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Price Spillovers from Decentralized Finance to CEE Stock Markets

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Abstract

Decentralized finance (DeFi) is a brand-new disruptive procedure that encourages the use of blockchain technology for developing and distributing a variety of financial goods and services. This study investigates the time-varying and asymmetric interplay between DeFi and CEE stock returns, concentrated around the COVID-19 outbreak and the Russo-Ukrainian conflict. While the associations between other cryptocurrencies and conventional assets have been studied, DeFi assets have not. For this purpose, we employ the multivariate DECO-GARCH model and cross-quantilogram framework. The results reveal a positive equicorrelation between DeFi and CEE stock market returns. Notably, the influence of DeFi on CEE stock markets is greater during the COVID-19 outbreak and the Russo-Ukrainian conflict than in the other periods. Furthermore, the cross-quantilogram estimations uncover that CEE stock markets depend less on the DeFi market at longer lag lengths. This means that the diversification benefits of DeFi against CEE stock market returns are more important for long-run investment horizons. In general, our research offers a new understanding of dependence structures, which might help investors make better investment decisions and direct their trading strategies.

Keywords: DeFi, stock markets, DECO-GARCH, cross-quantilogram, CEE regions

JEL Classification: C58, G11, G15

1. Introduction

Since their launch, blockchain-based digital asset classes have sparked the interest of portfolio managers and investors as an alternative investing platform (Chowdhury *et al.*, 2023). New blockchain asset classes such as decentralized finance (DeFi), together with other well-known traditional

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cryptocurrencies, have significantly contributed to the asset market's recent growth (Chu *et al*., 2023). Along with the remarkable success of traditional cryptocurrencies, blockchain technology has resulted in a market valuation of over 1 trillion USD for NFTs (non-fungible tokens) and DeFi-related products (Ghosh *et al*., 2023). Moreover, NFTs and DeFi have effectively attracted significant media and investor attention while being relatively specialized in the digital financial markets, which ultimately led to a large capital inflow.

DeFi is quickly becoming another watershed moment in global finance's technological growth (Yousaf *et al*., 2022). It is a new umbrella word for certain financial services that operate peer-to-peer with no centralized authority (Corbet *et al*., 2022). Online wallets, margin trading, lending, spot trading, borrowing, the provision of interest-earning assets, market-making and derivatives are all examples of this. One could say that DeFi loans do not require physical collateral (Corbet *et al*., 2023). It marks a paradigm shift and calls for rethinking the typical financial institution services now offered, which have been damaged by the COVID-19 outbreak and the low interest rate environment (Yousaf *et al*., 2022).

It is worth noting that traditional banking and financial assets have an indisputable effect on sectoral returns, which has been extensively contrasted in the financial literature (Wang *et al*., 2022). Nevertheless, the influence of novel financial assets such as DeFi on sector portfolio performance is an issue that has received little attention in the financial literature (Yousaf *et al*., 2023; Corbet *et al*., 2022). With this study, we take the initial steps towards identifying how to explore the association between DeFi and stock returns, especially in the setting of economic and financial instability, such as COVID-19 and the Russo-Ukrainian crisis. Due to their role as risk-diversifying or risk-hedging assets, DeFi assets are priceless for many investors regardless of their market value, and a portion of the population who cannot access traditional banking receives incredibly helpful services from them, and they are, of course, more affordable than standard financial services (Bennett *et al*., 2023). Therefore, investing in various digital asset classes has consequently grown in popularity among all market participants. In general, DeFi assets differ from standard cryptocurrencies; hence, it is critical to investigate the patterns of interconnection between these assets and more conventional ones.

Early evidence suggests that DeFi markets have been considerably detached from the dynamics of conventional financial markets such as natural resources, bonds and stocks (Bejaoui *et al*., 2023). Nevertheless, current evidence on the safe haven and hedging characteristics of DeFi is inconclusive and seems to change over time. For example, Piñeiro-Chousa *et al*. (2022) documented that DeFi, like other cryptocurrencies, serves as a safe haven. Cevik *et al*. (2022) suggested that DeFi tokens can offer efficient hedging for investors in gold and crude oil. Nevertheless, according to Yousaf *et al*. (2023), the optimal hedge ratios between DeFi and stock markets increased somewhat during the COVID-19 period. In recent publications, scholars have acknowledged that more research into the relationship between DeFi and conventional financial assets is required (Cevik *et al*., 2022; Corbet *et al*., 2022; Yousaf *et al*., 2023). Therefore, the present paper advances this line of study.

Investors are increasingly interested in cryptocurrencies (Cevik *et al*., 2022). In other words, investors, financial institutions, regulators and policymakers have all become more interested in them. Currently, blockchain and fintech are two of the most important tools used by financial technology pioneers (González-López, 2022). The ability to use cryptocurrencies as a form of payment in a growing number of countries as well as support from businesses such as Meta, Tesla, Starbucks, Microsoft, Dell, etc., in the USA are evidence of the growing interest in cryptocurrencies (Gambarelli *et al*., 2023). Recently, Bhimani *et al*. (2022) conducted a thorough examination of the proliferation of cryptocurrencies across economies.

The growth of cryptocurrencies, DeFi and NFTs has accelerated since the COVID-19 outbreak, with a total market value of approximately 3,000 billion USD expected in November 2021. Despite the recent crises of many crypto market participants and the dramatic decline in total market value, crypto continues to develop, with over 22,000 coins traded on over 530 exchanges in December 2022 (Gambarelli *et al*., 2023). Despite not being intended for investment, cryptocurrencies have drawn more and more savers, particularly young retail investors. Indeed, the interdependence of digital currencies in industrialized countries has attracted much attention over the years.

In fact, Jeris *et al*. (2022) carried out a thorough study of the cryptocurrency-stock market nexus utilizing 151 papers from 2008 to 2021 and discovered that several articles had investigated such a link in emerging economies, particularly in the European region. Against this backdrop, we study the impact of DeFi on CEE stock market returns, as analysing the co-movement of crypto-CEE stock market pairs in a time-varying framework can provide additional insights for portfolio managers and investors in relation to diversification benefits.

We hypothesize a weak connection between DeFi assets and conventional financial markets based on the most recent findings in the literature (Cevik *et al*., 2022; Karim *et al*., 2022; Yousaf *et al*., 2022; Wang *et al*., 2022; Corbet *et al*., 2022). Since DeFi assets are somewhat novel and obscure financial vehicles, they may be disconnected from other assets due to information asymmetry (Şoiman *et al*., 2023). Nevertheless, it has lately been clear that the volatility of cryptocurrency markets can affect other assets that have little or minimal link with traditional assets (Yousaf *et al*., 2022). Modern portfolio theory holds that when markets are loosely correlated, portfolios provide more diversification benefits (Fabozzi *et al*., 2002).

The creation of a new crypto asset class dubbed DeFi tokens is one of the most recent innovations in the field of digital finance. It is important to note that the existence of a new token class will be used to increase diversification if it has unique drivers for its price changes. DeFi, known as a new market in the crypto universe, is made possible by the use of blockchain technology in many areas. If their price innovations are sufficiently distinctive, this characteristic enables us to utilize these assets in diversification strategies. For instance, González-López (2022), Corbet *et al*. (2023) and Chowdhury *et al*. (2023) have disclosed that DeFi tokens demonstrate several idiosyncratic properties that make them potentially a separate asset class.

This study explores the interaction between DeFi and Central and Eastern European stock markets (CEE-5), including Hungary, Poland, the Czech Republic, Romania and Croatia, for the period from June 2019 to May 2023. DeFi is a relatively recent technology, and there has not been much research based on price spillovers (Piñeiro-Chousa *et al*., 2022). As a result, it is a preliminary investigation into this new field.

In the context of CEE countries, in recent years, market development in emerging economies with a very high and stable growth rate has been particularly noteworthy in CEE countries, and they are typically solid selections for market participants seeking to diversify their portfolios globally (Joseph *et al*., 2020; Hung, 2020b; Živkov *et al*., 2023). In other words, in terms of investment, portfolio allocation and diversification, CEE economies have numerous key traits. In addition, the macroeconomic effects of regional financial integration also include a seamless transmission of monetary policy signals from the European Central Bank, which is crucial for countries that are currently a part of or are planning to join the euro area soon. It should be emphasized that the mission statement of the Eurosystem specifically mentions enhancing financial integration (Beck and Stanek, 2019). Therefore, the main objective of this study is to conduct an in-depth analysis of the dynamic intercorrelation that exists between DeFi and stock markets, and considering empirical research into the time-varying relationship between CEE stock and DeFi markets has been required in the context of portfolio diversification and hedging techniques.

In this article, we take into account time-varying return spillovers between DeFi and CEE-5 stock markets over the period 2018–2023. Recent COVID-19 and Russo-Ukrainian crises have made stock markets in the CEE area more integrated with cryptocurrency markets (Corbet *et al*., 2023; Ahmed *et al*., 2023; Hung and Vo, 2023). This paper examines the linkages and dependence structures between DeFi and CEE-5 stock markets using the multivariate DECO-GARCH model proposed by Engle and Kelly (2012) and the cross-quantilogram (CQ) framework introduced by Han *et al*. (2016). The DECO model produces a single dynamic correlation coefficient that quantifies the degree of asset connection. As a result, the DECO model allows us to assess market integration across the CEE stock and DeFi markets using a single number rather than evaluating each pairwise correlation to investigate market co-movements (Demiralay and Golitsis, 2021; Kang *et al*., 2019). More specifically, by displaying the most likely combinations in their extreme quantiles, a CQ can study the predictability of spillovers for substantial lags (Dai *et al*., 2022), which allows us to highlight dependencies between DeFi and stock returns during adverse and extreme circumstances (Sinha *et al*., 2022). Furthermore, the cross-quantilogram technique is independent of moment conditions and is able to calculate all *k* lags concurrently, making it resistant to misspecification errors (Naeem *et al*., 2022). It also estimates granular dependency among quantiles while accounting for noise and structural changes in the non-linear associations between two variables (Razzaq *et al*., 2022). Thereby, we utilize the DECO-GARCH model and the CQ approach to highlight the market integration and extreme quantile dependencies between DeFi and CEE stock markets.

Overall, the present study aims to fill the practical gap regarding the time-varying impact of the DeFi market on CEE stock returns by using the multivariate DECO-GARCH model and the cross-quantilogram approach. Only a few studies, to our knowledge, have specifically examined the connection between DeFi and stock markets in a variety of emerging economies. In contrast to previous work, this study is the first to investigate the equicorrelation and extreme dependences between DeFi and CEE stock markets. Additionally, by comparing such associations with the outbreak of the COVID-19 epidemic and the Russo-Ukrainian war, this study contributes to the current discussion about the comovement of diverse asset classes with the occurrence of extraordinary and unexpected events. Our work also utilizes the CQ, which concentrates on the left tail of the distribution, to examine the effectiveness of the DeFi market as a hedge against market declines on stock markets.

