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# Managing Portfolio Risk During the BREXIT Crisis: A Cross-Quantilegram Analysis of Stock Markets and Commodities Across European Countries, the US, and BRICS

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## Abstract

Against the backdrop of the United Kingdom's withdrawal from the European Union (BREXIT), this study examines predictability in the stock markets of sixteen European countries, the United States, and the BRICS (Brazil, China, India, Russia, and South Africa) by analyzing how their returns predict the returns of sixteen commodities at different quantile levels. The study builds upon existing literature on predictability and extends it by investigating the impact of the BREXIT crisis on these markets. The findings suggest that investors can hedge their portfolios with various commodities during times of the BREXIT crisis, but caution is advised, and the trend of both equities and commodities should be closely monitored before making investment decisions.

**Keywords:** Equity markets, commodity markets, predictability, BREXIT

## 1. Introduction

Predictability in financial markets has been a topic of research for over a century. In the early 20th century, Cowles (1933) conducted an analysis of 45 financial agencies forecasting common stock prices. Since then, various studies have been conducted on predictability in stock markets, with a focus on integration and risk structure. For instance, Campbell and Hamao (1992) studied the integration of long-term capital markets in the US and Japan, Pajuste et al. (2000) analyzed risk factors that might influence equity market fluctuations, the importance of European integration, and the predictability of returns in five Central and Eastern European equity markets, and Rockinger and Urga (2001) tested whether markets in Czech, Polish, Hungarian, and Russian become more efficient and integrated over time. Other studies, such as those by Lanne (2002), Mateus (2004), and Chang et al. (2004), investigated predictability in returns of EU countries, emerging stock markets, and various other regions. Bannigidadmath et al. (2015) analyzed the relationship between crude oil prices and stock markets in India, while Westerlund and Narayan (2015) studied the predictability of stock returns in Asia and the Pacific. Other works have focused on factors such as market inefficiency, volatility dependence, and sign dependence, as well as the use of variable moving averages and trading range breaks to forecast stock returns.

All the studies mentioned above have focused on the predictability of stock returns using various predictors such as dividend price ratios and macroeconomic variables within an asset pricing framework. However, some recent studies have explored the predictability of stock returns using other asset returns such as commodities and Bitcoin. For instance, Jordan et al. (2016) found that commodity returns can forecast Canadian equities returns, while Salisu et al. (2018) used Bitcoin prices as predictors and found that Bitcoin outperformed all other predictors except for interest rates. Iyke and Ho (2020) combined historical series of commodity and stock prices to successfully predict stock returns. Urom et al. (2020) examined dynamic spillovers between Bitcoin, crude oil, gold, and equities and found strong dependence and positive directional predictability. Hing and Yogo (2010) and Iyke and Ho (2020) also examined the predictability between equities and commodities in various studies.

It is important to choose appropriate components of an investor's portfolio to significantly optimize and minimize negative effects of crises, as an increase in correlations between various assets increases their risk. Based on the phenomenon of financialization and the above studies, this paper hypothesizes that commodity prices can be predicted by analyzing the behavior of stock returns. The study tests the predictability of commodity returns from stock returns using the cross-quantilogram model based on the estimation process of Han et al. (2016). The study tests how the returns of stock markets of sixteen European countries, the United States and the BRICS predict the returns of sixteen commodity types in different quantile levels during the BREXIT crisis.

This is the first study to combine a wide range of equities and commodities from different regions to detect the power of predictability of stock markets on commodity returns during the BREXIT crisis and within various quantiles. Although stocks are not predictable in short time horizons, the study expects that the power of predictability of stock markets on commodity returns is low during each of the crises. The study suggests that knowing the behavior of commodity markets by looking at stock markets would help traders choose the appropriate commodities to hedge their portfolios by referring to the phenomenon of financialization.

The findings suggest that various commodities could be taken into portfolios made of European, American, and BRICS stocks to hedge these assets during the BREXIT crisis. However, investors should pay great attention to when they buy, hold or sell their assets, depending on the trend of both equities and commodities over time. The cross-quantilogram methodology enables the prediction of the behavior of commodities from the trend of equities in different quantiles during the crisis period. These findings align with the assumption of Irwin and Sanders (2011) that financialization made investors focus on getting commodities, suggesting that the negative correlation would diminish later. This is supported by the findings of Ayadi et al. (2021), who documented that investors were already aware of the equity-commodity relationship and started investing in them to protect their portfolios during the BREXIT, creating a positive contagion effect.

The rest of the paper is structured as follows. Section 2 presents the data and estimation strategy employed in the empirical analysis. Section 3 presents the model. Section 4 discusses the results of the empirical analysis. Section 5 provides the conclusion of the study.

## **2. Data and descriptive statistics**

### *2.1. Data*

In this study, we investigated the occurrence of equity-commodity contagion in various crises between March 12th, 2007 and December 31st, 2018. The equities analyzed included the benchmark indices of the S&P 500, Austrian ATX, Belgian BEL 20, Danish OMX Copenhagen 20, Finnish OMX Helsinki 25, French CAC 40, German DAX 30, Greek ATHEX 20, Irish ISEQ 20, Italian FTSE MIB, Dutch AEX, Norwegian OBX, Portuguese PSI 20, Spanish IBEX 30, Swedish OMX Stockholm 30, Swiss Market Index, and British FTSE 100. Additionally, the indices used for BRICS were the Brazilian Ibovespa, Chinese Shanghai index, Indian BSE SENSEX, Russian RTX index, and South African FTSE/JSE 40. The commodities analyzed were equally weighted indices that we constructed, grouped as follows: Crude Oil, Natural Gas, Electricity, Metals, Precious Metals, Agricultural Oils, Chemicals, Feeds, Fibers, Forestry Products, Grains, Live Stocks, Oil Seeds, Seeds, Semi-Conductors, and Softs. The crises investigated were the subprime crisis (September 2007 to June 2011), Irish banking crisis



(September 2008 to March 2011), Greek debt crisis (April 2010 to February 2012), and BREXIT (June 2016 to December 2016).

## 2.2. Descriptive statistics

Table 1 provides descriptive statistics for various commodities over the period of March 2007 to December 2018. The table shows the number of observations (Obs), minimum, mean, maximum, and standard deviation (Std Dev) for each variable. Skewness and kurtosis statistics are also reported to measure the shape of the distribution. Additionally, the JQ-Bera and ARCH tests are reported to test for the presence of autocorrelation and heteroscedasticity, respectively.

Looking at the means, we can observe that most commodities have positive returns, except for crude oil, which has a negative mean return of -0.037%. Among all the commodities, Fibers have the highest mean return of 0.114%, while Semi-Conductors have the lowest mean return of -0.168%. Regarding volatility, natural gas has the highest standard deviation of 12.729%, indicating that it is the most volatile commodity. Forestry Products have the lowest volatility of 1.141%, indicating that they are the least volatile commodity. The JQ-Bera test indicates that none of the commodities show significant evidence of autocorrelation. However, the ARCH test indicates that crude oil, precious metals, agricultural oils, feeds, oil seeds, and chemicals exhibit heteroscedasticity, suggesting that the volatility of these commodities changes over time. The normality tests show that all commodities have normal distributions.

**Table 1: Descriptive statistics.**

Variable	Obs	Min	Mean	Max	Std Dev	Skewness	Kurtosis	JQ-Bera	ARCH Test
Crude oil	617	-26.336	-0.037	24.457	4.976	0.124	0.546	0.287	58.477***
Natural Gas	617	-109.47	-0.152	100.05	12.729	0.409	1.074	1.432	0.181
Electricity	617	-14.198	-0.014	19.45	4.188	-0.524	0.771	1.305	9.135***
Metals	617	-14.755	-0.009	14.588	1.848	0.114	1.376	1.569	1.391
Precious Metals	617	-10.704	0.045	8.073	2.352	0.074	1.039	0.888	45.703***
Agricultural Oils	617	-9.922	0.015	6.955	1.99	0.227	0.731	0.587	21.859***
Feeds	617	-11.602	0.055	8.519	2.418	-0.572	0.694	1.372	12.607***
Fibers	617	-24.308	0.114	41.006	2.777	1.304**	1.685	7.392**	0.003
Forestry Products	617	-8.589	0.0383	4.309	1.141	0.435	0.495	0.766	0.0243
Grains	617	-12.714	0.034	8.602	2.469	-0.150	1.869***	92.171***	8.949***
Live Stocks	617	-32.314	-0.049	18.962	2.757	0.259	0.444	0.360	2.752
Oil Seeds	617	-14.039	0.027	12.263	2.879	-0.502	0.0387	0.758	14.526***
Seeds	617	-29.691	0.063	18.394	3.453	0.923*	0.013	2.554	6.387***
Semi-Conductors	617	-33.178	-0.168	19.924	2.969	0.595	0.297	1.132	0.977
Softs	617	-13.204	0.049	18.296	3.043	-0.551	0.265	0.967	9.409***
Chemicals	617	-12.439	-0.039	12.985	2.642	-0.525***	3.612***	363.66***	9.008***

Notes: The table presents the usual statistics such as the number of observations, the minimum, mean, maximum, standard deviation, skewness, kurtosis, Jarcques-Bera test and ARCH test. The \*, \*\* and \*\*\* represent the 10%, 5% and 1%

significance levels respectively. To account for seasonal variations that may impact oil prices, we used de-seasonalized series from the MSCI Inc. Indexes and Data. These series are typically de-seasonalized using X-12-ARIMA Seasonal-Adjustment filters.

Table 2 presents the correlation matrix between the commodities and equity return factors for the whole period. The values with \* corresponds to significance at the 5% level.

As may be seen in Table 3, beginning with crude oil, results show significant correlations with the three factors. However, this correlation is weak, ranging from 8.42% with the US factor to 12.62% with the BRICS factor. As for the Europe factor, the correlation is significantly negative, reaching 14.05%. Regarding natural gas, results show significantly strong positive correlation with Europe (84.68%) and significantly weak negative correlation with the BRICS (8.47%). As for the US, the correlation is insignificant. Electricity is significantly, positively and weakly correlated with the US and the BRICS, with correlation coefficients under 11%. The correlation between metals and all the three factors is positive, yet it is weak and insignificant. The same case applies for chemicals and semi- conductors. These coefficients do not exceed 6%. As for precious metals, along with grains and oil seeds, they exhibit positive and significant correlations with the US and the BRICS. Yet these correlations are weak, ranging between 8% and 12.8%. For agricultural oils, the only significant correlation coefficient is that with the BRICS, it has a value of 9.18%. Feeds and forestry products correlate significantly with the US only, with weak positive coefficients of 11%. However, for fibers, livestock and softs, the correlations with all the factors appear to be insignificant and weak. These results suggest that overall; the equity-commodity relationship is rather weak, with most of the coefficients being insignificant. Moreover, most of the significant correlation coefficients are negative. Consequently, we predict that the equity-commodity contagion would be inexistent for most of the commodities. The ones that would show significant evidence of contagion would probably decouple, showing promising portfolio diversification elements.

**Table2 : Correlation matrix**

***	EUR Factor	US Factor	BRICS Factor
EUR Factor	1.000		
US Factor	0.0717	1.0000	
BRICS FACTOR	-0.0511	0.2825*	1.0000
Crude Oil	-0.1405*	0.0845*	0.1262*
Natural Gas	0.8468*	-0.0018	-0.0847*
Electricity	-0.0166	0.0843*	0.1056*
Metals	0.0208	0.0458	0.0264
Precious Metals	-0.0002	0.0801*	0.1038*
Agricultural Oils	0.0076	0.0177	0.0918*
Chemicals	0.0129	0.0422	0.0635

Feeds	−0.0068	0.1187*	0.0605
Fibers	−0.0307	0.0406	0.0045
Forestry Products	−0.0176	0.1171*	0.0173
Grains	0.0270	0.1233*	0.1085*
Livestock	−0.0072	−0.0021	−0.0010
Oil Seeds	0.0105	0.1280*	0.0969*
Seeds	−0.0007	−0.0189	0.0364
Semi Conductors	0.0038	0.0024	0.0199
<hr/>			
Softs	−0.0012	0.0322	0.0234

### 3. Empirical Framework

Han et al. (2016) discussed the quantilogram, a method introduced by Linton and Whang (2007), which measures predictability in different parts of the distribution of a stationary time series. The authors tested the null hypothesis that the past information of a stationary time series does not improve the prediction about whether the current value will be above or below the unconditional quantile. This test was conducted by comparing the quantilogram to a pointwise confidence band. The quantilogram has several advantages over other methods used to detect predictability. It is based on quantile hits and does not require moment conditions, making it simple to interpret and well-suited for heavy-tailed time series. It also allows for the consideration of long lags and the measurement of predictability across different quantiles. Han et al. (2016) expanded the methodology to include multivariate series and conditional quantiles, allowing for the comparison of two time series after controlling for information at the time of prediction. Additionally, the cross-quantilogram provides a more complete picture of the relationship between predictor and predicted variables than linear quantile regression.

Let  $\{(y_t, x_t) : t \in Z\}$  be a strictly stationary time series with  $y_t = (y_{1t} + y_{2t})^T \in R^2$  and

$x_t = (x_{1t}, x_{2t}) \in R^{d_1} \times R^{d_2}$ , where  $x_{it} = [x_{it}^{(1)}, \dots, x_{it}^{(d_i)}] \in R^{d_i}$  with  $d_i \in \mathbb{N}$  for  $i = 1, 2$ . We use  $F_{y_i|x_i}(\cdot | x_{it})$  to denote the conditional distribution function of the series  $y_{it}$  given  $x_{it}$  with density function  $f_{y_i|x_i}(\cdot | x_{it})$ , and the corresponding conditional quantile function is defined as

$q_{i,t}(\tau_i) = \inf\{v : F_{y_i|x_i}(v | x_{it}) \geq \tau_i\}$  for  $\tau_i \in (0, 1)$ , for  $i = 1, 2$ . Let  $T$  be the range of quantiles we are interested in evaluating the directional predictability. For simplicity, we assume that  $T$  is a Cartesian product of two closed intervals in  $(0, 1)$ , that is  $T \equiv T_1 \times T_2$ , where

$T_i = [\underline{\tau}_i, \bar{\tau}_i]$  for some  $0 < \underline{\tau}_i < \bar{\tau}_i < 1$ .

We consider a measure of serial dependence between two events  $\{y_{1t} \leq q_{1,t}(\tau_1)\}$  and

$\{y_{2,t-k} \leq q_{2,t-k}(\tau_2)\}$  for an arbitrary pair of  $\tau = (\tau_1, \tau_2)^T \in T$  and for an integer  $k$ . In the literature,  $\{1[y_{it} \leq q_{i,t}(\cdot)]\}$  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 process*:

$$\rho_{\tau}(k) = \frac{E \left[ \psi_{\tau_1} \left( y_{1t} - q_{1,t}(\tau_1) \right) \psi_{\tau_2} \left( y_{2,t-k} - q_{2,t-k}(\tau_2) \right) \right]}{\sqrt{E \left[ \psi_{\tau_1}^2 \left( y_{1t} - q_{1,t}(\tau_1) \right) \right]} \sqrt{E \left[ \psi_{\tau_2}^2 \left( y_{2,t-k} - q_{2,t-k}(\tau_2) \right) \right]}} \quad (1)$$

For  $k = 0, \pm 1, \pm 2, \dots$ , where  $\psi_a(u) \equiv 1[u < 0] - a$ . the cross-quantilogram captures serial dependence between two times series at different conditional quantile levels. The cross-quantilogram is invariant to any strictly monotonic transformation applied to both the series, such as the logarithmic transformation. To construct the sample analogue for the cross quantilogram ( $\{(y_t, x_t)\}_{t=1}^T$ ), it is necessary to estimate the conditional quantile function. The authors let  $q_{i,t}(\tau_i) = x_{it}^T \beta_i(\tau_i)$  with a  $d_i \times 1$  vector of unknown parameters  $\beta_i(\tau_i)$  for  $i=1,2$ . The estimation of the parameters  $\beta(\tau) \equiv (\beta_1(\tau_1)^T, \beta_2(\tau_2)^T)^T$  is done by separately estimating the following minimization problem

$$\hat{\beta}_i(\tau_i) = \arg \min_{\beta_i \in R^{d_i}} \sum_{t=1}^T \varrho_{\tau_i}(y_{it} - x_{it}^T \beta_i) \quad (2)$$

Where  $\varrho_{\tau_i}(u) \equiv (a - 1[u < 0])$ . Let  $\hat{\beta}(\tau) \equiv (\hat{\beta}_1(\tau_1)^T, \hat{\beta}_2(\tau_2)^T)^T$  and  $\hat{q}_{i,t}(\tau_i) = x_{it}^T \hat{\beta}_i(\tau_i)$  for  $i=1,2$ . The sample cross-quantilogram is defined by:

$$\hat{\rho}_{\tau}(k) = \frac{\sum_{t=k+1}^T \psi_{\tau_1} \left( y_{1t} - \hat{q}_{1,t}(\tau_1) \right) \psi_{\tau_2} \left( y_{2,t-k} - \hat{q}_{2,t-k}(\tau_2) \right)}{\sqrt{\sum_{t=k+1}^T \psi_{\tau_1}^2 \left( y_{1t} - \hat{q}_{1,t}(\tau_1) \right)} \sqrt{\sum_{t=k+1}^T \psi_{\tau_2}^2 \left( y_{2,t-k} - \hat{q}_{2,t-k}(\tau_2) \right)}} \quad (3)$$

For  $k = 0, \pm 1, \pm 2$ . Given a set of conditional quantiles, the cross-quantilogram considers dependence in terms of directional deviation from conditional quantiles. Consequently, it enables the measure of directional predictability from one series to another. The construction of the model stipulates that  $\hat{\rho}_{\tau}(k) \in [-1, 1]$  with  $\hat{\rho}_{\tau}(k)$  corresponding to the case of no directional predictability.

Supposing that  $\tau \in T$  and  $p$  are given, it is interesting to test the *null hypothesis*

$H_0: \rho_{\tau}(1) = \dots = \rho_{\tau}(p) = 0$  against the alternative hypothesis  $\rho_{\tau}(k) \neq 0$  for some  $k \in \{1, \dots, p\}$ . This tests the directional predictability of events up to  $p$  lags  $\{y_{2,t-k} \leq q_{2,t-k}(\tau_2): k = 1 \dots p\}$  for  $\{y_{1t} \leq q_{1,t}(\tau_1)\}$ .

For this hypothesis, it is possible to use the Box-Pierce type statistic: yet in practice, the Box-Ljung version:  $\check{Q}_{\tau}^{(p)} \equiv T(T+2) \sum_{k=1}^p \hat{\rho}_{\tau}^2(k) / (T-k)$ , which has small sample improvements, is recommended by the authors (Han et al. (2016)).

It is also possible to test a stronger null hypothesis, which is that of the absence of directional predictability over a set of quantiles  $H_0 = \rho_{\tau}(1) = \dots = \rho_{\tau}(p) = 0$ ,  $\tau \in T$ ; against the null hypothesis that  $\rho_{\tau}(k) \neq 0$  for some  $(k, \tau) \in \{1, \dots, p\} \times T$  with  $p$  fixed. In this case, the sup version of the statistic can be used:

$$\sup_{\tau \in T} \hat{Q}_{\tau}^{(p)} = \sup_{\tau \in T} T \sum_{k=1}^p \hat{\rho}_{\tau}^2(k) \quad (4)$$

#### 4. Results

We use the quantilogram model described above in order to investigate the predictability from the equity markets of the US, Western Europe and the BRICS to sixteen types of commodities: crude oil, natural gas, electricity, metals, precious metals, agricultural oils, chemicals, feeds, fibers, forestry products, grains, livestock, oil seeds, seeds, semi-conductors and softs. Following Han et al. (2016), we check for the predictability between equity markets and commodity markets. In our framework, we chose equity markets as the predictor. We test how equity markets in their low ( $\tau_2$  is the 10% quantile) and their high performance is ( $\tau_2$  is the 90% quantiles) enable to predict the performance of commodity markets in different performance levels ( $\tau_1$  is the 5%, 10%, 20%, 30%, 50%, 70%, 80%, 90% and 95% quantiles). The estimations are calculated individually between each of the equity market indices and the commodity indices for the crisis period for both of the quantiles of the predictor (i.e. equity market indices). It is worth mentioning that the indices for the equity markets are made as follows: the returns of the S&P500 for the US Factor, value weighted index of the returns of each of the BRICS countries stock market indices (Brazil, China, India, Russia and South Africa) for the BRICS factor and value weighted index of the stock returns of the indices of the Western European countries (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom). As for the commodities, they are established as equally weighted indices made of the returns of the various commodities mentioned above. In the result interpretations, we follow the logic of Urom et al. (2020)

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Figure 1(a) shows the sup version Box-Ljung test statistic for each lag  $p$  to detect directional predictability for  $\tau_2 = 0.1$ . Figure 1(b) shows the sup version Box-Ljung test statistic for each lag  $p$  to detect directional predictability for  $\tau_2 = 0.9$ . Figure 1(c) shows the cross quantilogram for  $\tau_2 = 0.1$ , and for  $\tau_2 = 0.9$ .

The first thing to notice is that the Ljung-Box graphics show that the directional predictability from the Europe factor towards the various commodities is low and insignificant.

The graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from European equities towards natural gas has an overall negative pattern in the commodity's low quantiles. For the middle and high quantiles, the directional predictability turns to be overall positive. This suggests that when European stocks are low, natural gas prices are expected to hold their already very low. But when the performance of the commodities is near the median or in its highest levels, the returns are expected to increase over the course of the next weeks. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability holds the same sign such as the case when  $\tau_2 = 0.1$ . Consequently, when European equities are high, natural gas commodities are expected to increase in the next weeks if it is already low. The performance of the commodities is expected to drop in the next weeks if it is very high.

The findings show that when  $\tau_2 = 0.1$ , the directional predictability from European equities towards agricultural oils is overall positive, suggesting that these commodities will have poor performance during the next weeks when European stocks are low. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability remains overall positive, except for the cases when  $\tau_1 = 0.95$  and  $\tau_1 = 0.9$ . This suggests that overall, over the course of the next weeks; agricultural oils will exhibit good returns when European stocks are high.

The graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from European stocks towards chemicals is overall positive. This suggests that when European stocks are low, chemicals returns are expected to have poor returns during the next weeks. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability remains overall positive, with a rather fluctuating trend for the cases when  $\tau_1 = 0.7$  and  $\tau_1 = 0.8$ . These results suggest that when European stocks are high, the returns of the chemicals commodities will also be high during the next weeks.

The results of our estimations show that when  $\tau_2 = 0.1$ , the directional predictability from European stocks towards electricity commodities is negative for the commodity's lowest quantile, then turns mostly positive for the rest of the quantiles, with more clustering and significant relationship for electricity's uppermost quantile. This suggests that when European stocks are low, electricity returns are expected to increase if they are already very low, but the performance is expected to drop over the course of the next weeks for rest of the commodity's quantile ranges. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability holds its overall positive trend, but it switches signs to become negative when  $\tau_1 = 0.95$ . Consequently, unless their returns are already very high, electricity commodities are expected to have a good performance in the next weeks when European stocks are high.

The graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from European stocks towards feeds commodities is overall positive, with more clustering and significant relationship for feeds uppermost quantile. This suggests that when European stocks are low, feeds are expected to have poor returns during the next weeks. This weakening in the commodity's performance is more pronounced when feeds are already having high returns. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability between European equities and feeds holds its overall positive patten. But in this case, the results are more clustering and significant in the commodity's lowest quantile. This suggests that when European equities are high, feeds are expected to have good returns in the next weeks. This strengthening in the commodity's performance is more pronounced when their returns are already very low.

The findings for fibers reveal that when  $\tau_2 = 0.1$ , the directional predictability they receive from European stocks is overall positive, suggesting that fibers will also have poor returns during the next weeks when European stocks are low. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability between the two assets holds its overall positive trend, with some fluctuations in the commodity's uppermost quantile. This

suggests that when European stocks are high, fibers commodities are also expected to have good returns over the course of the next weeks.

The findings of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from European stocks to forestry products commodities is overall positive. This suggests that when European stocks are low, forestry products returns are expected to be also low in the next weeks. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability holds its overall positive trend, but it turns negative for the commodity's uppermost quantile. These results show that when European stocks are high, forestry products are also expected to have good returns in the next weeks. Despite this fact, the performance of these commodities will eventually drop if they are already experiencing very high returns.

The graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from European stocks towards grains is dominated by a positive pattern, yet a negative trend is remarkably present when  $\tau_1 = 0.05$  and  $\tau_1 = 0.8$ . This suggests that when European stocks are low, grains are expected to have an overall low performance in the next weeks, except when the commodities have an already poor performance. In that case, the returns will eventually increase. Turning to the case when  $\tau_2 = 0.9$ , the findings show that the directional predictability is fluctuating and has very few spikes. This makes it unlikely to determine a final prediction about an overall direction of the returns of grains commodities when European stocks are high.

The graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from European equities to livestock commodities has an overall negative trend. Consequently, it could be said that when European equities are low, livestock returns are expected to increase in the upcoming weeks. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability switches signs compared to the other case, in order to become mostly positive. This does not stand for the commodity's uppermost quantile, where the directional predictability is found to be overall negative. As a result, when European stocks are high, livestock are also expected to have good returns in the next weeks, except when their performance is already at its highest level. In that case, the returns will eventually drop.

Our results show that when  $\tau_2 = 0.1$ , the directional predictability from European stock markets to metals commodity markets is overall positive. This positive relationship is more pronounced in the commodity's uppermost quantile, where it is more clustering and significant. These results show that when European equities are having poor returns, it is expected that the performance of metals commodities will also be low in the upcoming weeks. Turning to the case where  $\tau_2 = 0.9$ , the directional predictability between the two assets holds its dominating positive trend, suggesting that when European equities are high, metals are expected to have good returns over the course of the upcoming weeks.

Turning to oil seeds, the graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from European equities towards those commodities is overall positive, which suggests that when European stocks are low, oil seeds are also expected to exhibit low performance during the next



weeks. Regarding the case when  $\tau_2 = 0.9$ , the directional predictability between the two assets is shown to be mostly negative, except for the commodity's lowest quantile. This suggests that when European stocks are high, oil seeds are expected to have low returns during the next weeks, except when the commodities are already having very returns. In that case, the returns of oil seeds commodities is expected to increase in the next weeks.

The graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from European stock markets to precious metals markets is negative for the commodity's low quantiles, fluctuating in its middle quantiles and positive in its upper quantiles. This suggests that when European stocks are low, precious metals are expected to have good returns in the next weeks if their performance is already low, and to have poor returns in the next weeks if their performance is already high. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability is shown to be overall positive which suggests that when European equities are high, precious metals are expected to have good returns over the course of the upcoming weeks. The graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from European stock markets to seeds markets is overall negative, but it switches signs to become positive in the commodity's upper quantiles. This suggests that when European stocks are low, seeds prices are expected to have good returns in the next weeks. But this does not stand when the commodities are already experiencing high returns. In this case, the performance of the seeds commodities is expected to drop in the next weeks. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability is found to be mostly positive. As a result, it is expected that seeds commodities will have good returns in the upcoming weeks when European stocks are high.

The graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from European stock markets to semi-conductors' markets is overall positive. This positive relationship is more pronounced in the commodity's uppermost quantile when it is shown to be more clustering and significant. This suggests that when European stocks are low, semi-conductors are expected to have poor returns over the course of the upcoming weeks, especially when the commodities are already experiencing very high returns. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability holds its overall positive trend, which suggests that when European equities are high, semi-conductors are expected to have overall good returns in the upcoming weeks.

Turning to softs, the graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from European equities towards these commodities is overall negative for softs' lowest quantile and mostly positive for its upper quantiles. For the rest of the quantile ranges, the directional predictability is highly fluctuating. These findings suggest that when European equities are low, the returns of softs are expected to increase in the next weeks if they are very low, and they are expected to decrease in the next weeks if they are very high. For the rest of the commodity's quantile ranges, it is unlikely to predict the behavior of softs from the performance of European equities. Regarding the case when  $\tau_2 = 0.9$ ,



the directional predictability is positive for softs lowest quantile and negative for their uppermost quantile. For the rest of softs' quantile ranges, the directional predictability is highly fluctuating. Again, this suggests that when European equities are high, softs will have good returns if these are already low and will have poor returns if they are having their highest possible performance already.

The graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from European stocks to crude oil is overall positive. Consequently, when European stocks are low, it is expected that crude oil returns will be also low in the upcoming weeks. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability holds its overall positive pattern, except for crude oil's uppermost quantile where it turns negative. This suggests that when European stocks are high, crude oil is expected to have good returns, except when its performance is already very high. In that case, crude oil returns are expected to drop.

Insert Figure 1.a

Insert Figure 1.b

Insert Figure 1.c

- *The US factor*

Figure 2(a) shows the sup version Box-Ljung test statistic for each lag  $p$  to detect directional predictability for  $\tau_2 = 0.1$ . Figure 2(b) shows the sup version Box-Ljung test statistic for each lag  $p$  to detect directional predictability for  $\tau_2 = 0.9$ . Figure 2(c) shows the cross quantilogram for  $\tau_2 = 0.1$ , and for  $\tau_2 = 0.9$ .

The first thing to notice is that the graphics of the Ljung-Box test show that the power of directional predictability from US stock market towards the various commodity markets is low and insignificant.

Starting with livestock, the graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability these commodities receive from the US stocks is overall negative in the commodity's low and middle quantiles, yet it is mostly positive in its upper quantiles. This suggests that when US stocks are low, it is expected that the returns of livestock will increase in the upcoming weeks if they are low and will decrease if they are already very high. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability is negative for some lags before becoming positive for the later lags (for the commodity's lower and middle quantiles). For livestock upper quantiles, the directional predictability starts positive before turning negative for later lags. This suggests that when US equities are high, livestock will have high performance in the next weeks if they are very low and will drop eventually after good realizations if they are already very high. For the rest of livestock's quantile ranges, they are expected to have low returns in the next weeks for some time before exhibiting an increase in returns.

The graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from US stock market towards electricity market is mostly positive, suggesting that when US stocks are low, electricity commodities are expected to have an overall poor performance in the upcoming weeks. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability between the two assets is shown to be overall negative. This

suggests that when American stocks are high, electricity prices are expected to have low returns in the upcoming weeks.

The graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from US stock market to feeds market is overall positive. Consequently, when American equities are low, feeds are expected to have low returns in the upcoming weeks. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability between the two assets is shown to be negative. This suggests that when American equities are high, feeds are expected to have low returns in the next weeks.

The results of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from US equity market to fibers commodity market has an overall positive trend. It is also worth mentioning that fibers' lowest quantile range exhibits negative predictability in its later lags. These results suggest that when US stocks are low, fibers are expected to have a poor performance in the upcoming weeks. Yet when the performance of the commodities is already very low, their returns are expected to increase after a period of bad performance. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability between the two assets is overall negative. Consequently, it could be said that when US stocks are high, fibers are expected to exhibit low returns in the next weeks.

Our findings show that when  $\tau_2 = 0.1$ , the directional predictability from US stock market towards natural gas market is overall negative, except for the commodity's uppermost quantiles ( $\tau_1 = 0.9$  and  $\tau_1 = 0.95$ ), where the directional predictability has a more clustering positive pattern. This suggests that when American equities are low, natural gas prices are expected to have overall good returns in the upcoming weeks. Yet if their returns are already very high, the performance is expected to decrease in the upcoming weeks. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability is shown to be overall positive, suggesting that natural gas commodities would have good returns in the next weeks when American stocks are high.

The graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from US equity market towards grains commodity market has an overall positive trend, except for the commodity's lowest quantile range, where a negative predictability is more pronounced. This suggests that when American equities are low, grains are expected to have an overall poor performance in the upcoming weeks, except when their returns are already very low. In that case, their performance will increase a little. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability from American stock market to grains market is mostly negative. These results suggest that when US stocks are high, grains are expected to have an overall low performance in the upcoming weeks.

The graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from US stock market to metals commodity market is overall negative, except when metals are already having their lowest possible returns. This suggests that when American stocks are low, the prices of metals commodities are expected to have low returns in the upcoming weeks. This does not stand when the commodities are having

their lowest performance. In that case, the returns will increase in the next weeks. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability is found to be mostly negative, suggesting that the metals would have poor returns in the next weeks when American equities are high.

The graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from US stock market towards crude oil market is mostly positive, suggesting that when American equities are low, crude oil prices will have a low performance in the upcoming weeks. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability is found to be overall negative. This suggests that when American equities are high, crude oil commodities are expected to have low returns in the next weeks.

The graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from US stock market towards oil seeds commodity market has an overall positive trend. Despite this fact, the directional predictability is mostly negative for oil seeds' lowest quantile. This suggests that when American stocks are low, oil seeds are also expected low performance over the course of the upcoming weeks. Yet when the commodities are already having their lowest returns, the performance might experience a small increase. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability is found to be mostly negative, with some spikes of positive relationship in the later lags of the commodity's lowest quantiles. This shows that overall, when American stocks are high, oil seeds will have poor returns in the next weeks. But when the commodities are already very low, there is a chance that their performance will increase a bit after a period of poor returns.

The findings of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from US stock market to precious metals markets is negative for the commodity's low quantiles ( $\tau_1 = 0.05$  to  $0.3$ ) and positive for the rest of the quantiles ( $\tau_2 = 0.5$  to  $0.95$ ). This suggests that when American stocks are low, precious metals will have good returns in the upcoming weeks when their performance is already low, and will have bad returns when the performance is already high. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability is positive for precious metal's low quantiles and negative for their upper quantiles. Consequently, it could be predicted that when US stocks are high, precious metals having already low returns will exhibit an increase in their performance in the next weeks, while precious metals having high returns will have poor performance over the course of the next weeks.

The graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from US stocks towards seeds is mostly negative, except for the commodities uppermost and lowest quantiles ( $\tau_1 = 0.05$  and  $\tau_1 = 0.95$ ). In these two cases, the directional predictability is overall positive. This suggests that when American stocks are low, seeds commodities are expected to have good returns in the next weeks. But this does not stand when the commodities' returns are either very low or very high. In that case, the performance is expected to increase in the next weeks. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability is found to be overall negative. These findings suggest that when American stocks are high, seeds commodities are expected to have overall poor returns in the next weeks.

Regarding semi-conductors, the cross-correlogram shows that when  $\tau_2 = 0.1$ , the directional predictability these commodities receive from US stocks is overall negative, except when  $\tau_1 = 0.9$  and  $\tau_1 = 0.95$ . In those cases, the directional predictability is mostly positive. As a result, it could be said that when American stocks are low, semi-conductors are expected to have good returns over the course of the next weeks, except when their performance is already very high. In that case, the returns of semi-conductors will decrease eventually. For the case when  $\tau_2 = 0.9$ , the directional predictability is found to be mostly negative, suggesting that when American stocks are high, semi-conductors will have poor returns in the next weeks. The findings for softs show that when  $\tau_2 = 0.1$ , the directional predictability from US stocks towards softs commodity markets is overall negative. This suggests that when American stocks are low, softs are expected to have an overall good performance over the course of the next weeks. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability between the two assets holds its overall negative trend. Consequently, it is predicted that when American equities are high, softs would have low returns in the next weeks.

The graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from American equities to agricultural oils is overall negative, suggesting that when US stocks are low, agricultural oils are expected to have a good performance over the course of the next weeks. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability between the two assets holds its overall negative trend (despite some spikes of positive relationship for the commodity's middle quantiles). This suggests that when American equities are high, agricultural oils are expected to have poor returns during the next weeks.

Regarding chemicals, the graphics of the cross-correlogram shows that when  $\tau_2 = 0.1$ , the directional predictability from US stocks towards chemicals commodities is mostly negative, except for the commodity's uppermost quantiles ( $\tau_1 = 0.9$  and  $\tau_1 = 0.95$ ) where it turns positive. This suggests that when American stocks are low, chemicals are expected to exhibit high performance during the next weeks, yet this does not stand if their returns are already very high. In that case, the performance is expected to plummet. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability holds its overall negative pattern, suggesting that when US stocks are high, chemicals will have poor returns in the next weeks.

The results of the cross correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from US stocks towards forestry products is overall positive, suggesting that when American stocks are low, forestry products will also exhibit low returns in the upcoming weeks. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability is found to be mostly negative. Consequently, forestry products are expected to have an overall low performance in the next weeks when American stocks are high.

Insert Figure 2.a

Insert Figure 2.b

Insert Figure 2.c

- *The BRICS factors*

Figure 3(a) shows the sup version Box-Ljung test statistic for each lag  $p$  to detect directional predictability for  $\tau_2 = 0.1$ . Figure 3(b) shows the sup version Box-Ljung test statistic for each lag  $p$  to detect directional predictability for  $\tau_2 = 0.9$ . Figure 3(c) shows the cross quantilogram for  $\tau_2 = 0.1$ , and for  $\tau_2 = 0.9$ .

The first thing to notice is that the graphics of the Ljung-Box test show that the power of directional predictability from the BRICS stock markets towards the various commodity markets is low and insignificant.

The graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from BRICS stock markets towards agricultural oils has an overall negative trend, especially for the commodity's low and middle quantiles. For the upper quantiles, the directional predictability is positive for the first 30 lags before becoming negative for the last 30 lags. This suggests that when BRICS stocks are low, agricultural oils are expected to have good returns in the upcoming weeks. This positive behavior follows a period of low returns when agricultural oils are already performing well. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability is mostly negative. This negative relationship is more pronounced for agricultural oils' upper quantiles, where it is more clustering and significant.

The graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from BRICS equities to feeds is overall positive, suggesting that when BRICS stocks are low, feeds are expected to have poor returns in the upcoming weeks. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability is found to be overall negative. This shows that when BRICS equities are high, feeds would have a bad performance over the course of the upcoming weeks.

The graphics of the quantilogram model show that when  $\tau_2 = 0.1$ , the directional predictability from BRICS stock markets towards natural gas commodity markets is overall negative. It is also worth mentioning that this relationship turns positive in the last 20 lags of natural gas' uppermost quantiles. This suggests that overall, when BRICS stocks are low, natural gas is expected to have a good performance over the course of the next weeks. Nevertheless, the returns will eventually decrease when natural gas is already having very high returns. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability is found to be positive for the middle and upper quantiles and negative for the commodity's lower quantiles. This suggests that when BRICS stocks are high, natural gas returns will increase during the next week, except if the commodities already have a poor performance.

The results of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from BRICS equities to grains commodities has an overall positive trend. This suggests that when BRICS stocks are low, grains are expected to have low returns in the upcoming weeks. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability holds its overall positive pattern, but it has a more negative trend in the commodity's upper quantiles. This shows that when BRICS stocks are high, grains are expected to have an

overall good performance in the upcoming weeks. Despite this, the returns of the commodities will be low if they are already in the low quantile ranges.

The findings of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from BRICS stock markets towards livestock markets has an overall negative pattern for the commodity's upper quantiles and in the last lags of the low and middle quantiles. This suggests that when BRICS stocks are low, livestock will have poor returns for some period followed by an increase in its returns after a period of time when their performance is already low or around the median. When the commodities are high, they are expected to continue their good performance for during the upcoming weeks. Regarding the case when  $\tau_2 = 0.9$ , the directional predictability is overall positive. Consequently, it is predicted that livestock will have good returns in the next weeks.

According to the graphics of the cross-correlogram, the directional predictability from BRICS stock markets to metals commodity markets is overall positive when  $\tau_2 = 0.1$ . This positive relationship is more clustering and significant when the commodities are in their uppermost quantile ranges. This suggests that overall; when BRICS stocks are low, metals will exhibit low returns during the next weeks. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability has an overall negative trend. Consequently, it is expected that metals will have poor returns in the next weeks when BRICS equities are high.

The results of the cross-correlogram shows that when  $\tau_2 = 0.1$ , the directional predictability from BRICS stock markets to crude oil markets is mostly positive, suggesting that when BRICS stocks are low, crude oil returns are expected to drop over the course of the next weeks. Turning to the case when  $\tau_2 = 0.9$ , the graphics show that the directional predictability is mostly negative. This suggests that when BRICS equities are high, crude oil will have a poor performance in the next weeks.

The results of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from the BRICS stock markets towards oil seeds markets is mostly positive. This shows that when BRICS stocks are low, oil seeds are expected to have poor returns during the next weeks. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability is found to be mostly negative. Consequently, when BRICS stocks are high, oil seeds are expected to have low returns in the upcoming weeks.

The graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from BRICS stocks to semi-conductors is positive for a period before switching signs to become negative in the later lags of all the commodity's quantiles. It is also worth mentioning that the positive relationship persists for a longer period than the negative relationship. This suggests that when BRICS stocks are low, semi-conductors are expected to exhibit poor returns for a period before having an increase in their performance. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability is shown to be mostly negative, with few lags at the end of each quantile range of the commodity showing a positive relationship. This suggests that when BRICS stocks are high, semi-conductors are expected to have overall poor returns in the upcoming weeks.



The cross-correlogram model suggests that when  $\tau_2 = 0.1$ , the directional predictability from BRICS equities towards seeds is overall negative for the commodity's low and middle quantiles while it is positive for its upper quantile. This shows that when BRICS stocks are low, seeds are expected to have good returns in the upcoming weeks, except when their returns are already very high. In that case, their performance is expected to drop. Regarding the case when  $\tau_2 = 0.9$ , the directional predictability is mostly negative, suggesting that when BRICS stocks are high, seeds will have low returns in the next weeks.

Turning to forestry products, the findings of the quantilogram model show that when  $\tau_2 = 0.1$  the directional predictability they receive from BRICS stocks is overall positive, yet the lowest quantiles of the commodities have some lags of a negative relationship. This suggests that overall, when BRICS stocks are low, forestry products are expected to have a poor performance over the course of the next weeks. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability from BRICS equities to forestry products is mostly negative. Consequently, it is expected that forestry products will have low returns over the course of the upcoming weeks when BRICS stocks are high.

The graphics of the cross-correlogram shows that when  $\tau_2 = 0.1$ , the directional predictability from BRICS stock markets to chemicals commodity markets is mostly positive. Consequently, when BRICS stocks are low, it is expected that chemicals will have low returns in the next weeks. Turning to the case when  $\tau_2 = 0.9$ , the graphics show that the directional predictability turns to be overall negative, suggesting that when BRICS stocks are high, chemicals are expected to have an overall low performance over the course of the next weeks.

The results of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from BRICS equity markets towards electricity markets is mostly negative. It is worth mentioning that electricity's uppermost quantiles show evidence of negative relationship in its later lags. This suggests that when BRICS stocks are low, electricity prices are expected to have a poor performance over the course of the next weeks. The performance will increase after a period of a low level when the commodities are already having high returns. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability turns to be overall positive. Consequently, it is predicted that when BRICS stocks are high, electricity returns will be low during the next weeks. When electricity is its lowest quantile, the directional predictability is mostly positive. This shows that overall; when BRICS stocks are high, electricity commodities are expected to have low returns in the upcoming weeks. Despite this fact, when the commodities have already a poor performance, their returns are expected to increase in the next weeks when the BRICS stocks are high.

The graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from BRICS stock markets to fibers commodity markets is overall positive, suggesting that when BRICS stocks are low, fibers are expected to have low returns in the upcoming weeks. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability is shown to be mostly negative. This suggests that when BRICS stocks are high, fibers are expected to perform badly in the next weeks.

The graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability from BRICS equities towards precious metals is mostly negative for the commodity's low quantiles ( $\tau_1 = 0.05$  to  $\tau_1 = 0.3$ ) and overall positive for the rest of precious metals' quantile ranges. This suggests that when BRICS stocks are low, precious metals are expected to have an overall poor performance during the next weeks. But this does not stand when the commodities are already having low returns. In that case, their performance is expected to increase over the course of the next weeks. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability is fluctuating with a rather negative trend. This suggests that when BRICS stocks are high, precious metals are expected to have an overall low performance in the upcoming weeks. Turning to softs, the graphics of the cross-correlogram show that when  $\tau_2 = 0.1$ , the directional predictability they receive from BRICS stocks switches signs between negative and positive for all the commodity's quantile ranges. This suggests that when BRICS stocks are low, softs will exhibit poor returns and high returns over the course of the next 60 weeks. Turning to the case when  $\tau_2 = 0.9$ , the directional predictability holds its fluctuating trend between negative and positive signs. Again, this shows that when BRICS stocks are high, softs will undergo both good and bad returns over the course of the upcoming 60 weeks

Insert Figure 3.a

Insert Figure 3.b

Insert Figure 3.c

## 5. Conclusion

After the Asian crisis of 1997, there were numerous studies documenting equity market contagion, where financial crises in one market transmit shocks to other markets through various transmission channels. This would lead investors to diversify their portfolios by investing in other asset classes, particularly commodities, which has been termed as the financialization of commodities. Recent research by Ayadi et al. (2021) found evidence of significant contagion during the BREXIT, although commodities appeared to decouple from the stock markets during the Global financial crisis and the European debt crisis.

Various studies have examined the predictability of stock returns from commodity and Bitcoin returns, but few have explored the predictability of commodities from stock returns. In this paper, we investigate how stock returns of sixteen European countries, the United States, and the BRICS countries predict the returns of sixteen commodity types during the BREXIT crisis. Using the cross-quantilogram model suggested by Han et al. (2016) and following the logic of Urom et al. (2020), we aim to determine which commodities can effectively hedge equity markets by testing how stock market returns predict commodity market returns at different quantiles.



Our results suggest that commodities can be used to hedge European, American, and BRICS stocks in times of the BREXIT crisis, but investors need to be mindful of when to purchase or sell these commodities to minimize portfolio risk. This finding is consistent with the financialization phenomenon identified by Irwin and Sanders (2011). This study is the first to explore the predictability of commodities from stock returns under different quantiles during the BREXIT timeline, providing avenues for further research into commodities that investors should allocate their funds into.

