Economic Modelling xxx (xxxx) xxx

Contents lists available at ScienceDirect

Economic Modelling

journal homepage: www.journals.elsevier.com/economic-modelling

Does international oil volatility have directional predictability for stock returns? Evidence from BRICS countries based on cross-quantilogram analysis

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ARTICLE INFO

Keywords:
Quantile dependence
Directional predictability
Cross-quantilogram
Oil volatility
Stock returns
BRICS countries

ABSTRACT

While numerous studies have investigated the relationship between oil volatility and stock returns, it is surprising that little research has examined the quantile dependence and directional predictability from oil volatility to stock returns in BRICS (Brazil, Russia, India, China, and South Africa) countries. We address this issue by using the cross-quantilogram model proposed by Han et al. (2016). The empirical results show that, overall, oil volatility has a directional predictability for the stock returns in BRICS countries. When the oil volatility is in a low quantile (lower than its 0.1 quantiles), it is less likely to show either a large loss or a large gain in the stock market. In contrast, there is an increased likelihood of either large loss or a large gain in the stock market when the oil volatility is in a high quantile (higher than its 0.9 quantiles). The directional predictability from the oil volatility to stock returns depends on the net position of oil imports and exports of these BRICS countries in the oil market. The net oil exporters (Russia and Brazil) are less likely to have large gains and large losses in the stock market than are the net oil importers (India, China, and South Africa) when the oil volatility is in a low quantile. The net oil exporters are more likely to have large gains and large losses than are the net oil importers when the oil volatility is in a high quantile. The results are robust to change in the variable of oil volatility and the sample interval.

1. Introduction

Traditionally, policymakers and financial investors pay close attention to the interconnections between crude oil volatility and stock market returns (Joo and Park, 2017; Smyth and Narayan, 2018). A clear interpretation of this relationship is of great significance for designing and implementing macroeconomic and energy policies, international financial regulation activities and risk management strategies aimed at mitigating the adverse effects of oil volatility (Bouri et al., 2018). Numerous studies believe that oil volatility has an important impact on the stock market, mainly for the following three reasons. First, as crude oil is one of the most important input factors and traded commodities in the world, sudden and huge volatility of its prices leads to huge shocks in productive capacity and brings further economic and stock market fluctuations. Second, oil price volatility causes changes of related macroeconomic policy that then affect the stock market. For example, a surge in the oil price commonly brings heavy inflationary pressure, which the central banks of countries usually cope with by raising interest rates. Third, crude oil shows financial attributes. Because of its high level of liquidity, it has been widely used as a financial product to hedge stock market risk (Basher and Sadorsky, 2016). A growing number of hedging operations have strengthened the connection between the crude oil market and the stock market. Moreover, nowadays, useful insights for policymaking and financial risk management can be gained by comparing the reactions of stock markets to oil volatility in different countries.

However, can oil volatility directionally predict stock market returns? Under different levels of oil volatility, does oil volatility have the same predictability for stock returns in different quantiles? As different net oil importers or exporters have different degrees of dependence on crude oil, is there a difference in the predictability of oil volatility to their stock markets? Addressing these questions is of great significance and can help us review the nexus between the oil market and the stock market and further guide investment in different stock markets under different levels of oil volatility. As we know, few studies have yet solved these problems.

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https://doi.org/10.1016/j.econmod.2018.11.021
Received 17 August 2017; Received in revised form 12 November 2018; Accepted 27 November 2018
Available online xxxx
0264-9993/

Please cite this article as: Zhou, Z. et al., Does international oil volatility have directional predictability for stock returns? Evidence from BRICS countries based on cross-quantilogram analysis, Economic Modelling, https://doi.org/10.1016/j.econmod.2018.11.021

Table 1
Descriptive statistics.

	OVX	China	Russia	India	Brazil	South Africa
Mean	37.372	−0.011	−0.020	0.031	0.008	0.008
Median	34.615	0.069	0.000	0.000	0.000	0.090
Maximum	100.420	9.034	20.204	15.990	13.678	12.353
Minimum	14.500	−12.764	−14.717	−11.604	−12.096	−13.566
Std. Dev.	13.972	1.792	2.264	1.444	1.754	1.984
Skewness	1.325	−0.638	0.014	0.336	0.150	−0.115
Kurtosis	5.671	7.624	12.269	14.497	9.174	6.963
Jarque–Bera	1390.707 (0.00)	2260.415 (0.00)	8219.181 (0.00)	12710.91 (0.00)	3661.616 (0.00)	1510.173 (0.00)

Table 2
Unit root tests.

Variables	DF-GLS		PP	
	Intercept	Intercept & trend	Intercept	Intercept & trend
OVX	−2.199(8)**	−2.443(8)**	−3.334(7)**	−3.255(7)*
China	−7.557(12)***	−20.747(3)***	−48.648(6)***	−48.655(5)***
Russia	−1.508 (24)	−3.146(24)***	−44.234(23)***	−44.223(23)***
India	−46.038(0)***	−46.037(0)***	−46.218(12)***	−46.207(12)***
Brazil	−1.548(19)	−3.360(19)**	−50.139(26)***	−50.126(26)***
South Africa	−2.650(24)***	−42.968(0)***	−47.220(30)***	−47.208(30)***

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The numbers in parentheses are the lag order in the DF–GLS and PP tests. The lag parameters are selected based on the SIC, maxlag = 27.

This study is the first to investigate the quantile dependence and directional predictability from international crude oil volatility to stock returns in BRICS countries (Brazil, Russia, India, China, and South Africa) by using the cross-quantilogram model recently proposed by Han et al. (2016).

So far, a strand of studies focuses on stock predictability in BRICS countries (Narayan et al., 2018). Tiwari and Kyophilavong (2014) use a wavelet unit root test and support the predictability of stock market indices in BRICS countries except for Russia. Aye et al. (2014) find the stock returns of BRICS countries are predictable by using the autoregressive fractionally integrated moving average models. Narayan et al. (2015a), Westerlund and Narayan (2016), and Narayan and Sharma (2016) find order imbalances, core macroeconomic indicators and S&P500 futures returns can predict Chinese stock returns. Xue and Zhang (2017) prove the stock return predictability in the Chinese stock market by applying the threshold quantile autoregressive model. Zhang et al. (2018) prove an intraday momentum can significantly predict the last half-hour return both in- and out-of-sample in Chinese stock market. Hong et al. (2018) examine the predictability of the China's stock returns and find that considering structural breaks in model parameters could improve the stock return predictability. Narayan et al. (2014a), Bannigidadmath and Narayan (2016) prove India stock returns are predictable. Narayan and Bannigidadmath (2015) find that a mean combination forecast approach delivers significant out-of-sample performance in India stock market. Some scholars provide evidence that macro-financial variables (Sousa et al., 2016), economic policy uncertainty, financial news and global fear (Narayan and Bannigidadmath, 2017; Yu et al., 2018; Bouri et al., 2018), investor sentiment and geopolitical risks (Han and Li, 2017; Balcilar et al., 2018), consumption and aggregate wealth (Ren and Xie, 2018) can predict stock market in BRICS countries. Narayan et al. (2014b) find institutions factors can predict stock returns in Brazil, China and South Africa and macroeconomic factors can predict returns in China. Narayan et al. (2015b) support country-level governance quality can predict stock market returns but only in countries where governance quality is poor based on data of 38 countries (including BRICS). Narayan et al. (2018) argue that U.S. stock excess returns predict stock market returns for 77 technology-investing countries (including BRICS). The above literature enriches the studies on stock prediction in BRICS countries and enlightens us beneficially. Unlike the existing literature, in this paper, we pay more attention to the directional predictability from oil volatility to stock returns in BRICS countries.

Another strand of studies that concentrate on the co-movement between crude oil market and the stock market in BRICS countries and proves oil price can predict or affect stock market (Smyth and Narayan, 2018); however, their results are mixed. Overall, according to the difference of selected indexes that reflect the price characteristics of the crude oil market and the stock market, the studies on the relationship between the crude oil market and the stock market can be divided into four categories, as follows.

Firstly, numerous researchers have explored the volatility spillovers between oil and the stock markets. For example, Singhal and Ghosh (2016) claim that it has direct volatility spillover from oil market to Indian stock market including auto, power and finance sector. Boubaker and Raza (2017) confirm the spillover effects of volatility and shocks between oil prices and the BRICS stock markets by using wavelet approach. Using an APARCH model, Bagchi (2017) finds that there exist volatility spillovers between crude oil price and stock markets in BRIC countries. Ji et al. (2018) investigate the dynamic dependence between BRICS stock returns and different types of oil price shocks (demand shocks and supply shocks).

Secondly, some studies focus on the conditional mean spillovers between oil and the stock markets. For example, Aloui et al. (2012) argue that there are significant effects of oil price changes on stock markets in BRICS countries. Gupta and Modise (2013) and Fang and You (2014) find oil price shocks have critical impact on stock returns in South Africa, Russia, India and China. Using copula models, Reboredo and Ugolini (2016) support that there are close relationships between the oil price movements and stock returns in BRICS. Using a quantile regression approach, Zhu et al. (2016) find that there is a heterogeneity dependence between crude oil price changes and industry stock market returns in China.

Thirdly, some researchers pay attention to the impact of oil price shocks on stock volatility. For instance, Bhar and Nikolova (2009) find that the level of impact of oil price returns on equity returns and volatility in BRIC countries depend on the extent to which these countries are net importers or net exporters of oil. Wei and Guo (2017) support that the responses of the volatilities and returns of the sub-index in China's stock market to oil shocks vary greatly.

Finally, some studies focus on the impact of oil volatility on the stock returns. For example, Cong et al. (2008) argue that oil volatility increases the stock returns of mining and petrochemical industry in China. Zhang and Chen (2011) find that China's stock returns are correlated only with expected volatilities in world oil prices. Caporale et al. (2015) find the impact of oil price uncertainty on sectoral stock returns in China during periods with demand-side shocks for oil.

To sum up, the above discussion suggests that stock returns in BRICS countries have predictability, and oil price fluctuation and stock market are mainly associated with each other. However, they can be improved

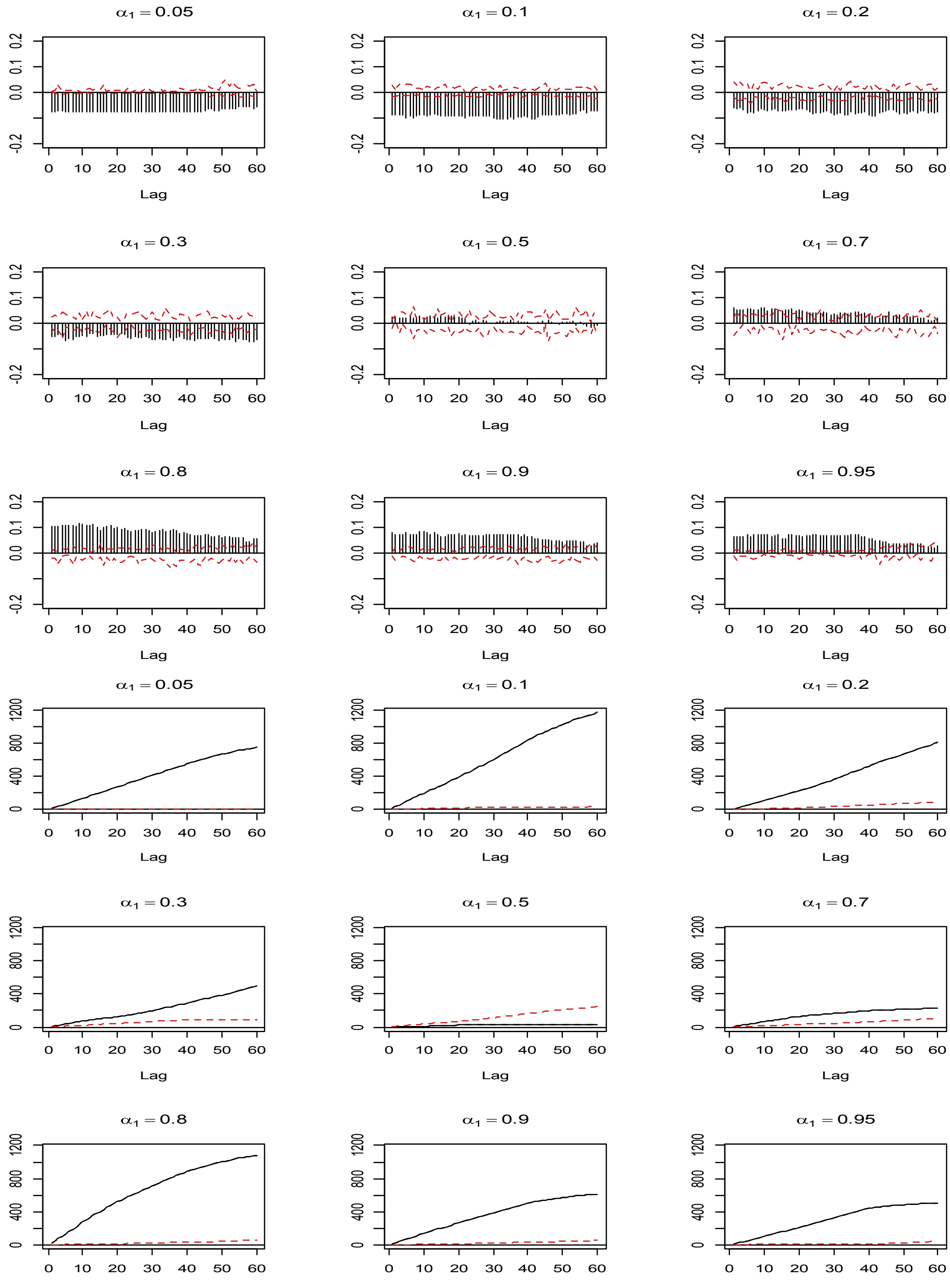

Fig. 1. **(a)** The sample cross-quantilogram $\widehat{\rho}_\alpha(k)$ with $\alpha_2 = 0.1$ to detect directional predictability from the oil volatility to China's stock returns. Bar graphs describe the sample cross-quantilogram, and lines are the 95% bootstrap confidence intervals centred at zero. **(b)** Box–Ljung test statistic $\widehat{Q}_\alpha^{(p)}$ for each lag p and quantile α using $\widehat{\rho}_\alpha(k)$ with $\alpha_2 = 0.1$ in China's stock market. The dashed lines are the 95% bootstrap confidence intervals centred at zero.

upon for the following reasons. Firstly, the methods used in the existing literature generally depend on modelling conditional variance and conditional correction between the oil market and stock markets based on the estimation of the conditional mean; therefore, they cannot provide a quantile-based detailed relationship between oil volatility and stock returns. Meanwhile, they cannot further provide a tool to examine the directional predictability from the oil volatility to stock returns. Secondly, the impact of crude oil volatility on the stock returns may be asymmetric. That is, different levels of crude oil volatility may have a significantly different impact on the stock market. So far, the previous related studies mainly concentrate on the linear relationship between the oil volatility and stock returns, without much consideration of the difference of impacts of oil volatility on the stock returns at different levels of oil volatility. Moreover, the existing literature cannot provide an

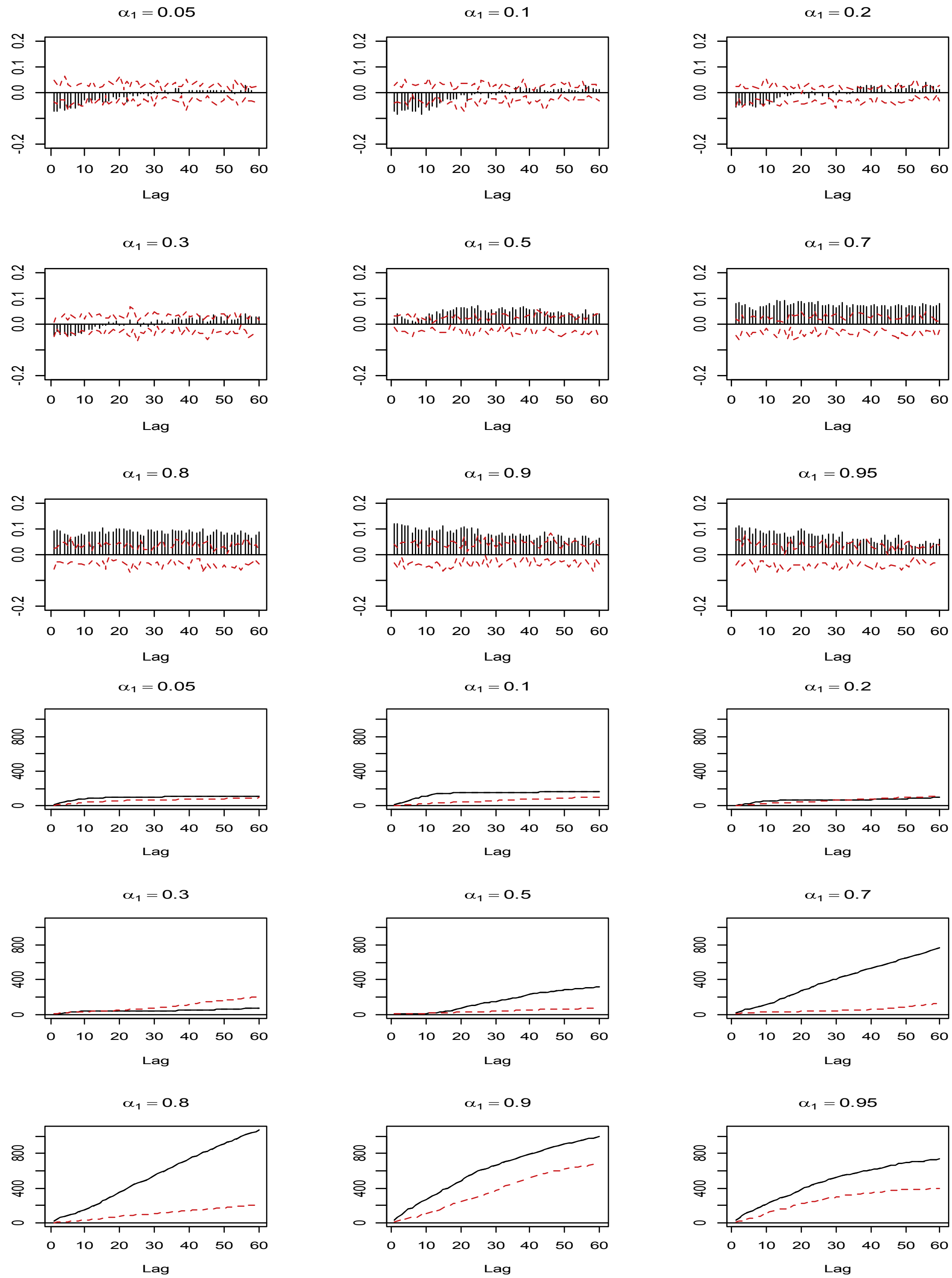

Fig. 2. **(a)** The sample cross-quantilogram $\widehat{\rho}_\alpha(k)$ with $\alpha_2 = 0.9$ to detect directional predictability from the oil volatility to China's stock returns. Same as Fig. 1(a). **(b)** Box–Ljung test statistic for each lag p and quantile α using $\widehat{\rho}_\alpha(k)$ with $\alpha_2 = 0.9$ in China's stock market. Same as Fig. 1(b).

observable dynamic indicator to depict the price volatility of the crude oil market and further examine the directional predictability from the international crude oil volatility to stock returns. Finally, although some studies have investigated the stock return predictability in BRICS countries, little is concerned about the directional predictability of oil volatility to stock market in BRICS countries. In addition, the existing studies do not investigate the difference of directional predictability of oil volatility to stock returns among BRICS countries based on the different net position in the international oil markets.

