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Quantile Dependence of United States and Emerging Stock Markets: A Cross-Quantilogram Analysis

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Abstract

This study examines the quantile dependence and directional predictability from the US to a vast range of emerging equity markets (EMs). This issue is addressed using the cross-quantilogram approach and daily data from January 2004 to April 2025. Our findings confirm that extreme conditions in the US market affect various quantiles of stock returns in EMs; however, the detailed picture of the dependence patterns varies significantly between quantile orders. A large sharp decrease (increase) in US stock returns increases the likelihood of an immediate extreme low (high) return in EMs, and the directional predictability is much higher at the tails of the distribution than at the median. We also find evidence of an asymmetric effect across quantiles, with negative spillovers having a stronger impact than positive spillovers. Furthermore, a higher degree of connectedness is observed between the US and EMs in the Americas than in other regions. The predictability remains pronounced after controlling for different global uncertainty measures, such as the Volatility Index (VIX), Economic Policy Uncertainty (EPU), Equity Market-related Economic Uncertainty Index (EMU), and Geopolitical Risk Index (GPR). Notably, EMs exhibited stronger connections with the US during the 2008 Global Financial Crisis than during the COVID-19 pandemic or the Russia-Ukraine war.

Keywords: cross-quantilogram, emerging markets, quantile dependence, financial spillover effects

JEL Classification: G15, C58

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1 Introduction

The turbulence in financial markets in the aftermath of the COVID-19 pandemic or the Russia-Ukraine war motivates market professionals to proactively seek ways to reduce the risk of financial losses. It is widely known that the Global Financial Crisis (GFC) in 2008-2009 was exacerbated by increased interconnections among financial markets, which was reflected by extreme rises in global volatility. On the one hand, the bursts of global volatility posed the question of the validity of the portfolio diversification argument (Ilmanen and Kizer, 2012; Rudolph and Schwetzler, 2013; Page and Panariello, 2018). However, the global economy has been witnessing strong capital liberalization, particularly in developing countries (Kose and Prasad, 2022), resulting in an ongoing flow of investments, especially from developed to emerging countries. Among developed countries, the US economy is the largest, with a nominal GDP roughly three times larger than that of the next two largest economies, Japan and Germany (The World Bank, 2023). Emerging economies are gaining global economic relevance based on their substantial share in global trade, good access to global capital markets (including sovereign and domestic corporations and financial institutions), and higher economic growth rates than the overall global economy (see S&P Global, 2024; Tiwari et al., 2024). It is also forecasted that by 2035, emerging economies will produce approximately 65% of global economic growth, with the main contributors being Asia-Pacific, including China, India, Vietnam, and the Philippines (S&P Global, 2024). Nevertheless, investments in these markets may still suffer from potential risks because the level of transparency, market regulations, and overall operational efficiency may remain in the developmental stages. From a management perspective, the dependence structure between the US and emerging equity markets (EMs) plays a key role in international portfolio allocation, as it allows investors to benefit from the diversification opportunities. Furthermore, the increased volatility during turmoil periods raises the question of whether EM dependence on the US market has been stable or strongly varying over time.

A large body of literature has focused on examining volatility co-movements or more complex risk spillovers between financial markets (e.g. Choudhry and Osoble, 2015; Sarwar and Khan, 2017; Bhowmik and Wang, 2018; Zhou et al., 2019; Bhowmik et al., 2022; Mao et al., 2024; Tiwari et al., 2024; Zhang et al., 2025; among others). Many studies on the predictability of the conditional expectations of stock returns have also been recently conducted (e.g. Zhang et al., 2019; Engelberg et al., 2023; Cakici et al., 2024; Hollstein et al., 2025). Distinct from these studies, however, in this study, we focus on tail dependence between return distributions using the cross-quantilogram (CQ) approach proposed by Han et al. (2016). This methodology has several advantages over existing methods for inferring directional linkages in financial time series data. The CQ captures the cross-dependence structure between random variables more granularly than other methods. In contrast to the well-recognized multivariate variants of generalized autoregressive conditional

heteroskedasticity (GARCH) models or the dynamic conditional correlation (DCC) specifications that focus on the interdependencies between the first or second moments of the conditional distributions, the CQ approach is more informative about how a given quantile of a distribution affects any other quantile of another distribution. In addition, compared to the standard quantile regression (QR) model, the CQ approach adds one more informative dimension related to a chosen τ^{th} quantile of the explanatory variable. Thus, instead of describing how the incremental increase in an explanatory variable affects a conditional quantile of the dependent variable (which can be formally assessed using traditional QR models), the CQ approach allows for the examination of the direct quantile-to-quantile lead-lag relationships across different quantile orders for both time series under study. It is worth mentioning that the non-Gaussianity of empirical distributions for daily financial returns renders the CQ methodology especially appropriate (Cho and Han, 2021). By considering different quantile orders, the CQ approach enables dependency and directionality analyses that are specific to different market conditions (i.e., bearish, normal, or bullish). Han et al. (2016) supplemented the CQ approach with the partial CQ (PCQ) method which allows for controlling the directional cross-quantile dependence between variables with additional covariates, allowing for the examination of the dependence structure under different states of the global economy.
The main objective of this study is to investigate the quantile-to-quantile impact of the US market on a broad range of EMs. We contribute to the literature on extremal dependence and contagion by investigating directional quantile dependence over the period 2004-2025, covering the GFC, COVID-19 pandemic, and the Russia-Ukraine war. Thus, our results provide a more complete picture of contagion and risk-return dependence structures between the US and twenty-three EMs. The EMs we consider are four markets in Latin America, ten in Europe, the Middle East, and Africa, and eight in the Asia-Pacific region. Vietnam was included in this analysis.
The remainder of this paper is organized as follows. A literature survey is presented in the next section. Section 3 introduces the methods used to analyze quantile dependence between markets. Section 4 describes the data used in this study, and Section 5 reports the main results. Finally, Section 6 concludes the paper.

2 Literature review

A large body of literature exists on the relationship between the US and emerging EMs. Several studies have focused on the so-called ‘mean-to-mean’ dependence, where the impact of different explanatory variables on the conditional expectation of equity returns is investigated. For instance, Narayan et al. (2018) found that US stock excess returns have predictive power for stock returns in 77 countries, including emerging markets (EMs). Sarwar and Khan (2017) examined the effects of US stock market uncertainty (VIX) on stock returns in Latin America and aggregated EMs. They found that an increase in the VIX resulted in immediate and delayed declines in

EMs. Li and Giles (2015) examined the linkages between the USA, Japan and six Asian developing countries and documented the significant unidirectional shock and volatility spillovers from the US equity market. Beirne et al. (2009); Bhowmik and Wang (2018); Habiba et al. (2020); and Bhowmik et al. (2022) also confirmed the spillover effects between the US and the emerging Asian economies corresponding to both return and volatility levels. Meanwhile, Beirne et al. (2009); Li and Giles (2015); Mensi et al. (2016); Gulzar et al. (2019); Zhang et al. (2025) documented volatility spillovers from the US to EMs. A stream of studies has investigated market connectedness between developed and emerging countries using the GARCH framework. For example, Liu et al. (2023) and Cardona et al. (2017) analyzed the correlations between the US and selected EMs. They found that the correlation between these stock markets varied under extreme market conditions. Meanwhile, Malik et al. (2022); Shehzad et al. (2021); Yousaf et al. (2020); Bhuyan et al. (2016) examined the return-and-volatility spillover from the US to developing markets. All results suggest that the US stock market has significant return and volatility spillover effects on the selected EMs. Further scholarly efforts are related to the use of implied volatility to explore interconnections across financial markets. For example, Dutta (2018) found strong evidence of the long-run transmission of uncertainty from the US market to China and Brazil. Thakolsri et al. (2016) concluded that implied volatility movements in the US influence the Thai stock market. Meanwhile, Rababaa et al. (2025) and Gupta et al. (2023) revealed that the US market exerts a significant spillover effect on other markets by examining the realized volatility. Applying cointegration analysis to a sample of Arab, US, and EMs, Elfakhani et al. (2008) conclude that only three of the 11 Arab countries are cointegrated with the US market. Markets that are not cointegrated with the US market may still offer good diversification alternatives.

Another strand of studies concentrates on the relationship between developed and EMs across the sectoral level rather than the national indices. For example, Jiang et al. (2017) and Zhu et al. (2024) analyzed agricultural futures markets and confirmed significant spillovers from the US to China. Han et al. (2013) and Hernandez et al. (2014) also investigated the spillover effects induced by the U.S. agricultural markets. Meanwhile, Choudhry and Osoble (2015) focused on the relationships between the industrial sectors of the US stock market and three EMs (Brazil, Malaysia, and South Africa).

Another branch of research sheds light on the quantile dependence between the US and emerging markets (EMs) using the quantile regression (QR) approach. For instance, Mensi et al. (2014) and Zhang et al. (2024) investigated the dependence between the US stock market (the S&P 500 index) and the BRICS stock markets. Yang et al. (2018); Zhang and Li (2014) examined the China-US stock market linkages under extreme conditions. Dong et al. (2020) presented the dependence structures for six regional stock markets through the application of the quantile regression approach. As far as the applications of the CQ methodology are concerned, the literature focuses mostly on the dependence patterns between stock markets and other segments of the global financial market (energy, gold, oil, and foreign exchange). For example, Tiwari et al. (2024) investigate the energy, foreign exchange, and stock markets in E7+1 EMs. Similarly, Uddin et al. (2019) analyzed the quantile dependence between green energy stock returns and aggregate stock returns, oil and gold price changes, and exchange rates using quantile regression. Naeem et al. (2023) hightlighted the positive correlation between oil and cryptocurrencies while Zhang et al. (2023) investigated the connectedness among energy stock returns. Zhou et al. (2019) documented directional predictability from oil volatility to stock returns in BRICS countries (Brazil, Russia, India, China, and South Africa). Similarly, Sim and Zhou (2015) and Reboredo and Ugolini (2016) investigated the effect that selected quantiles of oil price shocks exert on the quantiles of stock returns. Baumöhl and Štefan Lyócsa (2017) investigated the directional predictability from the sectorial stock market indices to gold and concluded that the safe haven properties of gold have been changing over time. Meanwhile, Jiang et al. (2016) examined spillovers and directional predictability of agricultural futures markets between the US and China. Mensi et al. (2023) focused on the stock markets of US, China, and Vietnam, along with three other developed markets. In this context, our study is most closely related to Labidi et al. (2018), who examined cross-quantile dependence between the stock returns of the US and six EMs and three frontier markets. However, Labidi et al. (2018) used monthly data and investigated only a selection of EMs.

The literature highlights the significant influence of the US stock market on EMs. This study contributes to the literature by investigating the dynamic patterns of the quantile-to-quantile impact of US daily stock returns on EMs returns over the period 2004-2025. Our work differs from Labidi et al. (2018) and other studies in the following ways: (i) we quantify a quantile-to-quantile dynamic relationship between returns, moving beyond traditional methods that generally depend on modelling conditional expectation or conditional variance; (ii) we use the most recent data, including different periods of both prosperity and turmoil; (iii) we expound the effect of the 2008 GFC, COVID-19 pandemic, and the recent Russia-Ukraine war on the dependence of the US on EMs; (iv) we use large datasets covering EMs across the Americas, Europe, Middle East, and Africa (EMEA), and Asia Pacific (APAC) regions; and (v) we estimate the partial cross-quantilogram model to examine the nature of the dependence structure between the US and EMs while controlling for different measures of global market uncertainty.

3 Methodology

Extending the quantilogram concept of Linton and Whang (2007) into a multivariate setting, Han et al. (2016) provide a comprehensive picture of the predictability structure between two time series using the notion of conditional quantiles. This section formally introduces the general concept of the cross-quantilogram approach used in our empirical analysis.

3.1 Cross-quantilogram (CQ)

Let the log return observed on day t $(t = 1, 2, \ldots, T)$ in the market m be denoted as y_t^{m} (m $\in$ {EM, US}), where the superscript EM denotes the daily log return on a chosen emerging stock market (among 23 EMs under examination), and the superscript US denotes the daily log return in the US stock market. The series y_t^{m} is assumed to be stationary. We use $F_{y^{\mathrm{EM}}|y^{\mathrm{US}}}(\,\cdot \mid y_t^{\mathrm{US}})$ to denote the conditional cumulative distribution function of y_t^{EM} given y_t^{US} with the density function $f_{y^{\mathrm{EM}}|y^{\mathrm{US}}}(\,\cdot \mid y_t^{\mathrm{US}})$. Observe that the conditional quantile function of y_t^{EM} is defined as $q_t^{\mathrm{EM}}(\tau_{\mathrm{EM}}) = \inf\{\upsilon : F_{y_t^{\mathrm{EM}}|y_t^{\mathrm{US}}}(\upsilon|y_t^{\mathrm{US}}) \geq \tau_{\mathrm{EM}}\}$, where $\tau_{\mathrm{EM}} \in (0, 1)$. Thus, τ_{EM} represents the quantile level (order) selected for a given emerging market. Similarly, we define the conditional quantile function for y_t^{US}, i.e., $q_t^{\mathrm{US}}(\tau_{\mathrm{US}}) = \inf\{\upsilon : F_{y_t^{\mathrm{US}}|y_t^{\mathrm{EM}}}(\upsilon|y_t^{\mathrm{EM}}) \geq \tau_{\mathrm{US}}\}$, where $\tau_{\mathrm{US}} \in (0, 1)$ represents a given quantile level (order) for the daily US return variable, and $F_{y_t^{\mathrm{US}}|y_t^{\mathrm{EM}}}(\upsilon|y_t^{\mathrm{EM}})$ is the associated conditional cumulative distribution function.

