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Crude oil and stock markets: Causal relationships in tails?

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ABSTRACT

This paper considers the causal relationships between WTI and Dubai crude oil returns and five stock index returns (S&P 500, Nikkei, Hang Seng, Shanghai, and KOSPI) within the quantile causality framework by using daily data for a period from January 1, 1996, to October 12, 2012. The quantile causality test is useful for a comprehensive understanding of the causal relationship between two returns. The test reveals several noteworthy results. First, although WTI returns are not closely related to Asian countries, some financial markets such as Nikkei and Hang Seng Granger-cause WTI returns. Second, the significance of causality from one market to another derives only from lower and upper levels of quantiles except for the case of causality from Nikkei to WTI returns. Third, all stock index returns Granger-cause Dubai crude oil returns over almost all quantile levels except for Shanghai returns. Fourth, Dubai crude oil returns Granger-cause all Asian stock index returns except for S&P 500 returns. Finally, the results indicate asymmetric causality from Dubai crude oil returns to Shanghai returns and KOSPI returns to Dubai crude oil returns.

1. Introduction

Crude oil is a vital source of energy for the world and continuesto play a prominent role for many decades to come, although some progress has already been made in finding alternative energy sources. Because crude oil is the main input for producing products, it is clear that its price has considerable direct or indirect influence on the economy. For example, an increase in oil prices can directly affect consumers by raising fuel costs for vehicles. In addition, this increase can reduce the profitability of firms highly dependent on oil, thereby influencing their stock prices because the increase raises production costs. Therefore, it is important to determine whether this argument holds empirically in the real world.

Since the seminal work by Jones and Kaul (1996), a number of studies have examined the impact of oil shocks on stock markets, including Kilian and Park (2009) for US stock market, Park and Ratti (2008) for US and some European stock markets, Basher and Sadorsky (2006) for emerging stock markets and Cong et al. (2008) for Chinese stock markets. Miller and Ratti (2009) interpret the impact of oil price changes on stock markets as follows: First, because crude oil is an important input in production, an oil price shock can influence the corporate cash flow, eventually impacting stock market performance. Second, as the world's largest commodity futures market, crude oil can dominate prices of other commodities. For example, a spike in the summer of 2008 and the subsequent decrease in the price of crude oil have led to booms and busts in other commodity markets (see, Irwin et al., 2009). Therefore, an oil price spike is likely to increase prices of other commodities and impose inflation pressure. The expected rate of inflation is then reflected in the discount rate for the corporate cash flow and finally transmitted to the stock market.

There is also another causal relationship, although it has not received close attention in the literature. One may want to know how a stock market affects the global price of crude oil. Some studies have analyzed how the demand and supply of crude oil influence the price of crude oil (see, Alquist and Gervais, 2011; Hamilton, 2009; Till, 2009) and found that there exist strong relationships between the demand and supply shocks for crude oil and the price of crude oil. Other studies have analyzed the relationship between speculative pressure in the futures market and crude oil prices (see, Cho, 2008; Ding et al., 2014; Khan, 2009; Masters, 2008; Singleton, 2014). Along with the effects of the futures market, some studies have considered stock spot markets. Lee et al. (2012) provides

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some evidence for causality from sectoral stock price changes to oil price changes in eight of nine sectors in Germany and most sectors in other G7 countries except for Japan. Equipped with a panel cointegration and Granger causality framework, Li et al. (2012) find a long-term Granger causality from sectoral stocks to oil prices in China.

However, the previous studies identify the causal relationship based on estimated conditional mean behavior. For many cases, the conditional mean approach may not describe the complete causal relationship between two time-series variables. This paper analyzes the causal relationship between crude oil and stock index returns by using the Granger non-causality test in mean and quantiles. For this, we employ daily time series data on WTI and Dubai crude oil prices and five stock indexes (S&P 500, Nikkei, Hang Seng, Shanghai, and KOSPI) for a period from January 1, 1996, to October 12, 2012. For the Granger non-causality test in quantiles, we apply the method proposed by Chuang et al. (2009), which allows the test to be implemented in a simple framework.[1] There are three advantages to apply the quantile causality test compared to the classical causality tests: (i) the traditional Granger non-causality test based on the OLS framework is designed to investigate the average causal relationship of the time-series variables. This classical method is limited in the sense that it does not consider different locations and scales of the conditional distribution. Because heterogeneity is not an exception but a usual characteristic of time-series variables, the traditional methods may provide an incomplete description of the true causal relationship. For example, Chuang et al. (2009) investigates the dynamic relationship between the stock market index returns and trading volume from the perspective of conditional quantiles, and they provide an evidence that there exists heterogeneity in the volume-return causal relationship across different quantile levels, which cannot be fully uncovered by the conditional mean approach; (ii) the second advantage of the quantile causality approach is that it can deal with “asymmetric effects”. By using the quantile regression approach, Lee and Zeng (2011) finds that the oil–stock linkage differs greatly over different quantile levels of the dependent variable. To provide some evidences for the “asymmetric effects” for the oil–stock relation, we adopt quantile causality test in our study. The conditional quantile method allows us to capture different responses of one market on the other market under various market conditions. For example, if there exists a causal relationship from the oil price to the changes in the stock price, it can be interpreted that under bull stock market condition, oil price change would more influence stock markets; (iii) the quantile levels for conditional distribution of economic variables can indicate the states of an economy. For the study of the causal relationship between the stock and crude oil returns, the dependent variables are the stock returns or crude oil returns. The different conditional quantile levels for the returns reflect different market states, for example, high, medium and low quantile levels are, respectively, corresponding to the high, medium and low return states. Therefore, existence of the causal relationship may depend on the market states, and the quantile causality test provide a efficient tool to take care of this non-linearity in the causal relationship without assuming a specific form of the model; (iv) a sample splitting procedure is usually required when investigating the response of stock returns to oil shocks under various stock market situations. More specifically, one first splits the whole sample into several sub-samples according to the level of stock returns and then employs the traditional method for each sub-sample. However, this approach inevitably reduces the sample sizes and, moreover, loose the time dependence structure in the original data (Lee and Li, 2012). By employing the quantile causality approach, we can avoid the above problems because quantile causality allows for testing causal relationships at any chosen conditional quantile level without selecting some arbitrary sub-samples.

In our empirical analysis, we find that the Granger non-causality test in mean indicates that Dubai crude oil returns Granger-cause all Asian stock index returns in the sample. In addition, neither WTI returns nor Dubai crude oil returns Granger-cause S&P 500 returns. Within the classical Granger causality framework, these results are quite consistent with the findings of previous studies. On the other hand, we find that U.S. stock returns Granger-cause WTI and Dubai crude oil returns. For Asian stock markets, all stock markets in the sample except for Chinese markets Granger-cause Dubai crude oil returns. Among all the stock markets, the Chinese stock market is the least influential one in terms of showing a causal relationship with crude oil returns.

We also investigate the causal relationship in various quantile intervals between WTI crude oil and stock markets and determine that the significance of causality from one market to another derives only from lower and upper levels of conditional quantiles except for the case of causality from Nikkei to WTI returns. For example, there is causality from stock returns to WTI crude oil returns only around the conditional tail quantile interval such as [0.05,0.2]. However, KOSPI does not Granger-cause WTI returns at every quantile interval. For Dubai, we observe that Shanghai index returns do not Granger-cause Dubai crude oil returns at every quantile interval, although China shows the greatest demand for Dubai crude oil. By contrast, the Japanese stock market, Nikkei, has a significant effect on Dubai crude oil returns over the whole distribution. Hang Seng and KOSPI influence Dubai crude oil returns only at higher quantile intervals, i.e., a high rate of increase in Dubai crude oil returns. On the other hand, there is causality from Dubai crude oil returns to stock returns for almost all quantile intervals, which implies that the Asian stock markets considered in this study are greatly influenced by Dubai crude oil returns regardless of the level of stock returns.

The rest of this paper is organized as follows: Section 2 summarizes the literature, and Section 3 presents the data and some preliminary results. Section 4 provides an empirical analysis based on both classical and quantile non-causality tests, and Section 5 concludes the paper with a summary.