The rest of the study is organized as follows: Section 2 represents the related literature. Section 3 presents the data and methodology. Section 4 shows the empirical results. Section 5 provides a discussion and Section 6 concludes.

2. Literature Review

The dynamic relationship between stock returns and crypto assets has been empirically investigated by numerous scholars (Bejaoui *et al*., 2023; Tiwari *et al*., 2019; Hung, 2020a; Alshater *et al*., 2023). In this sense, several academics have shifted their attention to advanced countries in order to investigate the connections between cryptocurrencies and stock markets (Wang *et al*., 2022; Umar *et al*., 2020). Few studies, however, have looked into this connectedness in developing countries (Bejaoui *et al*., 2023). Additionally, a thorough examination of cryptocurrency studies published from 2009 to August 2018 by Corbet *et al*. (2019) revealed that there are several gaps in the literature on the subject. Despite being a new technology, DeFi is now the subject of a subfield of cryptocurrency literature (Yousaf and Yarovaya, 2022). According to Yousaf *et al*. (2022), the term "DeFi" (decentralized finance) is a newly coined umbrella term for a variety of financial services that function peer-to-peer in the absence of a centralized authority. In this section, we present the nexus between DeFi and financial assets.

Bejaoui *et al*. (2023) investigated the dynamic nexus between GCC and BRICS stock returns with digital assets, namely NFTs, DeFi and gold, and determine the nontrivial time-varying relationship between DeFi and stock returns. Yousaf and Yarovaya (2022) revealed weak static price and risk transmissions between NFTs and DeFi assets and major financial markets. Put differently, they suggested that DeFi is still somewhat decoupled from conventional asset classes. Piñeiro-Chousa *et al*. (2022) documented that DeFi acts, similar to other crypto assets, as a safe haven. In the same vein, the study done by Cevik *et al*. (2022) investigated the intercorrelation between natural resources and DeFi assets and revealed that the return and volatility structure of natural resources are affected by DeFi, especially during times of crisis. Moreover, Şoiman *et al*. (2023) reported that DeFi markets are influenced by their own network characteristics as well as the bitcoin market. Additionally, Karim *et al*. (2022) documented remarkable volatility spillovers between NFTs, DeFi and cryptocurrencies.

Another study by Yousaf *et al*. (2022) looked into the price connectedness between four well-known DeFi assets using the spillover index. Their results support dynamic price spillovers and a sharp increase in market connectivity between DeFi and currencies during the COVID-19 timeframe. More specifically, the authors also indicated that during the first COVID-19 year, DeFi markets mostly served as net shock transmitters. Wang *et al*. (2022) demonstrated that speculative bubbles occur in both the NFT and DeFi sectors; however, NFT bubbles are more prevalent and have larger average explosive magnitudes than DeFi bubbles. Furthermore, price bubbles in the NFT and DeFi markets are strongly linked to market enthusiasm and overall market instability on the cryptocurrency market. Similarly, Corbet *et al*. (2022) evaluated drivers of DeFi token prices and test the impact and connectedness between bitcoin, DeFi and Google Trends. The authors highlighted varying causal links between these variables, but these relationships are limited to bear markets. Corbet *et al*. (2023) focused on the persistence of bubbles in traditional and DeFi-focused cryptocurrencies, arguing that the DeFi market should be considered a different asset class from traditional cryptocurrencies. Recently, Chowdhury *et al*. (2023) analysed the asymmetric multifractal characteristics of NFTs, cryptocurrencies, DeFi and conventional markets. The findings reveal that DeFi-DigiByte is the most efficient, while cryptocurrency-Tether is the least efficient. According to Chu *et al*. (2023), returns on DeFi prices appear to be notably positive in certain circumstances but negative in others when the trading volume is experiencing large rises.

Research has also asserted that DeFi may contribute to diversification. Ali *et al*. (2023) employed the TVP-VAR technique to examine the interaction between industrial metals, precious metals and DeFi assets. Their results disclose that the association between DeFi and metal markets is weaker compared to the nexus between conventional precious and industrial metals. Additionally, DeFi assets had a significant relationship with other markets during the COVID-19 crisis. Based on the same method, Ghosh *et al*. (2023a) revealed that automated market makers have strong connections with DeFi during the COVID-19 and Russo-Ukrainian crises. Similarly, the predictive performance rationalizes the framework's ability to precisely estimate the prices of the majority of NFTs and DeFi assets throughout the present financial crisis (Ghosh *et al*., 2023b).

In light of the needs of the market, it emerges from the literature survey that there is not enough evidence provided by recent research. Interestingly, the DeFi-stock relationship has become an interesting topic for global investors (Corbet *et al*., 2023). The present study uncovers several gaps in the discussion of the aforementioned literature. Although there are some studies that centre on the connection between DeFi and major financial assets, and some investigate the price spillovers between DeFi and stock markets, relatively little research is conducted that looks into the transmissions to and from the DeFi markets, in particular to and from CEE stock markets along with the DeFi assets. This innovative type of digitized financial asset is often regarded as distinct from existing standard cryptocurrencies (Yousaf *et al*., 2022). More importantly, the influence of DeFi on CEE stock markets during the recent COVID-19 pandemic and the Russo-Ukrainian war is also taken into account. In addition, our research offers DeFi-tested investors with a more thorough grasp of the features of this new asset class, particularly in times of crisis. Moreover, the present paper also tackles the literature gap regarding the CEE stock returns by addressing the following key concerns: Do DeFi market shocks have a significant impact on CEE-5 stock prices? Is there a difference in the effect of DeFi fluctuations when viewed from different angles? What is the financial basis for the interaction between the DeFi and CEE stock markets during crises? It is imperative to examine these issues so as to comprehend the origins of DeFi price changes and how they affect the behaviour of CEE stock returns. As it helps illustrate opportunities for investors to deliver the best portfolio returns, it is necessary to examine the interplay between the DeFi market and CEE stock markets.

Furthermore, based on the above discussion of existing literature, the equicorrelation and dependence structures between DeFi and CEE-5 stock markets have not yet been explored. We employ both the multivariate DECO-GARCH model and the cross-quantilogram approach to capture the equicorrelation and the directional quantile predictability between DeFi and CEE stock markets. The proposed empirical approaches improve our study by implicitly taking into account the effect of the high volatility that the DeFi market experienced during the COVID-19 outbreak and the Russo-Ukrainian war on CEE stock returns.

3. Methodology

This section depicts the empirical methods. It starts with a multivariate DECO-GARCH model introduced by Engle and Kelly (2012), which estimates the equicorrelation between DeFi and CEE stock markets. We also utilize the cross-quantilogram developed by Han *et al*. (2016), which determines extreme dependence structures among these markets.

3.1 DECO-GARCH model

The DECO-GARCH model, suggested by Engle and Kelly (2012), can remove the computational and presentational challenges of high-dimension systems. The DECO model is a specific instance of the DCC model in which all asset pairs have equal correlations, but their common equicorrelation varies with time. The return on the stock return *i* at the time *t* and DeFi can be written as follows:

$$r_t = \mu + \alpha r_{t-1} + \varepsilon_t \tag{1}$$

$$h_t^2 = \omega_i + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma\varepsilon_{t-1}^2 I_{t-1} \tag{2}$$

where r_t is the stock returns and h_t^2 represents the conditional variance; $\varepsilon_{t-1} < 0$, we have $I_{t-1} = 1$, α depicts the effects of earlier squared errors on the current conditional variance, β captures the effects of lagged volatility on the current volatility, γ shows the asymmetric effects of positive and negative shocks. Let us denote $\mathbf{H}_t$ as the conditional covariance matrix:

$$\mathbf{H}_t = \mathbf{D}_t^{1/2}\mathbf{R}_t\mathbf{D}_t^{1/2} \tag{3}$$

where $\mathbf{R_t}$ is the conditional correlation matrix and $\mathbf{D}_t$ is the diagonal matrix of conditional variance.

The DECO specification is derived from Engle's (2002) DCC model, which corresponds to the correlation matrix; $\mathbf{R}_t^{\mathbf{DDC}}$ can be defined as:

$$\mathbf{R}_t^{\mathbf{DDC}} = \left(Q_t^*\right)^{-\frac{1}{2}} Q_t \left(Q_t^*\right)^{-\frac{1}{2}} \tag{4}$$

$$Q_t = (1 - \psi - \zeta)K + \psi\eta_{t-1}\eta'_{t-1} + \zeta Q_{t-1} \tag{5}$$

where $\psi + \zeta < 1$, η_t represents the standardized residuals and unconditional covariance matrix of η_t is $\mathbf{K}$ $(n \times n)$. $\mathbf{R}_t^{\mathbf{DECO}}$ in the equicorrelation form as follows:

$$\mathbf{R}_t^{\mathbf{DECO}} = (1 - \rho_t)\,\mathbf{I}_n + \rho_t\mathbf{J}_n \tag{6}$$

where the conditional equicorrelation is ρ_t, $\mathbf{I}_n$ is the *n*-dimensional identity matrix and $\mathbf{J}_n$ presents the unit matrix $(n \times n)$.

The DECO model sets ρ_t equal to the average DCC correlations:

$$\rho_t^{DECO} = \frac{1}{n(n-1)}(\mathbf{J}'_n\mathbf{R}_t^{\mathbf{DDC}}\mathbf{J}_n - n) = \frac{2}{n(n-1)}\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \tag{7}$$

The scalar version of the DECO model can be written as:

$$Q_t = \left(1 - \lambda - \pi\right)K + \lambda\eta_{t-1}\eta'_{t-1} + \pi Q_{t-1} \tag{8}$$

3.2 Cross-quantilogram approach

The cross-quantilogram (CQ) introduced by Han *et al*. (2016) is also employed to measure the dependence structures for different quantile pairs of DeFi and stock markets. Therefore, this model is appropriate for capturing the potential asymmetric nexus or different time investment horizons or directionality between markets.

Let us consider two stationary time series as $\{x_{i,t}, t \in Z\}$, $I = 1, 2$. In the present study, $x_{1,t}$ and $x_{2,t}$ stand for the DeFi and CEE stock markets, respectively. The density and distribution functions of the series $x_{i,t}$ are denoted as $f_i(.)$ and $F_i(.)$. The quantile of $x_{i,t}$ is expressed as $q_i(\alpha_i) = \inf\{v: F_i(v) \geq \alpha_i\}$ for $\alpha_i \in (0, 1)$, and the expression of two-dimensional series of quantiles is written by $q_1(\alpha_1)\ q_2(\alpha_2))^\tau$ for $\alpha \equiv (\alpha_{1,}\ \alpha_2)^\tau$.

