THE VOLATILITY SPILLOVER EFFECTS BETWEEN COVID-19 AND STOCK MARKETS: A RESEARCH OVER OECD COUNTRIES

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ABSTRACT

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Master's Program in Business Administration

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The COVID-19 pandemic caused unprecedented impacts on stock markets. This thesis analyzes return and volatility spillover effects between seven OECD stock markets; namely Colombia, France, the U.S., Germany, Italy, Mexico, and the U.K. which are selected according to the highest number of daily deaths due to COVID-19 infection. Applying the Multivariate BEKK methodology, the empirical findings indicate that there is evidence of contagion effect among the selected OECD stock markets from January, 1 2019 to September, 30 2021 which proves the existence of volatility spillover effects between these markets.

Keywords: COVID-19, OECD Stock Markets, Volatility Spillover

ÖZET

COVID-19 İLE HİSSE SENEDİ PİYASALARI ARASINDA VOLATİLİTENİN YAYILMA ETKİSİ: OECD ÜLKELERİ ÜZERİNE BİR ARAŞTIRMA

Özgöz, İdil

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COVID-19 pandemisi hisse senedi piyasaları üzerinde benzeri görülmemiş etkilere neden olmuştur. Bu tez, yedi OECD ülkesinin hisse senedi piyasaları arasındaki getiri ve oynaklık yayılma etkilerini 1 Ocak 2019 - 30 Eylül 2021 tarihleri arasındaki günlük verileri kullanılarak analiz etmektedir. COVID-19 enfeksiyonu nedeniyle en fazla günlük ölüm sayısına göre Kolombiya, Fransa, Almanya, İtalya, İngiltere, Meksika ve ABD ülkeleri seçilmiştir. BEKK temsili ile VAR-GARCH modeli çerçevesinde, ampirik bulgularda, seçilen OECD ülkelerinin hisse senedi piyasalarının belirtilen dönem boyunca korelasyon katsayılarının ortalamalarında önemli bir artış gösterdiği gözlemlenmiş, bu sonuç da ülkelerin hisse senedi piyasalarındaki oynaklık yayılma etkilerinin varlığını kanıtlamaktadır.

Anahtar Kelimeler: COVID-19, OECD Hisse Piyasaları, Oynaklık Yayılımı

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LIST OF ABBREVIATIONS

ADF: Augmented Dickey-Fuller test

ARCH: Autoregressive Conditional Heteroscedastic

BEKK: Baba, Engle, Kraft, Kroner

BMV: Bolsa Mexicana de Valores

BRICS: Brazil, Russia, India, China, and South Africa

CCC: Constant Conditional Correlation

COVID-19: Coronavirus disease

DCC: Dynamic Conditional Correlation

FSE: The Frankfurt Stock Exchange

GARCH: Generalized AutoRegressive Conditional Heteroskedasticity

GLS: Generalized Least Squares

GIPSI: Greece, Ireland, Portugal, Spain, and Italy

JB: Jarque-Bera

MENA: The Middle East and North Africa

MGARCH: Multivariate Generalized Autoregressive Conditional Heteroskedasticity

NYSE: New York Stock Exchange

OECD: Organization for Economic Co-operation and Development

PP: hillips–Perron test

SETS: Stock Exchange Electronic Trading Service

The U.K.: United Kingdom

The U.S.: United States

VCC: Varying Conditional Correlation

VAR: Vector Autoregressive

CHAPTER 1: INTRODUCTION

After the developments in globalization, liberalization, and new technological advances, the integration of world financial markets has amplified. In the financial markets, financial instruments are exchanged and traded. The financial markets have three important functions, which can be counted market liquidity, information, and risk-sharing. In today's world, businesses and governments require capital that should be huge to continue their operations with financing. Therefore, financial markets have an important role in the countries' economies. The dynamic relationship between the countries' financial markets has drawn considerable research attention from academics, investors, and policymakers.

The global crises have significantly affected financial markets in history. The great depression, the energy crisis, Asian Crisis, the 2007-2009 financial crisis, European sovereign debt crises, previous pandemics, SARS, and Ebola can be counted if we consider the size and spread of those events. Stock markets are generally regarded as a significant indicator of a country's financial market. Starting from the beginning of 2020, several shocks have been noted in financial markets because of the Coronavirus disease (COVID-19). Financial markets face a high level of uncertainty due to this pandemic effect.

Prior studies handled many events that had huge effects on stock market returns, for example, financial crises (Hesse and Frank, 2009; Neaime, 2012), political events (Bash and Alsaifi, 2019; Shanaev and Ghimire, 2019), disasters (Kowalewski and Śpiewanowski, 2020), pandemics (Nippani and Washer, 2004; Ichev and Marinč; 2018). Many studies also stood on that stock markets are volatile and interconnected during times of uncertainty such as the Mexican peso crisis (Calvo and Reinhart, 1996), the Brazilian crisis in 1998 (Goldfajn and Baig, 2000), Asian currency crisis between 1997 and 1998 (Caporale et al., 2005), the Russian debt crisis in 1998 (Kenourgios et al., 2011). Compared to other natural disasters (e.g. hurricanes, floods, storms, and droughts), earthquakes start rapidly and it becomes a surprise to stock markets since their timing is uncertain. As an example, Cavallo et al. (2010) handled the earthquake that affected Haiti in 2010. Ferreira and Karali (2015) also examined the effects of large earthquakes on returns and stock market indices' over the previous twenty years in 35 global markets. The financial crises are examples of the major events which cause mobility in the sock markets. Starting from the Great Depression, there were many financial crises around the world history and some of them caused regional and some of them caused global effects. Aggarwal et al. (1999), for example, handled the 1994 Mexico Peso Crisis, then Forbes (2000) examined the impact of the Asian and Russian crises on stock returns around the world. Bekiros et al. (2017) examined the occurrence of several unexpected occurrences, such as the subprime crisis in 2007, the global financial crisis, the fall of the internet bubble, and previous European crises. The pandemics also affect the stock markets. The time of pandemics has also been valuable for observing volatility and volatility spillover across the countries' stock markets. Nippani and Washer (2004) and Chen et al. (2007) aimed to indicate the effects of the SARS epidemic. Ebola disease held in 2014 was also approached by many studies (Topliceanu and Sorcaru, 2019; Baker et al., 2019) as well in the past.

The importance of the volatility and volatility spillover as an input for making decisions and understanding the interconnectedness became vulnerable with the increasing trade relationships (Dornbusch and Claessens, 2000). It brings both negative effects and positive effects. As an example of the negative effects, due to easy transmission of the effects during big events like shocks, attacks, and crises, it has been observed that it causes small or large-scale tremors in other regions and countries. (Abou-Zaid, 2011; Forbes and Rigobon, 2000). For instance, the events caused by the terrorist attack on September 11, 2001, and the financial reporting scandals in the U.S. in many regions adversely affected the world economy. This example explains the connectedness between uncertainty in financial markets and public confidence. Therefore, policymakers frequently trust the market prediction of volatility as a parameter.

The financial markets generally tend to become more interconnected when the level of volatility is high during crisis periods (Lai and Hu, 2021) and it is also holding the interest of investors, academics, and policymakers. For an effective portfolio decision, it is important to monitor the movements and interconnectedness of the global stock markets. Engle (2002) studied the necessity of a time-varying and dynamic aspect of correlation. This has also helped to quantify the contagion effect between cross-country markets.

The COVID-19 pandemic started in Wuhan, China, and as it quickly spread to other countries, it grew into a major pandemic that caused enormous losses in international markets. The outbreak started on December 31, 2019, when the Chinese government alerted the World Health Organization (WHO) to the presence of many individuals in Wuhan, Hubei province, who had symptoms resembling the flu. The first death due to novel coronavirus was reported on January 11 2020 in Wuhan, China. Through the period between February and March 2020, its shock started to resonate all around the world. The increasing number of infections caused some governments to take significant countermeasures, while some other governments applied more relaxed policies without quarantine. COVID-19 hit the world's economic mood since the world was unprepared for such a large spread pandemic and it brought uncertainty to global stock markets. This outbreak was declared a global pandemic on March 11 2020 by the WHO. Towards the last days of April 2020, approximately fifty percent of the nations went to quarantine restrictions. (De Vito and Gomez, 2020) mentioned that, as a consequence of quarantine times, financial activities were limited, particularly in the airline sector, tourism sector, and many other service sectors.

Most of the empirical studies reveal that a large body of work (Aggarwal et al., 1999; Abou-Zaid, 2011; Ahmad et al., 2013; Gjika and Horváth, 2013; Li, and Giles, 2015; Rai and Garg, 2021) has been done to analyze the interdependence between stock markets. The objective of this thesis is to investigate the interdependence of the major OECD stock markets, specifically those of Colombia, France, Germany, Italy, Mexico, the U.K., and the U.S. according to the highest-ranking COVID-19 mortality rates.

There is a three-fold contribution of this thesis to prior studies and the literature. To begin with, to the best of the author's knowledge, this study is a ground-breaking investigation of spillover effects among the stock markets of the chosen seven OECD countries. The data period is between January 1, 2019, and September 30, 2021 and therefore, this thesis brings fresh insights and knowledge to the current literature. The main stock market indices of Colombia, France, Germany, Italy, Mexico the U.K., and, the U.S., are considered the highest-ranking of daily COVID-19 mortality rates. Secondly, by using the VAR-BEKK GARCH model, it analyzes the effects of return and volatility spillover. From the methodological perspective, prior studies generally use several existing models, namely, simple OLS, and GARCH models, for example, Kumar and Anandarao (2019) and Guler (2020). The investors need to understand the volatility transmission linkage over these selected markets and volatility transmission to make well-diversified portfolio allocation decisions and create risk management strategies. Lastly, utilizing a comprehensive and up-to-date dataset identify knowledge of the information transmission mechanism among the stock markets of OECD countries, and stipulates valuable information for all market participants.

This thesis involves six sections. The introduction includes the scope and aim of this research. The second section explains the literature review. The third section outlines the statistical tests, followed by the econometric methodology. Section fourth represents summary statistics along with the data. In section fifth, the empirical results are given and finally, conclusions are included in section sixth.

CHAPTER 2: LITERATURE REVIEW

Financial crises affect countries due to domestic and foreign economic reasons and shake the basic economic structure of the countries. In the most recent history, the global crisis experienced in 2008 affected nearly all over the world; Asia and Europe, especially the U.S.. The stock markets of these countries have been affected by this shock that originated in the U.S. In the literature, many studies examined the linkages between crises and stock markets and highlighted the volatility in stock markets and volatility spillover between stock markets during the crises. Global pandemics like SARS and Ebola have been also interesting subjects like the economic crises. COVID-19 which originated in Wuhan, China is one of these pandemics which turned into an economic crisis, and many studies evidenced the volatility spillover between stock markets observed during the COVID-19 outbreak and it has significant effect.

2.1. Volatility and Volatility Spillovers in Stock Markets

Increasing trade relationships, regional reasons, and macroeconomic similarities become undefended to countries to the volatility (Dornbusch and Claessens, 2000). In the literature, tock markets and volatility in stock markets were examined widely. Hong et al. (2019) handled the stock markets and volatility spillover effects previously. Mensi et al. (2018) and Guo and Tanaka (2020) also examined the volatility spillover effects over the stock markets.

Volatility is also important for investors, policymakers, and portfolio managers. Hameed and Ashraf (2006) mentioned the importance of volatility as important for taking decisions about diversification in hedging plans, portfolio management, and understanding linkages. This interconnectedness brings out easily transmission of the effects of big events like shocks, and crises across countries because of their relationships (Abou-Zaid, 2011).

There are many challenges for the individual and institutional investors, portfolio managers, and policy makers while understanding the volatility transmission between the stock markets. This transmission is called volatility spillover and it can be explained as the spread of market discomforts from one region or country to another. This event can be observed through movements in exchange rates, capital flows, or stock prices (Dornbusch and Claessens, 2000). The volatility spillover can be associated with the term contagion. The description of contagion as a term is alterable in the literature. Forbes and Rigobon (2000) assumed that contagion occurs when a cross-market co-movement rises significantly after a sudden shock. According to Ivanov et al. (2016), the economic prospect is when the two economies are well integrated through trade, investment, and financial relations.

Volatility in stock markets has been examined and found wide coverage in the literature. Some of the studies have investigated volatility spillover by comparing countries as some classifications (according to their growth levels, regions, etc.). For instance, Wei et al. (1995) examined the emerging, and developed markets and volatility transmission between their stock markets. According to Lhost's (2004) study among emerging and developed markets, stock markets with more asymmetric information, such as emerging economies, will be more susceptible to contagion than developed markets. Bartram et al. (2007) and Savva et al. (2009) concentrated on the global volatility spillovers in developed markets, like Japan, the U.S., and European markets. Especially, the U.S. stock market has been investigated in many studies. Abou-Zaid (2011) aimed to analyze the global stock market indices' volatility transmission movements from the U.S. and the U.K. to Isreal, Turkey, and Egypt using the technique of multivariate GARCH in Mean. The volatility of the three markets; the U.S., the U.K., and one of the emerging markets has been modeled synchronous. Moreover, Li and Giles (2015) the connections between the U.S., Japan, Malaysia, China, Indonesia, Thailand, India, and the Philippines by using an asymmetric multivariate GARCH model.

