# Portfolio Diversification and Volatility Spillovers between Energy Stocks and Fossil Fuel Energy Commodities

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# ABSTRACT

In this thesis, we investigate the volatility spillovers among major energy stocks, the electricity index, and fossil fuel energy commodities (crude oil, natural gas, and coal) using firm-level data in an emerging market, Turkey over the period July 18, 2006–December 31, 2021, which covers important economic events worldwide. To do this, we employ [1] Diebold and Yilmaz's (2012) approach to examine both time-varying and invarying volatility spillovers among markets. Our findings reveal that Turkish energy stocks and the fossil fuel energy markets have high interdependencies, which are significantly affected by global political, financial, and extreme events. The volatility spillovers among markets during the COVID-19 outbreak in 2020 exceeded the 2008 global financial crisis. We also examine the volatility connectedness between markets based on frequency domain using various frequency bands (short term, medium term, long term). To do so, we adopt [2] Barunik and Krehlik's (2018) approach and find that the highest performance is recorded in the long horizon compared to short and medium horizons, implying that the impact of volatility spillover transmission from one market to others is persistent (long-lasting) in the Turkish market. Finally, we calculate dynamic conditional correlations (DCC-GARCH), hedge ratios, and optimal portfolio weights for Turkish energy stocks, the electricity index, and fossil fuel energy commodities (crude oil, natural gas, and coal). Implications for both governments and global investors are provided accordingly based on our results.

**Keywords**: Volatility Spillovers, Crude Oil, Natural Gas, Coal, Electricity, Stock Markets

# ÖZ

Bu tezin amacı, firma düzeyinde veri kullanarak Türkiye'deki en büyük enerji şirketlerinin hisseleri, Borsa Istanbul elektrik indeksi ile fosil yakıt enerji hammaddeleri (petrol, doğal gaz, kömür) arasındaki volatilite (oynaklık) yayılımlarını incelemektir. Çalışma küresel olarak önemli ekonomik olayları içeren 18 Temmuz 2006 ve 31 Aralık 2021 tarihlerini kapsamaktadır. Bu amaçlar doğrultusunda tez, iki bölümden oluşmaktadır. Birinci bölümde, piyasalar arasında hem statik hem de dinamik oynaklık yayılmalarını incelemek için [1]Diebold ve Yılmaz'ın (2012) yaklaşımı kullanılmıştır. Bu analizin sonuçlarına göre, Türkiye enerji hisseleri ve fosil yakıt enerji piyasaları arasındaki karşılıklı oynaklık bağımlılığı küresel siyasi, finansal ve diğer krizlerden önemli ölçüde etkilenmektedir. Ayrıca, bulgularımıza göre, 2020'de ortaya çıkan COVID-19 salgını sırasında piyasalar arasındaki oynaklık yayılmaları 2008 küresel finansal krizi sırasındaki seviyeyi geçmektedir. İkinci bölümde ise çeşitli frekans bantlarını (kısa vadeli, orta vadeli, uzun vadeli) kullanarak piyasalar arasındaki oynaklık bağlantısı incelenmiştir. Bunun için [2]Barunik ve Krehlik'in (2018) yaklaşımı kullanılmış ve en yüksek oynaklık yayılma aktarımının uzun dönemde gerçekleştiği görülmüştür. Diğer bir deyişle, Türkiye'de bir piyasadan diğerine volatilite yayılma aktarımının etkisi kalıcıdır (uzun vadelidir). Son olarak ise yatırımcılar için dinamik koşullu korelasyonlar (DCC-GARCH), hedge rasyoları (riskten korunma oranları) ve portföylerindeki varlıklar için optimal portföy ağırlıkları hesaplanmıştır.

**Anahtar Kelimeler**: Oynaklık Yayılmaları, Petrol, Doğal Gaz, Kömür, Elektrik, Hisse Senedi Piyasası

# DEDICATION

*Dedicated to My Family*

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| | |
|---|---|
| AIC | Akaike Information Criterion |
| ARCH | Autoregressive Conditional Heteroskedasticity |
| ARMA | Autoregressive Moving-Average Models |
| BIST | Borsa Istanbul |
| BRICS | Brazil, Russia, India, China, South Africa |
| CAPM | Capital Asset Pricing Model |
| DCC | Dynamic Conditional Correlations |
| EU | European Union |
| G7 | Group of Seven |
| GARCH | Generalized Autoregressive Conditional Heteroskedasticity |
| GCC | Gulf Cooperation Council |
| GFC | Global Financial Crisis |
| GFEVD | Generalized Forecast Error Variance Decomposition |
| JB | Jarque-Bera |
| MENA | Middle East and North Africa |
| MGARCH | Multivariate Generalized Autoregressive Conditional Heteroskedasticity |
| MPT | Modern Portfolio Theory |
| MSCI | Morgan Stanley Capital International |
| NBP | National Balancing Point |
| OPEC | Organization of the Petroleum Exporting Countries |
| RW | Rolling Window |
| TCI | Total Connectedness Index |
| U.S. | United States |

| | |
|---|---|
| UK | United Kingdom |
| VAR | Vector Autoregression |

# Chapter 1

# INTRODUCTION

Global primary energy demand is expected to increase by over 25% from 2017 to 2040, and this rate could double if sufficient energy improvements are not implemented [3]. More specifically, the largest share of global energy demand belongs to fossil fuels such as crude oil, natural gas, and coal, which has remained unchanged for 25 years [3]. Therefore, crude oil, natural gas, and coal are the main energy commodities of the global energy system. In this regard, the impact of these fossil fuel energy commodities on the stock markets is of great importance for investors' portfolio strategies and policymakers. Crude oil is a major energy commodity for the stock markets because it directly affects expected cash flows or discount rates as a strategic material for production and can affect the demand for output at both the sector and national level [4]. It is also important to note that unexpected increases in oil prices cause inflation, and as a result, central banks implement contractionary monetary policies as a precaution, causing interest rates to rise. Hence, higher interest rates will increase discount rates, which in turn will lower stock prices [5]. In terms of volatility connectedness among oil-stock markets, Sadorsky [6] can be considered one of the pioneering studies indicating the existence of a relationship between oil volatility shocks and stock returns, followed by Papapetrou [7] and some more recent evidence [8–14]. Furthermore, natural gas is another vital energy commodity and has a strong linkage with crude oil in terms of being an alternative input for production [15]. Hence, natural gas is considered a substitute energy commodity for crude oil, and their volatility can affect each other [5]. Similar to crude oil, higher natural gas prices may cause higher inflation in oil-importer countries, and stock markets can be affected negatively [16, 17]. Regarding volatility connectedness between natural gas and stock markets, recent researches [16, 18–23] offer fresh evidence from the literature. Finally, coal is also an important energy commodity, accounting for 27% of the world's primary energy consumption in 2019. Moreover, 36.4% of total electricity generation was produced by coal worldwide in 2019 [24]. It can be also considered as a substitute for crude oil in case of higher crude oil prices [10]. Regarding volatility spillovers among coal and stock markets, [25–29] are the researchers who have examined coal in the energy literature. Overall, the interest in the volatility of other fossil fuel energy commodities, such as natural gas and coal, has been relatively limited compared to crude oil. To fill this gap, we examine three main energy commodities (crude oil, natural gas, and coal) together and explore their volatility connectedness with energy stocks in an emerging market.

Our sample country is Turkey. The reasons for choosing this country can be described as follows. First, the country has highly limited fossil fuel reserves compared to its demand. Therefore, Turkey is import dependent in terms of energy [30]. For instance, Turkey is more than 99% dependent on natural gas imports, and owing to the country's limited natural oil resources, more than 90% of its crude oil needs are supplied through imports. These are among the main reasons for the increase in the foreign trade deficit in Turkey [31]. Second, according to the Turkish Energy Market Outlook [30], fossil fuel energy commodities such as crude oil, natural gas, and coal are the primary energy sources in Turkey. In detail, the electric power sector has the highest primary energy consumption (43.8%), and natural gas and coal are the main energy sources of this sector (41% each). Transportation is the second-largest sector (20.2%), and 98% of the sector's energy need is met by oil. Moreover, the lowest energy user is the industry sector (16.2%), and the main source of the sector is coal followed by natural gas, with 57% and 37% respectively. Therefore, fossil fuel energy commodities are vital for the sectors and households of Turkey. In this regard, fluctuations in fossil fuel prices caused by global economic and political events will also affect a net importer such as Turkey significantly. Third, individual country studies can shed more light on volatility connectedness between the energy market and energy stocks, and to the best of our knowledge, this connectedness between energy stocks by considering all three main commodities (crude oil, natural gas, and coal) of the energy market has not been studied for the Turkish market before. Hence, our study will probably be the first to concern the volatility spillovers in the fossil fuel energy market by taking into account crude oil, natural gas, and coal together as well as Turkish energy stocks at the firm level.

Our contributions to the empirical literature can be described in three ways. (1) The existing literature on the volatility connectedness between fossil fuel commodity and stock markets is generally focused on crude oil–stock market linkage by covering advanced stock markets at the aggregate or sectoral level. However, the response of individual stocks to energy prices may vary, and the reaction of emerging stock markets to different fossil fuel energy commodities (e.g., natural gas, coal) still needs to be explored. Because using the aggregate or sectoral level indices prevents us from investigating the heterogeneity at the firm level, we fill this gap in the growing literature by using individual stocks of energy companies in an emerging country (Turkey) and examining their volatility transmission mechanism with crude oil, natural gas, and coal. To do this, we use publicly Turkish-listed firms in the energy sector (TUPRS, COSMO, IPEKE, TRCAS) based on their market capitalization because they are the largest players in the Turkish market and can represent the dynamics of Turkish energy stocks. We also use the Borsa Istanbul (BIST) Electricity Index to take into account firms that make up the electrical energy sector in Turkey. (2) We examine time-invarying and time-varying volatility spillovers using a new method of Diebold and Yilmaz (2012) among fossil fuel energy commodities (crude oil, natural gas, coal), Turkish energy stocks, and electricity index considering important global economic and political events such as the 2008 global financial crisis (GFC) and 2020 COVID-19 pandemic crisis. The method allows us to investigate spillovers among markets in a directional manner, which is important for portfolio diversification and policy decisions. Therefore, we can examine which crisis period and which fossil fuel volatility has the greatest impact on the volatility of Turkish energy stocks. (3) To capture more comprehensive dynamics of interlinkage among markets, we also adopt another new method by Barunik and Krehlik (2018). This method enables us to examine volatility spillovers at various investment horizons (short-term, medium-term, and long-term). Further, we can examine whether volatility spillover transmission from one market to others is persistent (long-lasting) or temporary with this method. (4) Finally, we calculate dynamic conditional correlations (DCC-GARCH), hedge ratios and portfolio weights of Turkish energy stocks and fossil fuel commodities, which will provide more insightful information to investors in the energy market.

