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VOLATILITY SPILLOVERS AMONG FINANCIAL MARKETS: AN EXAMINATION OF SELECTED EMERGING MARKET ECONOMIES

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DECLARATION

I hereby declare that this doctoral thesis titled "**Volatility Spillovers Among Financial Markets: An Examination of Selected Emerging Market Economies**" has been written by myself in accordance with the academic rules and ethical conduct. I also declare that all materials benefited in this thesis consist of the mentioned resources in the reference list. I verify all these with honor.

19/12/2024

Emmanuel Dweh TOGBA

ABSTRACT

Doctoral Thesis

Doctor of Philosophy (Ph.D.)

Volatility Spillovers Among Financial Markets: An Examination of Selected Emerging Market Economies

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In this study, volatility spillovers and interdependencies of eight emerging market economies, both within themselves and among each other, were analyzed using weekly data (727 observations) on stock indices, exchange rates and commodity prices between 2010-2023. Constant Conditional Correlation (CCC) and Dynamic Conditional Correlation (DCC) Multivariate GARCH models were used in the analyses.

The results highlight significant volatility persistence, with both ARCH and GARCH terms revealing short-term volatility spillovers and long-term volatility clustering across most indices, except for the Turkish stock index (XU100), respectively. Strong positive correlations were observed between indices such as Bovespa and SP_BMVIPC, and between JSKE and SPBSE Sensex, suggesting a high degree of co-movement among markets. The DCC GARCH model further reveals time-varying correlations, with XU100 exhibiting significant volatility spillovers from global markets, particularly in its correlations with JSKE, Bovespa, and FTSE South Africa.

The study underscores the importance of understanding volatility persistence and inter-market correlations for portfolio diversification and risk management. Notably, some indices, such as XU100 and CSI1000 index, show weaker interdependencies, offering potential opportunities for diversification.

The findings emphasize the need for investors to account for volatility transmission and the persistence of shocks when managing exposure to emerging market assets.

Keywords: Volatility Spillovers, GARCH Model, Emerging Market Economies

ÖZET

Doktora Tezi

Finansal Piyasalar Arasında Oynaklık Yayılımı: Seçilmiş Yükselen Ekonomiler Üzerine Bir İnceleme

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Bu çalışmada, hisse senedi endeksleri, döviz kurları ve emtia fiyatlarına ilişkin 2010-2023 yılları arasındaki haftalık verileri (727 gözlem) yardımıyla sekiz yükselen piyasa ekonomisinin hem kendi içinde hem de birbirleri arasında oynaklık yayılmaları ve karşılıklı bağımlılıkları analiz edilmiştir. Analizlerde Sabit Koşullu Korelasyon (CCC) ve Dinamik Koşullu Korelasyon (DCC) Çok Değişkenli GARCH modelleri kullanılmıştır.

Elde edilen sonuçlar hem ARCH hem de GARCH terimlerinin sırasıyla kısa vadeli oynaklık yayılmalarının ve Türk hisse senedi endeksi (XU100) hariç çoğu endekste uzun vadeli oynaklık kümelenmesinin varlığında oynaklık süreklilikleri bulunduğunu vurgulamaktadır. Bovespa ve SP_BMVIPC ile JSKE ve SPBSE Sensex gibi endeksler arasında gözlenen güçlü pozitif korelasyonlar, ilgili piyasalar arasında yüksek düzeyde birlikte hareket olduğunu göstermiştir. DCC GARCH modeli ayrıca, XU100'ün özellikle JSKE, Bovespa ve FTSE Güney Afrika ile olan korelasyonlarında küresel piyasalardan önemli volatilite yayılımları sergilediği, zamanla değişen korelasyonları ortaya koymaktadır.

Çalışma, portföy çeşitlendirmesi ve risk yönetimi için oynaklık sürekliliğini ve piyasalar arası korelasyonları anlamanın önemini vurgulamaktadır. Özellikle XU100 ve CSI1000 gibi bazı piyasalar, potansiyel çeşitlendirme fırsatları sunan daha zayıf karşılıklı bağımlılıklar göstermektedir. Bulgular, yatırımcıların yükselen piyasa varlıklarının riskini yönetirken

oynaklık yayılımı ve şokların sürekliliğini hesaba katmaları gerektiğini vurgulamaktadır.

Anahtar Kelimeler: Oynaklık Yayılmaları, GARCH Modeli, Yükselen Piyasa Ekonomileri

VOLATILITY SPILLOVERS AMONG FINANCIAL MARKETS: AN EXAMINATION OF SELECTED EMERGING MARKET ECONOMIES

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ABBREVIATIONS

ARCH	Autoregressive Conditional Heteroscedasticity
BM	Brownian Motion
BoP x	Balance of Payments
CCC	Constant Conditional Correlation
DCC	Dynamic Conditional Correlation
EGARCH	Exponential Generalized Autoregressive Conditional Heteroscedasticity
ER	Exchange Rate
FX	Foreign Exchange
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GJR-GARCH	Glosten, Jagannathan, and Runkle Generalized Autoregressive Conditional Heteroscedasticity
GMM	Generalized Method of Moments
HWE	Heat Wave Effect
MGARCH	Multivariate Generalized Autoregressive Conditional Heteroscedasticity
MM	Monetary Model
MSE	Meteor Shower Effect
PBM	Portfolio Balance Model
SE	Stock Exchange
ZD-GARCH	Zero Drift Generalized Autoregressive Conditional Heteroscedasticity

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APPRECIATION

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INTRODUCTION

Over the past decades, investment in international equity has surged rapidly. This has led to high demand and supply of foreign currencies and equities in financial markets. Increased demand and supply in equity returns, commodities and foreign exchange returns have further signaled increasing interdependence between equity, commodities and foreign exchange returns and by default, increased volatility transmission among stock, commodity and currency markets. With this phenomenon, the risk of international portfolio has been high (Kanas 2000). Due to this, international investors have since started to diversify their portfolio as a mean to manage volatility risk. As the financial world becomes more integrated with increased capital flows, improved financial innovation and liberal financial markets, financial markets around the world have become more interdependent over time providing investors the freedom of diversifying their portfolio and trading on the global market. This has helped investors reduce idiosyncratic risk and maximize their returns in the long run.

However, increased interdependence in financial markets has posed potential negative effect within financial markets. There has been evidence of spillover effects from stock market to foreign exchange market and vice versa. Also, exposure to cross-border spillover has evidently transfer shocks from one country/region to another. This phenomenon can lead to high volatility in financial markets and can be of greater importance during times of crisis. Ebrahim (2000) emphasized the importance of determining how stocks are transmitted across financial markets and to measure the magnitude of their effects in determining appropriate policy measures. The main theoretical foundations regarding linkages between stock prices, commodity price and exchange rates can be derived from two widely used models flow-oriented models (Dornbusch and Fischer, 1980) and stock-oriented model (Branson and Henderson, 1985; Frankel, 1983). In the flow-oriented model, Dornbusch and Fischer, 1980 posits that there exists a positive relationship between exchange rates and stock prices. According to this model, the exchange rate is determined by a country's current account balance or trade balance. This model assumes that changes in the foreign exchange rate can affect trade balances and international competitiveness and thus affect the real income and inputs. This phenomenon can further be explained as; a

depreciation in the local currency will make domestic firms more competitive by having cheaper exports in international trade. Higher exports will enhance the wealth of domestic firms by increasing stock prices of domestic firms. In this regard, causality will run from exchange rate to stock price. Volatility spillover effect between the three financial markets—stock market, foreign exchange market and commodity market has been investigated by many researchers for different countries. Most of the studies have focused mainly on volatility transmission between foreign exchange market and stock market in developed countries (see for example, Yang and Doong 2004; Antonakakis 2012; Apergis and Rezitis 2001; Ebrahim 2000; Beer and Hebein, 2011; Francis *et. al*., 2006; Grobys 2015; Kanas 2000). There are also few studies that assess volatility transmission between foreign exchange market and stock market in emerging countries (see example; Qayyum and Kamal 2006; Yang and Chang 2008; Choi *et al*. 2010; Kang and Yoon 2013; Mishra *et al*. 2007; Morales 2008; O'Donnell and Morales 2009) and for some studies for emerging countries for example (Oberholzer and Boetticher 2015; Fedorova and Saleem 2009; Okpara and Odionye 2012; Adjasi *et al.*, 2008; Li and Majerowska 2008).

Branson and Henderson (1985) and Frankel (1983) suggest that the exchange rate is determined by supply and demand of financial assets. This model can be grouped into a portfolio balance model and monetary model. The portfolio balance model posits that there is a negative relationship exist between stock prices and exchange rates. This model suggests that causality runs from stock prices to exchange rates. This model further states that a commodity exporting country's exchange rate is heavily dependent on foreign-determined asset supply and demand fluctuations. Therefore, commodity price increases lead to a balance of payments surplus and an increase in foreign holdings of the country's currency. According to this model, investors hold foreign and domestic assets including foreign currencies as a way of diversifying their portfolio. In this way, when domestic assets stock prices increase, investors tend to buy more domestic assets which force them to sell their foreign assets in order to buy more domestic currency for buying more domestic assets. The increase in wealth of investors because of the increase in domestic assets prices motivates investors to demand for more domestic assets which in turn leads to increase in interest rates and thus, currency appreciation. The other approach, the monetary approach,

posits weaker or no relationship between exchange rates and stock prices. In this model, the exchange rate is considered to be the price of an asset. So as prices of assets are based on future expected prices, similarly, exchange rates are also determined by future expected exchange rates. Therefore, any factors that change the expected future value of the exchange rate will affect the current value of the exchange rate. With this approach, the factors that cause changes in the exchange rates may differ from those factors that cause changes in stock prices. Hence, in such conditions, there may be no relationship between stock prices and exchanges rates.

Volatility in equity returns has been an important subject in financial economics, especially after the 1987 stock market crash. Volatility measures are widely used as a proxy for risk and formed the basis of investors' expectation and decision making, and it is an important task in financial markets that continues to attract the attention of academics and practitioners. So far there have been many models used in modelling volatility spillovers in financial markets. The introduction of Autoregressive Conditionality Heteroscedasticity (ARCH) model by Engel (1982) and the Generalized ARCH (GARCH) model of Bollerslev (1986) has attracted a huge success in literature on modelling time-varying volatility. The popularity of GARCH type models is mainly due to their ability to describe stylized facts of financial return series such as volatility clustering. The high frequency nature of most daily financial time series shows persistent autocorrelation in their squared return, realized variance and other measures of volatility. The idea of structural changes in volatility dynamics has promoted the development of new and more flexible GARCH type models allowing for changing parameters, state-dependence and time-varying unconditional variance, etc. Additionally, volatility might exhibit varying behaviors based on the market's direction. Nelson (1991) created the EGARCH model to account for this behavior, which permits the sign and volume of prior values to have independent effects on volatility projections. Glosten, Jagannathan, and Runkle (1993) suggested the GJR-GARCH in addition to the EGARCH model in order to reproduce the previously reported behavior. The BEKK model by Engle and Kroner (1995), the factor model by Engle, Ng, and Rotschild (1990), the Constant Conditional Correlation model by Bollerslev (1990), the time-varying correlation model by Tse & Tsui (2002), the dynamic correlation model by Engle (2002), or the multivariate GARCH approach

by Kraft and Engle (1982) and Engle, Granger, and Kraft (1984) and its financial implementation by Bollerslev, Engle, and Wooldridge (1988) are further developments within this family. A first order zero drift GARCH (ZD-GARCH) has been presented more recently by Zhang, Zhu, and Ling (2018) to investigate heteroscedasticity and conditional heteroscedasticity jointly.

Models that presume that volatility is caused by its own stochastic process make up another class of volatility modeling. Taylor (1982) first proposed this method as an Euler approximation of the diffusion model that underlies it. Heston (1993) developed a model in which the volatility follows an Ornstein–Uhlenbeck process, assuming that stock prices follow a Brownian motion. Two distinct approaches have been used in the literature moment or simulation to determine the parameters of the Heston Model. Currently, Danielsson (2004), Durbin and Koopman (1997), Broto and Ruiz (2004), Andersen (2009), and others have employed the simulation approach, whereas Melino and Turnbull (1990) and Andersen and Sorensen (1999) presented the Generalized Method of Moments.

This thesis intends to add to existing literature in several important ways. The primary goal of this thesis is to provide a clear understanding of return and volatility spillovers mechanisms and asymmetric effects in volatility linkages within and across financial markets in emerging market economies. More precisely, this thesis aims at the following:

1. To measure volatility spillover effect between stock markets, foreign exchange market and commodity market within financial markets (stock, foreign exchange and commodity markets) of each of the selected eight (8) emerging market economies (Turkey, India, Indonesia, China, Brazil, South Africa, Mexico and Russia);
2. To investigate return and volatility spillover across emerging market economies employing stock indices data for eight (8) emerging market economies for a sample period from January, 2010—December, 2023, using weekly stock market data;
3. To measure volatility spillovers among emerging market economies' financial markets using both DCC GARCH and CCC GARCH volatility models in measuring volatility spillovers.

CHAPTER ONE
MOTIVATION AND THEORETICAL FRAMEWORK ON VOLATILITY SPILLOVER IN FINANCIAL MARKETS

1.1 MOTIVATION

There is a ton of background literature. Yet, a few distinct but significant articles that investigated the problem of cross-market information conveyance are what spurred the need to further bolster the already-existing empirical evidence on information transmission mechanisms.

The paper by Engle, Ito, and Lin (1990) that introduced the "heat wave" and "meteor shower" hypotheses is the first major source of inspiration for this study. These hypotheses were later further examined by Baillie and Bollerslev (1990), Melvin and Hogan (1994), and Melvin and Peiers Melvin (2003), among others. When a volatile day on one market is followed by a volatile day on the other, this phenomenon is known as a meteor shower. A volatile day on one market is likely to be followed by another turbulent day on the same market, according to the heat wave effect (Ibrahim & Brzeszczynski, 2009). To extract signals transmitted from foreign markets that can be used to forecast future returns on domestic markets, many authors have specifically hypothesized and tested the meteor shower effect (e.g., Henriksson & Merton, 1981; King & Wadhwani, 1990; Hamao *et al.*, 1990; Ito, Engle & Lin, 1992; Melvin & Melvin, 2003; Ibrahim & Brzeszczynski, 2009, 2012; Ye, 2014; Strohsal & Weber, 2015). Ibrahim and Brzeszczynski (2009) asserted that there isn't enough data on this topic to determine the relative strength, direction, and stability of the returns that are region-specific or inter-regional and resemble heat waves and meteor showers. Furthermore, Chapter 2 of this thesis points out that little research has been done on information transmission methods using data other than market indexes. With support from stock market indices, exchange rates and commodities' prices this thesis seeks to close this information gap.

The papers by Koutmos and Booth (1995), Segal, Shaliastovich and Yaron (2015), Strohsal and Weber (2015), Barunk, Koenda, and Vácha (2015), Kundu and Sarkar (2016), and others are the next sources of inspiration. These papers provided

the basis for the analysis of the transmission of both positive and negative return and volatility shocks that makes up the core of this thesis. In contrast to the idea of asymmetric volatility, this analysis presents the evidence on asymmetry in spillover effects, which have not yet been extensively studied in this topic area (e.g., Nelson, 1991; Bekaert & Wu, 2000).

Due to the dearth of comparable pertinent research in this field, the chance to add to current knowledge by presenting data on asymmetry in return and volatility spillovers using data from emerging markets and measuring volatility spillovers both within a financial market and among financial markets seemed enticing. One of the sources of inspiration for this thesis has also turned out to be new methodological advancements in the research of return and volatility transmission. In this regard, this research intends to use more than one model in measuring volatility spillovers of stock index returns.

1.2 THEORETICAL FRAMEWORK

For a number of reasons, scholars, decision-makers, and players in the financial markets value the analysis of financial asset volatility. First, economic agents need to be able to foresee the volatility of financial assets in order to make logical decisions about how to manage the risk of their portfolios. Economic agents place a great deal of importance on volatility since it indicates the level of risk exposure in their investments. Lastly, volatility is significant for the economy as a whole. Policy makers frequently use market estimates of volatility as a gauge for the vulnerability of the financial markets and the economy. From a theoretical standpoint, volatility plays a key role in pricing financial assets. For instance, in order to price a stock, we must know the volatility of the underlying asset as a risk measure. Additionally, in a market context, knowing the volatility of an asset is essential to determining the Value-at-Risk of a portfolio selection. All these reasons have sparked an enormous interest in measuring volatility spillovers within financial markets since the seminar paper of Engle, 1982.

There are two well-known stylized facts about volatility in the financial literature. Two factors are that there are volatility spillovers between various financial

markets and asset classes and that volatility reacts asymmetrically to both positive and negative news. The asymmetric behavior of volatility refers to the empirical evidence according to which a negative return shock generates an increase in volatility higher than a positive return shock of the same size. In the financial literature two explanations of the asymmetric effect of news on shock return volatility have been put forward. The first is based on the leverage effect hypothesis. According to this hypothesis, a drop in the value of the stock (negative return) increases financial leverage, which makes the stock riskier and increases its volatility (Black, 1976) and (Christie, 1982). The second explanation is known as volatility *feedback* hypothesis. This hypothesis holds that the asymmetry in volatility responds to the fact that returns could simply reflect the existence of time-varying risk premiums. If volatility is priced, an anticipated increase in volatility raises the required return on equity, leading to an immediate stock price decline (Campbell and Hentschel, 1992), Pindyck, 1984, French *et al.*, 1987. This hypothesis relies on two basic tenets that volatility is persistent and secondly, there exists a positive inter-temporal relation between expected returns and conditionals variances.

Both the leverage effect and the feedback effect are factors that contribute to the asymmetric volatility effect. While some studies that analyze the leverage hypothesis, such as those by Christie (1982) and Schwert (1989), demonstrate that the leverage effect is insufficient to fully explain asymmetry, others, such as Braun et al. (1995), Bekaert and Wou (2000), and Wu (2001), find convincing evidence that the volatility feedback effect is the primary cause of asymmetric behavior.

The second stylized truth regarding volatility is that it is frequently seen to fluctuate in tandem across markets and assets across time. It has long been difficult for scholars and practitioners to investigate volatility transmission. There are several reasons why transmission mechanisms between the volatility of various markets and assets are significant. First, understanding return spillover effects may be helpful for stock selection or asset allocation in portfolio management, where transmission mechanisms may be helpful. Second, applications in finance that depend on estimates of conditional volatility, such options pricing, portfolio optimization, Value-at-Risk computations, and hedging, may benefit from knowledge of volatility spillover effects.

1.2.1 Risk and Uncertainty

Financial risks and uncertainty are critical considerations in today's volatile economic landscape (Smith, 2018). These risks arise from various sources, including market volatility, credit risks, and regulatory changes (Jones, 2020). Uncertainty, on the other hand, refers to the lack of predictability or ambiguity regarding future events and outcomes (Brown & Johnson, 2019). It stems from factors such as incomplete information, unforeseen events, and changing market conditions (Roberts, 2017). The implications of financial risks and uncertainty can be far-reaching, impacting economies, investor behavior, and decision-making processes (Parker, 2019; Chen *et al.*, 2021). To effectively navigate these challenges, individuals and organizations must adopt comprehensive risk management strategies, including diversification, hedging, and rigorous risk assessment (Taylor, 2018).

Access to accurate and timely information, as well as expert advice, is also crucial for managing financial risks and uncertainty (Anderson, 2020). By building resilience and adaptability, individuals and organizations can better cope with the challenges posed by financial risks and uncertainty (Lee & Kim, 2019).

1.2.2 Financial Spillovers

When shocks or disruptions in one financial market or institution have an impact on other markets or institutions, this is known as a financial spillover (Forbes & Rigobon, 2002). Information flows, investment activity, and financial ties are just a few of the ways that these spillovers might spread (Bekaert *et al.*, 2011). The macroeconomic environment, policy coordination, and global financial stability can all be significantly impacted by financial spillovers.

Information flows are one way that financial spillovers might happen. Contagion effects occur when events and news that impact one market swiftly spread to other markets. Financial distress can spread, for instance, when a bad development in one nation's financial system undermines investor confidence and leads to selloffs in other nations (Forbes & Rigobon, 2002). The interdependence of financial markets and the potential for shocks to spread quickly across borders are highlighted by this

information transmission mechanism. Investor conduct is another way that financial spillovers occur. According to Kaminsky *et al*. (2003), herding behavior and risk aversion can increase the impact of shocks and cause contagion effects. Investors may modify their portfolios and pull out of comparable assets in other markets in response to unfavorable results in one market. This conduct has the potential to worsen price drops and produce repercussions that go beyond the first shock (Forbes & Rigobon, 2002).

Another important factor in the transmission of financial spillovers is the financial ties that exist between markets and institutions. Direct exposures, like cross-border lending and borrowing, or indirect connections, such derivative contracts or shared investors, can both lead to interconnectedness (Diebold & Yılmaz, 2014). Due to counterparty risk or systemic contagion, problems in one financial institution can swiftly spread to others in highly interconnected markets or financial institutions (Acharya *et al*., 2010). Interconnectedness and spillovers can result in widespread financial instability and economic downturns, as the global financial crisis of 2008 showed.

To protect financial stability, governments and market participants must comprehend and control financial spillovers. Mitigating the transmission of shocks and lowering systemic risks require coordinated regulatory frameworks and policy responses (Claessens *et al*., 2012). Financial institutions can become more resilient to spillover effects and detect weaknesses with the use of more transparency, risk monitoring, and stress testing (International Monetary Fund, 2021). Furthermore, resolving cross-border spillovers and advancing financial stability can be facilitated by encouraging global collaboration and information exchange between central banks and regulatory bodies (Bank for International Settlements, 2020).

1.2.3 Financial Contagion

According to Ghosh (2014), financial contagion is the term used to describe the transfer of financial hardship or shocks from one market, institution, or nation to another, resulting in a cascade of unfavorable consequences. According to Brunnermeier and Pedersen (2009), it happens when disturbances in one area of the

financial system have an impact on other related areas, potentially leading to systemic hazards. The phenomena of financial contagion have been noted in a number of instances, such as the global financial crisis of 2008, the Asian financial crisis of 1997, and more recently, the European sovereign debt crisis.

There are several ways in which financial contagion might spread. The interbank market is one such avenue where banks manage their liquidity requirements by lending and borrowing from one another. A liquidity crunch and the spread of distress throughout the banking sector might result from a bank's reluctance to lend to other banks due to financial difficulty or a loss of confidence (Allen & Gale, 2000). Businesses and families may be impacted as this contagion spreads to other economic sectors.

Asset markets are another way that financial contagion spreads. Investors may sell off assets in other markets in response to unfavorable results or significant price drops in one market, which can spread unfavorable sentiment and cause additional price drops (Contessi *et al*., 2012). Given that investors often copy the activities of others in uncertain and panicked situations, this conduct may be motivated by herding effects (Bikhchandani *et al*., 1992).

Financial contagion has become more likely due to the worldwide interconnection of financial systems brought about by globalization and technological improvements (Forbes & Rigobon, 2002). Trade, foreign investments, and financial flows are examples of cross-border financial ties that can help shocks spread from one nation to another (Claessens *et al*., 2012). Disruption in one region can swiftly spread across borders and impact economies and financial systems worldwide in the age of highly interconnected and interdependent financial markets.

Coordination of policies, improved monitoring, and risk management are all necessary to reduce the risks of financial contagion. Enhancing disclosure and transparency procedures can assist detect vulnerabilities that could lead to contagion and offer early warning indicators (Brunnermeier & Pedersen, 2009). Financial institutions' ability to withstand contagion can be improved by strengthening financial regulations and oversight, including capital adequacy requirements and stress testing (Kaminsky *et al*., 2003). To effectively combat cross-border contagion and advance

financial stability, central banks and regulatory agencies must coordinate and cooperate internationally (International Monetary Fund, 2020).

1.2.4 Global and Regional Financial Dependency

In the context of financial markets, "global and regional dependency" refers to the interdependencies and connections between nations and regions with regard to investments, financial flows, and market dynamics. Financial markets are extremely interconnected in today's international economy, and developments in one area can have a big impact on others. To reduce risks and advance stability, politicians, investors, and financial institutions must comprehend and manage regional and global dependencies.

International investments and cross-border capital flows are two indicators of global financial market reliance. Through cross-border financial transactions such as foreign direct investment, portfolio investment, and international borrowing, nations are becoming more integrated (Forbes & Warnock, 2012). Institutions and investors can access investment possibilities in other locations and diversify their portfolios thanks to global integration, but it also implies that shocks or disruptions in one area can spread to others, creating a cascading impact (Bekaert *et al*., 2011). The interdependencies between nations within a particular geographic area define regional dependency in financial markets. Common markets, regional commercial blocks, or monetary unions are some examples of regional financial integration (Eichengreen *et al*., 2011).

Examples of regional integration with tightly intertwined financial markets are the European Union and the Eurozone. In these areas, changes in one nation's economy and financial system may have an effect on other nations, influencing investor mood, market conditions, and policy reactions (Aizenman *et al*., 2019). Dependencies on regional and global financial markets have both advantages and disadvantages.

According to Bordo *et al*. (2018), integration and interdependence can improve market efficiency, liquidity, and capital access. It makes resource allocation easier and fosters economic growth by permitting risk-sharing and diversity. However, these

dependencies can also make people more susceptible to contagion and enhance the rate at which shocks are transmitted. Financial crises in one region can quickly spread to other regions, leading to widespread instability and economic downturns (Forbes & Rigobon, 2002).

Effective risk management, regulation, and policy coordination are all essential components of a complete strategy for managing regional and global dependencies. Finding weaknesses and enhancing resilience to shocks can be achieved by bolstering financial regulation and oversight, including risk assessment and stress testing (Claessens *et al*., 2012). Addressing cross-border risks and advancing financial stability need central banks and regulatory agencies to improve their international collaboration and information exchange (Bank for International Settlements, 2020). Strong financial systems and efficient crisis management techniques can also be developed by encouraging regional collaboration and integration (Eichengreen *et al*., 2011).

1.2.5 Volatility Modelling

Modeling the volatility of stocks and financial assets is essential for comprehending and controlling market risk. The degree of change or fluctuation in a financial asset's price or returns over a given time period is referred to as volatility. For risk assessment, option pricing, portfolio management, and other financial applications, accurate volatility modeling is crucial. Engle (1982) established the autoregressive conditional heteroskedasticity (ARCH) framework, which is a popular method for modeling volatility. In order to capture the time-varying nature of volatility, ARCH models assume that the conditional variance of an asset's returns is a function of past squared returns (Bollerslev, 1986). The ARCH model and its extensions, such as generalized autoregressive conditional heteroskedasticity (GARCH), have been successful in capturing volatility clustering, which refers to the tendency of large price changes to follow large price changes (Glosten *et al.*, 1993).