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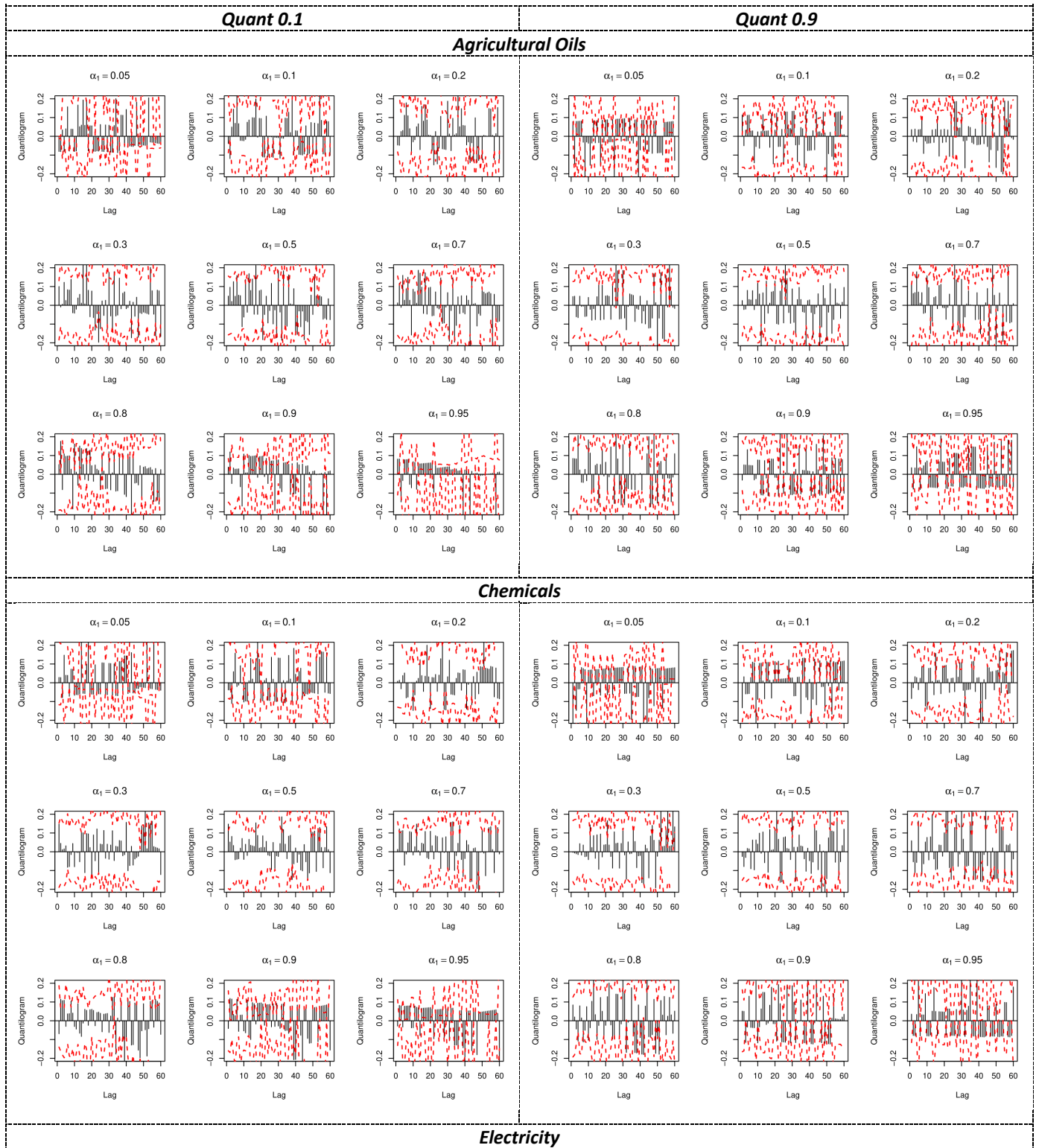
Figure 1 (a) – Ljung-Box test; Equities in the 0.1 quantile, Europe Factor

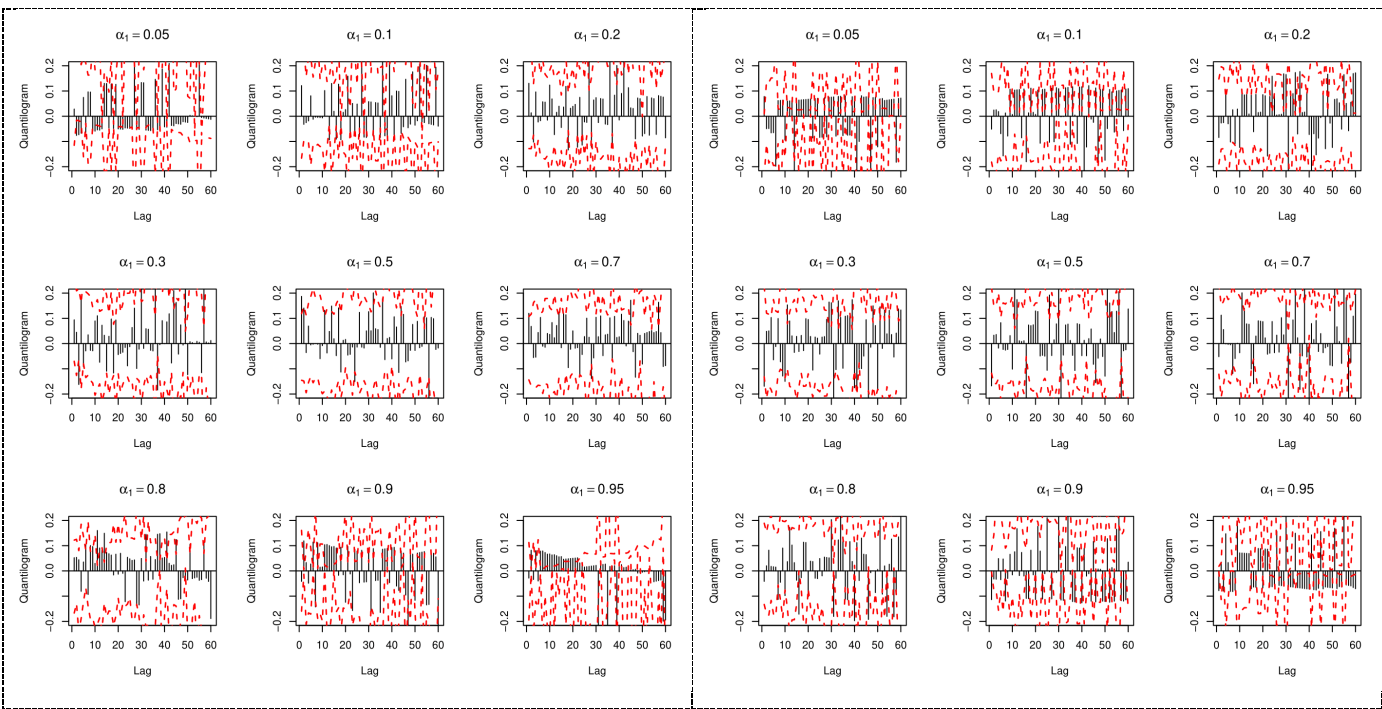


Figure 1 (b): – Ljung-Box test; Equities in the 0.9 quantile, Europe Factor

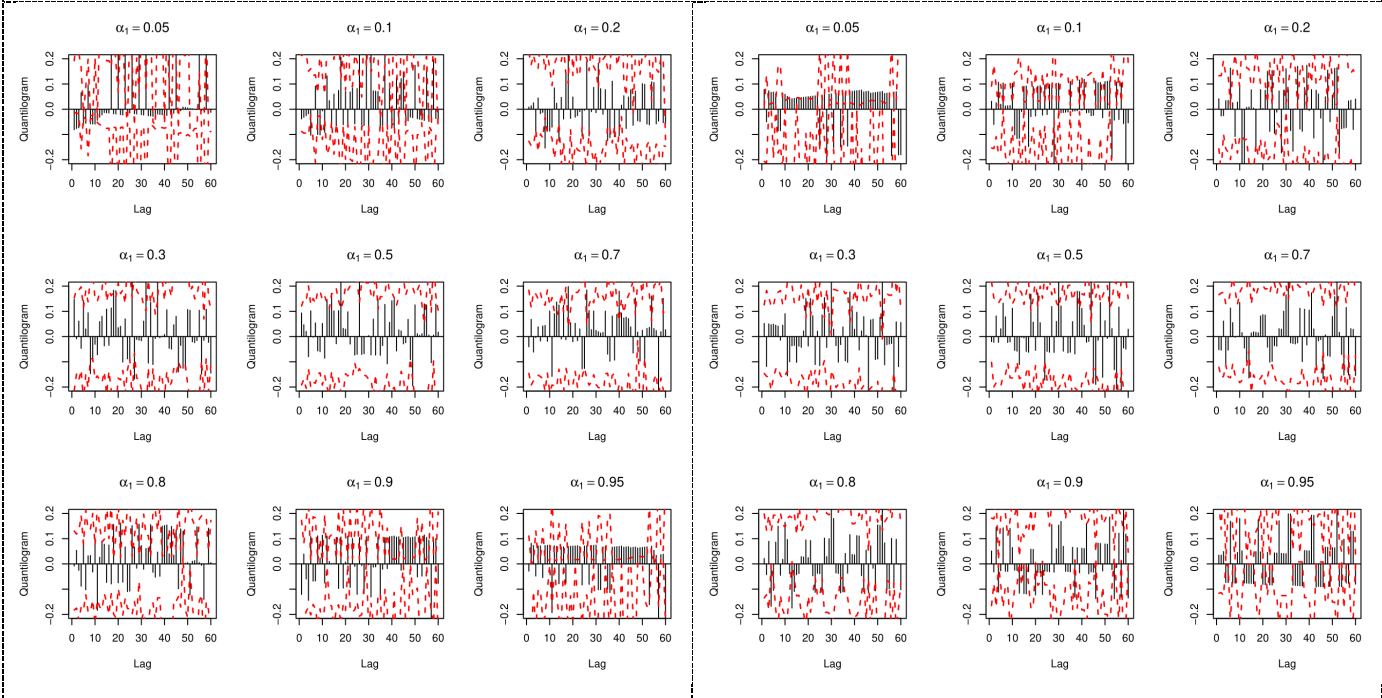


Figure 1 (c): – cross quantilegram for  $\tau_2 = 0.1$ , and for  $\tau_2 = 0.9$ , EUROPE Factor