The cross-quantilogram for α-quantile with k lags can be written as:

$$\rho_\alpha(k) = \frac{E\left[\Psi_{\alpha 1}\left(x_{1,t} - q_1(\alpha_1)\right)\Psi_{\alpha_2}\left(x_{2,t-k} - q_2(\alpha_2)\right)\right]}{\sqrt{E\left[\Psi^2_{\alpha 1}\left(x_{1,t} - q_1(\alpha_1)\right)\right]}\sqrt{E\left[\Psi^2_{\alpha_2}\left(x_{2,t} - q_2(\alpha_2)\right)\right]}} \tag{9}$$

For $k = 0, \pm 1, \pm 2, \ldots$, and where $\psi_\alpha(\mu) \equiv 1\ [\mu < 0]$, 1(.) represents the indicator function and $1[x_{i,t} \leq q_i(\alpha_i)]$ is the quantile exceedance process.

Han *et al*. (2016) established the test statistic of Ljung–Box:

$$Q^*_\alpha(\rho) = T(T+2)\sum_{k=1}^{p} \widehat{\rho}^2_\alpha(k)/(T-k) \tag{10}$$

where $\widehat{\rho}^2_\alpha(k)$ is the sample cross-quantilogram, which is given as:

$$\widehat{\rho}^2_\alpha(k) = \frac{\sum_{t=k+1}^{T}\Psi_{\alpha 1}\left(x_{1,t} - q_1(\alpha_1)\right)\Psi_{\alpha_2}\left(x_{2,t-k} - \widehat{q}_2(\alpha_2)\right)}{\sqrt{\sum_{t=k+1}^{T}\Psi^2_{\alpha_1}\left(x_{1,t} - \widehat{q}_1(\alpha_1)\right)}\sqrt{\sum_{t=k+1}^{T}\Psi^2_{\alpha_2}\left(x_{2,t-k} - \widehat{q}_2(\alpha_2)\right)}} \tag{11}$$

where $\hat{q}_{i,t}(\alpha_i)(i = 1, 2)$ represents the estimated quantile function for each variable.

The cross-quantilogram based on the bootstrapped sample is:

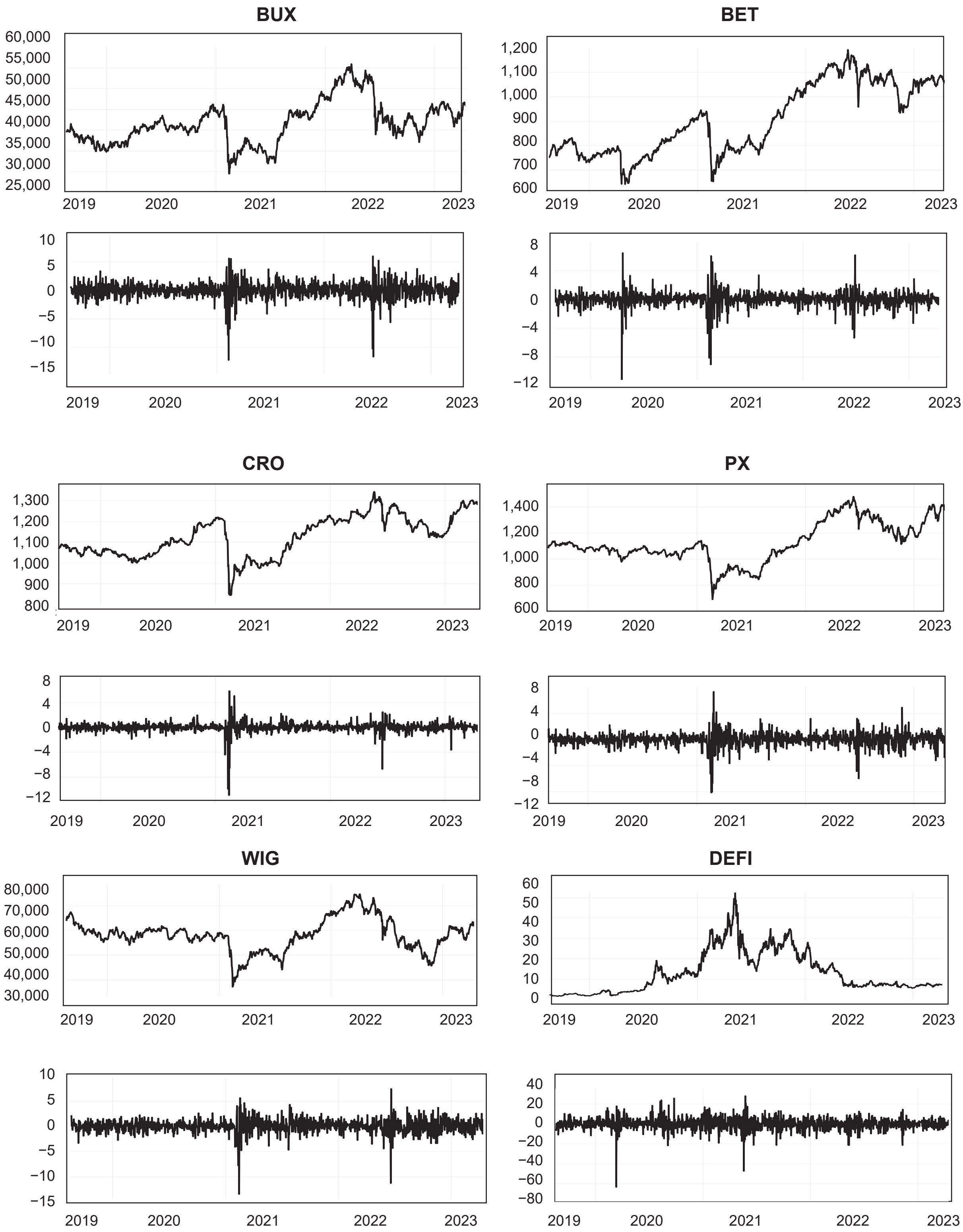
$$\widehat{q}^*_\alpha(k) = \frac{\sum_{t=k+1}^{T}\Psi_{\alpha_1}\left(x^*_{1,t} - \widehat{q}^*_{1,t}(\alpha_1)\right)\Psi_{\alpha_2}\left(x^*_{2,t-k} - \widehat{q}^*_{2,t-k}(\alpha_2)\right)}{\sqrt{\sum_{t=k+1}^{T}\Psi^2_{\alpha_1}\left(x^*_{1,t} - \widehat{q}^*_{1,t}(\alpha_1)\right)}\sqrt{\sum_{t=k+1}^{T}\Psi^2_{\alpha_2}\left(x^*_{2,t-k} - \widehat{q}^*_{2,t-k}(\alpha_2)\right)}} \tag{12}$$

3.3 Data

This article aims to explore the influence of DeFi on the CEE-5 stock markets. As in Cevik *et al*. (2022) and Corbet *et al*. (2022), we take into account daily ChainLink (DeFi) prices for the DeFi market because of the longest sampling period and the highest market cap. We obtain the daily stock market indices at the close of the markets in five CEE countries: Hungary (BUX), Poland (WIG), the Czech Republic (PX), Romania (BET) and Croatia (CRO) for the period from June 2019 to May 2023. The sample period includes some significant economic and political events, such as the COVID-19 pandemic with its various waves, the global fall in oil demand and the Russo-Ukrainian conflict. The data for all the variables were collected from Bloomberg. We create a logarithmic return series by taking the logarithmic difference from the price series.

Figure 1 represents the long-term trends and returns of different financial markets. Note that the high variations in the six price series are quite similar. More importantly, extreme risk events such as the recent COVID-19 outbreak and the Russo-Ukrainian war frequently led to an extreme downward trend in the selected series. In addition, the returns of these price indices also show the same volatility clustering as the recent crises. Nevertheless, the reaction of various financial markets to extreme shocks has been heterogeneous in time. These properties offer a chance to highlight price spillovers from DeFi markets to CEE stock markets.

Figure 1: Daily prices and returns of DeFi, BUX, BET, PX, CRO and WIG market indices



Source: Author’s own elaboration

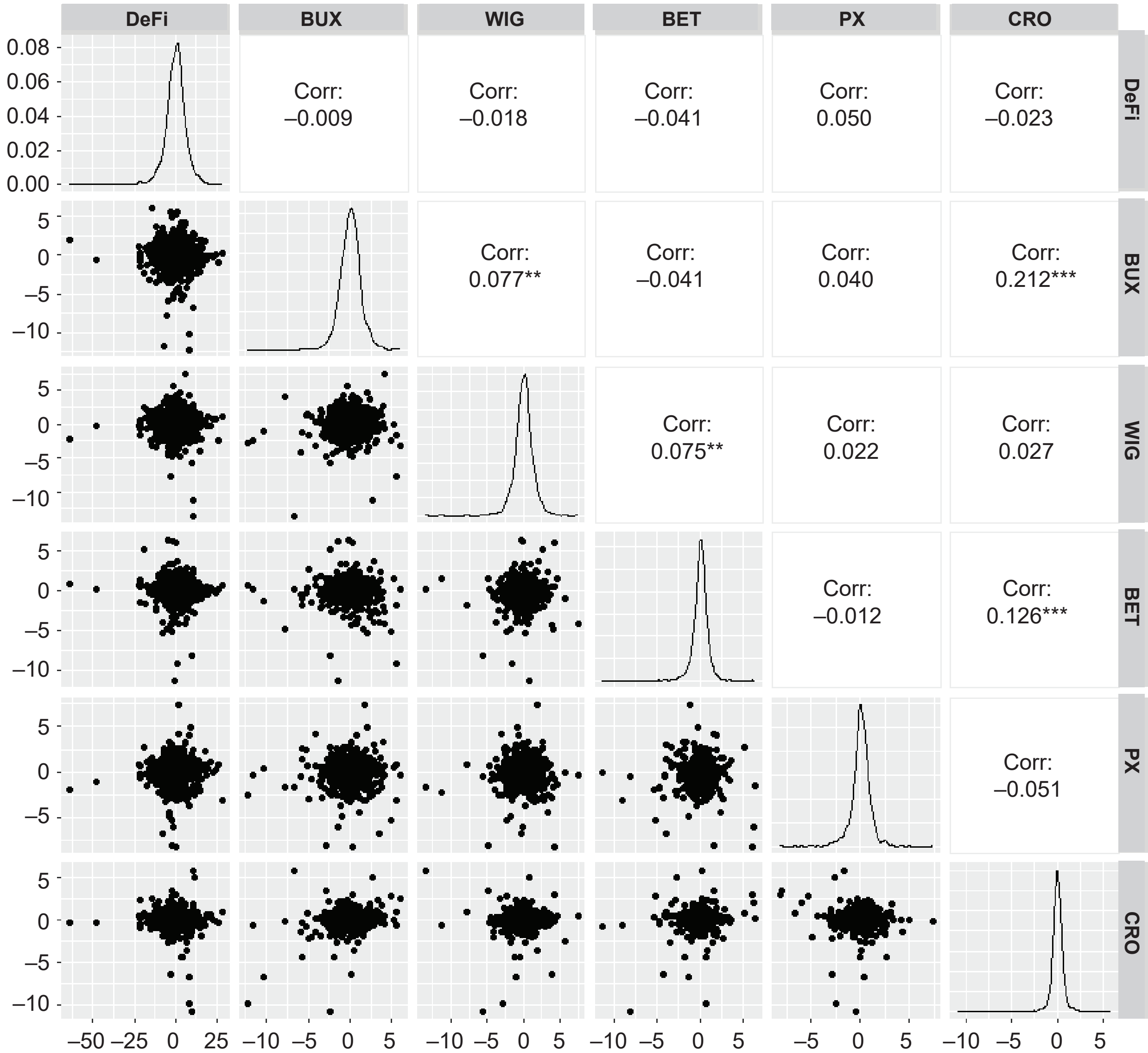
Table 1: Descriptive statistics of sample return data

