Directional predictability from energy markets to exchange rates and stock markets in the Emerging market countries (E7+1): New evidence from cross-quantilogram approach

Aviral Kumar Tiwari,

Rajagiri Business School, Rajagiri Valley Campus, Kochi, India, email: aviral.eco@gmail.com

Muhammad Shahbaz,

Center for Energy and Environmental Policy Research, Beijing Institute of Technology, Beijing 100081, China, email: muhdshahbaz77@gmail.com

Rabeh Khalfaoui*,

College of Sciences and Humanities, Shaqra University, Saudi Arabia, email:rabeh.khalfaoui@gmail.com

Rizwan Ahmed,

University of Kent, Kent Business School

United Kingdom, email: r.ahmed@kent.ac.uk

Shawkat Hammoudeh

Lebow College of Business, Drexel University, Philadelphia, USA, E-mail: shawkat.hammoudeh@gmail.com

Abstract

We examine the directional predictability of energy stock returns on exchange rates and stock market in the E7+1 emerging market economies, which include India, China, Indonesia, South Korea, Turkey, Brazil, Mexico, and Russia, over the period 4 January 2000 to 31 May 2018. To achieve this, we carried out a cross-quantile analysis in the static and dynamic frameworks, using the bi-variate cross-quantilogram (CQ) and the partial cross-quantilogram (PCQ) approaches and a dynamic variant of such approaches. The predictability of the stock returns on the energy prices for WTI, Brent, OPEC, heating oil and natural gas is examined. Further relationships are also conditioned by using two measures of geopolitical risk, including the general geopolitical risk (GPRD), and the geopolitical risk threats (GPRD_Threat). The overall results highlight the importance of employing the partial cross-quantilogram approach in examining the predictability of different pairs of the energy prices, exchange rates and stock markets. They also indicate that controlling for GPRD and GPRD_Threat significantly improves the predictability of these variables. Policy implications of the empirical findings have been elaborated and discussed.

JEL classification: C58, G10, Q02

Keywords: Oil, Exchange rates; Emerging stock markets; Directional predictability; Cross-quantilogram.

1. Introduction

Quantile dependence methods have been a subject of increasing debate in economic and financial literature. Quantile dependence measures can examine and analyse non-linear dependence structures and can also deal with different outliers at different quantiles of the distribution. Appropriate to financial applications, the specific robust conditions that deal with the outliers have been a key feature of the debate, serving to develop the analysis further. For instance, Linton and Whang (2007) examined the diagnostic tool called the quantilogram test which considered the correlation between the quantile-hit processes. The univariate Linton and Whang (2007) study was extended by Han et al. (2016) who introduced the multivariate method of cross-quantilogram. Moreover, several frequency domain versions have also been highlighted in the literature (as a means?) to examine cross-quantilogram (e.g., Hagemann, 2011; Li, 2008 and 2012; Dette et al., 2015). The quantilogram aims to investigate the directional predictability, defined as a predictability that is observed through a magnitude that is economically meaningful. Thus, it can be exploited through appropriate trading strategies, and in addition, , it tests hypotheses on the assumption that a given time series has no directional predictability. This analysis is based on measuring the correlogram of quantile hits which can be used to identify the confidence intervals.

Directional predictability is able to forecast, so it can help in designing trading strategies as it can verify whether or not markets are efficient. In this paper, we are interested in the predictability of three major markets: the energy, foreign exchange and stock markets, which play a significant role in the overall economy. We are also concerned with determining the directional forecasting which is of interest to researchers, market participants and policymakers. A robust energy market may impact the overall economy and also this further impacts the directions of major domestic markets such the foreign exchange and stock markets, and consequently, trading strategies.

This study complements the earlier literature which tests predictability by adopting the sign and rank statistics (Cowles and Jones, 1937; Dufour et al., 1998; Christoffersen and Diebold, 2002). More specifically, it investigates the energy (market's?) directional predictability of the return series of the exchange rates and the stock markets in the E7+1 emerging economies,[1] which consists of India, China, Indonesia, South Korea, Turkey, Brazil, Mexico and Russia. The motivation for the selection of the E7+1 economies are as follows. First, these countries have high economic growth rates and are likely to become developed economies in the mid/long term. Second, they also have a unique risk profile in currency exchange rates due to the high demand for their foreign currencies and a shortage in their supplies, which results in an appreciation of their exchange rates. Third, in comparison with developed economies they have lower per capita incomes associated with a high variation in consumption performance,; however, they maintain greater potential for economic growth. Fourth, their level of transparency, market regulations and overall operational efficiency remain in development stage and are likely to improve in the future. Finally, they have unique overall economic and political conditions which are stabilising over time.

Our paper extends existing research in three unique areas. First, it is unique in analysing the directional predictability of exchange rates and stock markets in those E7+1 emerging stock markets through providing new evidence from the cross-quantilogram approach. Second, it employs the recent methodology of cross-quantilogram measuring quantile dependence and tests directional predictability between the time series following Han et al. (2016). Thus, it aims to obtain robust findings for the directional predictability in the E7 + 1 context. Third, it measures the cross-quantile analysis in the static and dynamic frameworks by using the bi-variate cross-quantilogram (CQ) and the partial cross-quantilogram (PCQ) approaches and applying the dynamic variants of those approaches. Our predictability of the series is measured through the energy price series of WTI, Brent, OPEC basket, heating oil and natural gas. Additionally, the relationship is conditioned on using two measures of geopolitical risk including the general geopolitical risk (GPRD), and

[1] The term E 7 was coined by economists, John Hawksworth and Gordon Cookson, at PricewaterhouseCoopers in 2006.

geopolitical risk threats (GPRD_Threat). GPRD is related to several geopolitical events, such as wars, terrorist acts, and conflicts between states (Caldara and Iacoviello, 2018). The geopolitical risk index is divided into two subindexes: the geopolitical threat index and the geopolitical acts index. The geopolitical threat index measures the direct effect of geopolitical events, and the geopolitical acts index assesses the pure effect of geopolitical risks. This study adds to the existing literature by applying the cross-quantilogram and partial cross-quantilogram approaches of Han et al. (2016) to examine the directional predictability for the different oil-based pairs: the oil prices-exchange rates, oil prices-stock indices, and oil prices and other energy prices.

We have considered three different crude oil types which are the WTI, Brent and OPEC basket, in pairs, along with the exchange rates and stock returns of the E7 +1 countries. We have also included three other forms of energy such as heating oil, natural gas and Dubai. The main purpose is to examine the transmission mechanism and directional predictability pattern between oil, exchange rates, stocks and other energy resources during the process of normal and unpredictable market scenarios as well as over quantiles.

The results are explained in four time intervals; daily, weekly, monthly and yearly lags, i.e., 1, 5, 22 and 66 lags. Moreover, the cross-quantile correlation coefficients are shown in the heatmap form. In every heatmap, the x-axis denotes the quantiles for oil (WTI, Brent, or OPEC) returns, while the y-axis indicates the quantiles of the exchange rates, stocks and other energy returns individually.

We consider the advantages of examining the directional predictability through the quantilogram test methodology based on the following considerations. First, the quantilogram test is therotically appealing and easy to understand and interpret. Second, this test is developed on the quantile hits, and therefore the moment conditions such as the ordinary correlogram and the variance ratio are not required to implement (e.g., Mikosch and Starica, 2000). As a result, it works well on the fat tails of the financial data. (e.g., Mandelbrot, 1963; Fama, 1965; Embrechts et al., 1997; Rachev and Mittnik, 2000; Ibragimov et al., 2009; Ibragimov, 2009). Third, the test also provides researchers with tools to measure long lags, which comes in contrast with the conventional regression techniques (Engle and Manganelli, 2004).

Cross-quantilogram is economically significant for two primary reasons. First, the cross-quantilogram approach determines the relationship between the different pairs by considering all measures of distributions which includes, for example, the central, extreme negative and extreme positive events and, therefore, it provides a comprehensive dependence structure between the pairs in the quantiles. Second, it provides simplicity which helps examine the lead-lag relationship between the pairs in the granger causality at different lags and quantiles (Baumohl and Lyocsa, 2017). In this paper, we estimate the cross-quantile correlation across diverse lag lengths and the results are shown in heatmaps.

There are several motivations for selecting the E7+1 markets in this paper. First, these countries are currently extending their awareness with regard to global warming and climate change. Moreover, they are working to achieve sustainable economic growth, including upgrading the efficiency of their energy consumption. Second, E7+1 countries are keen to promote their carbon emission reduction strategies obtained through the adoption of alternative renewable resources. Finally, E7+1 countries have rapidly growing economies in comparison with the overall global economy. For example, E7 + 1 countries are planning to increase their GDP from 35% to 50% of the global GDP by 2050. Therefore, sustainable energy measures would be effective in achieving these goals.

Theoretically, the evidence exists for the directional predictability between energy stock returns and the returns series of exchange rates and stock markets. First, most energy prices are priced in US dollars. When the dollar strengthens, those energy prices expressed in domestic currencies would spike, which in turn affects the costs of production for goods and services in almost all economic sectors. Consequently, corporate earnings and stock prices would suffer. On the other hand, higher energy prices depress aggregate demand, which leads to higher rates of inflation and/or a weakening of the economy and softer exchange rates. Empirically, oil prices in the last decade have shown a sharp volatility of prices which coincided with a closer relationship between those prices on one hand and the stock prices and exchange rates on the other hand. The empirical research has highlighted a strong negative correlation between the spot oil prices and the US dollar exchange rate since the early 2000s. The literature also elaborates on the relationship between oil prices and the individual markets for financial assets. For instance, Killian and Park (2009) illustrated that oil prices affect individual asset prices on a monthly frequency data for the US stock markets. Moreover, according to Chen, Rogoff and Rossi (2009), the currency values of commodity exports, such as oil, contain information about the future price movements of commodities, while commodity prices, such as the oil price, also have a predictive influence on commodity currencies in at least high data frequencies.

Our findings illustrate that the partial cross-quantilogram approach demonstrates a statistical significance of the results and indicates that the inclusion of the general GPRD and GPRD_Threat variables meaningfully improves the predictability of diverse pairs of energy prices, exchange rates and stock markets. It also shows that the presence of GPRD and GPRD_Threat significantly improves the predictability of these variables.

Specifically, we examine the cross-quantile analysis in static and dynamic frameworks using the bi-variate cross-quantilogram and the partial cross-quantilogram approaches. The overall results show that after controlling for GPRD_Threat, there exists an increase in the degree of dependence between the WTI and exchange rates, and the influence of WTI persists until 66 lags. Out of all the analysed exchange rates, the dependence between the WTI-exchange rate pair is significantly negative over all quantiles, while the relationship between the exchange rates of Turkey, Mexico and Brazil are found to be more strongly positively dependent. Further, the results on predictability for the stock returns suggest a more pronounced and persistent positive connection for oil (WTI) with all stocks and exchange rates, and in all cases after controlling for GPRD_Threat, thus highlighting that controlling for GPRD_Threat leads to a clearer transmission mechanism for investors, market deciders and hedgers. These findings are also confirmed by controlling for GPRD, which exhibits a strong significant directional predictability of the stock and exchange rates originating from the oil prices (the only exception being the Turkish stock market returns).

The remainder of this paper is organised as follows: Section 2 presents the literature review. Section 3 provides the quantile-based methodologies including the cross-quantilogram and the partial cross-quantilogram approaches to deal with directional predictability. Section 4 sets out and elaborates upon the results. Section 5 concludes with valuable policy implications.

2. Literature review

In the existing literature, there is evidence of either extending or applying the CQ methodology. Davis and Mikosch (2009), for example, applied an analog of autocorrelation function, the extremogram, and showed that this application fits only with the extreme values in a particular sequence. Moreover, they also examined the natural estimator for the extremogram and explained the properties of the asymptotic under α-mixing. Davis et al. (2012) extended the study of Davis and Mikosch (2009), highlighting the development of reliable confidence bands for the extremogram by. adopting a stationary bootstrap methodology for the extremogram through several time series analyses. Davis et al. (2013) presented their study in two ways. First, they studied classical and current methods of serial extremal dependence in a strictly stationary time series as well as their (own time?) estimation. Second, they examined recent models of heavy-tailed time series, which reflects regular variations and max stable processes. They have used the measure of extremogram to max-stable processes and applied an estimation of the extremogram in time and frequency areas.

Li (2008) introduced a unique type of periodogram known as the Laplace periodogram by substituting the least squares with the least absolute deviations in a harmonic regression, which produced the periodogram of a time series. Li further highlighted that asymptotic analysis indicates a relationship between the Laplace periodogram and the zero-crossing spectrum. Therefore, this paper argues that the use of the Laplace periodogram stands as a nonparametric instrument for examining the serial dependence of the time series data. Moreover, the Laplace periodogram has the advantage of handling heavy-tailed noises and nonlinear biases through simulations. Li (2012) established that quantile periodograms developed from the trigonometric quantile regression are influenced by different interpretations of the ordinary periodogram. Li (2012), therefore, demonstrated a relationship between the quantile periodograms and the level crossing spectrum via asymptotic analysis.

Moreover, Hong (2000) applied the Fourier domain method to measure the statistics constructed on the distributions. The Fourier domain method was also adopted by Hagemann (2013) and Dette et al. (2015). Laurini et al. (2008) used the quantilogram methodology to investigate the microstructure for the BRL/US$ exchange rate market by examining high frequency bid and ask quote data. Moreover, they also used the quantilogram and quantile autoregression to measures the asymmetry effects.

Similarly, Chang and Shie (2011) applied the quantile regression method to the Taiwan stock market. Their empirical evidence shows a positive association between the relative order imbalance and the intraday future returns. They also indicated that the positive association is relatively stronger for the lower level of intraday quantiles of the future stock market returns than for the higher quantiles. Their results further indicate a compensation for uncertainty and a lack of liquidity for the relatively lower returns into the Taiwan future stock market.

In more recent applications of the Cross-quantilogram methodology, Jiang et al. (2016) proposed spillovers and directional predictability with the cross-quantilogram analysis. They studied the US and Chinese agricultural futures markets. The findings indicate a significant bi-directional dependency among these two markets, through commodities, for which the dependency is higher in the lower and upper quantiles and larger from the United States to China. Using a cross-quantilogram analysis, of Baumohl and Lyocsa (2017) studied the directional predictability from the stock market sector indices to gold. They showed that the pre- and post- global financial crisis periods have a limited quantile dependence, and that gold can be considered as a safe haven for most companies, except those in the industrial sector.

Using the directional predictability of intraday stocks in Australia, Todorova (2017) utilised a cross-quantilogram analysis and found the presence of bad news in intraday reversals after the overnight periods. However, the results of the short-term reactions to very positive overnight returns were mixed. Su et al. (2017) studied the quantile serial dependence in crude oil markets through a quantilogram analysis with quantile wild bootstrapping and documented that WTI and Brent are serially dependent in all quantiles, except the median quantile.

In a recent study, Uddin et al. (2019) examined the cross-quantilogram-based correlation and the dependence between renewable energy stock and other asset classes. They identified that renewable energy stock returns provide a positive impact on the switching in the prices of oil and the overall stock market. Further, the connection is asymmetric through the quantiles and is greater in the coarser lags. Another study based on the directional predictability of oil volatility for stock returns was implemented by Zhou et al. (2018). This study documented directional predictability among the BRICS countries using cross-quantilogram analysis. The empirical results indicated that oil volatility has a directional predictability for stock returns in BRICS countries.

To conclude the literature review, the results on directional predictability between exchange rates and stock markets are found to be mixed at best. The implementation of a narrowly defined directional predictability between exchange rates and stock markets for E7+1 countries, through cross quantilogram and partial cross-quantilogram analysis, is unique in our current paper. Therefore, our paper contributes to the existing literature by analysing the predictability to time series of energy series, (i.e., WTI, Brent, OPEC, heating oil and natural gas) of the foreign exchange and stock markets, and examining the relationship using two measures of geopolitical risk, namely GPRD, and GPRD_Threat, which is not researched in the literature.

3. Quantile-based methodologies

This section describes the methods implemented in the study to examine the nonlinear interconnection and directional predictability among the considered variables in a pairwise manner. The novel frameworks utilised for the purposes of this study are the cross-quantilogram (CQ) and the partial cross-quantilogram (PCQ) of Han et al. (2016) as follows.

3.1. The cross-quantilogram approach

In order to study the asymmetric dependence and to evaluate the directional predictability of the used variables in several quantiles, we followed the methodology proposed by Han et al. (2016). By way of background, Han et al. (2016) extended the univariate quantilogram of Linton and Whang (2007) to a bivariate case known as the cross-quantilogram (CQ). The CQ methodology provides two key advantages. (i) It captures the connectedness between different pairs (of quantiles?)via the inclusion of all parts of the distributions, such as the central, extreme negative and extreme positive events, and thereby offers a clear and complete dependence structure between pairs in the quantiles. (ii) It renders a wider openness to evaluate the lead-lag connectedness among the pairs, in the sense of Granger causality, at several lags and quantiles (Baumohl and Lyocsa, 2017). In our empirical analysis, the estimates of the cross-quantile correlation are displayed in heatmap graphs across several lag lengths. These diagrams are graphical representations of the bivariate cross-quantile correlations that can capture the dependence structure in its entirety in a more precise manner. We portray the quantile distribution of the two time-series in the horizontal and vertical lines in a given diagram.

As documented in Han et al. (2016), consider the continuous returns $X_{it}, i = 1,2$ and $t = 1, \ldots, T$, where the index i denotes either returns of oil or returns of stock/exchange rate. The time series should follow a strictly stationary stochastic process with unconditional distribution function $F_i(\bullet)$ and unconditional density function $f_i(\bullet)$. The unconditional quantile function is as below:

$$q_i(\tau_i) = \inf\{\upsilon = F_i(\upsilon) \geq \tau_i\} \quad \text{for } \tau_i \in (0,1) \tag{1}$$

Through the arbitrary selection of the pair of quantiles $\tau = (\tau_1, \tau_2)'$, we estimate the dependence between two events: $\{X_{1t} \leq q_{1t}(\tau_1)\}$ and $\{X_{2t} \leq q_{2t}(\tau_2)\}$. The CQ measures the cross-correlation of the so-called quantile hits or quantile exceedances. However, for an integer $k = \pm 1, \pm 2, \ldots$, we represent below the sample counterpart of the CQ:

$$\rho_\tau(k) = \frac{\mathrm{E}\left[\psi_{\tau_1}\left(X_{1t} - q_{1t}(\tau_1)\right)\psi_{\tau_2}\left(X_{2,t-k} - q_{2,t-k}(\tau_2)\right)\right]}{\sqrt{\mathrm{E}\left[\psi^2_{\tau_1}\left(X_{1t} - q_{1t}(\tau_1)\right)\right]}\sqrt{\mathrm{E}\left[\psi^2_{\tau_2}\left(X_{2t} - q_{2t}(\tau_2)\right)\right]}} \tag{2}$$

The quantilogram of Linton and Whang (2007) is obtained where the two given time series have a similar distribution function. Now, when $q^*_i(\tau_i)$ denotes the unconditional estimate of $q_i(\tau_i)$, the expression of the sample counterpart of the CQ is given as follows:

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

The aforementioned formula quantifies the serial dependence and the directional predictability between the two events: $X_{1t} \leq q_{1t}(\tau_1)$ and $X_{2t} \leq q_{2t}(\tau_2)$. The values of $\rho_\tau^*(k)$ are supposed to be in $(-1,1)$.[2] We have no cross-dependence or directional predictability between the pairs of two events for $\rho_\tau^*(k)=0$, whereas we have a serial dependence or a directional predictability between the two events if $\rho_\tau^*(k)=1$. Following Han et al. (2016), to test the absence or presence of predictability between two time series in terms of quantiles, the null hypothesis of no mutual predictability is $\mathrm{H}_0 : \rho_\tau(k)=0$ versus $\mathrm{H}_\mathrm{a} : \rho_\tau(k) \neq 0$ for $k \in (1,\ldots,p)$. Han et al. (2016) proposed the use of a Ljung-Box-type test statistic. The implementation of this test is as follows:

$$Q_\tau^*(p) = T\left(T+2\right)\sum_{k=1}^{p}\frac{\rho_\tau^{*2}(k)}{T-k} \tag{4}$$

As documented by Han et al. (2016), the asymptotic distribution is approximated by using the stationary bootstrap process of Politis and Romano (1994). For further information about the bootstrapping procedure, refer to Politis and Romano (1994) and Han et al. (2016).I

3.2. The partial cross-quantilogram approach

We also apply the concept of partial cross-quantilogram (PCQ) and include uncertainty measures in accordance with Han et al. (2016). In other words, instigate control for the influence of the GPRD_Threat and GPRD uncertainties on the cross-quantile connectedness between the pairwise of the energy-exchange rate pairs and the energy-stock market pairs. Han et al. (2016) defined the PCQ method as an extension of the cross-quantilogram approach that controls for intermediary scenarios ranging among t and $t-k$ for the following two scenarios: $X_{1t} \leq q_{1t}(\tau_1)$ and $X_{2,t-k} \leq q_{2,t-k}(\tau_2)$.

The incorporation of the uncertainty measures, following the PCQ of Han et al. (2016), allows us to include of the control variables, expressed as:

[2] For instance, suppose that $X_{\mathrm{oil},t}$ is the continuous returns of oil and $X_{\mathrm{ER},t}$ is the continuous returns of the exchange rate in a given country. $\rho_\tau^*(1)=0$ indicates that if the oil return is above (below) the quantile $q_2(\tau_2)$ at time $t-1$, it does not help for the prediction of whether the exchange rate return is above (below) the quantile $q_1(\tau_1)$ at time t (Baumohl and Lyocsa, 2017).

$$z_t \equiv \left[\psi\left(X_{\tau_3}(X_{3t} - q_{3t}(\tau_3))\right),\ldots,\psi\left(X_{\tau_3}(X_{3t} - q_{3t}(\tau_3))\right)\right]' \tag{5}$$

where $l = 3, 4, \ldots, n$. We express the matrix of correlations which is transposed in the following form:

$$R_{\bar{\tau}}^{-1} = \mathrm{E}\left[h_t(\bar{\tau})h(\bar{\tau})'\right]' = P_{\bar{\tau}} \tag{6}$$

where $h_t(\bar{\tau})$ denotes a vector of the quantile hit process and is expressed as:

$$h_t(\bar{\tau}) = \left[\psi\left(X_{1t} - q_{1t}(\tau_1)\right),\ldots,\psi_{\tau l}\left(X_{lt} - q_{lt}(\tau_l)\right)\right]' \tag{7}$$

and $P_{\bar{\tau}}$ is given by the following formula:

$$\rho_{\bar{\tau}|z} = \frac{-p_{\bar{\tau},12}}{\sqrt{p_{\bar{\tau},11}p_{\bar{\tau},22}}} \tag{8}$$

The term $\rho_{\bar{\tau}|z}$ defines the cross-quantilogram dependence conditioning on the control variable z. (In the case of our analysis, the GPRD_Threat and GPRD). The PCQ $\rho_{\bar{\tau}|z}$ dependence can also be defined as:

$$\rho_{\bar{\tau}|z} = \delta\sqrt{\frac{\tau_1(1-\tau_1)}{\tau_2(1-\tau_2)}} \tag{9}$$

where δ is a scalar obtained from the following regression:

$$\psi\left(X_{1t} - q_{1t}(\tau_1)\right) = \delta\psi_{\tau_2}\left(X_{2t} - q_{2t}(\tau_2)\right) + \gamma' z_t + u_t \tag{10}$$

and z_t is a control variable for the scalar of the PCQ. Han et al. (2016) shows that testing $\mathrm{H}_0 : \rho_{\bar{\tau}|z} = 0$ is analogous to checking the Granger causality through the two time-series.

4. Results and discussion

4.1. Data description and preliminary perusal

The data employed in our study covers different streams of crude oil including WTI, Brent, OPEC, Tapis, Dubai, and Heating oil, as well as natural gas. The stock market indices and exchange rates for the

E7+1 emerging countries were also used, as well as geopolitical risks. The data on crude oil prices were obtained from (www.eia.gov), the data on the stock market indices were downloaded from (www.investing.com), and the data on the exchange rates were sourced from (www.imf.org). The global geopolitical risk index was introduced by Caldara and Iacoviello (2018) in order to measure the geopolitical risk. This index was constructed via the text-search results of eleven major international newspapers covering words related to geopolitical tensions, terrorist attacks, and other forms of geopolitical events. These included the Financial Times, The Times, The New York Times, Los Angeles Times, The Guardian, The Boston Globe, Chicago Tribune, The Daily Telegraph, The Washington Post, The Wall Street Journal, and The Globe and Mail. The data was collected from the website (https://www.matteoiacoviello.com//gpr.htm).

To distinguish between the effect of geopolitical tensions and the effect of pure geopolitical risks, Caldara and Iacoviello (2018) also developed two determinants of political risk: The geopolitical threat (GPRD_Threat) index and the geopolitical acts (GPRD_Act) index. The geopolitical threat index includes words related to military force threats and nuclear menaces, while the geopolitical acts index includes words related to terrorism and war, such as the 1990-1991 Gulf war, the November 2015 Paris terror attack, the March 2004 Madrid bombing, the 2003 Iraq invasion, the 2014 Russia-Ukraine tension, the 9/11 terrorist attack, and so on.

Before addressing our research, we first analysed the nature and characteristics of the data. The plots of the variables in level and returns respectively are presented in Figs. 1 and 2, while the descriptive statistics of the data are presented in Table 1. In Fig. 1, a very sharp fall in all the series of energy prices (with exception of natural gas) is observed during the years 2008-09 and 2016 which evidences drastic collapses in oil prices. A similar behavior was observed for the stock market index series for all the countries considered. However, for the exchange rates, all countries show a fall in the exchange rates relative to the USD, except for the Chinese Yuan. Fig. 2 also shows clear evidence of volatility clustering during the 2002-2003, 2008-2009 and 2015-2016 sub-periods for all energy, stock and exchange rates series.

We also observe from Table 1 that all the returns series are non-normally distributed since they have both significant kurtosis and skewness. While further evidence shows that the series are stationary (based on the results from the ADF test), they are also auto-correlated and have a significant ARCH effect. Hence, the use of a model that is based on the Gaussian assumption or the normality of data may be misleading. As a result, we it was advantageous to use the cross-quantilogram and partial cross-quantilogram (PCQ) approaches in line with Han et al. (2016).

Table 1: Descriptive statistics

	Mean	Median	Max	Min	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	L-B	L-B^2	ARCH-LM	Obs.
WTI	0.02	0.028	16.414	-17.092	2.403	-0.158 *	7.336 *	3737.2 *	-22.032 *	77.5 *	2524.4 *	686.1 *	4746
Brent	0.024	0.018	17.969	-18.725	2.298	-0.104 *	7.747 *	4465.0 *	-20.773 *	52.5 *	1168.8 *	424.1 *	4746
OPEC	0.025	0.079	12.804	-15.631	1.744	-0.261 *	7.657 *	4342.8 *	-19.981 *	374.4 *	1816.6 *	520.0 *	4746
Tapis	0.025	0	14.142	-11.545	2.088	-0.08961	5.913 *	1684.3 *	-20.526 *	120.3 *	2902.1 *	698.5 *	4746
Dubai	0.026	0.062	18.283	-16.502	2.372	-0.099 *	7.025 *	3210.9 *	-20.901 *	117.9 *	2507.0 *	627.7 *	4746
HeatingOil	0.028	0.057	8.143	-9.398	1.63	-0.184 *	5.434 *	1198.0 *	-21.018 *	94.6 *	1312.8 *	414.4 *	4746
NaturalGas	0.006	0	32.435	-19.899	3.431	0.447 *	8.330 *	5774.9 *	-20.998 *	101.9 *	760.6 *	280.8 *	4746
IndiaS	0.039	0.035	15.99	-11.809	1.445	-0.194 *	11.183 *	13269.9 *	-20.646 *	81.8 *	2388.6 *	568.8 *	4746
ChinaS	0.017	0	9.401	-9.256	1.541	-0.327 *	8.411 *	5875.5 *	-20.162 *	104.0 *	1629.8 *	467.3 *	4746
IndonesiaS	0.045	0.049	7.623	-10.954	1.313	-0.687 *	10.319 *	10965.8 *	-21.523 *	80.1 *	1843.1 *	526.2 *	4746
SouthKoreaS	0.017	0.016	11.284	-12.805	1.484	-0.599 *	10.256 *	10696.0 *	-21.758 *	39.5 *	2456.6 *	663.4 *	4746
TurkeyS	0.037	0.008	17.774	-19.979	2.082	-0.05734	11.283 *	13570.7 *	-20.862 *	58.5 *	2431.7 *	758.0 *	4746
BrazilS	0.033	0	13.678	-12.096	1.746	-0.098 *	7.172 *	3450.3 *	-21.731 *	48.6 *	4797.9 *	1119.7 *	4746
MexicoS	0.041	0.042	12.758	-8.45	1.328	0.064984	9.115 *	7397.4 *	-21.666 *	116.0 *	3561.4 *	817.3 *	4746
RussiaS	0.057	0	25.226	-20.657	2.027	-0.173 *	19.060 *	51026.1 *	-22.552 *	76.0 *	3704.7 *	1066.2 *	4746
IndiaER	0.009	0	3.933	-3.323	0.39	0.265 *	12.724 *	18755.7 *	-19.325 *	113.0 *	4256.5 *	977.2 *	4746
ChinaER	-0.005	0	1.833	-2.032	0.117	-0.610 *	45.300 *	354134.6 *	-18.603 *	103.6 *	194.9 *	112.7 *	4746
IndonesiaER	0.014	0	5.903	-8.978	0.618	-0.438 *	25.029 *	96114.8 *	-18.724 *	121.7 *	688.4 *	388.4 *	4746

SouthKoreaER	-0.001	-0.007	10.259	-13.236	0.663	-0.686 *	56.100 *	557960.1 *	-21.997 *	194.0 *	2526.5 *	1271.7 *	4746
TurkeyER	0.045	0	35.695	-8.28	1.11	7.663 *	237.765 *	10945335.2 *	-21.211 *	142.1 *	119.2 *	56.2 *	4746
BrazilER	0.015	0	7.112	-10.344	1.05	0.118 *	9.684 *	8845.4 *	-20.721 *	133.9 *	4892.2 *	990.5 *	4746
MexicoER	0.015	-0.01	7.977	-6.653	0.707	0.806 *	15.091 *	29423.9 *	-20.385 *	97.0 *	3253.7 *	948.9 *	4746
RussiaER	0.017	0	17.001	-17.346	0.789	0.435 *	106.526 *	2119565.7 *	-18.303 *	194.2 *	2748.0 *	1893.2 *	4746
GPRD	0.013	-0.87	313.809	-268.398	68.838	0.110 *	4.193 *	291.2 *	-30.346 *	1143.5 *	730.3 *	476.7 *	4746
GPRD_Threat	0.019	-0.481	322.335	-268.398	72.597	0.059402	3.836 *	140.9 *	-30.713 *	1149.5 *	522.2 *	337.0 *	4746

Note: * denotes statistical significance at the 1% level. GPRD is the global geopolitical risk index which was introduced by Caldara and Iacoviello (2018) in order to measure geopolitical risk. This index was constructed via the text-search results of eleven major international newspapers, covering words related to geopolitical tensions, terrorist attacks, and other forms of geopolitical events. GPRD_Threat is the geopolitical threat index which includes words related to military force and nuclear threats.

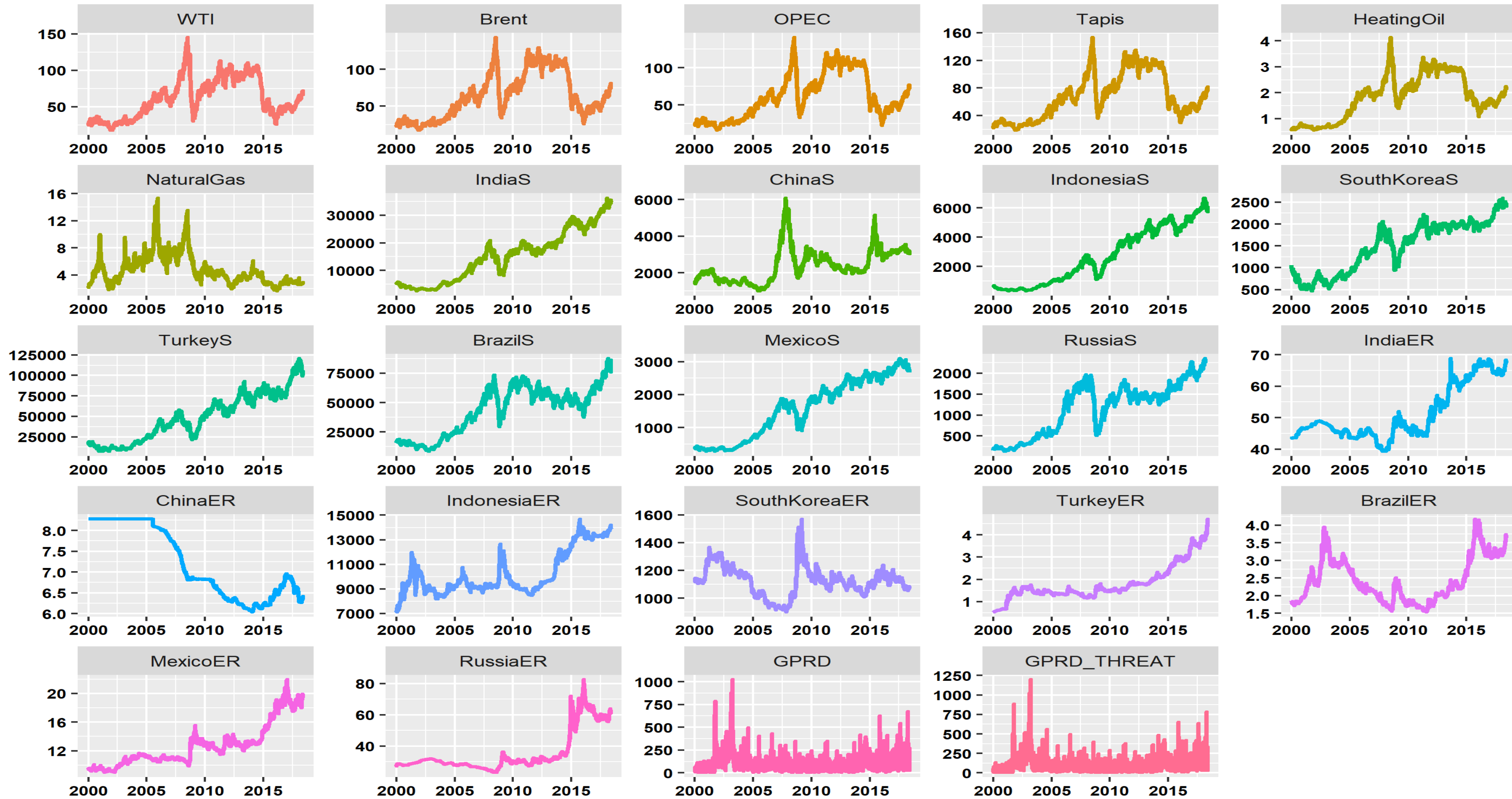

Fig. 1 Time series plots of the variable in levels.

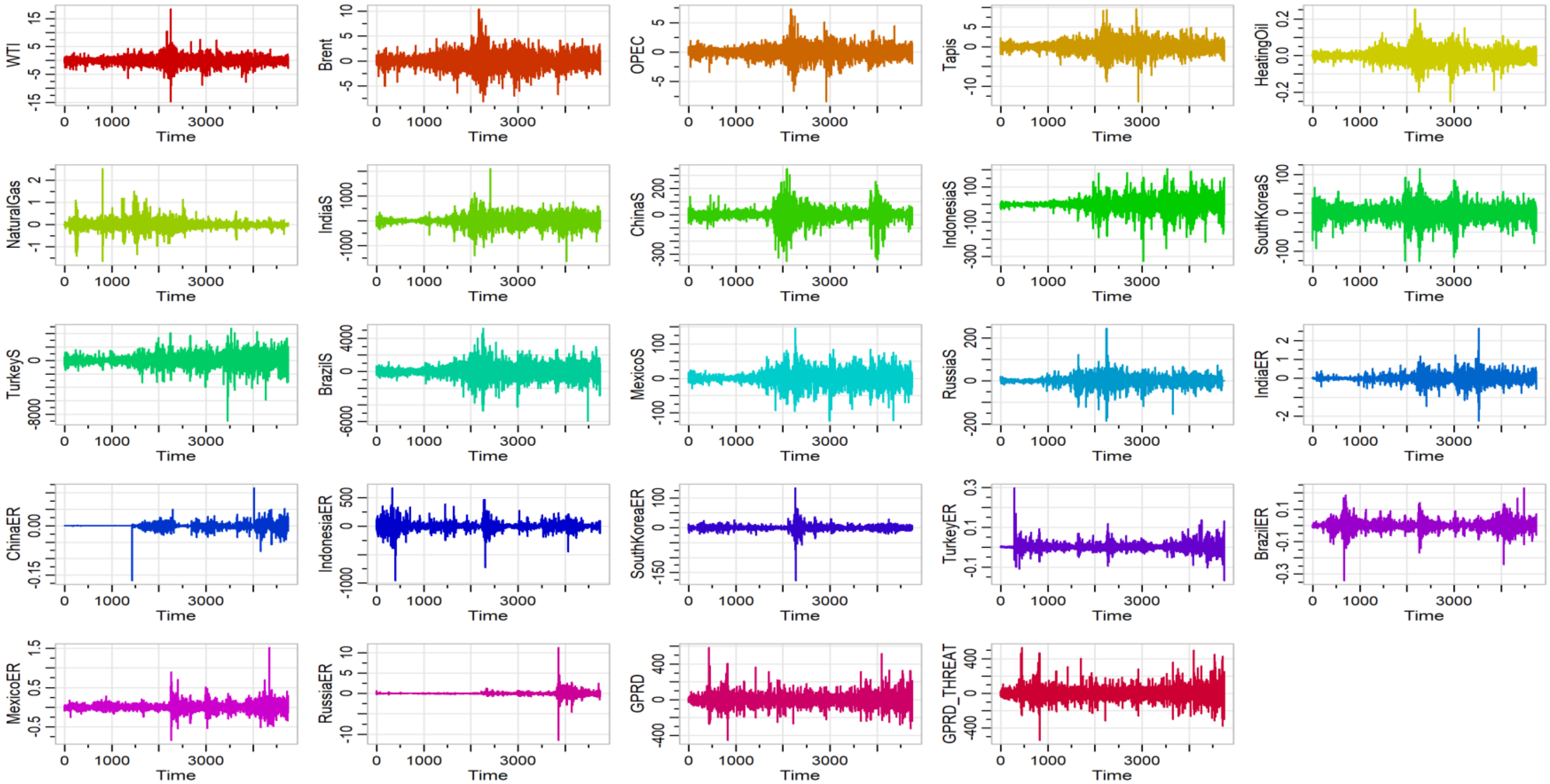

Fig. 2 Time series plots of the variable in returns.

4.2. The cross-quantilogram analysis

To examine the directional predictability of the returns for the different pairs: oil-exchange rate, oil-stock, and oil-other energy, we employed the CQ analysis. We considered three different oil types, namely WTI, Brent and OPEC and the exchange rates of the E7+1 countries. We further considered three other energy measures: U.K. heating oil, U.S. natural gas and Dubai crude oil. The objective was to analyse the transmission mechanisms and the directional predictability patterns between oil/energy, exchange rates, stocks, and other energy pairs during normal and extreme market events, as well as over quantiles.

Our results are displayed for four different lags: 1 (one day), 5 (one week), 22 (one month) and 66 (over two months), corresponding to the lower (lags 22 and 66), medium (lag 5) and higher (lag 1) quantiles. The cross-quantile correlation coefficients are reported in a heatmap format. In each heatmap, the x-axis denotes the quantiles of oil (WTI, Brent, OPEC) returns, while the y-axis indicates the quantiles of the exchange rate, stock, and other energy returns. The intensity of the estimated cross-quantile correlation values spans between deep blue (highly negative significant dependence) and deep red (highly positive significant dependence), which is represented by the multicolour bar displayed at the end of each Figure. We focus our directional predictability analysis on WTI, Brent, OPEC basket, heating oil and natural gas and we present a brief summary of the results on the analysis of the dependence structure from oil (Dubai) to the exchange rates and stock market returns.

The directional predictability of returns for different pairs, using the cross-quantilogram, has been examined in prior literature. For example; Baumöhl and Lyócsa (2017) adopted the cross-quantilogram methodology into gold relative to US stock market sector indices and their analysis and visualization of the results are similar as we have examined in our study. They have computed 32,490 significant coefficients and consider gold is safe haven for most of the industries. On the other hand, Zhou et al. (2019) examined similar to our study measured the directional predictability of oil volatility to stock returns in BRICS. The results indicates that oil volatility has robust directional predictability to the stock returns in BRICS. Our study is comparable and further extension from Zhou et al . (2019) through using three different oil types i.e. WTI, Brent and OPEC and the exchange rates of the E7+1 countries. Jiang et al. (2016) and Bekiros et al. (2018) also used cross-quantilogram. Studies are considering the agricultural commodities and spillover effects on US stock market respectively. However, our study has comparative advantage for policymakers to analyze different types of commodities from E7+1 countries.

4.2.1. Directional predictability from oil (WTI)

The heatmaps of the directional predictability of the pairwise oil (WTI)-exchange rate are portrayed in Fig. A.1. They show an absence of blue colours at lag 5, lag 22 and lag 66 for all pairs, with the exception of South Korea. The dominance of the green colour in the lowest left-corners of the heatmaps reveals that no directional predictability exists between oil (WTI) and exchange rate returns, suggesting a noticeable disconnection between oil (WTI) and the exchange rate returns of the E7+1 countries at the extreme lower quantiles. WTI does not serves as a good global benchmark because of logistics within the U.S. On the other hand, at lag 1, several colours (green, blue and red) are registered on each heatmap, suggesting a time-varying directional predictability between oil (WTI) and exchange rates across the quantiles. For instance, at lag 1, for the case of Brazil, the blue colour appears at the higher left-corner and lower right-corner of the heatmap, evidencing a significant negative predictability from oil (WTI) to exchange rate returns at the extreme lower and the extreme higher quantiles. Furthermore, the red colour is present in the lower left-corner of the heatmap at the same lag, indicating a significant positive predictability between oil (WTI) and exchange rate.

For the case of South Korea, it is worth noting that at one lag length (one day) and five lag length (one week), the blue colours dominate the heatmaps, thereby implying a significant strong negative predictability from oil (WTI) to exchange rate at both the extreme lower and extreme higher quantiles. This suggests that extreme negative/positive oil (WTI) market events can be followed by positive/negative exchange rate shocks in the future and for the following periods. In addition, the dependence in the quantiles from oil (WTI) to exchange rate (South Korea) disappears across lags.

In Fig. A.2, we depict the directional causality from oil (WTI) to the stock returns of the E7+1 countries. It is found that the oil (WTI) price return has no influence on Turkey's stock market returns across the entire range of quantiles and over time lags, as shown by a single green heatmap for all lags. This suggests there is no dependence among the quantiles between oil (WTI) and Turkish stock market returns. The Turkish market is dominated by foreign investors. The result may indicate that Turkey's stock index cannot be considered as a safe haven for oil (WTI) prices. For the case of the stock markets for Brazil, China, Indonesia, Russia and South Korea, there exists a dominance of the red colour in the lower left-corner of each heatmap, implying a strong significant positive dependence between the Brazilian, Chinese, Indonesian, Russian, and South Korean stock market returns and oil (WTI) returns. In addition, there is an absence of the blue and light blue colour regions, indicating a very high negative independence between the variables. It is also clearly noticeable that the degree of dependence and directional predictability between oil (WTI) and the stock markets under consideration decreases through time lags, except for the case of Turkey.

From the aforementioned results, the positive influence of oil (WTI) on stock market returns at the lower quantiles indicates that during extreme market events, such as when oil (WTI) price returns and stock market returns are extremely weak, oil (WTI) prices affect the stock market returns of the E7+1 countries (with the exception of the Turkish stock market). This effect persists over one day (lag 1), three weeks (lag 22) and two months (lag 66) for the case of Indonesia, South Korea, and Russia, respectively. This may imply that the directional predictability mechanism for oil (WTI)-stock return pairs demeans through time.

To understand the dependence structure for the oil (WTI)-exchange rate and oil (WTI)-stock returns in greater depth, we examined the directional predictability after controlling for GPRD_Threat, and GPRD. To do that, we applied the partial cross-quantilogram (PCQ) analysis. Fig. A.3 presents heatmaps of the oil (WTI)-exchange rate returns after controlling for GPRD_Threat. In examining the heatmaps depicted in Fig. A.3, the following prominent results are evident. (i) There is an overall increase in the degree of dependence between oil (WTI) and exchange rate after controlling for GPRD_Threat and the influence of oil (WTI) price persists until lag 66. (ii) The blue and light blue colours are more pronounced at lag 1 for all pairs, suggesting a significant negative dependence over quantiles. (iii) Compared to others, the oil (WTI)-exchange rate pairs, oil (WTI)-Turkey, oil (WTI)-Mexico and oil (WTI)-Brazil couples were more strongly positively dependent through the quantiles and over the time lags. (iv) This may suggest that the oil (WTI) price and exchange rate of Turkey, Mexico and Brazil are likely to follow the same directional interactions. Accordingly, any extreme negative (positive) oil market conditions (for instance an oil price decrease) will convey a negative (positive) response to the exchange rate.

The directional causal interplay from oil (WTI) to the stock market returns of the E7+1 countries, after conditioning on the GPRD_Threat, is depicted in Fig. A.4. Referring to different heatmaps of oil (WTI)-stock returns, a high positive connection is registered for all pairs and in the majority of lags, as shown by the dominance of the red- and orange-coloured areas. Compared to the CQ heatmaps, the PCQ displays more red/orange-coloured regions in the lower left corners, indicating that the directional predictability between the oil (WTI) and stock market indices becomes more pronounced after controlling for the GPRD_Threat. On the other hand, contrary to the results shown in the CQ heatmaps, as the dependence structure for oil (WTI)-stock returns deteriorates over the time lags, the PCQ reveals that the directional predictability persists across lags, thus implying a long-term positive dependence between oil (WTI) and stock returns of the E7+1 countries in the 5th, 50th and 95th quantiles. As a matter of fact, it is possible to infer from this that controlling for GPRD_Threat in the variable pair of oil (WTI)-stock returns leads to a clear transmission mechanism for investors, market participants and hedgers.

Fig. A.5 displays the heatmaps of the PCQ coefficients for the oil (WTI)-exchange rate pairs. In the case of lag 1, the oil (WTI) returns exhibit a positive influence on the exchange rates for Brazil, Mexico, and Turkey after controlling for GPRD, as indicated by the significant red/orange-coloured areas are in the lower left-corners. Further, over one week of time (i.e., lag 5), the blue/light blue-coloured regions are registered at the lowest left-corner for all pairs, except for Turkey and South Korea, thereby indicating that the PCQ coefficients are negative. This may suggest that extreme negative oil (WTI) market events (for instance a decline in the price of oil (WTI)) is likely to induce a future positive response of the exchange rate in the next period. Overall, after controlling for GPRD, the heatmaps of the PCQ for oil (WTI) versus exchange rate exhibit less green-coloured areas, thus indicating a strong and significant directional predictability between the variables.

Fig. A.6 portrays the results of the directional predictability between oil (WTI) and stock returns after conditioning for GPRD. It is noteworthy that all heatmaps demonstrate the presence of red- and orange-coloured areas, which suggests the presence of positive causal-flows between oil (WTI) and stock returns of the E7+1 countries where GPRD is controlled. Further, it appears that an increase in oil (WTI) price returns may be followed by a positive response of stock returns in the lower or upper quantiles. Additionally, there is a dominance of red- and orange-coloured areas over one day (lag 1), thereby implying a strong short-term dependence structure between those variables. This result indicates that extreme oil (WTI) market conditions may immediately affect stock market returns, with the impact evident the next day. The exception is shown for the case of the oil (WTI)-Turkey stock returns pair where Fig. A.6 shows no directional predictability among oil (WTI) and the returns of Turkey's stock market. This means that controlling for GPRD has no influence in the transmission mechanism between the two markets.

