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Oil shocks and financial stability in MENA countries

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Abstract

We examine the link between financial stress and three sources of commodity fluctuations in MENA countries, namely: *(i)* oil demand shocks; *(ii)* oil supply shocks; and *(iii)* (financial) risk shocks. To do so, we use a novel quantile coherency approach and daily data for 11 MENA countries over the period September 21, 2006 – August 19, 2021, thus, improving upon the existing studies that typically rely on single-frequency and time-frequency dependence. As a result, we are able to capture both varied market conditions and different investment horizons. We find that financial stress is particularly acute during extreme oil demand and oil supply shocks, especially at longer horizons. By contrast, (financial) risk shocks appear to be more prominent in generating financial stress at relatively shorter horizons and regardless of the quantiles of the distribution. This empirical evidence can have strong implications for policymakers in the region, as well as portfolio managers.

Keywords: Oil demand; oil supply; (financial) risk; financial contagion; cross-quantilogram approach; cross-spectral quantile coherency.

JEL Classifications: Q41, Q43, G11.

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1. Introduction

Oil prices have typically been described as a leading economic indicator, with price spikes in this commodity being associated with sharp declines in future economic activity (Hamilton, 2003). Not surprisingly, understanding the linkages between oil prices and the economy has long been a key question even though the classification of oil price changes as being driven by variation in demand or by fluctuations in supply is challenging (Ready, 2018).

For the Middle East and the North Africa (MENA) region in particular, such distinction in the nature of oil price shocks is even more prominent, as the large share of this commodity sector in the economy can quickly turn those shocks into episodes of financial contagion and volatility spillovers (Elsayed *et al.*, 2021).

Yet, despite the importance of commodity price fluctuations for the stability of the banking sector in the economies of the MENA region, the empirical literature has either looked at the contagion among MENA's equity markets (Neaime, 2005, 2016; Lagoarde-Segot and Lucey, 2009; Chau *et al.*, 2014) and between these and those of advanced economies (Darrat *et al.*, 2000; Graham *et al.*, 2013; Maghyereh *et al.*, 2015; Neaime, 2012) or the interdependence across difference asset classes (e.g., bonds, commodities, currencies and equities) (Uddin *et al.,* 2022). Thus, financial co-movement is perceived as reflecting savings mobilisation and capital re-allocation to promote risk diversification and operating as the counter-part of the intensification of trade flows (Levine, 1997).

In this context, assessing how developments in the oil market morph into potential financial stress in the MENA region remains largely unexplored and is the main goal of our paper. Therefore, our research represents a major step towards investigating the intersections between the commodity sector and financial conditions. As such, our work is highly indebted to the studies of Ghosh (2016), Chau *et al.* (2014) and Elsayed and Yarovaya (2019), who analyse how (major) policy events or uncertainty spill into financial risk and financial stress.

More specifically, we contribute to the existing literature along different dimensions. First, we follow the methodology of Ready (2018) and use it to decompose oil price variation into oil demand shocks, oil supply driven changes and unexpected (financial) risk dynamics for a group of 11 MENA countries over the period spanning between 21 September 2006 and 19 August 2021. Second, we rely on daily data for the banking sector, the stock market and the foreign exchange market and the framework proposed by Apostolakis and Papadopoulos (2015) and successfully tested by Elsayed and Yarovaya (2019) to construct financial stress indices for those MENA economies. Third, we examine the direct linkages between the above mentioned three major shocks hitting the oil price sector and the constructed financial stress indices using a novel quantile coherency approach developed by Barunik and Kley (2019). Thus, instead of exploring a mean or volatility dependence (Dungey *et al.*, 2006; Claeys and Vasicek, 2014; Gómez-Puig and Sosvilla-Rivero, 2014; Bekiros *et al.*, 2018) or focusing on a single data frequency (Mensi *et al.*, 2014; Sim, 2016; Chuliá *et al.*, 2017), we explore the interdependence between financial stress and commodity price shocks across quantiles (that capture different positions in the business cycle or contrasting market conditions) in different frequencies (that track alternative investment horizons). In this regard, our paper brings valuable added value to the asset return dependence literature (Pal and Mitra, 2017; Tiwari *et al.*, 2020), in particular, by building the macro-financial bridge between the commodity sector and financial conditions in the MENA region.

Our main empirical findings are threefold. First, financial stress is particularly acute during extreme oil demand and oil supply shocks. Second, the link between financial stress and oil shocks is more prominent at relatively long horizons. Third, regardless of the quantiles of the distribution, (financial) risk shocks are associated with heightened financial stress at relatively short horizons.

All in all, this evidence can have strong implications for policymakers in the region, as well as portfolio managers. Specifically, policymakers should pay particular attention at designing macro-prudential policies aimed at the oil sector with the ultimate goal of avoiding contagion that might spill into financial market (in)stability. As for portfolio managers and practitioners, they should factorise the limitations of financial markets as a hedge against unfavourable oil price fluctuations in light of the strong dependence between the oil sector and financial stress during extreme market conditions.

The rest of the paper is as follows. Section 2 briefly discusses the econometric methodology, while Section 3 describes the data. In Section 4, we present the empirical results. Finally, Section 5 concludes.

2. The cross-spectral quantile coherency

The cross-quantilogram method developed by Han *et al.* (2016) allows one to assess both dependence and directional predictability in different quantiles of the distribution of the time-series of interest. This approach is the bivariate version of the quantilogram by Linton and Whang (2007), which is obtained from sample correlations by comparing correlograms of "quantile hits" to pointwise confidence intervals. Han *et al.* (2016) extends it to a multivariate setup, and we use it to investigate the (tail) dependence structure in the full quantile-space between financial stress and three major sources of shocks in the MENA region: *(i)* oil demand shocks; *(ii)* oil supply shocks; and *(iii)* (financial) risk shocks.[4]

While different methods can measure correlation and dependence (e.g., Multivariate GARCH (MGARCH) models),[5] these do not typically track the full distribution of the dependent variable, thus, missing differences in investors' behaviour during alternative market periods or at varied time horizons.

The dependence in parts of the distribution of the dependent variable can be estimated using extremograms (Davis and Mikosch, 2009), quantile regressions (Koenker and Hallock, 2001; Koenker, 2005), or copulas (Fan and Patton, 2014). However, while extremograms only provide quantile dependence estimates, quantile regressions do not allow one to link (arbitrarily chosen) quantiles of the dependent variable with any (arbitrary selected) quantile of the explanatory variables. As for copulas, they can capture tail-dependence, but not partial dependence.

In this context, the cross-spectral quantile coherency is a much better fit given that it does not require the computation of moment conditions, it captures dependence structures in different market states and frequencies, and it is not sensitive to time-series transformations. In fact, this approach proposed by Barunik and Kley (2019) only relies on two strictly stationary time series and is able to reveal their dependencies across quantiles and frequencies. Moreover, it addresses the disadvantage of the time-frequency connectedness method by identifying the sign of the relationship between the variables of interest. Additionally, one can use it to estimate systemic risk.

Let $Y_t = (Y_{1t}, \ldots, Y_{it})'$ be strictly a stationary process, so $Y_{it,}\ i = 1, \ldots, d,$ denotes its components. These are stationary time series with marginal distributions that have quantiles $q_{it}(\tau_t)$ where $\tau\ \epsilon\ \alpha\ and\ 0 < \alpha < 1$, while τ_t is a specific conditional or unconditional quantile of y_{it}.

Following Stenvall *et al.* (2022), the quantilogram approach measures the serial dependence of two events $\{y_{1t} \leq q_1(\tau_1)\}$ and $\{y_{2t-k} \leq q_2(\tau_2)\}$ for any arbitrary pair of τ_t and a positive lag integer k. This is called the quantile hit process and can be written as $\{1[y_{it} \leq q_{it}(\cdot)]\}$.

The cross-correlation of quantile hits is analysed by the quantilogram approach

[4] Cross-quantilograms have been applied to measure dependence among commodity markets (Jiang *et al.*, 2016), and for analysing dependence between oil and precious metals (Shahzad *et al.*, 2018).

[5] Multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) models include the BEKK model by Baba *et al.* (1990) and Engle and Kroner (1995), the Dynamic Conditional Correlation (DCC) model by Engle (2002), and the varying correlation (VC) model by Tse and Tsui (2002).

$$\rho_\tau(k) = \frac{E\left[\psi_{\tau1}\left(y_{1t}-q_{1,t}(\tau_1)\right)\psi_{\tau2}\left(y_{2,t-k}-q_{2,t-k}(\tau_2)\right)\right]}{\sqrt{E\left[\psi_{\tau1}^2\left(y_{1t}-q_{1,t}(\tau_1)\right)\right]}\sqrt{E\left[\psi_{\tau2}^2\left(y_{2,t-k}-q_{2,t-k}(\tau_2)\right)\right]}}, \quad (1)$$

where $\psi_{\tau1}\left(y_{1t} - q_{1t}(\tau_1)\right)$ = $1[y_{it} \leq q_{it}(\tau_i)]$ - τ_i , and the quantile hit process is denoted by $\psi_\alpha = 1[u < 0] - \alpha$. The higher the correlation coefficient ψ_τ is, the higher the $\rho_\tau(k)$ will be.

Assume, y_1 is the financial stress index with the quantile $q_1(0.05)$ at time t and y_2 is the oil demand/supply/risk shock with $q_2(0.05)$ at $t-1$. If $\rho_\tau(1) \neq 0$, there is directional predictability from the shock to the financial stress index at the 0.05 quantile, implying tail-dependence. By contrast, if $\rho_\tau(1) = 0$, there is no predictability.

Given the sample quantile $\hat{q}_{it}(\tau_t)$, one computes the sample counterpart of the quantilogram that takes the following form:

$$\hat{\rho}_\tau(k) = \frac{\sum_{t=k+1}^{T}\psi_{\tau1}\left(y_{1t}-\hat{q}_{1,t}(\tau_1)\right)\psi_{\tau2}\left(y_{2,t-k}-\hat{q}_{2,t-k}(\tau_2)\right)}{\sqrt{\sum_{t=k+1}^{T}\psi_{\tau1}^2\left(y_{1t}-\hat{q}_{1,t}(\tau_1)\right)}\sqrt{\sum_{t=k+1}^{T}\psi_{\tau2}^2\left(y_{2t}-\hat{q}_{2,t}(\tau_2)\right)}} \quad (2)$$

If there is no cross-dependence or directional spillover, $\hat{\rho}_\tau(k)$ will be zero. However, if $\hat{\rho}_\tau(k) = 1$, then, there is most likely quantile dependence or directional spillovers. This is tested using the Box-Ljung significance test for autocorrelation so that:

$$H_0: \hat{\rho}_\tau(1) = \ldots = \hat{\rho}_\tau(k) = 0 \quad (3)$$

$$H_1: \hat{\rho}_\tau(k) \neq 0 \; for\ one\ or\ multiple\ k.$$

The Box-Ljung test takes the form:

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

If $\hat{\rho}_\tau(k) = 0$, we reject H_1 and there is most likely no dependence.

To account for the set of control variables represented by the vector $\bar{\mathbf{z}}_t = [\psi(y_{\tau3} - q_{3t}(\tau_3)), \ldots, \psi(y_{\tau n} - q_{nt}(\tau_3))]^{\intercal}$, we incorporate the partial cross-quantilogram. This measures the dependence between the two events $\{y_{1t} \leq q_1(\tau_1)\}$ and $\{y_{2t-k} \leq q_2(\tau_2)\}$, while controlling for events between t and $t-k$ and state variables that exceed a given quantile.

Consider a set of quantiles, such that $\bar{\tau} = (\tau_1, \ldots, \tau_n)^{\intercal}$, and let $\mathrm{h_t}(\bar{\tau})$ be a vector of quantile hit processes, so that $\mathrm{h_t}(\bar{\tau}) = \psi_{z1}(y_{1t} - q_{1t}(\tau_1)), \ldots, \psi_{zn}(y_{nt} - q_{nt}(\tau_1))]^{\intercal}$. The partial cross-quantilogram is defined below:

$$\rho_{\bar{\tau}|z} = -\frac{\rho_{\overline{\tau,12}}}{\sqrt{\rho_{\bar{\tau},11}\rho_{\bar{\tau},22}}} \quad (5)$$

$$\rho_{\bar{\tau}|z} = \delta\frac{\tau_1(1-\tau_1)}{\tau_2(1-\tau_2)} \quad (6)$$

where δ is a scalar parameter. Therefore, testing $\rho_{\bar{\tau}|z} = 0$ can be described as testing for predictability between two quantile hits with respect to the chosen control variables $\bar{z}$.

The sample performance of the Box-Ljung test statistics is based on stationary bootstrap procedures. The bootstrap procedure takes our data sample as a proxy for the population and, thereafter, it draws random samples from it. The range of samples provides information about the variability between them, so that confidence intervals can be constructed and hypothesis testing can be performed.