We add to the literature on the relationship between the oil volatility and stock returns in three ways. Firstly, to the best of our knowledge, the cross-quantilogram proposed by Han et al. (2016) is employed for the first time in this paper; this allows analysis of the dependence of and directional predictability from the oil volatility to stock returns at different quantiles, rather than just at the median. The cross-quantilogram is a correlation statistic of quantile hit processes, and it measures dependence between a quantile range of one time series and a quantile range of another time series (Han et al., 2016). Therefore, it can reveal quantile-based dependence between two financial markets. Moreover, it is particularly appropriate in analysing financial time series

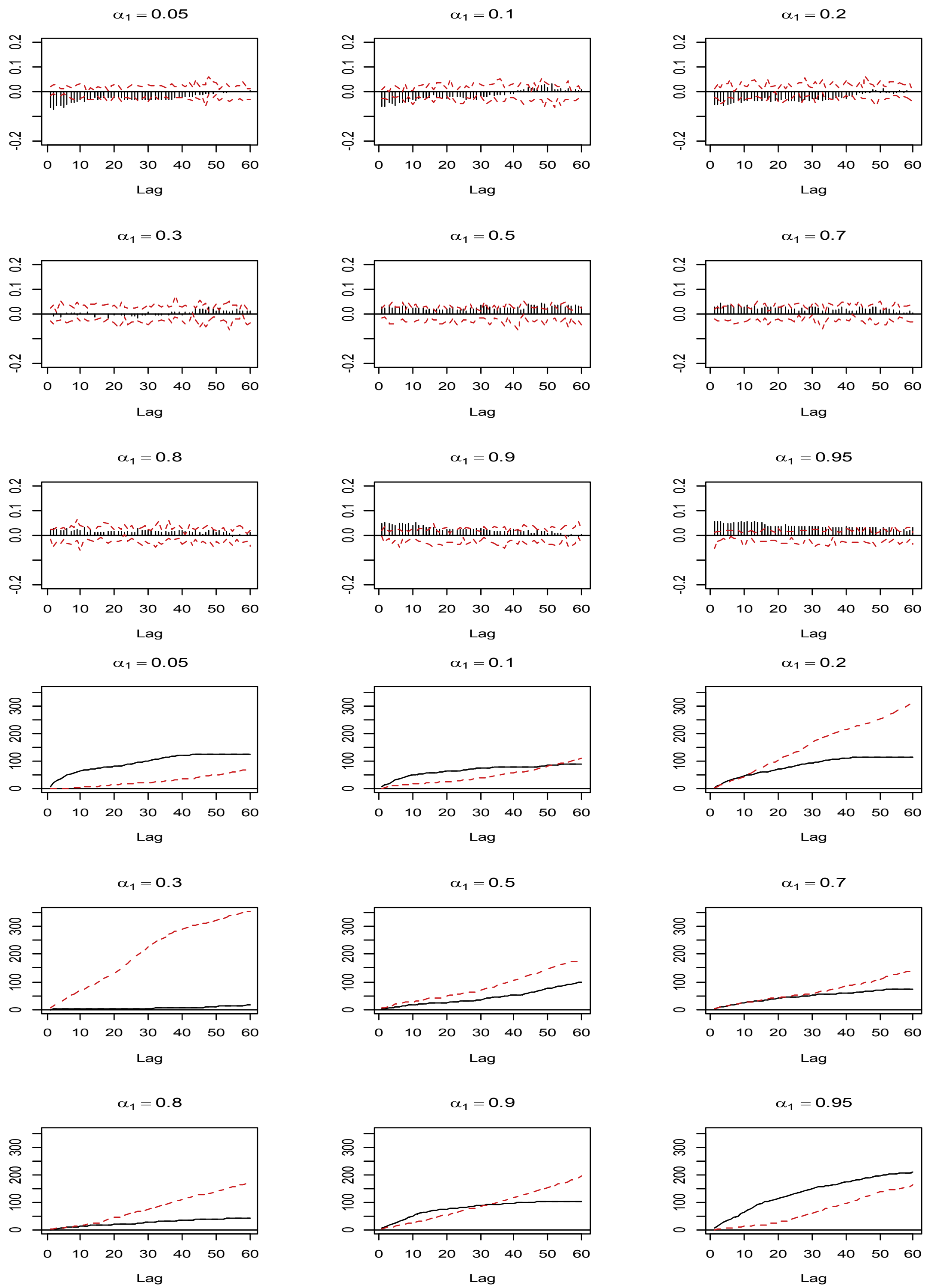

Fig. 3. **(a)** The sample cross-quantilogram $\widehat{\rho}_\alpha(k)$ with $\alpha_2 = 0.1$ to detect directional predictability from the oil volatility to Brazil's stock returns. Same as Fig. 1(a). **(b)** Box–Ljung test statistic $\widehat{Q}_\alpha^{(p)}$ for each lag p and quantile α using $\widehat{\rho}_\alpha(k)$ with $\alpha_2 = 0.1$ in Brazil's stock market. Same as Fig. 1(b).

because it does not require any moment condition of time series. It is well known that finite fourth moments do not exist for most stock returns, even if commonly-used models, such as multivariate GARCH models, generally assume the existence of finite fourth moments of time series.

Secondly, we examine whether the implied crude oil volatility index (OVX), a forward-looking measure of oil market uncertainty published by Chicago Board Options Exchange (CBOE), has directional predictability for stock returns in BRICS countries. OVX is derived from option prices and is generally considered to be an effective indicator of oil market uncertainty (Liu et al., 2013; Dutta et al., 2017). Moreover, implied volatilities not only contain historical volatility information but also depict investors' expectations of future market conditions (Liu et al., 2013; Maghyereh et al., 2016). Currently, some other scholars also apply OVX to their research. For example, Dutta et al. (2017) investigate whether the OVX affects the realized volatility of the Middle East and African stock markets. This is the closest to our work. However, existing

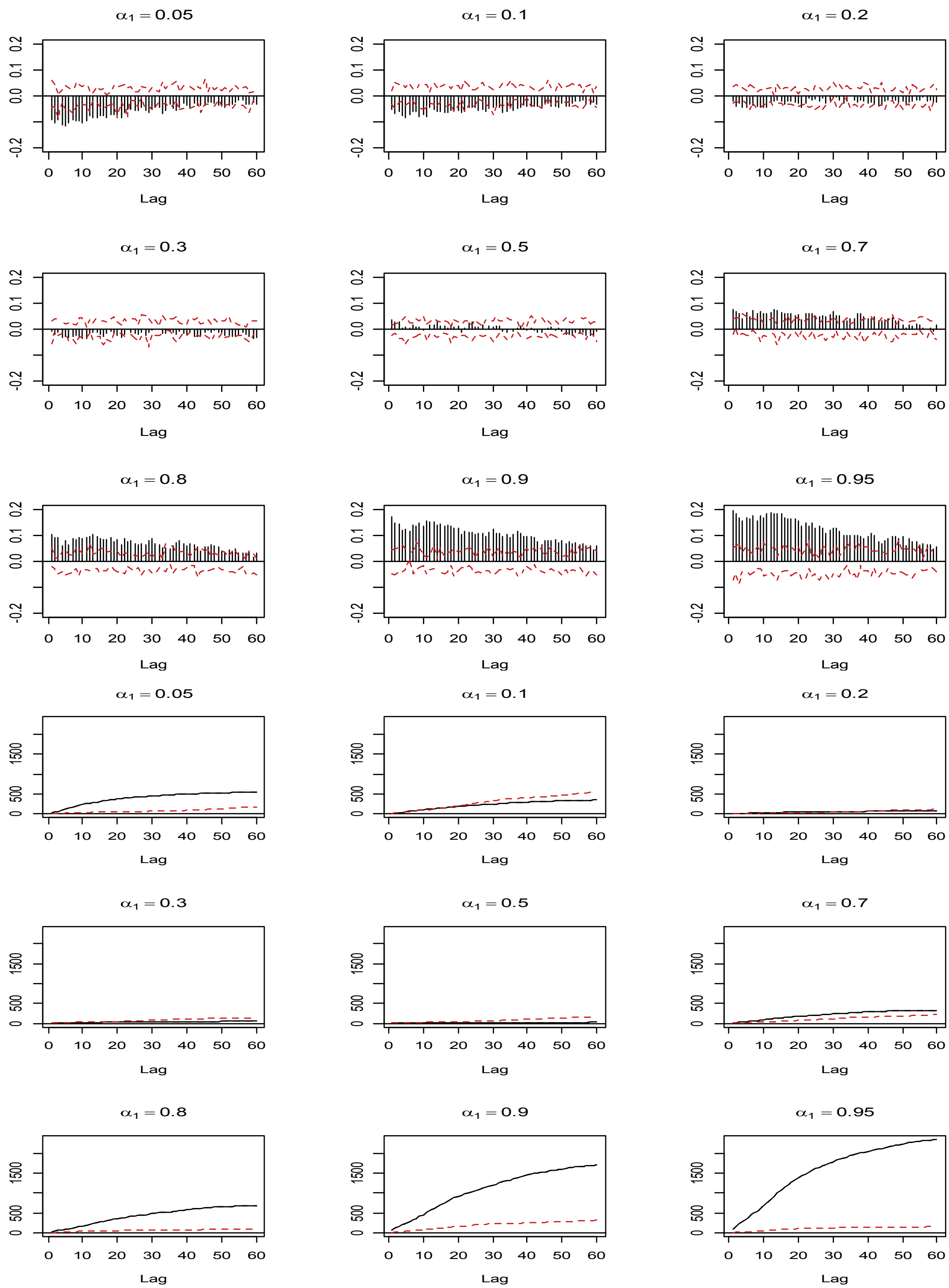

Fig. 4. **(a)** The sample cross-quantilogram $\widehat{\rho}_\alpha(k)$ with $\alpha_2 = 0.9$ to detect directional predictability from the oil volatility to Brazil's stock returns. Same as Fig. 1(a). **(b)** Box–Ljung test statistic $\widehat{Q}_\alpha^{(p)}$ for each lag p and quantile α using $\widehat{\rho}_\alpha(k)$ with $\alpha_2 = 0.9$ in Brazil's stock market. Same as Fig. 1(b).

studies ignore the problem of whether OVX has a directional predictability for the stock returns in emerging major countries such as BRICS countries.

In the end, we focus on the directional predictability from oil volatility to the stock returns in BRICS countries, the most promising emerging market countries in the world. Meanwhile, the fact that these countries having different degrees of dependence on crude oil allows us to investigate whether the level of directional predictability from oil volatility to the stock market depends on whether the country is either a net importer or a net exporter in the oil market.

This paper focuses on the BRICS countries for at least two reasons. On the one hand, from a general economic perspective, these countries are the five most important emerging economies and oil consumers in the world, and their rate of their contribution to world economic growth was 30.48% in 2015 (data sourced from the World Bank website). The stock markets of these countries have become increasingly integrated with those of the most developed economies by means of trade and investment. Still, their economic systems exhibit remarkable differences in

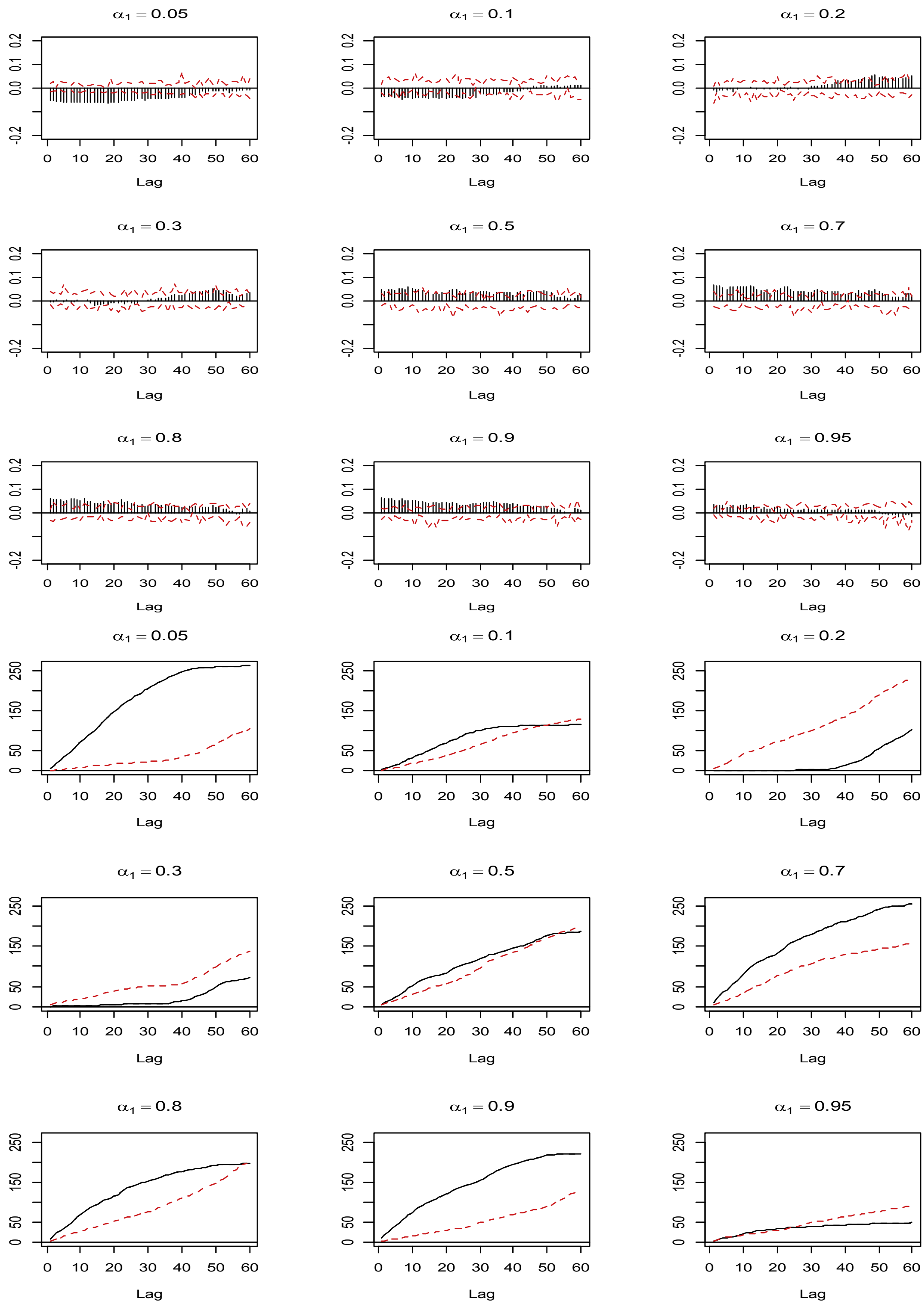

Fig. 5. **(a)** The sample cross-quantilogram $\widehat{\rho}_\alpha(k)$ with $\alpha_2 = 0.1$ to detect directional predictability from the oil volatility to Russia's stock returns. Same as Fig. 1(a). **(b)** Box–Ljung test statistic $\widehat{Q}_\alpha^{(p)}$ for each lag p and quantile α using $\widehat{\rho}_\alpha(k)$ with $\alpha_2 = 0.1$ in Russia's stock market. Same as Fig. 1(b).

terms of policy interventions, economic reforms, and financial regulation activities, which makes comparative study of the stock market reactions to oil price shocks extremely informative. On the other hand, from a perspective that is more specifically related to the international oil market, among the BRICS members, Russia and Brazil are net oil exporters, and the other three countries (India, China, and South Africa) are net-importers. As of 2017, BP data show that China and India were, respectively, the first and third largest net-importers of crude oil in the world, and Russia had become the largest global net-exporter of crude oil.

The remainder of this paper is organised as follows. Section 2 presents the data and the empirical methodologies. Section 3 discusses the empirical results. Section 4 summarises the conclusions and policy implications.