The results in this study are connected to the works of Shahzad et al. (2017), examined the directional predictability from the oil market uncertainty to the sovereign credit default swap. Their study focus on GCC oil exporting countries i.e. (Bahrain, Qatar, Saudi Arabia and United Arab Emirates) and other five oil exporting countries (Brazil, Mexico, Norway, Russia and Venezuela). The results are aligned with our study argument that significant directional predictability observed from oil uncertainty. Further, Benk and Gillman (2020) concludes that how nominal factors granger predictability of oil prices after the great recession and Iworiso and Vrontos (2020) examined directional predictability of equity premium. Our study is aligned with the existing studies to examine the directional predictability. However, the focus of our study is advanced directional predictability between oil (WTI) and stock returns after conditioning for GPRD.

4.2.2. Directional predictability from oil (Brent)

The directional quantile-based causal connectedness from oil (Brent) to exchange rate returns and from oil (Brent) to stock market returns is depicted in Figs. B.1 and B.2, respectively. According to Fig. B.1, it seems that the results exhibit a negative connection with oil (Brent) and exchange rate returns at lag 5 with the blue-light colour though the results are quite weak. The exception is noted for South Korea, which has no directional predictability. At lag 1, South Korea and Indonesia demonstrate a significant negative connection with oil (Brent) in the extreme upper quantiles under the blue- and light blue-coloured areas. This may signify that increases in oil (Brent) price volatility decrease the Indonesian and South Korean exchange rate volatilities the following day. In Fig. B.2, we set out the directional causality mechanism between oil (Brent) and stock market returns. It is readily observable that the case of no dependence is absent in each heatmap at lags 1 and 5 for all pairs. At lags 1 and 5, we see red-coloured areas in all heatmaps, which is an indication of a strong positive predictability between oil (Brent) and stock market returns under the extreme market conditions (e.g., Dai and Kang, 2021). This result implies that when variations in oil (Brent) volatility are negative (positive) and very big in extent, it is very likely that the volatility of stock returns will also encounter great negative (positive) changes in the next period. For instance, a strong positive predictability in the lowest quantile (0.05) suggests that a very large decrease in oil (Brent) price volatility will also induce a great decline in the stock market volatilities over the following five days (approximately one week). At lag 1, for the case of Turkey, some blue-coloured areas are localised in the median quantiles, which highlights the presence of a negative predictability between the markets at the median quantiles. Consequently, during normal market conditions coupled with a decline in oil (Brent) returns, the Turkish stock market returns are likely to increase the next day.

The PCQ analysis of oil (Brent) versus each of the exchange rates and the stock market returns of the E7+1 countries, after controlling for the GPRD_Threat variable, is displayed in Figs. B.3 and B.4 respectively. By observing the results, we emphasise the presence of a heterogenous dependence structure between oil (Brent) price returns and the exchange rate (Fig. B.3), as well as the presence of a time-varying directional predictability for the oil (Brent)-exchange rate pair. We can see that most of the heatmaps depict both blue- and red-coloured areas across all quantiles and over different time lags, which suggests that in certain times oil (Brent) return has an extreme negative impact on exchange rate at the lower (upper) quantiles and in other times it has an extreme positive influence on exchange rate at the lower (upper) quantiles. For the case of India, there is no directional predictability between the two time series.

Fig. B.4 depicts the directional causality between oil (Brent) and stock returns after controlling for the GPRD_Threat. With reference to the heatmaps, oil (Brent) return demonstrates a positive dependence on all stock market returns after controlling for the GPRD_Threat. The positive causal interplays are more concentrated in the lower quantiles and over one day (lag 1). Nonetheless, the lower left-corners of each heatmap portray red- and orange-coloured areas for the oil (Brent)-China, oil (Brent)-Brazil, oil (Brent)-Russia, and oil (Brent)-South Korea pairs, indicating that after controlling for the GPRD_Threat, oil (Brent) volatility has a positive influence on the stock market volatilities for China, Brazil, Russia and South Korea the next day. This directional predictability pattern persists until lag 5 (one week), an indication of short-term and mid-term dependence for these market pairs. We also notice that the lower quantiles of oil (Brent) can predict variations in the stock market spreads for Brazil, China, Russia and South Korea. It is clearly noticeable that the dependence pattern among oil (Brent) and stock market returns disappears over time lags and the strength of connectivity is weak in the longest lag (lag 66) and the shortest lag (lag 1).

The empirical findings of the directional predictability, after controlling for GPRD from all quantiles of oil (Brent) to exchange rate returns of the E7+1 economies, are presented in Fig. B.5. It is found that Brazil and Mexico report similar patterns of the directional causality mechanism, as their corresponding heatmaps contain red-coloured areas in the lowest left-corners at each lag. However, the directional predictability from oil (Brent) to exchange rate seems to be higher in the lower quantiles, evidencing that the positive predictability and oil (Brent) return cannot be regarded as a weak/strong safe haven for the exchange rates of Brazil and Mexico. In other pairs, except for oil (Brent)-South Korea, the heatmaps reveal a dominance of the green coloured-regions, specifically at lags 5 (one week), 22 (one month) and 66 (over two months). This result unveils no predictable connectivity between oil (Brent) and exchange rates in the mid- and long-term horizons. Apparently, the effect of oil (Brent) changes is limited to the short-term, and changes in oil (Brent) volatility can predict changes in the exchange rate only the next day (lag 1), which is not a positive indication for investors and economic decision-makers.

In Fig. B.6, we present the results of the PCQ analysis for oil (Brent) versus stock returns, using the control variable GPRD. We can emphasise that Brazil, China, Russia and South Korea have a similar pattern of directional predictability between lags 1 and 5. However, the daily lag 1 and weekly lag 5 changes in stock return volatilities are likely to follow the previous oil (Brent) volatility. For instance, bad news (negative shocks) in oil (Brent) volatility has a positive impact on the volatility of stock returns the next day and/or over the next five days.

Other studies in the literature for example Dai and Kang (2021) argues that bond yield can competently predict oil price, they observed significant association between oil market and bond yield sentiments.

Scarcioffolo (2019) also used similar methodology of cross-quantilogram to examine the directional predictability for different energy markets at different quantiles. Su et al. (2017) examine the efficiency of two crude oil markets i.e. WTI and Brent. The result in the literature are aligned with our results as WTI and Brent are strong directional predictability to exchange rate and stock markets.

4.2.3. Directional predictability from oil (OPEC basket)

In this section, we consider the dependence structure between oil (OPEC basket) and exchange rates. The heatmaps are displayed in Fig. C.1. With regard to the first row, the low quantile oil (OPEC) returns are positively connected with the low quantile returns in the Brazilian exchange rate for lags 1, 22 and 66. Accordingly, if the oil (OPEC) market is bearish, then it has a positive effect on the Brazilian exchange rate if the latter is also bearish. This result is highlighted for both the short- (lag 1) and long- (lags 22 and 66) terms. We also document that the India and China exchange rates present no predictability with the oil (OPEC) returns at all time lags and for all quantiles. In both one-day and one-week lags, Indonesia and South Korea show a negative directional predictability from oil (OPEC) returns.

The heatmaps indicate that the high quantile oil (OPEC) return has a negative influence on the low quantile on the Indonesian and South Korean exchange rate returns over a one-day or one-week period. Further, we see that the negative and positive causal predictabilities from oil (OPEC) to the exchange rate returns deteriorate over time, and are absent at the medium and higher lags, thus indicating an absence of mid- and long-term directional predictability between oil (OPEC) and exchange rate returns. In the last row of Fig. C.1, Turkey's exchange rate returns show a strong dependence on oil (OPEC) returns, compared to its dependence on oil (WTI) and oil (Brent). This result may indicate that Turkish investors are more dependent on changes of the oil (OPEC) market price volatility than on the changes in oil (WTI) and oil (Brent) market volatilities. Turkey imports 89% of its oil from OPEC oil exporting countries.

In Fig. C.2, we display the quantile dependence of oil (OPEC) on the E7+1 stock returns. Overall, the findings show a lower dependence between oil (OPEC) and the E7+1 stock market returns in the mid- and long-term horizons. The green colour is more pronounced in each heatmap, and sometimes we find only a green-coloured heatmap. On the other hand, at the shortest lag, oil (OPEC) returns demonstrate a significant positive impact on the returns of stock markets, except in the case of Turkey. At extreme the lower quantiles (0.05, 0.10, 0.25), oil (OPEC) returns respond positively to the low and medium E7+1 quantile stock returns for the one-day lag. In other words, as indicated by the red-coloured areas in the lower left-corners of the heatmaps for the majority of the oil (OPEC)-stock return couples, an extreme negative market event (a decrease in the oil (OPEC) price) for oil (OPEC) market returns will convey negative future (one-day lag) stock returns. This result can be found at lag 5 for some pairs, such as the oil (OPEC)-Brazil, the oil (OPEC)-Russia and the oil (OPEC)-South Korea, implying a persistence of a positive oil (OPEC) low quantile effect on the low quantile stock returns of the Brazilian, Russian and South Korean markets. This persistence of positive predictability until lag 5, registered in the extreme left quantiles, indicates that an oil (OPEC) price decline will be followed by a decrease in the prices of the Brazilian, Russian and South Korean stock market indices. However, a plausible explanation of such phenomenon is that both pairs of markets: the oil (OPEC)-Brazil, the oil (OPEC)-Russia, the oil (OPEC)-South Korea) are likely to boom together.

In regards to the control of the GPRD_Threat, the dependence structure between oil (OPEC) and exchange rate returns is portrayed in Fig. C.3. We observe that the following outcomes: (i) the low quantile oil (OPEC) returns positively affect the low quantile Brazilian exchange rate returns for lag 1, lag 22 and lag 66, and affect the low quantile Mexican exchange rate returns for all lags; (ii) the high quantile oil (OPEC) returns negatively influence the low quantile Indonesian exchange rate returns for lag 1, 5 and 22; (iii) the high quantile oil (OPEC) returns have a negative effect on the low and middle quantile Russian exchange rate returns for both short- (lag 1) and mid- (lag 5) terms; (iv) at the middle and high quantiles, oil (OPEC) returns exercise a negative influence over the low and middle quantile South Korean exchange rate returns; (v) a positive predictability from oil (OPEC) returns is found in the lowest quantile oil (OPEC) returns and lower quantile Turkish exchange rate returns for all lags; (vi) in reference to outcome (v) it is possible to conclude when the oil (OPEC) market is bearish, it predicts the low quantile Turkish exchange rate returns with a positive sign over all time periods; (vii) a heterogenous and time-varying quantile dependence structure is observed after controlling for GPRD_Threat for all pairs, except in the case of India; and (viii) quantile oil (OPEC) returns have no directional predictability with regard to the quantile Indian exchange rate returns.

Fig. C.4 sets out the directional predictability from oil (OPEC) on the returns of the E7+1 stock markets whilst controlling on GPRD_Threat across several lags. Based on the heatmaps, we highlight the following primary outcomes: (i) the red-coloured regions are more pronounced, suggesting a strong positive quantile dependence between variables; (ii) at lags 1 and 5 there is a dominance of the red-coloured zones in the extreme lower left-corners for all oil (OPEC)-stock return couples, except in the case of the Turkish stock market; (iii) there is a clearly noticeable weakness with regard to the impact of the quantile oil (OPEC) on the quantile E7+1 stock market returns across lags, which persists until lag 66, implying a long-term dependence structure between the variables; (iv) the low quantile oil (OPEC) returns have a positive effect on the low and middle quantile returns for the Brazilian, Chinese, Indian, Indonesian and Mexican stock returns at lag 1. This implies that when the oil (OPEC) market is bearish and the Brazilian, Chinese, Indian, Indonesian and Mexican markets are also bearish, or in the normal state, they express causal interplay; (v) specifically for lag 1, the lower and middle quantile oil (OPEC) returns positively influence the lower and middle quantile Russian and South Korean stock returns. This is likely attributable to the fact that the oil (OPEC) - Russian and oil (OPEC) - South Korean stock markets are booming together; (vi) in the case of Turkey, at lags 1, 5 and 66, higher quantile returns are found to be positively connected with the higher quantile oil (OPEC) returns after controlling on GPRD_Threat. This may suggest that oil (OPEC) and Turkish stock markets seem to co-move together across all time intervals when both markets are bullish.

We now discuss the directional predictability between oil (OPEC) and exchange rate returns after controlling on GPRD. The results are presented in Fig. C.5. We document a weak dependence for the oil (OPEC)-China, oil (OPEC)-Indonesia, oil (OPEC)-Russia, and oil (OPEC)-South Korea pairs at almost all lags. Over the one-day time interval, the blue-coloured areas displayed in extreme lower and extreme upper corners are dominant, accounting for the negative predictability nexus between oil (OPEC) and Mexican, and South Korean exchange rates. This negative dependence at lag 1 moves to positive dependence at lags 5, 22 and 66. This result may indicate that in the short-term (one-day lag), changes in Mexican and South Korean exchange rate returns respond inversely to changes in oil (OPEC) returns. In the case of Turkey, the effect of the quantile oil (OPEC) returns on the quantile Turkish exchange rate returns is positive, highlighted by the dominance of red-coloured regions in the extreme lower left-corners of each heatmap for all lags.

In Fig. C.6, we set out the CQ correlation estimations between oil (OPEC) and the E7+1 stock returns, while conditioning on GPRD through different quantile ranges. We highlight the following primary outcomes. (i) The red colour is more intense in the extreme lower left-corners of the heatmaps for all the different pairs and over all time lags (with the exception of Turkey). This implies that the variable for extreme negative oil (OPEC) market conditions (negative oil (OPEC) returns) is highly connected with extreme negative stock market returns. However, the oil (OPEC) market and the E7+1 stock markets are likely to boom or diminish together. (ii) The Mexican, Russian, and South Korean stock market returns are associated more in the short-term with oil (OPEC) returns, as compared to other stock market returns. In addition, the low and middle quantile oil (OPEC) returns positively predict the low and middle quantile returns for Mexico, Russia and South Korea, evidenced by several red-coloured areas scattered across the extreme lower left- and central higher-corners of the heatmaps. (iii) Considering the Mexican, Russian and South Korean stock returns and oil (OPEC) returns, after controlling on GPRD and before controlling on GPRD_Threat, there is a large variation in the dependence structure, suggesting that controlling on GPRD is insightful in determining the directional predictability running from the oil (OPEC) market to stock markets of Mexica, Russia and South Korea, specifically at the one-day lag.

Relevant studies found similar results for e.g., Shahzad et al. (2017) measure the directional predictability from the oil market uncertainty to the sovereign credit default swap. Their study focus on GCC oil exporting countries i.e. (Bahrain, Qatar, Saudi Arabia and United Arab Emirates) and other five oil exporting countries (Brazil, Mexico, Norway, Russia and Venezuela). Our study is also considering the similar countries that is dependence structure between oil (OPEC basket) and exchange rates. Beckmann et al. 2020 measured the association between oil prices and exchanges rates. Their results are aligned with our results and indicate that exchange rates and oil prices are useful predictor for each other in short run. Dahmani and Al-Osaimy (2001) analyses OPEC oil production and market fundamentals and our results are broadly aligned with them.

4.2.4. Directional predictability from heating oil

Fig. D.1 sets out the directional CQ-based connectedness between heating oil and exchange rate returns. We highlight the main following outcomes. (i) Extreme and/or lower left-corners of the heatmaps for the heating oil-Brazilian exchange rate, heating oil-Mexican exchange rate, and heating oil-Turkish exchange rate pairs are red/orange at all lags, indicating evidence of a positive predictability from heating oil returns to the E7+1 exchange rate returns. (ii) Overall, heating oil returns present a strong significant quantile dependence with the majority of E7+1 exchange rate returns, under the red- and blue-coloured areas in the heatmaps. (iii) Chinese, Indonesian, Russian and South Korean exchange rate returns depict a similar quantile dependence structure with the heating oil returns. Additionally, at lag 1, the Chinese, Indonesian, Russian and South Korean exchange rate returns all show a negative directional predictability from heating oil returns, while at the other lags these exchange rate markets exhibit a weak positive causality via the quantile ranges. (iv) The low to high positive heating oil returns are connected with the low to high negative Chinese and Indonesian exchange rate returns. Notably, an increase in heating oil volatility seems likely to induce a large decrease in the exchange rate returns of China and Indonesia. (v) For the heating oil-Russian exchange rate and heating oil-South Korean exchange rate pairs, the blue and light blue colours are more pronounced in the extreme lower right-corners, implying that the extreme high quantile heating oil returns have a negative impact on the extreme low quantile Russian and South Korean exchange rate returns over the one-day lag. (vi) The negative directional predictability from heating oil returns to the Chinese, Indonesian, Russian and South Korean exchange rate returns for lag 1 changes to positive predictability for lags 5, 22 and 66, but with a weak degree of connectedness. (vii) The heating oil returns in the central quantile are positively associated with the Turkish exchange rate returns central quantile for lag 1, indicating that when both markets are in the normal state, they move in the same direction in the short-term.

In Fig. D.2, we set out the quantile dependence of heating oil returns on stock returns. Overall, the evidence shows a dominance of red/orange-coloured areas in the heatmaps, specifically for lag 1, which implies that the E7+1 stock markets are more dependent on the heating oil market, in comparison to their dependence on oil (WTI), oil (Brent) and oil (OPEC). We notice that the quantile dependence between heating oil and the E7+1 stock market returns is more intense for the one-day lag, and this dependence deteriorates over the time lags. We further highlight that all emerging markets respond positively to changes in the heating oil market. The exception is found at lag 1 for the Brazilian stock market returns, where the extreme high quantile heating oil returns negatively affect the low quantile Brazilian stock returns. For lags 1 and 5, a common feature is noted for the majority of the heating oil-stock market pairs, whereby the lower left-corner of each heatmap contains red/orange-coloured zones. This indicates a positive directional predictability of the heating oil returns of the emerging stock returns. This result may suggest that heating oil is a weak safe haven for the E7+1 emerging stock markets. The Indian and Mexican stock market returns show less dependence on heating oil returns compared to the other E7+1 markets. More precisely, these two stock markets respond very weakly to changes in the heating oil returns for the one-week, two-week and two-month lags. The absence of a negative predictability of heating oil returns for all combinations of quantiles informs us that heating oil does not represent an advantageous portfolio diversification opportunity for E7+1 investors.

The quantile association among the returns of heating oil and Turkish stock exhibits evidence of no directional predictability over the time lags (that is, the heatmaps are empty in their entirety). This is with the exception of the 0.8 and 0.9 quantiles, whereby the heating oil returns positively predict the 0.6, 0.7, 0.8, and 0.9 quantile Turkish stock returns for the next trading day. Finally, we reveal from the heatmaps of the heating oil-E7+1 stock market pairs that, in general, the strength of the directional predictability declines with the increase in the lag-time, which supports a short-term behavioral pattern for the cross-quantile-based nexus among heating oil returns and the E7+1 stock returns.

In Fig. D.3, we evidence a partial cross-quantile dependence between heating oil and exchange rate returns after controlling for GPRD_Threat. Fig. D.3, in comparison with Fig. D.1, shows that the heatmaps alternate somewhat. This means by not controlling for GPRD_Threat in the dependence structure for the heating oil-exchange rate couple, erroneous deductions will result. For instance, once we control for GPRD_Threat, the Indian exchange rate returns exhibit a positive and/or negative dependence on the heating oil returns across the quantiles. Further, the directional predictability from heating oil returns is more pronounced for all cases and for all combinations of quantiles. On the other hand, we notice that after controlling for GPRD_Threat, the magnitude of the negative predictability for the heating oil returns of the Chinese, Indian, Indonesian, Russian and South Korean exchange rate returns is more intense at lag 1, and it changes to a positive dependence for lags 5 and 22, then it returns again to the negative dependence for some pairs at lag 66, indicating a lower predictability for the heating oil returns on the emerging stock market returns.

The cross-quantile correlation for heating oil and returns of stock markets after controlling for the effect of GPRD_Threat variable is set out in Fig. D.4. In general, when looking at all the heatmaps, we observe that for the majority of lags and stock market pairs, the blue coloured-zones are absent. Nonetheless, it appears that there are very few blue coloured-areas at lag 5 for Brazil, India and South Korea. This result is similar to the evidence prior to controlling for GPRD_Threat for the heating oil-stock markets pairs. Interestingly, the extreme lower left-corners of each heatmap are red/orange in all the quantile dependence pairs, except for the heating oil-Turkish stock market pair. This indicates that heating oil returns are likely to have a strong positive influence on any of the E7+1 stock market returns (except in the case of Turkey). For that reason, a rise in heating oil volatility corresponds to a rise in the stock market volatilities of the E7+1 emerging markets.

From an economical point of view, this result supports the so-called "substitution effect". In fact, owing to the high-level prices of heating oil, the energy-using firms try to find other energy sources that are relatively inexpensive (Uddin et al., 2019). Other important outcomes can be observed from the quantile dependence between the heating oil and stock market returns after controlling for GPRD_Threat, as follows. (i) A positive predictability effect of the heating oil on the stock market returns weakens and sometimes disappears in the longer lags. (ii) A positive directional predictability from the market of heating oil is evident in the 5th, 50th and 95th quantiles, implying that the causal predictability of stock markets persists at the extreme and normal circumstances. Thus, when the heating oil market and the E7+1 stock markets are bearish, bullish or in their normal state, they are likely to co-move in the same direction. (iii) The quantile dependence between the heating oil and Turkish stock returns after controlling for GPRD_Threat is similar to that before controlling on GPRD_Threat, which is indicative of the stability of heating oil returns on Turkish market returns across the quantile ranges of the distribution. (iv) Compared to the results in Fig. D.2, a positive dependence for heating oil on the Turkish stock returns is evident in the longer time-lags in the 0.80:0.90 quantiles for both heating oil and Turkish stock returns.

Fig. D.5 sets out the results of the cross-quantile correlation between heating oil and exchange rates pairs whilst controlling on GPRD. In all lags, it can be seen that the lower left-corners of the pairs: heating oil-Brazilian exchange rate, heating oil-Mexican exchange rate and heating oil-Turkish exchange rate all display red-coloured zones, demonstrating that heating oil returns positively affect the exchange rate returns for Brazil, Mexico and Turkey. Thus, heating oil returns can predict these three aforementioned exchange rate returns, but only during the lower and upper market circumstances, as the dependency pattern is concentrated in the lower quantiles.

For lag 1, the heatmaps corresponding to the pairs: heating oil-South Korean exchange rate, heating oil-Russian exchange rate, heating oil-Indonesian exchange rate, heating oil-Indian exchange rate, and heating oil-Chinese exchange rate all exhibit blue-coloured areas, which implies a negative directional predictability effect from heating oil to the exchange rate returns of China, India, Indonesia, Russia and South Korea. The heating oil's negative dependence weakens and/or disappears for lags 5, 22 and 66, and it changes to a positive dependence for the same lags. However, the heating oil returns negatively predict the Chinese, Indian, Indonesian, Russian and South Korean exchange rate returns for the shortest trading days (one-day lag) and positively predicts the exchange rates in the mid- and long-term time-lags, suggesting a time-varying predictability in terms of behavior from the heating oil market to exchange rates. Overall, no dependence predictability is documented in the middle and upper quantiles for the pairs: heating oil-Brazilian exchange rate and heating oil-Mexican exchange rate, which may suggest that the intensity of the market volatility results in a persistence of the dependence in the long-term that is perhaps due to a sustained volatility spillover between heating oil asset from one side and the Brazilian and Mexican exchange rates from another side.

Fig. D.6 sets out the quantile association of heating oil to emerging stock markets with control for GPRD, presented in cross-quantilograms . We can observe an absence of the blue coloured-areas in the heatmaps, especially at lag 1, and also, that the red colour is more pronounced for all cases, indicating a strong positive dependence of heating oil returns with emerging stock markets. Furthermore, all heating oil-stock market pairs display red coloured zones in the extreme lower left-corners. The exception for this is the heating oil-Turkish stock pair. Likewise, the heating oil returns are likely to positively cause emerging stock markets returns at their lower quantiles in the following trading day. In fact, during extreme market conditions (i.e., when heating oil and stock market volatilities are low), the two markets are likely to boom or diminish together. The Turkish stock market returns are disconnected with heating oil returns for lags 5 and 22. On the other hand, when heating oil returns quantiles are in the 0.80:0.90 and the Turkish stock returns quantiles are in 0.60:0.70, 0.70:0.80, and 0.80:0.90, we find a positive dependence between the two markets.

Similar studies on the directional predictability on heating oil have been conducted by Wang and Yang (2010) they observe the intraday competence of four main energy (crude oil, heating oil, gasoline, natural gas) futures markets. Their results shows inefficiency in heating oil and natural gas future markets. Naeem et al. (2021) examined association between green bond and commodities (including heating oil) by using similar approach i.e. cross- quantilogram. The results indicate asymmetric association between green bonds and commodities. However, our study highlights relationship between heating oil, exchange rate and stock market returns with control of GPRD.

4.2.5. Directional predictability from natural gas

In consideration of the transmission mechanism between the quantiles for natural gas returns and exchange rate returns, the results of the dependence structure are set out in Fig. E.1. In observing the heatmaps of natural gas-exchange rate pairs, we do not see any quantile dependence at lags 5, 22 and 66. At lag 1, we can see a weak directional causality from natural gas to exchange rate returns. For instance, the low quantile natural gas returns positively predict the low quantile Mexican and Turkish exchange rate returns over the one-day lag. As can be shown in Fig. E.2, the quantile dependence structure from the natural gas returns to the E7+1 stock market returns reports a similar pattern to that observed between the exchange rate returns and natural gas returns. We can conclude, certainly for the case of Mexico, that there exists a short-lived directional negative predictability at the extreme high quantile. That is, the blue-coloured zones are reported in the extreme upper quantile of natural gas, indicating that when the natural gas market is bearish, it is very likely that the Mexican stock market will boom the next day (lag 1).

Fig. E.3 sets out the heatmaps of the cross-quantile correlation estimations between natural gas returns and the E7+1 exchange rate returns after controlling for GPRD_Threat. In contrast to the dependence of the natural gas-exchange rate returns pairs, without controlling for GPRD_Threat, the heatmaps presented in Fig. E.3 exhibit a directional predictability from natural gas returns to exchange rate returns (observed via blue- and red-coloured areas in some heatmaps). In the case of Brazil, at lag 1, a positive causal predictability of the exchange rate returns for its very lower quantiles is observed through the lowest quantile of natural gas returns, which indicates that the two markets co-move together in the short-term. Therefore, the middle quantile natural gas returns have a positive influence on the central quantile Brazilian exchange rate returns over one trading day. For the five-day lag, two-week lag and two-month lag, there is a dominance of the green colour, which is an indication of the absence of/weak dependence between the quantiles of natural gas returns and that of the Brazilian exchange rate returns.

The results also reveal a positive dependence between natural gas returns and the Mexican and Turkish exchange rate returns. For Mexico, the directional predictability is pronounced only at lag 1, and it is found that the lower to middle quantiles for natural gas returns positively affect the lower quantile Mexican exchange rate returns. A similar result is reported for the case of Turkey, not only for lag 1, but also extended into the mid- (lag 5) and long- (lag 66) term. This result highlights that a low to middle quantile natural gas volatility positively predicts the low quantile Turkish exchange rate in the next day, next week and the next two months, and thereby, Turkish investors, market deciders, hedgers and portfolio managers can benefit from this behavioral pattern of the natural gas-Turkish exchange rate pair in their portfolio diversification strategy. The Indian and Russian exchange rates demonstrate a negative directional predictability through quantiles after controlling for GPRD_Threat. The two exchange rates depict a similar pattern at all quantile ranges and for the four lags. Obviously, the middle to high quantile natural gas returns have a negative influence on the higher quantile Indian and Russian exchange rate returns for lags 1, 5 and 22.

In addition, we can observe that the negative dependence from natural gas to Indian and Russian exchange rate returns deteriorates over the lags, and completely disappears at lag 66. However, the negative predictability of the natural gas volatility and the volatility of the Indian and Russian exchange rates vanishes over time, which suggests there is likely to be good diversification opportunities for Indian and Russian investors. Meanwhile, South Korean exchange rate returns depict a more complex dependence structure with natural gas returns after controlling for GPRD_Threat. This result exhibits a time-varying directional predictability from natural gas to the South Korean exchange rate. As can be deduced from the heatmaps, the negative predictability of natural gas returns to South Korean exchange rate returns is more intensified at lag 1 than other lags.

A careful appraisal of the dependence structure among the natural gas and stock returns of the E7+1 countries, after controlling for GPRD_Threat, is set out in the heatmaps of Fig. E.4. It is clearly observable that the South Korean stock returns present no directional predictability with respect to the natural gas returns across all lags, indicated by the green-coloured areas. This may suggest that natural gas is a weak indication for the South Korean stock market. We can additionally observe that the extreme high natural gas returns are likely to have a strong negative effect on the extreme lower quantile Brazilian, Indian and Mexican stock market returns for lag 1. This may imply that natural gas provides good diversification advantages for short-term investors in the Brazilian, Indian, and Mexican markets. We also find that extreme higher natural gas returns have a strong significant influence over the high quantile Mexican stock returns in the following five trading days. However, when the natural gas market is bullish, it can predict the Mexican market downturn over approximately one week. The Russian stock market returns are found to be more positively correlated with the natural gas returns than the other markets.

In Fig. E.5, the directional predictability of the E7+1 exchange rate returns from natural gas returns, after controlling on GPRD, is illustrated. As can be seen from the results, in general, the Indian, Indonesian and Russian exchange rates show a similar transmission mechanism of the cross-quantile correlations with the natural gas market. Notably, we observe a negative directional predictability from natural gas to the exchange rate returns for India, Indonesia and Russia. At approximately a three-week lag and a two-month lag, the degree of dependence is very weak and close to zero, indicating the inability of the gas returns to predict the Indian, Indonesian and Russian exchange rate returns in the long-term. The natural gas-Mexican exchange rate pair shows that the lower quantile of the Mexican exchange rate positively responds to the extreme lower to middle quantile natural gas returns for the next trading day. A quite similar scenario is observed in the case of the Turkish exchange rate with the natural gas market after controlling for GPRD. Finally, as can be seen from the results, the majority of the emerging exchange rates present a weak directional predictability from the natural gas market in the long-term (lag 66). Thus, after controlling for GPRD, the quantile natural gas returns serve as a good predictor, but only in the short-term.

Fig. E.6 sets out the directional predictability from the natural gas returns to the stock market returns of the E7+1 countries after controlling for GPRD. It is worth noting that there is no significant dependence between the natural gas returns and the South Korean stock market returns through all of the combinations of the quantiles. This suggests that natural gas is a very good hedge for the South Korean stock market. We further note that there is a similar result for the Brazilian, Chinese, Indian, Indonesian and Mexican stock markets for lag 66, but not for other lags. It is shown that the middle quantile positive natural gas returns are linked with the middle to high positive Chinese stock market returns, indicating that when the natural gas market is in the normal state, it can predict the Chinese stock market when the latter is in the normal state or booming. With regard to the heatmaps of the natural gas-Russian stock market, quantile dependence from natural gas to the Russian stock market returns has an alternating nature, as there are times when extreme negative natural gas market conditions are followed by extreme negative Russian stock returns. There are also times when extreme negative natural gas returns respond to extreme positive Russian stock returns. This situation is more pronounced for lags 1 and 5. In addition, the Russian stock market returns appear to be more correlated with the natural gas returns at all combinations of the quantiles, in comparison with the other stock markets.

Studies conducted on directional predictability from natural gas are for e.g., Shahzad et al., (2017) highlight in their studies that Qatar has highest export of natural gas which balance its oil revenue. Scarcioffolo and Etienne (2019) examines the directional predictability between energy prices. The results indicate weak evidence between crude oil and natural gas. Jena et al. (2019) illustrates nonparametric causality in quantile tests and concluded that causality in variance is bi-directional in bull markets for all commodities except for natural gas. Our results are also mixed and found weak predictability of natural gas after controlling GPRD.

4.2.6. Directional predictability from oil (Dubai)

The results derived from the directional predictability in from oil (Dubai) to the exchange rates of the E7+1 emerging markets are set out in Fig. F.1. Regarding the heatmaps, Brazil, Mexico and Turkey show various orange-coloured areas in the lower left corners for all lags, which may indicate that extreme negative future returns in the oil (Dubai) market will generate negative future returns in the Brazilian, Mexican and Turkish exchange markets. The blue-coloured regions detected in the extreme left corners of their heatmaps for the case of China, Indonesia and South Korea may suggest that the expected oil (Dubai) decreases will be followed by an increase in the exchange rate for the three abovementioned countries.

The directional predictability from the oil (Dubai) market to the E7+1 stock markets is presented in Figs F.1. and F.2. A close look at the heatmaps reveals a dominance of the orange-coloured areas displayed in the extreme lower left corners, indicating a significant positive dependence between oil (Dubai) returns and the E7+1 stock market returns. From this result, we can deduce that positive oil (Dubai) returns are likely to positively predict E7+1 stock returns. However, there is some synchronicity in the oil (Dubai) market and the stock markets of the E7+1 countries, whereby they are booming together.

Now we turn to the directional predictability results after conditioning on GPRD_Threat and GPRD. The heatmaps for the exchange rates and stock market returns after conditioning on GPRD_Threat are set out in Figs. F.3 and F.4The heatmaps after controlling for GPRD are set out in Figs. F.5 and F.6. The primary observation from these heatmaps is that the orange and blue colours are intensified (more pronounced). We see more orange- and blue-coloured areas compared to the heatmaps without controlling on the geopolitical risk indexes. Thus, this result may indicate that, after controlling for geopolitical risk indicators, the extreme negative (positive) oil (Dubai) returns can strongly predict the extreme negative (positive) E7+1 stock market returns. Due to the large size of the paper, all the results related to oil (Dubai) directional predictability are available upon request.

Therefore, due to the voluminous size of the paper and the enormous results, we have underlined in Subsection 4.2 that we do not discuss the results of the oil (Dubai) case. However, all the results related to oil (Dubai) are available upon request. Our results are consistent by the studies (e.g., Li et al., 2019; Bouri, 2019; and Bouri et al., 2020).

4.2.7. Rolling window analysis

To evaluate the robustness of the findings of the CQ analysis, we consider a rolling window exploration for the CQ correlation coefficients. Specifically, this is a rolling window cross-quantilogram for the oil-exchange rate and oil-stock market return pairs at three different quantiles: low ($\tau = 0.05$), median ($\tau = 0.50$) and high ($\tau = 0.95$). Owing to major market events that occurred over the financial sampling, one may conclude that the rolling window analysis and the time varying estimation procedure is likely to uncover structural breaks in the volatility spread mechanism between the variables under consideration. The CQ estimated coefficients are computed after selecting the first two years of the sample data. Then, we roll over to the second year and re-calculate the CQ coefficients. This exercise is pursued up to the end of the entire study period. The rolling quantilogram results of the time-varying quantile dependence effect from oil (WTI), oil (Brent), oil (OPEC), heating oil, natural gas, and oil (Dubai) to the returns of the exchange rates of the E7+1 emerging markets are portrayed in Figs. G.1, G.3, G.5, G.7, G.9, and G.11, respectively. The results from the abovementioned energy sources? to the stock market returns of the E7+1 emerging markets are displayed in Figs. G.2, G.4, G.6, G.8, G.10, and G.12, respectively. At each plot, the horizontal axis denotes the starting year of the rolling window, while the vertical axis refers to the CQ-estimated coefficients. The 5% (lower), 50% (middle), and 95% (upper) quantiles are depicted in the second, third and fourth columns of each Fig., respectively. The time-varying CQ correlations for the different pairs of the energy-exchange rate and energy-stock market returns are marked by the blue lines. Several interesting results are observed:

(i) For the oil (WTI) and exchange rate returns, we observe at the lower quantiles of both distributions a significant positive directional predictability running from oil (WTI) to the exchange rates of the E7+1 stocks, since 2007 to the end of the studied period.

(ii) The time-varying rolling window directional predictability from oil (WTI) to the stock returns of the E7+1 emerging markets presents similar behavior as given in (i).

(iii) At the lower quantiles, for the oil (WTI)-exchange rate and oil (WTI)-stock market returns pairs, we highlight a sharp but small peak in 2008 in almost all cases, which indicates an increase in the quantile dependence between the energy markets and E7+1 emerging markets in a period of financial crises.

(iv) At the middle quantiles, the oil (WTI) returns have a weak impact on the exchange rates and stock returns of the E7+1 emerging markets, as the CQ correlation coefficients are close to zero for the majority of cases.

(v) At higher quantiles, overall, there is a noticeable quantile dependence between oil (WTI) from one side, and exchange rates and stock returns from another side, which is indicative of a changing pattern. Sometimes oil (WTI) returns negatively affect the exchange rates and stock returns, and at other times they have a positive influence on the exchange rates and stock market returns. Also, the CQ correlation coefficients span from -0.05 to 0.10, which implies a weak predictability connectedness in the long-term between oil (WTI) and the exchange rates/stock market returns of the E7+1 emerging markets.

(vi) Regarding the rolling-window quantile predictability from the oil (Brent) returns to exchange rate and stock market returns, we show that the exchange rates and stock market returns respond positively at the lower and middle quantiles, more precisely after the year 2008 and until the end of the time period. Additionally, there are some peaks in 2008 (at the 5% quantile), highlighting the importance of the impact of the global financial crisis on the causal predictability interplays between the energy markets and exchange rates/stock markets of the E7+1 countries.

(vii) With reference to the upper quantiles, the rolling window predictability from oil (Brent) to exchange rate returns and stock market returns reveals a weakly significant influence of the energy market (Brent) on exchange rates and stock markets (either negatively or positively).

(iix) Overall, at the upper quantiles and before 2008, oil (Brent) negatively predicts the exchange rates and stock market returns, whereas the response pattern changes to positive after 2008, which indicates that the global financial crisis is likely to be considered as a turning point for the long-term quantile dependence between the different pairs.

(ix) Compared to the upper quantiles, the lower quantiles present stronger spikes of the time-varying CQ correlation coefficients during the rolling window estimation period, suggesting the significant role of the financial turmoil effect on the short quantile dependence structure between the energy market returns and exchange rates/stock market returns of the E7+1 countries.

(x) At the lower quantiles and with regard to the rolling window quantile predictability of the oil (OPEC) returns and exchange rates/stock market returns, we find similar results as those found in the case of oil (WTI) and oil (Brent), whereby the oil (OPEC) may negatively predict exchange rates/stock market returns until the appearance of the 2008 global financial crisis.

(xi) We observe that the negative response of the exchange rates and stock market returns registered before the 2008 global financial crisis changes to positive during such financial turmoil periods as the global financial crisis and the Eurozone debt crisis, among others. This may be owing to the asymmetric sources of shocks related to oil price (Kilian, 2008; Ready, 2018).

(xii) The middle and upper quantiles depict a similar, stable pattern of the rolling window quantile dependency system among the oil (OPEC) and exchange rates/stock market returns, thus indicating a weak causal predictability effect of oil (OPEC) in the mid- and long-termtime-lags.

(xiii) The rolling window quantile dependence results are consistent with those of the standard quantile dependence analysis, as they reveal a decrease in the directional predictability between the different energy-exchange rates/stock returns market pairs over time.

(xiv) Similar results are found for the heating oil-exchange rate returns and the heating oil-stock market returns as revealed from oil (WTI), oil (Brent), and oil (OPEC) towards the exchange rates and the stock markets of the E7+1 countries. However, the degree of the rolling window quantile dependence between markets increases during the financial turmoil of 2008 (in the short-term) and tends to be stable afterwards.

(xv) Looking at the rolling-window directional predictability between the natural gas and exchange rates/stock markets, we can conclude that the negative influence of quantiles for the natural gas returns on the quantiles of the exchange rates/stock market returns is more pronounced for almost all cases and in the majority of the rolling window sample periods.

(xvi) Finally, in general, the rolling-window quantile dependence results highlight that periods of financial turmoil increase the causal predictability interplays between energy markets and the exchange rates/stock markets of the E7+1 emerging markets, and notably, at the lower quantiles of both distributions.

5. Conclusion and policy implications

We examine the cross-quantile analysis for oil prices and exchange rates, and oil prices and stock markets for the E7+1 countries in static and dynamic frameworks, using the bi-variate cross-quantilogram and partial cross-quantilogram approaches. The overall results show that, after controlling for GPRD_Threat, there exists an increase in the degree of dependence between WTI and exchange rates, and the influence of WTI persists until 66 lags. Out of all the analysed exchange rates, the dependence between WTI exchange rates is significantly negative over all quantiles, while the exchange rates of Turkey, Mexico and Brazil are found to be more strongly positively dependent. Further, the results on predictability for stock returns suggests a more pronounced and persistent positive connection for all pairs and in all cases after controlling for GPRD_Threat, thus indicating that controlling for GPRD_Threat leads to a clear transmission mechanism for investors, market deciders and hedgers. These findings are also confirmed by controlling for GPRD, which exhibits a strong significant directional predictability of the stock and exchange rates from oil prices (with the only exception being the Turkish stock market returns).

Additionally, the results between Brent and exchange rates, after controlling for GPRD_Threat, show that in certain times the Brent return has an extreme negative impact on the exchange rate at the lower (upper) quantiles and at other times it has an extreme positive influence on the exchange rate at the lower (upper) quantiles, and for India we observe no directional predictability from Brent to the Rupee-USD exchange rates. Moreover, when we controlled for GPRD, we find that Brazil and Mexico report a similar pattern of the directional causality mechanism. Further, the directional predictability from Brent to exchange rate seems to be higher at lower quantiles, demonstrating a positive predictability, and so the Brent return cannot be regarded as a weak/strong safe-haven for the exchange rates of Brazil and Mexico. Moreover, with the exception of the South Korean exchange rates, no predictability at any time-lag/period of time is found across the quantiles. The results relating to the predictability of stock returns by Brent, while on GPRD, show a similar pattern of the directional predictability until lags 1 and 5 for Brazil, China, Russia and South Korea, and meanwhile, for India and Turkey, the positive predictability from Brent to stock returns disappears in lags 5, 22 and 66. In addition, our empirical study showed the dependence structure for oil (OPEC), heating oil, and stock market returns.

Finally, the results related to the natural gas-exchange rate and natural gas stock market returns relationships do not show any quantile dependence at lags 5, 22 and 66. After controlling for GPRD, the quantile natural gas returns serve as a good predictor, but only in the short-term. Moreover, after controlling for GPRD_Threat, we find that for Brazil at a middle quantile, the natural gas returns have a positive influence on the Brazilian central quantile exchange rate returns over one trading day. For a five-day lag, a two-week lag and a two-month lag, it is possible to observe an absence/weak dependence between the natural gas returns and that of the Brazilian exchange rate returns. The results also reveal a positive dependence between the natural gas returns and the Mexican and Turkish exchange rate returns. The Indian and Russian exchange rates demonstrate a negative directional predictability through the quantiles after controlling for GPRD_Threat. The two exchange rates depict a similar pattern at all quantiles ranges and for the four lags. Further, the results exhibit a time-varying directional predictability from natural gas to the South Korean exchange rate at lag 1. Once we control for GPRD_Threat, we find that the South Korean stock returns present no directional predictability with natural gas returns across all lags, thus indicating that natural gas is a weak safe-haven for the South Korean stock market. However, at the extreme high quantile, the natural gas returns are likely to have a strong negative effect on the extreme lower quantile of the Brazilian, Indian and Mexican stock market returns for lag 1. This may imply that natural gas holds good diversification advantages for short-term investors in the Brazilian, Indian, and Mexican markets.

Finally, after controlling on GPRD, we observe a negative directional predictability from natural gas to the exchange rate returns for India, Indonesia and Russia. At approximately a three-week lag and a two-month lag, the degree of dependence is very weak and close to zero, underlying the inability of natural gas returns to predict the Indian, Indonesian and Russian exchange rate returns in the long-term. The evidence from the natural gas-Mexican exchange rate pair shows that the lower Mexican exchange rate volatilities positively respond to the extreme lower to middle quantile natural gas returns the next trading day. Further, when we control for GPRD, while analysing the relationship between natural gas and the stock market returns of the E7+1 economies, we find that natural gas is a very good hedge for the South Korean stock market, and we also find a similar result for the Brazilian, Chinese, Indian, Indonesian and Mexican stock markets for lag 66 and not for other lags. Further, the evidence shows that the natural gas returns can positively predict the stock market returns of Russia and Turkey for some quantiles and at all lags. The quantile predictability from natural gas returns to the Russian stock market returns have an alternating pattern. Obviously, Russian stock market returns appear to be more correlated with natural gas returns at all combinations of quantiles, in comparison with the other stock markets.

Our empirical results also provide some crucial economic and policy implications for international investors, portfolio managers and portfolio decision makers. The fact that the different oil markets (WTI, Brent, OPEC, heating oil, Dubai) and the natural gas market present several degrees of connectedness over the quantiles on the exchange rates and stock returns of the E7+1 economies, this data could be used to support international investors and portfolio decision makers in making beneficial hedging strategies for risk minimisation via the creation of the most optimal portfolios. Investors should be cautious when adopting market-timing-strategy investments. In general, our empirical results are crucial for portfolio diversification and hedging strategies. For instance, since the OPEC basket has no dependence on the Indian stock exchange after controlling for GPRD as well as under normal and bull market circumstances, it is possible to conclude that a portfolio that combines the two markets may provide a diversification profit when the returns are in the median and high quantiles. Further, after controlling on GPRD_Threat and during normal or/and bull market conditions, natural gas has no dependence on the Brazilian stock exchange, which suggests that natural gas is likely to be an advantageous hedge for investing in the Brazilian stock exchange. Another important portfolio implication for the natural gas and exchange rate market pair is that during the normal and bull market events, the former provides a diversification benefit when it is combined with exchange rate for India, Indonesia and Russia. Therefore, investors may adopt their investment strategies in a portfolio that couples natural gas with the Indian exchange rate, or in a portfolio that combines natural gas and the Indonesian exchange rate stocks, or in portfolio that combines natural gas and the Russian exchange rate.

Acknowledgments

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Data Availability Statement

We have provided the sources of data in our paper. The data that support the findings of this study are available from the author upon reasonable request.

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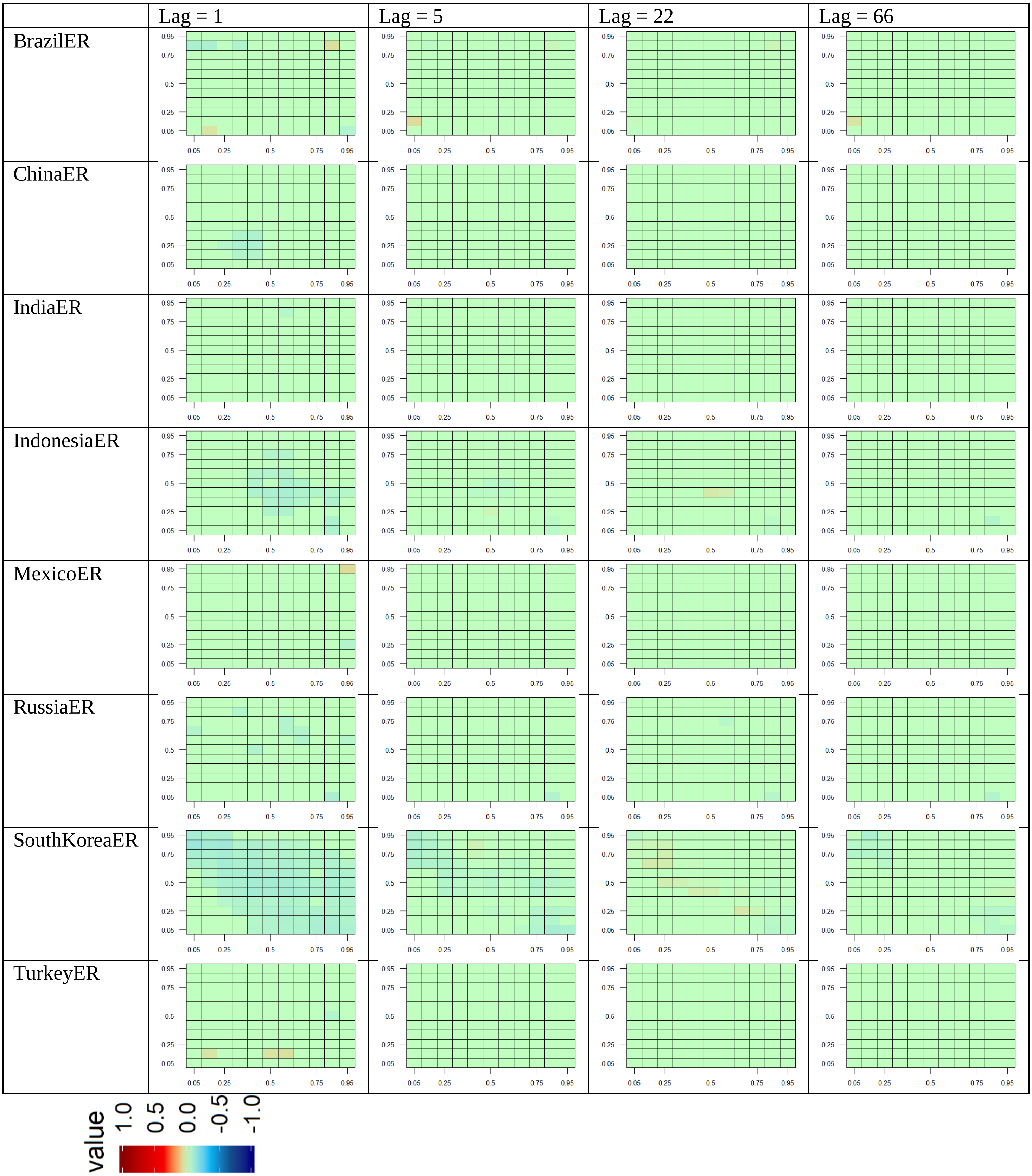
Appendix. See appendices A., B., C., D., E., and F.