As for the quantile coherency kernel between a pair of time-series, y_{1t} and y_{2t} - i.e., our dynamic dependence measure - it can be specified as follows:

$$\Re^{j_1 j_2}(\omega : \tau_1, \tau_2) = \frac{q^{j_1 j_2}(\omega : \tau_1, \tau_2)}{q^{j_1 j_1}(\omega : \tau_1, \tau_2) q^{j_2 j_2}(\omega : \tau_1, \tau_2)} \tag{7}$$

where $q^{j_1 j_2}, q^{j_1 j_1}$ and $q^{j_2 j_2}$ are the quantile spectral and cross-spectral densities, $j \in \{1, \dots, d\}$ and $\tau = [0,1]$.

The spectral densities can be obtained using the Fourier transform of the matrix of quantile cross-spectral covariance kernels, which is defined as the following:

$$\Gamma_k(\tau_1, \tau_2) = (\gamma_k^{j_1 j_2}(\tau_1, \tau_2))_{j_1, j_2 = 1, \dots, d} \tag{8}$$

where *k* belongs to the set of integers, and the spectral covariance kernel $\gamma_k^{j_1 j_2}(\tau_1, \tau_2)$ is:

$$\gamma_k^{j_1 j_2}(\tau_1, \tau_2) = cov(I\{Y_{t+k, j_1} \leq f_{j_1}(\tau_1)\}, I\{Y_{t, j_2} \leq f_{j_2}(\tau_2)\} \tag{9}$$

where $\tau_{1,2} \in [0, 1]$, I{A} stands for the indicator function of the event A and $f_{j_i, i=1,2}$ are the marginal distribution functions of y_{1t} and y_{2t}.

Finally, under adequate mixing conditions in the frequency domain, the last two equations retrieve the quantile cross-spectral density kernel matrix (Barunik and Kley, 2019):

$$Q(\omega;\ \tau_1, \tau_2) = (q^{j_1 j_2}(\omega;\ \tau_1 \tau_2))_{j_1, j_2 = 1, \dots, d} \tag{10}$$

where $\omega \epsilon R$, $\tau_1, \tau_2 \in [0, 1]$ and $q^{j_1 j_2}(\omega;\ \tau_1 \tau_2) = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \gamma_k^{j_1 j_2}(\tau_1, \tau_2) e^{-ik\omega}$.

3. Data

Our sample includes 11 Middle East and North Africa (MENA) countries over the period from September 21, 2006 to August 19, 2021, namely: Bahrain (BH), Egypt (EG), Jordan (JO), Kuwait (KW), Morocco (MA), Oman (OM), Qatar (QA), Saudi Arabia (SA), Tunisia (TN), Turkey (TR), and United Arab Emirates (AE). These are chosen based on data availability and all variables are collected from Refinitiv Datastream.

Our paper analyses dependence structures of financial stress vis-à-vis three main sources of risk in the MENA region, i.e.: (i) oil demand shocks; (ii) oil supply shocks; and (iii) financial risk shocks.

Compared with individual indicators, aggregated Financial Stress Indices provide more accurate and informative measures of financial health and the soundness of a country's financial system due to the ability to capture different types of risk and sources of financial instability. Thus, using the approach of Apostolakis and Papadopoulos (2015), the Financial Stress Index of country *i* ($FSI_t^{Country_i}$) is calculated based on variance-equal weighting of three sub-indices: *(i)* the banking sector stress index (FSI_t^{Bank}); *(ii)* the stock market stress index (FSI_t^{Stock}); and *(iii)* the foreign exchange market stress index ($FSI_t^{ExchangeRate}$), where an equal weight is assigned to all variables used in the construction process:

$$FSI_t^{Country_i} = \frac{1}{3}\left(FSI_t^{Bank} + FSI_t^{Stock} + FSI_t^{ExchangeRate}\right), \quad (11)$$

where the banking sector stress index (FSI_t^{Bank}) comprises three variables (i.e., the beta of the banking sector calculated as a 60-day rolling window of standard beta of capital asset pricing model, negative bank equity returns, and banking sector unconditional volatility), the stock market stress index (FSI_t^{Stock}) includes two variables (i.e., negative stock returns computed as equity returns multiplied by minus one, and the unconditional volatility of the stock market), and the foreign exchange market stress index ($FSI_t^{ExchangeRate}$) is simply the unconditional volatility of the foreign exchange mark (Elsayed and Yarovaya, 2019).[6]

As for oil price shocks, they are estimated using the methodology of Ready (2018). In this setup, demand shocks are identified as returns to an index of oil producing firms that are orthogonal to unexpected changes in the VIX index, while oil supply shocks capture the remaining variation in oil prices. To construct the series of supply and demand shocks, one needs: *(i)* an index of oil producing firms; *(ii)* a measure of oil price changes; and *(iii)* a proxy for changes in expected returns. Thus, the World Integrated Oil and Gas Producer Index is an index of oil producing firms that covers as much of the global oil industry as possible, including large publicly traded oil producing firms with the exception of nationalized oil producers. Unexpected changes in the oil price are captured by the 1-month returns on the second nearest maturity NYMEX Crude - Light Sweet Oil futures contract. Finally, the CBOE volatility index (VIX) is used as a proxy for changes in the discount rate (i.e., changes in expected returns). This index is calculated from options data, providing a measure of the risk-neutral expectation of volatility. As shown in Bollerslev *et al.* (200), the variance risk premium captured in the

[6] The equal-variance aggregation approach is widely used in the literature, as it avoids the problem of different measurement units, and it is a very efficient method in constructing financial indices due to the simplicity of calculations and its accuracy in representing and signalling financial stress and episodes of turbulence (Cardarelli et al., 2011; Kliesen *et al.*, 2012; MacDonald *et al.*, 2018).

VIX index is both strongly negatively correlated with stock returns and positively predict stock returns in the time series, suggesting that it may be a reasonable proxy for changes in risk.

Table 1 provides descriptive statistics of country-level financial stress indices, as well as oil demand (*DS*), oil supply (*SS*), and risk (*RS*) shocks. In particular, the Table shows the first four statistical moments of the underlying series (i.e., mean, standard deviation, skewness and excess kurtosis) along with normality (*JB*), stationarity (ERS), and autocorrelation and heteroscedasticity tests (*Q(10)* and *Q2(20)*).

As can be seen, the means of all variables under consideration are very close to zero in all cases and rather small compared to their respective standard deviations. All series are positively skewed, i.e. their distributions have a tail extended to the right. The excess kurtosis statistic is also greater than one (i.e., the kurtosis statistic is greater than three) for all series, suggesting that distributions are leptokurtic (i.e., higher peaked around the mean with fatter tails compared to the normal distribution). The departure of the normality assumption is confirmed by the Jarque–Bera (*JB*) test, which rejects the null hypotheses of normality for all series. The Augmented Dickey-Fuller-Generalized least squares (ADF-GLS) unit root tests by Elliott *et al.* (1996) (*ERS*) confirm stationarity for all series. In addition, the Ljung–Box test statistics (*Q*, *Q2*) up to the 10th order and provides evidence of serial correlation and non-linear dependencies for all series.

[Insert Table 1 here.]

4. Empirical results

4.1 Overall quantile coherency between shocks and financial stress

In Figures 1-3, we start by displaying the results from the overall quantile coherency between financial stress and oil demand shocks, oil supply shocks and (financial) risk shocks, respectively. The overall coherency is calculated by taking the mean of the quantile coherency in each frequency for all possible pair of variables under consideration.

In each Figure, the *y*-axis shows the overall dependence, while the *x*-axis displays the frequencies. Moreover, we can observe how the overall dependence changes according to the observed frequency. Thus, we follow Barunik and Kley (2019) and let vertical lines named by the letters W, M, and Y represent the weekly, monthly, and yearly cycles, respectively. In addition, while (0.05|0.05) denotes the mean coherency when each asset pair is in their lower quantile (0.05), (0.5|0.5) shows the coherency for the median quantiles, and (0.95|0.95) displays the coherency in the high quantile (0.95). The corresponding confidence intervals are also represented by the shaded areas. From an economic perspective, lower quantiles can be interpreted as periods of extremely low financial stress or shocks, while the high quantile represents periods of extremely high financial stress or shocks.

We start by analysing the results for oil demand shocks (Figure 1). It can be seen that the strength of the dependence varies over the different frequencies. In particular, the strength of the dependence with financial stress seems to be more acute at relatively shorter horizons.

Additionally, we observe that the solid red line, which shows the dependence for the median quantiles of the financial stress index, is typically below the dashed (0.05|0.05) or the dotted (0.95|0.95) lines. Therefore, the dependence between financial stress and oil demand shocks is stronger during extreme market circumstances than normal conditions. Overall, the strength of dependence ranges, approximately, between -0.2 and 0.2 for all displayed quantile pairs across the frequencies (which is shown by the *y*-axis of the Figure).

[Insert Figure 1 here.]

Figure 2 summarises the findings for oil supply shocks. The empirical evidence is very similar to that for oil demand shocks. Therefore, there is both positive and negative dependence between financial stress and oil supply shocks. In fact, the strength of the dependence typically varies between -0.2 and 0.2.

As before, we find a somewhat higher dependence in the yearly frequency compared to the monthly or weekly frequencies, although the differences are small. In the same vein, the strength of the dependence between financial stress and oil supply shocks seems to be stronger during extreme market circumstances (i.e., at the tails of the distribution) than normal conditions (i.e., around the median of the distribution). Despite this, there are instances in which the lines that show different quantiles combinations (i.e., the solid red (0.50|0.50) and the dashed (0.05|0.05) or the dotted (0.95|0.95) lines) cross each other.

[Insert Figure 2 here.]

Finally, Figure 3 plots the quantile coherency for (financial) risk shocks. Overall, the strength of the dependence is positive, varying between 0 and 0.2, even though it can also be (modestly) negative. We also show that while the strength of the linkage with the financial stress index seems stronger at longer horizons, there are instances in which such relationship is more acute at shorter horizons. In this context, the existing literature has also documented a strong co-movement and contagion among financial markets during extreme market events (Bekaert *et al.*, 2005; Phylaktis and Xia, 2009; Dungey and Gajurel, 2014; Labidi *et al.*, 2018). In addition, although the dependence structures between financial stress and (financial) risk shocks can be strong during extreme market circumstances, there are also cases in which such relationship is important regardless of the quantiles of the distribution of the financial stress index. This comes as the outcome of several intersections between the different quantile lines.

4.2 Spectral quantile cross-correlations from shocks to financial stress

To ease interpretation, the cross-quantilogram output is presented as heatmaps. The *X*- and the *Y*-axis represent eleven different quantiles, i.e. $q = (0.05, 0.1, 0.2, \ldots, 0.95)$. In total, the heatmaps consist of 121 squares representing different quantile combinations of the variables of interest. These are presented based on a *colour* scale, indicating correlations between -1 (dark blue) to 1 (dark red). No correlation (green) is set for zero, which indicates that there is no predictability of quantile dependence.

The results for the spectral quantile cross-correlations from different shocks to financial stress at the lag length of one (i.e., daily), five (i.e., weekly), 22 (i.e., monthly) and 66 (i.e., quarterly) are plotted in Figures 4-14. Each Figure summarises the evidence for a specific country, with the vertical axis displays the quantiles of financial stress and the horizontal axis reports the quantiles of oil demand, oil supply and financial risk shocks. The lower (e.g., 0.05) and the upper (e.g., 0.95) quantiles are often denoted as the "tails" of the distributions, as they represent "abnormal" market conditions. By contrast, normal market conditions are captured by the median (i.e., quantile 0.5).

The empirical evidence suggests the existence of very similar patterns across the different countries, with a few exceptions. Thus, for Bahrain, Jordan, Oman, Qatar and Saudi Arabia, there is a strong and positive correlation between financial stress and oil demand shocks at the 0.95 quantiles. In this context, when oil demand shocks are abnormally large and positive, financial stress appears to be extremely high, implying tail-dependence between the two. By contrast, this correlation shifts sign at the left tail of the distribution of the financial stress index. In particular, abnormally large and positive oil demand shocks are also associated with extremely low financial stress.

While this pattern is observed across different frequencies, the empirical evidence also shows that, over longer horizons (in our case, the quarterly time-frame), the correlation between oil demand shocks and financial stress tends to be positive (negative) when financial stress is abnormally large (low) regardless of the quantile of the distribution of oil demand shocks. Put it differently, at short horizons, spikes in oil demand shocks are linked with extreme financial stress, while, at long horizons, such extreme variation in financial stress tends to be observed even when the amplitude of changes in oil demand is not so large.

Concerning oil supply shocks, the empirical findings resemble those associated with oil demand shocks, with little qualitative and quantitative differences vis-à-vis the characterization of the structure dependence detected for oil demand shocks. However:

- in Kuwait, the dependence pattern is similar regardless of the horizon considered;
- for Morocco, Turkey and the UAE, extremely high (low) financial stress is positively (negatively) associated with oil demand or oil supply shocks regardless of the quantiles of the distribution of these shocks;
- while for Tunisia, the previous pattern holds true at long (i.e., monthly and quarterly) horizons only; and
- for Egypt, the evidence does not support the existence of a clear-cut (tail) dependence between the quantiles of the distribution of financial stress and both shocks at longer horizons.