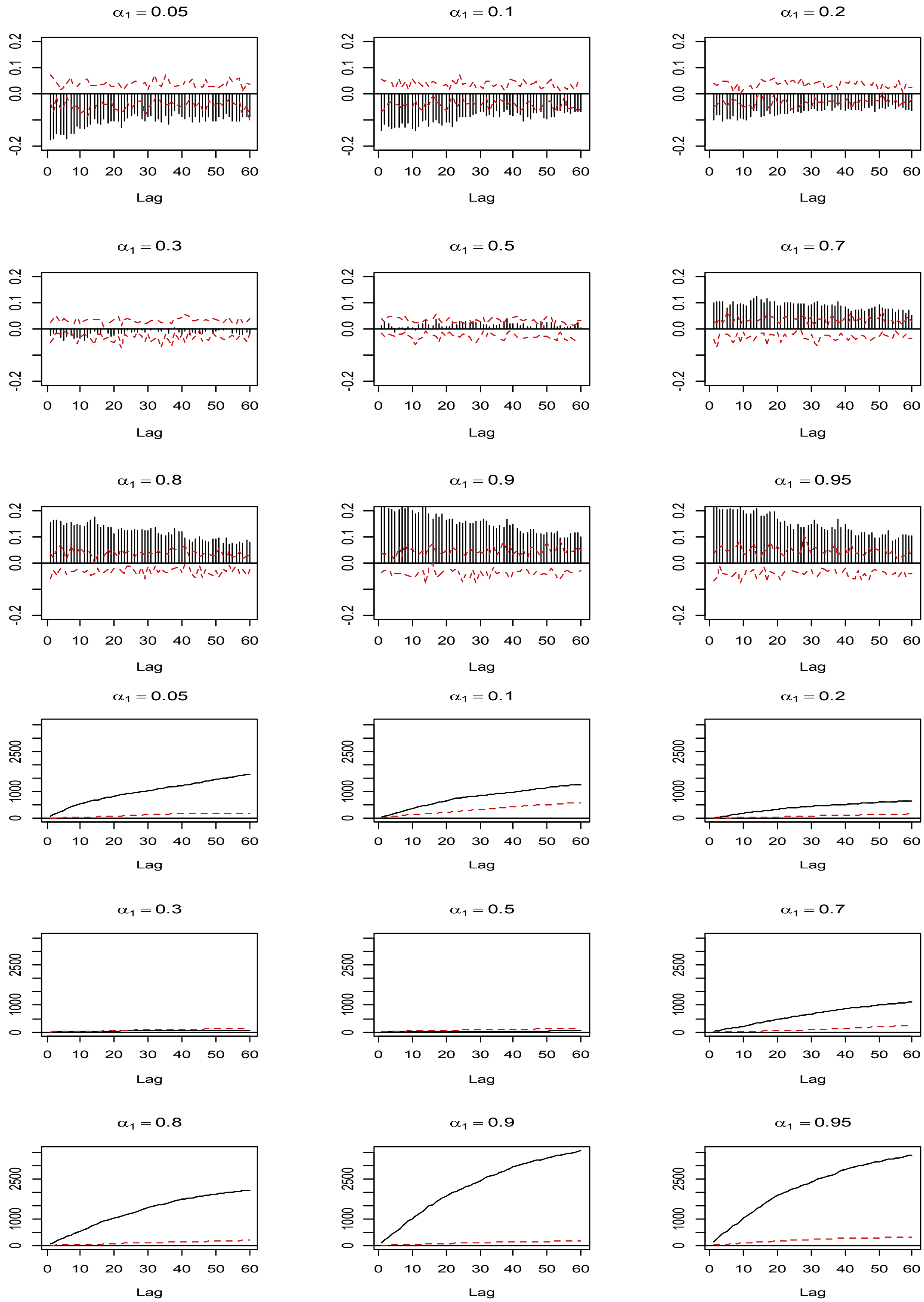

Fig. 6. **(a)** The sample cross-quantilogram $\hat{\rho}_\alpha(k)$ with $\alpha_2 = 0.9$ to detect the directional predictability from the oil volatility to Russia's stock returns. Same as Fig. 1(a). **(b)** Box–Ljung test statistic $\hat{Q}_\tau^{(p)}$ for each lag p and quantile α using $\hat{\rho}_\alpha(k)$ with $\alpha_2 = 0.9$ in Russia's stock market. Same as Fig. 1(b).

2. Data and methodology

2.1. Data

We investigate the quantile dependence and directional predictability from the oil volatility to stock returns in BRICS countries. The daily time-series sample covers the period from May 10, 2007 to May 16, 2017. The sample period is decided by the availability of the OVX. We select the OVX as a measure of oil market uncertainty published by CBOE. The stock market price indices of these five BRICS countries are Brazil's BOVESPA, China's Shanghai SEA index, India's SENSEX30, Russia's RTS index, and South Africa's Morgan Stanley Capital International index (MSCI index). We define daily stock returns as the logarithmic difference of stock index, $\ln(PI_t/PI_{t-1})$, where PI_t is the closing price of the stock

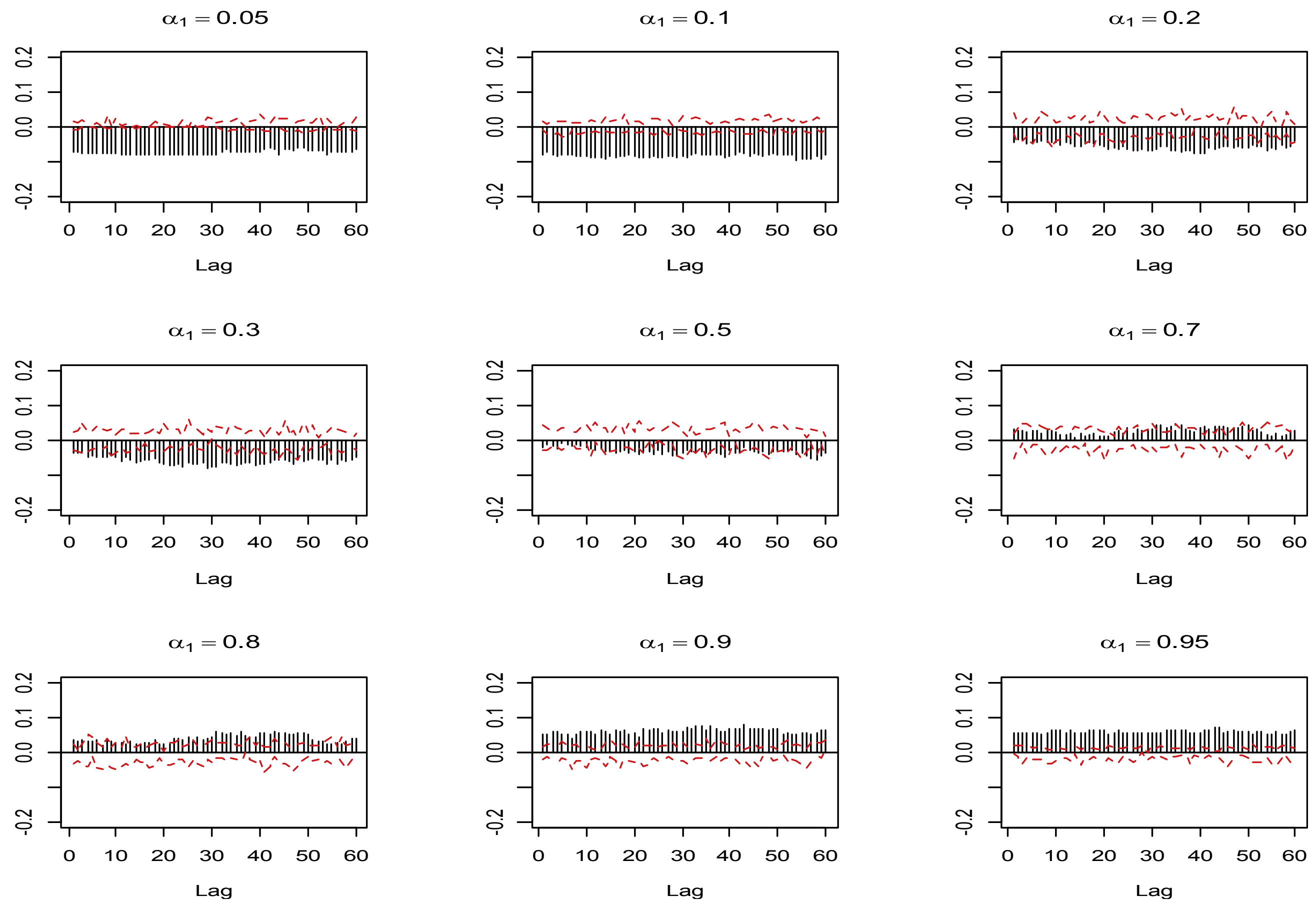

Fig. 7. (a) The sample cross-quantilogram $\widehat{\rho}_\alpha(k)$ with $\alpha_2 = 0.1$ that detects directional predictability from the oil volatility to India's stock returns. Same as Fig. 1(a). **(b)** Box–Ljung test statistic $\widehat{Q}_\alpha^{(p)}$ for each lag p and quantile α using $\widehat{\rho}_\alpha(k)$ with $\alpha_2 = 0.1$ in India's stock market. Same as Fig. 1(b).

prices' index for each BRICS country at time t.

Table 1 displays the results of descriptive statistics for OVX and the stock returns in BRICS. We find that the means of stock returns for BRICS are all close to zero, but the means of India's stock returns exceed the means of the other countries' stock returns. Moreover, the returns of Russia's stock market have the highest standard deviation among BRICS countries, which indicates that the return series of Russia's stock is more volatile than are those of the other countries. The skewness coefficients for all times series are positive, except for the stock returns in China and South Africa. Then, all kurtosis coefficients are above three, and they indicate that all the time series follow the fat-tailed and skewed non-normal distribution, which is also proved by the Jarque–Bera test that rejects the normality.

The cross-quantilogram model is applicable to the time series variables that are stationary (Han et al., 2016). Therefore, it is necessary to do unit root tests for each variable. As seen from Table 2, the Phillips–Perron test (PP) (Phillips and Perron, 1988.) and Dickey–Fuller unit root test (DF–GLS) (Elliot et al., 1996) tests suggest that the implied crude oil volatility index (OVX) and stock returns in BRICS countries follow stationary processes, which implies that the cross-quantilogram model is suitable.

2.2. The cross-quantilogram model

This section describes the cross-quantilogram model proposed by Han et al. (2016). The methodology is constructed to reveal cross-quantile predictability of two-time series. As explained by Han et al. (2016), the cross-quantilogram has advantages for examining the quantile dependence and directional predictability between two series. We use it to measure the quantile dependence and test the directional predictability from international oil volatility to stock returns in BRICS.

Let $\{x_{it}, t \in Z\}, i = 1, 2$ be the two-dimensional strictly stationary time series. We set x_{1t}, x_{2t} as the stock returns and OVX, respectively. Let $F_i(\cdot)$ denote the distribution function of the series x_{it} with density function $f_i(\cdot)$. The quantile function of the time series x_{it} is defined as $q_i(\alpha_i) = \inf\{\nu : F_i(\nu) \geq \alpha_i\}$ for $\alpha_i \in (0, 1)$. Let $\tilde{\alpha}$ be the range of quantiles we are interested in evaluating the directional predictability. For simplicity, we assume that $\tilde{\alpha}$ is a Cartesian product of two closed intervals in (0, 1), that is $\tilde{\alpha} \equiv \tilde{\alpha}_1 \times \tilde{\alpha}_2$, where $\tilde{\alpha}_i = [\underline{\alpha}_i, \overline{\alpha}_i]$ for some $0 < \underline{\alpha}_i < \overline{\alpha}_i < 1$.

We consider a measure of serial dependence between two events $\{x_{1t} \leq q_1(\alpha_1)\}$ and $\{x_{2t} \leq q_2(\alpha_2)\}$ for arbitrary quantiles. In the literature, $\{1[x_{it} \leq q_i[\cdot]]\}$ is called the quantile-hit or quantile-exceedance process for $i = 1, 2$.

The cross-quantilogram is defined as the cross-correlation of the quantile-hit processes

$$\rho_\alpha(k) = \frac{E\left[\psi_{\alpha_1}(x_{1t} - q_1(\alpha_1))\psi_{\alpha_2}(x_{2,t-k} - q_2(\alpha_2))\right]}{\sqrt{E\left[\psi^2_{\alpha_1}(x_{1t} - q_1(\alpha_1))\right]}\sqrt{E\left[\psi^2_{\alpha_2}(x_2 - q_2(\alpha_2))\right]}} \tag{1}$$

For $k = 0, \pm1, \pm2, \ldots,$ where $\psi_a(\mu) \equiv 1[\mu < 0] - a$, the cross-quantilogram captures serial dependency between the two series at different quantile levels. Note that it is well-defined even for processes $\{(x_{1t}, x_{2t})\}_{t \in N}$ with infinite moments. Like the quantilogram, the cross-quantilogram is invariant to any strictly monotonic transformation applied to both series, such as the logarithmic transformation.

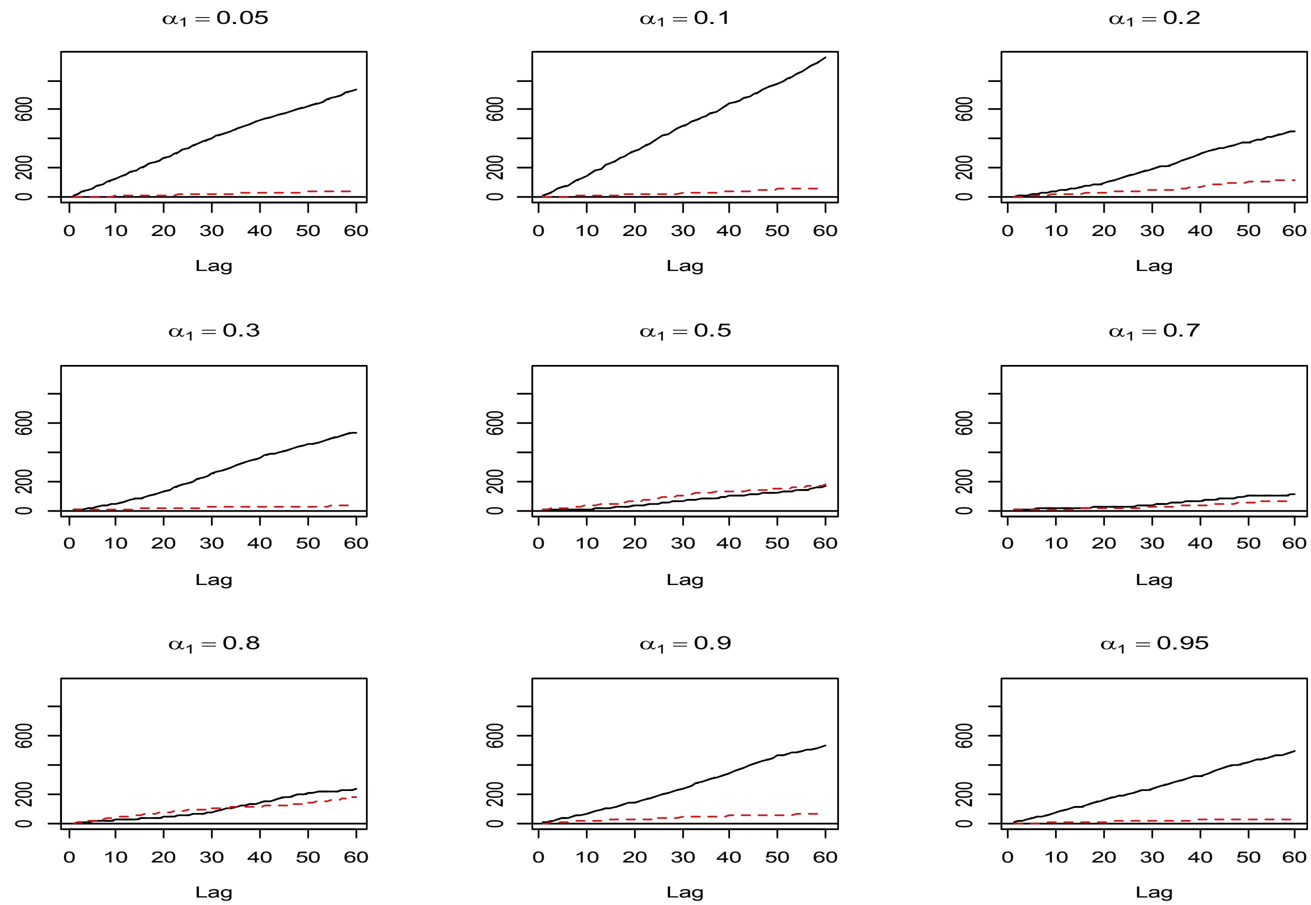

Fig. 7. (*continued*).

To construct the sample analogue of the cross-quantilogram based on observations $\{x_1, \ldots, x_T\}$, we estimate the unconditional quantile functions by solving the following minimisation problems separately: $\widehat{q}_1(\alpha_1) = \operatorname{argmin}_{\nu_1 \in R} \sum_{t=1}^{T} \pi_{\alpha_1}(x_1 - \nu_1)$ and $\widehat{q}_2(\alpha_2) = \operatorname{argmin}_{\nu_2 \in R} \sum_{t=1}^{T} \pi_{\alpha_2}(x_2 - \nu_2)$, where, $\pi_a(\mu) \equiv \mu(a - 1[\mu < 0])$. And then, the sample cross-quantilogram is defined as:

$$\rho_a(k) = \frac{\sum_{t=k+1}^{T} \psi_{\alpha_1}\left(x_{1t} - \widehat{q}_1(\alpha_1)\right) \psi_{\alpha_2}\left(x_{2,t-k} - \widehat{q}_2(\alpha_2)\right)]}{\sqrt{\sum_{t=k+1}^{T} \psi_{\alpha_1}^2\left(x_{1t} - \widehat{q}_1(\alpha_1)\right)} \sqrt{\sum_{t=k+1}^{T} \psi_{\alpha_2}^2\left(x_{2t-k} - \widehat{q}_2(\alpha_2)\right)}} \tag{2}$$

For $K = 0, \pm1, \pm2, \ldots$, $\widehat{\rho}_a(k) \in [-1, 1]$, with $\widehat{\rho}_a(k) = 0$ corresponding to the case of no directional predictability from the implied crude oil volatility index to stock returns in BRICS. If $\widehat{\rho}_a(k) \neq 0$, there is a directional predictability from the implied crude oil volatility index to stock returns in BRICS countries.

Suppose that p is given. One may be interested in testing the null hypothesis

$H_0 : \rho_a(k) = 0$ against the alternative hypothesis that $H_1 : \rho_a(k) \neq 0$ for all $k \in \{1, \ldots p\}$. This is a test for the directional predictability of events up to p lags $\{x_{2t-k} \le q_{2,t-k}(\alpha_2)\}$ for $\{x_{1t} \le q_{1,t}(\alpha_1)\}, k = 1, \ldots, p$. To discriminate between these hypotheses, we will use the test of Box-Ljung version: $\widehat{Q}_\alpha^{(P)} = T(T+2)\sum_{k=1}^{p} \widehat{\rho}_\alpha^2(k)/(T-k)$. The portmanteau test $\widehat{Q}_\alpha^{(P)}$ can be used to test the directional predictability of returns from one time series to another for events up to p lags at a pair of quantiles.

3. Empirical results and discussions

Figs. 1(a)–10(b) show the results of cross-quantilogram $\widehat{\rho}_\tau(k)$ and Box-Ljung test statistics $\widehat{Q}_\tau^{(p)}$ for BRICS at different quantiles. With these results in hand, we can examine the quantile dependence and directional predictability from oil volatility to stock returns in BRICS countries. In particular, we mainly analyse the direct predictability and dependence of oil price volatility on stock returns when the former is both at a low level and at a high level. For the quantiles of oil volatility $q_2(\alpha_2)$, we set $\alpha_2 = 0.1$ and 0.9. For the stock returns $q_1(\alpha_1)$, we set stock returns in quantiles $\alpha_1 = 0.05, 0.1, 0.2, 0.3, 0.5, 0.7, 0.8, 0.9, 0.95$.