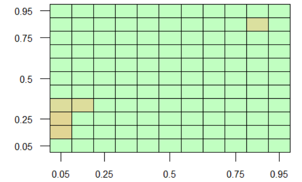
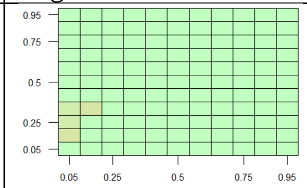
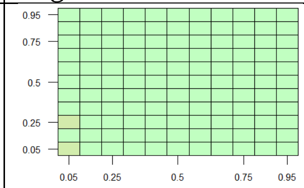
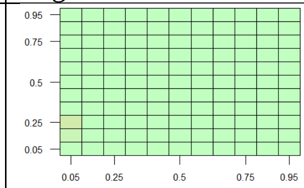
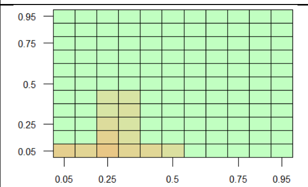
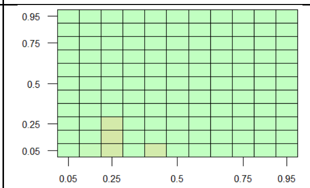
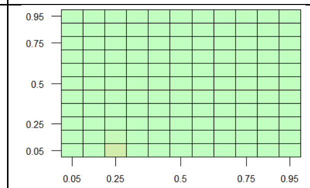
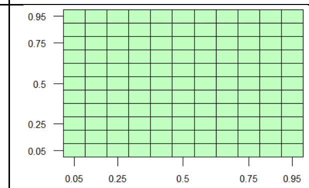
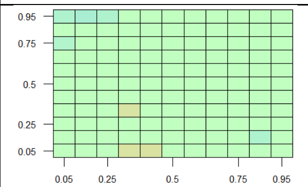
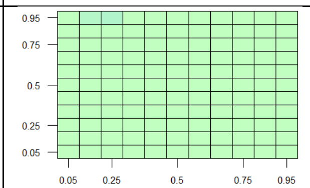
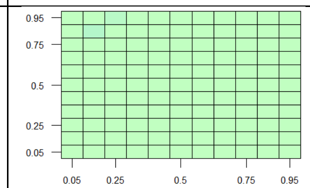
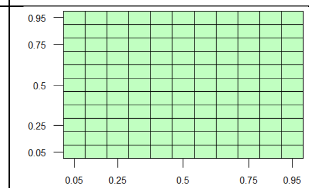
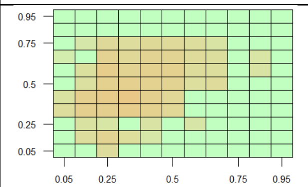
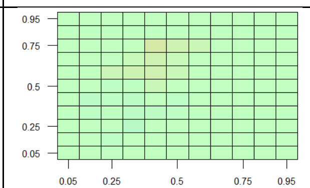
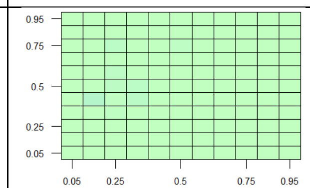
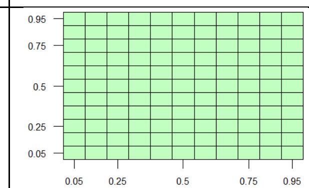
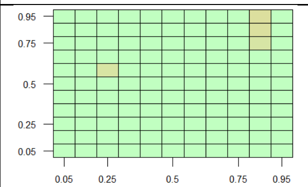
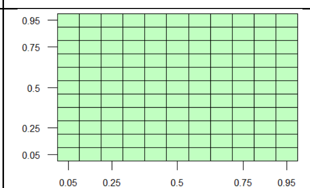
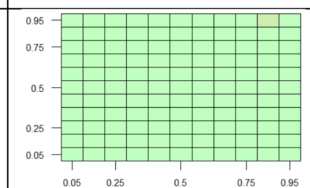
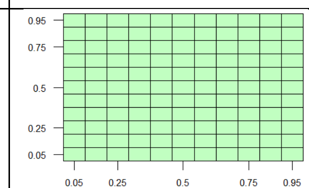
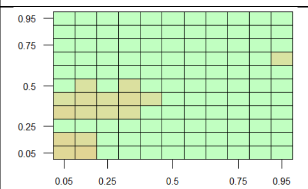
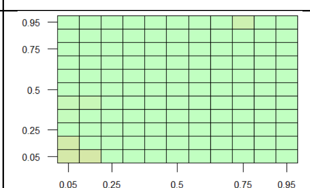
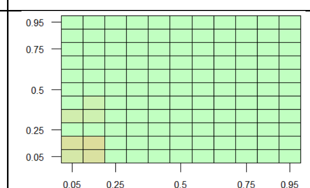
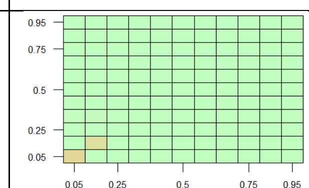
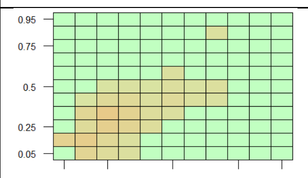
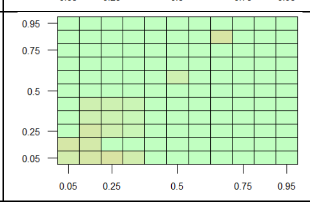
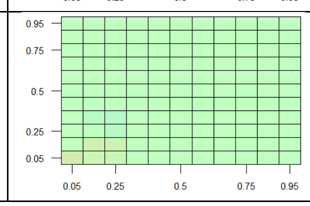
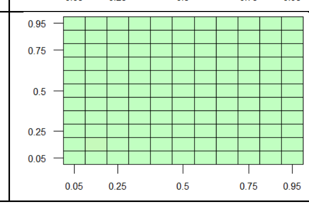
Appendix A. See Figs. A.1-A.6.



Lag = 1
Lag = 5
Lag = 22
Lag = 66
BrazilER
ChinaER
IndiaER
IndonesiaER
MexicoER
RussiaER
SouthKoreaER
TurkeyER
0.05
0.25
0.5
0.75
0.95
value
1.0
0.5
0.0
-0.5
-1.0

Fig. A.1.

Cross-quantilogram heatmap for predictability running from oil (WTI) to the exchange rates of emerging market (E7+1). Notes: the heatmap depicts the values of the cross-quantile correlations. In the horizontal axis, quantiles of returns WTI are depicted, while in the vertical axis quantiles of returns exchange rate are reported. The intensity of the extent of cross-quantile correlations is shown by the colored bar.

	Lag = 1	Lag = 5	Lag = 22	Lag = 66
BrazilS				
ChinaS				
IndiaS				
IndonesiaS				
MexicoS				
RussiaS				
SouthKoreaS				

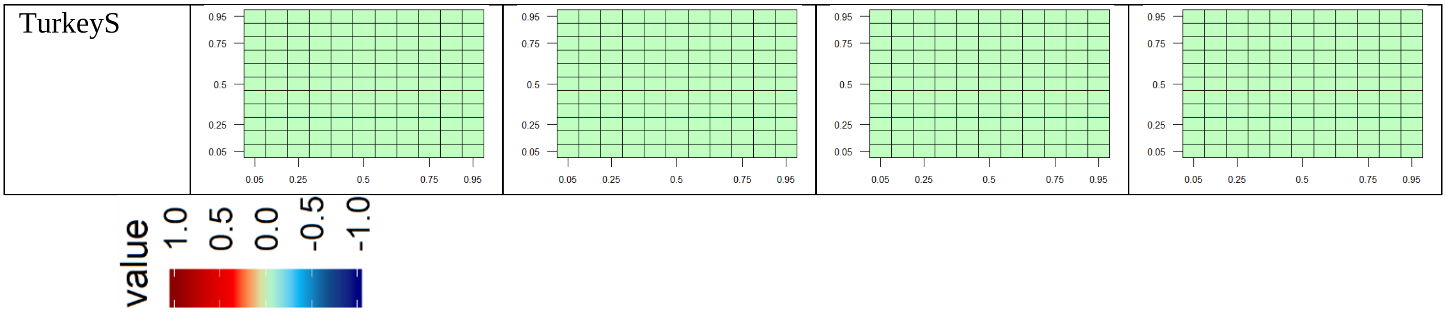
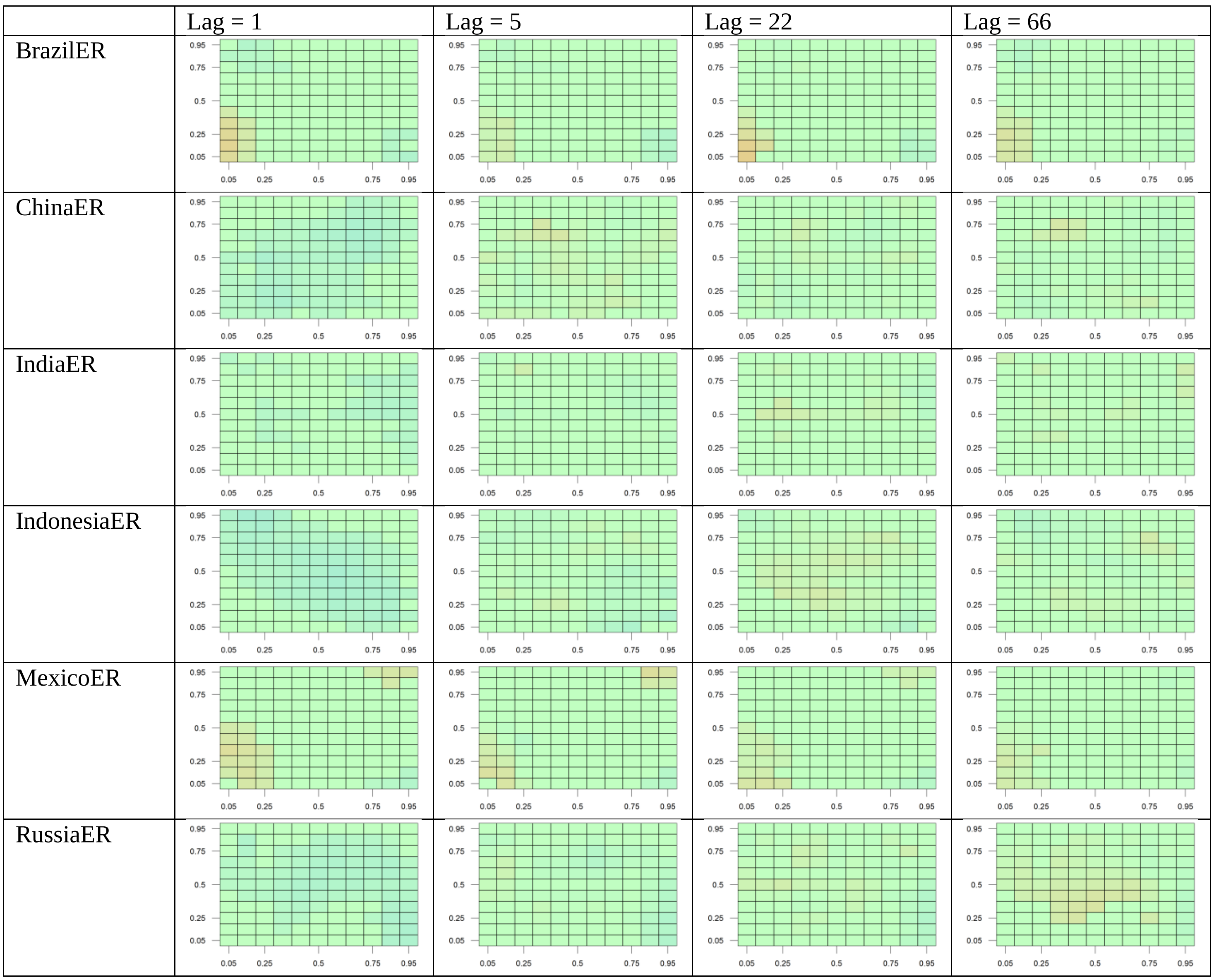


Fig. A.2.

Directional predictabilities in quantiles from oil (WTI) to emerging stock markets (E7+1). Notes: please refer to the notes in Fig. A.1.



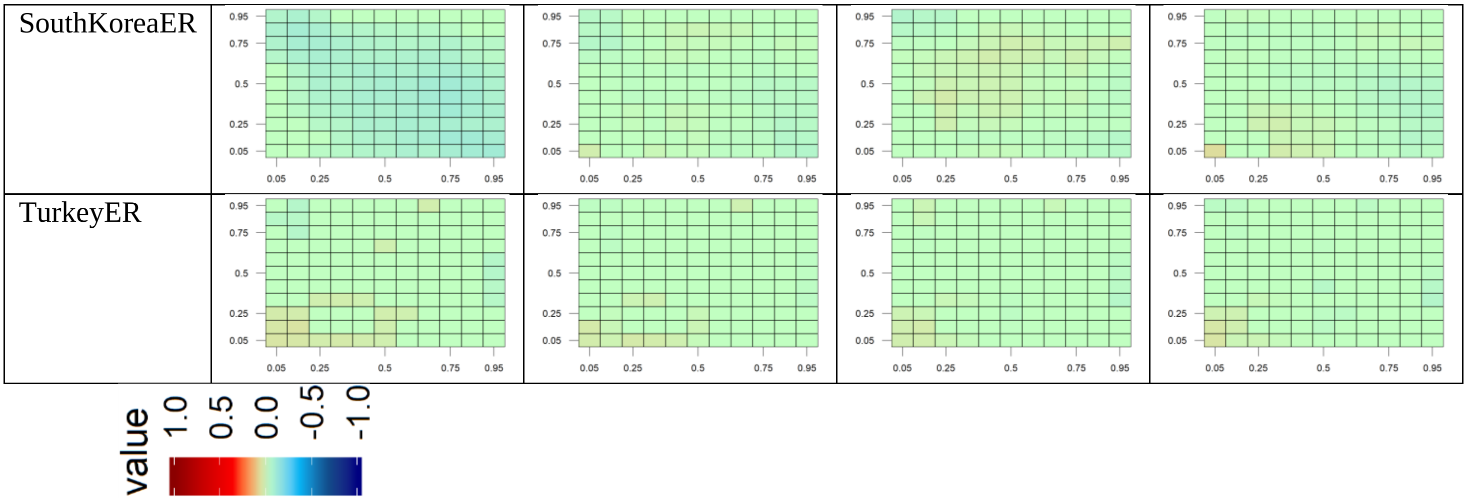
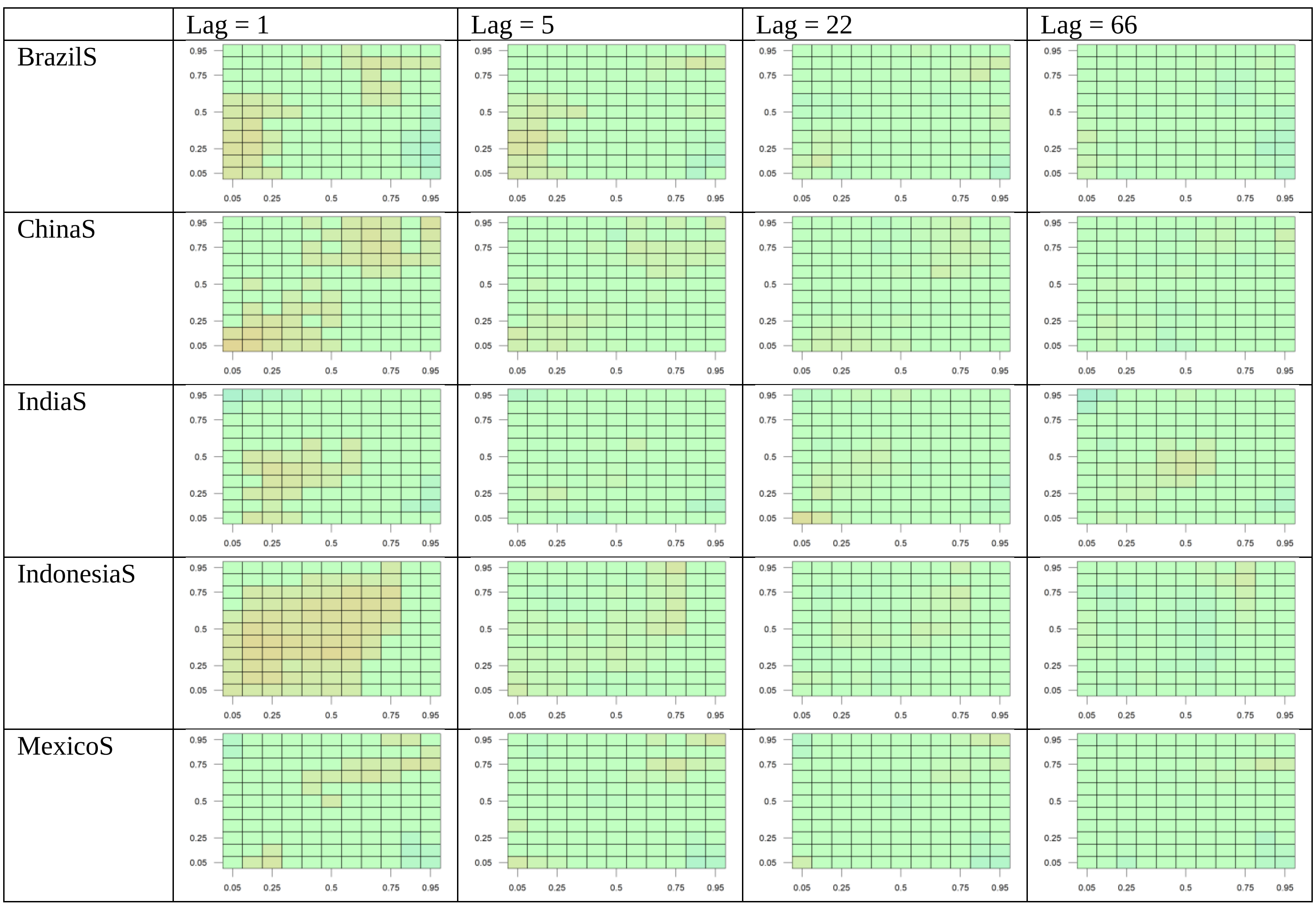


Fig. A.3.

Partial cross-quantile correlations between oil (WTI) and the exchange rates in emerging markets (E7+1). The control variable is GPRD_Threat. Notes: please refer to the notes in Fig. A.1.



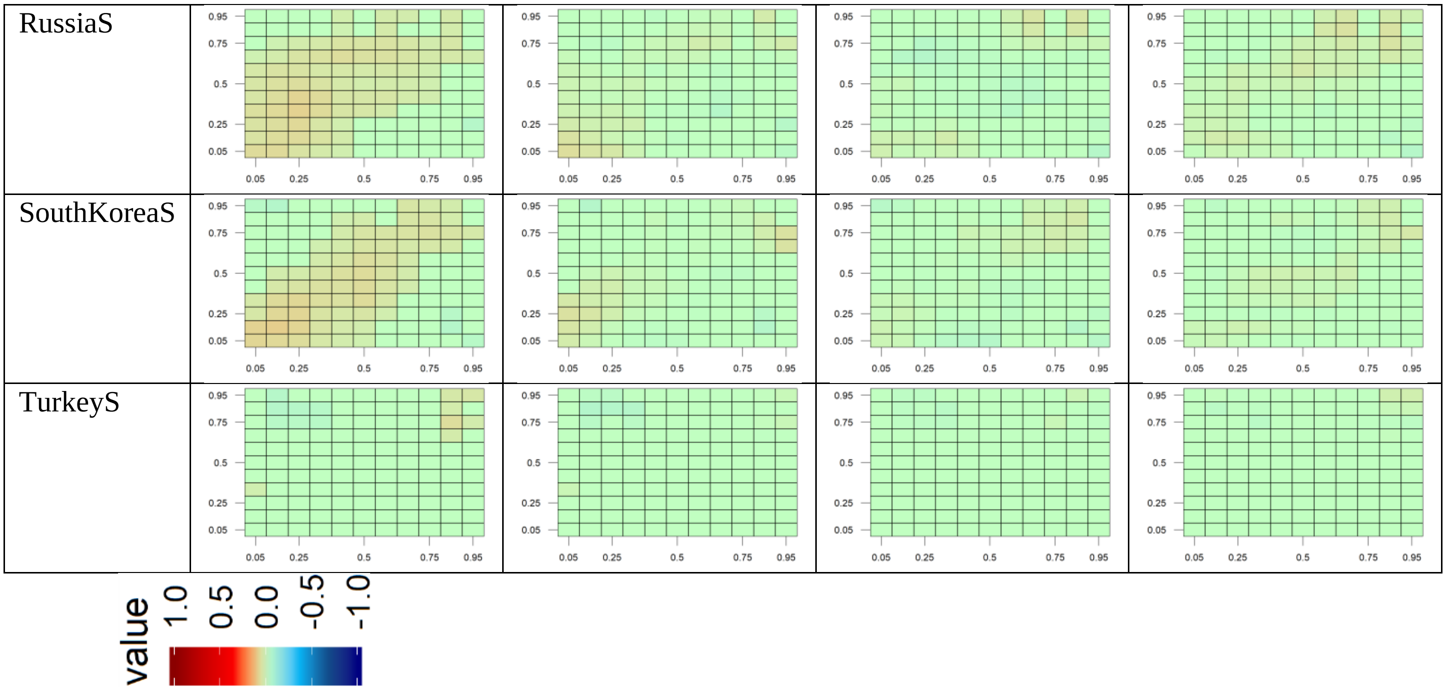
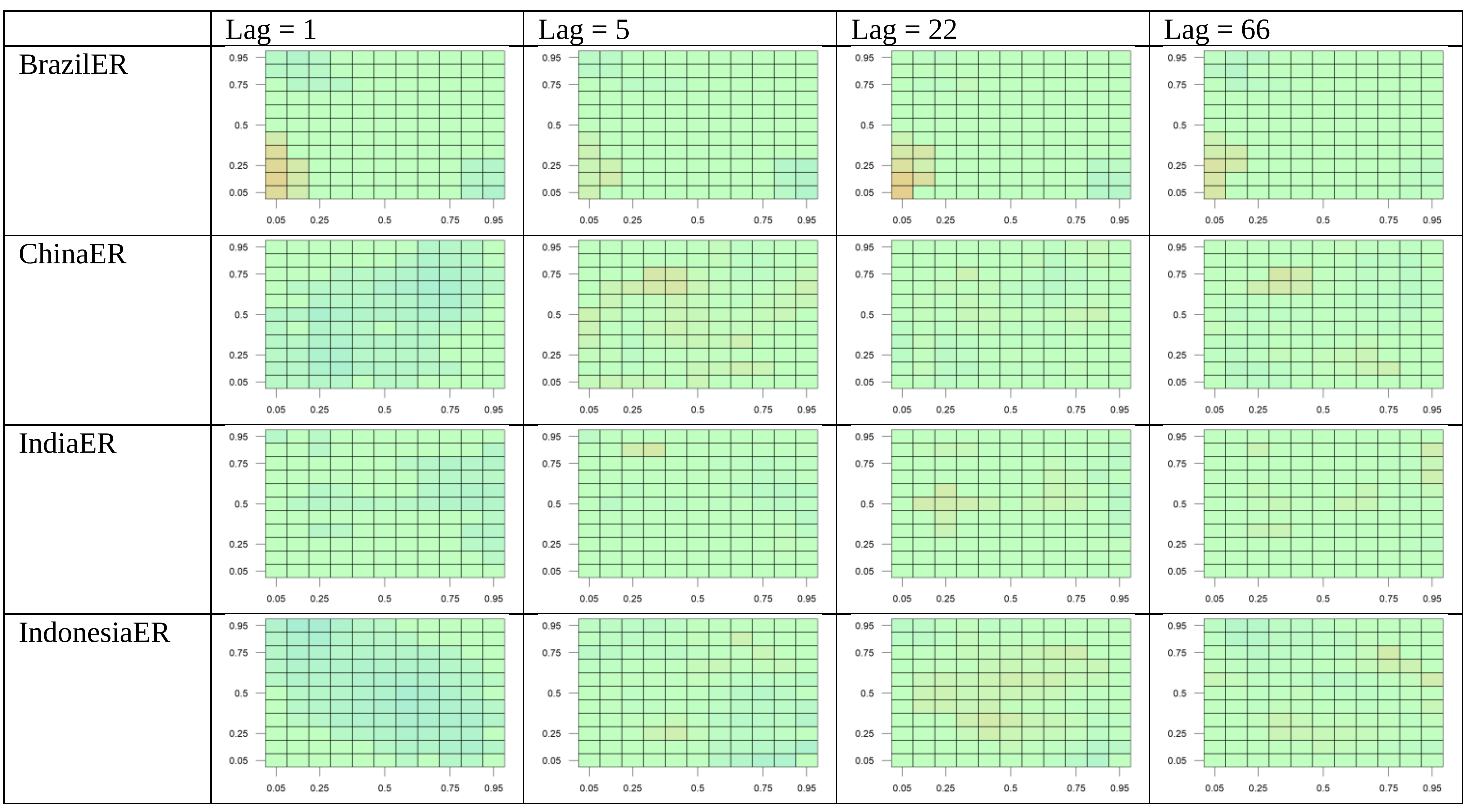


Fig. A.4.

Partial cross-quantile correlations between oil (WTI) and the emerging stock market (E7+1). The control variable is GPRD_Threat. Notes: please refer to the notes in Fig. A.1.



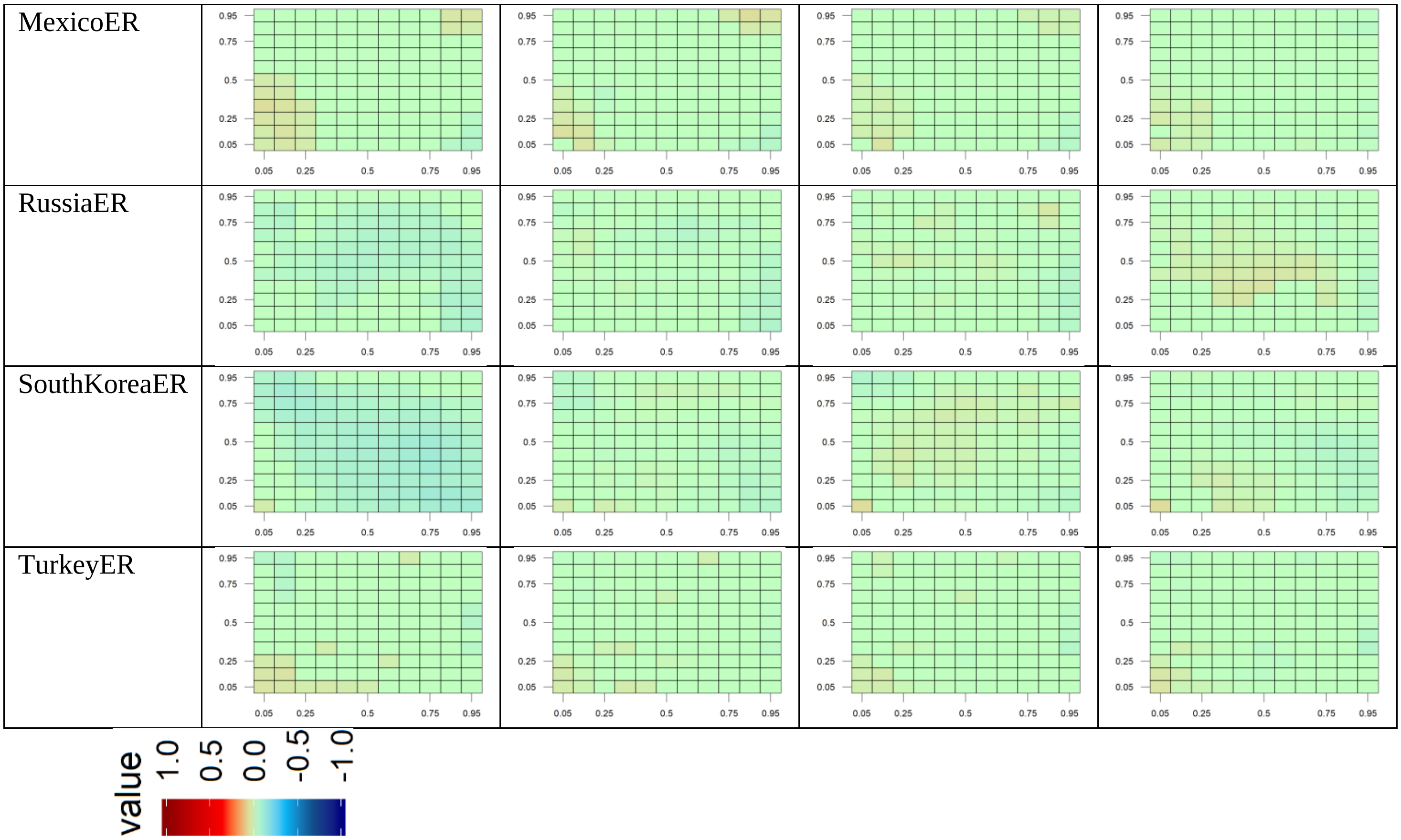
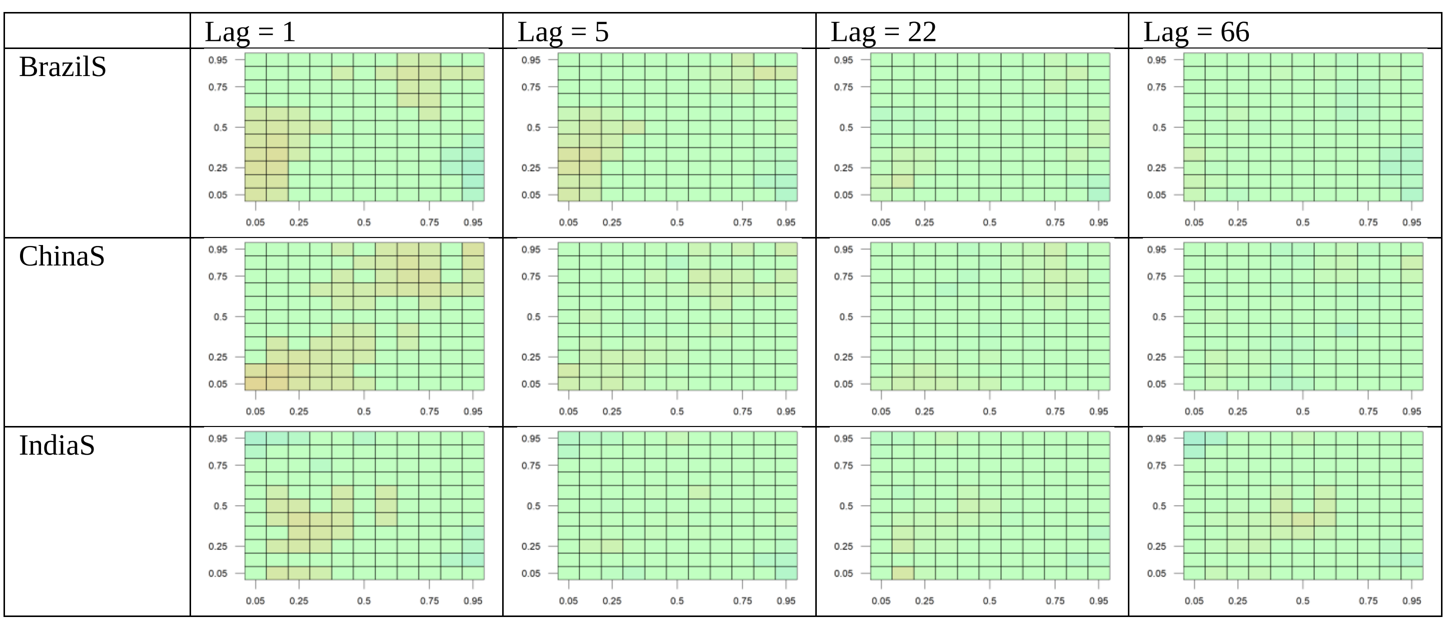


Fig. A.5.

Partial cross-quantile correlations between oil (WTI) and the exchange rates in emerging markets (E7+1). The control variable is GPRD. Notes: please refer to the notes in Fig. A.1.



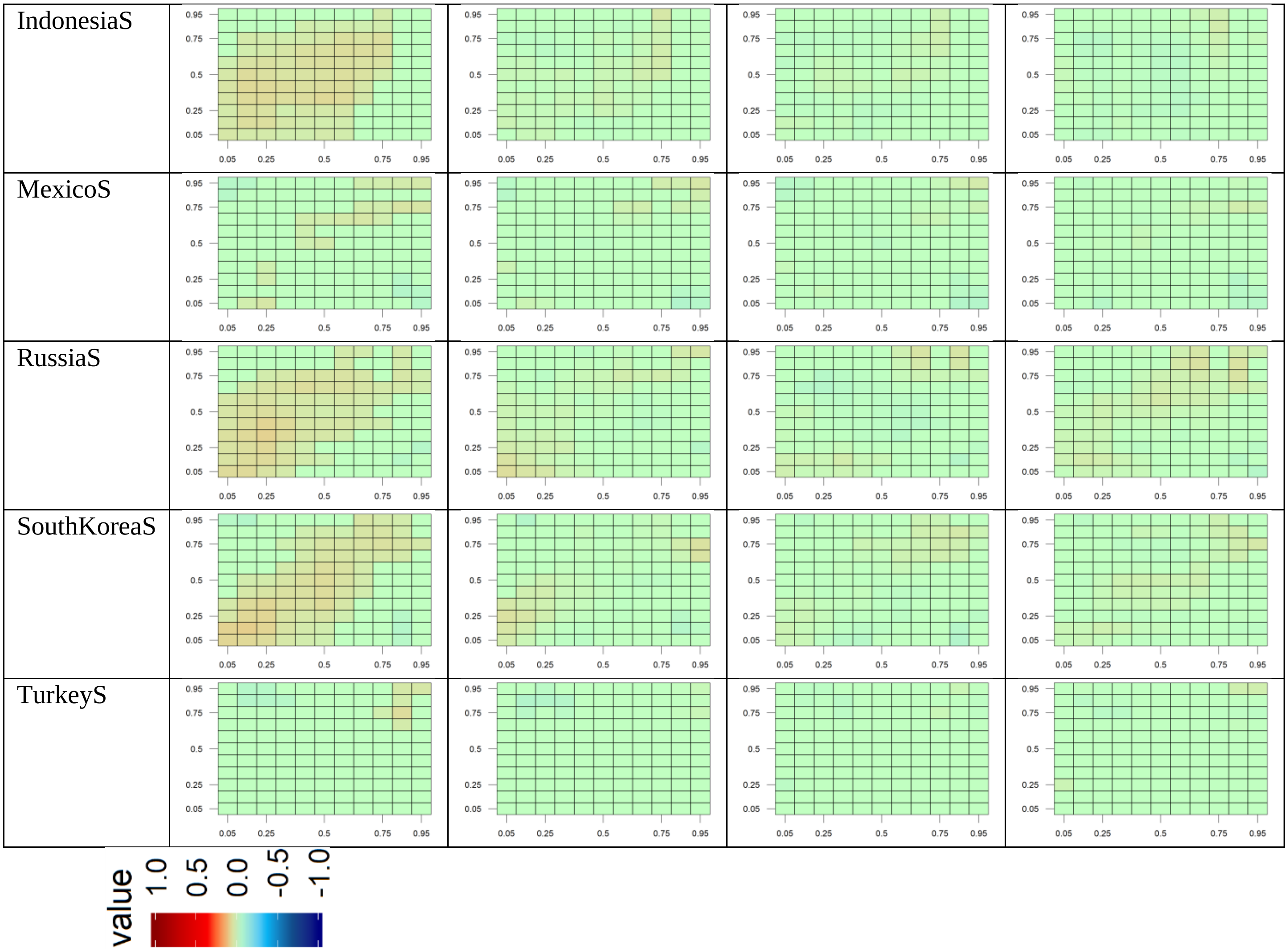
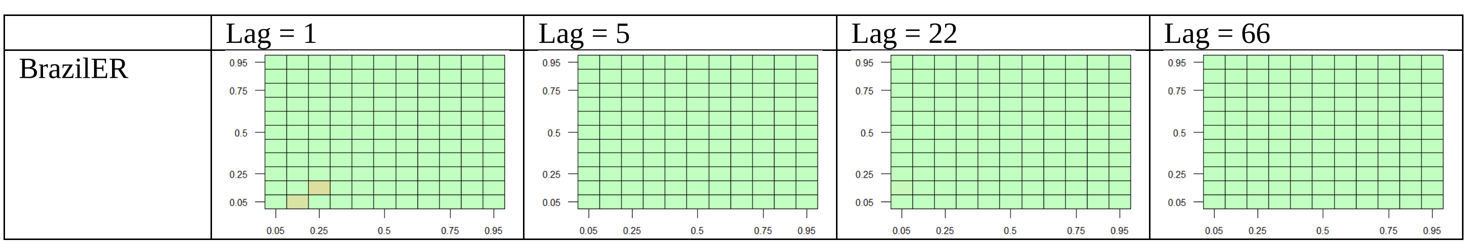


Fig. A.6.

Partial cross-quantile correlations between oil (WTI) and the emerging stock market (E7+1). The control variable is GPRD. Notes: please refer to the notes in Fig. A.1.

Appendix B. See Figs. B.1-B.6.



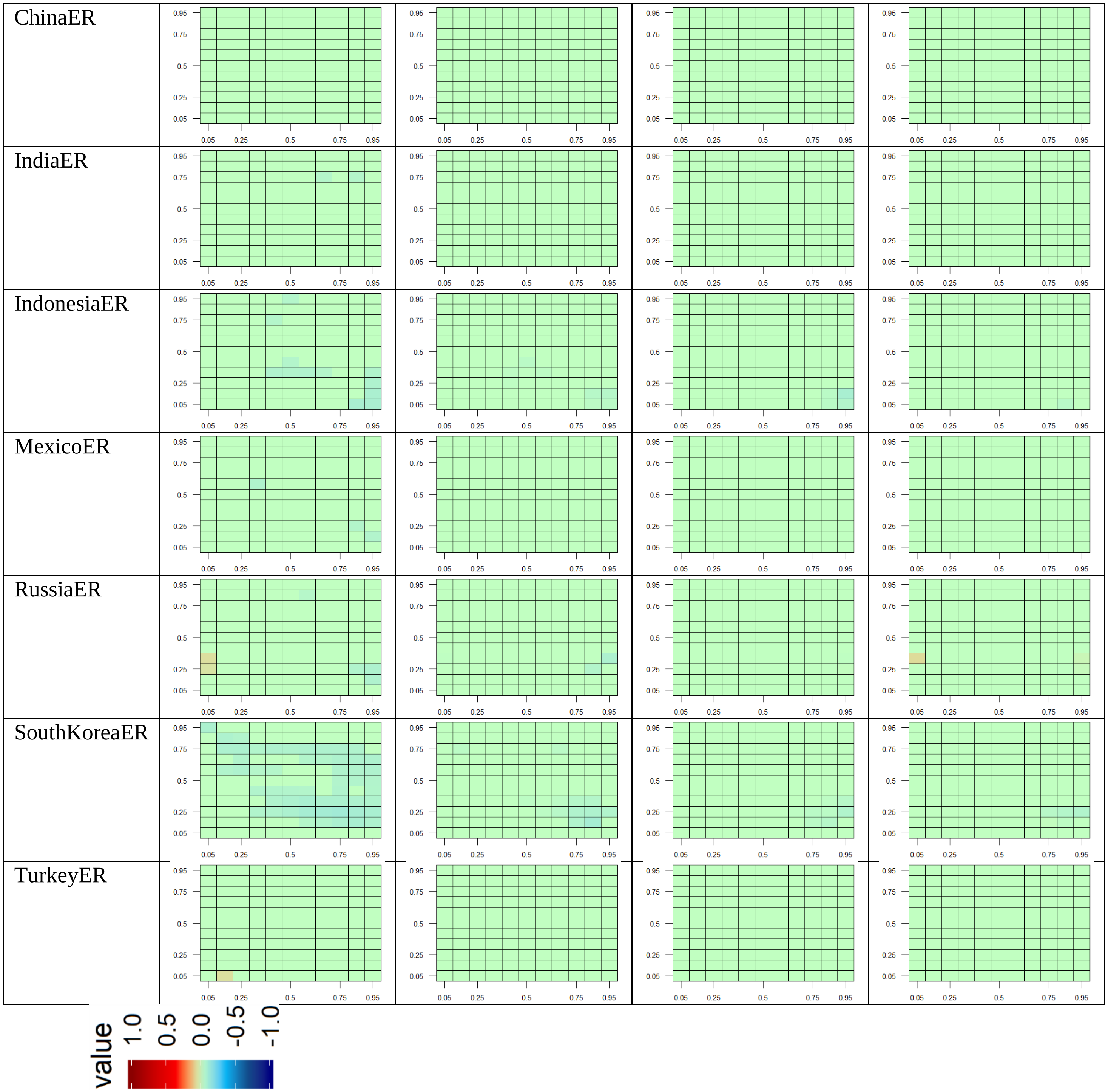


Fig. B.1.

Cross-quantilogram heatmap for predictability running from oil (Brent) to the exchange rates of emerging market (E7+1). Notes: please refer to the notes in Fig. A.1.

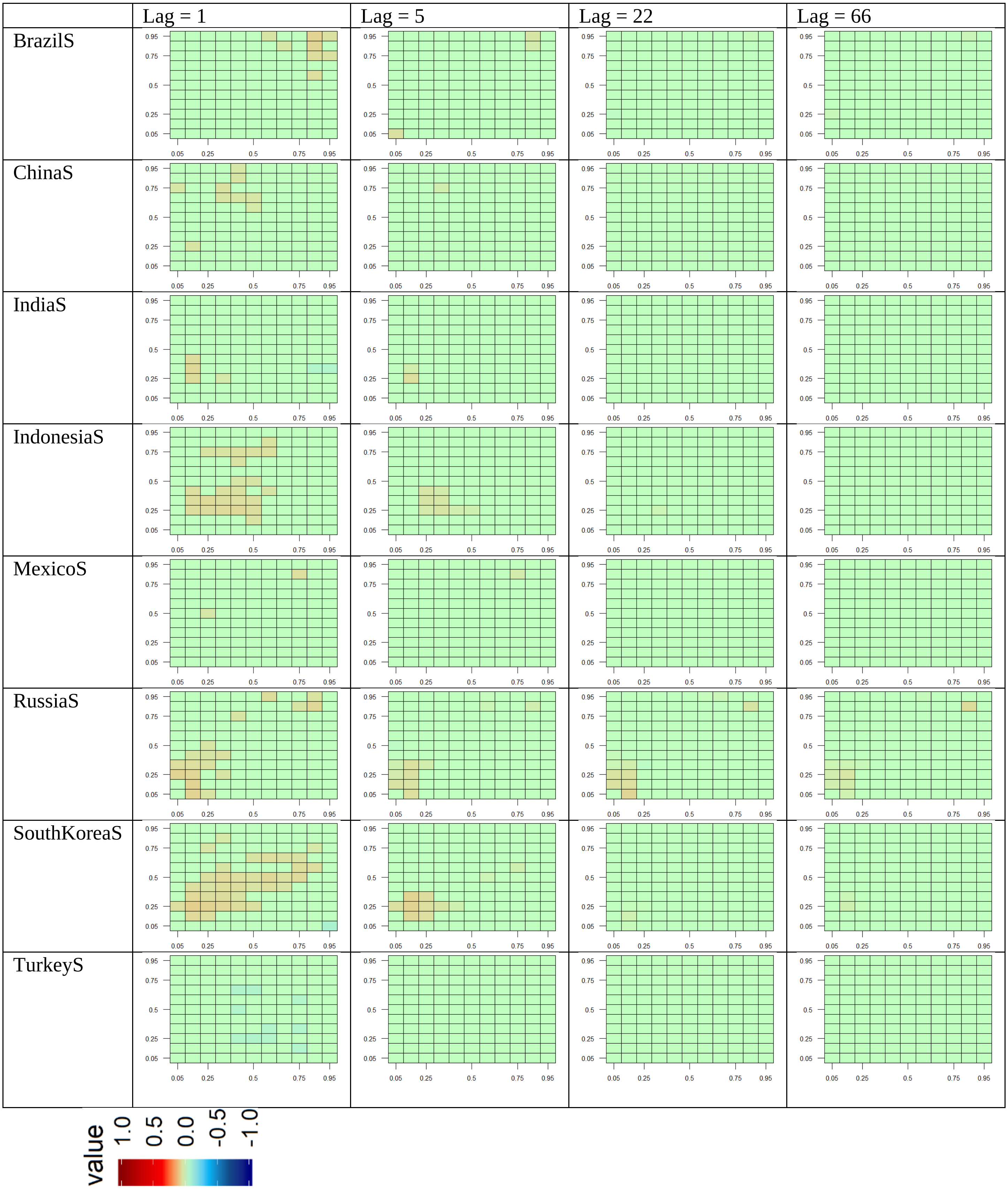
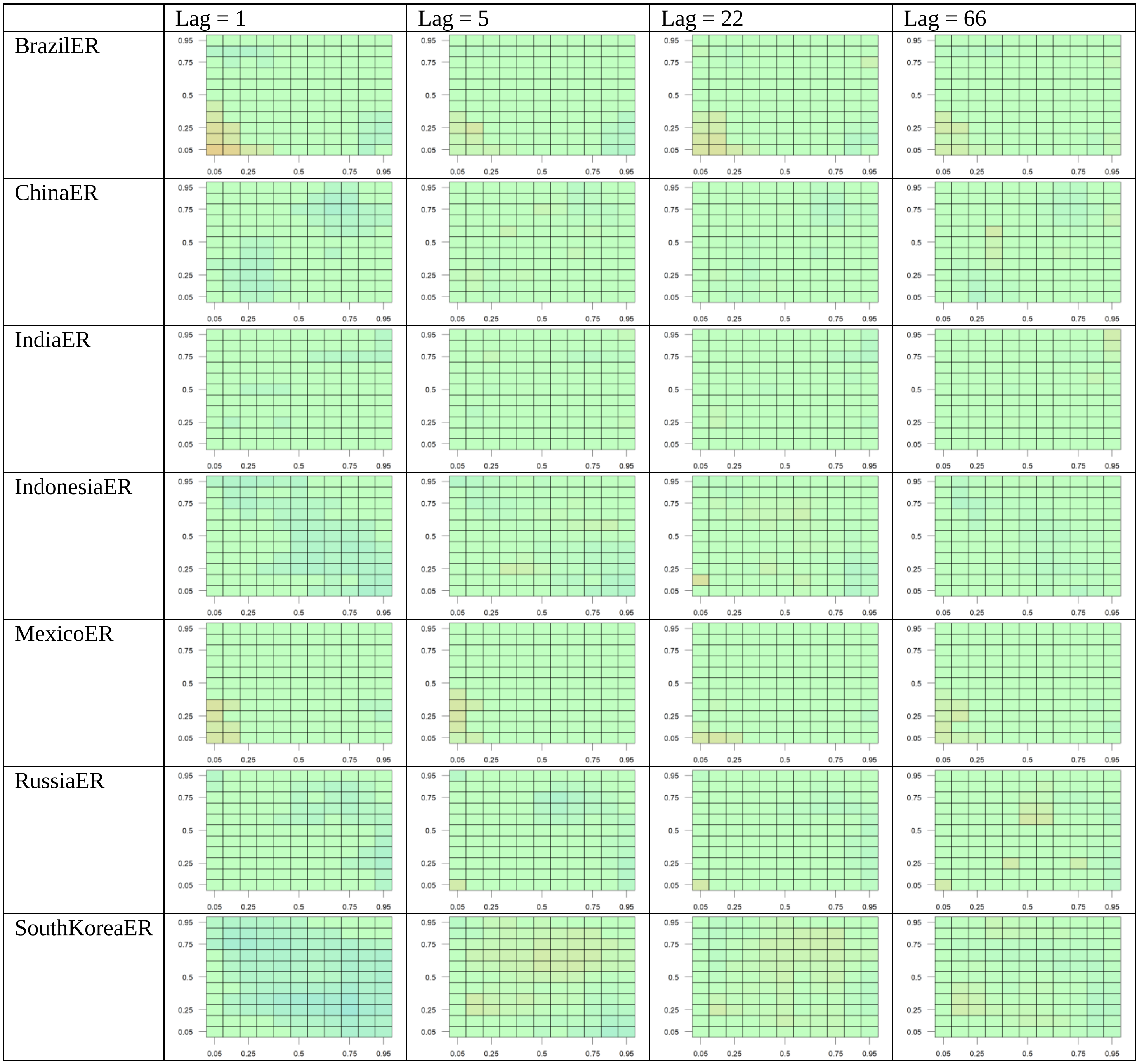

Lag = 1
Lag = 5
Lag = 22
Lag = 66
BrazilS
ChinaS
IndiaS
IndonesiaS
MexicoS
RussiaS
SouthKoreaS
TurkeyS
0.05
0.25
0.5
0.75
0.95
value
1.0
0.5
0.0
-0.5
-1.0

Fig. B.2.