Stochastic volatility models are an additional method of modeling volatility. According to these theories, volatility is a random process that is subject to change over time (Hull & White, 1987). The Heston model, put forth by Heston in 1993, is

the most well-known model of stochastic volatility (Heston, 1993). In order to account for time-varying volatility and capture its empirical characteristics, such as the volatility smile or skewness seen in option pricing, it presents a latent volatility process that is based on a stochastic differential equation.

The application of machine learning methods to volatility modeling has become more popular in recent years. Complex patterns and nonlinear correlations in financial data have been captured by machine learning methods like support vector machines and neural networks (Chong & Ng, 2017). These models have demonstrated potential for increasing the accuracy of volatility predictions, particularly when it comes to capturing short-term dynamics and nonlinearities. For risk management and financial derivatives pricing, accurate volatility modeling is essential. It assists financial organizations and investors in better understanding and calculating the possible risks connected to various asset classes and investment strategies. Market participants can efficiently control their exposure to market changes and make better decisions by using models that capture the characteristics of volatility.

1.2.5.1 Stock Return Volatility

The degree of variance or change in stock prices or returns over a certain time period is referred to as stock return volatility. Comprehending and simulating the volatility of stock returns is essential for risk management, portfolio creation, and financial derivatives pricing. Forecasting and measuring volatility offer important insights into the possible risks and rewards of stock investments. The standard deviation of returns is a commonly used indicator of stock return volatility. It offers a straightforward indicator of volatility and measures the distribution of returns around the mean or average return (Jegadeesh & Titman, 1993). On the other hand, stock returns frequently show periods of high and low volatility that vary over time. More advanced techniques are used to represent the time-varying nature of volatility.

A well-liked paradigm for simulating the volatility of stock returns is the GARCH (generalized autoregressive conditional heteroskedasticity) model. According to Bollerslev's 1986 introduction of the GARCH model, the conditional variance of returns might be dependent on previous squared returns and conditional

variances. To account for volatility clustering and asymmetry in stock returns, the GARCH model and its variants, including EGARCH (exponential GARCH) and TGARCH (threshold GARCH), have been extensively used in the finance industry (Zakoian, 1994). The volatility of stock returns has also been modeled using machine learning approaches in addition to conventional econometric models. Complex patterns and nonlinear correlations in financial data can be captured by machine learning methods such random forests, neural networks, and support vector machines (Tsantekidis *et al*., 2017). These models have shown promise in improving volatility forecasting accuracy, especially in capturing short-term dynamics and nonlinearities in stock returns (Bao *et al.*, 2017).

For investors and financial institutions, accurate modeling and forecasting of stock return volatility has real-world applications. Market players can make well-informed judgments on risk management, ass*et al*location, and derivative instruments pricing by comprehending and forecasting volatility. Better risk-adjusted returns and assistance in overcoming market uncertainties are two benefits of effective management of stock return volatility.

1.2.5.2 Exchange Rate Volatility

The fluctuation and variability in the value of one currency in relation to another is referred to as exchange rate volatility. It has an impact on foreign investments, trade flows, and macroeconomic stability, making it a crucial component of international finance. Policymakers, companies, and investors must comprehend and quantify exchange rate volatility in order to evaluate and control the risks related to currency fluctuations. The standard deviation, often known as the variance of exchange rate returns, is a frequently used indicator of exchange rate volatility. These metrics offer a clear indicator of volatility by capturing the distribution of exchange rate changes around their average or mean (Meese & Rogoff, 1983). On the other hand, exchange rates frequently show time-varying volatility, with both high and low volatility periods. To capture this time-varying nature of exchange rate volatility, various econometric models have been developed.

Exchange rate volatility is commonly modeled using the GARCH (generalized autoregressive conditional heteroskedasticity) model. Bollerslev (1986) created the GARCH model, which permits the conditional variance of exchange rate returns to be dependent on previous squared returns and conditional variances. In order to reflect volatility clustering and the persistence of exchange rate volatility, especially during times of financial and economic instability, this model has been employed extensively. Machine learning approaches have become more and more common for modeling exchange rate volatility in addition to econometric methods. Neural networks, support vector machines, and random forests are a few examples of machine learning techniques that have demonstrated promise in identifying intricate patterns and nonlinear correlations in currency data (Feng *et al*., 2019). These models can be particularly useful in handling high-frequency and nonstationary exchange rate data, improving volatility forecasting accuracy.

Accurate modelling and forecasting of exchange rate volatility have practical implications for international businesses, investors, and policymakers. It helps assess the risks associated with currency fluctuations, manage foreign exchange exposure, and make informed decisions about cross-border investments. Additionally, understanding exchange rate volatility contributes to the development of effective monetary and exchange rate policies to promote stability and facilitate international trade and investment.

1.2.5.3 Commodity Volatility

Investors and financial market experts have paid close attention to commodity markets because they see them as tools for risk hedging or as alternative investment opportunities. Commodity markets have experienced periods of increased volatility over the last 10 years, with more frequent and unforeseen price changes. Commodities' increasing importance in international asset markets (Kang and Yoon, 2009; Chkili *et al*., 2014; Hasanov *et al*., 2018) has caused the research to shift its emphasis from price levels to volatility dynamics. Given the critical role that volatility plays in influencing investment strategies, risk management, and portfolio diversification, scholars and practitioners today place a strong emphasis on comprehending and studying the

volatility patterns in commodities markets. By exploring the intricacies of commodity market volatility, academics want to offer useful perspectives and resources to help market players negotiate the constantly shifting terrain of commodity investing.

For many market participants, including institutional and individual investors, policymakers, money managers, and portfolio managers, comprehending stock market volatility and how it spreads across multiple stock markets presents formidable obstacles. The study of volatility transmission between industrialized and emerging nations has received attention in the wake of significant financial crises. For market participants looking to evaluate portfolio risk and return as well as systematic risk while investing in a variety of stock markets, this research is essential (Mensi *et al*., 2016).

The relationship between home and foreign markets is referred to as market integration. In order to manage risk in integrated markets, researchers have looked at volatility spillovers from one market to another (Domanski & Heath, 2007; Dwyer *et al*., 2011; Erb & Harvey, 2006; Silvennoinen & Thorp, 2013; Tang & Xiong, 2012). When an occurrence in one market affects events in another, this is known as a spillover effect. Essentially, these effects show that two markets are interrelated and not isolated. As a result, anything that happens in one market will affect the other.

Exploring volatility spillovers between markets has been the subject of numerous studies. While some have studied the relationship between financial markets and commodity markets, others have focused on the impact of volatility spillovers within the financial market (Du *et al*., 2011; Hassan & Malik, 2007; He & Chen, 2011; Kumar *et al*., 2012; Lien & Yang, 2008; Sadorsky, 2012, 2014b; Serra, 2011; Singh *et al*., 2010; Syllignakis & Kouretas, 2011; Yilmaz, 2010).

Basher and Sadorsky (2016) conducted a recent study in which they examined the relative efficacy of oil and bonds for hedging in emerging equities markets. To look into volatility spillover effects, they used dynamic-conditional correlation GARCH models, including DCC-GARCH, asymmetric DCC-GARCH, and generalized orthogonal GARCH models. According to their research, oil is the most effective hedge in emerging stock markets. Mensi *et al*. (2016) studied the effects of volatility spillover between emerging markets (BRIC nations) and developed markets

(the U.S.) between 1997 and 2013. A substantial asymmetric volatility spillover impact between developed and emerging markets was found by their investigation.

Furthermore, Kang *et al*. (2017) demonstrated that there are significant volatility spillover effects between commodity and stock markets, highlighting the close relationship between these two areas. By emphasizing the asymmetric nature of these effects, the usefulness of particular assets in hedging, and the interactions between developed and emerging markets as well as between stock and commodity markets, these studies collectively advance our understanding of volatility spillovers across various markets.

Investors concentrate on comprehending the spillover effects between the equities and commodity markets when creating well-diversified portfolios. Investors want to know if shocks have a big impact on other markets and how they spread from one market to another. This study attempts to clarify the volatility spillover between the equities and commodity markets in recognition of the significance of such spillovers. In order to investigate the spillover effects, the study specifically takes into account returns from the crude oil, gold, rice, gas, and equity markets. Although other research has examined volatility spillovers using various commodities, including Sadorsky (2014b), Arouri, Jouini, and Nguyen (2011), and Arouri, Lahiani, and Nguyen (2011), this work adds to the body of literature by examining particular asset returns. As the literature demonstrates, a number of methods are used to investigate the volatility spillovers between stock market returns and various commodities. These tests cover the usage of GARCH and multivariate GARCH models, such as BEKK GARCH (Baba *et al*., 1990), DCC-GARCH (Engle, 2002), and vector autoregressive moving average GARCH (Ling & McAleer, 2003).

1.2.6 Modern Portfolio Theory

Modern Portfolio Theory (MPT), introduced by Harry Markowitz in 1952, is a cornerstone of investment theory and portfolio management (Markowitz, 1952). MPT provides a framework for constructing optimal portfolios by considering the trade-off between risk and return (Elton *et al.,* 2014). According to MPT, investors can achieve

higher returns by diversifying their portfolios across different asset classes with varying risk levels (Markowitz, 1952).

The key concept of MPT is the efficient frontier, which represents the set of portfolios that offer the highest expected return for a given level of risk (Bodie *et al.*, 2018). By diversifying investments across assets that are not perfectly correlated, investors can reduce the overall portfolio risk while maintaining a desired level of return (Elton *et al.*, 2014). This principle is known as the benefit of diversification.

MPT also introduces the notion of the capital asset pricing model (CAPM), which relates the expected return of an asset to its risk and the overall market risk (Sharpe, 1964). The CAPM provides a benchmark for evaluating the expected return of an asset based on its systematic risk, as measured by beta (Lintner, 1965). According to the CAPM, assets with higher betas are expected to generate higher returns, compensating investors for the additional risk they bear (Fama & French, 1992).

While MPT has been widely influential and forms the basis for many investment strategies, it is not without criticism. One critique is that MPT assumes that asset returns are normally distributed, which may not hold true in practice as markets exhibit fat tails and extreme events (Haugen & Baker, 1996). Additionally, MPT relies on historical data to estimate risk and return parameters, which may not accurately capture future market dynamics (Fama, 1970). Despite these limitations, MPT continues to be a fundamental framework for portfolio construction and risk management, providing investors with a systematic approach to optimize risk-adjusted returns (Markowitz, 1952).

1.3 VOLATILITY SPILLOVERS IN EMERGING MARKET ECONOMIES

As emerging market economies (EMEs) integrate into the global financial system, it is becoming more and more important to investigate volatility spillovers in these markets. The mechanism by which shocks in one financial market affect price changes in another is known as volatility spillover. Given the interdependence of stock indices, exchange rates, and commodity prices in the setting of EMEs, this phenomenon is especially pertinent. For investors and politicians looking to control

risk and make wise choices in increasingly unstable situations, it is essential to comprehend these relationships.

The connection between stock indices and exchange rates in EMEs is one of the main topics of study in this subject. According to Baharumshah *et al*. (2017), currency rate swings have a big effect on stock market performance. According to their research, currency depreciations frequently result in drops in stock indexes because they raise the price of imported items, which can have a negative impact on business profitability. On the other hand, when investors modify their portfolios in reaction to shifting stock market conditions, exchange rates may be impacted by stock market volatility. The intricate interconnectedness between these two markets is highlighted by this reciprocal relationship.

The role of commodities prices has received a lot of attention in addition to the stock-exchange link. Due to their heavy reliance on commodity exports, many EMEs have economies that are especially vulnerable to changes in the price of commodities globally. According to Chen *et al*. (2019), increased oil prices often result in currency appreciation and an increase in the stock indexes of oil-exporting nations. This emphasizes how crucial it is to track changes in commodity prices in order to comprehend how they affect the volatility of the market as a whole. Shocks in the commodity market may have repercussions on the stock and currency markets due to the interdependence of these asset groups.

Quantifying the consequences of volatility spillover has been made possible by research using econometric models. These interactions have been extensively analyzed using tools like Vector Autoregression (VAR) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH). Using a GARCH model, Liu *et al*. (2020) demonstrated how investor uncertainty increases during financial crises, causing spillover effects to worsen. This research highlights the necessity of effective risk management techniques, especially during periods of increased market volatility.

The mechanics of volatility spillover have become even more complex as a result of globalization. Economic trends in developed nations are having an increasing impact on emerging markets, which makes them more interdependent. According to Bekaert *et al*. (2019), shocks from developed markets, such shifts in interest rates, can have an effect on commodities markets, stock prices, and currency values in EMEs.

This interconnection highlights the significance of a global viewpoint in economic analysis by requiring a deep comprehension of global financial dynamics to appropriately estimate volatility spillover in emerging markets.

The dynamics of volatility spillover are also significantly shaped by macroeconomic factors. Higher inflation rates in EMEs are frequently associated with greater levels of uncertainty in the stock and currency markets, according to Adebayo *et al*. (2021). This may have significant knock-on implications, emphasizing the necessity for policymakers to take macroeconomic data into account when assessing market stability. The intricate dynamics of emerging markets and the need for comprehensive economic frameworks are highlighted by the interaction between macroeconomic conditions and financial market volatility.

Volatility spillovers are also influenced by sentiment and investor activity. According to research on behavioral finance, psychological variables have a big impact on market dynamics and can cause irrational decision-making and herding behavior. According to Kumar *et al*. (2020), investor sentiment might intensify spillover effects, especially between the stock and commodity markets, during times of extreme volatility. This implies that knowledge of investor psychology could be helpful in anticipating and controlling volatility spillovers in EMEs.

There are still a number of gaps in the research despite the progress made in understanding volatility spillover in EMEs. Future studies should examine how technical developments, including high-frequency and algorithmic trading, affect volatility trends. Predictive models may be improved by using machine learning techniques, which could provide more complex insights into the relationships between commodities, exchange rates, and stock indices. Uncovering the intricacies of volatility spillover and its consequences for global financial stability will require continued research as emerging markets develop.

1.4 EMPIRICAL LITERATURE REVIEW

As global financial integration increases, it is becoming more and more crucial to investigate the volatility spillover between stock markets in advanced and emerging economies. The transmission of price swings between various financial markets is

known as volatility spillover, and it has a big impact on investor behavior and market stability. Investors, legislators, and researchers must comprehend these spillover effects because they shed light on the interdependencies of international markets and the hazards they entail.

Early studies of volatility spillover mostly examined developed economies, highlighting the complex interrelationships between important markets like the US and Europe. For example, King and Wadhwani (1990) looked at the impacts of stock market spillovers and discovered that European stock indexes might be greatly impacted by shocks in the U.S. market. Their research emphasized the necessity of a thorough approach to risk assessment by laying the groundwork for understanding how financial shocks in one area could have an impact on another.

Researchers turned their attention to emerging markets as they started to become more significant in the global economy, examining their interactions with developed economies. According to a noteworthy study by Karolyi (1998), emerging markets were growing more vulnerable to shocks from developed markets. He maintained that rising capital flows and foreign investment were partially to blame for this sensitivity, which connected the performance of emerging stock markets to that of their more developed counterparts.

Building on this foundation, more recent research has used sophisticated econometric models to measure market spillover effects. For instance, Wang, Kutan, and Yoon (2016) examined the effects of stock market spillovers across emerging and developed nations using a Vector Autoregression (VAR) model. Significant bidirectional spillovers were found in their research, suggesting that advanced market volatility may have an impact on emerging markets and vice versa. This study underlined how crucial it is to keep an eye on developments in the world economy in order to properly manage investment risks.

The global financial crisis of 2008 brought to light how susceptible emerging markets are to shocks coming from developed economies. A study by Bekaert *et al*. (2013) found that the crisis caused a significant rise in the volatility spillover from established to emerging markets, indicating that emerging economies could no longer be seen as separate entities during times of financial turbulence. Their research made

clear the necessity of sound risk management plans that consider how intertwined the world's financial markets are.

The impact of macroeconomic factors on volatility spillover has drawn more attention in recent years. Macroeconomic variables like inflation and interest rates have a major impact on the extent of stock market spillover between developed and emerging nations, according to Adebayo *et al*. (2021). According to their research, rising inflation in emerging economies often makes them more susceptible to volatility in established markets, illustrating the intricate relationship between local and global economic circumstances.

Furthermore, the picture of volatility spillover has become even more complex with the introduction of high-frequency trading and algorithmic trading. These trading tactics can increase spillover effects, especially during times of market stress, according to research by Liu *et al*. (2020). They proposed that higher volatility transmission between emerging and established markets may result from the quick execution of trades based on algorithmic signals, calling for closer examination of trading methods and their effects on market stability.

The dynamics of volatility spillover are significantly influenced by behavioral factors as well. The effect of investor sentiment on spillover effects between advanced and emerging stock markets was studied by Kumar and Singh (2022). According to their research, rising sentiment in established markets may encourage more capital to flow into emerging markets, which would exacerbate the spillover of volatility. This emphasizes how crucial it is to take psychological aspects into account when analyzing financial markets, especially during a time of increased global uncertainty.

The effects of geopolitical threats on volatility spillovers have also been studied recently. Because global markets are interconnected, volatility can spread more quickly than in the past as tensions increase in different countries. Nascimento and Rodrigues (2023), for instance, discovered that geopolitical tensions had a major impact on spillover dynamics, with emerging markets becoming more volatile in reaction to shocks in advanced economies. This emphasizes how important it is to have a sophisticated grasp of how geopolitical developments affect market dynamics.

CHAPTER TWO
DATA AND METHODOLOGY

2.1 DATA

Data used for this study were gathered from yahoofinance.com and Investing.com and were extracted as daily prices for all the assets including stock indices (Turkey, Mexico, India, Indonesia, South Africa, Russia and China), exchange rates (Turkey, Mexico, India, Indonesia, South Africa, Russia and China) and commodity prices (Gold, Silver, crude oil, natural gas) covering the period from January 1, 2010 to December 31, 2023 (727 observations) thereby considering multiple crises periods. The data were then transformed to weekly data for all the indices and prices quoted in United States dollars. The Istanbul Stock Exchange (ISE) (XU100) Index, serving as the primary market indicator of the ISE, is a market capitalization-weighted index that encompasses a minimum of 75% of the overall market capitalization, traded value, number of shares traded, and number of trades executed in the market (Bildik, 2001).

Table 2.1 presents a list of the various variables used during this study. Given the difficulty in access spot prices for all of the variables from one source, the data were gathered from multiple sources. The various sources are presented in the table below.

Table 2.1: List of Variables and Sources

Variable	Name	Country	Source
Istanbul Stock Exchange BIST 100	XU100	Türkiye	Investing.com
CSI 100 Index	CSI 100	China	Yahoofinance.com
IDX Composite (Jakarta Stock Exchange Composite) Index	JKSE	Indonesia	Investing,com
MOEX Russia Index	MOEX	Russia	Yahoofinance.com
South Africa Stock Exchange	FTSE South Africa	South Africa	Investing,com
Indian Stock Exchange	S&P BSE Sensex Index	India	Investing,com
Brazilian Stock Exchange	Bovespa Index	Brazil	Investing,com
Mexican Stock Exchange	S&P BMV IPC Index	Mexico	Investing,com
United States Dollars to Turkish Lira	USD/TRY	Türkiye	Investing,com
United States Dollars to Chinese Yuan	USD/CNY	China	Investing,com
United States Dollars to Brazilian Real	USD/BRL	Brazil	Investing,com
United States Dollars to Indonesia Rupiah	USD/IDR	Indonesia	Investing,com
United States Dollars to India Rupees	USD/INR	India	Investing,com
United States Dollars to South African Rand	USD/ZAR	South Africa	Investing,com
United States Dollars to Russian Ruble	USD/RUB	Russia	Investing,com
United States Dollars to Mexico Peso	USD/MXN	Mexico	
Natural Gas	Natural Gas		US Energy Information Administration
WTI Crude Oil	WTI Crude Oil		Federal Reserve Bank of St. Louis
Gold	Gold		Investing.com
Copper	Copper		Federal Reserve Bank of St. Louis
Silver	Silver		Investing,com

***Source**: Author's compilation*

The weekly asset prices and indices were transformed into a logarithmic return series using this formula:

$$R_t = 100\ x\ [\ln\ P_{i,t} - \ln P_{i,t-1}] \quad (13)$$

Table 2.2 below displays the descriptive statistics for the return series for stock market indices. The tables reveal that stock returns, as well as exchange rate returns in the emerging markets, exhibit fat tails (excess kurtosis) and negative skewness. The XU100 Index has a mean return of -0.0287, signifying that the index has, on average, experienced a slight decline. The S&P BSE Sensex, with a median of 0.0014, shows that half of the returns were above this value and half below. The data shows that

Bovespa reached a maximum return of 0.0719 (7.19%), while the XU100 saw a dramatic minimum of -0.25997 (-25.997%). The table also includes metrics for volatility and distribution characteristics. The XU100 Index has a standard deviation of 0.06804, suggesting high volatility, while the CSI1000 Index has a much lower standard deviation of 0.01642, indicating less fluctuation. Skewness measures the asymmetry of returns, with a negative skew indicating more frequent large negative returns. The MOEX Index stands out with a highly negative skew of -2.1885, suggesting that it experienced frequent large losses. The MOEX Index has an exceptionally high kurtosis of 21.8016, signaling that it had numerous extreme price movements. Overall, these statistics provide a clear picture of the performance, volatility, and risk characteristics of each index over the observed period.

Table 2.3 below presents descriptive statistics for the returns series of all the commodities and exchange rates assets. The average return for each asset ranges from as low as 0.0000253 for USD/CNY to 0.0017847 for USD/TRY, indicating varying average returns across the assets. For the median returns, both USD/ZAR and USD/CNY show values close to zero, while USD/TRY has a higher median value of 0.0011596. The standard deviation shows that huge volatility in the assets returns, with natural gas and WTI crude oil exhibiting the highest levels of volatility (0.0449762 and 0.0433564, respectively), indicating higher risk.

Additionally, USD/TRY has a very high kurtosis (87.22398), suggesting a distribution with extreme outliers or fat tails, while WTI crude oil also has a high kurtosis (228.2195), reflecting significant outlier behavior in its returns. USD/TRY has a very negative skew of -2.94131, indicating that its returns are predominantly lower than the mean, while USD/ZAR has a positive skew (0.448125), implying more frequent positive returns. Commodities like natural gas (0.00202) and WTI crude oil (0.00188) show higher variance than many of the exchange rates.

Table 2.2: Descriptive Statistics for the Return Series for Stock Market Indices

	XU100 Index	CSI1000 Index	S&P BSE Sensex index	JKSE Index	MOEX Index	South Africa	Bovespa	S&P BMV IPC
Mean	-0.0287196	0.0001719	0.0008393	0.0006339	0.0004873	0.0005446	0.0003932	0.0003411
Median	-0.198903	0.0009912	0.0014453	0.0012678	0.0011676	0.0006475	0.0009831	0.0006329
Maximum	0.1222724	0.0631769	0.045795	0.0376951	0.0456781	0.0393027	0.0719285	0.0327055
Minimum	-0.2599735	-0.0519404	-0.0233462	-0.0329319	-0.0362998	-0.0283234	-0.0328496	-0.022975
Std. Dev	0.068042	0.0164234	0.0099364	0.0095369	0.0132031	0.0106339	0.0134884	0.0093432
Skewness	-0.8420595	-0.737893	-1.171417	-1.299109	-2.188519	-0.6211413	-0.5102636	-0.2200118
Kurtosis	4.480523	6.456969	14.24301	10.27982	21.80162	7.572172	7.1812101	4.585312
# of Observations	727	727	727	727	727	727	727	727

Source: *Author's calculations.*

Table 2.3: Descriptive Statistics for Currencies and Commodities

Variable	Obs	Means	Median	Std. Dev.	Min	Max	Kurtosis	Skewness	Variance
USD/RUB	727	0.0006578	0.0002888	0.0110714	-0.0582505	0.1022033	16.14227	1.147412	0.000123
USD/ZAR	727	0.0005507	0.000000	0.0093709	-0.0253713	0.0443225	3.985	0.448125	0.000088
USD/INR	727	0.0003465	0.0003265	0.0038685	-0.0142376	0.0181507	5.33774	0.199767	0.000015
USD/IDR	727	0.0002973	0.0003115	0.0040731	-0.0378627	0.0328996	21.3965	-0.67184	0.000017
USD/BRL	727	0.0006204	0.000721	0.0089319	-0.0318736	0.0327972	3.949578	-0.03185	0.000080
USD/MXN	727	0.0001511	-0.0001375	0.0074426	-0.0293472	0.0472886	7.289475	0.722673	0.000055
USD/TRY	727	0.0017847	0.0011596	0.0125029	-0.1879839	0.1020502	87.22398	-2.94131	0.000156
USD/CNY	727	0.0000253	-0.0000354	0.0020921	-0.0088925	0.0125526	7.389907	0.490687	0.000004
Natural Gas	727	-0.000474	-0.0010041	0.0449762	-0.6292813	0.4200663	68.67646	-2.50384	0.00202
WTI Crude Oil	727	-0.000010	0.0014893	0.0433564	-0.7824899	0.6750381	228.2195	-2.90769	0.00188
Gold	727	0.000372	0.0006561	0.0090166	-0.0392089	0.0348709	4.545721	-0.31800	0.00008
Silver	727	-0.0000644	0.0001259	0.0134994	-0.0786852	0.060647	10.01693	-0.82885	0.00032
Copper	727	0.0001886	0.0000653	0.0177579	-0.129181	0.0710082	5.477194	-0.13861	0.00018

Source: *Author's calculations.*

Strong evidence of stationarity across all analyzed indices and asset prices can be found in Table 2.4, which displays the results of the Phillips-Perron (PP) and Augmented Dickey-Fuller (ADF) tests. For any series, both tests yield negative statistics; the more negative the test statistic, the more support there is for stationarity and against the null hypothesis, which postulates the existence of a unit root. The stationarity of the bulk of the tested commodities, currencies, and indices—including the XU100, CSI1000, USD/TRY, WTI Crude Oil, and Natural Gas—is confirmed by their extremely negative test statistics. Furthermore, the outcomes of the "Trend" condition, which takes into consideration the potential for a deterministic trend, frequently offer much more convincing proof of stationarity.

ADF values of -3.947 (non-constant) and -4.499 (trend), for instance, and PP test statistics of -4.357 (non-constant) and -5.040 (trend) on the XU100 Index all fall below conventional critical limits, indicating that the series is stationary. With PP values of -25.44 and -25.414 and ADF values of -25.416 and -25.391, both far below the essential limits, the CSI1000 Index offers even more proof of stationarity. Stationarity is supported by similar findings for the S&P BSE Sensex Index, JKSE Index, MOEX Index, FTSE South Africa, and Bovespa, where both PP and ADF values continuously fall below crucial levels. Lastly, stationarity in both tests is also confirmed by the S&P BMV IPC index. These results indicate that the majority of the series analyzed are stationary, making them suitable for modeling with time series techniques that assume stationarity.