3.1. Directional predictability of oil volatility

The empirical results show that there is less likelihood of large losses and large gains for stock returns in BRICS when the oil volatility is at a low state. Meanwhile, when oil volatility is higher than its 0.9 quantiles, there is an increased likelihood of large losses and large gains in stock returns.

Specifically, taking China as an example, based on Eqs. (1) and (2), the quantile dependence and directional predictability from oil volatility to China's stock returns are obtained in Figs. 1(a)–2(b). In Fig. 1(a) and (b), we examine quantile dependence and directional predictability from oil volatility to China's stock returns when the oil volatility is in a low quantile, i.e., $\alpha_2 = 0.1$. The cross-quantilogram $\widehat{\rho}_\alpha(k)$ for $\alpha_1 = 0.05, 0.1, 0.2, 0.3$ is negative and statistically significant for many lags. It applied that when oil volatility is in the low state, there is less likelihood of a large loss in China's stock market. On the other hand, the cross-quantilogram $\widehat{\rho}_\tau(k)$ for $\alpha_1 = 0.7, 0.8, 0.9, 0.95$ is positive and significant for many lags. It indicates that there is less likelihood of a large gain in China's stock market as well. However, the cross-quantilogram for $\alpha_1 = 0.5$ is mostly insignificant. Fig. 1(b) shows that the Box–Ljung test statistics are mostly significant, except for $\alpha_1 = 0.5$.

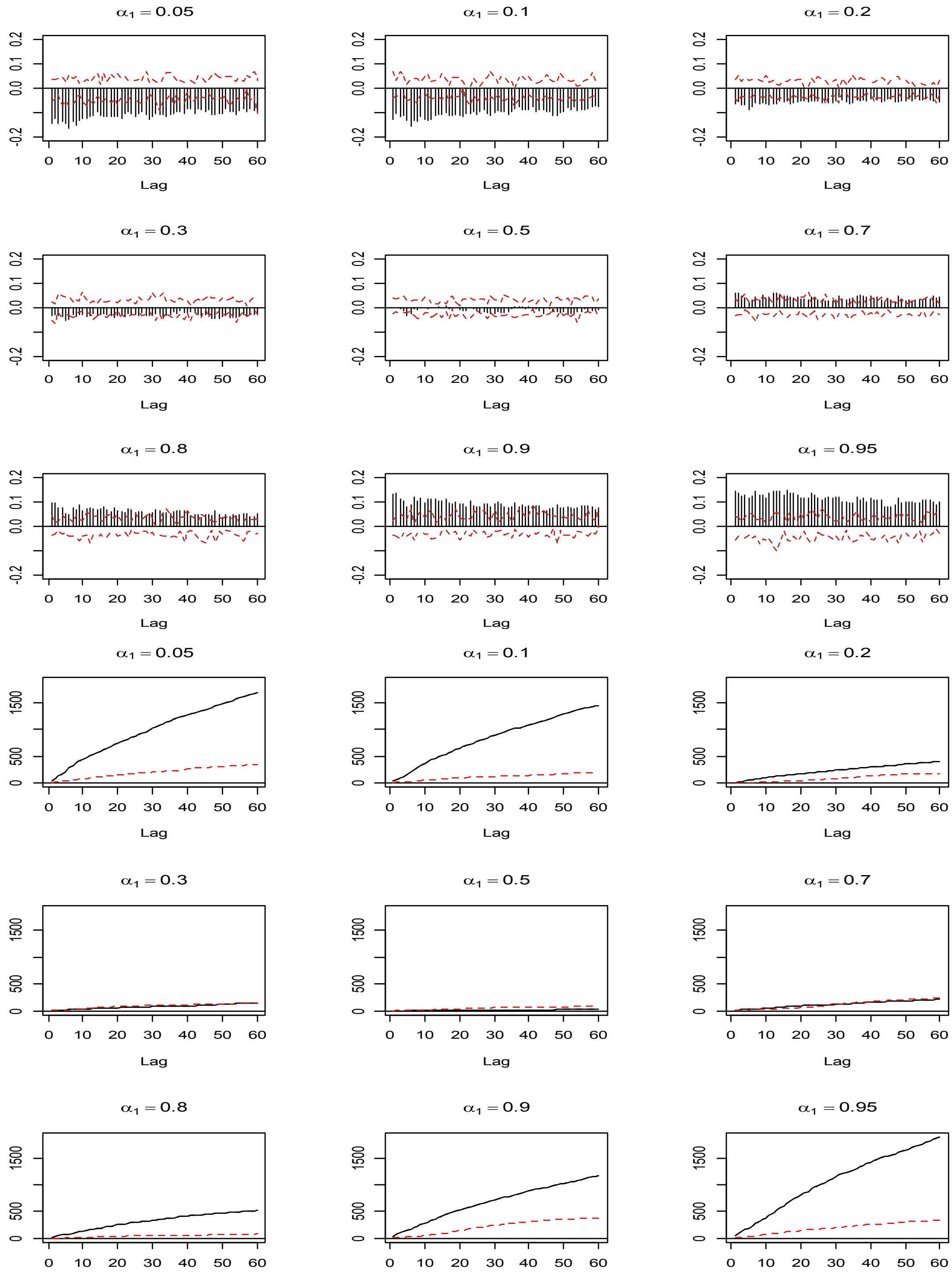

Fig. 8. (a) The sample cross-quantilogram $\widehat{\rho}_{\alpha}(k)$ with $\alpha_2 = 0.9$ that detects directional predictability from the oil volatility to India's stock returns. Same as Fig. 1(a). **(b)** Box–Ljung test statistic $\widehat{Q}_{\alpha}^{(p)}$ for each lag p and quantile α using $\widehat{\rho}_{\alpha}(k)$ with $\alpha_2 = 0.9$ in India's stock market. Same as Fig. 1(b).

Fig. 2(a) and (b) provide the quantile dependence and directional predictability from oil volatility to China's stock returns for the case when oil volatility is in a high quantile, $\alpha_2 = 0.9$. Specifically, such as when $\alpha_1 = 0.05$, the cross-quantilogram is significantly negative for short lags. This means that, when oil price volatility is higher than 0.9 quantiles, there is increased likelihood of a very large loss for a few days (less than 20 days) in China's stock market. For $\alpha_1 = 0.95$, the cross-quantilogram is positive and significant for lags of approximately 60 days. This implies that, when oil volatility is very high (higher than the 0.9 quantiles), there is an increased likelihood of a very large gain in China's stock market for the next 60 days. For other quantiles of China's stock returns, we find that the cross-quantilogram and Box–Ljung test statistics for $\alpha_1 = 0.3$ are insignificant. However, for $\alpha_1 = 0.1, 0.2$, we find that the cross-quantilogram and Box-Ljung test statistics have small absolute values and are significant only for within 20 days' lag. In comparison, for $\alpha_1 = 0.7, 0.8, 0.9$, the cross-quantilogram is positive and significant for many

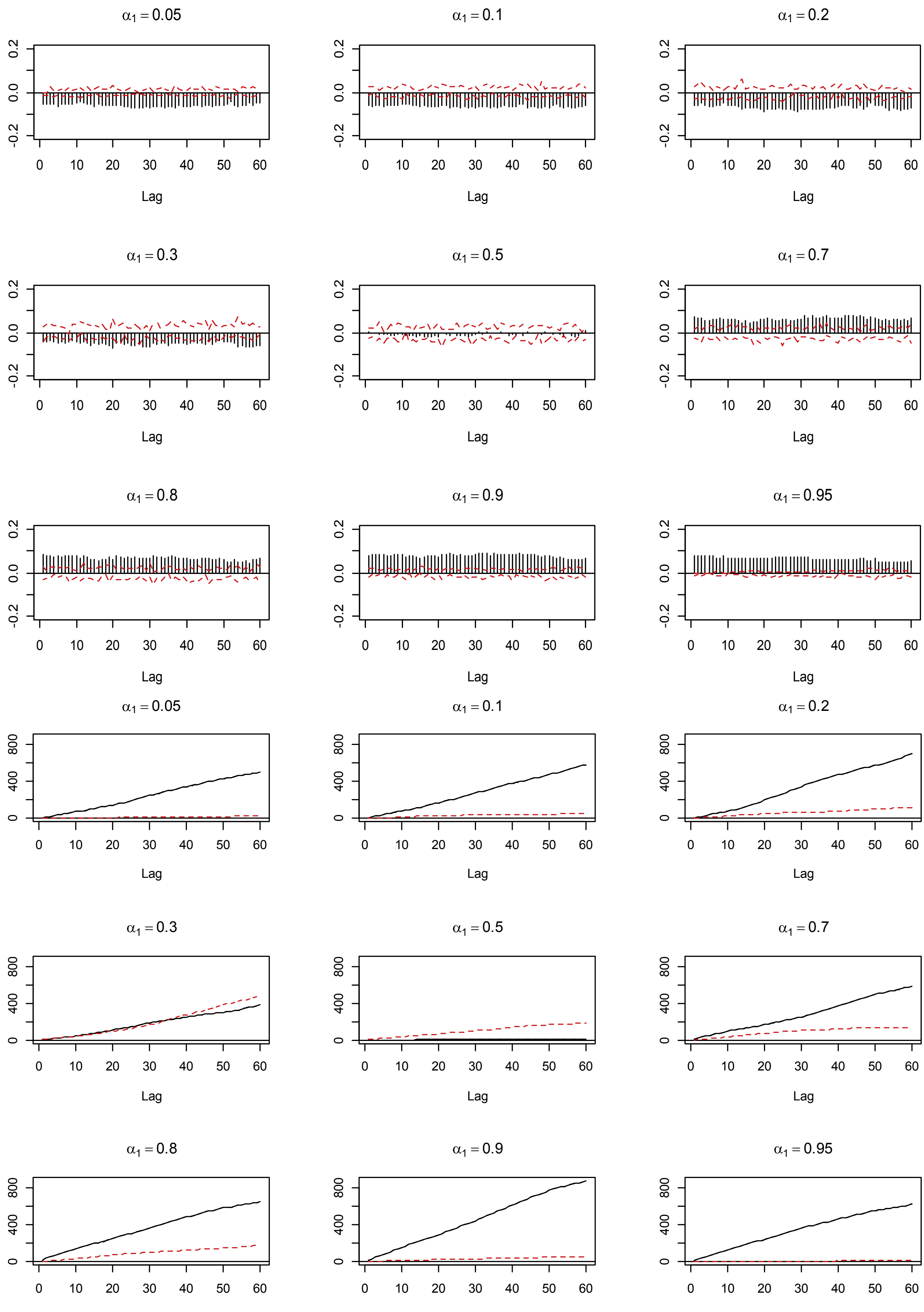

Fig. 9. **(a)** The sample cross-quantilogram $\widehat{\rho}_{\alpha}(k)$ with $\alpha_2 = 0.1$ that detects the directional predictability from oil volatility to South Africa's stock returns. Same as Fig. 1(a). **(b)** Box–Ljung test statistic $\widehat{Q}_{\alpha}^{(p)}$ for each lag p and quantile α using $\widehat{\rho}_{\alpha}(k)$ with $\alpha_2 = 0.1$ in South Africa's stock market. Same as Fig. 1(b).

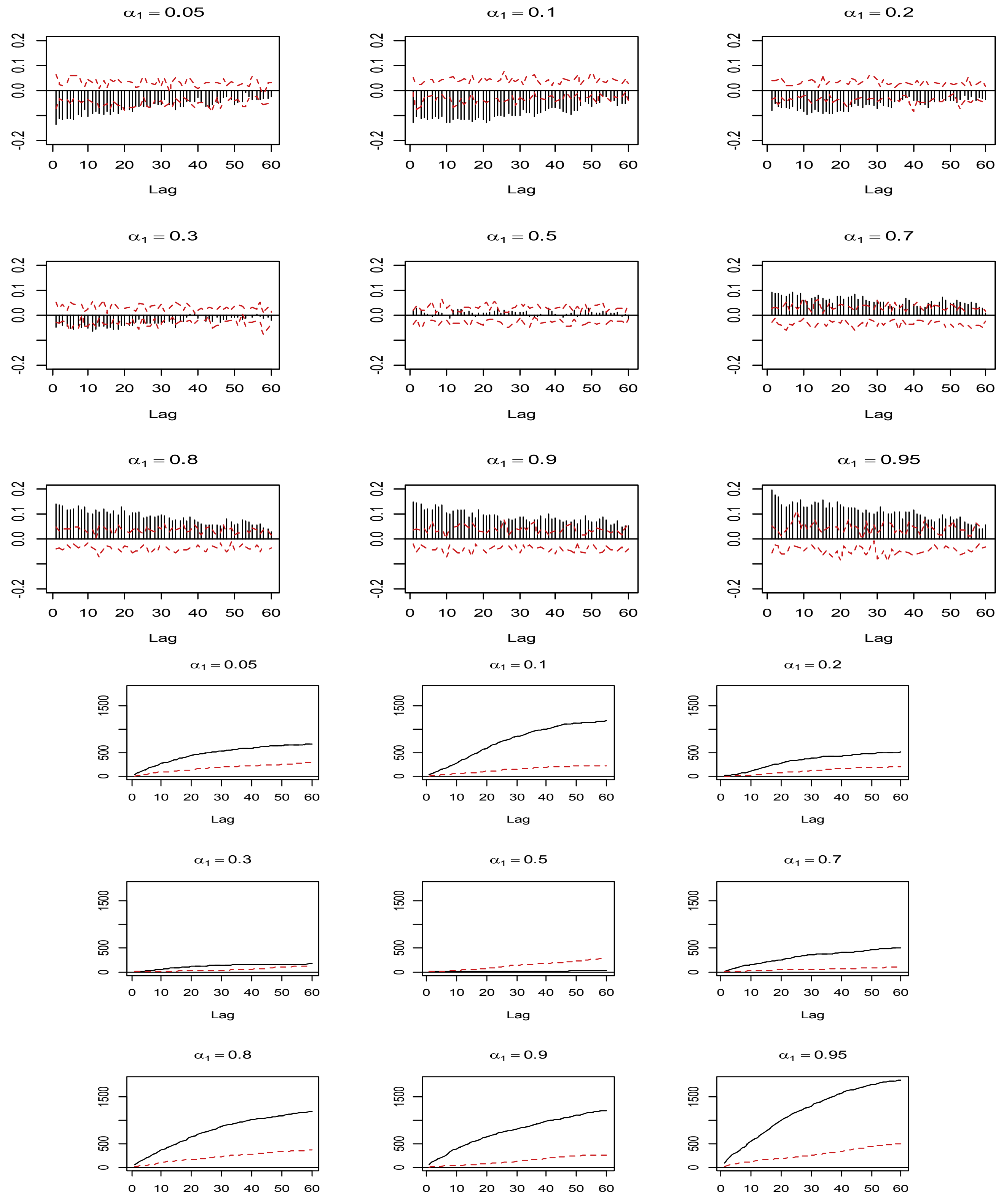

Fig. 10. **(a)** The sample cross-quantilogram $\widehat{\rho}_\alpha(k)$ with $\alpha_2 = 0.9$ to detect directional predictability from oil volatility to South Africa's stock returns. Same as Fig. 1(a). **(b)** Box–Ljung test statistic $\widehat{Q}_\alpha^{(p)}$ for each lag p and quantile α using $\widehat{\rho}_\alpha(k)$ with $\alpha_2 = 0.9$ in South Africa's stock market. Same as Fig. 1(b).

Table 3
Summaries on directional predictability from the oil volatility to stock returns.

	Oil volatility	Stock returns								
	α	0.05	0.1	0.2	0.3	0.5	0.7	0.8	0.9	0.95
Brazil	0.1	✓	✓	×	×	×	×	×	✓	✓
	0.9	✓	✓	×	×	×	✓	✓	✓	✓
Russia	0.1	✓	✓	×	×	✓	✓	✓	✓	×
	0.9	✓	✓	✓	×	×	✓	✓	✓	✓
India	0.1	✓	✓	✓	✓	×	✓	✓	✓	✓
	0.9	✓	✓	✓	×	×	✓	✓	✓	✓
China	0.1	✓	✓	✓	✓	×	✓	✓	✓	✓
	0.9	✓	✓	✓	×	✓	✓	✓	✓	✓
South Africa	0.1	✓	✓	✓	✓	×	✓	✓	✓	✓
	0.9	✓	✓	✓	✓	×	✓	✓	✓	✓

Notes: ✓ denotes that directional predictability from the international oil volatility to stock returns for BRICS; and × denotes no directional probability.

Table 4
The estimation results for the quantile regression (coefficients $\beta(\alpha)$).

	0.05	0.1	0.2	0.3	0.5	0.7	0.8	0.9	0.95
Brazil	−0.054***	−0.042***	−0.024***	−0.009***	0.000	0.010***	0.024***	0.031***	0.052***
Russia	−0.093***	−0.071***	−0.039***	−0.024***	0.000	0.023***	0.041***	0.059***	0.081***
India	−0.048***	−0.039***	−0.028***	−0.015***	−0.002	0.004***	0.014***	0.025***	0.051***
China	−0.057***	−0.044***	−0.024***	−0.012***	0.001	0.013***	0.020***	0.030***	0.037***
South Africa	−0.068***	−0.055***	−0.035***	−0.026***	−0.003	0.020***	0.027***	0.047***	0.069***

Notes: *** Indicates significance at the 1% level.

lags, and Box-Ljung test statistics are also significant, which implies that, when oil volatility is high (higher than its 0.9 quantiles), there is an increased likelihood of a very large gain in China's stock market. Our findings are in line with those of Fang and You (2014) and Luo and Qin (2017), who find that the oil price volatility has a significant effect on China's stock market.

Due to the limited space, and to avoid the redundancy of narration, we do not list the analysis results of predictability from the oil price volatility to stock returns in other BRICS countries (Brazil, Russia, India, and South Africa). As can be seen from Table 3 and the charts of the cross-quantilograms $\widehat{\rho}_\alpha(k)$ and Box-Ljung test statistics [see Figs. 3(a)–10(b)], there is still less likelihood of large losses and large gains for stock returns when oil volatility is in the low state (lower than its 0.1 quantiles). However, when oil volatility is higher than its 0.9 quantile, there is an increased likelihood of large losses and large gains for stock returns. In addition, we summarise the results of directional predictability from the oil price volatility to stock returns in BRICS countries, as shown in Table 3. We also find some other intriguing results, as follows.