Directional predictabilities in quantiles from oil (Brent) to emerging stock markets (E7+1). Notes: please refer to the notes in Fig. A.1.



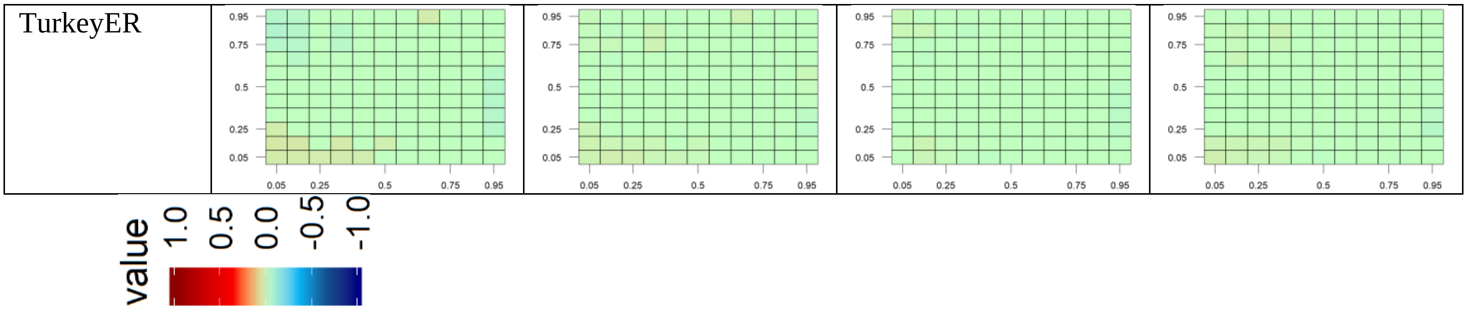
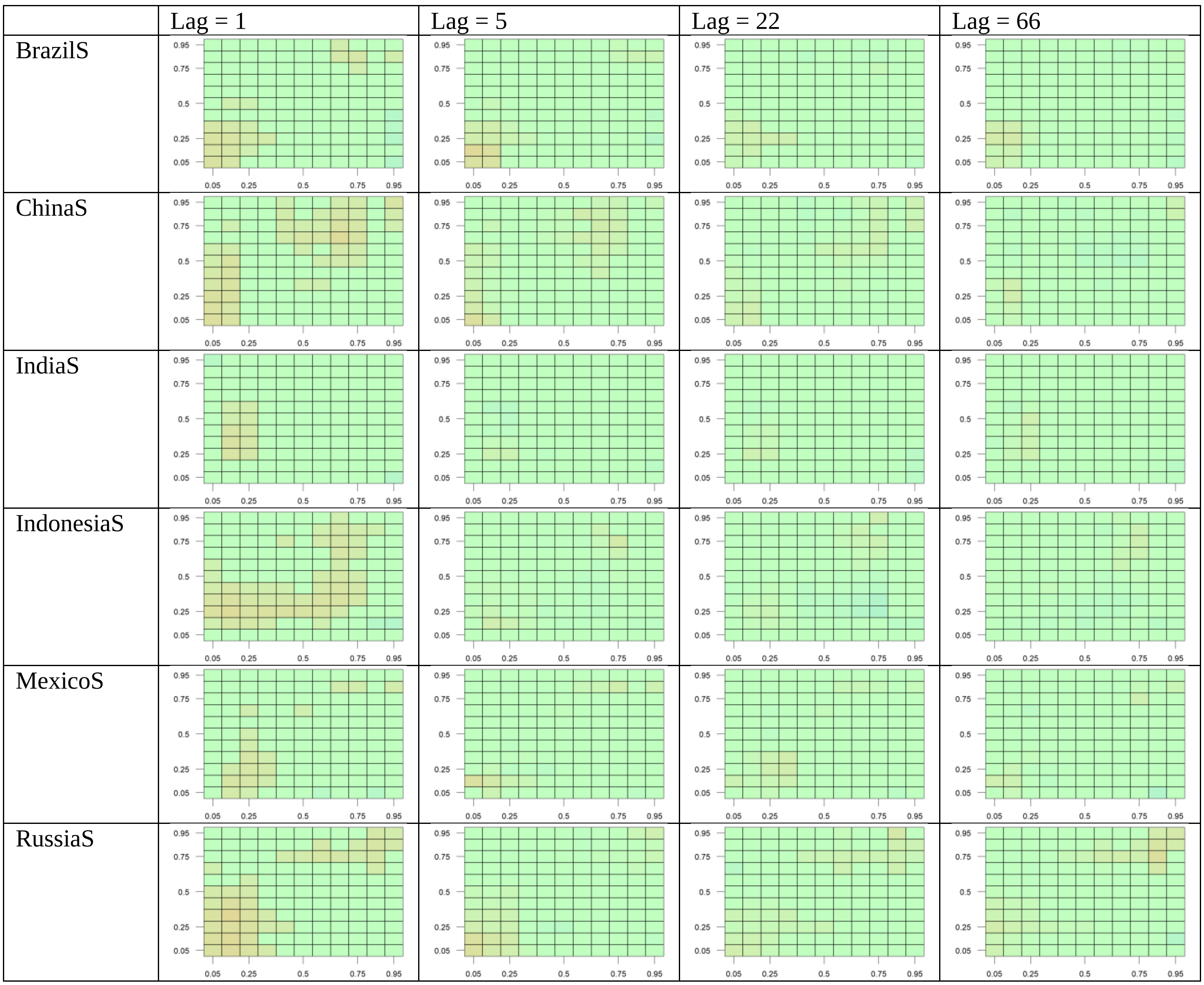


Fig. B.3.

Partial cross-quantile correlations between oil (Brent) and the exchange rates in the emerging markets (E7+1). The control variable is GPRD_Threat. Notes: please refer to the notes in Fig. A.1.



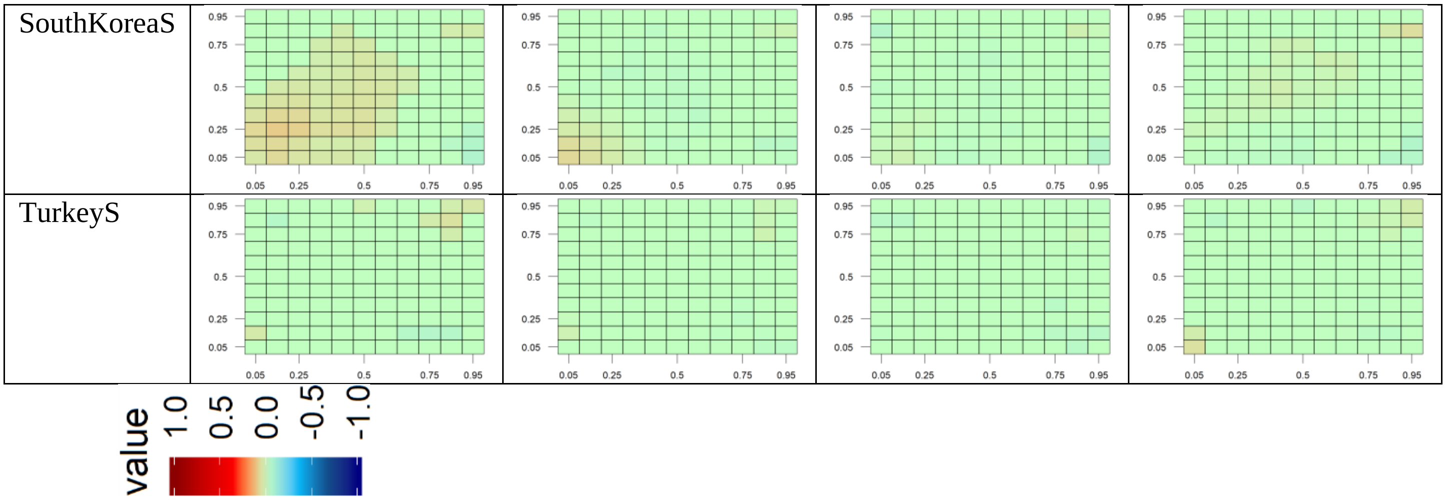
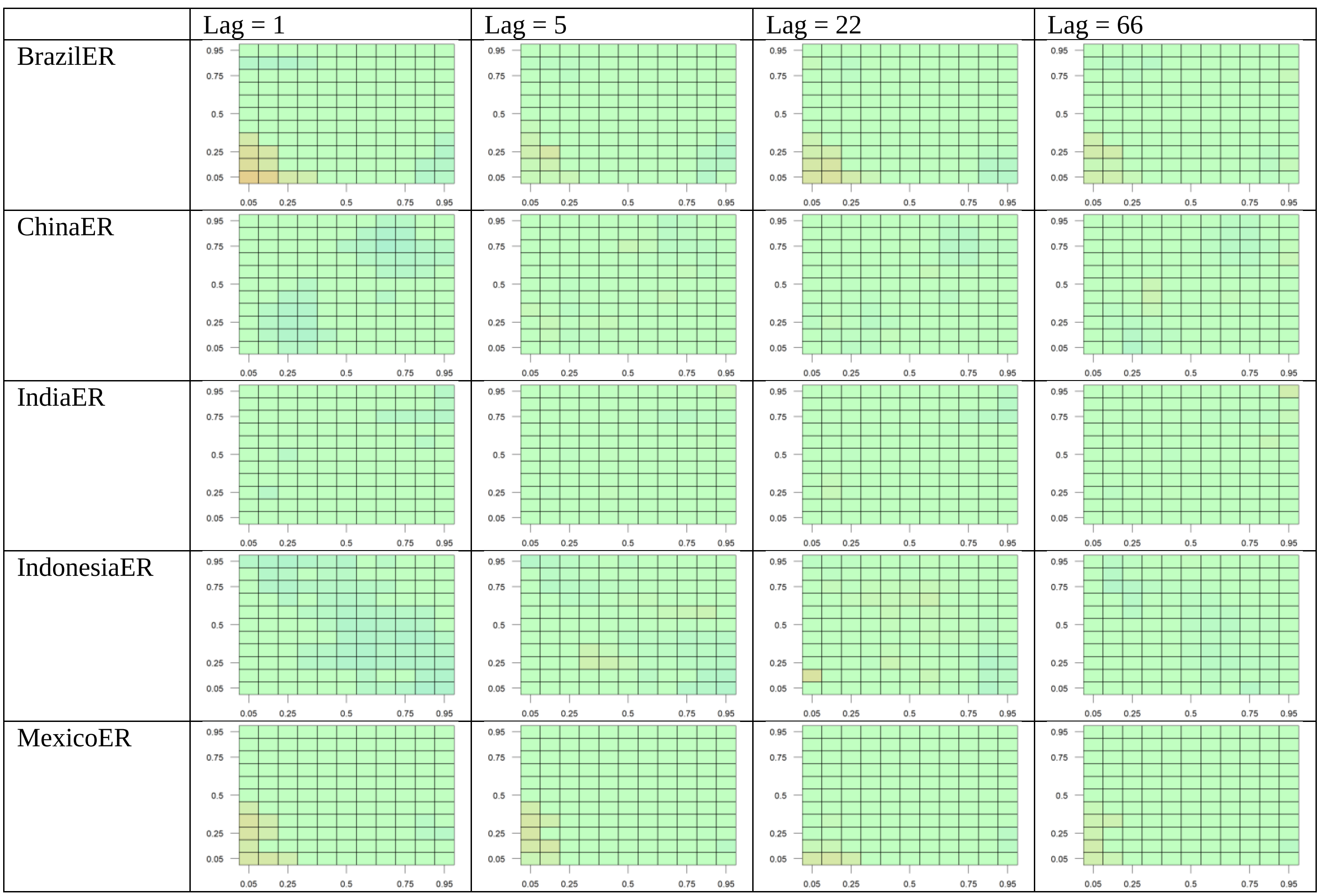


Fig. B.4.

Partial cross-quantile correlations between oil (Brent) and the emerging stock market (E7+1) returns. The control variable is GPRD_Threat. Notes: please refer to the notes in Fig. A.1.



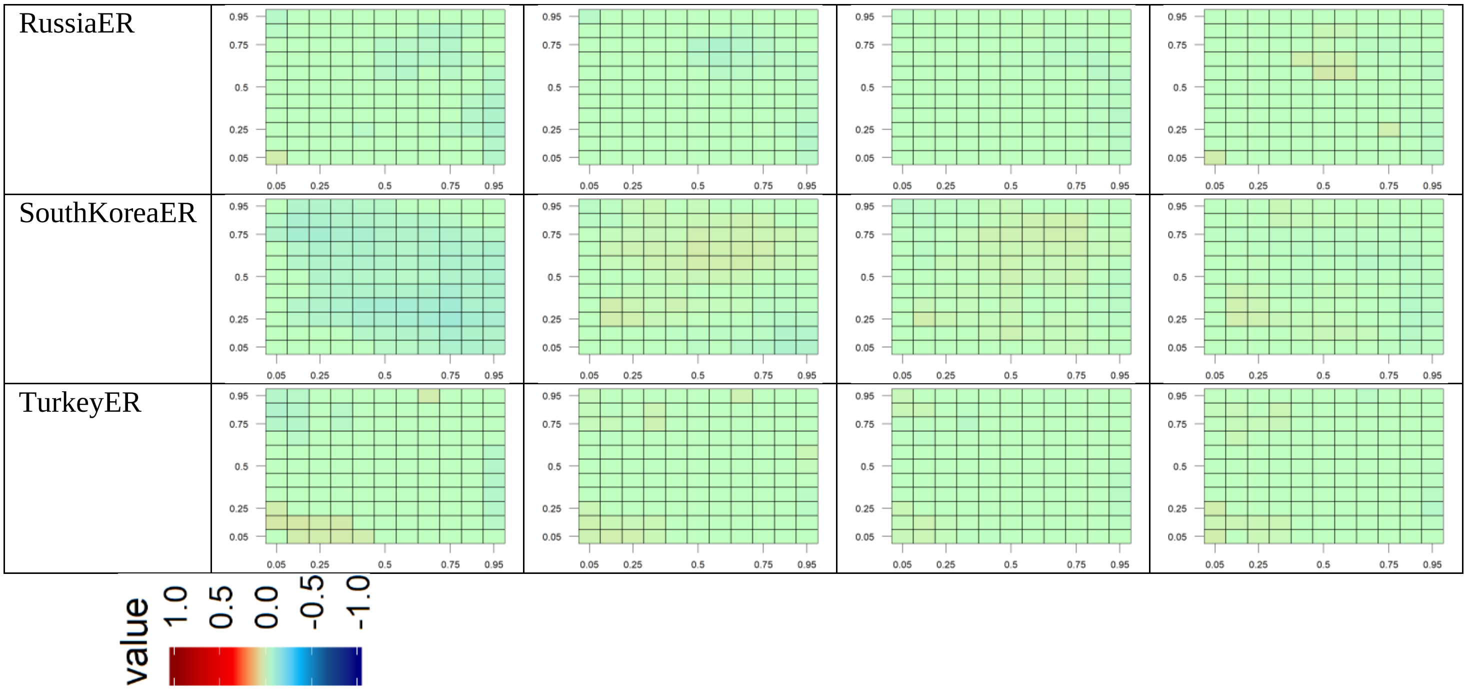
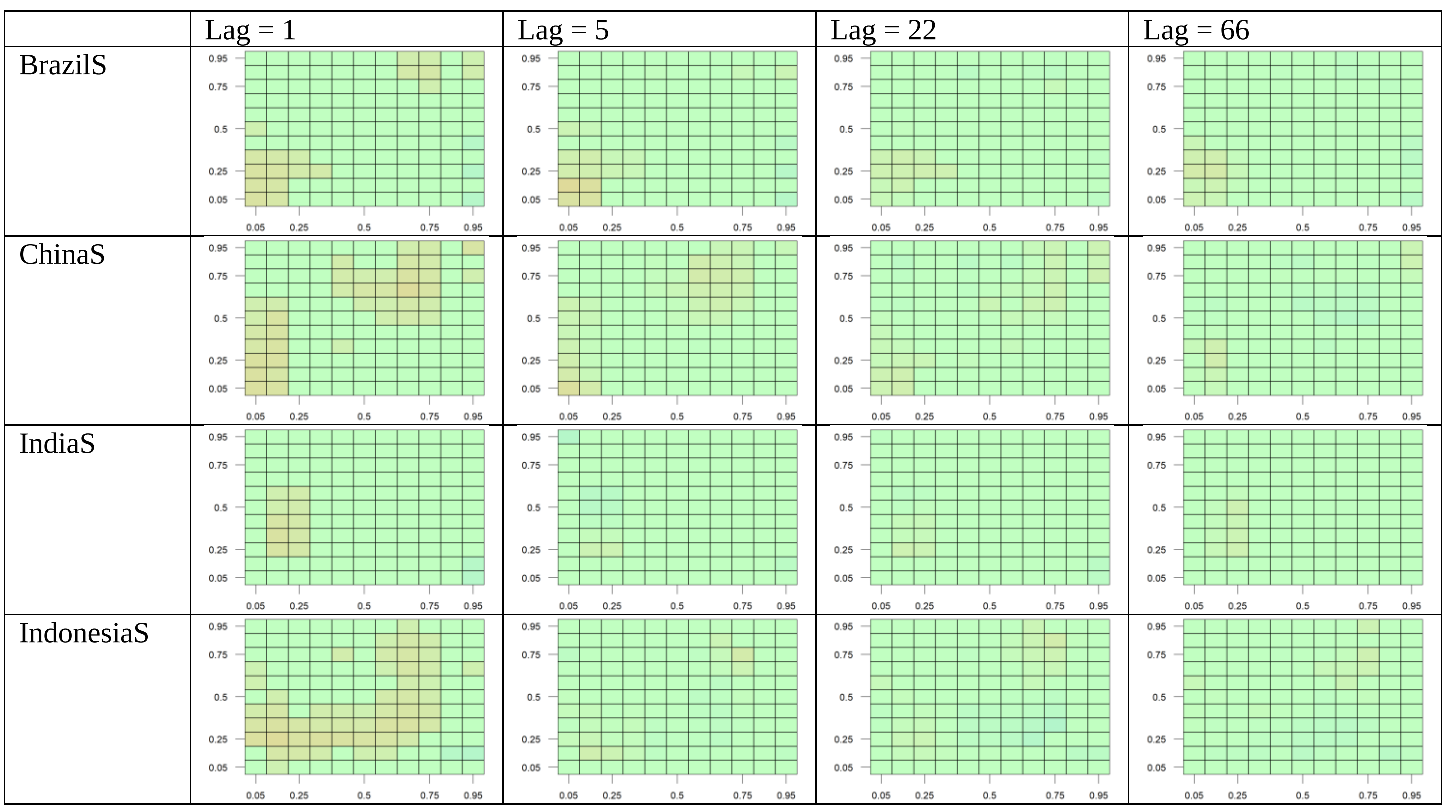


Fig. B.5.

Partial cross-quantile correlations between oil (Brent) and the exchange rates in emerging markets (E7+1). The control variable is GPRD. Notes: please refer to the notes in Fig. A.1.



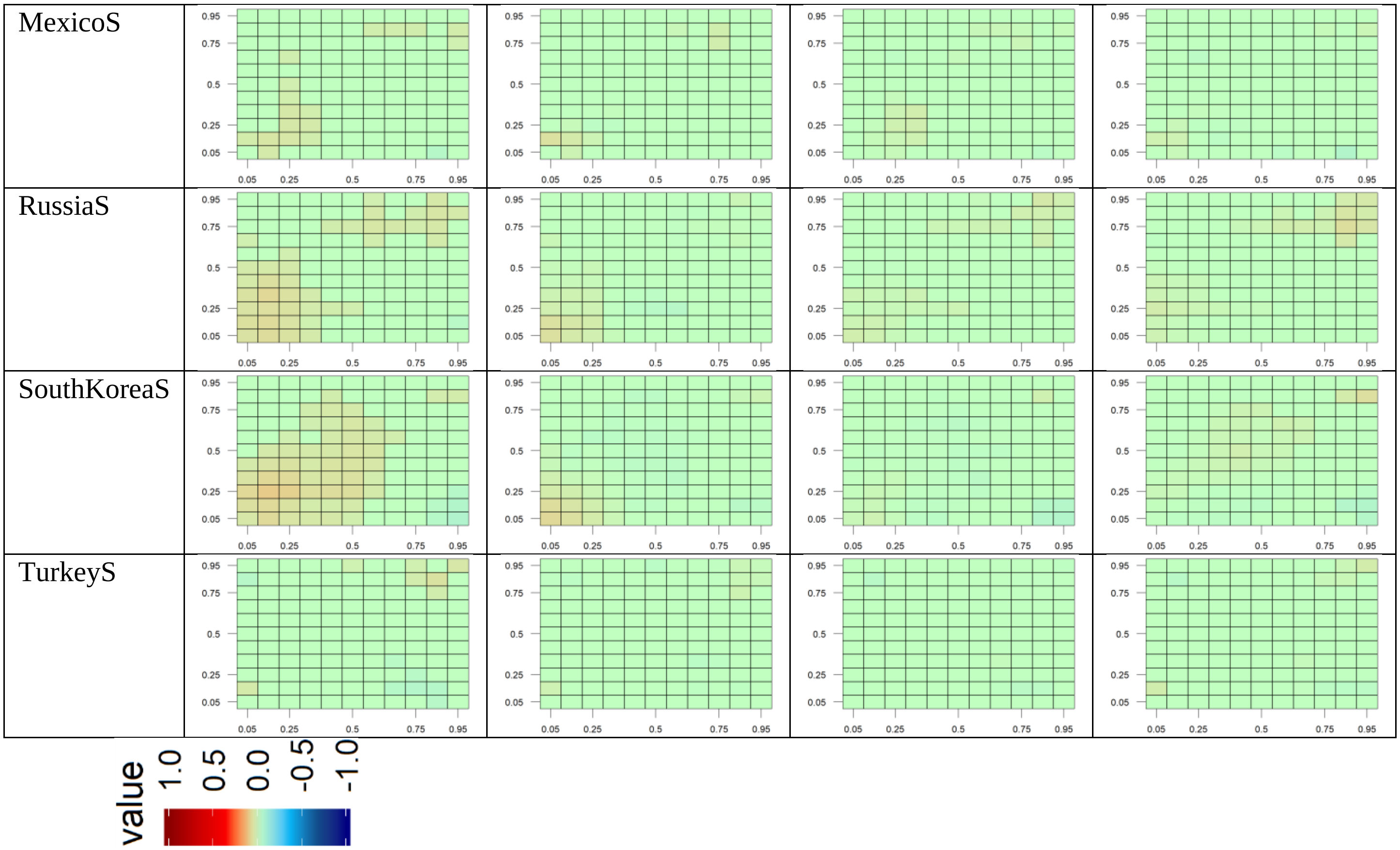
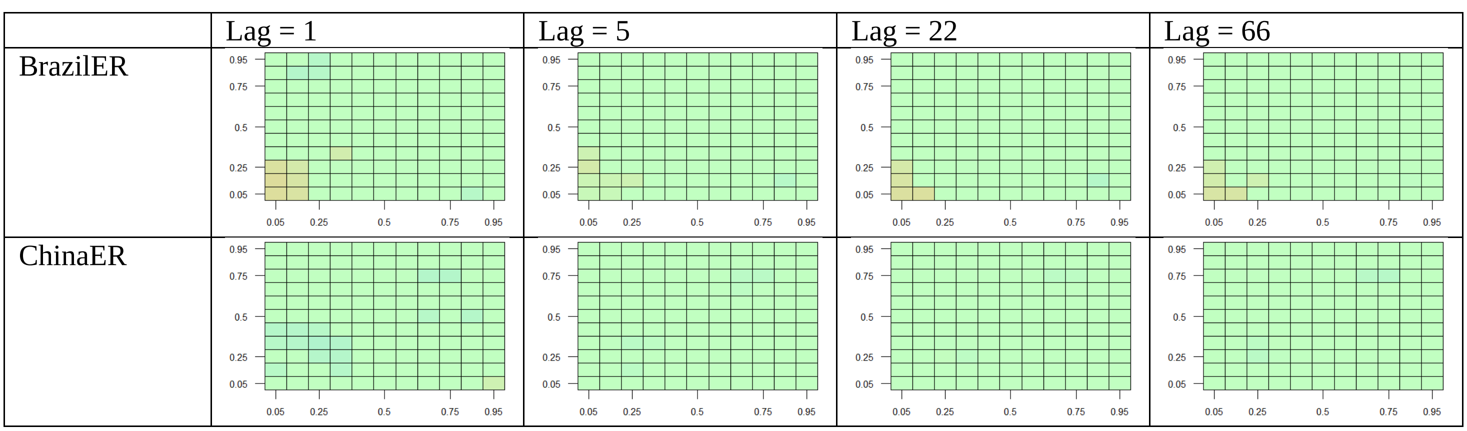


Fig. B.6.

Partial cross-quantile correlations between oil (Brent) and the emerging stock market (E7+1). The control variable is GPRD. Notes: please refer to the notes in Fig. A.1.

Appendix C. See Figs. C.1-C.6.



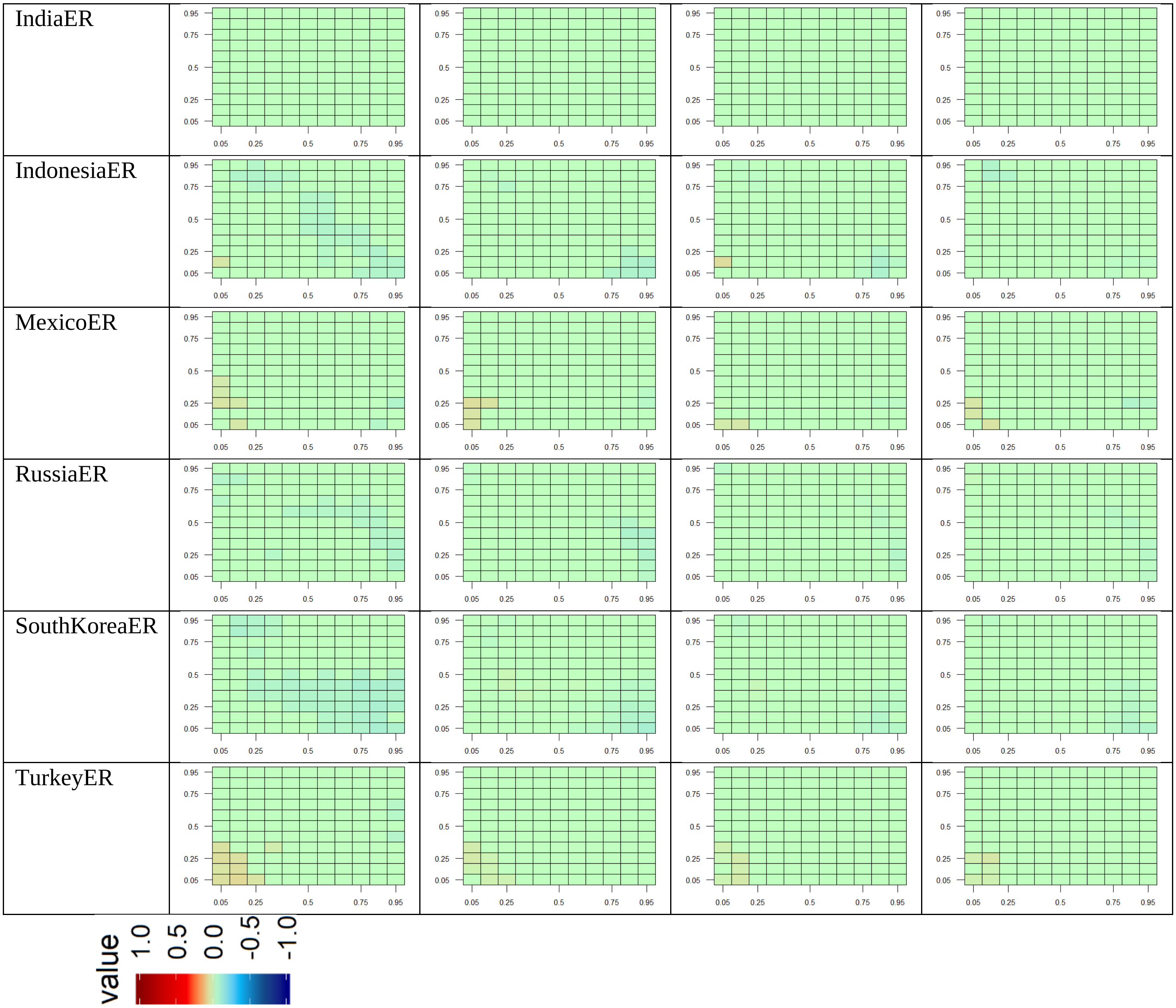
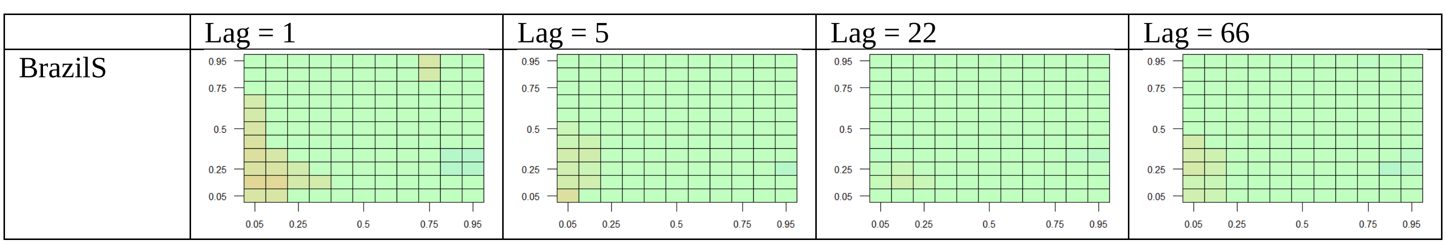


Fig. C.1.

Cross-quantilogram heatmap for predictability running from oil (OPEC) to the exchange rates of emerging market (E7+1). Notes: please refer to the notes in Fig. A.1.



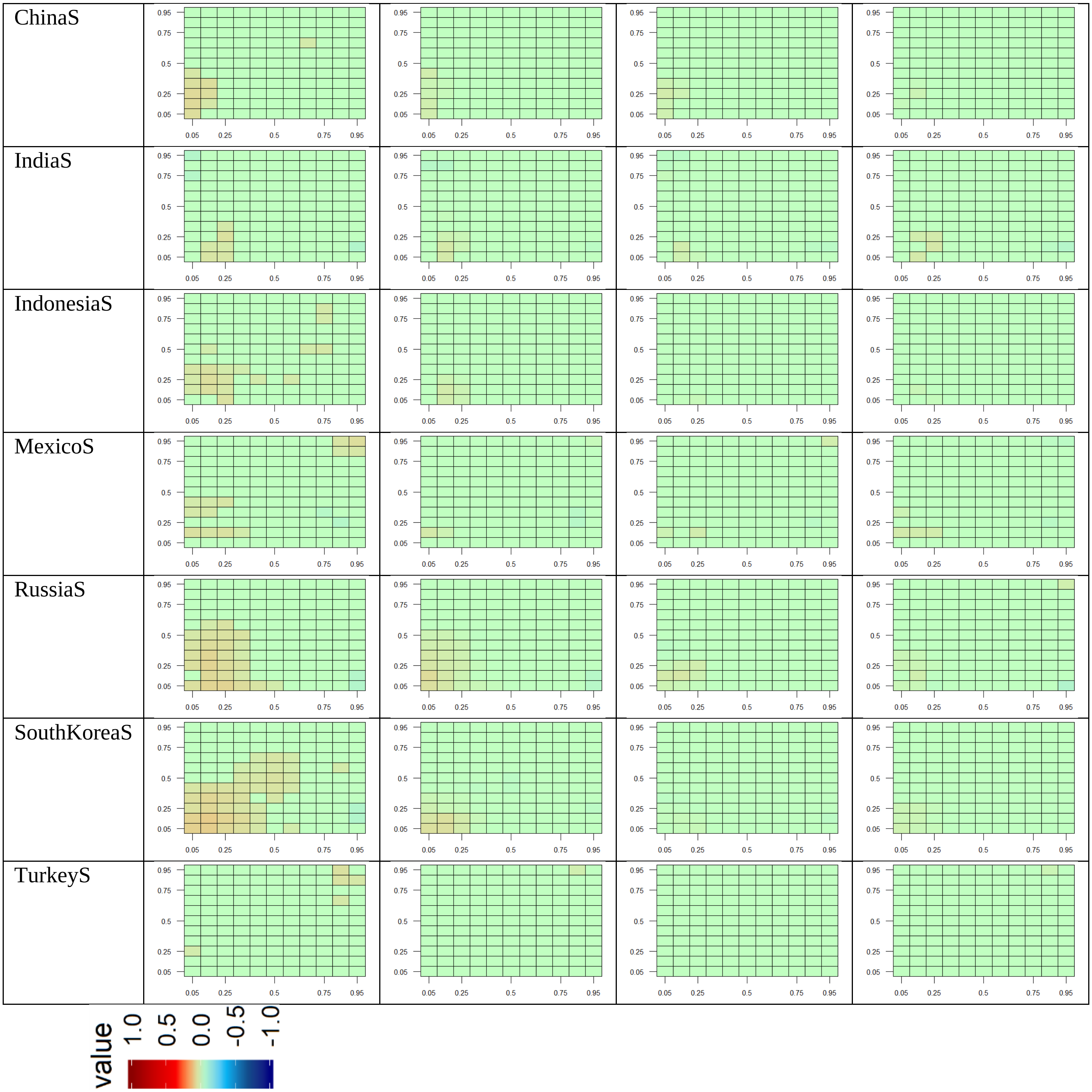


Fig. C.2.

Directional predictabilities in quantiles from oil (OPEC) to emerging stock markets (E7+1). Notes: please refer to the notes in Fig. A.1.

	Lag = 1	Lag = 5	Lag = 22	Lag = 66

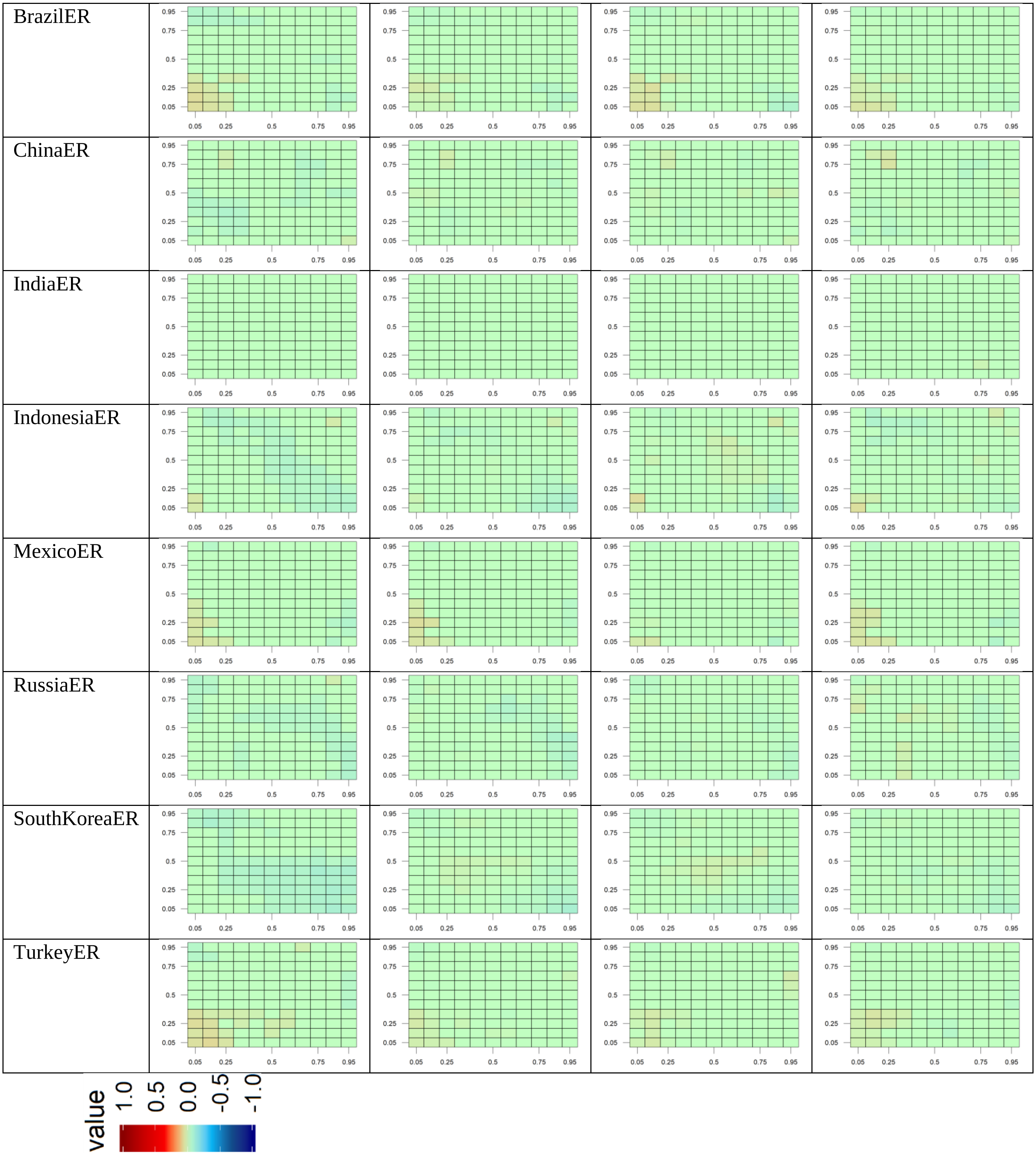
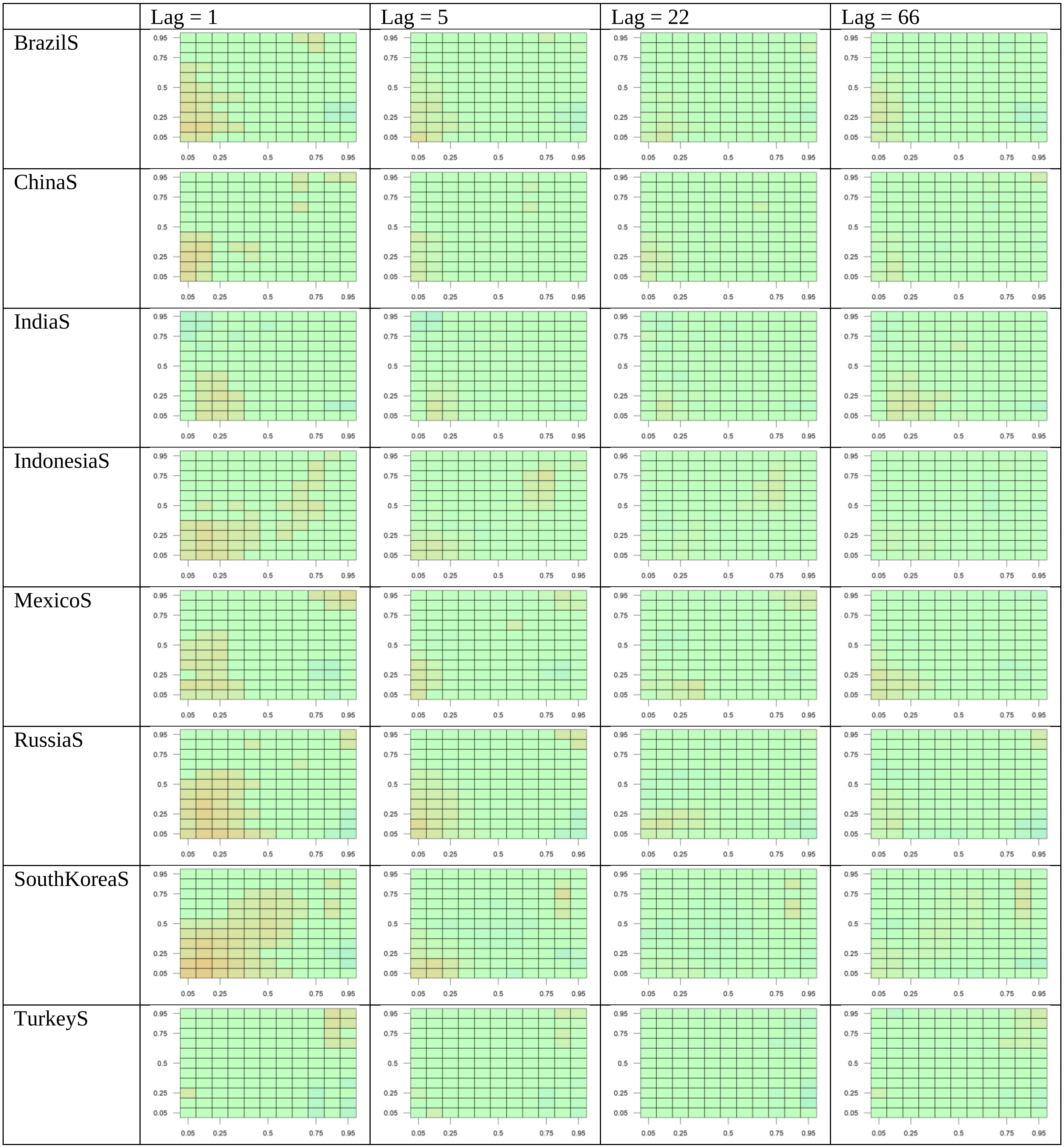

BrazilER
ChinaER
IndiaER
IndonesiaER
MexicoER
RussiaER
SouthKoreaER
TurkeyER
0.05
0.25
0.5
0.75
0.95
value
1.0
0.5
0.0
-0.5
-1.0

Fig. C.3.

Partial cross-quantile correlations between oil (OPEC) and the exchange rates in emerging markets (E7+1). The control variable is GPRD_Threat. Notes: please refer to the notes in Fig. A.1.



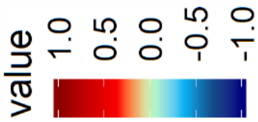
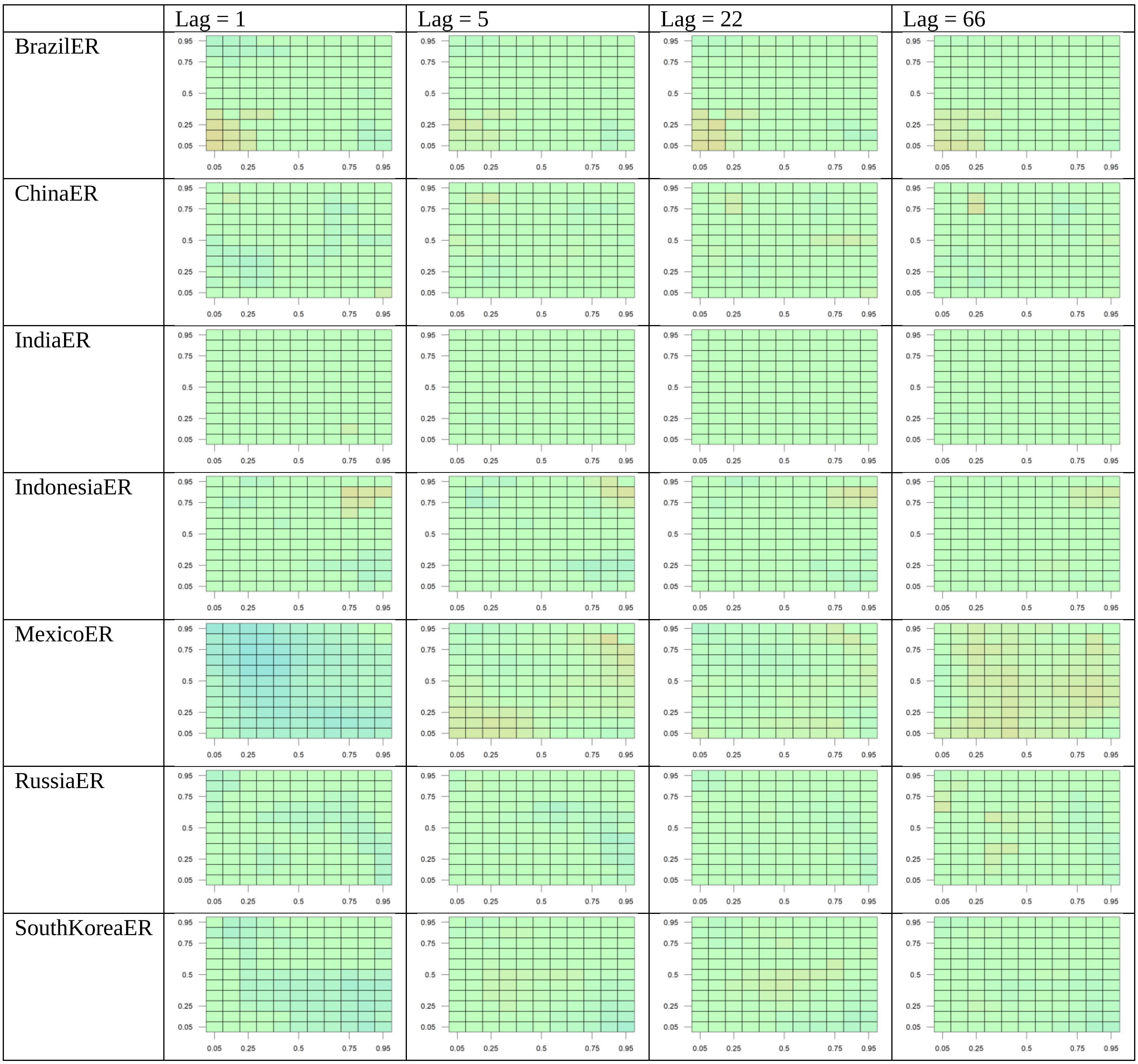
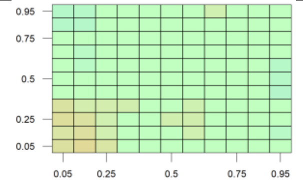
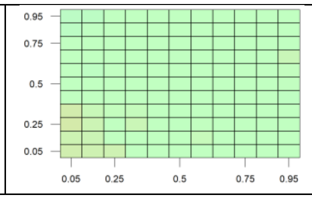
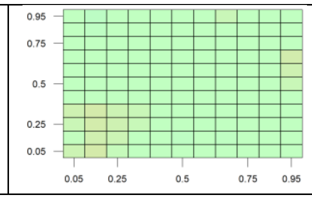
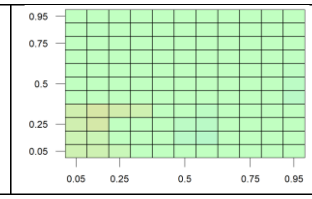


Fig. C.

Partial cross-quantile correlations between oil (OPEC) and the emerging stock market (E7+1). The control variable is GPRD_Threat. Notes: please refer to the notes in Fig. A.1.



TurkeyER				

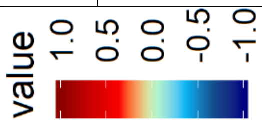


Fig. C.5.

Partial cross-quantile correlations between oil (OPEC) and the exchange rates in emerging markets (E7+1). The control variable is GPRD. Notes: please refer to the notes in Fig. A.1.