2. Literature review

Given the importance of crude oil prices, many studies have investigated the effects of crude oil price shocks on macroeconomic activity (see, Cologni and Manera, 2008; Cuñado and Pérez de Gracia, 2003; Hamilton, 1983, 2003; Herrera and Pesavento, 2009; Kilian, 2008; Tang et al., 2010). The seminal work of Hamilton (1983) focusing on the relationship between crude oil prices and economic activity has stimulated a number of studies in various subfields. Here an important topic is the relationship between oil prices and stock markets, which has received close attention from many researchers. Previous studies have generally analyzed the relationship between oil prices and stock markets by using data from a single country. In terms of U.S. stock markets, Jones and Kaul (1996) find that U.S. stock returns are affected by oil shocks and that this relationship can be fully explained by the impact of these shocks on the real cash flow. Using a vector autoregression method, Sadorsky (1999) provides evidence suggesting the important role of crude oil prices in real stock returns. Kilian and Park (2009) argue that 22% of the long-term

[1] There is a growing finance literature that applies quantile regression approach. Applications include studies on mutual fund investment styles (Bassett and Chen, 2001), value at risk (Engle and Manganelli, 2004), the return-volume relation in the stock market (Chuang et al., 2009), the firm bankruptcy prediction (Li and Miu, 2010) and the diversification-performance relations in firms (Lee and Li, 2012).

variation in real stock returns in the U.S. can be explained by demand and supply shocks from crude oil prices. Instead of examining the impact of crude oil price on stock returns, Chen (2010) takes a fresh look at the relationship between oil prices and stock market behaviors by using a time-varying transition-probability Markov switching model and finds that a rise in oil prices increases the likelihood of a bear market. In the case of China, the second largest oil consumer in the world after the U.S., its role in the world oil market is becoming increasingly important. Before the mid-1990s, the correlation between the domestic oil price in China and the world oil price is very low because of regulations by the central and local governments, and this is the main reason why the starting point of empirical analyses of oil prices in China is usually set around the mid-1990s (e.g., Cong et al., 2008; Du et al., 2010; Li et al., 2012). Based on a vector autoregressive model, Cong et al. (2008) find no significant effect of oil price shocks on real stock returns for most stock market indices in China. To address the problem of the low power of tests and the small-sample bias from insufficient data in time series contexts, Li et al. (2012) use sectional data within a panel data framework and provide clear evidence that the real oil price has a positive effect on sectoral stocks in the long term. In addition, they find long-term Granger causality from sectoral stocks to oil prices for the period from July 2001 to October 2005, indicating that China is a driver of oil prices and can even influence the world oil price. This result is inconsistent with their expectation in that China's stock markets are underdeveloped and may not have considerable influence on the world oil price. They argue that this is due to the choice of data frequency. The present paper uses daily data and finds that the stock market in China has no impact on WTI and Dubai crude oil prices, which is consistent with their conjecture. Except for studies of the two largest oil-consuming countries, some studies have provided multi-country analyses of the relationship between stock prices and oil markets. Based on a vector autoregressive model, Park and Ratti (2008) find a significant effect of oil price shocks on real stock returns in the U.S. and 13 European countries. Using a vector error correction model, Miller and Ratti (2009) examine six OECD countries and find that in the long term, an increase in oil prices has negative effects on stock market indices for the periods from January 1971 to May 1980 and from February 1988 to September 1999. In this paper we consider the largest two oil-consuming countries, the U.S. and China and Hong Kong, South Korea, and Japan in the sample because the main focus of this paper is on Asian countries.

Asymmetric effects of oil price shocks on macroeconomic variables are well documented. Following Hamilton (1983), Mork (1989) investigates asymmetric responses to oil prices and finds that an increase has a greater effect on real GNP growth than a decrease. Jones et al. (2012) provide a good summary of previous research on asymmetric effects of oil price increase and decrease on macroeconomic variables. This indicates a need for examining the asymmetric effects of increases and decreases in oil prices on stock markets. By investigating the U.S. and 13 European countries, Park and Ratti (2008) provide no evidence of significant asymmetric effects for oil-importing European countries, although there are some evidences of asymmetric effects for the U.S. and Norway. Nandha and Faff (2008) investigate the effects of oil price changes on 35 industrial sectors and find significant negative effects on equity returns for all sectors except for mining and oil and gas industries. However, they find no asymmetric effects on equity markets. Similarly, Cong et al. (2008) provide no significant evidence of asymmetric effects of oil price shocks on oil companies′ stock returns in China. This suggests that the response of stock markets are quite symmetric in comparison with those of macroeconomic variables. However, the above findings of symmetric behavior may be limited since the empirical results are based on condition mean behavior. Lee and Zeng (2011) find that the estimates of quantile regression are quite different from those of linear regression models. Within the quantile regression framework, they provide evidences for asymmetric behavior of oil price shocks on stock returns in most G7 countries such that the degree of causal relationship between crude oil and stock returns are different over different levels of the returns. In this paper, we also consider "asymmetry" effects from the perspective of conditional quantiles. The conditional quantile method allows us to capture different responses of one market under various market conditions in the other market. For example, we can check whether oil shocks would influence stock markets differently under the bear and bull markets.

3. Data and preliminary tests

We consider WTI and Dubai crude oil prices, both of which are usually used as price benchmarks for crude oil markets, for the analysis. Based on data from the EIA[2], the Middle East accounts for 51% of China's total oil imports in 2011. Japan imports 33% and 23% of its oil from Saudi Arabia and the United Arab Emirates, respectively, and 56% of Korea's total oil imports are from Saudi Arabia, Kuwait, and Iraq. From the 2011 Hong Kong Energy Statistics, 38.7% of aviation gasoline and kerosene imports of Hong Kong are from mainland China, and 26.3%, from Korea. Therefore, oil prices in Asian countries have a strong relationship with Dubai crude oil prices. The case of the U.S. is different in that its non-OPEC oil imports account for about 60%, whereas they are 24% and 11% for Canada and Mexico, respectively. This suggests a weak relationship between U.S. crude oil prices and Dubai. On the other hand, WTI prices are used mainly in the U.S.. Fig. 1 plots WTI and Dubai crude oil prices from January 1, 1996, to October 12, 2012. Although WTI and Dubai crude oil prices are used in various markets, they show similar patterns and fluctuations. These prices are relatively stable before 2003 but start to increase and peak in the summer of 2008, dropping sharply afterward.

For an examination of the causal relationship between oil and stock prices, we consider the composite indices of five stock markets: four in Asia (China, Hong Kong, Korea, and Japan) and one in the U.S.[3] Fig. 2 clearly tracks the comovement across these stock markets. For example, all these five stock markets show good performance in 2006 and 2007 but collapse after the recent financial crisis.[4] However, although there may be some relationships between these stock markets, different stock markets perform differently. We can observe from the lower panel of Fig. 2 that the U.S. stock market rises before 2000, whereas the Japanese stock market is stuck in a crushing bear market.

Asset prices exhibit trending or non-stationary behavior. As such, we conduct three unit root tests and a stationarity test. For the unit root tests, we consider the augmented Dickey–Fuller (ADF, Dickey and Fuller, 1981), Phillips–Perron (PP, Phillips and Perron, 1988) and Ng and Perron (NP, Ng and Perron, 1995) tests. In these tests, the null hypothesis is that the series has a unit root. For the stationarity test, we consider the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS, Kwiatkowski et al., 1992) test, whose null is that the series is stationary. Table 1 shows the test results. At the 5% significance level, all test results provide evidence of a unit root except for the MSB and the MPT (two of the NP test). If the series contains a unit root, then the standard assumptions for an asymptotic analysis are not valid.

[2] This information can be found at http://www.eia.gov/.

[3] The five stock indices are the Shanghai Stock Exchange Composite Index, the Hang Seng Stock Market Index, the Korea Composite Stock Price Index (KOSPI), the Nikkei Stock Average, and Standard & Poor's 500 (S&P 500).

[4] The comovement has been explained by interdependence and contagion among markets (see, Billio and Pelizzon, 2003; Forbes and Rigobon, 2002).