The remainder of this thesis is as follows. In Chapter 2, we review the literature on each fossil fuel energy commodity and stock markets separately. In Chapter 3, we provide the theoretical background of the research. In Chapter 4, we explain the data and the methodology used in the study. In Chapter 5, we present empirical findings, and we calculate dynamic conditional correlations (DCC-GARCH), time-varying hedge ratios and optimal portfolio weights in Chapter 6. Finally, we conclude with policy implications for governments and global investors in Chapter 7.

# Chapter 2

# LITERATURE REVIEW

## 2.1 Oil–Stock Markets Volatility Spillover Nexus

In the energy finance literature, numerous researchers examine the volatility spillover transmission between crude oil and stock markets at different levels of stock market aggregation. Ågren [32] was one of the earliest authors to confirm the strong evidence of volatility spillovers between oil and five developed stock markets, namely Japan, Norway, Sweden, the United Kingdom, and the United States, except for the Swedish stock market. Similarly, Khalfaoui et al. [33], who also examined the spillover relationship between developed equity and oil markets, stated that there is a significant volatility spillover between oil and G7 stock markets with the dominant transmission role of the oil market. To model the volatility transmission, Maghyereh et al. [34] adopted 11 major global stock exchanges and oil prices for a sample from 2008–2015. They found a bidirectional volatility spillover. However, it was significantly dominated by the oil market to stock markets. The authors also indicated that the intensity of the volatility spillover relationship varies over time. The most intense period is when the recovery from the impacts of the 2008 GFC began (from mid-2009 to mid-2012). According to Ewing and Malik [35], strong volatility spillovers only exist when structural breaks are taken into account. Otherwise, there is no significant volatility linkage. On the contrary, some researchers [36, 37], who also examined the spillover relationship between major global equity markets and oil prices, found little or limited evidence of volatility spillovers between the oil market and financial markets. Whereas the aforementioned scholars adopted advanced stock markets as a sample, many other researchers have also examined the volatility spillover relationship between oil and stock markets for mixed samples using developed and emerging markets, or only emerging stock markets. For instance, Malik and Hammoudeh [38] examined the volatility interaction among global oil prices, the U.S. stock market, and Gulf countries' stock markets from 1994–2001. Their findings show a significant interaction between global oil prices and the U.S. stock market. The authors also indicated that the oil market is a volatility transmitter to three Gulf stock markets, whereas only the Saudi equity market is a volatility transmitter to the global oil market. To capture the connectedness between oil and stock markets, Antonakakis et al. [39] analyzed equity markets of major oil-importing and oil-exporting countries and Brent crude oil prices from 1995–2013. The authors concluded that there is a connectedness between variables that varies across time, and the direction of connectedness changes according to global economic developments. In their mixed sample study, Cevik et al. [40] indicated that there is no Granger-causality-in-variance stemming from global oil market prices to stock market returns, however, there is causality from stock returns of G7 countries to the stock returns of MSCI emerging countries. Yıldırım et al. [41] investigated the dynamic relationship between crude oil prices and BRICS stock markets for the periods of 1995-2016. They found that the stock markets (except China) give a positive and statistically significant reactions to an unexpected oil price shock in the case of a high-volatility regime. Arouri et al. [42] measured the relationship between oil prices and Gulf Cooperation Council (GCC) equity markets from 2005–2010. They found that a significant volatility spillover exists between oil and GCC equity markets, and this interaction has been observed mainly during the crisis sub-period. Similarly, Awartani and Maghyereh [43] investigated volatility transmission between oil and stock markets of GCC countries for the period of 2004–2012. Their findings suggested a bidirectional volatility transmission. Besides, the oil market transmits more volatility to other markets than it receives, and these patterns in oil intensified after the 2008 GFC. In a recent study, Tien et al. [13] also analyzed the volatility spillovers transmission between stock markets of GCC countries and the oil market for the period of 2008–2019. The authors underlined the presence of time-varying characteristics of volatility transmission between oil prices and GCC equity markets. They also intimated that these spillover impacts spread in different periods. Cevik et al. [44] is another study examining a developing country and found a significant volatility spillover impact stemming from crude oil price to stock market returns for Saudi Arabia between 2001-2018. Bouri [45] studied volatility interaction between the oil market and stock indices of Jordan and Lebanon, which are two members of MENA, from 2003–2013. According to their findings, volatility spillover is much more obvious from the global oil market to the equity market of Jordan than in the opposite direction. Adversely, oil volatility is not found as a good predictor of volatility in the Lebanese equity market. Cevik et al. [46] focused on the linkage between oil prices and the Turkish stock market index from 1990–2017. The authors concluded that there is no significant spillover impact from oil prices on Turkish stock market returns in the full sample. On the contrary, significant spillover effects were observed in 1993 and during the 2008–09 GFC. In a recent study, Wu et al. [47] found significant predictive information of spillovers transmitted by stock markets to the oil market. In another recent study, Mensi et al. [11] stated that volatility spillover is found among oil, the U.S. stock market, and gold for the sample period of 2018–2020.

Existing empirical studies' authors have also investigated the oil–stock market volatility spillover interaction at the sectoral/industrial level. For example, Malik and

Ewing [48] provided evidence of significant volatility co-movement between oil prices and some of the examined industries by using five major market sectors in the United States. Furthermore, Elyasiani et al. [49] also analyzed oil prices and sectoral stock returns in the United States. They provided a more comprehensive study by using more sectors. The results show that 9 out of 13 sectors are affected by oil futures returns and/or oil futures return volatility. Further, volatilities of industry excess returns were found to be time-varying, and return volatility of some sectors has a long memory. Arouri et al. [50] adopted two different samples of U.S. and European equity markets. They concluded that there is a significant volatility transmission between oil and sectoral stock returns. The direction of the spillover was found to be mostly one-way from oil markets to equity markets in Europe, and two-way in the United States. Moreover, Sadorsky [51] examined the volatility linkage between stock prices of companies in two different industries and oil markets in the United States for the period 2001–2010. They indicated that the correlation between the U.S. stock prices of clean energy and technology firms is higher than between clean energy and oil price volatility. In another study on the sectoral level, Antonakakis et al. [52] used 12 major oil and gas firms. Findings suggest that a significant volatility spillover impact between oil and oil and gas companies exists, and the direction of spillover is mostly one-way from stock volatility of oil and gas companies to oil volatility. Regarding the emerging stock markets, Caporale et al. [53] and, recently, Li et al. [10] questioned how the volatility transmission between oil and sectoral stock markets varies in China. According to Caporale et al. [53], oil price volatility increases stock returns (except in the consumer services, financials, and oil and gas sectors) during demand-side shock periods, whereas it is found to be insignificant in precautionary demand shock periods. The conclusion obtained from the recent study by Li et al. [10] is that the international crude oil market transmits strong volatility spillover to

Chinese energy futures markets in the long run. This transmission was observed significantly during the COVID-19 outbreak. In their study, Soytas and Oran [54] examined whether there was a volatility spillover among world oil spot returns, Turkish electricity index return, and the aggregate stock market index from 2003–2007. The authors revealed that world oil spot returns have a limited bidirectional volatility spillover with Turkish electricity returns, but they do not have a spillover relationship with stock market returns. Moreover, Hamma et al. [55] investigated the volatility linkage between the oil market and seven sector indices of Tunisia for the sample period of 2006–2012. According to their findings, volatility transmission is mainly one-way from the oil market to the Tunisian stock market.

As we have mentioned, the volatility spillover nexus between oil and stock markets has been investigated in previous literature from different perspectives using developed and emerging stock markets at either aggregate or sectoral levels. However, the relationship between other energy commodities such as natural gas or coal and stock markets in terms of volatility transmission has not been deeply investigated. In the following subsection, we will explain the newly growing literature on the volatility relationship between the stock market and other energy commodities (natural gas and coal).

## 2.2 Natural Gas, Coal–Stock Markets Volatility Spillover Nexus

The existing literature on the volatility spillovers among the natural gas, coal, and stock markets can be divided into two groups based on the aggregation of stock markets. At the aggregated stock market level, Vardar et al. [23] focused on the five major commodity prices, including natural gas and crude oil, and stock market indices of 10 major advanced and emerging countries for the period of 2005–2016. Their findings revealed a bidirectional volatility spillover between stock and commodity returns for both developed and emerging countries. Moreover, they indicated that most of the spillover effects were observed during the crisis and postcrisis period instead of the precrisis period for all countries. In contrast, Ahmed [18] found a one-way mean and volatility spillover transmission impacts from natural gas prices to the stock market of Qatar, and the stock market reacts slowly to changes in natural gas. To model the volatility spillover linkage among coal, natural gas prices, carbon emissions, and German energy markets, Green et al. [20] revealed that volatility spillover impacts have a considerable magnitude and vary over time and across commodities. During the sample period of 2008–2016, coal and natural gas generated nonnegligible spillovers. In another study, Kumar et al. (2020) [17] used a more extended sample period from 1997–2019. They explained that energy commodities (natural gas and crude oil) do not transmit volatility spillover to the Indian equity market. Besides, crude oil and exchange rates do not give volatility spillovers to natural gas; however, it receives spillovers from the stock market and gold prices. To analyze how the volatility transmission varies in the crisis periods (i.e., 2008 GFC and COVID-19 pandemic), Jebabli et al. [21] investigated natural gas and oil prices and global, European, and emerging stock market indices between 2000 and 2021. Their findings suggested that volatility spillovers between energy and stock markets hit a new record during the COVID-19 pandemic, surpassing the 2008 GFC. During the 2008 GFC, all stock markets were net volatility transmitters to energy markets. During the COVID-19 pandemic, the world stock market is a net transmitter to the energy market; on the contrary, the European stock market is a net receiver of volatility from energy markets. During the COVID-19 pandemic, the emerging stock market gives volatility spillover to crude oil and receives volatility spillover from natural gas. Geng et al. [16] examined the volatility spillovers among natural gas prices, uncertainty indices, and stock market indices in the United States and Europe. According to their findings, the North American natural gas market is the volatility transmitter to other variables except the U.S. stock market and stock market volatility index. Conversely, the European natural gas market is the volatility transmitter for the stock market and energy market uncertainty and receiver from economic policy uncertainty. In a recent study, Costola and Lorusso [19] used three energy prices (natural gas, coal, and oil). They aimed to analyze the volatility linkage among the mentioned three energy prices, international equity markets (United States, China, EU), the Russian stock market index, and six Russian sectoral stock indices for the period of 2005–2022. The authors concluded that energy industries are net volatility spillover transmitters to energy commodities in Russia. From their sector-specific findings, Costola and Lorusso [19] also indicated that the oil and gas sector provide the highest volatility spillovers during energy discussions and geopolitical tensions. For the metals and mining sector, the highest spillovers are obtained when there is a specific shock to the industry. Moreover, the energy commodity volatility spillovers are affected by geopolitical uncertainty in Russia.