Chaudhary et al. (2020) also analyzed the international stock markets and volatility subject. The impact of COVID-19 on the stock return and volatility of the stock market indices were examined. In this research, the top 10 countries were selected based on GDP, and the econometric model - Generalized Autoregressive Conditional Heteroscedasticity (GARCH) was applied. The GARCH system becomes a frequently used method while modeling volatility for the financial time series, therefore, Bai et al. (2021) also used the GARCH model but with using MIDAS framework to show the impact of COVID-19 volatility in stock markets.

The time-varying nature of volatility spillovers has been highlighted in the literature. For example, Baele (2005) focused on the time-varying volatility spillovers to 13 regional European stock markets from the European and American stock markets. Between January 1980 and August 2001, he investigated whether growing economic, monetary, and financial integration efforts in Europe altered the severity of shock spillovers from the U.S. and the entire European market to 13 European stock markets. Li (2021) investigated the time-varying volatility spillovers among the ten countries. In these studies, it is found that developed markets are the main risk transmitters, and emerging markets are the main risk receivers. Christos et al. (2021) also demonstrated that shock spillover is subsample dependent and constant over time through a time-varying spillover shock analysis. The result of this paper showed both shocks of the global financial crisis and COVID-19 had significant effects on the connectedness of stock markets.

Many studies employed the GARCH models for showing volatility spillover. Ahmad et al. (2013) applied the MDCC-GARCH model and showed the effects of the volatility spillover over the GIPSI countries, the U.S., the U.K., and Japan stock markets on the BRICKS stock markets. Gjika and Horváth (2013) adopted the asymmetric DCC-GARCH models to the stock markets in Central Europe and found proof of significant correlations between these stock markets in the euro area countries. MGARCH model was also used to show the impact of the U.S. financial crisis on five Asian countries' stock markets (Kim et al., 2015). Yavas and Dedi (2016) studied the linkages between stock returns and transmission of volatilities in Austria, Germany, Poland, Russia, and Turkey using Multivariate Autoregressive Moving Averages and the GARCH methodologies. The conclusions involve the presence of meaningful co-movement of returns among the sampled countries. Additionally, Turkish and Russian stock markets were more volatile than Germany, Poland, and Austria.

2.2. Crises and Volatility Spillovers

Crises and unexpected/sudden events are always a valuable subject for studies and observing volatility spillover. Talib (2001) highlighted the theory of the Black Swan that is associated with crises-unexpected events which happened suddenly and may impact the global stock markets, trade activities, and service sectors. The black swans are also described as unpredictable events and these events are characterized by their extreme rarity, severe impact, and widespread insistence and so they can cause catastrophic damage to economies like crises. Briefly, the Black Swan Theory refers that these events are generally uncertain and unpredictable. The effects of these events on the markets and economy of countries are at an overwhelming level. Since these events are difficult to predict, Diebold and Yılmaz (2012) pointed out that the spillovers between stock markets are measured earlier is important for the crises.

There are many samples in the literature about the studies that have examined volatility spillovers and crises. When looking at the past crises, the Great Depression was the largest crisis spread worldwide in the earliest times. Later, in 1987, there was a U.S. stock crash in the stock markets of many countries. Koutmos and Booth (1995) also analyzed the volatility spillovers across the New York, Tokyo, and London stock markets before and after October 1987 crash with the linkages and interactions between those markets, and according to the results, the interactions increased in the post-crash era.

In the history of the crises, the 1994 Mexican Peso Crisis was one of the major financial crises due to a sudden devaluation of the Mexican peso, and it caused a sharp decrease in other currencies of Latin America as well. For example, the shifts in the volatility of stock markets returns between 1985, and 1995 which includes the Mexican Peso crisis using the GARCH framework were studied in the existing literature (Aggarwal et al., 1999). Neaime (2012) also studied the Mexican market fall and its effects on other Latin American markets.

The Asian financial crisis, also named the "Asian Contagion," was another crisis that started in 1997 and expanded through many Asian markets. Forbes (2000) examined the impact of the Asian crisis and Russian crisis on stock returns around the world. It was concluded that the trade linkages were significant predictors of firms' stock returns during these crises. Dungey and Martin (2007) also analyzed the volatility transmission between markets during the Asian crisis by studying spillovers and contagion effects between various currency and stock markets. Kenourgios et al. (2011) investigated the contagion on 2 developed and 4 emerging stock markets during the Asian and Russian crises, the Technology Bubble Collapse, the Brazilain crisis, and the subprime crisis. The results of the study ensured that there is a contagion effect during the Asian, Russian, and subprime crises.

In the most recent past, the financial crisis (2007-2009) began with cheap cheaper credits and low-interest rates and it created a housing bubble. It was an epic economic collapse that caused many banks to fail and cost ordinary people as well. Hesse and Frank (2009) examined potential financial linkages between the advanced countries' and emerging market stock markets during the global financial crisis. A multivariate GARCH model was applied to evaluate the extent of the movements of these variables between the stock markets. The results indicated that the concept of possible divergence in financial markets was misplaced. On the other hand, Ali and Afzal (2010) studied the India and Pakistan stock markets to show the impact of the global financial crisis by employing the E-GARCH model from 1st January 2003 to 31st August 2010. According to the results, both stock markets have asymmetry information. For example, the bad news had a higher impact than good news on the stock returns. Aloui et al. (2011) focused on Global Financial Crisis by handling

Brazil, Russia, India, and China countries stock markets, and resulted in proof of interconnection among these countries' stock markets. MGARCH model was applied in the study while reach the results. Kazi et al. (2011) also applied the dynamic conditional correlation GARCH model on daily stock price data between 2002 and 2009 which covered the Global Financial Crisis period and investigated the contagion effect between the stock markets of the U.S. and sixteen OECD countries. Regarding empirical results, there was an upward trend in dynamic conditional correlations in all sample markets from October 2007 and beyond. This evidence was reinforced by the fact that in most cases, during the Global Financial Crisis, cross-market correlation coefficients exceeded 50%. Neaime (2012) also pointed out that, in contrast to the Asian financial crisis, the global financial crisis was the most severe and largest financial crisis since Great Depression (1927). They focused on the linkages between the MENA stock markets and the developed stock markets globally and regionally. Slimane et al. (2013) found that interrelationships among European markets increased substantially during the period of the global financial crisis. Bekiros et al. (2017) also analyzed the cause of portfolio investment diversification in recent past years due to the emergence of many sudden and unexpected events. The European sovereign debt crisis was a period of financial collapse which was experienced by European countries. It started in 2008 but the crisis peaked between 2010 and 2012. Mac Donald et al. (2018) and McIver and Kang (2020) studied the European crisis and volatility transmission between the stock markets. They have analyzed the co-movements and impacts of spillovers. When comparing all major crises, it is concluded that the studies reached out stronger volatility effects during those crisis periods.

2.3. Pandemics and Volatility Spillovers

The unexpected/sudden events are also including pandemics that affect the stock markets. The time of pandemics has also been valuable for observing volatility spillovers across the countries' stock markets.

SARS which stands for Severe acute respiratory syndrome was a disease firstly seen at the end of February 2003 in China and expanded to 4 other countries. Nippani and Washer (2004) and Chen et al. (2007) aimed to show the effects of the SARS epidemic.

Referring to Black Swan Theory again, in terms of investors' decisions, the epidemics are also rare and sudden events and they could create panic actions by international investors (Burch et al. 2016). Ebola (2013) was another disease and it turned into a public health crisis in Guinea and then spread to other countries which are Liberia, Guinea, and Sierra Leone. The Ebola epidemic caused 11,000 deaths, slow down the influenced countries' economic growth, and affected businesses. Furthermore, the Ebola outbreak created equity capital problems in Africa since the investors were affected (Del Giudice and Paltrinieri, 2017) and the U.S. stock markets as well (Ichev and Marinc, 2018). These epidemics (SARS and Ebola diseases), and volatility spillover have been examined by many other studies as well (Topliceanu and Sorcaru, 2019; Baker et al. 2019).

In this century, the world faced the largest pandemic, named Covid-19 which originated in Wuhan in China. Due to this pandemic's extreme diffusion speed, and global effects on both health and economic consequences this topic is very interesting and worth of study in several areas.

Some studies (Pavlyshenko, 2020; He et al., 2020; Topcu and Gulal, 2020; Kasumahadi et al., 2021; Umar et al., 2021; Ashraf, 2020) examine the effect of the COVID-19 pandemic on the stock markets. Alfaro et al. (2020) also studied the stock markets and the impact of the COVID-19 pandemic and concluded that there is a negative response from the stock markets when the confirmed COVID-19 cases increased. In addition to the study of Alfaro et al. (2020) and Zhang et al. (2020) used data from the 12 most-affected countries during the COVID-19 and investigated linkages between countries' stock markets in pre-crisis and post-crisis periods. The findings indicated that this period exacerbated the dangers in the world's financial markets and they concluded that the uncertainty brought by the pandemic and the associated economic losses caused markets to become volatile and unpredictable.

Spillovers also are pointed out in the literature since the markets' interconnectedness is increasing extremely because of many elements and reasons. These factors can be counted as developments in technologies, a more global world, and the rising demand trend of consumers. Guo et al. (2021) examined, that during the period of COVID-19 the global market connections are getting closer. In the study, 40 countries/regions have been chosen and took one index from each of them, and then measured the correlation coefficients and distances between each pair of the indices were. In contrast to Guo et al. (2021), Hanif et al. (2021) studied the effects of the COVID-19 outbreak on the spillovers between 10 U.S. and Chinese stock markets, and the results indicated that spillover directions are coming from Chinese stock markets to the U.S. stock markets during the time of COVID-19. Like Hanif et al. (2021) and Nguyen (2021) mainly investigated the comparison of China and the U.S. stock markets with the global stock market during the COVID-19 pandemic.

Zhang et al. (2021) found that the effect of returns volatility coming from the most advanced countries to China was not significant stock market using the TGARCH model. On the contrary, China had an impact on the volatility of the Netherlands, Sweden, Switzerland, and the U.K. stock markets.

Li (2021) investigated the asymmetry and volatility spillovers between the stock markets of Brazil, Canada, China, France, Germany, India, Italy, Japan, and the U.K. stock markets using the Diebold-Yilmaz spillover index. It was found that while the risk transmitters were developed markets, the receivers were the emerging markets. Aslam et al. (2021) also used to Diebold-Yilmaz spillover index methodology to predict the spillovers among twelve European stock markets data between 2 December 2019 and 29 May 2020. According to the results of the study, the Swedish and Dutch stock markets convey the highest intraday gross directional volatility spreads. Other exchanges transfer the maximum spread to the Belgian and German stock markets, with minimal spread to Poland.

Unlike other studies, Rai and Garg (2021) investigated the stock markets and exchange rate relationship in BRICS countries by focusing on the COVID-19 period. The results indicated that there is a dynamic correlation between the exchange rates and stock returns, except for Brazil and Russia.

2.4. Crises, Stock Markets, and OECD Countries

Studies on stock markets and crises have also intensified for OECD countries. Kazi et al. (2011) aimed to investigate the impact of contagion on the U.S. and OECD countries during the Global Financial Crisis. Since October 2007, they observed that there was an upward trend in the dynamic conditional correlations. Min and Hwang (2012) examined the period in three phases which are pre-crisis, first and second phases of the global financial crisis, and applied the DCC model to the U.S. and OECD countries.

Yang and Deng (2021) also examined the moderating role of government interventions but they have also explored the influence of COVID-19 on stock market returns in OECD countries. The study found that the emergence of COVID-19 harmed the stock market returns of the selected OECD countries and in addition to this finding, any increase in the number of total confirmed cases of COVID-19 had a significant; but, negatively directed effect on stock market returns. On the other hand, the restrictions which were announced by the government like testing, and social distancing, positively affected the stock returns.

This large volume of literature supports and indicates the conclusion that stock market volatilities and interrelationships depend significantly on unpredictable, rare, and widespread events like financial and health crises.

CHAPTER 3: METHODOLOGY

This thesis estimates the dynamic conditional correlations by employing the GARCH model. At first, the unit root tests have been applied to verify whether the series are stationary, and then the ARCH-LM test is implemented to control the presence of the ARCH effect.

3.1 Unit Root Tests

The unit root tests are widely used in finance literature for the stationarity of time series data. Two of the unit root tests can be given as an example. These are the Phillips-Perron (PP) (Phillips and Perron, 1988) and the Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1981) tests for which the null hypothesis is on series have a unit root, hence is not stationary.

Under the null hypothesis of a unit root, it derives asymptotic findings and the statistics do not follow the conventional Student's t-distribution (Dickey and Fuller, 1979). In the ADF test formula, where alpha is a constant and beta is the coefficient on a time trend, and *p is* the lag order of the autoregressive process:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \varphi_1 \Delta y_{t-1} + \cdots + \varphi_{p-1} \Delta y_{t-p+1} + \varepsilon_t \qquad (1)$$

Phillips and Perron (1988) also developed several unit root tests for the analysis of financial time series. The test regression for the Phillips-Perron tests is:

$$\Delta y_t = \beta t D_t + \pi y_{t-1} + u_t \qquad (2)$$

where u_t is $I(0)$ and maybe heteroskedastic.