	DeFi	BUX	WIG	BET	PX	CRO
Mean	0.088686	0.011272	−0.000886	0.025257	0.018397	0.014071
Maximum	28.26367	6.003321	7.432619	6.458422	7.369186	5.863497
Minimum	−63.71529	−12.26837	−13.52654	−11.33015	−8.160496	−10.87854
Std. Dev	6.238134	1.421789	1.339822	1.059019	1.042234	0.812853
Skewness	−1.076265	−1.359904	−1.269824	−1.829373	−1.025464	−3.682397
Kurtosis	14.54913	14.40132	16.50659	24.18911	13.96326	53.86191
Jarque–Bera	7688.634***	7653.625***	10522.07***	25757.57***	6930.083***	147135.4***
ADF	−40.00280***	−19.44496***	−36.49971	−22.59512***	−22.25121***	−15.89975***
ARCH-LM	14.25608***	88.91440***	82.60457***	42.41237***	47.26326***	114.3491***

Notes: ADF is the computed statistics of the Augmented Dickey and Fuller unit root test. ARCH-LM checks for the presence of ARCH effects; ** and *** denote significance at 5% and 1%, respectively.
Source: Author's own calculations

Table 1 illustrates the primary descriptive statistics for the total data sample for each series. We can observe that the average daily return is positive for all the indices except Poland and co-varies within assets. The DeFi market provides the greatest mean return to CEE stock markets. However, it has a very large average daily volatility, while the CEE stock markets experience fewer risks. Specifically, it is clear that the skewness coefficients are negative for all the markets, which means a greater opportunity that these markets have gone down rather than up during COVID-19 and the Russo-Ukrainian war. Compared to the normal distribution, the kurtosis of all the daily returns is positive and high, suggesting the persistence of fat tails in the data. Moreover, the estimates of the ADF test demonstrate that the examined variables are stationary. Finally, Table 1 shows the findings of the ARCH effect for the series during the period. The ARCH effect demonstrates the existence of autocorrelation and heteroskedasticity problems in data. In other words, there is strong evidence of the persistence of ARCH in all the examined variables. Therefore, the DECO-GARCH model and cross-quantilogram approach can be utilized for further analysis of the impact of the DeFi market on CEE stock returns.

Figure 2: Heatmap correlation matrix



Source: Author's own elaboration

Figure 2 depicts the correlation matrix between each series using heatmap representations for the sample period. We can observe that the DeFi market has no significant relationship with CEE stock returns, while there is a correlation among the CEE stock indices. These results reveal that DeFi would be utilized as a diversifier.

4. Empirical Results

This section consecutively represents the results of the interplay between DeFi and CEE stock markets using the DECO-GARCH model and the cross-quantilogram approach.

4.1 DECO-GARCH model results

We can derive a single dynamic correlation coefficient for all six financial markets using the DECO-GARCH model. Correlations produced by the DECO model can also indicate the process of market integration. Table 2 documents the parameter estimates of the multivariate AR(1)-GARCH(1,1) model with DECO specifications.

Table 2: Estimation results of AR-GARCH model with DECO specification

	DeFi	BUX	WIG	BET	PX	CRO
Panel A: Univariate AR-GARCH model						
μ	0.190700 (0.140280)	0.050332 (0.030927)	0.021488 (0.039292)	0.094792*** (0.022364)	0.038052* (0.022117)	0.024562 (0.024775)
φ	−0.049160 (0.031709)	0.039902 (0.028465)	0.060293* (0.032650)	0.063928* (0.036714)	0.037440 (0.030030)	0.098398** (0.035611)
ω	1.550531*** (0.394218)	0.074537*** (0.014461)	1.164536*** (0.082990)	0.073169*** (0.010369)	0.031633*** (0.006431)	0.429466*** (0.020015)
ARCH	0.154417*** (0.020105)	0.129746*** (0.012149)	0.150000*** (0.013273)	0.271919*** (0.020794)	0.142657*** (0.015357)	0.150000*** (0.007604)
GARCH	0.823198*** (0.023085)	0.828946*** (0.017200)	0.142787*** (0.041966)	0.692638*** (0.024231)	0.827231*** (0.016864)	0.085003*** (0.028178)
Panel B: DECO model						
Average p_{ij}	0.029942*** (0.006132)					
A_{DECO}	0.009039*** (0.000079)					
B_{DECO}	0.840085** (0.085503)					
Panel C: Diagnostic tests						
Q (10)	11.860 [0.221]	6.4156 [0.698]	10.763 [0.292]	10.084 [0.344]	11.940 [0.217]	8.0406 [0.500]
Q^2 **(10)**	1.7194 [0.998]	0.5305 [0.767]	4.1573 [0.401]	0.5400 [0.999]	4.7512 [0.907]	4.6768 [0301]
ARCH-LM	0.019120 [0.8900]	0.057422 [0.8106]	4.1455 [0.417]	0.036217 [0.8491]	0.334591 [0.5630]	4.662902 [0.308]

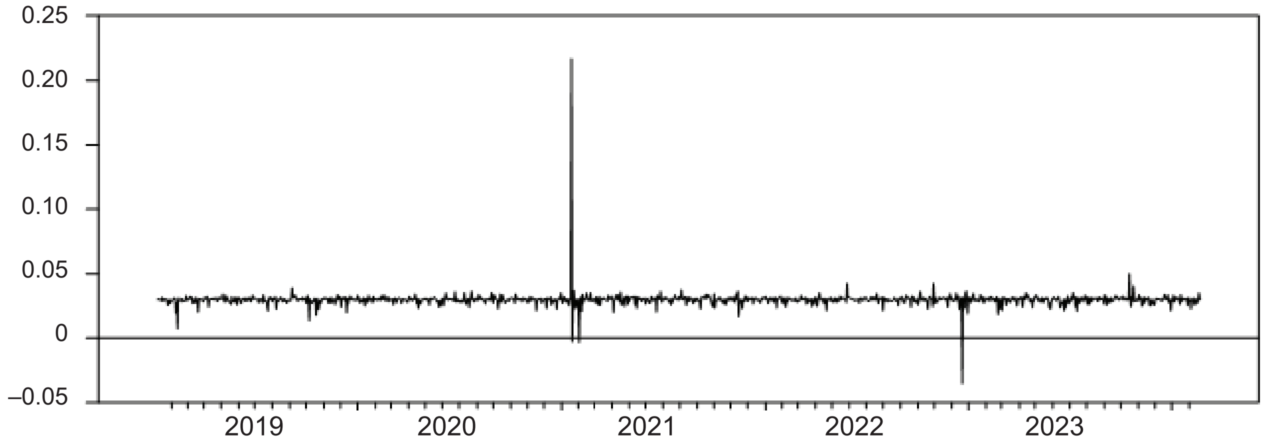
Notes: Q (10) and $Q^2(10)$ are the Ljung–Box test statistics applied to the standard residuals and the squared standardized residuals, respectively. Standard errors are presented in parentheses; *p*-values are shown in square brackets; *, ** and *** represent 10%, 5% and 1% significance level, respectively.

Source: Author's own calculations

Based on the AIC and SIC minimized, we select the lag order of the AR(1)-GARCH(1,1). We must better comprehend the relationships between the variables in the sample using these multivariate GARCH models. Panel A of Table 2 reports the estimates of the AR-GARCH model: the coefficients in the mean equation are positive and statistically significant at the 10% level for Romania and the Czech Republic. The values of ARCH and GARCH are statistically significant at the 5% level for all the concerned series. The sum of the two values is less than one, suggesting stability. In addition, these coefficients are also significantly positive and close to unity, which implies the existence of innovations or volatility.

Regarding the DECO equation, as indicated in Panel B of Table 2, there is evidence of its existence and long-term volatility due to the coefficient B_{DECO} (0.840085), which is statistically significant and close to unity. Similarly, the value of A_{DECO} is significant and positive for all the examined markets, which uncovers the significance of innovations between DeFi and CEE-5 stock markets. More importantly, the sum of these parameters is less than one, revealing that the conditional pairwise correlations have a slow mean reversion. The significant and positive dynamic equicorrelation coefficient (0.029942) suggests a low degree of integration in the nexus across markets under consideration. Put differently, this result proves that the equicorrelations between DeFi and CEE-5 stock markets would be stable, with few outliers. As indicated in Panel C of Table 2, the estimated results of diagnostic testing on the squared and standard residuals do not reject the null hypothesis of no serial correlation for all the cases. Moreover, the ARCH-LM tests fail to reject the null hypothesis of homoscedasticity; therefore, there is no evidence of statistical misspecification in the multivariate DECO-GARCH model.

