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COVID-19 Pandemic and Romanian Stock Market Volatility: A GARCH Approach

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Abstract: This paper investigates the volatility of daily returns on the Romanian stock market between January 2020 and April 2021. Volatility is analyzed by means of the representative index for Bucharest Stock Exchange (BSE), namely, the Bucharest Exchange Trading (BET) index, along with twelve companies traded on BSE. The quantitative investigation was performed using GARCH approach. In the survey, the GARCH model (1,1) was applied to explore the volatility of the BET and BSE traded shares. Conditional volatility for the daily return series showed noticeable evidence of volatility that shifts over the explored period. In the first quarter of 2020, the Romanian equity market volatility increased to a level very close to that recorded during the global financial crisis of 2007–2009. Over the next two quarters, volatility had a downward trend. Besides, after VAR estimation, no causal connection was found among the COVID-19 variables and the BET index.

Keywords: Romanian stock market; volatility clustering; autocorrelation; COVID-19; GARCH models; vector autoregression model; Granger causality



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1. Introduction

The coronavirus malady (COVID-19) is a sanitary and economic turning point that has harmed the basis of the human condition (Verma and Gustafsson 2020), it being one of the most acute health emergencies in the recent past (Vera-Valdés 2021). The occurrence of the disease hurt the global economies and caused insecurity on worldwide equity markets (Engelhardt et al. 2021). The extensive uncertainty of the plague and its related economic failures has triggered markets to turn extremely volatile and unpredictable (Zhang et al. 2020). Baker et al. (2020) suggested that no prior contagious virus outburst, including the Spanish Flu, has disturbed the equity market as strongly as the COVID-19 pandemic. Since it was difficult to expect and has never hitherto arose, this slump was described as a “black swan” event (Yarovaya et al. 2021). As compared with the 2008 crash which commenced in the United States and progressively diffused to other nations with a substantial time postponement, the coronavirus disease rapidly brought the worldwide economy to a stoppage by instantaneously hampering demand and supply lines around the globe due to extensive lockdowns (Ozkan 2021). Anser et al. (2021) noticed that COVID-19 contaminated cases are the central element that impedes financial activities and reduces money allocation, but a growing number of recovered cases offer investors’ trust to boost stock trade across nations. Agarwalla et al. (2021) documented that the rescue package had limited the extreme tail risks, but the volatility level persisted at a high level. Ghorbel and Jeribi (2021) claimed that equity indices and financial assets rely not only on their earlier volatility, but also on the preceding volatility of the fuel prices. Therefore, in the aftermath of SARS-CoV-2 virus diffusion, the unpredictability in stock exchanges substantially increased, thus causing huge shortfalls for investors (Farid et al. 2021). The decline of the composite indicator of systemic stress among February and April 2020 was equivalent to the failures it recorded at the beginning of the 2008 global financial crisis and the 2011–2012 sovereign debt crisis, whereas the collapse in March 2020 was

the fourth-greatest monthly change since the commence of the euro (Borgioli et al. 2020). Pan et al. (2021) emphasized that the level of sovereign credit default swap enlarged throughout periods when the coronavirus pandemic turned out to be more critical. S&P 500 and EURONEXT 100 indices plummeted by nearly 30–38% between January and 15 June 2020 (data.europa.eu 2020), whilst Romania ranked ninth by considering the top ten best-performing leading European indices in the first half of 2020 (Bucharest Stock Exchange 2020).

However, although the COVID-19 pandemic undesirably affected worldwide economies and stock exchanges, Fernandez-Perez et al. (2021) proved that culture significantly influences market volatility since nations with reduced individualism and great uncertainty avoidance respond more adversely and with larger instability than nations with high individualism and weak uncertainty avoidance. Thus, Hunjra et al. (2021) supported that East Asian markets reacted differently to manifold sanitation arrangements and virus security strategies. Additionally, Bannigidmath et al. (2021) explored 25 nations and showed that their reaction to government measures was dissimilar, claiming that in states where the guidelines counted, the impact was mainly harmful. Orhun (2021) supported that equity markets of nations with greater health outflow, better promptitude for diseases and superior GDP per capita are more protected against the coronavirus crisis. Harjoto and Rossi (2021) proved that the current pandemic had a significantly larger adverse effect to the equity markets in emerging nations than in the developed states.

COVID-19 induced panic and concerns amidst investors, thus contributing to social mindsets such as the herding behavior (Mnif et al. 2020). Shaikh and Huynh (2021) documented that investors' concern came out to be greater in the equity sector first—ever since the stock market crash of 1987 and the global financial crisis of 2008–2009. For instance, Subramaniam and Chakraborty (2021) found a robust negative relationship among COVID-19 fear and stock returns. Hence, returns were adversely influenced by fear through rising the market risk premium claimed by stockholders (Aggarwal et al. 2021). Bourghelle et al. (2021) found that the COVID-19 shock caused further oil price instability, primarily attributable to intensified insecurity, alongside stockholder tension and fear. Chang et al. (2020) argued that different to the Global Financial Crisis, investors panic about assuming risks, so they may imprudently get rid of all their holdings. Karamti and Belhassine (2021) advised that concern in the US market dispersed to the worldwide markets at the longer investment horizons. Hence, Kizys et al. (2021) documented herding conduct in the first three months of 2020, along with Espinosa-Méndez and Arias (2021), which confirmed that the pandemic heightened herding conduct in European equity markets. Ortmann et al. (2020) established that investors raised their brokerage deposits and launched further accounts, whereas mean weekly trading intensity expanded by 13.9% as the number of cases duplicated. Moreover, Pagano et al. (2021) proved that retail investors lessened momentum trading and heightened contrarian trading operations throughout the preliminary stage of this turning point, whilst Smales (2021) claimed that individual traders are more inclined to perform online explorations for facts to settle dwelling insecurity in the course of the corona crisis. On the contrary, Sun et al. (2021) argued that coronavirus-associated reports and economic-related publications do not generate unreasonable investment judgments. Besides, Hong et al. (2021) advised that the pandemic period was related with market inefficiency, establishing rewarding prospects for dealers and opportunists.

Prior papers were focused on volatility examination for African equity markets (Lo et al. 2021; Takyi and Bentum-Ennin 2021; Zoungrana et al. 2021), the Australian stock market (Brueckner and Vespignani 2021), BRICS and G7 states (Yu et al. 2021), Canada and the US (Xu 2021), the Chinese stock market (Chen et al. 2021; Liu et al. 2021b; Shahzad et al. 2021), seven emerging countries (Hashmi et al. 2021), euro area stock markets (Duttilo et al. 2021), the Indian financial market (Bora and Basistha 2021), the South Korea stock market (Hoshikawa and Yoshimi 2021), Thailand (Hongsakulvasu et al. 2020), the Tunisian sectorial stock market (Fakhfekh et al. 2021), the US stock market (Curto and Serrasqueiro 2021; Hong et al. 2021), Vietnam and Philippines (Le and Tran 2021), Visegrad

Group member states (Czech et al. 2020), or several international markets (Al-Najjar et al. 2021; Al-Qudah and Houcine 2021; Anser et al. 2021; Banerjee 2021; Chowdhury et al. 2021; Contessi and Pace 2021; Engelhardt et al. 2021; Höhler and Lansink 2021; Rouatbi et al. 2021; Szczygielski et al. 2021b; Topcu and Gulal 2020; Vera-Valdés 2021; Youssef et al. 2021; Zhang et al. 2020). This paper aims to examine the volatility throughout the Romanian financial market during the COVID-19 pandemic. Investigating volatility is crucial, as an unexpected and substantial rise in instability may cause a financial meltdown (Uddin et al. 2021). We investigate an emerging stock exchange as long as these markets are more exposed to insecurity of pandemics and epidemics than developed markets (Salisu et al. 2020).

In the present article, it was analyzed how the volatility on the Romanian stock market manifested itself due to the COVID-19 pandemic outbreak. Thus, in order to fulfill the objective of the study, coronavirus daily data were used between January 2020 and April 2021 for the following markets: USA, Italy, and Romania. For the Romanian capital market, we selected the representative index for Bucharest Stock Exchange (BSE), namely, the Bucharest Exchange Trading (BET) index, as well as a number of twelve shares, these being positioned in the top of the most traded on BSE at the time of this research. Regarding the variables used as proxies for COVID-19, they are related to the evolution of the new number of cases of COVID-19 registered in the USA, Italy, and Romania. Italy was the epicenter of the COVID-19 pandemic in Europe, whereas the USA had the highest number of COVID-19 cases. Moreover, the USA has some of the largest stock markets that have a strong impact on other markets. For instance, Celik (2012) proved that emerging markets appear to be the most affected by the contagion consequences from the U.S. Moreover, Le and Tran (2021) found evidence that Vietnamese and the Philippine stock markets are affected by the contagion effect from the US stock market throughout the COVID-19 pandemic.

So far, the evidence for BSE is limited, this being, to the best of our knowledge, among the first studies that address the impact of COVID-19 on the Romanian capital market.

The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the dataset and quantitative techniques. Section 4 presents and discusses the empirical outcomes. Section 5 concludes the study.

2. Literature Review

The occurrence of COVID-19 has harmful effects on worldwide markets (Naeem et al. 2021), being expected to be the largest economic shock in human history (Insaiddoo et al. 2021). Broadly, Xu (2021) noticed an adverse effect of a rise in the COVID-19 cases on the financial market. Chowdhury et al. (2021) claimed that European financial markets were the most terrible victim related to others. In the same vein, Youssef et al. (2021) noticed that European equity markets, excepting Italy, spread more spillovers to the whole other financial markets than they obtained, mainly through the coronavirus outburst. Szczygielski et al. (2021b) showed that pandemic insecurity has affected nearly all territories via smaller returns and heightened market volatility. Hence, the insecurity triggered by the COVID-19 outbreak and the rapidity with which the novel coronavirus dispersed around the world produced a panic in international financial markets (Lo et al. 2021). As such, Zhang and Hamori (2021) noticed that the effect of disease on the volatility of the oil and stock markets surpassed that of the 2008 global financial crisis. Moreover, Szczygielski et al. (2021a) proved that no national energy market was unharmed by COVID-19 insecurity. Hence, coronavirus disease lessened stock market liquidity involving equally the depth and the tightness facets (Mdaghri et al. 2021). For S&P 500 enterprises, Chebbi et al. (2021) documented a negative link among the quotidian increase in the numbers of coronavirus cases and fatalities and stock liquidity. Moreover, for the Shanghai stock market, Ftiti et al. (2021) confirmed the rise of stock market volatility and liquidity risk justified by a ripple effect triggered by the vulnerability of the sanitary sector. However, Curto and Serrasqueiro (2021) argued that coronavirus occurrence did not strike evenly across all the US segments and stock quotes. For instance, Milcheva (2021) noticed that the most affected segments in the US are

retail and hotels, but in Asia the most affected segment is the office. Nevertheless, [Höhler and Lansink \(2021\)](#) noted that the food sector was less influenced by the pandemic than other segments.

