariance matrix (Σ_x) of the observable X_t and volatilities of the identified shocks (σ_S, σ_D and σ_R).

2.2 Causality in quantiles

To measure the causality, we adopt the causality-in-quantiles approach proposed by Balcilar et al., (2016). This approach is based on the earlier works of Nishiyama et al., (2011) and Jeong et al., (2012). The nonlinear causality in a sectoral SM (y_t) is tested with the predictor CO shock (x_t). The quantile-based causality may be defined as:

The CO shock does not cause SM return with respect to lag vector $\{y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\}$ in the θ-quantile if

$$Q_\theta(y_t | y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}) = Q_\theta(y_t | y_{t-1}, \dots, y_{t-p}) \tag{4}$$

The conditional quantiles $Q_\theta(y_t| \cdot)$ indicates the θ-th quantile of y_t and depends on t. The quantiles can take the values between zero and one, i.e., $0 < \theta < 1$.

This test allows for historical values of CO shock to predict the value of CO return in θ^{th} quantile but, restricts other quantiles. To test the causality in second moment, this test augments the approach of Jeong et al., (2012). However, while combining the statistic for a joint null in equation 4 an issue of mutual correlation arises (Nishiyama et al., 2011). To overcome the stated complication, this test closely follows the sequential testing method suggested by Nishiyama et al., (2011).[1]

3. Data and preliminary analysis

[1] For details about the methodology followed in this study please see, Ready (2017) and Balcilar *et al.,* (2016).

We employed the Morgan Stanley Capital International - Emerging Market Sectoral Index (MSCI-EMSI)[2] from December 1994 to November 2018. We used the dollarized daily closing prices of the MSCI-EMSI comprising of 6236 observations. Data was accessed using Bloomberg database services. MSCI has classified emerging markets in 11 sectors and these include: communication services, consumer discretionary, consumer staples, energy, financials, health care, industrials, information technology, materials, real estate and utilities.

We considered the MSCI All Country World Index (ACWI) Energy Index to represent the index of energy firms. One-month returns on the New York Mercantile Exchange (NYMEX) - Light Sweet Oil contracts, were used as a proxy for changes in oil price. Finally, the Chicago Board Options Exchange - Volatility Index (CBOE-VIX) was considered to measure the required rate of return (discount rate). Ready (2017) and Bollerslev et al. (2009) suggested that VIX has the ability to capture changes in the risk, as not only VIX exhibits a negative correlation with stock returns but also has an ability to predict them in the time-series. To measure the unexpected changes in VIX, the residuals from an ARMA (1,1) process were estimated and used as innovations.

The non-linear characteristics of time-series is widely recognized in the past (Tsay, 1986), and therefore, linear Granger causality analysis may show a spurious association between the series under investigation (Babalos & Balcilar, 2016; Bekiros, Gupta, & Kyei, 2016). To test for nonlinearity, we employed BDS test (Broock, Scheinkman, Dechert, & LeBaron, 1996)) which suggests a strong nonlinear characteristic of the selected time series (Table 1). In addition, we employed Bai and Perron's (2003) multiple structural break test and found a strong evidence of multiple structural breaks (Table 2). Therefore, we employed the nonlinear causality technique proposed by Balcilar *et al.,* (2016), which is robust to the nonlinear characteristic of the data. Causality-in-quantiles differs from Granger causality in at least two fronts. First, the non-parametric causality-in-quantiles approach can identify the causal relationship for the entire range distribution (bullish, bearish and normal market states), whereas Granger causality relies on the center of distribution. Second, this approach not only allows to test the causal relationship in mean (first moment) but also allows to test the causality-in-variance (second moment).