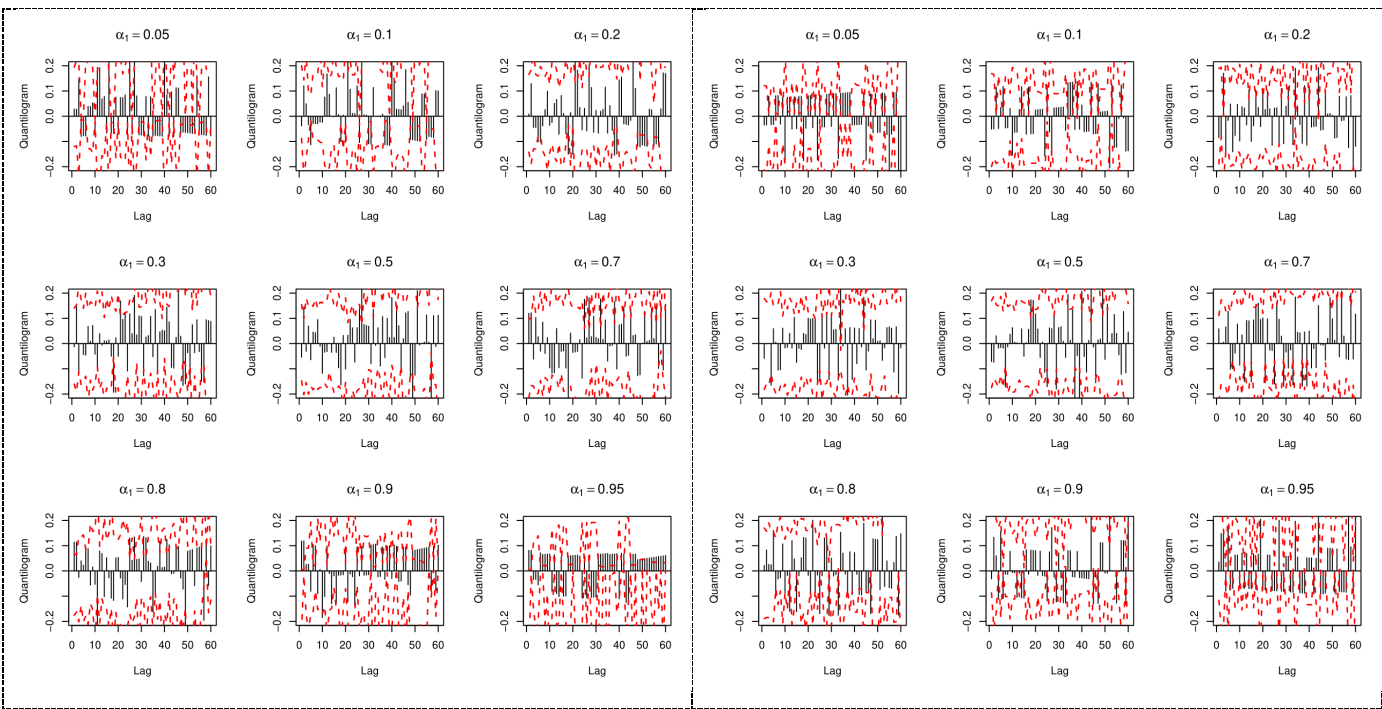


**Feeds**

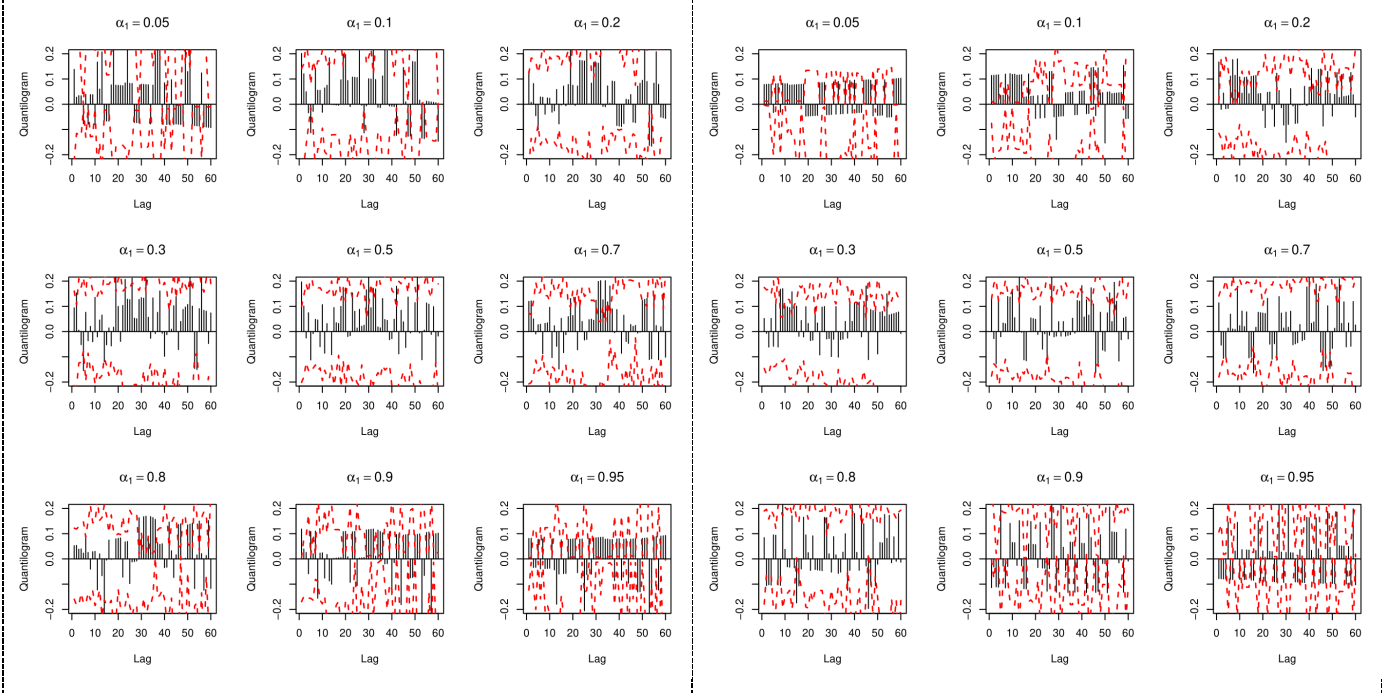


**Fibers**

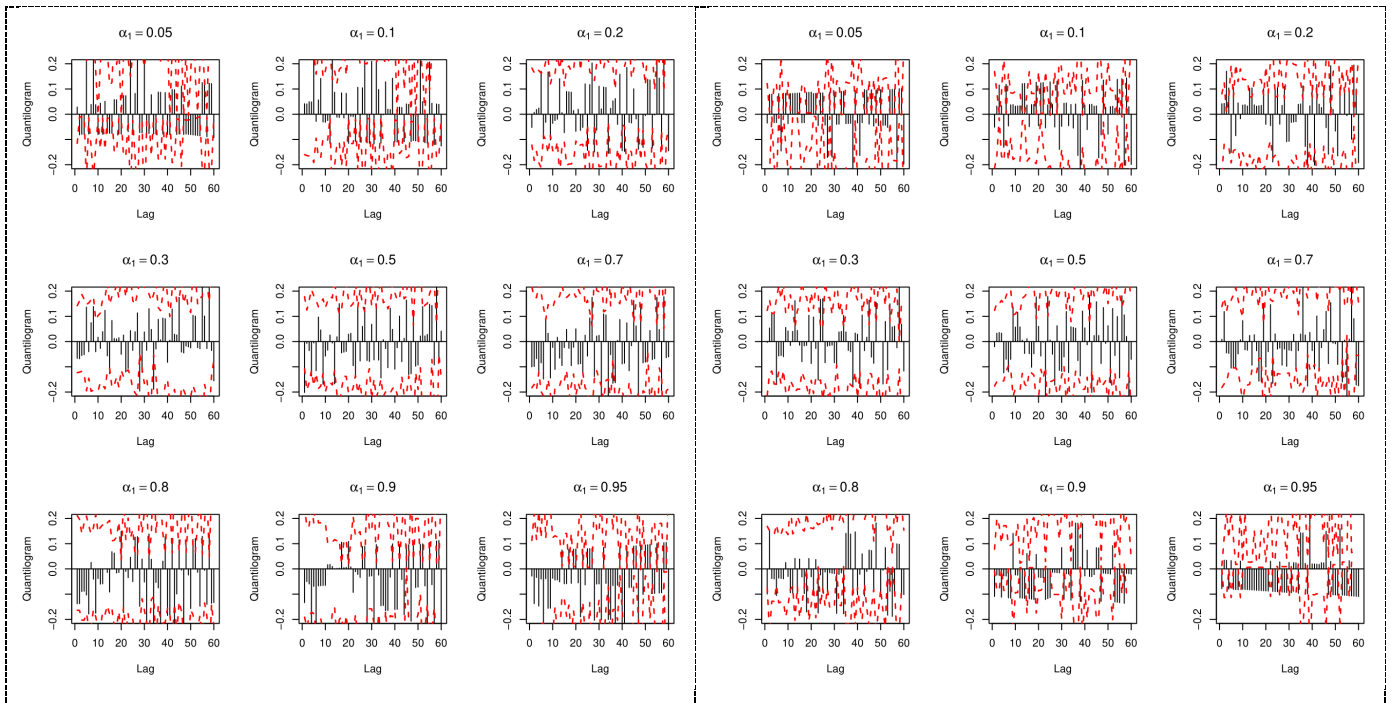




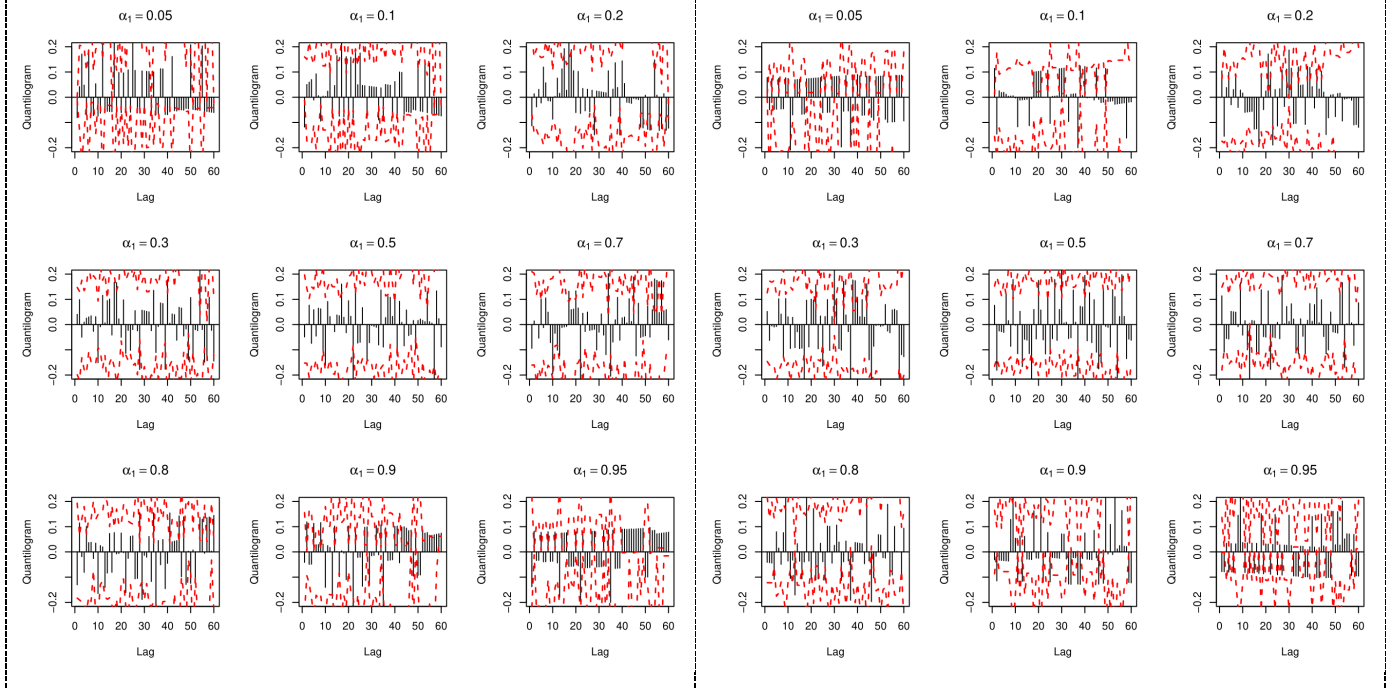
**Forestry products**



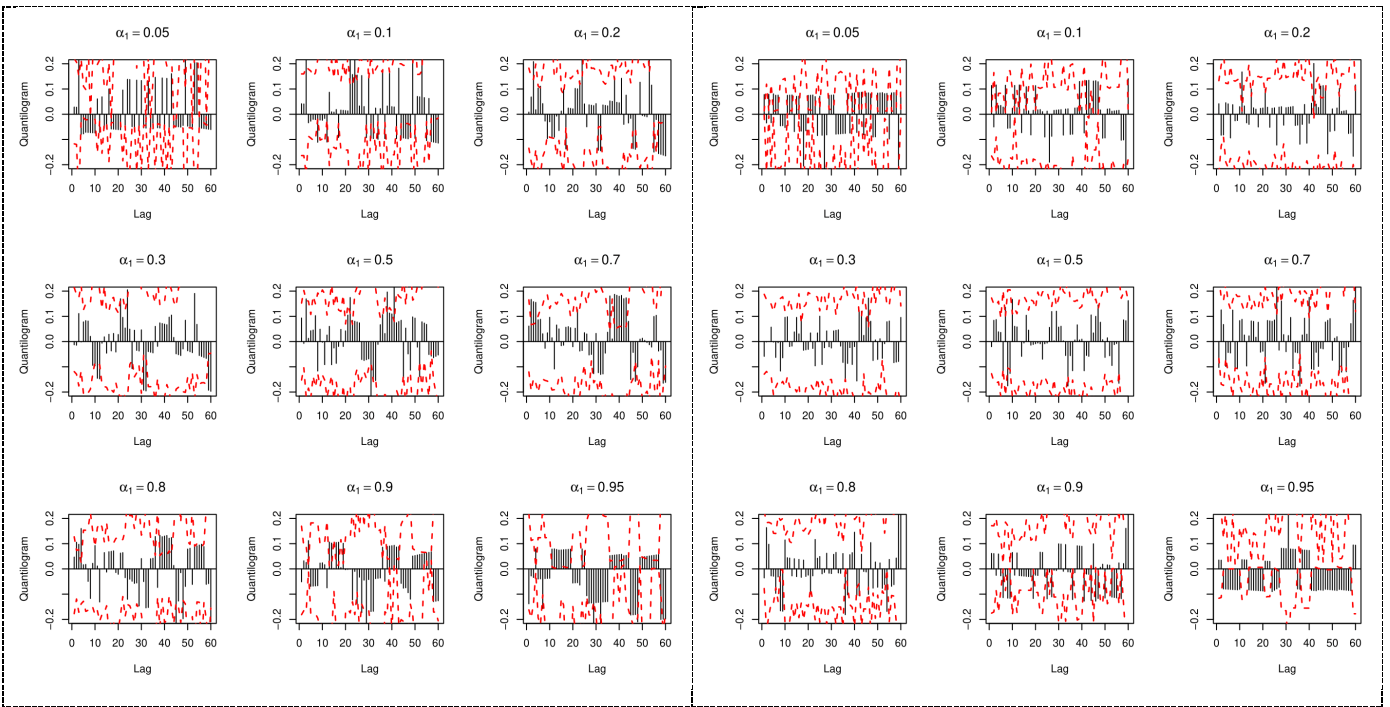
**Natural Gas**



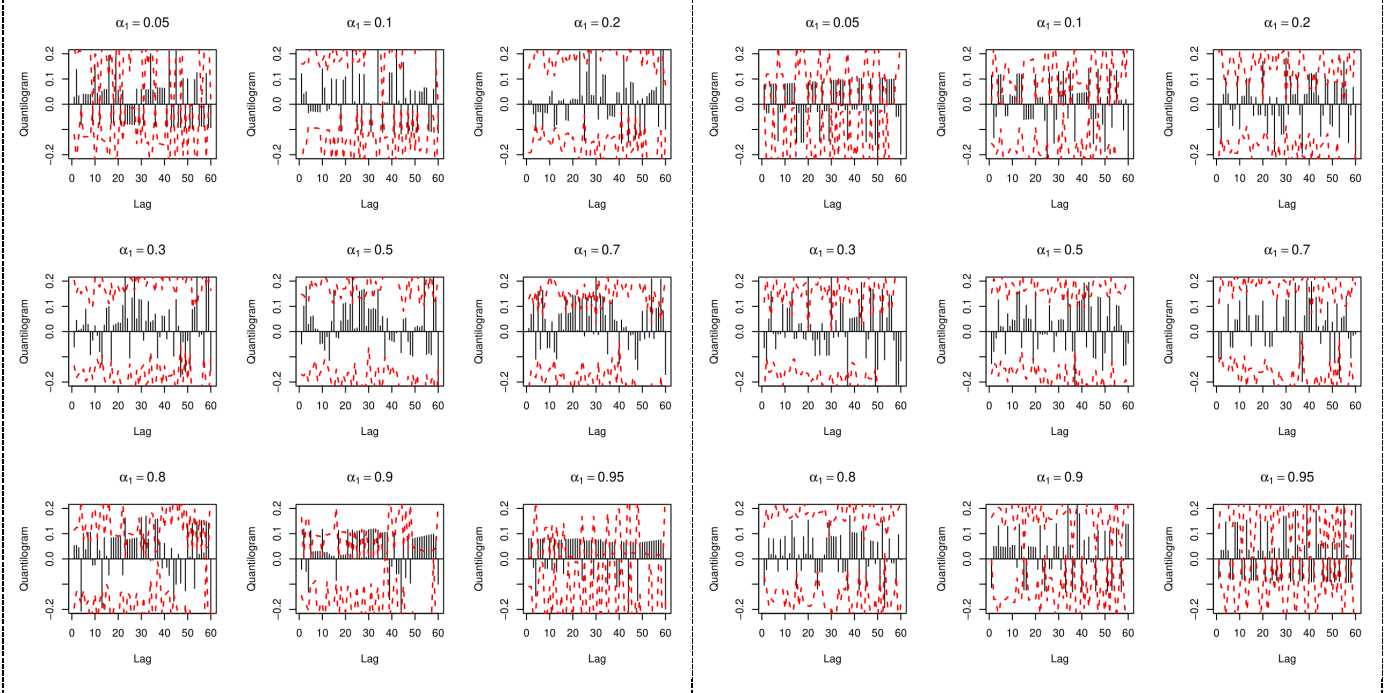
**Grains**



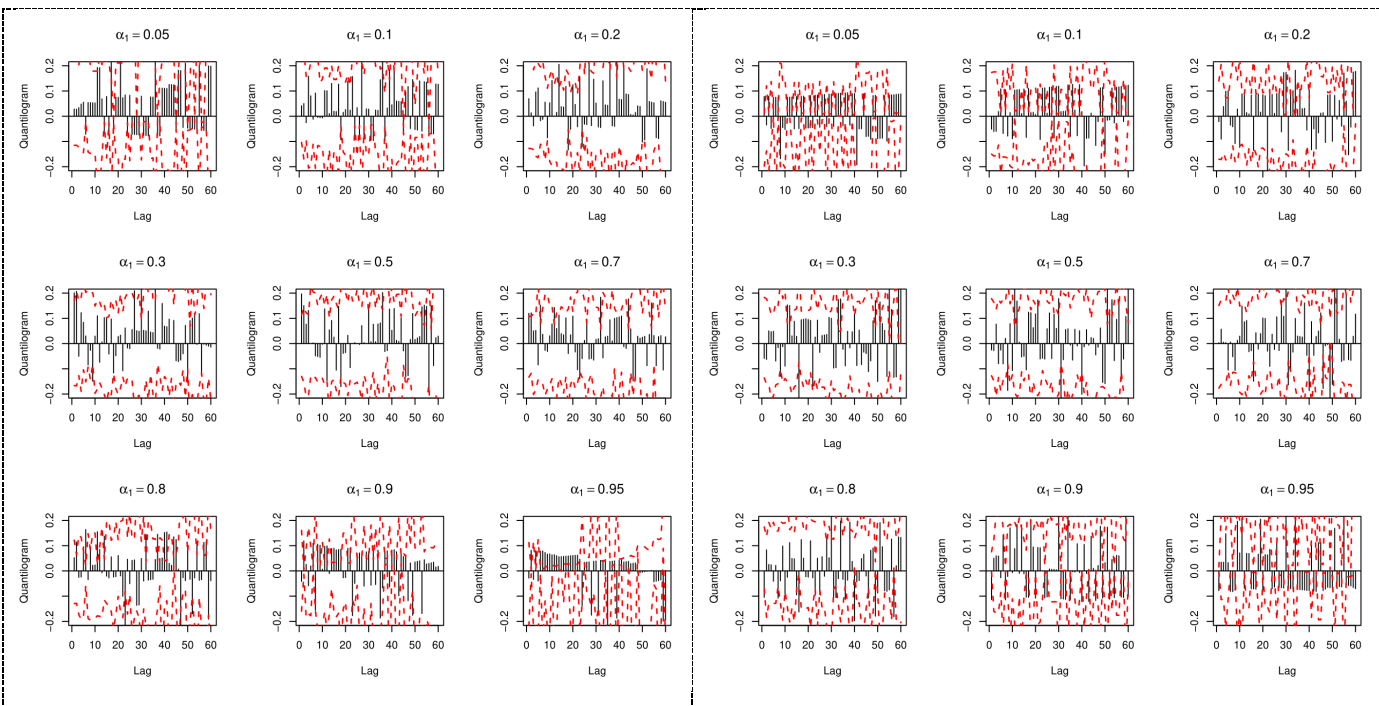
**Livestocks**



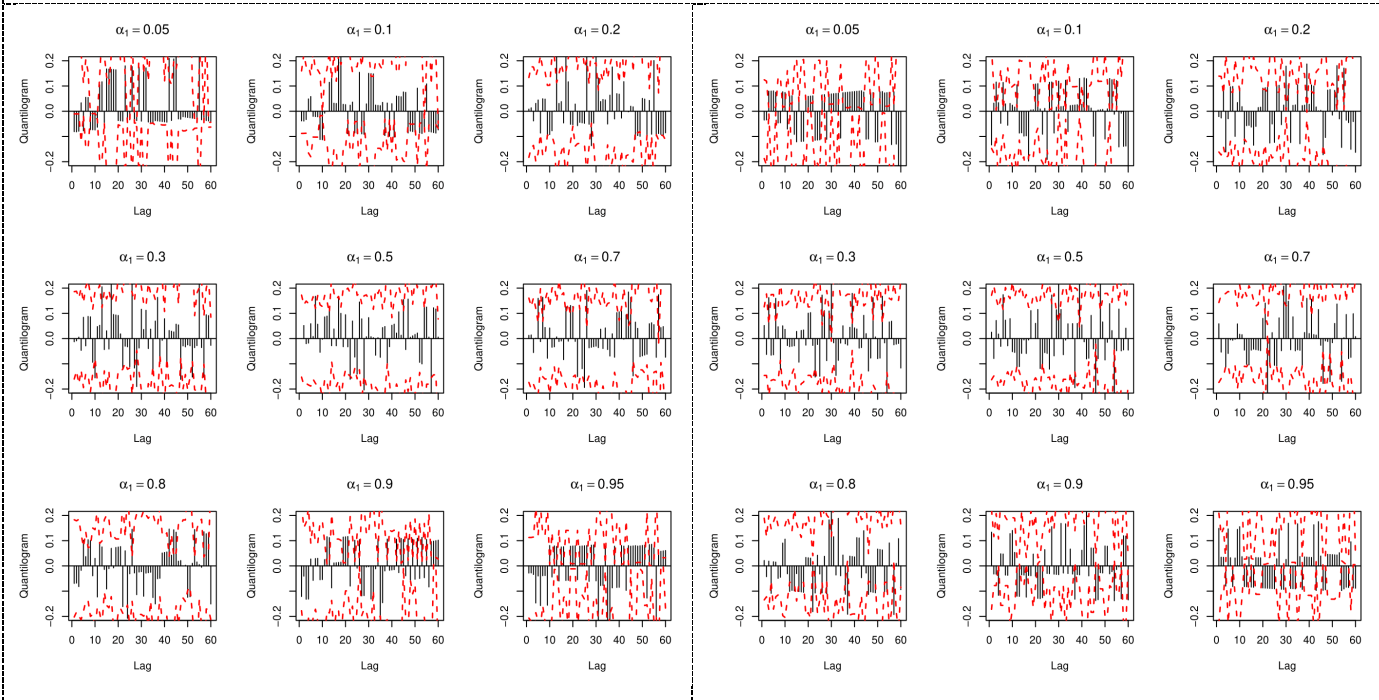
**Metals**



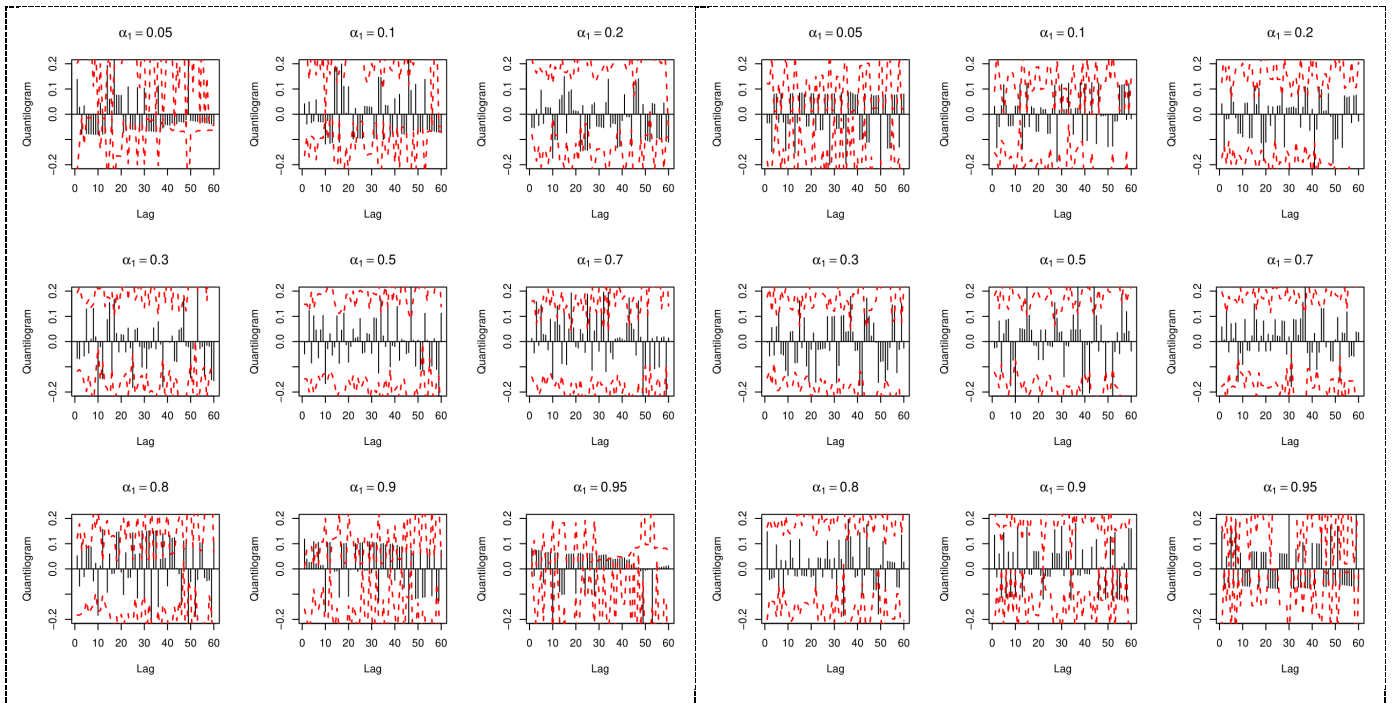
**Crude Oil**



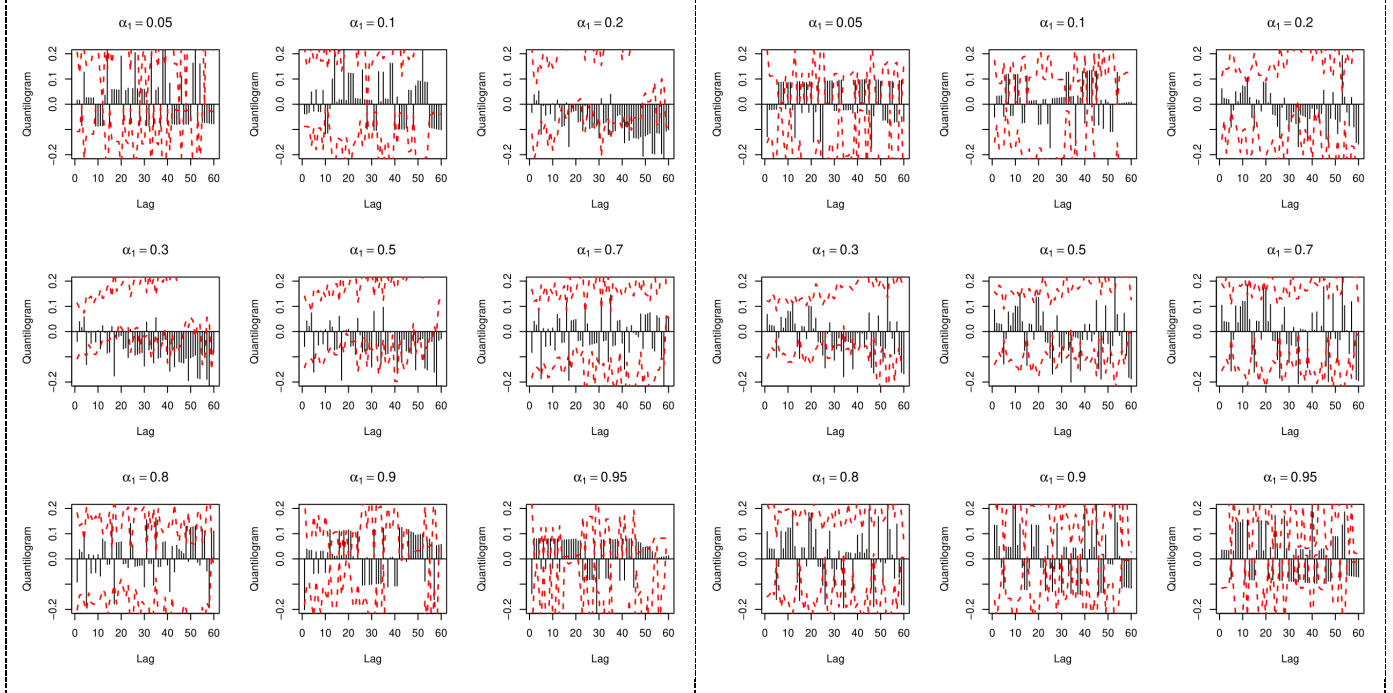
