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THE BAYESIAN APPROACH TO MEASURING FINANCIAL CONTAGION

PODEJŚCIE BAYESOWSKIE W POMIARZE ZARAŻENIA FINANSOWEGO

This paper investigates financial contagion between the US and emerging European markets during recent turbulent periods, including the COVID-19 pandemic, the Russia-Ukraine war, the US presidential election, and changes in US tariff policy in 2025. The S&P 500 and STOXX Europe 50 indices are employed to capture global and regional factors affecting emerging markets in Europe. Using daily returns from January 2013 to April 2025, I conduct a structural break test and endogenously determine the start date of the COVID-19 pandemic. This approach avoids the arbitrary selection of crisis dates, allowing event timings and their market impact to be determined empirically. The paper then estimates returns models for individual emerging markets using the Bayesian approach. The results indicate that emerging countries' stock markets are more affected by regional factors than the US market. Moreover, there is a significant increase in the influence of the STOXX Europe 50 on emerging markets during periods of turmoil. Finally, the paper evaluates whether there is contagion across markets based on Bayesian estimation in the dynamic conditional correlation DCC model. To account for the heavy tails associated with financial returns, this paper assumes that the corresponding error terms follow a skewed Student's *t*-distributions. The findings also confirm stronger evidence of contagion from regional factors to the examined emerging markets during the episodes of market turmoil. Additionally, the results indicate interdependence, but no contagion, from the US market to emerging European markets.

Keywords: Bayesian approach; COVID-19 pandemic; DCC model; emerging markets; financial contagion
JEL: C51, C58, G15

Przedmiotem artykułu jest zjawisko zarażania finansowego pomiędzy rynkiem amerykańskim a rynkami wschodzącymi w Europie w okresach podwyższonej zmienności, następujących po kluczowych wydarzeniach o charakterze globalnym, takich jak pandemia COVID-19, wojna rosyjsko-ukraińska, wybory prezydenckie w Stanach Zjednoczonych oraz zmiany w polityce taryfowej USA w 2025 r. Do uchwycenia globalnych i regionalnych czynników wpływających na rynki wschodzące w Europie wykorzystano indeksy S&P 500 oraz STOXX Europe 50. Korzystając z dziennych stóp zwrotu z okresu od stycznia 2013 do kwietnia 2025 r., przeprowadzono testy strukturalnych przełomów i endogenicznie określono daty rozpoczęcia okresu pandemii COVID-19. Dzięki zastosowaniu tego podejścia unika się arbitralnego wyboru daty wystąpienia kryzysu, co pozwala na empiryczne określenie momentu zdarzenia oraz jego wpływu na rynek. Następnie oszacowano

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modele stóp zwrotu dla poszczególnych rynków wschodzących, stosując podejście bayesowskie. Wyniki badania wskazują, że rynki akcji w krajach wschodzących są bardziej podatne na czynniki regionalne niż na rynek amerykański. Ponadto w okresie zawirowań obserwujemy znaczący wzrost wpływu indeksu STOXX Europe 50 na rynki wschodzące. W zakończeniu artykułu zawarto ocenę, czy istnieje zjawisko zarażenia między rynkami, na podstawie estymacji bayesowskiej w modelu dynamicznej korelacji warunkowej (DCC). Aby poradzić sobie z ciężkimi ogonami związanymi ze zwrotami finansowymi, założono, że odpowiadające im błędy podążają za rozkładem skośnym *t*-Studenta. Wyniki potwierdzają również silniejsze dowody na zarażenie czynnikami regionalnymi rynków wschodzących w okresach zawirowań na rynku. Dodatkowo stwierdzono jedynie istnienie współzależności, a nie zarażenia, między rynkiem amerykańskim a rynkami wschodzącymi w Europie.

Słowa kluczowe: podejście bayesowskie; pandemia COVID-19; model DCC; rynki wschodzące; zarażanie finansowe
JEL: C51, C58, G15

I. INTRODUCTION

In recent years, technology and financial services revolutions have driven the deep and wide integration of global economic activities and interdependence across financial markets. From one perspective, this trend provides investors more opportunities to optimally allocate and restructure their investment portfolio globally. Markowitz (1952) suggested that investors might reduce the total variance of the portfolio through appropriate asset diversification. Global financial integration, however, also undermines the gain from diversification (Das & Uppal, 2004; Bekaert & Ang, 1999), especially in times of crises when co-movement between global financial markets increases (Chen et al., 2020). Along with the innovation of modern financial services, these trends have intensified the volatility linkages of international asset prices and corresponding cross-border contagion. The COVID-19 pandemic that broke out in 2019 devastated and challenged the stability of the global financial market (Deniz & Elif, 2021; Baker et al., 2020; McKibbin & Fernando, 2020; Zhang et al., 2020). Historically, the evolution of the disease and its economic impact were highly uncertain. Such uncertainty complicates the formulation of appropriate macroeconomic policy responses (Bloom et al., 2005; Chou & Kuo, 2004; Smith, 2006). In addition, previous studies find evidence of contagion from financial sector stocks to the real economy during turmoil periods (Deniz & Elif, 2021; Allen & Gale, 2000; Baur, 2012; Bittlingmayer, 1998; Chen et al., 2020; Kenourgios & Dimitriou, 2015; Ţilică, 2021). More recently, the US presidential election in 2024 and changes in US tax policy in 2025 exerted substantial influence on global equity markets. Throughout the period of crises, financial markets have been central and played a pivotal role in the global economy. Given the complexity and integration of the global financial system, it has become crucial for policymakers, regulators, and portfolio strategists to study contagion across financial markets during periods of turmoil.