Table 2.4: Unit Root Test Results

	Phillip Perron Test		Augmented Dickey Fuller Test	
	Non Constant	Trend	Non Constant	Trend
XU100 Index	-4.357	-5.040	-3.947	-4.499
CSI1000 Index	-25.44	-25.414	-25.416	-25.391
S&P BSE Sensex index	-25.031	-25.177	-25.065	-25.223
JKSE Index	-28.713	-28.860	-28.747	-28.876
MOEX Index	-25.937	-25.934	-25.926	-25.920
FTSE South Africa	-30.130	-30.265	-29.785	-29.845
Bovespa	-26.932	-26.952	-26.871	-26.900
S&P BMV IPC	-27.939	-27.941	-27.926	-27.923
USD/TRY	-32.366	-33.648	-32.941	-34.031
USD/MXN	-28.143	-28.154	-28.165	-28.174
USD/INR	-25.057	-25.207	-25.016	-25.199
USD/RUB	-22.898	-22.919	-22.833	-22.874
USD/ZAR	-28.135	-28.233	-28.034	-28.101
USD/IDR	-24.180	-24.247	-23.985	-24.089
USD/BRL	-27.349	-27.456	-27.350	-27.461
USD/CNY	-24.578	-24.598	-24.005	-24.046
Natural Gas	-32.274	-32.241	-31.287	-31.251
WTI Crude Oil	-33.797	-33.749	-32.826	-32.782
Gold	-26.156	-26.165	-26.149	-26.153
Copper	-28.404	-28.379	-28.313	-28.286
Silver	-26.403	-26.366	-26.393	-26.358

Source: *Author's calculations*.

The currency pairs, including USD/TRY, USD/MXN, USD/INR, and others, demonstrate robust evidence of stationarity, with test statistics significantly lower than typical critical values. While the USD/RUB shows relatively less negative values, it still indicates stationarity.

For commodities, both Natural Gas and WTI Crude Oil present very strong indications of stationarity, supported by their low-test statistics. Gold, Copper, and Silver also confirm stationarity with their respective results. Overall, the consistent findings from both the Phillips-Perron and Augmented Dickey-Fuller tests across all variables suggest that these series are stationary. This crucial insight facilitates reliable modeling and prediction in subsequent time series analyses.

2.2 METHODOLOGY FOR MEASURING VOLATILITY SPILLOVERS

Understanding the interdependencies and shock transmission across financial markets requires measuring volatility spillovers. To identify and quantify these spillover effects, a number of approaches have been developed, enabling investors, market participants, and regulators to evaluate risks and make well-informed decisions. This paper offers a thorough analysis of the techniques used to quantify volatility spillovers, emphasizing their advantages, disadvantages, and possible uses.

To quantify volatility spillovers, GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models, both univariate and multivariate, have been used extensively. Individual market volatility is estimated by univariate GARCH models, such as GARCH and ARCH (Autoregressive Conditional Heteroskedasticity). The approach is extended to capture the interdependence and spillover effects among many markets using multivariate GARCH models, such as BEKK (Baba, Engle, Kraft, and Kroner) and DCC (Dynamic Conditional Correlation) models. These models offer important insights into the conditional correlations across markets, the influence of market linkages, and the transmission of volatility shocks.

The net directional volatility spillovers between several markets are measured using spillover index models, such as the Diebold and Yilmaz (DY) spillover index. This method highlights whether markets are net transmitters or receivers of volatility shocks, quantifies the overall impact of spillovers, and determines the directionality of the spillovers. Systemic risks can be identified, and market interdependencies can be evaluated thanks to the spillover index models, which offer a thorough overview of the dynamics and intensity of volatility spillovers.

Market interdependencies and connectivity are evaluated in terms of volatility spillovers using connectedness metrics like network analysis and variance decomposition methodologies. Network research techniques that show market relationships and pinpoint the most influential nodes include minimum spanning trees and correlation-based networks. The relative significance of shocks coming from various markets and their contributions to overall volatility are measured by variance decomposition techniques like the generalized forecast error variance decomposition.

These metrics provide important information on how volatility spillovers are structured and how they spread throughout markets.

2.2.1 Financial Time Series Tests

Understanding the dynamics and behavior of many financial variables, including stock prices, interest rates, and currency rates, depends heavily on financial time series analysis. Researchers and practitioners use a variety of statistical tests created especially for evaluating financial time series data in order to glean important information and arrive at well-informed conclusions. An overview of popular financial time series tests is given in this essay, along with a discussion of their methods and uses in financial research.

The existence of a unit root or nonstationarity in a time series is investigated by unit root tests, such as the Phillips-Perron (PP) test and the Augmented Dickey-Fuller (ADF) test. These tests aid in identifying if a variable behaves stationarily or randomly. Since many financial variables are nonstationary, unit root tests are crucial for effectively modeling and forecasting financial time series. Choosing the right econometric models requires an understanding of a series' stationarity characteristics.

Cointegration tests, such as the Engle-Granger test and the Johansen test, assess the long-term relationship between two or more nonstationary time series. Cointegration analysis helps identify whether variables share a common stochastic trend, indicating a stable equilibrium relationship. Cointegration tests are widely used in finance, particularly in analyzing relationships between exchange rates, interest rates, and asset prices. They provide insights into long-term equilibrium relationships and can be used to construct pairs trading strategies and risk management techniques.

The existence of volatility clustering and conditional heteroskedasticity in financial time series is investigated by volatility tests, such as the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) and ARCH (Autoregressive Conditional Heteroskedasticity) tests and its variations. A key element of risk assessment and portfolio management is the time-varying character of volatility, which is captured by these tests. Volatility tests enable the estimate of

conditional volatility models, including the well-known GARCH family models, and assist in identifying times of high or low volatility.

Granger causality tests assess the causal link between variables in a time series environment. Examples of these tests are the Granger causality test and the Toda-Yamamoto causality test. These tests determine if historical data on one variable may be used to predict another. Granger causality analysis is used in a number of financial domains, including the investigation of the correlation between stock prices and macroeconomic variables, the impact of news on market returns, and the dissemination of shocks among multiple financial markets. Tests of financial time series are essential instruments for examining the linkages and dynamics found in financial data. The tests covered in this essay, such as Granger causality tests, unit root tests, cointegration tests, and volatility tests, help practitioners and scholars understand the features and relationships of financial time series. By using these tests, analysts can improve their forecasting accuracy, create efficient risk management plans, and comprehend the intricate workings of financial markets on a deeper level.

2.2.2 Conditional Volatility Models

In order to capture time-varying volatility in time series data, conditional volatility models—such as the ARCH (Autoregressive Conditional Heteroscedasticity) and GARCH (Generalized Autoregressive Conditional Heteroscedasticity) models—are essential in financial econometrics. These models offer important insights into risk management, option pricing, and portfolio optimization and are frequently employed to account for volatility clustering. With the help of pertinent citations from reliable sources, this essay examines the idea of conditional volatility models, their equations, and their importance in financial analysis.

Conditional volatility models address the limitations of traditional time series models by incorporating the time-varying nature of volatility. They capture the phenomenon of volatility clustering, where periods of high volatility are followed by periods of high volatility and vice versa. Two widely used conditional volatility models are the ARCH(1) and GARCH(1,1) models. Conditional volatility models

have significant implications for various areas of financial analysis. They are widely used in risk management to assess and manage market risks. Option pricing models, such as the Black-Scholes model, often incorporate GARCH models to account for volatility clustering, which improves the accuracy of option pricing. Additionally, conditional volatility models aid in portfolio optimization by providing insights into the time-varying nature of asset volatilities.

2.2.2.1 CCC-GARCH Model

The Conditional Correlation Covariance (CCC) GARCH model was used to measure volatility spillovers. The Multivariate GARCH (1,1) model generalizes the univariate GARCH (1,1) framework to multiple time series, capturing not only the conditional variances but that conditional covariances between the series. One common form is Constant Conditional Correlation (CCC) model proposed by Bollerslev (1990). The return equation for a *N* – dimensional time series is:

$$r_t = \mu + \epsilon_t \quad (8)$$

Here r_t is a *N* x 1 vector of returns, and μ is a *N* x 1 vector of mean returns. ϵ_t is the *N* x 1 vector of shock terms. The shock term is modelled as:

$$\epsilon_t = H_t^{1/2} \boldsymbol{z_t} \quad (9)$$

Here, H_t is a N x N conditional covariance matrix, $H_t^{1/2}$ is a N x N positive definite matrix, and z_t is a N x 1 vector of standard normal innovations.

In the CCC-GARCH (1,1) model, the conditional covariance matrix H_t is constructed as

$$H_t = D_t R D_t \quad (10)$$

Where $D_t = \frac{diag(h_t)1}{2}, and\ h_t$ is a *N* x 1 vector whose element are univariate GARCH (1,1) variances for each time series. R is a positive definite constant conditional correlation matrix.

2.2.2.2 DCC-GARCH Model

The dynamic conditional correlation (DCC) estimator was first presented by Engel (2002) and offers a number of benefits over multivariate GARCH models. Correlation and volatility spillover between and among assets can be detected with its help. In order to capture dynamic time-varying covariance, the DCC-GARCH model was introduced. Because there are so many parameters to estimate in multivariate GARCH models, this model has the advantage of being able to be applied to enormous correlation matrices. The number of correlated series has no bearing on the number of parameters in the DCC model. As a univariate GARCH model, these characteristics give the DCC estimators flexibility and simplicity. With time-varying mean, variance, and covariance of the return series r_t, the DCC-GARCH model is a dynamic model where:

$$r_t = u_t + \varepsilon_t$$

$$\varepsilon_t | \Omega_{t-1} \rightarrow (N0_1 H_t)$$

The conditional variance of each return is derived from the residuals of the mean equation such as:

$$h^2{}_{i,t} = \alpha_0 + \sum_{j=1}^{pi} \alpha_j \, x^2{}_{i,t-j} + \sum_{j=1}^{qi} \beta_j \, \sigma^2{}_{i,t-j}$$

$$\text{where } \sum_{j=1}^{pi} \alpha_j + \sum_{j=1}^{qi} \beta_j < 1. \qquad (11)$$

Then, the multivariate conditional variance H_t can be estimated as:

$$H_t = D_t R_t D_t$$

D_t contains a (k x k) diagonal matrix of time varying standard deviations obtained obtained from the univariate GARCH specification in equation (10), and R_t is the (k x k) time varying matrix. To obtain $\eta_k = \frac{\varepsilon_k}{\sqrt{h_{it}{}^2}}$, the residuals of the mean equation (11) of the univariate GARCH model are first normalized with their conditional standard deviations derived from Equation (11). The standardized residuals are then used to estimate the parameters of conditional correlation as per Equations (10) and (11):

$$R_t = (diag(Q_t))^{-\frac{1}{2}} \; Q_t (diag(Q_t)^{-\frac{1}{2}})$$

$$Q_t = (1 - \theta_1 - \theta_2)Q + \theta_1 \eta_{t-1} \acute{\eta}_{t-1} + \theta_2 Q_{t-1} \quad (12)$$

Where Q (bar) is the unconditional covariance of the standardized residuals. Generally, Q_t does not have ones on the diagonal so it is scaled as in Equation (3) to derive R_t, which is a positive definite matrix. In this model, the conditional correlations are dynamic or time varying. From Equation (11), θ_1 and θ_2 are assumed to be positive scalars with $\theta_1 + \theta_2 < 1$.

Finally, the conditional correlation coefficient, p_j, between any two foreign exchange rates (or any two stock indices or commodity prices), i and j, is expressed by the following equation:

$$p_j = \frac{q_{jt}}{\sqrt{q_{j,t} q_{j,t}}}, i, j = 1,2 \dots \dots \dots, n, and\ i \neq j$$

$$p_j = \frac{(1 - \theta_1 - \theta_2)q_{-12} + \theta_1 \eta_{1,t-1} \eta_{2,t-1} + \theta_2 q_{12,t-1}}{\sqrt{\left[(1 - \theta_1 - \theta_2)q_{-11} + \theta_1 \eta^2{}_{1,t-1} + \theta_2 q_{11,t-1}\right]} \sqrt{\left[(1 - \theta_1 - \theta_2)q_{-22} + \theta_1 \eta^2{}_{2,t-1} \theta_2 q_{22,t-1}\right]}}$$

The parameters of the DCC model are estimated using the likelihood of this estimator and can be written as follows:

$$L = -\frac{1}{2} \sum_{t-1}^{T} (n \log(2\pi) + 2\log|D_t| + \log|R_t| + \acute{\eta}_t R^{-1}{}_t \eta_t) \quad (13)$$

Where $D_t = dlog\{\sqrt{h_{i,t}}\}$ and R_t is the time varying correlation matrix.

One of the stylized facts usually observed in financial time series data is that they deviate in two ways from the usual white noise generated under a Gaussian stochastic process. The unconditional distribution is extremely leptokurtic, to start. This indicates that, contrary to what the Guassian law would imply, it is more peaked in the center and has fat tails with more exceptionally large and small observations. In order to make the variance seem predictable, they also show volatility clustering, which is the observation of both calm and volatile periods (Chinzara & Aziapono, 2009). As a result, the DCC-GARCH procedure's Gaussian assumptions may be broken. The t-DCC-GARCH technique, which applies the DCC model under the premise that market yields follow a multivariate t-distribution as proposed by Pesaran and Pesaran (2007), will be used in this study to get around this issue.

CHAPTER THREE
ANALYSIS OF VOLATILITY MODELS AND RESULTS

3.1 VOLATILITY MEASUREMENT WITH STOCK, FOREIGN EXCHANGE AND COMMODITY MARKETS

XU100 Index (Turkey): From January 2010 to mid-2018, the XU100 index showed notable volatility, indicating a dynamic market environment with significant downturns and recoveries. Beginning with somewhat negative returns in early 2010, the index experienced a dramatic increase before plunging to a low of roughly -0.104 in June 2010. Global financial uncertainty and other domestic and international economic pressures all contributed to this period of increased volatility. After that, the index experienced a strong recovery from late 2010 to early 2011, reaching a peak of about 0.115 in April 2011. This rebound was brief, though, as volatility reappeared in the following months, most notably in 2014, when prolonged drops finished with a low of roughly -0.114. This pattern underscores the XU100's sensitivity to economic shifts and geopolitical developments, particularly in a context like Turkey, where domestic factors heavily impact market behavior. Overall, the index's performance during this period highlights its susceptibility to volatility and the cyclical nature of market sentiment influenced by broader economic contexts.

CSI 100 Index (China): From 2010 to 2018, the CSI 100 index showed a great deal of volatility, with returns that fluctuated sharply, including both large gains and dramatic drops. Initial volatility in early 2010 was marked by significant weekly fluctuations, including a 2.3% spike on January 10 and a 1.8% decrease the next week. With notable swings like a 3.0% increase on May 23, 2010, and a 5.4% decline on June 27, 2010, this trend of swift fluctuations continued. The most volatile time frame was from the middle of 2015 to the beginning of 2016. It was characterized by a sharp decline of more than 9% in late June 2015, which was a sign of market panic and outside economic forces. Even with recovery efforts, investor hesitancy frequently resulted in more volatility. Among the noteworthy recoveries was a 5.4% rise on May 10, 2015. A mixed performance in January 2018 is an example of how the index continued to negotiate geopolitical tensions and policy changes as the data moved

closer to 2018. This volatility highlights the necessity for investors to stay aware and flexible by illuminating the intricate interactions between market forces.

JSKE Index (Indonesia): From 2010 until mid-2018, the JSKE index showed notable volatility, which was indicative of the state of the market. Moments of instability caused by broader economic causes were indicated by sharp declines, such as a decrease of -0.0353 in early May 2010 followed by another decline of -0.0373 the following week. On the other hand, significant positive spikes, such as a 0.0283 increase in late June 2013, demonstrated times of hope and recovery. The frequent swings, which were marked by changes from positive to negative values, indicated a high level of investor uncertainty. With a peak of 0.0377 in early October 2015 and subsequent drops, drastic shifts were visible. Investors face both opportunities and disadvantages as a result of this volatility, which highlights the necessity of cautious research and calculated decision-making while managing these fluctuations.

S&P BSE Sensex Index (India): The S&P BSE Sensex index showed significant volatility between early 2010 and mid-2018, reflecting shifts in the economy and market sentiment. Beginning in January 2010 with a negative return of roughly -0.47%, the index fluctuated from week to week with both gains and losses. Midway through 2010, there was a noticeable decline of -2.04% in early May, followed by recoveries. A string of drops in the second half of 2011 culminated in a sharp decline of -2.88% in November. Volatility continued into 2015, with a notable decline of -1.93% in November that was offset by weeks of gains. Sharp drops persisted throughout 2017 and into 2018, with a -2.33% dip in February. This performance underscores the interplay of domestic and global economic factors, contributing to Sensex’s characteristic volatility.

Bovespa Index (Brazil): Brazil's primary stock market index, the Bovespa Index, showed notable swings between 2010 and 2018, suggesting a very volatile market driven by a number of economic variables. The index first saw slight swings in early 2010, but as time went on, the volatility increased. The sharp decline of -0.0457 in July 2011 and the subsequent recovery of +0.0252 in August of the same year were notable fluctuations. The market's reaction to outside forces, such as international circumstances and economic policies, is reflected in this behavior. The index regularly fluctuated between positive and negative returns during the course of

the time, indicating investor nervousness. For example, during a decline in January 2016, values fell to -0.0283, which was consistent with more general economic difficulties, whereas in March 2016, there was a significant increase of +0.0719. The overall trend highlights Bovespa's susceptibility to volatility driven by both domestic and international factors.

S&P BMV IPC Index (Mexico): Because of its intrinsic unpredictability, the S&P BMV IPC index showed noticeable fluctuations between positive and negative weekly returns from January 2010 to the end of 2018. Among the notable oscillations were the sharp declines of -0.03325 in September 2011 and -0.02831 in January 2016, which indicated increased market stress. On the other hand, significant recoveries were noted, including increases of 0.02044 in October 2011 and 0.02857 in June 2013. The regularity and severity of these swings point to the market's susceptibility to both internal and external factors, such as macroeconomic data and geopolitical unrest. Weekly returns showed a wide range of fluctuations, with some weeks seeing only slight changes and others seeing swings of over 0.020, indicating high levels of trading activity. This volatility serves as a valuable indicator for investors, emphasizing the importance of short-term and long-term strategies in navigating the complexities of the Mexican equity market.

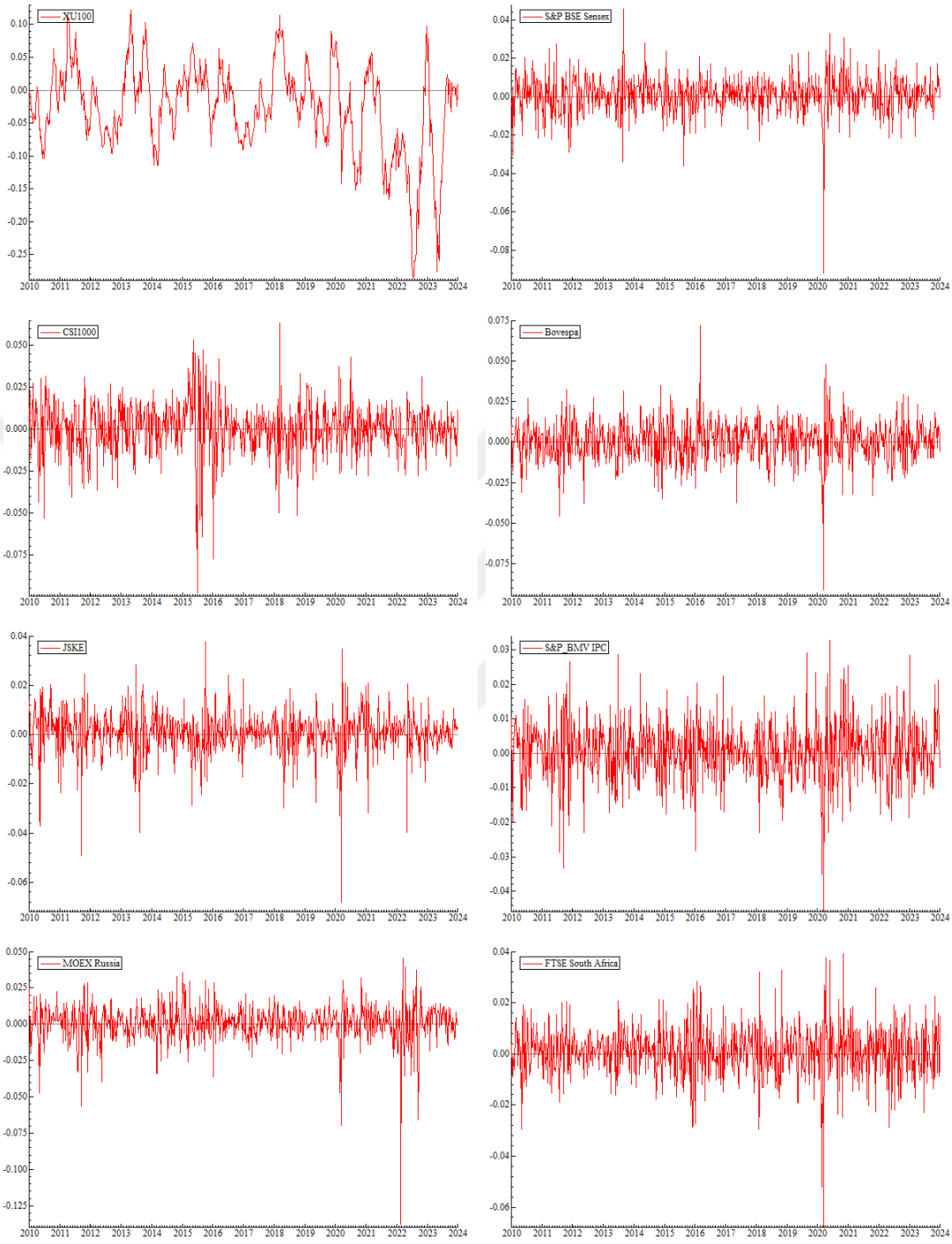
FTSE South Africa Index: Throughout its history, the FTSE South Africa Index has exhibited significant volatility, reflecting the nation's ever-changing economic environment. Periods of significant gains and losses are revealed by analyzing weekly returns, which suggests shifting market sentiment. For instance, there were positive recoveries, such a rise of 0.0149 a week later, in contrast to steep drops, like -0.0295 in early May 2010. This volatility persisted in the following years, especially in late 2015 and early 2016, with returns ranging from -0.0288 to 0.0254 in December 2015. The index's vulnerability to both internal and external shocks is highlighted by this volatility. These surges were frequently followed by stable periods that suggested possible recovery phases, but the index still reflected underlying market worries. Mid-2018 witnessed consistent oscillations, illustrating a market caught between optimism and pessimism. Overall, the FTSE South Africa Index serves as a barometer of market volatility, characterized by sharp fluctuations essential for investors navigating the complex South African equity landscape.

MOEX Russia Index: From early 2010 until the end of 2018, the MOEX Russia Index was marked by substantial volatility, with weekly returns fluctuating significantly. The pattern of alternating positive and negative returns found in the investigation illustrates the Russian market's intrinsic instability. For example, January 2010 started off with a slight increase, but there were further declines, including a drop of about -0.047 in May 2010. With a startling return of -0.056 at its peak in September 2011, the volatility demonstrated the market's vulnerability to outside shocks and economic forces. Performance in the following months was inconsistent, with brief rebounds punctuated by steep drops. This pattern continued into 2018, when returns varied as a result of regional economic circumstances as well as more general geopolitical factors. Overall, the volatility in the MOEX Russia Index illustrates the complexities faced by investors navigating emerging markets impacted by fluctuating oil prices and political tensions.

The variation in the different return series is depicted in Figure 3.1 below. From 2010 to 2018, the data monitors weekly percentage changes in the USD/RUB exchange rate. Whereas negative values show a stronger ruble (USD depreciating), positive values show a weaker ruble (USD appreciating). According to the data, a 0.645% decline in the USD/RUB rate indicates ruble strength, while a 0.45% gain indicates ruble weakness. Variations associated with global events, including the 2014 crisis and shifts in the price of oil, are noteworthy trends. Significant fluctuations in the currency rate are indicative of larger political and economic issues, such as changes in the oil market and sanctions. The data shows how unstable the USD/RUB is, and more research might look into long-term patterns or connections to particular world events.

Weekly variations in the USD/ZAR exchange rate from March 2010 to August 2018 are depicted in the data, indicating both steady and notable periods. The variations show how the USD gained or lost value in relation to the South African Rand (ZAR), depending on a number of variables like local and international economic conditions as well as market sentiment. Certain weeks exhibit notable volatility, underscoring the fluidity of currency markets.

Figure 3.1: Return Series for Stock Indices



Source: *Author's compilation.*

The USD/INR exchange rate fluctuates often, with both little and significant percentage movements, according to data from January 2010 to August 2018. There were times when the exchange rate fluctuated, with major changes like a sharp decline

in January 2012 and an increase in September 2011. Overall, the shifts were frequently slight, but sporadic, more significant swings point to the influence of more significant geopolitical or economic developments. There is no discernible rise or negative trend in the data, which shows short-term market volatility.

The data shows both the appreciation and depreciation of the USD in relation to the IDR. It shows weekly percentage changes in the exchange rate between the USD and the IDR from 2010 to 2018. Whereas negative values imply the USD weakened, positive values show it strengthened. Significant volatility and abrupt fluctuations are evident in the statistics, especially during times like 2015–2016. These oscillations are caused by domestic economic issues in Indonesia, shifts in US monetary policy, and events in the global economy. Larger fluctuations in the exchange rate occur more frequently with time, reflecting changes in investor attitude, market circumstances, and outside economic factors like political unrest or changes in the price of oil. The analysis highlights the impact of broader economic factors on the USD/IDR exchange rate, especially during times of market uncertainty or crisis.

Weekly percentage variations in the USD/BRL (US Dollar/Brazilian Real) exchange rate between 2010 and 2018 are displayed in the data. The figures show significant swings throughout this time frame, which is indicative of the volatility frequently seen in emerging markets. Periods of appreciation and depreciation of the Brazilian Real in relation to the US Dollar are indicated by the many examples of both positive and negative developments. Sharp increases in either direction, like in March 2015, March 2016, and May 2017, are a few noteworthy trends that could be the result of important market reactions, policy changes, or economic events. The exchange rate fluctuates a lot, frequently in response to the state of the world economy, commodity prices, Brazilian political developments, and general market sentiment.