Table 1. BDS test

	m

[2] Emerging market countries in MSCI emerging market sectoral index include: Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Qatar, Russia, Saudi Arabia, South Africa, Taiwan, Thailand, Turkey and United Arab Emirates. For further details please visit https://www.msci.com

	2	3	4	5	6
Communication Services	22.67***	27.21***	30.68***	33.57***	36.62***
Consumer Discretionary	18.08***	23.08***	27.32***	30.59***	33.99***
Consumer Staples	19.63***	24.05***	27.29***	29.45***	31.77***
Energy	19.45***	24.67***	28.51***	31.40***	34.44***
Financials	20.17***	25.30***	29.01***	31.83***	34.73***
Health Care	5.00***	8.70***	11.40***	12.62***	14.53***
Industrials	23.63***	28.75***	32.52***	35.70***	38.94***
Information Technology	15.06***	20.81***	24.59***	28.07***	32.00***
Materials	21.65***	26.29***	29.76***	32.33***	35.04***
Real Estate	20.32***	25.58***	29.27***	32.38***	35.31***
Utilities	23.87***	28.29***	32.01***	34.59***	37.41***

Note: *m* indicates the number of embedding dimensions. Values indicate BDS z-statistic for the null hypothesis that the series is independently and identically distributed. The null hypothesis is rejected at 1% (***) level of significance.

Table 2. Multiple structural breaks

	Break dates				
Communication Services	10-05-1999	11-03-2003	29-10-2007	23-09-2011	24-04-2015
Consumer Discretionary	05-10-1998	10-10-2002	11-05-2006	25-05-2010	27-08-2014
Consumer Staples	10-05-1999	11-03-2003	29-10-2007	04-07-2011	24-04-2015
Energy	05-10-1998	21-03-2003	12-12-2007	26-07-2011	16-03-2015
Financials	05-10-1998	17-03-2003	31-10-2007	23-09-2011	24-04-2015
Health Care	21-09-1998	26-07-2002	05-05-2006	22-09-2011	23-04-2015
Industrials	01-09-1998	10-10-2002	31-10-2007	23-09-2011	24-04-2015
Information Technology	29-03-2000	24-11-2003	16-07-2007	23-09-2011	24-04-2015
Materials	31-08-1998	12-03-2003	29-10-2007	26-07-2011	16-03-2015
Real Estate	06-10-1998	17-03-2003	01-11-2007	23-09-2011	24-04-2015
Utilities	31-08-1998	16-10-2002	31-10-2007	23-09-2011	24-04-2015