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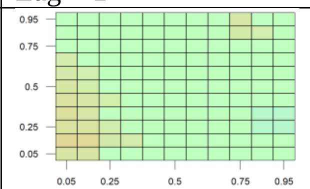
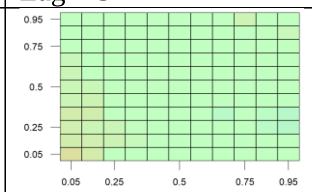
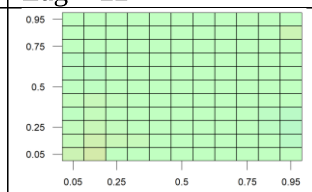
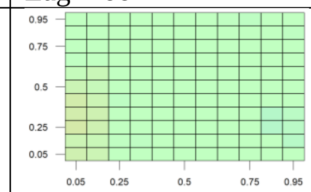
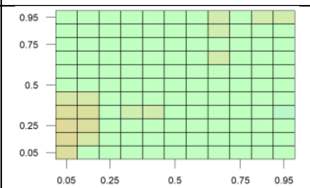
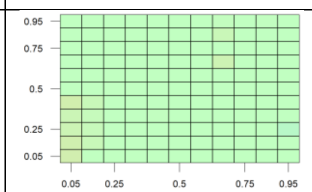
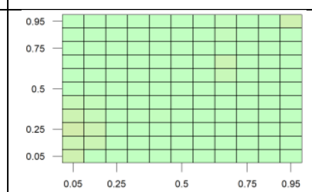
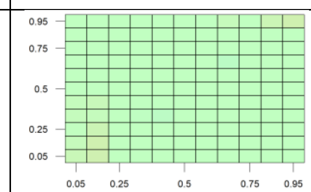
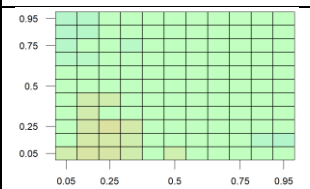
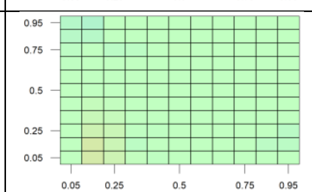
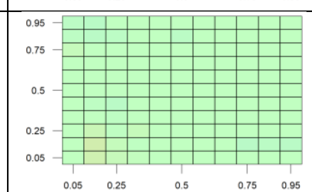
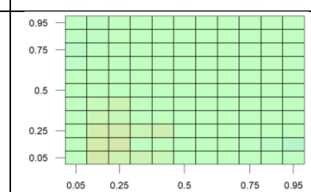
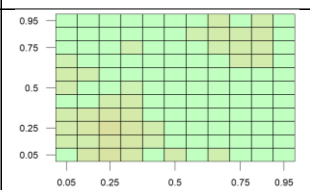
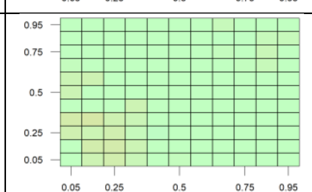
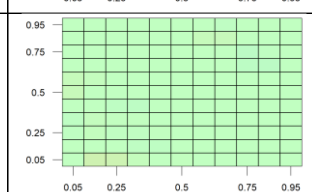
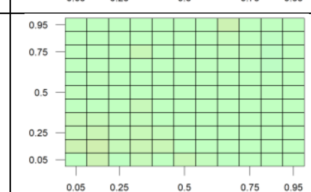
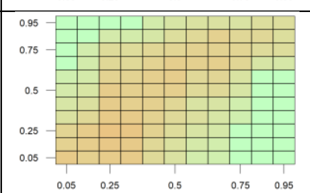
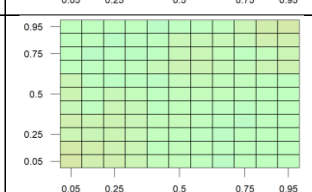
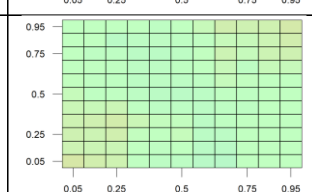
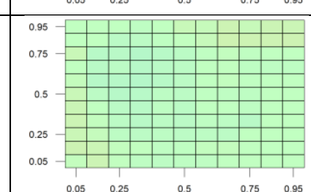
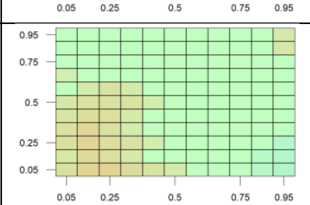
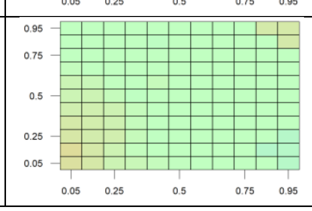
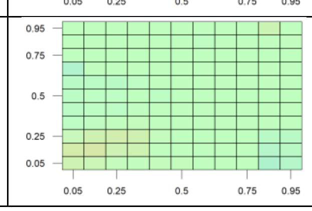
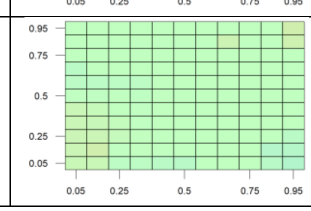
BrazilS				
ChinaS				
IndiaS				
IndonesiaS				
MexicoS				
RussiaS				

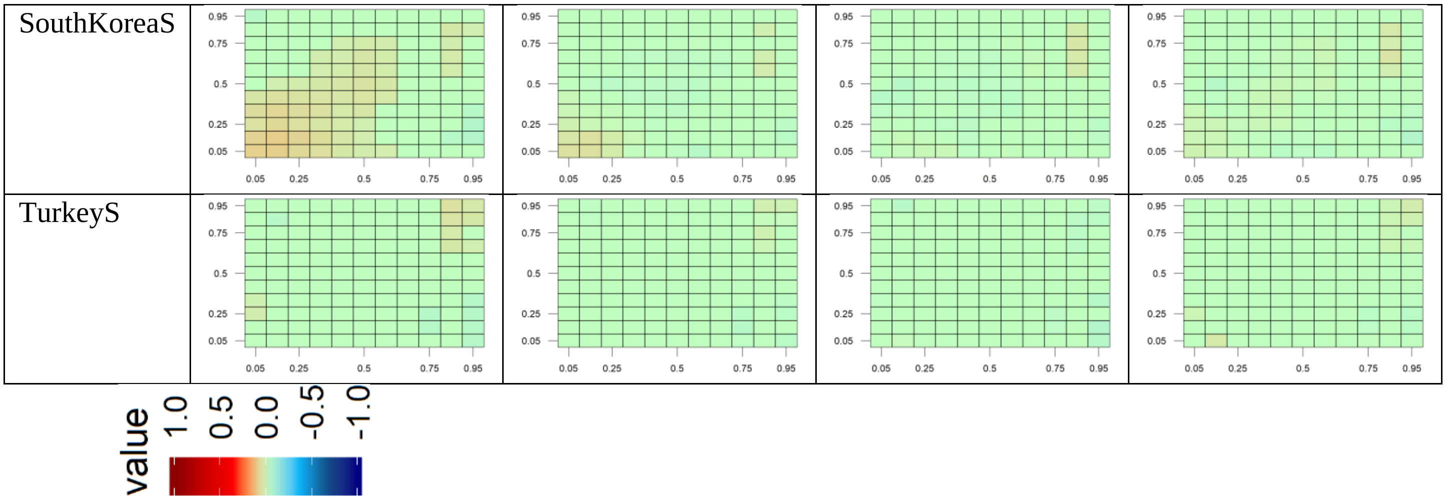
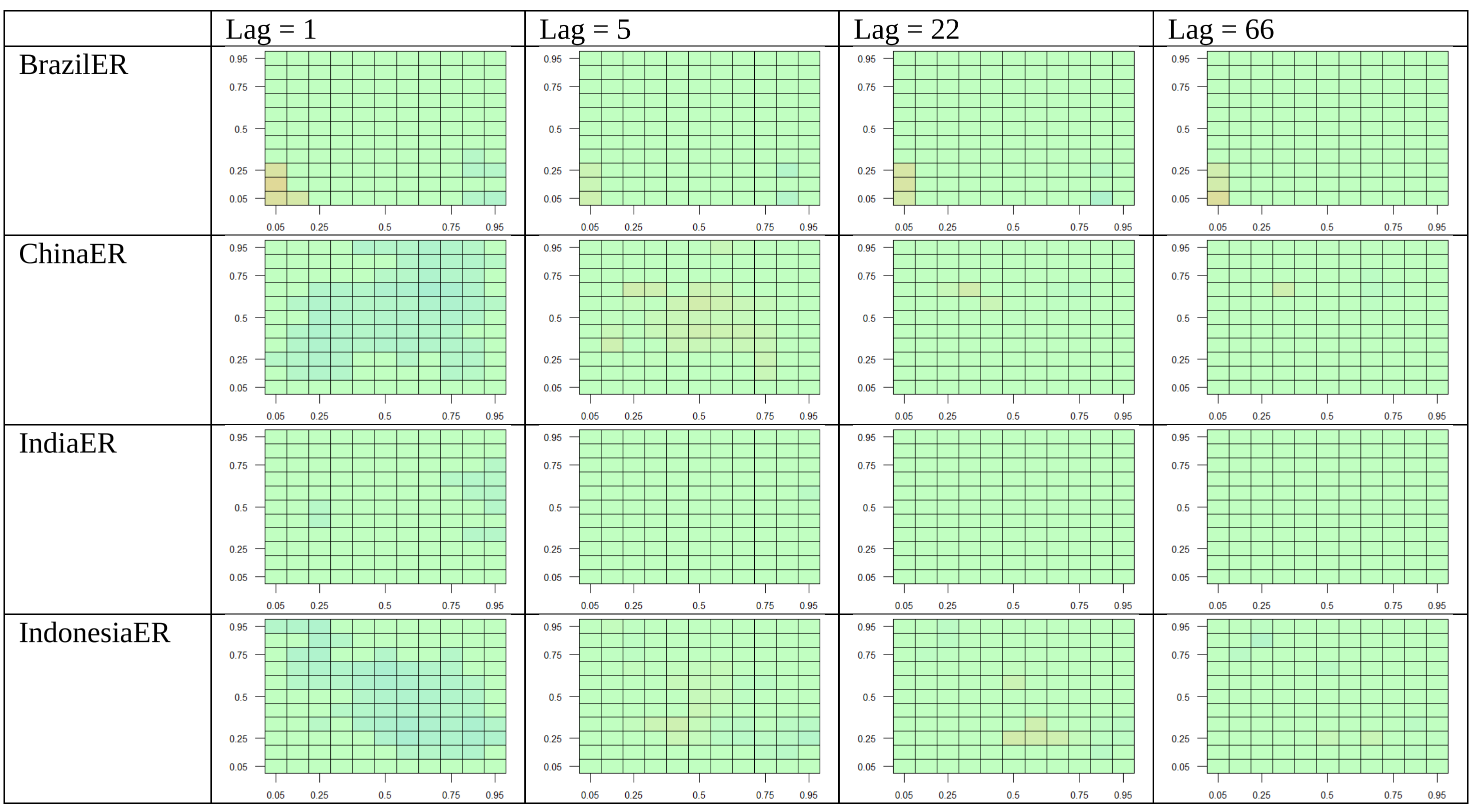


Fig. C.6.

Partial cross-quantile correlations between oil (OPEC) and the emerging stock market (E7+1). The control variable is GPRD. Notes: please refer to the notes in Fig. A.1.

Appendix D. See Figs. D.1-D.6.



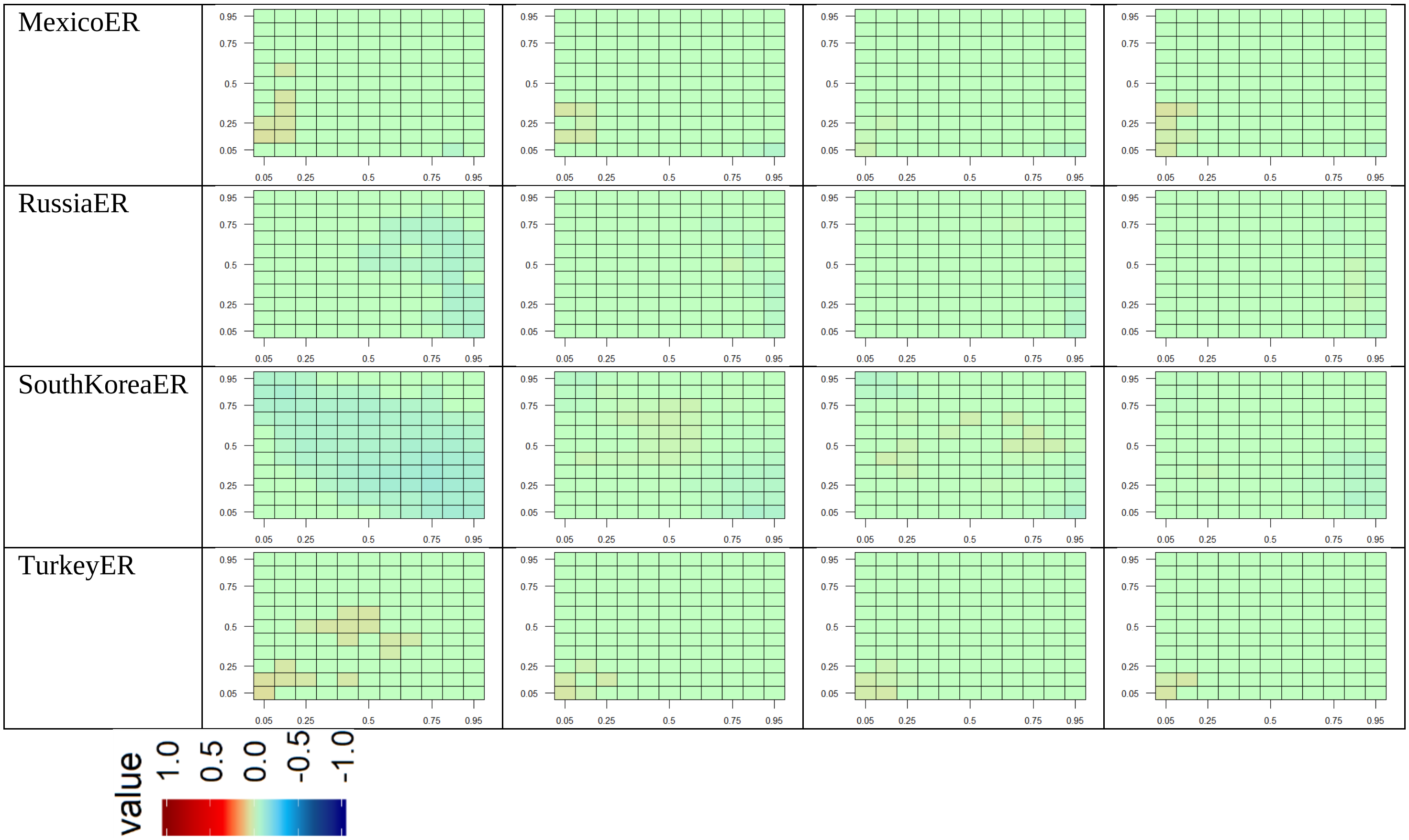
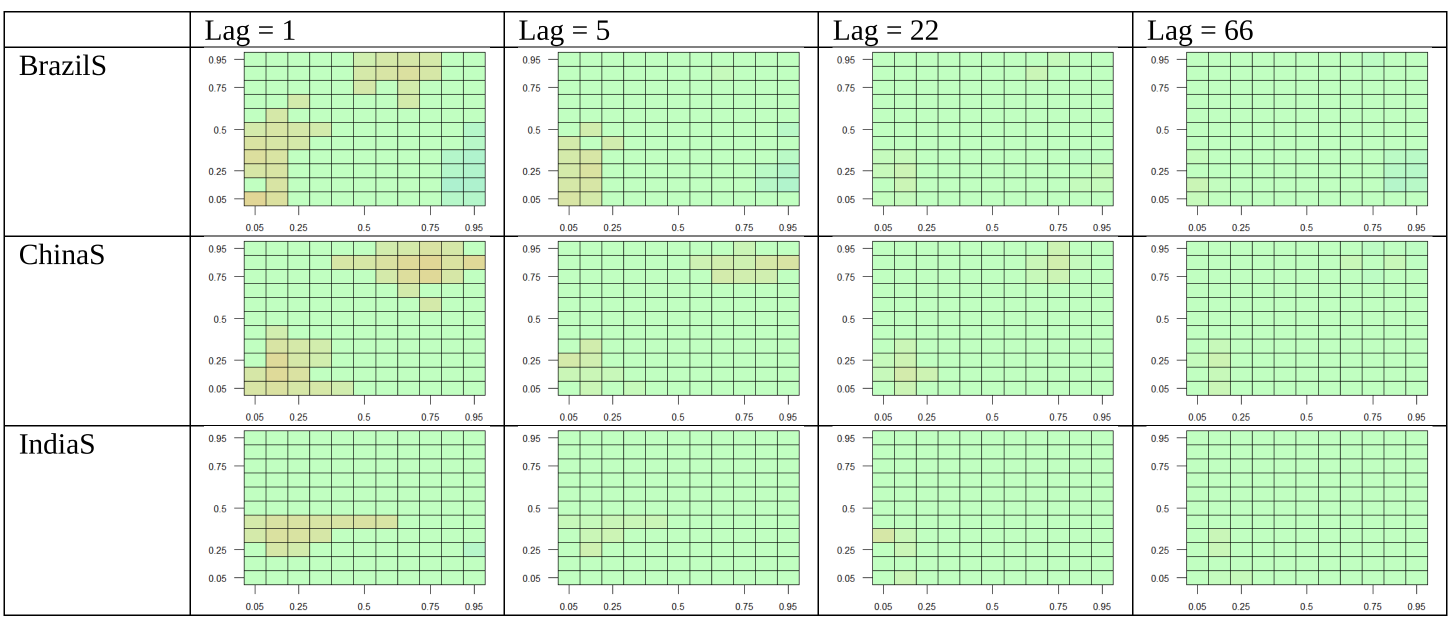


Fig. D.1.

Cross-quantilogram heatmap for predictability running from heating oil to the exchange rates of emerging market (E7+1). Notes: please refer to the notes in Fig. A.1.



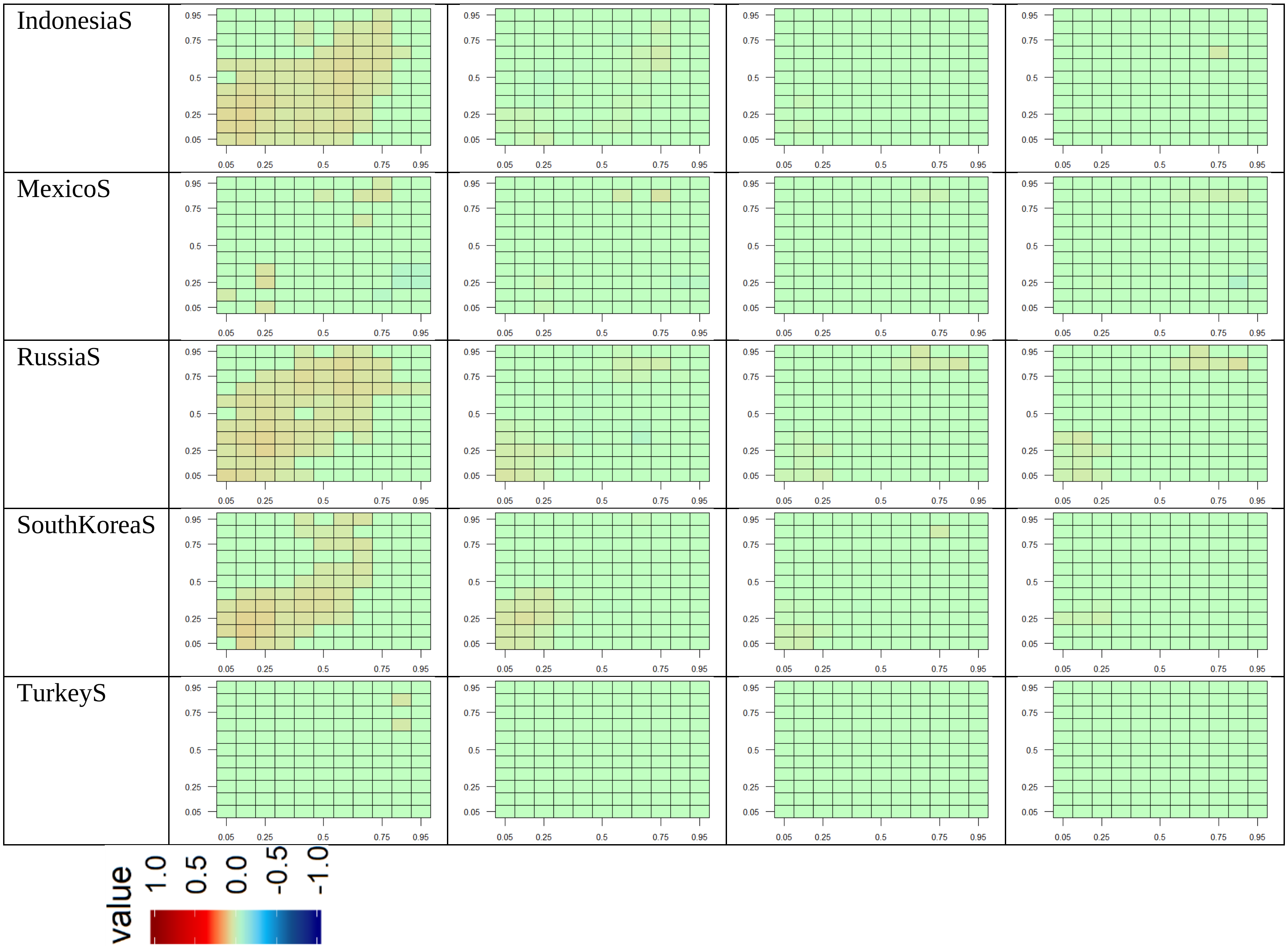
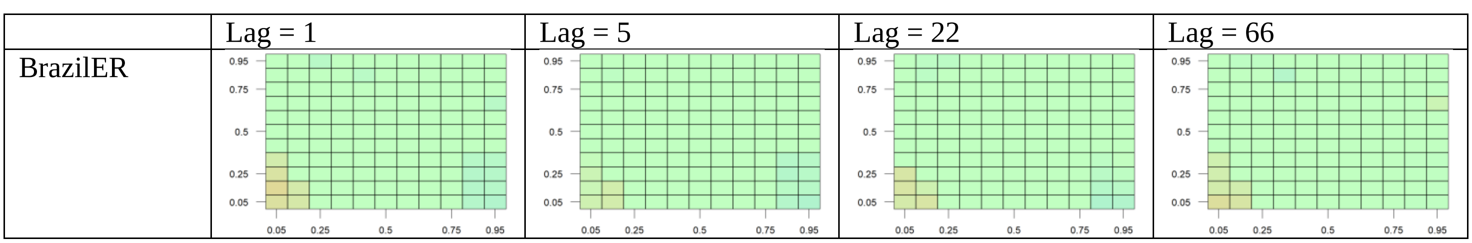


Fig. D.2.

Directional predictabilities in quantiles from heating oil to emerging stock markets (E7+1). Notes: please refer to the notes in Fig. A.1.



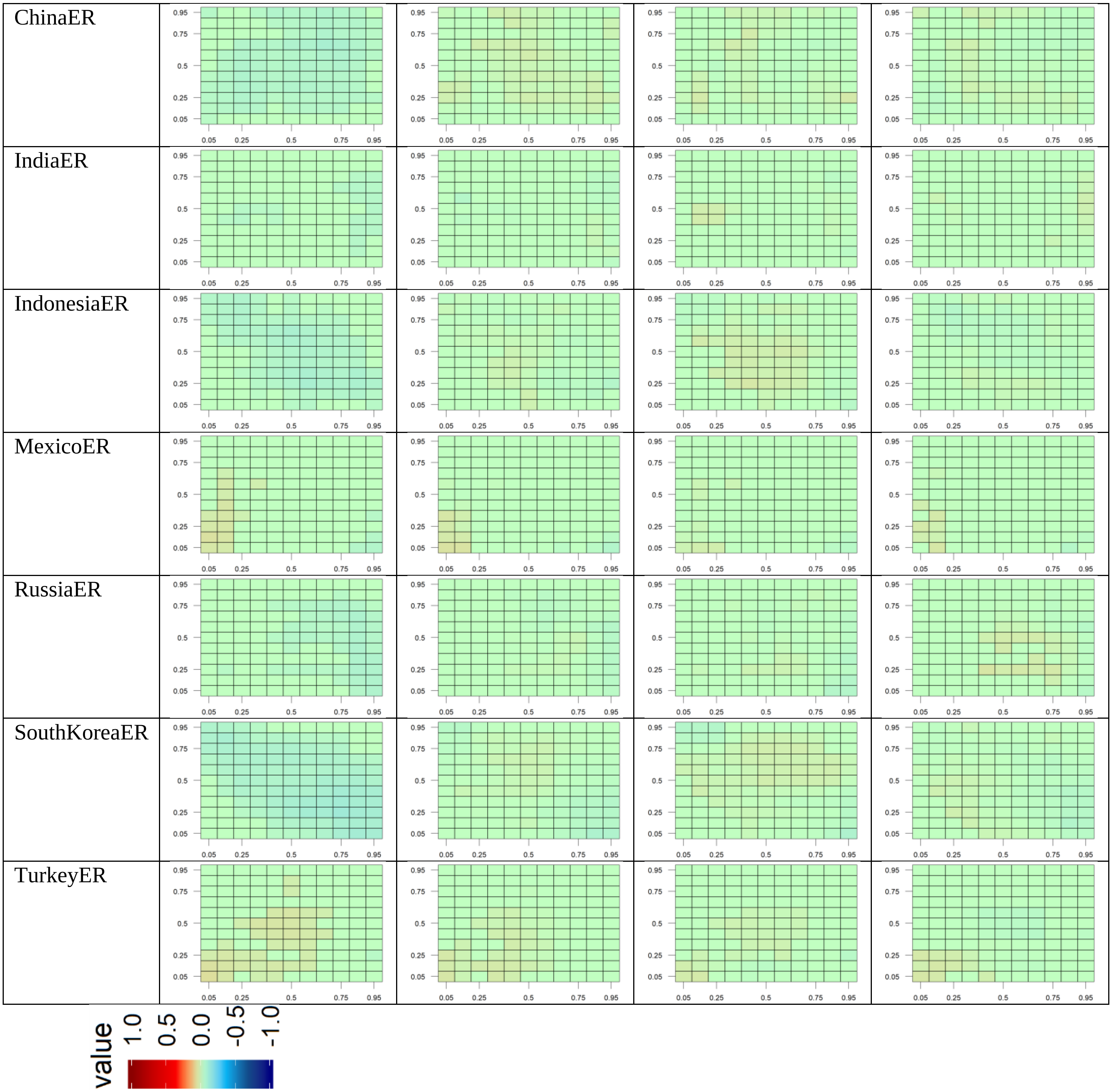
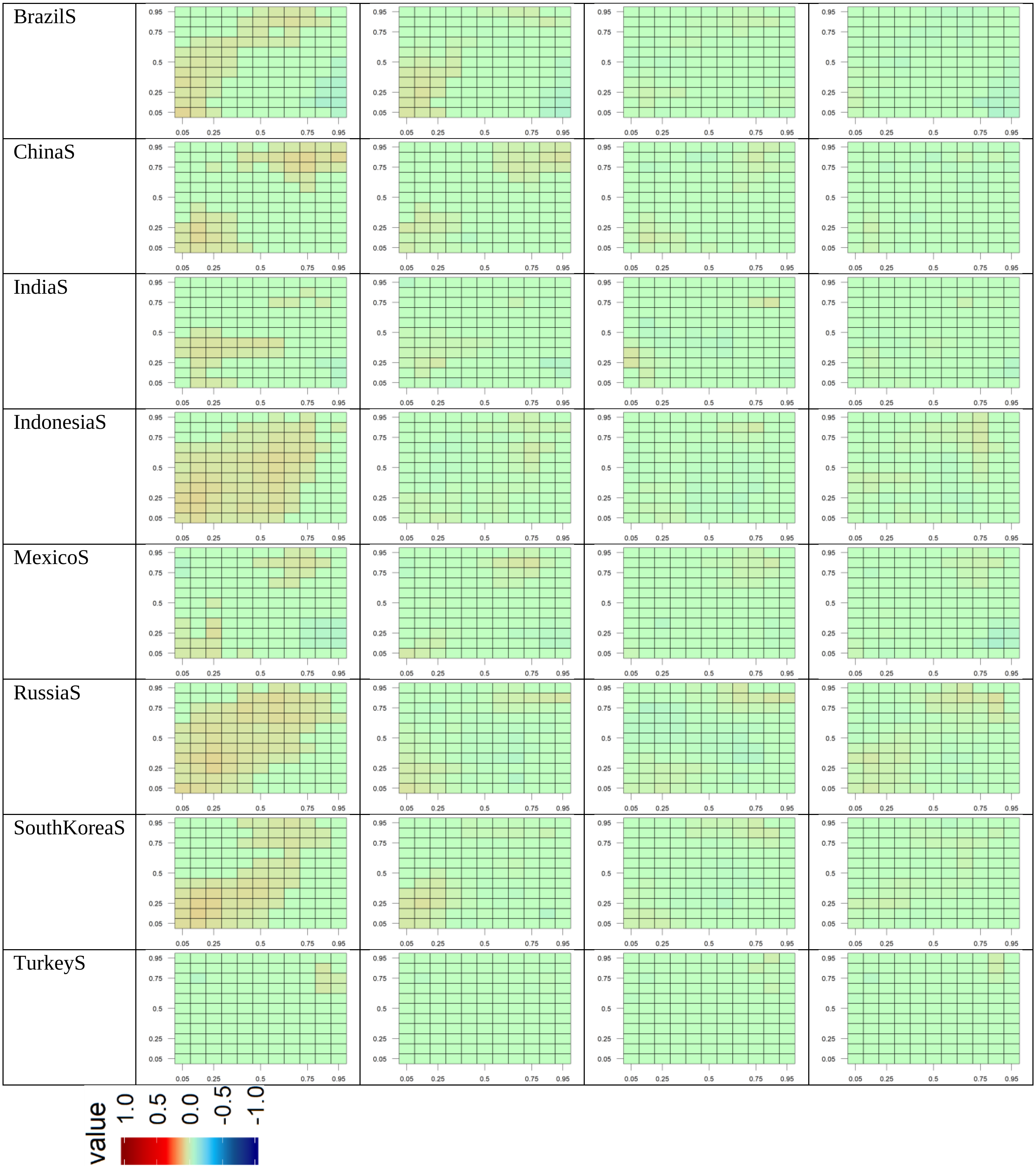


Fig. D.3.

Partial cross-quantile correlations between heating oil and the exchange rates in emerging markets (E7+1). The control variable is GPRD_Threat. Notes: please refer to the notes in Fig. A.1.

	Lag = 1	Lag = 5	Lag = 22	Lag = 66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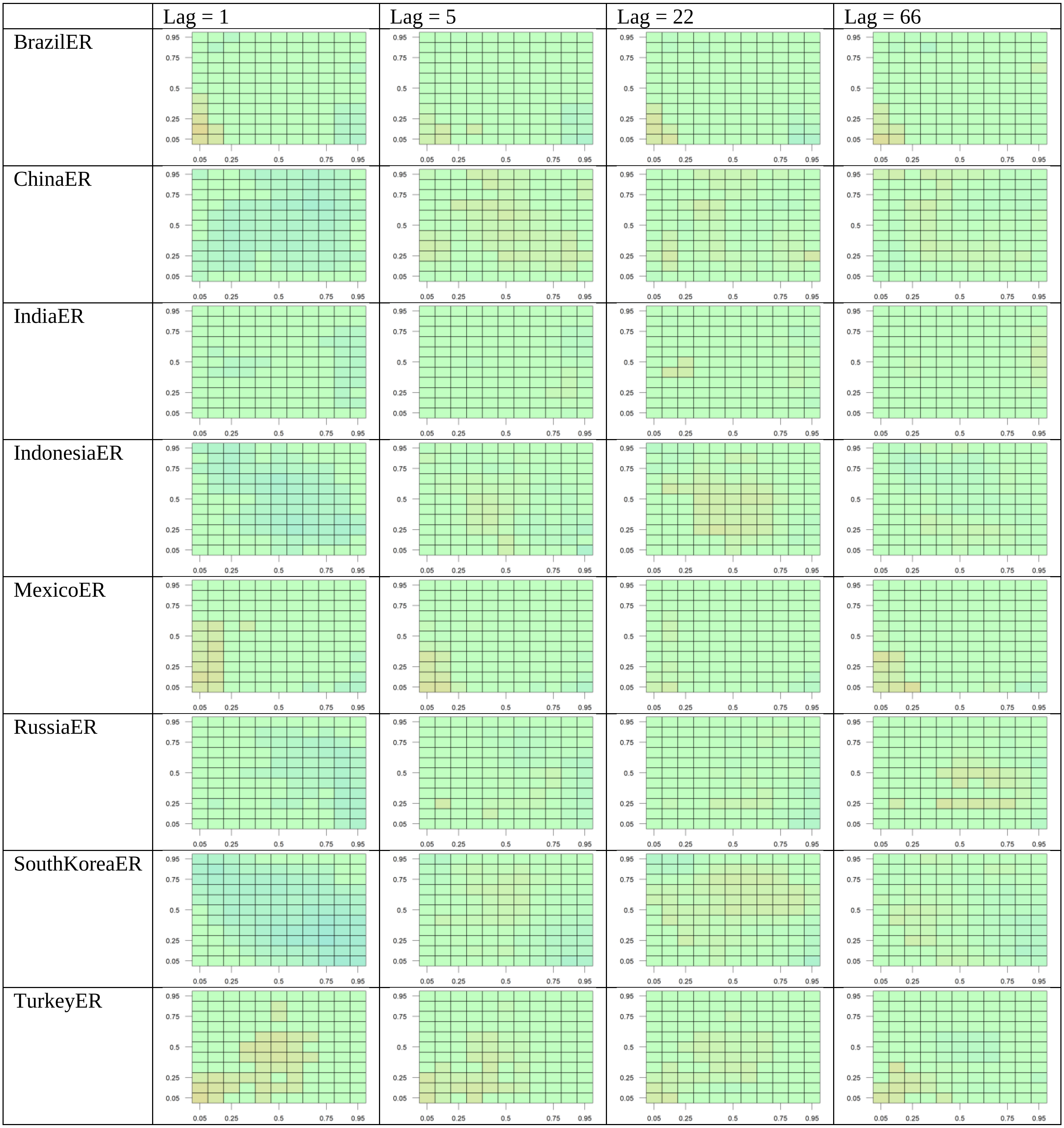
IndiaS
IndonesiaS
MexicoS
RussiaS
SouthKoreaS
TurkeyS
0.05
0.25
0.5
0.75
0.95
value
1.0
0.5
0.0
-0.5
-1.0

Fig. D.4.

Partial cross-quantile correlations between heating oil and the emerging stock market (E7+1). The control variable is GPRD_Threat. Notes: please refer to the notes in Fig. A.1.



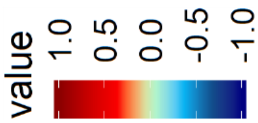
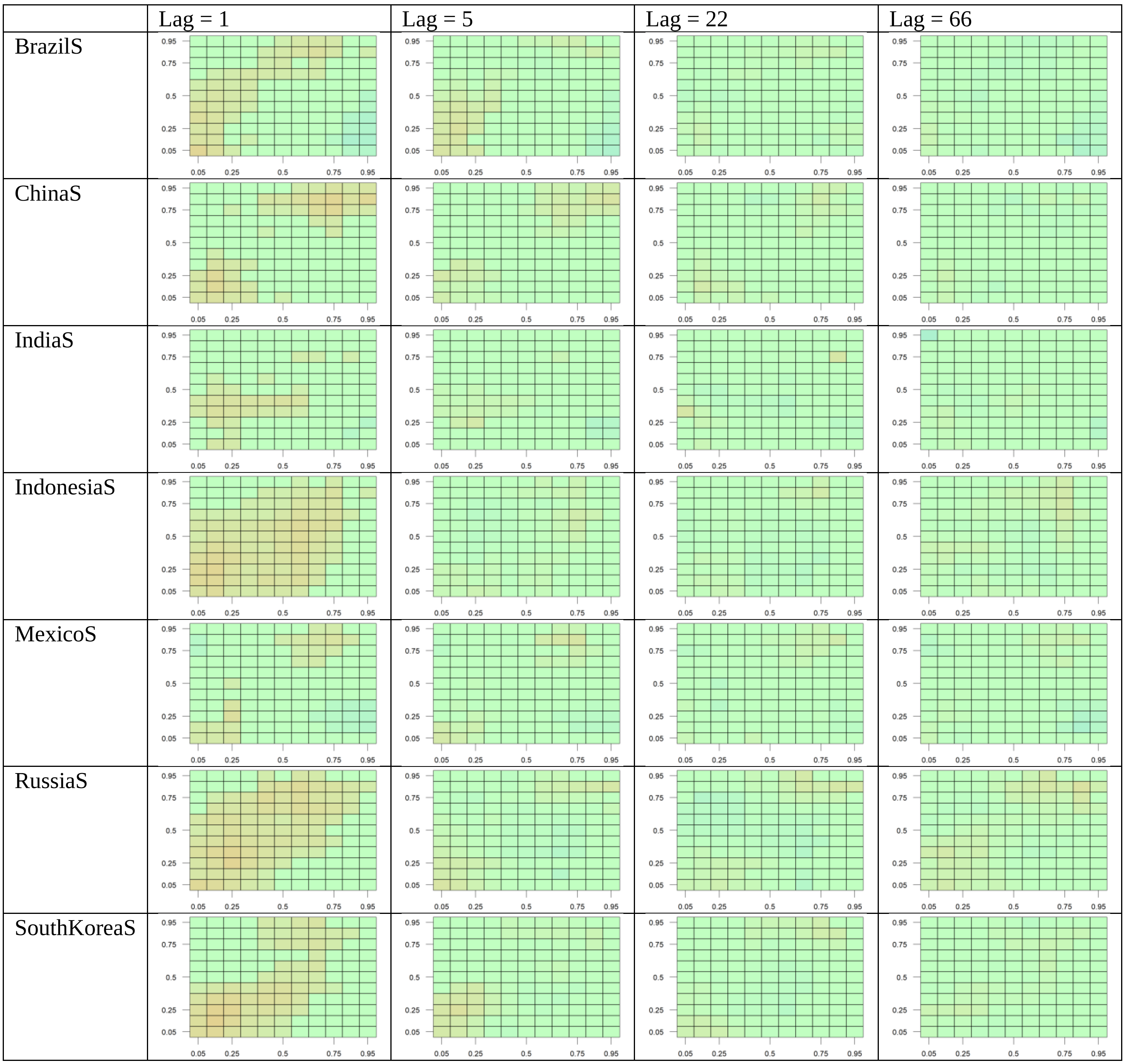


Fig. D.5.

Partial cross-quantile correlations between heating oil and the exchange rates in emerging markets (E7+1). The control variable is GPRD. Notes: please refer to the notes in Fig. A.1.



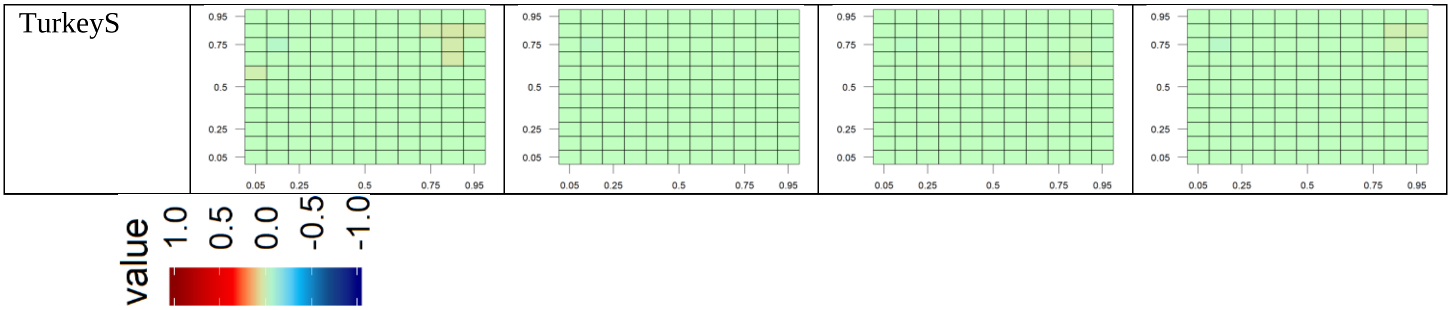
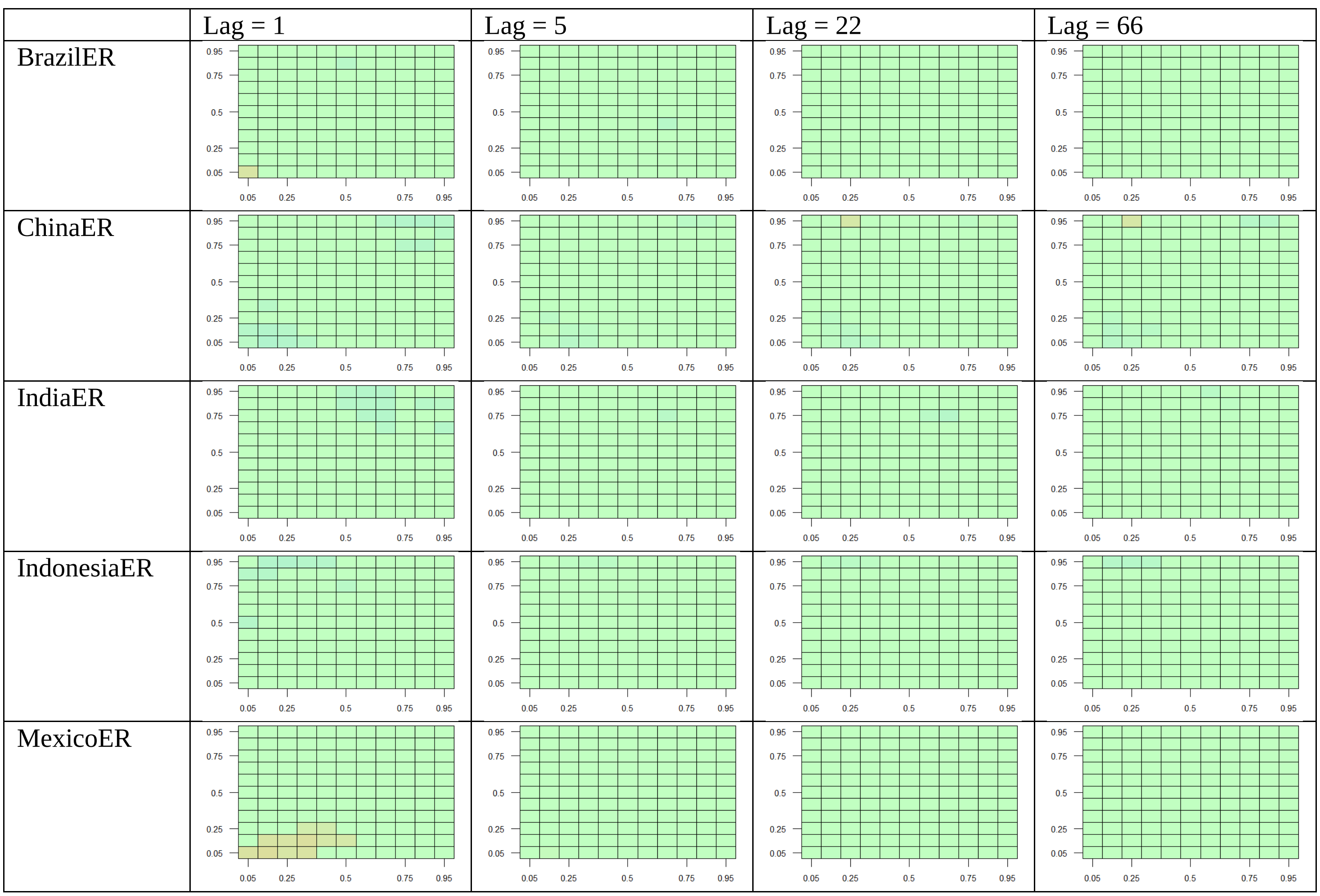


Fig. D.6.

Partial cross-quantile correlations between heating oil and the emerging stock market (E7+1). The control variable is GPRD. Notes: please refer to the notes in Fig. A.1.

Appendix E. See Figs. E.1-E.6.



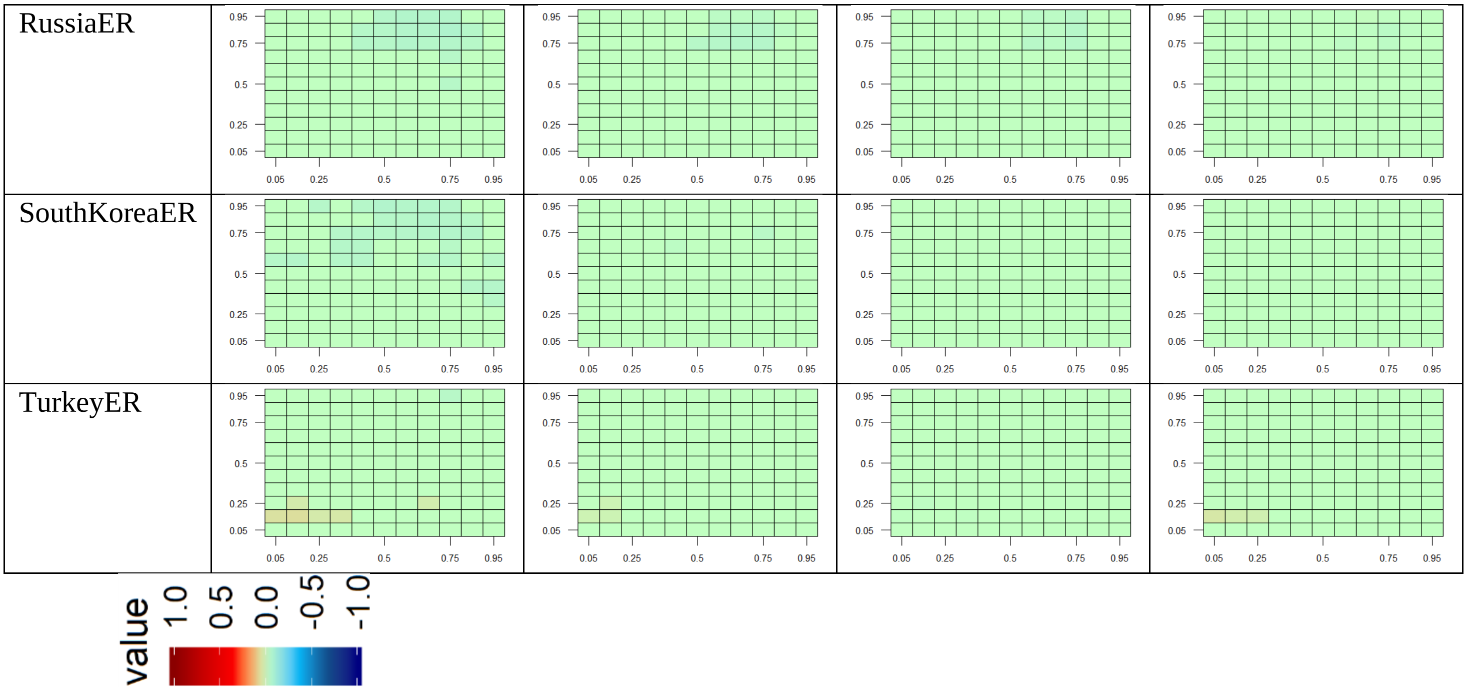
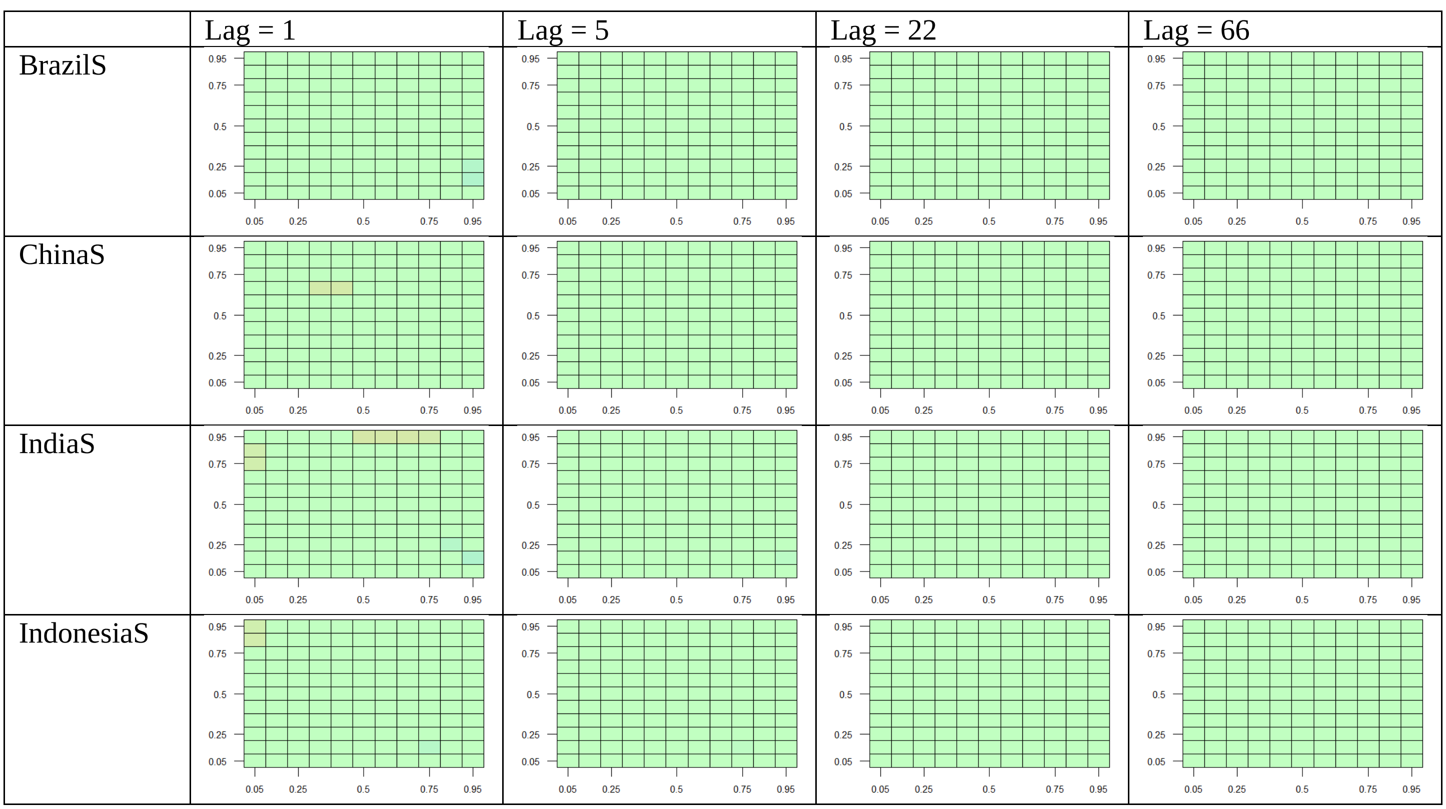


Fig. E.1.