Through comparative analysis, first, we find that oil volatility can explain more quantiles of stock returns of net oil importers than of net oil exporters. As can be seen from Table 3 and the charts of the cross-quantilograms $\widehat{\rho}_\alpha(k)$ and Box-Ljung test statistics, when the oil volatility is in a low quantile ($\alpha_2 = 0.1$), stock returns in the quantiles $\alpha_1 = 0.2, 0.3, 0.5, 0.7, 0.8$ for the oil net exporter Brazil cannot be predicted by the oil volatility. Likewise, for Russia, three quantiles ($\alpha_1 = 0.2, 0.3, 0.95$) of the stock returns cannot be predicted by the oil volatility. In contrast, for the oil net importers China, India, and South Africa, there is no directional predictability from the oil volatility to their stock returns in the quantile $\alpha_1 = 0.5$, but it is valid for other quantiles. Thus, it is found that, apart from India, more quantiles in the stock returns of net oil importers can be predicted by the oil volatility than is the case with net oil exporters when the oil volatility is very low. Moreover, when the oil volatility is in a high quantile ($\alpha_2 = 0.9$), three quantiles of stock returns for Brazil ($\alpha_1 = 0.2, 0.3, 0.5$) which cannot be predicted by oil volatility. For Russia, two quantiles in the stock returns ($\alpha_1 = 0.3, 0.5$) cannot be predicted by oil volatility. By comparison, only one quantile for the stock returns in China ($\alpha_1 = 0.3$) and South Africa ($\alpha_1 = 0.5$) cannot be explained by the oil volatility. However, in the case of India, there are two quantiles ($\alpha_1 = 0.3, 0.5$). This finding confirms that there is wider predictability for oil volatility to stock returns in the oil net importers, namely China, India, and South Africa, than in the oil net exporters, namely Russia and Brazil. The reason for this finding is that the three oil net importers have a greater dependence on crude oil than do the two net oil exporters, which is consistent with Boldanov et al. (2016) and Wang et al. (2013). On the one hand, when crude oil prices rise, wealth is transferred from crude oil net importers, such as China, to net exporters, such as Russia, and capital flight is detrimental to the stock market in the oil importing country. Meanwhile, different from the oil-exporting countries, higher oil prices deteriorate the terms of trade of the oil-importing countries (Kilian and Park, 2009). On the other hand, net oil importers must face the increased production costs and inflationary pressures caused by rising crude oil prices (Jung and Park, 2011). These factors together will make the stock markets of crude oil importing countries (within BRICS countries) more sensitive to crude oil prices.

In addition, we find that, for all BRICS countries, oil volatility in a high quantile ($\alpha_2 = 0.9$) has more directional predictability for stock returns than does oil volatility in a low quantile ($\alpha_2 = 0.1$). Specifically, by comparing the absolute value of the cross-quantilogram $\widehat{\rho}_\alpha(k)$ when the oil volatility is, respectively, in a low quantile ($\alpha_2 = 0.1$) and a high quantile ($\alpha_2 = 0.9$), we find that the absolute value of the cross-quantilogram in the former case is always smaller than in the latter case. This means that high oil volatility has stronger predictability for stock returns in BRICS, and the investors have an increased likelihood of large losses and large gains in the future when the oil volatility is very high. This is because only a very high level of volatility of crude oil prices will have an impact on production and the macro-economy. In other words, when the volatility of crude oil prices is very small, entrepreneurs will not be forced to adjust their operations, and policy makers will not introduce relevant economic policies.

Finally, there are significant differences between directional predictability in net oil importers and exporters at different states of oil volatility. Specifically, by comparing the cross-quantilograms $\widehat{\rho}_\alpha(k)$ in the oil net importers and net exporters, we find that the absolute value of cross-quantilogram in net oil exporters is smaller than is that of net oil

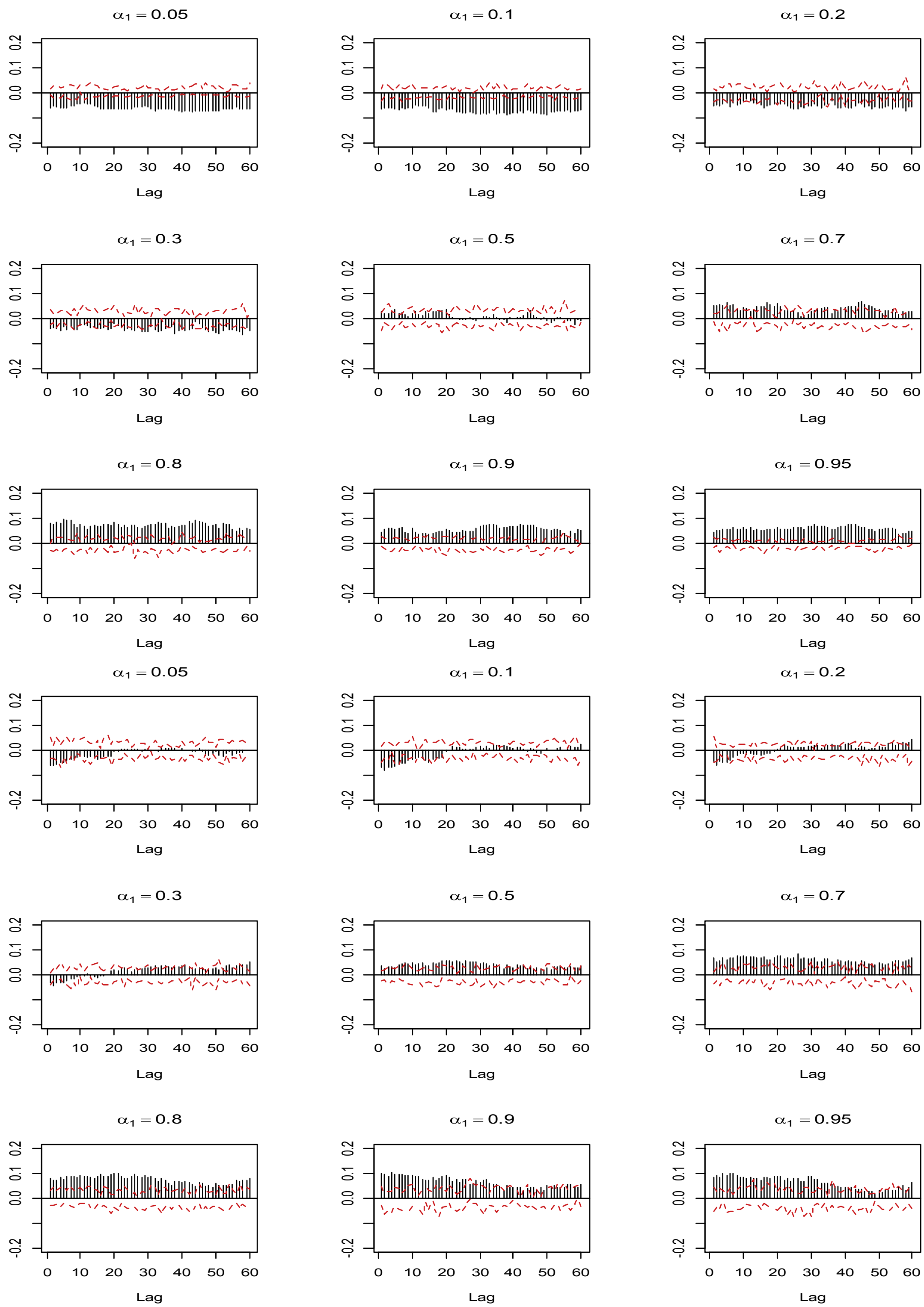

Fig. 11. **(a)** The sample cross-quantilogram $\widehat{\rho}_\alpha(k)$ with $\alpha_2 = 0.1$ to detect directional predictability from the oil volatility to China's stock returns. Same as Fig. 1(a). **(b)** The sample cross-quantilogram $\widehat{\rho}_\alpha(k)$ with $\alpha_2 = 0.9$ to detect directional predictability from the oil volatility to China's stock returns. Same as Fig. 1(a).

importers when oil volatility is in a low quantile. This indicates that, when oil volatility is in a low quantile, net oil exporters have a smaller chance of getting large returns on the stock market than do net oil importers. Meanwhile, it also reveals that there is a lower likelihood of a loss in the net oil exporters' stock market than in the net oil importers' stock market. However, the absolute value of the cross-quantilogram for net oil exporters is larger than is that for net oil importers when oil volatility is in a high quantile. This indicates that the net oil exporters are not only more likely to have a large gain than are the net oil importers but are also more likely to have a loss than are the net oil importers. Our results confirm the finding of Wang and Liu (2016), who have proven that oil price risk can be better hedged by investing in stocks of

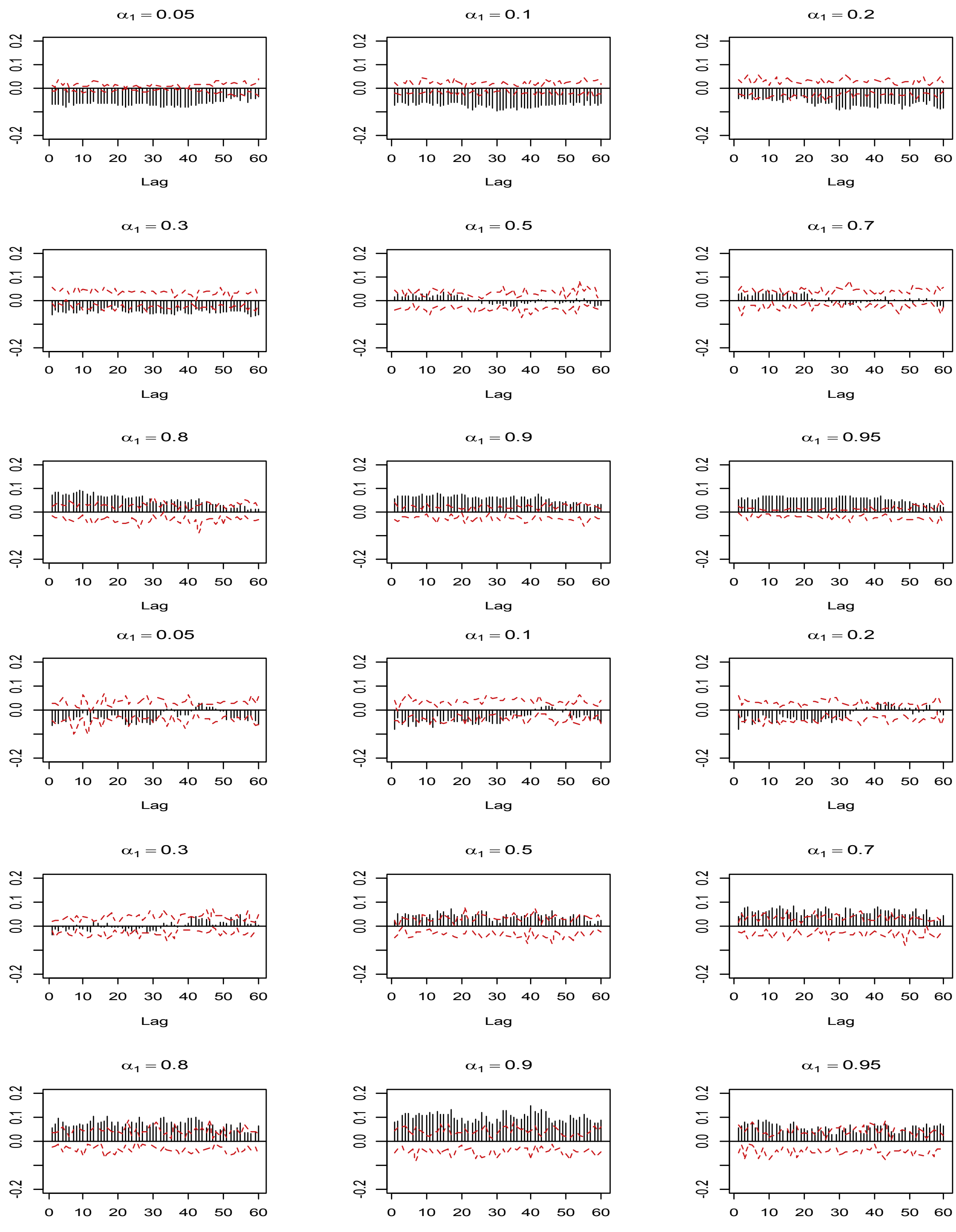

Fig. 12. (a) The sample cross-quantilogram $\widehat{\rho}_\alpha(k)$ with $\alpha_2 = 0.1$ to detect directional predictability from oil volatility to China's stock returns after the global financial crisis. Same as Fig. 1(a). **(b)** The sample cross-quantilogram $\widehat{\rho}_\alpha(k)$ with $\alpha_2 = 0.9$ to detect directional predictability from oil volatility to China's stock returns after the global financial crisis. Same as Fig. 1(a).

oil-exporting countries (e.g., Russia, Canada, and Norway) than in those of oil-importing countries (e.g., China and India).

3.2. Comparison analysis with quantile regression

For the sake of comparability and robustness, we build the quantile regression model (Koenker and Bassett, 1978), as shown, $Q_{R_t}(\alpha|OVX) = \varepsilon(\alpha) + \beta(\alpha)OVX_t$. Where $Q_R(\alpha|OVX)$ denotes the α *th* conditional quantile of R_t; R_t denotes the stock returns for BRICS, and OVX_t represents the oil price volatility. The coefficient $\beta(\alpha)$ is the estimated parameter in the equation, and ε represents the unobserved effect. Table 4 shows the quantile regression estimations. We find that, for BRICS countries, when the stock market is in a bearish market, the oil price volatility accelerates the decline of the stock price. By contrast, when the stock market is in a bullish market, the oil price volatility promotes the rise of stock price. The results of the quantile regression estimations indicate that oil price volatility has a noticeable effect on the stock market returns in BRICS countries. However, the traditional quantile regression model cannot identify the difference in the impact of the oil price volatility at different levels on the different kinds of stock returns. The cross-quantilogram model can effectively solve this problem. We find that, when the oil volatility is in a low quantile (lower than its 0.1 quantiles), there is less likelihood of large losses and large gains in the stock market. In contrast, there is an increased likelihood of large losses and gains in the stock market when the oil volatility is in a high quantile (higher than its 0.9 quantiles).

3.3. Robustness analysis

We analyse the robustness of our model results from the perspective of different proxies of international oil volatility and different sample periods.

3.3.1. Based on a new proxy for oil price volatility

As the WTI crude oil price is one of the major benchmarks of world crude oil pricing, we set it as the proxy of the international oil price. We choose the oil conditional volatility calculated by the GARCH (1, 1) model (Bollerslev, 1986) as the proxy of oil price volatility in the oil market and then re-estimate the cross-quantilogram model to verify the robustness of our results. Although there are differences in risk appetite between the implied crude oil volatility index—OVX—and the conditional oil volatility, the conditional volatility of oil prices based on the GARCH model estimation has been widely used in reflecting the volatility of the crude oil market (e.g., Narayan and Narayan, 2007; Kang et al., 2009; Wei et al., 2010). Lastly, the empirical results show that the new cross-quantilogram measures $\widehat{\rho}_{\tau}(k)$ have similar patterns (see Fig. 11(a) and (b) for China's stock market), which also proves the robustness of our main results. Due to limited space, we do not show the results of predictability from the conditional volatility of oil price to stock returns here for other countries; however, the results are both proven to be robust and available in Appendix A (see Fig. A1(a)–Fig. A4(b)).

3.3.2. Based on a different sample period

Crude oil prices experienced sharp fluctuations and showed huge bubbles in 2008, which may have an impact on the estimation of the model. Therefore, we cut off the data before June in 2009 (it is generally believed that the financial crisis ended in June 2009) and only retain the data after the financial crisis to re-estimate the cross-quantilogram model. Taking China's stock market as an example, the empirical results show that the predictability and dependence of OVX on China's stock market have not changed [see Fig. 12(a) and (b)]. The results for the other four countries can be seen in Appendix A [see Fig. A5(a)–Fig. A8(b)]. Our results prove robust.

4. Conclusions

The objective of this study is to examine the quantile dependence and directional predictability from the international oil volatility to stock returns in BRICS (Brazil, Russia, India, China, and South Africa) countries. To this end, we employ the cross-quantilogram model proposed by Han et al. (2016), which can address quantile-based dependence between two stationary variables. Several findings that stem from our analysis are as follows.

First, when oil volatility is in a low quantile, there is reduced likelihood of large losses and large gains in the stock market for all BRICS countries. By comparison, when the international oil volatility is in a high quantile, there is increased likelihood of large losses and gains in the stock market. Meanwhile, for all BRICS countries, international oil volatility in a high quantile has more directional predictability for stock returns than does international oil volatility in a low quantile. Overall, this proves that oil volatility has strong directional predictability for the stock returns in BRICS countries.

Second, the level of directional predictability of oil volatility to stock returns in the BRICS countries depends on the extent to which these countries are either net importers or net exporters of oil. The net oil exporters (Russia and Brazil) are less likely to have large gains and losses in the stock market than are the net oil importers (India, China, and South Africa) when the oil volatility is in a low quantile. Meanwhile, the net oil exporters are more likely to have large gains and losses than are the net oil importers when the oil volatility is in a high quantile. The results are robust to change in the variable of oil volatility.

The results of this study also have certain implications for investors, for example, when the oil volatility is in a high quantile, there is an increased likelihood of large losses and gains in the stock market. At this point, investors with an appetite for risk can increase their investment in the stock market; however, investors who are risk-averse, should reduce their investment in the stock market. Moreover, if multinational investors want higher stock returns when oil volatility is in a high quantile they should increase their investment in the stock markets of net oil exporters, rather than in the stock markets of net oil importers.

Acknowledgments

We gratefully acknowledge the financial support from the National Natural Science Foundation of China (Nos. 71771082, 71371067, 71431008) and the Hunan Provincial Natural Science Foundation of China (No. 2017JJ1012).