It is also important to highlight the role of emerging markets in recent years. Compared to twenty years ago, emerging countries, in aggregate, play a significantly more prominent role, with increasing weight in the global economy. They account for more than half of global GDP (at purchasing power parity) as well as gross capital flows (Chițu & Quint, 2018). Developments in these economies could therefore have a sizable and significant impact on global outlook. Alongside ongoing capital account liberalization and domestic financial market development, emerging markets have become increasingly attractive to foreign investors, both for diversification purposes and for the acquisition of higher-quality assets. Nonetheless, the financial markets in such countries remain highly vulnerable to fluctuations in international capital flows. They have also been subject to bouts of financial market volatility (Stiglitz, 1998). Recent financial contagions have underscored the severe vulnerability of developing economies, which must contend with external speculative pressures and disturbances emanating from global financial markets (Chițu & Quint, 2018; Ruiz-Tagle, 2000). Large outflows during periods of financial turbulence have further increased the vulnerability of these economies. This phenomenon was observed when several equity price indices in the US, Europe and Asia plunged sharply immediately after the outbreak of the COVID-19 pandemic. To mitigate the impact of the pandemic, for the first time, many central banks implemented asset purchase programs and foreign exchange interventions to support the financial markets and the overall economy (International Monetary Fund, 2020). However, these economies remain exposed to risks due to significant recent global events. The seriousness of the current circumstances, along with the perceived level of systemic risk, has fueled the growing demand for a reassessment of financial globalization and its effects on emerging economies.

Within this context, to better understand possible effects of the COVID-19 pandemic and a series of recent geopolitical conflicts and events, this paper addresses two questions. First, whether international factors affect emerging European markets. Second, whether there is contagion across these markets during periods of turmoil. The motivation for the sample selection is that, when compared to other emerging markets, stock market development in Central-Eastern European post-transition economies has followed a similar trajectory, shaped by their shared history, capitalist model, the large-scale liberalization and privatization reforms (Kiss et al., 2024). Enhanced trade, financial integration, and convergence with Western Europe, along with the removal of capital barriers through European Union membership, have further stimulated these markets (Iloskics et al., 2021). However, these emerging markets are still undergoing numerous structural, political, social, and economic transformations (Ligocká, 2023; Zyznarska-Dworczak, 2018). These ongoing changes may significantly influence the development of stock markets in the region.

In this paper, I conduct a structural break test (the OLS-based CUSUM test) to determine the start dates of the COVID-19 pandemic from the US to the European market from January 2013 to April 2025. I then apply Bayesian statistics to return regression models for individual emerging stock markets with the US (global) and the European (regional) factors as the source of idiosyncratic shocks. The results show that the emerging stock markets in Europe are more affected by the regional impact (the STOXX Europe 50) compared to the US. Moreover, during the period of market turmoil following the outbreak of the COVID-19 pandemic, the coefficient of regional factors witnessed a substantial rise. Meanwhile, this paper finds no evidence of a broadening effect of the US. Finally, using the Bayesian approach in the DCC model with a skewed Student's t-distribution, I test for financial contagion from global and regional factors to emerging European markets. Our findings confirm that there was financial contagion from regional factors to the Czech, Greek, Polish, and Hungarian markets. For US markets, only interdependence is observed, with no evidence of contagion to emerging markets, except in the case of Hungary.

This paper contributes to the literature in three main ways: First, I analyse daily returns for five emerging stock markets in Europe using the Bayesian approach. Historically, numerous papers have studied financial contagion using this approach in times of crisis (e.g. the 2015 European Sovereign Debt Crisis, the 2008 Global financial crisis). However, to the best of our knowledge, few researchers used this approach to test for financial contagion during recent global periods of turmoil. Second, properly identifying the date of the onset of a crisis period is extremely crucial for the accurate testing of financial contagion (Adesanya, 2020). To address this concern, I use a structural break test (the OLS-based CUSUM test) which contains cumulative sums of standardized residuals, according to Bai and Perron (2003) and Zeileis et al. (2004), to determine the start date of the COVID-19 pandemic. Third, regarding the test contagion effect, apart from a t-test, a Mann-Whitney U test is also employed to obtain robust results.

The remainder of this paper is structured as follows. The next section conducts a literature review of dynamic financial interdependence and contagion across markets. In section III, the methodologies are described. Section IV reports data descriptive statistics, and empirical results. Section V contains some concluding remarks.