Figure 3: Dynamic equicorrelation for returns of CEE-5 stock and DeFi markets

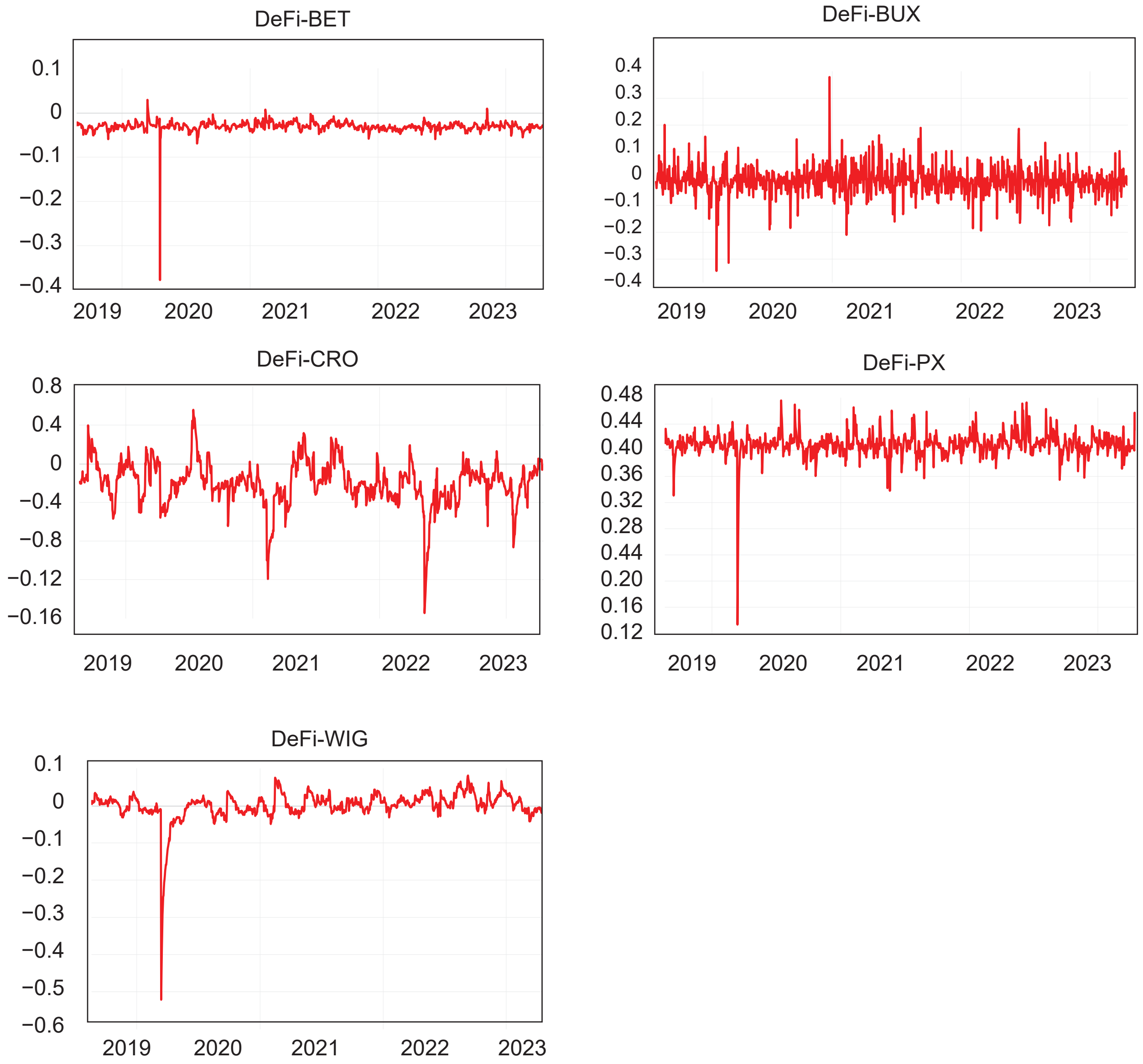


Source: Author's own elaboration

Moving to the graph of return equicorrelation (Figure 3), there is evidence of time-varying patterns with values between −0.05 and 0.25. Importantly, the equicorrelation peaked at 0.25 in July 2020 and reached its bottom around May 2022. The rapid COVID-19 epidemic coincided with a significant surge and trough, indicating a rise in the level of market integration around the pandemic. During that moment of increased financial market uncertainty, crude oil prices plummeted, cryptocurrencies increased and stock markets decreased remarkably (Demiralay and Golitsis, 2021; Kang *et al*., 2019). As a result, the markets under consideration appear to be more susceptible to contagious effects when one indicator, such as DeFi, experiences a price rise. Nevertheless, the event of February 2022 has a strong negative influence on these markets, followed by a negative the next day. While all the markets witnessed a significant decrease during the Russo-Ukrainian war, we saw a very lengthy surge in Poland and Romania, which caused this index to reach new record highs. During this time, the level of integration rose to 0.08, consistent with expectations of economic stimulus. These findings support recent studies indicating that the level of interdependence between global equities rises during times of stress (Hung, 2023). Additionally, the level of price equicorrelation was stable towards the end of the sample period and it remains relatively low. In general, the results demonstrate more integration between DeFi and CEE stock markets when there is financial turmoil and are consistent with the previous studies documented in the literature (Cevik *et al*., 2022; Yousaf *et al*., 2023). This impact is able to intensify, especially during the COVID-19 outbreak and the Russo-Ukrainian conflict, reducing the advantages of global portfolio diversification for investors.

In order to validate the results of the DECO-GARCH model, we also employ dynamic conditional correlation models to estimate the relationship between DeFi and CEE stock market returns. Figure 4 reveals that the pairwise DCC findings are in line with the DECO outcomes reported in Figure 3. The DCC level between DeFi and CEE stock market returns increased remarkably during the COVID-19 pandemic and declined in the Russo-Ukrainian war period, suggesting a contagion effect. A significant long-run dynamic conditional correlation between DeFi and CEE stock market returns, and the absence of a linear association add more complexity to understanding the nexus. Consequently, the pairwise DCC estimations affirm our results obtained for the nexus between DeFi and CEE stock markets based on the DECO model.

Figure 4: Dynamic conditional correlation between returns of CEE-5 countries and DeFi market



Source: Author's own elaboration

After this, we analyse how the cross-quantilograms between DeFi and CEE-5 stock markets affect each other under extreme market conditions. Firstly, the heatmaps suggest quantile-based interaction. Secondly, the cross-quantilograms between DeFi and stock markets illustrate the systemic risk (Razzaq *et al*., 2022).

4.2 Cross-quantilogram estimates

In Figure 5, we show the mutual directionality and cross-quantilogram correlation between the DeFi and CEE-5 stock markets. We take into consideration four lag lengths (K = 1 (DAY), 5 (WEEK), 22 (MONTH) and 66 (QUARTER) and eleven quantiles q = (0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 0.95). Figure 5 illustrates the cross-quantilogram correlation from DeFi to the CEE-5 stock markets. Each heatmap consists of 121 units. The horizontal axis represents the quantiles of CEE-5 stock returns, and the vertical axis represents the quantiles of DeFi. For the statistical significance of the predicted directionality, the Ljung–Box test is performed, and all insignificant correlations are set to zero, where red shows a positive CQ correlation, blue presents a negative CQ correlation, and the stronger the association, the darker the colour. It is set to 0 and represented in green when it is statistically irrelevant. In other words, the magnitude and direction of the impact of DeFi on stock markets are estimated by a convenient colour scheme, which indicates that blue, red and green colours characterize a negative, positive and neutral relationship, respectively.

In Hungary, we observe positive correlations in the upper right and left corners at lag 1. Moreover, a negative relationship between DeFi and BUX was found in the middle return quantiles, proving that DeFi failed to create any safe-haven options in the short run. Nevertheless, we can see that there is no red colour in the heatmap that describes the nexus between DeFi and BUX in the medium and long run, corresponding to lags 5, 22 and 66. These outcomes suggest the presence of prospective safe haven options for medium-term and long-term equity investors on DeFi market.

Similarly, in Poland, we find that there is a positive relationship between DeFi and WIG in the short run because the cross-quantilogram heatmaps from DeFi to WIG are orange at the higher left and lower right corners. This suggests that high returns in DeFi remarkably cause high returns in WIG the following day. No evidence of return spillovers from DeFi to WIG is found in the median quantiles due to the predominant green. This outcome uncovers that an upward movement in the DeFi market tends to result in an upward movement in WIG stock returns. However, the impact of DeFi on WIG becomes insignificant when the lag length rises (week, month and quarter lags), which provides diversification benefits in the medium and long run.

In Romania, row 1 of Figure 5 reveals the cross-quantilogram between DeFi and BET markets at the short-tun investment horizon ($k = 1$). DeFi has a negative impact on BET when both of them are in their lower and higher quantiles, which reveals that during extreme market conditions due to the downward movement of the DeFi and BET prices, DeFi affects BET. This influence weakens, and hence, DeFi can predict movements in the stock market in Romania in the short term. However, at lags 5, 22 and 66, the directional transmissions running from DeFi to BET become smaller and insignificant. This is shown by the dominance of the green colour in the heap maps for the week, month and quarter lags. Put differently, the integration among markets dissipates over time. Therefore, a portfolio that combines DeFi investments with BET stock returns might offer diversification benefits in the medium and long term.

Figure 5: Cross-quantilogram heat maps between DeFi and CEE-5 stock market returns