Appendix A

A1. Based on Conditional volatility

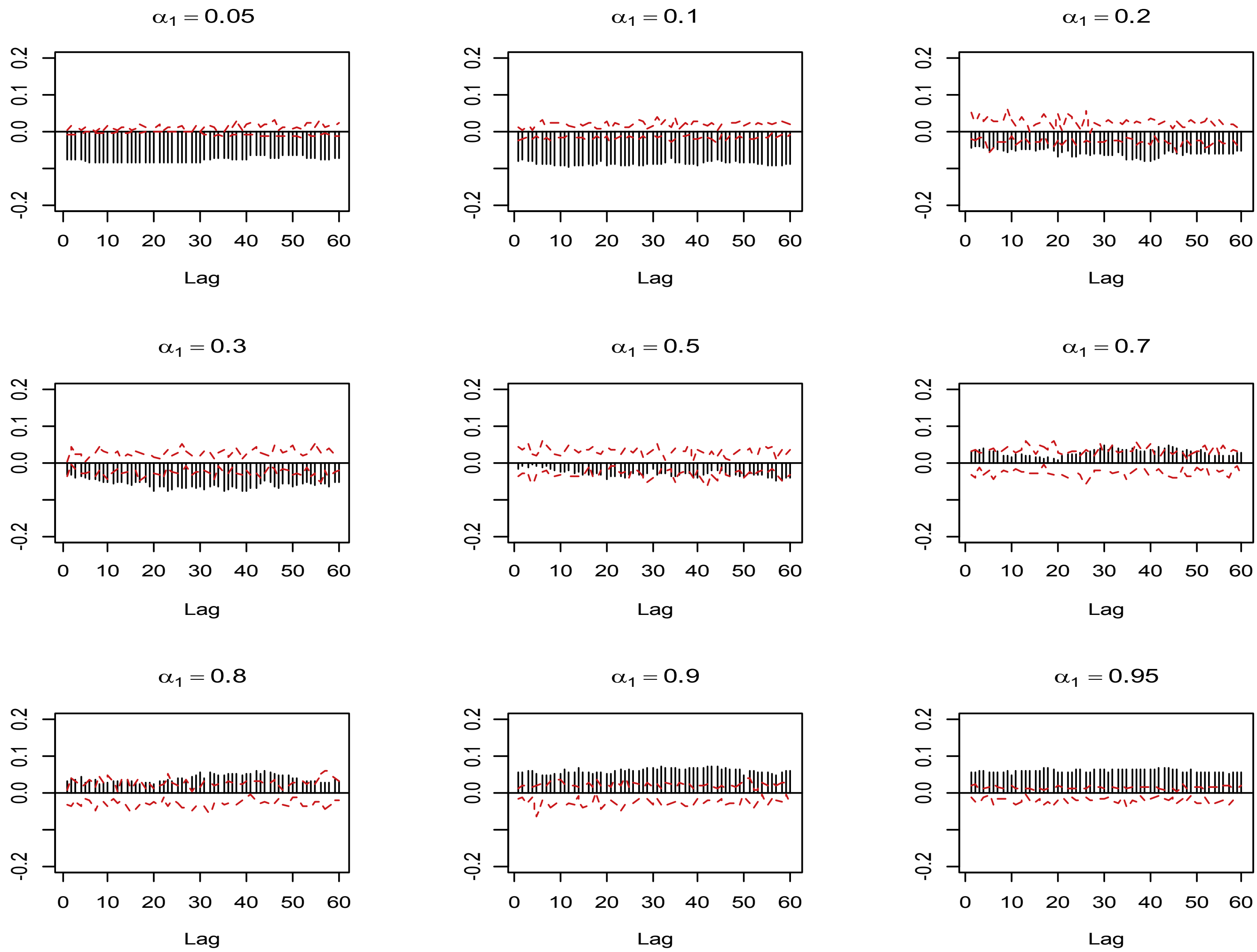

Fig. A1a. The sample cross-quantilogram $\widehat{\rho}_\alpha(k)$ with $\alpha_2 = 0.1$ to detect directional predictability from oil volatility to India's stock returns. Same as Fig. 1(a).

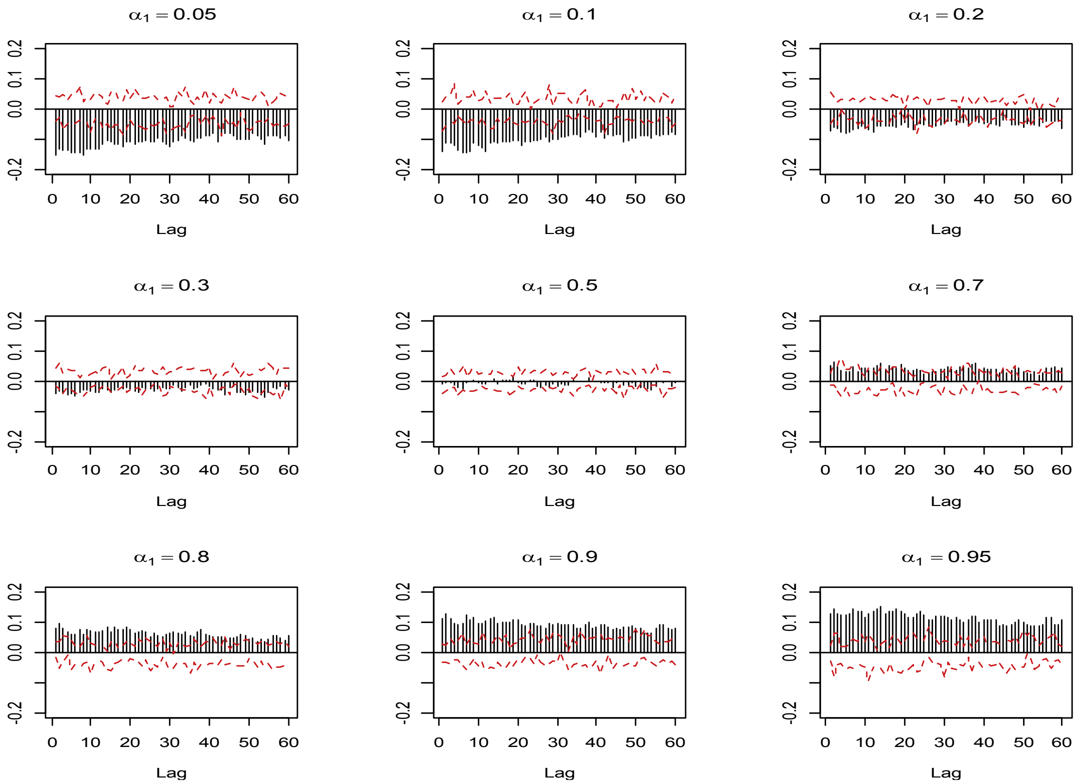

Fig. A1b. The sample cross-quantilogram $\widehat{\rho}_{\alpha}(k)$ with $\alpha_2 = 0.9$ to detect directional predictability from oil volatility to India's stock returns. Same as Fig. 1(a).

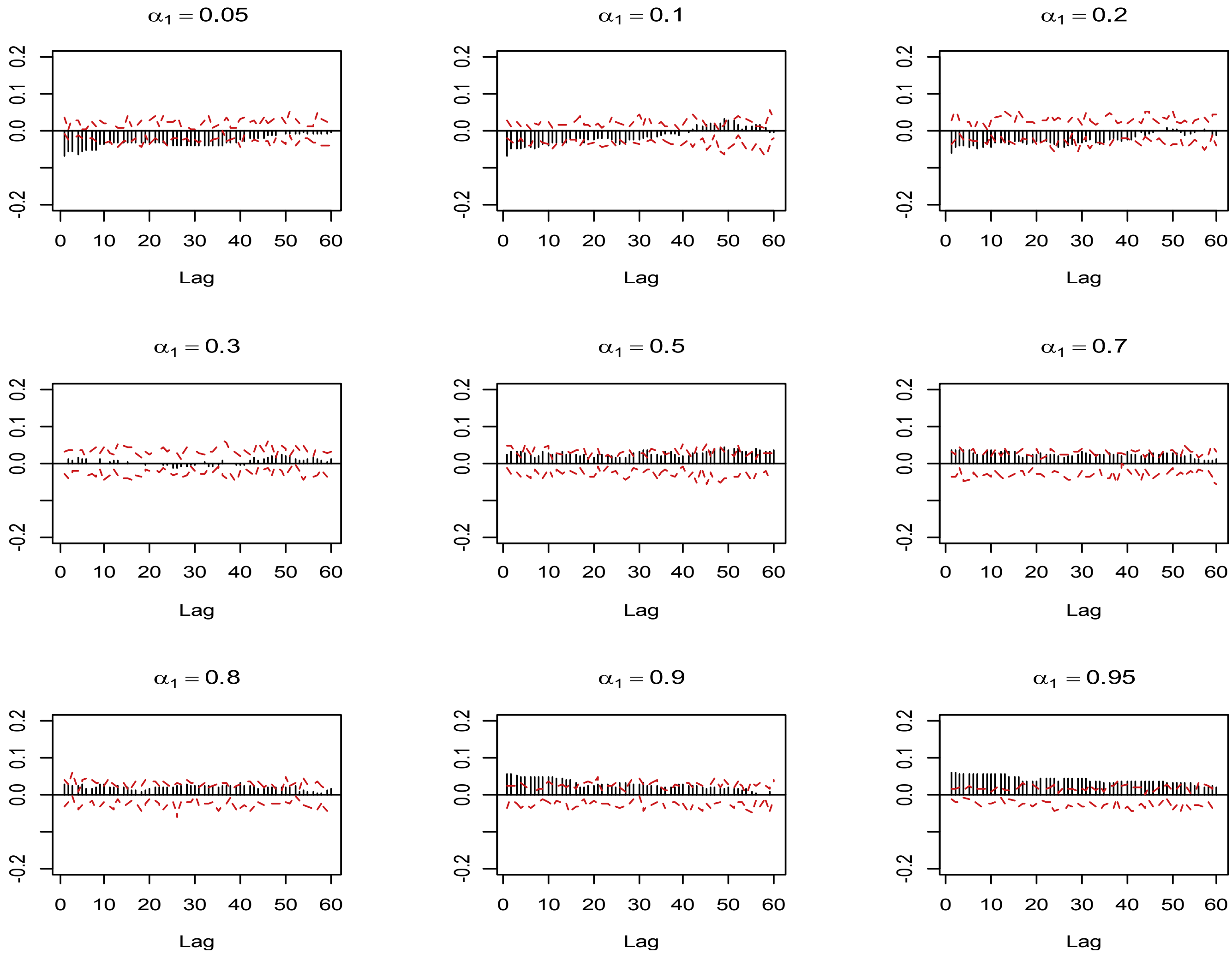

Fig. A2a. The sample cross-quantilogram $\widehat{\rho}_\alpha(k)$ with $\alpha_2 = 0.1$ to detect directional predictability from oil volatility to Brazil's stock returns. Same as Fig. 1(a).

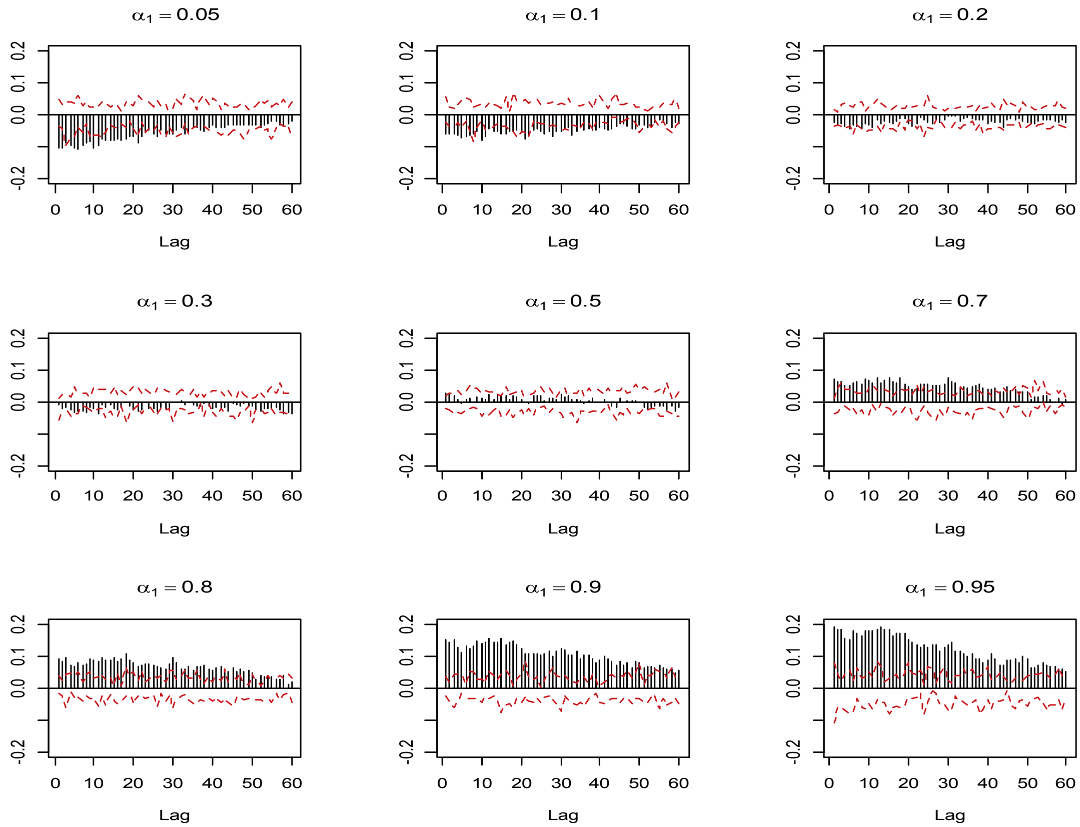

Fig. A2b. The sample cross-quantilogram $\hat{\rho}_\alpha(k)$ with $\alpha_2 = 0.9$ to detect directional predictability from oil volatility to Brazil's stock returns. Same as Fig. 1(a).

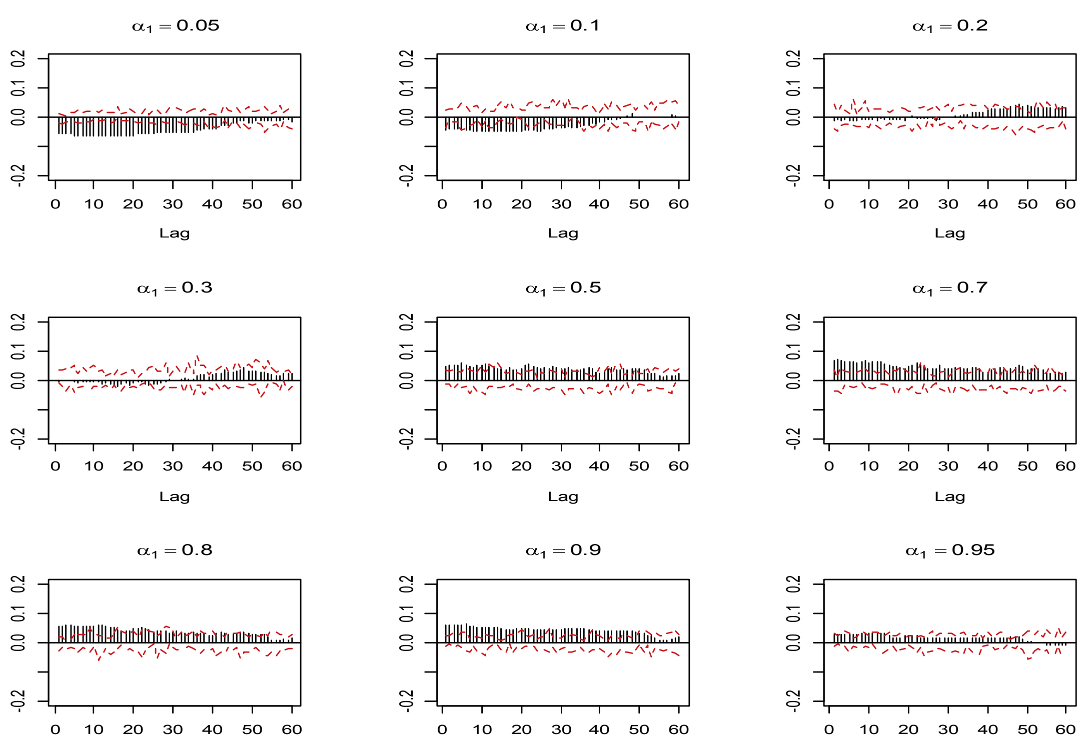

Fig. A3a. The sample cross-quantilogram $\hat{\rho}_\alpha(k)$ with $\alpha_2 = 0.1$ to detect directional predictability from oil volatility to Russia's stock returns. Same as Fig. 1(a).

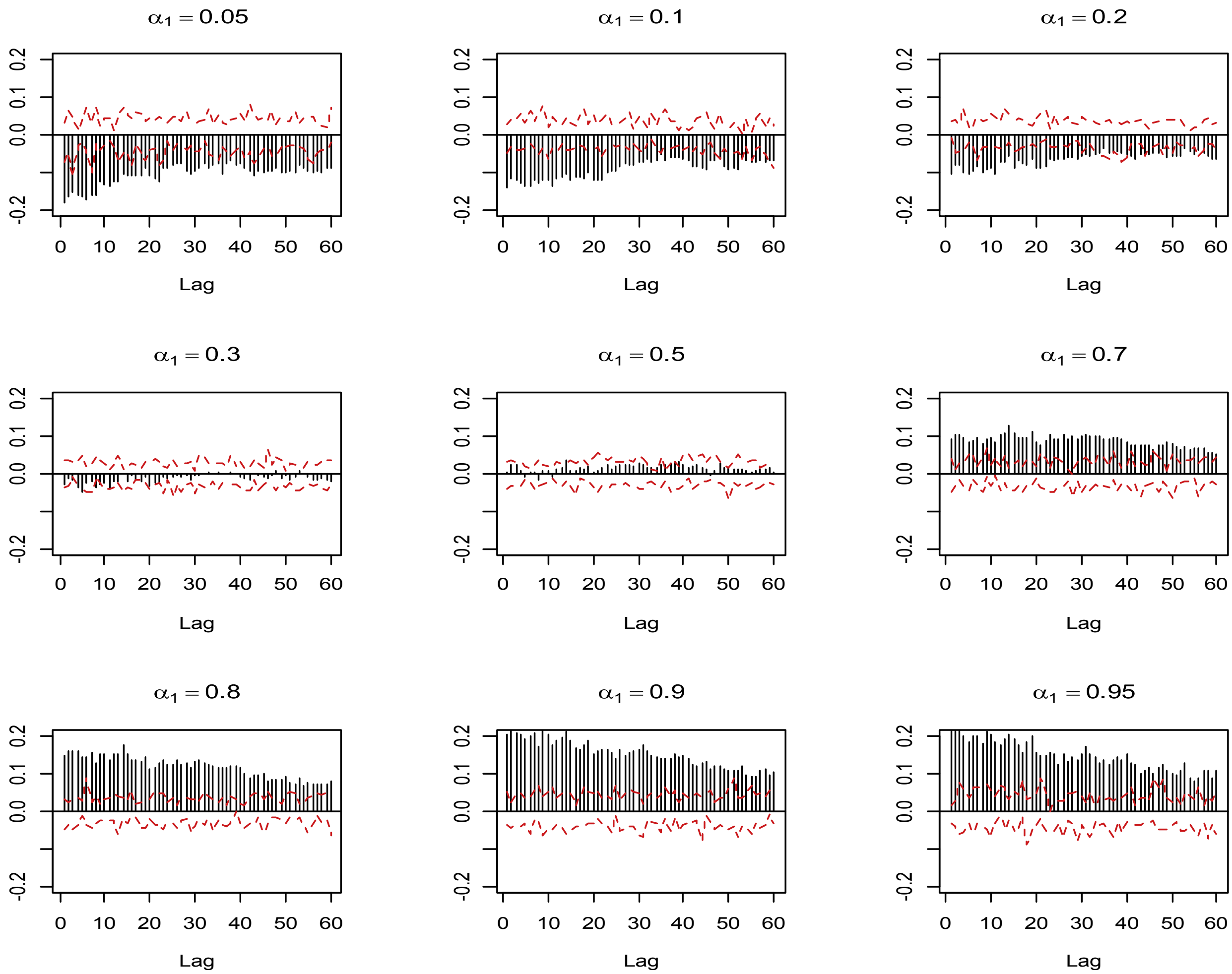

Fig. A3b. The sample cross-quantilogram $\widehat{\rho}_{\alpha}(k)$ with $\alpha_2 = 0.9$ to detect directional predictability from oil volatility to Russia's stock returns. Same as Fig. 1(a).