II. LITERATURE REVIEW

Financial contagion has been the subject of much attention and has been extensively studied for decades, especially during turbulent periods. This section reviews the existing empirical and theoretical literature on contagion.

There is still no consensus on how to define the term 'contagion' exactly. Generally, it refers to the spread of shocks, mostly on the negative side, from one market to others through a variety of channels (Claessens & Forbes, 2013). A more stringent definition focuses on cross-market linkages, whereby contagion is defined as a significant increase in cross-market linkages after a shock or crisis occurs in one market and spreads to others (Forbes & Rigobon, 2002). In empirical studies, this approach is important and intuitive, allowing straightforward statistical tests of the existence of contagion (Claessens & Forbes, 2013). In this paper, this convention is employed to evaluate the empirical work on this subject. Contagion may occur through direct channels, such as real economic linkages, or through indirect channels, including changes in investor behaviour and sentiment.

The COVID-19 pandemic that started in China fueled a surge of interest in international financial contagion in both developed and emerging markets. In the context of stock market contagion, with several econometric methodologies employed, Belaid et al. (2021), Bissoondoyal-Bheenick et al. (2021), Okorie and Lin (2021), So et al. (2021), and Yousfi et al. (2021) found significant contagion effects on stock market returns and volatility. For instance, based on the Diebold and Yilmaz spillover index and the Toda–Yamamoto and Dolado–Lütkepohl causality approach, Belaid et al. (2021) developed a combination of statistical methods to investigate the interdependencies between 22 advanced and emerging markets. Their results confirmed that during the COVID-19 pandemic, emerging markets were affected by advanced economies. Okorie and Lin (2021) found the fractal contagion effects of the COVID-19 pandemic on 22 stock markets using Detrended Moving Cross-Correlation Analysis and Detrended Cross-Correlation Analysis techniques. Yarovaya et al. (2022) provided a comprehensive review of the approaches and methodologies for studying financial contagion across four levels of information transmission.

In terms of currency markets, Gunay (2021) examined the effects of the COVID-19 pandemic and then compared it to the 2008 global financial crisis (GFC). He concluded that compared to the 2008 GFC, with the COVID-19 pandemic the total volatility spillover was about eight times higher. Several studies also investigated the correlation between stock markets and cryptocurrency and confirmed evidence of inverse correlations during the COVID-19 pandemic (Akhtaruzzaman et al., 2019; Akyildirim et al., 2020). These studies provided evidence that supports diversification strategies. Meanwhile, Conlon et al. (2020) and Corbet et al. (2020) found that cryptocurrencies did not serve as a safe haven for the majority of international equity markets examined, as they increased portfolio downside risk during the pandemic. From the firm-level perspective, Akhtaruzzaman et al. (2021) found that during the COVID-19 pandemic, financial firms in G7 countries and China experienced more severe and rapid contagion compared to non-financial firms. This phenomenon was also confirmed by Kenourgios and Dimitriou (2015), who concluded that some sectors seem to be less affected by the crisis.

One of the largest strands of the literature on detecting contagion focuses on analyses conducted during the 2008 GFC. These studies provide evidence of contagion effects from the US to both advanced and emerging markets (Baur, 2012; Bekiros, 2014; Dungey & Gajurel, 2014; Hwang et al., 2013; Luchtenberg & Vu, 2015; Nguyen et al., 2022; Zhang et al., 2013). On the other hand, Samarakoon (2011) found that there is no contagion from the US to emerging markets, except for Latin America during the GFC.

Due to the adverse effects of financial contagion, many argue that the changes in investors' sentiment in one market can lead to subsequent difficulties in others, rather than being attributed solely to their own economies. Moreover, like developing economies, emerging markets suffer the most regardless of whether global markets rise of fall (Claessens & Forbes, 2013; Gunay, 2021). To be effective in tackling the drawbacks of volatility and contagion, policy reform proposals must be based on a thorough understanding of financial contagion. Much more work on this subject is therefore necessary. This might provide practical information not only for investors in designing investment strategies but also for authorities seeking to respond proactively to market movements.

Furthermore, due to the presence of heteroscedasticity and the endogeneity of financial time series, the tests for contagion may be biased (Forbes & Rigobon, 2002). An increase in correlations might not imply contagion, but may simply be a continuation of strong transmission mechanisms that existed before. In addition, the existing literature has documented empirical evidence about financial contagion across markets during periods of turmoil, but the starting date of the pandemic is arbitrary. Absent an appropriate crisis start date, the results might be incomplete, and potentially incorrect (Adesanya, 2020). Meanwhile, a Bayesian framework is more flexible than a frequentist one and has become increasingly accessible and efficient (Bernardo, 2011; Lenart et al., 2021; Modrzejewska & Pajor, 2017; Mokrzycka, 2019; Osiewalski & Pajor, 2019; Osiewalski & Pipień, 2005; Osiewalski et al., 2020; Pajor & Wróblewska, 2017; Permai & Tanty, 2018; Wróblewska & Pajor, 2019). Moreover, when dealing with multivariate returns, the mutual dependence between markets should be taken into account. Combining Bayesian estimation in the DCC model with skewed Student's *t*-distribution provides greater flexibility to capture characteristic features of financial time series (Fioruci et al., 2014). Kumari et al. (2023) also argued that the financial network of the global stock markets changed significantly during the Russia-Ukraine war. Recently, the US presidential election and changes in US tariff policy significantly impacted global financial markets. Therefore, the persistence of this gap in the literature is not surprising and further research is required.