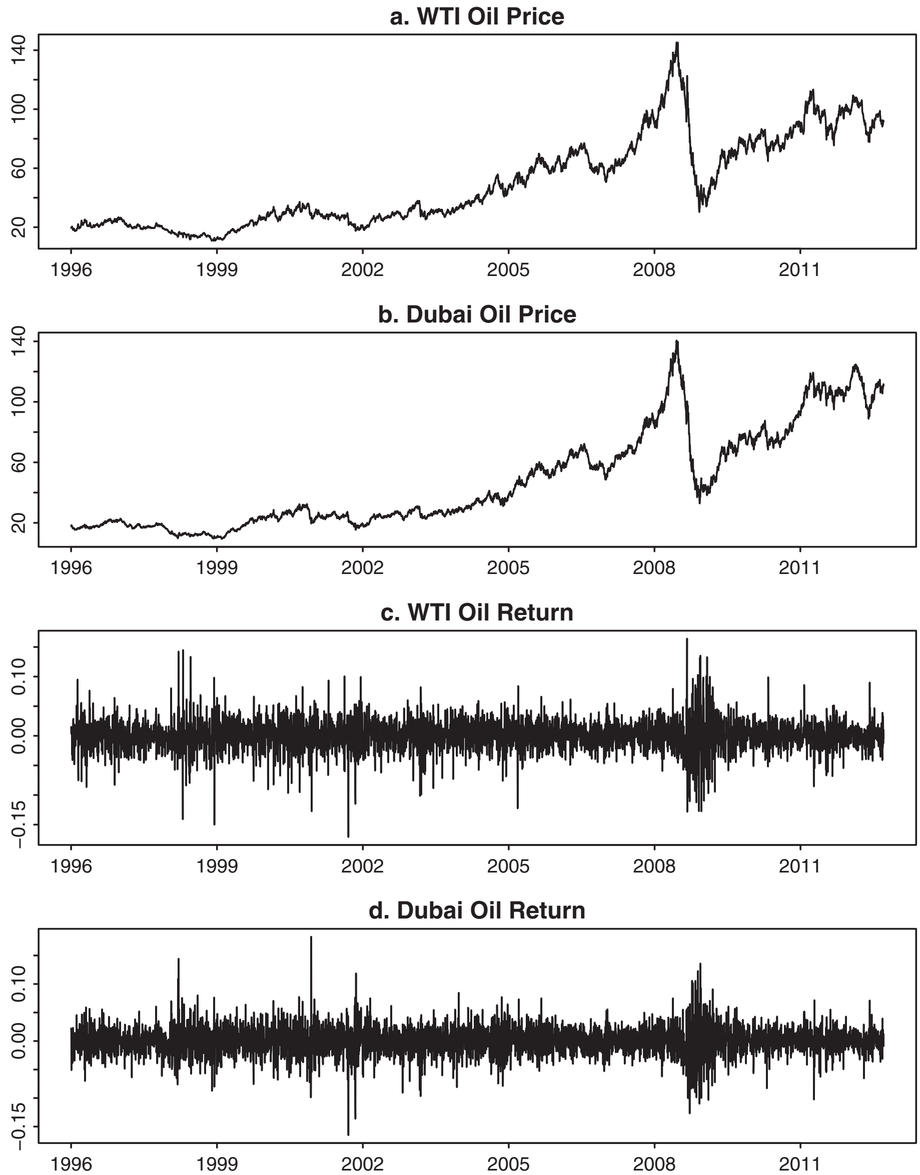


Fig. 1. Time series data: oil prices and returns.

For example, the presence of a unit root changes all usual asymptotic properties of estimators, and therefore, we cannot perform the usual statistical inference. In this regard, we consider the log-differenced series to test the causal relationship between stock and oil returns in the following sections.

To determine the existence of any autocorrelation or cross-correlation in stock and oil return series, we compute the multivariate Ljung–Box test statistics proposed in Hosking (1980) and Li and McLeod (1981). As shown in Fig. 3, the null hypothesis of no autocorrelation and cross-correlation between stock and oil return series is rejected at the 5% significance level, verifying the existence of serial dependence in bivariate return series.

As shown in Figs. 1 and 4, the return series are quite volatile, which may lead to the inefficiency of estimators when only conditional mean functions are used to analyze causal relationships between variables. However, conditional quantile estimates are robust since they are rarely affected by outliers. In the next section, we examine causal relationship by using not only the classical Granger non-causality test but a quantile causality test.

4. Empirical analysis

4.1. Non-causality test in mean

Granger (1969) originally proposes a novel idea to test the causal relationship between two time series variables. Here we can say that the random variable x_t does not Granger-cause the random variable y_t if

$$F_{y_t}(z|(\mathcal{Y},\mathcal{X})_{t-1}) = F_{y_t}(z|\mathcal{Y}_{t-1}), \quad \forall z \in \mathbb{R}, \tag{4.1}$$

holds where $F_{y_t}(\cdot|\mathcal{F})$ is the conditional distribution of y_t denoting $\mathcal{F}$ by the information set available at time $t-1$ and $(\mathcal{Y},\mathcal{X})_{t-1}$ denotes

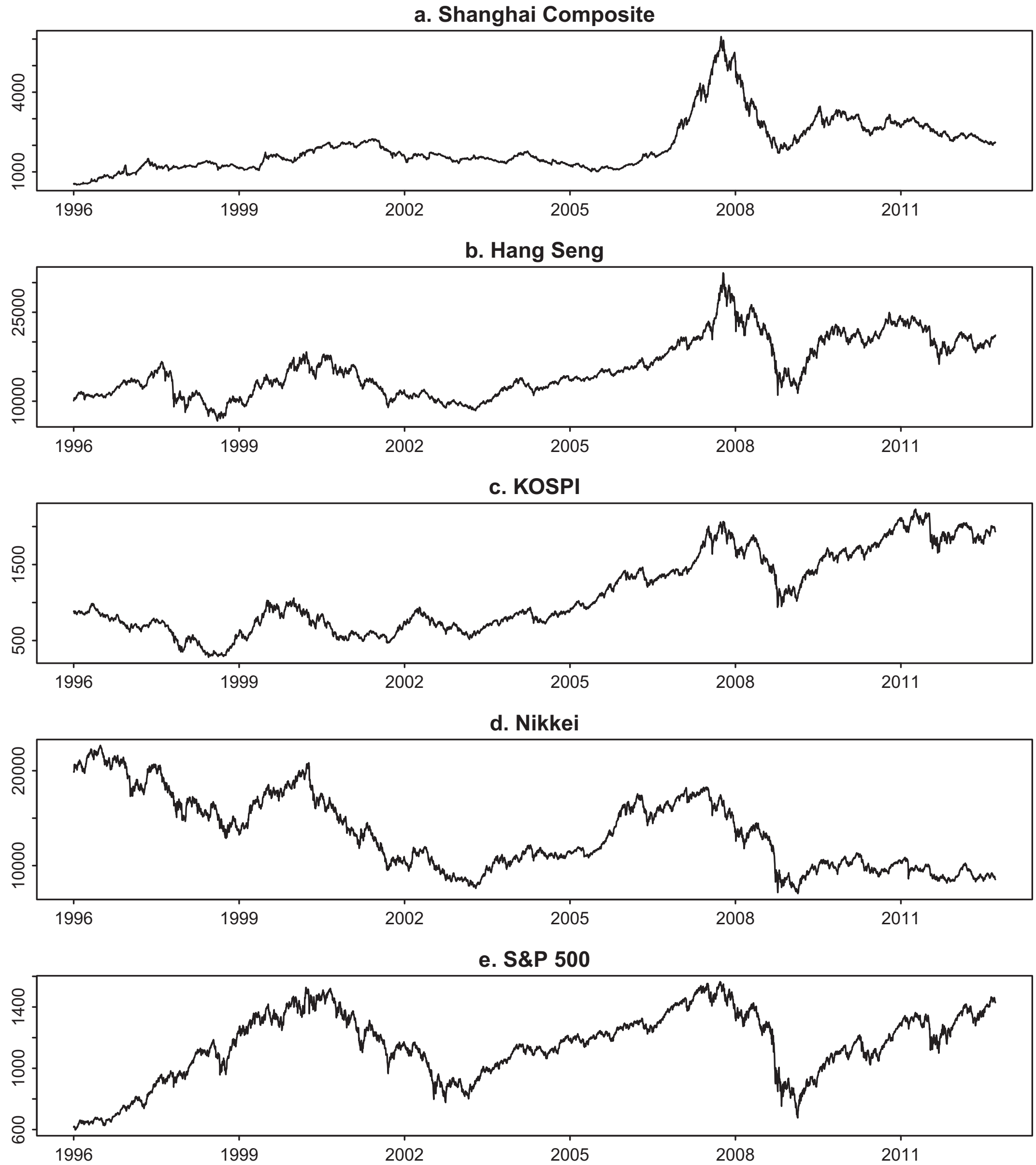


Fig. 2. Time series data: stock prices.

the information set generated by y_t and x_t up to time $t-1$. We can write a simpler and necessary condition for Eq. (4.1) by using the conditional expectation

$$\mathbb{E}(y_t|(\mathcal{Y},\mathcal{X})_{t-1}) = \mathbb{E}(y_t|\mathcal{Y}_{t-1}), \quad \text{a.s.,} \tag{4.2}$$

where $\mathbb{E}(y_t|\mathcal{F})$ is the mean of $F_{y_t}(\cdot|\cdot)$. Here we say that x_t does not Granger cause y_t in mean if Eq. (4.2) holds.