Dickey and Fuller (1979) found the Dickey-Fuller test to decide the existence of a unit root. The formula of this test is as follows:

$$y_i - y_{i-1} = \varphi y_{i-1} + \varepsilon_i - y_{i-1} \tag{3}$$

When the delta operator is used, it is defined by $\Delta y_i = \ y_i - y_{i-1}$ and set $\beta = \varphi - 1$, this then takes on the form of a linear regression equation:

$$\Delta y_i = \beta y_{i-1} + \varepsilon_i \tag{4}$$

where $\beta \leq 0$ and hence φ test is converted to a test with the parameter of slope $\beta = 0$. Thus, there is a one-tailed test (because β cannot be positive) in which:

H_0: $\beta = 0$ (equivalent to $\varphi = 1$)
H_1: $\beta < 0$ (equivalent to $\varphi < 1$)

According to the alternative hypothesis, if b is OLS, namely, ordinary least square, estimation of β, and hence φ-bar = 1 + b is the OLS estimation of φ, therefore it is sufficient:

$$\sqrt{n}\ (\emptyset - \emptyset^{\sim}) \sim N(, s.e.) \tag{5}$$

where;

$$s.e = \sqrt{1 - \emptyset^2} \tag{6}$$

There is a noteworthy result if the calculated t-statistics value is smaller than the crucial value in the critical values table; otherwise, the null hypothesis is accepted, indicating that the series is stationary and there is a unit root.

The test proceeds as follows (Stock, 1994) :

Let $z_t = (1, t)$. For the time series z_t, regress$[y_{1,}, (1 - \alpha L)y_2, \dots, (1 - \alpha L)y_T]$ on $[z_{1,}, (1 - \alpha L)z_2, \dots, (1 - \alpha L)z_T]$ yielding $\beta_{\tilde{GLS}}$ where $\alpha = 1 + c^{-}/T, u_0 = 0$, and

$c^{-} = -13.5$ for the detrended statistic. Detrended $\tilde{y}_t = y_t - z_t' \beta_{GLS}^{\sim}$ is then employed in the (augmented) Dickey-Fuller regression, with no intercept nor time trend. The t−statistic on $\tilde{y}_{t-1}$ is the DF-GLS statistic. For the demeaned case, the *t* is omitted from z_t , and $\bar{c}$ = -7.0.

The descriptive statistics have been also implemented after taking returns of the daily stock prices. The frequently used descriptive statistics are, namely, the mean, median, maximum and minimum, standard deviation, skewness, kurtosis, Jarque-Bera (JB), probability, sum, and sum square deviation have been used in this thesis under the descriptive statistics.

Due to the benefit of making a profit, the stock price must be analyzed firstly by looking at the return of the stock price for making buy and/or selling decisions. Due to this risk in the game, the decisions and analyses that are taken must be appropriate to avoid losses. These analyses are named time series analysis and an investor does not only invest in one financial instrument or the same financial instrument therefore that there are more than one return data that requires to be analyzed. Therefore, the multivariate time series are more suitable than the univariate time series when making these analyzes. Tiao and Box (1981) found this analysis which applies to several time series at the same time.

3.2 ARCH LM test

Engle's (1982) ARCH-LM test is used to detect autoregressive conditional heteroscedasticity. The equation of the ARCH-LM test is as follows;

$$r_t^2 = a_0 + a_0\, r_{t-1}^2 + \cdots + a_0\, r_{t-1}^2 + \varepsilon_t \tag{7}$$

$$H_0 :\ a_1 = 0, for\ i = 1,2, \ldots, p$$
$$H_1 :\ a_1 \neq 0, for\ at\ least\ one\ i$$

3.3 GARCH Models

The models of Autoregressive Conditional Heteroskedasticity (ARCH) can be mentioned as the most popular way to measure volatility. (Teräsvirta, 2009) The ARCH model is based on the basic prediction variance. It can change over time and is estimated with previous estimation errors (Engle, 1982).

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is an extension model of the ARCH model that was improved by Bollerslev (1986). This model is generally used for modeling the volatility of the time series. An alternative and more flexible lag structure are usually assured by the generalized ARCH, or GARCH*(p,q)* model propounded independently by Bollerslev (1986) and Taylor (1986):

$$\varepsilon_t \mid \psi_{t-1} \sim N(0, h_t), \tag{8}$$

$$h_t = \alpha_\sigma + \sum_{i-1}^{q} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \, h_{t-j} \tag{9}$$

where ψ_{t-1} is the set of information available at time t-1.

The technique allows for both autoregressive (AR) and moving average (MA) components in heteroscedastic variance. This is the generalized Autoregressive Conditional Variable Variance, GARCH (p, q), model. (Aliyev et al., 2020)

GARCH models can be categorized as univariate and multivariate models. This categorization is according to the number of variables.

3.4 Multivariate GARCH Models

The model of Multivariate Generalized Autoregressive Conditional Heteroskedasticity (MGARCH) is employed to forecast or model the volatility of time series and these time series have some linkages. MGARCH is the study of the relations between the volatilities and co-volatilities of several markets and it should be flexible enough to be able to represent the dynamics of the conditional variances and covariances.

The MGARCH models are generally used for investigating, monitoring, and quantifying the volatility of the time series and contagion effects (Hafner, 2020). To sum up, the Multivariate GARCH model is studied to know the relationship between volatilities and co-volatilities of several univariate variables/markets, so it deals with the impact of one univariate time series on another univariate time series. The multivariate GARCH model answers "Does volatility of one market affects the volatility of the other market? or "Does a shock on one market increase the volatility of another market?" questions.

There are different kinds of multivariate GARCH models: Constant Conditional Correlation GARCH (CCC GARCH), Dynamic Conditional Correlation GARCH (DCC GARCH), Varying Conditional Correlation (VCC GARCH), and Baba, Engle, Kraft, Kroner GARCH (BEKK GARCH).

3.5 VAR Model

For empirical analysis of volatility spillover, the Vector Autoregressive (VAR) model is used to predict the price spillover effect for the selected stock markets. The model developed by Sims (1980) has been widely employed. It is a flexible framework to analyze macroeconomic data. VAR model is used to a large extent, for example, Stock and Watson (2001) and Warsono et al. (2019) used the application of the VAR model. According to the minimum Akaike Information Criterion principle, the model of VAR (1) was selected and the equation is as follows:

$$R_t = \mu + \varphi R_{t-1} + \varepsilon_t \tag{10}$$

where $R_t = (r_t^B, r_t^A)'$ with r_t^B and r_t^A being the returns on countries' stock indices at time t, respectively; φ is a $(2x2)$ form of coefficients' matrix $\varphi = \begin{pmatrix} \varphi_{11} & \varphi_{12} \\ \varphi_{21} & \varphi_{22} \end{pmatrix}$; the form of constant terms' $(2x1)$ vector is μ; $\varepsilon_t = (\varepsilon_t^B, \varepsilon_t^A)'$ with ε_t^B and ε_t^A are the error terms of two stock markets' mean equations, B and A. φ_{11} and φ_{22} measure own spillovers of stock markets and φ_{12} and φ_{12} measures the cross-mean spillovers.

3.6 BEKK GARCH Model

The BEKK-GARCH model which is studied by Engle and Kroner (1995) narrows down the version of the VECH model that needs fewer parameters rather than other models due to this fact this model is widely applied in the economy and finance literature. The BEKK model also does not impose any restrictions on the correlation structure between variables. Furthermore, this model also purposes to formulate the multivariate procedure to be sure of favorable certainty (Engle and Kroner, 1995).

GARCH model's BEKK representation model is a conditional covariance matrix of the error term ε_t, which is a vector of residuals from the mean equation.

Let be ε_t a martingale difference sequence, a zero conditional mean stochastic process, i.e.

$E(\varepsilon_t | \, \Omega_{t-1})$ for any conditional covariance matrix, almost certain for every t:

$$Cov(\varepsilon_t | \, \Omega_{t-1}) = H_t^{-\frac{1}{2}} Cov(z_t | \, \Omega_{t-1}) H_t^{-\frac{1}{2}} = H_t \tag{11}$$

where $H_t^{\frac{1}{2}}$ is a symmetric positive definite square root of H_t which can be acquired by Cholesky factorization (Lütkepohl, 2005).

$$\varepsilon_t = H_t^{\frac{1}{2}} z_t , \quad z_t \sim i.i.d.(0, I) \tag{12}$$

I is n × n identity matrix, n being the number of variables.

In the applications, the simplest form of the BEKK-GARCH model can be formulated as follows;

$$H_t = CC' + A'e_{t-1}e'_{t-1}A + B'H_{t-1}B, \tag{13}$$

where C is a lower triangular matrix and A and B are $N\times N$ parameter matrices.

An example of the BEKK model could be:

$$H_t = C_0C_0^* + \sum_{k=1}^{k} \sum_{i=1}^{i} A_{ik}^* \varepsilon_{t-1}\varepsilon_{t-1}^* A_{ik} + \sum_{k=1}^{k} \sum_{i=1}^{i} B_{ik}^* H_{t-1} B_{ik} \tag{14}$$

Here H_t is the conditional covariance matrix and C_0 is the NxN upper triangle matrix.

In this study, the quasi-maximum likelihood (QML) method and BFGS which stands for Broyden Fletcher Goldfarb Shanno and one way algorithm were used to predict VAR-BEKK GARCH model. The L(θ) is represented as:

$$L(\theta) = \sum_{t=1}^{T} L_t(\theta), \tag{15}$$

$$L_t = -ln2\pi - 1/2\, ln|H_t(\theta)| - 1/2\, \varepsilon'(\theta)H_t^{-1}(\theta)\varepsilon_t(\theta) \tag{16}$$

where T refers the observation numbers, and the predicted parameters' vector symbolized as θ.

CHAPTER 4: DATA AND SUMMARY STATISTICS

In this section, the data are explained, and the methods are applied to analyze whether there are volatility spillovers among the stock markets of OECD countries. The econometric software RATS version 9.0 and Eviews are used in the analysis of the series.

4.1 Data description

In this study, the daily OECD countries' stock price indices; namely, S&P Colombia Select Index.SPCOSL from Colombia, Deutsche Boerse DAX Index .GDAXI from Germany, CAC 40 Index.FCHI from France, FTSE MIB Index .FTMI from Italy, S&P/Bmv Ipc .MXX from Mexico, FTSE 100 Index .FTSE from the U.K., and NYSE Composite Index .NYA from the U.S., is used that are represented in Table 1.

Table 1. Descriptions of sample countries and countries stock indices

Country	Country Stock Index
Colombia	S&P Colombia Select Index
France	CAC 40 Index
Germany	Deutsche Boerse DAX Index
Italy	FTSE MIB Index
Mexico	S&P/Bmv Ipc
U.K.	FTSE 100 Index
U.S.	NYSE Composite Index

The data period is from January 1, 2019, to September 30, 2021, and the data is obtained from Eikon Database by Thomson Reuters. Seven OECD countries, the U.S., Mexico, the U.K., Italy, Colombia, France, and Germany were selected according to the highest number of daily deaths due to COVID-19 infection in OECD countries. The first seven OECD countries according to the daily mortality due to COVID-19 infection from January 2020 to September 2021 are shown in Table 2.

Table 2. The Total Mortality Numbers in Selected OECD Countries

	Countries	Total Number of Deaths
1	U.S.	689,343
2	Mexico	282,227
3	U.K.	160,852
4	Italy	131,301
5	Colombia	126,655
6	France	117,052
7	Germany	94,209

Note: The data is retrieved from the OECD website.

4.1.1 The Selected Stock Markets and Stock Market Indices' Characteristics

In this study, seven stock markets – Colombia, France, Germany, and Italy stock markets which are European Union members; Colombia, Mexico, the U.K., and The U.S. stock markets were selected, and they are not European Union members.

4.1.1.1 Colombia Stock Market- S&P Colombia Select Index (.SPCOSL)

The S&P Colombia Select Index is a major index that includes the 24 most liquid stocks traded on the Colombia Stock Exchange (Bolsa de Valores de Colombia).

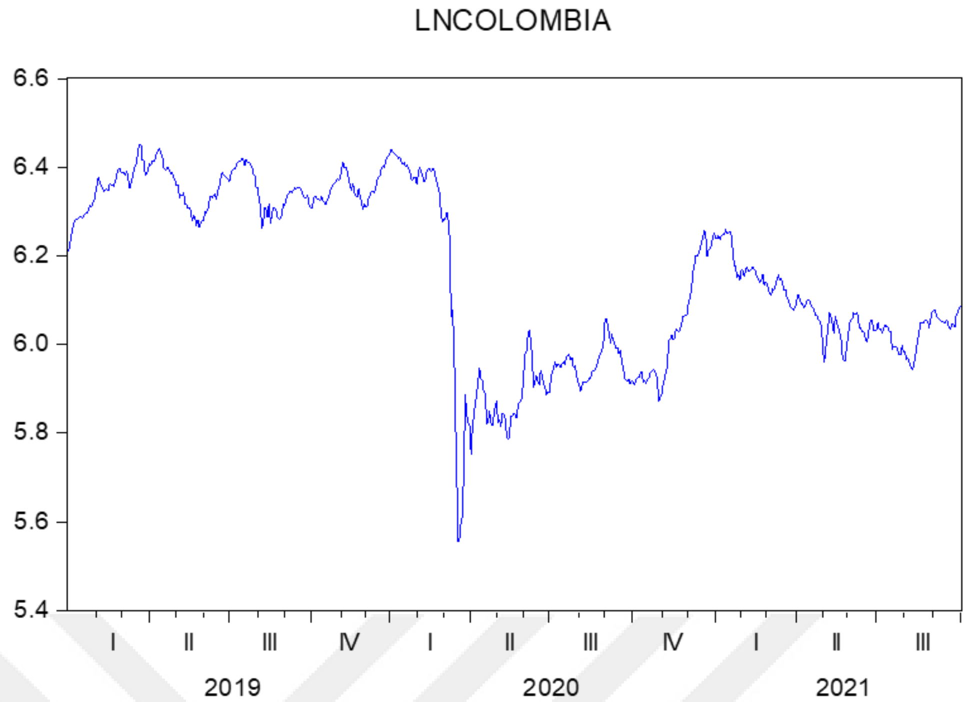

Figure 1. S&P Colombia Select Index (.SPCOSL)

As can be seen from Figure 1, the line chart displays the S&P Colombia Index between January 2019 and September 2021 and it can be observed that in the first quarter of 2020, The line has bottomed around 5.5.