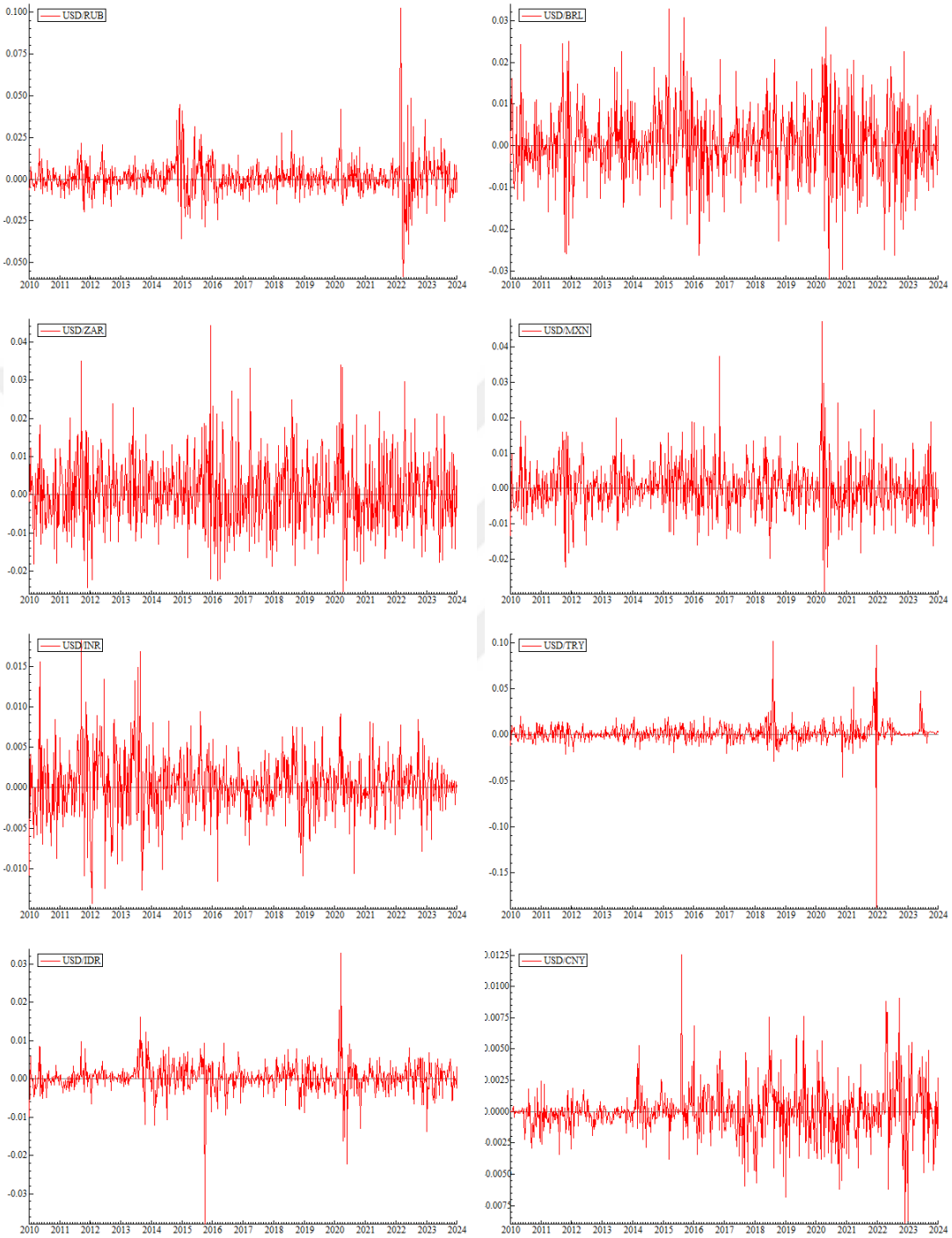
The data shows both periods of gains and losses in the USD/MXN exchange rate across a number of years. Because of the frequent swings in both positive and negative values, which can be ascribed to a combination of global economic forces, geopolitical events, market emotion, and central bank actions, these movements appear to lack a discernible long-term pattern. Significant increases or decreases, for instance, may correspond with significant financial or political developments, whereas minor oscillations indicate market turbulence and transient investor responses. The exchange

rate's apparent high volatility and lack of a clear trend over the long run highlight how intricate foreign currency markets are. In some periods, such as late 2015 and mid-2017, there are instances of more pronounced shifts, potentially indicating a response to macroeconomic data or specific market events. The recurring nature of positive and negative changes highlights the inherent uncertainty and the need for careful analysis in currency forecasting.

Weekly fluctuations in the USD/TRY exchange rate throughout a number of years, from January 2010 to August 2018, are represented in the data. The figures show changes in the value of the Turkish lira relative to the US dollar. These weekly variations seem to indicate times when the value of the lira in relation to the dollar has significantly increased and decreased. For example, the exchange rate exhibits significant positive fluctuations during certain times (such as a gain of 0.102 in August 2018), which suggests that the Turkish lira is weakening or that the dollar is strengthening, and sharp declines during other times (such as -0.0215 in October 2011), which indicate that the Turkish lira is revaluing. This data likely correlates with economic, political, and global factors that affect exchange rates, such as inflation, interest rates, government policies, or external market forces. Overall, the results highlight the volatility and unpredictability of the exchange rate, with substantial fluctuations over time.

The findings indicate daily or weekly changes in the value of the Chinese yuan in relation to the US dollar, as well as periodic oscillations in the USD/CNY exchange rate over several years. While some weeks exhibit notable shifts (e.g., -0.003415664 or 0.007573979), others observe very slight alterations near zero (e.g., 3.81669E-05). Market attitude, governmental regulations, global trade circumstances, and macroeconomic variables like inflation, interest rates, and political developments are some of the causes of these swings. While there are discernible times of higher volatility (such as in mid-2015 and early 2016), which are probably caused by more significant economic events or changes in the global financial environment, the data generally illustrates the volatility of the foreign exchange market and the intricate dynamics affecting currency exchange rates over time.

Figure 3.2: Return Series for Exchange Rates



Source: *Author's compilation.*

The information shows the weekly percentage changes in natural gas prices from 2010 to 2018. The large range of values suggests that natural gas prices were

quite volatile throughout that time. While some weeks see steep losses, as the drop on December 28, 2014, other weeks see dramatic gains, like the significant increases seen on December 3, 2017, and January 3, 2010. The intricate and dynamic character of energy markets is reflected in this volatility, which is impacted by a variety of variables such as weather patterns, geopolitical developments, changes in supply and demand, and market speculation. Around the end of each year, there are particularly noticeable spikes in volatility, and distinct seasonal trends show up, with some months (such January, March, and December) seeing more volatility than others. Overall, the data underscores the unpredictable nature of natural gas prices, making them sensitive to both external shocks and regular market dynamics.

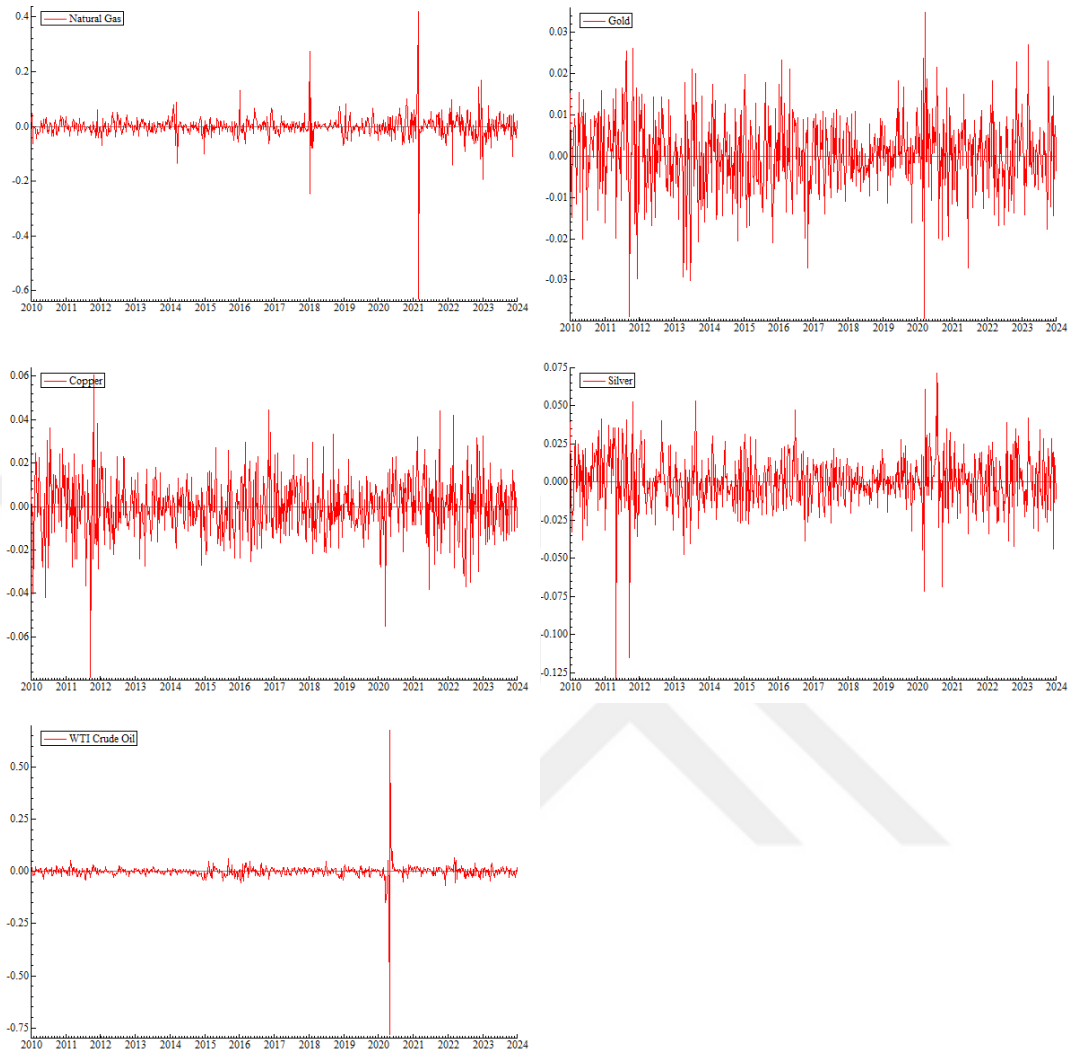
These findings, which demonstrate notable volatility and fluctuations, are based on weekly percentage changes in the price of WTI Crude Oil over a number of years. Periods of rising and falling oil prices are indicated by the data, which includes both positive and negative weekly changes. Some months exhibit major fluctuations, while others have cycles of steady increases and declines (e.g., steep drops in early 2016 and late 2014, amid large jumps in mid-2015 and mid-2017). Strong recovery periods after steep drops (as in mid-2016 and early 2017) and recurrent oscillations from 2010 to 2018 connected to general economic circumstances, geopolitical events, or shifts in the world's oil supply and demand are important trends. These fluctuations highlight the inherent instability of oil markets, where prices can swing significantly within short time frames.

The findings demonstrate weekly variations in gold prices, revealing both favorable and unfavorable shifts in value. The gold market seems erratic throughout the 2010–2018 timeframe, with some noteworthy upswings and downswings. The price of gold had significant increases in some weeks, such mid-2011 and early-2016, but there were significant drops in other weeks, like in 2011, 2013, and late 2014. Notably, moderate recoveries frequently followed times of more volatility (such as the notable declines in 2013 and 2015). According to the statistics, investor sentiment, global economic considerations, and possibly more general geopolitical events all influence gold prices on a regular basis. Despite these changes, the general pattern seems cyclical, with short bursts of expansion interspersed with continuous market corrections.

Weekly percentage variations in copper prices from January 2010 to August 2018 are depicted in the data. The copper market was very volatile throughout this time, seeing many periods of both positive and negative swings. There were a number of notable price fluctuations, including notable drops in early 2011, mid-2013, and early 2015, as well as notable price hikes in late 2016 and early 2017. All things considered, copper prices had a propensity to oscillate in cycles, with periods of rise and fall that frequently corresponded to more general economic trends or market shocks, such as changes in supply-demand dynamics or global economic slowdowns. This fluctuation likely reflects factors such as changes in industrial demand, global economic conditions, and investor sentiment, which can cause both short-term volatility and longer-term price trends.

Weekly fluctuations in silver prices over a number of years (2010–2018) are displayed in the data. These figures demonstrate that the price of silver fluctuates significantly, both positively and negatively. There are noticeable drops (like May 2011 and late 2015) after periods of consistent growth (like early 2011 and mid-2016). Periods of increased volatility are frequently caused by these changes, which are frequently influenced by more general economic factors like market demand, global economic conditions, or geopolitical events. While some weeks display more significant movements, pointing to market shocks or adjustments, other weeks show very modest gains or declines, reflecting generally stable market conditions. Despite the volatility, silver tends to have periodic surges, such as in the latter part of 2010, 2016, and again towards the end of 2017. Overall, the data reflects a market characterized by both long-term trends and short-term fluctuations, influenced by external forces and investor sentiment.

Figure 3.3: Return Series for Commodity Prices



Source: *Author's compilation.*

3.2 CCC-GARCH AND DCC-GARCH MODELS RESULTS

An estimate of conditional correlations between the returns of different stock indexes from 2010 to 2023 is shown in Table 3.1, which presents the findings of the Constant Conditional Correlation (CCC) Multivariate GARCH model for eight emerging market economies.

Table 3.1: CCC-GARCH Model Results for Volatility Spillover Among Stock Market Indices

Variable	ARCH(1) Coefficient	GARCH(1) Coefficient	p-value (ARCH(1))	p-value (GARCH(1))
XU100	0.9506	0.0184	0.000	0.545
CSI1000	0.1031	0.8595	0.000	0.000
JSKE	0.1332	0.6673	0.000	0.000
SPBSE Sensex	0.1382	0.7099	0.000	0.000
Bovespa	0.1008	0.7379	0.000	0.000
SP_BMVIPC	0.0798	0.8276	0.000	0.000
MOEX Russia	0.2134	0.7400	0.000	0.000
FTSE South Africa	0.1513	0.6521	0.000	0.000

Correlation Estimates between Pairs	Coefficient	z-statistic	p-value	95% CI (Lower, Upper)
(XU100, CSI1000)	0.0829	2.25	0.024	(0.0107, 0.1550)
(XU100, JSKE)	0.0633	1.7	0.089	(-0.0097, 0.1364)
(XU100, SPBSE Sensex)	0.0302	0.81	0.416	(-0.0426, 0.1030)
(XU100, Bovespa)	0.1079	2.93	0.003	(0.0357, 0.1802)
(XU100, SP_BMVIPC)	0.1231	3.35	0.001	(0.0511, 0.1951)
(XU100, MOEX Russia)	0.1291	3.52	0.000	(0.0572, 0.2010)
(XU100, FTSE South Africa)	0.1397	3.81	0.000	(0.0678, 0.2116)
(CSI1000, JSKE)	0.1205	3.29	0.001	(0.0488, 0.1922)
(CSI1000, SPBSE Sensex)	0.0611	1.66	0.098	(-0.0112, 0.1335)
(CSI1000, Bovespa)	0.1363	3.73	0.000	(0.0647, 0.2078)
(CSI1000, SP_BMVIPC)	0.1801	5.02	0.000	(0.1097, 0.2505)
(CSI1000, MOEX Russia)	0.1658	4.6	0.000	(0.0951, 0.2365)
(CSI1000, FTSE South Africa)	0.1600	4.41	0.000	(0.0888, 0.2311)
(JSKE, SPBSE Sensex)	0.2588	7.47	0.000	(0.1909, 0.3267)
(JSKE, Bovespa)	0.3725	11.5	0.000	(0.3090, 0.4359)
(JSKE, SP_BMVIPC)	0.3589	11.01	0.000	(0.2951, 0.4228)
(JSKE, MOEX Russia)	0.2877	8.41	0.000	(0.2207, 0.3548)
(JSKE, FTSE South Africa)	0.3916	12.15	0.000	(0.3284, 0.4548)
(SPBSE Sensex, Bovespa)	0.2535	7.24	0.000	(0.1849, 0.3221)
(SPBSE Sensex, SP_BMVIPC)	0.2636	7.64	0.000	(0.1960, 0.3313)
(SPBSE Sensex, MOEX Russia)	0.1879	5.26	0.000	(0.1178, 0.2579)
(SPBSE Sensex, FTSE South Africa)	0.2399	6.68	0.000	(0.1695, 0.3103)
(Bovespa, SP_BMVIPC)	0.5492	21.09	0.000	(0.4982, 0.6003)
(Bovespa, MOEX Russia)	0.4286	14.11	0.000	(0.3691, 0.4881)
(Bovespa, FTSE South Africa)	0.5004	17.74	0.000	(0.4451, 0.5557)
(SP_BMVIPC, MOEX Russia)	0.4085	13.21	0.000	(0.3479, 0.4691)
(SP_BMVIPC, FTSE South Africa)	0.6011	25.14	0.000	(0.5542, 0.6480)
(MOEX Russia, FTSE South Africa)	0.4168	13.52	0.000	(0.3564, 0.4772)

Source: *Author's computation.*

While the GARCH (1) terms are substantial for all save XU100, indicating reduced volatility clustering in that index, the ARCH (1) terms are significant for the majority of indices, indicating short-term volatility persistence. Significant positive correlations can be seen between a number of index pairs, such as JSKE and SPBSE Sensex (0.2588), Bovespa and SP_BMVIPC (0.5492), and SP_BMVIPC and MOEX Russia (0.4085). With a Wald chi-squared statistic of 4.39, a p-value of 0.4943, and a log-likelihood of 17,590.515, the model appears to be a good match, even though the conditional correlations may not be substantially different from zero overall. Strong associations between JSKE and FTSE South Africa (0.3916) are also evident, as are positive correlations indicating that indices such as Bovespa, SP_BMVIPC, and MOEX Russia tend to move together. Although more research may be required for certain correlations, like those with XU100, these findings show notable volatility clustering and interdependence across emerging market indexes, offering useful insights for risk analysis and portfolio management.

In an ARCH (Autoregressive Conditional Heteroskedasticity) model, the DCC GARCH results in Table 3.2 below illustrate the dynamics of a financial asset (XU100) and its interactions with many international equity indices over time. With a z-statistic of 82.69, the coefficient for the lag of the XU100 itself (L.XU100 = 0.9502) is very significant, indicating that the XU100's historical values substantially predict its future values. Only the S&P BSESensex index's lag (L.SP_BSESensex = 0.1535) among the other global stock indices exhibits a borderline significant effect (p-value = 0.058); the FTSE South Africa, CSI1000, JSKE, and Bovespa do not. All of the analyzed indices (XU100, CSI1000, JSKE, etc.) have significant volatility spillovers into the XU100, according to the ARCH terms, which measure volatility clustering. All of the p-values are below 0.05, suggesting that there is significant conditional heteroskedasticity and volatility transmission among the markets.

Table 3.2: DCC-GARCH Model Results for Volatility Spillover Among Stock Market Indices

Variable	Coefficient	Std. Err.	z-Statistic	p-Value
XU100 (ARCH)				
L.XU100	0.9502	0.0115	82.69	0.000
L.CSI1000	-0.0433	0.0435	-0.99	0.320
L.JSKE	0.00796	0.0919	0.09	0.931
L.SP_BSESensex	0.1535	0.0811	1.89	0.058
L.Bovespa	0.0603	0.0724	0.83	0.405
L.SP_BMVIPC	-0.0225	0.1085	-0.21	0.836
L.FTSE South Africa	-0.0171	0.0951	-0.18	0.857
L.MOEX Russia	0.0154	0.0664	0.23	0.817
ARCH (Lag 1)				
XU100 (ARCH)	0.0553	0.0158	3.5	0.000
CSI1000 (ARCH)	0.1082	0.0226	4.78	0.000
JSKE (ARCH)	0.1347	0.0334	4.03	0.000
SPBSE Sensex (ARCH)	0.1454	0.0369	3.94	0.000
Bovespa (ARCH)	0.1009	0.0234	4.31	0.000
SP_BMVIPC (ARCH)	0.0788	0.0195	4.04	0.000
FTSE South Africa (ARCH)	0.1417	0.0336	4.22	0.000
MOEX Russia (ARCH)	0.1996	0.0375	5.32	0.000
Dynamic Conditional Correlations				
(XU100, CSI1000)	0.0374	0.0414	0.9	0.366
(XU100, JSKE)	0.224	0.0397	5.64	0.000
(XU100, SPBSE Sensex)	0.1513	0.0403	3.76	0.000
(XU100, Bovespa)	0.2581	0.0387	6.66	0.000
(XU100, SP_BMVIPC)	0.2835	0.038	7.47	0.000
(XU100, FTSE South Africa)	0.3078	0.0375	8.2	0.000
(XU100, MOEX Russia)	0.2068	0.0397	5.21	0.000
(CSI1000, JSKE)	0.1207	0.0414	2.92	0.004
(CSI1000, SPBSE Sensex)	0.0523	0.0416	1.26	0.208
(CSI1000, Bovespa)	0.1274	0.0415	3.07	0.002
(CSI1000, SP_BMVIPC)	0.1644	0.0411	4	0.000
(CSI1000, FTSE South Africa)	0.1512	0.0409	3.69	0.000
(CSI1000, MOEX Russia)	0.1638	0.0408	4.02	0.000
(JSKE, SPBSE Sensex)	0.2335	0.0397	5.88	0.000
(JSKE, Bovespa)	0.3458	0.0374	9.25	0.000
(JSKE, SP_BMVIPC)	0.3626	0.0368	9.86	0.000
(JSKE, FTSE South Africa)	0.3707	0.037	10.01	0.000
(JSKE, MOEX Russia)	0.261	0.0401	6.51	0.000
Adjustment Parameters				
lambda1	0.0195	0.0059	3.29	0.001
lambda2	0.7899	0.0642	12.3	0.000

Source: *Author's computation.*

The findings of the Dynamic Conditional Correlation (DCC) show how XU100 and other indices have time-varying correlations. There appears to be little co-movement between these indices, as seen by the low and statistically insignificant correlation between XU100 and CSI1000 (0.0374). Nonetheless, with p-values all below 0.05, XU100 shows substantial positive correlations with a number of other indexes, such as FTSE South Africa (0.3078), Bovespa (0.2581), S&P BSESensex (0.1513), and JSKE (0.224), all of which show stronger co-movement over time. Additionally noteworthy is the 0.2068 correlation between XU100 and MOEX Russia. Significantly, the correlations between other index pairs (such as JSKE and Bovespa or JSKE and SPBSE Sensex) are continuously positive and strong, indicating that these markets typically move in tandem. The model's volatility structure is further highlighted by the adjustment parameters (lambda1 = 0.0195, lambda2 = 0.7899), where lambda2 is highly important and shows that volatility shocks in the data are persistent.

The CCC-GARCH model results for commodities, foreign currency rates, and the Borsa Istanbul (XU100) are shown in Appendix 1. These results provide important information about the volatility dynamics of these markets. Strong short-term volatility persistence is demonstrated by the ARCH (L1) coefficients for markets such as the XU100 and USDTRY. The XU100's high ARCH coefficient (0.9250) indicates extended periods of high volatility following significant shocks. Commodities with lower ARCH values, such as gold and copper, on the other hand, show more consistent volatility patterns. Long-term volatility persistence is captured by the GARCH (L1) coefficients, and commodities with high values (such as copper at 0.9151 and gold at 0.8852) suggest that previous volatility has a significant impact on future volatility. The XU100, in contrast, has a low GARCH coefficient (0.0218), suggesting that short-term shocks cause higher volatility. While commodities like gold and silver exhibit a strong positive correlation (0.8004) in volatility, suggesting they move together, the correlation study shows a negative association between the volatility of the USDTRY and the XU100 (-0.1673), suggesting diversification effects. Additionally, there are negative connections between USDTRY and precious metals, suggesting that the volatility of gold and silver tends to decline as the Turkish lira becomes more volatile. Overall, the findings highlight that while short-term volatility is significant across

most assets, commodities exhibit higher long-term volatility persistence, with notable cross-market correlations, particularly within energy and precious metal markets.

Significant volatility dynamics and correlations between different commodities, exchange rates, and the Indonesia stock index are revealed by the Constant Conditional Correlation (CCC) Multivariate GARCH model results, which are shown in Appendix 3. With exceptionally high GARCH terms for USDIDR (0.8037), Copper (0.9177), and Silver (0.8894), demonstrating great volatility persistence, all ARCH and GARCH coefficients are statistically significant (p-value < 0.05), suggesting that historical volatility significantly affects future volatility for each asset. According to the correlation analysis, JSKE has a negative association with USDIDR (-0.4345) and a substantial positive correlation with copper (0.2727) and silver (0.2511). Furthermore, the USDIDR has negative correlations with both gold (-0.2378) and silver (-0.2996), but gold and silver have a relatively high positive correlation (0.8014). Certain correlations, like those between WTI Crude Oil and Gold and Natural Gas and Gold, are negligible and suggest that the assets have weak ties to one another. Overall, the results highlight how crucial it is for financial risk analysis and portfolio management to comprehend the persistence of volatility and the interdependencies across asset returns.

The CCC-GARCH model's findings for Mexico are displayed in Appendix 6. These findings showed a strong correlation between the assets' examined volatilities. All variables have substantial prior volatility persistence (all p-values < 0.05), according to the ARCH parameters, which account for short-term volatility impacts. The highest short-term effect is seen in Natural Gas (ARCH_Natural Gas = 0.5736). Copper (GARCH_Copper = 0.9128) and silver (GARCH_Silver = 0.8884) have the most stable volatilities, according to the GARCH parameters, which measure long-term volatility persistence. This suggests that these assets are less susceptible to abrupt fluctuations in volatility. With the Mexican stock index (SP_BMVIPC) and exchange rate (USDMXN) displaying a significant negative correlation (-0.4703), indicating an inverse relationship between their volatilities, the correlation data demonstrate how asset volatilities co-move. There are positive correlations between copper and gold (0.26) and copper and silver (0.4331). The correlation between gold and silver is particularly high (0.8009), indicating that their volatility move in tandem. Conversely,

the correlations between USDMXN and copper (-0.3176) and gold (-0.2297) are negative, suggesting that the volatilities of these commodities tend to decline when exchange rate volatility rises. These results have important ramifications for risk management and portfolio diversification since they shed light on the interdependencies and volatility dynamics of the assets.