III. METHODOLOGY

To establish the start date of the COVID-19 pandemic, I conduct a test for structural changes (the OLS-based CUSUM test) which is based on Bai and Perron (2003) and Zeileis et al. (2004). Following Zeileis et al. (2004), I implement structural break tests using the daily data of European index (STOXX Europe 50 Index) and US stock returns (the S&P 500 Index). The STOXX Europe 50 allows us to deal with fewer time-series and estimate fewer break dates. The US return is utilized to interpret the European return and examine whether the coefficients in the linear regression model vary over time. The algorithm of Bai and Perron (2003) aims to obtain global minimizers of the sum of squared residuals based on the principle of dynamic programming, while Bayesian information criterion (BIC) is employed in selecting the number of breakpoints.

After identifying the start date of the COVID-19 pandemic, I measure the propagation mechanism from the US and the European factors to the emerging markets. In the preliminary analysis, using the approach of Vo (2019); Bekaert et al. (2014), the return equation for individual emerging markets is:

$$r_{t,i} = \beta_{0,i} + \beta_{t,i}^{US} r_{t-1}^{US} + \beta_{t,i}^{EU} r_t^{EU} + e_{t,i}, \tag{1}$$

where $r_{i,t}$ is the daily return of the stock index for country i at time t. r_{t-1}^{US} and r_t^{EU} are the US and Europe returns, representing global and regional contagion, respectively. The US stock market returns are used for US factors. This paper then orthogonalizes the STOXX Europe 50 returns by simply regressing them on the US stock returns and use the estimated residuals as the EU factor (Vo, 2019).

As there is a time zone difference between the US and European markets, the emerging markets in Europe close before the US market. Therefore, any shock of the US trading at time t–1 will affect the European markets at time t. Details on the Bayesian inference framework in Equation A1 are given in Appendix 2.[1] Our aim is to investigate whether the coefficients of the US and the Europe factors changed after the COVID-19 pandemic outbreak.

The presence of heteroskedasticity and heavy-tailed distribution in financial time series might lead to a bias in the estimated regression models. Therefore, the Bayesian DCC-GARCH model is employed to uncover contagion from the US and Europe factors to emerging markets.

DCC-GARCH model

Fioruci et al. (2014) consider a multivariate time series of stock returns $r_t = (r_{1t}, r_{2t}, ..., r_{kt})$, thus we have:

$$r_t = H_t^{1/2} \epsilon_t, \tag{2}$$

where H_t is the positive definite conditional covariance matrix and ϵ_t is independent and identically distributed error term, with $E(\epsilon_t) = 0$. This paper estimates the conditional correlation matrix using the DCC model of Engle (2002), specified as follows:

$$H_t = D_t R_t D_t, \tag{3}$$

[1] Appendices are available at https://doi.org/10.14746/rpeis.2026.88.1.09

D_t is a diagonal matrix with the conditional variances of each asset along the diagonal, $D_t = diag(h_{11,t}^{\frac{1}{2}}, \dots, h_{kk,t}^{\frac{1}{2}})$. Each conditional variance in D_t is specified based on a univariate GARCH model, as follows:

$$h_{ii,t} = \omega_i + \alpha_i y_{i,t-1}^2 + \beta_i h_{ii,t-1}, i = 1, 2, \dots, k, \tag{4}$$

with , $\omega_i > 0, \alpha_i \geq 0, \beta_i \geq 0$ and $\alpha_i + \beta_i < 1$.

R_t is the time dependent correlation matrix and given by:

$$R_t = diag\left(q_{11,t}^{-\frac{1}{2}} \dots q_{kk,t}^{-\frac{1}{2}}\right) Q_t\, diag\left(q_{11,t}^{-\frac{1}{2}} \dots q_{kk,t}^{-\frac{1}{2}}\right), \tag{5}$$

where the matrix $Q_t = (\rho_{ij,t})$ is positively definite and given by

$$Q_t = (1 - \theta - \vartheta)\bar{Q} + \theta u_{t-1} u_{t-1}' + \vartheta Q_{t-1}, \tag{6}$$

with $u_t = D_t^{-1} y_t$ are the standardized residual and $\bar{Q}$ being the unconditional variance matrix $k \times k$ of u_t. Also, θ and ϑ are the non-negative parameters satisfying $\theta + \vartheta < 1$.