Most empirical studies have checked Eq. (4.2), instead of dealing with Eq. (4.1), to test the hypothesis that x_t does not Granger-cause y_t. This can be done empirically by considering a bivariate autoregressive model for two stationary time series, namely crude oil price changes (Δop_t) and stock returns (Δsp_t):

$$\Delta op_t = \alpha_0 + \sum_{i=1}^{p_1} \alpha_i \Delta op_{t-i} + \sum_{i=1}^{p_1} \beta_i \Delta sp_{t-i} + \epsilon_{op,t}, \tag{4.3}$$

$$\Delta sp_t = \phi_0 + \sum_{i=1}^{p_2} \phi_i \Delta sp_{t-i} + \sum_{i=1}^{p_2} \varphi_i \Delta op_{t-i} + \epsilon_{sp,t}, \tag{4.4}$$

where $\epsilon_t = (\epsilon_{op,t}, \epsilon_{sp,t})'$ denotes a vector of i.i.d random disturbance. The null hypothesis of Granger non-causality in mean from Δsp_t to Δop_t is rejected if the coefficients of lagged Δsp_t in Eq. (4.3), that is, $\beta_1, \beta_2, \cdots, \beta_{p_1}$, are jointly and significantly different from zero. Similarly, if the coefficients of $\Delta op_{t-1}, \cdots, \Delta op_{t-p_1}$ in Eq. (4.4) are significantly different from zero, then we can conclude that Δop_t Granger causes Δsp_t in mean.

We use the Wald test to conduct the Granger non-causality test in mean, and Tables 2 and 3 show the results. We select the optimal lag truncation order by the Akaike Information Criterion (AIC). The estimation results in Table 2 show that S&P 500 returns Granger-cause WTI returns. In addition, although the WTI market is not closely related to Asian countries, some returns of stock indexes such as KOSPI and Hang Seng, Granger-cause WTI price changes. However, Shanghai and Nikkei indices do not Granger-cause WTI returns. This

Table 1
Unit-root tests.

	ADF	PP	KPSS	MZa	MZt	MSB	MPT
WTI	−3.19	−3.05	0.41	−14.79	−2.72	0.18	6.17
	[0]	[10]	[52]	[0]	[0]	[0]	[0]
Dubai	−2.58	−2.64	0.67	−7.60	−1.89	0.25	12.15
	[1]	[11]	[52]	[1]	[1]	[1]	[1]
Shanghai	−1.81	−1.67	0.28	−6.59	−1.73	0.26	13.90
	[4]	[10]	[52]	[4]	[4]	[4]	[4]
Hang Seng	−2.71	−2.66	0.50	−14.49	−2.69	0.19	6.29
	[0]	[3]	[52]	[0]	[0]	[0]	[0]
KOSPI	−2.84	−2.86	0.86	−5.10	−1.56	0.31	17.71
	[0]	[2]	[52]	[0]	[0]	[0]	[0]
Nikkei	−2.18	−2.11	0.66	−8.10	−2.01	0.25	11.25
	[1]	[12]	[52]	[1]	[1]	[1]	[1]
S&P 500	−2.50	−2.39	0.45	−4.92	−1.57	0.32	18.51
	[1]	[28]	[52]	[1]	[1]	[1]	[1]
c.v. 1%	−3.97	−3.97	0.22	−23.80	−3.42	0.14	4.03
c.v. 5%	−3.42	−3.42	0.15	−17.30	−2.91	0.17	5.48
c.v. 10%	−3.13	−3.13	0.12	−14.20	−2.62	0.19	6.67

Notes: Numbers in square brackets are selected lags. ADF and PP are, respectively, augmented Dickey–Fuller and Phillips–Perron statistics for the null hypothesis of a unit root for the time series. KPSS denotes the stationary test for the null hypothesis of stationarity. The last four statistics are Ng–Perron test statistics.

result is consistent with the findings of Lee et al. (2012), who provide evidence for causality from sector changes in stock prices to changes in oil prices in eight of nine sectors in Germany and in most sectors in other G7 countries except for Japan. WTI returns also do not Granger-cause S&P 500 returns.

As shown in Table 3, although the Dubai crude oil market is not strongly related to North American countries, the U.S. stock market Granger-causes Dubai crude oil returns. In terms of the causal relationships between Dubai crude oil price changes and Asian stock index returns, all stock indexes except for those for China show pricing power for Dubai crude oil. On the other hand, Dubai crude oil returns Granger-cause all Asian stock index returns except for S&P 500 returns.

Although some of the above results are consistent with the findings of previous research, it is well known that the sample conditional mean is not robust. The results are based on two regression models (4.3) and (4.4), in which unknown parameters are estimated using the least squares method. Even though the empirical results are useful to see the causal relationship between two variables, it cannot provide the full information of the causal relationship since the results are based on the conditional mean represented by Eq. (4.2).

4.2. Non-causality test in quantiles

For a comprehensive understanding of the causal relationship between x_t and y_t, Chuang et al. (2009) consider Granger causality in quantiles:

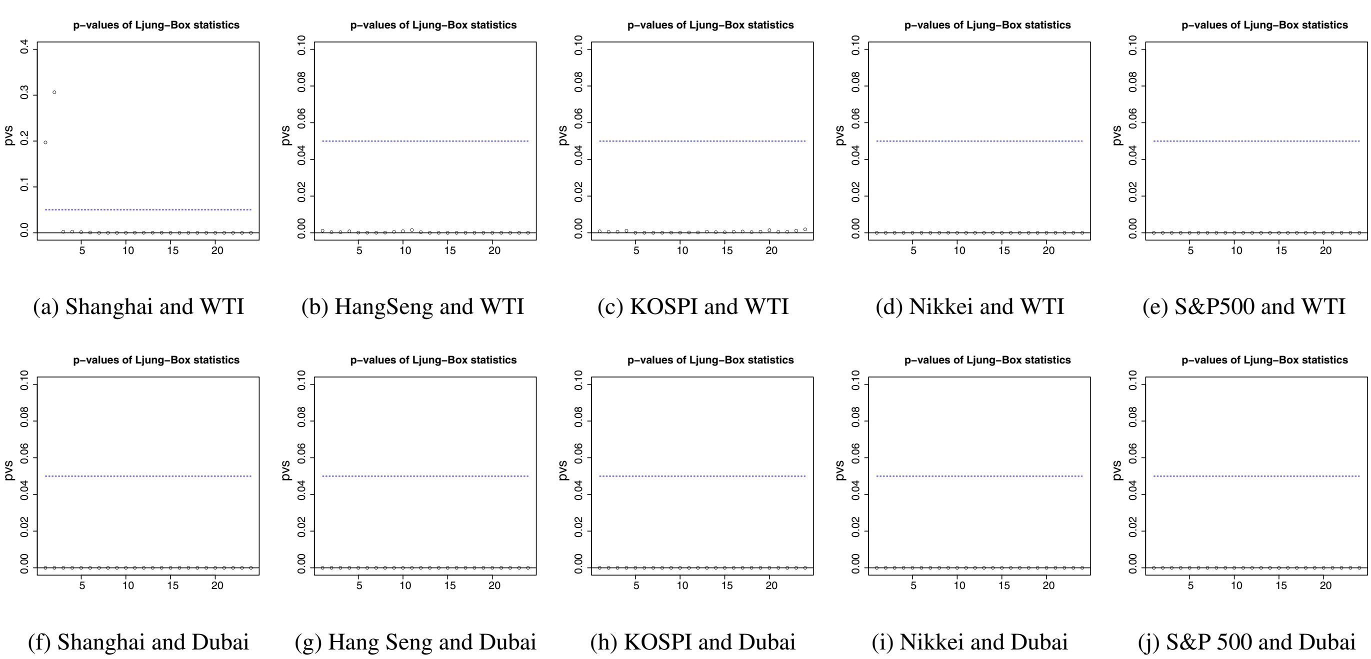
$$Q_{y_t}(\tau|(\mathcal{Y},\mathcal{X})_{t-1}) = Q_{y_t}(\tau|\mathcal{Y}_{t-1}), \quad \forall\tau \in [a,b] \quad \text{a.s.}, \tag{4.5}$$