For an arbitrary pair of quantile orders $\tau = (\tau_{\mathrm{EM}}, \tau_{\mathrm{US}})$ and a lag order k, with $k \in \mathbb{N}$, we are interested in evaluating the serial dependence between two events $\{y_t^{\mathrm{EM}} \leq q_t^{\mathrm{EM}}(\tau_{\mathrm{EM}})\}$ and $\{y_{t-k}^{\mathrm{US}} \leq q_{t-k}^{\mathrm{US}}(\tau_{\mathrm{US}})\}$.

Let $\mathbb{1}_{\{\cdot\}}$ be the indicator function delivering a value of 1 if its argument is true, and 0 otherwise. The stochastic process $\{\mathbb{1}_{\{y_t^{\mathrm{m}} \leq q_t^{\mathrm{m}}(\tau_{\mathrm{m}})\}}\}_{t=1,2,\ldots}$ is commonly referred to as a quantile-hit or quantile-exceedance (quantile-event) process. The CQ $\rho_\tau(k)$ is defined as the cross-correlation of two distinct quantile-hit processes, exhibiting the serial dependence between two time series of returns at the selected quantile levels:

$$\rho_\tau(k) = \frac{\mathbb{E}[\psi_{\tau_{\mathrm{EM}}}(y_t^{\mathrm{EM}} - q_t^{\mathrm{EM}}(\tau_{\mathrm{EM}}))\psi_{\tau_{\mathrm{US}}}(y_{t-k}^{\mathrm{US}} - q_{t-k}^{\mathrm{US}}(\tau_{\mathrm{US}}))]}{\sqrt{\mathbb{E}[\psi^2_{\tau_{\mathrm{EM}}}(y_t^{\mathrm{EM}} - q_t^{\mathrm{EM}}(\tau_{\mathrm{EM}}))]}\sqrt{\mathbb{E}[\psi^2_{\tau_{\mathrm{US}}}(y_{t-k}^{\mathrm{US}} - q_{t-k}^{\mathrm{US}}(\tau_{\mathrm{US}}))]}}, \tag{1}$$

for $\psi_{\tau_{\mathrm{m}}}(y_t^{\mathrm{m}} - q_t^{\mathrm{m}}(\tau_{\mathrm{m}})) = \mathbb{1}_{\{y_t^{\mathrm{m}} \leq q_t^{\mathrm{m}}(\tau_{\mathrm{m}})\}} - \tau_{\mathrm{m}}$. The sample CQ is based on (1), and is given as

$$\hat{\rho}_\tau(k) = \frac{\sum_{t=k+1}^{T} \psi_{\tau_{\mathrm{EM}}}(y_t^{\mathrm{EM}} - \hat{q}_t^{\mathrm{EM}}(\tau_{\mathrm{EM}}))\psi_{\tau_{\mathrm{US}}}(y_{t-k}^{\mathrm{US}} - \hat{q}_{t-k}^{\mathrm{US}}(\tau_{\mathrm{US}}))}{\sqrt{\sum_{t=k+1}^{T} \psi^2_{\tau_{\mathrm{EM}}}(y_t^{\mathrm{EM}} - \hat{q}_t^{\mathrm{EM}}(\tau_{\mathrm{EM}}))}\sqrt{\sum_{t=k+1}^{T} \psi^2_{\tau_{\mathrm{US}}}(y_{t-k}^{\mathrm{US}} - \hat{q}_{t-k}^{\mathrm{US}}(\tau_{\mathrm{US}}))}}. \tag{2}$$

By construction $\hat{\rho}_\tau(k) \in [-1, 1]$. If $\hat{\rho}_\tau(k) = 0$, there is no directional predictability between the two series for a given lag order k. In other words, the event $\{y_{t-k}^{\mathrm{US}} \leq q_{t-k}^{\mathrm{US}}(\tau_{\mathrm{US}})\}$ does not help in predicting whether the event $\{y_t^{\mathrm{EM}} \leq q_t^{\mathrm{EM}}(\tau_{\mathrm{EM}})\}$ occurs. In contrast, $\hat{\rho}_\tau(k) \neq 0$ corresponds to the case of directional predictability between the two series under study. The critical values for $\hat{\rho_\tau}(k)$ can be estimated using the stationary bootstrap procedure of Politis and Romano (1994) to obtain asymptotically valid confidence intervals.

Using the CQ coefficients, the following portmanteau test can be performed:

$$\begin{aligned} H_0: &\quad \rho_\tau(k) = 0 \quad \forall \quad k \in \{1, 2, \ldots, p\} \\ H_1: &\quad \exists\, k \in \{1, \ldots, p\}, \quad \rho_\tau(k) \neq 0. \end{aligned}$$

Han et al. (2016) proposed the CQ Ljung-Box test statistics which has the following form:

$$Q^*_\tau(p) = T(T+2) \sum_{k=1}^{p} \frac{\hat{\rho}^2_\tau(k)}{T-k}, \tag{3}$$

where T is the sample size, and p is the maximum number of lags under consideration. The bootstrap critical values for the CQ Ljung-Box test statistics can be derived using bootstrapped replicates, as suggested by Han et al. (2016).

3.2 The partial cross-quantilogram (PCQ)

The PCQ approach enables the evaluation of cross-quantile dependence structures by controlling for other covariates. Accordingly, by extending the CQ approach, the PCQ allows us to control for other economic variables (measured between times $t-k$ and t) that can influence the relationship between the two events: $\{y_t^{\mathrm{EM}} \leq q_t^{\mathrm{EM}}(\tau_{\mathrm{EM}})\}$ and $\{y_{t-k}^{\mathrm{US}} \leq q_{t-k}^{\mathrm{US}}(\tau_{\mathrm{US}})\}$.

Let the return on an EM to be denoted as $y_t^{\mathrm{EM}} := y_{1,t}$, and the return on the US market as $y_t^{\mathrm{US}} := y_{2,t}$. Accordingly, let the quantile level for an EM market be denoted as $\tau_{EM} := \tau_1$ and the quantile level for the US as $\tau_{US} := \tau_2$. Correspondingly, $q_{EM,t}(\tau_{EM}) := q_{1,t}(\tau_1)$ and $q_{US,t}(\tau_{US}) := q_{2,t}(\tau_2)$. Let $y_{i,t}$ for $i \in \{3, 4, ..., M\}$ represent the ith stationary variable (a covariate) measuring the “market state” or “market uncertainty” at time t, and $q_{i,t}(\tau_i)$ is the corresponding quantile for the probability level τ_i. Accordingly, $\mathbf{z}_t \equiv [\psi_{\tau_3}(y_{3,t} - q_{3,t}(\tau_3)), \ldots, \psi_{\tau_M}(y_{M,t} - q_{M,t}(\tau_M))]^T$ is a $(M-2) \times 1$ vector representing the quantile-hit process for $(M-2)$ covariates. As pointed out by Han et al. (2016), reliance on the hit processes instead of the original “market state” variables provides the robustness of the methodology without the necessity of declaring any additional moment conditions. The expressions provided below rely on a single set of quantiles $\bar{\tau} = (\tau_1, \tau_2, \ldots, \tau_M)^\top$ and a single lag $k = 0$ (therefore, there is no dependence on k):

The correlation matrix associated with the M vector of hit processes:
$\mathbf{h}_t(\bar{\tau}) = [\psi_{\tau_1}(y_{1,t} - q_{1,t}(\tau_1)), \ldots, \psi_{\tau_M}(y_{M,t} - q_{M,t}(\tau_M))]^T$ is given as following:

$$\mathbf{R}_{\bar{\tau}} = \mathbb{E}[\mathbf{h}_t(\bar{\tau})\mathbf{h}_t(\bar{\tau})^T], \tag{4}$$

with a sample analogue:

$$\hat{\mathbf{R}}_{\bar{\tau}} = \frac{1}{T}\sum_{t=1}^{T}[\hat{\mathbf{h}}_t(\bar{\tau})\hat{\mathbf{h}}_t(\bar{\tau})^T]. \quad (5)$$

The sample PCQ that is conditional on $\mathbf{z}_t$ can be derived as follows:

$$\hat{\rho}_{\bar{\tau}|\mathbf{z}} = -\frac{\hat{p}_{\bar{\tau},12}}{\sqrt{\hat{p}_{\bar{\tau},11}\hat{p}_{\bar{\tau},22}}}, \quad (6)$$

where $\hat{p}_{\bar{\tau},ij}$ denotes the element (i,j) of the matrix $\hat{\mathbf{R}}_{\bar{\tau}}^{-1}$, which is the inverse of the estimated correlation matrix. The value of $\hat{\rho}_{\bar{\tau}|\mathbf{z}}$ can then be used to test the null hypothesis of no quantile predictability, similar to the case of CQ (see Han et al., 2016).

4 Data description

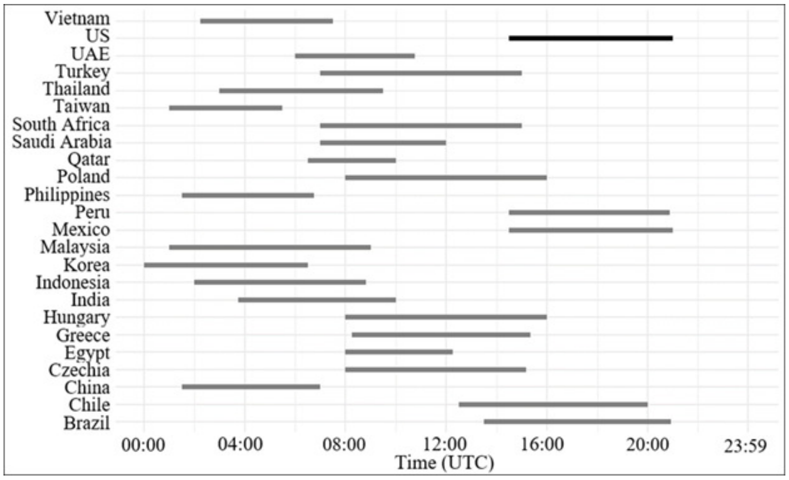
Our data sample consists of the daily stock prices (along with the corresponding daily log returns) of EMs and the US market from January 1, 2004, to April 25, 2025, covering 21 years of data. EMs are defined based on the Morgan Stanley Capital International (MSCI) market classification (see Appendix A1). Colombia and Kuwait were excluded from the study because of a lack of data. However, we included Vietnam in our analysis. We consider twenty-four indices: S&P 500 (US), Sao Paulo SE Bovespa Index (Brazil), S&P IPSA CLP Index (Chile), S&P/Bmv Ipc (Mexico), S&P/BVL Peru General Index (Peru), PX Prague SE Index (Czech Republic), Athex Composite Share Price Index (Greece), Warsaw SE WIG Poland Index (Poland), EGX 30 Index (Egypt), Budapest SE Index (Hungary), Qatar Exchange General Index (Qatar), Tadawul FF Index (Saudi Arabia), BIST 30 Index (Turkey), FTSE ADX General Index Real Time (UAE), FTSE/JSE SA Top 40 Companies Index (South Africa), Shanghai Shenzhen CSI 300 Index (China), S&P BSE Sensex Index (India), Korea SE Kospi Index (Korea), The Philippine Stock Exchange PSEi Index (Philippines), Taiwan SE Weighted Index (Taiwan), Jakarta SE Composite Index (Indonesia), FTSE Bursa Malaysia KLCI Index (Malaysia), SET Index (Thailand), and Vietnam Index (Vietnam).

The sample period was chosen to encompass the GFC, COVID-19 pandemic, and the Russia-Ukraine war, as the literature suggests that spillover effects among financial markets typically intensify as an aftereffect of such financial turmoil.

A graphical presentation of the stock indices under investigation is provided in Appendix A1. A very sharp decrease in equity prices in all EMs is observed during the GFC, which parallels the drastic collapse of the US equity market. A similar downward trend was evident during the COVID-19 pandemic and the Russia-Ukraine war, with equity prices dropping in all markets.

Because stock exchanges in EMs operate in different time zones, the overlap in trading hours differs, which, in turn, can have a vital effect on the dependence structure across

Figure 1: Trading hours in the US and EMs based on UTC time



Notes: In the US, Poland, Hungary, Greece, Egypt, the Czech Republic, and Chile, daylight saving time holds from March to October (from April in Egypt), and trading hours begin and end one hour earlier during this period. Daylight Saving Time is no longer used in Turkey (since Sep 2016), Mexico (Oct 2022), and Brazil (Feb 2016).

the stock indices. Figure 1 illustrates the trading hours of all markets in Coordinated Universal Time (UTC). We can see that the EMs located in the Americas trade almost simultaneously with the US, while all Asian markets are already closed when the US market opens. In some countries, trading hours in Europe and South Africa overlap with US trading hours by only one hour. Consequently, for EMs with entire or partial trading times overlapping with the US, we examine both contemporaneous and lagged impacts of US stock price movements. However, for these markets (the UAE, Qatar, Saudi Arabia, Egypt, and all Asian markets) that close before the US market opens, we focus only on the lagged impact.

Table 1 presents the preliminary descriptive statistics for returns used in the investigation. Specifically, the table reports the sample mean, median, standard deviation, skewness, and kurtosis, as well as the Jarque-Bera test statistic for normality tests.