The fact that both oil demand and oil supply shocks show similar dependence structures with financial stress suggests that, in times of extreme booming and bearish oil demand and oil supply, financial stress intensifies, even though the time horizon at which this materialises might differ across country.

All in all, in those countries, investors in the oil market might not find a good diversifier for such exposure in the financial market in light of the potential for financial stress at the tails of the distribution of the shocks. By contrast, in the case of countries where oil demand and oil supply shocks are more moderate, investments in the financial sector could be a good hedge against those shocks given the low correlation between such shocks and the financial stress index during normal condition, i.e. at their middle quantiles.

Finally, in what regards risk shocks, the evidence is more muted albeit there is some segmentation across countries. Specifically, on the one hand, for Bahrain, Morocco and Tunisia, while there is often a positive (negative) relationship between financial stress and risk shocks when financial stress is abnormally high (low), such link is more evenly distributed across the quantiles of the distribution of both variables. Therefore, the dependence pattern is not so clear. On the other hand, in the case of Egypt, Jordan, Kuwait, Saudi Arabia, and Turkey, the results point to a positive and large correlation between financial stress and risk shocks when both are high, and a negative and large link between the two variables when financial stress is abnormally low. However, this pattern of dependence is only observed at very short horizons, with the exception of the UAE, where these dynamics are observed regardless of the horizon under consideration.

Summing up, for some countries, there is no significant dependence structure between financial stress and (financial) risk shocks while, for others, financial stress naturally emerges when the country is subject to extreme (financial) risk shocks.

[Insert Figures 4-14 here.]

5. Conclusion

In this paper, we use daily data for 11 MENA countries over the period September 21, 2006 – August 19, 2021, to examine the link between financial stress and three sources of commodity fluctuations, namely: *(i)* oil demand shocks; *(ii)* oil supply shocks; and *(iii)* (financial) risk shocks.

Compared to the existing literature that either focused on the contagion among MENA's equity market and the spillovers between these and those of advanced economies or the interdependence across difference asset classes, our approach is much more granular in identifying the relationship between the dynamics of the oil sector and financial stability. Thus, we rely on the novel cross-spectral quantile coherency method of Barunik and Kley (2019), which allows us to capture the time-varying dynamics of between financial stress and each of the three shocks at several frequencies representing the time-domain and potential interdependences in a wide range of quantiles.

We find that financial stress is particularly acute during extreme oil demand and oil supply shocks, especially at longer horizons. By contrast, (financial) risk shocks appear to be more prominent in generating financial stress at relatively shorter horizons and regardless of the quantiles of the distribution.

Our results have important implications for both policymakers and portfolio managers in the region. Indeed, given the nature of the interdependence between different quantiles of the financial stress distribution and oil shocks at different frequency bands, we conclude that such interdependence varies according to the position of the economy in the business cycle, market condition and investors' horizons. Thus, the design of macro-prudential policies targeting the oil sector should take financial stability into account. Similarly, financial markets might not be a good diversifier against oil price shocks during extreme conditions.

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List of Tables

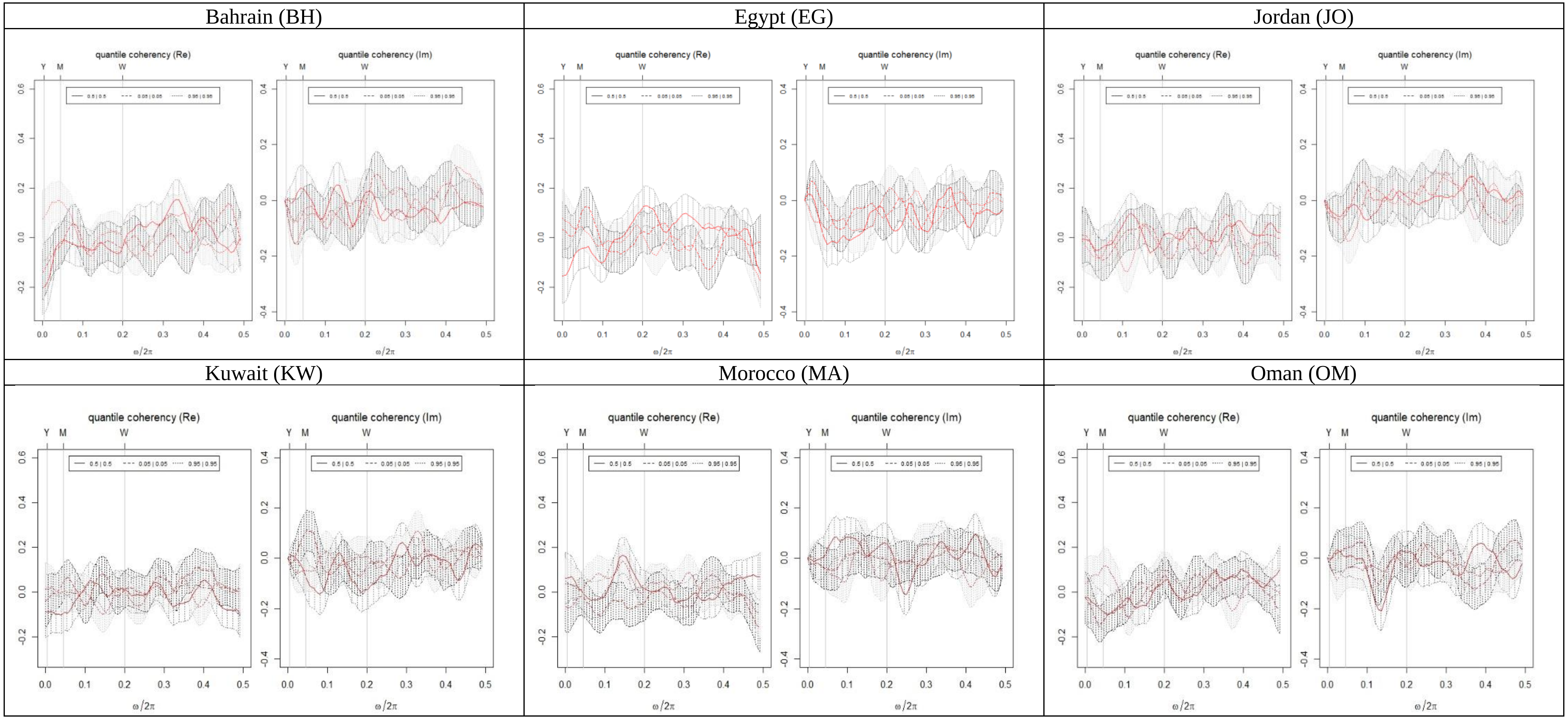
Table 1: Descriptive statistics.

	BH	EG	JO	KW	MA	OM	QA	SA	TN	TR	AE	DS	SS	RS
Mean	0.002	0.001	-0.005	0.004	0.001	0.002	0.01	-0.005	0.002	0	0.001	-0.02	0.009	0.011
Variance	0.231	0.282	0.238	0.242	0.34	0.293	0.183	0.284	0.224	0.32	0.284	1.586	4.038	56.813
Skewness	2.231***	1.939***	1.461***	2.672***	2.408***	2.509***	1.859***	2.770***	1.424***	1.755***	2.540***	0.092**	0.430***	1.273***
Ex. Kurtosis	23.148***	9.340***	4.402***	13.346***	14.366***	11.495***	15.760***	16.786***	41.785***	5.792***	11.209***	17.882***	12.430***	7.127***
JB	90101.425***	16582.380***	4525.654***	33504.362***	37219.959***	25503.617***	42510.531***	50659.232***	284384.528***	7435.315***	24554.902***	51848.811***	25169.674***	9286.505***
ERS	-9.170***	-10.406***	-6.356***	-5.845***	-7.967***	-10.249***	-11.083***	-8.244***	-12.751***	-8.782***	-11.077***	-17.308***	-18.173***	-22.346***
Q(10)	5832.816***	6402.423***	4611.659***	7709.984***	8504.454***	7066.751***	3660.028***	7855.651***	5402.717***	8082.213***	6626.711***	50.466***	72.797***	14.468***
Q2(10)	2551.201***	3971.828***	2948.425***	5070.602***	4739.027***	3554.139***	2117.932***	5454.392***	2903.248***	7005.791***	4337.570***	1332.027***	2048.895***	171.638***

Notes*:* This Table shows descriptive statistics of the variables under consideration. Country-level financial stress indices: Bahrain (BH), Egypt (EG), Jordan (JO), Kuwait (KW), Morocco (MA), Oman (OM), Qatar (QA), Saudi Arabia (SA), Tunisia (TN), Turkey (TR), and United Arab Emirates (AE). Oil price shocks are denoted by DS (oil demand shocks), SS (oil supply shocks) and RS (financial risk shocks). *JB* is the Jarque-Bera test for Normality. *ERS* is the Augmented Dickey-Fuller-Generalized least squares (ADF-GLS) unit root test by Elliott *et al.* (1996), which tests the stationarity properties of the series under consideration, with the appropriate lag orders chosen in accordance with the (minimum value of the) Bayesian Information Criterion (BIC). *Q(20)* and *Q2(20)* is the Ljung-Box statistic for serial correlation in raw series and squared residuals, respectively.

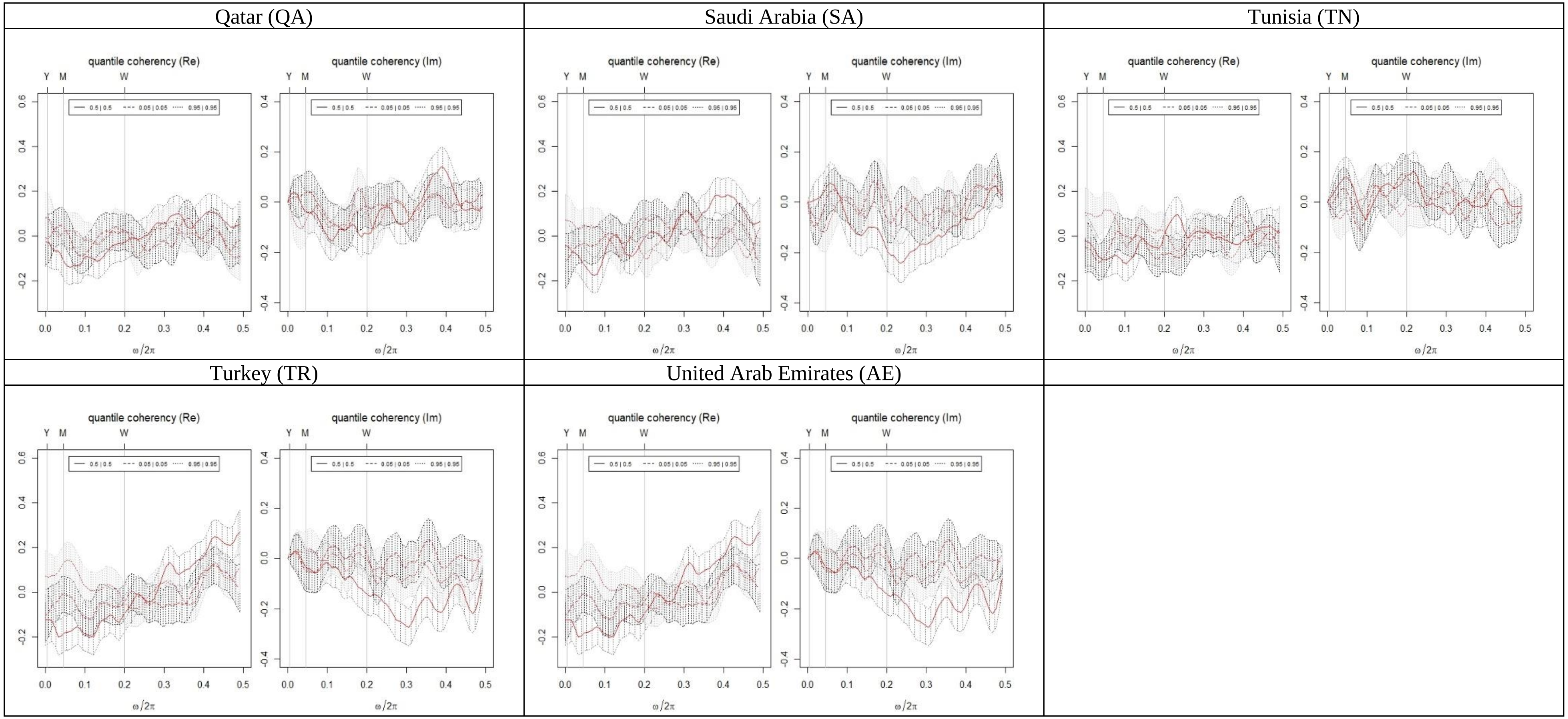
List of Figures

Figure 1: Quantile coherency between financial stress and oil demand shocks.