Another line that the previous researchers has explored is the linkages among natural gas, coal, and stock markets at the sectoral/industrial level. For instance, Lin and Chen [26] examined the volatility spillover connectedness among the coal market, stock market of new energy companies, and Chinese carbon emission trading market from 2013–2017. They underlined the volatility spillovers transmission from the coal market to the new energy stock market and vice versa. To capture the volatility interrelationship between energy and electricity markets, Liu et al. [56] investigated three energy markets (coal, natural gas, and oil) and the electricity market in Europe over the period of 2007–2019. The authors suggested that the highest return spillover effect is obtained from natural gas to spot and futures electricity markets, which are followed by coal and oil. Furthermore, they found that volatility spillovers are sensitive to extreme financial events. Similarly, Zhang et al. [29] also examined the volatility relationship between energy and electricity markets between 2009 and 2019. The researchers questioned whether excluding coal and including North America would have an impact on the volatility connectedness between variables. According to their findings, first, volatility and return spillovers are stronger in Europe compared to North America; second, crude oil has a greater volatility spillover than natural gas for North American and European electricity utility stock indices. In addition, volatility and return remained constant in North America and Europe from 2009–2012, which may be owing to the 2008 GFC. Then, a fluctuation started at the end of 2013 because of some extreme events, implying that spillover effects can be significantly affected by such events.

In summary, the relevant literature on the volatility linkage between fossil fuel energy and stock markets is generally focused on oil–stock market linkage by adopting advanced stock markets at the aggregate or sectoral level as aforementioned. However, the connectedness between firm-level energy stocks and the fossil fuel energy market in terms of volatility may change. In addition, the reaction of emerging stock markets to different fossil fuel energy commodities (e.g., natural gas, coal) has not been deeply investigated. The only two papers to concern this matter Jebabli et al. [21] and Liu et al. [56] are similar to our study in terms of their authors investigating the volatility spillovers between energy commodities and stock markets. These scholars investigated the volatility connectedness between main energy commodities such as oil, natural gas, and coal and the aggregate/sectoral stock market and electricity indices in developed countries. To consider heterogeneity at the firm level, we use individual stocks of energy companies in an emerging country, Turkey, and examine their volatility transmission with oil, natural gas, and coal.

# Chapter 3

# THEORETICAL BACKGROUND

This chapter aims to explain two main theories to figure out how to optimally manage a portfolio. These main theories are the Modern Portfolio Theory (MPT) and the Capital Asset Pricing Model (CAPM).

## 3.1 Modern Portfolio Theory

The MPT has been introduced by Harry Markowitz [57], and it is comprised of both Markowitz' Portfolio Selection theory introduced in 1952, and William Sharpe's contributions to the theory of financial asset price formation, first introduced in 1964, and known as the Capital Asset Pricing Model (CAPM) [58]. The MPT is based on the "risk-return" framework. This theory helps investors to minimize market risk while maximizing their return. According to the theory, it is possible to design an optimal portfolio (efficient portfolio) that maximizes returns by taking on a quantifiable amount of risk. The risk that investors take can be reduced through diversification using a quantitative method.

The modern portfolio theory has three main components: the risk and the return of the investment, and the correlation of the investment with other investments in the portfolio [59]. The definition of financial risk is the deviation away from expected historical returns during a certain period. The Markowitz's portfolio selection theory states that the essential aspect is the contribution of each asset to the risk of the aggregate portfolio instead of the risk of each asset [60]. The MPT considers two types of risk for security in the portfolio and assumes that these risks are both crucial for each portfolio. The first type of risk is called systematic risk (undiversifiable risk, market risk, volatility, or common risk), and the second type of risk is an unsystematic risk (diversifiable risk). Systematic risk has a form of macro-level risk, and it has an impact on the overall market, not only on a specific industry or stock. For instance, economic, and financial factors (e.g. recessions, the level of inflation, and interest rates, fluctuations in exchange rates) or geopolitical conditions such as war are all examples of systematic risk and they can not be eliminated. On the other hand, unsystematic risk has a form of micro-level risk, and it is specific to an individual company, or a single asset. The management of the company causes lower credit ratings or strikes, and the financial condition of the company may cause unsystematic risk. However, the unsystematic risk can be reduced through diversification [61].

According to modern portfolio theory, the expected return is used in order to anticipate a portfolio's (or security) expected return. In this regard, a risky asset portfolio's expected return is described in Eq 3.1 below:

$$E\left(r_p\right) = \sum_{i=1}^{n} w_i E\left(r_i\right) \tag{3.1}$$

where $E\left(r_p\right)$ represents the expected return of the portfolio, $w_i$ indicates the weight of each security in the portfolio, and $E\left(r_i\right)$ represents the expected return for this security in the portfolio. The correlation (correlation coefficient) indicates the co-movement between two assets [62]. To measure the correlation between two securities, we can use correlation coefficient which can be calculated by dividing the covariance to standard deviations of those two securities as follows:

$$\rho(x,y) = \frac{\operatorname{cov}(x,y)}{\sigma(x), \sigma(y)} \tag{3.2}$$

where $\rho(x,y)$ represents the correlation coefficient between two securities (X and Y), cov(X,Y) indicates the covariance between those securities, and $\sigma(x)$,$\sigma(Y)$ defines the standard deviation of the securities. If the correlation coefficient between a pair of assets is positive $\rho(x,y) > 0)$, then these assets are positively correlated. However, if the correlation is negative $\rho(x,y) < 0)$ between two assets, then these assets are negatively correlated. In the case of correlation of zero between two assets $(\rho(X,Y) = 0)$, those two assets are uncorrelated [63]. The lower correlation between stocks in the portfolio leads higher benefits from diversification. In other words, the lower correlation between securities in the portfolio, the higher the returns of the portfolio for a same level of risk [62]. Hence, the correlation is crucial factor for investors to have a greater risk reduction for their portfolios.

The allocation of the investor's wealth which is called the "Diversification or Diversification Effect" is a main principle of Markowitz's portfolio theory. The concept of diversification allows investors to maximize their returns and minimize the risk in their portfolio. To do this, investors can allocate their investments among different financial instruments. For instance, they can use stocks, various asset classes such as bonds, real estate, etc., and different types of commodities (gold, silver, oil, natural gas etc.) as financial instruments. Moreover, the benefits of investors' diversification increase when more financial instruments (not perfectly correlated) are added to the portfolio. However, there are two arguments regarding diversification. First, portfolio diversification causes transactional costs. Therefore, investors must take into account the transactional costs of their portfolio diversification, and evaluate whether costs are higher than benefits. Secondly, diversification can not eliminate all risk as Markowitz [64] argued. The reason behind this is the systematic risk (market risk, undiversifiable risk) which is caused by external factors, and has a significant impact on all companies. Hence, the systematic risk can not be eliminated or decreased by diversification.

The Efficient Frontier which is also called Markowitz Efficient Frontier includes the best combination of securities (combinations that give maximum expected return for a given risk level) [65]. Fig 3.1 represents the relationship between expected returns of portfolio and variance (riskiness or volatility) of the portfolio. Portfolios lying on the blue line between B and C are referred optimal portfolios with the highest return for a given level of variance (risk or volatility), while other portfolios on the graph are considered as not optimal portfolios.

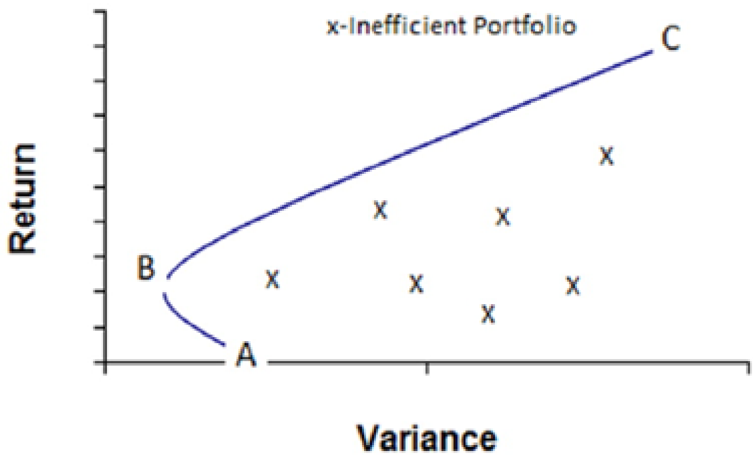



Figure 3.1: Markowitz efficient frontier

Markowitz's portfolio theory has some limitations besides its theoretical importance. The assumptions of the theory are criticized for being not in line with the real world. The first critics stem from irrational decisions of investors. The MPT assumes the adverse that investors are rational and their aim is to maximize their portfolio's return and minimize the risk of their portfolio. However, market participants have "herd behavior" in their investment decisions and tend to 'hot' sectors. This leads to speculative excesses, and the market booms or bursts regularly [66]. The MPT is also assuming that higher risk means a higher return. In other words, the theory assumes that investors are willing higher risks if they are compensated with higher expected returns. On the other hand, investment strategies may require investors to take on a perceived risky investment such as futures or derivatives to decrease overall risk [61]. Moreover, the MPT assumes that the markets are perfectly efficient [64]. Conversely, there are some potential failures in the market, and the theory does not consider them. For instance, information asymmetry, externalities (benefits or costs which are not transferred by security prices), etc. [66]. Other examples to indicate that markets are not efficient can be a market crisis, bubbles, booms, and busts. It is also important to note other critics of the MPT regarding its assumptions such as transaction costs and taxes, perfect information, unlimited access to capital, etc.

## 3.2 Capital Asset Pricing Model

To manage an optimal portfolio, the Capital Asset Pricing Model (CAPM) is the second theory which that has been developed by William Sharpe [67]. Sharpe (1964) [68] defined a market equilibrium of asset prices under the risk, and add two additional assumptions to obtain a market equilibrium based on the same foundation as Markowitz and Tobin. First, each investor can both borrow and lend without being exposed to any restriction at the risk-free rate. Second, the theory assumes that every investor has homogeneous preferences [68]. According to the CAPM, systematic risk and firm-specific risk need to be separated since the return on an investment is affected by systematic risk, however, firm-specific risk does not have an impact on the return of an investment [67]. The following equation is the definition of the expected return according to the CAPM. As the CAPM is based on the risk-return framework, the equation indicates the relationship between the risk and the return of an investment [69] as follows:

$$E\left(r_i\right) = r_f + \beta_i \left[E\left(r_M - r_f\right)\right] \tag{3.3}$$

where $E(r_i)$ represents the expected return of asset i, $r_f$ indicates the risk-free rate, and $E(r_M)$ is the expected return of the market portfolio. $\beta_i$ defines the sensitivity between asset i and the market portfolio.