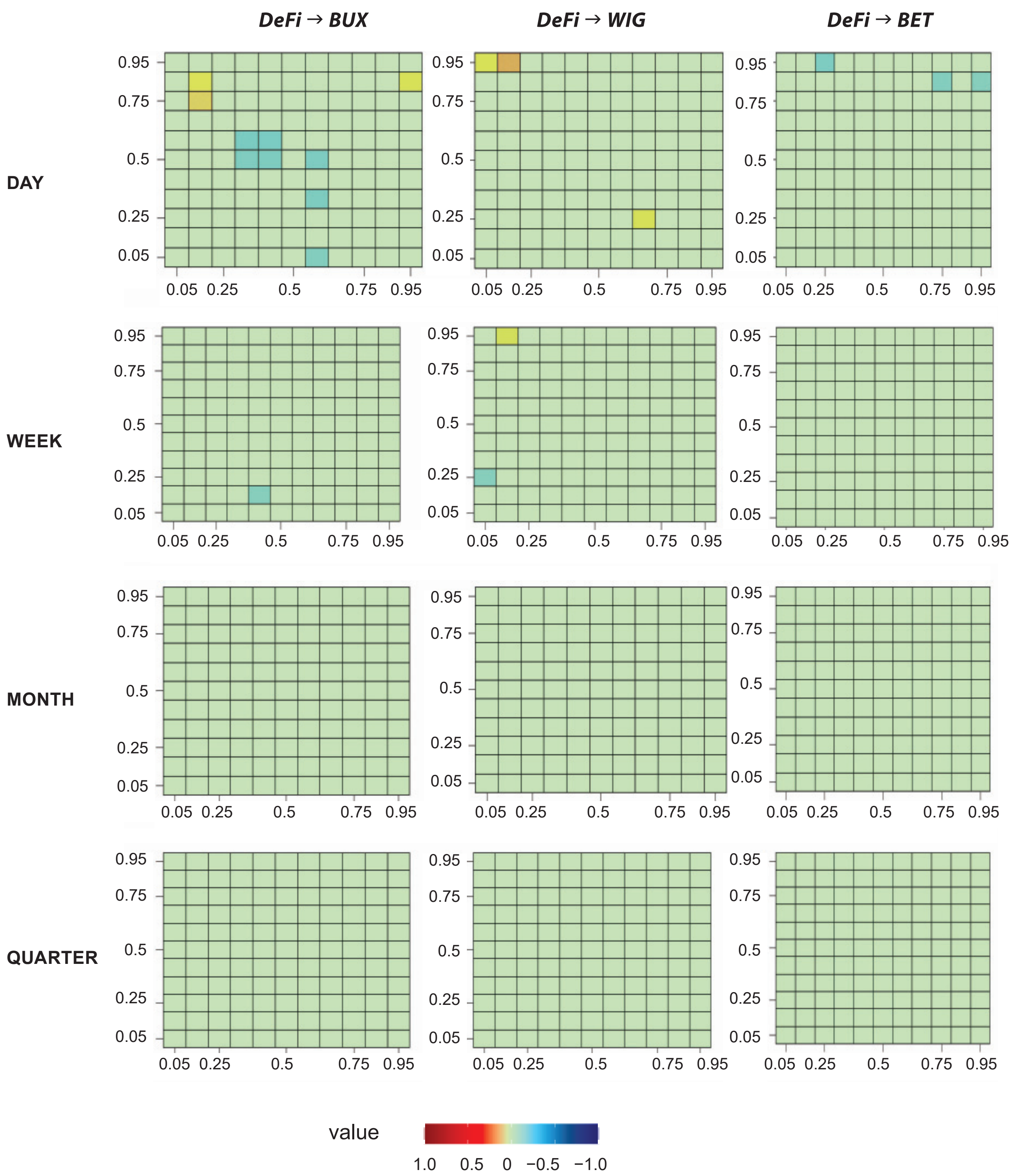
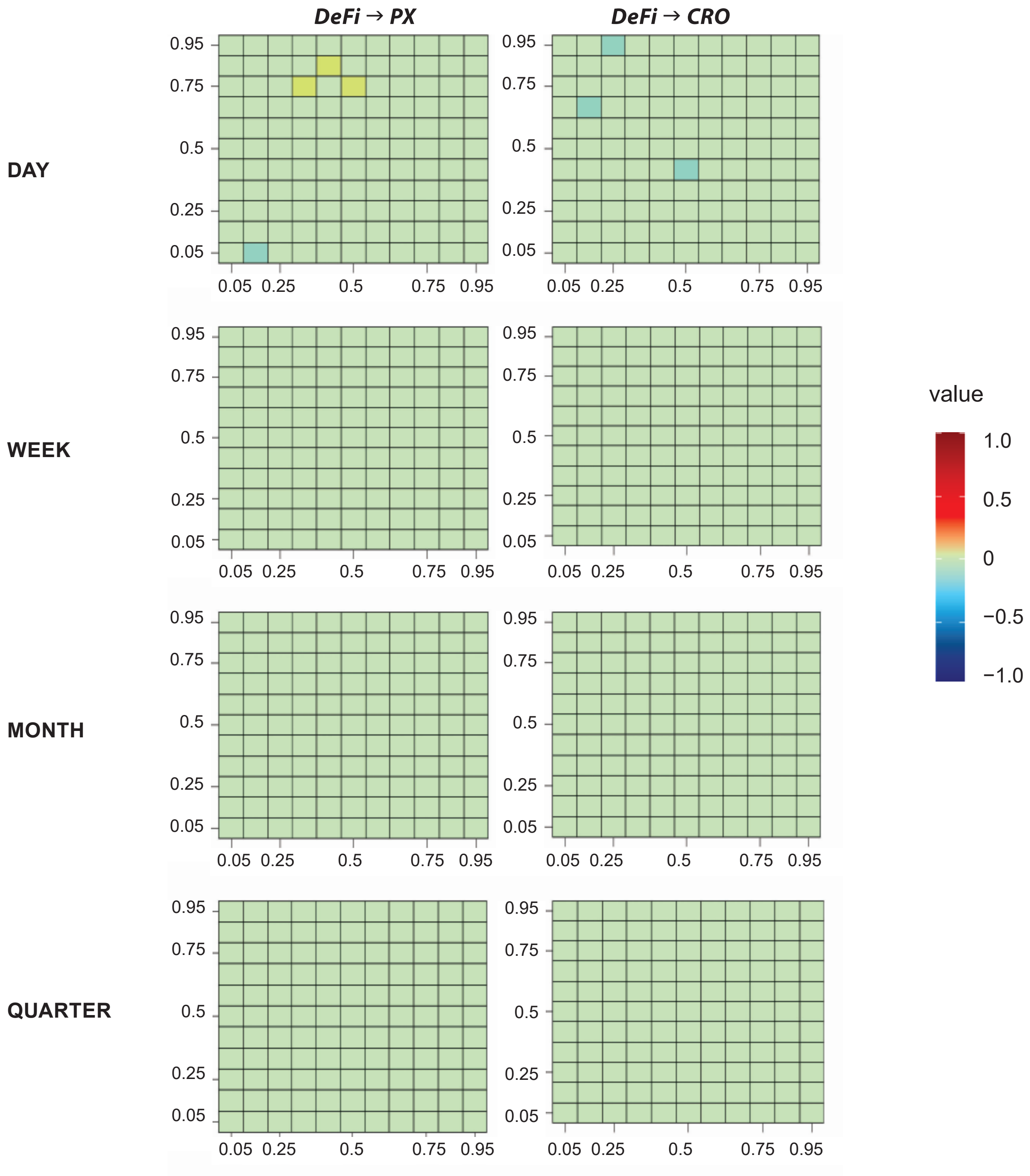


Figure 5: continuation



Source: Author's own elaboration

Furthermore, in the Czech Republic and Croatia, the findings of the cross-quantilogram analysis between DeFi, PX and CRO stock markets are reported. We observe no significant dependence between DeFi and stock markets across the majority of the quantiles, but a few combinations of significant coefficients are visible in the middle quantiles of both DeFi and stock markets.

In other words, we find a positive impact of DeFi on the PX stock market and a negative influence of DeFi on CRO stock returns at lag 1 (DAY) in the short run, but only for a few quantile combinations. Note that the price spillovers from DeFi to PX and CRO stock markets are not statistically significant when returns are at lags 5, 22 and 66. Put another way, it is suggested by the dominance of the green colour in the heat maps for the week, month and quarter lags. These findings indicate that DeFi can effectively hedge COR and PX in the medium and long run.

In summary, the CQ estimations uncover that the advantages of diversification of DeFi for CEE-5 stock markets co-vary between bullish, normal and bearish market conditions. More importantly, our findings emphasize that CEE-5 stock markets depend less on the DeFi market at longer lag lengths. This means that the advantages of diversification of DeFi against CEE stock market returns are more important for long-run investment horizons. These results extend the outcomes obtained by Yousaf *et al*. (2022) and Yousaf and Yarovaya (2022), who used TVP frameworks and found a weak nexus between DeFi and stock markets during the COVID-19 period.

4.3 Portfolio analysis

The outcomes from the dynamic conditional correlation and dependence structure suggest that the associations between DeFi and CEE stock markets change over time. This implies that the hedging performance of DeFi against stock markets also changes over time. Based on that, we analyse risk management techniques, such as optimal weights and hedge ratios during the sample period using the estimated results of the DECO-GARCH model.

We determine the optimal portfolio weights as per Kroner and Ng (1998), and we do it as follows:

$$w_{DS,t} = \frac{h_{SS,t} - h_{DS,t}}{h_{DD,t} - 2h_{DS,t} + h_{SS,t}} \tag{13}$$

with:

$$w_{DS,t} = \begin{cases} 0, & if\ w_{DS,t} < 0 \\ w_{DS,t}, & if\ 0 \le w_{DS,t} \le 1 \\ 1, & if\ w_{DS,t} > 1 \end{cases} \tag{14}$$

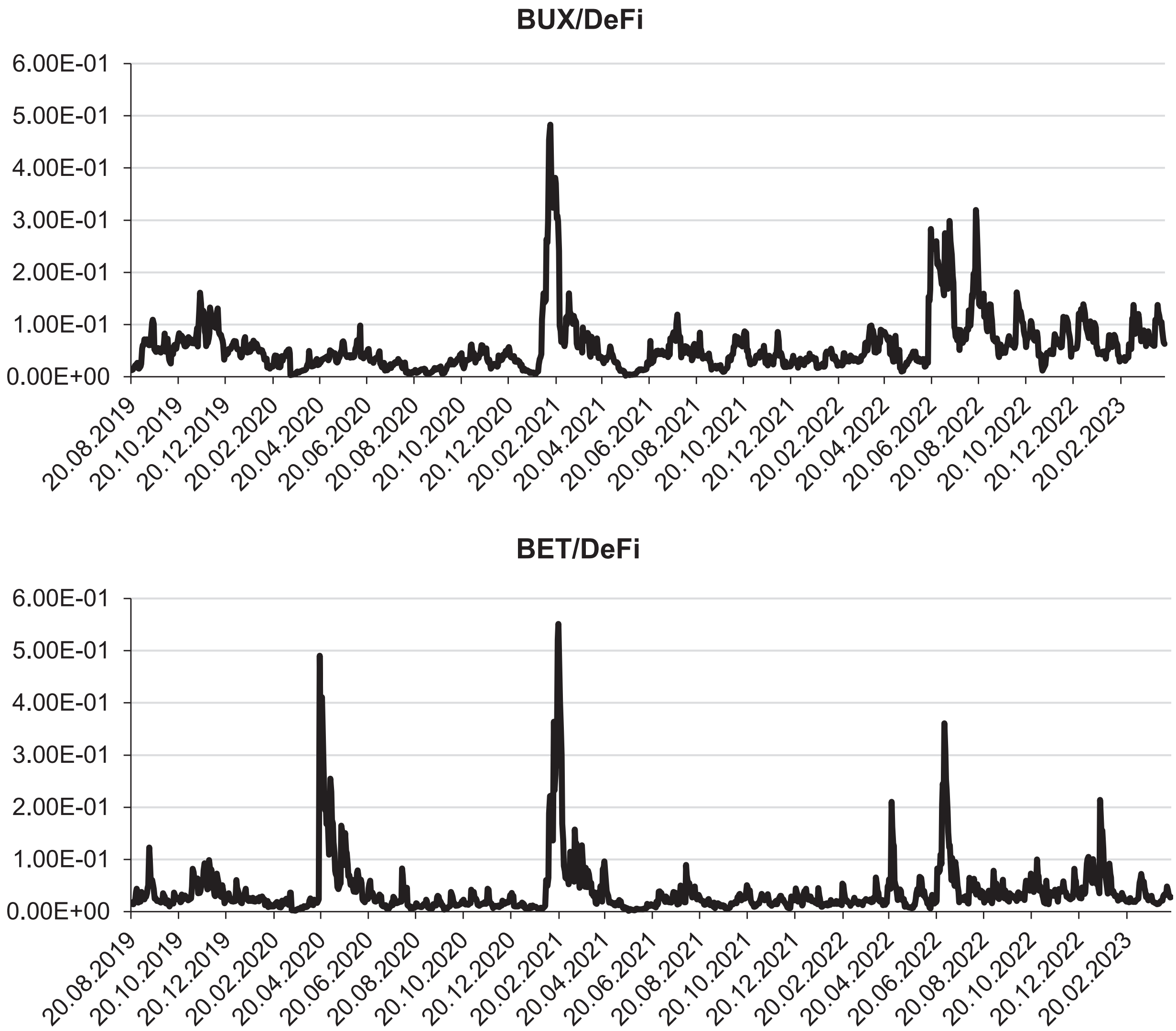
where $w_{DS,t}$ is the weight of DeFi in a portfolio, $h_{DD,t}$ is the conditional variance of DeFi, $h_{SS,t}$ is the conditional variance of stock markets, and $h_{DS,t}$ shows the conditional covariance between DeFi and stock markets at the time *t*. Therefore, the optimal weight of the stock market return is $1 - w_{DS,t}$.