A first strand of literature was focused on the reaction of stock returns to the existing pandemic. [Topcu and Gulal \(2020\)](#) exhibited that Asian markets were the most influenced by the pandemic, succeeded by South America and the Middle East. As such, [Hongsakulvasu et al. \(2020\)](#) revealed that COVID-19 disquiet negatively influenced every kind of Thailand's stock return. [Al-Najjar et al. \(2021\)](#) claimed that coronavirus incidents exert an adverse impact on equity market indices of G8 countries. [Al-Qudah and Houcine \(2021\)](#) noticed that the surge in established cases of COVID-19 negatively influenced stock returns for the main affected nations in the WHO Regions. For Central, North, and the South American realm, [Amin et al. \(2021\)](#) concluded that COVID-19 cases undesirably influence market indexes. [Takyi and Bentum-Ennin \(2021\)](#) revealed that African financial markets performance lessened between -2.7% and -20% throughout and subsequently the incidence of the pandemic. [Czech et al. \(2020\)](#) reported a negative association among the Visegrad stock market indices and the COVID-19 diffusion. For the case of emerging markets, [Hashmi et al. \(2021\)](#) advised that the number of coronavirus cases negatively influences stock prices mainly when these financial markets are in a bearish condition. Contrariwise, [O'Donnell et al. \(2021\)](#) found that the everyday amounts of COVID-19 cases did not explain the index price variations in China, Spain, Italy, the United Kingdom, and the United States. [Zoungrana et al. \(2021\)](#) revealed for the West African Economic and Monetary Union's (WAEMU) stock market that weekly validated cases do not influence stock returns, even if the impact of death cases is harmful. However, [Brueckner and Vespignani \(2021\)](#) documented that COVID-19 contaminations had a positive influence on the performance of the Australian equity market.

Another strand of research was oriented on how COVID-19 news influences stock returns and oil prices because terrific fear caused by the mass media is related with growing volatility in the financial markets ([Haroon and Rizvi 2020](#)). [Chundakkadan and Nedumparambil \(2021\)](#) provided evidence that emphasis on the pandemic has generated a pessimistic reaction between market players and weakened the stock exchanges. [Weng et al. \(2021\)](#) established that news throughout the coronavirus pandemic has more forecasting information, which is essential for the transient volatility estimating of fuel futures, whereas [Salisu and Vo \(2020\)](#) reinforced that considering health reports over illnesses boosts stock return foresight. [Baek et al. \(2020\)](#) advised a negativity tendency since adverse announcements concerning the number of fatalities are twice as impactful as optimistic facts with respect to recoveries. [Wu et al. \(2021\)](#) argued that media can stimulate the forecast of oil cost and usage over the COVID-19 contagion. [Atri et al. \(2021\)](#) noticed that the number of casualties and the COVID-19 panic adversely impact petroleum value, but the COVID-19 media coverage positively influences fuel cost in the short run.

Further studies were exploring safe-haven assets throughout ongoing health crises. [Huang et al. \(2021\)](#) suggested that Bitcoin can promote efficient diversification and risk alleviation, whereas [Mariana et al. \(2021\)](#) strengthened that Ethereum is a superior safe-haven than Bitcoin. Similarly, [Disli et al. \(2021\)](#) advised that gold, oil, and Bitcoin offer diversification benefits at extended investment perspectives. [Ji et al. \(2020\)](#) underlined that gold and soybean futures may uphold the worth of an investment. Contrariwise, [Będowska-Sójka and Kliber \(2021\)](#) claimed that cryptocurrencies rarely performed as weak safe-haven assets during several market disorders, whilst [Conlon and McGee \(2020\)](#) argued that Bitcoin does not behave as a safe haven over the bear market stemming from the coronavirus disease. For financial markets of Africa, [Omane-Adjepong and Alagidede \(2021\)](#) concluded that the safe-haven potential of precious metals, particularly gold, has diminished. In the same vein, [Umar et al. \(2021\)](#) contradicted the safe-haven feature of precious metals over the coronavirus plague, apart from silver. For the case of Chinese portfolios, [Pho et al. \(2021\)](#) found that Bitcoin is appropriate to risk-prone investors, whereas gold is adequate to prudent investors.

A summary of prior literature exploring equity market volatility due to the coronavirus pandemic is exhibited in Table 1.

Table 1. Brief review of earlier studies towards the effect of the COVID-19 pandemic on stock market volatility.

Author(s)	Sample	Period	Quantitative Methods	Outcomes
Shahzad et al. (2021)	CSI 300 sector index series for ten sectors	3 January 2019–30 September 2020	Vector autoregressive model	Bad volatility spillover shocks dominate good volatility spillover shocks
Salisu and Ogbonna (2021)	Prices of Bitcoin, Ethereum, Litecoin and Ripple	2 September 2019–29 September 2020	GARCH MIDAS	Return unpredictability of cryptocurrencies is riskier throughout the pandemic as related to prior financial slumps
Abuzayed et al. (2021)	14 country-specific stock markets	7 January 2016–1 July 2020	Dynamic conditional correlation (DCC) conditional autoregressive heteroscedastic (GARCH) model	Developed stock exchanges in North America and Europe spread and received more marginal extreme risk to and from the worldwide market index compared to Asian equity markets
Bai et al. (2021)	US, China, UK, and Japan financial markets	4 January 2005–30 April 2020	GARCH-MIDAS	Pandemic positively influence perpetual volatility up to 24-month lag
Li (2021)	G7 and 3 emerging nations (China, India, and Brazil)	1 June 2009–28 August 2020	Asymmetry in volatility spillovers	Equity markets of Japan, China, India, and Brazil are risk receivers Stock markets of the US, Germany, the U.K., France, Italy, and Canada are risk spreaders
Tian and Ji (2021)	MSCI indices of the US, the UK, France, Germany and the MSCI developed markets	2 January 2001–31 December 2020	GARCH copula quantile regression-based CoVaR model	Germany exhibits the greatest risk spillovers, succeeded by France, the US and, the UK
Malik et al. (2021)	Brazil, Russia, India, China, South Africa	1 January 2013–24 April 2020	Baba-Engle-Kraft-Kroner (BEKK) model	The US, China and Brazil exhibited the highest individual volatility spillovers
Yousfi et al. (2021)	S&P 500 index and the CSI 300 index	5 January 2011–21 September 2020	GARCH models, DCC process, and wavelet coherence	Higher volatility spillover among US and Chinese equity markets throughout the pandemic period than before it
Contessi and Pace (2021)	18 main stock market indices	1 November 2019–29 May 2020	Generalized Supremum ADF (GSADF) test	Volatility spread from the Chinese equity market to all other markets
Liu et al. (2021a)	16 main equity markets in the world	24 January 2019–30 December 2020	Spillover analysis in time and frequency domain	Following the outbreak of COVID-19 pandemic, the integration of global stock markets increases considerably and the market risk contagion between them also raised substantially

Table 1. Cont.

Author(s)	Sample	Period	Quantitative Methods	Outcomes
Zaremba et al. (2020)	67 nations	1 January 2020–3 April 2020	Regression models	Government interventions increase worldwide stock markets' volatility
Duttalo et al. (2021)	European stock markets	4 January 2016–31 December 2020	Threshold GARCH	The first wave of pandemic affected stock market volatility of euro area nations with middle-large financial centers, but the second wave impacted merely stock market volatility of Belgium
Banerjee (2021)	China and its key trading partners' index futures contracts	1 August 2015–31 July 2020	Bivariate asymmetric dynamic conditional (ADCC) GARCH model	Substantial financial contagion in most developed and emerging markets showing sizeable business relations with China throughout COVID-19 period
Liu et al. (2021b)	Shanghai A shares	1 January 2017–31 March 2020.	GARCH with skewness	The pandemic boosts financial market crash risk
Hoshikawa and Yoshimi (2021)	Volatility index of the South Korean Stock market (KVI)	2 January 2019–31 August 2020	VAR, OLS, GARCH	The rise of new infection cases caused an upsurge in stock market volatility
Bora and Basistha (2021)	Nifty and Sensex stock indices	3 September 2019–10 July 2020	GJR GARCH	Indian equity market has undergone volatility throughout the pandemic
Fakhfekh et al. (2021)	12 sectorial indices	4 January 2016–30 April 2020	EGARCH, FIGARCH, FIEGARCH, TGARCH	Subsequent COVID-19 eruption, volatility is frequent in all series
Yousaf (2021)	Precious metals, industrial metals and, energy markets	22 January 2020–4 January 2021	BEKK-MGARCH	Volatility diffusion is significantly negative from the COVID-19 to gold, palladium, and brent oil markets, but positively spread to the WTI oil market

Source: Authors' work based on the literature review.

3. Data and Methodology

3.1. Sample Selection

For our study, we selected the most traded companies on the Bucharest Stock Exchange (BSE)—ALR, BRD, BVB, COTE, EL, FP, SNG, SNP, TEL, TLV, TRP and WINE—for the period January 2020–April 2021. To capture the types of causality between the variables regarding COVID-19 and the Romanian stock exchange, we decided to select the latest number of cases of COVID-19 registered in the USA, Italy, and Romania. The selected measures are presented in Table 2.

Table 2. Variables' descriptions.

Variables	Description
Variables regarding Romanian financial market	
BET	Bucharest Exchange Trading is the first index developed by BSE and signifies the reference index for the Romanian equity market. BET indicates the performance of the most traded corporations on BSE's regulated market, apart from financial investment enterprises. It is a free float market capitalization weighted index, with the highest weight of its components of 20%.
ALR	Alro is affiliate of Vimetco N.V., a worldwide, vertically-integrated primary and processed aluminium manufacturer. Field of activity: Aluminium production.
BRD	BRD Groupe Societe Generale is the second leading bank in Romania and the fourth market capitalization on the BSE. Field of activity: Other monetary intermediation.
BVB	The Bucharest Stock Exchange is the most significant organization of the local capital market. It coordinates and operates the regulated markets of financial instruments under European guidelines. Field of activity: Administration of financial markets.
COTE	CONPET delivers specific gas transport services via tubes and by rail, ensuring the supply of the factories with domestic and imported crude oil and derivatives. It manages a 3800 km pipeline grid encompassing 24 Romanian counties. Field of activity: Transport via pipeline.
EL	Societatea Energetica Electrica is a major participant in the energy sharing and supply market in Romania. Field of activity: Business and other management consultancy activities.
FP	Fondul Proprietatea is a joint stock company running as a closed-end investment company (Alternative Investment Fund) short of a set period, integrated in Romania, trading on the BSE since January 2011, and on the London Stock Exchange since April 2015. Field of activity: Trusts, funds and similar financial entities.
SNG	Romgaz is the leading natural gas manufacturer and the key provider in Romania. It is a joint stock corporation whose majority stockholder is the Romanian State owning a 70% share. Field of activity: Extraction of natural gas.
SNP	OMV Petrom is the leading energy corporation in Southeastern Europe. The firm is involved along the whole energy value chain: from exploration and fabrication of oil and gas, to processing and fuels supply, and further on to power production and advertising of gas and power. Field of activity: Extraction of crude petroleum.
TEL	Transelectrica is the Romanian Transmission and System Operator which performs a vital position in the Romanian electricity market. It operates and runs the energy spread system and delivers the electricity connections among the Central and Eastern European nations as a member of European Network of Transmission and System Operators for Electricity. Field of activity: Transmission of electricity.
TLV	Banca Transilvania is the first largest bank in Romania in terms of total assets. Field of activity: Other monetary intermediation.
TRP	TeraPlast SA is the parent corporation of the TeraPlast Group, respectively the major Romanian manufacturer of construction materials. Field of activity: Manufacture of plastic plates, sheets, tubes and profiles.
WINE	Purcari Wineries Group is a prominent participant in the wine and brandy sectors in the Central and Eastern Europe area, handling around 1,300 hectares of vineyards and 4 wineries placed in Romania and the Republic of Moldova. Field of activity: wineries.
Variables regarding COVID-19 pandemic	
RO_COVID	Number of new cases of COVID-19 in Romania
IT_COVID	Number of new cases of COVID-19 in Italy
US_COVID	Number of new cases of COVID-19 in USA

Source: Authors' own work.