Most returns have higher medians than means, implying that the log return distributions are skewed to the left. The descriptive statistics reveal that the mean value of each asset return is close to zero, as expected for daily data. While almost all market returns display positive mean values, the Greek market stands out with a slightly negative mean and the largest standard deviation, indicating that it experienced more volatile conditions during the sample period than other markets. The Turkish stock market recorded the highest mean return (0.0007) and the second

Table 1: Descriptive statistics, panel i)

Descriptive statistics for the logarithmic returns							
Variable	Median	Mean	Std. Dev.	Skewness	Kurtosis	JB	ADF
US	0.0007	0.0002	0.0120	-0.2874	11.8466	26,306***	-10.7456***
Brazil	0.0007	0.0002	0.0170	-0.3406	7.8975	11,751***	-19.0275***
Chile	0.0004	0.0004	0.0110	-0.2676	13.6418	34,853***	-18.2561***
Mexico	0.0006	0.0004	0.0117	-0.0610	6.2138	7,224***	-16.8772***
Peru	0.0005	0.0004	0.0141	-0.5358	11.1028	23,267***	-13.6752***
Europe, Middle East, and Africa (EMEA)							
Czech Republic	0.0006	0.0002	0.0129	-0.6631	17.1585	60,206***	-20.7254***
Poland	0.0005	0.0003	0.0124	-0.7262	7.6469	12,307***	-36.8294***
Greece	0.0008	-0.0001	0.0185	-0.5384	8.2873	14,065***	-12.7841***
Hungary	0.0006	0.0004	0.0148	-0.4166	8.4730	14,692***	-18.726***
Turkey	0.0010	0.0007	0.0179	-0.2685	3.4856	2,516***	-24.8376***
UAE	0.0003	0.0003	0.0113	-0.2179	11.2819	21,134***	-16.3539***
Qatar	0.0003	0.0002	0.0129	-0.3944	8.5746	12,010***	-25.5806***
Saudi Arabia	0.0010	0.0002	0.0143	-0.9401	11.3231	19,246***	-15.4621***
Egypt	0.0011	0.0006	0.0159	-0.9522	8.5651	12,101***	-11.0245***
South Africa	0.0008	0.0004	0.0130	-0.1786	4.9443	4,984***	-19.9093***
Asia Pacific (APAC)							
China	0.0006	0.0003	0.0163	-0.4717	4.222	3,486***	-42.2605***
India	0.0009	0.0005	0.0135	-0.2094	11.8659	26,915***	-10.7456***
Indonesia	0.0010	0.0004	0.0125	-0.5690	8.5788	14,121***	-13.5285***
Korea	0.0006	0.0002	0.0122	-0.4510	8.6923	14,566***	-13.3002***
Malaysia	0.0002	0.0001	0.0073	-0.8255	13.0541	32,909***	-32.5201***
Philippines	0.0006	0.0003	0.0129	-0.9269	10.4125	21,179***	-13.6986***
Taiwan	0.0007	0.0002	0.0113	-0.4565	4.2176	3,501***	-14.0132***
Thailand	0.0005	0.0002	0.0117	-1.2395	18.9331	68,434***	-16.8486***
Vietnam	0.0008	0.0003	0.0141	-0.3595	2.1276	971***	-22.4822***

Notes: Panel i) shows descriptive statistics for the logarithmic returns. The period is from January 2004 to April 2025. JB denotes the Jarque-Bera normality test statistic, and ADF is the Augmented Dickey-Fuller test statistic. The optimal lag structure for the ADF test was selected based on the Akaike information criterion (AIC). Symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 1: Descriptive statistics, panel ii)

Unconditional correlations between the US returns and emerging market returns					
	Brazil	Chile	Mexico	Peru	
Day t for the US and Americas	0.6152	0.4487	0.6339	0.4284	
	Europe, Middle East, and Africa (EMEA)				
	Czech	Poland	Greece	Hungary	Turkey
Day t for the US; Day t for EMEA	0.3692	0.3927	0.3133	0.3440	0.2794
	UAE	Qatar	Saudi Arabia	Egypt	South Africa
	-	-	-	-	0.4128
	Czech	Poland	Greece	Hungary	Turkey
Day t for the US; Day $t-1$ for EMEA	0.1696	0.1139	0.0921	0.1175	0.0678
	UAE	Qatar	Saudi Arabia	Egypt	South Africa
	0.1541	0.1753	0.0772	0.1768	0.1245
	Asia Pacific (APAC)				
	China	India	Indonesia	Korea	Malaysia
Day $t-1$ for the US; Day t for APAC	0.1137	0.2049	0.2896	0.3065	0.2737
	Philippines	Taiwan	Thailand	Vietnam	
	0.3149	0.3168	0.1979	0.2215	

Notes: Panel ii) presents linear correlation coefficients between US and each of the emerging markets.

highest standard deviation (0.0179). In contrast, the Malaysian market has the lowest standard deviation (0.0073). Notably, only Greece and Malaysia feature lower mean stock returns than the US does.

As expected, the empirical distributions of daily log returns are not Gaussian because they are characterized by both strong excess kurtosis and negative skewness. Accordingly, our data exhibit a higher likelihood of extreme events than that implied by a Gaussian distribution. The results of the Jarque-Bera normality test formally confirm that the null hypothesis of the Gaussian distribution for financial returns should be rejected at the 1% significance level for all countries. The CQ approach assumes that the time series data are stationary. According to the results of the ADF tests in Table 1, the null hypothesis of non-stationarity is rejected for all the countries. Finally, panel ii) in Table 1 displays the linear correlation coefficients (Pearson correlations) between the daily log returns on the stock markets. We observe that the EMs in the Americas exhibit the highest contemporaneous correlation with the US market, which can be explained by the fact that they mostly operate within the same trading hours as the US market does. Among the Middle Eastern and African markets, Saudi Arabia shows the lowest contemporaneous correlation with the US (0.0772), suggesting potential diversification and hedging opportunities for investors. In contrast, South Africa is strongly contemporaneously correlated with the US market, with a correlation coefficient of 0.4128. Interestingly, despite the fact that the time overlap of trading sessions between the US and South Africa is equal to 1 hour only, the linear correlation between these markets and the US market on the same day is much higher than the correlation corresponding to day $t-1$ in the US and day t in South Africa. In addition, it is worth noting that the Chinese market, despite being the world's second-largest economy, has a moderate correlation with the US market.

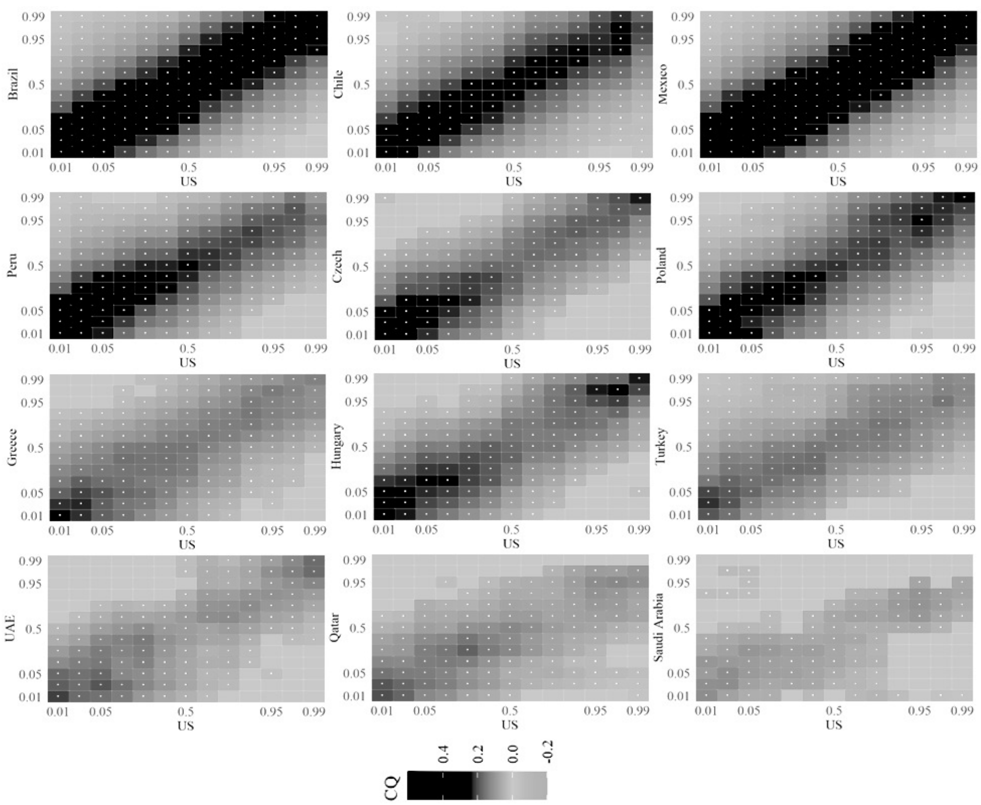
5 Empirical Findings and Discussion

In this section, we present the dependence patterns between the analyzed time series of financial returns using the CQ approach.

5.1 General perspective on the dependence structure

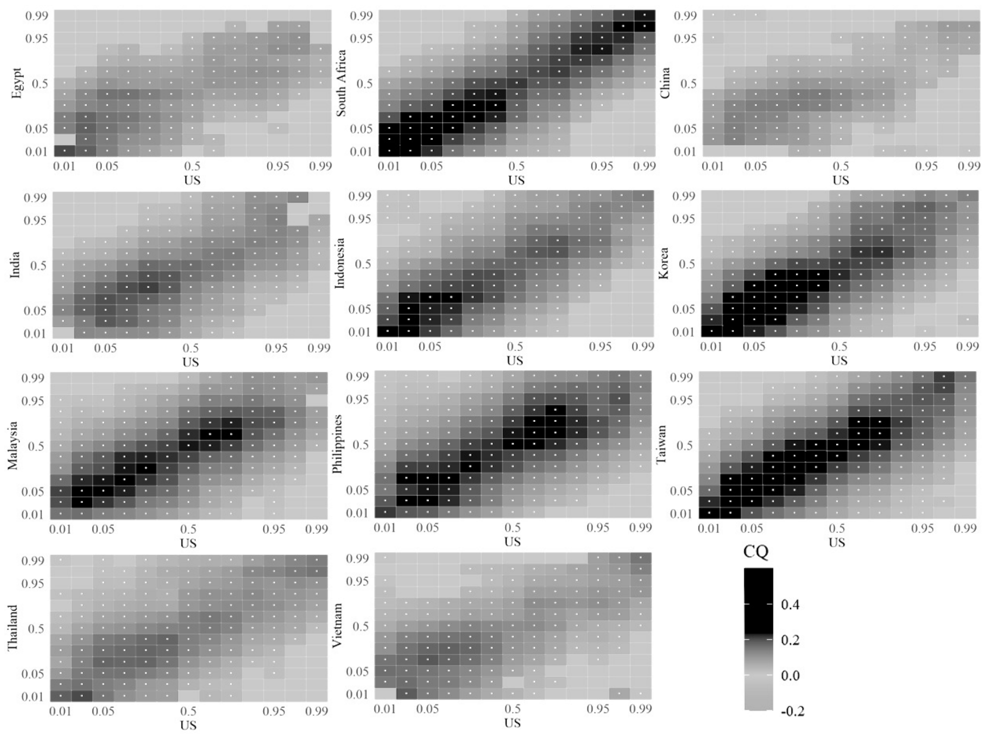
Figure 2 and 3 report the sample CQ in heatmap form, where the coloring in shades of gray on distinct panels represents values of $\hat{\rho}_\tau(k)$ with $k = 0$ for the EMs with overlapping trading hours with the US, and $k = 1$ for those with non-overlapping trading sessions. Statistically significant values (at the 5% level) are marked with white dots. The heatmaps offer a detailed outlook on the instantaneous reaction of different EMs to US price fluctuations at various quantile orders, since the quantile orders for both τ_{EM} and τ_{US} range between 0.01 and 0.99. Three major observations can be formulated based on this bird's - eye view of the dependence structures.

Figure 2: The sample CQ between emerging markets and United States in heatmap form



Note: The period under study is between January 2004 and April 2025. The coefficients with no predictable directionality were set as zero. The white dots indicate that the Ljung-Box test statistics associated with CQ are statistically significant. In each heatmap, the horizontal axis represents the quantile orders for the US, while the vertical axis displays the quantile orders for the emerging markets. For countries with overlapping trading hours with the US (i.e. all EMs in Latin America, Europe and South Africa), the heatmap is reported at lag 0 ($k = 0$); for the remaining countries, it is reported at lag 1 ($k = 1$).

Figure 3: The sample CQ between emerging markets and United States in heatmap form

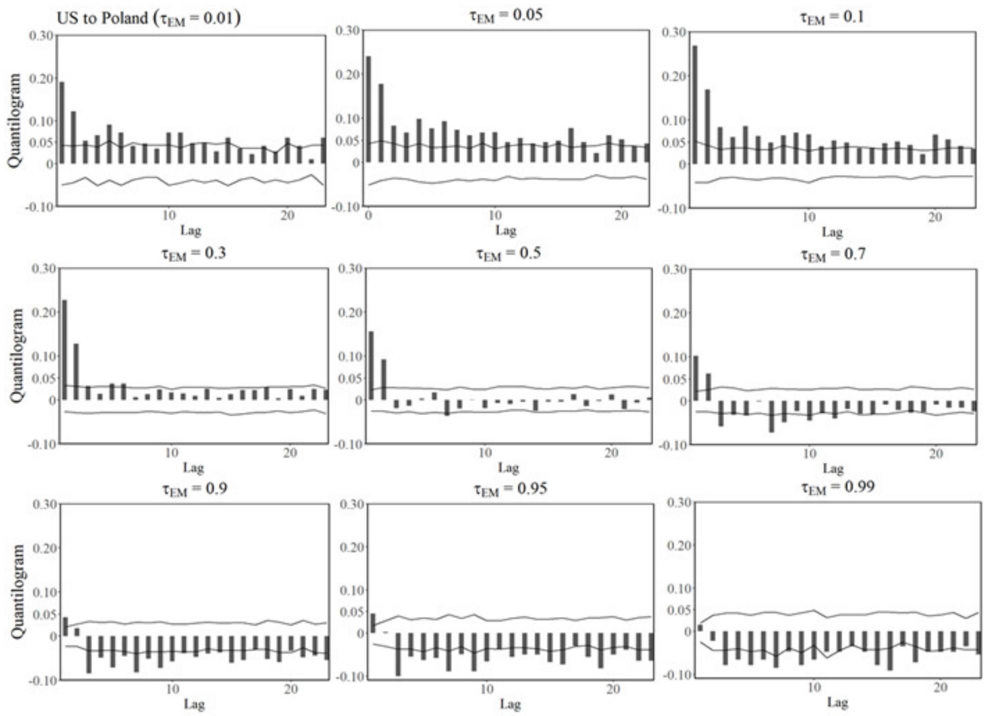


First, we can see that in most EMs, CQ patterns are not the same. However, $\hat{\rho}_\tau(k)$ coefficients are mostly positive and statistically significant along the counterdiagonal of the heatmaps, as indicated by the dotted darker rectangles at the matching quantiles. Hence, EMs tend to move in the same direction as the US market. When compared to other countries, the EMs in Latin America show the strongest contemporaneous co-dependence with the US market, especially during extreme upward or downward movements in US prices. Second, quantile dependence is more pronounced following an extreme negative shock than a positive shock in the US market. This can be prominently observed in Peru, the Czech Republic, Poland, South Africa, and South Korea, where the "darkest" rectangles are located in the lower left corner of the heatmaps. Third, a predictable correlation exists in the middle quantiles. When compared to the matching extreme quantiles, these $\hat{\rho}_\tau(k)$ coefficients are substantially smaller but still positive and statistically significant. This means that median returns in the US market contemporaneously affect EM median returns. However, it is worth noting that the heatmaps are constructed for $k = 0$ or $k = 1$, and hence, they represent only the contemporaneous or one-day-ahead influence of the US market on EMs, respectively. Therefore, in the next section, we provide information on the reactions of EMs to the US stock market in the longer term.