Cross-quantilogram heatmap for predictability running from natural gas to the exchange rates of emerging market (E7+1). Notes: please refer to the notes in Fig. A.1.



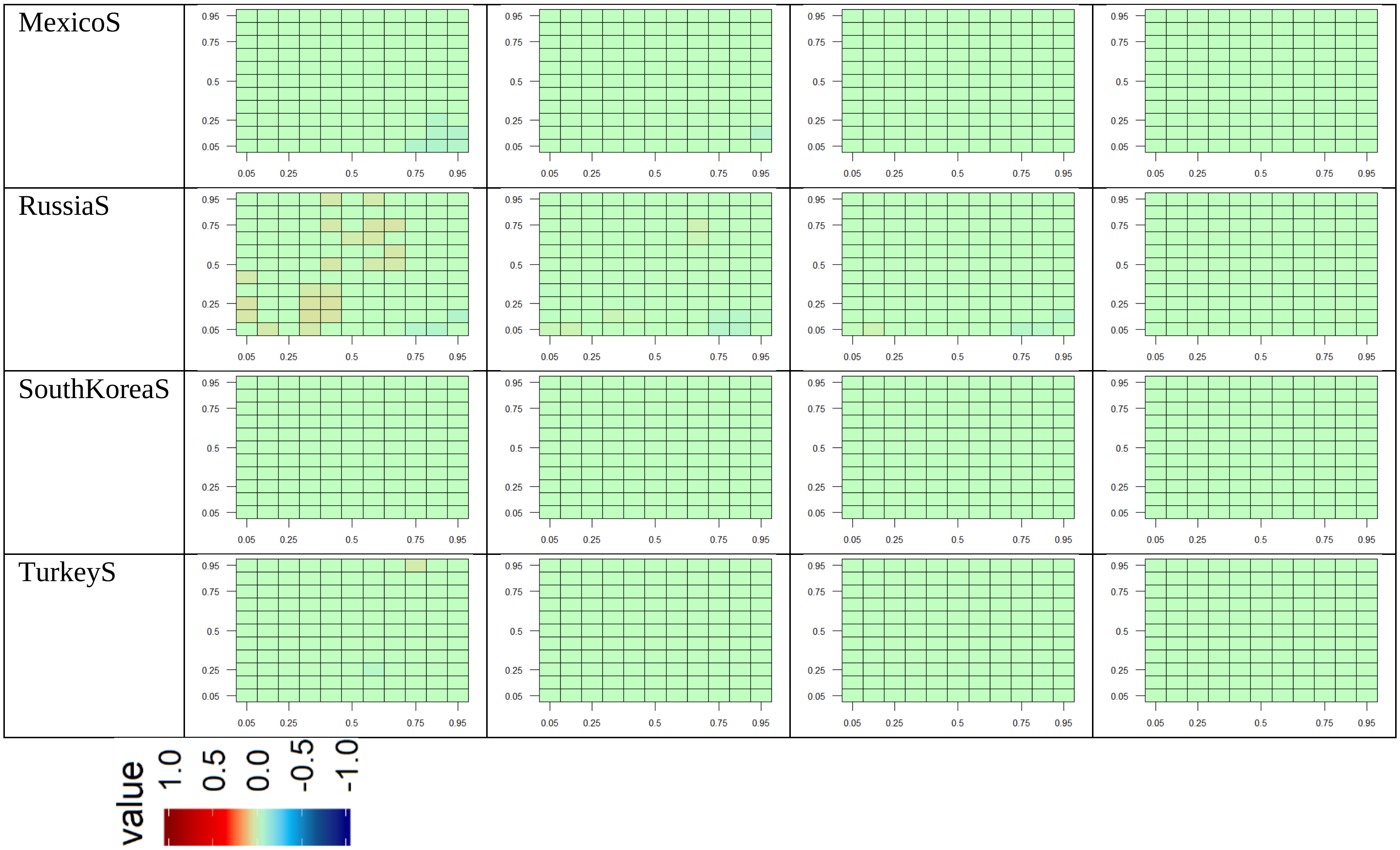
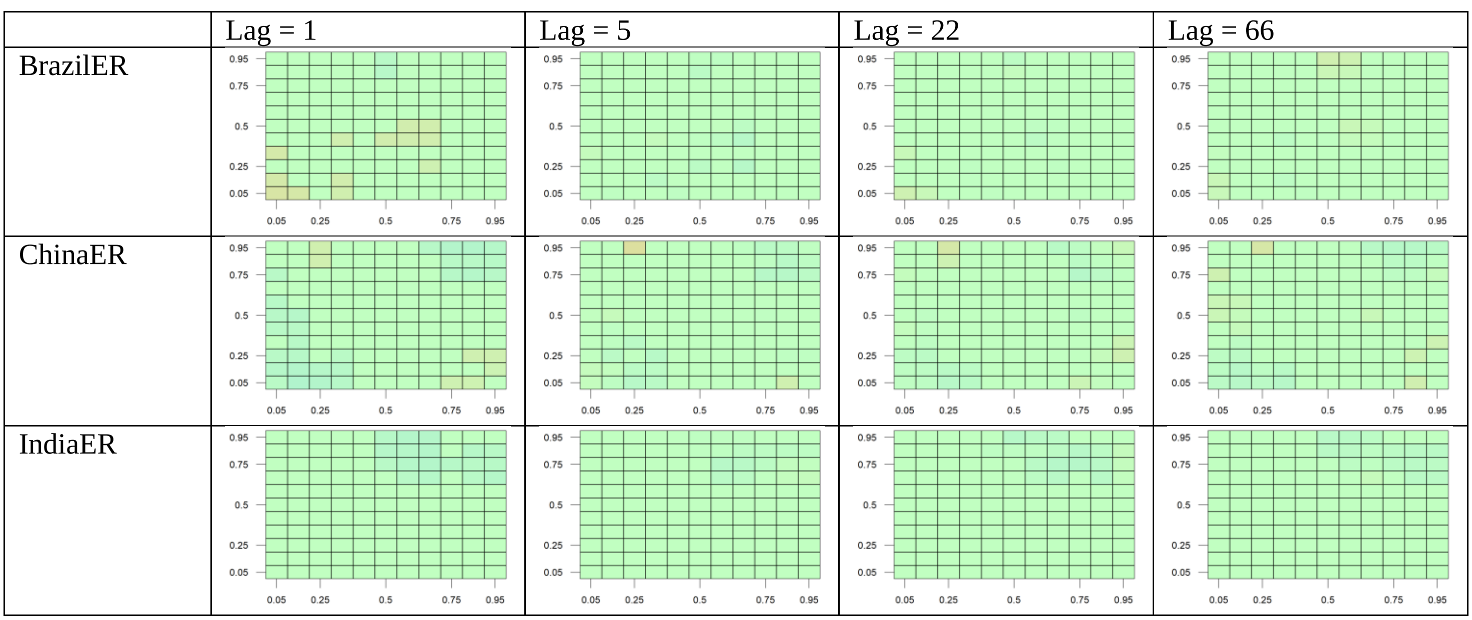


Fig. E.2.

Directional predictabilities in quantiles from natural gas to emerging stock markets (E7+1). Notes: please refer to the notes in Fig. A.1.



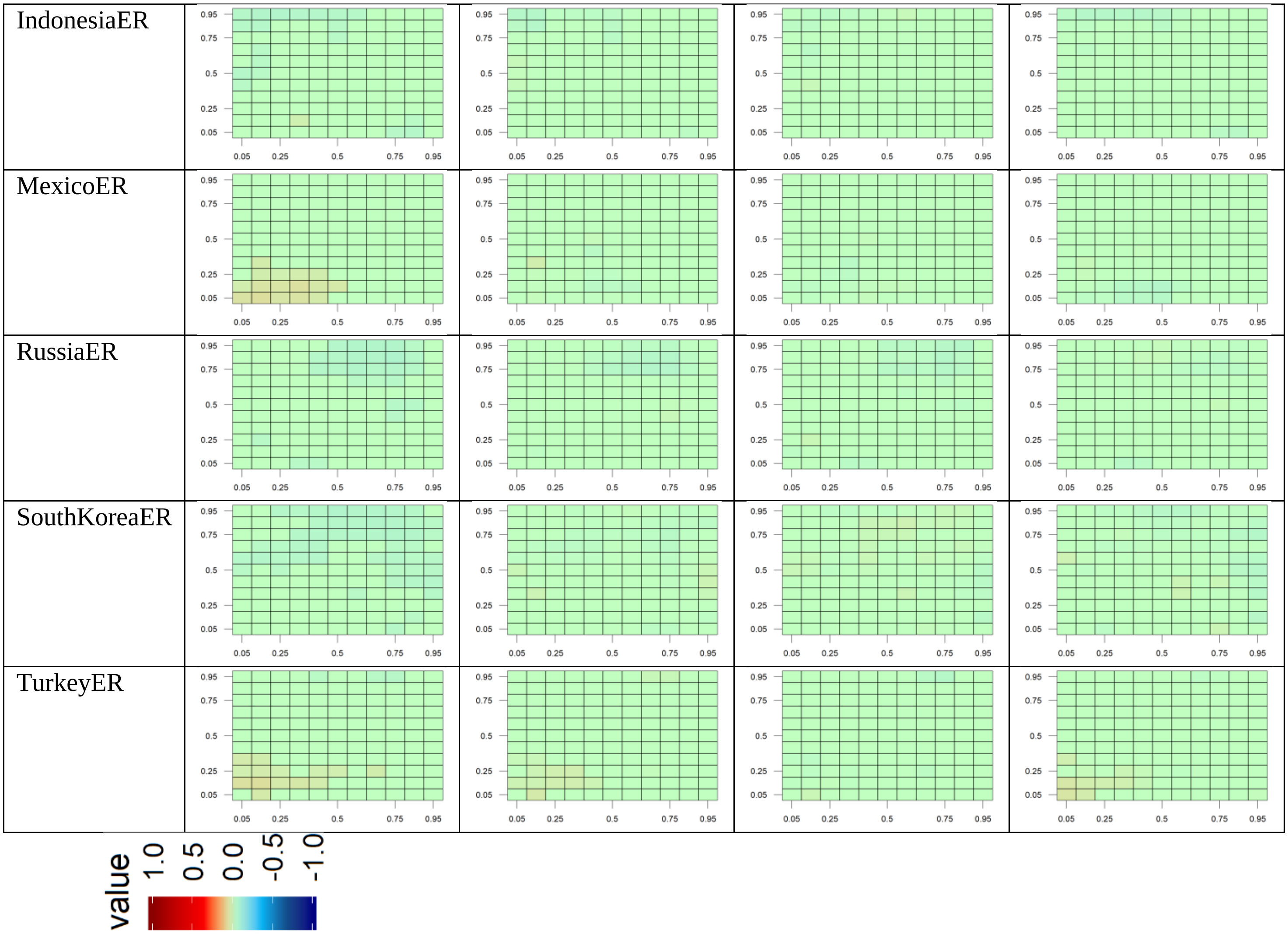
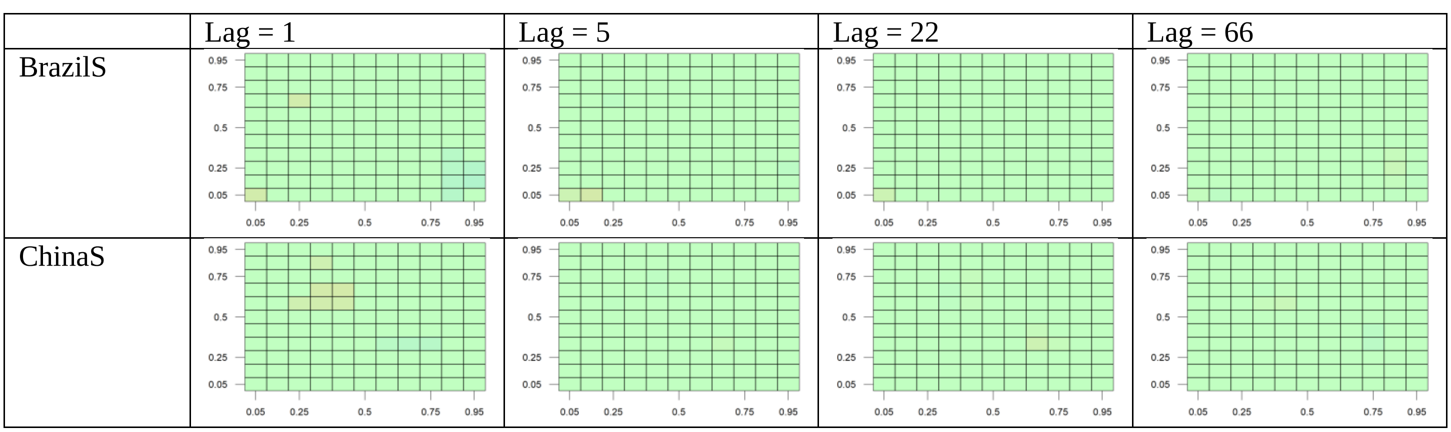


Fig. E.3.

Partial cross-quantile correlations between natural gas and the exchange rates in emerging markets (E7+1). The control variable is GPRD_Threat. Notes: please refer to the notes in Fig. A.1.



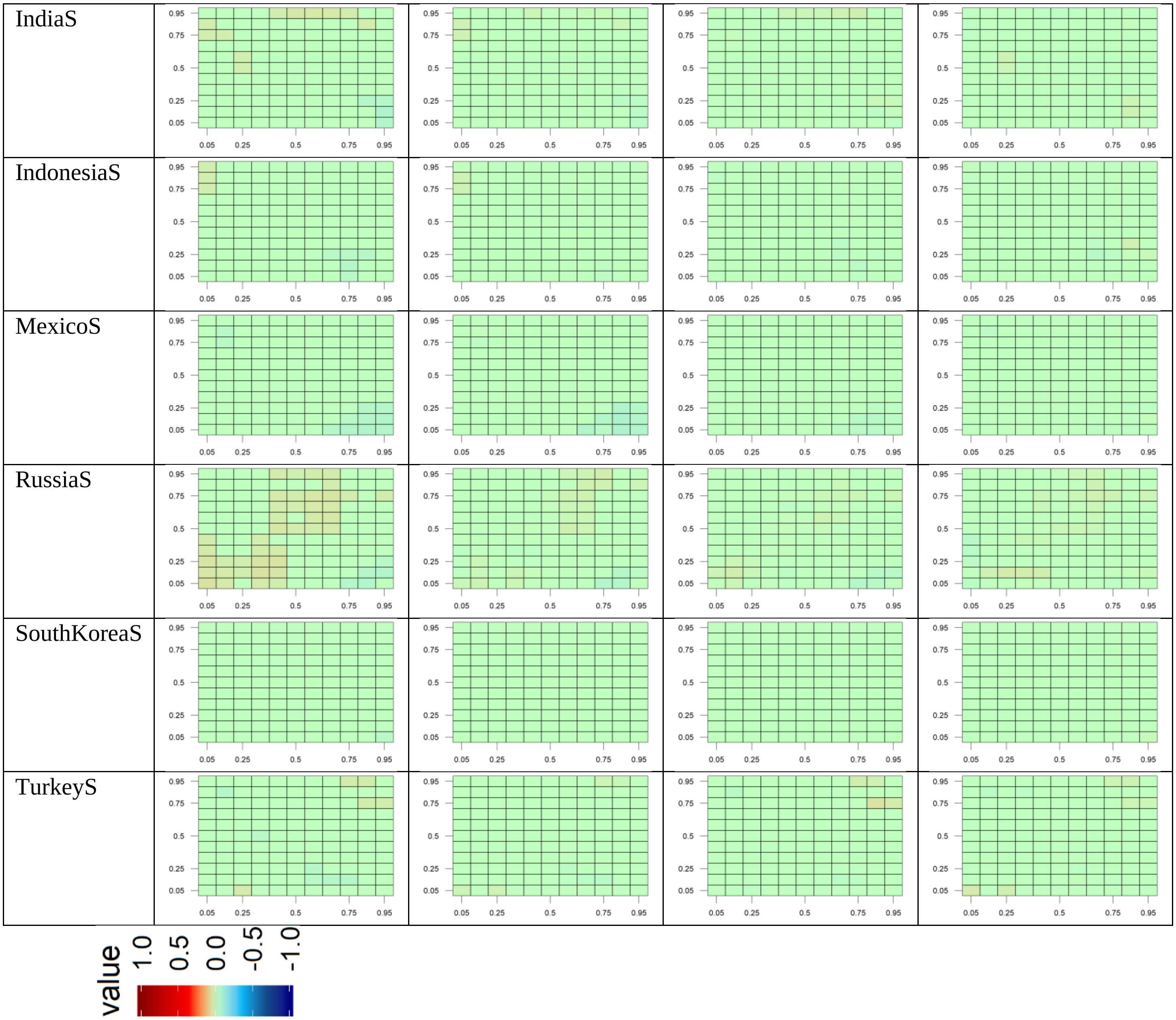
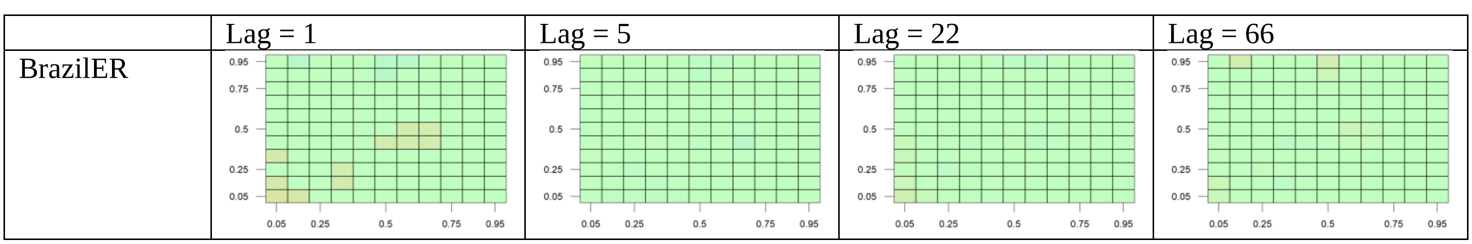


Fig. E.4.

Partial cross-quantile correlations between natural gas and the emerging stock market (E7+1). The control variable is GPRD_Threat. Notes: please refer to the notes in Fig. A.1.



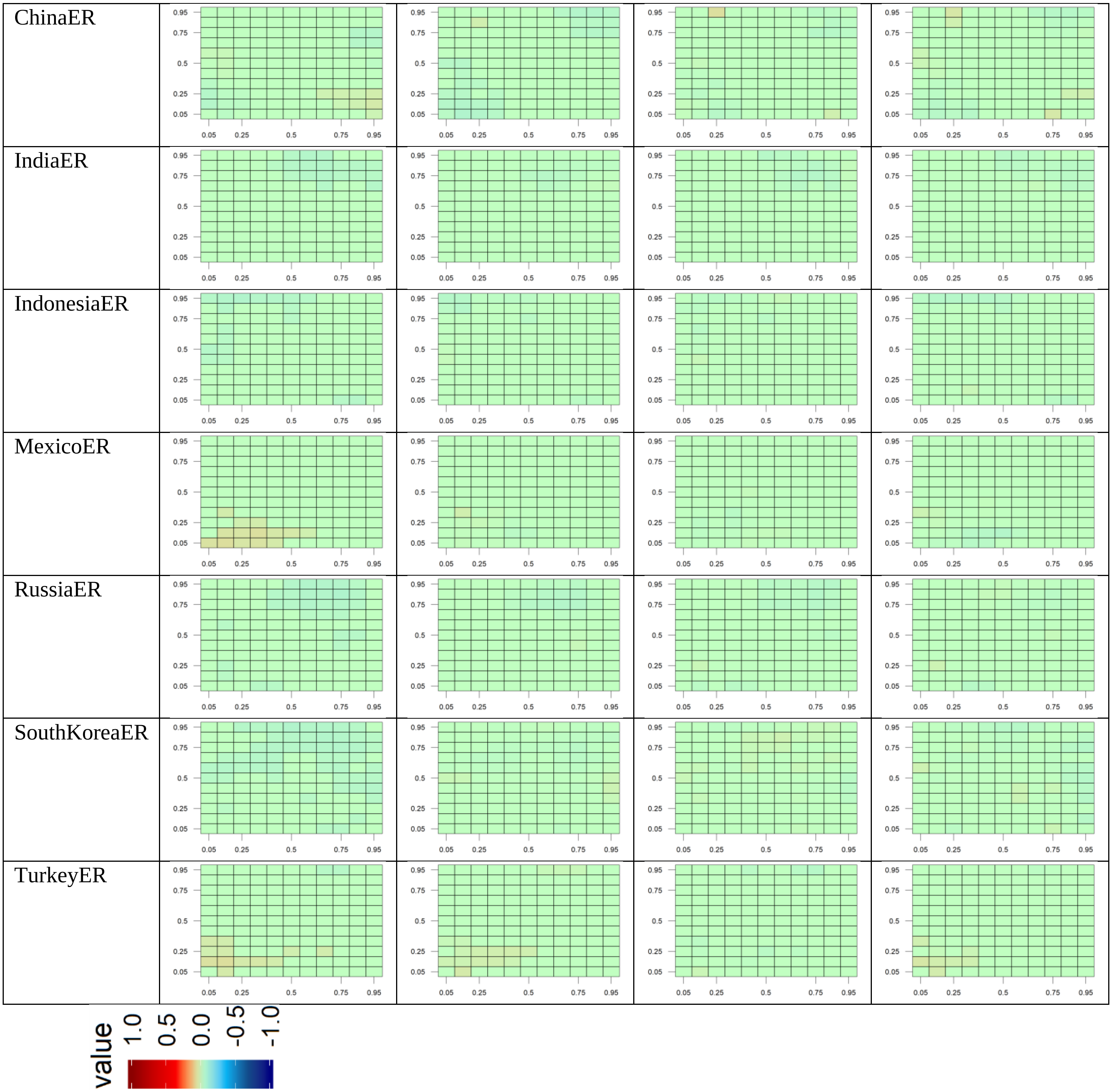


Fig. E.5.

Partial cross-quantile correlations between natural gas and the exchange rates in emerging markets (E7+1). The control variable is GPRD. Notes: please refer to the notes in Fig. A.1.

	Lag = 1	Lag = 5	Lag = 22	Lag = 66

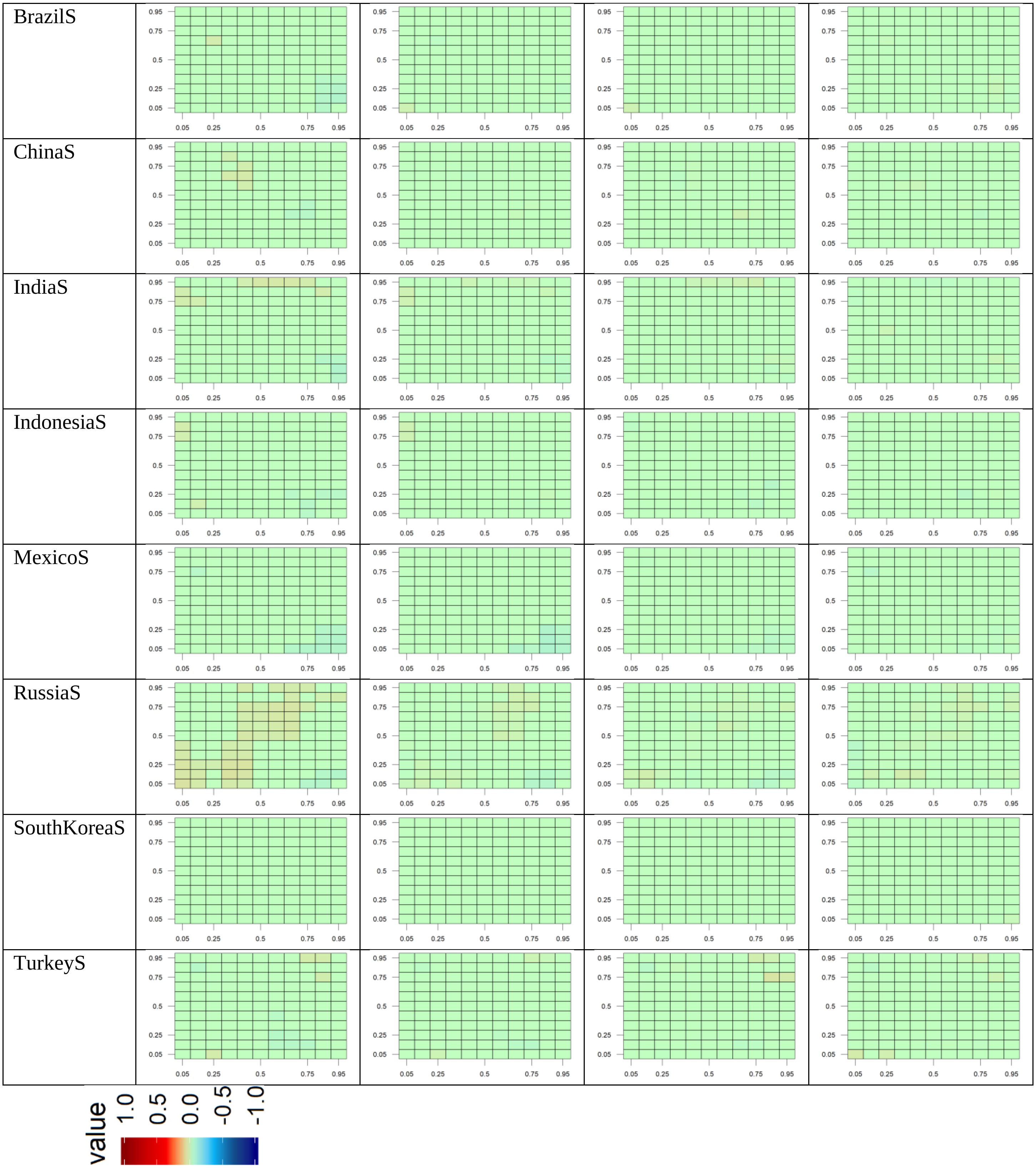
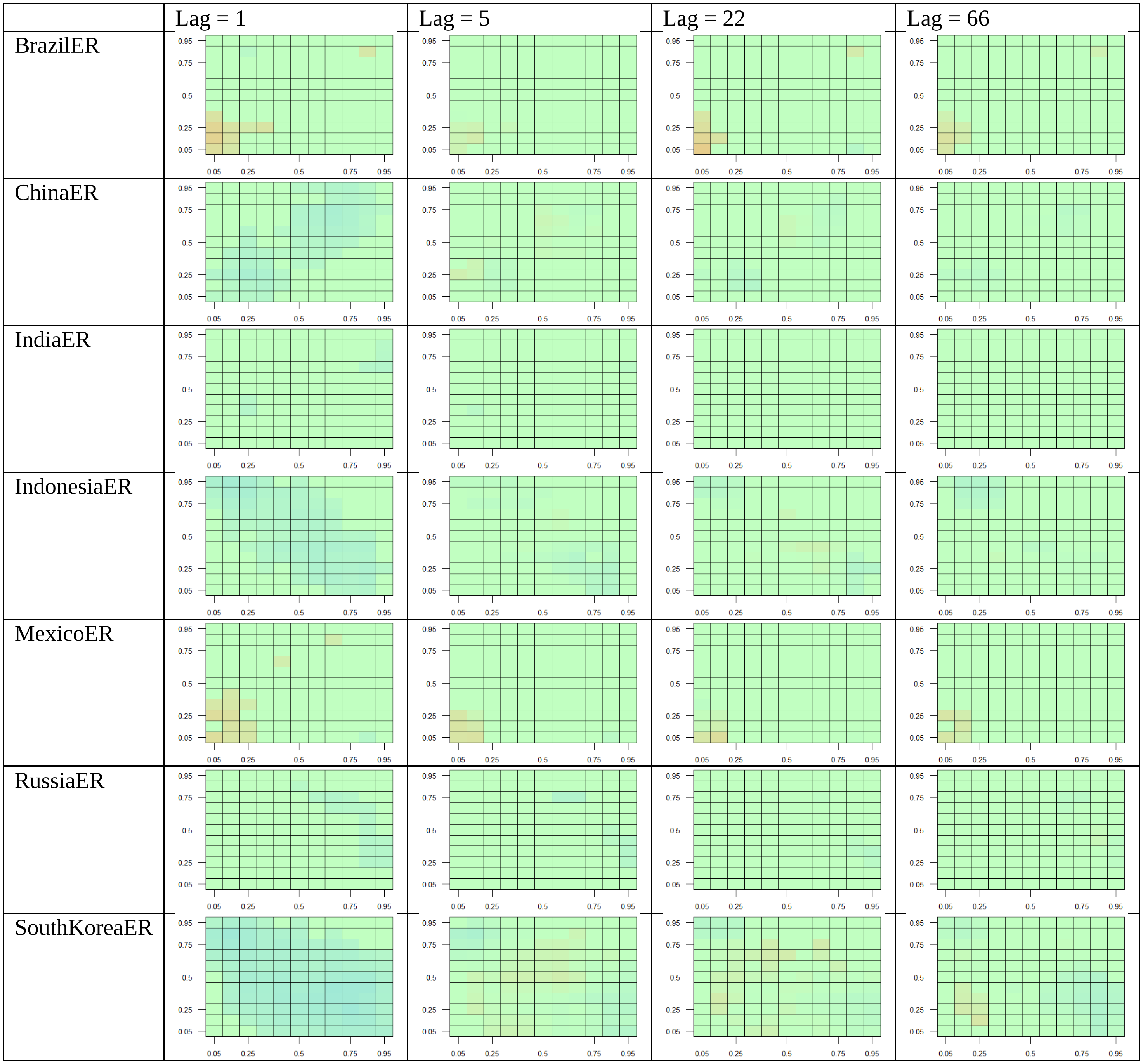

BrazilS
ChinaS
IndiaS
IndonesiaS
MexicoS
RussiaS
SouthKoreaS
TurkeyS
0.95
0.75
0.5
0.25
0.05
value
1.0
0.5
0.0
-0.5
-1.0

Fig. E.6.

Partial cross-quantile correlations between natural gas and the emerging stock market (E7+1). The control variable is GPRD. Notes: please refer to the notes in Fig. A.1.

Appendix F. See Figs. F.1-F.6.



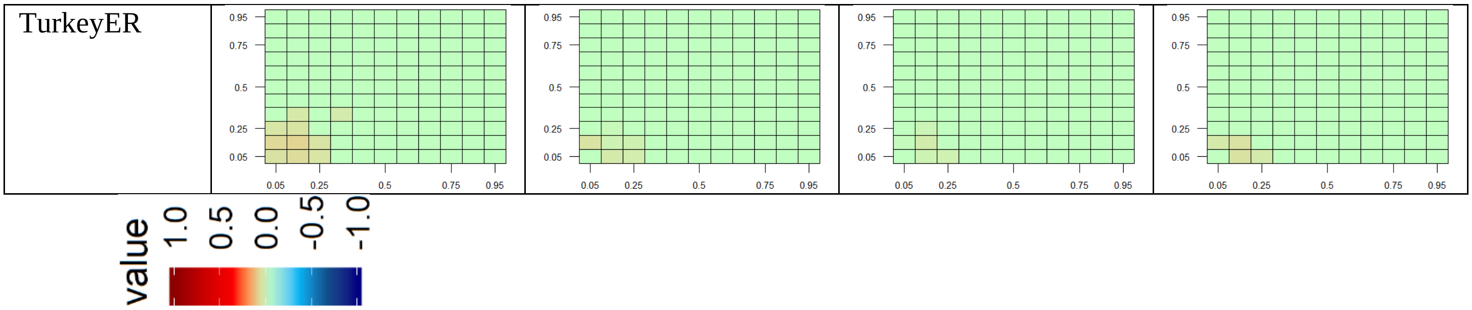
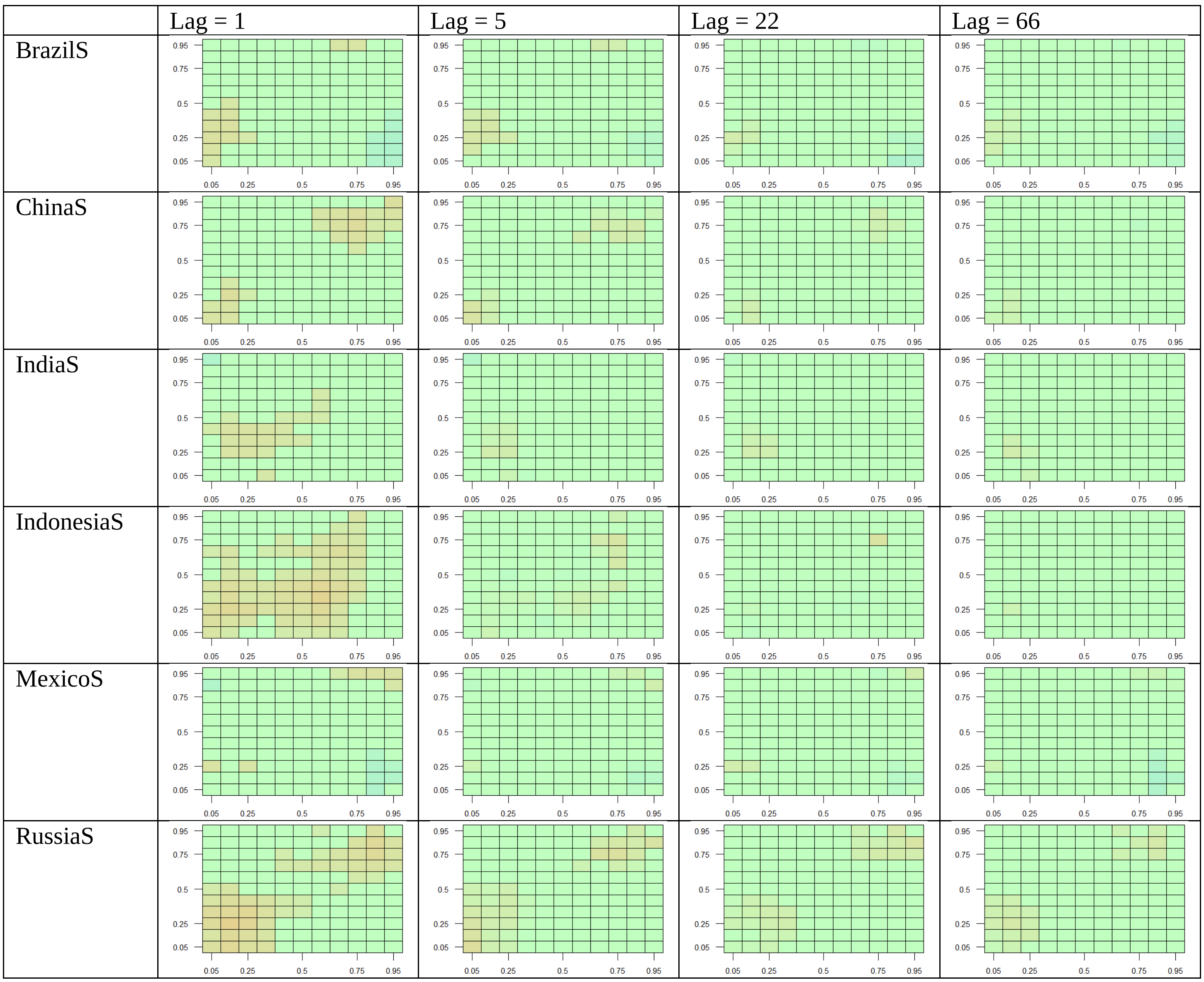


Fig. F.1.

Cross-quantilogram heatmap for Directional predictabilities in quantiles from oil (Dubai) to the exchange rates of emerging market (E7+1). Notes: please refer to the notes in Fig. A.1.



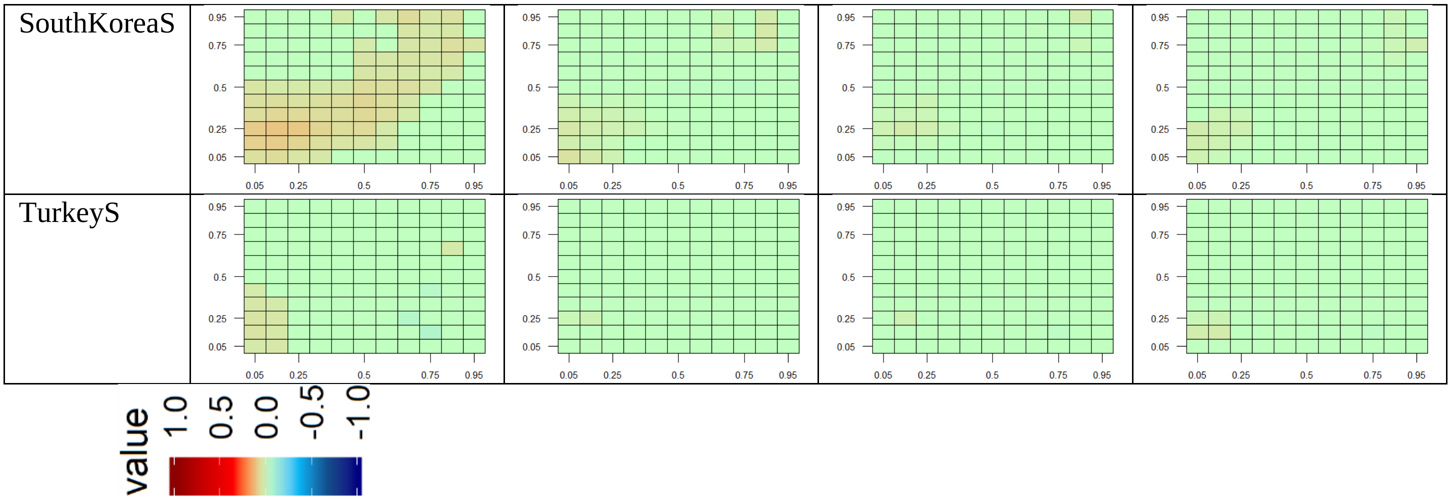
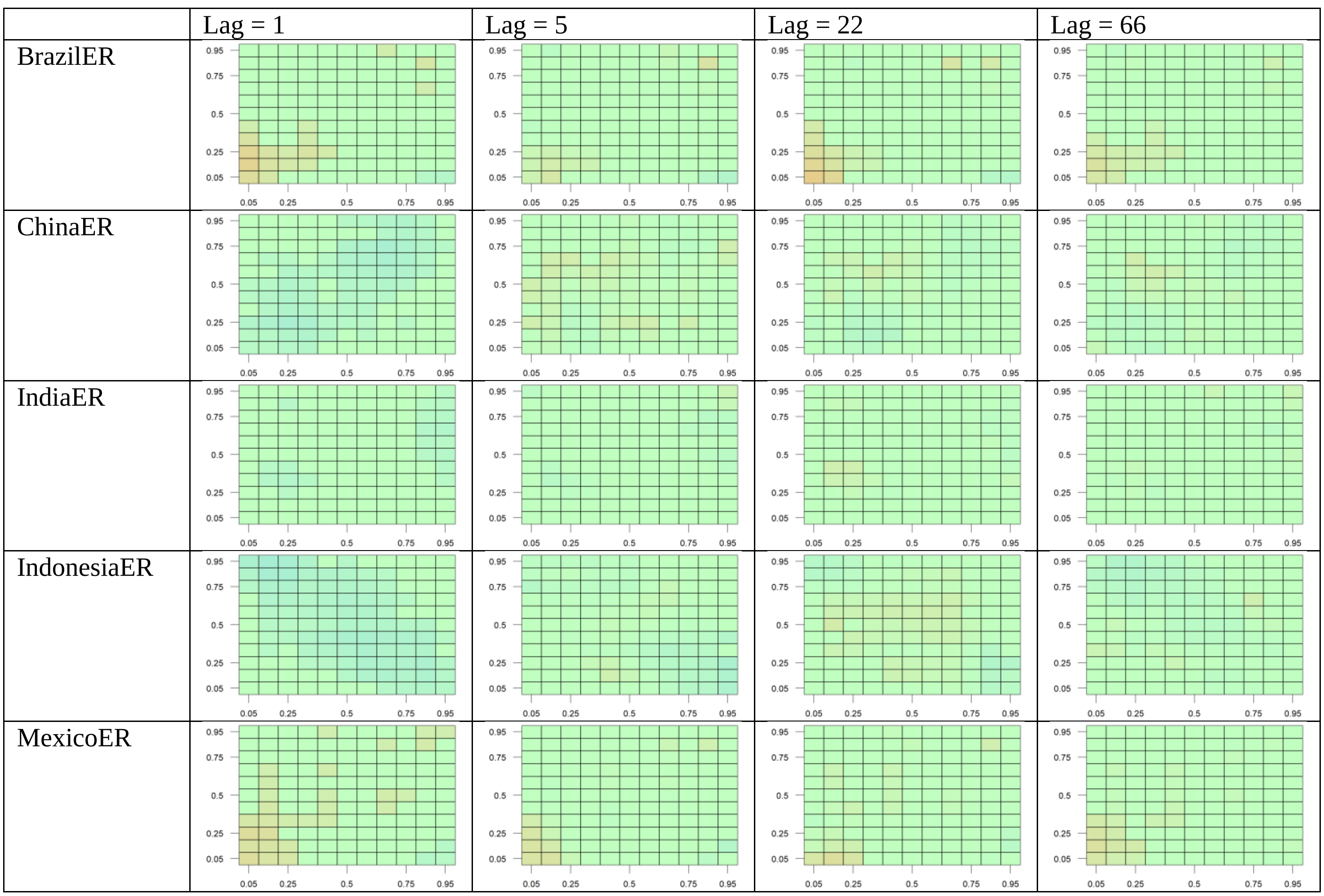


Fig. F.2.

Directional predictabilities in quantiles from oil (Dubai) to emerging stock markets (E7+1). Notes: please refer to the notes in Fig. A.1.



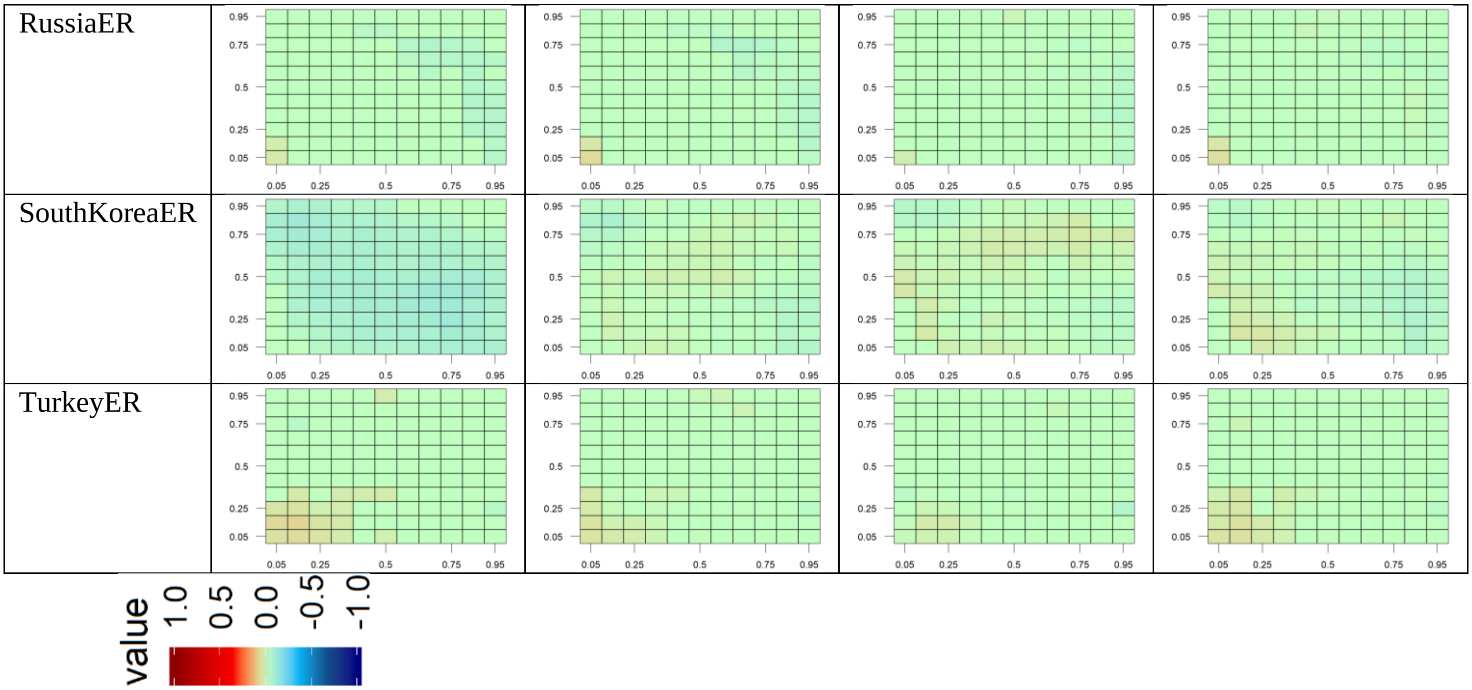
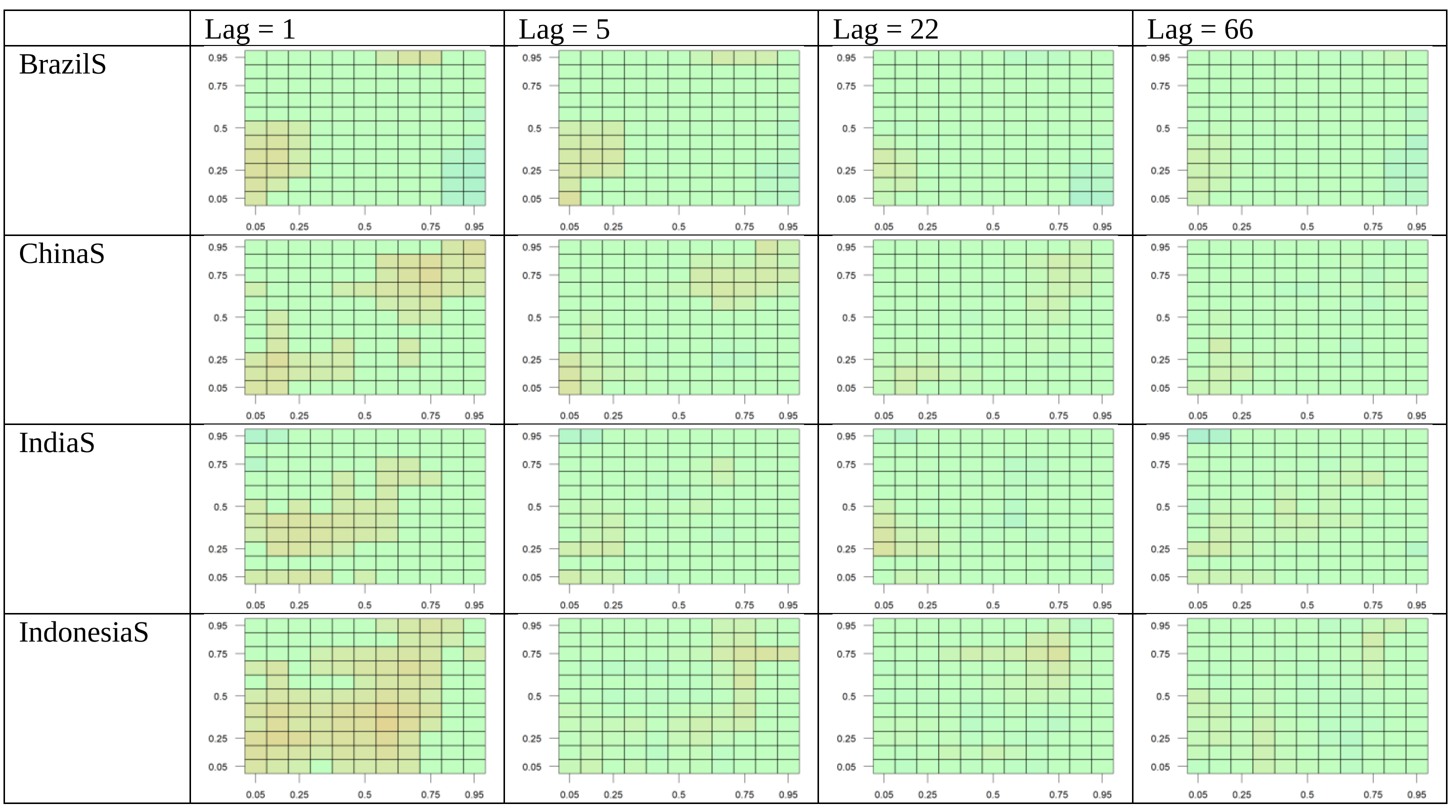


Fig. F.3.