The data consist of daily observations. For the variables regarding the Romanian financial market, the data source was Thomson Reuters Datastream, whereas for the variables regarding the COVID-19 pandemic, the data source was Our World in Data.

The formula for daily yields is in line with Banerjee (2021); Bora and Basistha (2021); Curto and Serrasqueiro (2021); Duttalo et al. (2021); Fakhfekh et al. (2021); Ftiti et al. (2021); Ghorbel and Jeribi (2021); Höhler and Lansink (2021); Hong et al. (2021); Hongsakulvasu et al. (2020); Le and Tran (2021); Orhun (2021); Tian and Ji (2021); Yousfi et al. (2021); Yu et al. (2021); Zoungrana et al. (2021):

$$R_{i,l} = \ln\left(\frac{P_{i,l}}{P_{i,l-1}}\right) \tag{1}$$

where $R_{i,l}$ is the yield of the index/asset i in period l , $P_{i,l}$ is the asset price/stock market index value i in period l and $P_{i,l-1}$ is the price of the asset/stock market index value in the $l-1$ period. Logarithmic yields were used because they are expected to have a normal distribution.

3.2. Quantitative Methods

To explore the selected financial time series, we will employ ARCH/GARCH models as in prior studies (Salisu and Ogbonna 2021; Abuzayed et al. 2021; Bai et al. 2021; Banerjee 2021; Bora and Basistha 2021; Curto and Serrasqueiro 2021; Czech et al. 2020; Duttalo et al. 2021; Fakhfekh et al. 2021; Farid et al. 2021; Ghorbel and Jeribi 2021; Harjoto and Rossi 2021; Haroon and Rizvi 2020; Hongsakulvasu et al. 2020; Insaideo et al. 2021; Le and Tran 2021; Liu et al. 2021b; Malik et al. 2021; Mariana et al. 2021; Omane-Adjepong and Alagidede 2021; Szczygielski et al. 2021a, 2021b; Uddin et al. 2021; Vera-Valdés 2021; Xu 2021; Yousaf 2021; Yousfi et al. 2021; Yu et al. 2021; Zhang and Hamori 2021; Zoungrana et al. 2021). These models simultaneously evaluate and test processes of yields and volatility processes.

ARCH models were introduced by Engle (1982) and Generalized (GARCH) by Bollerslev (1986). A GARCH model allows conditional variation to be dependent on its previous lags. GARCH models transform the AR process from the ARCH model into an ARMA process by adding an MA process. The GARCH model (p, q) has the following form:

$$y_t = \mu + \varepsilon_t \sim N(0, \sigma_t^2) \tag{2}$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \dots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \dots + \beta_p \sigma_{t-p}^2 \tag{3}$$

where $\omega > 0$ and $\alpha_i \geq 0, \beta_i \geq 0$.

From Equations (2) and (3), it can be seen that the conditioned variance of random perturbations depends both on the historical values of the shocks and on the values of the variance in the past. The coefficients of σ_{t-p}^2 represent persistence of volatility, whereas the coefficients of ε_{t-q}^2 signify the rate of reaction of volatility to shocks in the financial market. Parameter p is the order of the terms GARCH and q is the order of the ARCH terms.

According to Baybogan (2013), the core issue with an ARCH specification is that it involves a substantial number of lags to seize the type of the volatility, whereas the GARCH framework is generally much more parsimonious for the reason that it integrates much of the evidence that a larger ARCH model with considerable lags would cover.

In order to analyze the causality between the BET index and the number of new COVID-19 cases, we will estimate in the first instance three vector autoregression (VAR) models, much like those found in Anser et al. (2021), Chen et al. (2021), Chowdhury et al. (2021), and Youssef et al. (2021), incorporating the stock market index and each COVID-19 pandemic measure, as described below:

$$BET_t = \delta_1 + \sum_{j=1}^k \beta_j BET_{t-j} + \sum_{j=1}^k \gamma_j COVID_{t-j} + u_{1t} \tag{4}$$

$$COVID_t = \delta_2 + \sum_{j=1}^k \psi_j COVID_{t-j} + \sum_{j=1}^k \varphi_j BET_{t-j} + u_{2t} \tag{5}$$

where δ_1 and δ_2 are the intercepts, β, γ, ψ , and φ are the endogenous variables coefficients, whereas u are the residual terms.

Further, for each estimated VAR model, we will employ the Granger causality test, as in earlier literature (Bourghelle et al. 2021; Chen et al. 2021; Liu et al. 2021b). So as to perform the causality test, the data series must be stationary and zero average (Granger 1969). The null hypothesis is that b does not cause Granger on c and that c does not cause Granger on b . The following bivariate regressions are given:

$$c_t = \alpha_0 + \alpha_1 c_{t-1} + \dots + \alpha_p c_{t-p} + \beta_1 b_{t-1} + \dots + \beta_p b_{t-p} + \epsilon_t \tag{6}$$

$$b_t = \alpha_0 + \alpha_1 b_{t-1} + \dots + \alpha_p b_{t-p} + \beta_1 c_{t-1} + \dots + \beta_p c_{t-p} + u_t \tag{7}$$

Thus, a first step in the present study is the examination of the stationarity of the selected variables, which is an important stage in any econometric study. This will be verified by the ADF test, much like Bai et al. (2021) and Chen et al. (2021). Next, we intend to model BSE volatility through the GARCH model and identify the types of causality that are established between BSE and COVID-19 variables through the Granger causality test after VAR estimation.

The research hypotheses are formulated as follows:

Hypothesis 1 (H1). *The COVID-19 pandemic negatively influences the return of the Bucharest Exchange Trading Index.*

Hypothesis 2 (H2). *The COVID-19 pandemic adversely impacts the return of the companies traded on the Bucharest Stock Exchange.*

4. Empirical Results

4.1. Preliminary Statistics

Table 3 shows descriptive statistics for the daily logarithmic returns of the shares traded on BSE, as well as for the BET stock market index, whereas Figure 1 reveals the density graphs. The selected shares have a negative skewness (except for the TRP share) in line with Agarwalla et al. (2021), Banerjee (2021), Malik et al. (2021), Yousaf (2021), and Zhang and Hamori (2021). As a common condition of financial markets, skewness is negative, suggesting an asymmetry to the left.

Table 3. Descriptive statistics for daily logarithmic returns.

Variables	Mean	Std. Dev.	Skewness	Kurtosis	Jarque–Bera	Probability
BET	0.000328	0.013891	−1.69758	16.55179	2748.758	0
ALR	0.000654	0.024085	−1.52064	18.71394	3607.831	0
BRD	-8.72×10^{-5}	0.018169	−0.82825	7.13984	280.0083	0
BVB	-6.82×10^{-5}	0.014499	1.201959	21.34744	4822.239	0
COTE	0.000448	0.016037	−1.33521	16.31311	2596.545	0
EL	0.000723	0.016134	−0.64638	8.430259	438.822	0
FP	0.000995	0.020352	−0.23783	34.51292	13,988.84	0
SNG	−0.000359	0.01451	−0.52513	6.038829	145.5867	0
SNP	-8.05×10^{-5}	0.020049	−1.47295	14.83691	2095.471	0
TEL	0.000837	0.01552	−0.65783	7.630885	326.3964	0
TLV	6.32E−05	0.01956	−0.99008	7.62791	356.8519	0
TRP	0.003905	0.023626	1.82107	19.48105	4012.206	0
WINE	0.000398	0.016247	−0.52416	7.145975	257.5572	0

Source: Authors’ calculations. Notes: Variables’ descriptions are provided in Table 2.

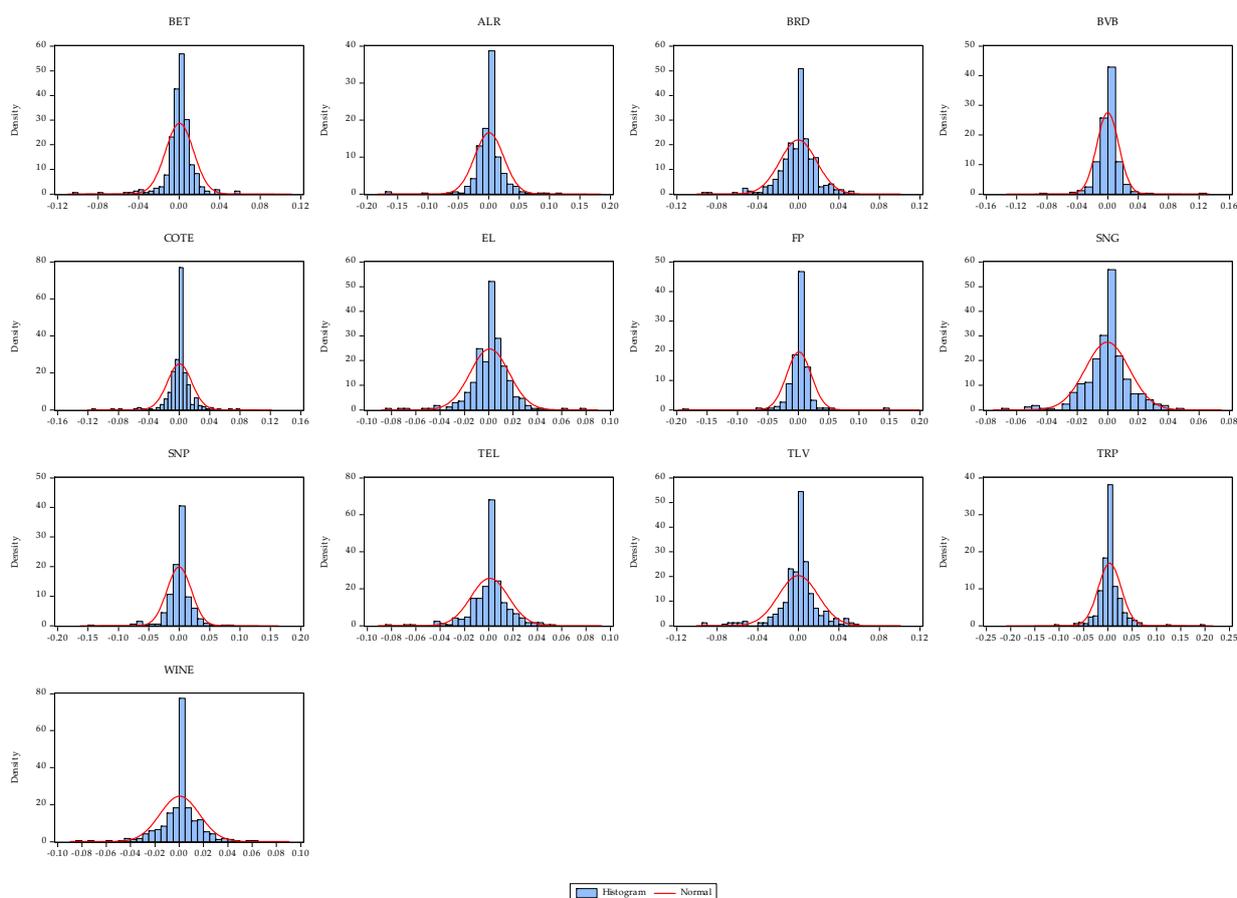


Figure 1. Density plots for daily logarithmic returns. Source: Authors’ own work. Notes: Variables’ descriptions are provided in Table 2.