Additionally, we consider the hedging problem of a dollar portfolio that includes a long position in DeFi and a short position on a stock market that reduces risk while maintaining the level of projected returns. According to Kroner and Sultan (1993), the ideal hedge ratio is as follows:

$$\beta_{DS,t} = \frac{h_{DS,t}}{h_{S,t}} \tag{15}$$

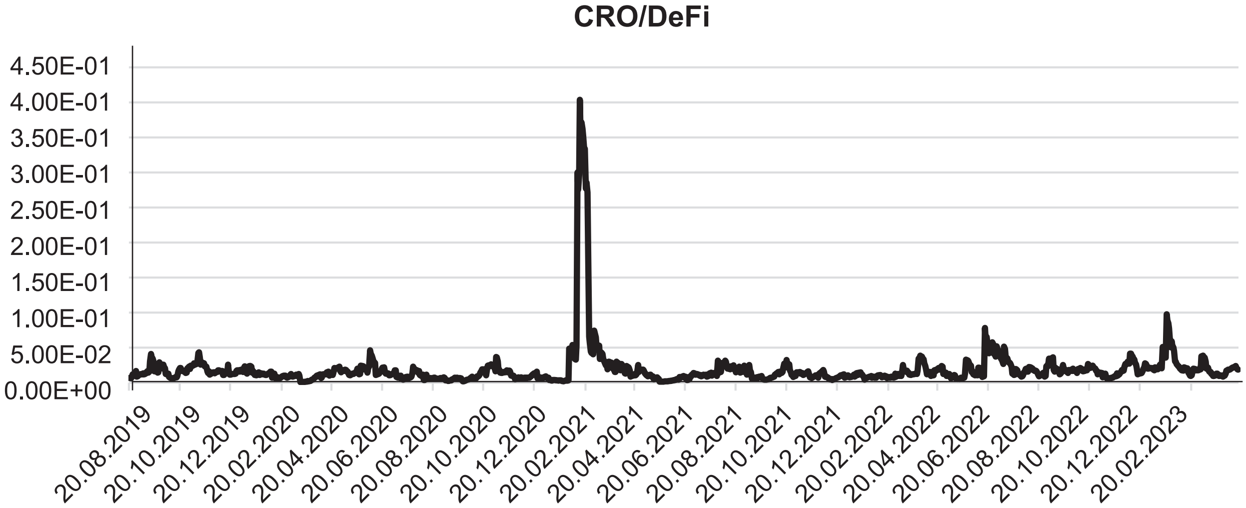
where $\beta_{DS,t}$ is the hedge ratio, $h_{DS,t}$ is the conditional covariance between DeFi and stock markets, and $h_{S,t}$ is the conditional variance of the CEE stock returns.

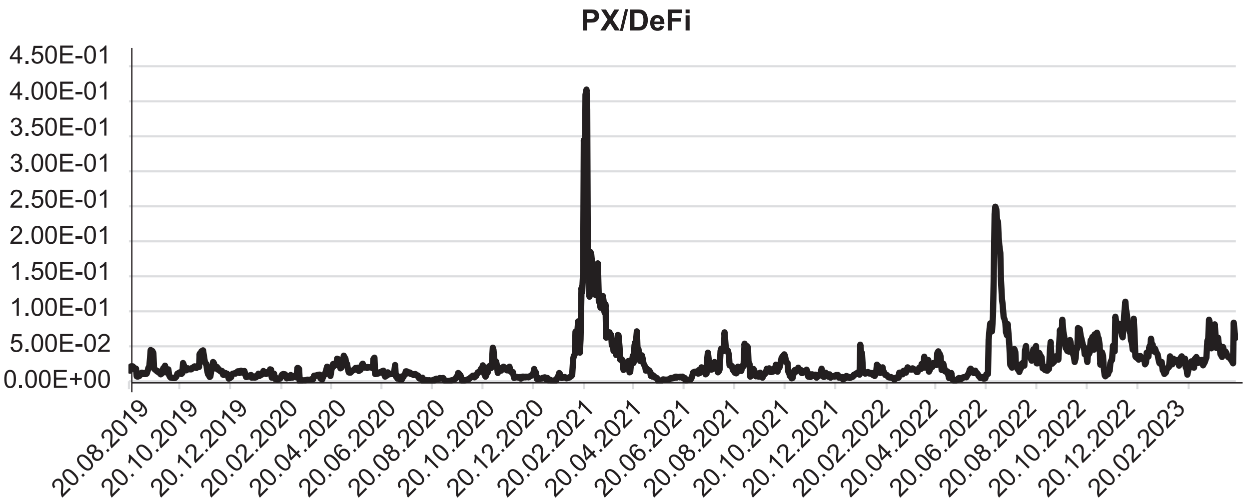
Figure 6: Time-varying portfolio weights of DeFi and CEE stock market returns



Source: Author's own elaboration

Figure 6: continuation





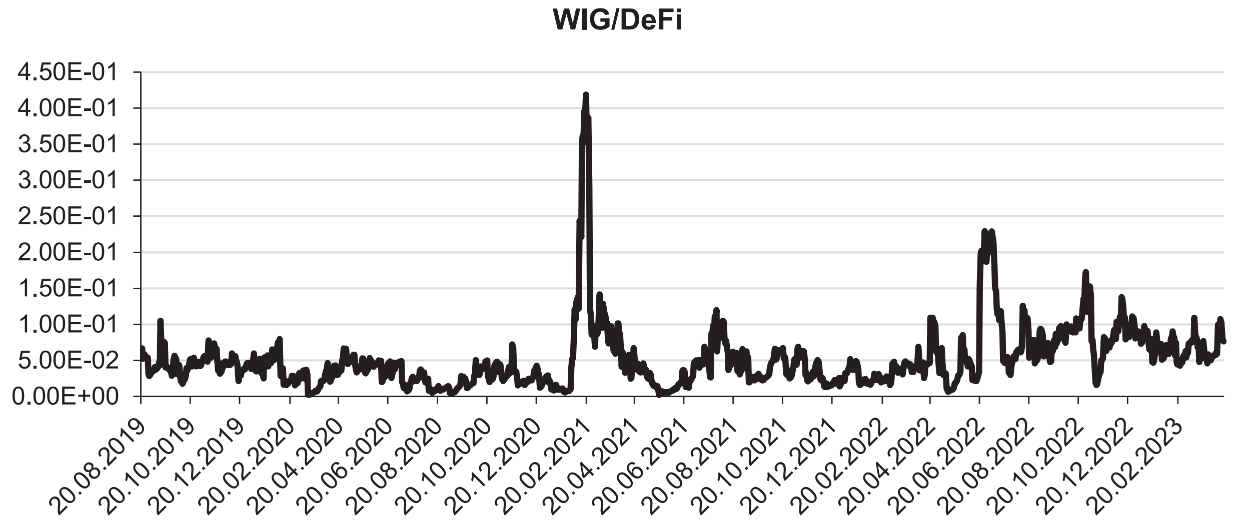


Figure 7: Timeline of dynamic hedge ratio for DeFi

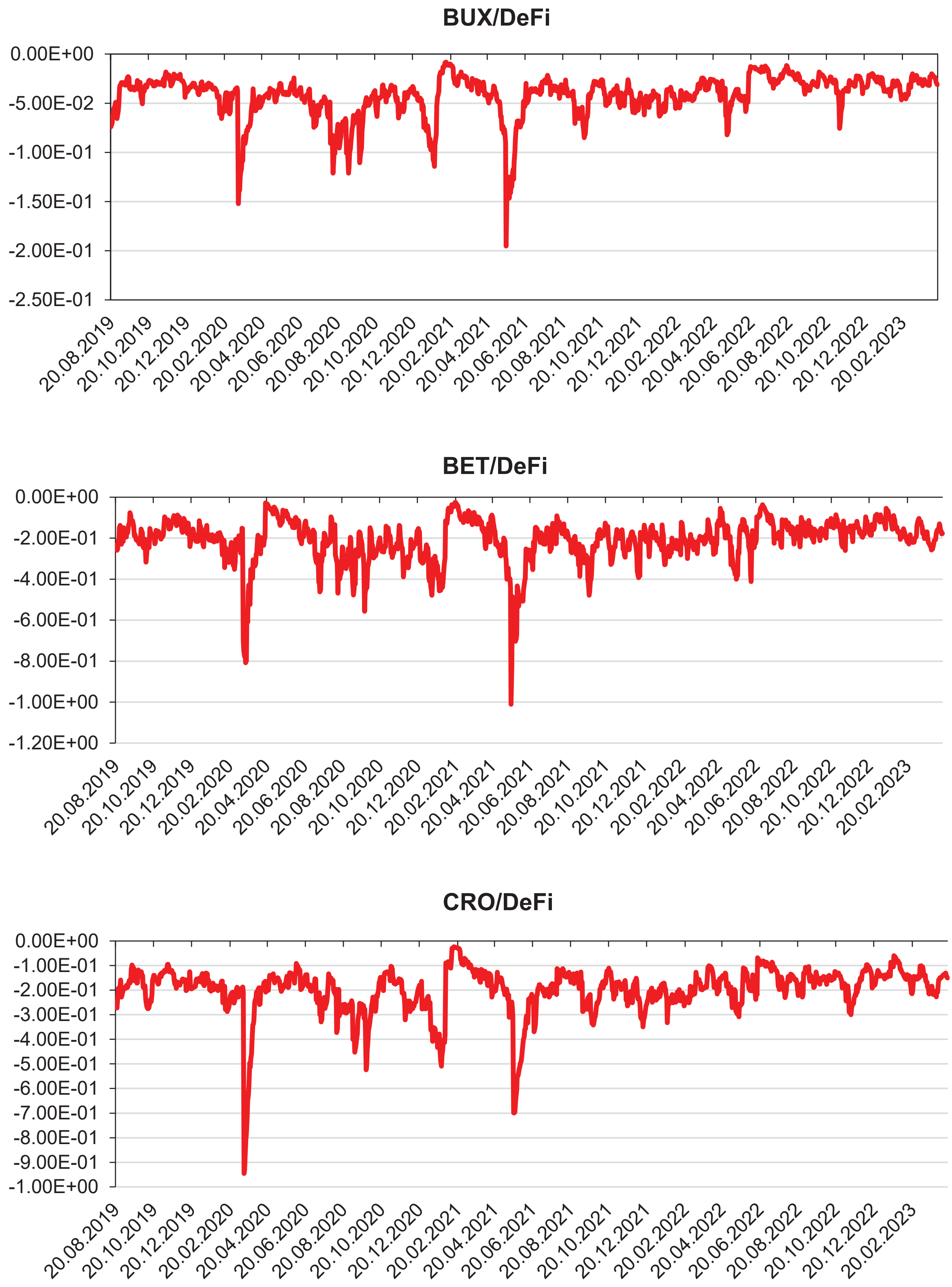
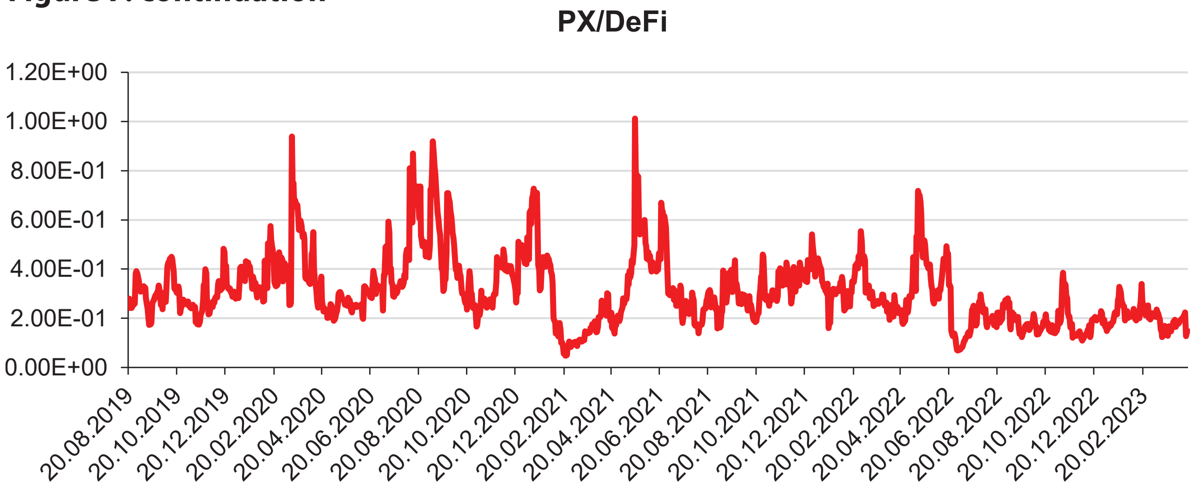
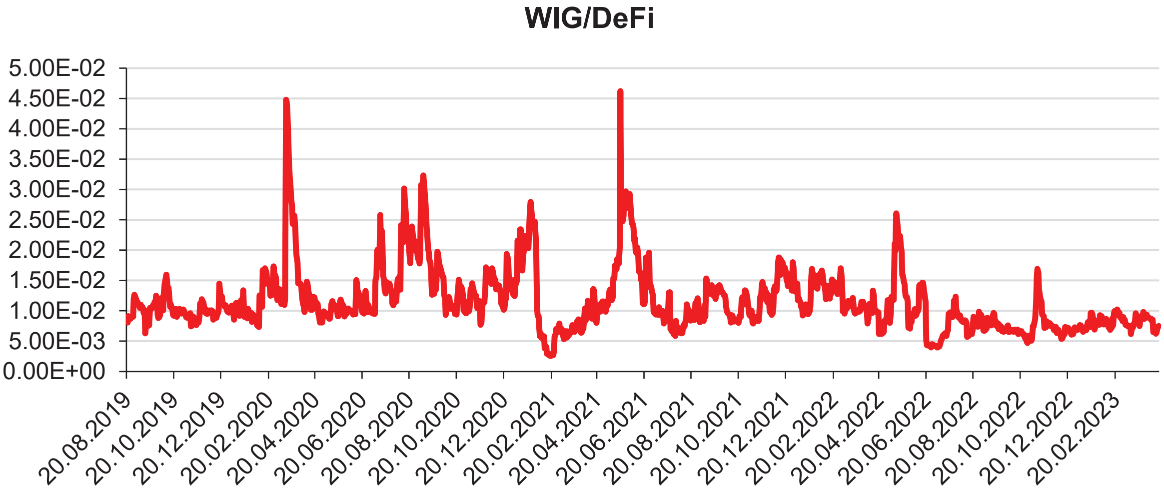