# Chapter 4

# DATA AND METHODOLOGY

## 4.1 Data

In this study, we used daily prices (in US$) from 07/18/2006–12/31/2021 for publicly Turkish-listed firms in the energy sector (TUPRS, COSMO, IPEKE, TRCAS), the BIST Electricity Index (XELKT), which is traded on the Borsa Istanbul (BIST), and main fossil fuels futures markets (Brent crude oil, natural gas, and coal). The data descriptions are indicated in Table 4.1. To calculate volatility for each series, we used absolute of return series. We collected all data from Datastream, including a total of 3,640 observations. The chosen period enabled us to examine various important economic events that affected not only global markets but also the Turkish market. The choice of Turkish energy firms that are traded on the Istanbul stock exchange was based on their market capitalization (for more information, see Table 4.2). Selected firms with the highest market capitalization can be considered the largest players in the Turkish market and may represent the dynamics of Turkish energy stocks. We also used Brent crude oil, natural gas, and coal as a representative of the energy market. For benchmarks of energy futures, we considered Brent Crude Energy Future, Rotterdam Coal Energy Future, and United Kingdom (UK) National Balancing Point (NBP) Natural Gas Energy Future, which are traded on the Intercontinental Exchange Futures Europe commodities market. The reasons for using them are as follows. First, we used Brent-type crude oil because it is one of the most liquid crude oil markets in the world and is generally employed in Turkey. Second, we used the UK NBP natural gas futures because it is considered a major benchmark in Europe. Third, we employed Rotterdam Coal Futures because it is the standard benchmark price reference for coal imported into northwest Europe. The descriptive statistics for all volatility series are presented in Table 4.3. According to our findings, natural gas is the most volatile market. Regarding skewness, all volatility series are greater than the reference value of 0, implying that they are right-skewed. The skewness value of coal is the highest, followed by natural gas. This is an indication that the largest extreme movements or largest realized volatility occur in coal and natural gas, respectively. Based on kurtosis, all volatility series have a kurtosis value greater than the reference value of 3, implying that they are leptokurtic, and tails are fat and peaked. We also found a fairly high kurtosis value for coal, and it was followed by natural gas once again. For the normality test of Jarque-Bera, we rejected the null hypothesis of the existence of normal distribution for all volatility series at a 1% significance level. Finally, we checked stationarity based on the Augmented-Dickey Fuller (ADF) and Phillips-Perron (PP) tests (see Appendix Table A.1 and A.2). This is because we used Diebold and Yilmaz's (2012) method in our study, and this method is based on the VAR model, which requires stationarity. According to the results of ADF and PP, all series are stationary at a 1% significance level.

Table 4.1: Data description

| **Variable Name** | **Symbol** | **Source** |
|---|---|---|
| Türkiye Petrol Rafinerileri A.S. | TUPRS | Datastream |
| Ipek Doğal Enerji Kaynakları Araştırma ve Üretim A.S. | IPEKE | Datastream |
| Turcas Petrol A.S. | TRCAS | Datastream |
| Cosmos Yatırım Holding A.S. | COSMO | Datastream |
| BIST Electricity Index | XELKT | Datastream |
| Brent Crude Energy Future | OIL | Datastream |
| UK NBP Natural Gas Energy Future | GAS | Datastream |
| Coal Energy Future | COAL | Datastream |

Table 4.2: Market profiles of Turkish energy firms based on 2022

| BIST Code | Industry | Market Cap |
|---|---|---|
| TUPRS | Oil, Gas & Consumable Fuels | 63.9 billion TL |
| IPEKE | Oil, Gas & Consumable Fuels | 5.3 billion TL |
| TRCAS | Oil, Gas & Consumable Fuels | 1.5 billion TL |
| COSMO | Oil, Gas & Consumable Fuels | 58.5 million TL |

Table 4.3: Descriptive statistics of volatility series

| | Mean | Median | Max | Min | SD | S | K | JB |
|---|---|---|---|---|---|---|---|---|
| tuprs | 1.93 | 1.42 | 21.08 | 0.00 | 1.86 | 2.68 | 16.98 | 33963.65* |
| cosmo | 2.60 | 1.62 | 21.12 | 0.00 | 2.88 | 2.21 | 8.88 | 8201.68* |
| ipeke | 2.75 | 1.84 | 34.82 | 0.00 | 2.98 | 2.58 | 13.52 | 20780.98* |
| trcas | 2.18 | 1.59 | 23.71 | 0.00 | 2.28 | 2.88 | 16.85 | 34092.12* |
| xelkt | 1.77 | 1.24 | 18.95 | 0.00 | 1.90 | 3.10 | 18.74 | 43340.28* |
| oil | 1.61 | 1.10 | 27.98 | 0.00 | 1.80 | 3.96 | 36.63 | 180796.2* |
| gas | 2.38 | 1.56 | 47.54 | 0.00 | 3.00 | 4.87 | 45.29 | 285193.9* |
| coal | 0.89 | 0.41 | 53.84 | 0.00 | 1.78 | 10.94 | 245.02 | 8941538* |

Note: * indicates rejection of the null hypothesis of normal distribution at 1% significance level for JB Test (1980)

## 4.2 Methodology

We divide our empirical analysis into two steps. First, we will investigate the volatility spillovers among Turkish energy stocks, the electricity index, and the fossil fuel energy commodities in the time domain based on Diebold and Yilmaz (2012) [1] approach. Second, we will examine mentioned interlinkage between markets in the frequency domain based on Barunik and Krehlik (2018) [2] approach.

### 4.2.1 Diebold and Yilmaz (2012) Approach

Our study employs Diebold and Yilmaz (2012) approach to investigate the volatility spillovers among Turkish energy stocks (tuprs, cosmo, ipeke, trcas), the electricity index (XELKT) and the fossil fuel energy market (brent crude oil, natural gas, and coal). This approach is built based on the generalized forecast error variance decomposition (GFEVD) of a vector autoregressive (VAR) model by Sims [70]. It can be considered as a generelized version of Diebold and Yilmaz (2009) by preventing to give order-dependent findings because of Cholesky factor orthogonalization. To do this, first, we construct the basic stationary VAR(M) model with N variables as follows:

$$y_t = \sum_{i=1}^{M} w_i y_{t-i} + \varepsilon_t \tag{4.1}$$

where $y_t$ is a N-dimensional vector of endogenous variables at time t which can be shown as $y_t = (y_{1t}, y_{2t}, y_{3t,...}, y_{NT})$ represents N x N coefficient matrices. $\varepsilon_t$ is the error vector of disturbances distributed identically and independently. The VAR(M) model in Eq. 4.1 can have a moving-average ($\infty$) representation which can be explained by $y_t = \sum_{n=0}^{\infty} x_n \varepsilon_{t-n}$ where $x_n$ is N x N coefficient matrices and it has a recursion that can be shown as $X_n = \partial_1 X_{n-1} + \partial_2 X_{n-2} + \partial_n X_{n-r}$. Here, $X_0$ is the identity matrix (N x N) and $X_n = 0$ in case of $n < 0$. According to Diebold and Yilmaz (2012) [1], the coefficients of the moving-average are crucial to understand the dynamic of the system. To have invariant forecast error variance decompositions regarding variable orders, the generelized VAR approach can be used Koop et al. [71]. Hence, the H-step ahead GFEVD can be written as follows:

$$\varnothing_{ab}^{i}(H) = \frac{\partial_{bb}^{-1} \sum_{h=0}^{H-1} \left(\alpha_a' X_h \sum \alpha_b\right)^2}{\sum_{h=0}^{H-1} \left(\alpha_a^{-1} X_h \Sigma X_h^1 \alpha_a\right)} \tag{4.2}$$

$\partial_{bb}$ is the error term's standard deviation for the b-th equation. $\phi$ indicated the error vector's variance matrix. $\alpha_a$ represents the selection vector which has the value of 1 for the $\alpha$-th element and has the value of 0 otherwise. However, the summation of the elements replaced in each row of the variance decomposition table is not one. For this reason, each component of the variance decomposition matrix is normalized as:

$$\tilde{\varnothing}_{ab}^{i}(H) = \frac{\phi_{ab}^{i}(H)}{\sum_{b=1}^{N} \phi_{ab}^{i}(H)} \tag{4.3}$$

where $\sum_{b=1}^{N} \tilde{\varnothing}_{ab}^{i}(H) = 1$ and $\sum_{a,b=1}^{N} \tilde{\varnothing}_{ab}^{i}(H) = N$. According to described elements, the total volatility spillover index can be calculated as follows:

$$S^i(H) = \frac{\sum_{a,b=1}^{N}(a \neq b)\tilde{\varnothing}^i{}_{ab}(H)}{\sum_{a,b=1}^{N}\tilde{\varnothing}^i{}_{ab}(H)} \cdot 100 = \frac{\sum_{a,b=1}^{N}(a \neq b)\tilde{\varnothing}_{ab}(H)}{N} \cdot 100 \tag{4.4}$$

By calculating total volatility index, we can examine the contribution of shocks on volatility spillovers among Turkish energy stocks and fossil fuel energy commodities crude oil, natural gas, and coal to the forecast error variance in total.

To find volatility spillovers transmitted from other markets to market i, we can use directional volatility spillovers as below:

$$S^i_{\alpha.}(H) = \frac{\sum_{a,b=1}^{N}\tilde{\phi}^i_{ab}b(H)}{\sum_{a,b=1}^{N}\tilde{\phi}^i_{ab}(H)} \cdot 100 = \frac{\sum_{a,b=1}^{N}(a \neq b)\tilde{\phi}^i_{ab}(H)}{N} \cdot 100 \tag{4.5}$$

We can also find volatility spillovers transmitted from market i to other markets using directional volatility spillovers as:

$$S^i_{.\alpha}(H) = \frac{\sum_{a,b=1}^{N}\tilde{\phi}^i_{ab}b(H)}{\sum_{a,b=1}^{N}\tilde{\phi}^i_{ab}(H)} \cdot 100 = \frac{\sum_{a,b=1}^{N}(a \neq b)\tilde{\phi}^i_{ab}(H)}{N} \cdot 100 \tag{4.6}$$

To examine the net volatility spillover from any market to others, we can take the difference between gross volatility shocks which send to and received from all other markets in the sample, as shown in Eq. (4.7). Moreover, we can also find net pairwise volatility spillover between two markets (e.g. i and j) as described in Eq. (4.8):

$$S^i(H) = S^i_{.\alpha}(H) - S^i_{\alpha.}(H) \tag{4.7}$$

$$S^i_{ab}(H) = \left(\frac{\tilde{\phi}^i_{ba}(H)}{\sum_{a,p=1}^{N}\tilde{\phi}^i_{ap}(H)} - \frac{\tilde{\phi}^i_{ab}(H)}{\sum_{b,p=1}^{N}\tilde{\phi}^i_{bp}(H)}\right) \cdot 100 = \left(\frac{\tilde{\phi}^i_{ba}(H) - \tilde{\phi}^i_{ab}(H)}{N}\right) \cdot 100 \tag{4.8}$$