**Oil Seeds**



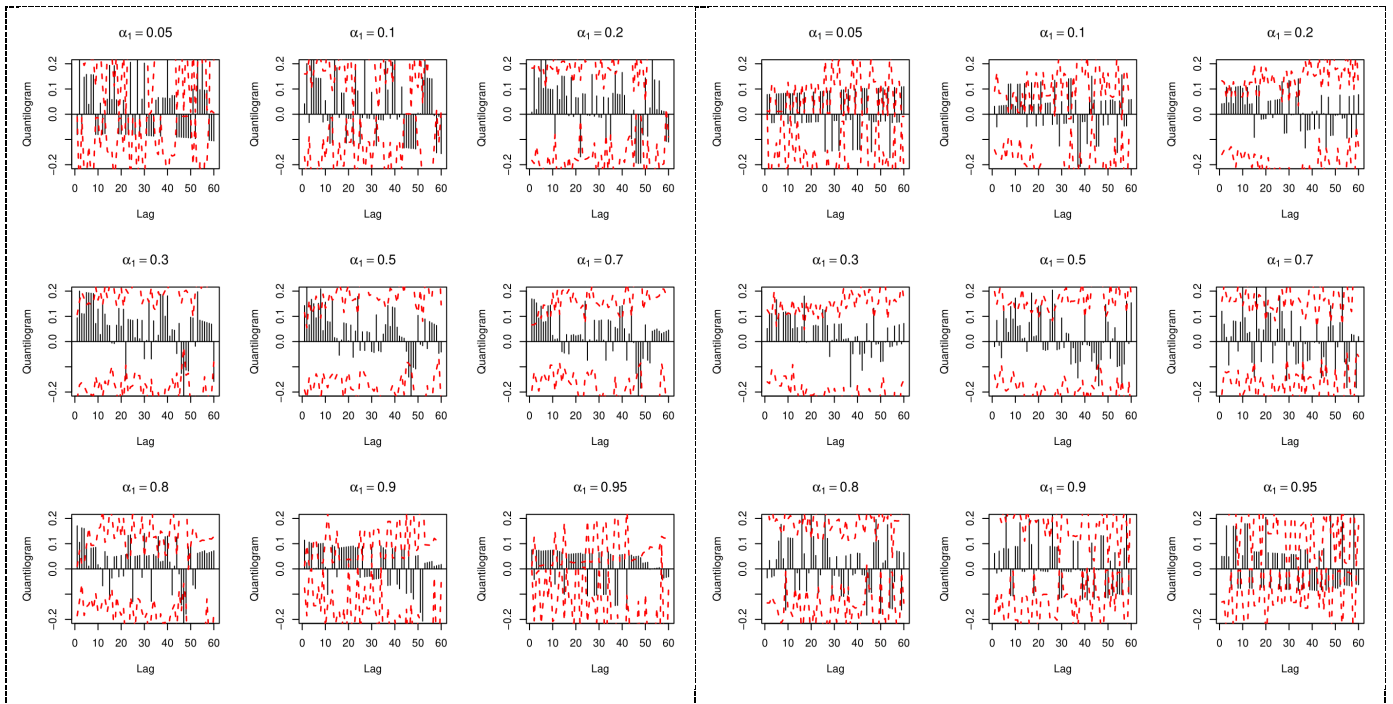
**Precious Metals**



**Seeds**



**Semi-Conductors**



*Softs*

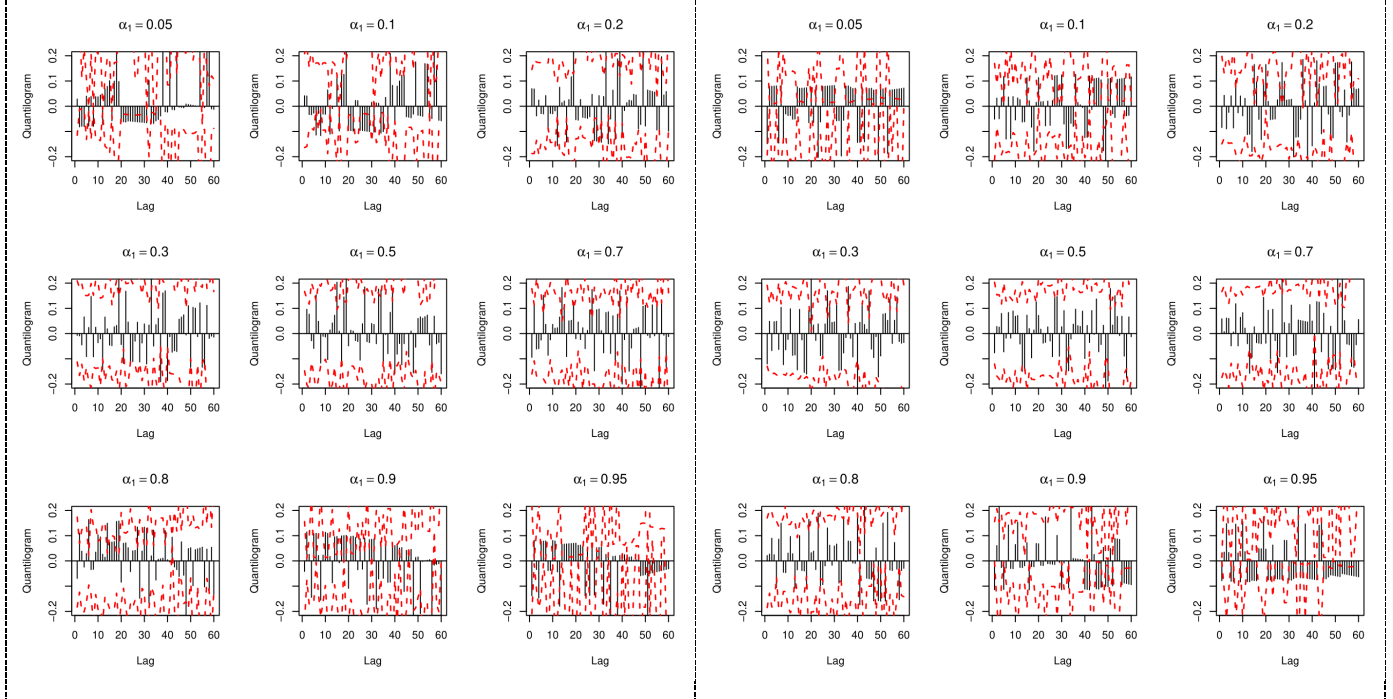




Figure 2 (a): – Ljung-Box test; Equities in the 0.1 quantile, US Factor

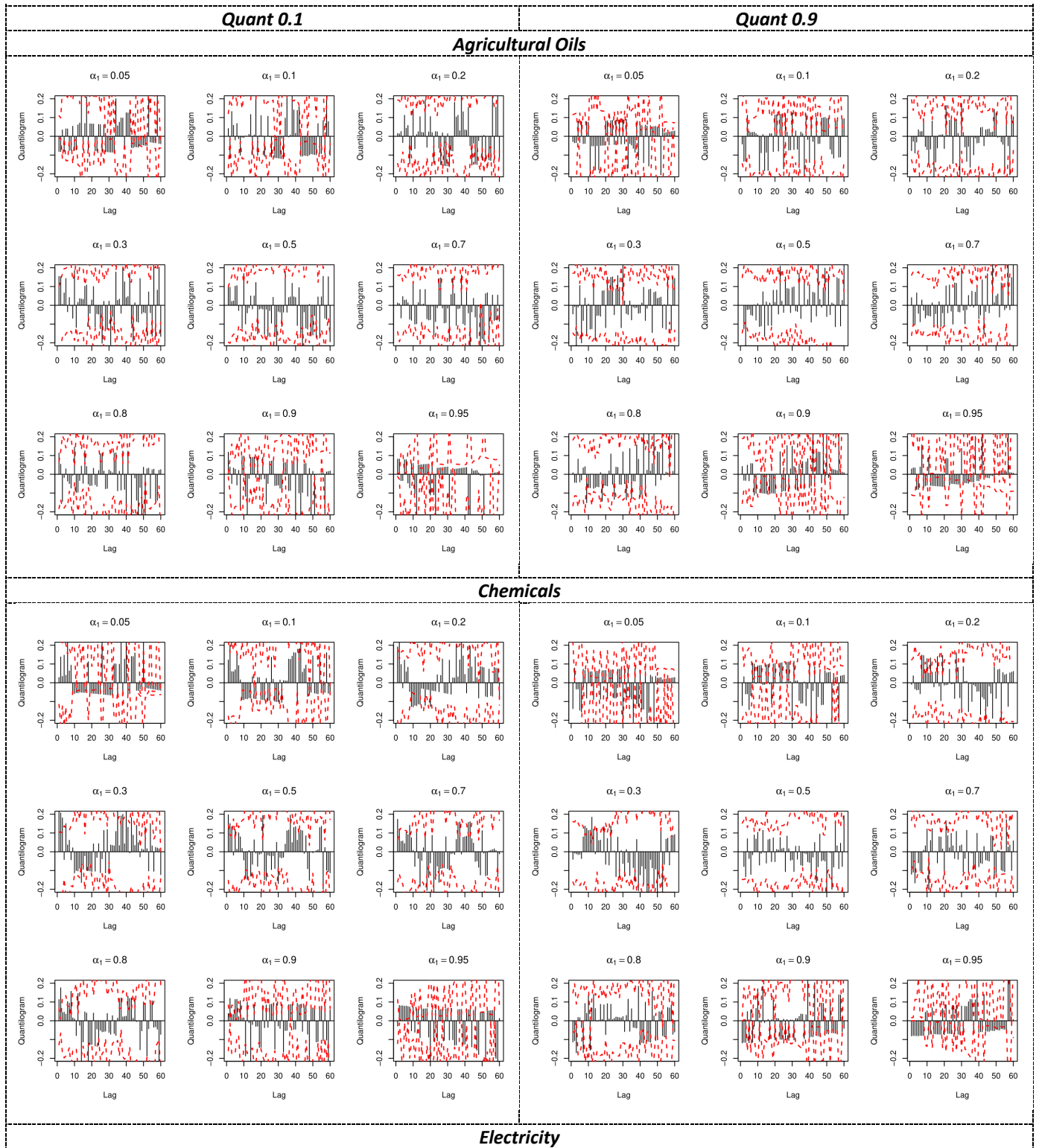


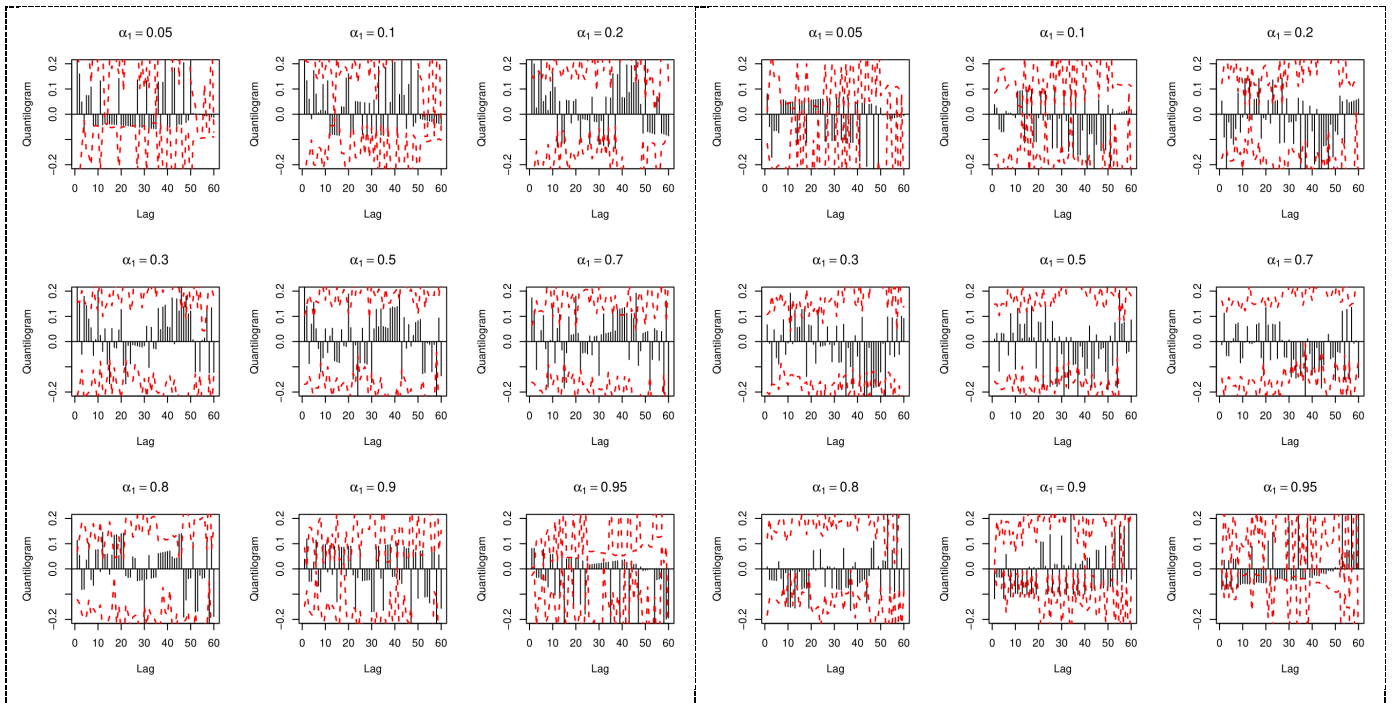
Figure 2 (b): – Ljung-Box test; Equities in the 0.9 quantile, US Factor



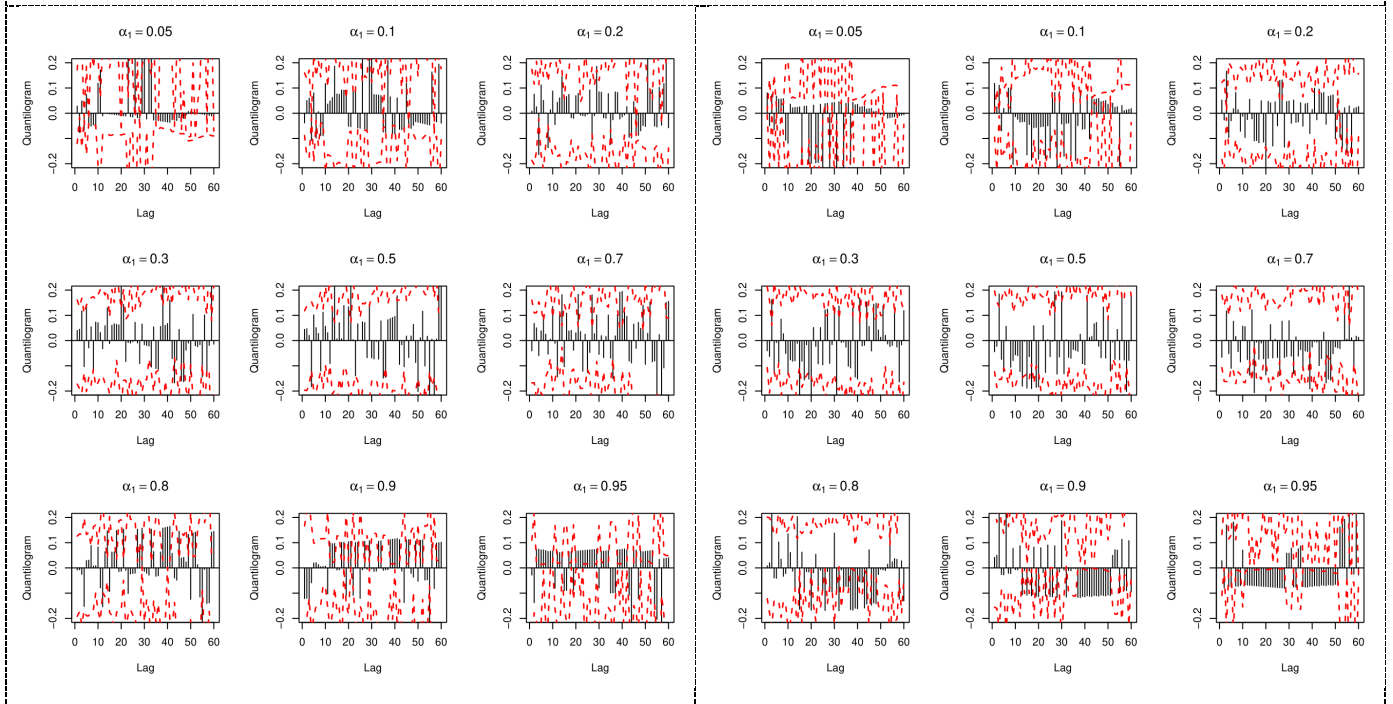


Figure 2 (c): – cross quantilogram for  $\tau_2 = 0.1$ , and for  $\tau_2 = 0.9$ , US Factor