Significant correlations between the return volatilities of several assets (FTSE South Africa, USDZAR, Natural Gas, WTI Crude Oil, Gold, Copper, and Silver) are revealed by the Constant Conditional Correlation (CCC) GARCH model results for South Africa, which are shown in Appendix 7. Both the generalized autoregressive conditional heteroskedasticity (GARCH) and autoregressive conditional heteroskedasticity (ARCH) parameters are positive and statistically significant ($p < 0.05$) for each asset, suggesting that the current volatility of each asset is influenced by both past conditional variance (GARCH terms) and past volatility (ARCH terms). For example, the GARCH term for Copper is particularly high (0.9198), suggesting that past volatility has a substantial impact on its future variance. The USDZAR has an inverse link with other assets, as evidenced by the significant negative correlations between it and gold (-0.3447) and copper (-0.4009). The FTSE South Africa, on the other hand, has positive correlations with both copper (0.3926) and silver (0.3159), suggesting that these assets typically move in tandem. Some correlations, like the one between Natural Gas and the FTSE South Africa ($p = 0.204$), are not significant, though, indicating that there is no discernible relationship in the volatility of these assets. All things considered, these findings imply that these assets' volatility is impacted by their historical performance, and the correlations shed light on how their volatilities move together, which has important ramifications for risk management and portfolio diversification.

Strong persistence in volatility over time is indicated by the CCC GARCH model results for Russia's primary commodities and currency rate, which demonstrate significant ARCH and GARCH effects over the financial time series. With p-values close to zero, the model's ability to capture time-dependent variance is confirmed by the significant lagged ARCH (L1) and GARCH (L1) terms found in each asset, including MOEX Russia, USDRUB, Natural Gas, WTI Crude Oil, Gold, Copper, and Silver. Interestingly, assets like copper and silver have even greater persistence, as

seen by GARCH coefficients near 1, whereas MOEX Russia, USDRUB, and WTI Crude Oil have significant GARCH coefficients, suggesting sustained volatility effects. Significant linkages can be seen in the correlations between the assets; for instance, MOEX Russia and USDRUB have a substantial negative correlation (-0.3487), whilst gold and silver have the largest positive correlation (0.8017), most likely as a result of their similar market dynamics. These findings emphasize volatility clustering and interdependencies, both of which are critical to comprehending the behavior of financial markets and risk management.

A DCC-GARCH model was used to analyze the conditional correlations and volatility dynamics between seven variables from 2010 to 2023: the stock index CSI1000, the exchange rate USDCNY, natural gas, WTI Crude Oil, gold, copper, and silver. Since the majority of p-values are higher than 0.05, the coefficients for the lagged variables show weak or no significant correlations between the CSI1000 and other assets. All series have high significance for the ARCH and GARCH parameters, and the volatility dynamics (ARCH and GARCH terms) for each asset exhibit great persistence.

This implies that any asset's future volatility is significantly influenced by its historical volatility. Gold and silver (0.795) and copper and gold (0.373) are two examples of asset pairs that exhibit significant correlations, indicating a tendency for these assets to move in tandem. However, USDCNY demonstrates inverse associations between the currency and commodity prices, as evidenced by its strong negative correlations with gold, copper, and silver. With lambda2 close to 1, which indicates substantial persistence in the conditional correlations, the adjustment parameters lambda1 and lambda2 imply that the model's dynamic adjustment mechanism is robust. All things considered, the model highlights significant co-movements and volatility transmission effects while offering insights into the interrelationships and spillovers of volatility among different financial instruments.

The Jakarta Stock Exchange Index (JSKE), the Indonesian Rupiah exchange rate (USDIDR), and commodity prices such as natural gas, crude oil, gold, copper, and silver are among the financial variables whose time-varying correlations and volatility are estimated by the DCC-GARCH model results shown here. Significant ARCH and GARCH factors are found in the model, suggesting that historical shocks and variances

have an impact on the volatility of these variables now. With some notable exceptions, such as the negative correlation between USDIDR and gold ($p = 0.009$), which indicates that when USDIDR increases, gold tends to decline, many variables exhibit minimal direct effects on one another. Co-movement in the prices of various assets is highlighted by significant correlations, such as the positive correlation between copper and gold (corr = 0.804) and gold and silver. The Wald test validates the correlations captured by the DCC-GARCH framework and indicates that the model's overall fit is substantial ($p < 0.0001$).

The S&P BSE Sensex, the USD/INR exchange rate, natural gas, WTI crude oil, gold, copper, and silver are all analyzed in the results of DCC-GARCH model. Using ARCH and GARCH terms, the model captures the short- and long-term volatility impacts while estimating the volatility and dynamic correlations of these assets. For instance, for the majority of assets, persistent volatility clustering is indicated by large ARCH and GARCH coefficients (L1). Furthermore, the correlation results show both significant positive and negative relationships between specific assets. For example, the USD/INR and gold or copper have a negative correlation, indicating that currency depreciation is typically linked to rising commodity prices, especially for those assets. The noteworthy correlations and coefficients shed light on how various markets are interdependent, which may be helpful for strategies involving portfolio diversification and hedging.

This output shows the findings of a DCC-GARCH model that was used to examine the correlations and time-varying volatility of financial variables such as the prices of gold, copper, silver, natural gas, the USD/BRL exchange rate, the Bovespa index, and WTI crude oil. Over the course of iterations, the model's log likelihood increased significantly, eventually stabilizing at 15117.62. Strong persistence in volatility is shown by significant coefficients in the model, which are indicated by low p-values (e.g., ARCH and GARCH terms for each variable); high GARCH coefficients imply sustained volatility effects. The joint significance of the model is demonstrated by the Wald test (chi-squared). Positive correlations between Bovespa and metals (such as copper, silver, and gold) are among the noteworthy relationships in the conditional correlation matrix, suggesting that these assets typically move in tandem.

Conversely, there are negative correlations between USD/BRL and some assets (e.g., gold, copper), suggesting hedging potential.

In the output, the variables SP_BMVIPC, USDMXN, Natural Gas, WTI Crude Oil, Gold, Copper, and Silver are subjected to a DCC-GARCH model. These financial variables' time-varying correlations and volatilities are estimated by the model. Every coefficient shows how one variable's lagged value affects the others, and statistical significance is indicated by the standard errors, z-values, and significance levels. WTI Crude Oil on Natural Gas and USDMXN on SP_BMVIPC are two examples of lagged relationships that have notable effects. Large and statistically significant coefficients indicate that the ARCH and GARCH terms indicate considerable persistence in conditional volatility for each series. The correlation estimates shed light on the dynamic interdependencies between various assets during the studied time. For example, there is a substantial negative connection between SP_BMVIPC and USDMXN. The significance of the entire model is confirmed by the Wald chi-square test ($p < 0.001$).

The findings come from a DCC-GARCH model that uses a sample of financial assets from 2010 to 2023 to evaluate the time-varying correlations between a set of financial assets (FTSE South Africa, USDZAR, Natural Gas, WTI Crude Oil, Gold, Copper, and Silver). Both conditional correlations and volatility dynamics (GARCH and ARCH effects) between these assets are captured by the model. A number of important conclusions are revealed. First, notable lags between various asset returns are apparent. For example, FTSE South Africa and USDZAR have a negative association, whereas FTSE South Africa and copper, gold, and silver have a positive correlation. Natural gas exhibits minor positive connections with other assets, such as copper and silver, and strong negative correlations with the FTSE South Africa. The ARCH and GARCH parameters for volatility are statistically significant for the majority of variables, suggesting that historical shocks and volatility levels have a significant impact on contemporary volatility. Co-movements in industrial and precious metals are suggested by the strong correlations between copper and silver (0.40) and gold and silver (0.82). Additionally, the Wald chi-squared test (191.88) and log-likelihood statistics (15,285.6) show that the model fits the data well, producing reliable findings at standard significance levels. With lambda values demonstrating

substantial persistence in volatility dynamics, the model additionally takes time-varying volatility into consideration.

The findings show the correlations between the MOEX Russia stock index, the USDRUB exchange rate, and the prices of several commodities (natural gas, crude oil, gold, copper, and silver). The model is a DCC-GARCH model that was estimated using weekly data from 2010 to 2023. A excellent model fit is suggested by the Wald chi-squared test (p-value < 0.0001) and the log-likelihood value of 15,125.61. The degree and direction of the conditional correlations between the variables are indicated by significant coefficients. For instance, MOEX Russia exhibits a negative connection with natural gas, WTI Crude oil, and gold, but a positive correlation with USDRUB (0.23), indicating that the Russian stock market typically performs better when the Russian ruble gains value. Additionally, the model shows that commodities like gold and silver (0.82), copper and silver (0.39), and copper and gold (0.24) have strong positive correlations, indicating that they typically move in comparable directions. With high significance for the lagged ARCH and GARCH parameters, the model's volatility structure—which is represented by the ARCH and GARCH terms—shows strong persistence in volatility shocks, especially for the USDRUB, Natural Gas, and WTI Crude Oil. This emphasizes how crucial recent volatility is in predicting future market behavior.

CONCLUSION AND DISCUSSION

Over the period of 2010–2023, the results of the Constant Conditional Correlation (CCC) Multivariate GARCH model demonstrate notable interdependencies among several emerging market stock indices. According to the model, the majority of indices exhibit considerable short-term volatility persistence (ARCH terms), indicating that recent volatility trends are still having an impact on present risk levels. With the exception of the Turkish stock index (XU100), all indices have statistically significant GARCH terms, which gauge long-term volatility persistence. This suggests that the market's volatility clustering is less. Bovespa and SP_BMVIPC (0.5492), SP_BMVIPC and MOEX Russia (0.4085), and JSKE and SPBSE Sensex (0.2588) are only a few of the stock indexes that show strong positive correlations, indicating that these indices frequently move in tandem. These findings highlight the significance of comprehending volatility spillovers and their possible effects on risk management and portfolio diversification by showing a high degree of interconnection among emerging market indices.

A more thorough examination of the time-varying correlations and volatility spillovers between the XU100 and other foreign stock indexes can be obtained using the Dynamic Conditional Correlation (DCC) GARCH model. As demonstrated by the high significance of the lagged XU100 coefficient (L.XU100 = 0.9502), the results reveal that past values of the XU100 index substantially predict future values. This implies that the XU100's short-term volatility is rather persistent. Additionally, there are notable conditional heteroskedasticity in all of the analyzed indices, including the FTSE South Africa, JSKE, and CSI1000, indicating that volatility spillovers from other markets to the XU100 are substantial. This suggests that volatility shocks in international markets have a tendency to spread to the Turkish market, highlighting the necessity for portfolio managers to take these spillovers into consideration while controlling exposure to emerging markets. Significant positive correlations between XU100 and a number of other indexes, such as JSKE (0.224), S&P BSE Sensex (0.1513), Bovespa (0.2581), and FTSE South Africa (0.3078), are revealed by the DCC GARCH model in terms of interrelationships. Both correlations imply that both

markets have a tendency to move in tandem over time, which has significant ramifications for portfolio diversification.

Notably, the weak correlation with MOEX Russia (0.2068) and the low correlation between XU100 and CSI1000 (0.0374) show that not all emerging markets are equally related. Given that some emerging market indexes may offer greater diversification benefits than others, investors wishing to spread their portfolios across these markets may find this variance in correlations to be helpful.

The DCC GARCH model's ability to represent the volatility structure is also significant, especially the adjustment parameters (lambda1 = 0.0195, lambda2 = 0.7899), which emphasize how persistent the volatility shocks are in the data. Given the high lambda2 value, it is likely that a market volatility shock will have a lasting impact. This persistence is especially important for portfolio managers since it implies that following shocks, markets such as the XU100 and other emerging indexes are likely to show extended periods of elevated volatility. Investors can make better judgments on risk management, hedging tactics, and the best asset allocation for portfolios exposed to emerging market stocks by having a better understanding of these time-varying linkages and the durability of volatility shocks.

The significance of volatility persistence in emerging markets is underscored by the outcomes of the CCC and DCC models. Investors and portfolio managers need to understand that historical volatility has a significant impact on future risk, particularly in markets like XU100. This persistence implies that market-specific volatility shocks (such as those affecting Turkish stocks) may have long-lasting effects, necessitating the use of strong risk management techniques that take extended stretches of high volatility into consideration. Using hedging techniques and volatility forecasting models to lessen the impact of market swings could be a proactive approach to risk management.

Diversification opportunities may be limited by the strong positive correlations between a number of emerging market indexes, such as Bovespa, SP_BMVIPC, and MOEX Russia, which imply that these markets frequently move in the same direction. Markets like the CSI1000, which have negligible or weak connections to other emerging indices, can provide more alluring diversification advantages for investors looking for greater diversity. When allocating assets, portfolio managers should

evaluate how interrelated markets are since markets with significant co-movement may offer less protection during times of market stress.

When managing portfolios with exposure to emerging economies, the DCC GARCH results highlight how crucial it is to take global market volatility into account. The notable volatility spillovers between the XU100 and other international indexes demonstrate how developed market shocks can significantly affect the performance of emerging markets. Investors should therefore be aware of the possibility of volatility transmission, especially when there is instability in the global market. One way to lessen susceptibility to these spillovers is to diversify across regions with weaker correlations.

The high lambda2 values in the DCC model, which represent the persistence of volatility shocks, imply that markets such as the XU100 and other emerging market indexes will endure protracted volatility after market disruptions. This suggests that dynamic ass*et al*location strategies that take into consideration fluctuating volatility over time are necessary for portfolio managers. Managers can make better decisions on when to modify portfolios, especially in response to world events that could lead to protracted periods of elevated risk, by comprehending the volatility structure and time-varying correlations.

In conclusion, the CCC and DCC GARCH models offer important new perspectives on the relationships and volatility patterns of emerging market indexes. These findings highlight how crucial it is for investors and portfolio managers to comprehend market co-movements, volatility persistence, and risk spillovers in order to maximize portfolio building, improve diversification, and successfully manage risk across international financial markets.

The CCC-GARCH and DCC-GARCH models provide a thorough examination of the dynamics of volatility in a range of financial markets, such as commodities, stock indices, and currency rates. Strong short-term volatility persistence is identified by the CCC-GARCH model, especially in markets such as the USDTRY exchange rate and the Turkish Stock Index (XU100). These markets' high ARCH coefficients imply that significant volatility shocks have long-lasting impacts. However, commodities with higher GARCH coefficients, like gold and copper, show that historical volatility is a major predictor of future price changes. While negative

correlations between USDTRY and precious metals suggest possible diversification benefits, correlations between assets such as gold and silver demonstrate considerable co-movement in volatility. These results underline how intertwined the world's financial markets are and how crucial it is to comprehend both short-term and long-term volatility persistence in order to manage risk effectively.

The DCC-GARCH results also show the time-varying and dynamic links between financial assets and global stock indexes, especially the volatility spillovers from other markets and the XU100's predictive relationship with historical values. Notable positive correlations between indices like the FTSE South Africa and the BSE Sensex indicate that these markets typically move in tandem over time, which is helpful for portfolio managers evaluating risk exposure. Since market interdependencies and volatility spillovers change in response to shifting global conditions, the time-varying character of these correlations emphasizes the necessity of flexible risk management techniques. Having this understanding is essential for creating strategies that adapt to changing asset class connections.

Strong volatility persistence is also demonstrated by the CCC-GARCH model applied to commodities, particularly in copper and silver, where high GARCH coefficients suggest that historical volatility has a major influence on future price dynamics. The correlations between various asset classes also show how changes in exchange rates can affect commodity prices. For example, the USD/BRL has a negative correlation with commodities like copper and gold. Investors looking to increase diversity or hedge risks will find these insights useful, especially in emerging markets where commodity and currency volatility are strongly correlated. Portfolio managers can improve portfolio resilience during times of market volatility by optimizing diversification strategies and modifying risk profiles in response to changes in the global market by having a thorough understanding of these interdependencies and time-varying correlations.

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APPENDICES

Appendix 1: CCC-GARCH Model Results for Borsa Istanbul Stock Index, Exchange Rate and Commodity Prices

Variable	Coefficient	Standard Error	z-Statistic	p-Value
ARCH_XU100				
Arch (L1)	0.925	0.0768	12.05	0.000
GARCH (L1)	0.0218	0.0335	0.65	0.514
Constant	0.0003	0.00005	6.84	0.000
ARCH_USDTRY				
Arch (L1)	0.5462	0.0892	6.12	0.000
GARCH (L1)	0.4568	0.088	5.19	0.000
Constant	0.000012	3.94E-06	3.04	0.002
ARCH_Natural Gas				
Arch (L1)	0.5783	0.0698	8.28	0.000
GARCH (L1)	0.4406	0.0476	9.26	0.000
Constant	0.0001	0.00003	4.45	0.000
ARCH_WTI Crude Oil				
Arch (L1)	0.3425	0.0442	7.76	0.000
GARCH (L1)	0.696	0.0321	21.67	0.000
Constant	0.00002	6.19E-06	3.37	0.001
ARCH_Gold				
Arch (L1)	0.0646	0.0152	4.26	0.000
GARCH (L1)	0.8852	0.0292	30.35	0.000
Constant	4.04E-06	1.56E-06	2.58	0.010
ARCH_Copper				
Arch (L1)	0.0511	0.0148	3.45	0.001
GARCH (L1)	0.9151	0.0243	37.59	0.000
Constant	5.98E-06	2.85E-06	2.1	0.036
ARCH_Silver				
Arch (L1)	0.0894	0.0147	6.07	0.000
GARCH (L1)	0.8854	0.016	55.49	0.000
Constant	8.86E-06	2.53E-06	3.5	0.000
Correlation Terms				
corr(XU100, USDTRY)	-0.1673	0.0361	-4.63	0.000
corr(XU100, Natural Gas)	0.0111	0.0371	0.3	0.765
corr(XU100, WTI Crude Oil)	0.0728	0.037	1.97	0.049
corr(XU100, Gold)	0.0267	0.0371	0.72	0.472
corr(XU100, Copper)	0.0453	0.0369	1.23	0.219
corr(XU100, Silver)	0.118	0.0408	2.89	0.004
corr(USDTRY, Natural Gas)	-0.0204	0.0371	-0.55	0.582
corr(USDTRY, WTI Crude Oil)	-0.0324	0.0373	-0.87	0.385
corr(USDTRY, Gold)	-0.2001	0.0357	-5.61	0.000
corr(USDTRY, Copper)	-0.196	0.0357	-5.5	0.000
corr(USDTRY, Silver)	-0.2389	0.0352	-6.79	0.000
corr(Natural Gas, WTI Crude Oil)	0.115	0.0367	3.13	0.002
corr(Natural Gas, Gold)	0.006	0.0371	0.16	0.872
corr(Natural Gas, Copper)	-0.0332	0.037	-0.9	0.369
corr(Natural Gas, Silver)	0.0096	0.0372	0.26	0.000

Source: *Author's computation*

Appendix 2: CCC-GARCH Model Results for Chinese Stock Exchange, Exchange Rate and Commodity Prices

Variable	ARCH(1) Coefficient	GARCH(1) Coefficient	Constant
CSI1000	0.1078***	0.8563***	8.84e-06**
USDCNY	0.0316***	0.9579***	5.02e-08*
Natural Gas	0.5714***	0.4451***	1.40e-04***
WTI Crude Oil	0.3438***	0.6950***	2.09e-05***
Gold	0.0636***	0.8896***	3.77e-06*
Copper	0.0489***	0.9154***	6.31e-06*
Silver (Lags)	-0.0001	0.8858***	8.67e-06***

Variable Pair	Correlation Coefficient	z-value	P-value
CSI1000 & USDCNY	-0.1036***	-2.78	0.0050
CSI1000 & Natural Gas	-0.0862**	-2.33	0.0200
CSI1000 & WTI Crude Oil	0.0139	0.37	0.7080
CSI1000 & Gold	0.0744*	2.01	0.0440
CSI1000 & Copper	0.2119***	5.98	0.0000
CSI1000 & Silver	0.1097***	2.99	0.0030
USDCNY & Gold	-0.2578***	-7.31	0.0000
USDCNY & Copper	-0.2899***	-8.4	0.0000

Source: *Author's computation*

Appendix 3: CCC-GARCH Model Results for Jakarta Stock Exchange, Exchange Rate and Commodity Prices

Variable	Coefficient	Std. Error	z-Value	p-Value
ARCH_JSKE				
ARCH (L1)	0.1524	0.035	4.36	0.000
GARCH (L1)	0.6519	0.073	8.88	0.000
ARCH_USDIDR				
ARCH (L1)	0.1871	0.028	6.67	0.000
GARCH (L1)	0.8037	0.024	33.58	0.000
ARCH_Natural Gas				
ARCH (L1)	0.5752	0.07	8.26	0.000
GARCH (L1)	0.4417	0.048	9.28	0.000
ARCH_WTI Crude Oil				
ARCH (L1)	0.3444	0.044	7.8	0.000
GARCH (L1)	0.6953	0.032	21.77	0.000
ARCH_Gold				
ARCH (L1)	0.064	0.015	4.31	0.000
GARCH (L1)	0.8869	0.028	31.15	0.000
ARCH_Copper				
ARCH (L1)	0.0487	0.014	3.44	0.001
GARCH (L1)	0.9177	0.024	38.23	0.000
ARCH_Silver				
ARCH (L1)	0.0882	0.014	6.14	0.000
GARCH (L1)	0.8894	0.015	58.15	0.000
Correlation Estimates				
corr(JSKE, USDIDR)	-0.4345	0.03	-14.36	0.000
corr(JSKE, Natural Gas)	0.0522	0.037	1.41	0.160
corr(JSKE, WTI Crude Oil)	0.0502	0.037	1.35	0.178
corr(JSKE, Gold)	0.1552	0.036	4.27	0.000
corr(JSKE, Copper)	0.2727	0.034	7.92	0.000
corr(JSKE, Silver)	0.2511	0.035	7.16	0.000
corr(USDIDR, Natural Gas)	-0.0244	0.037	-0.66	0.511
corr(USDIDR, WTI Crude Oil)	0.032	0.037	0.86	0.390
corr(USDIDR, Gold)	-0.2378	0.035	-6.78	0.000
corr(USDIDR, Copper)	-0.2579	0.035	-7.46	0.000
corr(USDIDR, Silver)	-0.2996	0.034	-8.83	0.000
corr(Natural Gas, WTI Crude Oil)	0.115	0.037	3.13	0.002
corr(Natural Gas, Gold)	0.006	0.037	0.16	0.871
corr(Natural Gas, Copper)	-0.033	0.037	-0.89	0.372
corr(Natural Gas, Silver)	0.0113	0.037	0.3	0.762
corr(WTI Crude Oil , Gold)	-0.0053	0.037	-0.14	0.888
corr(WTI Crude Oil , Copper)	0.0863	0.037	2.34	0.019
corr(WTI Crude Oil , Silver)	0.0444	0.038	1.18	0.237
corr(Gold, Copper)	0.2581	0.035	7.46	0.000
corr(Gold, Silver)	0.8014	0.013	60.46	0.000
corr(Copper, Silver)	0.429	0.03	14.17	0.000

Source: *Author's computation*

Appendix 4: CCC-GARCH Model Results for India Stock Exchange, Exchange Rate and Commodity Prices

Variable	Coefficient	Std. Err.	z-Value	p-Value
ARCH_SPBSE Sensex				
ARCH(L1)	0.1397	0.0338	4.13	0.000
GARCH(L1)	0.709	0.084	8.44	0.000
ARCH_USDINR				
ARCH(L1)	0.0776	0.0206	3.77	0.000
GARCH(L1)	0.8927	0.0312	28.64	0.000
ARCH_Natural Gas				
ARCH(L1)	0.5779	0.0698	8.28	0.000
GARCH(L1)	0.4398	0.0476	9.23	0.000
ARCH_WTI Crude Oil				
ARCH(L1)	0.3394	0.0438	7.75	0.000
GARCH(L1)	0.6979	0.032	21.82	0.000
ARCH_Gold				
ARCH(L1)	0.0646	0.0151	4.29	0.000
GARCH(L1)	0.8841	0.0292	30.32	0.000
ARCH_Copper				
ARCH(L1)	0.049	0.0148	3.31	0.001
GARCH(L1)	0.9113	0.0274	33.31	0.000
Silver				
SPBSE Sensex(L1)	0.0282	0.0364	0.78	0.437
USDIDR(L1)	0.0797	0.086	0.93	0.354
Natural Gas(L1)	-0.0017	0.0072	-0.24	0.807
WTI Crude Oil (L1)	0.0108	0.0126	0.86	0.392
Gold(L1)	-0.0124	0.0406	-0.3	0.761
Copper(L1)	0.0426	0.0271	1.57	0.115
ARCH_Silver				
ARCH(L1)	0.0897	0.0151	5.93	0.000
GARCH(L1)	0.8825	0.0168	52.68	0.000
Correlation Pair				
corr(SPBSE Sensex, USDINR)	-0.256	0.0347	-7.39	0.000
corr(SPBSE Sensex, Natural Gas)	0.0001	0.037	0	0.998
corr(SPBSE Sensex, WTI Crude Oil)	0.0673	0.0373	1.81	0.071
corr(SPBSE Sensex, Gold)	0.0264	0.037	0.71	0.475
corr(SPBSE Sensex, Copper)	0.1343	0.0363	3.7	0.000
corr(SPBSE Sensex, Silver)	0.1052	0.0368	2.86	0.004
corr(USDINR, Natural Gas)	-0.0049	0.0371	-0.13	0.896
corr(USDINR, WTI Crude Oil)	-0.0736	0.037	-1.99	0.047
corr(USDINR, Gold)	-0.2492	0.0348	-7.15	0.000
corr(USDINR, Copper)	-0.3304	0.0331	-9.98	0.000
corr(USDINR, Silver)	-0.3133	0.0336	-9.32	0.000
corr(Natural Gas, WTI Crude Oil)	0.1151	0.0367	3.13	0.002
corr(Natural Gas, Gold)	0.006	0.0371	0.16	0.872
corr(Natural Gas, Copper)	-0.0327	0.037	-0.89	0.375
corr(Natural Gas, Silver)	0.0094	0.0372	0.25	0.801

Source: *Author's computation*

Appendix 5: CCC-GARCH Model Results for Brazil Stock Index, Exchange Rate and Commodity Prices