5.2 Case of Poland and China

As the US and China are the two largest stock markets by market capitalization in the world (Statista, 2025), we are interested in examining the detailed dependency structure between these markets across different quantiles. Furthermore, among EMs, the Polish stock market stands out as the best-performing in Europe, with the WIG index increasing by more than 40% and nearly tripling from its 2022 low (The Economist, 2025). Therefore, for the sake of brief exposition, we will provide two detailed reports of the CQ analysis: for the US-Polish and US-China relationships. Because the heatmap in Section 5.1 reveals that the magnitude of the impact is greater under conditions of a sudden drop in US returns, we focus on very large negative US returns ($\tau_{\text{US}} = 0.1$) in this section. The maximum lag structure for the CQ method was set as $k = 22$, representing 22 consecutive business days. The CQ was derived for nine quantile orders $\tau_{\text{EM}} \in \{0.01, 0.05, 0.1, 0.3, 0.5, 0.7, 0.9, 0.95, 0.99\}$.
To provide an example of how the US affects EMs in Europe, in Figure 4 we present a sample CQ measuring temporal dependence between the US and the Polish stock market for $\tau_{\text{US}} = 0.1$, which represents a very large daily decrease in US stock prices. The red lines illustrate 95% confidence intervals for no predictability, which are obtained based on 1,000 bootstrapped replicates. As can be seen, directional predictability from the US to the Polish market exists across various quantile orders τ_{EM}. The CQ coefficients at lag zero ($k = 0$) are significant and positive for all quantile orders; however, the magnitude of positive dependence is the highest for the lower quantiles (i.e., $\tau_{\text{EM}} \in \{0.05, 0.1\}$), representing the left distribution tail of the broad stock index (WIG) in Poland. This means that large drops in the S&P 500 index significantly affect the WIG index. More specifically, the entire distribution of WIG returns reacts instantaneously by moving to the left on the same day when extreme declines occur in the US market. However, the degree of this left-shifting is not equal across different quantile orders: it tends to be larger for the lower quantiles, and hence, for the left tail of the distribution, and smaller for the right tail. Accordingly, the instantaneous aftermath of a collapse in the US stock market is that the Polish stock market is much more prone to a sharp decline (a daily WIG return in the region of its 0.05-quantile or 0.1-quantile) than to a sharp rise (a WIG return in the region of its 0.9-quantile, 0.95-quantile, or 0.99-quantile). This suggests that distress in the US market immediately impacts investor sentiment in Poland. The rapid transmission of shocks between these markets, driven by technological advancements, plays a key role in this dynamic relationship. As depicted in Figure 1, the overlap in trading hours between Poland and the US on the same day is only one or two hours. It is 1 h and 20 minutes for both daylight saving time (DST) and standard time. As the US and Poland adjust their clocks for DST on different dates – in the US from the second Sunday in March, and in Poland from the last Sunday in March – and DST ends on

Figure 4: The sample CQ, $\hat{\rho}_{\tau}(k)$, with $\tau_{\mathrm{US}} = 0.1$ to detect directional predictability from the US to Polish stock market

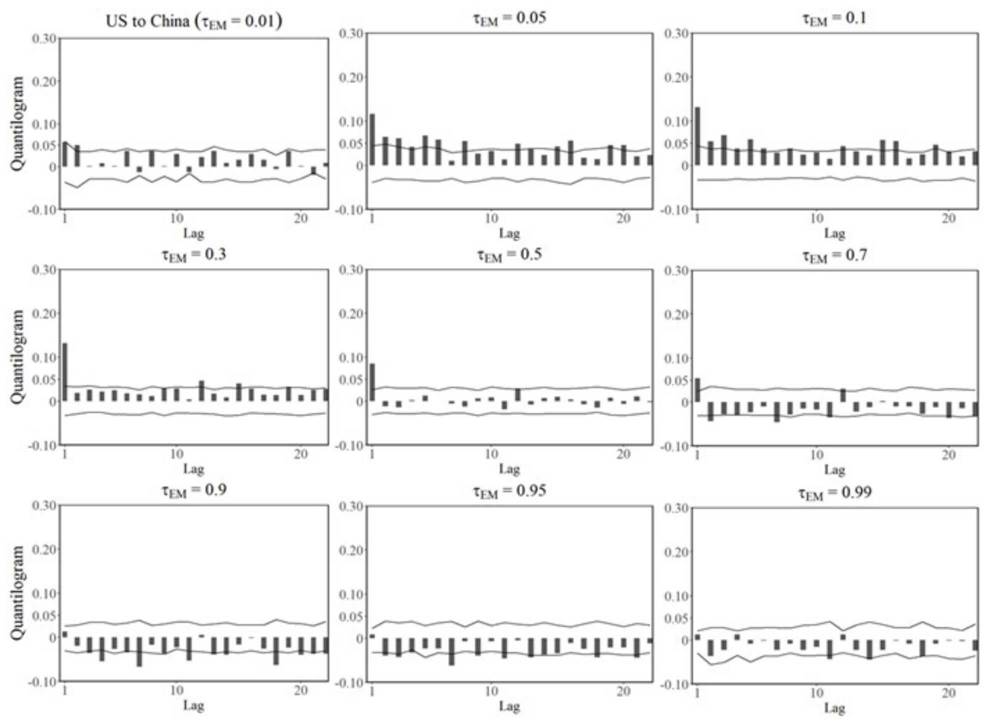


Note: Bar graphs describe the sample cross-quantilogram for $k \in \{0, 1, \ldots, 22\}$, and the horizontal curves denote the 95% bootstrap confidence intervals centered at zero.

the first Sunday of November in the US and the last Sunday of October in Poland, 2 hours and 20 minutes of trading overlap during these periods. Notwithstanding, the highest positive values of CQ coefficients for $\tau_{EM} \in \{0.01, 0.05, 0.1, 0.3, 0.5, 0.7\}$ are observed at the zero lag ($k = 0$), which represents the same trading day in the US and in Poland. This observation can be attributed to the findings of Boyarchenko et al. (2021), who studied the overnight drift phenomenon in US equity returns. Boyarchenko et al. (2021) found that the trading during the full overnight trading session in the US market (4:15 p.m. on day $t-1$ to 9:30 a.m. on day t in US Eastern time) generated 2.6 percent annualized returns, accounting for more than half of the 4.3 percent annualized close-to-close return over the sample period. This phenomenon is related to trading S&P 500 futures, according to the article. In addition, in the US, overnight trading sessions also occur for stocks with a trading volume exceeding 10,000 US stocks and ETFs between 8:00 PM and 3:50 AM US Eastern time, Sunday to Friday. Thus, overnight trading provides important insights for interpreting and predicting the closing price on day t. Notably, most overnight trading in the US occurs between 2 a.m. and 3 a.m. US Eastern Time, coinciding with the opening of the European stock markets. The US market then opens at 9:30 a.m., often preceded by large negative returns, known as an "opening reversal" pattern, which lasts until 12 p.m. Consequently, when the US market opens, especially during a significant sell-off (i.e., the opening price is very low), this shock will be quickly diffused and absorbed into the Polish market on day t, even within a one-hour window of overlapping trading hours.

What is worth emphasizing, from Figure 4 we can see that there is also statistical evidence of directional predictability in the middle range of the distribution for WIG returns ($\tau_{\text{EM}} = 0.3, 0.5, 0.7$). This positive dependence persists over the next day, that is, for $k = 1$, as the sample CQ between large declines in the US stock market and next-day large declines in the Polish stock market remains high and significant for the left tail and middle range of the WIG distribution. For lags higher than one (i.e., $k > 1$), however, the magnitude of the positive CQ correlation between the large negative returns in the US and large negative returns in Poland, that is, the predictability from low-to-low quantiles, gradually decreases as the lag order increases. Nevertheless, CQ coefficients remain statistically significant even for orders higher than 20, which is in line with the large persistence of extreme conditional quantiles (Engle and Manganelli, 2004). At the median ($\tau_{\text{EM}} = 0.5$), the CQ coefficients are positive and statistically significant only up to lag $k = 1$. Accordingly, the CQ analysis based on daily data indicates that an S&P 500 return observed two or more days earlier has no predictive power for the current median WIG return. If the paradigm of efficient markets holds, or even under turbulent conditions where information leakage occurs, new information is transmitted very quickly, rendering older events from the US market less relevant (Brunnermeier, 2005; Wang, 2022). Interestingly, the spillover effect of the US market turns negative for high quantiles ($\tau_{\text{EM}} \in \{0.9, 0.95, 0.99\}$) of WIG returns and remains statistically significant at several lags, starting from $k = 2$. This means that at least two or more days after a sharp decline in the US, there is an increased likelihood that the WIG return will experience high positive values. However, this does not indicate that Poland can be perceived as a safe-haven market because the likelihood of the Polish market experiencing large positive and large negative returns is significantly heightened. This is documented by negative and significant CQ coefficients for the higher quantiles ($\tau_{\text{EM}} \in \{0.9, 0.95, 0.99\}$) and positive for the lower quantiles (i.e., $\tau_{\text{EM}} = 0.01, 0.05, 0.1$) at $k \geq 2$. Therefore, large decreases in US prices induce a persistent increase in the dispersion and/or kurtosis of WIG returns, and hence, a significant and long-lasting burst of volatility and increased market risk in the Polish stock market. This is reflected by the shift of the corresponding 0.1-quantile to the left and the 0.9-quantile to the right. As a result, the diversification benefit might be rendered infeasible in practice because a huge drop in the US market is followed by the Polish stock market, suddenly spiking or falling over the next few days, in line with heightened volatility. Our results contradict the findings of Labidi et al. (2018), who concluded that no spillover exists from the US market to the Polish stock market across different quantiles. In our opinion, this discrepancy arises because (i) our data are more up-to-date and include highly volatile periods such as the COVID-19 pandemic in 2020, the invasion of Russia on Ukraine in 2022, and the US elections in 2024, and even more importantly, (ii) because we examine quantile dependence starting from lag 0 using daily data, whereas of Labidi et al. (2018) began at lag 1 using a monthly frequency. It is important to note that with the rapid advancement of technology and financial products, the connection between financial markets has strengthened, and information spreads faster (Engle and Campos-Martins, 2023). Therefore, price fluctuations in the US market, especially during extreme negative events, have an almost immediate impact on other markets.

Figure 5: The sample CQ $\rho_\tau(k)$ with $\tau_{\text{US}} = 0.1$ to detect directional predictability from the US to China's stock returns



Note: Bar graphs describe the sample cross-quantilogram for $k \in \{0, 1, \ldots, 22\}$, and the horizontal curves denote the 95% bootstrap confidence intervals centered at zero.

Figure 5 illustrates the CQ coefficients for China. There is directional predictability of extreme negative US shocks to the Chinese market; however, it exists only within certain quantile-order ranges. Unlike for the case of Poland, the presented lag structure for CQ coefficients starts at lag 1 ($k = 1$), which is in line with the non-overlapping trading hours in these markets. Owing to the different time zones, the Shanghai Stock Exchange closes before the New York Stock Exchange opens. Therefore, any shock occurring in the US equity market on day t affects the Chinese market on day $t+1$. At lag ($k = 1$), the CQ coefficients are positive and statistically significant for $\tau_{\text{EM}} \in \{0.05, 0.1, 0.3\}$. Hence, similar to the case of Poland, when US stock prices collapse, the probability of observing large decreases in the Shanghai Shenzhen index in the period spanning up to one month increases significantly. However, compared to Poland, the magnitude of the Chinese market's dependence on the US is much lower, and CQ is less persistent. This result is akin to expectations, especially given the geopolitical differences, capital controls and regulations in China, and restrictions on foreign investors (see Chen et al., 2010; Kenett et al., 2012; Zhang, 2022). These substantial government restrictions and interventions are responsible for the observed decoupling of the Chinese market from the US market. Interesting results were obtained for $\tau_{\text{EM}} = 0.9$ and $\tau_{\text{EM}} = 0.95$, because the CQ coefficients are not significantly different from zero at lag 1 but are significantly negative for some higher lags, implying an increased likelihood of observing large jumps in the Shanghai Shenzhen index not one day after the US market collapsed but later.

5.3 CQ at matching quantiles across markets

Table 2 summarizes the CQ for all EMs across multiple lags, including daily, weekly, and monthly time frames. For the Americas and EMEA that feature partial overlap of trading sessions with the US, we present the CQ coefficients for lags $k \in \{0, 1, 2, 3, 4, 5, 22\}$; for the remaining EMs, we use lags $k \in \{1, 2, 3, 4, 5, 22\}$. The analysis focuses on the matching quantiles, either for the very low or very high quantile levels, that is, for $\tau_{\text{US}} \in \{0.01, 0.05, 0.1\}$, representing adverse scenarios, or $\tau_{\text{US}} \in \{0.90, 0.95, 0.99\}$) representing positive scenarios of the US stock market.