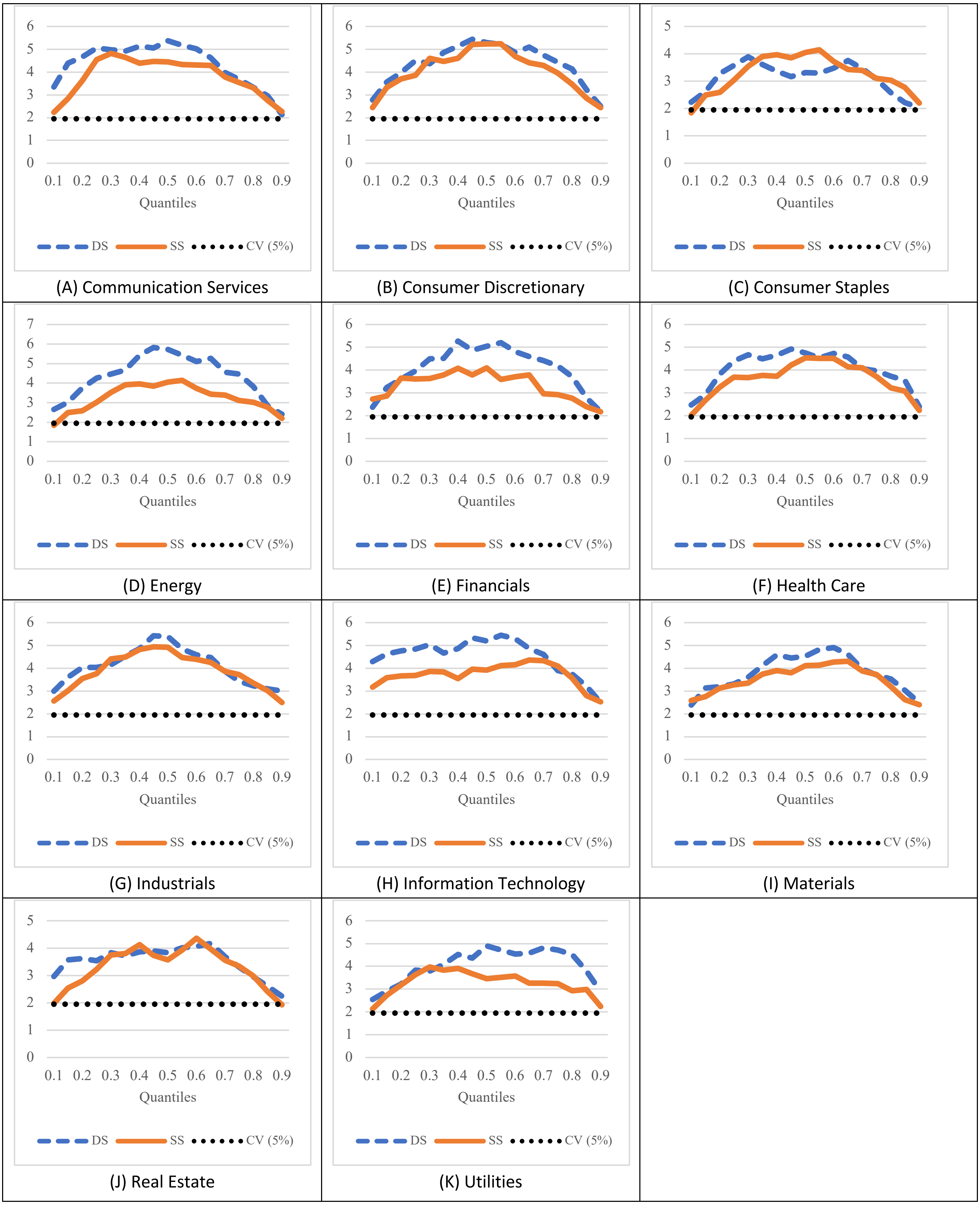
Note: The dates are in dd:mm:yyyy format

4. Empirical results

In the first step, oil shocks were segregated into demand and supply shocks. In the second step, causality-in-quantiles was estimated between oil shocks (demand & supply) and MSCI-EMSI. Figure 1 shows the result for causality-in-mean and figure 2 shows the result for causality-in-variance. These results show the causality-in-quantiles for both demand shocks and supply shocks with MSCI-EMSI.

The null hypothesis for the test presented in Figure 1-(A) states that a given shock (demand or supply) does not Granger causes return of communication services in mean. The vertical y-axis shows the test statistics and the horizontal x-axis shows the corresponding quantiles for the non-parametric causality-in-quantiles test. Figure 1-(A) shows the causality-in-quantiles in mean for both the demand (blue dotted line) and supply shock (orange solid line). The result indicates that the null hypothesis for both demand shock and supply shock do not Granger cause the sectoral index of communication services in mean is rejected at 5 % level of significance for the entire distribution. Causality-in-quantiles result for mean (Figure 1-(A) to 1-(K)) are almost identical for all other 10 sectors with a small exception in supply shocks in case of consumer staples, energy and real estate sectors. For consumer staples, results are not significant approximately for the quantile range of 0.12 and below (bearish). For energy sector, causality-in-quantiles test failed to reject null hypothesis approximately for the quantile range of 0.13 and below. However, for the real estate sector, causality-in-quantiles test failed to reject null hypothesis at both extremes, i.e. below 0.10 (bearish) and above 0.90 (bullish). Overall, both demand and supply shocks exhibit strong predictive power over the entire distribution in the first moment, but demand shocks appear to have even greater influence on individual sectors in comparison to supply shocks.