### 4.2.2 Barunik and Krehlik (2018) Approach

According to Barunik and Krehlik (2018) [2], the spectral representation of variance decompositions can be used based on frequency responses to shocks. The connectedness among markets at different frequencies (short-term, medium-term, or long-term) can be found using the spectral representation of variance decompositions. The frequency response function is $\psi\left(e^{-i\alpha}\right) = \sum_h e^{-i\alpha h}\psi_h$ where $\psi_h$ can be considered as the Fourier transform of the coefficients, with $i = \sqrt{-1}$. Note that $\alpha$ represents the frequency and $Z_t$ is the spectral density at $\alpha$-th frequency. We can indicate mentioned linkage as a Fourier transform of MA($\infty$) as:

$$S_z(\alpha) = \sum_{h=-\infty}^{\infty} E\left(z_t z'_{t-h}\right) e^{-i\alpha h} = \psi\left(e^{-i\alpha}\right)\Sigma\psi'\left(e^{+i\alpha}\right) \tag{4.9}$$

where $S_Z(\alpha)$ shows the distribution of $Z_t$ on $\alpha$. It should be also noted that $\psi\left(e^{-i\alpha}\right) = \sum_{h=0}^{\infty}\psi e^{-i\alpha}$. The following equation expresses the frequency domain equivalents of variance decomposition:

$$\phi_{ij}(\alpha) = \frac{\delta_{jj}^{-1}\sum_{h=0}^{\infty}\left|\psi\left(e^{ih\alpha}\Sigma\right)_{ij}\right|^2}{\sum_{h=0}^{\infty}\left(\psi\left(e^{-ih\alpha}\right)\Sigma\Psi\left(e^{ih\alpha}\right)\right)ii} \tag{4.10}$$

$\phi_i(\alpha)$ indicates the part of the j-th variable's spectrum at $\alpha$-th frequency based on shocks in i-th variable. Note that $\alpha \in (-\pi, \pi)$. To find the effect of any variable at a specific frequency, we can weight the $\phi_{ij}(\alpha)$ with $\Gamma_j\alpha$ as:

$$\Gamma_j(\alpha) = \frac{\left(\psi\left(e^{-i\alpha}\right)\sum\psi'^{(e+i\alpha)}\right)jj}{\frac{1}{2\pi}\int_{-\pi}^{\pi}\left(\psi\left(e^{-i\partial}\right)\right)_{jj}d\partial} \tag{4.11}$$

We can also generate connectedness table at the frequency band d using generalized variance decomposition (by denoting frequency band $d = (m,n) : m,n \in (-\pi,\pi), m < n$)

$$\left(\tilde{\phi}_d\right)_{ij} = \frac{1}{2\pi}\int_{-\pi}^{\pi}\Gamma_j(\alpha)\ \phi_{ij}(\alpha)d\alpha \tag{4.12}$$

Moreover, the within and frequency connectedness on the frequency band d can be calculated respectively as follows:

$$C_d^f = 100 \times \left(1 - \frac{\mathrm{Tr}_r\{\tilde{\Psi} d}{\Sigma\tilde{\varphi} d}\right) \tag{4.13}$$

$$C_d^f = 100 \times \left(\frac{\Sigma\tilde{\varphi d}}{\Sigma\tilde{\varphi}\infty} - \frac{T_r\{\tilde{\varphi}_d\}}{\Sigma\widetilde{\varphi_\infty}}\right) = C_d^w \times \frac{\Sigma\tilde{\varphi} d}{\Sigma\tilde{\varphi}_\infty} \tag{4.14}$$

In our empirical analysis, we used the VAR lag length as 2 based on Akaike Information Criterion (AIC). In addition, we used a 100-day ahead forecasting horizon (H) for variance decomposition since (H)<100 is giving invalid results according to Barunik and Krehlik (2018).

# Chapter 5

# EMPIRICAL RESULTS

## 5.1 Diebold and Yilmaz's (2012) Results

### 5.1.1 Static Analysis

We first applied static analysis to investigate time-invarying volatility transmission among four Turkish energy stocks (TUPRS, COSMO, IPEKE, TRCAS), BIST Electricity (XELKT) index, and three main energy commodities (oil, natural gas, and coal). We obtained useful findings on the static analysis that are presented in Table 5.1.

Table 5.1: Volatility spillovers among Turkish energy stocks and fossil fuel energy commodities based on full-sample estimation

| | **tuprs** | **cosmo** | **ipeke** | **trcas** | **xelkt** | **oil** | **gas** | **coal** | **FROM** |
|---|---|---|---|---|---|---|---|---|---|
| tuprs | 62.5 | 2.3 | 5.8 | 12.1 | 14.6 | 1.9 | 0.3 | 0.6 | 37.5 |
| cosmo | 3.0 | 84.5 | 1.7 | 4.7 | 4.6 | 1.1 | 0.3 | 0.2 | 15.5 |
| ipeke | 6.3 | 1.7 | 70.5 | 8.7 | 11.6 | 1.1 | 0.1 | 0.1 | 29.5 |
| trcas | 11.0 | 3.2 | 7.1 | 57.7 | 19.2 | 1.2 | 0.5 | 0.2 | 42.3 |
| xelkt | 13.0 | 3.0 | 9.5 | 18.2 | 54.5 | 1.3 | 0.3 | 0.3 | 45.5 |
| oil | 3.1 | 1.3 | 0.9 | 3.2 | 2.4 | 86.4 | 0.6 | 2.1 | 13.6 |
| gas | 0.3 | 0.4 | 0.2 | 0.4 | 0.6 | 0.5 | 94.4 | 3.3 | 5.6 |
| coal | 1.0 | 0.3 | 0.3 | 0.9 | 1.0 | 2.2 | 4.3 | 90.0 | 10.0 |
| TO | 37.6 | 12.2 | 25.3 | 48.2 | 53.9 | 9.3 | 6.4 | 6.8 | 199.6 |
| NET | 0.1 | -3.3 | -4.2 | 5.9 | 8.4 | -4.3 | 0.8 | -3.2 | TCI=25% |

The values in each row represent the volatility spillover transmitted to other markets (labeled as TO). Therefore, the values in each column denote the volatility spillover received from other markets including its own market (labeled as FROM). To find net volatility spillovers, we calculate their differences. Moreover, the total spillover index (25%), which is shown in the lower right corner of the table, can be considered as a summary of all contributions TO others and FROM others. The total spillover effect is calculated by summing received values (FROM) and dividing the result by the number of markets in the sample by taking its percentage (eight markets x 100% = 800%). There can be two explanations for this finding. First, the total connectedness index (TCI) (25%) is neither too high nor too low, indicating an interdependence between volatilities, but it needs to be explored in a time-varying manner to capture the impacts of cyclical trends and extreme events that change over time. Second, on average 25% of the volatility forecast error variance in these eight markets comes from spillovers, and the remaining 75% may represent idiosyncratic shocks. According to directional net volatility spillovers, the largest are from the XELKT to others (53.9 – 45.5 = 8.4%), followed by TRCAS, natural gas, and TUPRS, respectively. In the energy market, among the three energy commodities, crude oil has the highest volatility spillover to TUPRS at around 1.89%, and this is in line with recent papers by Bouri et al. [8] and Ahmed & Huo [72], who examined the interlinkage between crude oil and stock markets regarding the volatile crude oil market. Our finding is not surprising given TUPRS is the biggest oil importer in Turkey with a refinery capacity of 75% in the country. It is also the 7th largest refining company in Europe and 30th largest in the world [73]. When this is the case, TUPRS may be more responsive to volatility in crude oil, which will be caused by geopolitical issues such as sanctions on oil producer/exporter countries or supply concerns owing to Organization of the Petroleum Exporting Countries (OPEC) policies. Next, the coal also transmits the highest volatility to TUPRS by 0.60%, while natural gas transmits the highest volatility spillover to trcas (0.50%). In the case of supply cuts and price increases for crude oil because of global tensions, countries may tend to increase their demand for other energy commodities such as natural gas or coal to meet their energy needs. Hence, countries that are heavily dependent on energy such as Turkey may begin to be more affected by the volatility of these energy commodities. Among these three energy commodities, natural gas is the most influential market in the Turkish energy companies, being the net volatility spillover transmitter (6.4 – 5.6 = 0.8%). On the contrary, oil (9.3 – 13.6 = - 4.3%) and coal (6.8 – 10.0 = - 3.2%) are net receivers from other markets. Our result is consistent with Jebabli et al. [21], who compared volatility spillovers between stock and energy markets during the 2008 GFC and COVID-19 pandemic crisis. They concluded that an aggregated emerging stock market is a net volatility transmitter to crude oil; however, it is a net receiver from natural gas during the coronavirus pandemic. The possible explanation behind this may be a rapid decline in oil-based production and trade activities at the beginning of the pandemic as Jebabli et al. [21] explained.

### 5.1.2 Dynamic Analysis

Fig 5.1. illustrates the dynamics of total volatility connectedness among four Turkish energy stocks, electricity index, and energy markets (crude oil, natural gas, and coal) for 2006–2021.

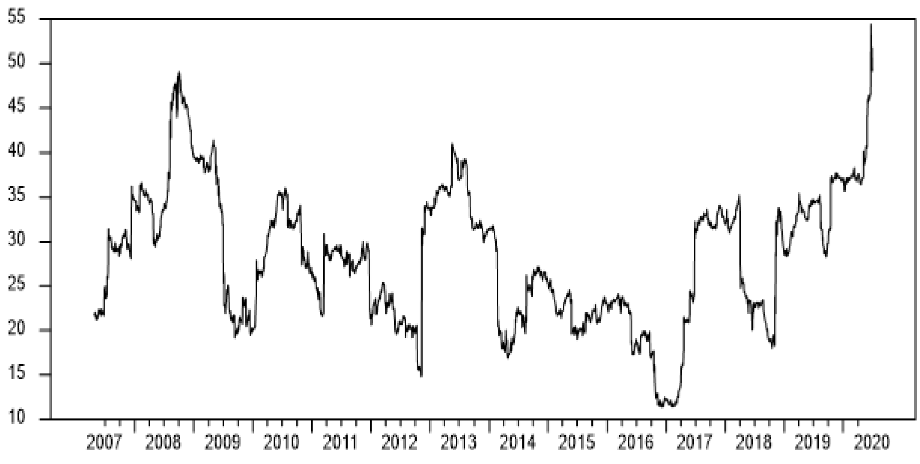



Figure 5.1: Total volatility spillovers based on Diebold and Yilmaz (2012)