Partial cross-quantile correlations between oil (Dubai) and the exchange rates in emerging markets (E7+1). The control variable is GPRD_Threat. Notes: please refer to the notes in Fig. A.1.



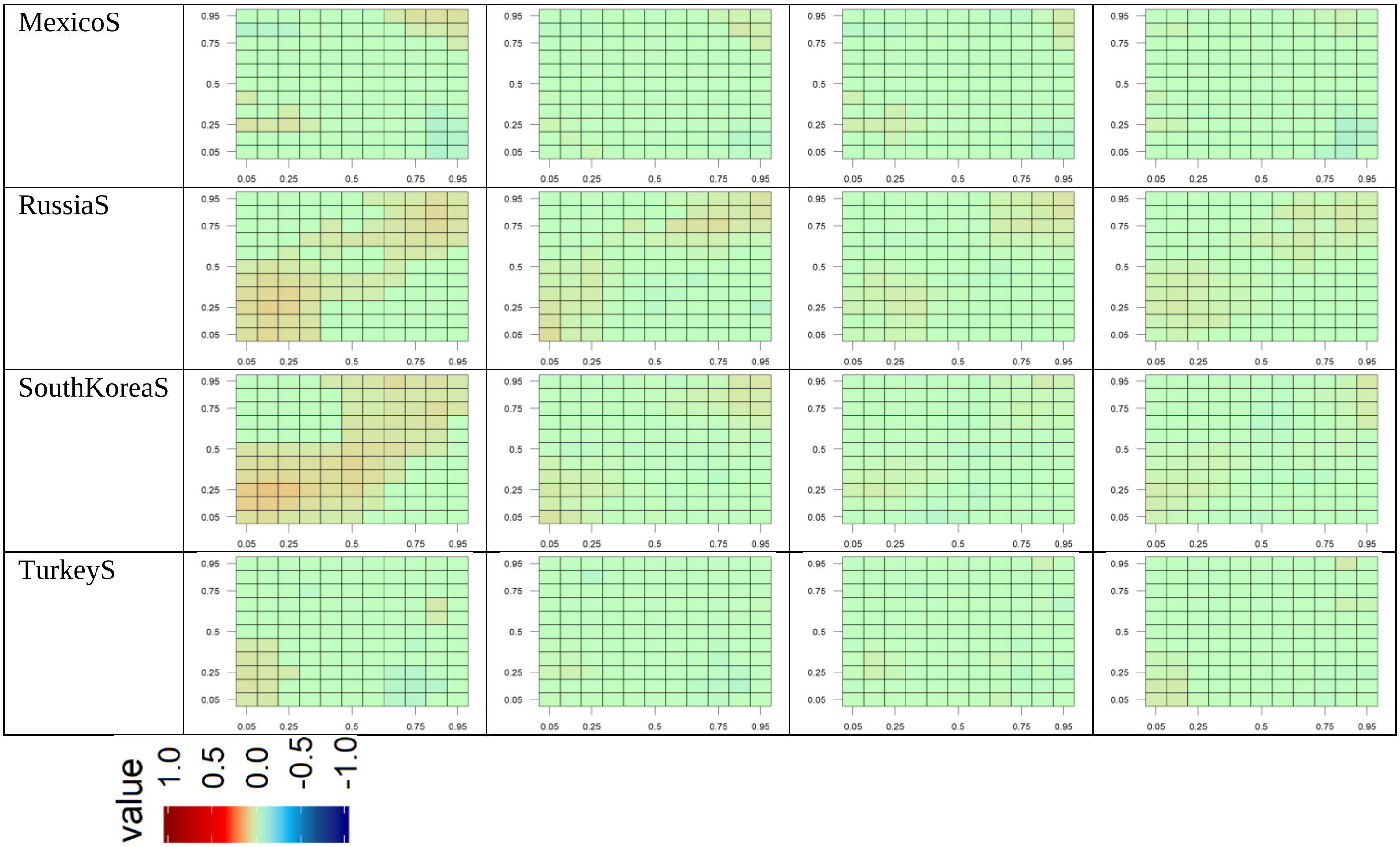
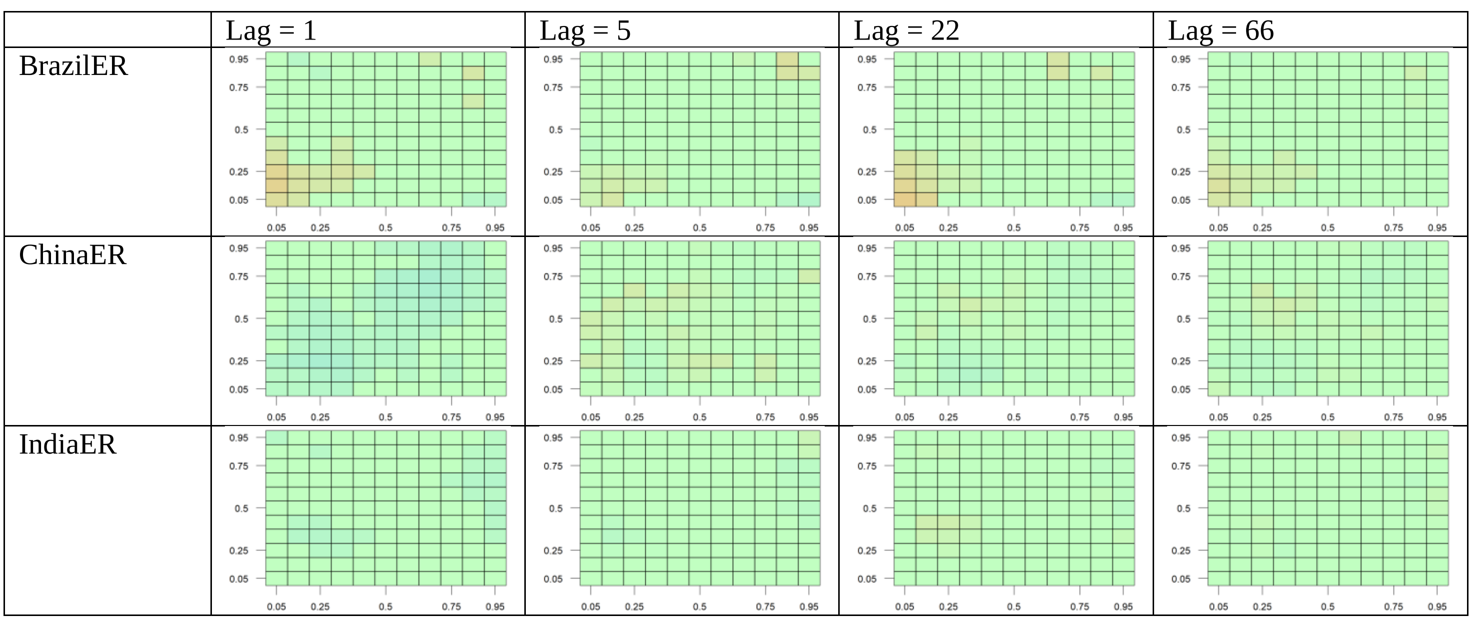


Fig. F.4.

Partial cross-quantile correlations between oil (Dubai) and the emerging stock market (E7+1). The control variable is GPRD_Threat. Notes: please refer to the notes in Fig. A.1.



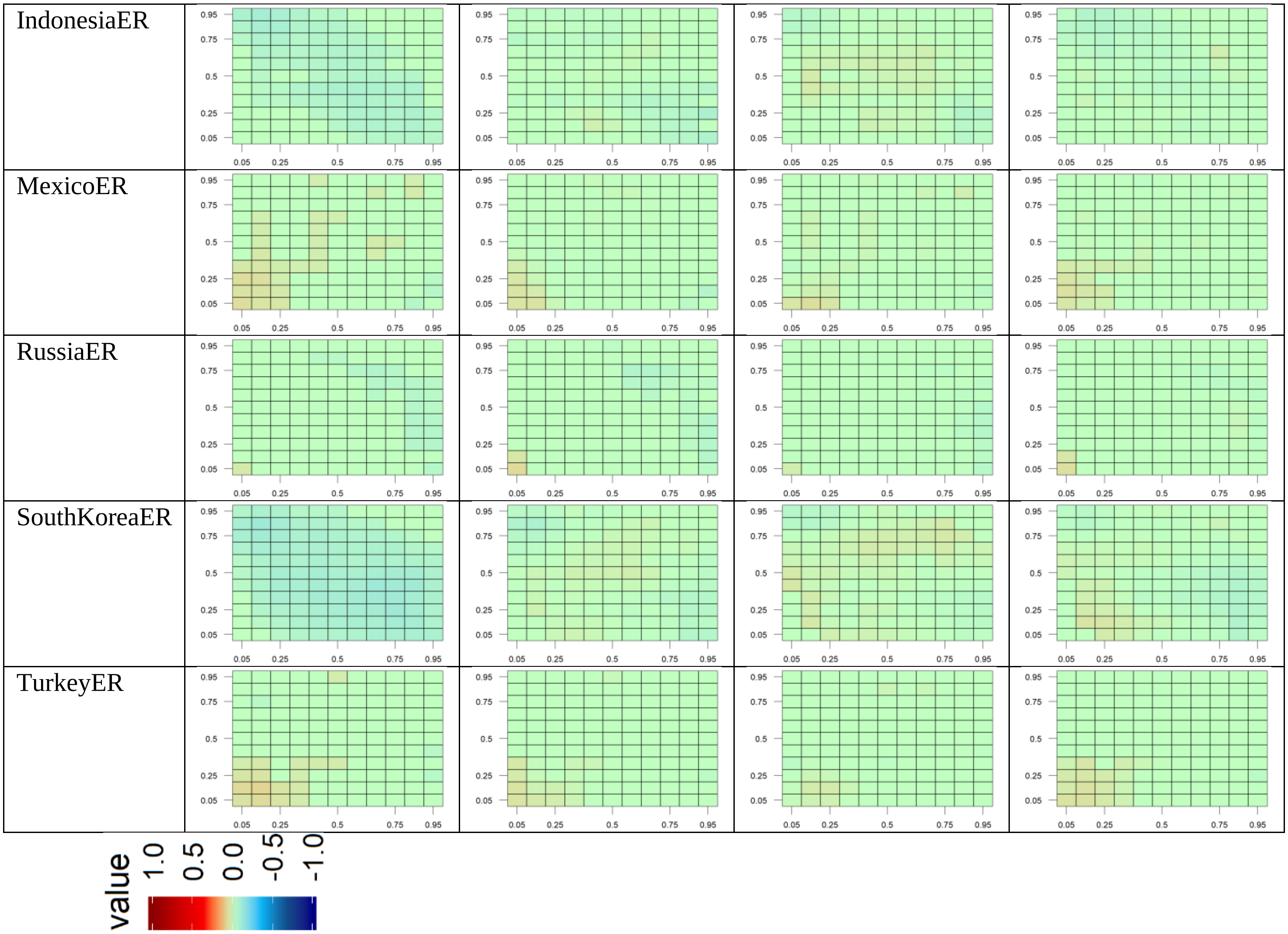
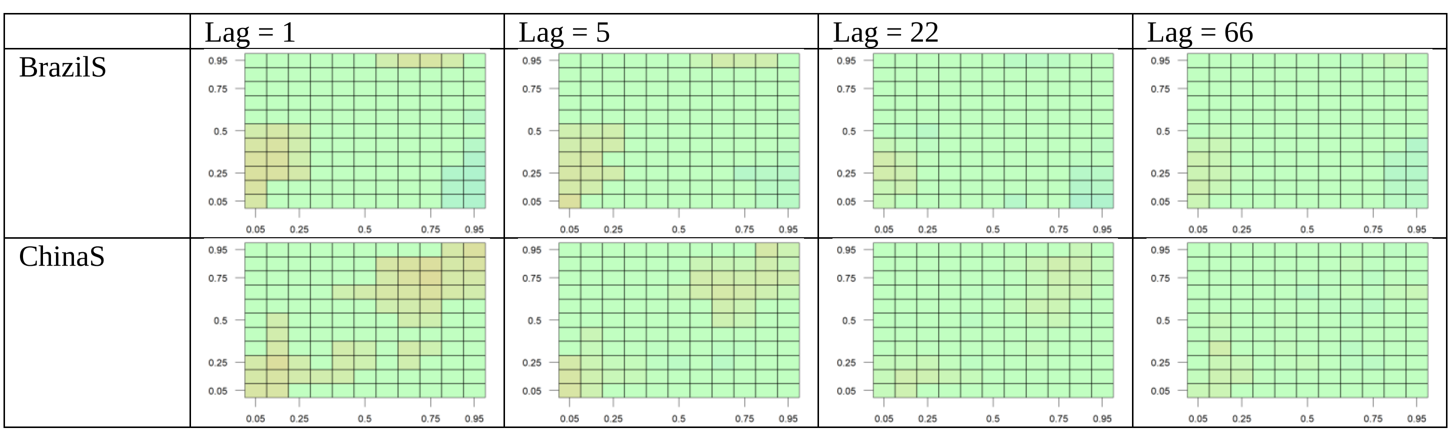


Fig. F.5.

Partial cross-quantile correlations between oil (Dubai) and the exchange rates in emerging markets (E7+1). The control variable is GPRD. Notes: please refer to the notes in Fig. A.1.



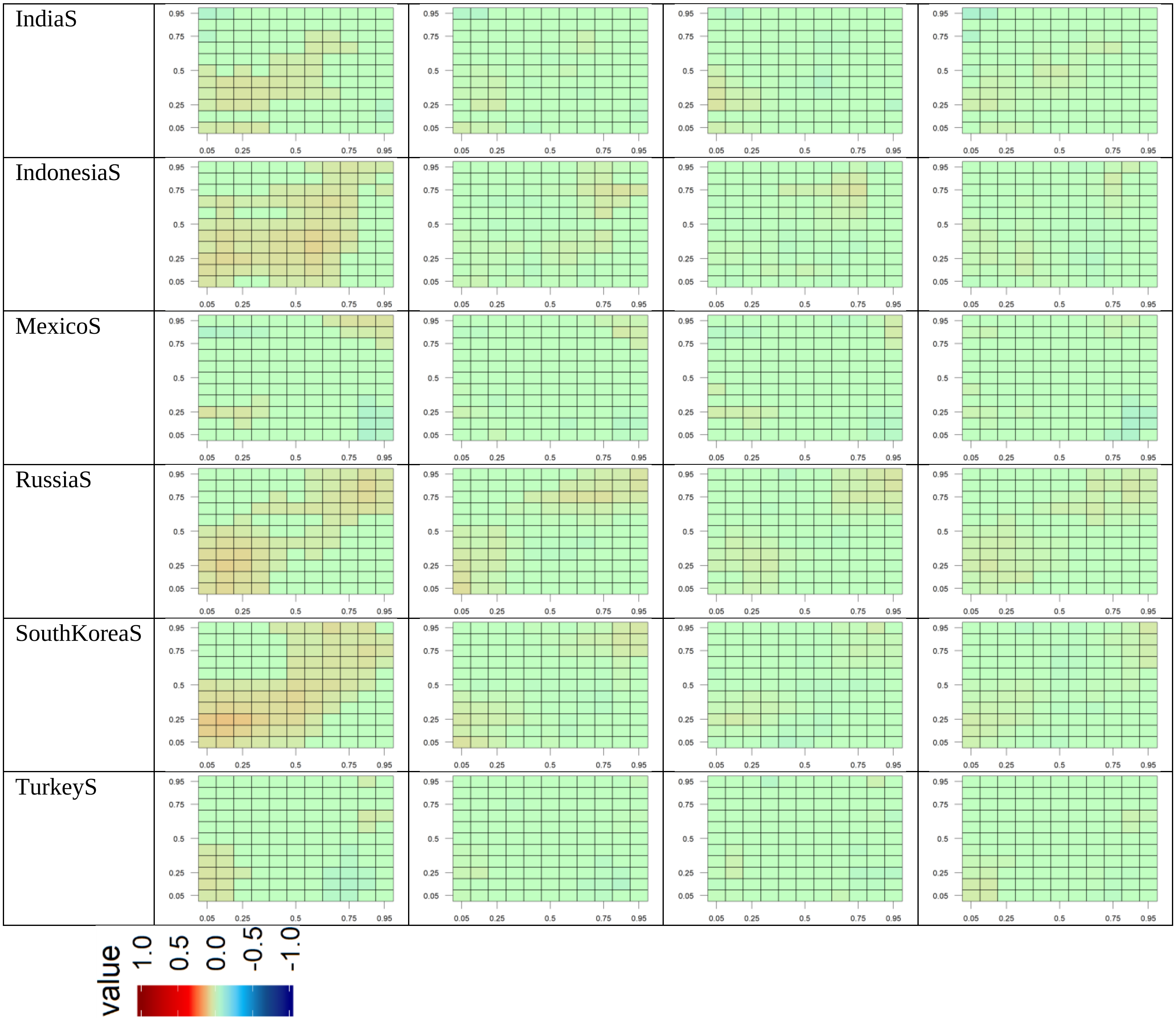


Fig. F.6.

Partial cross-quantile correlations between oil (Dubai) and the emerging stock market (E7+1). The control variable is GPRD. Notes: please refer to the notes in Fig. A.1.

Appendix G. See Figs. G.1-G.12.

	$\tau = 0.05$	$\tau = 0.5$	$\tau = 0.95$

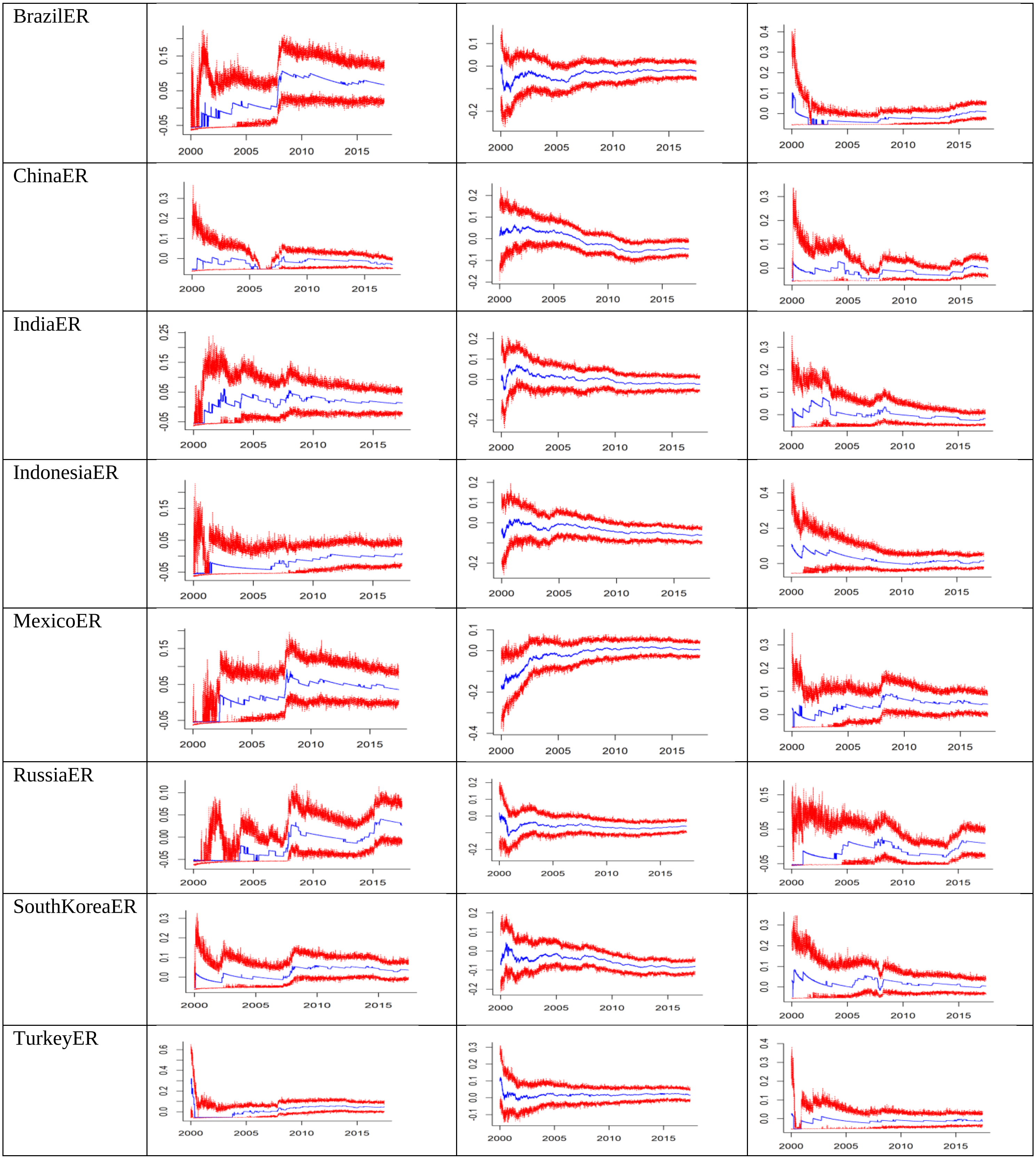
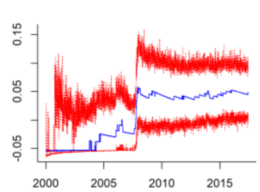
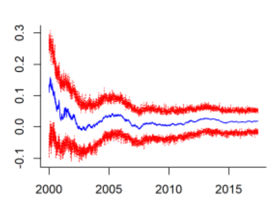
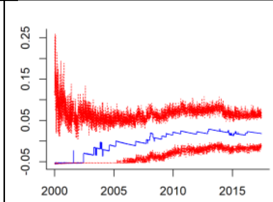
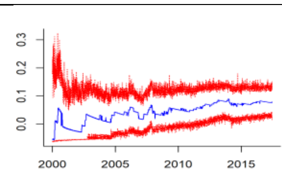
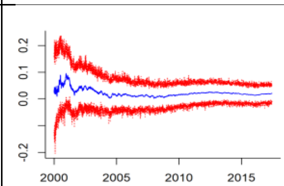
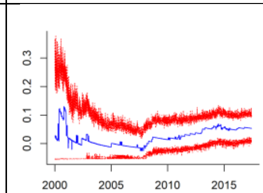
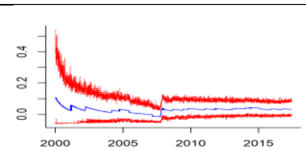
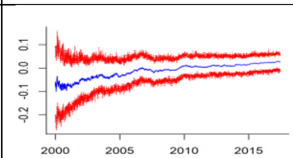
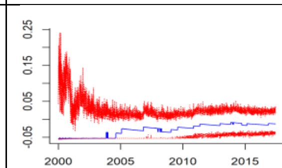
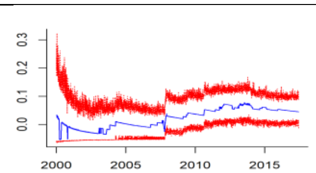
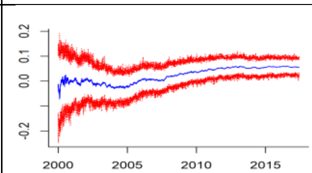
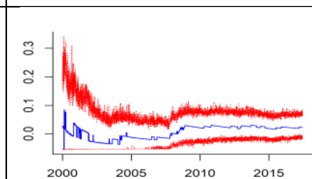
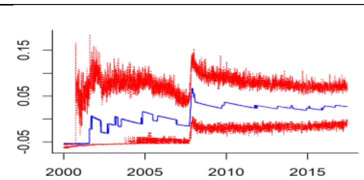
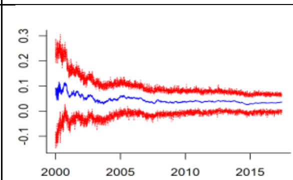
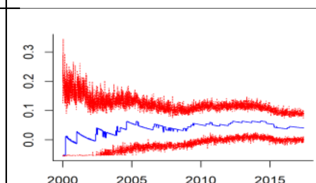
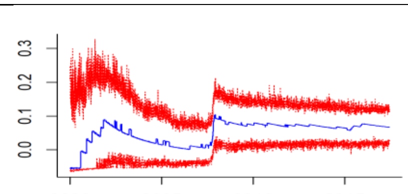
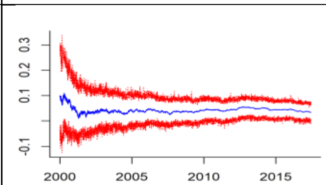
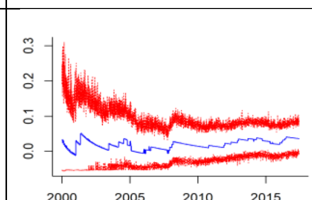
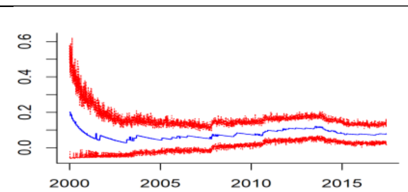
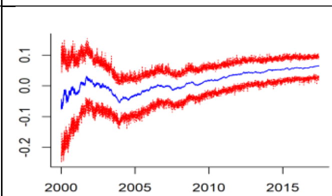
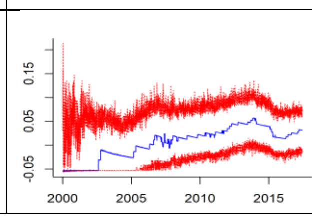

BrazilER
ChinaER
IndiaER
IndonesiaER
MexicoER
RussiaER
SouthKoreaER
TurkeyER
2000
2005
2010
2015

Fig. G.1.

Rolling window quantile dependence from oil (WTI) to exchange rates. Notes: The plots indicate a rolling window analysis for the estimated CQ coefficients. The year of departure for recursive subsampling is given in the horizontal axis. The 5th (low), 50th (median), and 95th (high) quantiles are presented in columns 2, 3, and 4, respectively. Lines in red signify 95% bootstrapping confidence interval for no predictability according to 1000 bootstrapped recurrences. Lines in blue display the time-varying cross-quantilogram values across recursive subsampling procedure.

	$\tau = 0.05$	$\tau = 0.5$	$\tau = 0.95$
BrazilS			
ChinaS			
IndiaS			
IndonesiaS			
MexicoS			
RussiaS			
SouthKorea S			

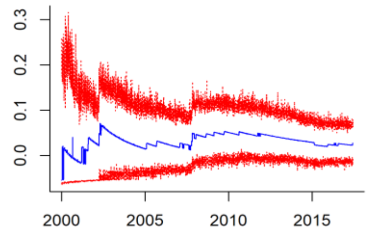
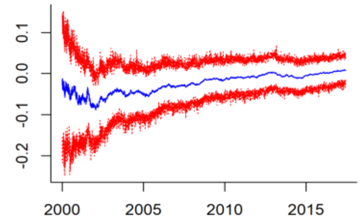
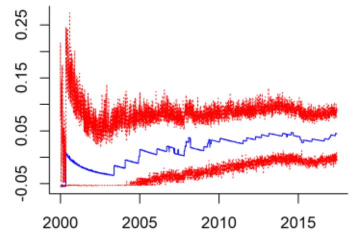
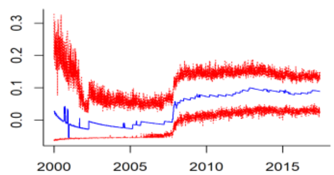
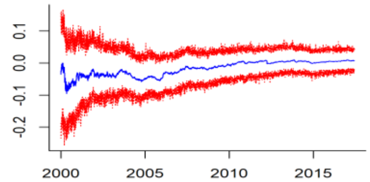
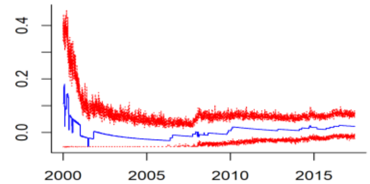
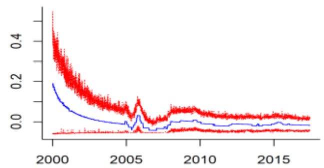
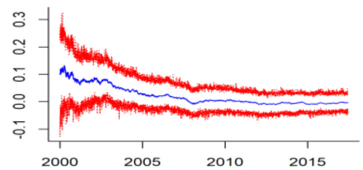
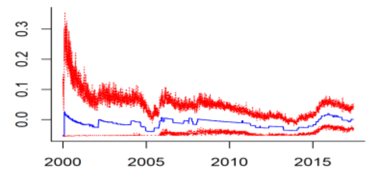
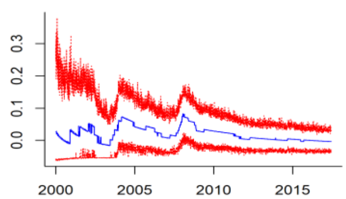
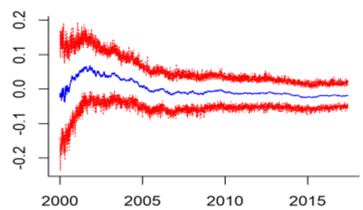
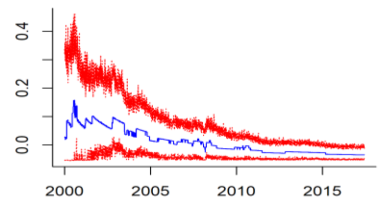
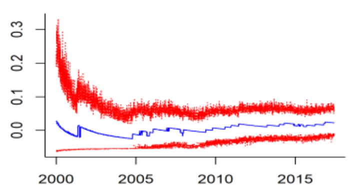
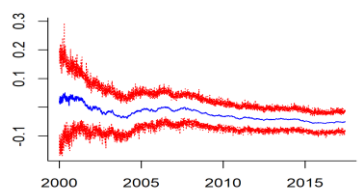
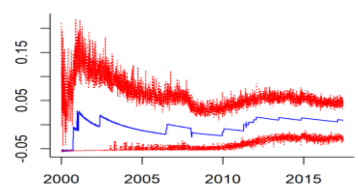
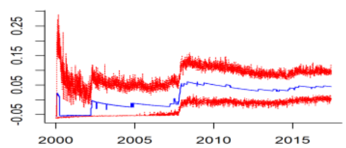
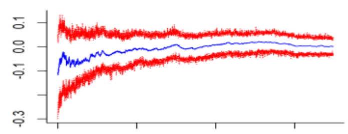
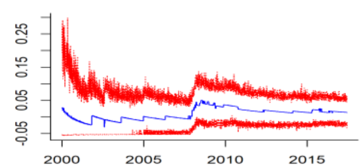
TurkeyS			

Fig. G.2.

Rolling window quantile dependence from oil (WTI) to stock returns. Notes: please refer to the notes in Fig. G.1.

	$\tau = 0.05$	$\tau = 0.5$	$\tau = 0.95$
BrazilER			
ChinaER			
IndiaER			
IndonesiaER			
MexicoER			

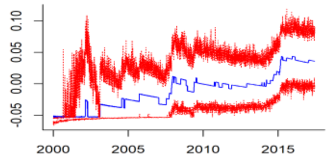
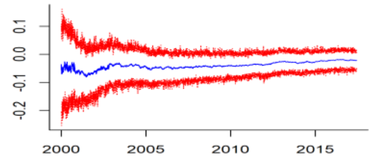
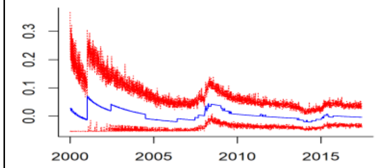
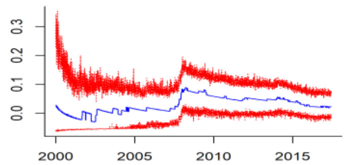
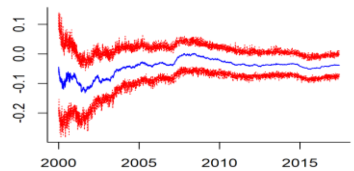
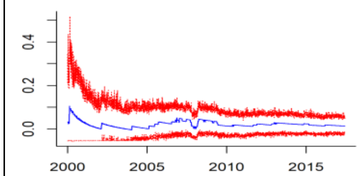
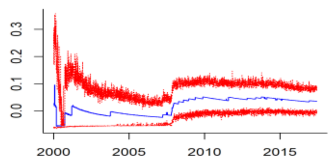
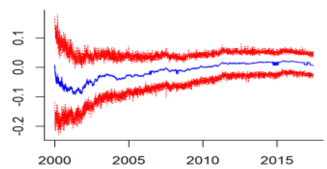
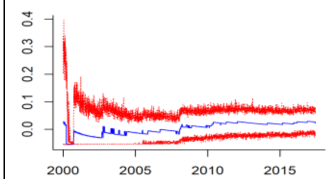
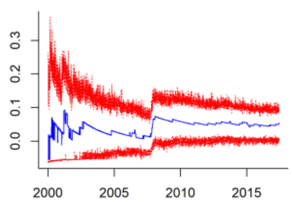
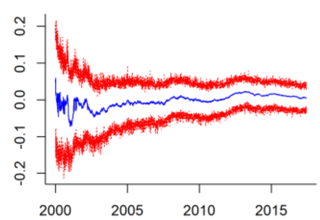
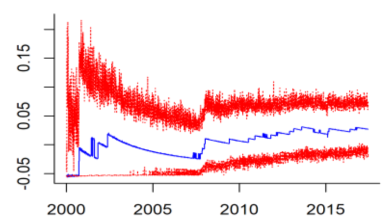
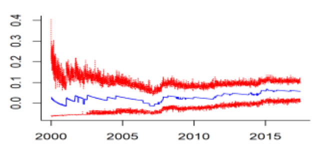
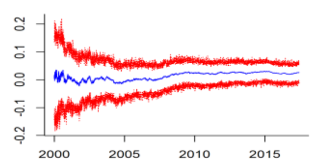
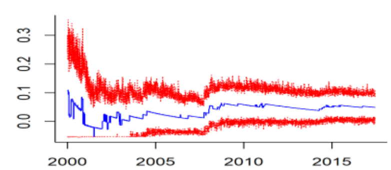
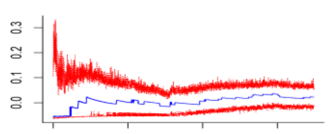
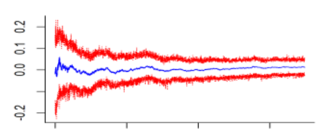
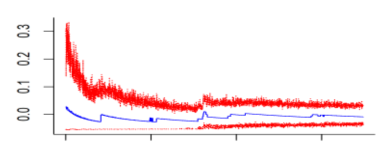
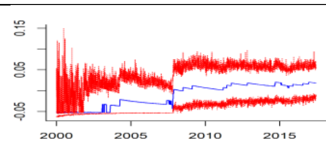
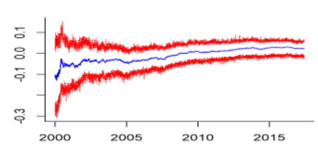
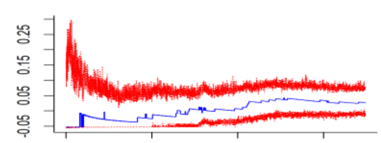
RussiaER			
SouthKoreaER			
TurkeyER			

Fig. G.3.

Rolling window quantile dependence from oil (Brent) to exchange rates. Notes: please refer to the notes in Fig. G.1.

	$\tau = 0.05$	$\tau = 0.5$	$\tau = 0.95$
BrazilS			
ChinaS			
IndiaS			
IndonesiaS			

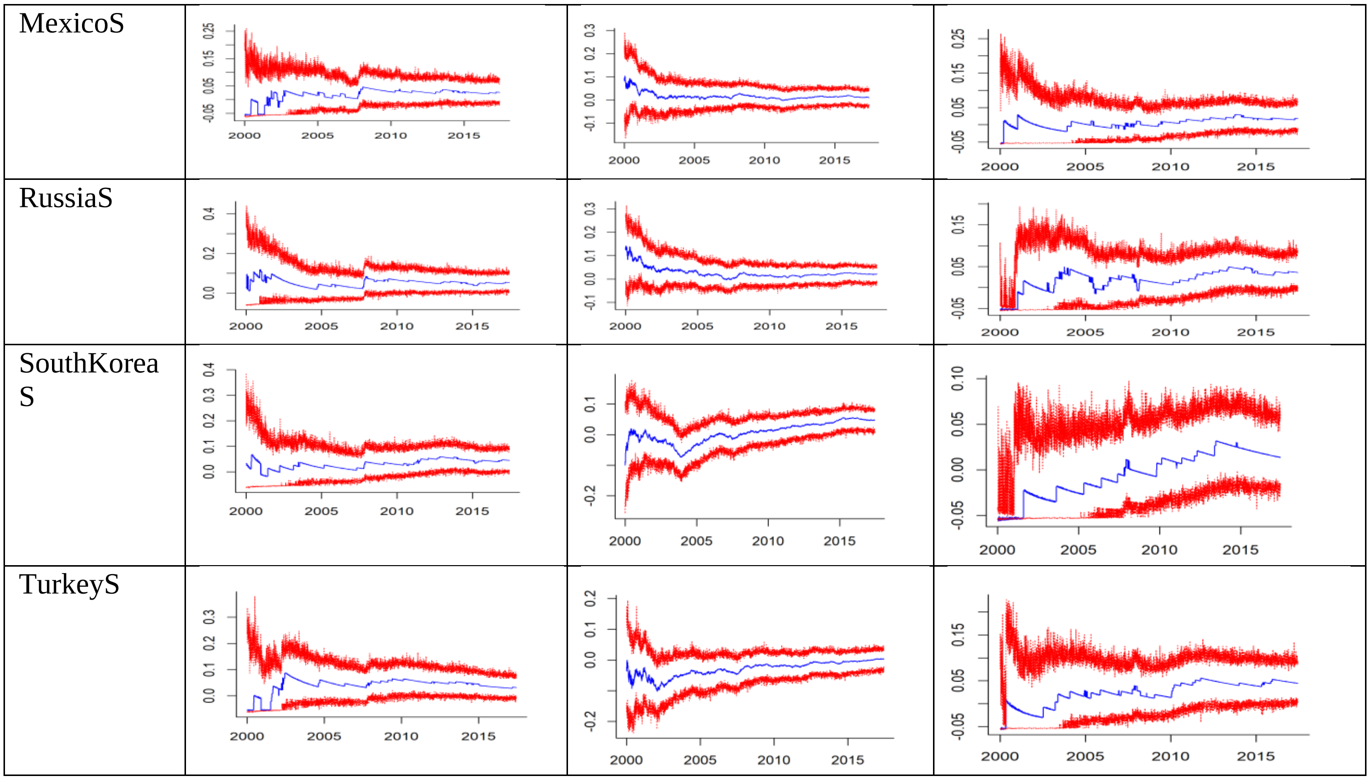
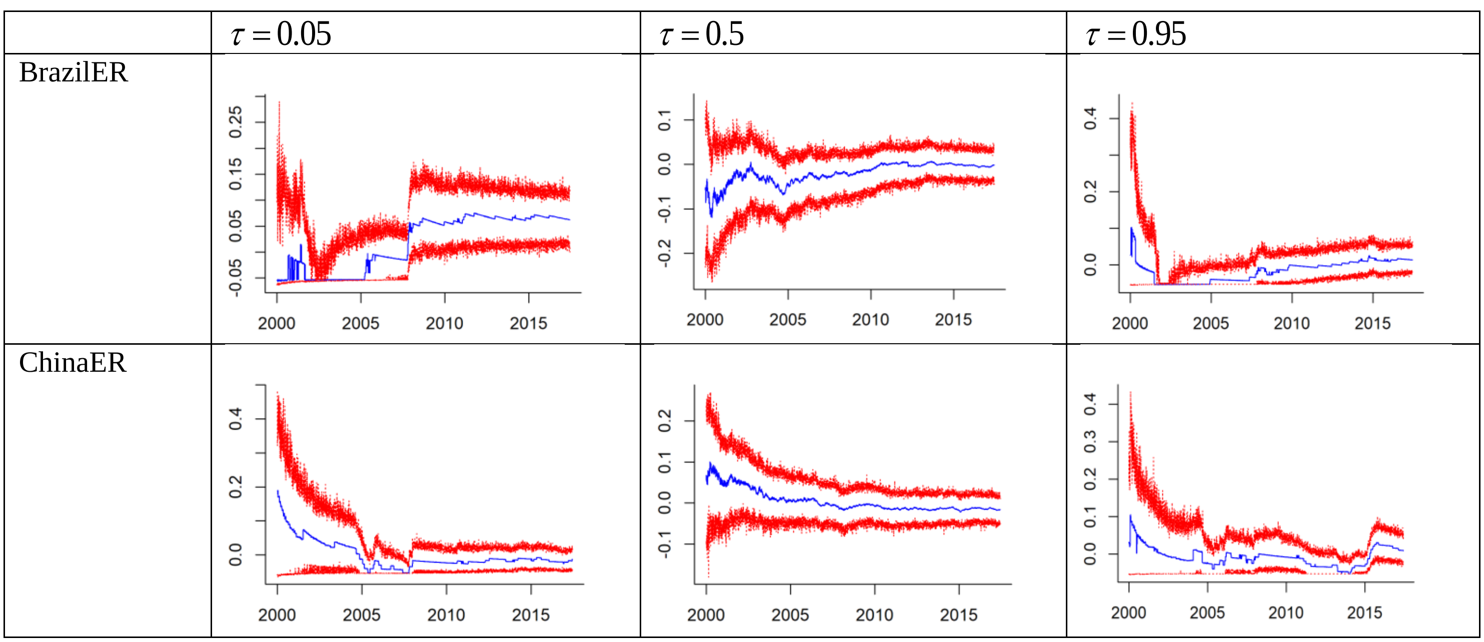


Fig. G.4.

Rolling window quantile dependence from oil (Brent) to stock returns. Notes: please refer to the notes in Fig. G.1.