Notes*:* The *y*-axis shows the overall dependence, while the *x*-axis displays the frequencies. Following Barunik and Kley (2019), the vertical lines named by the letters *W*, *M*, and *Y* represent the weekly, monthly, and yearly cycles, respectively. In addition, while (0.05|0.05) denotes the mean coherency when each asset pair is in their lower quantile (0.05), (0.5|0.5) shows the coherency for the median quantiles, and (0.95|0.95) displays the coherency in the high quantile (0.95). The corresponding confidence intervals are also represented by the shaded areas.

Figure 1: Quantile coherency between financial stress and oil demand shocks (cont.).



Notes*:* The *y*-axis shows the overall dependence, while the *x*-axis displays the frequencies. Following Barunik and Kley (2019), the vertical lines named by the letters *W*, *M*, and *Y* represent the weekly, monthly, and yearly cycles, respectively. In addition, while (0.05|0.05) denotes the mean coherency when each asset pair is in their lower quantile (0.05), (0.5|0.5) shows the coherency for the median quantiles, and (0.95|0.95) displays the coherency in the high quantile (0.95). The corresponding confidence intervals are also represented by the shaded areas.

Figure 2: Quantile coherency between financial stress and oil demand shocks.

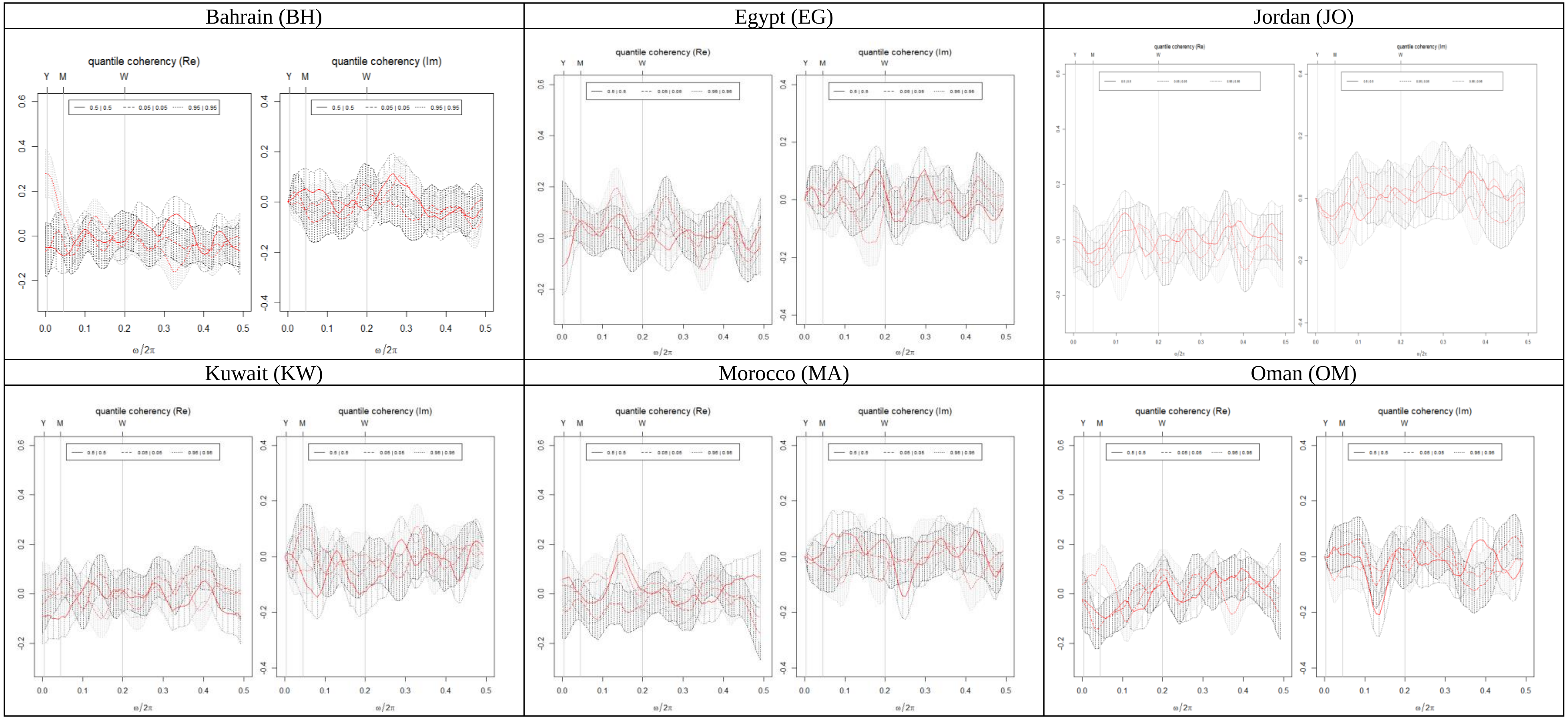


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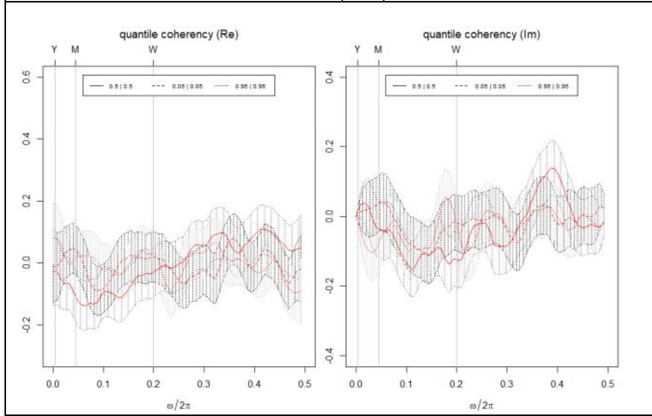
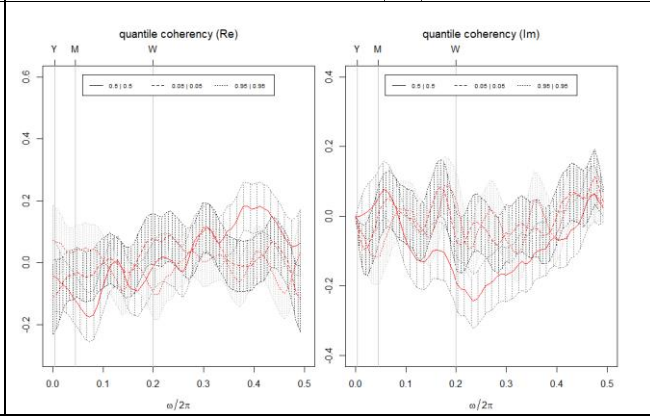
Figure 2: Quantile coherency between financial stress and oil demand shocks (cont.).

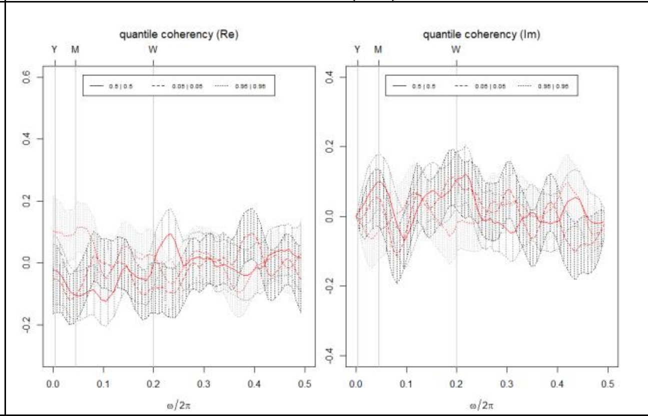
Qatar (QA)



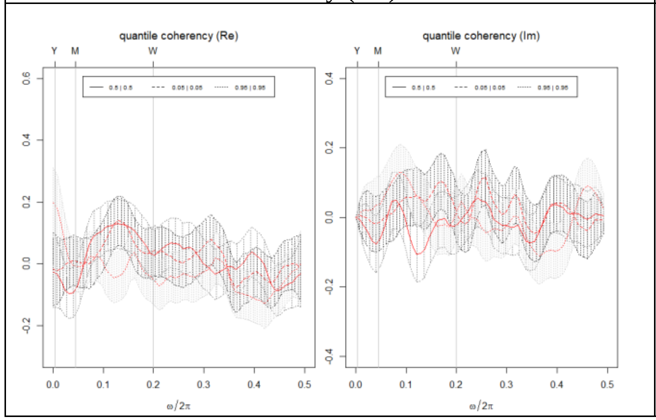
Saudi Arabia (SA)



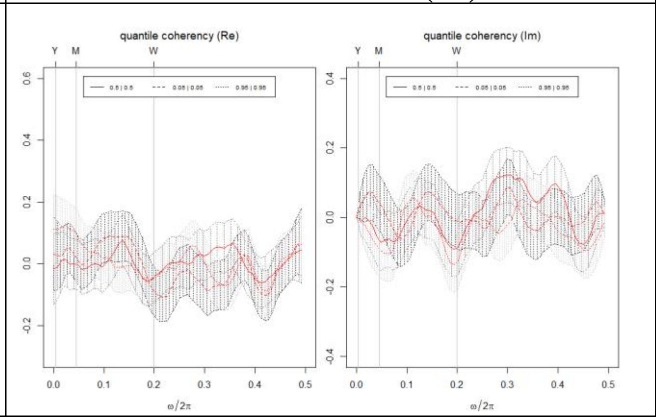
Tunisia (TN)



Turkey (TR)

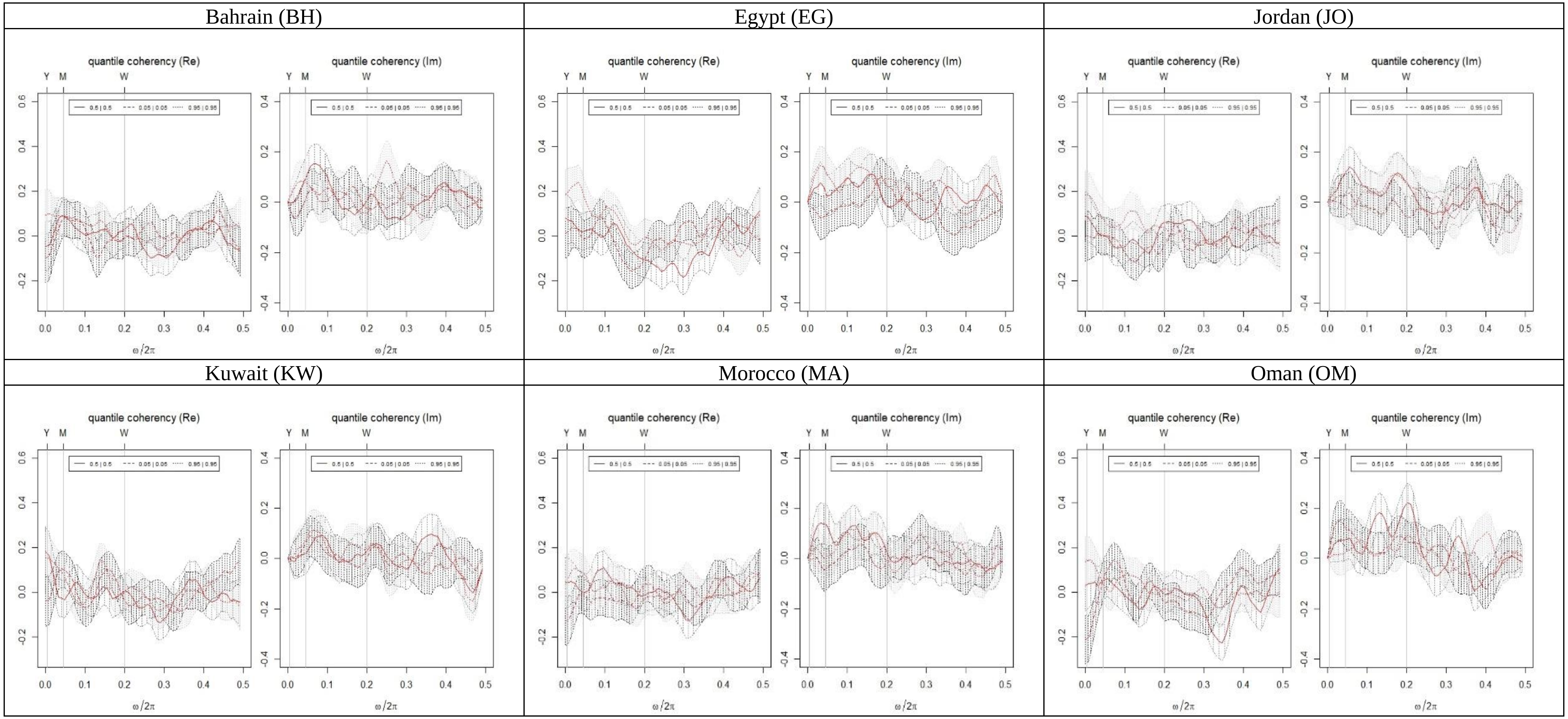


United Arab Emirates (AE)