where $Q_{y_t}(\tau|\mathcal{F})$ denotes the τ-th quantile of $F_{y_t}(\cdot|\mathcal{F})$. If Eq. (4.5) holds, then we can say that x_t does not Granger-cause y_t over the quantile interval $[a,b]$. Granger non-causality in quantiles can be tested by the usual quantile regression method proposed in Koenker and Bassett (1978) and Bassett and Koenker (1982). In addition to the non-causality test in mean, we can consider conditional quantile versions of Eqs. (4.3) and (4.4):

$$Q_{\Delta op_t}(\tau|\mathcal{X}_{t-1}) = \gamma(\tau) + \sum_{j=1}^{q} \alpha_j(\tau)\Delta op_{t-j} + \sum_{j=1}^{q} \beta_j(\tau)\Delta sp_{t-j}, \tag{4.6}$$

$$Q_{\Delta sp_t}(\tau|\mathcal{Y}_{t-1}) = \omega(\tau) + \sum_{j=1}^{q} \delta_j(\tau)\Delta sp_{t-j} + \sum_{j=1}^{q} \xi_j(\tau)\Delta op_{t-j}, \tag{4.7}$$

where $\mathcal{X}_{t-1}$ and $\mathcal{Y}_{t-1}$ denote the information set generated by past values of Δop_t and Δsp_t, respectively. Therefore, if the parameter vector $\beta(\tau) = (\beta_1(\tau), \beta_2(\tau), \cdots, \beta_q(\tau))'$ is equal to zero, then we can say that Δsp_t does not Granger-cause Δop_t at the τ quantile level. Similarly, $\xi(\tau) = (\xi_1(\tau), \xi_2(\tau), \cdots, \xi_q(\tau))' = 0$ implies that the oil price changes does not Granger-cause stock returns at the τ quantile level.



(a) Shanghai and WTI (b) HangSeng and WTI (c) KOSPI and WTI (d) Nikkei and WTI (e) S&P500 and WTI

(f) Shanghai and Dubai (g) Hang Seng and Dubai (h) KOSPI and Dubai (i) Nikkei and Dubai (j) S&P 500 and Dubai

Fig. 3. Multivariate Ljung–Box statistics for stock and crude oil returns. *Notes*: The x-axis is the lag length, and the y-axis is the p-value of the multivariate Ljung-Box statistics. "o" represents the p-value of the test statistic and the dotted lines denote 5% significant levels. The null hypothesis is there is no autocorrelation or cross-correlation.

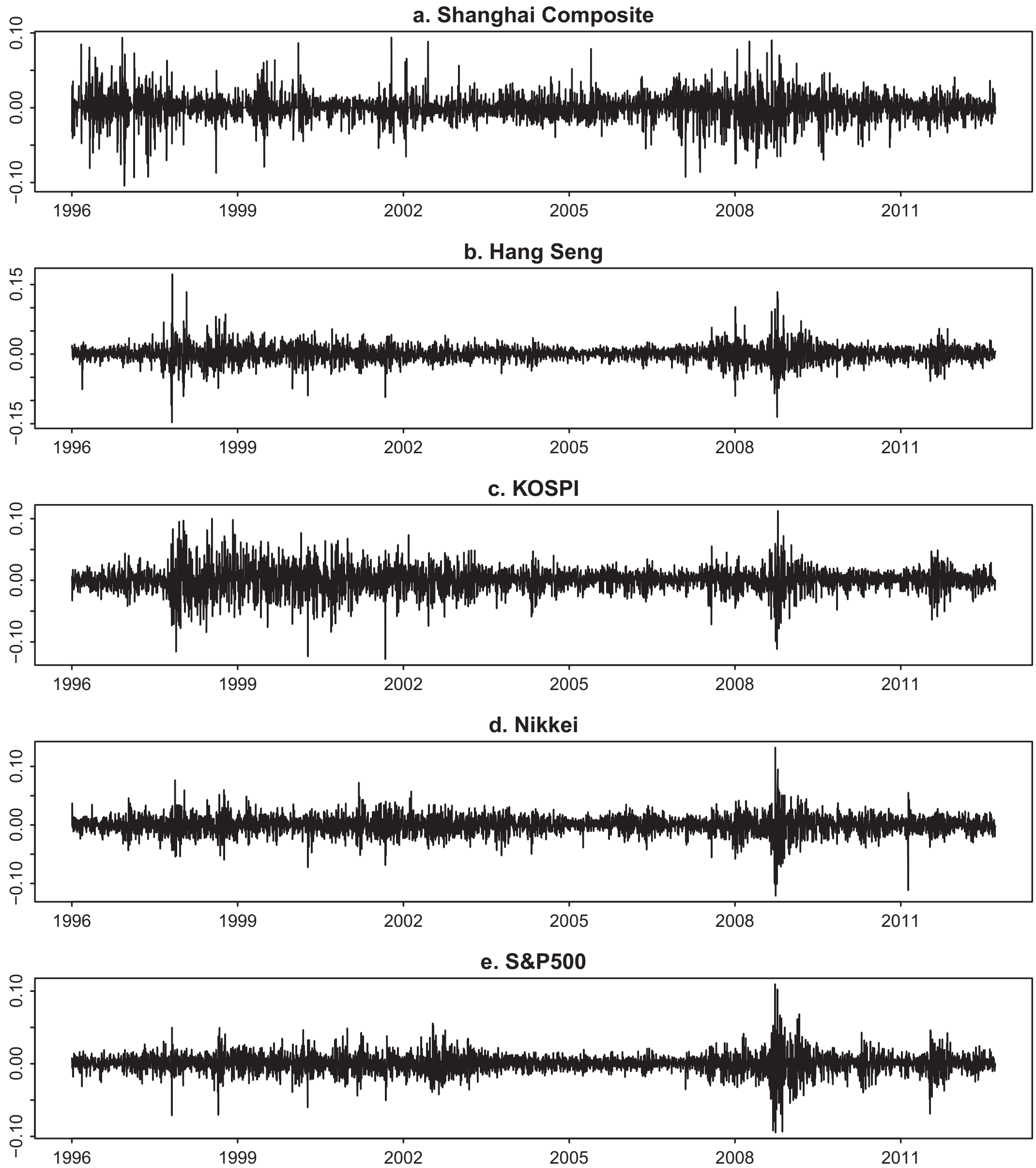


Fig. 4. Time series data: stock returns.

We can express the null hypothesis for Granger non-causality at the $\tau \in (0,1)$ quantile level by

$$H_0 : \beta(\tau) = 0$$

For fixed $\tau \in (0,1)$, we can write the Wald statistic of $\beta(\tau) = 0$ as

$$\mathcal{W}_T(\tau) = T\frac{\hat{\beta}_t(\tau)'\hat{\Omega}(\tau)^{-1}\hat{\beta}_T(\tau)}{\tau(1-\tau)},$$

where $\hat{\Omega}(\tau)$ denotes a consistent estimator of $\Omega(\tau)$, which is the variance–covariance matrix of $\beta(\tau)$.[5] However, the above Wald test addresses only non-causality at the fixed quantile level τ. In many cases, one may be interested in testing for non-causality in quantiles over some quantile intervals, say $\tau \in [a, b]$. Under suitable conditions and the null hypothesis $H_0 : \beta(\tau) = 0, \forall \tau \in \mathcal{T} \subset [a, b]$, Koenker and Machado (1999) show that the Wald statistic process follows the following weak convergence:

$$\mathcal{W}_T(\tau) \Rightarrow \left\| \frac{\mathbf{B}_p(\tau)}{\sqrt{\tau(1-\tau)}} \right\|^2, \quad \text{for} \quad \tau \in \mathcal{T},$$

where $\mathbf{B}_p(\tau) = [\tau(1-\tau)]^{1/2}\mathcal{N}(0, I_p)$ denotes a vector of p independent Brownian bridges and the weak limit is the sum of the square of p independent Bessel processes. Koenker and Machado (1999) suggest a sup-Wald test for the above null hypothesis. From the above results, we can write

$$\sup_{\tau\in\mathcal{T}} \mathcal{W}_T(\tau) \rightsquigarrow \sup_{\tau\in\mathcal{T}} \left\| \frac{\mathbf{B}_q(\tau)}{\sqrt{\tau(1-\tau)}} \right\|^2. \tag{4.8}$$

[5] In an autoregressive distributed lag model framework, Gavao et al. (2013) show that the regression quantile estimator is consistent and asymptotically normal.