At first glance, the sample CQ between the US market and the EMs seems to exhibit similar patterns to those discussed previously for Poland and China. The highest positive CQ coefficients are always observed for lags $k = 0$ or $k = 1$. This suggests that, in the short term, very large upward (or downward) movements in EMs are positively associated with extremely positive (or negative) US returns. Although a few faint impact patterns are seen at lag 5, they almost disappear at lag 22, indicating statistically insignificant linkages between US stock returns and other EM stock returns in the longer term.

A noteworthy observation is that, within the extreme negative conditions, the CQ coefficients at the 0.01-quantile are markedly greater than those at the 0.05 and 0.1-quantile levels for most EMs in Latin America (excluding Chile) and EMEA. This suggests that extremely negative shocks tend to propagate more strongly and exert heightened effects. This phenomenon can be explained by the psychological effects of rare, severe, and unforecastable events. Such shocks trigger heightened investor

Table 2: The sample CQ, $\hat{\rho}_\tau(k)$, at the matching left-tail or right-tail extreme quantiles

		(2a). When the US market sharply decreases													
		$\tau_{EM} = 0.01$ and $\tau_{US} = 0.01$							$\tau_{EM} = 0.05$ and $\tau_{US} = 0.05$						
		$k=0$	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=22$	$k=0$	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=22$
Latin America	Brazil	**0.43**	**0.09**	**0.14**	0.10	0.10	**0.16**	0.05	**0.37**	**0.07**	**0.09**	**0.07**	**0.08**	**0.07**	0.04
	Chile	**0.29**	**0.14**	**0.10**	0.12	0.08	**0.12**	0.03	**0.35**	**0.13**	**0.06**	**0.07**	**0.08**	**0.05**	**0.04**
	Mexico	**0.48**	**0.14**	0.05	0.08	**0.08**	**0.12**	0.05	**0.42**	**0.08**	0.04	**0.08**	**0.08**	**0.09**	0.04
	Peru	**0.35**	**0.14**	**0.14**	**0.10**	0.06	**0.16**	0.05	**0.30**	**0.14**	**0.07**	**0.09**	**0.08**	**0.09**	0.04
EMEA	Czech Republic	**0.36**	**0.18**	**0.12**	**0.14**	**0.12**	**0.16**	**0.12**	**0.26**	**0.21**	**0.12**	**0.10**	**0.11**	**0.10**	0.05
	Poland	**0.42**	**0.16**	**0.10**	0.08	0.10	0.08	**0.11**	**0.27**	**0.18**	**0.10**	**0.06**	**0.10**	**0.07**	**0.04**
	Greece	**0.25**	**0.16**	0.10	0.08	**0.08**	**0.12**	0.09	**0.20**	**0.13**	0.07	**0.05**	**0.10**	**0.03**	0.04
	Hungary	**0.29**	**0.16**	**0.18**	**0.08**	0.10	0.10	0.05	**0.23**	**0.15**	**0.08**	**0.09**	**0.10**	**0.08**	
	Turkey	**0.20**	**0.08**	**0.10**	0.08	0.05	0.05	0.03	**0.23**	**0.15**	**0.08**	**0.09**	**0.10**	**0.08**	0.07
	UAE	-	**0.21**	**0.15**	0.10	0.06	**0.10**	0.06	-	**0.18**	**0.07**	**0.10**	**0.06**	**0.09**	**0.04**
	Qatar	-	**0.20**	**0.13**	0.13	**0.11**	**0.08**	0.08	-	**0.15**	0.05	**0.07**	**0.04**	**0.03**	
	Saudi Arabia	-	**0.12**	0.09	0.07	0.07	0.09	**-0.01**	-	**0.10**	**0.08**	**0.09**	**0.04**	**0.04**	0.03
	Egypt	-	**0.21**	**0.13**	0.11	0.04	**0.11**	0.09	-	**0.16**	**0.06**	**0.08**	**0.09**	**0.07**	0.04
	South Africa	**0.36**	**0.14**	0.08	**0.12**	**0.10**	0.10	0.07	**0.27**	**0.18**	**0.09**	**0.08**	**0.14**	**0.07**	**0.07**
APAC	China	-	0.03	0.01	0.01	0.01	0.01	**-0.01**	-	**0.13**	**0.08**	**0.04**	**0.04**	**0.08**	0.03
	India	-	0.07	**0.12**	0.09	0.09	0.07	0.07	-	**0.20**	**0.06**	**0.08**	**0.10**	**0.05**	**0.04**
	Indonesia	-	**0.24**	**0.13**	0.13	**0.09**	**0.13**	0.05	-	**0.23**	0.04	**0.11**	**0.06**	**0.07**	0.03
	Korea	-	**0.28**	**0.12**	**0.12**	**0.10**	**0.12**	0.03	-	**0.29**	**0.11**	**0.11**	**0.08**	**0.08**	0.03
	Malaysia	-	**0.16**	0.10	0.09	**0.07**	0.07	0.05	-	**0.25**	**0.07**	**0.12**	**0.06**	**0.10**	0.03
	Philippines	-	**0.22**	0.09	0.10	0.07	0.07	0.07	-	**0.23**	**0.08**	**0.07**	**0.05**	**0.05**	**0.04**
	Taiwan	-	**0.24**	0.07	**0.10**	0.03	0.07	0.01	-	**0.26**	0.08	**0.12**	**0.08**	**0.06**	0.04
	Thailand	-	**0.18**	**0.11**	**0.11**	**0.11**	0.05	0.01	-	**0.16**	**0.09**	**0.08**	**0.05**	**0.07**	0.02
	Vietnam	-	0.12	0.05	0.08	0.03	0.03	0.01	-	**0.16**	**0.08**	**0.07**	**0.05**	**0.06**	0.03

Note: Bolded values represent statistically significant values at the 5% level.

Table 2: The sample CQ, $\hat{\rho}_\tau(k)$, at the matching left-tail or right-tail extreme quantiles, cont.

		(2a). When the US market sharply decreases $\tau_{EM} = 0.1$ and $\tau_{US} = 0.1$							(2b). When the US market sharply increases $\tau_{EM} = 0.99$ and $\tau_{US} = 0.99$						
		$k=0$	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=22$	$k=0$	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=22$
Latin America	Brazil	**0.39**	**0.05**	**0.08**	**0.05**	**0.05**	**0.06**	0.02	**0.41**	**0.09**	0.07	0.03	0.05	**0.09**	0.09
	Chile	**0.29**	**0.12**	**0.07**	**0.04**	**0.08**	0.02	0.03	**0.18**	0.06	0.05	0.03	0.05	0.05	0.01
	Mexico	**0.40**	**0.08**	0.03	**0.04**	**0.05**	**0.09**	0.02	**0.48**	**0.06**	0.06	0.05	0.03	0.06	0.07
	Peru	**0.30**	**0.13**	**0.07**	**0.06**	**0.07**	**0.07**	0.03	**0.10**	**0.10**	0.03	0.06	**0.06**	0.03	0.07
EMEA	Czech Republic	**0.25**	**0.23**	**0.09**	**0.07**	**0.09**	**0.09**	0.03	**0.23**	**0.12**	0.03	0.03	0.03	0.08	0.03
	Poland	**0.27**	**0.17**	**0.08**	**0.06**	**0.09**	**0.06**	0.04	**0.25**	**0.12**	0.08	0.01	**0.06**	**0.06**	0.03
	Greece	**0.16**	**0.14**	**0.06**	0.03	**0.06**	**0.04**	**0.04**	**0.14**	0.01	0.01	0.01	0.05	0.05	0.01
	Hungary	**0.25**	**0.17**	**0.06**	**0.07**	**0.10**	**0.07**	**0.06**	**0.23**	**0.16**	0.06	**0.08**	0.08	0.06	**0.08**
	Turkey	**0.16**	**0.12**	**0.06**	**0.05**	**0.04**	0.03	-0.00	**0.12**	0.08	0.01	0.01	0.03	0.01	**-0.01**
	UAE	-	**0.13**	**0.04**	**0.06**	**0.07**	**0.06**	0.02	-	**0.17**	0.03	0.03	0.03	0.08	**-0.01**
	Qatar		**0.15**	**0.06**	**0.06**	0.03	**0.05**	0.02	-	0.08	**-0.01**	0.01	**-0.01**	**-0.01**	**-0.01**
	Saudi Arabia	-	**0.09**	**0.07**	**0.05**	0.01	0.03	0.03	-	0.04	**-0.01**	0.02	0.02	0.02	**-0.01**
	Egypt	-	**0.15**	0.03	**0.11**	**0.07**	**0.06**	0.02	-	0.06	0.01	0.01	**-0.01**	**0.06**	0.04
	South Africa	**0.25**	**0.19**	**0.05**	**0.06**	**0.07**	**0.08**	**0.06**	**0.23**	**0.12**	**0.12**	0.03	0.05	**0.10**	0.05
APAC	China	-	**0.13**	**0.05**	**0.07**	0.04	**0.06**	0.03	-	0.07	0.01	0.01	0.05	**-0.01**	0.01
	India	-	**0.19**	**0.09**	**0.08**	**0.06**	**0.06**	0.02	-	0.10	0.09	**0.09**	**0.07**	0.07	0.01
	Indonesia	-	**0.24**	**0.05**	**0.10**	**0.05**	**0.06**	0.03	-	**0.15**	**0.07**	0.05	0.05	0.05	0.01
	Korea	-	**0.27**	**0.07**	**0.09**	**0.06**	**0.07**	**0.05**	-	**0.14**	0.07	**0.11**	0.03	0.09	0.05
	Malaysia	-	**0.24**	**0.04**	**0.10**	**0.05**	**0.08**	0.03	-	**0.10**	0.05	0.03	0.03	0.05	0.03
	Philippines	-	**0.24**	**0.05**	**0.07**	**0.04**	**0.05**	0.01	-	**0.12**	0.07	0.05	0.03	0.07	0.09
	Taiwan	-	**0.26**	**0.07**	**0.11**	**0.05**	**0.08**	0.02	-	**0.16**	0.03	**0.09**	0.03	0.03	0.05
	Thailand	-	**0.17**	**0.11**	**0.07**	**0.05**	**0.05**	0.02	-	**0.15**	0.01	0.07	0.05	0.05	0.03
	Vietnam	-	**0.18**	**0.08**	**0.09**	**0.08**	**0.07**	**0.05**	-	**0.16**	0.05	**-0.01**	0.01	0.01	0.03

Table 2: The sample CQ, $\hat{\rho}_\tau(k)$, at the matching left-tail or right-tail extreme quantiles, cont.

		(2b). When the US market sharply increases													
		$\tau_{EM} = 0.95$ and $\tau_{US} = 0.95$							$\tau_{EM} = 0.9$ and $\tau_{US} = 0.9$						
		$k = 0$	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$	$k = 22$	$k = 0$	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$	$k = 22$
Latin America	Brazil	**0.32**	0.04	**0.06**	**0.06**	**0.05**	**0.04**	**0.05**	**0.35**	0.02	**0.04**	**0.05**	**0.03**	**0.05**	**0.04**
	Chile	**0.23**	0.09	**0.07**	**0.03**	**0.06**	**0.06**	0.04	**0.24**	**0.07**	**0.04**	**0.04**	**0.04**	0.03	0.02
	Mexico	**0.36**	**0.05**	**0.07**	**0.06**	**0.06**	**0.06**	**0.05**	**0.34**	**0.06**	**0.04**	**0.05**	**0.04**	**0.04**	0.03
	Peru	**0.19**	0.09	**0.05**	**0.05**	**0.06**	**0.04**	0.05	**0.21**	**0.06**	**0.05**	**0.04**	**0.04**	**0.04**	0.03
EMEA	Czech Republic	**0.18**	0.16	**0.07**	**0.07**	**0.06**	**0.09**	**0.07**	**0.19**	**0.14**	0.03	**0.06**	**0.06**	**0.07**	**0.04**
	Poland	**0.24**	0.13	**0.09**	**0.06**	**0.05**	**0.07**	0.04	**0.20**	**0.12**	**0.04**	**0.05**	0.01	**0.05**	**0.04**
	Greece	**0.14**	**0.05**	**0.03**	**0.02**	**0.06**	**0.02**	**0.04**	**0.15**	**0.09**	0.02	0.03	0.02	0.02	**0.06**
	Hungary	**0.20**	0.09	**0.06**	**0.05**	**0.05**	**0.06**	0.06	**0.17**	**0.08**	**0.05**	**0.04**	**0.04**	**0.06**	**0.04**
	Turkey	**0.13**	0.07	0.00	**0.03**	**0.01**	**0.04**	0.00	**0.14**	**0.08**	0.02	0.03	0.02	**0.04**	0.01
	UAE	-	0.10	**0.02**	0.00	**0.01**	**0.03**	0.01	-	**0.11**	0.02	0.01	0.02	0.02	0.01
	Qatar	-	**0.12**	**0.03**	**0.04**	**0.01**	**0.03**	0.00	-	**0.09**	0.03	**0.05**	0.01	**0.04**	-0.01
	Saudi Arabia	-	0.08	**0.03**	**0.02**	**0.03**	**0.02**	0.00	-	**0.09**	**0.05**	**0.04**	0.02	0.01	-0.01
	Egypt	-	0.11	**0.04**	**0.08**	**0.01**	**0.07**	**0.03**	-	**0.10**	**0.04**	0.04	0.03	0.03	0.01
	South Africa	**0.23**	0.17	**0.08**	**0.07**	**0.07**	**0.08**	0.07	**0.23**	**0.13**	**0.05**	**0.06**	**0.04**	**0.05**	**0.05**
APAC	China	-	0.06	**0.03**	**0.02**	**0.02**	**0.05**	**0.02**	-	**0.06**	0.02	0.02	0.02	**0.04**	**0.03**
	India	-	0.14	**0.08**	**0.05**	**0.04**	**0.06**	0.07	-	**0.12**	**0.05**	**0.06**	**0.05**	0.05	**0.05**
	Indonesia	-	**0.14**	**0.03**	**0.05**	**0.05**	**0.03**	**0.02**	-	**0.15**	0.01	**0.06**	0.03	0.03	0.03
	Korea	-	0.17	**0.04**	**0.08**	**0.03**	**0.08**	0.04	-	**0.17**	**0.03**	**0.06**	0.02	**0.05**	**0.03**
	Malaysia	-	0.13	**0.05**	**0.08**	**0.04**	**0.05**	**0.04**	-	**0.18**	**0.06**	**0.05**	**0.04**	**0.06**	0.05
	Philippines	-	0.17	**0.02**	**0.04**	**0.03**	**0.02**	0.02	-	**0.21**	0.01	0.02	0.01	0.02	0.00
	Taiwan	-	**0.19**	**0.04**	**0.06**	**.07**	**0.04**	**0.04**	-	**0.19**	**0.03**	**0.04**	**0.03**	0.03	**0.04**
	Thailand	-	0.11	**0.03**	**0.09**	**0.07**	**0.01**	0.05	-	**0.13**	0.03	**0.07**	**0.03**	0.03	**0.05**
	Vietnam	-	0.09	**0.03**	**0.03**	**0.04**	**0.05**	**0.02**	-	**0.09**	**0.03**	**0.03**	**0.03**	**0.05**	0.01