The causality-in-quantiles results for variance show – (a) variability in comparison to mean as well as; (b) for demand and supply shocks. For communication services, demand shocks show a statistically significant impact on returns over the quantile range of 0.17 and above. However, for the same sector, supply shocks show significant results for the quantile range of 0.24 to 0.90. On an average, the results show a similar pattern for all other industries. Overall, quantile causality-in-variance is not significant in case of lower quantiles, but its significance increases towards the 0.75 quantile and then starts to decline towards higher quantiles. In comparison to supply shocks in variance, demand shocks are significant over more quantiles. However, there are two exceptions to the above pattern. First, both demand and supply shocks do not Granger cause the real estate sector index in variance. Second, both demand and supply shocks have a strong influence in variance on the real estate sector over the entire distribution. Similar to causality-in-mean, demand shocks appear to be stronger in variance in comparison to supply shocks.



(A) Communication Services
(B) Consumer Discretionary
(C) Consumer Staples
(D) Energy
(E) Financials
(F) Health Care
(G) Industrials
(H) Information Technology
(I) Materials
(J) Real Estate
(K) Utilities

Figure 1: Causality-in-mean

Figure shows the result of causality-in-quantile for both demand and supply shock with sectoral SM indices. The null hypothesis for the test states that the demand or supply shock does not Granger cause return in a given industry. For example, the null hypothesis for the test presented in Figure 1-(A)-(i) states that a given shock (demand (DS) or supply (SS)) does not Granger causes return of communication services in mean. The vertical (y) axis shows the test statistics and horizontal (x) axis shows the corresponding quantiles for the non-parametric causality-in-quantiles test. The horizontal dotted line (CV- Critical Value) represents the test statistics value of 1.95 and 5 percent level of significance.