The Kurtosis indicator measures the magnitude of the extreme values. Accordingly, in the current investigation, all the explored variables register a value of kurtosis greater than three. This fact indicates that the return series has fatter tails than the normal distribution, similar to Banerjee (2021), Bourghelle et al. (2021), Fakhfekh et al. (2021), Ftiti et al. (2021), Malik et al. (2021), Yu et al. (2021), and Zhang and Hamori (2021). This feature is referred to as leptokurtosis, which could be caused by volatility clustering.

Additionally, through the Jarque–Bera test, we can decide the distribution of variables. Consistent with the empirical results presented in Table 2, the probability accompanying the test is 0%. Hence, the test values are quite different from those of the normal distribution, proving that the series are not normally distributed, much like Curto and Serrasqueiro (2021), Liu et al. (2021a), Malik et al. (2021), Yousfi et al. (2021), and Zhang and Hamori (2021).

Figure 2 shows the Q–Q (quantile–quantile) plots. The quantiles–quantiles graph is a straightforward method used to compare two distributions. Therewith, it signifies the graph of an empirical distribution versus a theoretical distribution (normal distribution). If the empirical distribution is normal, the subsequent Q–Q graph should be the first bisector. However, in current investigation, the distribution is very different from the normal one.

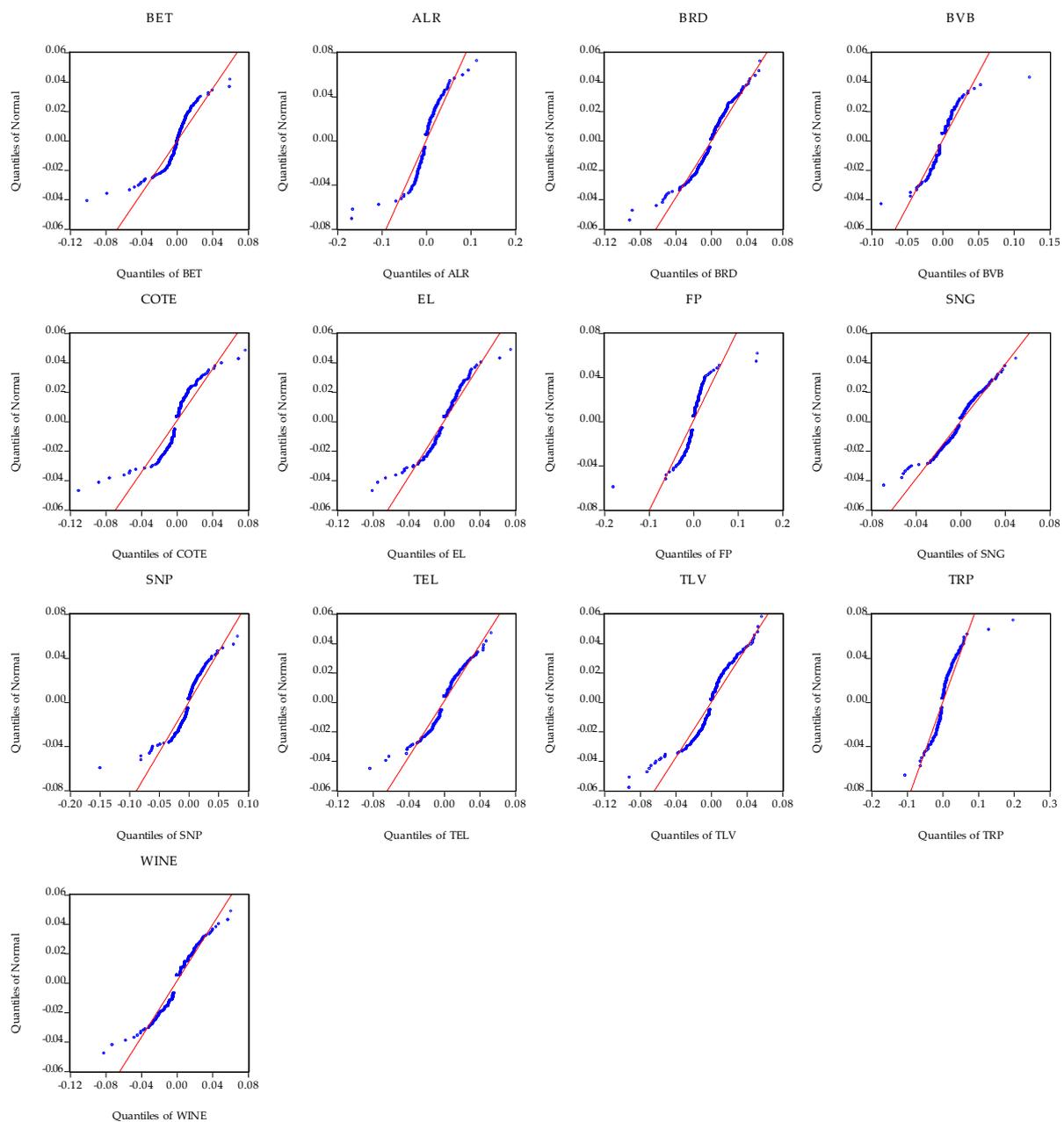


Figure 2. Q–Q plots for daily logarithmic returns. Source: Authors’ own work. Notes: Variables’ descriptions are provided in Table 2.

The density graph (see Figure 1) and Q–Q plot (see Figure 2) against the normal distribution show that the returns distribution also exhibits fat tails confirming the results in Table 2.

Further, we studied the stationarity of stocks and the stock market index using the ADF (Augmented Dickey–Fuller) test, much like [Abuzayed et al. \(2021\)](#), [Atri et al. \(2021\)](#), [Banerjee \(2021\)](#), [Bora and Basistha \(2021\)](#), [Insaiddo et al. \(2021\)](#), [Li \(2021\)](#), [Yousaf \(2021\)](#), [Yousfi et al. \(2021\)](#), and [Zhang and Hamori \(2021\)](#). ADF test is a very common method of assessing stationarity. The null hypothesis of the test is that the analyzed data series is not stationary and has a root unit. The outcomes of ADF test are revealed in Table 4.

Table 4. ADF test results for daily logarithmic returns.

Level	Augmented Dickey–Fuller Test Statistic	1% Level	5% Level	10% Level
BET	−7.012889	−3.44986	−2.87003	−2.571363
ALR	−7.440329	−3.44968	−2.86995	−2.571321
BRD	−18.45231	−3.44956	−2.8699	−2.571293
BVB	−16.64729	−3.44962	−2.86993	−2.571307
COTE	−10.02282	−3.44962	−2.86993	−2.571307
EL	−23.85922	−3.44956	−2.8699	−2.571293
FP	−7.815322	−3.44986	−2.87003	−2.571363
SNG	−16.81902	−3.44956	−2.8699	−2.571293
SNP	−17.54115	−3.44956	−2.8699	−2.571293
TEL	−17.88766	−3.44956	−2.8699	−2.571293
TLV	−17.41272	−3.44956	−2.8699	−2.571293
TRP	−15.9066	−3.44956	−2.8699	−2.571293
WINE	−6.367165	−3.44980	−2.8700	−2.571349

Source: Authors’ calculations. Notes: Intercept included in test equation. Lag length: Automatic selection based on Schwarz Info Criterion. Variables’ descriptions are provided in Table 2.

According to the results presented by the ADF stationarity test in Table 4, the null hypothesis of a unit root can be rejected, indicating that the daily logarithmic returns are significant at the 1% level, hence stationary, similar to Bai et al. (2021) and Yu et al. (2021). Thus, taking into account the empirical results of the ADF stationarity test, the examined variables are stationary and have an integration order I (0). Likewise, the stationarity of the series can be seen in Figure 3, where the daily yields of the analyzed series are represented.

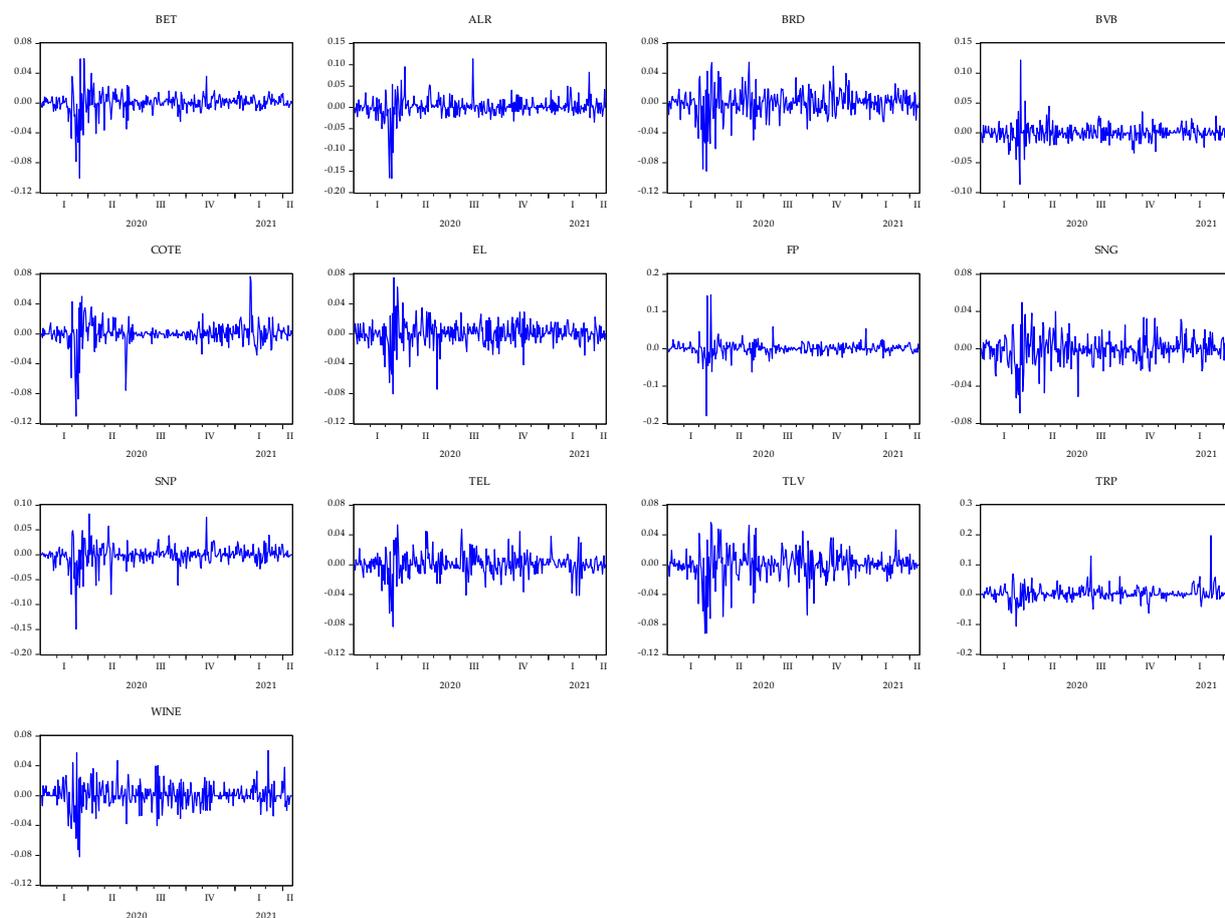


Figure 3. Daily values of the logarithmic returns. Source: Authors’ own work. Notes: Variables’ descriptions are provided in Table 2.