4.1.1.2 France Stock Market- CAC 40 Index (.FCHI)

The CAC 40 Index is a benchmark index in the French stock market. It includes 40 enterprises which are the most capitalized enterprises on Euronext Paris.

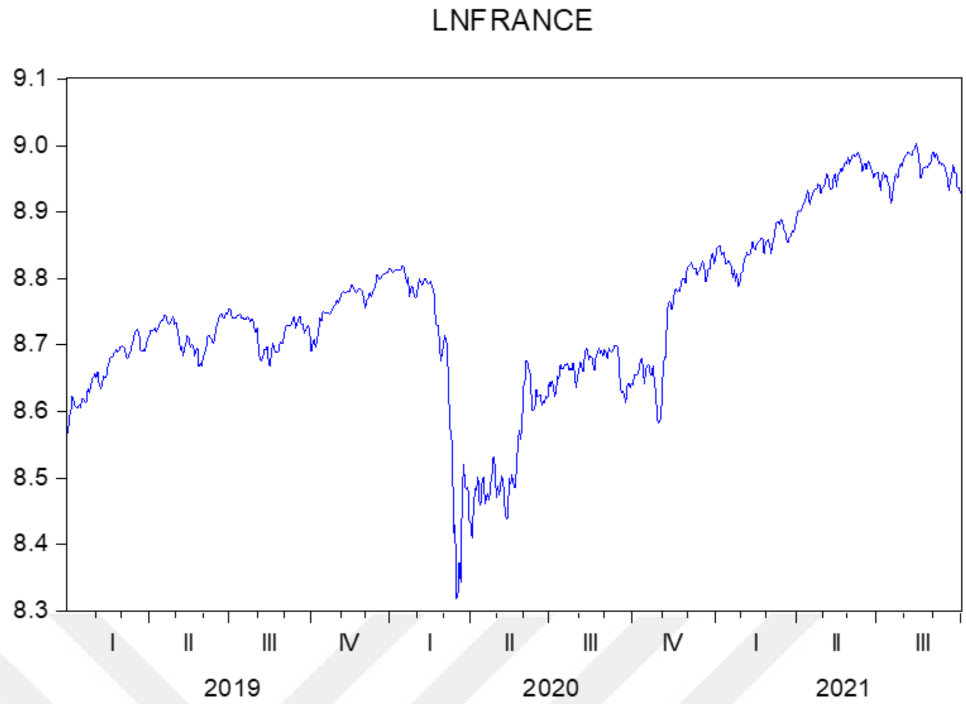

Figure 2. CAC 40 Index (.FCHI)

Figure 2 shows that the CAC 40 Index was between January 2019 and September 2021, with the line bottoming out at around 8.3 in the first quarter of 2020.

4.1.1.3 Germany Stock Market-Deutsche Boerse DAX Index (.GDAXI)

The DAX 30 Index is in the German stock market and is the benchmark index. There are 30 enterprises in this index and the come of the popular countries can be counted as Allianz, BMW, Adidas, etc.

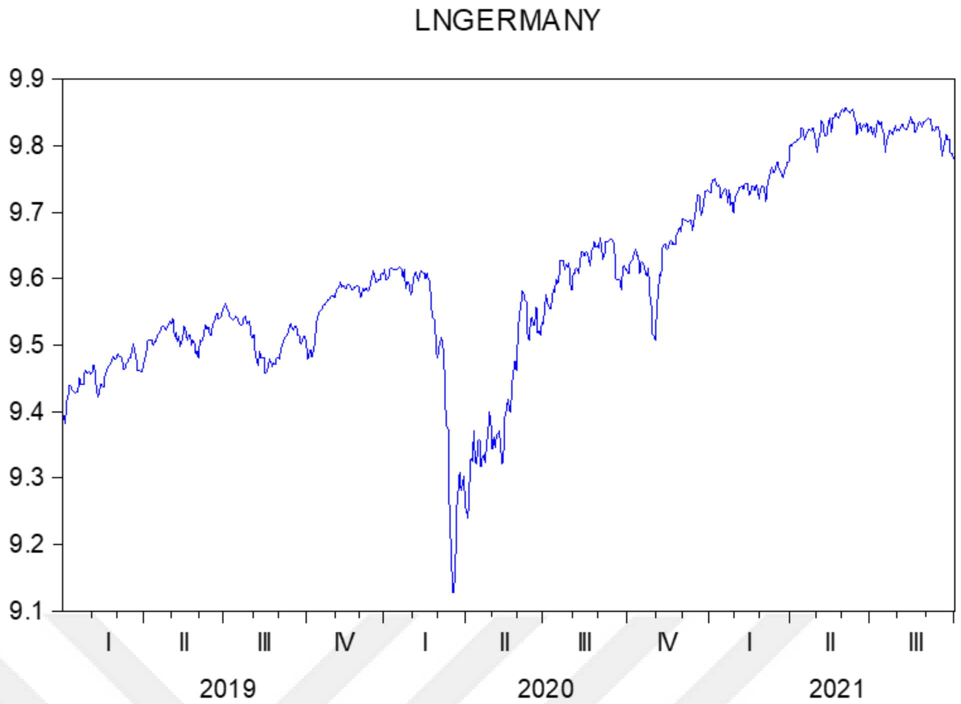

Figure 3. Deutsche Boerse DAX Index (.GDAXI)

Figure 3 illustrates the DAX 30 Index from January 2019 to September 2021. There was a steady decline at the beginning of 2020 and basically with bottoming in the first quarter of 2020.

4.1.1.4 Italy Stock Market-FTSE MIB Index (.FTMIB)

Borsa Italiana is the stock exchange which is based in Milan, Italy. It is regulating the procedures and leads to listing companies in the domestic market. This stock exchange's history goes back more than 200 years. Borsa Italiana became part of Euronext since April 2021.

The FTSE MIB involves 10 economic sectors and 40 largest companies and is established in 2009.

Figure 4. FTSE MIB Index (.FTMIB)

As can be seen from Figure 4, the line chart represents the FTSE MIB 40 Index from January 2019 to September 2021. There was a decline at the beginning of 2020 and it reached the bottom before April of 2020.

4.1.1.5 Mexico Stock Market-S&P/Bmv Ipc (.MXX)

The Mexican Stock Exchange, namely, Bolsa Mexicana de Valores (BMV) is one of the largest stock exchanges in Latin America.

Furthermore, the main benchmark stock index of The Bolsa Mexicana de Valores is Indice de Precios y Cotizaciones (IPC) is the biggest indicator of this stock exchange in overall performance.

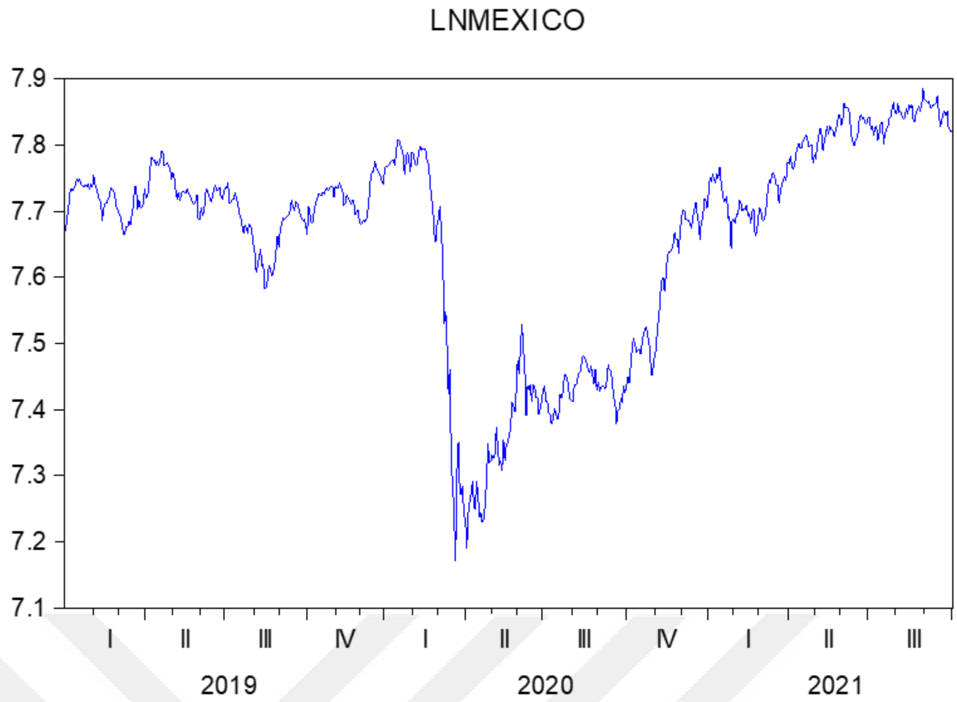

Figure 5. S&P/Bmv Ipc (.MXX)

As can be seen from Figure 5, the line chart demonstrates the S&P/Bmv Ipc. Index from January 2019 to September 2021. There was a fall at the beginning of 2020 and it reached the bottom before April of 2020.

4.1.1.6 U.K. Stock Market-FTSE 100 Index (.FTSE)

The FTSE 100 is an important capitalization-weighted price index and it involves the 100 companies which are most capitalized. Some of them are, namely, Coca-Cola, HSBC, Lloyds Banking Group, etc.

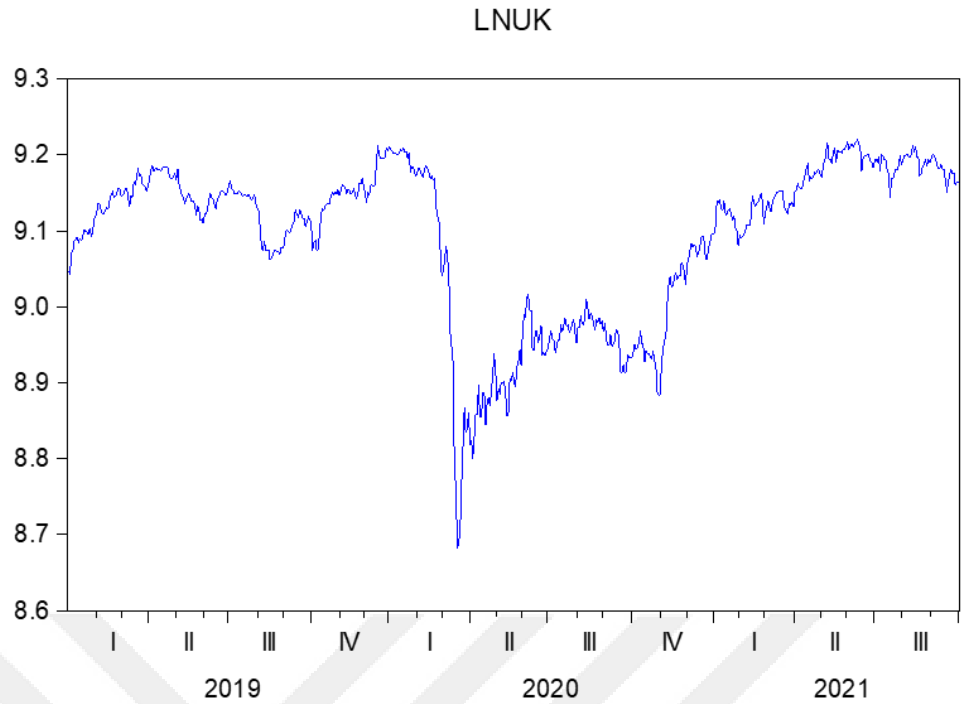

Figure 6. FTSE 100 Index (.FTSE)

Figure 6 illustrates between January 2019 and September 2021 the FTSE 100 Index. There was a sharp decrease at the beginning of 2020 and basically with bottoming before April of 2020.

4.1.1.7 The U.S. Stock Market-NYSE Composite Index (.NYA)

The New York Stock Exchange is one of the major stock exchanges in the U.S. The New York Stock Exchange (NYSE) is an American stock exchange in the Financial District of Lower Manhattan in New York City. In NYSE Composite Index, there are more than 2,400 international companies are listed.