Variable	Coefficient	Std. Err.	z-Statistic	p-value
ARCH (Bovespa)				
ARCHBovespa(L1)	0.1322	0.034	3.89	0.000
GARCHBovespa(L1)	0.6982	0.0702	9.95	0.000
Constant (Bovespa)	2.92E-05	9.37E-06	3.12	0.002
ARCH (USDBRL)				
ARCH USDBRL(L1)	0.1027	0.0233	4.4	0.000
GARCH USDBRL(L1)	0.854	0.0308	27.77	0.000
Constant (USDBRL)	3.49E-06	1.29E-06	2.7	0.007
ARCH (Natural Gas)				
ARCH NatGas(L1)	0.5769	0.0698	8.27	0.000
GARCH NatGas(L1)	0.4405	0.0476	9.25	0.000
Constant (Natural Gas)	0.000142	3.18E-05	4.46	0.000
ARCH (WTI Crude Oil)				
ARCHWTI(L1)	0.3368	0.0429	7.84	0.000
GARCHWTI(L1)	0.699	0.0313	22.37	0.000
Constant (WTI Crude Oil)	2.09E-05	6.11E-06	3.42	0.001
ARCH (Gold)				
ARCHGold(L1)	0.0639	0.0147	4.34	0.000
GARCHGold(L1)	0.8892	0.0276	32.24	0.000
Constant (Gold)	3.78E-06	1.47E-06	2.57	0.010
ARCH (Copper)				
ARCHCopper(L1)	0.0421	0.0129	3.27	0.001
GARCHCopper(L1)	0.9223	0.0239	38.6	0.000
Constant (Copper)	6.19E-06	2.91E-06	2.12	0.034
Silver (Effects from other variables)				
Bovespa(L1)	-0.0417	0.0295	-1.42	0.157
USDBRL(L1)	0.0057	0.0381	0.15	0.880
NatGas(L1)	-0.0019	0.0072	-0.27	0.789
WTI Crude Oil(L1)	0.0119	0.0128	0.92	0.355
Gold(L1)	-0.0149	0.0405	-0.37	0.713
Copper(L1)	0.0605	0.0276	2.2	0.028
ARCH (Silver)				
ARCH Silver(L1)	0.0866	0.0145	5.97	0.000
GARCH Silver(L1)	0.8892	0.0158	56.36	0.000
Constant (Silver)	8.53E-06	2.50E-06	3.41	0.001
Correlations				
corr(Bovespa, USDBRL)	-0.0959	0.0369	-2.6	0.009
corr(Bovespa, NatGas)	-0.0205	0.0372	-0.55	0.582
corr(Bovespa, WTI Crude Oil)	0.0758	0.0372	2.04	0.041

Source: *Author's computation*

Appendix 6: CCC-GARCH Model Results for Mexican Stock Index, Exchange Rate and Commodity Prices

Variable	Coefficient	Standard Error	z-value	p-value
ARCH_SP_BMVIPC (L1)	0.0806	0.0231	3.49	0.000
ARCH_USDMXN (L1)	0.14	0.0378	3.7	0.000
ARCH_Natural Gas (L1)	0.5736	0.0695	8.26	0.000
ARCH_WTI Crude Oil (L1)	0.3425	0.0441	7.76	0.000
ARCH_Gold (L1)	0.0616	0.0147	4.18	0.000
ARCH_Copper (L1)	0.0454	0.0146	3.12	0.002
ARCH_Silver (L1)	0.0821	0.0141	5.81	0.000
GARCH_SP_BMVIPC (L1)	0.8286	0.0449	18.46	0.000
GARCH_USDMXN (L1)	0.7006	0.0991	7.07	0.000
GARCH_Natural Gas (L1)	0.4422	0.0478	9.26	0.000
GARCH_WTI Crude Oil (L1)	0.6976	0.0319	21.87	0.000
GARCH_Gold (L1)	0.8836	0.0298	29.63	0.000
GARCH_Copper (L1)	0.9128	0.0289	31.63	0.000
GARCH_Silver (L1)	0.8884	0.0162	54.82	0.000
Correlation Parameters				
corr(SP_BMVIPC, USDMXN)	-0.4703	0.0291	-16.16	0.000
corr(SP_BMVIPC, Natural Gas)	-0.0603	0.037	-1.63	0.103
corr(SP_BMVIPC, WTI Crude Oil)	0.0202	0.0372	0.54	0.588
corr(SP_BMVIPC, Gold)	0.0929	0.0368	2.52	0.012
corr(SP_BMVIPC, Copper)	0.3828	0.0318	12.05	0.000
corr(SP_BMVIPC, Silver)	0.2463	0.035	7.03	0.000
corr(USDMXN, Natural Gas)	0.0046	0.0372	0.12	0.901
corr(USDMXN, WTI Crude Oil)	-0.0843	0.0371	-2.27	0.023
corr(USDMXN, Gold)	-0.2297	0.0352	-6.52	0.000
corr(USDMXN, Copper)	-0.3176	0.0334	-9.51	0.000
corr(USDMXN, Silver)	-0.327	0.0335	-9.77	0.000
corr(Natural Gas, WTI Crude Oil)	0.115	0.0367	3.13	0.002
corr(Natural Gas, Gold)	0.0061	0.0371	0.17	0.869
corr(Natural Gas, Copper)	-0.0323	0.037	-0.87	0.382
corr(Natural Gas, Silver)	0.0106	0.0371	0.29	0.776
corr(WTI Crude Oil , Gold)	-0.0044	0.0372	-0.12	0.905
corr(WTI Crude Oil , Copper)	0.0864	0.0369	2.34	0.019
corr(WTI Crude Oil , Silver)	0.0442	0.0376	1.17	0.240
corr(Gold, Copper)	0.26	0.0345	7.53	0.000
corr(Gold, Silver)	0.8009	0.0133	60.23	0.000
corr(Copper, Silver)	0.4331	0.0302	14.34	0.000

Source: *Author's computation*

Appendix 7: CCC GARCH Model Results for South African Stock Exchange, Exchange Rate and Commodity Prices

Variable	Coefficient	Std. Error	z-value	P-value
ARCH_FTSE South Africa (L1)	0.1435	0.0351	4.08	0.000
GARCH_FTSE South Africa (L1)	0.686	0.0743	9.23	0.000
_cons (FTSE South Africa)	1.78E-05	5.85E-06	3.04	0.002
ARCH_USDZAR (L1)	0.047	0.0178	2.64	0.008
GARCH_USDZAR (L1)	0.8888	0.0572	15.53	0.000
_cons (USDZAR)	5.61E-06	3.92E-06	1.43	0.153
ARCH_Natural Gas (L1)	0.5775	0.0697	8.29	0.000
GARCH_Natural Gas (L1)	0.4412	0.0474	9.31	0.000
_cons (Natural Gas)	0.000141	3.16E-05	4.45	0.000
ARCH_WTI Crude Oil (L1)	0.3409	0.0438	7.78	0.000
GARCH_WTI Crude Oil (L1)	0.6982	0.0318	21.96	0.000
_cons (WTI Crude Oil)	2.04E-05	6.1E-06	3.35	0.001
ARCH_Gold (L1)	0.0622	0.0146	4.26	0.000
GARCH_Gold (L1)	0.8885	0.0283	31.34	0.000
_cons (Gold)	3.96E-06	1.53E-06	2.59	0.010
ARCH_Copper (L1)	0.0439	0.0139	3.16	0.002
GARCH_Copper (L1)	0.9198	0.0268	34.26	0.000
_cons (Copper)	6.32E-06	3.21E-06	1.97	0.049
ARCH_Silver (L1)	0.0872	0.0142	6.13	0.000
GARCH_Silver (L1)	0.8881	0.0154	57.77	0.000
_cons (Silver)	8.67E-06	2.46E-06	3.53	0.000
Correlation				
corr(FTSE South Africa, USDZAR)	-0.4168	0.0309	-13.49	0.000
corr(FTSE South Africa, Natural Gas)	-0.0471	0.0371	-1.27	0.204
corr(FTSE South Africa, WTI Crude Oil)	0.0183	0.0372	0.49	0.624
corr(FTSE South Africa, Gold)	0.202	0.0357	5.65	0.000
corr(FTSE South Africa, Copper)	0.3926	0.0314	12.5	0.000
corr(FTSE South Africa, Silver)	0.3159	0.0336	9.39	0.000
corr(USDZAR, Natural Gas)	-0.0368	0.0372	-0.99	0.322
corr(USDZAR, WTI Crude Oil)	-0.0677	0.0373	-1.82	0.069
corr(USDZAR, Gold)	-0.3447	0.0328	-10.52	0.000
corr(USDZAR, Copper)	-0.4009	0.0312	-12.86	0.000
corr(USDZAR, Silver)	-0.4335	0.0303	-14.3	0.000
corr(Natural Gas, WTI Crude Oil)	0.115	0.0367	3.13	0.002
corr(Natural Gas, Gold)	0.0061	0.0371	0.16	0.869
corr(Natural Gas, Copper)	-0.0324	0.037	-0.88	0.381
corr(Natural Gas, Silver)	0.0108	0.0372	0.29	0.772

Source: *Author's computation*

Appendix 8: CCC-GARCH Results for Russian Stock Exchange, Exchange Rate and Commodity Prices

Variable	Coefficient	Std. Error	z-score	p-value
ARCH_MOEX Russia ARCH (L1)	0.2088	0.0414	5.04	0.000
ARCH_MOEX Russia GARCH (L1)	0.7497	0.0454	16.53	0.000
ARCH_USDRUB ARCH (L1)	0.3401	0.0547	6.22	0.000
ARCH_USDRUB GARCH (L1)	0.6389	0.0528	12.11	0.000
ARCH_Natural Gas ARCH (L1)	0.5787	0.0699	8.28	0.000
ARCH_Natural Gas GARCH (L1)	0.4388	0.0479	9.17	0.000
ARCH_WTI Crude Oil ARCH (L1)	0.3421	0.044	7.78	0.000
ARCH_WTI Crude Oil GARCH (L1)	0.698	0.0319	21.89	0.000
ARCH_Gold ARCH (L1)	0.0642	0.0148	4.33	0.000
ARCH_Gold GARCH (L1)	0.8873	0.028	31.64	0.000
ARCH_Copper ARCH (L1)	0.0542	0.0149	3.64	0.000
ARCH_Copper GARCH (L1)	0.9122	0.0239	38.11	0.000
ARCH_Silver ARCH (L1)	0.0905	0.0149	6.07	0.000
ARCH_Silver GARCH (L1)	0.8854	0.016	55.29	0.000
Correlation				
MOEX Russia, USDRUB	-0.3487	0.0327	-10.65	0.000
MOEX Russia, Gold	0.0917	0.0368	2.49	0.013
MOEX Russia, Copper	0.3058	0.0337	9.08	0.000
MOEX Russia, Silver	0.186	0.0359	5.18	0.000
USDRUB, WTI Crude Oil	-0.1013	0.0369	-2.75	0.006
USDRUB, Gold	-0.1677	0.0361	-4.64	0.000
Copper, Silver	0.4301	0.0303	14.22	0.000
Gold, Silver	0.8017	0.0132	60.54	0.000

Source: *Author's Compilation*

GENİŞLETİLMİŞ ÖZET

GİRİŞ

Son birkaç on yılda dünya çapında hisse senedi yatırımlarında meydana gelen artış, yabancı para birimleri, hisse senetleri ve emtia arz-talebini yükselterek bu piyasalar arasındaki karşılıklı bağımlılığı ve oynaklık yayılımını artırmıştır. Küresel portföylerle ilişkili artan risk nedeniyle yatırımcılar, oynaklığı kontrol altına almak amacıyla çeşitlendirmeye gitmektedir. Yatırımcılar, daha fazla sermaye akışı ve finansal inovasyonla desteklenen finansal piyasaların artan entegrasyonu sayesinde getirileri optimize ederken, kendilerine özgü riskleri en aza indirebilmektedir. Ancak bu birbirine bağlılık, aynı zamanda, özellikle kriz zamanlarında, bir piyasadaki veya bölgedeki şokların diğer piyasaları veya bölgeleri etkileyebilmesiyle sonuçlanan yayılma etkilerine de yol açmaktadır. Nedensellik ve oynaklık yayılmalarına odaklanarak, akış odaklı ve hisse senedi odaklı modeller gibi teorik modeller döviz kurları, hisse senedi fiyatları ve emtia fiyatları arasındaki ilişkileri incelemektedir. Piyasa bağlantıları ve oynaklık yayılımı açısından gelişmiş piyasalar üzerinde çok sayıda çalışma yapılmış olmasına karşın, gelişmekte olan ve yükselen ekonomiler üzerinde çok fazla çalışma bulunmamaktadır.

AMAÇ VE YÖNTEM

Bu tez, yükselen ekonomilerde finansal piyasaların kendi içinde ve birbirleri arasındaki getiri ve oynaklık yayılımı mekanizmaları yanında asimetrik oynaklık bağlantılarını araştırarak, önceki bilgi birikimini geliştirmeyi amaçlamaktadır. Bu amaçla, Çin, Brezilya, Güney Afrika, Meksika, Rusya, Hindistan, Endonezya ve Türkiye olmak üzere seçilmiş sekiz yükselen piyasa ekonomisindeki Ocak 2010'dan Aralık 2023 dönemine ait haftalık verilerden (727 gözlem) hareketle hisse senedi, döviz ve emtia piyasaları arasındaki getiri ve oynaklık yayılmaları analiz edilmiştir. Çalışmada, bu piyasalardaki oynaklık yayılma dinamiklerine ilişkin sağlam öngörüler sağlamak üzere Sabit Koşullu Korelasyon (CCC) ve Dinamik Koşullu Korelasyon (DCC) Çok Değişkenli GARCH modelleri kullanılmıştır.

BULGULAR

Birim Kök ve Getiri Serilerine İlişkin Zaman Yol Grafiklerinin Değerlendirilmesi

İlk olarak hem Phillips-Perron hem de Augmented Dickey Fuller Testleri kullanılarak birim kök incelenmiştir. Analiz edilen tüm endeksler ve varlık fiyatlarındaki durağanlığa dair güçlü kanıtlar, Phillips-Perron (PP) ve Augmented Dickey-Fuller (ADF) testlerinin sonuçlarını gösteren Tablo 1'de sunulmuştur. Test edilen emtiaların, para birimlerinin ve endekslerin istatistik değerleri kritik değerlerden küçük olduklarından tümünün durağan oldukları belirlenmiştir. Ayrıca, deterministik bir eğilim potansiyelini dikkate alan "Trend" koşulunun sonuçları, sıklıkla durağanlığa dair çok daha tatminkar kanıtlar sunmuştur. Bu sonuçlar, analiz edilen tüm serilerin durağan olduğunu ve durağanlık varsayan zaman serisi teknikleriyle modelleme için uygun olduğunu göstermektedir.

Tablo 1: PP ve ADF Test Sonuçları

	Phillip Perron Testi		Augmented Dickey Fuller Testi	
	Sabit Olmayan	Trend	Sabit Olmayan	Trend
XU100 Index	-4.357	-5.040	-3.947	-4.499
CSI1000 Index	-25.44	-25.414	-25.416	-25.391
S&P BSE Sensex index	-25.031	-25.177	-25.065	-25.223
JKSE Index	-28.713	-28.860	-28.747	-28.876
MOEX Index	-25.937	-25.934	-25.926	-25.920
FTSE Güney Afrika	-30.130	-30.265	-29.785	-29.845
Bovespa	-26.932	-26.952	-26.871	-26.900
S&P BMV IPC	-27.939	-27.941	-27.926	-27.923
USD/TRY	-32.366	-33.648	-32.941	-34.031
USD/MXN	-28.143	-28.154	-28.165	-28.174
USD/INR	-25.057	-25.207	-25.016	-25.199
USD/RUB	-22.898	-22.919	-22.833	-22.874
USD/ZAR	-28.135	-28.233	-28.034	-28.101
USD/IDR	-24.180	-24.247	-23.985	-24.089
USD/BRL	-27.349	-27.456	-27.350	-27.461
USD/CNY	-24.578	-24.598	-24.005	-24.046
Doğal Gaz	-32.274	-32.241	-31.287	-31.251
WTI Ham Petrol	-33.797	-33.749	-32.826	-32.782
Altın	-26.156	-26.165	-26.149	-26.153
Bakır	-28.404	-28.379	-28.313	-28.286
Gümüş	-26.403	-26.366	-26.393	-26.358

Kaynak: *Yazarın hesaplamaları.*

Durağanlık sınamasından sonra her bir getiri serisinin grafiksel analizi yapılmıştır. Borsa endeksi getiri serilerine ilişkin grafikler aşağıda Şekil 1'de yer almaktadır. Grafikler soldan başlayarak sütunlar halinde sırasıyla değerlendirilmiştir. XU100 Endeksinin (Türkiye), Ocak 2010'dan 2018 ortasına kadar gösterdiği önemli fiyat dalgalanmaları yani yüksek oynaklık dinamik bir piyasa yapısını göstermiştir. 2010 yılı başlarında negatif getirilerle sağlayan endeks, Haziran 2010'da -%10,4'lük bir düşüşten önce dramatik bir artış yaşamıştır. Küresel finansal belirsizlik ve diğer ulusal ve uluslararası ekonomik baskılar, bu artan oynaklık dönemine katkıda bulunmuştur. Bundan sonra endeks, 2010'un sonundan 2011'in başına kadar güçlü bir toparlanma yaşamış ve Nisan 2011'de yaklaşık %11,5'lik bir artışla zirveye ulaşmıştır. Toparlanma kısa sürmüş, özellikle uzun süreli düşüşlerin yaklaşık -%11,4'lük bir diple sona erdiği 2014'te yeniden ortaya çıkmıştır.

CSI 100 Endeksi (Çin) hem büyük kazançlar hem de dramatik düşüşler dahil olmak üzere dalgalanan getirilerle büyük bir oynaklık göstermiştir. 2010'un başlarındaki 10 Ocak'ta %2,3'lük bir artış ve sonraki hafta %1,8'lik bir düşüş dahil olmak üzere önemli haftalık dalgalanmalar yaşanmıştır. 23 Mayıs 2010'da %3,0'lük bir artış ve 27 Haziran 2010'da %5,4'lük bir düşüş gibi önemli dalgalanmalarla, bu hızlı dalgalanma eğilimi devam etmiştir. Oynaklığın en yüksek olduğu zaman dilimi 2015 ortasından 2016 başına kadar gerçekleşmiştir. Haziran 2015 sonlarında %9'dan fazla keskin bir düşüşle karakterize edilmiş, bu da piyasa paniği ve dış ekonomik güçlerin bir işareti olarak kabul edilmiştir. Kurtarma çabalarına rağmen, yatırımcıların tereddütlü davranmaları daha fazla oynaklığa yol açmıştır.

JSKE Endeksi (Endonezya) yine piyasanın durumunu gösteren önemli bir oynaklık sergilemiştir. Ekonomik istikrarsızlıklar sonucunda Mayıs 2010'un başlarında -%3,53'lük bir düşüşün ardından, bir sonraki hafta -%3,73'lük yeni bir düşüş yaşanmıştır.. Öte yandan, Haziran 2013'ün sonlarında %2,83'lük bir artış, umut ve iyileşmenin başladığı yönünde algılanmıştır.

MOEX Rusya Endeksi ise 2010'un başından 2018'in sonuna kadar yine önemli oynaklıklar sergilemiş ve haftalık getiriler önemli ölçüde dalgalanma göstermiştir. Pozitif ve negatif getirilerin dönüşümlü örüntüsü, Rusya piyasasının içsel istikrarsızlığını göstermektedir. Örneğin, Ocak 2010 hafif bir artışla başlamış, ancak Mayıs 2010'da yaklaşık -%4,7'lik bir düşüş de dahil olmak üzere daha fazla düşüş

yaşanmıştır. Eylül 2011'deki zirvesinde -%5,6'lık şaşırtıcı bir getiriyle, oynaklık piyasanın dış şoklara ve ekonomik güçlere karşı kırılganlığını göstermiştir.

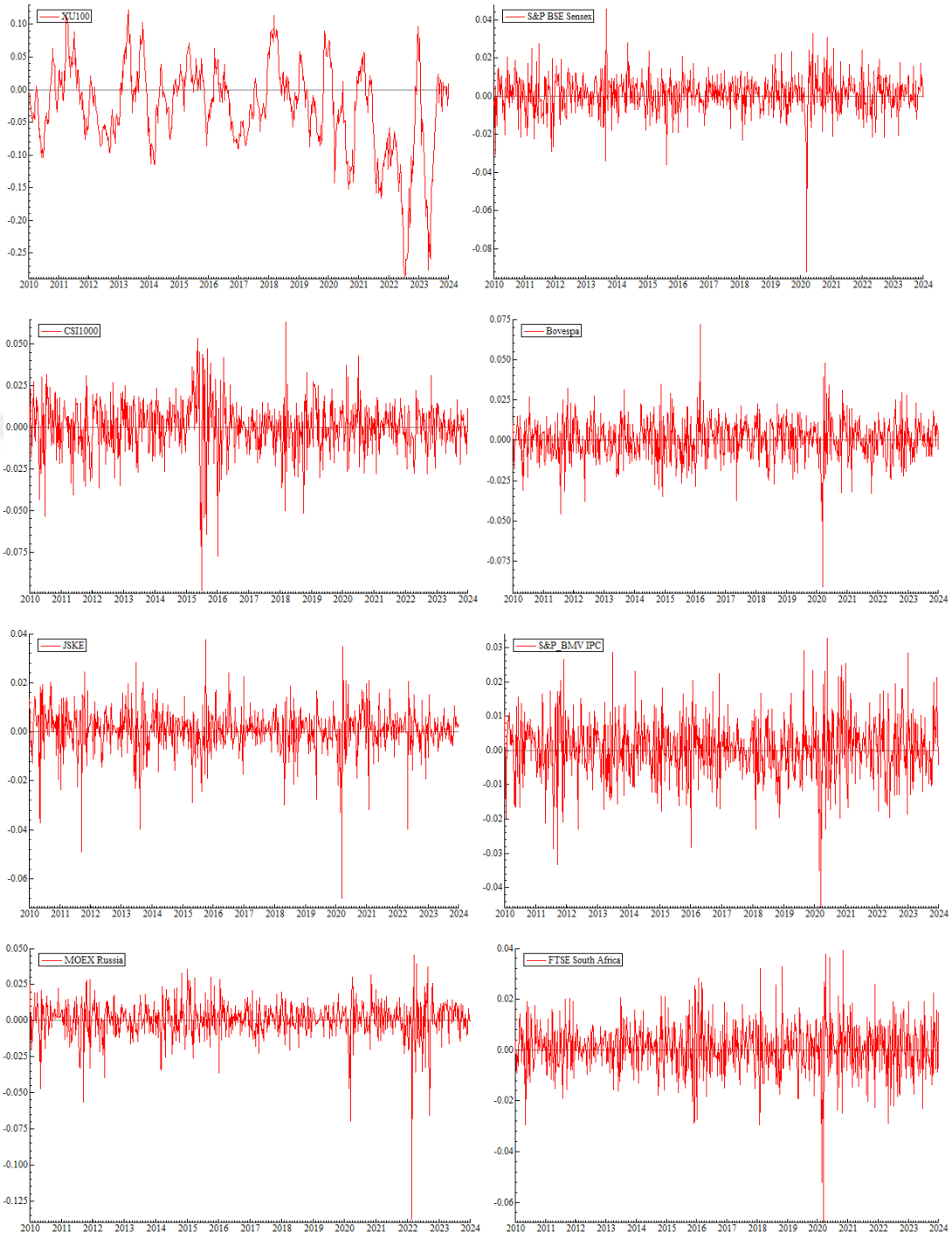
S&P BSE Sensex Endeksi (Hindistan) 2010'un başından 2018'in ortasına kadar ekonomideki ve piyasa duyarlılığındaki değişimleri yansıtan önemli bir oynaklık göstermiştir. Ocak 2010'da yaklaşık % -0,47'lik negatif getiriyle başlayan endeks, hem kazançlar hem de kayıplarla haftadan haftaya dalgalanmıştır. Mayıs 2010'da yaşanan -%2,04'lük belirgin düşüşün ardından toparlanmalar yaşanmıştır. 2011'in ikinci yarısındaki bir dizi düşüş, Kasım ayında -%2,88'lik keskin bir düşüşle sonuçlanmıştır. Kasım 2015'te -%1,93'lük belirgin bir düşüş yaşanmıştır. Keskin düşüşler 2017 boyunca ve 2018'de devam etmiş ve Şubat ayında yine -%2,33'lük bir düşüş yaşanmıştır. Bu performans, ulusal ve küresel ekonomik faktörlerin etkileşimini vurgulayarak Sensex'in karakteristik oynaklığına katkıda bulunmuştur.

Bovespa Endeksi (Brezilya), bir dizi ekonomik değişken tarafından yönlendirilen çok değişken bir piyasa yapısında 2010 ile 2018 arasında önemli dalgalanmalar göstermiştir. Endeks ilk olarak 2010'un başlarında hafif dalgalanmalar sergilemiş ancak zaman geçtikçe dalgalanma artmıştır. Temmuz 2011'deki -%4,57'lik keskin düşüş ve aynı yılın Ağustos ayındaki %2,52'lik artış toparlanma sinyali olarak görülmüştür.

İçsel öngörülemezliği nedeniyle, S&P BMV IPC endeksi (Meksika) Ocak 2010'dan 2018 sonuna kadar pozitif ve negatif haftalık getiriler arasında belirgin dalgalanmalar göstermiştir. Dikkat çekici salınımlar arasında Eylül 2011'de -%3,33 ve Ocak 2016'da -%2,83'lik keskin düşüşler, artan piyasa stresini yansıtmıştır. Öte yandan, Ekim 2011'de %2,04 ve Haziran 2013'te %2,86'lık artışlar da dahil olmak üzere önemli toparlanmalar göstermiştir. Haftalık getiriler %2,0'nin üzerinde dalgalanmalar sergilemiş, bu da yüksek düzeyde işlem hacmi olduğunu yansıtmıştır.

FTSE Güney Afrika Endeksi, tarihi boyunca ülkenin sürekli değişen ekonomik ortamını yansıtan önemli oynaklık düzeyleri sergilemiştir. Örneğin, Mayıs 2010'un başlarında -%2,95 gibi dik düşüşlerin aksine, bir hafta sonra %1,49'luk bir artış gibi olumlu toparlanmalar olmuştur. Bu oynaklık, özellikle 2015 sonu ve 2016 başında olmak üzere sonraki yıllarda da devam etti ve Aralık 2015'te getiriler -%2,88 ile %2,54 arasında değişmiştir. Endeksin hem iç hem de dış şoklara karşı kırılganlığı, bu oynaklıkla vurgulanmaktadır.

Şekil 1: Gelişmekte Olan Piyasa Ekonomilerinin Hisse Senedi Piyasalarının Getiri Serileri



Kaynak: *Yazar tarafından oluşturulmuştur.*

Farklı para birimlerine ilişkin getiri serileri aşağıda Şekil 2'de gösterilmiştir. Grafikler soldan başlayarak sütunlar halinde sırasıyla değerlendirilmiştir. USD/RUB döviz kurunda haftalık yüzdelik değişimler incelendiğinde, negatif değerler daha güçlü

bir ruble (USD değer kaybı) gösterirken, pozitif değerler daha zayıf bir ruble (USD değer artışı) göstermektedir. Verilere göre, örneğin USD/RUB döviz kurunda %0,645'lik bir düşüş rublenin gücünü gösterirken, %0,45'lik bir kazanç rublenin zayıflığını göstermektedir.