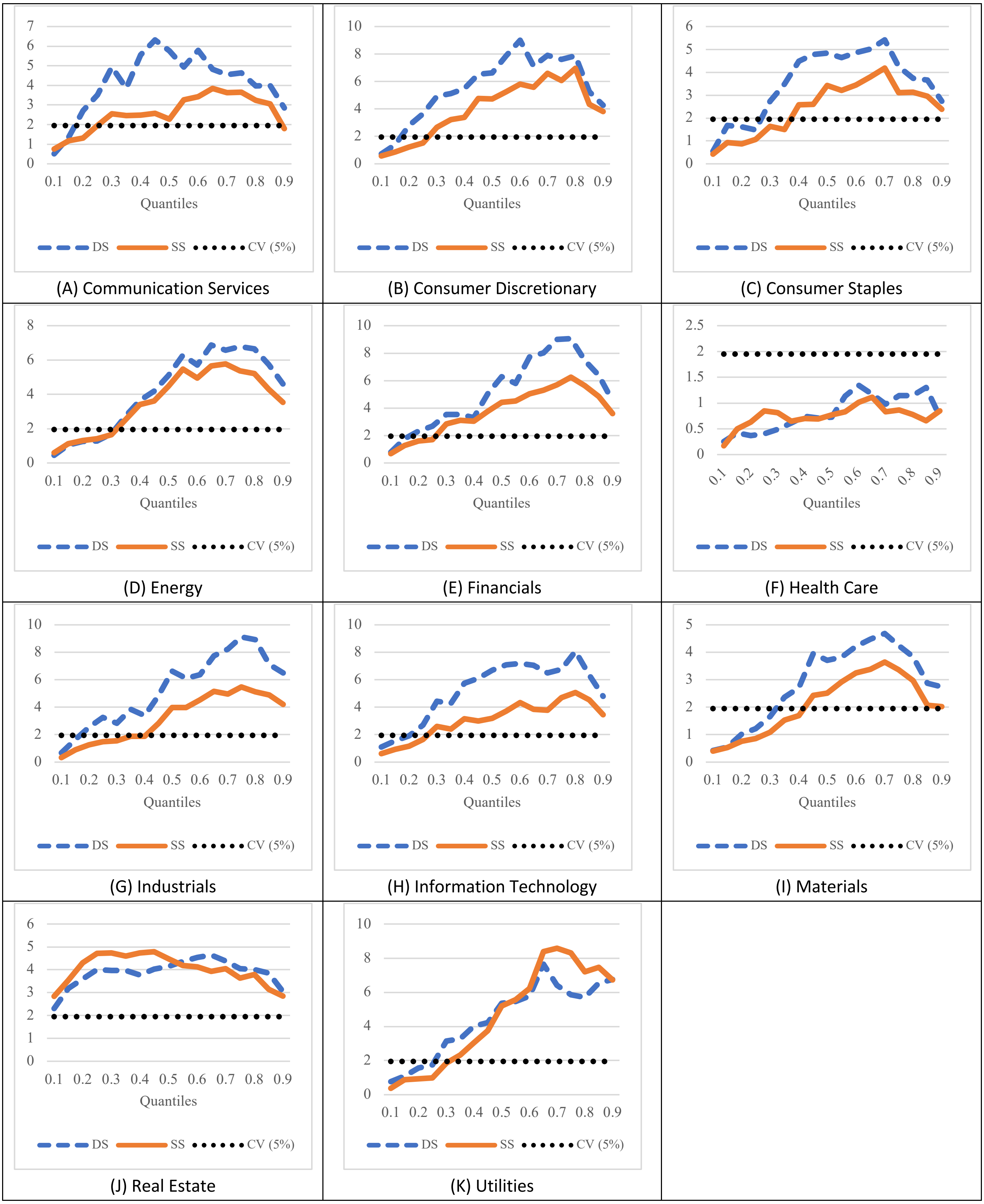


Figure 2: Causality-in-variance

Figure shows the result of causality-in-variance for both demand and supply shock with sectoral SM indices. The null hypothesis for the test states that the demand or supply shock does not Granger cause return in a given industry. For example, the null hypothesis for the test presented in Figure 2-A states that a given shock (demand (DS) or supply (SS)) does not Granger causes return of communication services in variance. The vertical (y) axis shows the test statistics and horizontal (x) axis shows the corresponding quantiles for the non-parametric causality-in-quantiles test. The horizontal dotted line (CV-Critical Value) represents the test statistics value of 1.95 and 5 percent level of significance.

5. Discussion and conclusion

The aim of this study was to investigate the impact of demand and supply shocks on various sectors by employing the non-parametric causality-in-quantiles approach. Results indicate that causal relationship between CO and SMs vary in the first and second moment. Results also indicate that CO has a very strong influence on SMs both from demand side and supply side. However, demand shocks appear to be stronger than supply shocks.

In case of causality-in-mean, the impact of CO on SMs to an extent is indifferent with respect to different market states (bullish, normal and bearish). Causality-in-variance exhibits a different pattern in comparison to mean. Industries behave differently in case of lower quantiles to both demand and supply shocks. On an average, results indicate that demand and supply shocks in CO do not influence the sectoral stock variance in the bearish market. Interestingly, health sector seems to be screened from volatility shocks in the CO market. However, there is a strong evidence of causality-in-variance in the bullish market.

These results increase our understanding of the dependence structure between CO and SMs both in return and volatility. Contrary to general perception, it is not only energy intensive sectors, but all the sectors have a significant impact of shocks to CO. It does not matter whether the shocks are demand shocks or supply shocks. Investors should look for alternate investment avenues whenever shocks hit CO market. These results can be helpful in moderating the impact of volatility shocks of CO to SMs. A possible future extension of this study could be to investigate the low volatility spillovers between CO and SMs in bearish market state.

Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Acknowledgement: Authors are thankful to Editor-in-Chief, Dr. Samuel Vigne and the anonymous reviewer for constructive comments and suggestions.

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