The total volatility spillovers vary from 10%–55% over time, which was estimated at 25% in the static total spillover index. Therefore, this is a significant indication that the time-varying approach provides wider information about volatility connectedness between stock and energy markets in comparison to static analysis. We notice that there are many fluctuations and sharp increases owing to extreme events around the world. The findings regarding Fig 5.1 reveal that the highest volatility spillovers between Turkish energy stocks and fossil fuel energy markets are observed during the COVID-19 pandemic, followed by the 2008 GFC. In other words, the volatility connectedness among these markets during the COVID-19 outbreak in 2020 exceeded (the volatility spillover index reached approximately 55%) the 2008 GFC, which is in accordance with [8, 29, 74]. These recent papers indicate that most countries experienced a sharp drop in real activities because of the effect of the coronavirus pandemic, which caused not only high volatility spillovers between markets but also record levels of uncertainty and degradation in investor sentiment. Besides these factors, we also observed significant sudden oscillations such as a sharp increase in 2010, late 2012, and 2017. Possible explanations for these fluctuations may be the 2011 Arab spring (political turmoil in Libya, Bahrain, Egypt, and Yemen) and the Syrian civil war, the 2014 international crude oil crisis, the 2016 increase in coal and natural gas prices, the 2016 Brexit event, and the 2016 OPEC policies (e.g., announcement about supply cuts for the end of 2017). Furthermore, the lowest transmissions of volatilities are recorded during the breakdown of oil prices in 2014–2015, as explained by [75]. We also agree with Diebold and Yilmaz (2012) [1], who analyzed the 2008 GFC and stated that volatility transfer intensified during the crisis. As a summary, Turkish individual energy stocks, the electricity index, and the fossil fuel energy commodities have a significant volatility interaction, and this is greatly affected by extreme events such as financial meltdown and price fluctuations

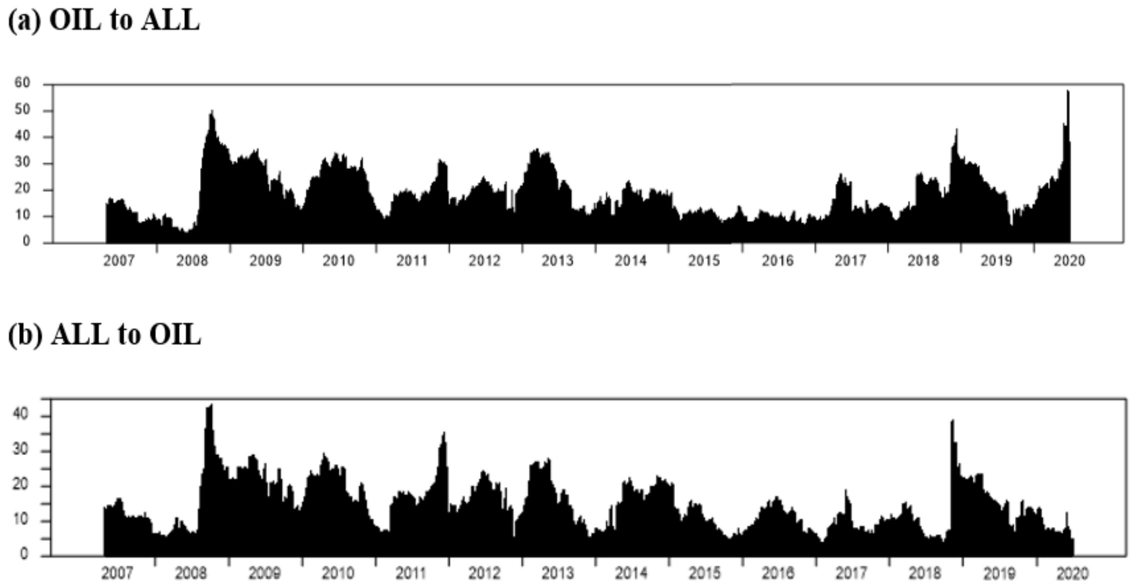



Figure 5.2: Directional volatility spillovers from (to) crude oil to (from) Turkish energ stocks

of energy commodities.

In Fig. 5.2 and Fig. 5.3, we present the directional volatility spillovers from energy commodities to Turkish energy stocks, and vice versa. According to panel (a), the highest volatility spillovers from crude oil to other markets are observed during the COVID-19 pandemic and 2008 GFC, reaching almost 60% and 50% respectively. During the whole period, spillovers fluctuate based on political and economic developments around the world. In panel (b), the volatility spillovers from others to crude oil vary significantly over time. The highest level of spillovers is recorded during the 2008 GFC. However, although crude oil transmits volatility to other markets during 2020, it does not receive as much volatility transmission from others in the same period. Instead, a significant volatility spillover is seen in late 2018.

Panels (c) and (d) show that the connectedness between natural gas and Turkish energy stocks is time-varying and seems to be largely dominated by the volatility transmission

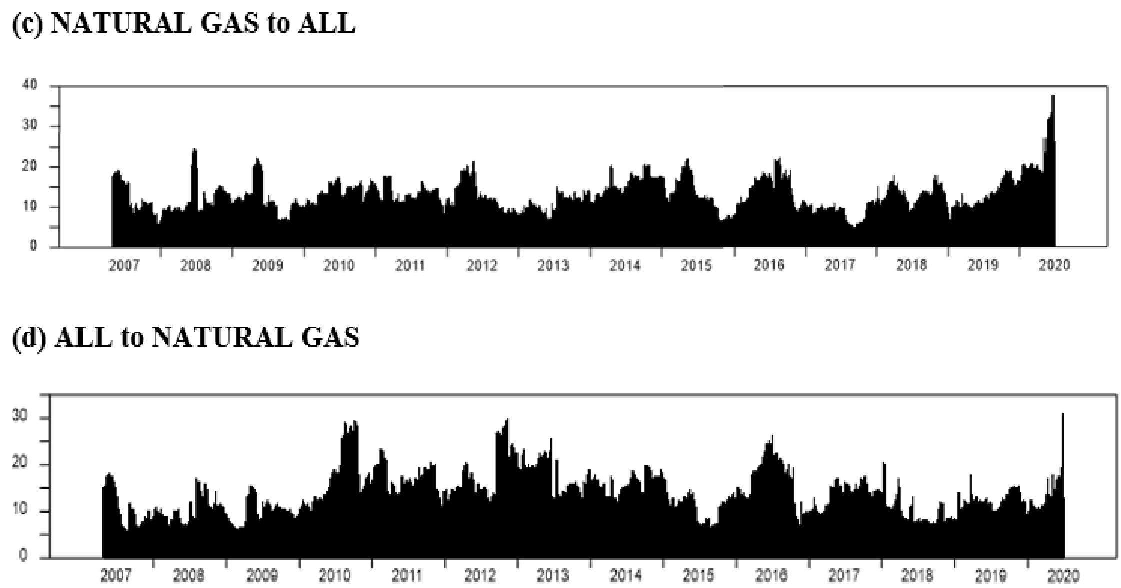
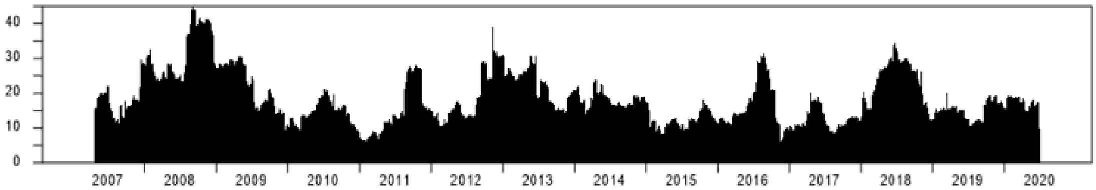



Figure 5.3: Directional volatility spillovers from (to) natural gas to (from) Turkis energy stocks

from all energy stocks to the natural gas market. Volatility spillovers fluctuate over the period and reach their highest point in 2020, as seen in panel (d). During 2020, which is the point that spillovers reach the largest level for both cases, natural gas transmits more than it receives when the net magnitude of transmission is considered. For instance, natural gas has the highest volatility transmission to others during the COVID-19 pandemic, which exceeds 30%, and the transmission from others to natural gas peaks in the same period but stays below 30%.

Concerning directional volatility spillovers from (to) coal to (from) Turkish energy stocks, a significant transfer is observed over the sample period. As seen in panel (e), the volatility transmission of coal to other markets intensifies during the 2008 GFC. Surprisingly, coal does not peak in volatility spillovers like other energy commodities during the COVID-19 outbreak. In addition, as seen in panel (f), coal receives volatility from other markets, especially in the 2008, 2016, and 2020 periods.

**(e) COAL to ALL**




**(f) ALL to COAL**

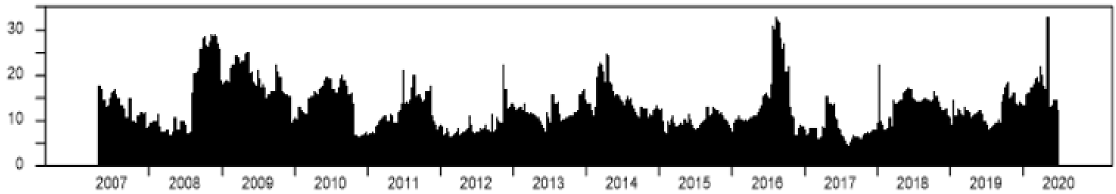



Figure 5.4: Directional volatility spillovers from (to) coal to (from) Turkish energ stocks

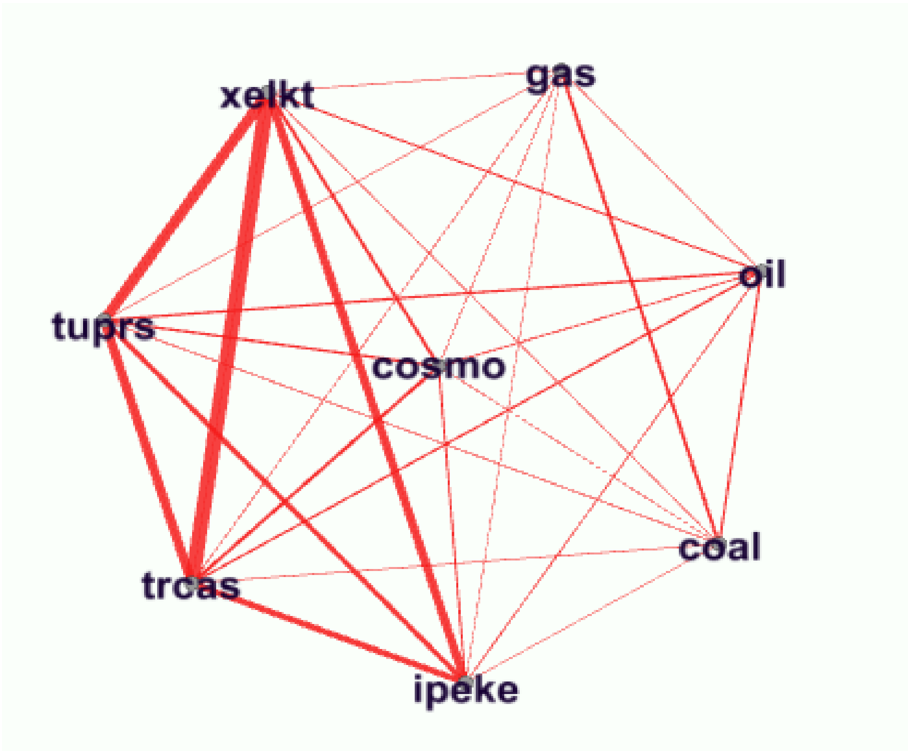



Figure 5.5: Network connectedness from each market to others based on Diebold an Yilmaz (2012)