anxiety and panic-driven behavior, leading to overreactions to losses (see Kahneman and Tversky, 1982) and rapid and severe declines in the stock market across different regions within a short time frame. Another interesting finding is that the impact of the US market at the 0.01-quantile is predominantly much shorter than that at the 0.05 and 0.1 quantile levels. Interestingly, we find no evidence of quantile predictability at the 0.01-quantile, and hence, from extreme negative US returns to extreme negative returns in China. We argue that when events become extreme (at the 0.01-quantile), governments are compelled to implement strong and immediate intervention measures to promptly stabilize investor sentiment and mitigate adverse effects on domestic stock markets, as exemplified by the so-called "Tax Liberalization Day" on April 2nd, 2025, or during the COVID-19 pandemic period (see Reuters, 2025; Chang et al., 2021). This rationale may be relevant in understanding another notable phenomenon observed in Panel (a) of Table 2: unlike in Latin American and EMEA countries, the sample CQ values at the 0.01 and 0.05 quantile levels for emerging Asian markets do not exhibit substantially higher values relative to those at the 0.1 quantile level. As Asian markets are closed when extreme shocks emerge in the US market, policymakers in these countries may benefit from a brief but critical window to enact stabilizing measures before markets reopen the following day (see Liu et al., 2023). Therefore, to better uncover the fundamental dependence between the US and EMs, in the sequel of the analysis, we focus on the 0.1-quantile for negative shocks and the 0.9-quantile for positive shocks.

Compared with other areas of the globe, the CQ coefficients for Latin America are the highest, with the US-Mexico pair at the top, followed by the US-Brazil pair. Our findings are in line with Lahrech and Sylwester (2011), who documented a very high degree of comovement between emerging Latin American equity markets and the US market. Moreover, The Office of the U.S. Trade Representative (2024) show a substantial rise in bilateral trade between Latin America and the US over time. Hamilton (2024) shows that by far, Mexico has been the US's top trading partner. Furthermore, because of the entirely coinciding trading session times, shocks from the US market affect these markets instantaneously, that is, on the same trading day. For lag $k = 1$, although the impact remains statistically significant and positive, its magnitude is considerably lower.

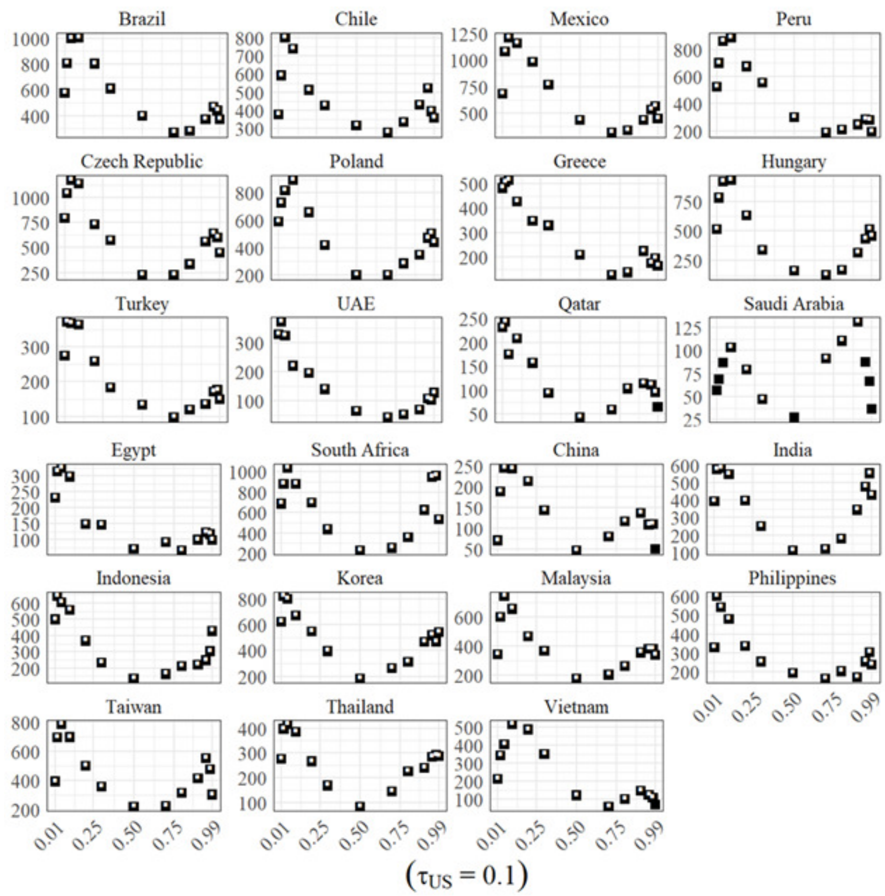
For the EMEA and APAC regions, the dependence patterns are similar, despite the CQ coefficients for $k = 0$ being much lower than those in Latin America. Furthermore, the quantile dependence is asymmetric, as evidenced by higher values of CQ coefficients for the left tail at the matching quantile orders $\tau_{\text{US}} = 0.1$ and $\tau_{\text{EM}} = 0.1$, compared to the right tail for $\tau_{\text{US}} = 0.9$ and $\tau_{\text{EM}} = 0.9$. In other words, in an optimistic market scenario, the pressure to adjust a trading strategy may not be as intense as in the pessimistic case (Kostopoulos et al., 2022). The result reaffirms the notion that during a severe downturn, due to increased risk aversion, all markets fall simultaneously as investors become more risk averse and can overreact, leading to losses spreading across other markets (see Berkelaar and Kouwenberg, 2009; Guiso,

2012; and Dahmene et al., 2021). Among the EMEA EMs, the Saudi Exchange is the most robust to negative shocks in the US, implying a promising place for international portfolio diversification. Interestingly, negative correlations are also observed between these markets at certain quantiles (i.e. $\tau_{EM} = 0.9,\ 0.95,\ 0.99$ and $\tau_{US} = 0.05$). This result also corroborates the study of (Cheng et al., 2010). Moreover, Qatar and the UAE are moderately affected by the US compared to other countries. In the literature, Gulf Cooperation Council (GCC) markets are, to some extent, considered to be segmented from international markets (see Elfakhani et al., 2008; Cheikh et al., 2018; and Bahloul and Amor, 2021). However, these EMs are very sensitive to regional political events (Charfeddine and Refai, 2019). Their stock markets are also heavily influenced by oil price movements, as these countries are large suppliers of oil to the global economy (Abuzayed and Al-Fayoumi, 2021; Mensi et al., 2021).
Regarding EMEA EMs with partial overlap of trading sessions with the US market (Czech Republic, Poland, Greece, Hungary, Turkey, and South Africa), for $k = 0$, the impact of the US market was strong. However, because the trading hours overlap by only approximately one hour, price fluctuations in the US on day $t - 1$ still significantly influence trading day t in these countries, albeit to a lesser extent. Another noteworthy highlight is the Chinese market. The CQ values for China are the lowest among the EMs in the APAC region, suggesting that the dependence between the US and Chinese markets is moderate, despite these economies being the two largest in the world. Even in the case of huge distress in the US market, its relationship with the next-day large price decreases in China is the lowest among the APAC countries. This finding is congruent with that of Mensi et al. (2023). Ouyang et al. (2025) recently also confirmed that China's market risk imported from external shocks on domestic financial markets is not as high as that of developed markets.

5.4 Monthly reactiveness to extreme US returns

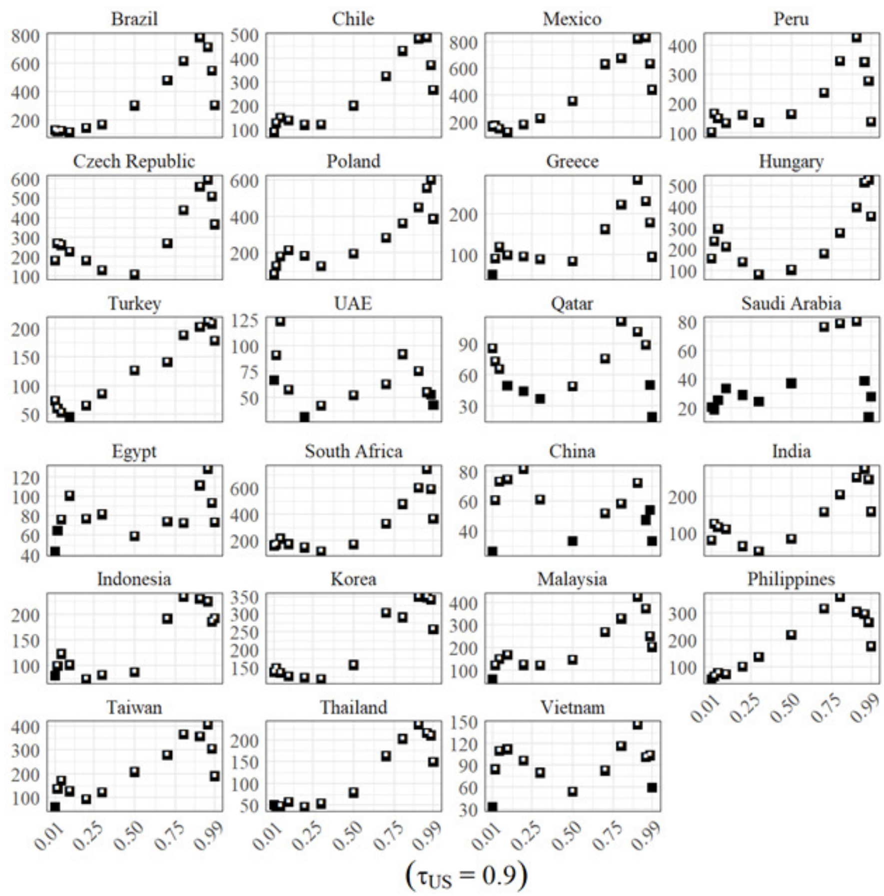
In Figures 6-7 we depict the CQ Ljung-Box test statistics $\hat{Q}^*_\tau(p)$, with $p = 22$ (see (3)), obtained for very large negative US returns ($\tau_{US} = 0.1$), or very large positive US returns ($\tau_{US} = 0.9$), respectively. The horizontal axis in each scatterplot represents the corresponding quantile orders for EM returns, while the vertical axis reports the values of the CQ Ljung-Box test statistics depicted as "squared" markers. These figures complement the former analysis of the persistence of the dependence of EM on US markets. This is because, based on (3), the $\hat{Q}^*_\tau(22)$ coefficient is, by definition, constructed as a weighted average of the squared CQ coefficients $\hat{\rho}_\tau(k)$ for $k \leq 22$. Accordingly, the magnitude of $\hat{Q}^*_\tau(22)$ (which is always positive) can inform us about the size of the longer-term impact of a large increase (or decrease) in US prices on future fluctuations in the different quantiles of EM returns. Because $\hat{Q}^*_\tau(22)$ aggregates (or cumulates) information about the reaction of the EM to US market movements on each day within a month (22 business days), we can treat this coefficient

Figure 6: CQ Ljung-Box test statistics at lag 22 ($\hat{Q}^*_\tau(22)$), presenting the degree of time-spread impact of a large negative US return ($\tau_{US} = 0.1$) on a EM return (at different quantiles)



Notes: The horizontal axis in each scatterplot represents the corresponding quantile orders for EM returns, while the vertical axis reports the values of the CQ Ljung-Box test statistics depicted with "squared" markers. The white dot on these markers indicates that a given CQ Ljung-Box test statistics is significant at 5% level.

Figure 7: CQ Ljung-Box test statistics at lag 22 ($\hat{Q}^*_\tau(22)$, presenting the degree of time-spread impact of a large negative US return ($\tau_{US} = 0.1$) on a given EM return (at different quantiles), cont.



Notes: The horizontal axis in each scatterplot represents the quantile orders for EM returns, while the vertical axis reports the values of the CQ Ljung-Box test statistics depicted with "squared" markers. The white dot on these markers indicates that a given CQ Ljung-Box test statistics is significant at 5% level.

as a synthetic (cumulative) measure of the monthly reactiveness of a given EM to the US market movements.