Figure 3 shows the evolution of the selected returns. Hence, there is acknowledged a phenomenon of “volatility clustering” and an alternation between periods of low volatility and those with high volatility, similar to [Abuzayed et al. \(2021\)](#), [Insaiddo et al. \(2021\)](#), [Malik et al. \(2021\)](#), and [Yousfi et al. \(2021\)](#). Moreover, “volatility clustering” implies a strong autocorrelation of returns.

Figures 4–6 reveal the evolution of the BET index against the new cases of COVID-19. The relationship between the evolution of the BET index and the number of new SARS-CoV-2 cases (USA, Italy, and Romania) is an indirect one. Thus, the increase in the number of infections (USA, Italy, and Romania) determined a decrease in the local stock market index and its return.

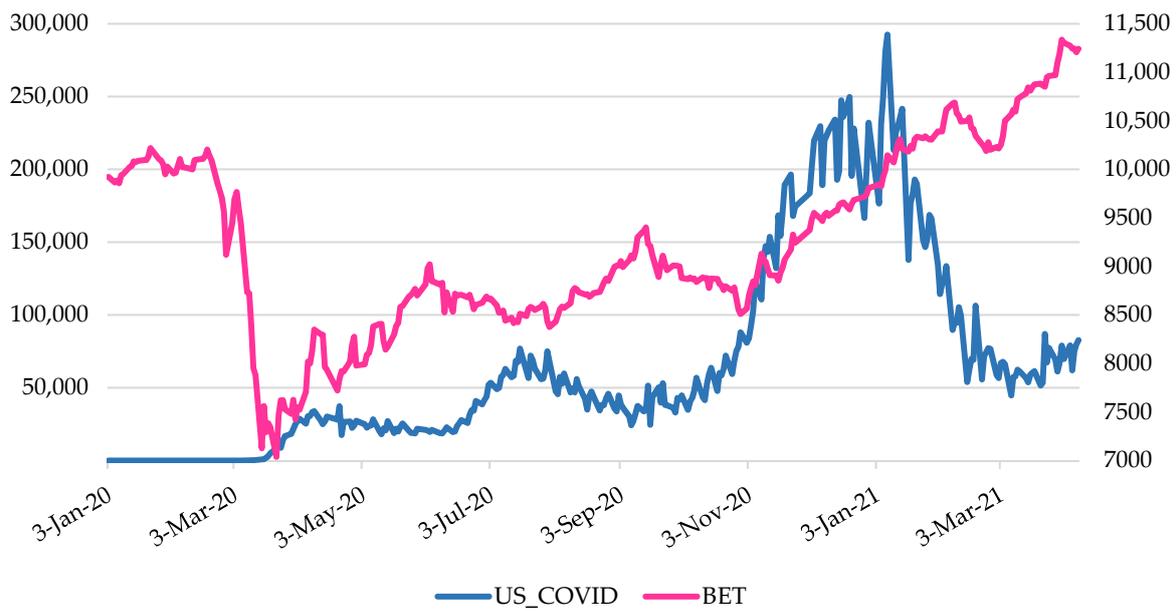


Figure 4. The evolution of the daily BET index quotes vs. no. of SUA new cases of SARS-COV-2. Source: Authors’ own work. Notes: Variables’ descriptions are provided in Table 2.

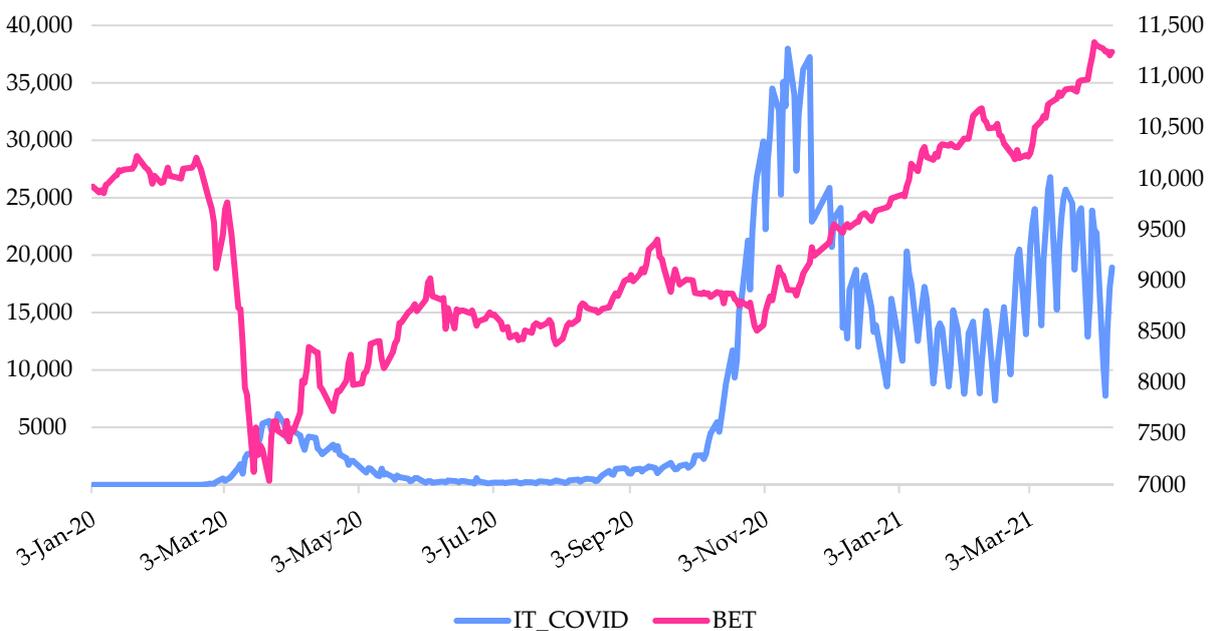


Figure 5. The evolution of the daily BET index quotes vs. no. of Italy new cases of SARS-COV-2. Source: Authors’ own work. Notes: Variables’ descriptions are provided in Table 2.

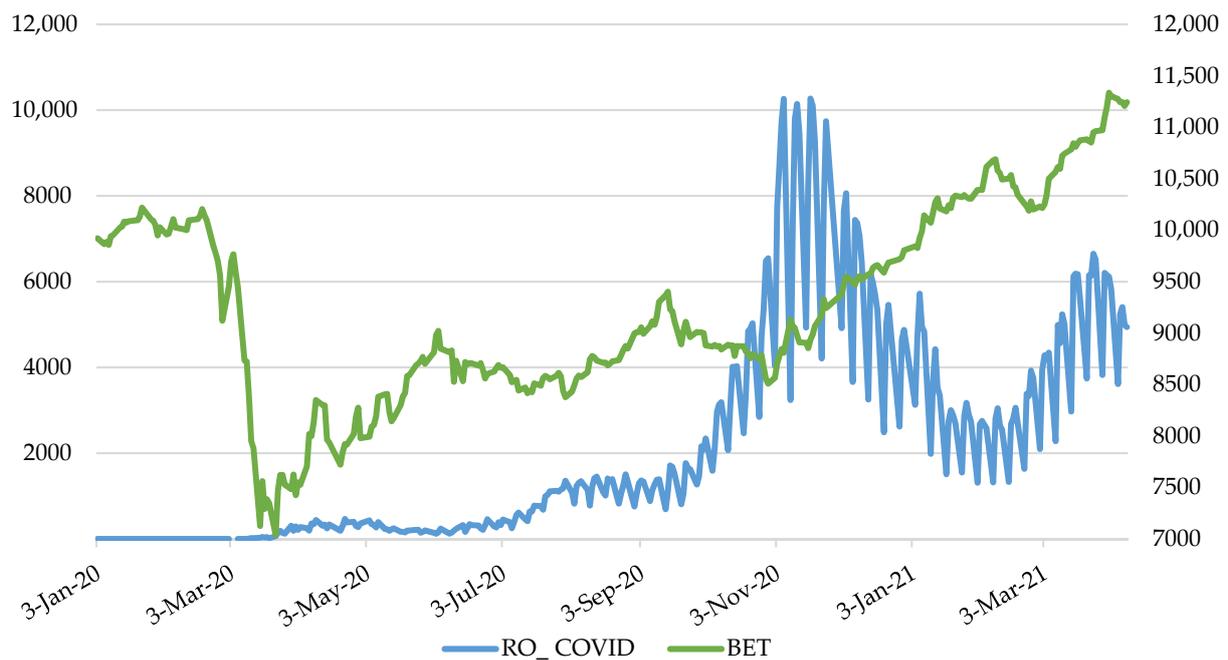


Figure 6. The evolution of the daily BET index quotes vs. no. of Romania new cases of SARS-COV-2. Source: Authors’ own work. Notes: Variables’ descriptions are provided in Table 2.

4.2. GARCH Outcomes

Before applying GARCH models, it is advisable to perform preliminary tests to detect the effects of ARCH. Heteroskedasticity was investigated by determining autocorrelation (AC), partial autocorrelation (PAC), and Q test. The number of offsets used for all the time series was 20. The outcomes of AC, PAC and Q-Stat are revealed in Table 5.

Table 5. Estimated autocorrelation (AC), partial autocorrelation (PAC) and Q-statistics with 20 lags for daily squared returns.

Variables	AC	PAC	Q-Stat	Prob
BET	0.013	−0.062	269.34	0.000
ALR	−0.017	−0.079	100.97	0.000
BRD	−0.039	−0.068	304.44	0.000
BVB	−0.020	−0.001	94.308	0.000
COTE	0.006	0.016	133.29	0.000
EL	−0.009	0.021	201.63	0.000
FP	−0.008	0.059	140.89	0.000
SNG	−0.028	−0.073	204.75	0.000
SNP	0.036	−0.024	80.962	0.000
TEL	−0.028	0.004	146.21	0.000
TLV	0.020	−0.012	220.99	0.000
TRP	−0.023	−0.028	7.8138	0.993
WINE	0.041	−0.071	204.04	0.000

Source: Authors’ own work. Notes: Variables’ descriptions are provided in Table 2.