USD/ZAR döviz kurunda Mart 2010'dan Ağustos 2018'e kadar haftalık değişimler hem istikrarlı hem de dikkate değer dönemleri göstermektedir. Değişimler, USD'nin Güney Afrika Randı'na (ZAR) göre yerel ve uluslararası ekonomik koşullar ve piyasa hissiyatı gibi çeşitli değişkenlere bağlı olarak nasıl değer kazandığını veya kaybettiğini yansıtmaktadır. Belirli haftalar, döviz piyasalarının akışkanlığını vurgulayan dikkate değer oynaklık düzeyleri sergilemektedir.

USD/INR döviz kuru Ocak 2010 ile Ağustos 2018 arasındaki verilere göre hem küçük hem de önemli yüzdelik hareketlerle sık sık dalgalanmıştır. Eylül 2011'de artış ve Ocak 2012'de keskin bir düşüş gibi büyük değişiklikler olmuştur.

USD/IDR döviz kurunda haftalık yüzdelik değişimlerindeki negatif değerler USD'nin zayıfladığını ifade ederken, pozitif değerler güçlendiğini göstermektedir. İstatistiklerde, özellikle 2015-2016 döneminde önemli oynaklık ve ani dalgalanma hareketleri belirgindir.

USD/BRL döviz kurunun haftalık yüzdelik değişimleri yine önemli dalgalanmalar göstermektedir ve bu da gelişmekte olan piyasalarda sıklıkla görülen oynaklığın göstergesidir. Brezilya Reali'nin ABD Doları'na göre değer kazanma ve değer kaybetme dönemleri hem olumlu hem de olumsuz gelişmelerin birçok örneğiyle gösterilmektedir.

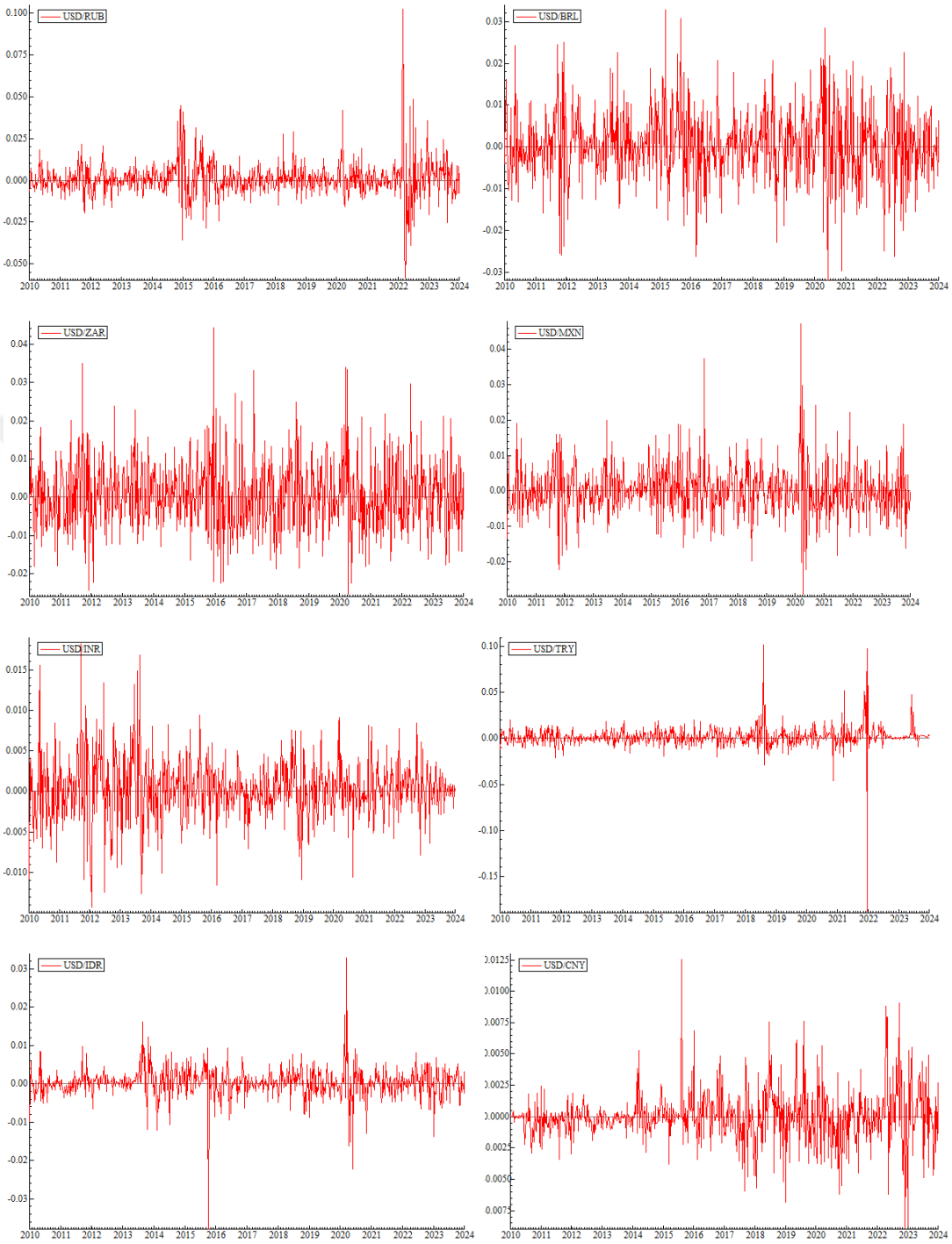
USD/MXN döviz kurunda küresel ekonomik güçler, jeopolitik olaylar, piyasa duygusu ve merkez bankası eylemlerinin bir kombinasyonuna bağlı dalgalanmalar olmasına karşın bu hareketlerin belirgin bir uzun vadeli örüntüden yoksun olduğu görülmektedir. Örneğin, önemli artışlar veya düşüşler önemli finansal veya politik gelişmelerle örtüşebilirken, küçük dalgalanmalar piyasa türbülansını ve geçici yatırımcı tepkilerini göstermektedir.

USD/TRY döviz kurunun belirli dönemlerde belirgin pozitif dalgalanmalar sergilemesi (örneğin Ağustos 2018'de %10,2'lik bir kazanç), Türk lirasının zayıfladığına veya doların güçlendiğine işaret ederken, diğer dönemlerde sert düşüşler

göstermesi (örneğin Ekim 2011'de -%2,15), Türk lirasının yeniden değerlendiğine işaret etmektedir.

USD/CNY döviz kurunda birkaç yıl boyunca periyodik dalgalanmalar olmuştur. Bazı haftalar önemli değişimler gösterirken (örneğin -0,003415664 veya 0,007573979), diğerleri sıfıra yakın çok hafif değişiklikler göstermiştir (örneğin 3,81669E-05). Piyasa tutumu, hükümet düzenlemeleri, küresel ticaret koşulları ve enflasyon, faiz oranları ve politik gelişmeler gibi makroekonomik değişkenler bu dalgalanmaların bazı nedenleridir.

Şekil 2: Gelişmekte Olan Piyasa Ekonomilerinin Döviz Kurları İçin Getiri Serisi



Kaynak: *Yazarın hesaplamaları.*

Aşağıdaki Şekil 3, emtia fiyatı getiri serilerine ilişkin grafikleri göstermektedir. Yine grafikler soldan başlayarak sütunlar halinde sırasıyla değerlendirilmiştir. Doğal gaz fiyatları analiz döneminde oldukça dalgalı olmuştur. Bazı haftalarda 28 Aralık

2014'teki düşüş gibi dik kayıplar yaşanırken, diğer haftalarda 3 Aralık 2017 ve 3 Ocak 2010'da görülen önemli artışlar gibi dramatik kazançlar görülmektedir. Enerji piyasalarının karmaşık ve dinamik karakteri, jeopolitik gelişmeler, arz ve talepteki değişiklikler ve piyasa spekülasyonu gibi çeşitli değişkenler oynaklığı etkilemektedir. Her yılın sonunda, oynaklıkta özellikle belirgin artışlar olur ve belirgin mevsimsel eğilimler ortaya çıkar, bazı aylar (Ocak, Mart ve Aralık gibi) diğerlerinden daha fazla oynaklık gösterir.

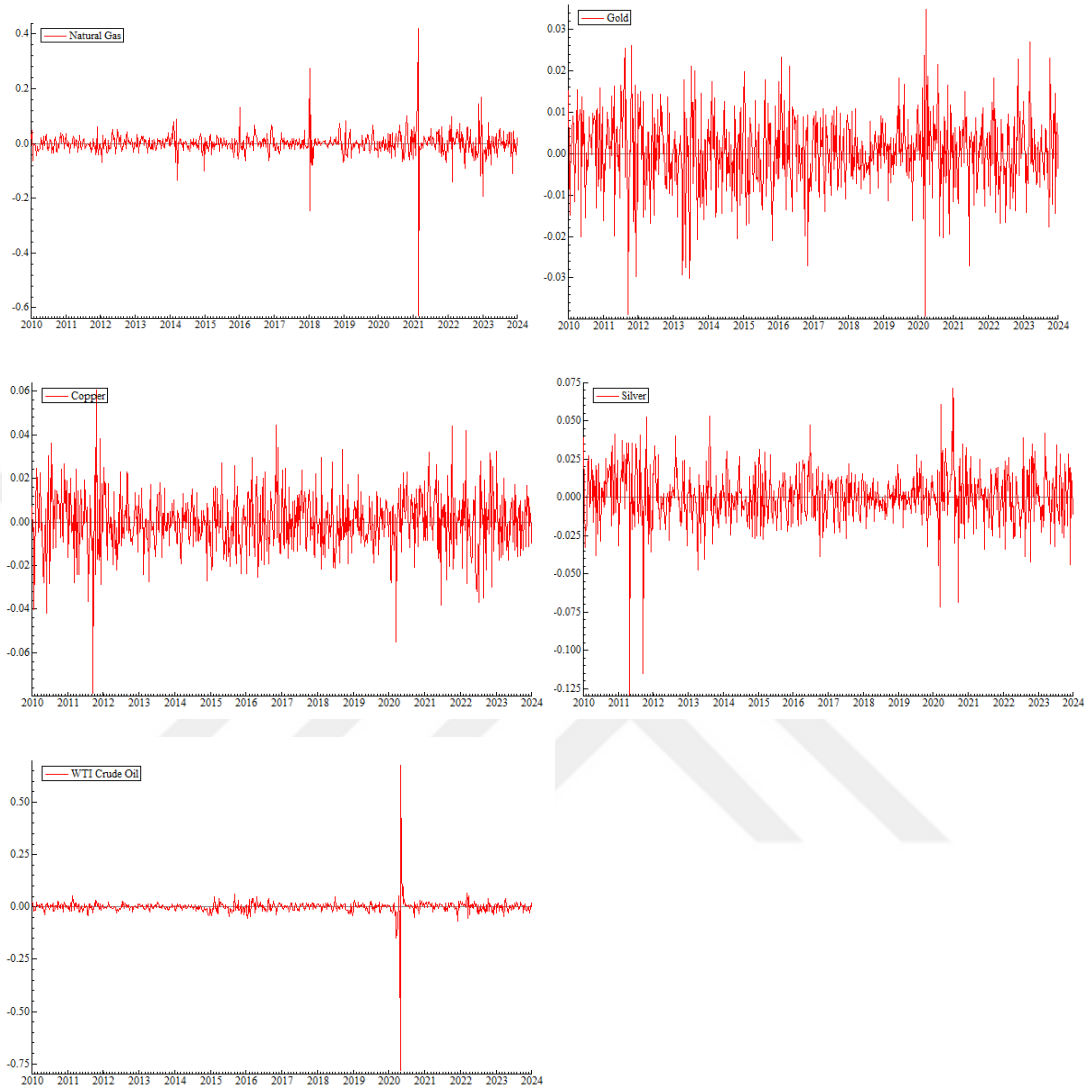
Bakır piyasası yine analiz dönemi boyunca hem olumlu hem de olumsuz dalgalanmalar nedeniyle yüksek oynaklık göstermiştir. 2011'in başlarında, 2013'ün ortalarında ve 2015'in başlarında önemli düşüşler ve 2016'nın sonlarında ve 2017'nin başlarında önemli fiyat artışları da dahil olmak üzere bir dizi önemli fiyat dalgalanması yaşanmıştır. Artış ve düşüş dönemleri genellikle arz-talep dinamiklerindeki değişiklikler veya küresel ekonomik yavaşlamalar gibi daha genel ekonomik eğilimlere veya piyasa şoklarına bağlı olarak gerçekleşmiştir.

WTI Ham Petrol fiyatlarındaki hem olumlu hem de olumsuz haftalık değişimler içeren veriler, petrol fiyatlarının yükseldiği ve düştüğü dönemleri göstermektedir. Bazı aylar büyük dalgalanmalar sergilerken, diğer bazı aylarda istikrarlı artış ve düşüş döngüleri gözlenmiştir (örneğin, 2016'nın başlarında ve 2014'ün sonlarında büyük düşüşler, 2015'in ortalarında ve 2017'nin ortalarında büyük sıçramalar). Dik düşüşlerden sonra güçlü toparlanma dönemleri (2016'nın ortalarında ve 2017'nin başlarında olduğu gibi) ve genel ekonomik koşullar, jeopolitik olaylar veya dünyanın petrol arz ve talebindeki değişimlerle bağlantılıdır.

Altın piyasası 2010-2018 zaman dilimi boyunca düzensiz fiyat hareketleri sergilemiştir. Altın fiyatları bazı haftalarda, örneğin 2011 ortası ve 2016 başı gibi önemli artışlar göstermiş ancak 2011, 2013 ve 2014 sonu gibi diğer haftalarda önemli düşüşler yaşanmıştır.

Gümüş fiyatları analiz döneminde hem olumlu hem de olumsuz yönde önemli ölçüde dalgalanmalar göstermiştir. Tutarlı artış dönemlerinden sonra (2011 başı ve 2016 ortası gibi) belirgin düşüşler (Mayıs 2011 ve 2015 sonu gibi) yaşanmıştır.

Şekil 3: Emtia Fiyatlarının Getiri Serisi



Kaynak: *Yazar tarafından oluşturulmuştur.*

CCC-GARCH ve DCC-GARCH Model Sonuçlarının Değerlendirilmesi

2010'dan 2023'e kadar farklı hisse senedi endekslerinin getirileri arasındaki koşullu korelasyonların tahmini, sekiz gelişmekte olan piyasa ekonomisi için Sabit Koşullu Korelasyon (CCC) Çok Değişkenli GARCH modelinin bulgularını sunan Tablo 1'de gösterilmektedir.

Tablo 1: Borsa Endeksleri Arasında Oynaklık Yayılımı İçin CCC-GARCH Model Sonuçları

Variable	ARCH(1) Coefficient	GARCH(1) Coefficient	p-value (ARCH(1))	p-value (GARCH(1))
XU100	0.9506	0.0184	0.000	0.545
CSI1000	0.1031	0.8595	0.000	0.000
JSKE	0.1332	0.6673	0.000	0.000
SPBSE Sensex	0.1382	0.7099	0.000	0.000
Bovespa	0.1008	0.7379	0.000	0.000
SP_BMVIPC	0.0798	0.8276	0.000	0.000
MOEX Russia	0.2134	0.7400	0.000	0.000
FTSE South Africa	0.1513	0.6521	0.000	0.000

Correlation Estimates between Pairs	Coefficient	z-statistic	p-value	95% CI (Lower, Upper)
(XU100, CSI1000)	0.0829	2.25	0.024	(0.0107, 0.1550)
(XU100, JSKE)	0.0633	1.7	0.089	(-0.0097, 0.1364)
(XU100, SPBSE Sensex)	0.0302	0.81	0.416	(-0.0426, 0.1030)
(XU100, Bovespa)	0.1079	2.93	0.003	(0.0357, 0.1802)
(XU100, SP_BMVIPC)	0.1231	3.35	0.001	(0.0511, 0.1951)
(XU100, MOEX Russia)	0.1291	3.52	0.000	(0.0572, 0.2010)
(XU100, FTSE South Africa)	0.1397	3.81	0.000	(0.0678, 0.2116)
(CSI1000, JSKE)	0.1205	3.29	0.001	(0.0488, 0.1922)
(CSI1000, SPBSE Sensex)	0.0611	1.66	0.098	(-0.0112, 0.1335)
(CSI1000, Bovespa)	0.1363	3.73	0.000	(0.0647, 0.2078)
(CSI1000, SP_BMVIPC)	0.1801	5.02	0.000	(0.1097, 0.2505)
(CSI1000, MOEX Russia)	0.1658	4.6	0.000	(0.0951, 0.2365)
(CSI1000, FTSE South Africa)	0.1600	4.41	0.000	(0.0888, 0.2311)
(JSKE, SPBSE Sensex)	0.2588	7.47	0.000	(0.1909, 0.3267)
(JSKE, Bovespa)	0.3725	11.5	0.000	(0.3090, 0.4359)
(JSKE, SP_BMVIPC)	0.3589	11.01	0.000	(0.2951, 0.4228)
(JSKE, MOEX Russia)	0.2877	8.41	0.000	(0.2207, 0.3548)
(JSKE, FTSE South Africa)	0.3916	12.15	0.000	(0.3284, 0.4548)
(SPBSE Sensex, Bovespa)	0.2535	7.24	0.000	(0.1849, 0.3221)
(SPBSE Sensex, SP_BMVIPC)	0.2636	7.64	0.000	(0.1960, 0.3313)
(SPBSE Sensex, MOEX Russia)	0.1879	5.26	0.000	(0.1178, 0.2579)
(SPBSE Sensex, FTSE South Africa)	0.2399	6.68	0.000	(0.1695, 0.3103)
(Bovespa, SP_BMVIPC)	0.5492	21.09	0.000	(0.4982, 0.6003)
(Bovespa, MOEX Russia)	0.4286	14.11	0.000	(0.3691, 0.4881)
(Bovespa, FTSE South Africa)	0.5004	17.74	0.000	(0.4451, 0.5557)
(SP_BMVIPC, MOEX Russia)	0.4085	13.21	0.000	(0.3479, 0.4691)
(SP_BMVIPC, FTSE South Africa)	0.6011	25.14	0.000	(0.5542, 0.6480)
(MOEX Russia, FTSE South Africa)	0.4168	13.52	0.000	(0.3564, 0.4772)

Kaynak: *Yazarın hesaplamaları.*

GARCH (1) terimleri XU100 hariç tüm endeksler için anlamlı olup bu endekste oynaklık kümelenmesinin azaldığını gösterirken, ARCH (1) terimleri

endekslerde kısa vadeli oynaklığın devam ettiğini gösterir. JSKE ve SPBSE Sensex (0,2588), Bovespa ve SP_BMVIPC (0,5492) ve SP_BMVIPC ve MOEX Rusya (0,4085) gibi endeks çifti arasında önemli pozitif korelasyonlar görülebilir. 4,39'luk bir Wald ki-kare istatistiği, 0,4943'lük bir p değeri ve 17.590,515'lik bir log-olasılık ile model, koşullu korelasyonlar genel olarak sıfırdan önemli ölçüde farklı olmasa dahi iyi bir tahminleme sergilemektedir. JSKE ve FTSE Güney Afrika (0,3916) arasında güçlü ilişkiler de belirgindir. Bovespa, SP_BMVIPC ve MOEX Rusya gibi endekslerin birlikte hareket etme eğiliminde olduğunu gösteren pozitif korelasyonlar da vardır. XU100 gibi bazı korelasyonlar için daha fazla araştırma gerekebilse de, bu bulgular gelişmekte olan piyasa endeksleri arasında dikkate değer oynaklık kümelenmesi ve karşılıklı bağımlılığın varlığını göstermekte olup risk analizi ve portföy yönetimi için yararlı bilgiler sunmaktadır.

Tablo 2'deki DCC GARCH sonuçları bir finansal varlığın (XU100) dinamiklerini ve zaman içinde birçok uluslararası hisse senedi endeksiyle etkileşimlerini göstermektedir. XU100'de 82,69'luk bir z istatistiğiyle, XU100'ün kendisinin gecikmesi için katsayı (L.XU100 = 0,9502) çok önemlidir ve bu da XU100'ün geçmiş değerlerinin gelecekteki değerlerini önemli ölçüde etkilediğini/tahmin ettiğini gösterir. Diğer küresel hisse senedi endeksleri arasında yalnızca S&P BSESensex endeksinin gecikmesi (L.SP_BSESensex = 0,1535) sınırda önemli bir etki göstermektedir (p değeri = 0,058); FTSE Güney Afrika, CSI1000, JSKE ve Bovespa için söz konusu değildir. Analiz edilen endekslerin tümü (XU100, CSI1000, JSKE, vb.) oynaklık kümelemesini ölçen ARCH terimlerine göre XU100'e önemli oynaklık yayılımlarına sahiptir. Tüm p değerleri 0,05'in altındadır ve bu da piyasalar arasında önemli koşullu değişen varyans ve oynaklık yayılımı olduğunu göstermektedir.

Tablo 2: Borsa Endeksleri Arasında Oynaklık Yayılımı İçin DCC-GARCH Model Sonuçları

Variable	Coefficient	Std. Err.	z-Statistic	p-Value
XU100 (ARCH)				
L.XU100	0.9502	0.0115	82.69	0.000
L.CSI1000	-0.0433	0.0435	-0.99	0.320
L.JSKE	0.00796	0.0919	0.09	0.931
L.SP_BSESensex	0.1535	0.0811	1.89	0.058
L.Bovespa	0.0603	0.0724	0.83	0.405
L.SP_BMVIPC	-0.0225	0.1085	-0.21	0.836
L.FTSE South Africa	-0.0171	0.0951	-0.18	0.857
L.MOEX Russia	0.0154	0.0664	0.23	0.817
ARCH (Lag 1)				
XU100 (ARCH)	0.0553	0.0158	3.5	0.000
CSI1000 (ARCH)	0.1082	0.0226	4.78	0.000
JSKE (ARCH)	0.1347	0.0334	4.03	0.000
SPBSE Sensex (ARCH)	0.1454	0.0369	3.94	0.000
Bovespa (ARCH)	0.1009	0.0234	4.31	0.000
SP_BMVIPC (ARCH)	0.0788	0.0195	4.04	0.000
FTSE South Africa (ARCH)	0.1417	0.0336	4.22	0.000
MOEX Russia (ARCH)	0.1996	0.0375	5.32	0.000
Dynamic Conditional Correlations				
(XU100, CSI1000)	0.0374	0.0414	0.9	0.366
(XU100, JSKE)	0.224	0.0397	5.64	0.000
(XU100, SPBSE Sensex)	0.1513	0.0403	3.76	0.000
(XU100, Bovespa)	0.2581	0.0387	6.66	0.000
(XU100, SP_BMVIPC)	0.2835	0.038	7.47	0.000
(XU100, FTSE South Africa)	0.3078	0.0375	8.2	0.000
(XU100, MOEX Russia)	0.2068	0.0397	5.21	0.000
(CSI1000, JSKE)	0.1207	0.0414	2.92	0.004
(CSI1000, SPBSE Sensex)	0.0523	0.0416	1.26	0.208
(CSI1000, Bovespa)	0.1274	0.0415	3.07	0.002
(CSI1000, SP_BMVIPC)	0.1644	0.0411	4	0.000
(CSI1000, FTSE South Africa)	0.1512	0.0409	3.69	0.000
(CSI1000, MOEX Russia)	0.1638	0.0408	4.02	0.000
(JSKE, SPBSE Sensex)	0.2335	0.0397	5.88	0.000
(JSKE, Bovespa)	0.3458	0.0374	9.25	0.000
(JSKE, SP_BMVIPC)	0.3626	0.0368	9.86	0.000
(JSKE, FTSE South Africa)	0.3707	0.037	10.01	0.000
(JSKE, MOEX Russia)	0.261	0.0401	6.51	0.000
Adjustment Parameters				
lambda1	0.0195	0.0059	3.29	0.001
lambda2	0.7899	0.0642	12.3	0.000

Kaynak: *Yazarın hesaplamaları.*

Dinamik Koşullu Korelasyon (DCC) bulguları, XU100 ve diğer endekslerin zamanla değişen korelasyonlara sahip olduğunu göstermektedir. XU100 ile CSI1000 (0,0374) arasındaki düşük ve istatistiksel olarak önemsiz korelasyondan da anlaşılacağı gibi, bu endeksler arasında çok az eş-hareket olduğu görülmektedir.

Bununla birlikte, p değerlerinin hepsi 0,05'in altında olduğundan, XU100, FTSE Güney Afrika (0,3078), Bovespa (0,2581), S&P BSESensex (0,1513) ve JSKE (0,224) gibi diğer endekslerla önemli pozitif korelasyonlar sergilemekte ve bunların hepsi zaman içinde daha güçlü eş-hareket göstermektedir. Ayrıca XU100 ile MOEX Rusya arasındaki 0,2068 korelasyonu da dikkate değerdir. Önemli olarak, diğer endeks çiftleri (örneğin JSKE ve Bovespa veya JSKE ve SPBSE Sensex) arasındaki korelasyonlar sürekli pozitif ve güçlüdür ve bu da bu piyasaların genellikle birlikte hareket ettiğini göstermektedir. Oynaklık şoklarının kalıcı olduğunu gösteren ayarlama/düzeltme parametreleri (lambda1 = 0,0195, lambda2 = 0,7899) özellikle lambda2 oldukça yüksek olup oynaklık sürekliliğini vurgulamaktadır.