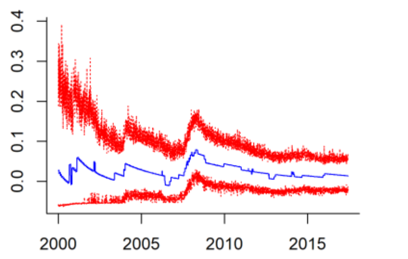
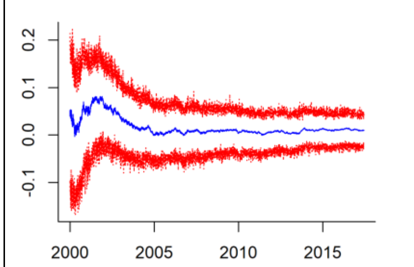
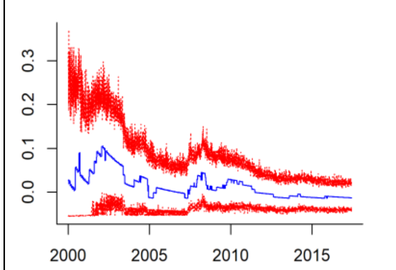
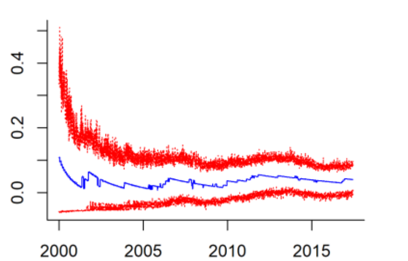
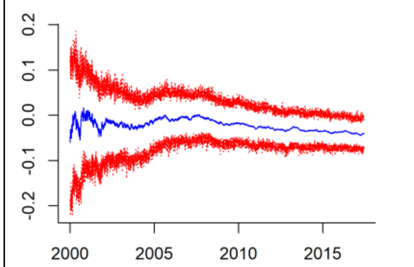
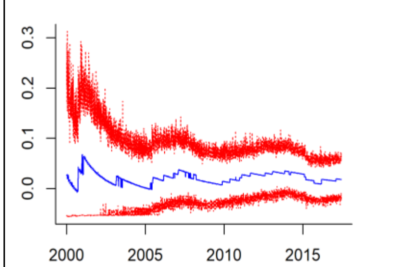
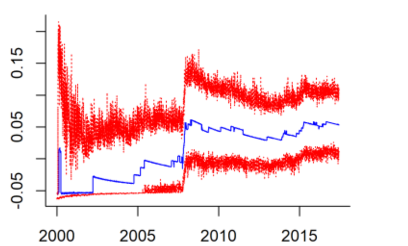
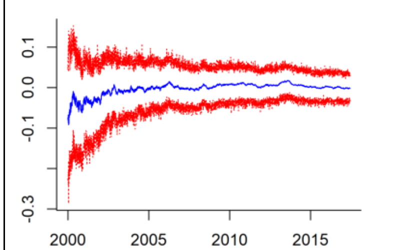
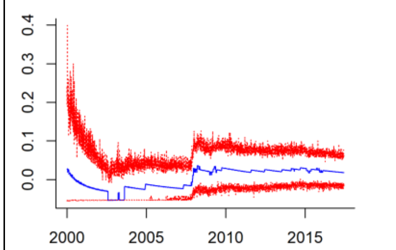
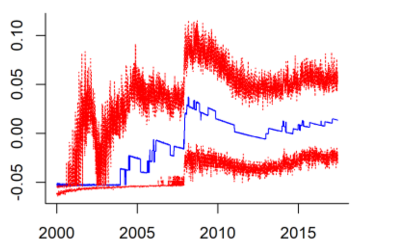
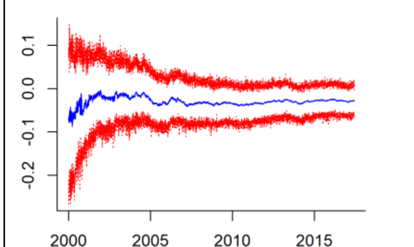
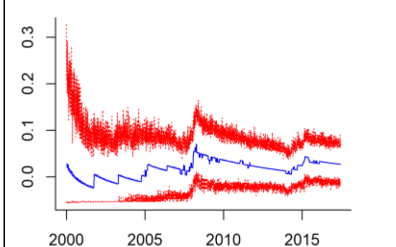
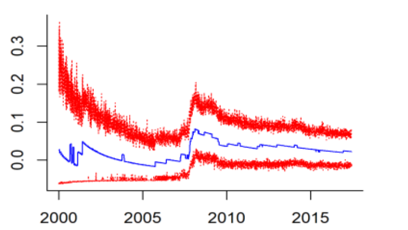
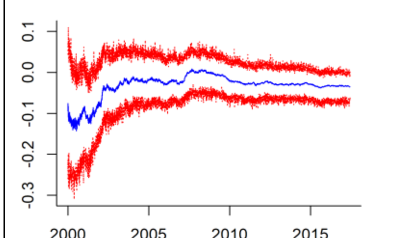
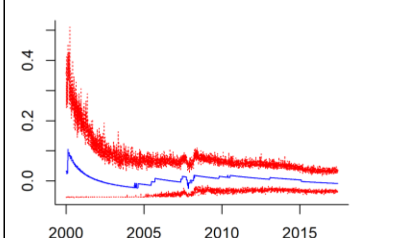
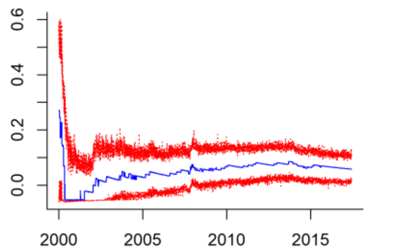
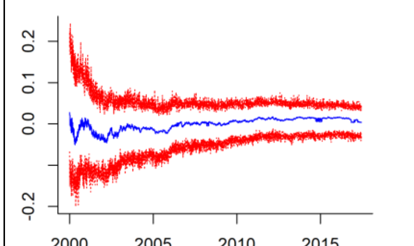
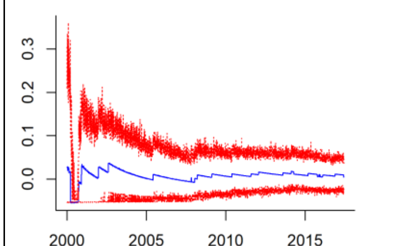
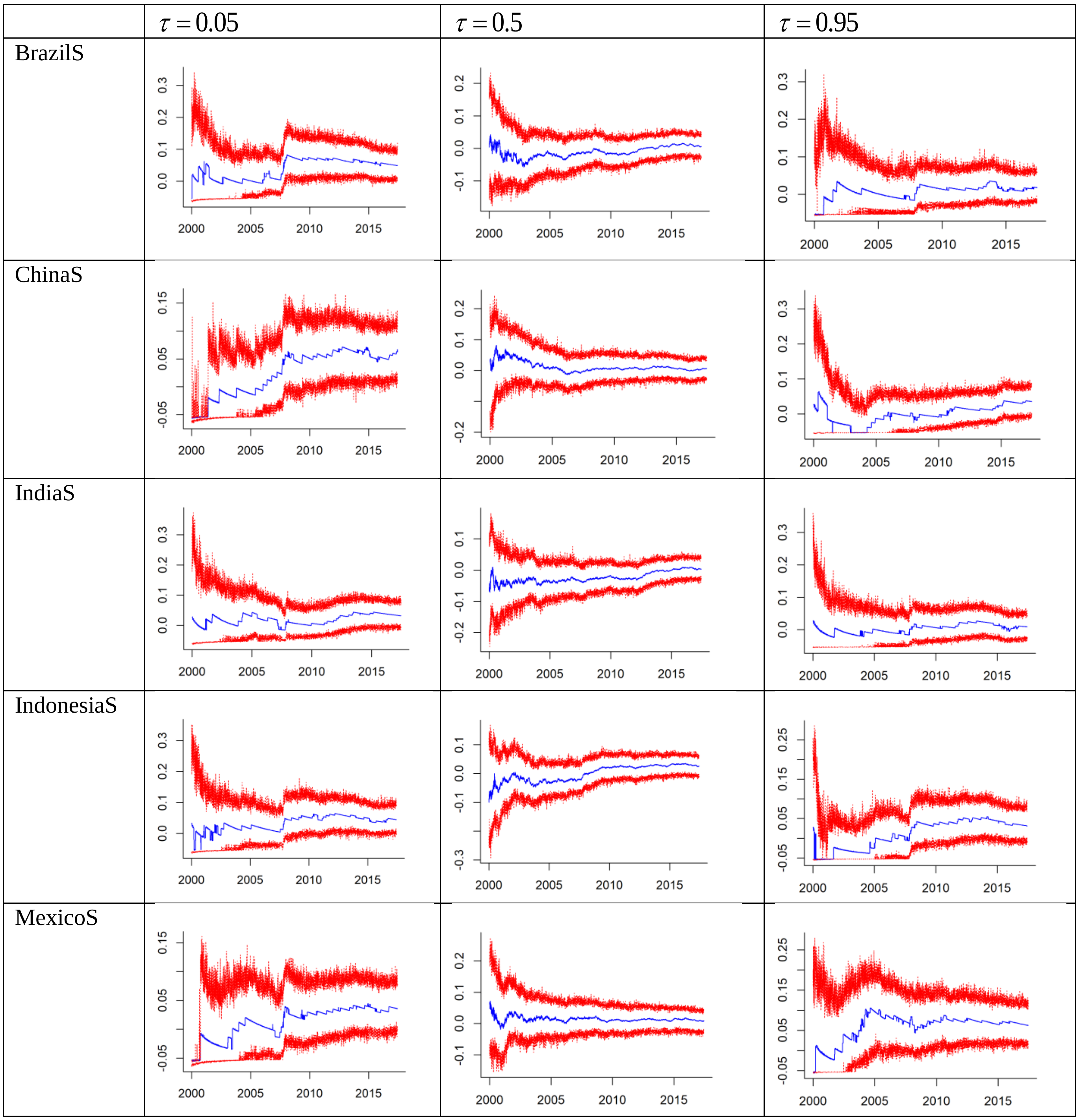
IndiaER			
IndonesiaER			
MexicoER			
RussiaER			
SouthKoreaER			
TurkeyER			

Fig. G.5.

Rolling window quantile dependence from oil (OPEC) to exchange rates. Notes: please refer to the notes in Fig. G.1.



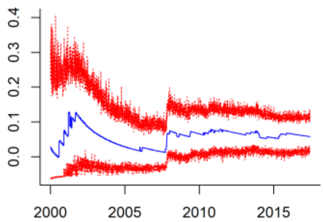
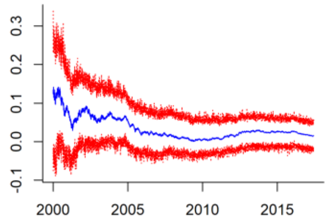
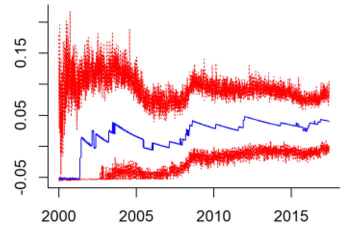
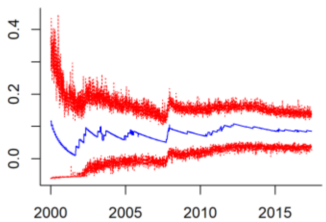
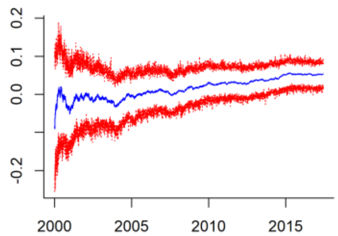
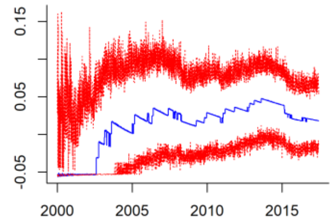
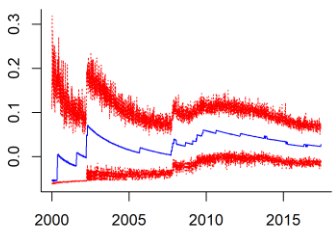
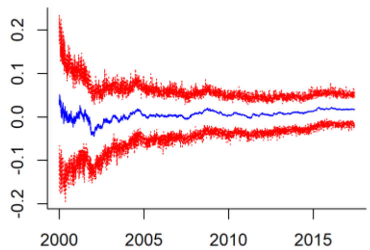
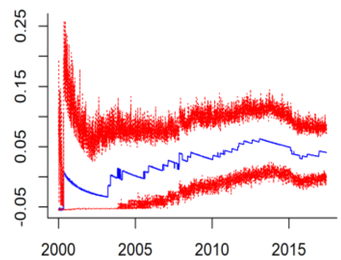
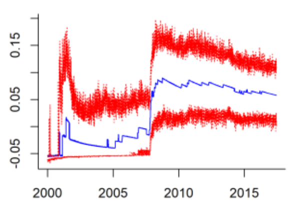
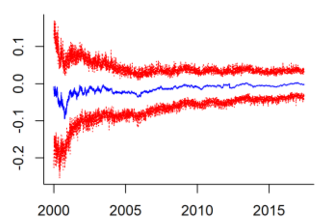
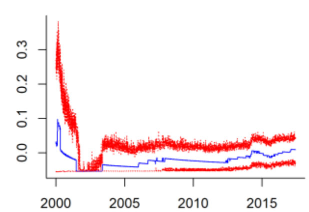
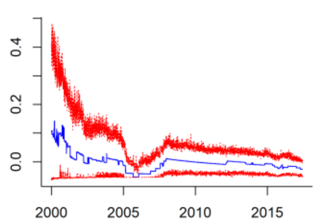
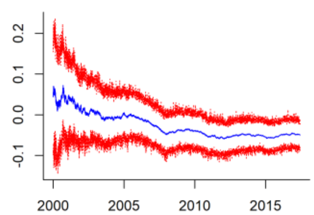
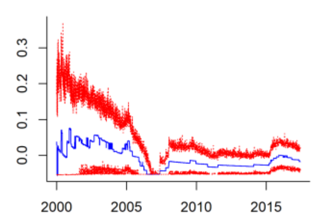
RussiaS			
SouthKorea S			
TurkeyS			

Fig. G.6.

Rolling window quantile dependence from oil (OPEC) to stock returns. Notes: please refer to the notes in Fig. G.1.

	$\tau = 0.05$	$\tau = 0.5$	$\tau = 0.95$
BrazilER			
ChinaER			

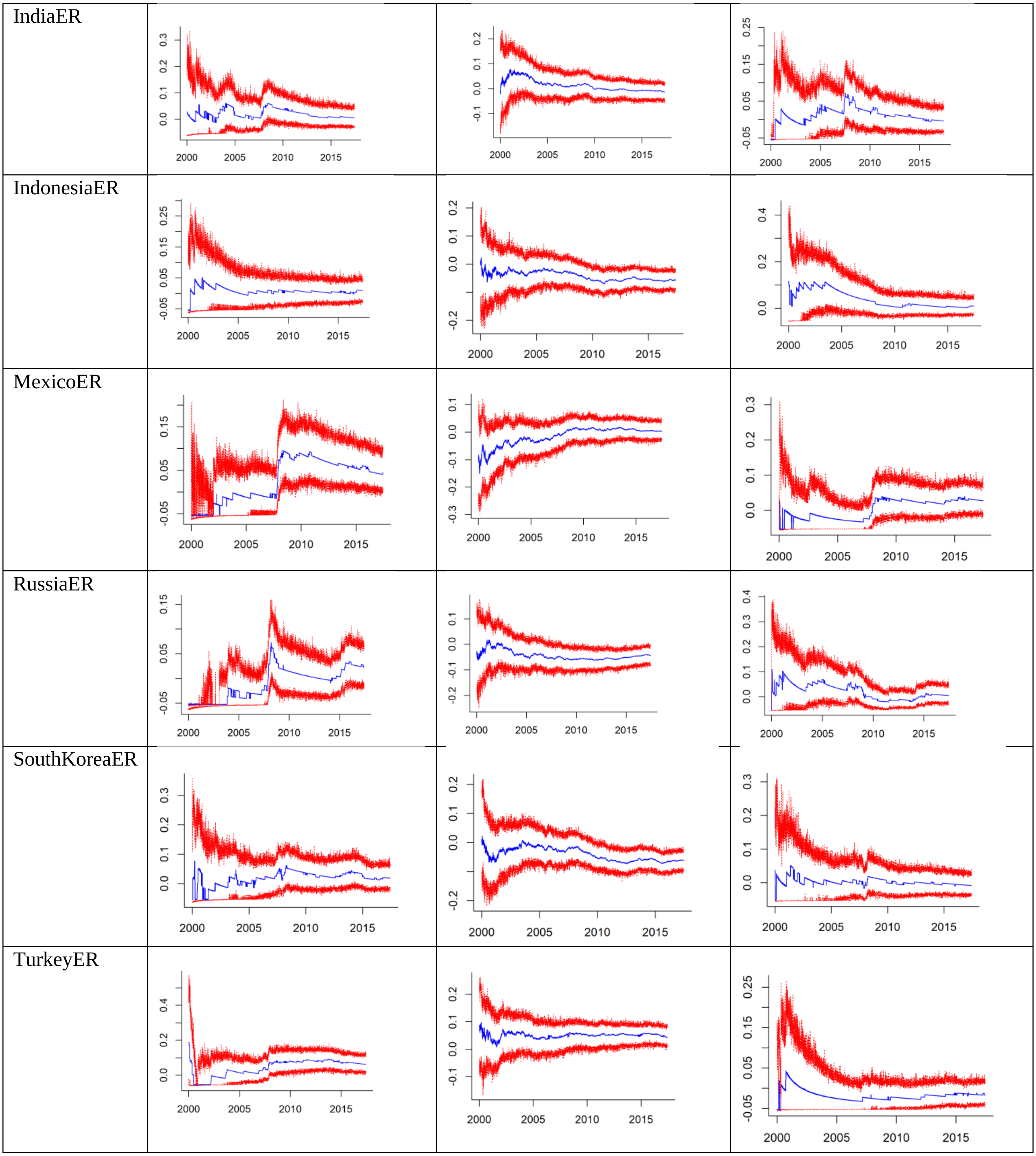
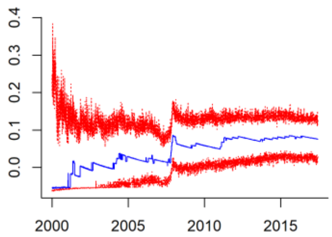
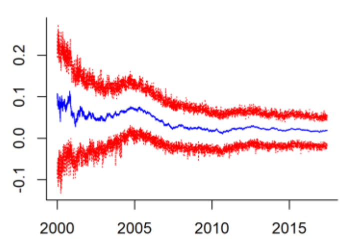
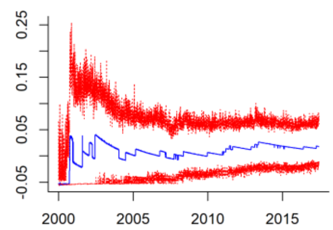
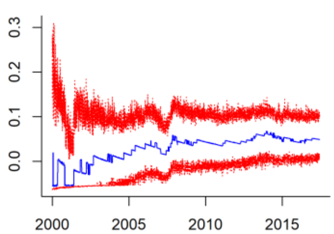
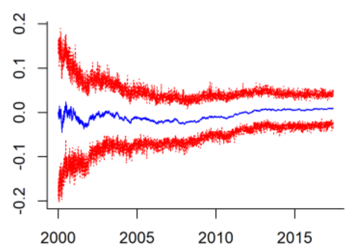
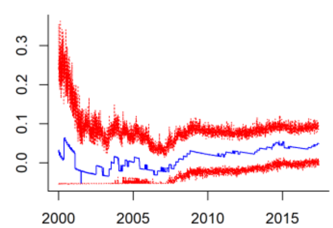
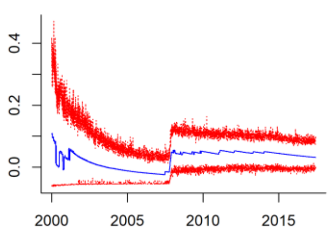
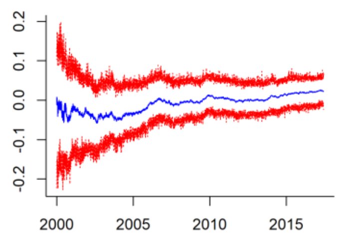
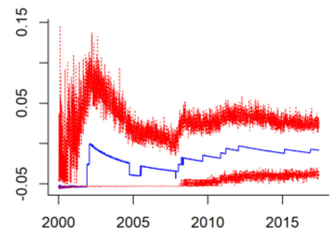
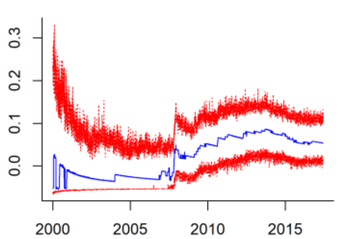
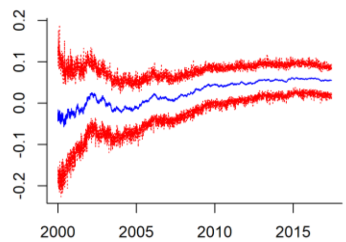
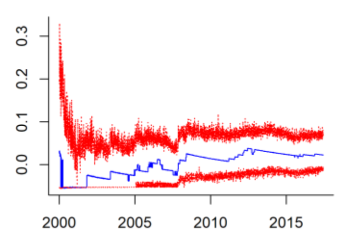
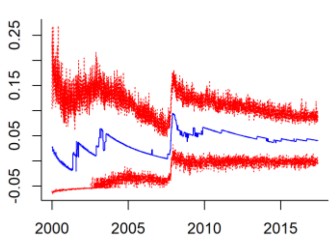
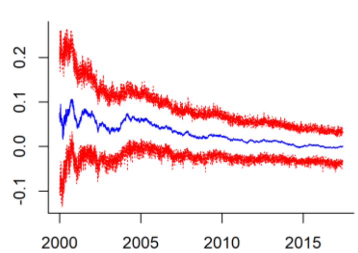
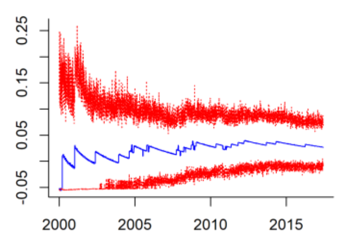

IndiaER
IndonesiaER
MexicoER
RussiaER
SouthKoreaER
TurkeyER

Fig. G.7.

Rolling window quantile dependence from heating oil to exchange rates. Notes: please refer to the notes in Fig. G.1.

	$\tau = 0.05$	$\tau = 0.5$	$\tau = 0.95$
BrazilS			
ChinaS			
IndiaS			
IndonesiaS			
MexicoS			

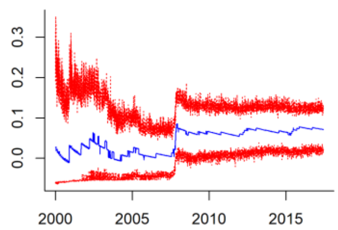
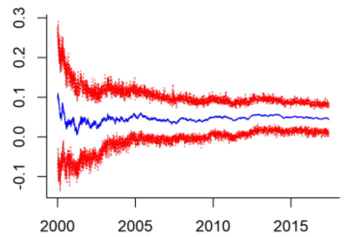
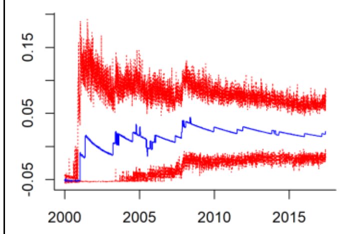
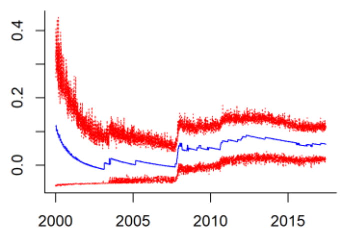
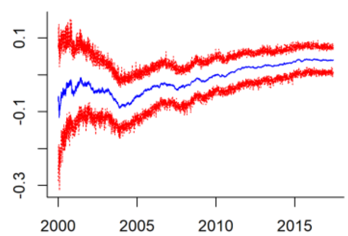
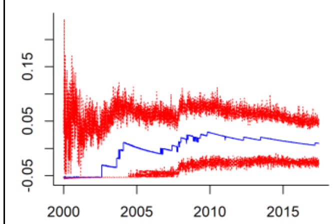
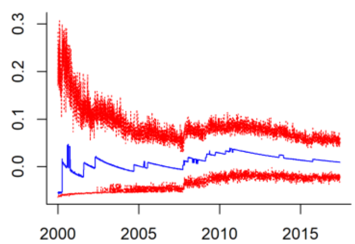
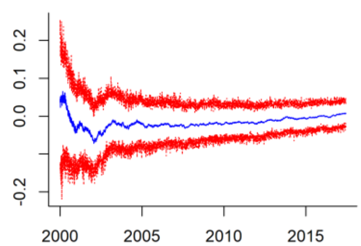
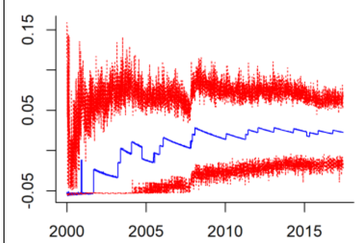
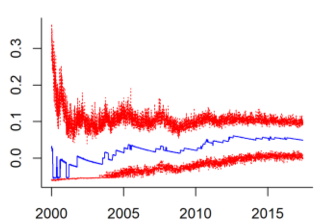
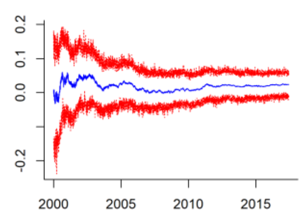
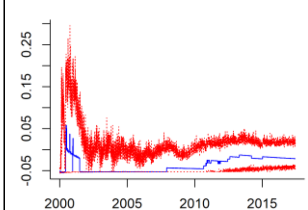
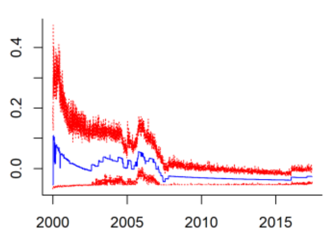
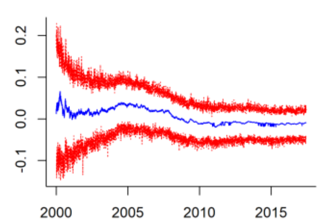
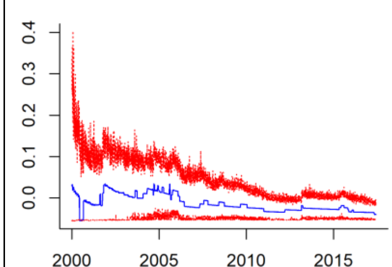
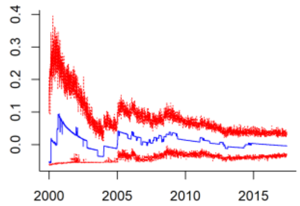
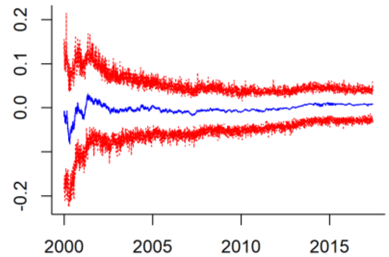
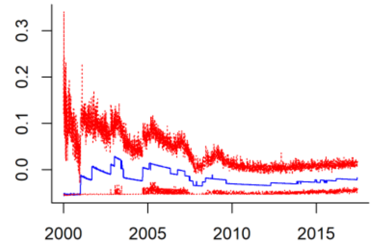
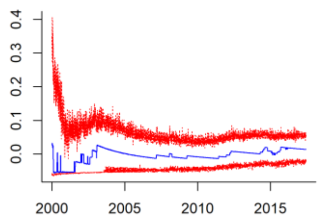
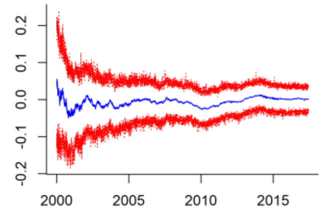
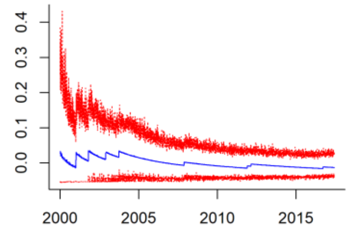
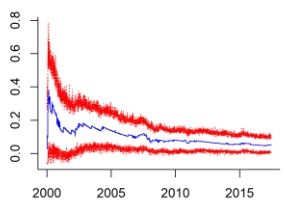
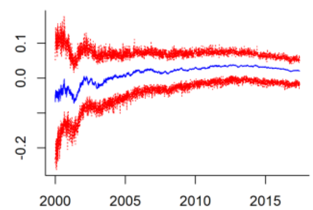
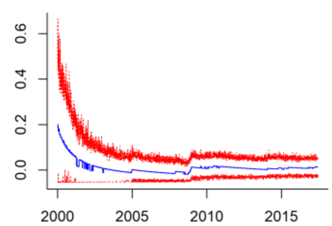
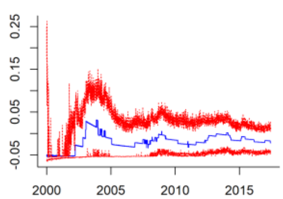
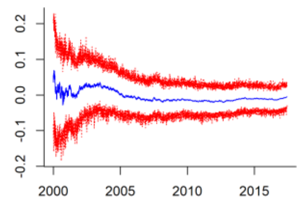
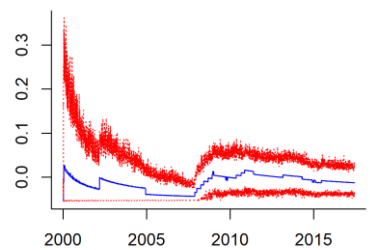
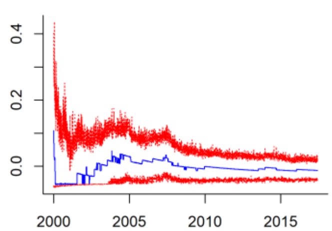
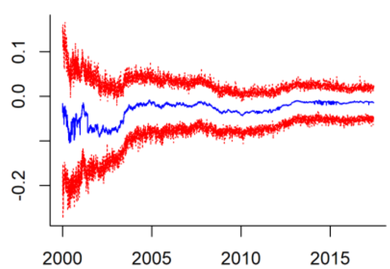
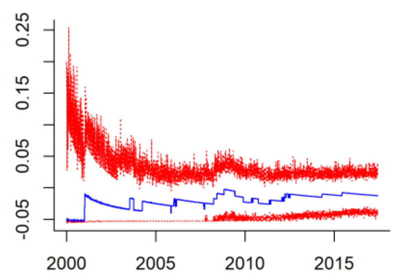
RussiaS			
SouthKorea S			
TurkeyS			

Fig. G.8.

Rolling window quantile dependence from heating oil to stock returns. Notes: please refer to the notes in Fig. G.1.

	$\tau = 0.05$	$\tau = 0.5$	$\tau = 0.95$
BrazilER			
ChinaER			

IndiaER			
IndonesiaER			
MexicoER			
RussiaER			
SouthKoreaER			

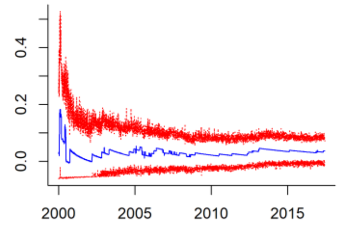
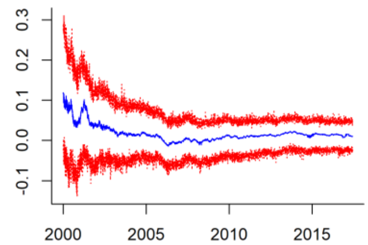
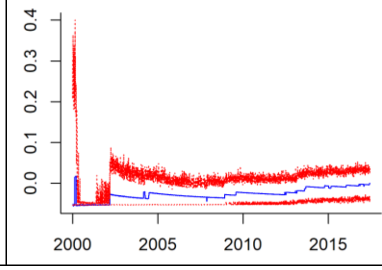
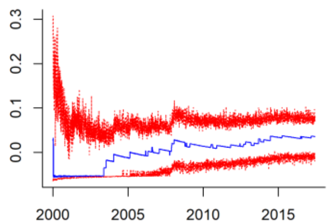
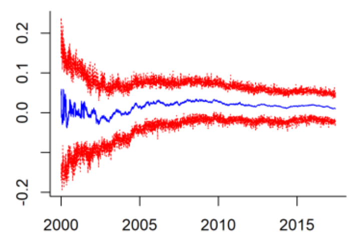
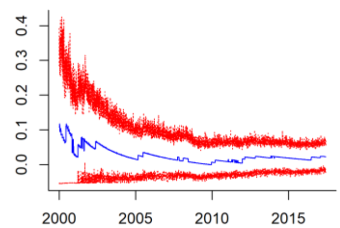
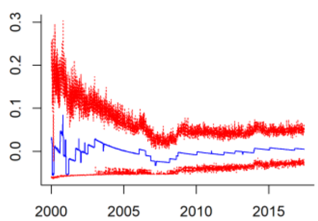
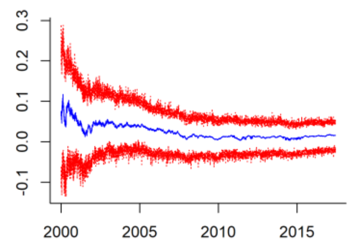
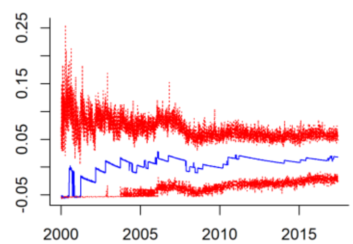
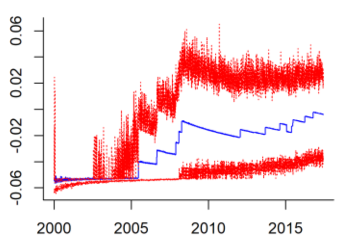
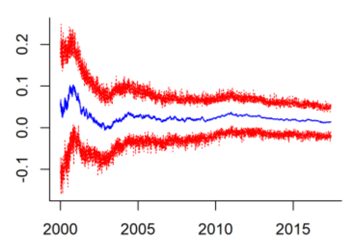
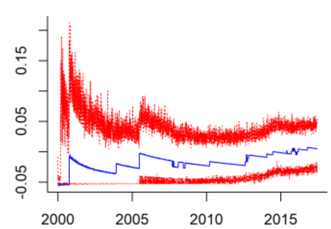
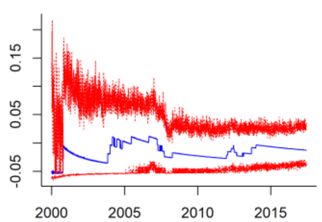
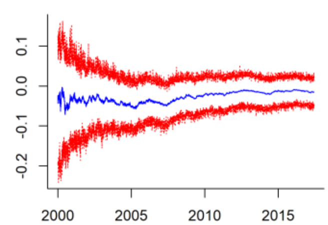
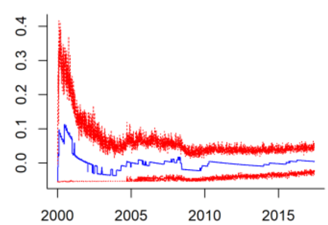
TurkeyER			

Fig. G.9.

Rolling window quantile dependence from natural gas to exchange rates. Notes: please refer to the notes in Fig. G.1.

	$\tau = 0.05$	$\tau = 0.5$	$\tau = 0.95$
BrazilS			
ChinaS			
IndiaS			
IndonesiaS			

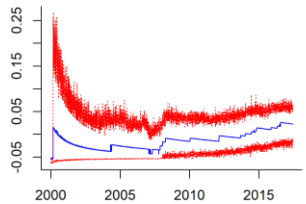
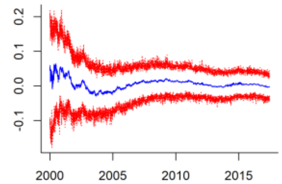
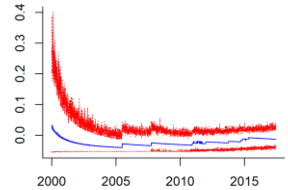
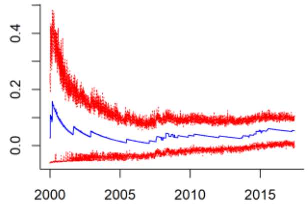
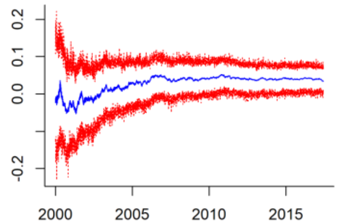
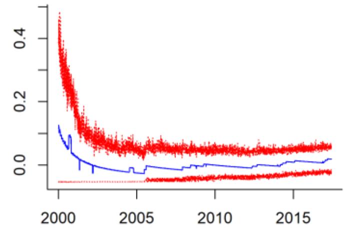
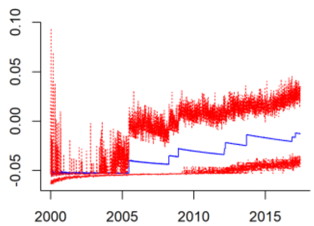
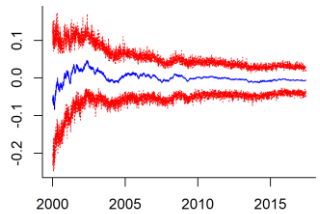
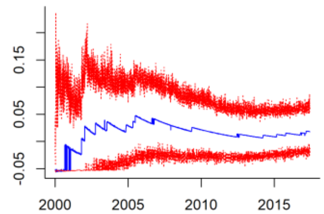
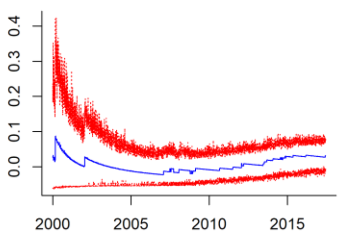
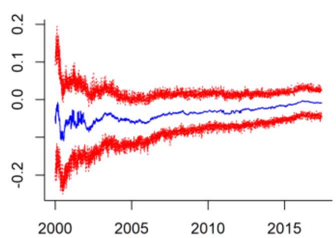
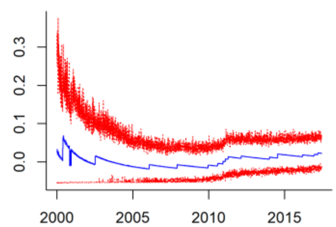
MexicoS			
RussiaS			
SouthKorea S			
TurkeyS			

Fig. G.10.

Rolling window quantile dependence from natural gas to stock returns. Notes: please refer to the notes in Fig. G.1.

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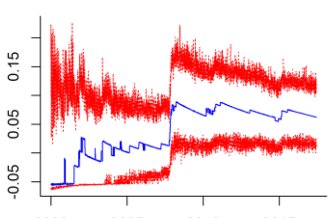
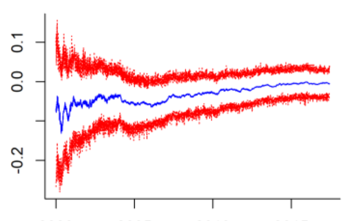
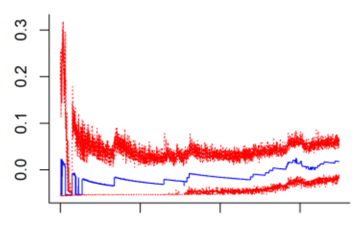
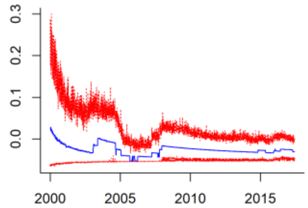
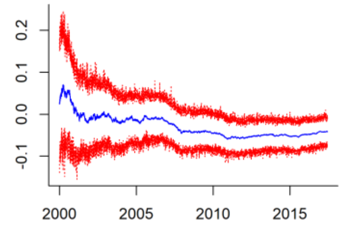
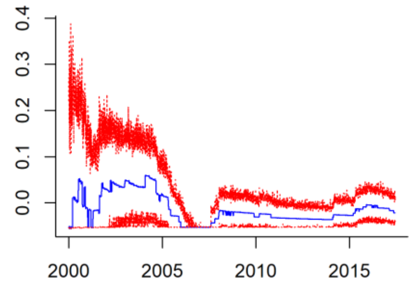
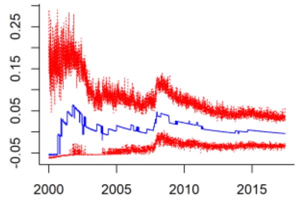
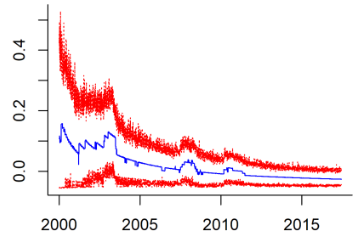
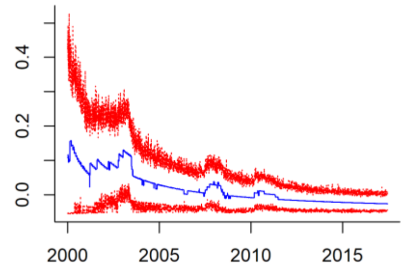
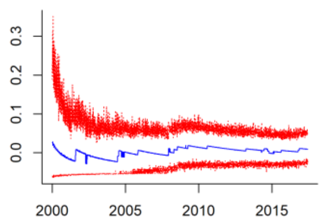
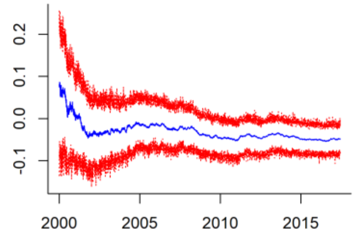
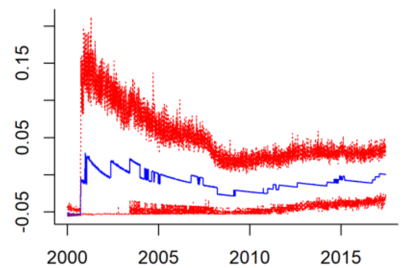
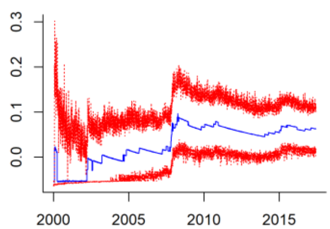
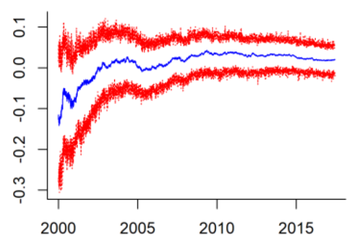
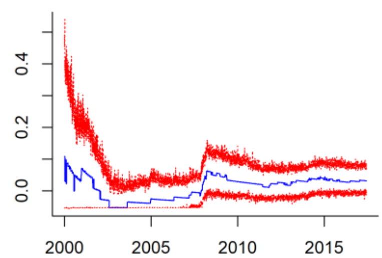
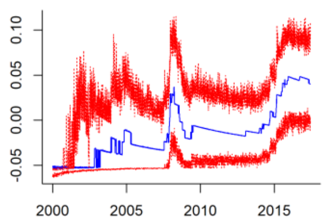
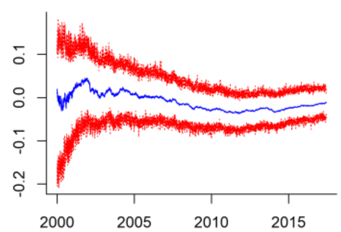
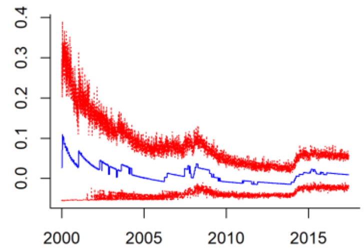
BrazilER			

ChinaER			
IndiaER			
IndonesiaER			
MexicoER			
RussiaER			

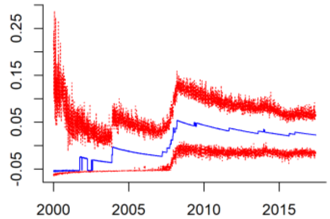
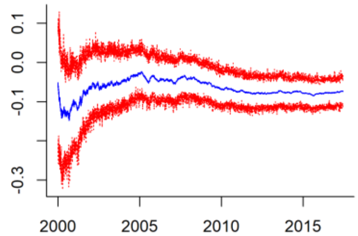
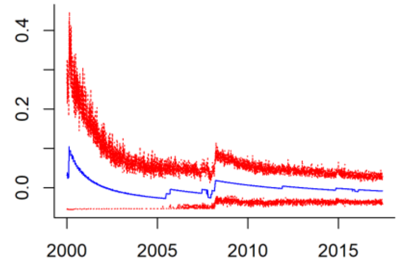
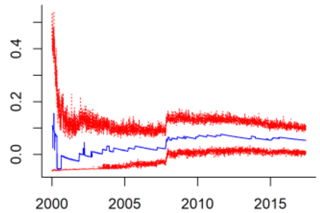
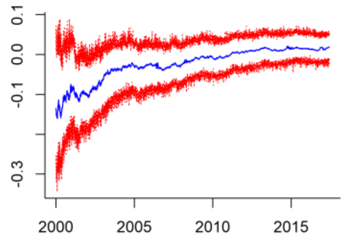
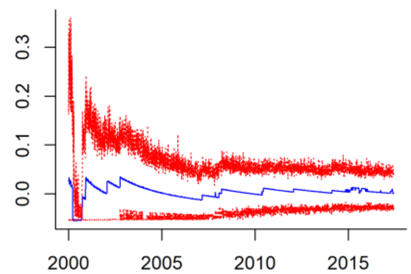
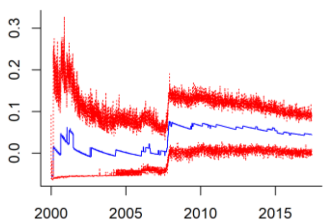
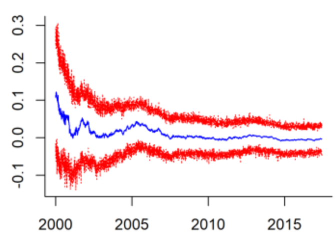
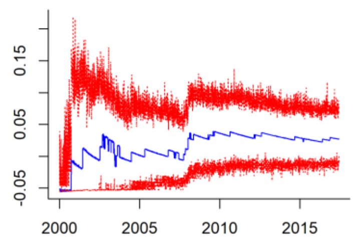
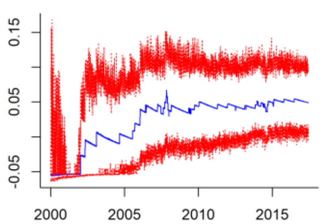
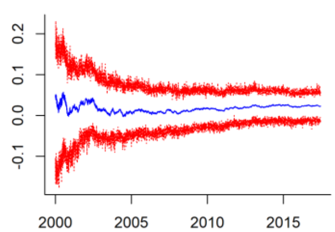
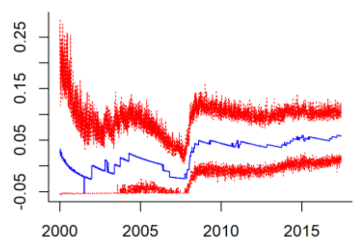
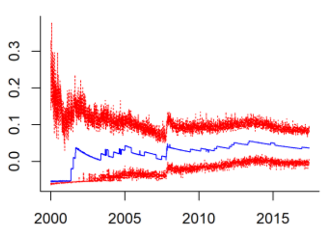
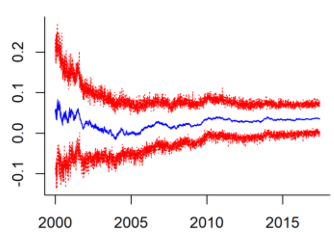
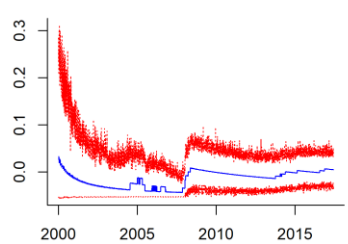
SouthKoreaER			
TurkeyER			

Fig. G.11.

Rolling window quantile dependence from oil (Dubai) to exchange rates. Notes: please refer to the notes in Fig. G.1.

	$\tau = 0.05$	$\tau = 0.5$	$\tau = 0.95$
BrazilS			
ChinaS			
IndiaS			

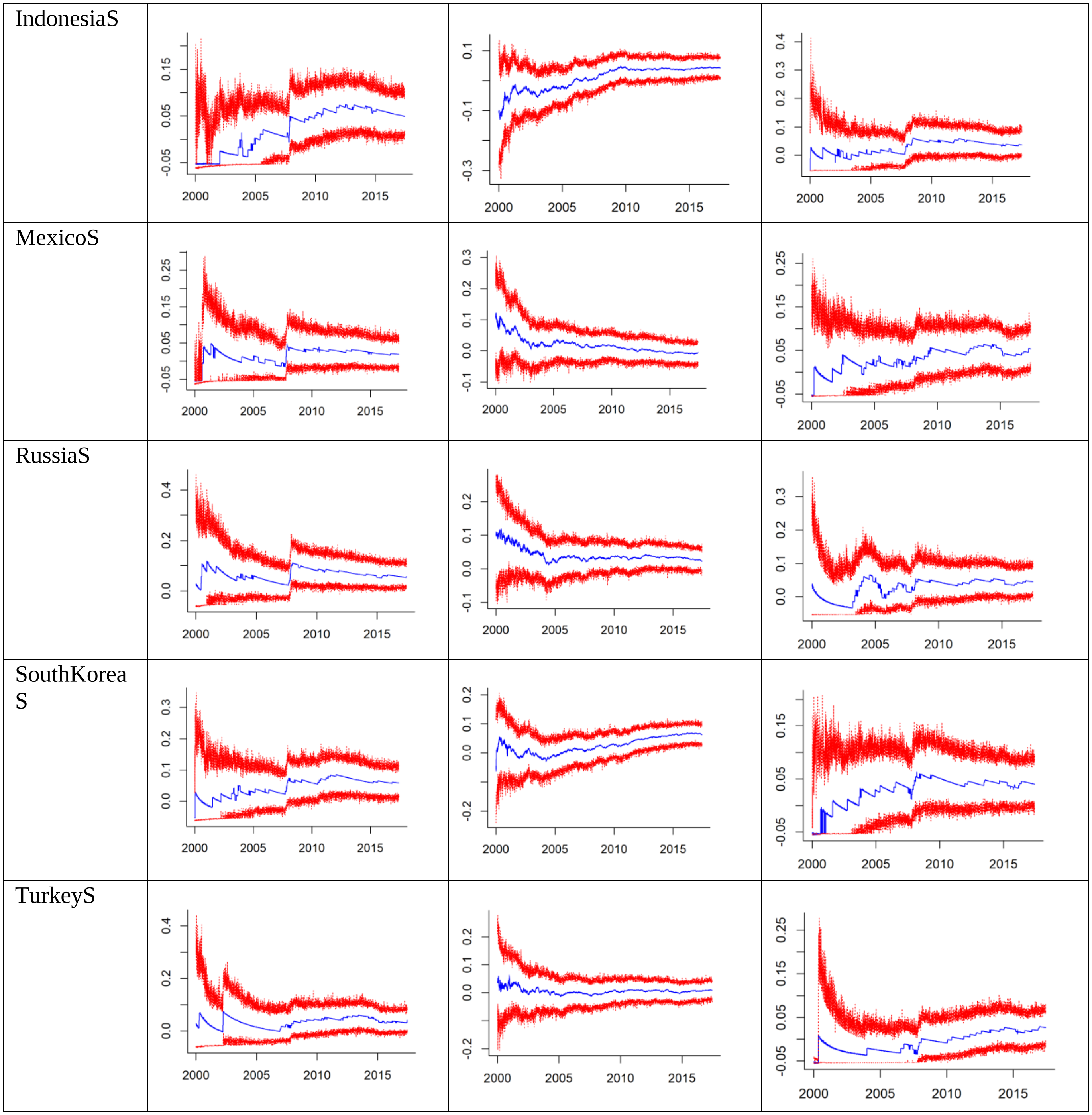


Fig. G.12.

Rolling window quantile dependence from oil (Dubai) to stock returns. Notes: please refer to the notes in Fig. G.1.