According to the results of the Q test, in most of the cases, the existence of the serial correlation, heteroscedasticity (p -value less than 5%), is confirmed. However, in the case of TRP, the probability is greater than 5% and the null hypothesis of the absence of the serial correlation up to lag 20 cannot be rejected. Therefore, the data series shows heteroscedasticity that can be modelled by GARCH models (except TRP, because heteroskedasticity is a pre-condition for applying GARCH models for financial time series, where we may not be able to match GARCH models).

Table 6 shows the outcomes of GARCH approach. The model used was GARCH (1,1), restriction-Variance target, error distribution: Student's t being selected to register among the smallest AICs among the other available variants, similar to Czech et al. (2020) and Xu (2021). Only valid models, whose coefficients are statistically significant and different from 0, have been selected.

Following the application of a GARCH model (1,1), we estimated the conditioned volatilities which are plotted in Figure 7.

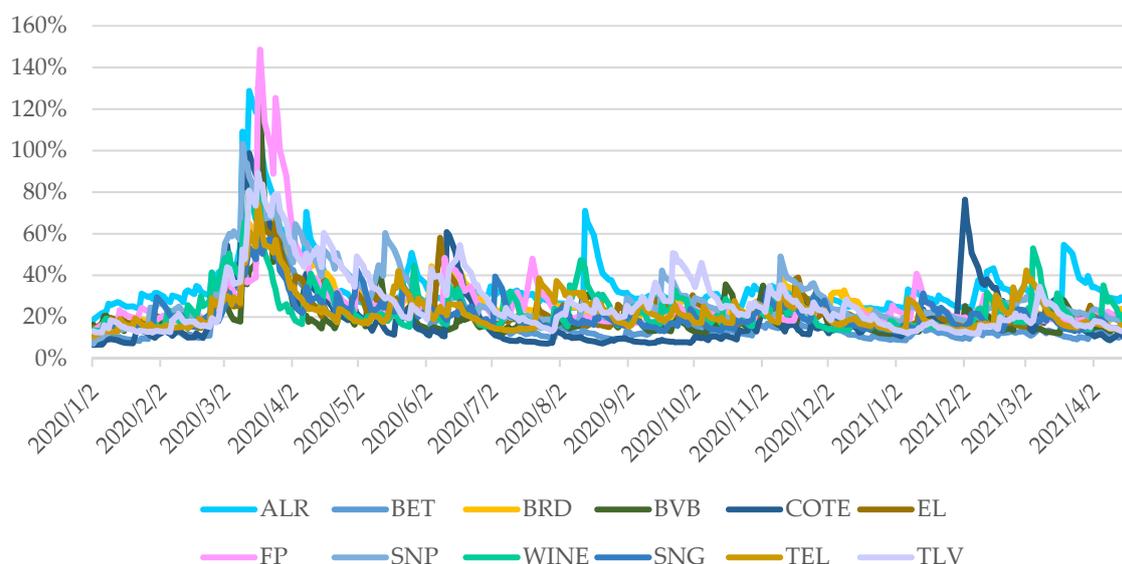


Figure 7. Conditional volatility of stock market shares and BET stock market index over January 2020–April 2021. Source: Authors' own work. Notes: Variables' descriptions are provided in Table 2.

We notice that in the first quarter of 2020, the volatility of the Romanian capital market increased to a level very close to that recorded during the global financial crisis of 2007–2009. Similarly, Curto and Serrasqueiro (2021) noticed an intensification of volatility following February 2020. Hence, this outcome is in line with both of the proposed hypotheses H1 and H2. Our results are consistent with Czech et al. (2020), which noted that Visegrad Group member countries were hit by the COVID-19 disease at the outset of March 2020 when the first case was registered.

Besides, in the next two quarters, volatility had a downward trend, argued by the fact that COVID-19 vaccine findings were declared (Yu et al. 2021). In the same vein, Rouatbi et al. (2021) reinforced that the launch and expansion of the vaccinations reduce stock market volatility.

Further, Figure 8 exhibits the daily evolution of selected shares' yields and the BET index for the period 2007–2021 in order to highlight the fact that the volatility in the period 2007–2009 was much more significant than that during the COVID-19 pandemic. This fact supports Le and Tran (2021), which pointed out for the case of Vietnam that the contagion effect throughout the coronavirus period was lesser than that over the global financial crisis.

Thus, the first two quarters of 2020 were marked by an increase in volatility on international financial markets, more pronounced in March and April, and the companies FP, ALR, SNP, and BVB had the highest volatilities during this period. August, September, and October show moderate volatility, being higher than before the outbreak of the COVID-19 pandemic.

Table 6. GARCH estimations.

Dependent Variable: BET					Dependent Variable: ALRO				
Variable	Coeff	Std. Error	z-Stat	Prob.	Variable	Coeff	Std. Error	z-Stat	Prob.
C	0.00118	0.000391	3.014619	0.0026	C	0.000289	0.000749	0.385655	0.6998
Variance Equation					Variance Equation				
C	4.76×10^{-6}				C	4.51×10^{-5}			
RESID(−1) ²	0.184229	0.054926	3.35414	0.0008	RESID(−1) ²	0.139141	0.050071	2.778885	0.0055
GARCH(−1)	0.7911	0.062407	12.67647	0	GARCH(−1)	0.782887	0.077865	10.05445	0
T-DIST. DOF	4.264243	0.887964	4.80227	0	T-DIST. DOF	2.915888	0.214055	13.62215	0
R-sq	−0.003773	Mean dependent var		0.000328	R-sq	−0.000231	Mean dependent var		0.000654
Adj R-sq	−0.003773	S.D. dependent var		0.013891	Adj R-sq	−0.000231	S.D. dependent var		0.024085
S.E. of regr	0.013917	Akaike info crit		−6.537876	S.E. of regr	0.024088	Akaike info crit		−5.236626
Sum sq resid	0.065275	Schwarz crit		−6.492633	Sum sq resid	0.195534	Schwarz crit		−5.191383
Log likelihood	1108.901	Hannan–Quinn crit		−6.519845	Log likelihood	888.9898	Hannan–Quinn crit		−5.218595
DW stat	2.106484				DW stat	1.936172			
Dependent Variable: BRD					Dependent Variable: BVB				
Variable	Coeff	Std. Error	z-Stat	Prob.	Variable	Coeff	Std. Error	z-Stat	Prob.
C	0.00077	0.000709	1.085874	0.2775	C	−0.000109	0.000504	−0.21581	0.8291
Variance Equation					Variance Equation				
C	1.43×10^{-5}				C	2.12×10^{-5}			
RESID(−1) ²	0.150634	0.043495	3.463245	0.0005	RESID(−1) ²	0.292829	0.072636	4.031475	0.0001
GARCH(−1)	0.806065	0.061517	13.10319	0	GARCH(−1)	0.606027	0.102678	5.902193	0
T-DIST. DOF	5.300367	1.31796	4.021645	0.0001	T-DIST. DOF	4.976087	1.251612	3.975743	0.0001
R-sq	−0.002232	Mean dependent var		$−8.72 \times 10^{-5}$	R-sq	−0.000008	Mean dependent var		$−6.82 \times 10^{-5}$
Adj R-sq	−0.002232	S.D. dependent var		0.018169	Adj R-sq	−0.000008	S.D. dependent var		0.014499
S.E. of regr	0.018189	Akaike info crit		−5.52442	S.E. of regr	0.014499	Akaike info crit		−6.126467
Sum sq resid	0.11149	Schwarz crit		−5.479177	Sum sq resid	0.07084	Schwarz crit		−6.081224
Log likelihood	937.627	Hannan–Quinn crit		−5.506389	Log likelihood	1039.373	Hannan–Quinn crit		−6.108436
DW stat	2.011758				DW stat	2.525927			

Table 6. Cont.

Dependent Variable: COTE					Dependent Variable: EL				
Variable	Coeff	Std. Error	z-Stat	Prob.	Variable	Coeff	Std. Error	z-Stat	Prob.
C	0.000205	0.00034	0.604738	0.5454	C	0.001186	0.000632	1.87812	0.0604
Variance Equation					Variance Equation				
C	4.99×10^{-6}				C	2.13×10^{-5}			
RESID(−1) ²	0.250596	0.04803	5.217482	0	RESID(−1) ²	0.209315	0.052881	3.958218	0.0001
GARCH(−1)	0.729937	0.053054	13.75829	0	GARCH(−1)	0.708624	0.078695	9.004646	0
T-DIST. DOF	3.486178	0.373561	9.332278	0	T-DIST. DOF	5.627834	1.419299	3.965221	0.0001
R-sq	−0.000229	Mean dependent var		0.000448	R-sq	−0.000828	Mean dependent var		0.000723
Adj R-sq	−0.000229	S.D. dependent var		0.016037	Adj R-sq	−0.000828	S.D. dependent var		0.016134
S.E. of regr	0.016039	Akaike info crit		−6.427494	S.E. of regr	0.016141	Akaike info crit		−5.754231
Sum sq resid	0.086694	Schwarz crit		−6.382251	Sum sq resid	0.087795	Schwarz crit		−5.708987
Log likelihood	1090.246	Hannan–Quinn crit		−6.409463	Log likelihood	976.465	Hannan–Quinn crit		−5.736199
DW stat	1.767033				DW stat	2.51603			
Dependent Variable: FP					Dependent Variable: SNP				
Variable	Coeff	Std. Error	z-Stat	Prob.	Variable	Coeff	Std. Error	z-Stat	Prob.
C	0.001227	0.000524	2.341939	0.0192	C	0.000648	0.001333	0.486339	0.6267
Variance Equation					Variance Equation				
C	2.92×10^{-5}				C	0.00016			
RESID(−1) ²	0.191734	0.06115	3.13549	0.0017	RESID(−1) ²	0.000401	0.007995	0.050126	0.96
GARCH(−1)	0.737594	0.078636	9.379818	0	GARCH(−1)	0.6	0.56513	1.061702	0.2884
T-DIST. DOF	2.80621	0.225963	12.41887	0	T-DIST. DOF	20	3.777537	5.294455	0
R-sq	−0.00013	Mean dependent var		0.000995	R-sq	−0.001325	Mean dependent var		-8.05×10^{-5}
Adj R-sq	−0.00013	S.D. dependent var		0.020352	Adj R-sq	−0.001325	S.D. dependent var		0.020049
S.E. of regr	0.020353	Akaike info crit		−5.925241	S.E. of regr	0.020062	Akaike info crit		−5.118899
Sum sq resid	0.139607	Schwarz crit		−5.879998	Sum sq resid	0.135641	Schwarz crit		−5.073656
Log likelihood	1005.366	Hannan–Quinn crit		−5.90721	Log likelihood	869.0939	Hannan–Quinn crit		−5.100868
DW stat	2.534692				DW stat	1.912486			

Table 6. Cont.