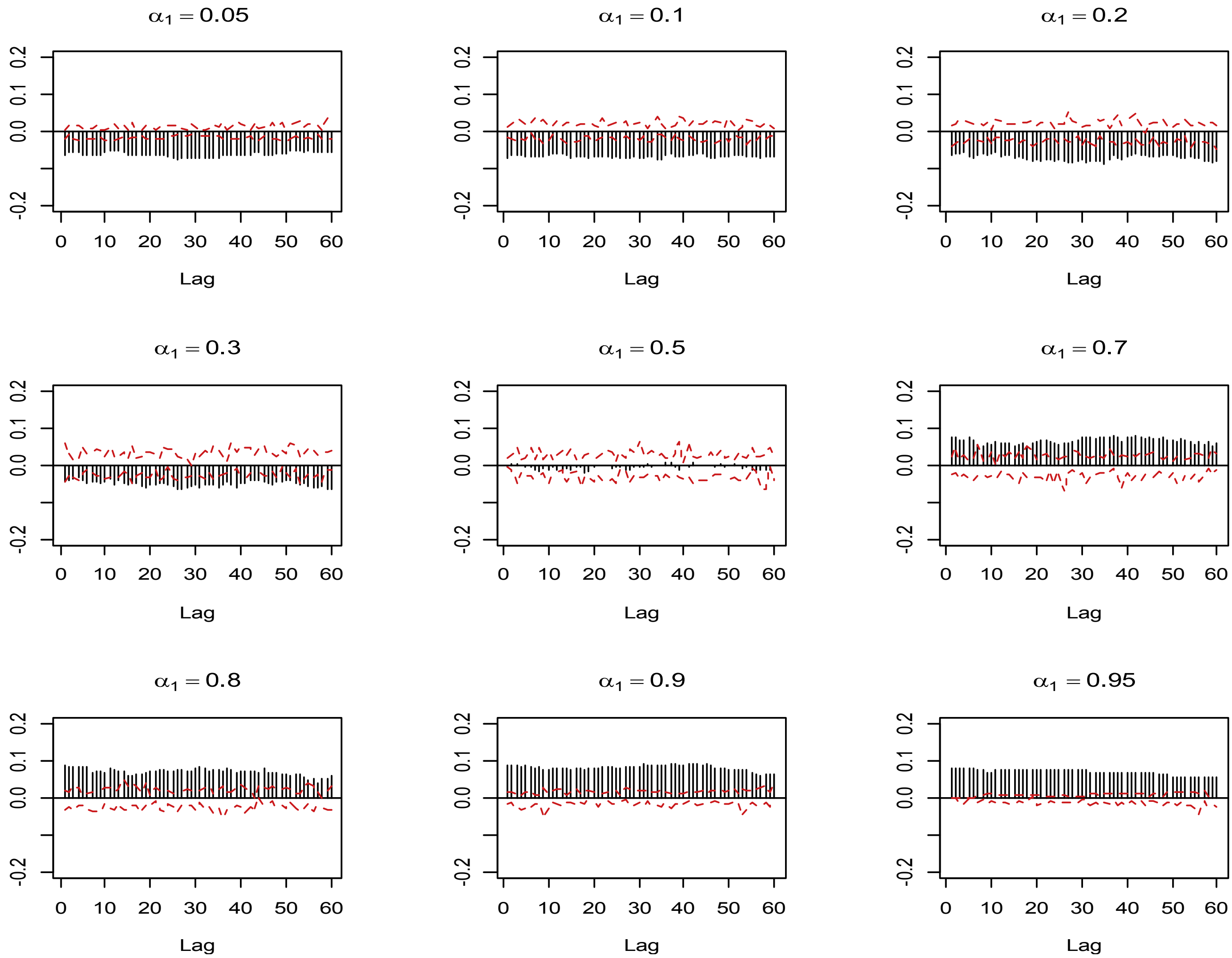

Fig. A4a. The sample cross-quantilogram $\widehat{\rho}_{\alpha}(k)$ with $\alpha_2 = 0.1$ to detect directional predictability from oil volatility to South Africa's stock returns. Same as Fig. 1(a).

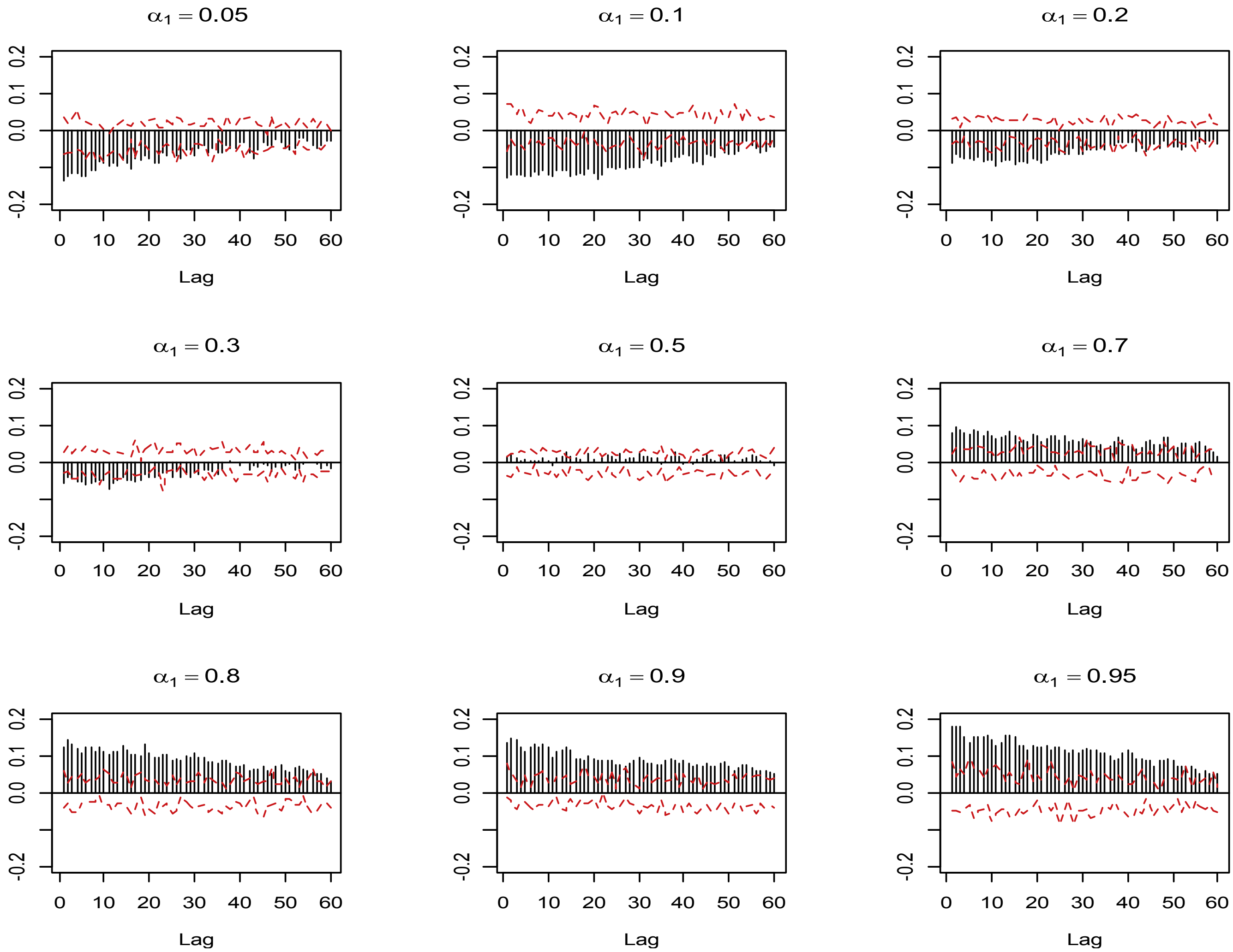

Fig. A4b. The sample cross-quantilogram $\widehat{\rho}_\alpha(k)$ with $\alpha_2 = 0.9$ to detect directional predictability from oil volatility to South Africa's stock returns. Same as Fig. 1(a).

A2. Based on a different sample period

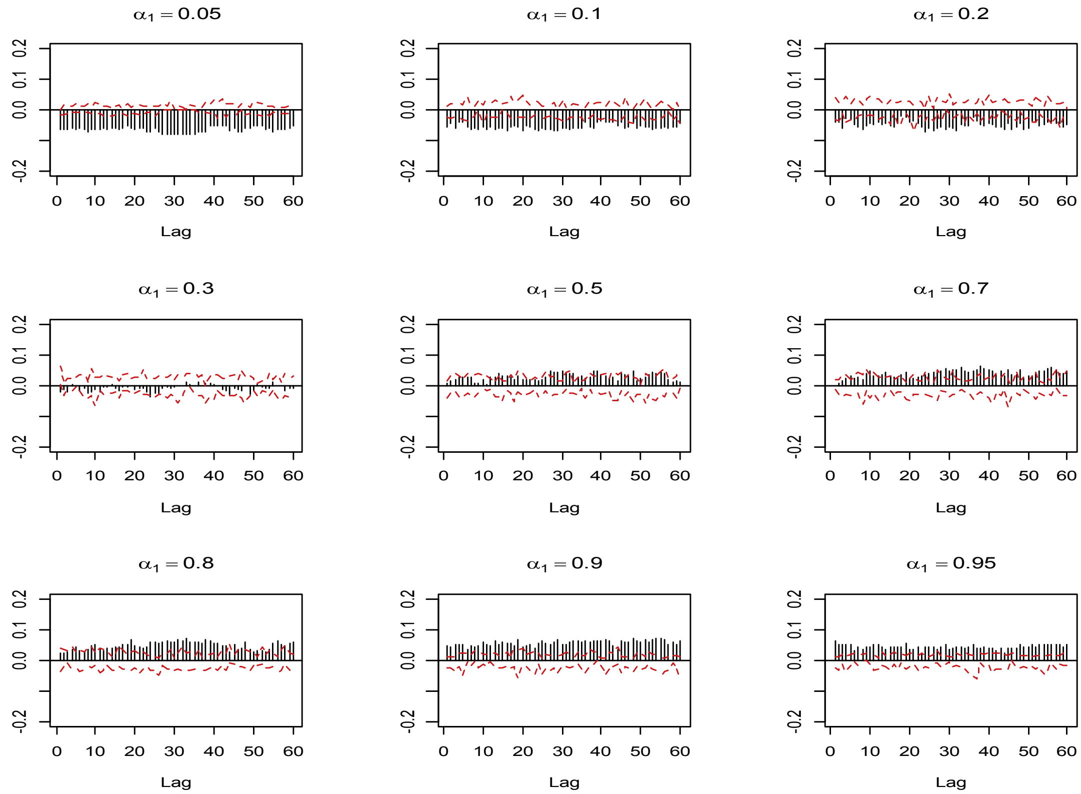

Fig. A5a. The sample cross-quantilogram $\widehat{\rho}_{\alpha}(k)$ with $\alpha_2 = 0.1$ to detect directional predictability from oil volatility to Brazil's stock returns after the global financial crisis.

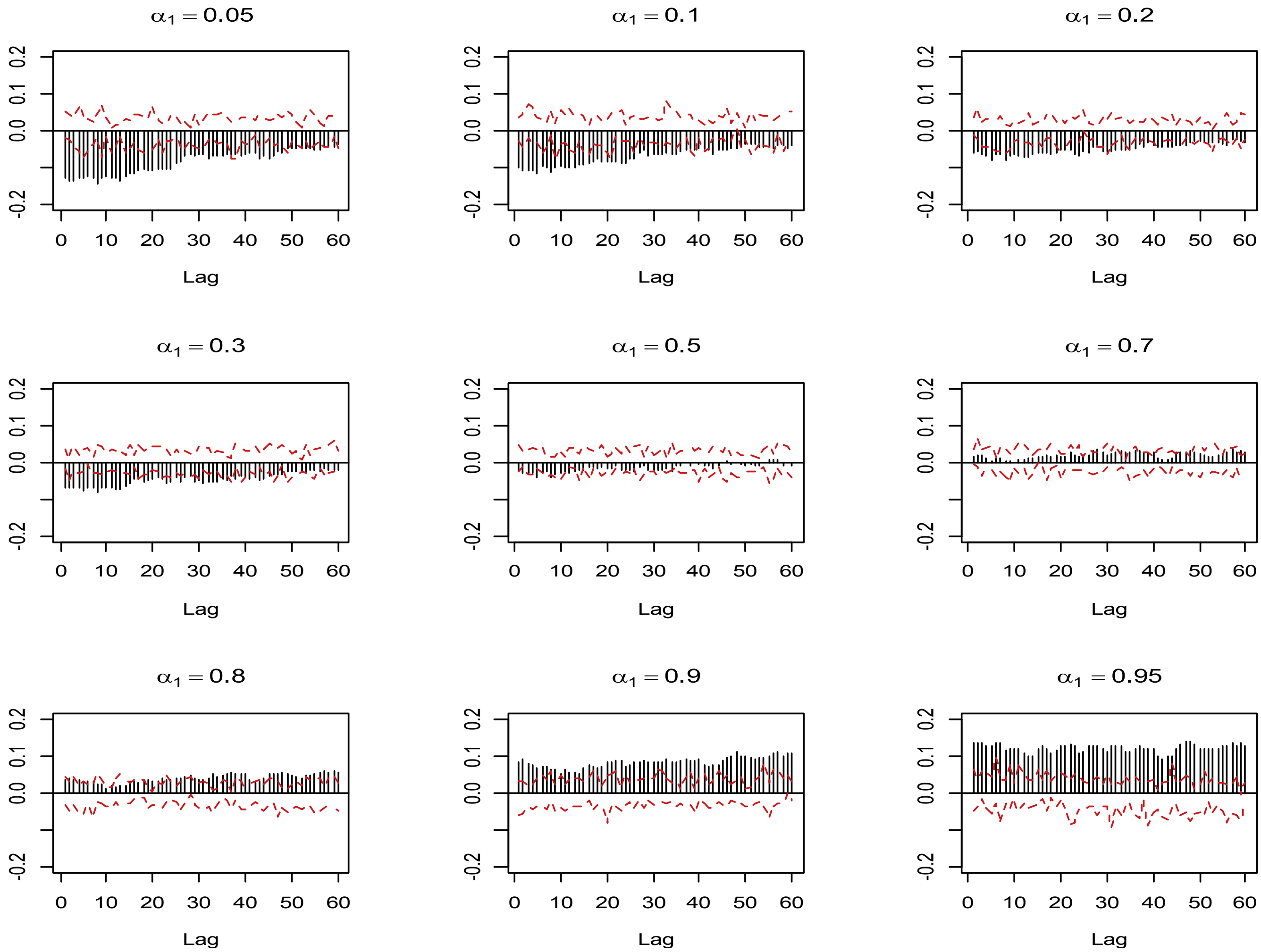

Fig. A5b. The sample cross-quantilogram $\widehat{\rho}_{\alpha}(k)$ with $\alpha_2 = 0.9$ to detect directional predictability from oil volatility to Brazil's stock returns after the global financial crisis.

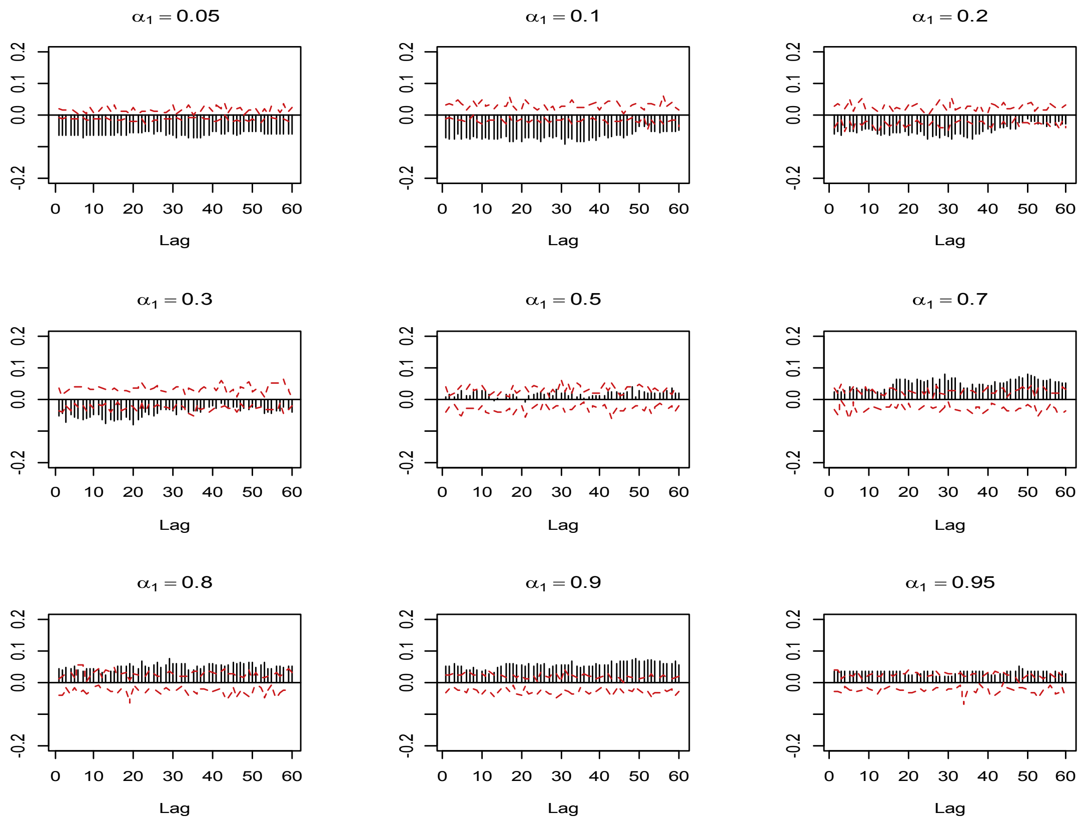

Fig. A6a. The sample cross-quantilogram $\widehat{\rho}_{\alpha}(k)$ with $\alpha_2 = 0.1$ to detect directional predictability from oil volatility to Russia's stock returns after the global financial crisis.