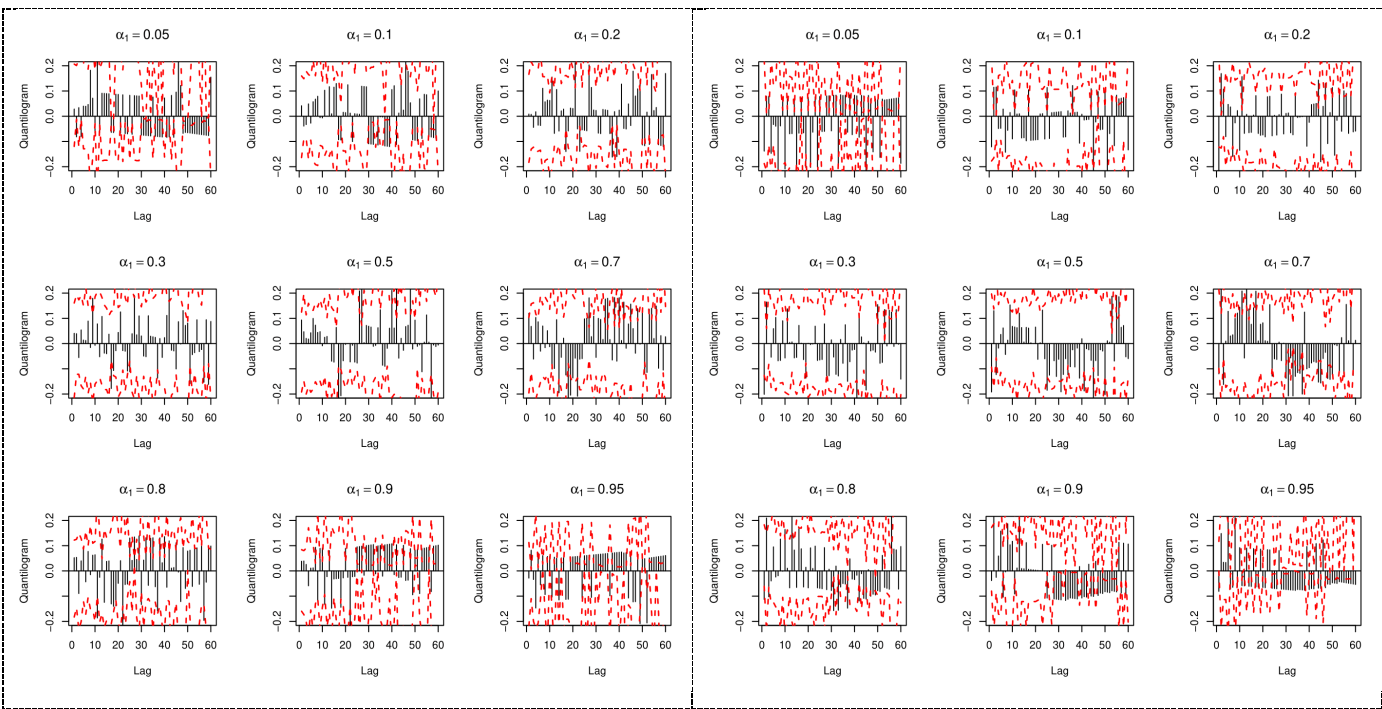




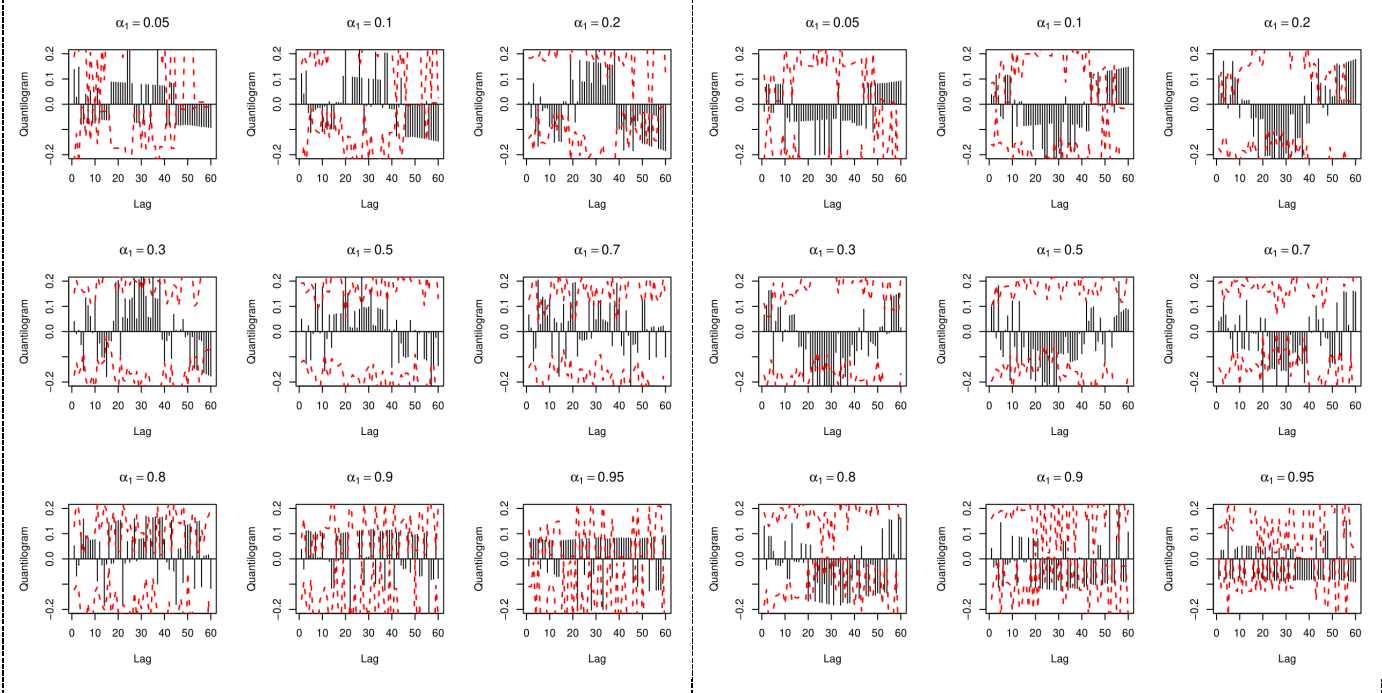
**Feeds**



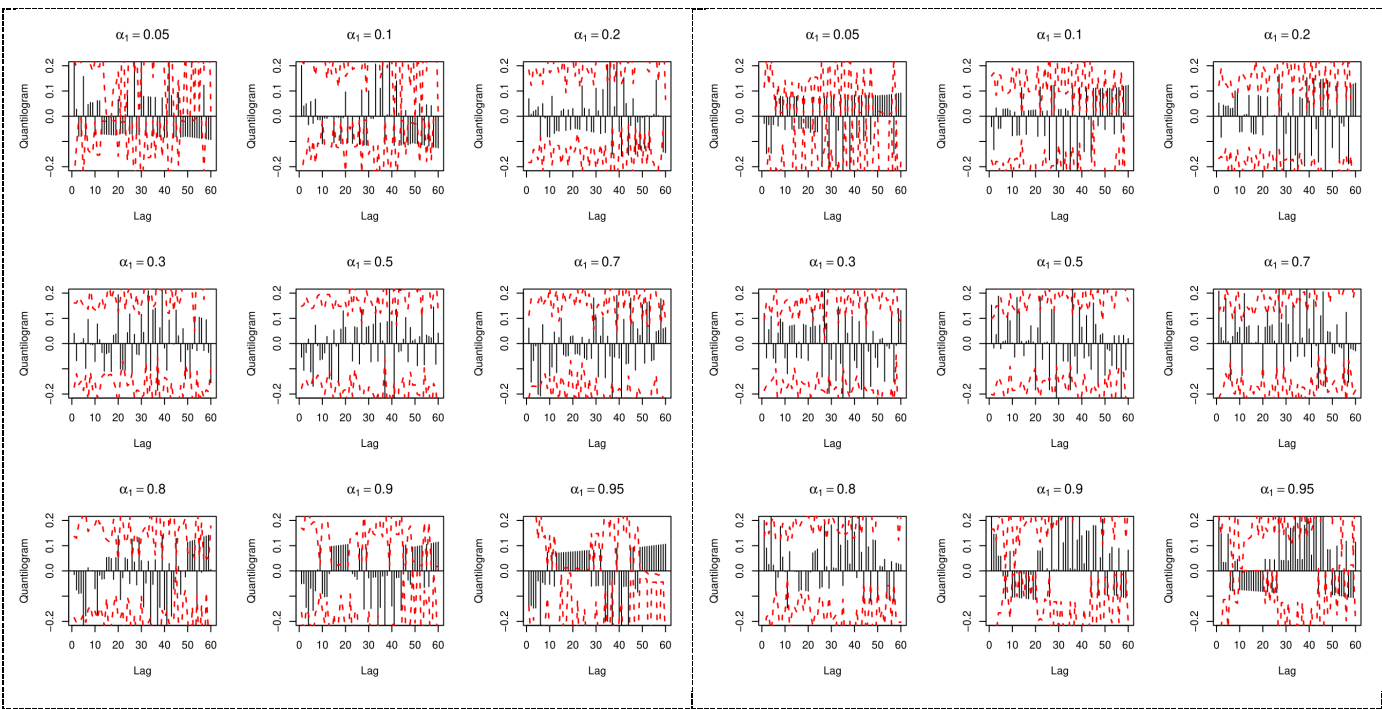
**Fibers**



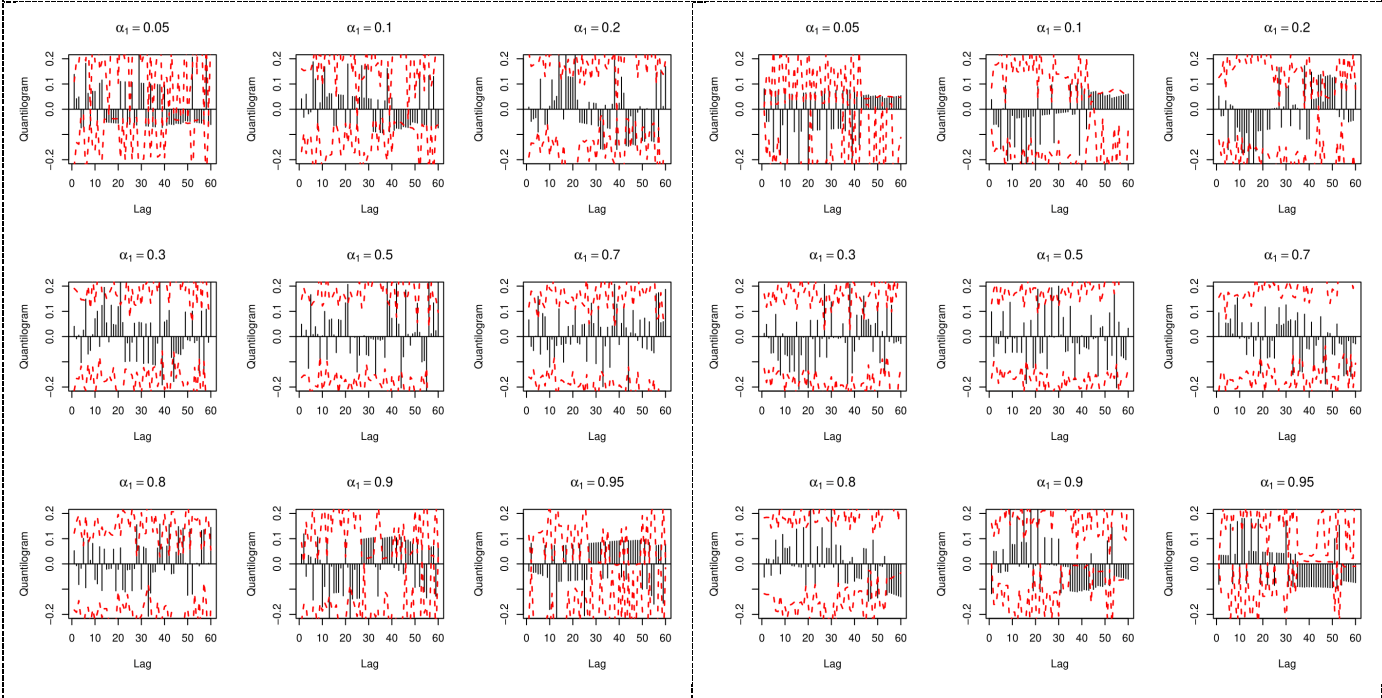
**Forestry products**



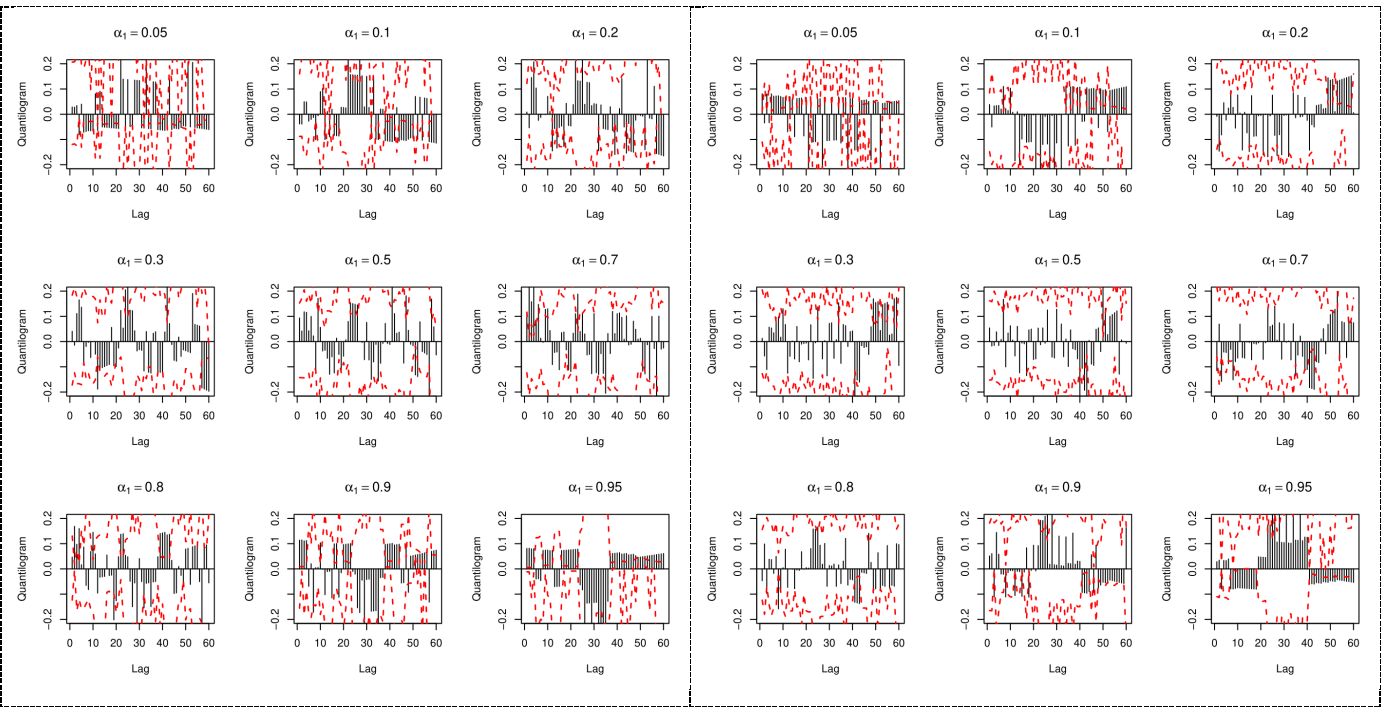
**Natural Gas**



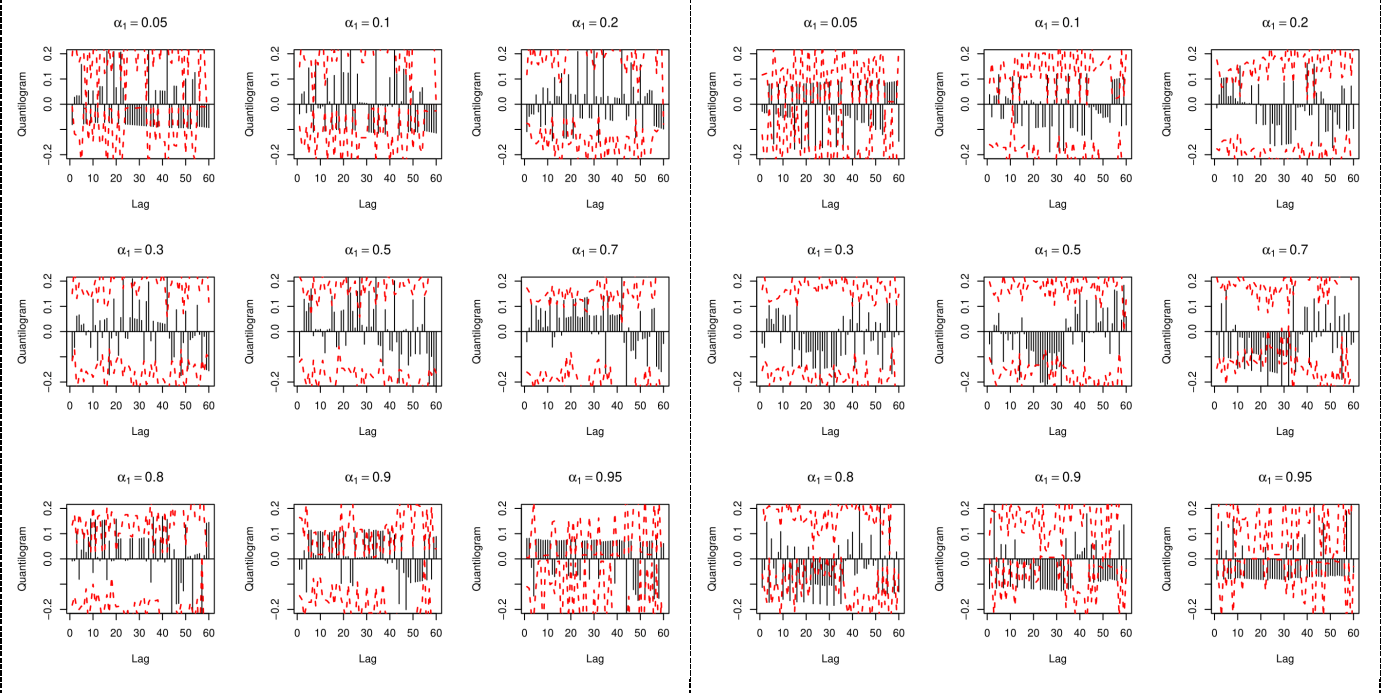
**Grains**



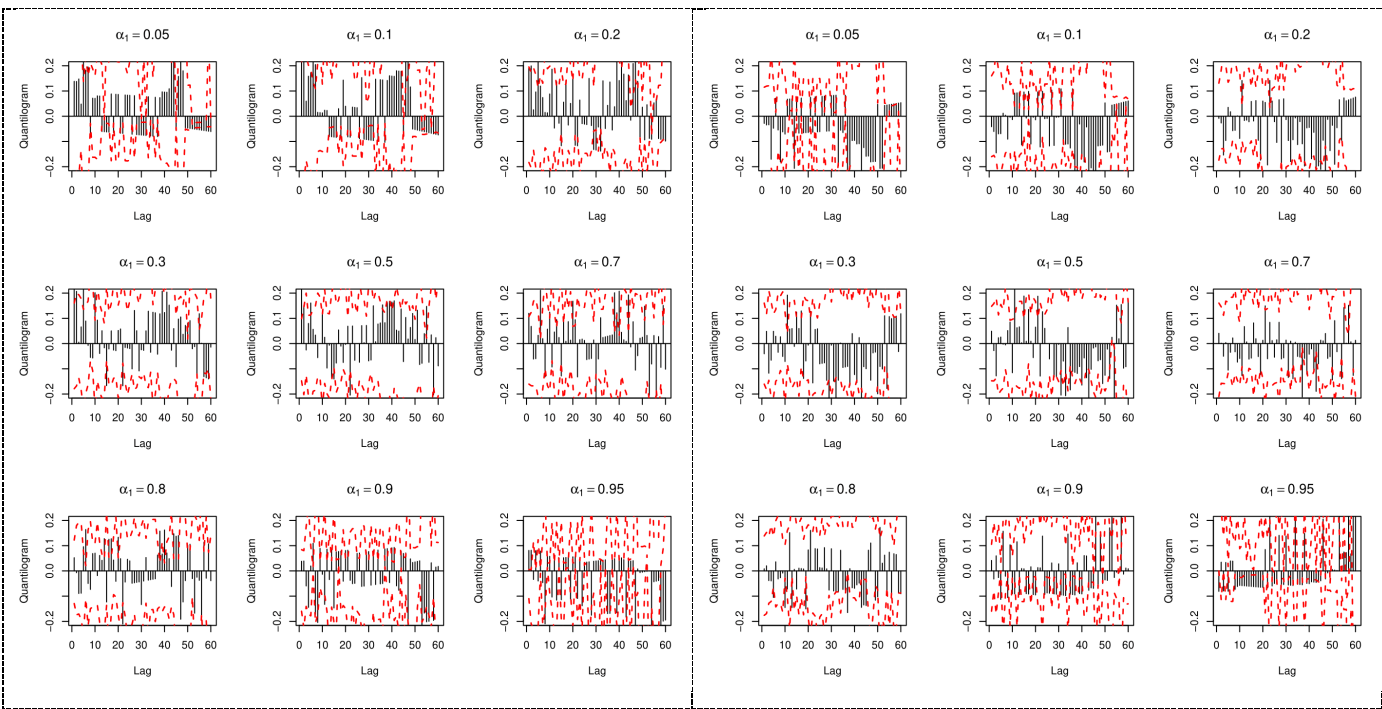
**Livestocks**



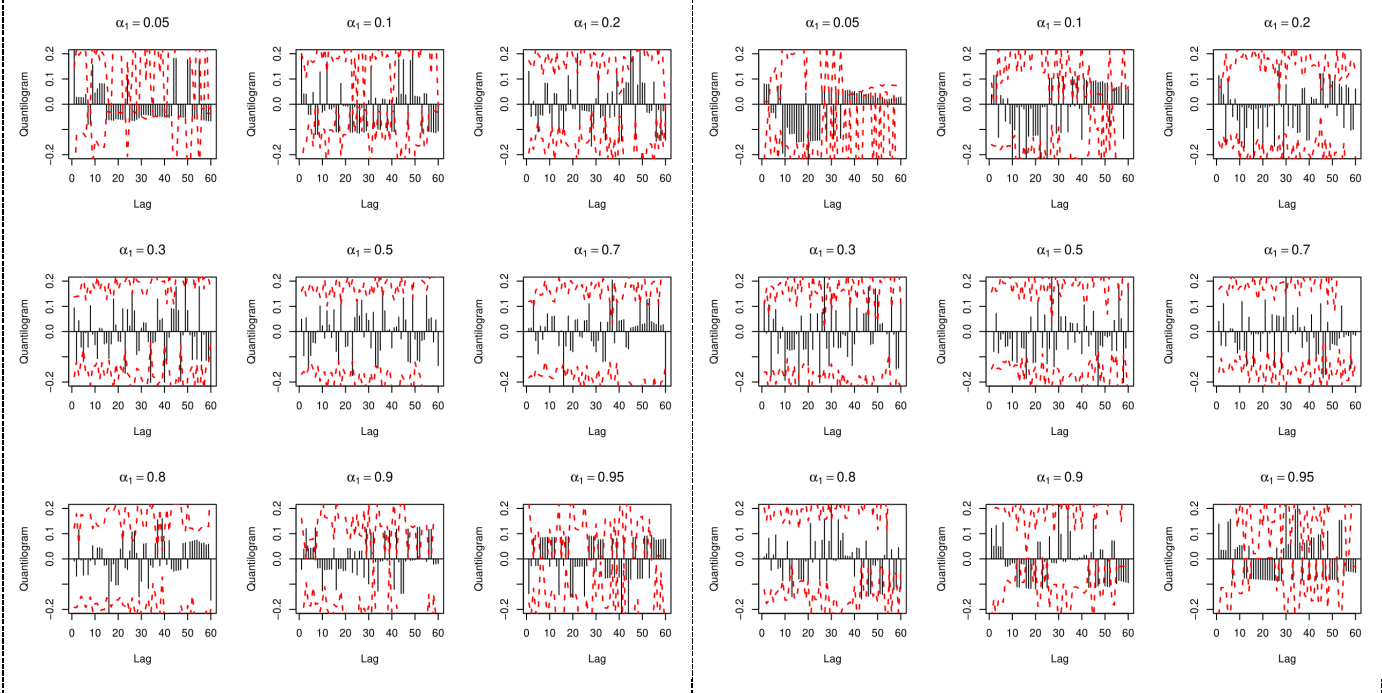
**Metals**



**Crude Oil**

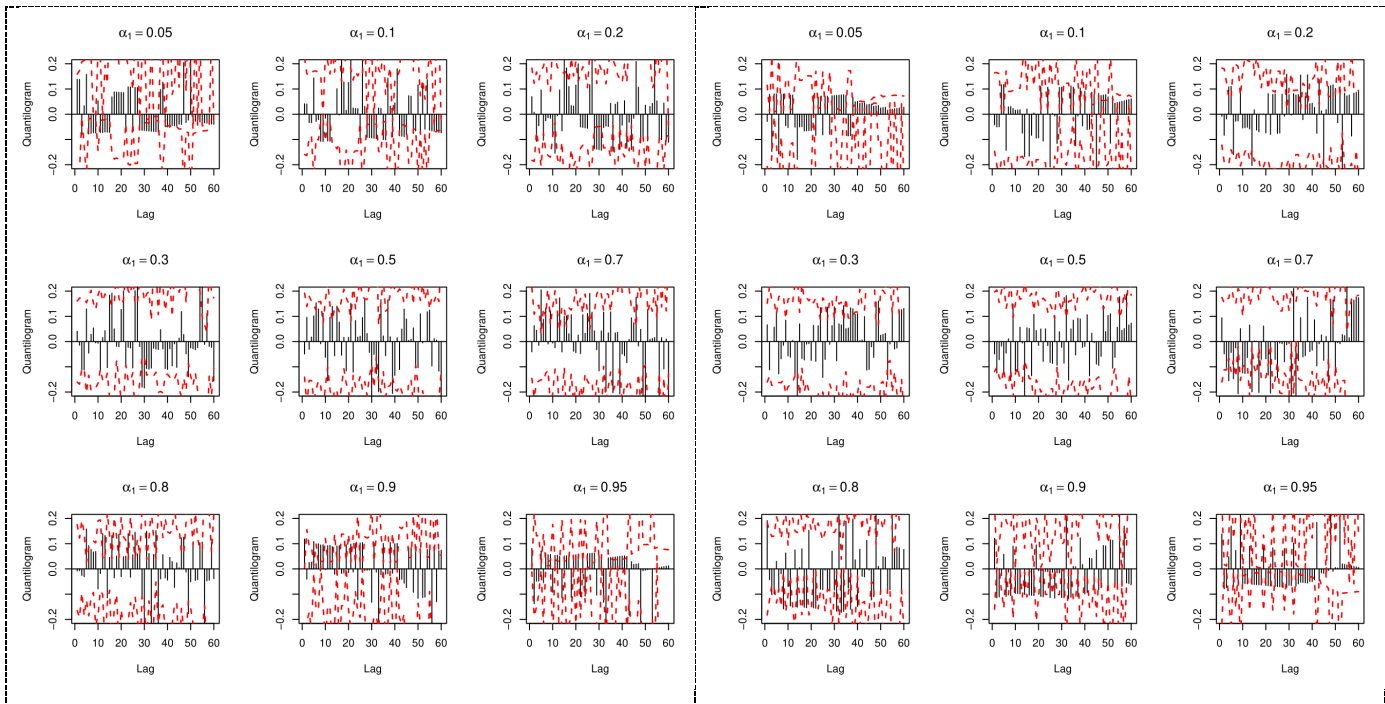


**Oil Seeds**

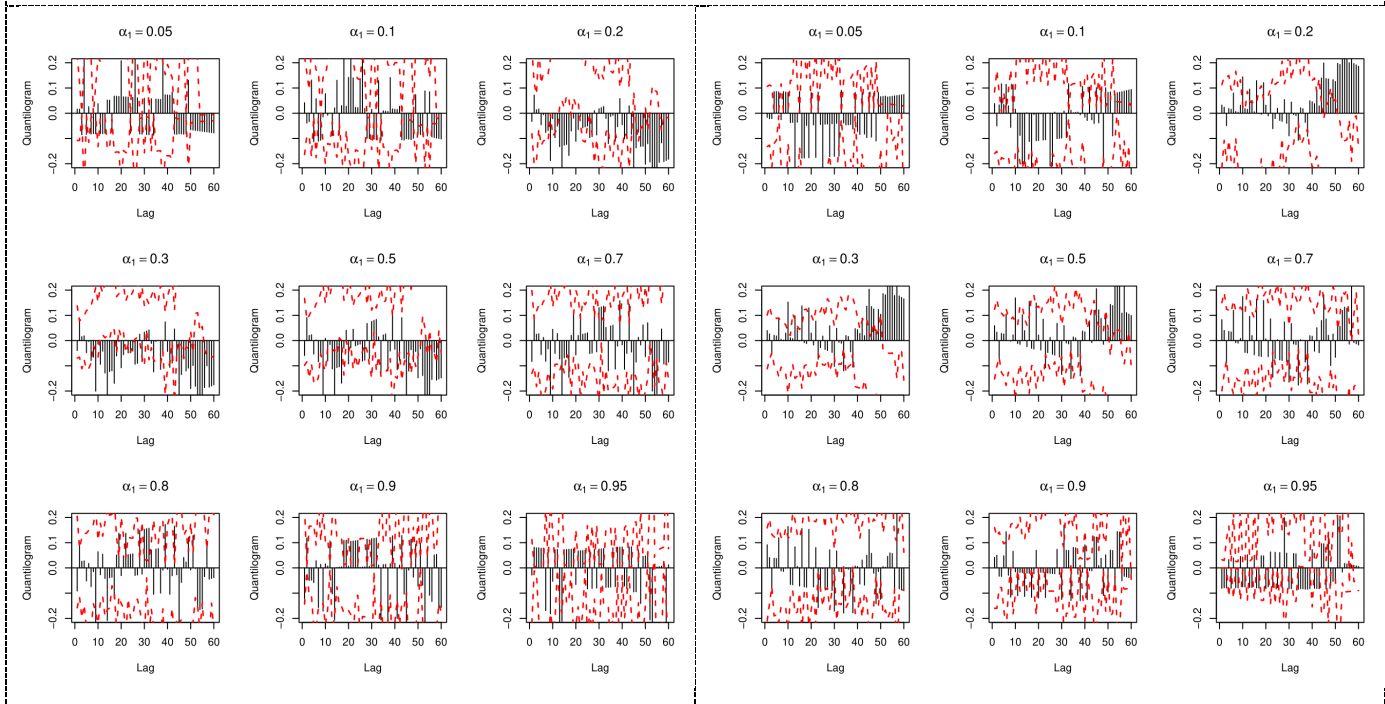