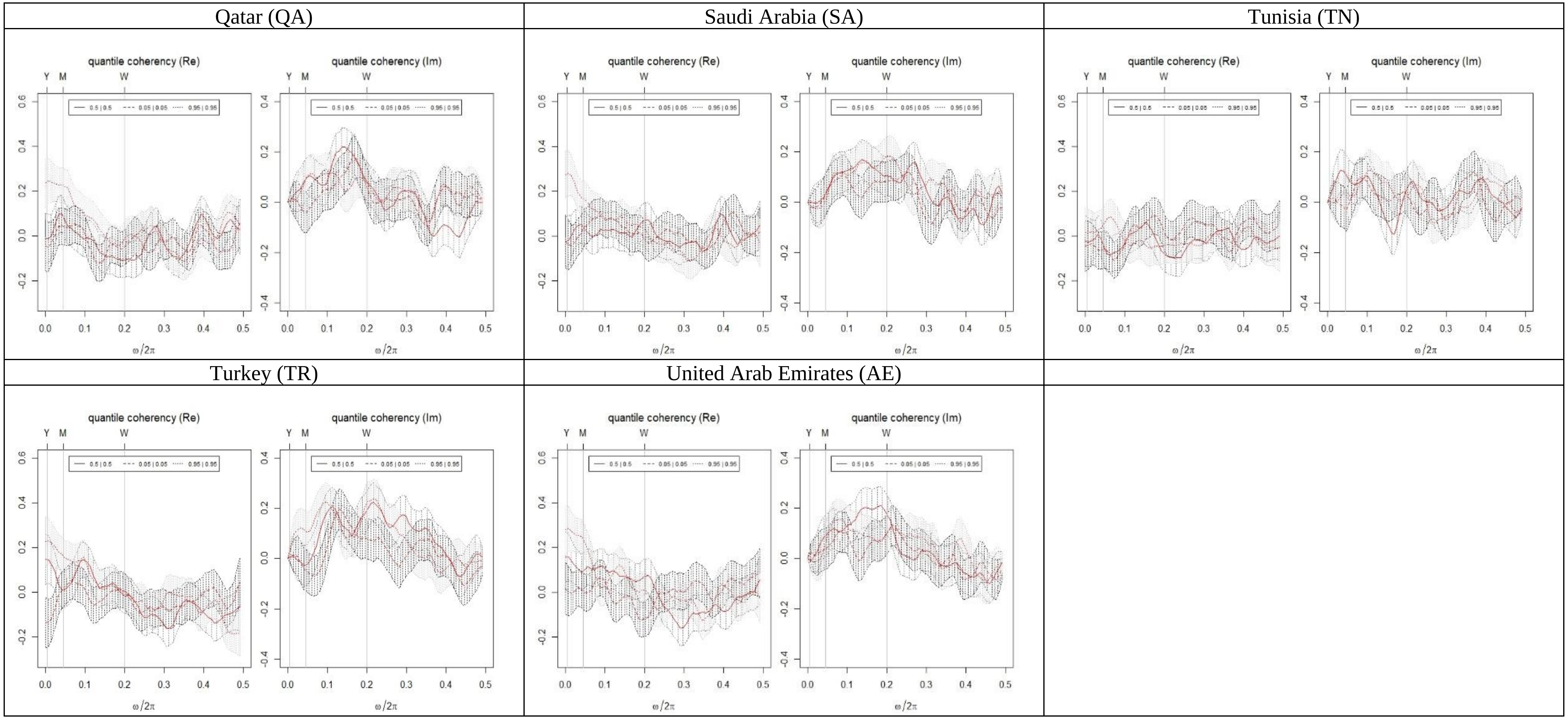
Notes*:* The *y*-axis shows the overall dependence, while the *x*-axis displays the frequencies. Following Barunik and Kley (2019), the vertical lines named by the letters *W*, *M*, and *Y* represent the weekly, monthly, and yearly cycles, respectively. In addition, while (0.05|0.05) denotes the mean coherency when each asset pair is in their lower quantile (0.05), (0.5|0.5) shows the coherency for the median quantiles, and (0.95|0.95) displays the coherency in the high quantile (0.95). The corresponding confidence intervals are also represented by the shaded areas.

Figure 3: Quantile coherency between financial stress and risk shocks.



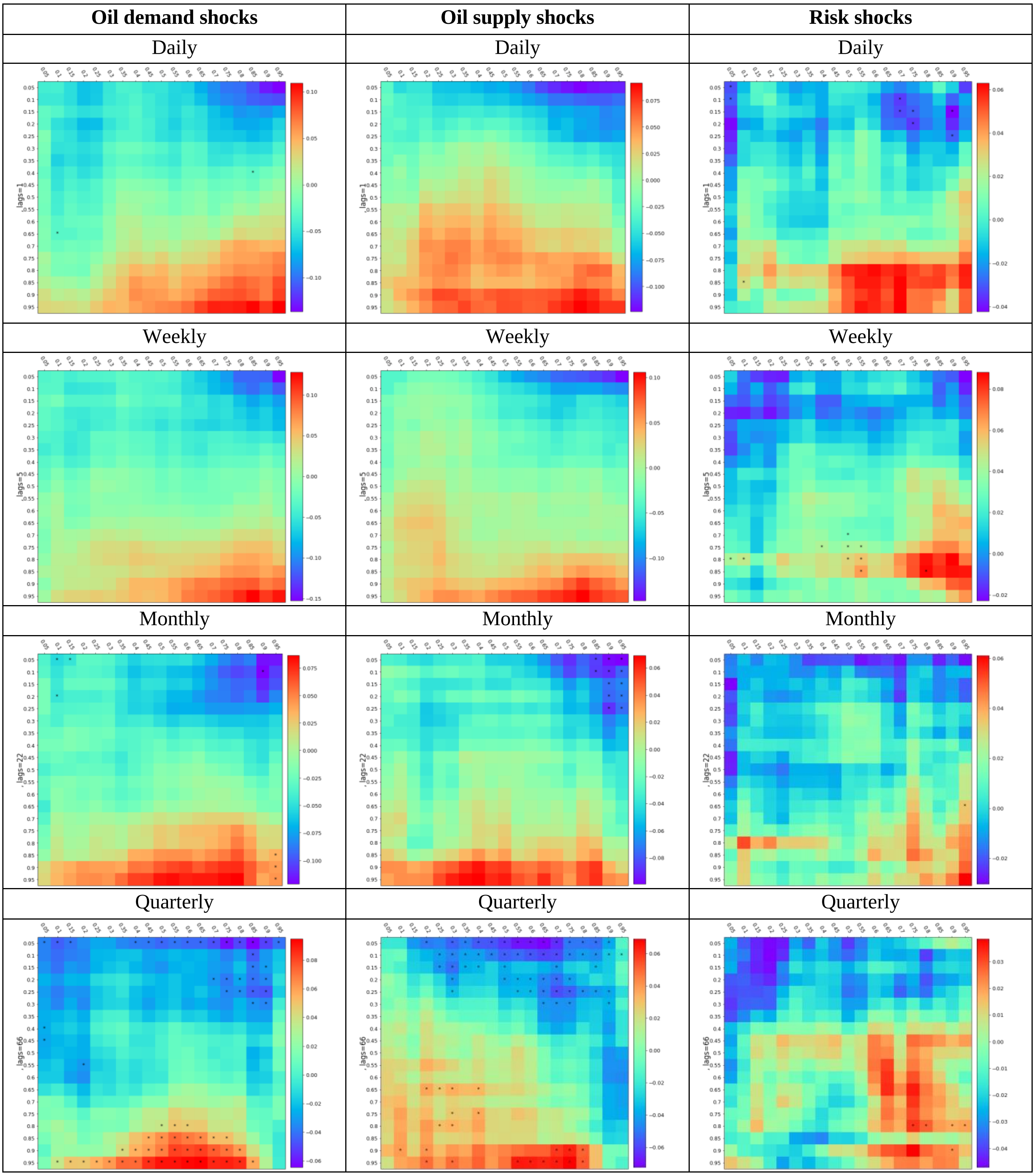
Notes: The *y*-axis shows the overall dependence, while the *x*-axis displays the frequencies. Following Barunik and Kley (2019), the vertical lines named by the letters *W*, *M*, and *Y* represent the weekly, monthly, and yearly cycles, respectively. In addition, while (0.05|0.05) denotes the mean coherency when each asset pair is in their lower quantile (0.05), (0.5|0.5) shows the coherency for the median quantiles, and (0.95|0.95) displays the coherency in the high quantile (0.95). The corresponding confidence intervals are also represented by the shaded areas.

Figure 3: Quantile coherency between financial stress and risk shocks (cont.).



Notes*:* The *y*-axis shows the overall dependence, while the *x*-axis displays the frequencies. Following Barunik and Kley (2019), the vertical lines named by the letters *W*, *M*, and *Y* represent the weekly, monthly, and yearly cycles, respectively. In addition, while (0.05|0.05) denotes the mean coherency when each asset pair is in their lower quantile (0.05), (0.5|0.5) shows the coherency for the median quantiles, and (0.95|0.95) displays the coherency in the high quantile (0.95). The corresponding confidence intervals are also represented by the shaded areas.

Figure 4: Spectral quantile cross-correlations from shocks to financial stress in Bahrain (BH).



Notes*:* Quantile cross-correlations in heatmaps. No predictable directionality is set to zero. The *coloure*d squares are regions where the Box-Ljung test statistic is statistically significant at the 5% level. The horizontal axis represents the quantiles for the financial stress index, while the vertical axis corresponds to the quantiles of oil demand, oil supply and risk shocks.

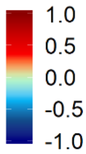
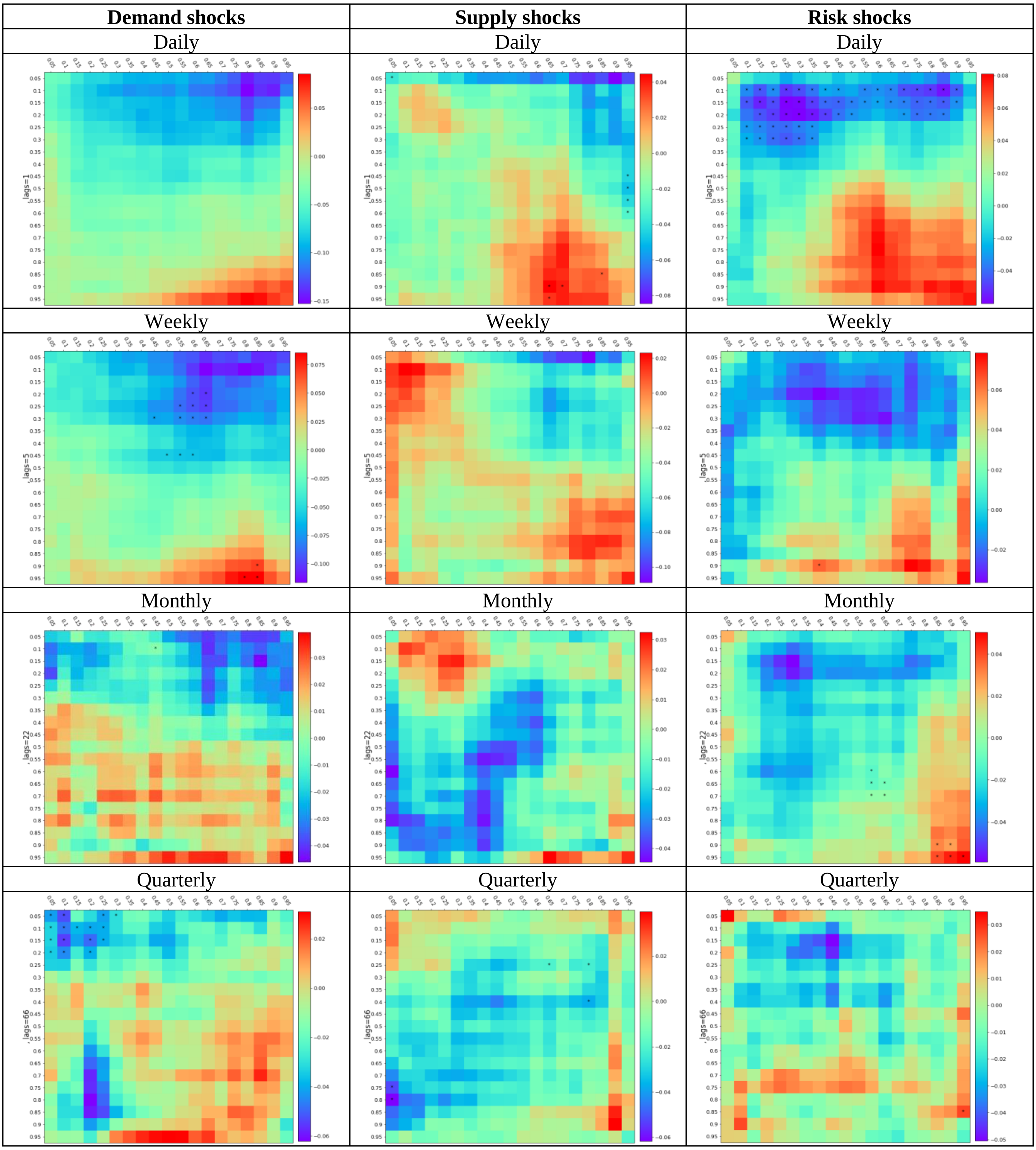


Figure 5: Spectral quantile cross-correlations from shocks to financial stress in Egypt (EG).