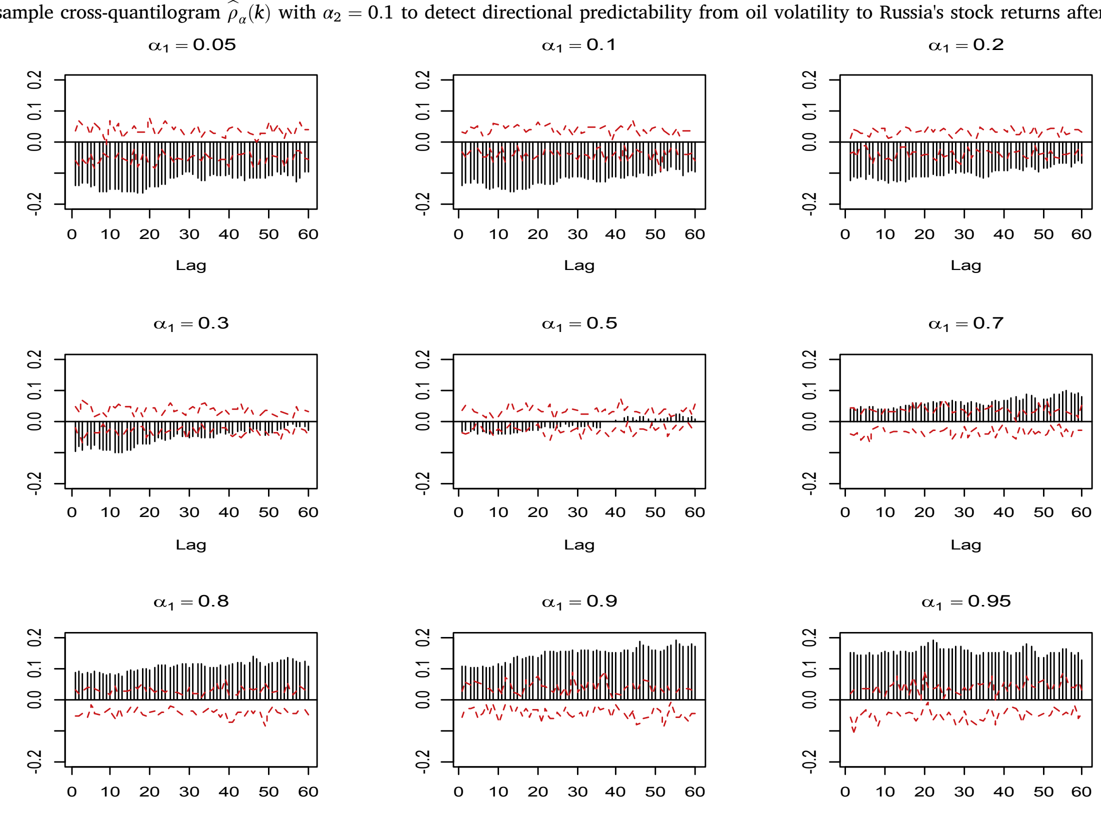

Fig. A6b. The sample cross-quantilogram $\widehat{\rho}_{\alpha}(k)$ with $\alpha_2 = 0.9$ to detect directional predictability from oil volatility to Russia's stock returns after the global financial crisis.

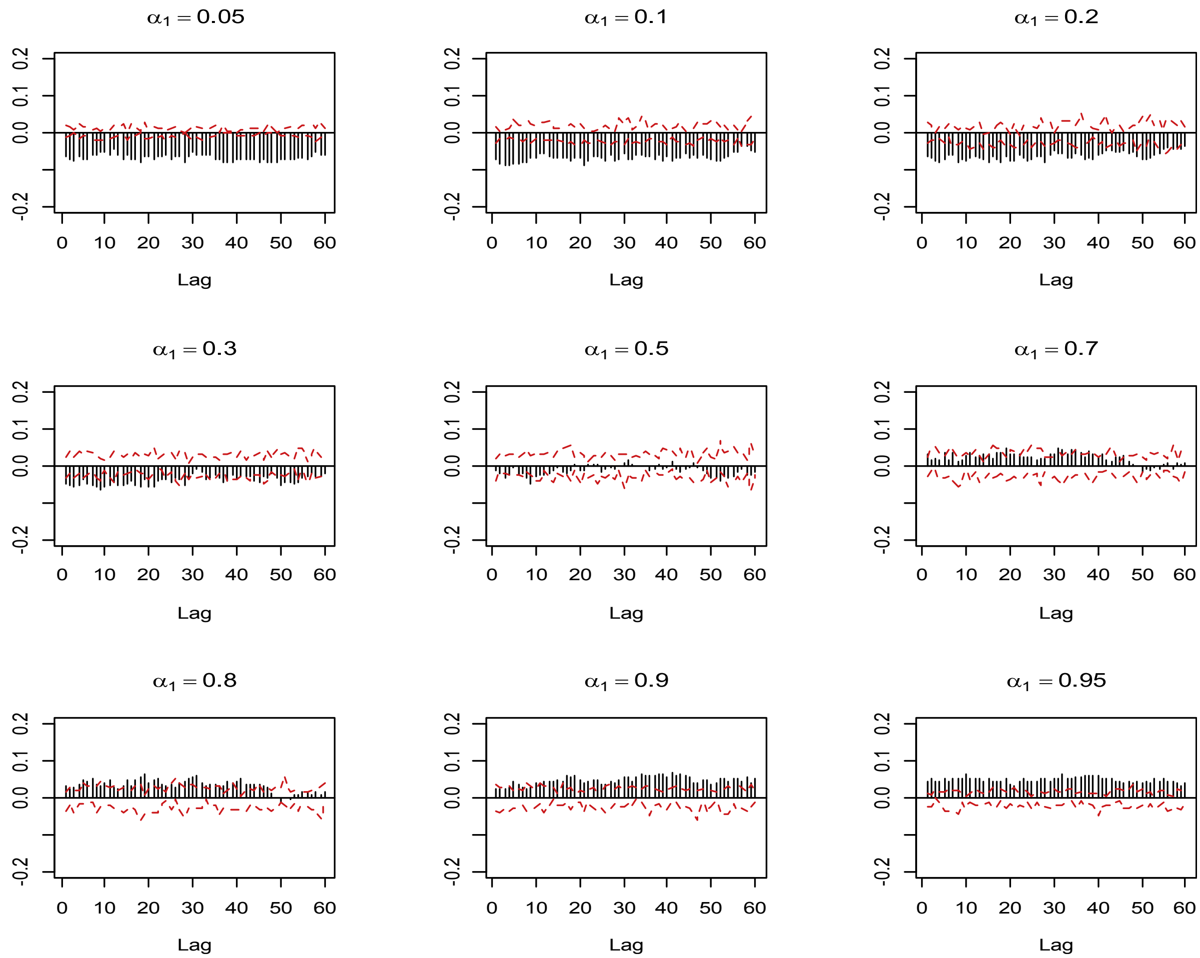

Fig. A7a. The sample cross-quantilogram $\widehat{\rho}_\alpha(k)$ with $\alpha_2 = 0.1$ to detect directional predictability from oil volatility to India's stock returns after the global financial crisis.

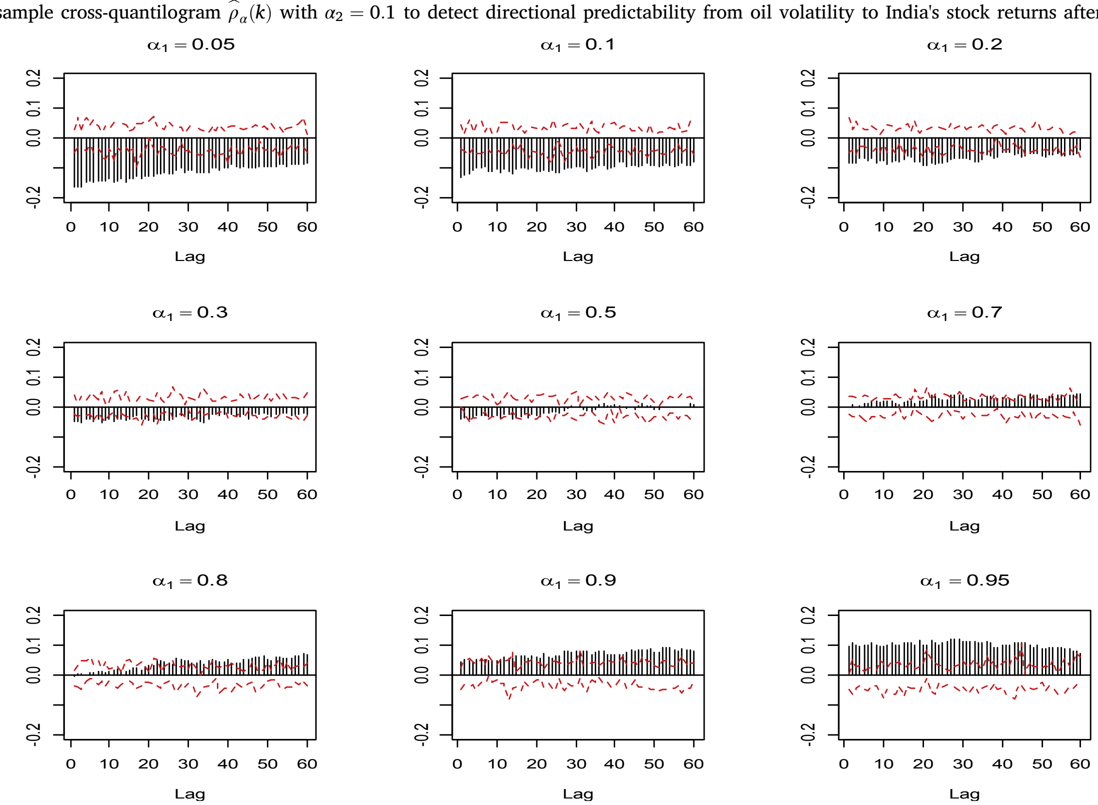

Fig. A7b. The sample cross-quantilogram $\widehat{\rho}_\alpha(k)$ with $\alpha_2 = 0.9$ to detect directional predictability from oil volatility to India's stock returns after the global financial crisis.

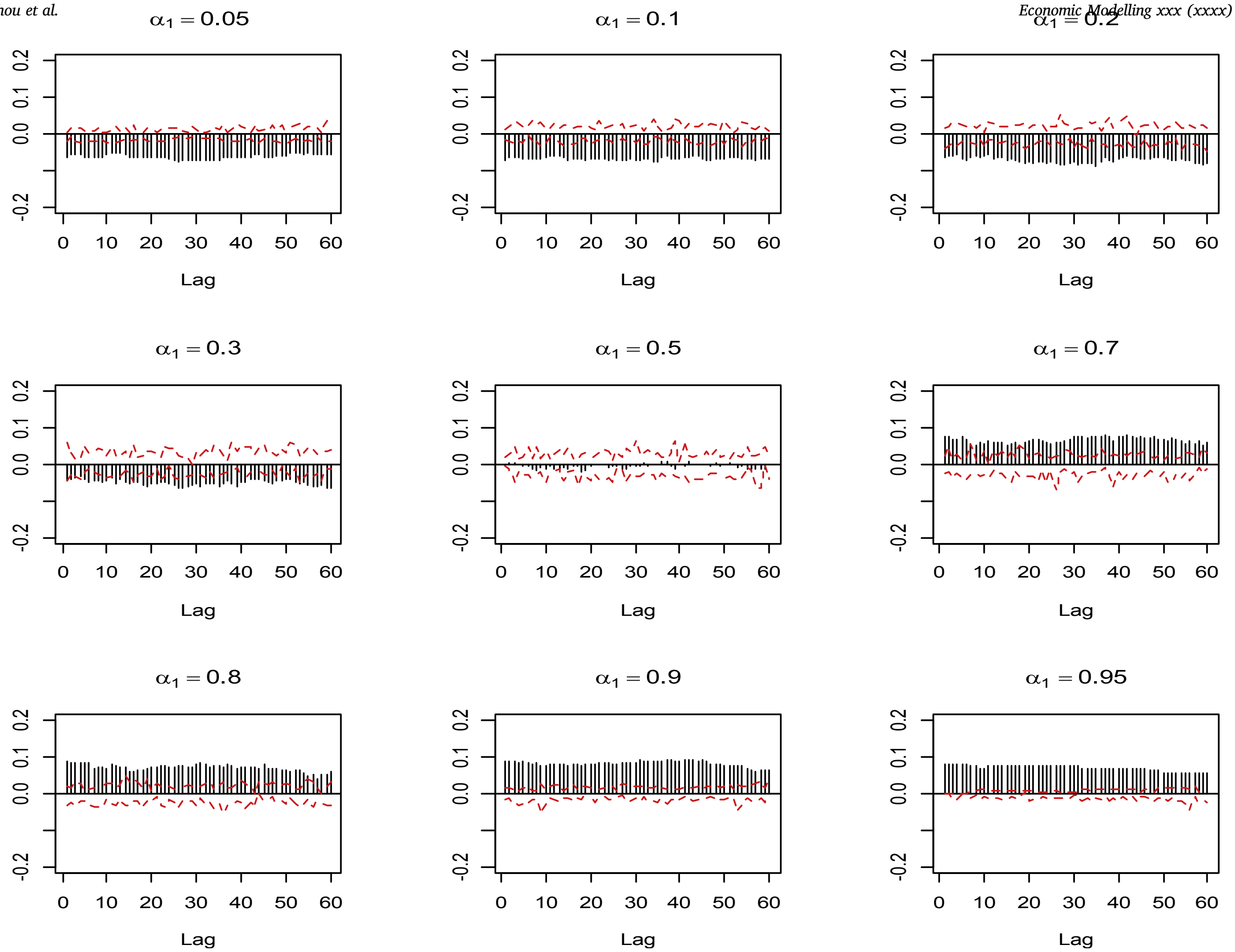

Fig. A8a. The sample cross-quantilogram $\widehat{\rho}_{\alpha}(k)$ with $\alpha_2 = 0.1$ to detect directional predictability from oil volatility to South Africa's stock returns after the global financial crisis.

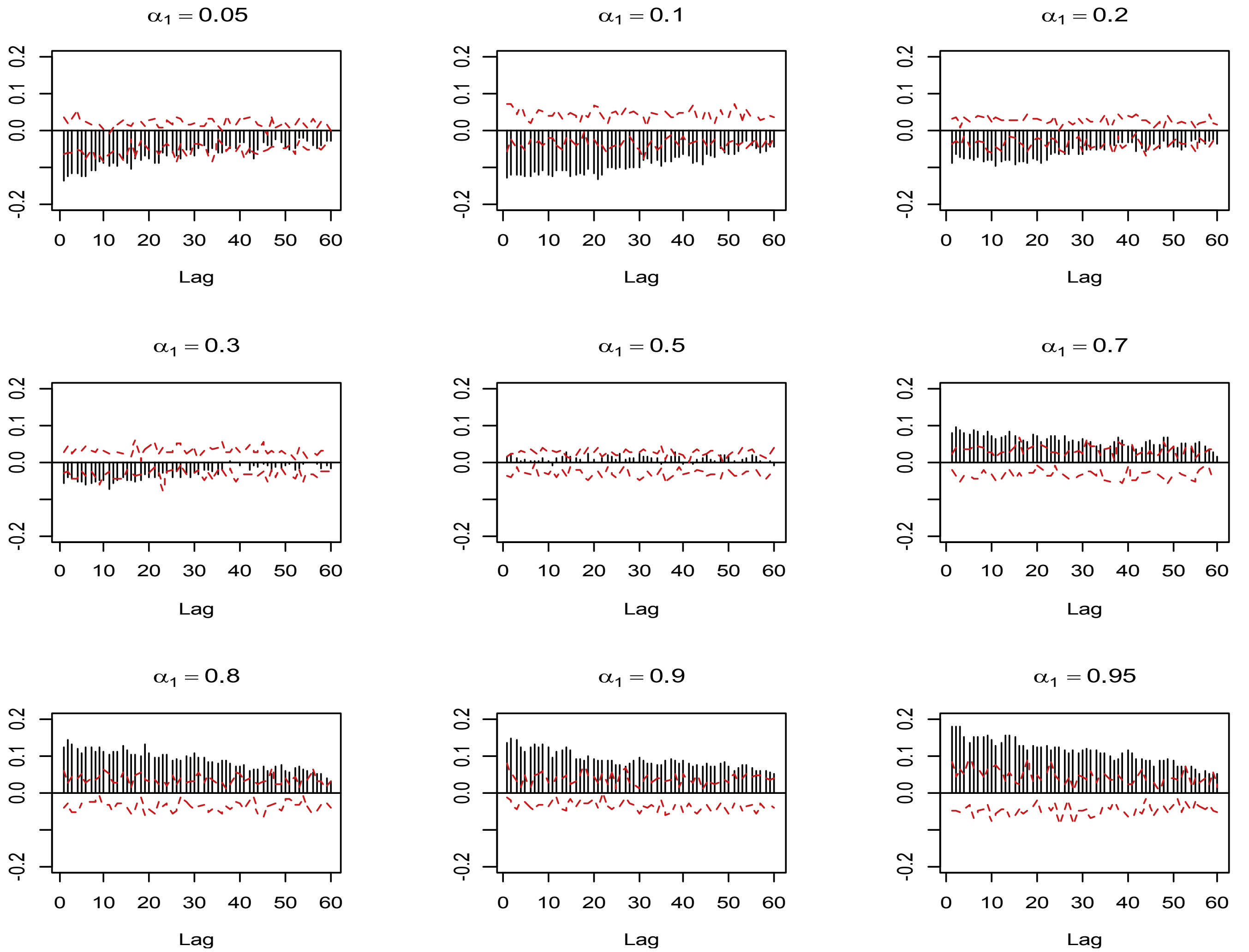

Fig. A8b. The sample cross-quantilogram $\widehat{\rho}_{\alpha}(k)$ with $\alpha_2 = 0.9$ to detect directional predictability from oil volatility to South Africa's stock returns after the global financial crisis.

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