**Precious Metals**



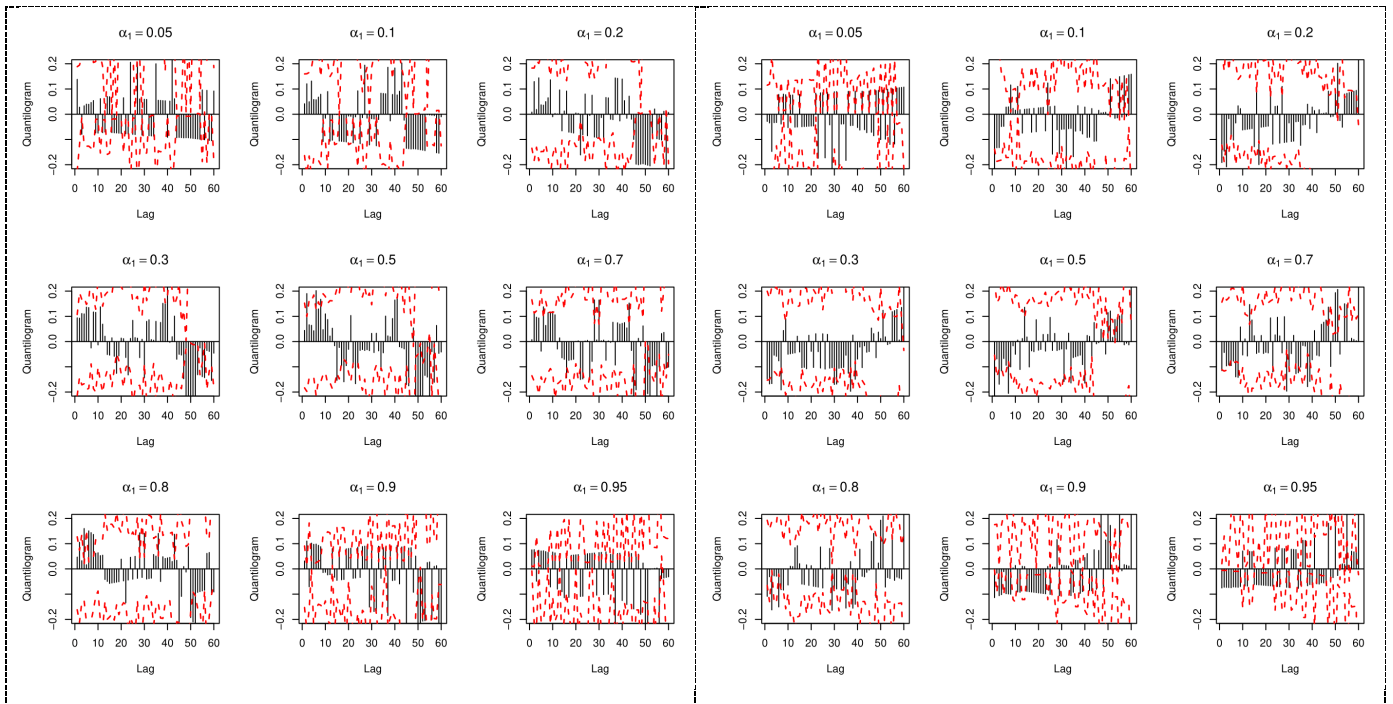


**Seeds**



**Semi-Conductors**





*Softs*

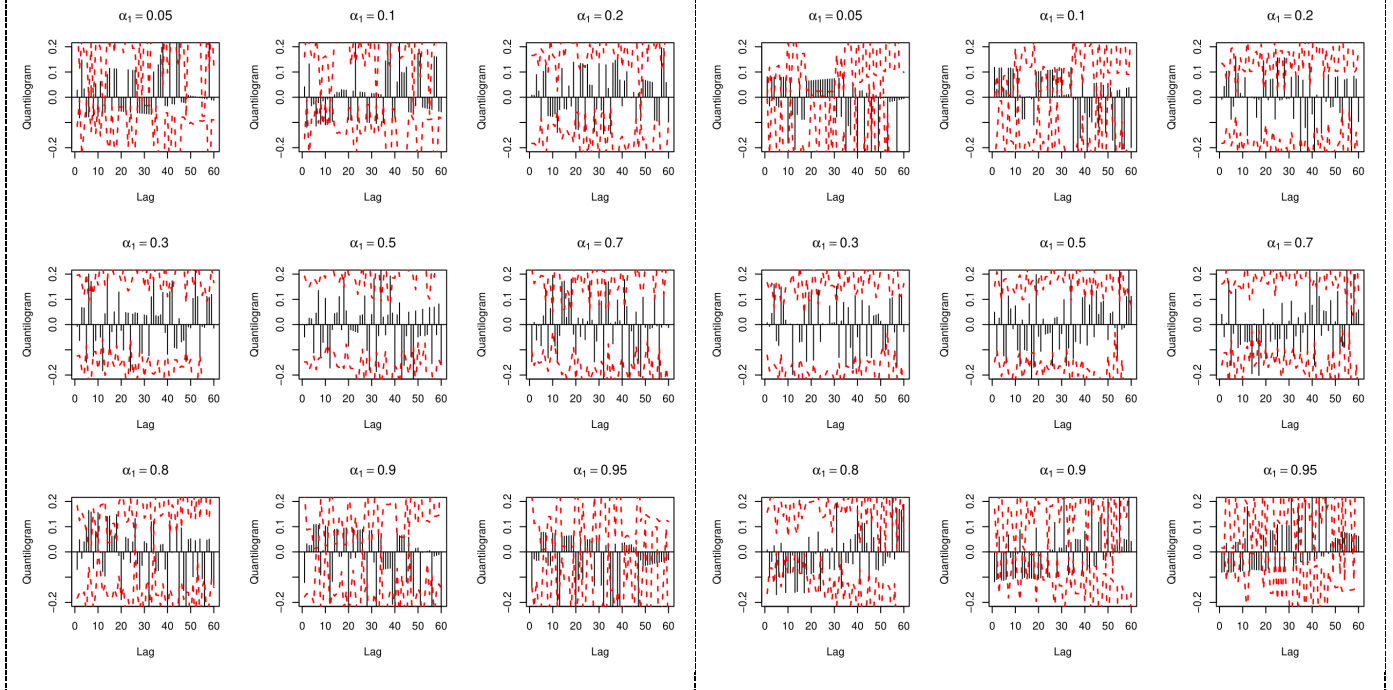


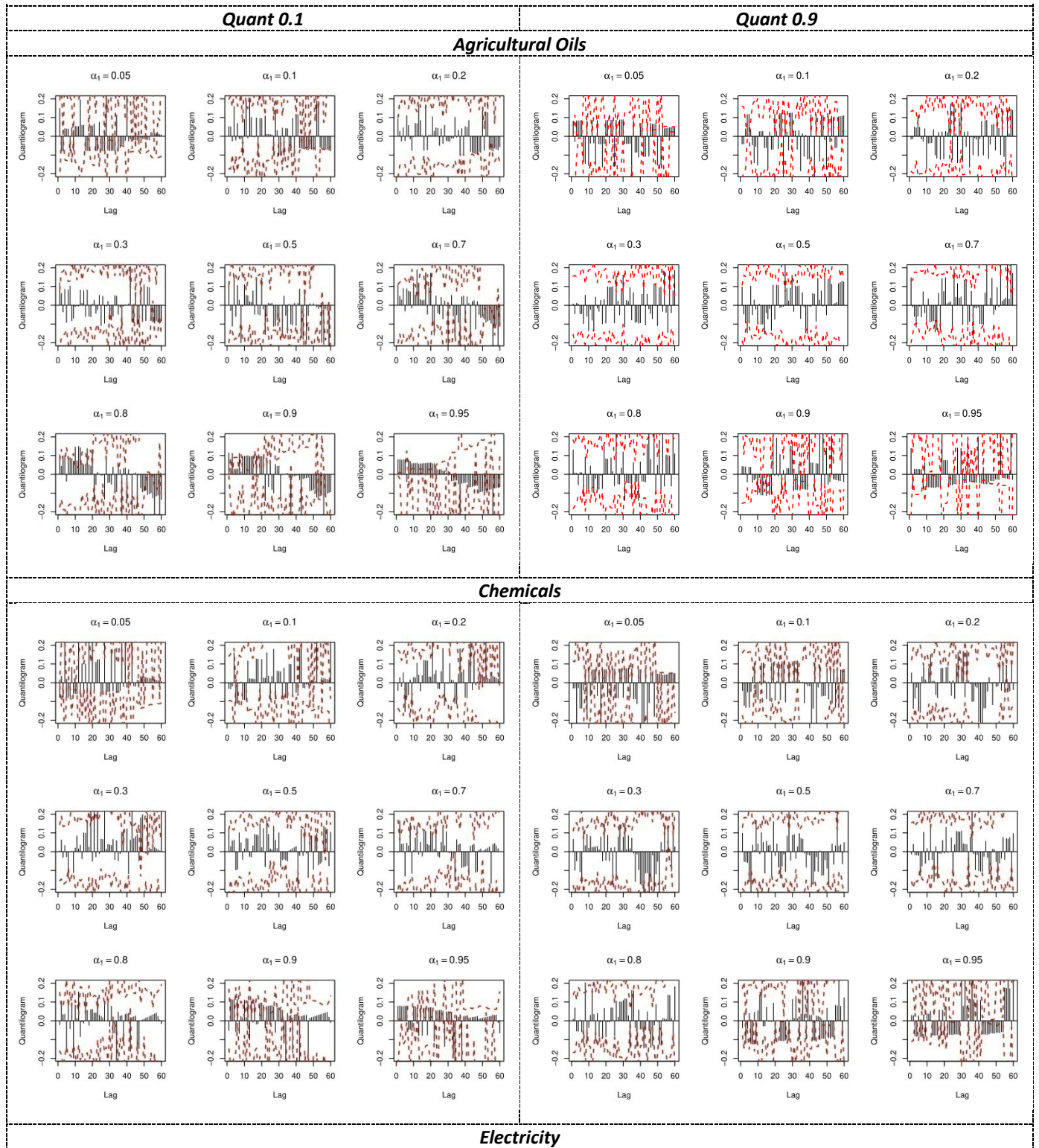
Figure 3 (a): – Ljung-Box test; Equities in the 0.1 quantile, BRICS Factor



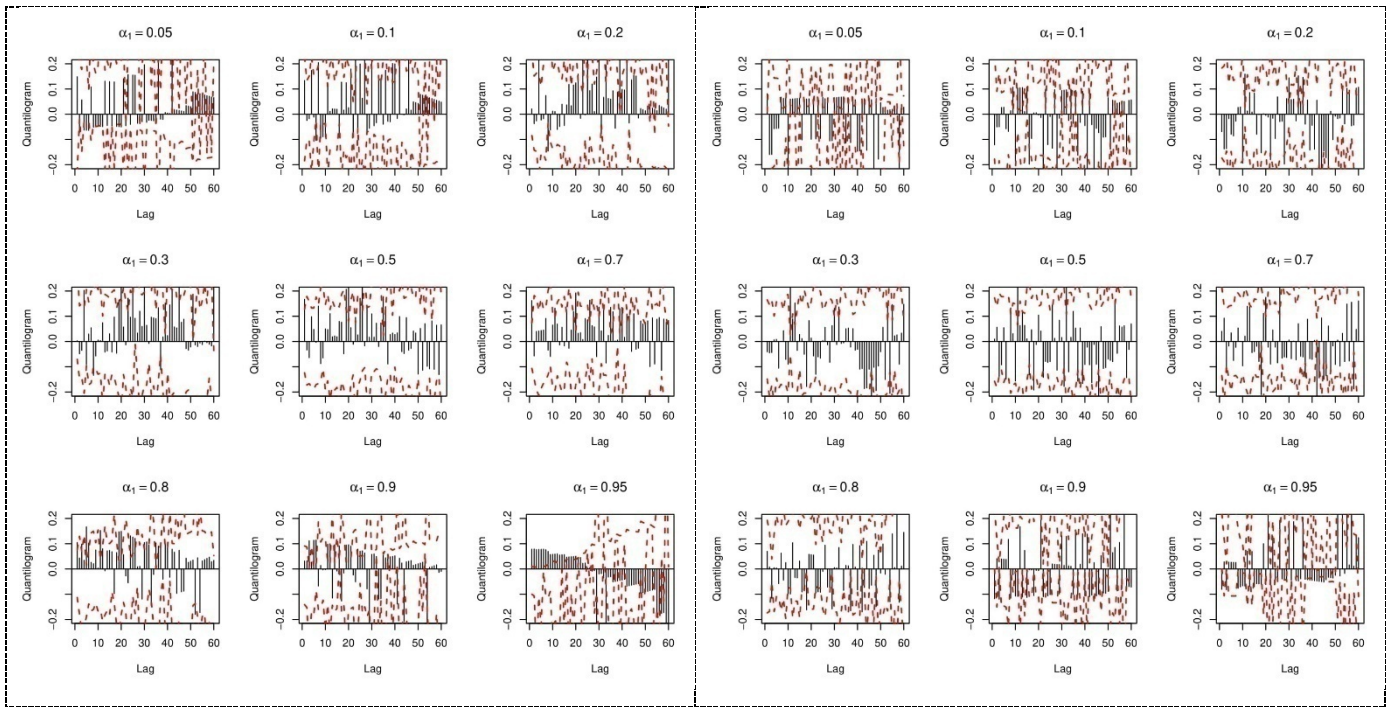
Figure 3 (b): – Ljung-Box test; Equities in the 0.9 quantile, BRICS Factor



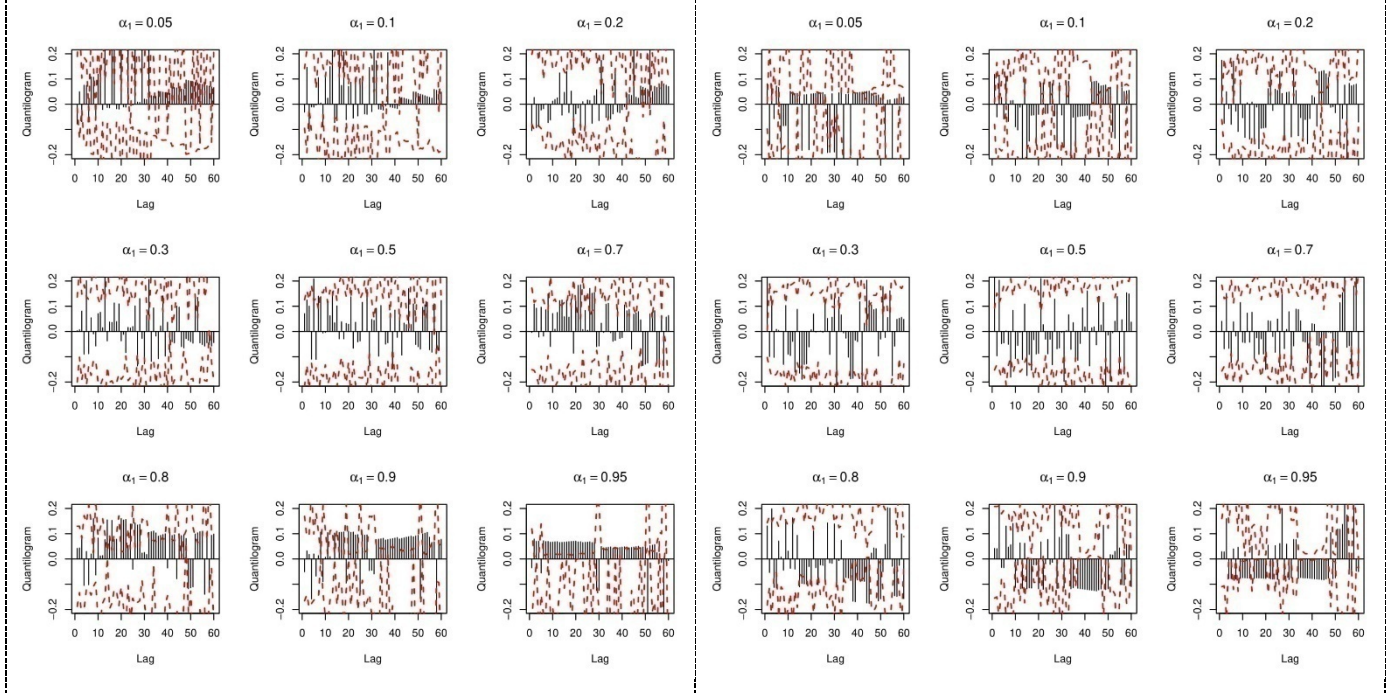
Figure 3 (c): – cross quantilegram for  $\tau_2 = 0.1$ , and for  $\tau_2 = 0.9$ , BRICS Factor