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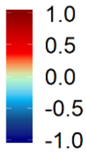
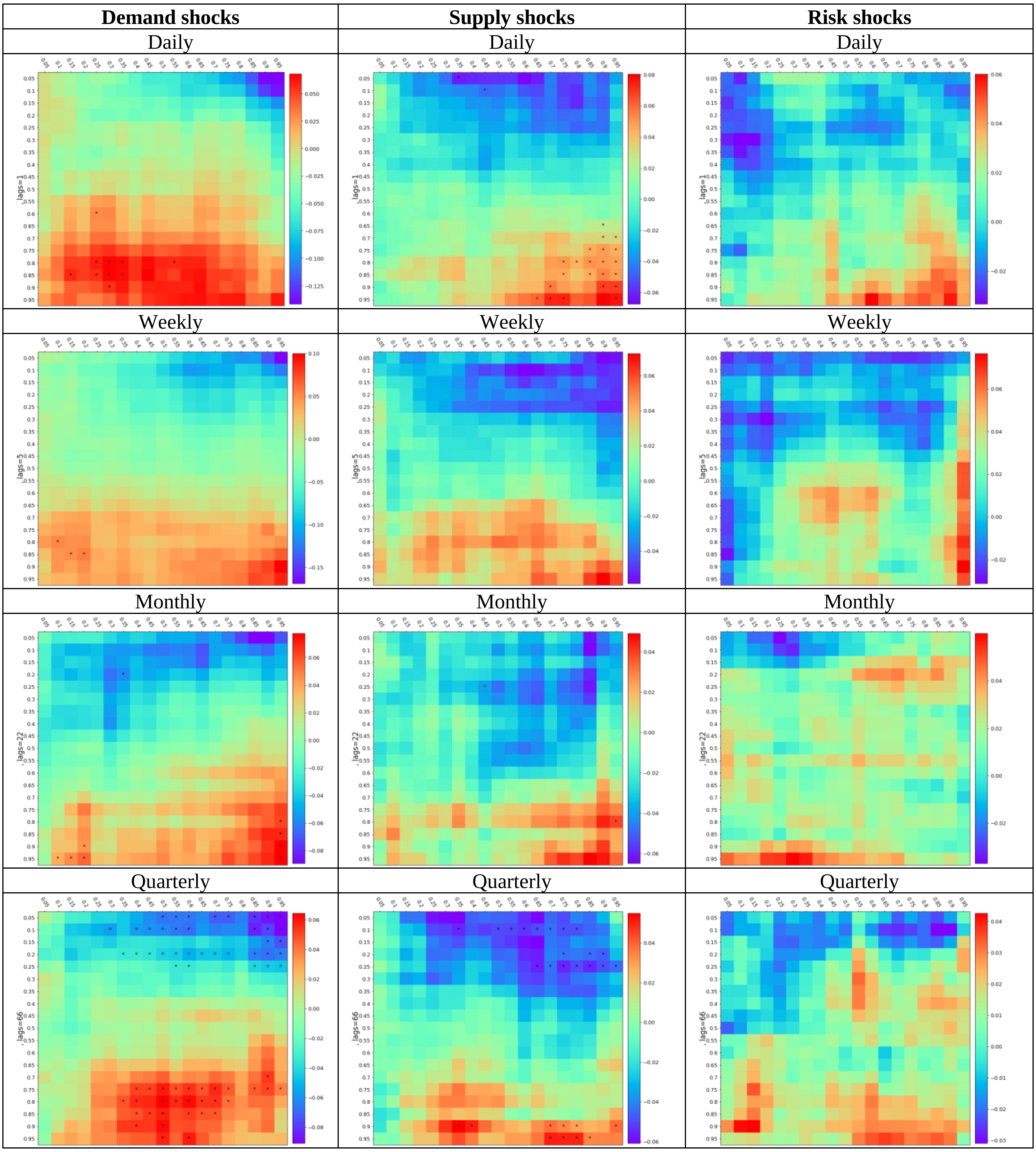


Figure 6: Spectral quantile cross-correlations from shocks to financial stress in Jordan (JO).



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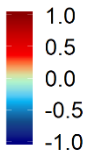
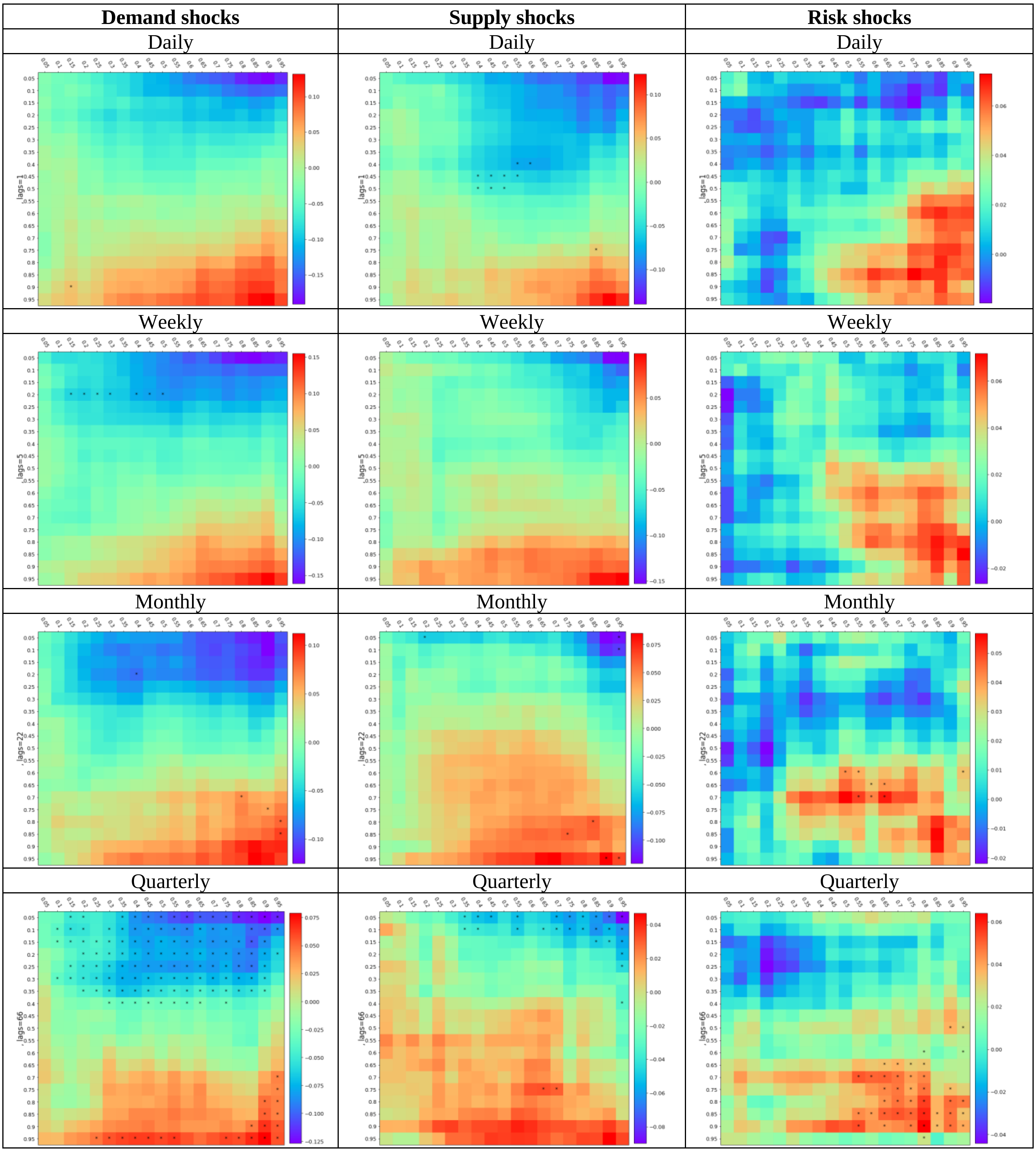


Figure 7: Spectral quantile cross-correlations from shocks to financial stress in Kuwait (KW).



Notes*:* Quantile cross-correlations in heatmaps. No predictable directionality is set to zero. The *colour*ed squares are regions where the Box-Ljung test statistic is statistically significant at the 5% level. The horizontal axis represents the quantiles for the financial stress index, while the vertical axis corresponds to the quantiles of oil demand, oil supply and risk shocks.

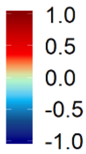
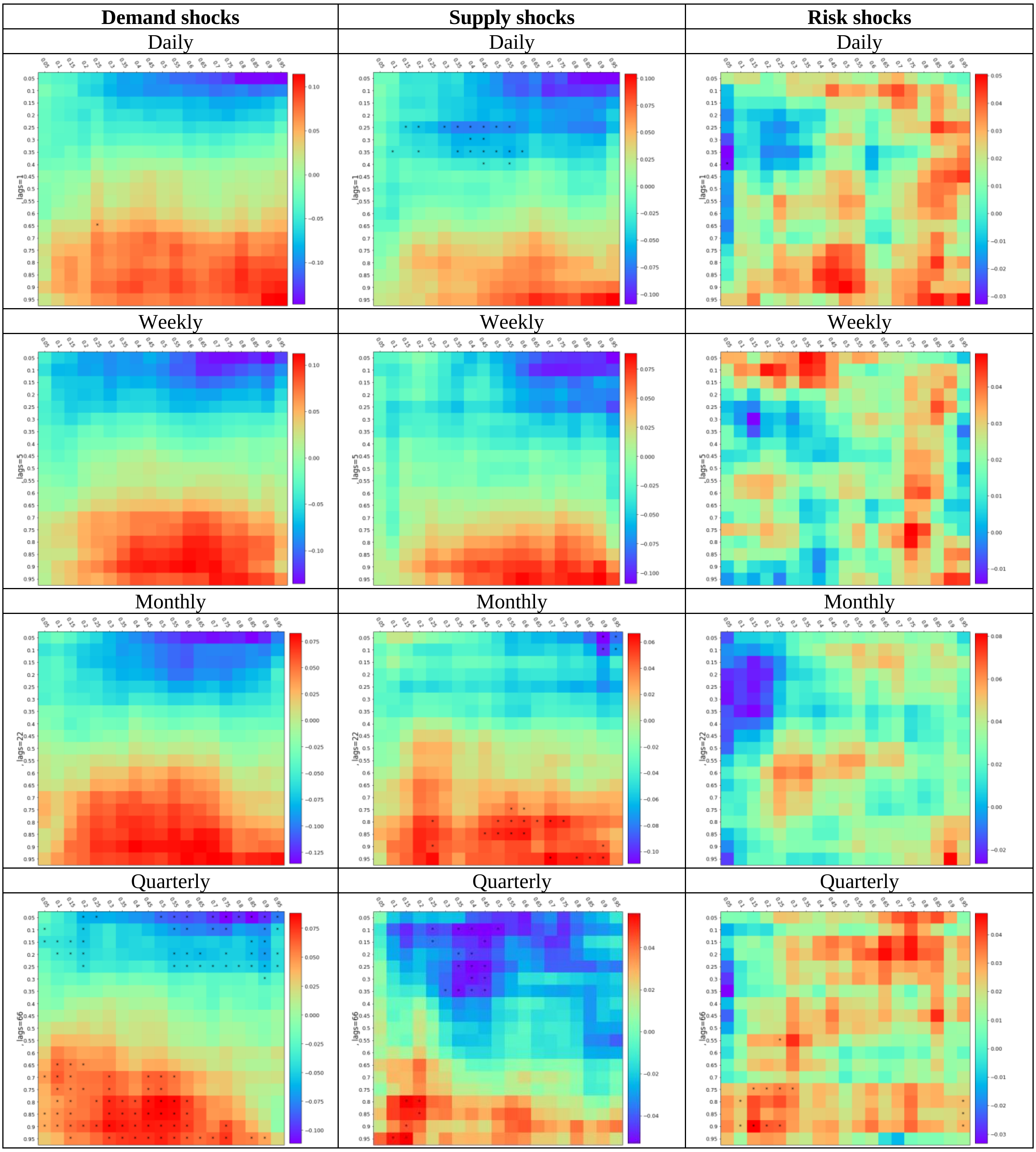


Figure 8: Spectral quantile cross-correlations from shocks to financial stress in Morocco (MA).