Figure 7: continuation





Source: Author's own elaboration

The development of the optimal weights for the DeFi and CEE stock markets in time is depicted in Figure 6. By comparing co-moves throughout the sample period, we can see that the conditional weights are not stable. Particularly, the BUX, BET and DeFi pairs have stronger optimal weights than the other pairs. This shows that the chances for diversification between the CEE stock markets and the DeFi markets are completely distinct from one another.

Figure 7 represents the time-varying hedge ratios between DeFi and CEE stock markets. The most vital result that we can see is that the hedge ratio is not stable and co-varies between negative and positive values during the period under consideration. This demonstrates the need to implement an active portfolio management strategy.

In general, the hedge ratios and optimal weights of all the pairs co-move over time, particularly during the early stages of COVID-19 and the Russo-Ukrainian war, suggesting the high costs of hedging; hence, investors should adjust their portfolio allocation and hedge risk over time and in stressful periods to get the highest risk-adjusted returns.

5. Discussion

The interdependence and effectiveness of financial markets are important for policymakers and investors. Attempts to systematically explain the components that make significant contributions to rising efficiency and new blockchain-based asset class interdependence, DeFi is still in its early phases, and we only have a limited understanding of what determines a market to be efficient or inefficient (Cevik *et al*., 2022). The empirical results of our work that have been identified thus far disclose the existence of price spillovers between DeFi and CEE stock markets and several vital pieces of information in connection with the dependence structure of DeFi and heterogenous CEE stock returns. Particularly, the magnitude of the spillover co-varies across different time and investment horizons. As a result, we investigate whether DeFi provides hedging efficiency for the CEE stock market by utilizing the multivariate DECO-GARCH model and cross-quantilogram developed by Han *et al*. (2016).

The findings may help clarify the severe reliance and time-varying relationship between the DeFi and CEE stock markets. Generally, investment demand for and public interest in DeFi and increased risk aversion played a significant role in driving the CEE stock market integration during the COVID-19 pandemic and the Russo-Ukrainian war. Our work is in line with the findings of Karim *et al*. (2022), Bejaoui *et al*. (2023) and Piñeiro-Chousa *et al*. (2022).

The co-movement of the CEE stock markets appears to be independent of major economic determinants, such as global oil, gold and exchange rate prices, that conventionally have some explanatory power on traditional markets (Joseph *et al*., 2020; Hung, 2020; Beck and Stanek, 2019). Nevertheless, as also shown by Corbet *et al*. (2023), although virtual currencies are unaffected by the economic realities that influence traditional assets, herding behaviour, especially in times of great uncertainty, may dictate price co-movements. There is a significant price spillover effect from DeFi to CEE stock markets. Notably, the influence of DeFi on CEE stock markets is stronger in the times of the COVID-19 pandemic and the Russo-Ukrainian conflict than in the other periods, which unveils that the price structures of CEE stock markets are affected by digital finance vehicles, particularly during crisis periods. Furthermore, the cross-quantilogram analysis demonstrates that the financial integration between the DeFi and CEE stock markets depends on market conditions. The equicorrelations between the markets are stable and positive in the DECO model estimations shown in Table 2 and Figure 3. By contrast, the cross-quantilogram estimations in Figure 5 illustrate a decline in financial market integration with DeFi over medium and long-run investment horizons. As a result, the DeFi market can provide hedging effectiveness for CEE stock investors.

The DeFi market has historically shown tremendous development but also severe volatility (Bejaoui *et al*., 2023). Therefore, this market can be extremely volatile, with DeFi asset prices fluctuating dramatically. This extreme volatility is attributable, in part, to the fact that the markets are still in their infancy, with a limited number of buyers and sellers (Chowdhury *et al*., 2023). Nevertheless, for DeFi and cryptocurrencies, where market players have varying degrees of information advantage over market maturity and random price fluctuations, returns and volatility are heavily driven by information asymmetry with a restricted number of buyers and sellers.

The CEE stock markets demonstrate no significant relationship with DeFi in the medium and long run, which is similar to the previous studies (Piñeiro-Chousa *et al*., 2022; Corbet *et al*., 2023). We can therefore conclude that there seems to be low integration of DeFi with the CEE stock markets. These findings have several implications. Firstly, not all CEE stock markets can be good predictors of the DeFi index. This could be attributed to the fact that these economies are not currently experiencing an increasing migration of interest from centralized to decentralized finance. In addition, such integration has not yet occurred in CEE economies due to their more traditional culture and more conservative regulatory authorities, which largely cherish the centralized structure of the traditional financial system. Furthermore, the lack of connectivity between DeFi markets and CEE stock markets shows that the function of DeFi assets in adequate hedging against stock market risks should be investigated further in future studies.

Furthermore, significant occurrences on financial markets caused by factors outside the system, rather than endogenous shocks, are frequently described as unexpected asset price volatility, which causes investors to be unsure about their investment selections (Cevik *et al*., 2022). Unknown asymmetrical nonlinear dynamics, scaling patterns, asset class self-similarity, long memory, herding behaviour, and, most importantly, asset nonconformity with the efficient market hypothesis all contribute to the degree of uncertainty.

6. Conclusion

Given the inherent increased level of unpredictability and volatility on blockchain markets, we explored extreme return spillovers between DeFi and CEE-5 stock markets between June 2019 and May 2023. By doing so, this study utilized the multivariate DECO-GARCH model and the cross-quantilogram approach. The empirical results of our work disclose the existence of price spillovers between DeFi and CEE stock markets and several vital pieces of information in connection with the dependence structure of DeFi and heterogenous CEE stock returns.

We highlight a positive equicorrelation between DeFi and CEE stock market returns. Notably, the influence of DeFi on CEE stock markets is greater in the times of the COVID-19 outbreak and the Russo-Ukrainian conflict than in the other periods, which unveils that the price structures of CEE stock markets are affected by digital finance vehicles, particularly during crisis periods. Furthermore, the CQ estimations uncover that the diversification benefits of DeFi for CEE-5 stock markets co-vary between bullish, normal and bearish market conditions. More importantly, our findings emphasize that CEE-5 stock markets depend less on the DeFi market at longer lag lengths. This means that the diversification benefits of DeFi against CEE stock market returns are more important over long-run investment horizons. Finally, we estimated, compared and provided fresh empirical guidance to investors and portfolio managers over the sample period for two indicators linked to portfolio construction.

Our empirical results may have important implications for a variety of market participants and researchers, particularly in periods of slowdown such as the Russian invasion of Ukraine in 2022, the COVID-19 pandemic, or any other event posing a systemic risk. Since blockchain markets, notably DeFi, offer significant risk-mitigation opportunities for investors and financial markets, policymakers and regulators might gain by restructuring their current policies of investing in blockchain markets and financial markets. Additionally, the rapidly developing DeFi tokens have significant investment potential due to their additional unique features as cryptocurrency futures and options. After that, our study offers practical conclusions and implications for legislation that can help investors profit from investing in blockchain markets and protect their money from volatile market conditions.

However, this paper has several limitations that can be taken into account in future research. Future research should include potential drivers of the relationship between DeFi and NFTs and developing stock markets such as investor sentiment, other cryptocurrencies and fake news indices, which would be helpful for investors to perceive such interaction.

Declarations

Availability of supporting data: Please contact author for data and program codes requests. R and Matlab were used to organize data.

Author's contributions: N. T. H.: Methodology, software, data curation, writing – original draft.

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Conflicts of interest: The authors hereby declare that this article was not submitted or published.

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