Table 2
Granger causality tests in mean (WTI and stock returns).

The null	WTI and stock returns	
	p-Value	Causality or not
	Shanghai	
rsp ⇏ rwti	0.166 (3)	No
rwti ⇏ rsp	0.383 (3)	No
	Hang Seng	
rsp ⇏ rwti	0.048 (3)	Yes
rwti ⇏ rsp	0.001 (3)	Yes
	KOSPI	
rsp ⇏ rwti	0.027 (5)	Yes
rwti ⇏ rsp	0.215 (5)	No
	Nikkei	
rsp ⇏ rwti	0.187 (2)	No
rwti ⇏ rsp	0.000 (2)	Yes
	S&P500	
rsp ⇏ rwti	0.000 (2)	Yes
rwti ⇏ rsp	0.335 (2)	No

Notes: rwti and rsp represent log changes in WTI and stock prices, respectively. The symbol ⇏ denotes the null hypothesis of Granger non-causality. The entry "Yes" indicates that the null hypothesis is rejected at the 5% significance level, whereas the entry "No" indicates that the null hypothesis of no Granger causality could not be rejected at the 5% significance level. Numbers in brackets indicate the selected lag order based on the Akaike information criterion (AIC).

By considering various $[a, b]$, we can capture the quantile range from which causal relationships arise. We simulate the critical values for various quantile ranges and report them in Table A1.

For the empirical analysis, we consider three large quantile intervals for the above conditional quantile functions, namely $[0.05, 0.95]$, $[0.05, 0.5]$ and $[0.5, 0.95]$, and five small quantile intervals, namely $[0.05, 0.2]$, $[0.2, 0.4]$, $[0.4, 0.6]$, $[0.6, 0.8]$ and $[0.8, 0.95]$. To conduct the sup-Wald test, we select the lag truncation order q^* for each quantile interval. We select the optimal lag truncation order by using a sequential lag selection method. For example, if the null $\beta_q(\tau) = 0$ for $\tau \in [0.05, 0.2]$ not rejected but the null $\beta_{q-1}(\tau) = 0$ for $\tau \in [0.05, 0.2]$ is rejected, then we set the desired lag order as $q^* = q-1$ for the quantile interval $[0.05, 0.2]$. However, if no test statistic is significant over that interval, then we select the lag truncation of order 1. We calculate sup-Wald test statistics to check the joint significance of all coefficients of lagged stock returns (or lagged oil price changes) for each quantile interval. For example, if the desired lag order is q^*, then the null hypothesis is $H_0 : \beta_1(\tau) = \beta_2(\tau) = \ldots = \beta_{q^*}(\tau) = 0$ for $\tau \in [0.05, 0.2]$. With the sup-Wald test statistics, we check whether stock returns Granger-cause oil returns over this specific quantile interval [0.05, 0.2].[6]

Table 3
Granger causality tests in mean (Dubai and stock returns).

The null	Dubai and stock returns	
	p-Value	Causality or not
	Shanghai	
rsp ⇏ rdubai	0.454 (3)	No
rdubai ⇏ rsp	0.037 (3)	Yes
	Hang Seng	
rsp ⇏ rdubai	0.000 (3)	Yes
rdubai ⇏ rsp	0.000 (3)	Yes
	KOSPI	
rsp ⇏ rdubai	0.002 (2)	Yes
rdubai ⇏ rsp	0.017 (2)	Yes
	Nikkei	
rsp ⇏ rdubai	0.000 (3)	Yes
rdubai ⇏ rsp	0.000 (3)	Yes
	S&P500	
rsp ⇏ rdubai	0.000 (2)	Yes
rdubai ⇏ rsp	0.177 (2)	No

Notes: rdubai and rsp represent log changes in Dubai Crude and stock prices, respectively. The symbol ⇏ denotes the null hypothesis of Granger non-causality. The entry "Yes" indicates that the null hypothesis is rejected at the 5% significance level, whereas the entry "No" indicates that the null hypothesis of no Granger causality could not be rejected at the 5% significance level. Numbers in brackets indicate the selected lag order based on the Akaike Information Criterion (AIC).

4.2.1. Causal relationship between WTI and stock returns

It is worthwhile to analyze the causal relationship between the stock index returns for four Asian countries and WTI returns, although it seems that supply and demand for WTI oil are not directly influenced by fluctuations in some Asian economies. As we can see clearly in Fig. 1, the movements of WTI and Dubai oil prices are quite similar. When we perform a cointegration test, we find that there exists a cointegrating relationship between these two series. Thus we can detect an indirect linkage between the U.S. crude oil market and the Asian stock markets by using the quantile causality test. The indirect interdependence could be interpreted as follows: it is well known that cross-country financial markets are interdependent (see, Forbes and Rigobon, 2002), thus the U.S. crude oil market may exert impact on the Asian stock market through the U.S. stock market.

To explore the causal relationship in quantiles between the stock and WTI returns, we consider the following conditional quantile functions:

$$Q_{RWTI_t}(\tau|\mathcal{X}_{t-1}) = \gamma(\tau) + \sum_{j=1}^{q_1} \alpha_j(\tau)RWTI_{t-j} + \sum_{j=1}^{q_1} \beta_j(\tau)RSP_{t-j}, \quad (4.9)$$

$$Q_{RSP_t}(\tau|\mathcal{Y}_{t-1}) = \omega(\tau) + \sum_{j=1}^{q_2} \delta_j(\tau)RSP_{t-j} + \sum_{j=1}^{q_2} \xi_j(\tau)RWTI_{t-j}, \quad (4.10)$$

where $RWTI_t$ and RSP_t denote the WTI returns and stock returns, respectively, and $\mathcal{X}_{t-1}$ and $\mathcal{Y}_{t-1}$ denote, respectively, the information sets generated by past values of $RWTI_t$ and RSP_t at time t.

Panel (a) of Table 4 reports the sup-Wald test statistics and the selected lag truncation order. For the quantile interval [0.05, 0.95], S&P 500, Hang Seng, and Nikkei returns Granger-cause the WTI price changes. However, Shanghai and KOSPI returns do not Granger-cause WTI returns for $\tau \in [0.05, 0.95]$. These results maybe due to a close relationship among U.S., Hong Kong and Japan stock markets. This interdependence among the stock markets enable for the Hang Seng and Nikkei stock returns to cause the WTI returns even though there is little relationship between WTI crude oil market and Hong Kong and Japanese economies. On the other hand, the non-causal relationship from the KOSPI and Shanghai returns to WTI returns implies Shanghai and KOSPI markets may not influence the U.S. stock market.

The results correspond to quantile sub-intervals that indicate that the significant causality from stock returns to WTI returns for $\tau \in [0.05, 0.95]$ derives from lower and upper levels of quantiles. For example, there is no causal relationship over the middle quantile levels [0.2,0.4], [0.4,0.6] and [0.6,0.8] for Hang Seng stock index. In the case of Nikkei, the quantile intervals [0.2,0.4] and [0.4,0.6] do not show causality from stock returns to WTI returns. These results also hold for S&P 500. This implies that there is causality from stock returns to WTI returns only for a high or low level of WTI returns. Therefore, we can say that when the WTI returns fluctuate nearby their median, the above stock returns have no significant effects on the WTI returns.

Panel (b) of Table 4 reports the test results for non-causality from WTI returns to index returns. All the sup-Wald statistics

[6] To conserve space we do not report the Results for lag order selection of the quantile causality tests but these can be obtained from the web page: http://www.sungpark.net/DKP_supplementfiles_EE.pdf.

Table 4
Test results for quantile causality between stock indices and WTI crude oil returns.