Notes*:* Quantile cross-correlations in heatmaps. No predictable directionality is set to zero. The *colour*ed squares are regions where the Box-Ljung test statistic is statistically significant at the 5% level. The horizontal axis represents the quantiles for the financial stress index, while the vertical axis corresponds to the quantiles of oil demand, oil supply and risk shocks.

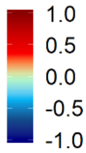
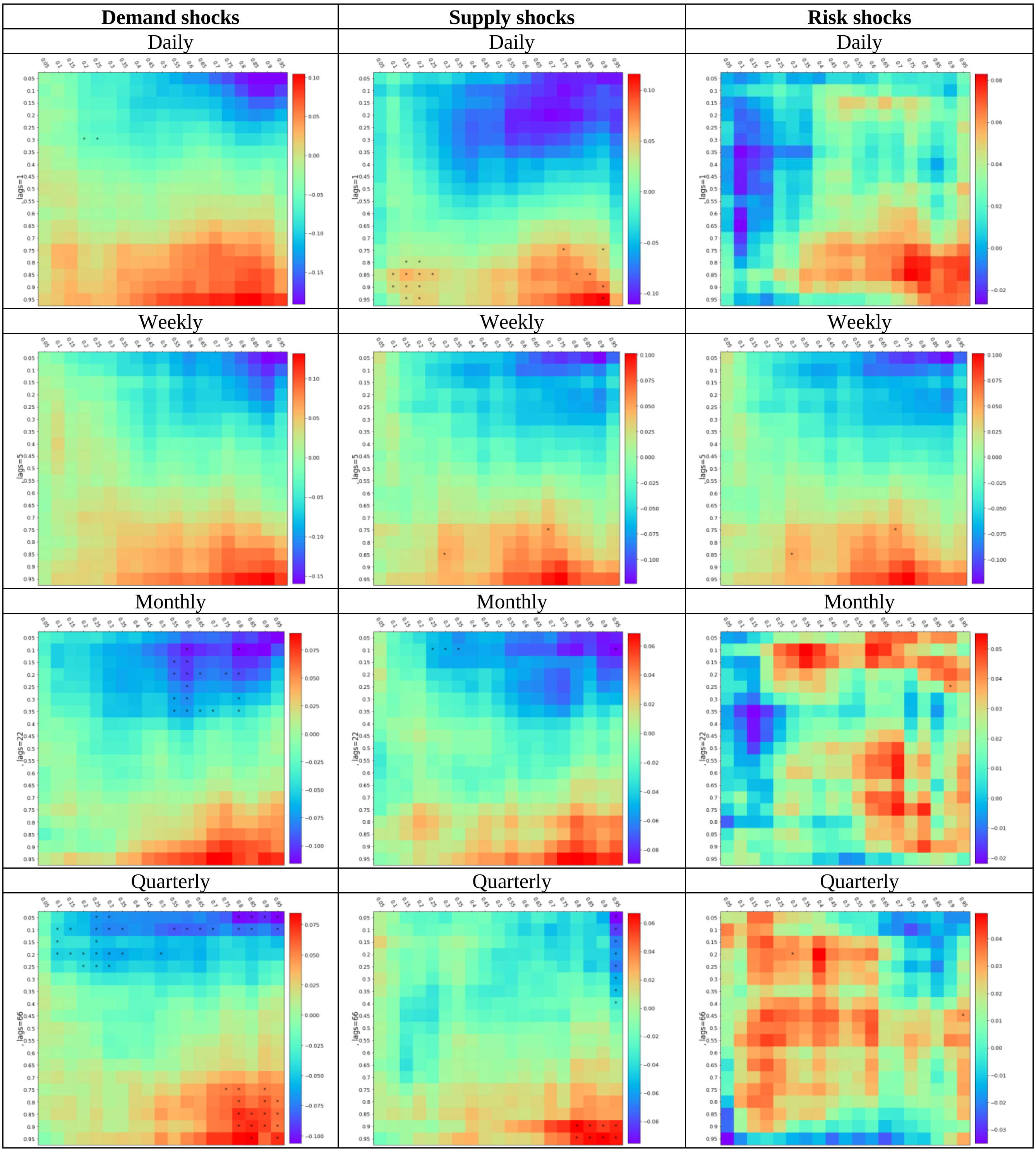


Figure 9: Spectral quantile cross-correlations from shocks to financial stress in Oman (OM).



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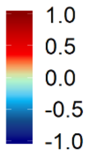
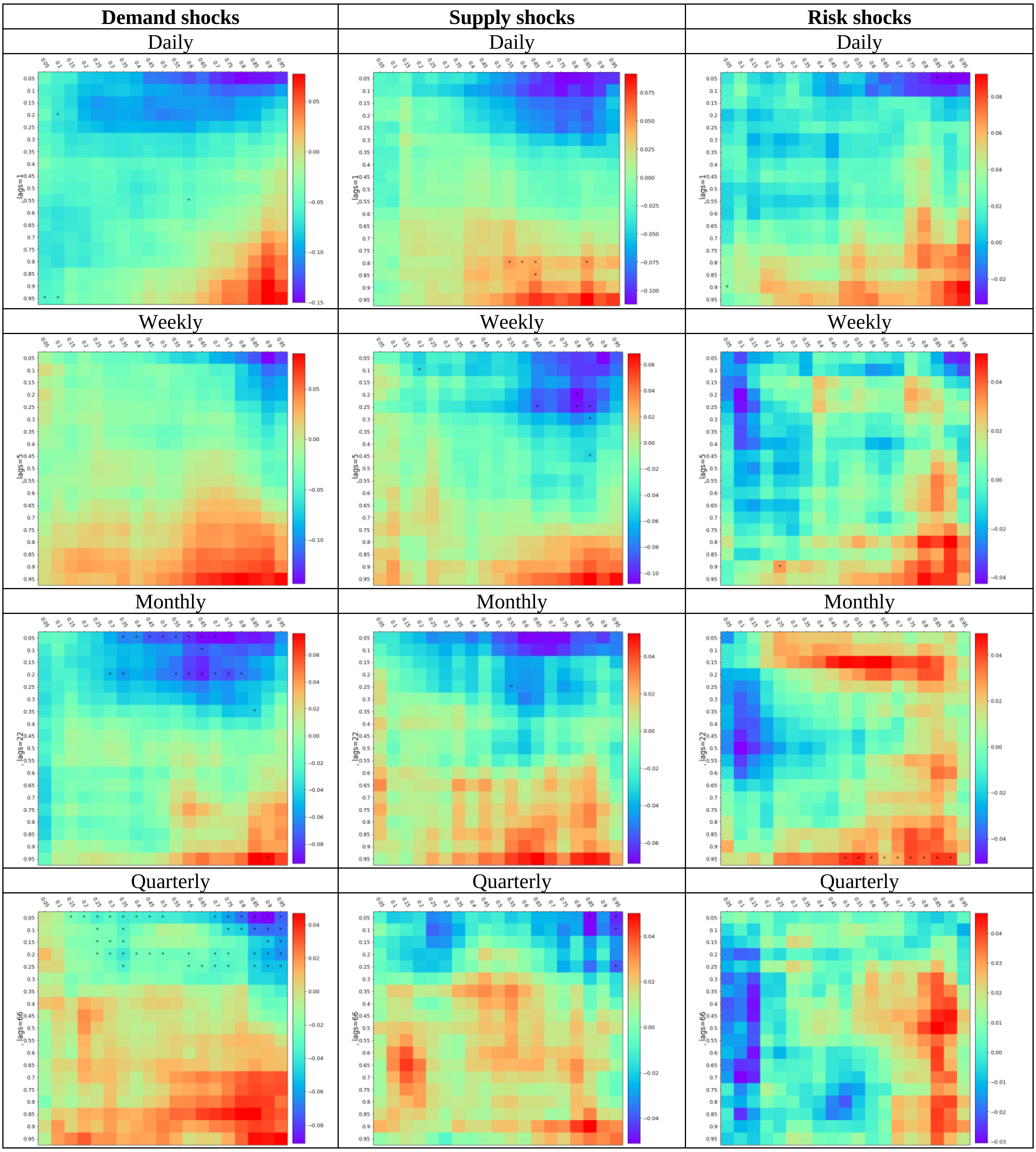


Figure 10: Spectral quantile cross-correlations from shocks to financial stress in Qatar (QA).



Notes*:* Quantile cross-correlations in heatmaps. No predictable directionality is set to zero. The *colour*ed squares are regions where the Box-Ljung test statistic is statistically significant at the 5% level. The horizontal axis represents the quantiles for the financial stress index, while the vertical axis corresponds to the quantiles of oil demand, oil supply and risk shocks.

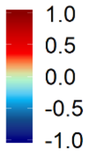
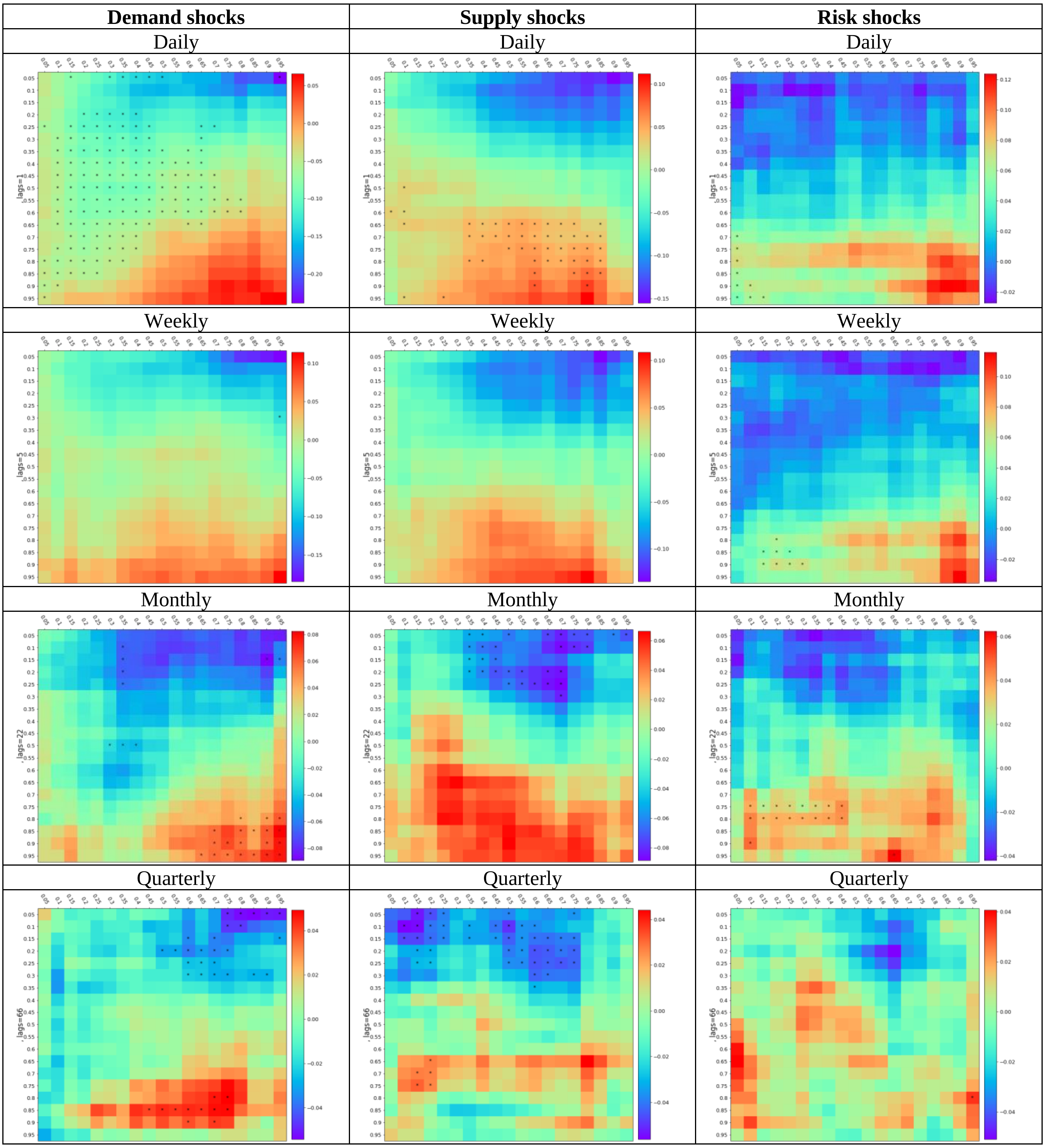


Figure 11: Spectral quantile cross-correlations from shocks to financial stress in Saudi Arabia (SA).