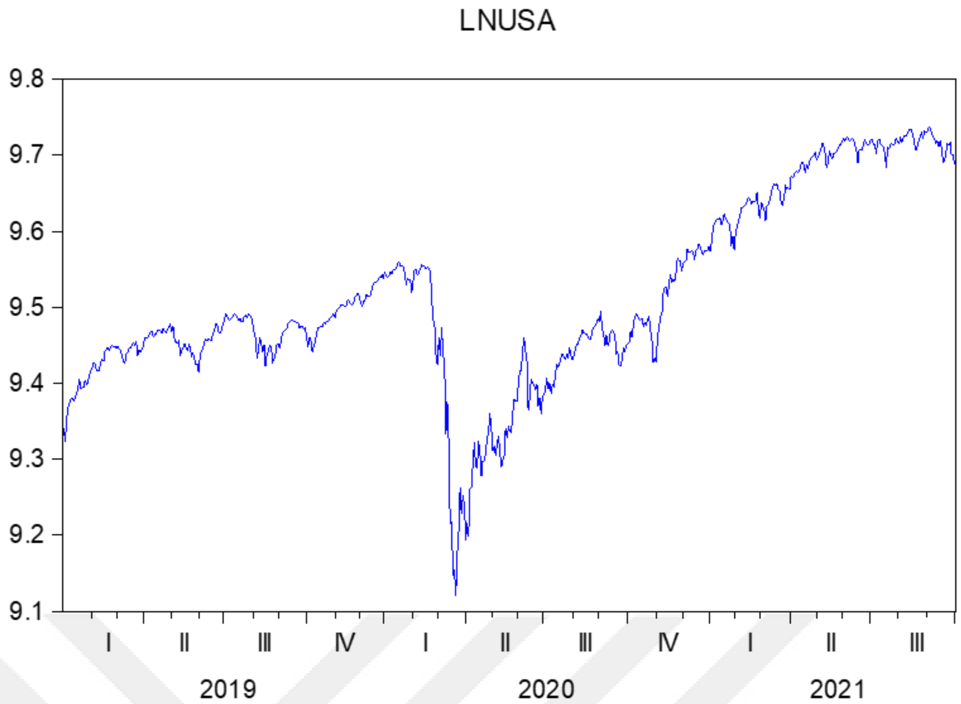

Figure 7. NYSE Composite Index (.NYA)

In Figure 7, the NYSE Composite Index from the beginning of 2019 to the September of 2021 can be shown in the line chart. There was a decline at the beginning of 2020 and it reached the bottom before April of 2020.

4.2 Descriptive Statistics

The dataset includes daily data for 7 OECD countries' stock indices according to the highest number of daily deaths due to COVID-19 infection; Colombia, France, Germany, Italy, Mexico, the U.K., and the U.S. between 1 January 2019 and 30 September 2021.

Returns, $R_{i,t}$ are computed as $R_{i,t} = ln\ (P_{i,t}) - ln\ (P_{i,t-1})$, where $P_{i,t}$ denotes the value of country's stock indices at time t.

Table 3. Descriptive Statistics

	Countries						
	Colombia	**France**	**Germany**	**Italy**	**Mexico**	**The U.K.**	**The U.S.**
Mean	-0.000197	0.000579	0.000617	0.000571	0.000240	0.000187	0.000557
Median	0.000606	0.001377	0.001023	0.001778	0.000942	0.000562	0.001307
Maximum	0.146788	0.139000	0.091543	0.083155	0.132274	0.057908	0.062249
Minimum	-0.171800	-0.138459	-0.138024	-0.192887	-0.148534	-0.134738	-0.105241
Standard Deviation	0.021932	0.016297	0.015748	0.016692	0.019182	0.014660	0.013622
Skewness	-1.705302	-0.548276	-1.006579	-2.828074	-0.767848	-1.599675	-1.377635
Kurtosis	24.28993	23.96661	16.00695	34.90565	13.96982	17.51221	15.03146
Jarque-Bera (JB)	12145.34	11515.93	4525.724	27430.28	3205.382	5769.447	3980.077
Probability	0.000000*	0.000000*	0.000000*	0.000000*	0.000000*	0.000000*	0.000000*
Number of Observations	627	627	627	627	627	627	627

Note: * denotes statistical significance at 1% level.

The summary statistics are presented in Table 3 for the country's stock indices. The German stock index exhibits the highest mean in daily returns (0.061%) followed by France's average (0.057%). On the other hand, the Colombia stock index has the lowest mean with -0.019%. To be more precise, in six of these seven countries' stock indices, all the means of returns were positive; only the Colombian stock index' means is negative. This represented an increasing trend in stock indices during this period, even though there were some fundamentally negative returns. Colombia's stock index exhibits the highest standard deviation (0.021932), while the U.S. has the lowest one (0.013622).

Referring to the distribution of returns, all indices are negatively skewed. In addition to this outcome, it was observed that all kurtosis values were higher than 3, indicating that all series had a heavy tail and peak relative to a normal distribution, the kurtosis of all returns surpassed a normal distribution (kurtosis=3), donated as leptokurtic distribution. Jarque-Bera (JB) Lagrange Multiplier test which tests the normality. The normality test is strongly rejected in all cases.

The returns series of seven OECD countries' stationarity is checked using the ADF and Phillips-Perron tests. These two unit root tests with three specifications (intercept, trend, and intercept and trend) are implemented both on the level and first differences of the series, and the test outcomes are reported in Table 4. The results of the return series show significant ADF and PP test results which means rejection of the null hypothesis of a unit root.

Table 4. Unit Root Tests Results of 7 OECD Countries Stock Market Indices

Variables	**Level Series**				**Return Series**			
	ADF		**PP**		**ADF**		**PP**	
OECD Countries Stock Indices	***Inter.***	***Trend + Inter.***	***Inter.***	***Trend + Inter.***	***Inter.***	***Trend + Inter.***	***Inter.***	***Trend + Inter.***
S&P Colombia Select Index	-2.001 [0.286]	-2.657 [0.294]	-1.748 [0.406]	-2.291 [0.437]	-17.561* [0.000]	-17.547* [0.000]	-17.485* [0.000]	-17.470* [0.000]
CAC 40 Index	-1.468 [0.549]	-1.931 [0.636]	-1.671 [0.445]	-2.058 [0.567]	-13.089* [0.000]	-13.080* [0.000]	-23.581* [0.000]	-23.562* [0.000]
Deutsche Boerse DAX Index	-1.652 [0.455]	-2.444 [0.355]	-1.589 [0.487]	-2.443 [0.356]	-22.242* [0.000]	-22.225* [0.000]	-22.159* [0.000]	-22.142* [0.000]
FTSE MIB Index	-1.537 [0.514]	-1.891 [0.657]	-1.537 [0.514]	-1.891 [0.657]	-15.401* [0.000]	-15.389* [0.000]	-23.804* [0.000]	-23.786* [0.000]
S&P/Bmv Ipc	-1.324 [0.619]	-1.405 [0.858]	-1.428 [0.569]	-1.500 [0.828]	-25.665* [0.000]	-25.665* [0.000]	-25.680* [0.000]	-25.667* [0.000]
FTSE 100 Index	-1.926 [0.320]	-1.928 [0.638]	-1.964 [0.302]	-1.967 [0.617]	-22.213* [0.000]	-22.195* [0.000]	-22.199* [0.000]	-22.181* [0.000]
NYSE Composite Index	-1.484 [0.541]	-2.111 [0.537]	-1.420 [0.573]	-1.998 [0.600]	-15.278* [0.000]	-15.265* [0.000]	-26.861* [0.000]	-26.841* [0.000]

Note: The numerical values in the bracket are *p* values. * denotes statistical significance at 1% level.

The means of a conditional heteroscedasticity model is used to analyze the volatility spillover effects between OECD countries' stock indices. Therefore, the ARCH-LM test is employed to test the existence of any ARCH effect. The ARCH-LM test findings are reported in Table 5. It is aimed to investigate the ARCH effect existence in the model for return series residuals. According to this result, it has been specified that it is appropriate to predict the return series of stock indices of all selected OECD countries by using alternative ARCH specifications.

Table 5. ARCH-LM Test Results of 7 OECD Stock Market Returns

Country	ARCH-LM statistics	Prob. Chi-square
Colombia	234.787	0.000
France	12.569	0.000
Germany	7.456	0.006
Italy	9.809	0.000
Mexico	21.050	0.000
The U.K.	3.062	0.080
The U.S.	15.778	0.000

CHAPTER 5: EMPIRICAL RESULTS

This chapter examines the development of mean and volatility spillover effects across the stock market indices of seven OECD nations. Tables 6, 8, 10, 12, 14, 16, and 18 provide the empirical results based on the MGARCH model with BEKK representations, whereas the summary findings are shown in Tables 7, 9, 11, 13, 15, 17, and 19.

Regarding the first-moment relationship, for the diagonal parameters, $\varphi(1)_{12}$ and $\varphi(1)_{21}$, (1) refers to Colombia, and (2) refers to stock exchange returns of other selected countries. $\varphi(1)_{12}$ represents the lagged spillover impacts in the mean from the stock exchange returns of Colombia to Germany, France, Italy, the U.S., Mexico, and the U.K. while $\varphi(1)_{21}$ denotes the same impact in the reverse direction as seen in Table 6. Only for France do these own mean spillover coefficients indicate that the lagged return of the France stock index aids in predicting its previous return, which is positive and statistically significant. Especially, the coefficient $\varphi(1)_{12}$ investigates the interrelation between the returns of two stock markets, meaning that present period returns in Colombia's stock index are significantly affected by lagged returns in the variable of other countries' stock indices, whereas $\varphi(1)_{21}$ measures the impact on the contrary direction. Surprisingly, the findings show that, except for Colombia and the U.S. pair, there is a mean spillover among all the country stock index pairs, indicating that there are no information flows exist between these two countries' stock markets.

This insight implies that a change in Colombia's stock market does not affect the U.S. stock market and vice versa.

The conditional volatility of the stock markets of all OECD countries is considered by both own-market shocks (a_{11}, a_{22}) while the results of the variance equation are revealed and own volatility persistence (b_{11}, b_{22}). The cross-market impacts between the stock markets of the chosen OECD countries are captured by the off-diagonal parameters, a_{12}, a_{21}, b_{12}, and b_{21}. As can be seen from Table 7, the results of the empirical analysis show there are bidirectional volatility transmission and cross-market shock for the pairs of Colombia-France and Colombia-Mexico stock markets.

For the pairs of Germany and selected OECD countries' stock indices, (1) represents Germany's stock index return, and (2) represents Colombia, Mexico, the U.K., the U.S., Italy, and France stock index returns, respectively for the estimated coefficients $\varphi(1)_{11}$ and $\varphi(1)_{22}$ in mean equations, as seen in Table 8. Both coefficients are statistically significant for two stock market pairs; Germany-Colombia, and Germany-France, implying that each market is impacted by its lagged return significantly. Moreover, the coefficient $\varphi(1)_{12}$ investigates the interconnection between the returns of two stock markets, meaning that present returns in Germany's stock index are affected by previous period returns of other countries' stock indices, whereas $\varphi(1)_{21}$ calculates the effect on the contrary direction. Among all the stock markets, the bidirectional return spillover is only existing in the stock markets of Germany and Mexico. Additionally, there is a unidirectional return spillover effect from the German stock market to Colombia, U.S., and France, while no return spillover effects are observed for the pairs of Germany-the U.K. and Germany-Italy stock markets.

In terms of the empirical results of the conditional variance equation in Table 9, between Germany-Colombia, Germany-Mexico, Germany-the U.S., and Germany-France stock markets, there is a bidirectional cross-market shock. The results also point out that bidirectional volatility spillover is observed for the pairs of Germany stock market and the U.K., the U.S., Italy, and France stock markets. As seen in Table 9, there are bidirectional shock and volatility transmission between the pairs of Germany-the U.S., and Germany-France stock markets. Although there is a bidirectional volatility spillover effect among Germany and Italy stock markets, the results indicate no evidence of shock volatility between these two stock markets.

Regarding the mean equation of Table 10, (1) represents France's stock index return, and (2) represents Germany, the U.K., the U.S., Italy Mexico, and Colombia's stock index returns. Both coefficients are statistically significant for the pairs of France stock market and Germany, Italy, and the U.S. stock markets, implying that there is an evidence of short-term predictability in these stock markets. While the coefficients $\varphi(1)_{12}$ and $\varphi(1)_{21}$ examine the linkage between France and selected OECD countries' stock markets, the empirical findings show that bidirectional return spillovers exist only between the pairs of France-the U.K. and France-Mexico. Also, there is a one-way return spillover from Germany, the U.K., Italy, the U.S., Mexico, and Colombia stock markets to France stock markets, indicating that a change in return of selected all OECD countries' stock indices affects France's stock index return. However, there is an absence of return spillover between France and Colombia stock markets.

As can be seen from Table 11 with regards to shock and volatility spillovers between France and all selected OECD countries' stock markets, the empirical results support the significant evidence of bidirectional cross-market shock between the pairs of the U.K.-France, France-Germany, The U.S.-France, France-Italy, France-Mexico, and France-Colombia stock markets, i.e. in all stock markets. Moreover, there is bidirectional volatility transmission between France and all countries' stock markets except for Mexico's stock market. An interesting finding is that volatility in Mexico's stock market is directly transmitted to France's stock market.