Two important observations can be made from Figure 6. First, the monthly reactiveness of EM to a large US price drop is different for different quantiles but seems to be the largest for the matching quantile $\tau_{\text{EM}} = 0.1$. This is vividly visible by the roughly L-shaped pattern formed by the scatterplots of $\hat{Q}^*_\tau(22)$ coefficients. As most of $\hat{Q}^*_\tau(22)$ values are statistically significant, all EMs are affected by the US's shock. However, these are the left distribution tails, and more specifically, the EM returns at the matching quantiles that react most significantly. Second, the Ljung-Box statistics are significant and highest for EM countries in Latin America, while the lowest values are observed for China and Middle Eastern markets. This provides further evidence that Latin American markets are the most strongly affected by adverse shocks originating from the US market. Apart from the extremely low and extremely high quantiles, the $\hat{Q}^*_\tau(22)$ coefficients for $\tau_{\text{EM}} = 0.5$ are also predominantly significant (except for Saudi Arabia), although the CQ Ljung-Box statistics are much lower than those corresponding to other quantiles. Third, Saudi Arabia's pattern diverges from that of other countries. The CQ Ljung-Box test statistics are significant only for some quantiles (that is, $\tau_{\text{EM}} = 0.1, 0.2, 0.3, 0.7, 0.8, 0.9$). Additionally, the statistics show the highest value at the 0.9-quantile but not at the corresponding 0.1-quantile. At the median and the extremes of the distribution, in both the left and right tail quantiles, the coefficient values are insignificant, which means that extremely negative US events are not helpful in predicting median or extreme returns on Saudi stocks.

Figure 7 shows that in the case of a very large spike in US returns, symmetrical patterns hold (except for the UAE, Qatar, and China), with the highest values occurring at the matching quantiles in the right tail ($\tau_{\text{EM}} = 0.9$). Nonetheless, when compared to the former case of large drops in the US market, the CQ Ljung-Box test statistics are significantly lower across all the quantiles. This result is consistent with the existence of asymmetric dependence structures induced by severe negative returns, as previously discussed in Sections 5.2-5.3. It is also worth noting that the CQ Ljung-Box test statistics are insignificant for some quantiles across multiple countries (Qatar, Saudi Arabia, and China), which implies that very high US returns show no directional predictability of these EMs' returns at particular quantiles.

5.5 CQ over turbulent periods

In this subsection, we investigate the impact of the US market on EMs during the 2008 GFC, COVID-19, and the Russia-Ukraine war. To this end, we distinguish three crisis sub-periods from the full dataset. According to the official timelines provided by the Bank for International Settlements (2009), the 2008 GFC period spanned from September 1, 2007, to December 31, 2009. For the COVID-19 pandemic, the first human cases were reported in Wuhan, China, on November 16, 2019. The World Health Organization (WHO) declared the COVID-19 outbreak a Public Health

Emergency of International Concern on January 30, 2020. Therefore, the COVID-19 period in this study spans from January 2020 to February 23, 2022, and to prevent the potential influence of the 2024 US election, the ongoing Russia-Ukraine war period spans from February 24, 2022, to October 2024.

Table 3 presents the CQ coefficients for $k = 0$ and $k = 1$ and three turmoil periods under investigation. A comparison of the CQ values reveals that during the 2008 GFC, the impact of the US market on EMs was the strongest. Specifically, almost all CQ coefficients are much higher during the GFC than during the COVID-19 pandemic, the Russia-Ukraine war, and the entire period under investigation. This can be explained by the different underlying causes of the crises. Unlike the 2008 GFC, which was rooted in systemic financial instability, the two latter turmoil periods were caused by health-related (COVID-19) or geopolitical (Russia-Ukraine war) issues. Our results support previous evidence that volatility and return spillovers from the US to EMs have varied over time and were particularly evident during the GFC (see Caporale et al., 2014; Bhowmik et al., 2022; among others). However, we also show that a large negative drop in US stock prices exerts a larger impact on EMs than a large positive US shock, and this holds true across several ranges of τ_{EM} values.

During the COVID-19 pandemic, the evidence of contagion effects is mixed; for $\tau_{\text{US}} = 0.1$, CQ coefficients that are higher than those corresponding to the entire period are observed for only 13 of the 23 countries (see Table 3). Interestingly, the spillover from the US market to Poland, Greece, Hungary, and South Africa during this period was even stronger than that during the 2008 GFC. In previous studies, Mensi et al. (2023) detected an increase in spillovers across selected stock markets during the COVID-19 pandemic. Mao et al. (2024) concluded that the COVID-19 pandemic has resulted in higher volatility in stock markets of US, China and India than was experienced during the 2008 GFC. Meanwhile, Choi (2022) confirmed that the interdependence between the US and Northeast Asia was stronger during the 2008 GFC than during the COVID-19 pandemic. Liu et al. (2020) showed the COVID-19 pandemic caused a huge slump in the global stock market, but then countries acted differently to cope with this turmoil. The researchers concluded that under the pandemic's impact, the speed of stock market readjustment depended on the development of the country's economy. Specifically, in higher-income countries, the stock market rebounded more swiftly than in lower-income countries. Moreover, Harjoto and Rossi (2023) found that stock markets in both developed and EMs recovered faster during the COVID-19 pandemic than during the 2008 GFC.

Very interesting results were obtained for China, as there was no directional predictability from US to Chinese returns in either distribution tail during the COVID-19 pandemic and the Russia-Ukraine war. There are two possible explanations for the distinct behaviors of the Chinese market. One explanation for this is that the COVID-19 pandemic originated in Wuhan, China. With this information advantage, China may have planned ahead to mitigate the potential disadvantages of its financial markets, including the stock market. The second explanation is

Table 3: Summaries on directional predictability, based on, $\hat{\rho}_{\tau}(k)$, from the US to EMs during turmoil periods

		When the US market sharply decreases ($\tau_{\text{US}} = 0.1$)											
		2008 GFC				COVID-19 pandemic				Russia-Ukraine war			
		$\tau_{\text{EM}} = 0.1$		$\tau_{\text{EM}} = 0.9$		$\tau_{\text{EM}} = 0.1$		$\tau_{\text{EM}} = 0.9$		$\tau_{\text{EM}} = 0.1$		$\tau_{\text{EM}} = 0.9$	
		$k = 0$	$k = 1$	$k = 0$	$k = 1$	$k = 0$	$k = 1$	$k = 0$	$k = 1$	$k = 0$	$k = 1$	$k = 0$	$k = 1$
Latin America	Brazil	**0.50**	**0.13**	**0.11**	-0.03	**0.40**	0.02	0.11	**-0.13**	**0.23**	-0.01	0.09	-0.09
	Chile	**0.49**	**0.14**	**0.09**	0.02	**0.31**	0.10	0.05	-0.01	**0.18**	-0.01	0.09	0.04
	Mexico	**0.65**	**0.10**	**0.11**	0.01	**0.56**	0.10	0.11	-0.06	**0.25**	0.08	0.09	0.01
	Peru	**0.40**	**0.12**	**0.11**	0.05	**0.39**	**0.14**	0.07	-0.01	**0.23**	0.14	0.09	0.01
EMEA	Czech Republic	**0.34**	**0.26**	**0.05**	**0.05**	**0.31**	**0.18**	-0.01	-0.01	**0.19**	**0.19**	-0.01	**0.09**
	Poland	**0.26**	**0.18**	**0.09**	0.05	**0.45**	**0.14**	0.03	-0.06	**0.21**	0.11	0.06	**0.06**
	Greece	**0.24**	**0.14**	**0.07**	-0.00	**0.34**	0.10	-0.02	-0.04	0.04	**0.19**	**0.09**	**0.09**
	Hungary	**0.26**	**0.22**	**0.11**	0.05	**0.37**	**0.20**	0.01	-0.01	0.13	**0.18**	0.02	-0.01
	Turkey	**0.32**	**0.16**	**0.09**	**0.07**	**0.27**	**0.08**	**0.07**	-0.02	0.01	0.01	**0.09**	0.04
	UAE	-	**0.33**	-	0.04	-	**0.15**	-	-0.09	-	0.09	-	0.04
	Qatar	-	**0.37**	-	0.02	-	**0.21**	-	- 0.07	-	**0.23**	-	0.05
	Saudi Arabia	-	**0.28**	-	0.01	-	0.05	-	-0.05	-	**0.20**	-	- 0.01
	Egypt	-	**0.38**	-	0.01	-	**0.27**	-	0.03	-	0.08	-	0.02
	South Africa	**0.30**	**0.24**	0.05	0.05	**0.33**	0.11	-0.01	-0.01	**0.16**	**0.11**	**0.06**	0.04
APAC	China	-	**0.15**	-	0.03	-	0.13	-	0.00	-	0.04	-	-0.04
	India	-	**0.25**	-	**0.07**	-	**0.25**	-	-0.02	-	**0.26**	-	0.04
	Indonesia	-	**0.37**	-	**0.09**	-	**0.25**	-	0.03	-	**0.20**	-	**0.09**
	Korea	-	**0.40**	-	0.04	-	**0.25**	-	-0.04	-	**0.19**	-	**0.09**
	Malaysia	-	**0.31**	-	**0.11**	-	**0.19**	-	**0.07**	-	**0.19**	-	**0.06**
	Philippines	-	**0.40**	-	**0.11**	-	**0.21**	-	0.05	-	**0.21**	-	0.01
	Taiwan	-	**0.33**	-	**0.11**	-	**0.30**	-	0.05	-	**0.27**	-	**0.11**
	Thailand	-	**0.15**	-	**0.07**	-	**0.21**	-	0.03	-	0.07	-	**0.06**
	Vietnam	-	**0.22**	-	0.05	-	**0.17**	-	0.03	-	**0.23**	-	0.02

Notes: The 2008 GFC period is from September 1st, 2007 to December 31st, 2009. The COVID-19 period was from January 1, 2020, to February 23, 2022. The Russia - Ukraine war period spans from February 24th, 2022, to October 30th, 2024. Owing to different trading hours, we set $k = 0$ and $k = 1$ for emerging countries in the Americas and EMEA, whose trading hours fully or partially overlap with the US market, and $k = 1$ for all other emerging countries.

Table 3: Summaries on directional predictability, based on, $\hat{\rho}_\tau(k)$, from the US to EMs during turmoil periods, cont.

		When the US market sharply increases ($\tau_{\text{US}} = 0.9$)											
		2008 GFC				COVID-19 pandemic				Russia-Ukraine war			
		$\tau_{\text{EM}} = 0.1$		$\tau_{\text{EM}} = 0.9$		$\tau_{\text{EM}} = 0.1$		$\tau_{\text{EM}} = 0.9$		$\tau_{\text{EM}} = 0.1$		$\tau_{\text{EM}} = 0.9$	
		$k=0$	$k=1$	$k=0$	$k=1$	$k=0$	$k=1$	$k=0$	$k=1$	$k=0$	$k=1$	$k=0$	$k=1$
Latin America	Brazil	0.09	0.01	**0.58**	0.05	0.09	-0.12	**0.39**	0.08	0.09	-0.06	**0.21**	0.06
	Chile	**0.11**	0.02	**0.38**	0.06	0.09	-0.01	**0.21**	0.08	0.09	0.04	**0.28**	**0.14**
	Mexico	**0.09**	0.01	**0.63**	0.01	0.09	-0.08	**0.27**	0.08	0.11	-0.03	**0.21**	**0.16**
	Peru	0.01	-0.01	**0.25**	**0.11**	0.11	0.01	**0.22**	0.03	0.11	-0.06	**0.31**	0.01
EMEA	Czech Republic	0.03	**0.05**	**0.24**	**0.22**	**0.07**	-0.08	**0.20**	0.10	**0.06**	-0.04	0.11	**0.16**
	Poland	**0.07**	0.03	**0.24**	**0.18**	**0.07**	0.01	**0.38**	0.04	**0.11**	-0.01	**0.26**	0.11
	Greece	0.04	**0.09**	**0.16**	**0.14**	**0.09**	-0.04	**0.26**	0.04	**0.06**	0.01	**0.18**	0.04
	Hungary	0.04	0.02	**0.26**	**0.12**	0.05	-0.08	**0.27**	0.04	0.01	-0.01	**0.20**	0.08
	Turkey	0.02	0.05	**0.28**	**0.18**	**0.07**	0.01	**0.21**	-0.04	**0.09**	0.01	-0.01	-0.01
	UAE	-	**0.11**	-	**0.21**	-	**0.06**	-	**0.15**	-	0.04	-	**0.23**
	Qatar	-	**0.09**	-	**0.15**	-	0.01	-	**0.15**	-	0.05	-	0.07
	Saudi Arabia	-	**0.08**	-	-0.01	-	-0.05	-	**0.21**	-	-0.01	-	**0.20**
	Egypt	-	**0.06**	-	**0.26**	-	**0.06**	-	0.13	-	-0.02	-	0.01
	South Africa	-0.01	**0.05**	**0.22**	**0.22**	**0.09**	-0.01	**0.29**	**0.12**	**0.09**	**0.06**	**0.23**	**0.23**
APAC	China	-	0.05	-	0.09	-	0.04	-	-0.00	-	0.03	-	0.12
	India	-	0.05	-	**0.19**	-	0.03	-	**0.21**	-	**0.09**	-	**0.26**
	Indonesia	-	0.01	-	0.09	-	0.03	-	**0.15**	-	0.01	-	**0.24**
	Korea	-	0.05	-	**0.14**	-	0.01	-	0.10	-	**0.06**	-	**0.24**
	Malaysia	-	**0.07**	-	0.03	-	0.05	-	**0.19**	-	**0.09**	-	**0.32**
	Philippines	-	**0.11**	-	**0.36**	-	0.03	-	**0.12**	-	0.04	-	**0.22**
	Taiwan	-	**0.11**	-	**0.23**	-	0.05	-	0.08	-	**0.09**	-	**0.32**
	Thailand	-	0.05	-	**0.13**	-	0.05	-	**0.13**	-	**0.09**	-	**0.22**
	Vietnam	-	**0.07**	-	**0.20**	-	0.05	-	0.02	-	**0.06**	-	0.06

the considerable restrictions and interventions (taxes, holding time requirements, laws, etc.) from the Chinese government in its financial markets. Moreover, as the second-largest economy in the world, China is globally acknowledged for its expanding influence on global economics over time, serving as a significant source of risk contagion (Greenwood-Nimmo et al., 2021). Compared to the existing literature, Ouyang et al. (2024) revealed that tail risk spillovers between the US and Chinese stock markets change with time. They found that from December 2016 to March 2020, China was the primary risk transmitter, and the US was the main recipient of tail risk. However, from March 2020 to March 2021, these roles were reversed, with the US becoming the primary transmitter and China the main recipient of risk.
The results in Table 3 show that the sample CQ during the 2008 GFC and the COVID-19 pandemic exhibits a similar pattern, with much higher CQ values for low-matching quantiles ($\tau_{\mathrm{EM}} = 0.1$ and $\tau_{\mathrm{US}} = 0.1$) than for high-matching quantiles ($\tau_{\mathrm{EM}} = 0.9$ and $\tau_{\mathrm{US}} = 0.9$). However, this pattern is unclear during the Russia-Ukraine war. Notably, during this period, the magnitudes of positive spillovers that exceeded negative spillovers were found for Chile, Peru, Poland, Hungary, the UAE, South Africa, and most Asian countries. To the best of our knowledge, this is a new result, as most studies confirm the stronger impact of negative shocks than positive ones (see Reboredo and Ugolini, 2016).