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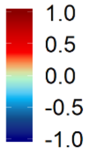
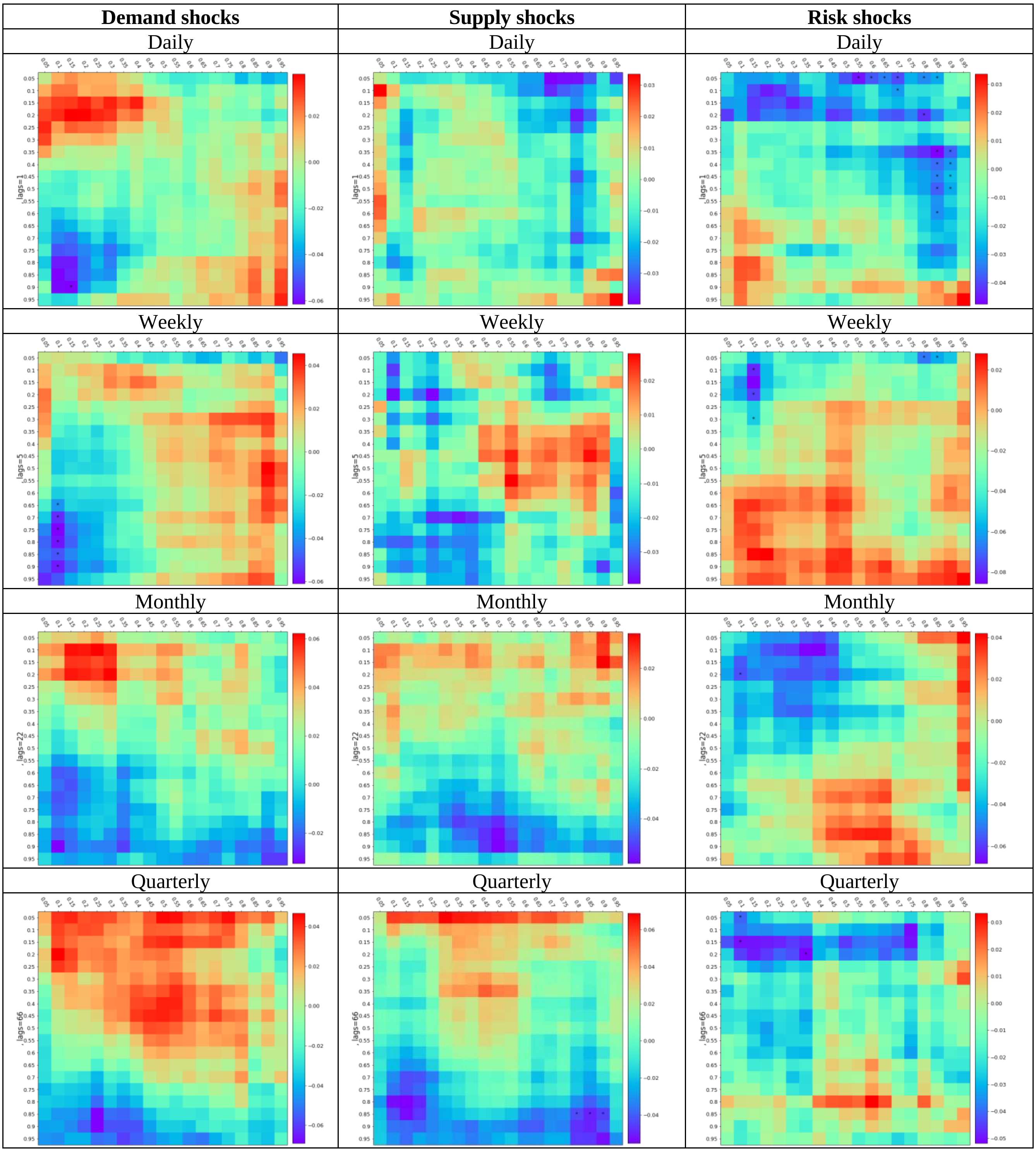


Figure 12: Spectral quantile cross-correlations from shocks to financial stress in Tunisia (TN).



Notes: Quantile cross-correlations in heatmaps. No predictable directionality is set to zero. The *colour*ed squares are regions where the Box-Ljung test statistic is statistically significant at the 5% level. The horizontal axis represents the quantiles for the financial stress index, while the vertical axis corresponds to the quantiles of oil demand, oil supply and risk shocks.

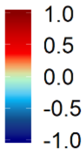
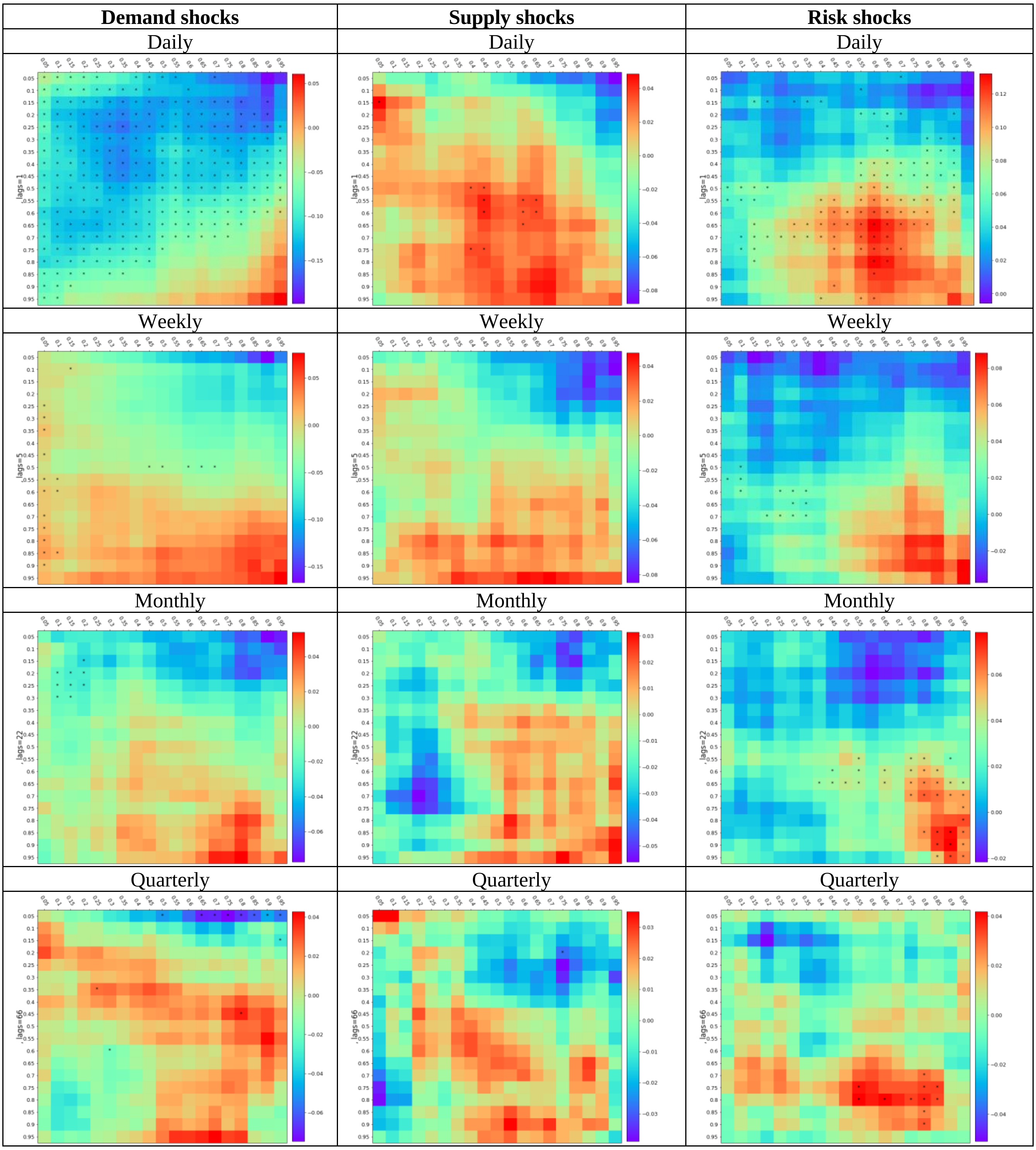


Figure 13: Spectral quantile cross-correlations from shocks to financial stress in Turkey (TR).



Notes*:* Quantile cross-correlations in heatmaps. No predictable directionality is set to zero. The *colour*ed squares are regions where the Box-Ljung test statistic is statistically significant at the 5% level. The horizontal axis represents the quantiles for the financial stress index, while the vertical axis corresponds to the quantiles of oil demand, oil supply and risk shocks.

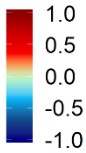
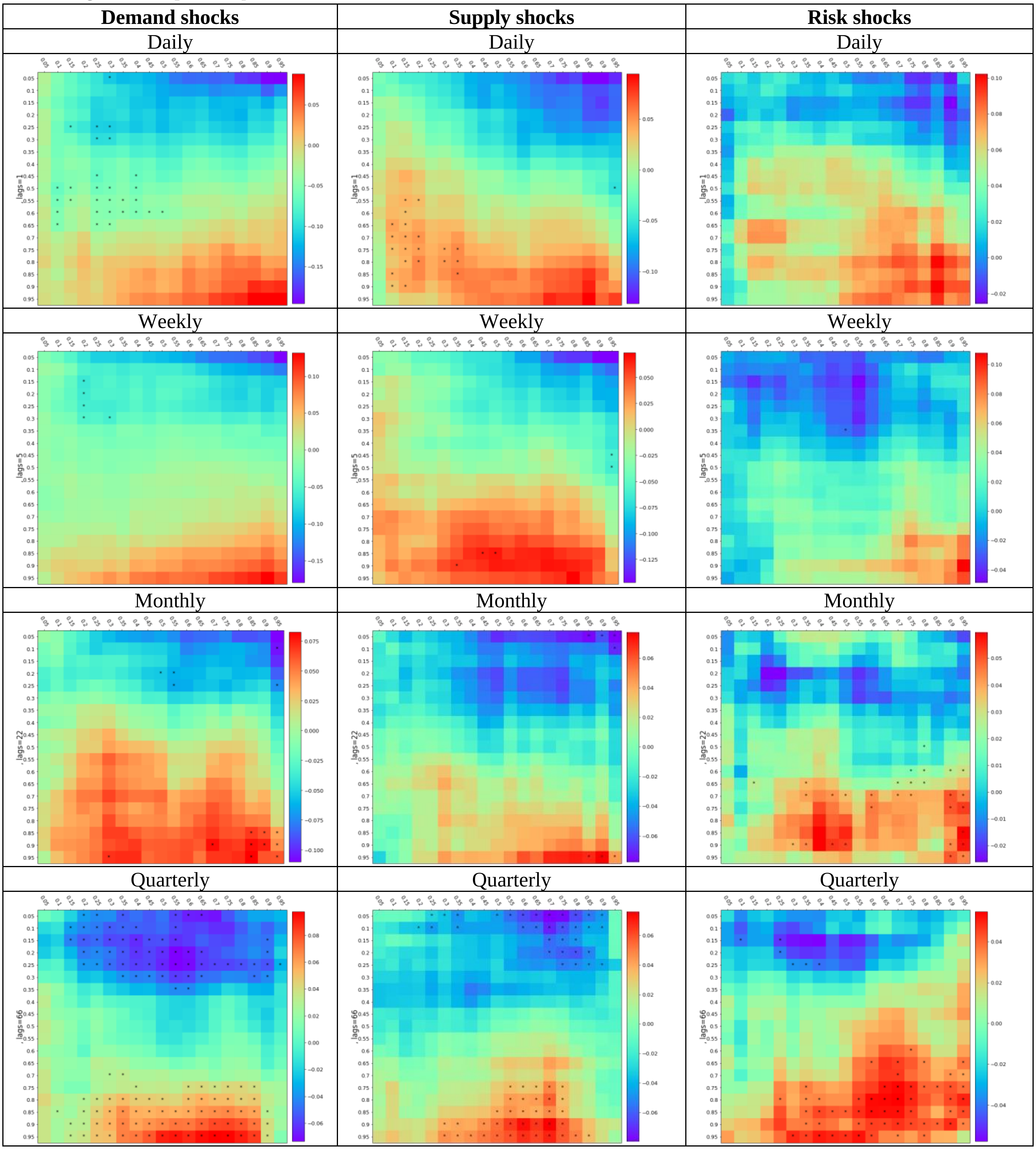


Figure 14: Spectral quantile cross-correlations from shocks to financial stress in United Arab Emirates (EA).



Notes*:* Quantile cross-correlations in heatmaps. No predictable directionality is set to zero. The *colour*ed squares are regions where the Box-Ljung test statistic is statistically significant at the 5% level. The horizontal axis represents the quantiles for the financial stress index, while the vertical axis corresponds to the quantiles of oil demand, oil supply and risk shocks.