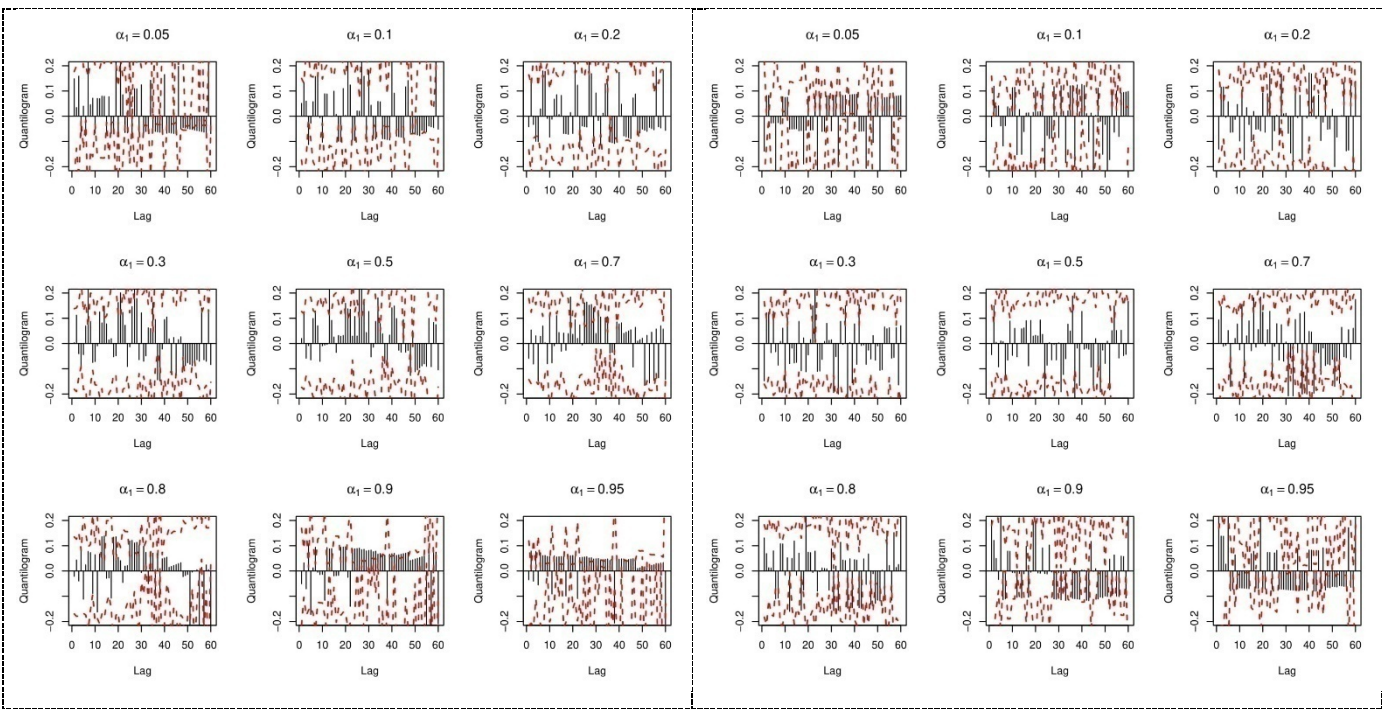




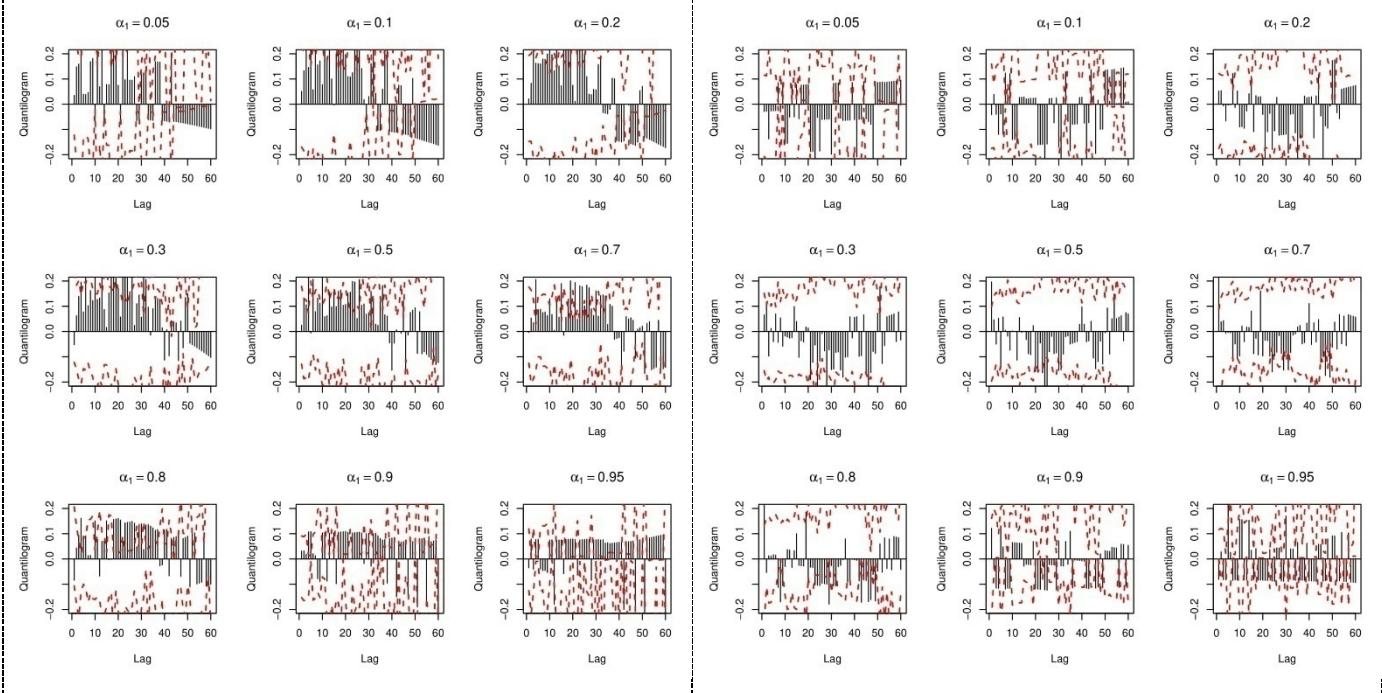
**Feeds**



**Fibers**

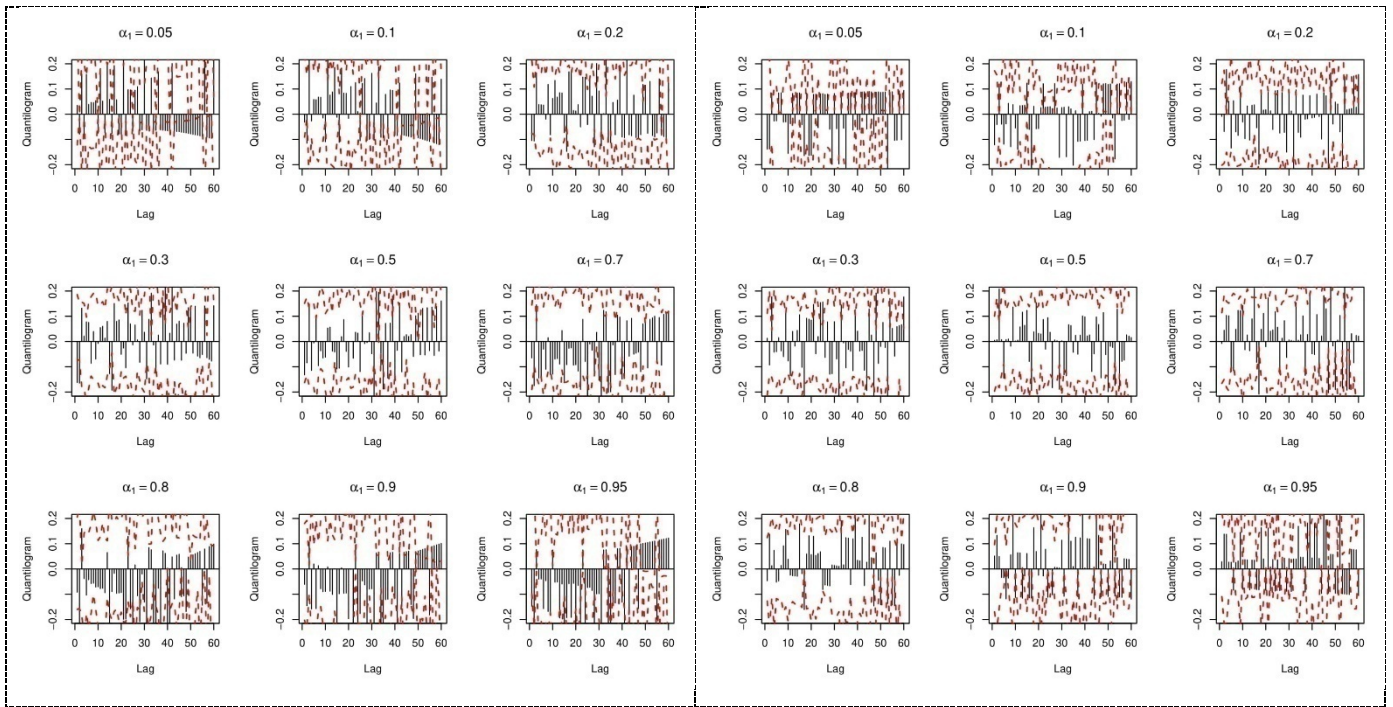


**Forestry products**

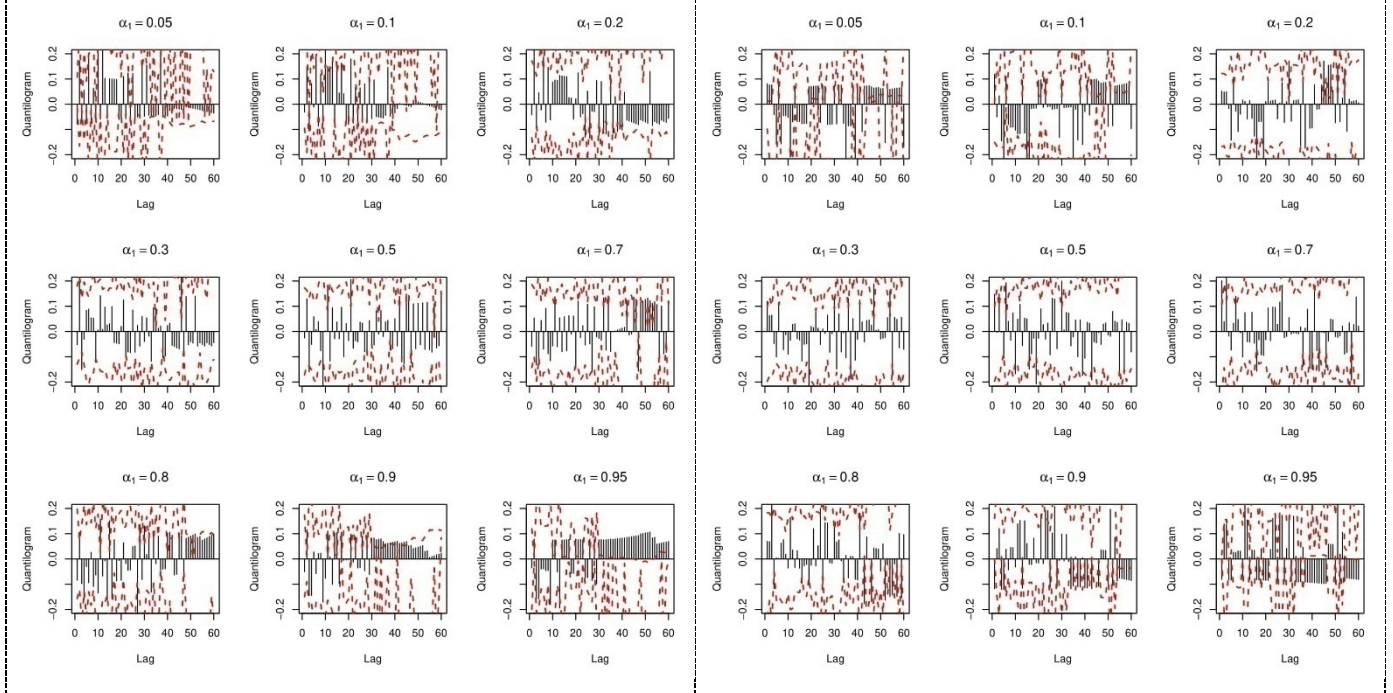


**Natural Gas**



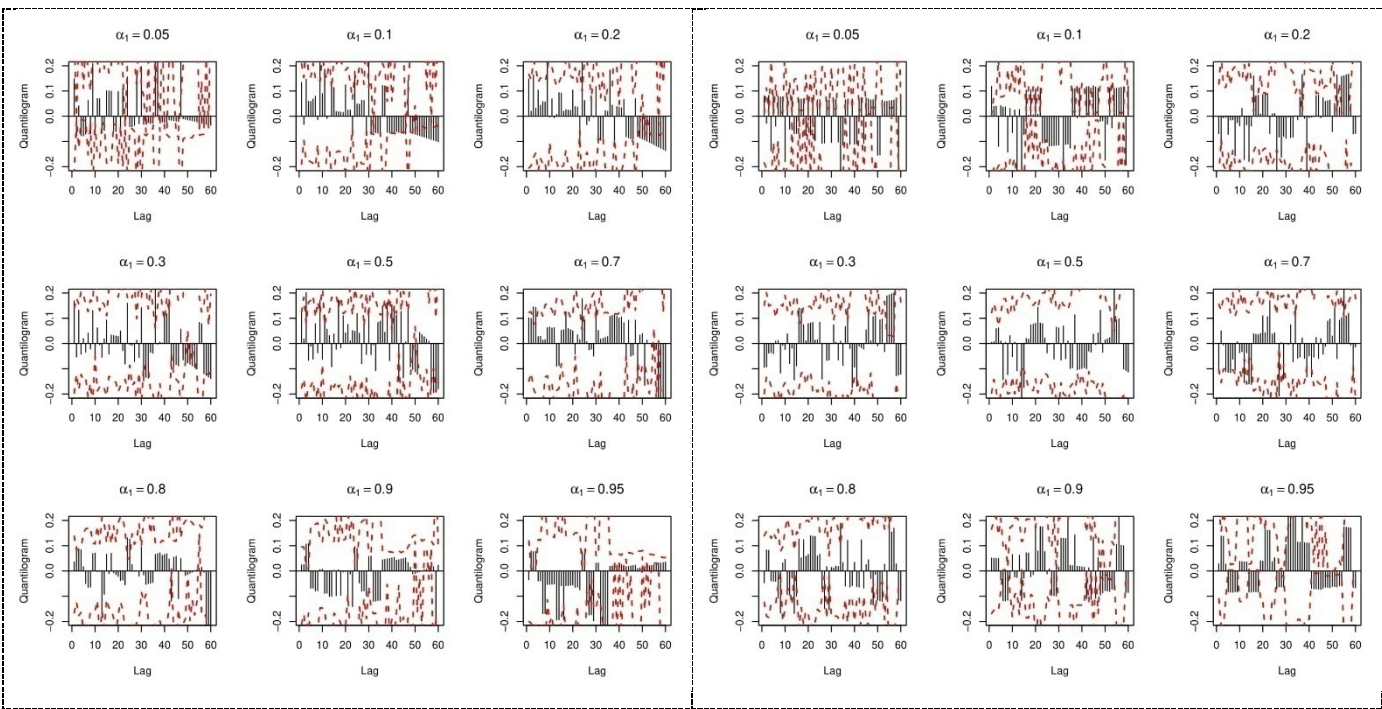


**Grains**

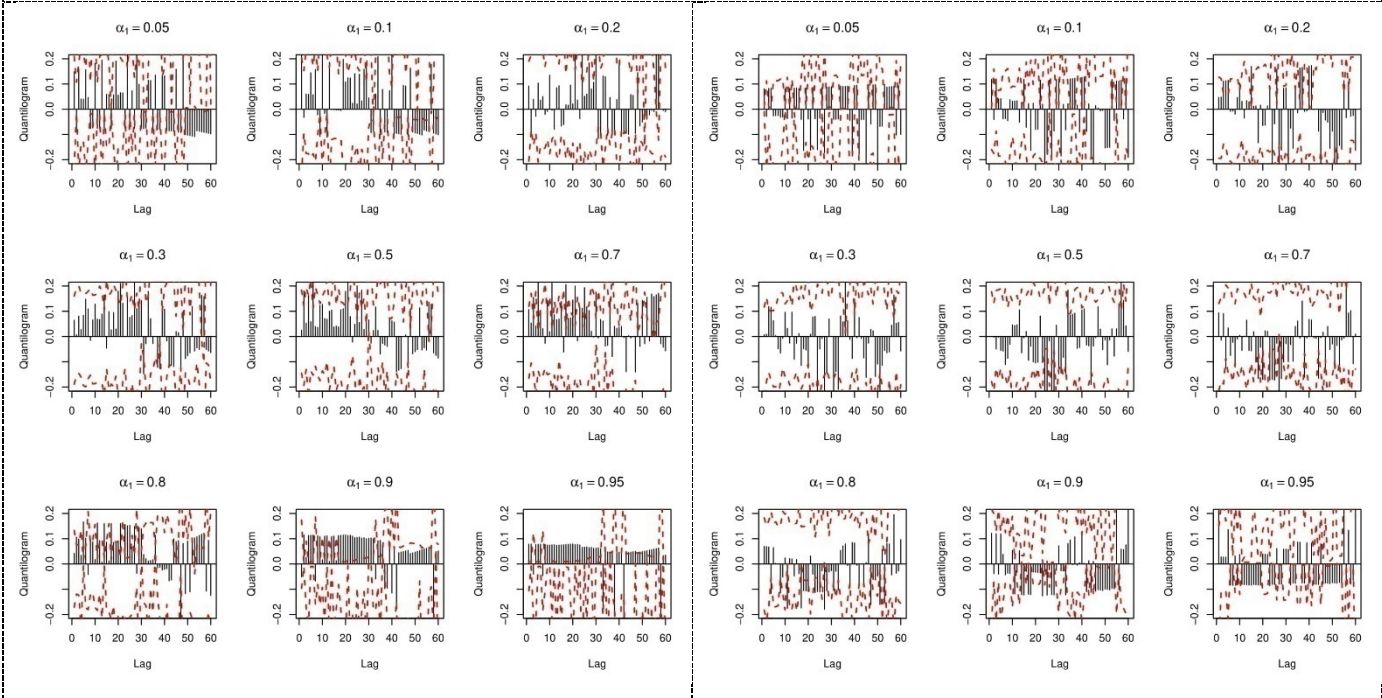


**Livestocks**

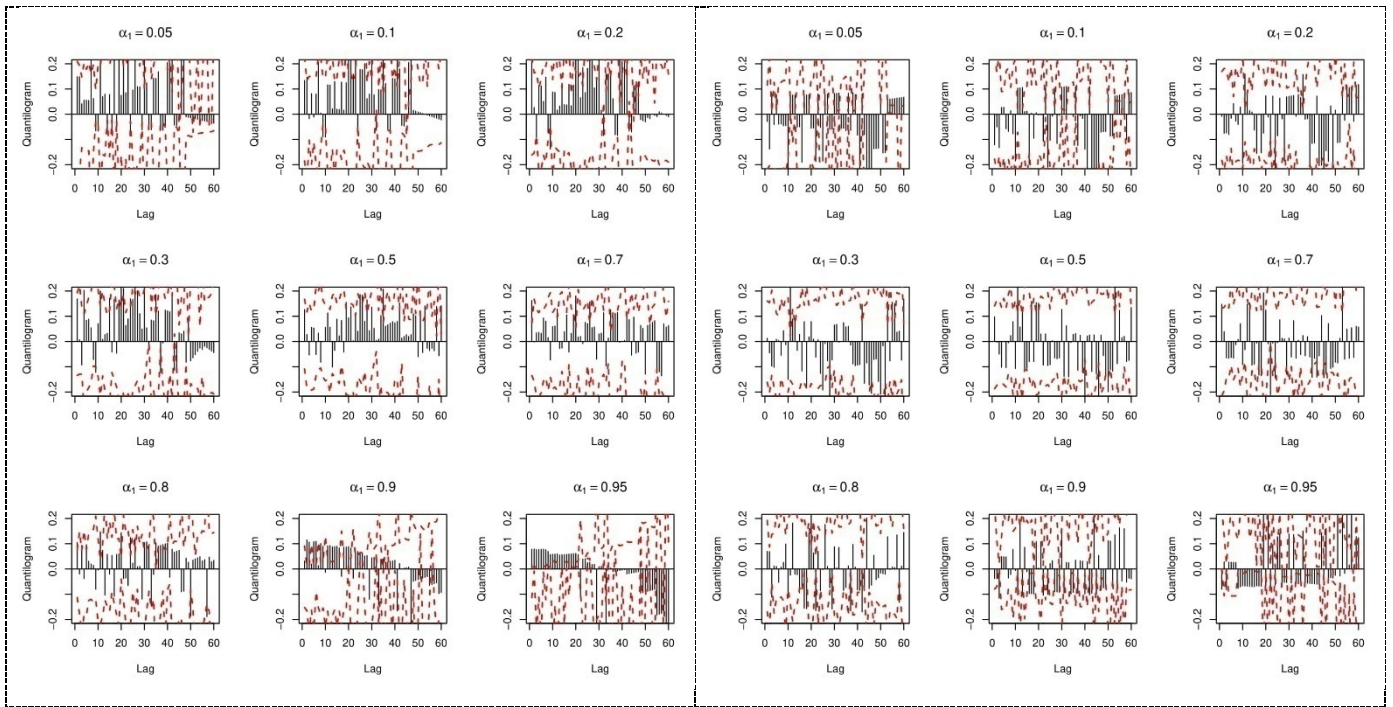




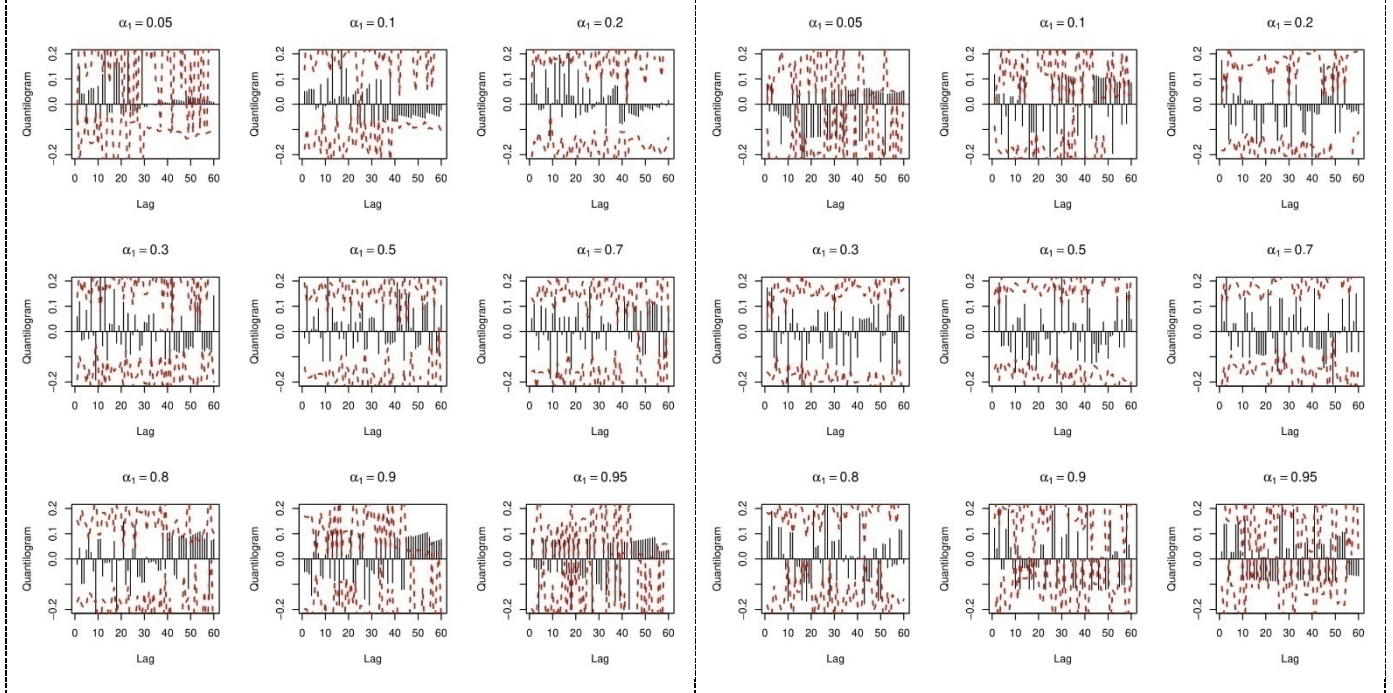
**Metals**



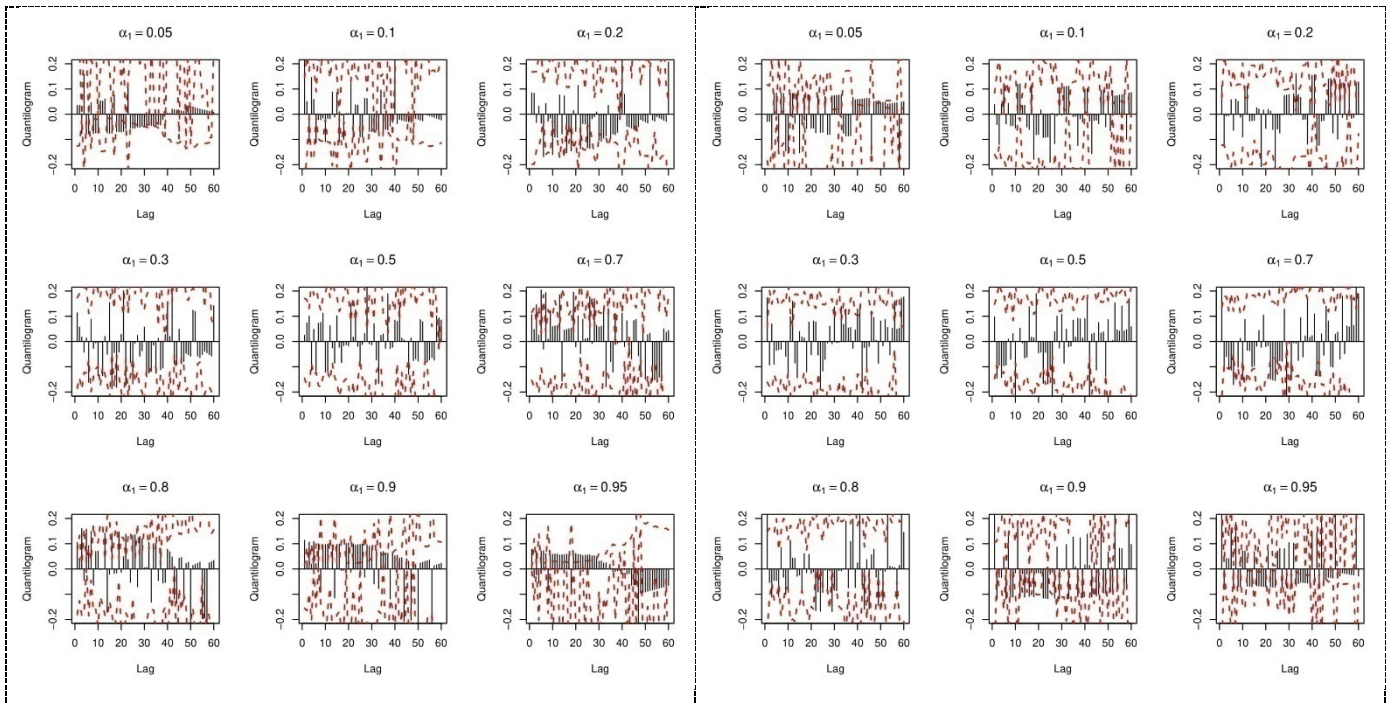
**Crude Oil**



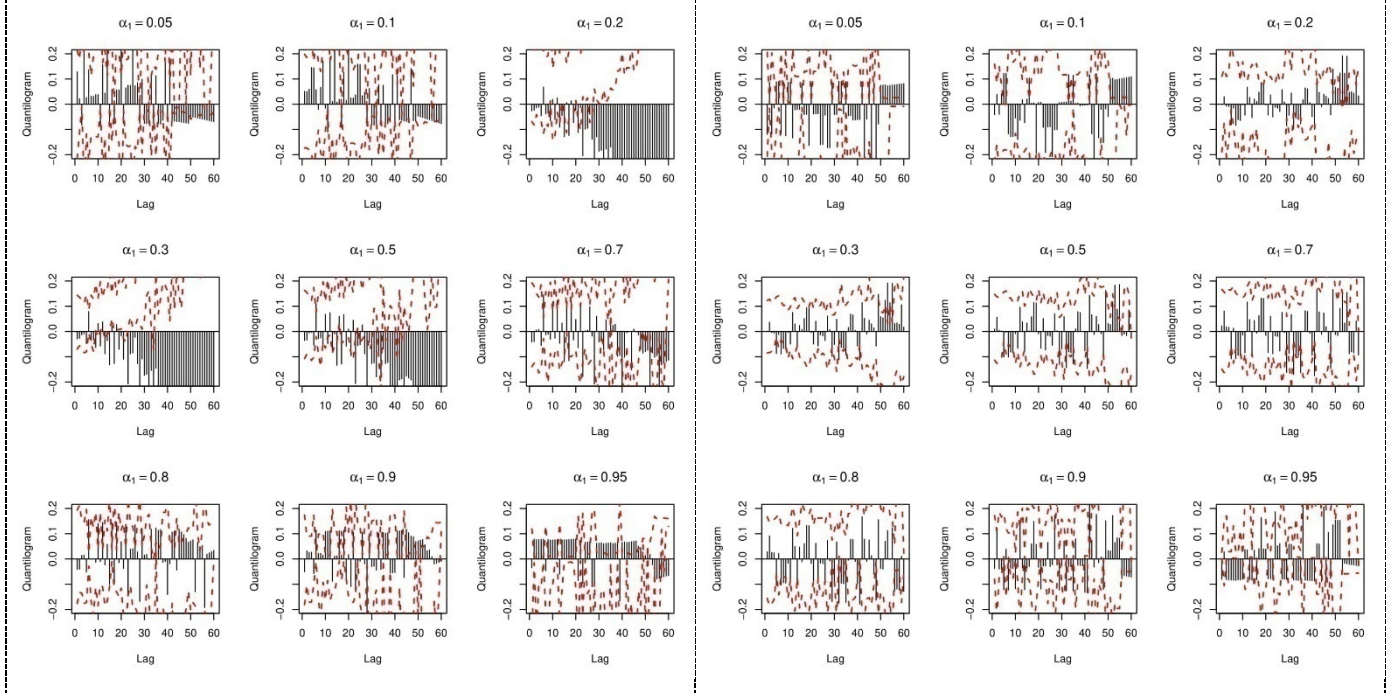
**Oil Seeds**



**Precious Metals**

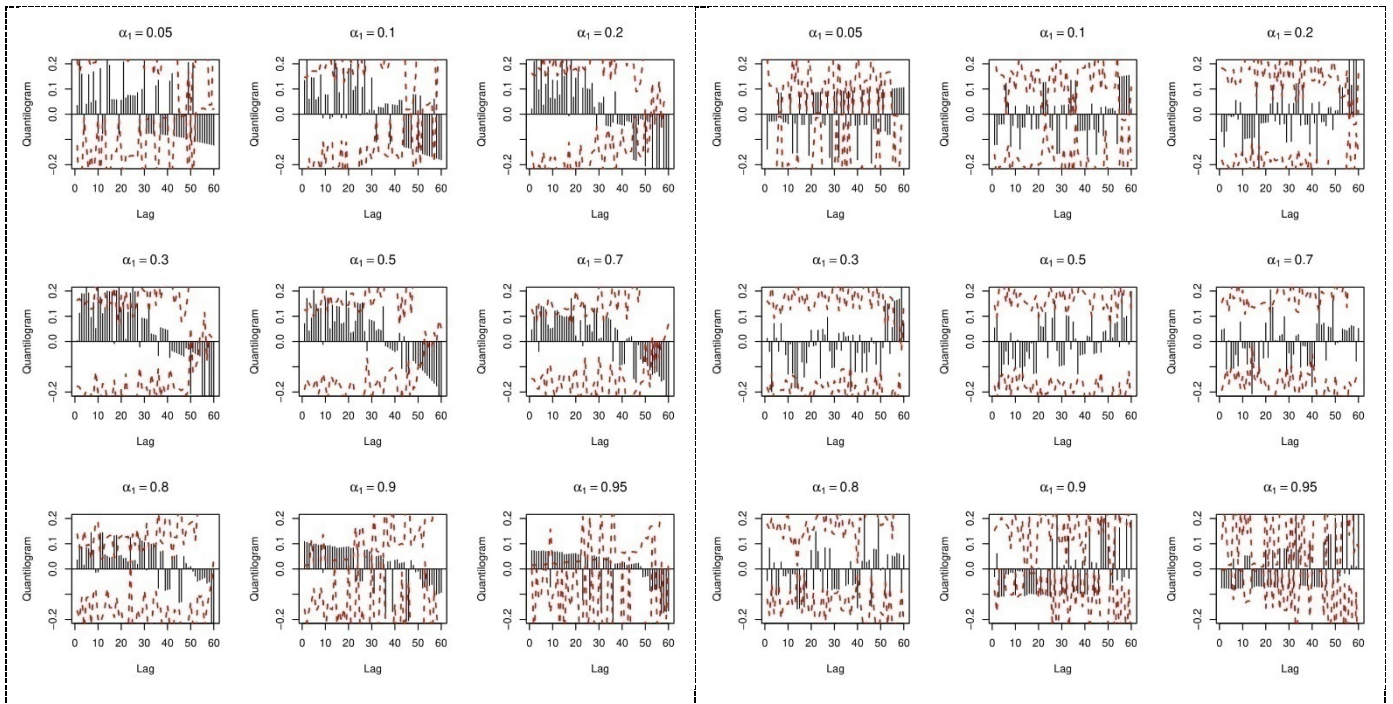


**Seeds**



**Semi-Conductors**





*Softs*