Dependent Variable: SNG					Dependent Variable: WINE				
Variable	Coefficient	Std. Error	z-Statistic	Prob.	Variable	Coeff	Std. Error	z-Stat	Prob.
C	−0.00011	0.000579	−0.190745	0.8487	C	0.00093	0.000575	1.616535	0.106
Variance Equation					Variance Equation				
C	0.0000175				C	2.53E-05			
RESID(−1) ²	0.206748	0.053863	3.838396	0.0001	RESID(−1) ²	0.274618	0.063641	4.315126	0
GARCH(−1)	0.709914	0.084466	8.404724	0	GARCH(−1)	0.629318	0.093136	6.757009	0
T-DIST. DOF	4.572915	0.814926	5.611448	0	T-DIST. DOF	4.076108	0.615755	6.61969	0
R-squared	−0.000296	Mean dependent var		−0.000359	R-sq	−0.001074	Mean dependent var		0.000398
Adjusted R-squared	−0.000296	S.D. dependent var		0.01451	Adj R-sq	−0.001074	S.D. dependent var		0.016247
S.E. of regression	0.014512	Akaike info criterion		−5.903807	S.E. of regr	0.016256	Akaike info crit		−5.761172
Sum squared resid	0.070969	Schwarz criterion		−5.858564	Sum sq resid	0.089052	Schwarz crit		−5.715929
Log likelihood	1001.743	Hannan–Quinn criter.		−5.885776	Log likelihood	977.6381	Hannan–Quinn crit		−5.743141
Durbin-Watson stat	1.830748				DW stat	2.292014			
Dependent Variable: TEL					Dependent Variable: TLV				
Variable	Coefficient	Std. Error	z-Statistic	Prob.	Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000993	0.00053	1.873592	0.061	C	0.000385	0.00059	0.652159	0.5143
Variance Equation					Variance Equation				
C	0.0000155				C	0.00000789			
RESID(−1) ²	0.184978	0.055272	3.346684	0.0008	RESID(−1) ²	0.169068	0.040267	4.198672	0
GARCH(−1)	0.750384	0.07748	9.684826	0	GARCH(−1)	0.810254	0.046858	17.2916	0
T-DIST. DOF	3.593242	0.439082	8.183526	0	T-DIST. DOF	3.940655	0.593309	6.64183	0
R-squared	−0.000102	Mean dependent var		0.000837	R-squared	−0.000272	Mean dependent var		0.0000632
Adjusted R-squared	−0.000102	S.D. dependent var		0.01552	Adjusted R-squared	−0.000272	S.D. dependent var		0.01956
S.E. of regression	0.015521	Akaike info criterion		−5.879238	S.E. of regression	0.019563	Akaike info criterion		−5.561135
Sum squared resid	0.081186	Schwarz criterion		−5.833995	Sum squared resid	0.128969	Schwarz criterion		−5.515892
Log likelihood	997.5912	Hannan–Quinn criter.		−5.861207	Log likelihood	943.8319	Hannan–Quinn criter.		−5.543104
Durbin-Watson stat	1.953884				Durbin-Watson stat	1.899838			

Source: Authors’ calculations. Notes: Variables’ descriptions are provided in Table 2. Method: ML ARCH—Student’s t distribution (BFGS/Marquardt steps). Included observations: 338. Coefficient covariance computed using outer product of gradients. Presample variance: backcast (parameter = 0.7).

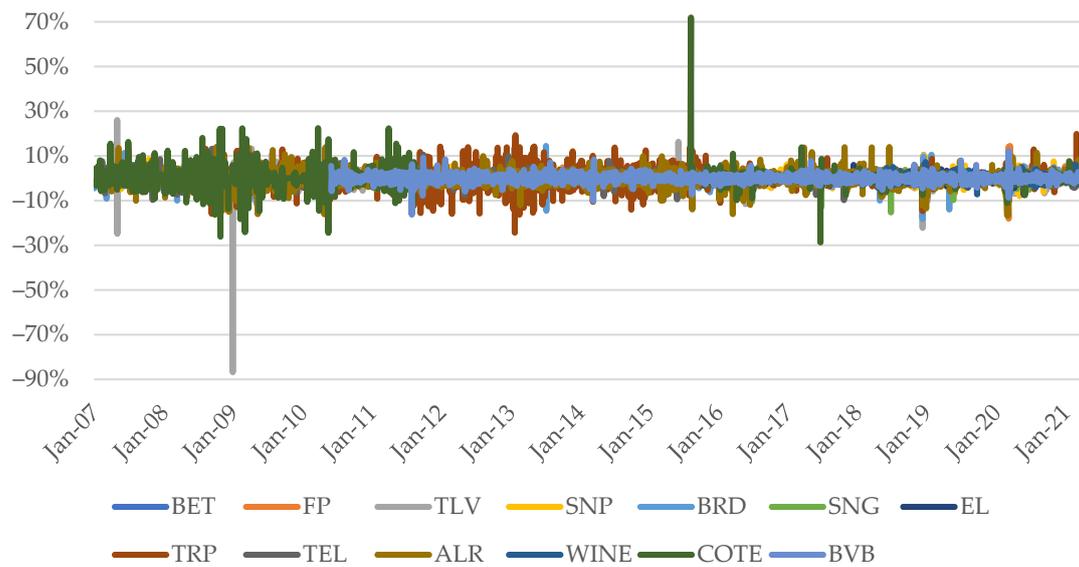


Figure 8. Daily values of the selected data over the period 2007–2021. Source: Authors’ own work. Notes: Variables’ descriptions are provided in Table 2.

4.3. Causality Analysis

Given that the health crisis has a significant impact on the global economy, we also aimed to explore the causal relationships that are established between the variables regarding COVID-19 and the BET stock market index. Primarily, it was checked if the stock market index and each COVID-19 pandemic measure were cointegrated. In this regard, Table 7 exhibits the outcomes of the Phillips–Ouliaris cointegration test. Accordingly, we reject the null hypothesis and decide that the series are cointegrated.

Table 7. The outcomes of the Phillips–Ouliaris cointegration test.

Series: RBET, DRO_COVID	Dependent	tau-Statistic	Prob.*	z-Statistic	Prob.*
Included observations: 312 after adjustments	RBET	−20.03971	0	−387.7359	0
	DRO_COVID	−37.24025	0	−316.0871	0
Series: RBET, DIT_COVID	Dependent	tau-Statistic	Prob.*	z-Statistic	Prob.*
Included observations: 316 after adjustments	RBET	−18.96646	0	−400.8999	0
	DIT_COVID	−23.96736	0	−284.9561	0
Series: RBET, DUS_COVID	Dependent	tau-Statistic	Prob.*	z-Statistic	Prob.*
Included observations: 316 after adjustments	RBET	−18.93794	0	−400.6069	0
	DUS_COVID	−27.8585	0	−369.0163	0

Source: Authors’ calculations. Notes: * MacKinnon (1996) *p*-values. Sample (adjusted): 6 January 2020–9 April 2021. Cointegrating equation deterministic: C. Long-run variance estimate (Bartlett kernel, Newey–West fixed bandwidth). No d.f. adjustment for variances. Variables’ descriptions are provided in Table 2.

Further, the lag selection criterion is explored. Table 8 reveals the related lag order selection criteria. Hence, the Schwarz information criterion suggests five and seven lags.

Table 8. VAR lag order selection criteria.

	Lag	LogL	LR	FPE	AIC	SC	HQ
Endogenous variables: RBET, DRO_COVID Exogenous variables: C Included observations: 296	0	−1607.62	NA	181.2816	10.87581	10.90074	10.88579
	1	−1587.74	39.35295	162.8402	10.76852	10.84333	10.79847
	2	−1559.53	55.4685	138.2672	10.60494	10.72961	10.65485
	3	−1551.44	15.79743	134.5	10.5773	10.75184	10.64718
	4	−1458.68	179.8884	73.8342	9.977539	10.20195	10.06739
	5	−1439.81	36.32215	66.78202	9.87712	10.1514	9.986937
	6	−1429.8	19.15297	64.12454	9.836468	10.16062	9.966253
	7	−1399.38	57.75557 *	53.64450 *	9.657959 *	10.03198 *	9.807711 *
	8	−1398.9	0.893729	54.94222	9.681783	10.10568	9.851501
Endogenous variables: RBET, DIT_COVID Exogenous variables: C Included observations: 308	Lag	LogL	LR	FPE	AIC	SC	HQ
	0	−2012.61	NA	1645.988	13.08185	13.10607	13.09153
	1	−2007.18	10.74477	1630.827	13.0726	13.14526	13.10165
	2	−1987.05	39.60666	1468.66	12.96785	13.08896	13.01628
	3	−1975.61	22.36096	1399.403	12.91954	13.08909	12.98733
	4	−1947.2	55.16232	1194.285	12.76102	12.97902	12.84819
	5	−1902.16	86.8554	914.9435	12.49456	12.76099 *	12.60109
	6	−1892.38	18.73185	881.2824	12.45703	12.77191	12.58293
	7	−1884.43	15.12514 *	859.0133 *	12.43138 *	12.79471	12.57666 *
8	−1883.75	1.295962	877.7618	12.4529	12.86467	12.61755	
Endogenous variables: RBET, DUS_COVID Exogenous variables: C Included observations: 308	Lag	LogL	LR	FPE	AIC	SC	HQ
	0	−2539.78	NA	50478.62	16.50506	16.52928	16.51474
	1	−2520.57	38.04213	45731.93	16.4063	16.47897	16.43536
	2	−2508.57	23.61618	43416.26	16.35434	16.47544	16.40276
	3	−2503.86	9.195366	43218.5	16.34976	16.51931	16.41756
	4	−2483.95	38.65642	38977.11	16.24645	16.46444	16.33361
	5	−2453.01	59.68167	32721.35	16.07148	16.33791 *	16.17801
	6	−2442.42	20.28741 *	31351.76 *	16.02868 *	16.34356	16.15458 *
	7	−2441.24	2.234599	31934.01	16.04703	16.41035	16.1923
8	−2439.71	2.89233	32452.48	16.06306	16.47483	16.2277	

Source: Authors’ calculations. Notes: Sample: 3 January 2020–9 April 2021. * indicates lag order selected by the criterion. LR: sequential modified LR test statistic (each test at 5% level). FPE: Final prediction error. AIC: Akaike information criterion. SC: Schwarz information criterion. HQ: Hannan–Quinn information criterion. Variables’ descriptions are provided in Table 2.

After estimating the VAR model for the stock market index and each COVID-19 variable (see Tables A1–A3), we proceed to explore the Granger causality relationships. According to Freeman (1983), a variable, X, which evolves over time, causes another variable in evolution, Y, if the predictions of the value Y based on its own past values and on the previous values of X are better than the predictions of Y based only on Y’s own past values. Table 9 shows the empirical results of the Granger causality test after VAR estimation.

Thus, for the analyzed period January 2020–April 2021, no causal relationship was identified between the COVID-19 variables and the BET index. This outcome is not consistent with Liu et al. (2021b), who found that fear sentiment causes stock market crash risk. Therefore, Yu et al. (2021) cannot be maintained either since it was found that the COVID-19 Anxiety Index causes stock market returns.

Table 9. The results of the VAR Granger causality/block exogeneity Wald tests.