Turning out the mean spillover effects, (1) represents Italy's stock index return, and (2) represents Germany, Mexico, the U.K., the U.S., France, and Colombia stock index returns respectively for the estimated coefficients $\varphi(1)_{11}$ and $\varphi(1)_{22}$, as shown in Table 12. Both coefficients are statistically significant for the pairs of Italy-the U.S. and Italy-France stock markets. Among all the stock markets, the results exhibit that there is only bidirectional return spillover between Italy and Mexico stock markets. We also observe that past stock index returns of Italy have a predictable effect on the U.S., France, and Colombia stock index returns. However, the insignificant estimations indicate the absence of return spillover effects between the pairs of Italy-Germany, and Italy-the U.K. stock markets as can be seen in Table 13.

Turning out the empirical results of the conditional variance equation, there is significant evidence of bidirectional shock transmission only between the pairs of Italy-the U.S., Italy-France, and Italy-Colombia stock markets as is seen in Table 13. However, there is no shock spillover observed for the rest of the countries' stock markets. For the volatility linkages, there are bidirectional transmissions only between the pairs of Italy-France and Italy-Germany stock markets, whereas unidirectional transmission exists from the Italy stock market to Mexico and Colombia stock markets. For the pair of Italy-the U.K. stock markets, the conditional volatility performs independently from the unexpected shocks and historical volatility of each stock market.

In Table 14, the estimated coefficients (1) represent Mexico's stock index return, and (2) represent France, the U.K., the U.S., Italy, Germany, and Colombia's stock index returns respectively. The estimation results exhibit that there is a bidirectional return spillover between the pairs of Mexico and most of the selected OECD countries with the exception of the U.K. and Colombia. The statistical significance of estimated coefficients provides unidirectional price spillovers between Mexico-the U.K. and Mexico-Colombia, which implies that the direction of the price transmission is from the U.K. and Colombia stock markets to Mexico stock market.

Regarding the shock and volatility spillovers represented in Table 15, among Mexico and all selected OECD countries' stock markets, there is a bidirectional cross-market shock with the exception of Italy's stock market. Surprisingly, there is no shock spillover between Mexico and Italy stock markets. Furthermore, the results also show that there are bidirectional volatility transmissions between Mexico and all selected OECD countries' stock markets except Germany's stock market.

In Table 16, (1) represents the U.K. stock index return, and (2) represents the U.S., France, Germany, Mexico, Colombia, and Italy stock index returns, respectively, for the estimated coefficients. Between all the stock returns, the results exhibit that there is an existence of the bidirectional return spillover effects between only the pair of the U.K.-Mexico while unidirectional return spillover is observed from the U.K. to the U.S., France, and Colombia stock markets. However, Germany and Italy's stock markets behave independently from the U.K. stock market. From the empirical results of the conditional variance equation in Table 17, it is observed that there is evidence of bidirectional cross-market shock between the U.K. stock market and the U.S., France, and Mexico stock markets. In addition, there are bidirectional volatility transmissions between the U.K. stock market and all selected OECD countries' stock markets with the exception of the German stock market.

Concerning the return-generating process, for the estimated coefficients, (1) represents the U.S. stock index return, and (2) represents the U.K., France, Germany, Mexico, Colombia, and Italy stock index returns, respectively, as seen in Table 18. The results indicate evidence of bidirectional return spillover between the U.S. and Mexico stock markets whereas no existence of the bilateral or unilateral return spillover is found between the U.S. and Colombia stock markets. This finding means that a change in the U.S. stock market does not influence Colombia's stock market and vice versa.

Investigating the off-diagonal elements of matrices mean and variance equations, the empirical results exhibit significant evidence of bidirectional cross-market shock between the U.S. stock market and the U.K., France, Germany, and Mexico stock markets. Moreover, there are bidirectional volatility transmissions between the U.S. and all selected OECD countries' stock markets as seen in Table 19. These results indicate that when the volatility increases in the U.S., the volatility in other selected OECD countries' stock prices also increases and vice-versa.

As a summary of the overall empirical results, it provides significant proof of volatility transfer between the pairs of Colombia-France, the-U.K.-France, Mexico-Germany, Colombia-Mexico, and the U.S.-France, France-Germany, France-Italy, France-Mexico, Germany-the U.S. and the U.K.-the U.S. stock markets and also cross-market shock between these pairs. Also, there is bidirectional volatility transmission between the pairs of Germany-the U.S., Germany-Italy, Germany-France, Italy-France, Mexico-the U.S., and Mexico-the U.K stock markets. These results are vital for market participants and policymakers when designing their asset allocation and policies, respectively. It is recommended that market participants and policymakers be aware of the volatility between countries' stock markets and prepare policies to support the market stability in the long term. As well as market participants and policymakers, the results are important for regulators, who must consider the hyperconnectedness of financial markets and changes in times of crisis. Future studies may take into account the volatility spillover in all OECD stock markets or at the regional level when accounting for the COVID-19 outbreak.

Table 6. The volatility spillover’s predicted results among Germany and selected OECD countries' stock indices based on the VAR-BEKK-GARCH model

Colombia	France	Italy	Mexico	The U.K.	The U.S.	Germany
1. Mean Equation						
$\varphi(1)_{11}$	0.1648 [4.9110]*	0.2216 [5.0359]*	0.1699 [4.5467]*	0.1668 [3.8467]*	0.1560 [3.6423]*	-0.0935 [-1.8553]***
$\varphi(1)_{12}$	0.5121 [11.762]*	-0.0353 [-0.7398]	0.4180 [11.079]*	-0.0503 [0.8967]	0.0362 [0.5269]	0.0707 [1.9429]***
μ_1	0.0064 [0.1152]	0.0143 [0.2880]	0.0060 [0.1191]	0.0556 [1.0463]	0.0381 [0.6991]	0.0925 [2.1441]**
$\varphi(1)_{21}$	0.0088 [0.3039]	0.0611 [1.7295]***	-0.0139 [-0.3342]	0.0782 [2.2399]**	0.0102 [-0.4949]	-0.0755 [-1.4039]
$\varphi(1)_{22}$	0.1090 [2.9589]*	-0.0613 [-1.3262]	-0.0224 [-0.5556]	-0.0919 [-2.0699]**	-0.0813 [-1.6267]	0.2495 [5.6887]*
μ_2	0.0578 [1.4792]	0.1200 [2.5625]	0.1564 [2.7160]*	0.0650 [1.6046]	0.1242 [4.0725]*	0.0103 [0.1997]
2. Variance Equation						
c_{11}	0.8985 [11.068]*	0.4821 [8.5619]*	0.5087 [6.5586]*	0.4912 [8.2820]*	0.6080 [6.6752]*	0.3102 [5.4381]*
c_{21}	0.0624 [0.8038]	-0.0450 [-0.6137]	0.1341 [1.1225]	-0.1341 [-1.4955]	0.1556 [2.4223]**	0.0698 [0.6876]
c_{22}	-0.0000 [-1.6609]	0.2354 [3.6754]*	-0.1293 [-0.3808]	-0.0000 [-7.8512]	0.0255 [0.0305]	0.4094 [5.6869]*
a_{11}	0.3015 [6.3488]*	0.4424 [6.5644]*	0.1320 [1.5871]	0.2548 [5.2969]*	0.1733 [3.0106]*	0.4450 [9.2685]*

Table 6 (continued). The volatility spillover's predicted results among Germany and selected OECD countries' stock indices based on the VAR-BEKK-GARCH model

a_{12}	0.1892 [6.2396]*	-0.0856 [-1.5610]	-0.2331 [-6.0785]*	0.1607 [5.1291]*	0.0447 [1.2649]	0.2666 [3.4670]*
a_{21}	-0.6346 [-10.359]*	0.1288 [1.6843]***	0.4164 [9.2086]*	0.1064 [1.0973]	0.3175 [3.2141]*	-0.1537 [-3.1836]*
a_{22}	0.0849 [1.5439]	0.3750 [9.7262]*	0.1049 [1.4834]	0.2990 [6.4953]*	0.5522 [7.6076]*	0.3301 [4.9932]*
b_{11}	0.4513 [5.3580]*	0.7919 [19.969]*	0.7995 [20.872]*	0.7699 [20.487]*	0.7684 [11.300]*	0.8292 [19.997]*
b_{12}	-0.2612 [-5.0480]*	0.0256 [0.6946]	0.1474 [3.0447]*	-0.1389 [-5.7574]*	-0.1466 [-2.6393]*	-0.0770 [-1.1388]
b_{21}	0.2245 [4.4567]*	0.0841 [1.8103]***	-0.0913 [3.4266]*	0.2915 [3.5587]*	0.2206 [1.8226]***	0.0987 [2.5128]**
b_{22}	0.9710 [63.955]*	0.9183 [28.570]*	0.9432 [44.354]*	0.9854 [46.850]*	0.9401 [13.008]*	0.8935 [20.871]*

The own-lagged effects of the variables are $\varphi(1)_{11}$ and $\varphi(1)_{22}$. The lagged spillover impacts are captured by $\varphi(1)_{12}$ captures in mean from Colombia to other selected OECD countries' stock exchange returns. The lagged spillover impact in the mean is $\varphi(1)_{21}$ from the selected OECD countries' stock exchange returns to Colombia. c_{11}, c_{21}, and c_{22} are constant terms. The effect of ARCH on the variables two indicates in a_{11} and a_{22}. The spillover effect of a prior shock in Colombia's stock exchange return on the present volatility of Germany, France, Italy, the U.S., Mexico, and, the U.K., is measured by a_{12}. On the other hand, the spillover effect in opposite direction is measured by a_{21}. The GARCH terms are represented by b_{11} and b_{22}. The spillover effect of the latest period's variance of Colombia's stock exchange return on the current variance of Germany, France, Italy, Mexico, the U.K., and the U.S. is measured by b_{12}. In contrast, the spillover effect in opposite direction is measured by b_{21}. *, **, *** refers to the significance of statistical levels at 1, 5, and 10 percent, respectively.

Table 7. The predicted findings' summary of the equations of mean and variance between Colombia, and the selected OECD countries' stock indices

	France	Italy	Mexico	The U.K.	The U.S.	Germany
1. Mean Spillovers						
Colombia	→	←	→	←	-	→
2. Shock Transmission						
Colombia	↔	←	↔	→	←	↔
3. Volatility Spillovers						
Colombia	↔	←	↔	↔	↔	←

Notes: → or ← illustrates a unilateral volatility transfer, ← refers to the relevant stock index which in the initial column is the volatility taker, in the contrary, → means the relevant stock index is the volatility transmitter. ↔ illustrates a bidirectional transmission of volatility, and - means there is no volatility transmission.

Table 8. The volatility spillover's predicted results among Germany and selected OECD countries' stock indices based on the VAR-BEKK-GARCH model

Germany	Colombia	Mexico	The U.K.	The U.S.	Italy	France
1. Mean Equation						
$\varphi(1)_{11}$	-0.0935 [-1.8553]***	-0.1030 [-2.6514]*	-0.0264 [-0.4361]	-0.2172 [-4.4805]*	0.0099 [0.1207]	-0.1085 [-4.9548]*
$\varphi(1)_{12}$	0.0707 [1.9429]***	0.3656 [11.904]*	-0.0132 [-0.1983]	0.4040 [6.3572]*	-0.0589 [-0.7707]	0.8965 [36.334]*
μ_1	0.0925 [2.1441]**	0.0693 [1.6669]***	0.0815 [1.9829]**	0.0472 [1.2046]	0.0673 [1.5104]	0.0187 [0.6945]
$\varphi(1)_{21}$	-0.0755 [-1.4039]	0.1715 [3.1647]*	0.0043 [0.0766]	0.0003 [0.0103]	0.0071 [0.0849]	-0.0586 [-1.5331]
$\varphi(1)_{22}$	0.2495 [5.6887]*	-0.0009 [-0.0251]	-0.0489 [-0.7586]	-0.0322 [-0.5883]	-0.0866 [-1.0585]	0.1018 [2.7095]*
μ_2	0.0103 [0.1997]	0.0158 [0.2802]	0.0418 [1.1196]	0.0990 [3.4089]*	0.0899 [1.8208]***	0.0385 [0.9147]
2. Variance Equation						
c_{11}	0.3102 [5.4381]*	0.5431 [4.2835]*	0.3626 [6.5694]*	-0.1242 [-2.5313]**	0.2618 [3.2095]*	0.3135 [10.467]*
c_{21}	0.0698 [0.6876]	0.6747 [3.5921]*	0.0606 [0.4933]	-0.2542 [-6.0156]*	0.3129 [2.5415]**	0.0087 [0.1160]
c_{22}	0.4094 [5.6869]*	0.1436 [0.2172]	0.2031 [1.9956]**	-0.0000 [-8.1045]	0.0906 [0.8742]	-0.2949 [-5.8232]*
a_{11}	0.4450 [9.2685]*	0.3447 [5.2244]*	0.2400 [3.3422]*	-0.1042 [-1.8217]***	0.1168 [0.6000]	0.3218 [5.1511]*

Table 8 (continued). The volatility spillover’s predicted results among Germany and selected OECD countries' stock indices based on the VAR-BEKK-GARCH model

b_{11}	0.8292 [19.997]*	0.7103 [8.3172]*	0.5746 [7.6711]*	1.1037 [56.650]*	1.1286 [22.349]*	0.6866 [15.731]*
a_{12}	0.2666 [3.4670]*	0.5335 [5.9419]*	0.1529 [2.4695]**	-0.2745 [-5.4694]*	-0.0994 [-0.4708]	-0.2892 [-4.2145]*
a_{21}	-0.1537 [-3.1836]*	-0.3352 [-7.0515]*	0.1285 [1.5910]	0.6466 [8.1179]*	0.2578 [1.5958]	0.3215 [8.7160]*
a_{22}	0.3301 [4.9932]*	-0.1156 [-1.8140]***	0.3146 [4.1632]*	0.9050 [12.559]*	0.4443 [2.7835]*	0.2639 [4.2728]*
b_{11}	0.8292 [19.997]*	0.7103 [8.3172]*	0.5746 [7.6711]*	1.1037 [56.650]*	1.1286 [22.349]*	0.6866 [15.731]*
b_{12}	-0.0770 [-1.1388]	-0.6254 [-5.4988]*	-0.2482 [-3.5911]*	0.1406 [5.6803]*	0.2066 [4.2072]*	0.2069 [2.0035]**
b_{21}	0.0987 [2.5128]**	0.0541 [0.7914]	0.3831 [3.9806]*	-0.3656 [-8.9672]*	-0.2404 [-4.8927]*	-0.0624 [-2.5242]**
b_{22}	0.8935 [20.871]*	0.7325 [8.4573]*	1.1036 [16.716]*	0.6112 [14.179]*	0.7326 [17.463]*	0.9019 [43.801]*

Notes: The variable 1 denotes Germany, 2 denotes Colombia, Mexico, the U.K., the U.S., Italy, and France stock indices, respectively.