Emtialar, döviz kurları ve Borsa İstanbul (XU100) için CCC-GARCH modelinin sonuçları Ek 1'de gösterilmiştir. Bu sonuçlar, bu piyasaların oynaklık dinamikleri hakkında önemli bilgiler sunmaktadır. Güçlü kısa vadeli oynaklık sürekliliği, XU100 ve USDTRY gibi piyasalar için ARCH (L1) katsayıları tarafından gösterilmiştir. XU100'ün yüksek ARCH katsayısı (0,9250), önemli şokların ardından uzun süreli yüksek oynaklık dönemlerini gösterir. Öte yandan, altın ve bakır gibi daha düşük ARCH değerlerine sahip emtialar daha tutarlı oynaklık yapıları gösterir. Uzun vadeli oynaklık sürekliliğini yansıtan GARCH (L1) katsayıları ve yüksek değerlere sahip emtialar (örneğin 0,9151'de bakır ve 0,8852'de altın) önceki dönem oynaklığının gelecekteki dönem oynaklığı üzerinde önemli bir etkiye sahip olduğunu gösterir. Buna karşılık, XU100'ün düşük bir GARCH katsayısı (0,0218) vardır ve bu da kısa vadeli şokların daha yüksek oynaklığa neden olduğunu gösterir. Altın ve gümüş gibi emtialar oynaklıkta güçlü bir pozitif korelasyon (0,8004) sergileyip birlikte hareket ettiklerini öne sürerken, korelasyon katsayısı USDTRY ve XU100'ün oynaklığı arasında negatif bir ilişki olduğunu (-0,1673) göstererek çeşitlendirme etkilerine işaret etmektedir. Ayrıca, USDTRY ve kıymetli madenler arasında negatif bağlantılar vardır. Bu da Türk lirası daha oynak hale geldikçe altın ve gümüşün oynaklığının azalma eğiliminde olduğunu ifade etmektedir. Genel olarak bulgular, kısa vadeli oynaklığın çoğu varlıkta önemli olduğunu, emtiaların ise özellikle enerji ve kıymetli maden piyasalarında kayda değer çapraz piyasa korelasyonlarıyla daha yüksek uzun vadeli oynaklık sürekliliği sergilediğini vurgulamaktadır.

Ek 3’ten görüleceği üzere Sabit Koşullu Korelasyon (CCC) Çok Değişkenli GARCH model sonuçları, farklı emtialar, döviz kurları ve Endonezya hisse senedi endeksi arasındaki önemli oynaklık dinamiklerini ve korelasyonları ortaya koymaktadır. USDIDR (0,8037), Bakır (0,9177) ve Gümüş (0,8894) için istisnai derecede yüksek GARCH terimleri ile büyük oynaklık kalıcılığı gösteren tüm ARCH ve GARCH katsayıları istatistiksel olarak anlamlıdır (p değeri < 0,05), bu da geçmiş oynaklığın her varlık için gelecekteki oynaklığı önemli ölçüde etkilediğini göstermektedir. Korelasyon analizine göre, JSKE'nin USDIDR ile negatif bir ilişkisi (-0,4345) ve bakır (0,2727) ve gümüş (0,2511) ile önemli bir pozitif korelasyonu vardır. Ayrıca, USDIDR'nin hem altın (-0,2378) hem de gümüş (-0,2996) ile negatif korelasyonları vardır, ancak altın ve gümüş nispeten yüksek bir pozitif korelasyona sahiptir (0,8014). WTI Ham Petrol ile Altın ve Doğal Gaz ile Altın arasındaki gibi belirli korelasyonlar ihmal edilebilir düzeydedir ve varlıkların birbirleriyle zayıf bağları olduğunu göstermektedir. Genel olarak, sonuçlar finansal risk analizi ve portföy yönetimi için oynaklığın sürekliliğini ve varlık getirileri arasındaki karşılıklı bağımlılıkları kavramanın ne kadar önemli olduğunu vurgulamaktadır.

Ek 6’da yer alan CCC-GARCH modelinin Meksika'ya ilişkin bulguları, incelenen varlıkların oynaklıkları arasında güçlü bir korelasyon olduğunu göstermiştir. ARCH parametrelerine göre, kısa vadeli oynaklık etkilerini hesaba katan tüm değişkenler önemli oynaklık sürekliliğine sahiptir (tüm p değerleri < 0,05). En yüksek kısa vadeli etki Doğal Gaz'da (ARCH_Doğal Gaz = 0,5736) görülmektedir. Uzun vadeli oynaklık sürekliliğini ölçen GARCH parametrelerine göre, Bakır (GARCH_Bakır = 0,9128) ve Gümüş (GARCH_Gümüş = 0,8884) en istikrarlı oynaklıklara sahiptir. Bu durum, bu varlıkların oynaklıktaki ani dalgalanmalara karşı daha az duyarlı olduğunu göstermektedir. Meksika hisse senedi endeksi (SP_BMVIPC) ve döviz kuru (USDMXN) önemli bir negatif korelasyon (-0,4703) göstererek oynaklıkları arasında ters yönlü bir ilişki olduğunu gösterirken, korelasyon verileri varlık oynaklıklarının nasıl birlikte hareket ettiğini göstermektedir. Bakır ve altın (0,26) ile bakır ve gümüş (0,4331) arasında pozitif korelasyonlar vardır. Altın ve gümüş arasındaki korelasyon özellikle yüksektir (0,8009), bu da oynaklıklarının birlikte hareket ettiğini gösterir. Bunun aksine, USDMXN ile bakır (-0,3176) ve altın (-0,2297) arasındaki korelasyonlar negatiftir, bu da döviz kuru oynaklığı arttığında bu

emtiaların oynaklıklarının azalma eğiliminde olduğunu gösterir. Bu sonuçlar, varlıkların karşılıklı bağımlılıkları ve oynaklık dinamikleri hakkında ışık tuttukları için risk yönetimi ve portföy çeşitlendirmesi için yine önemli sonuçlara sahiptir.

Ek 7'de yer alan Güney Afrika için CCC-GARCH model sonuçları, çeşitli varlıkların (FTSE Güney Afrika, USDZAR, Doğal Gaz, WTI Ham Petrol, Altın, Bakır ve Gümüş) getiri oynaklıkları arasındaki önemli korelasyonları ortaya koymaktadır. Hem GARCH hem de ARCH parametreleri her varlık için pozitif ve istatistiksel olarak anlamlıdır ($p < 0,05$), bu da her varlığın mevcut oynaklığının hem geçmiş koşullu varyans (GARCH terimleri) hem de geçmiş oynaklıktan (ARCH terimleri) etkilendiğini göstermektedir. Örneğin, Bakır için GARCH terimi özellikle yüksektir (0,9198), bu da geçmiş oynaklığın gelecekteki varyansı üzerinde önemli bir etkiye sahip olduğunu göstermektedir. USDZAR'ın diğer varlıklarla ters bir bağlantısı vardır, bu da altın (-0,3447) ve bakır (-0,4009) arasındaki önemli negatif korelasyonlarla kanıtlanmıştır. Öte yandan FTSE Güney Afrika'nın hem bakır (0,3926) hem de gümüş (0,3159) ile pozitif korelasyonları vardır, bu da bu varlıkların genellikle birlikte hareket ettiğini gösterir. Doğal Gaz ve FTSE Güney Afrika ($p = 0,204$) arasındaki gibi bazı korelasyonlar önemli değildir, bu da bu varlıkların oynaklığında fark edilebilir bir ilişki olmadığını gösterir. Tüm bunlar göz önüne alındığında, bu bulgular bu varlıkların oynaklığının tarihsel performanslarından etkilendiğini ve korelasyonların oynaklıklarının nasıl birlikte hareket ettiğine ışık tuttuğunu ve bunun risk yönetimi ve portföy çeşitlendirmesi açısından önemli sonuçlar doğurduğunu göstermektedir.

Zaman içinde oynaklığın güçlü bir şekilde devam ettiği, finansal zaman serileri üzerinde önemli ARCH ve GARCH etkileri gösteren Rusya'nın birincil emtiaları ve döviz kuru için CCC-GARCH model sonuçlarıyla gösterilmiştir. Sıfıra yakın p değerleriyle, modelin zamana bağlı varyansı yakalama yeteneği, MOEX Rusya, USDRUB, Doğal Gaz, WTI Ham Petrol, Altın, Bakır ve Gümüş dahil olmak üzere her varlıkta bulunan önemli gecikmeli ARCH (L1) ve GARCH (L1) terimleriyle doğrulanmıştır. MOEX Rusya, USDRUB ve WTI Ham Petrol önemli GARCH katsayılarına sahipken bakır ve gümüş gibi varlıklar, 1'e yakın GARCH katsayılarıyla görüldüğü gibi daha da büyük bir oynaklık sürekliliğine sahiptir. Varlıklar arasındaki korelasyonlarda önemli bağlantılar görülebilir; örneğin, MOEX Rusya ve USDRUB önemli bir negatif korelasyona (-0,3487) sahipken büyük olasılıkla benzer piyasa

dinamiklerinin bir sonucu olarak altın ve gümüş en büyük pozitif korelasyona (0,8017) sahiptir. Bu bulgular, hem finansal piyasaların davranışını hem risk yönetimini anlamak için oynaklık kümelemesi ve karşılıklı bağımlılıkların kritik önemini vurgulamaktadır.

Yine 2010-2023 dönemi için hisse senedi endeksi CSI1000, USDCNY döviz kuru, doğal gaz, WTI Ham Petrol, altın, bakır ve gümüş olmak üzere yedi değişken arasındaki koşullu korelasyonları ve oynaklık dinamiklerini analiz etmek için DCC-GARCH modeli kullanılmıştır. Burada p değerlerinin çoğunluğu 0,05'ten yüksek olduğundan, gecikmeli değişkenlerin katsayıları CSI1000 ile diğer varlıklar arasında zayıf veya hiç anlamlı korelasyon göstermemektedir. Tüm seriler ARCH ve GARCH parametreleri için yüksek öneme sahiptir ve her bir varlığın oynaklık dinamikleri (ARCH ve GARCH terimleri) önemli bir süreklilik göstermektedir.

Bu, herhangi bir varlığın gelecekteki oynaklığının tarihsel oynaklığından önemli ölçüde etkilendiği anlamına gelmektedir. Altın ve gümüş (0,795) ile bakır ve altın (0,373), bu varlıkların birlikte hareket etme eğilimini gösteren önemli korelasyonlar gösteren iki varlık çifti örneğidir. Ancak, USDCNY, altın, bakır ve gümüşle olan güçlü negatif korelasyonlarıyla kanıtlandığı gibi, döviz kuru ve emtia fiyatları arasında ters yönlü ilişkiler göstermektedir. Lambda2'nin lambda1'e yakın olması, koşullu korelasyonlarda önemli bir sürekliliği gösterirken, aynı zamanda modelin dinamik ayarlama mekanizmasının sağlam olduğunu ifade eder. Tüm sonuçlar dikkate alındığında, model önemli eş hareketleri ve oynaklık yayılma etkilerini vurgularken, farklı finansal araçlar arasındaki oynaklığın karşılıklı ilişkileri ve yayılmalarına ilişkin fikir sunar.

Jakarta Borsası Endeksi (JSKE), USDIDR döviz kuru ve doğal gaz, ham petrol, altın, bakır ve gümüş gibi emtia fiyatlarına ilişkin DCC-GARCH model sonuçları tarihsel şokların ve varyansların şu anda bu değişkenlerin oynaklığı üzerinde bir etkiye sahip olduğunu göstermektedir. USDIDR ve altın arasındaki negatif korelasyon (p = 0,009) gibi bazı dikkate değer istisnalar dışında, bu, USDIDR arttığında altının düşme eğiliminde olduğunu ve birçok değişkenin birbirleri üzerinde asgari düzeyde doğrudan etki gösterdiğini yansıtmaktadır.

S&P BSE Sensex, USD/INR döviz kuru, doğal gaz, WTI ham petrolü, altın, bakır ve gümüş için DCC-GARCH modelinin sonuçları, varlıkların çoğunluğu için

kalıcı oynaklık kümelenmesi (büyük ARCH ve GARCH katsayıları (L1)) göstermektedir. Ayrıca, korelasyon sonuçları belirli varlıklar arasında hem önemli pozitif hem de negatif ilişkiler gösterir. Örneğin, USD/INR ve altın veya bakır negatif bir korelasyona sahiptir ve bu da para birimi değer kaybının genellikle yükselen emtia fiyatlarıyla bağlantılı olduğunu göstermektedir.

Bovespa endeksi, USD/BRL döviz kuru, altın, bakır, gümüş, doğal gaz ve WTI ham petrolüne ilişkin DCC-GARCH modeli sonuçları, oynaklıktaki güçlü sürekliliği ortaya koymuştur. Bovespa ile metaller (bakır, gümüş ve altın gibi) arasındaki pozitif korelasyonlar, koşullu korelasyon matrisindeki dikkate değer ilişkiler arasındadır ve bu varlıkların genellikle birlikte hareket ettiğini gösterir. Tersine, USD/BRL ile bazı varlıklar (örneğin altın, bakır) arasında negatif korelasyonlar vardır ve bu da korunma potansiyelini gösterir.

SP_BMVIPC, USDMXN, doğal gaz, WTI ham petrol, altın, bakır ve gümüş değişkenlerine ilişkin DCC-GARCH modeli sonuçlarında büyük ve istatistiksel olarak anlamlı katsayılar, ARCH ve GARCH terimlerinin her seri için koşullu oynaklıkta önemli bir süreklilik gösterdiğini ifade eder. Korelasyon tahminleri, incelenen zaman boyunca çeşitli varlıklar arasındaki dinamik karşılıklı bağımlılıklara ışık tutar. Örneğin, SP_BMVIPC ile USDMXN arasında önemli bir negatif bağlantı vardır. Tüm modelin önemi, Wald ki-kare testi ($p < 0,001$) ile doğrulanır.

FTSE Güney Afrika, USDZAR, doğal gaz, WTI ham petrol, altın, bakır ve gümüşe ilişkin DCC-GARCH modeli sonuçlarına göre, FTSE Güney Afrika ve USDZAR negatif bir korelasyona sahipken, FTSE Güney Afrika ve bakır, altın ve gümüş pozitif bir korelasyona sahiptir. Doğal gaz, bakır ve gümüş gibi diğer varlıklarla küçük pozitif bağlantılar ve FTSE Güney Afrika ile güçlü negatif korelasyonlar sergilemektedir. Oynaklık için ARCH ve GARCH parametreleri değişkenlerin çoğu için istatistiksel olarak anlamlıdır ve bu da tarihsel şokların ve oynaklık seviyelerinin güncel oynaklık üzerinde önemli bir etkiye sahip olduğunu göstermektedir. Endüstriyel ve kıymetli madenlerdeki ortak hareketler, bakır ve gümüş (0,40) ile altın ve gümüş (0,82) arasındaki güçlü korelasyonlarla vurgulanmıştır. Ek olarak, Wald ki-kare testi (191,88) ve log-olasılık istatistikleri (15.285,6), modelin verilere iyi uyduğunu ve standart önem seviyelerinde güvenilir bulgular ürettiğini göstermektedir.

Lambda değerleri oynaklık dinamiklerinde önemli bir süreklilik gösterdiğinden, model ayrıca zamanla değişen oynaklığı da dikkate almaktadır.

MOEX Rusya hisse senedi endeksi, USDRUB döviz kuru ve çeşitli emtia fiyatları (doğal gaz, ham petrol, altın, bakır ve gümüş) arasındaki DCC-GARCH modeli sonuçlarına göre Wald ki-kare testi (p değeri < 0,0001) ve 15.125,61'lik log-olasılık değeri ile mükemmel bir model uyumu sergilemektedir. Değişkenler arasındaki koşullu korelasyonların derecesi ve yönü anlamlı katsayılara sahiptir. MOEX Rusya hisse senedi endeksi doğal gaz, WTI Ham petrol ve altınla negatif bir korelasyon gösterirken, USDRUB ile pozitif bir korelasyon göstermektedir (0,23), bu da Rus hisse senedi piyasasının genellikle Rus rublesi değer kazandığında daha iyi performans gösterdiğini ifade eder. Ek olarak, model altın ve gümüş (0,82), bakır ve gümüş (0,39) ve bakır ve altın (0,24) gibi emtiaların güçlü pozitif korelasyonlara sahip olduğunu gösterir, bu da söz konusu emtiaların genellikle karşılaştırılabilir yönlerde hareket ettiğini gösterir. ARCH ve GARCH terimleriyle temsil edilen modelin gecikmeli ARCH ve GARCH parametreleri için yüksek öneme sahip olan oynaklık yapısı, özellikle USDRUB, Doğal Gaz ve WTI Ham Petrol için oynaklık şoklarında güçlü bir süreklilik göstermektedir. Bu, yakın dönemdeki oynaklığın gelecekteki piyasa davranışını tahmin etmede ne kadar önemli olduğunu ortaya koymaktadır.

SONUÇ VE TARTIŞMA

2010-2023 arasındaki yılları kapsayan analiz döneminde, Sabit Koşullu Korelasyon (CCC) Çok Değişkenli GARCH modelinin sonuçları, çeşitli gelişmekte olan piyasa hisse senedi endeksleri arasında dikkate değer karşılıklı bağımlılıklar göstermektedir. Modele göre, endekslerin çoğunluğu önemli kısa vadeli oynaklık sürekliliği (ARCH terimleri) sergilemektedir ve bu da son oynaklık eğilimlerinin mevcut risk seviyeleri üzerinde hala etkili olduğunu göstermektedir. Borsa İstanbul hisse senedi endeksi (XU100) hariç, tüm endeksler uzun vadeli oynaklık sürekliliğini ölçen istatistiksel olarak anlamlı GARCH terimlerine sahiptir. Bu, piyasanın oynaklık kümelenmesinin daha az olduğunu göstermektedir. Bovespa ve SP_BMVIPC (0,5492), SP_BMVIPC ve MOEX Rusya (0,4085) ve JSKE ve SPBSE Sensex (0,2588), bu endekslerin sıklıkla birlikte hareket ettiğini gösteren güçlü pozitif

korelasyonlar gösteren hisse senedi endekslerinden sadece birkaçıdır. Bu bulgular, gelişmekte olan piyasa endeksleri arasında yüksek düzeyde bir bağlantı olduğunu göstererek, oynaklık yayılmalarının risk yönetimi ile portföy çeşitlendirmesi üzerindeki olası etkilerinin incelenmesindeki önemi vurgulamaktadır.

DCC-GARCH modeli kullanılarak XU100 ile diğer yabancı hisse senedi endeksleri arasındaki zamanla değişen korelasyonların ve oynaklık yayılmalarının incelemesi sonucunda, XU100 endeksinin geçmiş değerlerinin gelecekteki değerleri önemli ölçüde (L.XU100 = 0,9502) tahmin ettiği anlaşılmıştır. Bu, XU100'ün kısa vadeli oynaklığının oldukça sürekli olduğu anlamına gelir. Ek olarak, FTSE Güney Afrika, JSKE ve CSI1000 dahil olmak üzere analiz edilen endekslerin hepsinde dikkate değer koşullu değişen varyans yapısı vardır ve bu da diğer piyasalardan XU100'e oynaklık yayılmalarının önemli boyutta olduğunu göstermektedir. DCC GARCH modeli kullanılarak XU100 ile JSKE (0,224), S&P BSE Sensex (0,1513), Bovespa (0,2581) ve FTSE South Africa (0,3078) gibi diğer endeksler arasında elde edilen pozitif korelasyonlar, ikili piyasaların zaman içinde birlikte hareket etme eğiliminde olduğunu ve bunun portföy çeşitlendirmesi için önemli sonuçları olduğunu ifade etmektedir.

Özellikle, MOEX Rusya ile zayıf korelasyon (0,2068) ve XU100 ile CSI1000 arasındaki düşük korelasyon (0,0374), tüm gelişmekte olan piyasaların eşit derecede ilişkili olmadığını göstermektedir. Bazı gelişmekte olan piyasa endekslerinin diğerlerinden daha fazla çeşitlendirme avantajı sunabileceği göz önüne alındığında, portföylerini bu piyasalara yaymak isteyen yatırımcılar, korelasyonlardaki bu farklılığı yararlı bulabilirler.

DCC GARCH modelinin oynaklık yapısını temsil etme yeteneği, özellikle de oynaklık şoklarının verilerde ne kadar kalıcı olduğunu vurgulayan ayarlama/düzeltme parametreleri de önemlidir. Yüksek lambda2 değeri göz önüne alındığında, piyasada oynaklık şokunun sürekli bir etkiye sahip olması muhtemeldir. Bu süreklilik, özellikle portföy yöneticileri için önemlidir. Çünkü bu durum, şokların ardından XU100 ve diğer gelişmekte olan endeksler gibi piyasaların uzun süreli yüksek oynaklık gösterme olasılığının yüksek olduğu anlamına gelir. Yatırımcılar, bu zamanla değişen bağlantıları ve oynaklık şoklarının dayanıklılığını daha iyi anlayarak, gelişmekte olan

piyasa hisse senetlerine maruz kalan portföyler için risk yönetimi, korunma taktikleri ve en iyi varlık tahsisi konusunda daha iyi kararlar verebilirler.

Çeşitlendirme fırsatları, Bovespa, SP_BMVIPC ve MOEX Rusya gibi gelişmekte olan piyasa endeksleri arasındaki güçlü pozitif korelasyonlar nedeniyle sınırlı olabilir; bu da bu piyasaların sıklıkla aynı yönde hareket ettiğini gösterir. Diğer gelişmekte olan endekslerle ihmal edilebilir veya zayıf bağlantıları olan CSI1000 endeksi, daha fazla çeşitlilik arayan yatırımcılar için daha cazip çeşitlendirme avantajları sağlayabilir. Varlıkları tahsis ederken, portföy yöneticileri piyasaların ne kadar birbiriyle ilişkili olduğunu değerlendirmelidir; çünkü önemli ölçüde birlikte hareket eden piyasalar, piyasa stresi zamanlarında daha az koruma sağlayabilecektir.

DCC GARCH sonuçları, gelişmekte olan ekonomilere ait finansal varlıkların da yer aldığı portföyleri yönetirken, küresel piyasa oynaklığını hesaba katmanın ne kadar önemli olduğunu vurgulamaktadır. XU100 ile diğer uluslararası endeksler arasındaki dikkate değer oynaklık yayılmaları, gelişmiş piyasa şoklarının gelişmekte olan piyasaların performansını nasıl önemli ölçüde etkileyebileceğini göstermektedir. Bu nedenle yatırımcılar, özellikle küresel piyasada istikrarsızlık olduğunda oynaklık yayılımı olasılığının farkında olmalıdır. Bu taşmalara karşı duyarlılığı azaltmanın bir yolu, daha zayıf korelasyonlara sahip bölgeler arasında çeşitlendirme yapmaktır.

DCC modelindeki yüksek lambda2 değerleri, oynaklık şoklarının sürekliliğini temsil etmektedir. XU100 ve diğer gelişmekte olan piyasa endeksleri gibi piyasaların piyasa kesintilerinden sonra uzun süreli oynaklığa dayanacağını ifade eder. Bu, portföy yöneticileri için zaman içinde dalgalanan volatiliteyi dikkate alan dinamik varlık tahsis stratejilerinin gerekli olduğunu gösterir. Yöneticiler, volatilite yapısını ve zamanla değişen korelasyonları anlayarak, özellikle uzun süreli yüksek risk dönemlerine yol açabilecek küresel olaylara yanıt olarak portföyleri ne zaman değiştirecekleri konusunda daha iyi kararlar alabilirler.

Sonuç olarak, CCC-GARCH ve DCC-GARCH modelleri, gelişmekte olan piyasa endekslerinin ilişkileri ve oynaklık kalıpları hakkında önemli yeni bakış açıları sunmaktadır. Bu bulgular, yatırımcılar ve portföy yöneticilerinin portföy oluşturmayı en üst düzeye çıkarmak, çeşitlendirmeyi iyileştirmek ve uluslararası finans piyasalarında riski başarılı bir şekilde yönetmek için piyasa ortak hareketlerini,

oynaklık sürekliliğini ve risk yayılmalarını anlamalarının ne kadar önemli olduğunu vurgulamaktadır.

CCC-GARCH ve DCC-GARCH modelleri, emtialar, hisse senedi endeksleri ve döviz kurları gibi çeşitli finansal piyasalardaki oynaklık dinamiklerinin kapsamlı bir incelemesini sağlar. CCC-GARCH modeli, özellikle USDTRY döviz kuru ve Borsa İstanbul Hisse Senedi Endeksi (XU100) gibi piyasalarda güçlü kısa vadeli oynaklık sürekliliğini belirler. Bu piyasaların yüksek ARCH katsayıları, önemli oynaklık şoklarının uzun süreli etkilere sahip olduğunu gösterir. Ancak, altın ve bakır gibi daha yüksek GARCH katsayılarına sahip emtialar, tarihsel oynaklığın gelecekteki fiyat değişikliklerinin önemli bir tahmincisi olduğunu gösterir. USDTRY ile kıymetli madenler arasındaki negatif korelasyonlar olası çeşitlendirme faydalarını gösterirken, altın ve gümüş gibi varlıklar arasındaki korelasyonlar oynaklıkta önemli bir eş-hareketi gösterir. Bu sonuçlar, dünya finans piyasalarının ne kadar iç içe geçtiğini ve riski etkili bir şekilde yönetmek için hem kısa vadeli hem de uzun vadeli oynaklık sürekliliğinin önemli olduğunu gösterir.

DCC-GARCH sonuçları ayrıca finansal varlıklar ile küresel hisse senedi endeksleri arasındaki zamanla değişen ve dinamik bağlantıları, özellikle diğer piyasalardan gelen oynaklık yayılmalarını ve XU100'ün tarihsel değerlerle olan tahmin ilişkisini göstermektedir. FTSE Güney Afrika ve BSE Sensex gibi endeksler arasındaki dikkate değer pozitif korelasyonlar, bu piyasaların genellikle zaman içinde birlikte hareket ettiğini göstermektedir ve bu, portföy yöneticilerinin risk değerlendirmesi için faydalıdır. Piyasa bağımlılıkları ve oynaklık yayılmaları değişen küresel koşullara yanıt olarak farklılaştığından, bu korelasyonların zamanla değişen karakteri esnek risk yönetimi tekniklerinin gerekliliğini vurgular. Bu anlayışa sahip olmak, değişen varlık sınıfı bağlantılarına uyum sağlayan stratejiler oluşturmak için esastır.

Güçlü oynaklık sürekliliği, özellikle bakır ve gümüşte emtialara uygulanan CCC-GARCH modeli tarafından da ortaya koyulmuştur. Burada yüksek GARCH katsayıları, tarihsel oynaklığın gelecekteki fiyat dinamikleri üzerinde büyük bir etkiye sahip olduğunu göstermektedir. Çeşitli varlık sınıfları arasındaki korelasyonlar ayrıca döviz kurlarındaki değişikliklerin emtia fiyatlarını nasıl etkileyebileceğini göstermektedir. Örneğin, USD/BRL, bakır ve altın gibi emtialarla negatif bir

korelasyona sahiptir. Çeşitliliği artırmak veya riskleri dengelemek isteyen yatırımcılar, özellikle emtia ve döviz kuru oynaklığının güçlü bir şekilde ilişkili olduğu gelişmekte olan piyasalarda bu fikirleri yararlı bulacaktır. Portföy yöneticileri, bu karşılıklı bağımlılıkları ve zamanla değişen korelasyonları tam olarak anlayarak, çeşitlendirme stratejilerini optimize ederek ve küresel piyasadaki değişikliklere yanıt olarak risk profillerini değiştirerek piyasa oynaklığı dönemlerinde portföy dayanıklılığını artırabilirler.