5.6 CQ vs. global uncertainty

As equity markets are highly sensitive to changes in different states of global uncertainty levels (Kirci Altinkeski et al., 2024), these conditions may also affect the linkages among the individual markets. For example, Chiang (2019), Long and and (2023), and Choi (2024) showed that market co-movement is affected by changes in US economic policy uncertainty (EPU). Moreover, Caldara and Iacoviello (2017) argue that increases in geopolitical risk depress economic activity and stock returns and increase capital flows from emerging to developed countries. Therefore, we employ partial CQ analysis to investigate the quantile dependence between the US and emerging stock markets under different states of global uncertainty. We control for four uncertainty measures: the VIX, Economic Policy Uncertainty (EPU), Equity Market-related Economic Uncertainty Index (EMU) proposed by Baker et al. (2016), and the Geopolitical Risk Index (GPR) developed by Caldara and Iacoviello (2022). Following Han et al. (2016), we adopt the VIX index calculated by the Chicago Board of Options Exchange. It represents the market's expectation of the S&P500 volatility over the next 30 days and reflects both investor sentiment and risk aversion. A higher VIX value corresponds to a higher level of stock market uncertainty, which adversely affects equity returns. Han et al. (2016); Kirci Altinkeski et al. (2024) documented that extreme negative stock returns are usually associated with sharp rises of the VIX index. EPU represents ambiguity about possible changes in government policy and its impact on firm performance and is positively correlated with uncertainty in financial markets (Smales, 2020). We used the first differences in

Table 4: Summaries on directional predictability, based on PCQ coefficients, from the US to EMs after controlling for economic state variables

		$\tau_{US}=0.1$ and $\tau_{EM}=0.1$								$\tau_{US}=0.9$ and $\tau_{EM}=0.9$							
		VIX		EPU		EMU		GPR		VIX		EPU		EMU		GPR	
		$k=0$	$k=1$	$k=0$	$k=1$	$k=0$	$k=1$	$k=0$	$k=1$	$k=0$	$k=1$	$k=0$	$k=1$	$k=0$	$k=1$	$k=0$	$k=1$
Latin America	Brazil	**0.20**	**0.04**	**0.39**	**0.05**	**0.39**	**0.05**	**0.39**	**0.05**	**0.26**	-0.00	**0.35**	0.02	**0.35**	0.02	**0.35**	0.02
	Chile	**0.12**	**0.08**	**0.29**	**0.12**	**0.29**	**0.12**	**0.29**	**0.12**	**0.17**	**0.05**	**0.24**	**0.07**	**0.24**	**0.07**	**0.24**	**0.07**
	Mexico	**0.22**	**0.05**	**0.40**	**0.08**	**0.40**	**0.08**	**0.40**	**0.08**	**0.27**	0.03	**0.34**	**0.06**	**0.34**	**0.06**	**0.34**	**0.06**
	Peru	**0.17**	**0.06**	**0.30**	**0.13**	**0.30**	**0.13**	**0.30**	**0.13**	**0.17**	**0.04**	**0.21**	**0.06**	**0.21**	**0.06**	**0.21**	**0.06**
EMEA	Czech	**0.11**	**0.13**	**0.25**	**0.23**	**0.25**	**0.23**	**0.25**	**0.23**	**0.12**	**0.07**	**0.19**	**0.14**	**0.19**	**0.14**	**0.19**	**0.14**
	Poland	**0.11**	**0.10**	**0.27**	**0.17**	**0.27**	**0.17**	**0.27**	**0.17**	**0.15**	**0.06**	**0.20**	**0.12**	**0.20**	**0.12**	**0.20**	**0.12**
	Greece	0.03	**0.05**	**0.16**	**0.14**	**0.16**	**0.14**	**0.16**	**0.14**	**0.12**	0.02	**0.15**	**0.09**	**0.15**	**0.09**	**0.15**	**0.09**
	Hungary	**0.12**	**0.10**	**0.25**	**0.17**	**0.25**	**0.17**	**0.25**	**0.17**	**0.12**	0.03	**0.17**	**0.08**	**0.17**	**0.08**	**0.17**	**0.09**
	Turkey	**0.09**	**0.10**	**0.16**	**0.12**	**0.16**	**0.12**	**0.16**	**0.12**	**0.13**	**0.05**	**0.14**	**0.08**	**0.14**	**0.08**	**0.14**	**0.08**
	UAE	-	**0.05**	-	**0.09**	-	**0.13**	-	**0.13**	-	**0.06**	-	**0.11**	-	**0.11**	-	**0.11**
	Qatar	-	**0.09**	-	**0.15**	-	**0.15**	-	**0.15**	-	**0.06**	-	**0.09**	-	**0.09**	-	**0.09**
	Saudi	-	**0.06**	-	**0.09**	-	**0.09**	-	**0.09**	-	**0.04**	-	**0.09**	-	**0.09**	-	**0.09**
	Egypt	-	**0.08**	-	**0.15**	-	**0.16**	-	**0.15**	-	**0.06**	-	**0.10**	-	**0.09**	-	**0.10**
	South Africa	**0.11**	**0.10**	**0.25**	**0.19**	**0.25**	**0.20**	**0.25**	**0.19**	**0.17**	**0.05**	**0.23**	**0.13**	**0.23**	**0.13**	**0.23**	**0.13**
APAC	China	-	**0.10**	-	**0.13**	-	**0.13**	-	**0.13**	-	0.03	-	**0.6**	-	**0.06**	-	**0.06**
	India	-	**0.12**	-	**0.19**	-	**0.19**	-	**0.19**	-	**0.07**	-	**0.12**	-	**0.12**	-	**0.12**
	Indonesia	-	**0.13**	-	**0.24**	-	**0.24**	-	**0.24**	-	**0.09**	-	**0.15**	-	**0.14**	-	**0.14**
	Korea	-	**0.17**	-	**0.27**	-	**0.27**	-	**0.27**	-	**0.09**	-	**0.17**	-	**0.17**	-	**0.17**
	Malaysia	-	**0.14**	-	**0.24**	-	**0.24**	-	**0.24**	-	**0.13**	-	**0.18**	-	**0.18**	-	**0.18**
	Philippines	-	**0.11**	-	**0.24**	-	**0.24**	-	**0.24**	-	**0.15**	-	**0.21**	-	**0.21**	-	**0.21**
	Taiwan	-	**0.14**	-	**0.26**	-	**0.26**	-	**0.26**	-	**0.10**	-	**0.19**	-	**0.19**	-	**0.19**
	Thailand	-	**0.10**	-	**0.17**	-	**0.17**	-	**0.17**	-	**0.08**	-	**0.13**	-	**0.13**	-	**0.13**
	Vietnam	-	**0.09**	-	**0.18**	-	**0.18**	-	**0.18**	-	**0.06**	-	**0.09**	-	**0.09**	-	**0.09**

Notes: The results of the PCQ coefficients are reported for matching quantiles.

the VIX as the first uncertainty measure. For the other three variables (i.e., EPU, EMU, and GPR), similar to Labidi et al. (2018), we applied the first differences between consecutive log values. Negative tail events in stock returns are often accompanied by pronounced surges in economic policy uncertainty and geopolitical risk indices. Note that for each controlling variable, we constructed the corresponding 'hit process' ('quantile exceedance process' or 'quantile event process'), as described in Section 3.2. Accordingly, large bursts of uncertainty correspond to events when the differences in the VIX (log EPU, log EMU, and log GPR) exceed the high quantiles of these variables. Thus, we assumed that upward jumps in uncertainty could quantitatively affect the impact of very large drops in US stock prices on EMs. Similarly, the large falls in uncertainty indices can be attributed to 'tranquil times' when international markets become less sensitive to bad news because of increased prospects of corporate earnings, *inter alia*. Each control uncertainty-oriented variable, defined as an appropriate hit process, was included separately when yielding the PCQ coefficients. Accordingly, when constructing the hit processes, we set a high quantile of each control variable ($\tau_3 = 0.9$) paired with a low quantile of US daily returns ($\tau_2 = 0.1$), while a low quantile of the uncertainty-oriented variable ($\tau_3 = 0.1$) was paired with a high quantile of US stock returns ($\tau_2 = 0.9$).
The PCQ coefficients are listed in Table 4. In line with the CQ analysis, controlling for uncertainty does not qualitatively alter the dependence structure among the markets under investigation. However, the PCQ coefficients are significantly smaller than the CQ coefficients after controlling for VIX quantile events (Table 2). The difference between the CQ and PCQ coefficients provides a quantitative measure of how strong VIX-related tail events affect EMs. We observe that the magnitude of the interquantile dependency measures is highly sensitive to the scale of uncertainty shocks in the US equity market. This indicates that VIX extreme movements significantly affect emerging stock markets and notably contribute to the overall transmission of shocks. In other words, changes in global risk, as proxied by large VIX movements, drive the emerging stock markets. These results underscore the importance of accounting for exogenous sources of risk when measuring interdependence across the stock markets. Second, the VIX impact is more pronounced at lower matching quantiles ($\tau_{US} = 0.1$ and $\tau_{EM} = 0.1$) than at higher quantiles ($\tau_{US} = 0.9$ and $\tau_{EM} = 0.9$); hence, during times of financial distress. Thus, we can deduce that severe increases in the VIX level are a significant explanatory factor for large decreases in EMs stock prices, and they carry (absorb) the impact exerted originally by the decreases in the US market. This corroborates the results of of Chuliá et al. (2017), who found that uncertainty shocks exacerbate market distress scenarios, leading to falling prices, whereas these effects are relatively small during bullish episodes. In line with expectations, small changes in the VIX do not absorb the effect of US stock price increases on EMs.
Finally, the differences between the magnitudes of the PCQ and CQ coefficients for the remaining three controlling variables were quantitatively negligible. In contrast to the

VIX quantile events, which capture market-based volatility and risk sentiment, EPU, EMU, and GPR have almost no impact on tail co-movement between the US and EMs for both bullish and bearish conditions. This suggests that the dependence between the US and emerging stock markets is not sensitive to these variables. The results imply that tail dependence is likely attributable to global uncertainty, as proxied by the VIX, rather than policy-related uncertainty or geopolitical risk. The literature also indicates that EPU does not play a significant role in bull markets (see Kundu and Paul, 2022), but plays a predominant role in times of turmoil (see Shi and Wang, 2023).

6 Conclusions

In this study, we employed the CQ approach to detect directional predictability from the US stock market to EMs. This method provides flexibility, allowing us to capture the direction, duration, and magnitude of the US's impact on EMs. Our findings extend the literature by providing detailed insights into quantile-to-quantile spillovers in a vast number of emerging economies. Several key findings of this study are highlighted. The shocks from the US, the world's largest stock market, have effects far beyond its shores and can be useful for predicting returns in the investigated EMs. First, the results support the notion that there are limited opportunities for diversification strategies in most majority of EMs amid periods of stress in the US. This is because, after a huge negative US return, the middle range of the distribution of EM returns follows in the same direction. The impact of the US on EMs is pronounced for extreme-to-extreme quantiles, emphasizing strong tail-risk dependencies. The strongest effect of the US market is observed for the shortest time horizons (on the same day and for one-day lags). The impact on EMs is also asymmetric, as the strongest effect in the US corresponds to extremely negative returns. Moreover, directional predictability is most pronounced between the US and emerging countries in the Americas, whereas it is very small for the Saudi Arabian market.

After splitting the data into subsamples, we documented increased connectedness between the US and EMs during the 2008 GFC, particularly at very low matching quantile orders. While the literature documents the enormous consequences of the 2008 GFC, we contribute to this body of evidence by comparing its impact with those of more recent periods of turmoil (the COVID-19 pandemic and the Russia-Ukraine war). We also show that systemic risk from the US is still present after controlling for selected uncertainty measures related to economic policy, the stock market, and geopolitics. However, our results show that the VIX-related quantile events have the most important effect on the dependence predictability from the US to EMs, especially during periods of extremely negative US returns. Our analysis has important implications for international investors in the sense that the VIX is an important consideration in extreme market scenarios, such as pronounced rallies or market distress, which, in turn, could provide relevant information for managing risk.

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Appendix

Table A1: Emerging markets under investigation

EMs		
Latin Americas	EMEA	APAC
Brazil	Czech Republic	China
Chile	Egypt	India
Colombia	Greece	Indonesia
Mexico	Hungary	Korea
Peru	Kuwait	Malaysia
	Poland	Philippines
	Qatar	Taiwan
	Saudi Arabia	Thailand
	South Africa	
	Turkey	
	UAE	

Notes: EMEA - Europe, Middle East, and Africa; APAC - Asia Pacific

Figure A1: Stock indices over the period 2004 – 2025