Table 9. The predicted findings' summary of the equations of mean and variance between Germany and the selected OECD countries stock indices

	Colombia	Mexico	The U.K.	The U.S.	Italy	France
1. Mean Spillovers						
Germany	→	↔	-	→	-	→
2. Shock Transmission						
Germany	↔	↔	→	↔	-	↔
3. Volatility Spillovers						
Germany	←	→	↔	↔	↔	↔

Notes: Same with Table 7.

Table 10. The volatility spillover's predicted results among France and selected OECD countries' stock indices based on the VAR-BEKK-GARCH model

France	Germany	Italy	The U.K.	The U.S.	Mexico	Colombia
1. Mean Equation						
$\varphi(1)_{11}$	0.1018 [2.5444]**	0.0832 [2.0922]**	0.0427 [1.1576]	0.1173 [3.1265]**	0.0172 [0.4268]	0.0485 [1.2955]
$\varphi(1)_{12}$	-0.0586 [-1.4913]	-0.0275 [-0.8897]	-0.0672 [-1.6616]***	-0.0735 [-1.5329]	0.1267 [3.8951]*	-0.042 [-1.2185]
μ_1	0.0385 [0.8899]	0.0475 [0.1340]	0.0511 [1.1608]	0.1041 [2.3748]**	0.0397 [0.9932]	0.1045 [2.2982]**
$\varphi(1)_{21}$	0.8965 [32.460]*	0.9194 [31.429]*	0.7764 [27.418]*	0.5796 [23.347]*	0.1227 [2.3494]**	0.5772 [12.253]
$\varphi(1)_{22}$	-0.1085 [-5.0304]*	-0.0758 [-3.1868]*	-0.0989 [-4.0026]*	-0.2656 [2.4488]**	-0.0589 [-1.1871]	0.1270 [3.5554]*
μ_2	0.0187 [0.7243]	0.0079 [0.2799]	-0.0142 [-0.5274]	0.0565 [0.7243]	0.0000 [3.2263]	-0.0229 [-0.4419]
2. Variance Equation						
c_{11}	-0.2950 [-5.5896]*	0.1586 [0.8432]	0.1408 [1.6815]***	0.2793 [6.5455]*	0.3561 [4.8869]*	-0.1624 [-1.8706]***
c_{21}	-0.0093 [-0.1090]	-0.0184 [0.0750]	-0.3312 [-10.982]*	0.0635 [1.1432]	-0.6676 [-13.958]*	0.5498 [8.0475]*
c_{22}	0.3134 [9.3926]*	0.3763 [9.3260]*	-0.0000 [-2.7607]	0.1595 [5.4458]*	0.1024 [0.1538]	-0.0000 [-3.1088]
a_{11}	0.2639 [4.2778]*	0.1098 [1.7833]***	0.1005 [2.0425]**	0.1175 [2.5743]**	0.3544 [7.1850]*	0.1656 [3.4328]*

Table 10 (continued). The volatility spillover’s predicted results among France and selected OECD countries' stock indices based on the VAR-BEKK-GARCH model

a_{12}	0.3215 [8.3633]*	0.3526 [9.5751]*	0.2723 [10.274]*	0.2856 [10.767]*	0.3156 [4.4358]*	0.4503 [9.4589]*
a_{21}	-0.2892 [-4.4677]*	-0.4050 [-5.5988]*	-0.5509 [-7.0318]*	-0.5417 [-9.1633]*	-0.1163 [-2.5560]**	-0.2696 [-6.8740]*
a_{22}	0.3218 [4.9912]*	0.2194 [3.8693]*	0.1651 [3.4907]*	-0.0438 [-0.9425]	0.2693 [4.9785]*	0.1144 [1.2936]
b_{11}	0.9019 [43.819]*	0.8762 [27.031]*	0.8571 [27.820]*	0.8535 [35.459]*	0.6426 [7.2512]*	0.8455 [27.896]*
b_{12}	-0.0624 [-2.3826]**	-0.0799 [-3.5095]*	-0.0737 [-3.4816]*	-0.0812 [-5.0420]*	0.0449 [0.6694]	-0.1855 [-4.0380]*
b_{21}	0.2069 [2.1557]**	0.4328 [4.1925]*	0.5364 [6.7276]*	0.2929 [4.7692]*	0.3030 [4.1836]*	0.2671 [6.4947]*
b_{22}	0.6866 [14.015]*	0.6795 [13.393]*	0.7437 [18.685]*	0.9004 [34.933]*	0.7730 [16.863]*	0.8284 [23.7056]*

Notes: The variable 1 denotes France, 2 denotes Germany, Italy, the U.K., the U.S., Mexico, and Colombia stock indices, respectively.

Table 11. The predicted findings’ summary of the equations of mean and variance between France and the selected OECD countries' stock indices

	Germany	Italy	The U.K.	The U.S.	Mexico	Colombia
1. Mean Spillovers						
France	←	←	↔	←	↔	-
2. Shock Transmission						
France	↔	↔	↔	↔	↔	↔
3. Volatility Spillovers						
France	↔	↔	↔	↔	←	↔

Notes: Same with Table 7.

Table 12. The volatility spillover's predicted results among Italy and selected OECD countries' stock indices based on the VAR-BEKK-GARCH model

Italy	Germany	Mexico	The U.K.	The U.S.	France	Colombia
1. Mean Equation						
$\varphi(1)_{11}$	-0.0866 [0.9932]	-0.0691 [-1.5867]	-0.0529 [-0.8418]	-0.0920 [-1.6565]***	-0.0758 [-3.2967]*	-0.0613 [-1.3338]
$\varphi(1)_{12}$	0.0071 [0.0796]	0.3791 [11.822]*	-0.0256 [-0.3688]	0.1630 [1.6450]***	0.9194 [31.370]*	0.0611 [1.7257]***
μ_1	0.0900 [1.8011]***	0.0479 [1.0185]	0.0943 [2.0344]**	0.1202 [2.5439]**	0.0079 [0.2802]	0.1200 [2.6553]*
$\varphi(1)_{21}$	-0.0589 [-0.7788]	0.2441 [5.4066]*	-0.0304 [-0.5859]	0.0521 [1.2149]	-0.0275 [-0.8569]	-0.0353 [-0.7359]
$\varphi(1)_{22}$	0.0099 [0.1212]	-0.0075 [-0.1843]	-0.0413 [-0.6105]	-0.1640 [-2.8240]*	0.0832 [2.1689]**	0.2216 [4.8925]*
μ_2	0.0673 [1.5903]	0.0159 [0.2870]	0.0331 [0.8548]	0.0941 [3.1289]	0.0475 [1.1129]	0.0143 [0.2761]
2. Variance Equation						
c_{11}	0.3257 [3.0640]*	0.3156 [2.2649]**	0.3800 [4.1192]*	0.4661 [4.0830]*	0.3768 [9.8775]*	0.2397 [4.0308]*
c_{21}	0.2514 [2.4691]**	-0.2804 [-1.6756]***	0.3156 [4.7375]*	0.0036 [0.0616]	-0.0077 [-0.0749]	-0.0906 [-0.6175]
c_{22}	-0.0729 [-0.8235]	0.2522 [1.1580]	0.1571 [1.5458]	-0.0000 [-6.9256]	-0.1584 [-0.8218]	0.4735 [7.3354]*
a_{11}	0.4444 [2.5023]*	0.3285 [9.9672]*	0.4153 [3.6700]*	-0.4805 [-3.2905]*	0.2194 [3.7478]*	0.3750 [9.9875]*

Table 12 (continued). The volatility spillover’s predicted results among Italy and selected OECD countries' stock indices based on the VAR-BEKK-GARCH model

a_{12}	0.2578 [1.3633]	-0.0273 [-0.1712]	0.1382 [1.0650]	-0.4189 [-10.892]*	-0.4050 [-5.1395]*	0.1288 [1.7617]***
a_{21}	-0.0995 [-0.4089]	-0.1374 [-1.2086]	0.0116 [0.0750]	0.7482 [0.0000]*	0.3526 [9.4574]*	-0.0856 [-1.6487]***
a_{22}	0.1167 [0.4979]	0.3447 [6.4397]*	0.3184 [1.8898]***	0.3811 [3.5910]*	0.1098 [1.7847]***	0.4424 [7.1861]*
b_{11}	0.7326 [18.925]*	0.9147 [16.851]*	0.8757 [8.0682]*	0.8217 [7.0655]*	0.6795 [13.050]*	0.9183 [29.043]*
b_{12}	-0.2404 [-5.4646]*	0.2389 [4.7777]*	-0.0653 [-0.5021]	0.0376 [1.0781]	0.4328 [4.1796]*	0.0841 [1.6463]***
b_{21}	0.2066 [4.2788]*	-0.0484 [-1.1848]	0.0041 [0.0329]	0.0494 [0.4920]	-0.0799 [-3.3984]*	0.0256 [0.6979]
b_{22}	1.1286 [24.799]*	0.8662 [26.580]*	0.9190 [6.3138]*	0.8934 [28.931]*	0.8762 [27.231]*	0.7918 [19.679]*

Notes: The variable 1 denotes Italy, 2 denotes Germany, Mexico, the U.K., the U.S., France, and Colombia stock indices, respectively.

Table 13. The predicted findings’ summary of the equations of mean and variance between Italy and the selected OECD countries' stock indices

	Germany	Mexico	The U.K.	The U.S.	France	Colombia
1. Mean Spillovers						
Italy	-	↔	-	→	→	→
2. Shock Transmission						
Italy	-	-	-	↔	↔	↔
3. Volatility Spillovers						
Italy	↔	→	-	-	↔	→

Notes: Same with Table 7.

Table 14. The volatility spillover's predicted results among Mexico and selected OECD countries' stock indices based on the VAR-BEKK-GARCH model

Mexico	France	The U.K.	The U.S.	Italy	Germany	Colombia
1. Mean Equation						
$\varphi(1)_{11}$	-0.0878 [-2.0756]**	-0.0296 [-0.8229]	-0.0180 [-0.4460]	-0.0075 [-0.1683]	-0.0009 [-0.0242]	-0.0174 [-0.4731]
$\varphi(1)_{12}$	0.1204 [2.1790]**	0.0823 [1.6281]	0.1772 [3.1807]*	0.2441 [5.2853]*	0.1715 [3.1561]*	0.0230 [0.6338]
μ_1	0.0918 [1.6011]	0.1103 [2.2004]**	0.0540 [0.9574]	0.0159 [0.2894]	0.0158 [0.2912]	0.0616 [1.1674]
$\varphi(1)_{21}$	0.1207 [3.6105]*	0.3341 [10.836]*	0.3463 [16.148]*	0.3791 [11.345]*	0.3656 [11.949]*	0.4405 [11.326]*
$\varphi(1)_{22}$	-0.0411 [-1.0282]	-0.0657 [-1.8892]***	-0.1485 [-4.7284]*	-0.0691 [-1.6620]***	-0.1030 [-2.8902]*	0.1336 [3.6651]*
μ_2	0.0624 [1.6444]	0.0367 [1.1641]	0.0883 [3.2318]*	0.0479 [0.9801]	0.0693 [1.8136]***	-0.0145 [-0.2683]
2. Variance Equation						
c_{11}	0.7261 [7.6825]*	0.1604 [1.2058]	0.5689 [5.6312]*	0.3771 [3.5026]*	0.6898 [5.4566]*	0.4404 [2.7261]*
c_{21}	0.0050 [0.0630]	0.3954 [13.914]*	0.2031 [3.5388]*	-0.2348 [-1.1895]	0.5312 [2.9126]*	0.3232 [1.4818]
c_{22}	-0.0000 [-9.0624]	0.0202 [0.0924]	-0.0000 [-1.1334]	0.2110 [1.3971]	0.1130 [0.2152]	0.3621 [2.1320]**
a_{11}	0.2777 [2.9832]*	-0.0083 [-0.1380]	-0.2438 [-5.3559]*	0.3447 [6.0224]*	-0.1155 [-1.6378]	0.0954 [1.7333]***

Table 14 (continued). The volatility spillover’s predicted results among Mexico and selected OECD countries' stock indices based on the VAR-BEKK-GARCH model

a_{12}	0.1996 [4.0055]*	-0.3088 [14.265]*	0.1832 [8.4327]*	-0.1374 [-1.0764]	-0.3352 [-7.1269]*	0.4002 [11.058]*
a_{21}	-0.3973 [-3.9023]*	0.3503 [6.0177]*	0.3072 [3.1675]*	-0.0272 [-0.1537]	0.5335 [5.7560]*	-0.2989 [-6.9806]*
a_{22}	0.1430 [2.1454]**	-0.0091 [-0.1849]	0.3328 [7.5877]*	0.3285 [10.664]*	0.3446 [5.0053]*	-0.2062 [-3.8685]*
b_{11}	0.5638 [5.9537]*	0.8916 [51.505]*	0.7765 [20.280]*	0.8662 [26.184]*	0.7325 [8.1192]*	0.9153 [23.233]*
b_{12}	-0.2037 [-5.8355]*	-0.1664 [-8.5039]*	-0.1769 [-11.699]*	-0.0483 [-1.0694]*	0.0541 [0.8102]	0.1579 [4.9530]*
b_{21}	0.4797 [4.7896]*	0.4559 [6.2631]*	0.6620 [10.359]*	0.2389 [5.2165]*	-0.6254 [-5.4142]*	-0.3775 [-6.6316]*
b_{22}	1.0555 [36.745]*	0.7891 [49.465]*	0.8101 [23.456]*	0.9146 [14.965]*	0.7103 [8.5668]*	0.7682 [17.065]*

Notes: The variable 1 denotes Mexico, 2 denotes France, the U.K., the U.S., Italy, Germany, and Colombia stock indices, respectively.