The conditional likelihood function in Equation 2 is written as follows:

$$l(\delta) = \prod_{t=1}^{n} |H_t|^{-\frac{1}{2}} p_\epsilon\left((D_t R_t D_t)^{-\frac{1}{2}} r_t\right) = \prod_{t=1}^{n} \left[\prod_{i=1}^{k} h_{ii,t}^{-1/2}\right] |R_t|^{-1/2}\, p_\epsilon\left((D_t R_t D_t)^{-\frac{1}{2}} r_t\right), \tag{7}$$

where δ represents the set of all model parameters and p_ϵ *is* the joint density function of ϵ_t. To deal with the stylized features of financial time series, a skewed Student's t-distribution is employed.

The density function for this multivariate t-distribution is:

$$p_\epsilon = \frac{\Gamma((\upsilon+k)/2)}{\Gamma(\upsilon/2)[\pi(\upsilon-2)]^{k/2}} \left[1 + \frac{\epsilon_t' \epsilon_t}{\upsilon-2}\right]^{-(\upsilon+k)/2}, \tag{8}$$

where $\Gamma(.)$ is the Gamma function, and υ is the degree of freedom parameter.

Let γ denote the degree of asymmetry and follow Bauwens and Laurent (2005), for the multivariate skewed distribution, the density is constructed as follows:

$$s((x|\gamma) = 2^k \left(\prod_{i=1}^{k} \frac{\gamma_i \sigma_{\gamma_i}}{1+\gamma_i^2}\right) \frac{\Gamma((\upsilon+k)/2)}{\Gamma(\upsilon/2)[\pi(\upsilon-2)]^{k/2}} \left[1 + \frac{x^{*\prime} x^*}{\upsilon-2}\right]^{-(\upsilon+k)/2}, \tag{9}$$

where $x_i^* = \begin{matrix} \frac{x_i \sigma_{\gamma_i} + \mu_{\gamma_i}}{\gamma_i}\ if\ x_i \geq -\frac{\mu_{\gamma_i}}{\sigma_{\gamma_i}} \\ \left(x_i \sigma_{\gamma_i} + \mu_{\gamma_i}\right)\gamma_i\ f\ x_i < -\frac{\mu_{\gamma_i}}{\sigma_{\gamma_i}} \end{matrix}$.

A Bayesian approach is adopted to estimate DCC models with skewed and heavy tailed distributions for the errors.

Bayesian estimation in the DCC model

Bayesian estimation is implemented with the following steps: construct prior distribution, then update information from the data through the likelihood function, and finally obtain the posterior distribution (see Appendix 2). Following Fioruci et al. (2014) and Ardia (2006), coefficients in DCC-GARCH (1,1) the model has prior distributions as follow:

$$\omega_i \sim N(\mu_{\omega_i}, \sigma^2_{\omega_i}) I_{(\omega_i > 0)}, \alpha_i \sim N(\mu_{\alpha_i}, \sigma^2_{\alpha_i}) I_{(0<\alpha_i<1)}, \beta_i \sim N(\mu_{\beta_i}, \sigma^2_{\beta_i}) I_{(0<\beta_i<1)}, i = 1, 2, \dots, k.$$

The tail parameter, using the multivariate Student's t-distribution, is assigned a truncated $\upsilon \sim N(\mu_\upsilon, \sigma^2_\upsilon) I_{(\upsilon>2)}$. In equation 6, prior distributions of the parameters θ and ϑ are, respectively: $\theta \sim N(\mu_\theta, \sigma^2_\theta) I_{(0<\theta<1)}, \vartheta \sim N(\mu_\vartheta, \sigma^2_\vartheta) I_{(0<\vartheta<1)}$. The skewness parameters are based on truncated normal distributions on positive value, $\gamma_i \sim N(\mu_{\gamma_i}, \sigma^2_{\gamma_i}) I_{(\gamma_i>0)}$. Following Pesaran and Pesaran (2007)'s approach, the value of hyperparameter μ_υ is determined as the mean of the degrees of freedom estimated from the univariate t-GARCH model for each market. As proposed by Fioruci et al. (2014); the initial value of the μ_{ω_i} matrix is specified as 0.1 times the diagonal matrix of the sample variances. The remaining hyperparameters (μ_{α_i}; μ_{β_i}; μ_θ; μ_ϑ) are set as in the study by Fioruci et al. (2014). Since the full conditional posterior distributions are not of known form, the posterior distribution of parameters is built via the Metropolis-Hastings algorithm. New values are sampled in one block from a multivariate proposal distribution centered at the current state. The variance-covariance matrix is estimated as the negative inverse Hessian at the posterior mode. If optimization fails, a random-walk Metropolis is used to tune individual parameters, sampling from a normal distribution centered at its current value with the variance adjusted so that the acceptance rates stay between 0.20 and 0.50. In this case, the sample variance-covariance matrix is then scaled from the output of this algorithm.

Finally, in order to test contagion, our paper adopts the conceptual framework proposed by Forbes and Rigobon (2002). Let μ_1 and μ_2 denote the mean of conditional correlations between markets during the stable and turmoil periods, respectively. These conditional correlations are obtained by the Bayesian estimation in the DCC model.