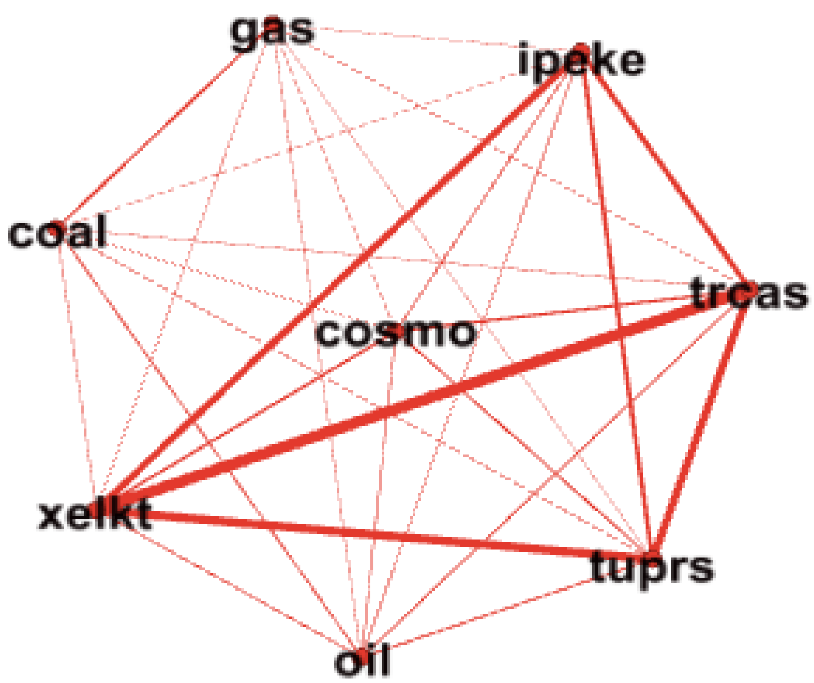



Figure 5.6: Network connectedness from others to each market based on Diebold an Yilmaz (2012)

To examine directional volatility connectedness based on network connectedness, we provide the channel of shocks from one variable to another as shown in Fig. 5.5. Furthermore, the network connectedness from other markets to each market can be seen in Fig. 5.6. In these figures, the width of the arrows represents the intensity of volatility spillovers which can be seen with the color of darker red. In this regard, we can support our previous findings in the section of dynamic analysis that XELKT, TUPRS, TRCAS, and natural gas are the dominant volatility transmitters to other markets in the sample, whereas crude oil, ipeke, and cosmo are the net volatility receivers in the system.

Moreover, when we examine whether Turkish energy stocks transmit volatility to the energy markets in both static and time-varying analysis, we observe that these stocks transfer significant volatility to all three fossil fuel energy commodities over the sample period. At this point, another question arises: how can an emerging market, Turkey's energy stocks affect global energy markets? The possible explanation of this is that Turkish energy stocks may have the same dynamics as the largest international energy companies, which have a significant influence on oil markets or possibly predict future movements [54].

## 5.2 Barunik and Krehlik's (2018) Results

To examine the dynamics of spillovers at various investment horizons, we used Barunik and Krehlik's (2018) [2] test, and the findings are displayed in Table 5.2, 5.3, 5.4. The table is split into three subsections, each representing a different frequency (short-term, medium-term, and long-term, respectively).

Table 5.2: The spillover table for band: 3.14–0.79 (roughly corresponds to 1 days to 4 days)

| | **tuprs** | **cosmo** | **ipeke** | **trcas** | **xelkt** | **oil** | **gas** | **coal** |
|---|---|---|---|---|---|---|---|---|
| tuprs | 0.52 | 0.01 | 0.02 | 0.04 | 0.05 | 0.01 | 0.00 | 0.00 |
| cosmo | 0.01 | 0.15 | 0.00 | 0.01 | 0.01 | 0.00 | 0.00 | 0.00 |
| ipeke | 0.01 | 0.01 | 0.17 | 0.02 | 0.03 | 0.00 | 0.00 | 0.00 |
| trcas | 0.03 | 0.00 | 0.02 | 0.17 | 0.05 | 0.00 | 0.00 | 0.00 |
| xelkt | 0.02 | 0.01 | 0.03 | 0.05 | 0.19 | 0.00 | 0.00 | 0.00 |
| oil | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.21 | 0.00 | 0.01 |
| gas | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.32 | 0.02 |
| coal | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.28 |
| To_Abs | 0.01 | 0.00 | 0.01 | 0.01 | 0.02 | 0.00 | 0.00 | 0.00 |
| To_With | 2.82 | 1.23 | 2.95 | 2.95 | 5.51 | 0.91 | 0.21 | 1.04 |
| From_Abs | 0.02 | 0.00 | 0.01 | 0.01 | 0.01 | 0.00 | 0.00 | 0.00 |
| From_With | 5.03 | 1.01 | 2.52 | 4.20 | 4.28 | 0.68 | 0.95 | 0.44 |
| TCI: 19.12 | | | | | | | | |

According to Table 5.2,5.3, and 5.4, the share of frequency of 10 days to infinity has the highest contribution in total connectedness, which is 26.32%. Moreover, the frequencies of 1–4 days and 4–10 days contribute to the system at around 19.12% and 11.85%, respectively. In the total volatility, the XELKT is the most contributory,

Table 5.3: The spillover table for band: 0.79–0.31 (roughly corresponds to 4 days to 10 days)

| | **tuprs** | **cosmo** | **ipeke** | **trcas** | **xelkt** | **oil** | **gas** | **coal** |
|---|---|---|---|---|---|---|---|---|
| tuprs | 0.10 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| cosmo | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| ipeke | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| trcas | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 |
| xelkt | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.00 | 0.00 | 0.00 |
| oil | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.00 | 0.00 |
| gas | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.00 |
| coal | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 |
| To_Abs | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| To_With | 1.28 | 0.96 | 1.65 | 2.86 | 3.83 | 0.45 | 0.29 | 0.53 |
| From_abs | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| From_with | 1.66 | 0.99 | 1.86 | 3.01 | 3.06 | 0.48 | 0.48 | 0.32 |
| TCI: 11.85 | | | | | | | | |

Table 5.4: The spillover table for band: 0.31–0.00 (roughly corresponds to 10 days to inf days)

| | **tuprs** | **cosmo** | **ipeke** | **trcas** | **xelkt** | **oil** | **gas** | **coal** |
|---|---|---|---|---|---|---|---|---|
| tuprs | 27.97 | 1.45 | 7.65 | 21.96 | 37.97 | 0.73 | 0.56 | 0.97 |
| cosmo | 1.59 | 88.09 | 1.07 | 3.73 | 4.72 | 0.19 | 0.20 | 0.21 |
| ipeke | 7.95 | 0.82 | 76.05 | 6.36 | 8.13 | 0.35 | 0.01 | 0.07 |
| trcas | 17.43 | 2.79 | 4.89 | 60.07 | 14.05 | 0.36 | 0.08 | 0.03 |
| xelkt | 28.23 | 3.17 | 6.08 | 13.13 | 48.77 | 0.17 | 0.11 | 0.02 |
| oil | 1.24 | 0.15 | 0.16 | 0.72 | 0.92 | 95.32 | 0.03 | 1.22 |
| gas | 0.56 | 0.22 | 0.08 | 0.02 | 0.24 | 0.00 | 97.37 | 1.16 |
| coal | 1.20 | 0.37 | 0.11 | 0.22 | 0.14 | 1.10 | 2.70 | 93.84 |
| To_Abs | 7.28 | 1.12 | 2.51 | 5.77 | 8.27 | 0.36 | 0.46 | 0.46 |
| To_With | 7.30 | 1.13 | 2.51 | 5.79 | 8.30 | 0.36 | 0.46 | 0.46 |
| From_abs | 8.91 | 1.47 | 2.96 | 4.95 | 6.36 | 0.55 | 0.28 | 0.73 |
| From_with | 8.94 | 1.47 | 2.97 | 4.97 | 6.39 | 0.56 | 0.28 | 0.73 |
| TCI: 26.32 | | | | | | | | |

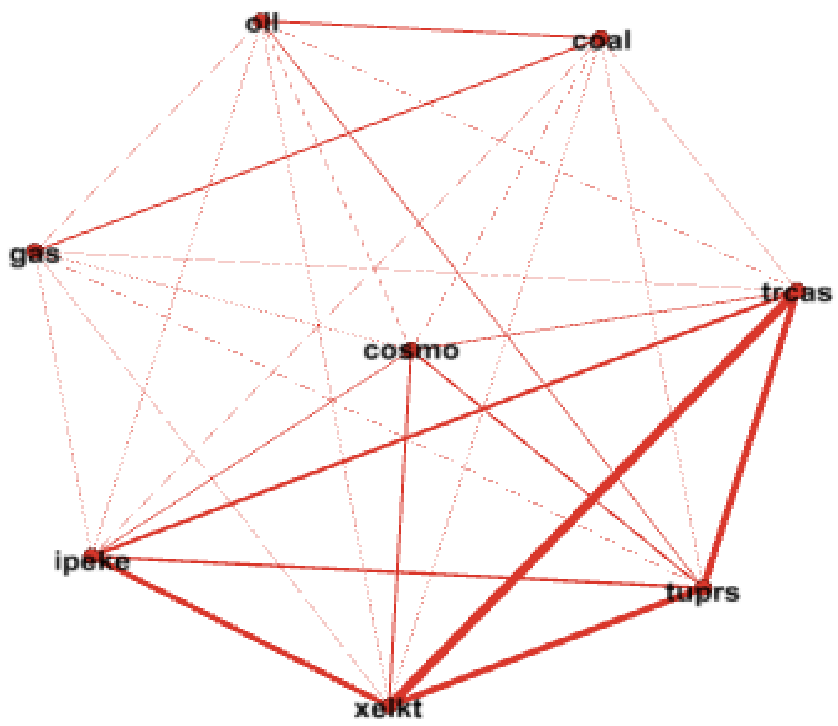


Figure 5.7: Short-term network connectedness from each market to others based o Barunik and Krehlik (2018)