Table 15. The predicted findings’ summary of the equations of mean and variance between Mexico and the selected OECD countries' stock indices

	France	The U.K.	The U.S.	Italy	Germany	Colombia
1. Mean Spillovers						
Mexico	↔	←	↔	↔	↔	←
2. Shock Transmission						
Mexico	↔	↔	↔	-	↔	↔
3. Volatility Spillovers						
Mexico	↔	↔	↔	↔	←	↔

Notes: Same with Table 7.

Table 16. The volatility spillover’s predicted results among the U.K. and selected OECD countries' stock indices based on the VAR-BEKK-GARCH model

The U.K.	The U.S.	France	Germany	Mexico	Colombia	Italy
1. Mean Equation						
$\varphi(1)_{11}$	-0.1935 [-3.6658]*	-0.0989 [-3.8470]*	-0.0488 [-0.7708]	-0.0657 [-1.8447]***	-0.0704 [-1.3833]	-0.0018 [-0.0290]
$\varphi(1)_{12}$	0.3225 [5.1003]*	0.7764 [27.106]*	0.0043 [0.0718]	0.3341 [11.877]*	0.0772 [2.3036]**	0.0075 [0.1400]
μ_1	0.0325 [0.8316]	-0.0142 [-0.5127]	0.0418 [1.1776]	0.0367 [0.9521]	0.0623 [1.5617]	0.0306 [0.7811]
$\varphi(1)_{21}$	-0.0005 [-0.0151]	-0.0672 [-1.6046]	-0.0132 [-0.1967]	0.0823 [1.8504]***	-0.0154 [-0.2479]	-0.0309 [-0.4376]
$\varphi(1)_{22}$	-0.0800 [-1.4978]	0.0427 [1.1364]	-0.0264 [-0.4195]	-0.0296 [-0.7659]	0.2144 [4.5991]*	0.0494 [0.7805]
μ_2	0.1133 [3.8864]*	0.0511 [1.2875]	0.0815 [2.0511]**	0.1103 [2.1176]**	0.0311 [0.5770]	0.0523 [1.1705]
2. Variance Equation						
c_{11}	0.4550 [10.763]*	0.3312 [9.9663]*	0.2116 [0.4348]	0.3960 [5.3662]*	0.4443 [6.8589]*	0.3840 [5.8281]*
c_{21}	0.2272 [4.9152]*	-0.1408 [-1.7714]***	0.1038 [0.4079]	0.1602 [0.9761]	0.0097 [0.0739]	-0.1406 [-1.8118]***
c_{22}	0.0000 [3.0464]	-0.0000 [-2.3065]	0.3474 [8.0246]*	0.0000 [8.7824]	0.3412 [2.5307]**	0.0000 [8.5508]
a_{11}	-0.3552 [-5.4726]*	0.1651 [3.1241]*	0.3145 [1.7875]***	0.0091 [0.1589]	0.3293 [4.5748]*	0.3894 [4.1948]*

Table 16 (continued). The volatility spillover’s predicted results among the U.K. and selected OECD countries' stock indices based on the VAR-BEKK-GARCH model

a_{12}	-0.2743 [-5.4452]*	-0.5509 [-7.1538]*	0.1284 [0.9565]	-0.3503 [-5.8321]*	0.4036 [5.3445]*	0.1109 [1.0251]
a_{21}	0.5371 [6.6927]*	0.2723 [9.8175]*	0.1530 [1.8007]***	0.3088 [8.5953]*	-0.0695 [-1.0657]	-0.1784 [-2.4203]**
a_{22}	0.7396 [10.092]*	0.1005 [2.0741]**	0.2401 [2.6964]*	0.0083 [0.1390]	0.2933 [4.5251]*	0.2357 [2.6133]*
b_{11}	0.6354 [9.7426]*	0.7437 [16.994]*	1.1040 [2.9410]*	0.7891 [17.350]*	0.7486 [11.022]*	0.4841 [4.9485]*
b_{12}	-0.2699 [-6.6236]*	0.5364 [6.9150]*	0.3833 [1.6665]***	0.4559 [5.9853]*	-0.1904 [-1.9015]***	-0.1531 [-1.7998]***
b_{21}	0.3114 [4.0048]*	-0.0737 [-3.3750]*	-0.2485 [-0.8022]	-0.1664 [-6.8653]*	0.1580 [2.8763]*	0.4139 [5.8395]*
b_{22}	1.0389 [21.369]*	0.8571 [28.818]*	0.5745 [3.1826]*	0.8917 [47.581]*	0.9255 [15.303]*	1.0521 [16.699]*

Notes: The variable 1 denotes the U.K., 2 denotes the U.S., France, Germany, Mexico, Colombia, and Italy stock indices respectively.

Table 17. The predicted findings' summary of the equations of mean and variance between the U.K. and the selected OECD countries' stock indices

	The U.S.	France	Germany	Mexico	Colombia	Italy
1. Mean Spillovers						
The U.K.	→	→	-	↔	→	-
2. Shock Transmission						
The U.K.	↔	↔	←	↔	→	←
3. Volatility Spillovers						
The U.K.	↔	↔	→	↔	↔	↔

Notes: Same with Table 7.

Table 18. The volatility spillover's predicted results among the U.S. and selected OECD countries' stock indices based on the VAR-BEKK-GARCH model

The U.S.	The U.K.	France	Germany	Mexico	Colombia	Italy
1. Mean Equation						
$\varphi(1)_{11}$	-0.0372 [-0.6589]	-0.2656 [-9.4159]*	-0.0728 [-1.3702]	-0.0978 [-3.0708]*	-0.0814 [-1.8382]***	-0.1406 [-2.7088]*
$\varphi(1)_{12}$	-0.0064 [-0.1720]	0.5796 [21.939]*	-0.0114 [0.3092]	0.3552 [15.691]*	-0.0102 [-0.4847]	0.0474 [1.2807]
μ_1	0.1047 [3.7336]*	0.0564 [2.4662]**	0.1092 [3.9787]*	0.0774 [2.4759]**	0.1242 [4.2821]*	0.1000 [3.4111]*
$\varphi(1)_{21}$	0.3718 [5.5934]*	-0.0735 [-1.5340]	0.3774 [5.5082]*	0.2186 [3.8194]*	0.0362 [0.5571]	0.2912 [4.4112]*
$\varphi(1)_{22}$	-0.1934 [-3.7561]*	0.1173 [2.9525]*	-0.2150 [-4.2210]*	-0.0097 [-0.2355]	0.1560 [3.9052]*	-0.1483 [-3.2155]*
μ_2	0.0198 [0.5393]	0.1041 [2.7827]*	0.0594 [1.4213]	0.0604 [1.2135]	0.0381 [0.4696]	0.0570 [1.2635]
2. Variance Equation						
c_{11}	0.2566 [6.8074]*	0.1717 [4.8226]*	0.2563 [6.1588]*	0.2348 [4.2861]*	0.1577 [3.1590]*	0.2560 [6.1986]*
c_{21}	0.1998 [2.7294]*	0.1033 [1.2005]	0.4616 [9.3089]*	-0.5709 [-6.8263]*	0.5999 [4.4650]*	0.4976 [3.7688]*
c_{22}	-0.1068 [-2.3727]	0.2596 [3.7200]*	-0.0000 [-6.0686]	-0.0000 [-4.0923]	0.0990 [0.1649]	-0.1545 [-0.6637]
a_{11}	0.8365 [11.045]*	-0.0438 [-0.9220]	0.6860 [6.9333]*	-0.1278 [-2.2447]**	0.5522 [8.2732]*	0.5720 [6.7763]*

Table 18 (continued). The volatility spillover's predicted results among the U.S. and selected OECD countries' stock indices based on the VAR-BEKK-GARCH model

a_{12}	0.6734 [7.7220]*	-0.5418 [-7.9066]*	0.2832 [2.1846]**	0.5983 [6.7157]*	0.3175 [3.4750]*	0.0927 [0.7433]
a_{21}	-0.2444 [-4.2269]*	0.2856 [10.556]*	-0.1681 [-2.8481]*	-0.2672 [-10.540]*	0.0447 [1.3616]	-0.1507 [-2.2635]**
a_{22}	-0.1011 [-1.3348]	0.1176 [2.1932]**	0.0088 [0.1011]	0.0822 [1.4155]	0.1733 [3.6811]*	0.0522 [0.5932]
b_{11}	0.7186 [15.546]*	0.9005 [29.637]*	0.9801 [19.207]*	0.6466 [12.143]*	0.9401 [28.874]*	1.0439 [14.661]*
b_{12}	-0.2738 [-5.8142]*	0.2929 [4.7894]*	0.2654 [3.5210]*	-0.3188 [-3.3124]*	0.2205 [3.2116]*	0.4107 [2.8494]*
b_{21}	0.0607 [1.7573]***	-0.0812 [-4.7866]*	-0.1911 [-5.0144]*	0.2053 [8.3412]*	-0.1466 [-11.931]*	-0.2089 [-2.6005]*
b_{22}	1.0287 [28.710]*	0.8535 [31.722]*	0.7234 [13.223]*	0.8826 [24.558]*	0.7684 [30.122]*	0.6513 [4.9566]*

Notes: The variable 1 denotes the U.S., 2 denotes the U.K., France, Germany, Mexico, Colombia, and Italy stock indices, respectively.

Table 19. The predicted findings' summary of the equations of mean and variance between the U.S. and the selected OECD countries' stock indices

	The U.K.	France	Germany	Mexico	Colombia	Italy
1. Mean Spillovers						
The U.S.	←	→	←	↔	-	←
2. Shock Transmission						
The U.S.	↔	↔	↔	↔	→	←
3. Volatility Spillovers						
The U.S.	↔	↔	↔	↔	↔	↔

Notes: Same with Table 7.

CHAPTER 6: CONCLUSION

In this dissertation, the spillover effects between stock markets of seven OECD countries are analyzed, using daily data between January, 1st 2019, and September, 30th 2021. The OECD countries used for analysis are Colombia, France, Germany, Italy, Mexico the U.K., and the U.S., which are selected according to the highest ranking of daily COVID-19 mortality rates. The empirical findings indicate satisfactory proof of spillover impacts during COVID-19 in the stock markets of selected OECD countries. Therefore, this investigation is meticulous to highlight the information transmission over time and among these countries' stock markets in order to make optimal portfolio allocation decisions.

Employing the VAR-BEKK GARCH model, the results show that there is a volatility transmission among the pairs of Colombia-France, the U.K.-the U.S., Colombia-Mexico, France-Germany, the U.S.-Germany, France-Italy, France-the U.K., France-the U.S., France-Mexico, and Germany-Mexico stock markets and bidirectional cross-market shock between these pairs. Also, there is bidirectional volatility transmission between the pairs of Germany-the U.S., Germany-Italy, Germany-France, Italy-France, Mexico-the U.S., and Mexico-the U.K stock markets.

This thesis takes part in a novel contribution since this is primary empirical research on the impact of the COVID-19 pandemic which studies OECD countries’ stock markets which are chosen according to the highest mortality rates using the VAR-BEKK GARCH model, which provides direction to investors and academicians during this time of COVID-19 pandemic. Hence, this study guides further research to explore implications and methods for assessing the impact of the COVID-19 pandemic on other global stock markets. Consequently, additional research is valuable in this environment because of the extraordinary condition of COVID-19 and its consequent impact on the global financial markets worldwide.

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