The t-test hypotheses are:

H_0: $\mu_1 = \mu_2$ (No contagion),
H_1: $\mu_1 < \mu_2$ (Contagion).

Following Celık (2012), t-tests are employed to verify whether there is a significant increase in the mean of these correlation coefficients during the crisis period, which would imply the contagion effect. The critical value for the t-test at the 5% significance level is 1.65.

For the sake of comparison, I can also derive contagion by cross-comparing the results from t-test to the non-parametric Mann-Whitney U test (for median differences), hence supporting the results. The Mann-Whitney U Test makes no assumption about the distribution of a population. Let m_1 and m_2 denote the median of conditional correlations between markets during the stable and turmoil periods, respectively.

The Mann-Whitney U test hypotheses are:

$$H_0: m_1 = m_2,$$
$$H_1: m_1 \neq m_2.$$

IV. DATA AND RESULTS

1. Data

The paper employs a dataset comprising country-level stock returns for individual emerging countries, the regional European index (STOXX Europe 50), and the S&P 500 for the global element (all denominated in US Dollar). According to the Morgan Stanley Capital International MSCI (2025), emerging European countries are Greece, Poland, the Czech Republic, Turkey, and Hungary. Daily stock price data are extracted from the LSEG Workspace, covering the period from January 2013 through April 2025. This dataset comprises 2701 observations. Stock returns are computed as the differences in the logarithms of prices between two consecutive trading days:

$$r_{i,t} = \ln(p_{i,t}) - \ln(p_{i,t-1}) = \ln\left(\frac{p_{i,t}}{p_{i,t-1}}\right),$$

where $r_{i,t}$ denotes stock returns in market i on day t; $p_{i,t}$ and $p_{i,t-1}$ represent the stock price of each market at the close of day t and $t-1$, respectively.

Daily returns of the examined markets fluctuate around a mean of zero (see Appendix 1). The sharp decline in stock returns in all markets occurred during the COVID-19 pandemic. The outbreak of the Russia-Ukraine war also had a significant impact on stock markets in the region. Notably, substantial fluctuations are also observed at the end of 2024 and the beginning of 2025, coinciding with the US presidential election and changes in US tariff policies in April 2025. The question arises of whether financial contagion exists during the period of turmoil after the COVID-19 pandemic.

Table 1 presents the descriptive statistics of stock returns for the pre-COVID-19 and post-COVID-19 pandemic periods. It is evident that the standard deviation of returns is considerably higher than the mean, implying stock return series are quite far from their mean. Before the COVID-19 pandemic, the mean stock return in the US exceeded that of nearly all emerging

Table 1

Descriptive statistics for returns (January 2013 – April 2025)

Indices	S&P 500		STOXX 50		Czech		Poland		Greece		Hungary		Turkey	
	Pre	In	Pre	In	Pre	In	Pre	In	Pre	In	Pre	In	Pre	In
Mean	0.0003	0.0004	0.0001	0.0004	−0.0341	0.0008	−0.0001	0.0009	0.0000	0.0009	0.0003	0.0008	−0.0002	0.0001
Median	0.0006	0.0008	0.0001	0.0005	0.0437	0.0009	0.0001	0.0010	0.0011	0.0012	0.0011	0.0007	0.0001	0.0006
Max	0.0484	0.0909	0.0356	0.0827	0.0351	0.0814	0.0407	0.0800	0.1190	0.1035	0.0505	0.0821	0.0851	0.1865
Min	−0.0790	−0.1276	−0.0933	−0.1224	−0.0663	−0.1163	−0.0582	−0.1352	−0.0196	−0.1237	−0.0804	−0.1387	−0.0169	−0.1823
Stdv.	0.0084	0.0133	0.0094	0.0116	0.0097	0.0135	0.0091	0.0173	0.0201	0.0158	0.0126	0.0180	0.0204	0.0225
Skewness	−0.65	−0.88	−0.93	0.12	−0.59	−0.82	−0.58	−0.29	−1.15	−0.23	−0.34	−0.77	−0.65	−0.64
Kutosis	4.77	15.81	7.68	5.55	2.69	11.04	3.52	4.58	12.49	8.91	2.05	7.53	5.16	10.97
Jarque–Bera	34243^{***}		23875^{***}		30006^{***}		7559.9^{***}		13252^{***}		13243^{***}		8015^{***}	

Note. 'Pre' denotes the pre-COVID 19 period (from 1 January 2013 to 10 March 2020); 'In' denotes the turbulent aftermath period (from 11 March 2020 to 25 April 2025). *** indicates the significance level at 1%.

Source: the author's own compilation based on data from LSEG Workspace.

markets (except for Hungary). Conversely, the standard deviation of returns in the US is substantially lower than in these emerging markets, suggesting that emerging markets are more volatile than mature ones. Interestingly, throughout and after the COVID-19 pandemic, all indices show significant increases in mean returns, remaining positive across all markets. However, the standard deviation values in all markets have also surged dramatically, indicating the eruption of the COVID-19 pandemic caused greater fluctuations in equity markets.