	(a) Stock returns → WTI							
$\tau \in$	[0.05,0.95]	[0.05,0.5]	[0.5,0.95]	[0.05,0.2]	[0.2,0.4]	[0.4,0.6]	[0.6,0.8]	[0.8,0.95]
Shanghai	7.47	7.56*	15.60	8.51**	4.79	0.49	3.31	15.60
	[1]	[1]	[9]	[1]	[1]	[1]	[1]	[9]
Hang Seng	20.60***	64.15***	20.60***	64.63***	0.52	1.49	1.59	20.60***
	[2]	[8]	[2]	[8]	[1]	[1]	[1]	[2]
KOSPI	18.29	1.41	18.12	13.15	0.82	1.32	2.04	19.43
	[8]	[1]	[8]	[5]	[1]	[1]	[1]	[8]
Nikkei	12.81**	35.93***	0.51	38.81***	0.81	0.58	9.72**	12.84**
	[2]	[8]	[1]	[8]	[1]	[1]	[2]	[2]
S&P500	39.17***	14.11**	11.01**	14.11***	10.45***	2.16	10.44	11.70***
	[3]	[2]	[1]	[2]	[1]	[1]	[4]	[1]
	(b) WTI → stock returns							
Shanghai	13.37**	23.84**	14.99**	24.40**	20.90**	10.77	8.11**	14.99***
	[2]	[7]	[2]	[7]	[7]	[7]	[1]	[2]
Hang Seng	26.67***	26.89***	6.57	24.82***	27.06***	4.76	6.57*	25.47**
	[1]	[1]	[1]	[1]	[1]	[1]	[1]	[9]
KOSPI	15.49***	15.49***	28.19***	24.83***	26.09***	1.93	0.64	28.19***
	[1]	[1]	[5]	[3]	[3]	[1]	[1]	[5]
Nikkei	27.05***	27.05***	6.29	27.05***	18.00***	10.01***	6.42*	2.67
	[1]	[1]	[1]	[1]	[1]	[1]	[1]	[1]
S&P500	34.35***	32.36***	32.32***	33.70***	12.45**	0.83	17.48	7.31**
	[9]	[9]	[8]	[9]	[3]	[1]	[8]	[1]

Notes: Prices of five stock indices are considered (Shanghai, Hang Seng, KOSPI, Nikkei, and S&P 500). Sup-Wald test statistics and the selected lag order (in square brackets) are reported.
*** Denotes significance at the 1% significance level.
** Denotes significance at the 5% significance level.
* Denotes significance at the 10% significance level.

for $\tau \in [0.05, 0.95]$ are significant at the 5% significance level, and WTI returns Granger-cause Shanghai and KOSPI returns over $\tau \in [0.05, 0.5]$ and $[0.5, 0.95]$, which is not the case in (a). Similar to the results in (a), the sup-Wald statistics over quantile subintervals show that there is no causal relationship around the conditional median $\tau \in [0.4, 0.6]$ except for the case of Nikkei. This shows that there is a strong causal relationship over the tail region of the conditional distribution.

4.2.2. Causal relationship between Dubai crude and stock returns

Similarly, we consider the following conditional quantile functions to explore the causal relationship between Dubai crude oil and stock returns:

$$Q_{RBD_t}(\tau|\mathcal{X}_{t-1}) = \gamma(\tau) + \sum_{j=1}^{q_1} \alpha_j(\tau) RBD_{t-j} + \sum_{j=1}^{q_1} \beta_j(\tau) RSP_{t-j}, \qquad (4.11)$$

Table 5
Test results for quantile causality between stock indices and Dubai crude oil returns.

	(a) Stock returns → Dubai							
$\tau \in$	[0.05,0.95]	[0.05,0.5]	[0.5,0.95]	[0.05,0.2]	[0.2,0.4]	[0.4,0.6]	[0.6,0.8]	[0.8,0.95]
Shanghai	3.08	2.96	3.08	1.70	2.96	1.51	3.24	14.65
	[1]	[1]	[1]	[1]	[1]	[1]	[1]	[7]
Hang Seng	42.24***	36.40***	23.62***	36.57***	8.52	5.24*	11.47***	24.04***
	[4]	[3]	[2]	[3]	[3]	[1]	[1]	[2]
KOSPI	28.26***	4.19	28.35***	19.76	3.04	7.53**	8.27**	30.21***
	[2]	[1]	[2]	[9]	[1]	[1]	[1]	[2]
Nikkei	25.07***	25.07***	24.98***	26.79***	7.05**	7.30**	14.66***	25.80***
	[3]	[3]	[2]	[3]	[1]	[1]	[2]	[2]
S&P500	16.03***	16.03***	5.45	9.02**	16.25***	6.85**	9.40	21.11**
	[1]	[1]	[1]	[1]	[1]	[1]	[3]	[7]
	(b) Dubai → stock returns							
Shanghai	22.46***	15.42	22.46***	15.83*	2.15	14.46**	19.46***	22.46***
	[1]	[5]	[1]	[5]	[1]	[3]	[1]	[1]
Hang Seng	29.65***	32.14***	17.51***	29.93***	32.14***	12.47***	17.47***	14.37***
	[1]	[1]	[1]	[1]	[1]	[1]	[1]	[1]
KOSPI	22.99***	24.08***	48.27***	24.24***	16.11***	6.24*	6.59*	48.27***
	[1]	[1]	[8]	[1]	[1]	[1]	[1]	[8]
Nikkei	25.14***	25.14***	16.75***	24.20***	26.34***	17.81***	15.38***	9.66**
	[1]	[1]	[1]	[1]	[1]	[1]	[1]	[1]
S&P500	14.16*	14.67**	23.62***	14.67**	15.07**	7.84	10.57	24.02***
	[3]	[3]	[1]	[3]	[3]	[5]	[5]	[1]

Notes: Prices of five stock indices are considered (Shanghai, Hang Seng, KOSPI, Nikkei, and S&P 500). Sup-Wald test statistics and the selected lag order (in square brackets) are reported.
*** Denotes significance at the 1% significance level.
** Denotes significance at the 5% significance level.
* Denotes significance at the 10% significance level.

Table 6
Summary of Granger non-causality test results (WTI and stock returns).

	Shanghai	Hang Seng	KOSPI	Nikkei	S&P500
$rsp \Rightarrow rwti^L$	Cause	Cause	Not cause	Cause	Cause
$rsp \Rightarrow rwti^M$	Not cause	Not cause	Not cause	Not cause	Not cause
$rsp \Rightarrow rwti^H$	Not cause	Cause	Not cause	Cause	Cause
$rsp \Rightarrow_{GC} rwti$	Not cause	Cause	Cause	Note cause	Cause
$rwti \Rightarrow rsp^L$	Cause	Cause	Cause	Cause	Cause
$rwti \Rightarrow rsp^M$	Not cause	Not cause	Not cause	Cause	Not cause
$rwti \Rightarrow rsp^H$	Cause	Cause	Cause	Not cause	Cause
$rwti \Rightarrow_{GC} rsp$	Not cause	Cause	Not cause	Cause	Not cause

Notes: "Cause" and "Not cause" denote, respectively, significant and non-significant causal relationship at the 5% significance level. The subscript *L*, *M* and *H* denote low, medium and high levels of associated variable. More specifically, *L*, *M* and *H* corresponds to [0.05, 0.2], [0.4, 0.6] and [0.8, 0.95] quantile intervals. "$\Rightarrow_{GC}$" represents the classical Granger causality test.

$$Q_{RSP_t}(\tau|\mathcal{Y}_{t-1}) = \omega(\tau) + \sum_{j=1}^{q_2} \delta_j(\tau) RSP_{t-j} + \sum_{j=1}^{q_2} \xi_j(\tau) RBD_{t-j}, \qquad (4.12)$$

where RDB_t and RSP_t denote Dubai crude oil price changes and stock index returns, respectively.