Sample: 3 January 2020–9 April 2021 Included observations: 298		Dependent variable: RBET			
		Excluded	Chi-sq	df	Prob.
		DRO_COVID	2.811942	7	0.9018
		All	2.811942	7	0.9018
		Dependent variable: DRO_COVID			
		Excluded	Chi-sq	df	Prob.
RBET	4.566812	7	0.7127		
All	4.566812	7	0.7127		
Sample: 3 January 2020–9 April 2021 Included observations: 311		Dependent variable: RBET			
		Excluded	Chi-sq	df	Prob.
		DIT_COVID	1.199299	5	0.9449
		All	1.199299	5	0.9449
		Dependent variable: DIT_COVID			
		Excluded	Chi-sq	df	Prob.
RBET	3.959237	5	0.5553		
All	3.959237	5	0.5553		
Sample: 3 January 2020–9 April 2021 Included observations: 311		Dependent variable: RBET			
		Excluded	Chi-sq	df	Prob.
		DUS_COVID	1.266153	5	0.9384
		All	1.266153	5	0.9384
		Dependent variable: DUS_COVID			
		Excluded	Chi-sq	df	Prob.
RBET	0.801005	5	0.977		
All	0.801005	5	0.977		

Source: Authors' calculations. Notes: Variables' descriptions are provided in Table 2.

5. Concluding Remarks

The COVID-19 virus has spread very rapidly around the globe, negatively impacting the economy, and according to the latest information, it undergoes various mutations, with new variants of COVID-19 always appearing. The study of volatility has always been a hotly debated topic by experts, especially now in these times of uncertainty. The impact of COVID-19 on the capital markets did not take long to appear, so it initially manifested itself on the largest stock markets in the world, then, due to the contagion effect, it was transmitted to the other smaller markets. To our knowledge, the studies conducted on the Romanian capital market related to the research of volatility during the pandemic are extremely limited, which led us to focus on analyzing the volatility of the BSE indices.

Our main goal of the article was to analyze the BSE volatilities during the COVID-19 pandemic, selecting indices and a group of traded shares (these being among the most traded on BSE, which are also found in the BET stock index). To study volatility, we used the GARCH model (1,1), and the graphical outputs capture the episodes of volatility. Finally, through the Granger causality test, after VAR estimation, we were able to identify the relationships to be established between BSE stock index, respectively, the shares traded on BSE and variables that capture the evolution of the COVID-19 pandemic in the USA, Italy, and Romania.

This research contributes to the existing literature, which is the reason that we studied the volatility of the main companies traded on the Bucharest Stock Exchange, between January 2020 and April 2021, a period subject to a major change due to the COVID-19 pandemic, using GARCH models. We found that the distribution of the daily return series for the Romanian stock market is leptokurtic, it is not normally distributed, and has

significant time dependencies. The GARCH (1,1) model was used to model volatility on the Romanian stock market.

The study revealed strong evidence of volatility that lasts over time, a trend of high and low volatility periods, and a high persistence of volatility on the Bucharest Stock Exchange. In the first quarter of 2020, capital market volatility in Romania increased to a level very close to that recorded during the global financial crisis of 2007–2009. In the next two quarters, volatility had a downward trend. Nevertheless, no causal association was noticed between the COVID-19 variables and the BET index.

The empirical outcomes could help investors and asset managers to adjust their trading strategies. Moreover, the government should consider economic relief packages and formulate policies to lessen severe falls in prices (Hashmi et al. 2021).

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Appendix A

Table A1. Vector autoregression estimates for stock market index and the number of new cases of COVID-19 in Romania.

	RBET	DRO_COVID
RBET(−1)	−0.039042	−1347.071
	−0.05944	−3387.07
	[−0.65686]	[−0.39771]
RBET(−2)	0.104624	−2907.972
	−0.05457	−3109.71
	[1.91723]	[−0.93513]
RBET(−3)	−0.008179	−1776.737
	−0.05343	−3044.46
	[−0.15309]	[−0.58360]
RBET(−4)	−0.017674	−1706.189
	−0.05245	−2988.76
	[−0.33699]	[−0.57087]
RBET(−5)	0.099649	−3998.206
	−0.05212	−2970.19
	[1.91184]	[−1.34611]
RBET(−6)	−0.195458	−2384.377
	−0.05129	−2922.5
	[−3.81120]	[−0.81587]

Table A1. Cont.

	RBET	DRO_COVID
RBET(−7)	−0.012525 −0.05213 [−0.24025]	1802.935 −2970.85 [0.60687]
DRO_COVID(−1)	-8.20×10^{-7} -9.40×10^{-7} [−0.87075]	−0.57646 −0.05368 [−10.7389]
DRO_COVID(−2)	1.33×10^{-7} -1.10×10^{-6} [0.12428]	−0.803286 −0.06107 [−13.1529]
DRO_COVID(−3)	2.53×10^{-8} -1.20×10^{-6} [0.02129]	−0.150507 −0.06772 [−2.22260]
DRO_COVID(−4)	5.87×10^{-7} -1.20×10^{-6} [0.50356]	−0.261028 −0.06638 [−3.93240]
DRO_COVID(−5)	-1.44×10^{-7} -1.20×10^{-6} [−0.12112]	0.637747 −0.06798 [9.38180]
DRO_COVID(−6)	4.04×10^{-7} -1.10×10^{-6} [0.37555]	0.306384 −0.06128 [4.99998]
DRO_COVID(−7)	3.67×10^{-7} -9.50×10^{-7} [0.38643]	0.4326 −0.05413 [7.99193]
C	0.001192 −0.00066 [1.79229]	31.51544 −37.8873 [0.83182]
R-squared	0.107799	0.729229
Adj. R-squared	0.063661	0.715834
Sum sq. resids	0.034824	1.13×10^8
S.E. equation	0.011093	632.1363
F-statistic	2.442354	54.44024
Log likelihood	926.2818	−2336.982
Akaike AIC	−6.115985	15.78511
Schwarz SC	−5.92989	15.97121
Mean dependent	0.00113	16.43289
S.D. dependent	0.011464	1185.836
Determinant resid covariance (dof adj.)		49.15166
Determinant resid covariance		44.32804
Log likelihood		−1410.638
Akaike information criterion		9.668714
Schwarz criterion		10.0409
Number of coefficients		30

Source: Authors' calculations. Notes: Standard errors in () and t-statistics in []. Sample (adjusted): 15 January 2020–9 April 2021. Included observations: 298 after adjustments. Variables' descriptions are provided in Table 2.

Table A2. Vector autoregression estimates for stock market index and the number of new cases of COVID-19 in Italy.

	RBET	DIT_COVID
RBET(−1)	−0.033198 −0.0569 [−0.58340]	−4632.009 −8536.69 [−0.54260]
RBET(−2)	0.246594 −0.05647 [4.36677]	−2994.404 −8471.69 [−0.35346]
RBET(−3)	0.029426 −0.05822 [0.50542]	−4806.22 −8734.25 [−0.55027]
RBET(−4)	−0.110034 −0.05661 [−1.94372]	−10,837.98 −8492.63 [−1.27616]
RBET(−5)	0.177356 −0.05708 [3.10725]	−8666.519 −8562.82 [−1.01211]
DIT_COVID(−1)	8.74×10^{-8} -3.40×10^{-7} [0.25850]	−0.211916 −0.05074 [−4.17662]
DIT_COVID(−2)	1.75×10^{-8} -3.40×10^{-7} [0.05158]	−0.302194 −0.05081 [−5.94763]
DIT_COVID(−3)	-3.00×10^{-8} -3.50×10^{-7} [−0.08468]	−0.169155 −0.05314 [−3.18296]
DIT_COVID(−4)	-2.90×10^{-7} -3.50×10^{-7} [−0.84012]	−0.204575 −0.05182 [−3.94743]
DIT_COVID(−5)	1.35×10^{-9} -3.50×10^{-7} [0.00386]	0.487342 −0.05253 [9.27781]
C	0.000266 −0.00079 [0.33573]	76.10105 −118.787 [0.64065]
R-squared	0.108079	0.452144
Adj. R-squared	0.078348	0.433882
Sum sq. resids	0.0579	1.30×10^9
S.E. equation	0.013892	2084.126
F-statistic	3.635264	24.75893
Log likelihood	894.2746	−2812.385
Akaike AIC	−5.680222	18.15682
Schwarz SC	−5.547947	18.28909
Mean dependent	0.000392	60.84887
S.D. dependent	0.014471	2769.942
Determinant resid covariance (dof adj.)		836.7493
Determinant resid covariance		778.6048
Log likelihood		−1917.822
Akaike information criterion		12.47474
Schwarz criterion		12.73929
Number of coefficients		22

Source: Authors’ calculations. Notes: Standard errors in () and t-statistics in []. Sample (adjusted): 13 January 2020–9 April 2021. Included observations: 311 after adjustments. Variables’ descriptions are provided in Table 2.

Table A3. Vector autoregression estimates for stock market index and the number of new cases of COVID-19 in the US.

	RBET	DUS_COVID
RBET(−1)	−0.033139 −0.05671 [−0.58440]	32,151.08 −50,868.3 [0.63205]
RBET(−2)	0.244778 −0.0564 [4.34020]	24,680.63 −50,592.7 [0.48783]
RBET(−3)	0.024836 −0.05813 [0.42722]	−17,993.17 −52,150.7 [−0.34502]
RBET(−4)	−0.108053 −0.05637 [−1.91689]	−26,717.78 −50,566.7 [−0.52837]
RBET(−5)	0.181611 −0.05668 [3.20434]	6054.621 −50,842.6 [0.11909]
DUS_COVID(−1)	2.85×10^{-8} -5.90×10^{-8} [0.48101]	−0.334621 −0.05323 [−6.28657]
DUS_COVID(−2)	4.52×10^{-8} -6.20×10^{-8} [0.72473]	−0.172527 −0.05599 [−3.08140]
DUS_COVID(−3)	5.78×10^{-9} -6.20×10^{-8} [0.09263]	−0.177546 −0.056 [−3.17063]
DUS_COVID(−4)	2.31×10^{-8} -6.20×10^{-8} [0.36926]	−0.151236 −0.05606 [−2.69776]
DUS_COVID(−5)	5.54×10^{-8} -6.00×10^{-8} [0.93125]	0.389606 −0.05339 [7.29772]
C	0.000223 −0.00079 [0.28226]	373.3586 −709.148 [0.52649]
R-squared	0.108277	0.360989
Adj. R-squared	0.078553	0.339689
Sum sq. resids	0.057887	4.66×10^{10}
S.E. equation	0.013891	12,461.02
F-statistic	3.64273	16.94756
Log likelihood	894.3091	−3368.533
Akaike AIC	−5.680444	21.73333
Schwarz SC	−5.548169	21.8656
Mean dependent	0.000392	265.91
S.D. dependent	0.014471	15,334.84
Determinant resid covariance (dof adj.)		29,925.76
Determinant resid covariance		27,846.27
Log likelihood		−2474.037
Akaike information criterion		16.05169
Schwarz criterion		16.31624
Number of coefficients		22

Source: Authors' calculations. Notes: Standard errors in () and t-statistics in []. Sample (adjusted): 13 January 2020–9 April 2021. Included observations: 311 after adjustments. Variables' descriptions are provided in Table 2.

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