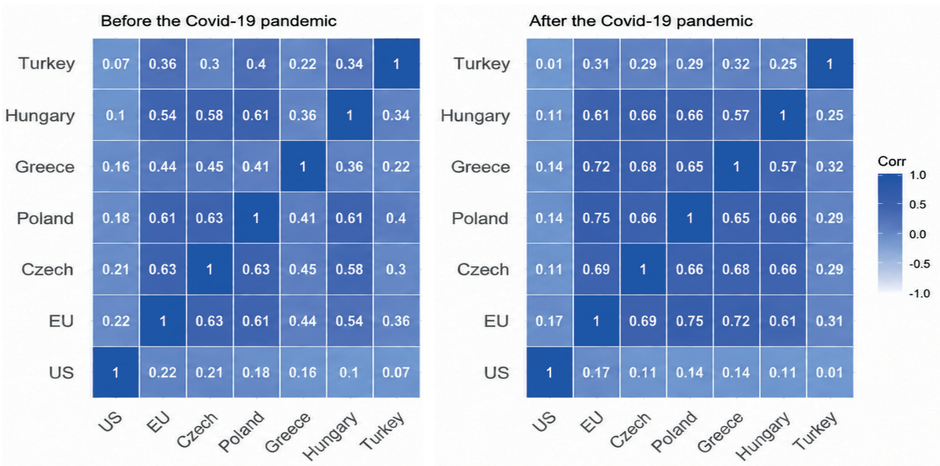
The skewness during the pandemic is left skewed. The stock returns' distributions for all markets are leptokurtic, which is typical of financial variables. Overall, our sample of daily stock returns have non-symmetrical distributions. Based on the Jarque–Bera test, our sample of daily stock returns exhibits non-normal distributions. Therefore, a skewed Student's *t*-distribution is employed.

2. Results

In this section, I first identify the breakpoint corresponding to the beginning of the COVID-19 pandemic. Second, a linear regression for emerging markets based on the Bayesian approach is employed. Finally, this paper presents the results for the financial contagion test employing the DCC-Bayesian method.

Figure 1

Heat map of pairwise unconditional correlations over the entire period 2013–2025



Source: the author's own compilation based on LSEG Workspace.

To determine the breakpoint, the regional index (STOXX 50) and US stock returns are incorporated into the linear regression model according to Bai and Perron (2003) and Zeileis et al. (2004). Following Amar et al. (2021); Schwarz

(1978), the Bayesian Information Criterion (BIC) is then utilized to support these results. Based on the results, the identified date is 11 March 2020. In reality, on this date, the World Health Organization (WHO) officially declared that COVID-19 was a global pandemic. In March 2020, the global stock market was hit by the COVID-19 pandemic, as traders panic-sold panic-sold out of fear. The US stock market triggered the circuit breaker mechanism four times within a two-week period that March. Concurrently with the US crash, stock markets in Europe and Asia experienced substantial declines. Due to uncertainty around the global coronavirus pandemic, central banks and authorities intervened immediately by implementing unprecedented policy instruments into the market.

The unconditional correlation between the US and emerging markets is quite low during the study period (see Figure 1). Meanwhile, the unconditional correlation within emerging countries and between the emerging markets and the regional European index are relatively high. During the global health crisis and the subsequent period, not only a rise in country-specific risks in stock markets is expected but also an increase in systemic risks. Interestingly, the unconditional correlations between the US and emerging markets are consistently low and exhibited a declining trend between 2020 and 2025. Meanwhile, these unconditional correlations within emerging countries and between them and the European regional index rise through time.

Table 2

Coefficient (Median) of the regression model (Equation A1) with the Bayesian approach

Country	US		EU	
	Pre-Covid	Post-Covid	Pre-Covid	Post-Covid
Czech	0.202	0.140	0.628	0.791
Poland	0.199	0.228	0.755	1.098
Greece	0.315	0.203	0.920	0.948
Hungary	0.110	0.176	0.727	0.928
Turkey	0.111	0.110	0.757	0.758

Source: the author's own compilation based on LSEG Workspace.

The medians of coefficients in the regression models based on the Bayesian approach for emerging stock markets are presented in Table 2. Due to space limitations, the full results are available from the author upon request. There is evidence that the regional European index had a stronger influence on emerging markets than the US market, notably throughout the tumultuous period following the COVID-19 pandemic.

These results raise two questions about whether there was contagion from the regional index to individual emerging markets and whether there was contagion from the US to these countries during the COVID-19 pandemic. In order to answer these questions, I conducted a test of contagion based on conditional correlation coefficients which are derived from the Bayesian estimation in the DCC-GARCH model with skew Student's *t*-distributions. To have robust empirical results, I proceeded with pairwise equality testing among a series of sub-samples using a *t*-test (based on conditional means, following Celık, 2012) and a Mann-Whitney U test (based on conditional medians). The results for these tests are reported in Table 3.