Panel (a) of Table 5 shows the results of the sup-Wald test for non-causality in quantiles from stock returns to Dubai crude oil returns. For $\tau \in [0.05, 0.95]$, the sup-Wald statistics for Hang Seng, KOSPI, Nikkei, and S&P 500 returns strongly reject the null hypothesis at the 1% significance level. However, Shanghai returns do not Granger-cause the Dubai crude oil returns, although China shows the greatest demand for Dubai crude oil. Moreover, for all quantile intervals, Shanghai returns do not Granger-cause Dubai crude oil returns. For Nikkei, the sup-Wald statistics are rejected at the 5% significance level for all quantile levels. However, the results for Hang Seng and KOSPI are different from those for Nikkei. Hang Seng returns, similar to the case of Nikkei, Granger-cause Dubai crude oil returns for both $\tau \in [0.05, 0.5]$ and [0.5,0.95]. However, the sup-Wald statistics for the quantile subintervals, [0.2, 0.4] and [0.4,0.6] are not significant. For KOSPI, the result is similar in that the sup-Wald statistics are not significant over [0.05, 0.2] and [0.2, 0.4]. This implies that KOSPI influences Dubai crude oil returns when growth rate of Dubai crude oil prices is relatively high.

Panel (b) of Table 5 shows the test results for non-causality from Dubai crude oil price changes to stock returns. The sup-Wald test statistics over $\tau \in [0.05, 0.95]$ show that Dubai crude oil price changes influence the four Asian stock indices. However, it turns out that Dubai oil change does not Granger-cause S&P 500 returns significantly over $\tau \in [0.05, 0.95]$. This result is different from that of the WTI oil price case. This maybe due to the weak relationship between Dubai oil market and U.S. economy. Although the significant causal relationship from Dubai oil price to the Asian stock markets can influence S&P 500 index returns due to the interdependent characteristics of the world stock markets, it seems that such indirect effect is not very strong to reject Granger non-causality of the S&P 500 case. For Hang Seng and Nikkei returns, the sup-Wald statistics are rejected at the 1% significance level for all quantile intervals. This implies that Dubai crude oil price changes have considerable influence on the stock markets in Hong Kong and Japan regardless of the level of stock returns. However, the results for Shanghai show an asymmetric behavior in which Dubai crude oil returns Granger-cause stock returns only for a high level of stock returns. For KOSPI and S&P 500, the test statistics over [0.4, 0.6] and [0.6, 0.8] cannot reject the non-causality. Thus the causal relationship from Dubai oil price to stock returns exist only in the tail area.

4.3. Summary of empirical results

As mentioned in Introduction section, the different quantile levels for the returns reflect different market states, for example, high, medium and low quantile levels are, respectively, corresponding to the high, medium and low return states. Thus in order to interpret the results for the quantile causality test easily we consider three quantile intervals, $\tau \in \mathcal{T}^L = [0.05, 0.2]$, $\tau \in \mathcal{T}^M = [0.4, 0.6]$, and $\tau \in \mathcal{T}^H = [0.8, 0.95]$. Since the return series are considered in the testing procedures it is clear that the three quantile intervals, $\mathcal{T}^L$, $\mathcal{T}^M$ and $\mathcal{T}^H$, correspond to negative returns, returns around median and positive returns, respectively.

Table 6 summarizes the results of Granger non-causality tests between the WTI and stock index returns. At first, it seems that the results for the classical Granger non-causality test and quantile non-causality tests are not consistent. However, it is not the case since while the classical Granger non-causality test only uncovers the causal relationship in average, the quantile non-causality test can show more complete picture in the sense that it can uncover the causal relationship over different levels of conditional quantiles of the dependent variable. As we can see clearly, the causal relationship between the WTI and stock index returns are not significant over the middle level of quantiles, $\tau \in \mathcal{T}^M$ except for the case of Nikkei (from WTI to Nikkei). However, there exist strong causal

Table 7
Summary of Granger non-causality test results (Dubai and stock returns)

	Shanghai	Hang Seng	KOSPI	Nikkei	S&P500
$rsp \Rightarrow rdubai^L$	Not cause	Cause	Not cause	Cause	Cause
$rsp \Rightarrow rdubai^M$	Not cause	Not cause	Cause	Cause	Cause
$rsp \Rightarrow rdubai^H$	Not cause	Cause	Cause	Cause	Cause
$rsp \Rightarrow_{GC} rdubai$	Not cause	Cause	Cause	Cause	Cause
$rdubai \Rightarrow rsp^L$	Not cause	Cause	Cause	Cause	Cause
$rdubai \Rightarrow rsp^M$	Cause	Cause	Not cause	Cause	Not cause
$rdubai \Rightarrow rsp^H$	Cause	Cause	Cause	Cause	Cause
$rdubai \Rightarrow_{GC} rsp$	Cause	Cause	Cause	Cause	Not cause

Notes: "Cause" and "Not cause" denote, respectively, significant and non-significant causal relationship at the 5% significance level. The subscript *L*, *M* and *H* denote low, medium and high levels of associated variable. More specifically, *L*, *M* and *H* corresponds to [0.05, 0.2], [0.4, 0.6] and [0.8, 0.95] quantile intervals. "$\Rightarrow_{GC}$" represents the classical Granger causality test.

relationship in tails. This implies that the strong causal relationships are highly likely present when one market shows very good or very poor performance. For example, while there is no significant causal relationship from the S&P500 returns to the WTI returns over $\tau \in \mathcal{T}^M$, S&P500 returns strongly Granger-cause the WTI returns when the WTI returns are in the lower or higher levels of quantile, $\tau \in \mathcal{T}^L$ or $\tau \in \mathcal{T}^H$. For the case of the Shanghai returns, the Shanghai returns Granger-cause the low level of the WTI returns but do not Granger-cause the high level of the WTI returns. This implies that the Shanghai returns only cause the WTI returns when the WTI prices decrease, and moreover, shows asymmetric effects of the Shanghai returns on the WTI returns. The similar interpretation can be applied to the causal relationship from the WTI returns to the Nikkei returns. These results can be related with systemic risk. According to Baur and Schulze (2004), dependence or systemic risk increases under extreme market conditions and reduces the stability of the financial system. Therefore, when the market (crude oil market or stock market) faces an extreme condition, it is likely to be affected by a shock from another financial market due to its unstable system.

Table 7 summarizes the test results between the Dubai and stock index returns. For the causality from the stock index returns to the Dubai returns the Nikkei and S&P500 returns cause the Dubai returns regardless of the quantile levels, which is also consistent with the results for the classical Granger non-causality test. The KOSPI returns have asymmetric effects on the Dubai returns such that the KOSPI returns Granger-cause the lower level of the Dubai returns only. Interestingly, the Shanghai returns do not cause the Dubai returns for all quantile levels. However, the Dubai returns cause the Shanghai returns over the middle and high levels of quantiles but do not cause the low level of the Shanghai returns. This implies that when the Shanghai stock prices decrease, the Dubai crude oil prices are not the factor which causes the variation of the stock prices. The test results show that there exists a bi-directional causal relationship between the Nikkei and Dubai returns for all quantile levels. However, even though the classical Granger non-causality test shows there are bi-directional relationships between Hang Seng and KOSPI returns and the Dubai returns, the quantile causality tests show that there exists only uni-directional causal relationship for Hang Seng and KOSPI when low and middle quantile intervals, $\mathcal{T}^L$ and $\mathcal{T}^M$, are considered, respectively.

5. Concluding remarks

This paper investigates the causal relationship between crude oil and stock markets from the perspective of quantile causality. The results of the quantile causality test indicate that the significant causal relationship between WTI and stock returns derives from tail quantile intervals. The results imply that when one financial market faces extreme conditions, it is likely to be affected by another market. This suggests that investors should be cautious about information from oil markets when stock markets are under extreme conditions. In addition, oil-dependent firms should hedge against risks from oil price fluctuations in a bear or bull market. Finally, governments should develop appropriate policy measures to minimize systemic risk in the oil stock system under extreme conditions.

Because of the close relationship between the price of Dubai crude oil and the economy of Asian countries, it is important to investigate the causal relationship between Dubai crude oil prices and stock index prices in Asia. Although China is the second largest oil-consuming country in the world, its index returns indicate that they have no significant impact on Dubai crude oil price changes for all quantile intervals. By contrast, Nikkei returns influence Dubai crude oil price changes over the whole distribution. Hang Seng and KOSPI influence Dubai crude oil returns only over high quantile intervals for a high growth rate of Dubai crude oil prices. On the other hand, there is causality for almost all quantile intervals for Asian index returns, which implies that the Asian stock markets are highly dependent on Dubai crude oil price changes regardless of the level of stock returns.

Further research should focus on the transmission mechanism underlying the discovered causality in quantiles. In addition, the causal relationship may be a regime dependent on financial volatility. Therefore, future research should identify the determinants of such causality in quantiles. This will be pursued in our future study.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2016.07.013.

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