In the light of the test results, it is striking to find that there was no contagion from the US market to emerging markets. For the majority of the examined emerging countries, this paper finds evidence of interdependence, and contagion in the limited case of Hungary. Numerous studies have documented that the dramatic movement in the US stock market during the 2008 GFC had a strong impact on other markets across the globe (Aloui et al., 2011; Baur, 2012; Bekaert et al., 2014; Guo et al., 2011; Hwang et al., 2013; Mollah, et al., 2016). The results in this paper can be explained by the unique characteristics of the COVID-19 pandemic and the causes of the associated events. The COVID-19 pandemic originated with causes outside of economic factors, different from the previous 2008 GFC. Likewise, the Russia-Ukraine war and the US presidential election are mainly shaped by geopolitical issues. However, their consequences have a heavy impact on all global economies. In addition, Amar et al. (2021) also confirmed that during the COVID-19 pandemic, instead of the US market, the European stock index (SPEUR) had a major effect on market sentiment and influenced all the other indices. The results are also in line with Nguyen et al. (2022), implying that the US market influenced the other markets to a lesser extent during the COVID-19 pandemic. Compared to other countries in the region, Turkey appears to be the least affected. Agyei (2023) also confirmed that Turkish stocks possess significant diversification potential for investors.

During the turbulent period from 2020 to 2025, all the studied emerging markets in Europe, except for Turkey, exhibit significant increases in conditional correlations, suggesting contagion with the regional index. The results are consistent with theories of geographical financial linkages (Bekaert & Mehl, 2019; Carrieri et al., 2007; Hardouvelis et al., 2006). Within the same geographic region, having many similarities in terms of market structure as well as tight trade and finance linkages, any fluctuation from the regional index is quickly passed on to emerging countries. Moreover, almost all the emerging markets in Europe belong to the European Union, which has similar macroeconomic conditions, and asset market linkages are becoming greater. Belaid et al. (2021) also confirmed that during the COVID-19 pandemic, the financial markets of advanced economies in Europe appeared to be the primary driver of contagion and transmission of contagion to all other regional markets. Moreover, due to their geographical proximity to the war zone, the Russia–Ukraine war appears to have had a more pronounced impact on European Union stock markets. In addition, Kiss et al. (2024) confirmed that these Central-Eastern European stock markets exhibited strong intra-regional in-

Table 3

Conditional correlation of daily returns (1 January 2013 – 25 April 2025)

Indices	**US**					**EU**				
	Pre-	In-	*t*-statistic	U statistic	Contagion	Pre-	In-	*t*-statistic	U statistic	Contagion
Czech	0.210	0.140	–	–	N	0.607	0. 634	−38.01***	221,280***	C
Poland	0.172	0.147	–	–	N	0.614	0. 711	−137.16***	5,260***	C
Greece	0.200	0.168	–	–	N	0. 436	0. 642	−230.33***	2,076***	C
Hungary	0.098	0.104	−5.20***	73217***	C	0. 533	0. 561	−31.59***	282,756***	C
Turkey	0.069	0.040	–	–	N	0. 372	0. 291	–	–	N

Note. The stable period before the COVID-19 pandemic is from 1 January 2013 to 10 March 2020. The turmoil period is determined from 11 March 2020 to 25 April 2025. '*C*' indicates that the *t*-value is greater than the critical value, and thus contagion has occurred. '*N*' indicates that the *t*-value is less than or equal to the critical value and therefore there is no contagion. *** indicates the significance level at 1%.

Source: the author's own calculations based on LSEG Workspace.

teractions and were significantly affected by shocks from major Western European stock markets (Germany, Austria, France, and the Netherlands).

To sum up, our findings suggest that following the COVID-19 pandemic, the level of dependence between the US market and emerging ones in Europe decreased. The results also indicate decisive evidence of contagion from the regional index (the STOXX 50) to all emerging markets, except for Turkey.

V. CONCLUSIONS

The COVID-19 pandemic and recent global events have continued to be remarkable in their severity and effect on the global economy. This paper aims to investigate the global financial contagion in European equity markets during the period following the COVID-19 pandemic outbreak. Despite being the world's largest economy, this paper finds no evidence of contagion from US markets to emerging European markets (except Hungary). Meanwhile, contagion exists from the STOXX 50 index to the studied emerging equity markets, including the Czech Republic, Greece, Poland, and Hungary.

From the investor's perspective, if market correlations increase after a negative shock, this would largely undermine the rationale for international diversification. Significant changes in cross-market linkages, therefore, might influence investors' portfolio decisions. Consequently, investigating stock market contagion can enhance our comprehension of investors' decisions regarding optimal portfolio diversification strategies. Evidence of financial contagion could also justify multilateral intervention to deal with periods of turmoil. For instance, the detection of financial contagion would underscore the necessity for interventions by organizations such as the International Monetary Fund to deal with the crisis at the global level and mitigate systemic exposure to further contagion. These results may also provide practical guidance for policymakers responsible for prudential oversight of the financial system, enhancing the economy's resilience to financial contagion.

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