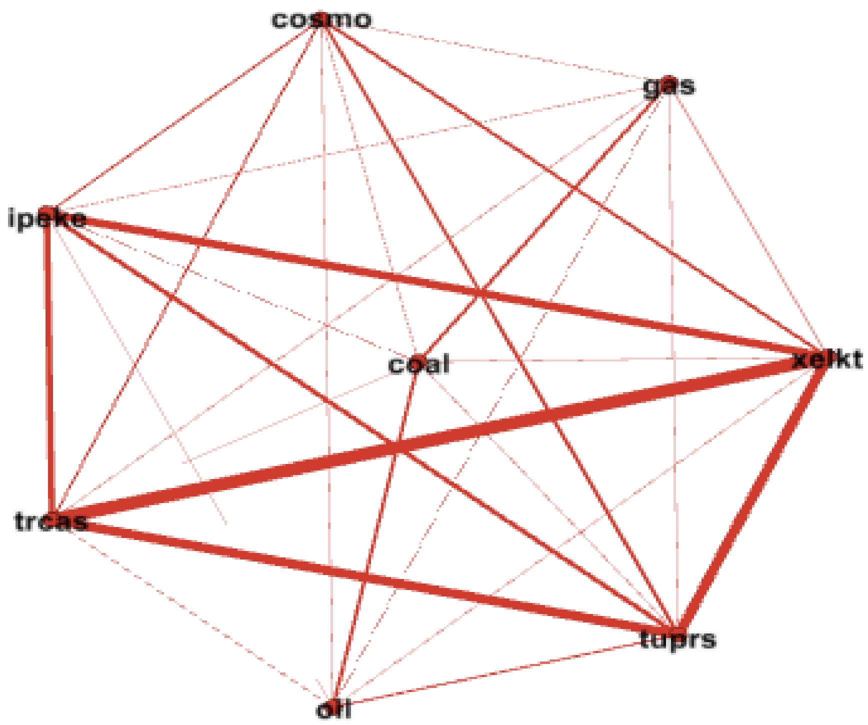


Figure 5.8: Short-term network connectedness to each market from others based o Barunik and Krehlik (2018)

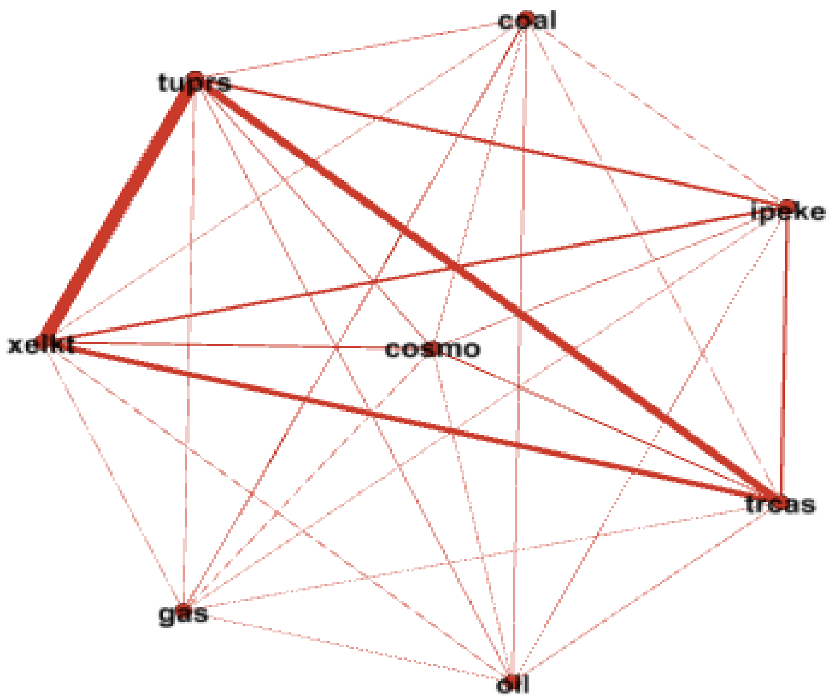



Figure 5.9: Long-term network connectedness from each market to others based o Barunik and Krehlik (2018)

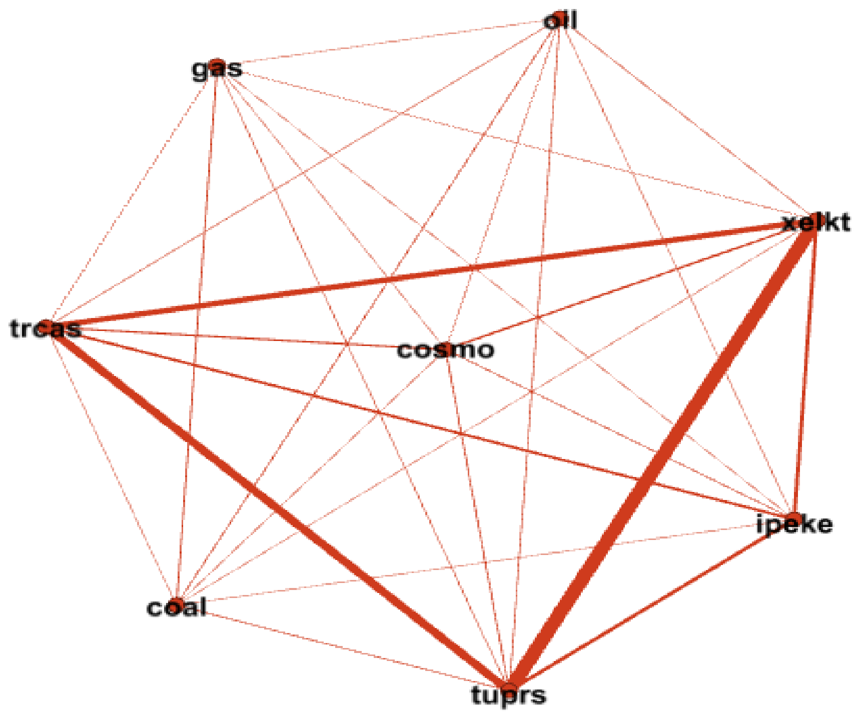



Figure 5.10: Long-term network connectedness to each market from others based o Barunik and Krehlik (2018)

accounting for 5.51%, 3.83%, and 8.30%, respectively. Among fossil fuel energy commodities, coal is the most significant contributor in the first two frequencies with 1.04% and 0.53%; however, it has the same impact as natural gas in the system at the last frequency level (10 days to infinity). Overall, we can conclude that the highest performance is recorded in the long horizon compared to short and medium horizons, implying that the impact of volatility spillover transmission from one market to others is persistent (long-lasting). This finding is expected because volatility transmission from one market to others needs time (Barunik and Krehlik, 2018). Our results are also in line with Liu and Hamori [27], in that they found most of the volatility spillovers among crude oil, natural gas, stock market and volatility index, bonds, and renewable stock markets in the long term (at a low frequency). Finally, according to the findings of network connectedness between markets (Fig. 5.7, Fig. 5.8, Fig. 5.9, and Fig. 5.10), we can support the findings of Barunik and Yilmaz (2018) [2] through the pathway of volatility spillovers in both short-term and long-term.

## 5.3 Robustness Check of Empirical Findings

Checking the robustness or validity of the empirical analysis is important because the rolling window (RW) size can be selected arbitrarily. Therefore, a quite low RW size may lead to sensitivity to extreme outliers in the total connectedness. On contrary, a quite large RW size may cause the potential impact of various outcomes to smoothen out [39]. Hence, we checked different RW sizes (i.e. 200, 300, 400, 500) to analyze the robustness of our empirical findings. According to time-varying total spillovers shown in Fig. 5.11, there is no sensitivity at different RW sizes. In other words, our results are not by chance; they do not change against low/high RW sizes, indicating robust empirical results.

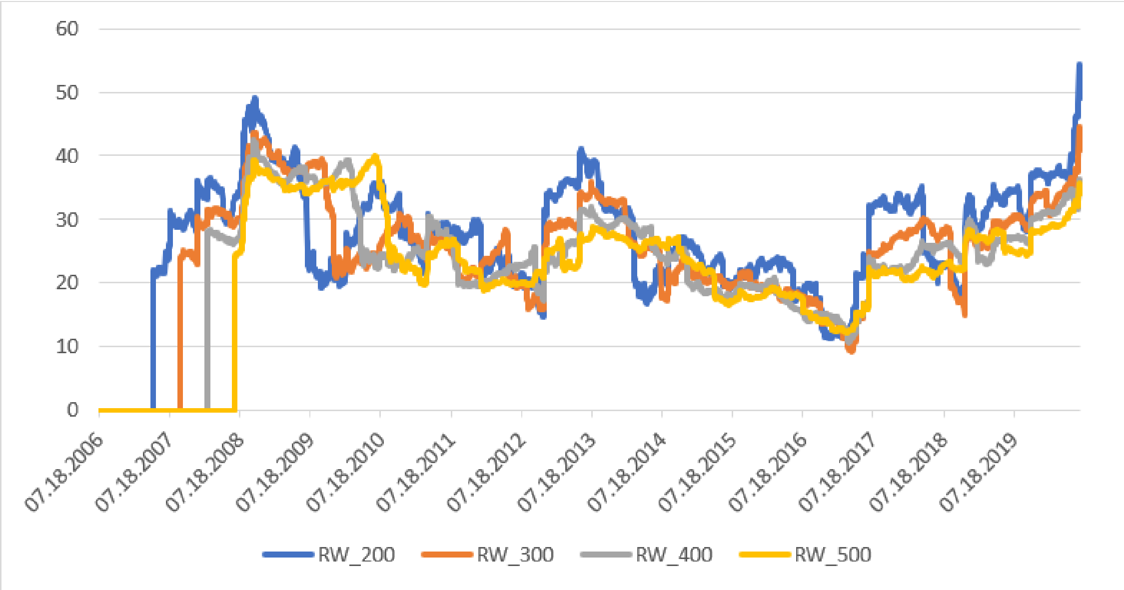



Figure 5.11: Total spillover plots reached from Diebold and Yilmaz (2012) at differen rolling windows (RW) sizes

# Chapter 6

# PORTFOLIO DIVERSIFICATION STRATEGIES

In this chapter, we used multivariate GARCH models (MGARCH) to model conditional correlations between Turkish-listed firms in the energy sector (TUPRS, COSMO, IPEKE, TRCAS), the BIST Electricity Index (XELKT), which is traded on the Istanbul stock exchange, and main fossil fuels futures markets (Brent crude oil, natural gas, and coal) from 07/18/2006 to 12/31/2021. To do this, first, we adopted time-varying conditional correlations from the dynamic conditional correlations (DCC) GARCH model. Second, the estimates of the DCC model are used to construct the hedge ratios and optimal portfolio weights [76].

## 6.1 Multivariate GARCH (MGARCH) Models

Since the Autoregressive Conditional Heteroskedasticity (ARCH) model was introduced in the seminal study by Engle [77], modeling volatility in financial time series has received a lot of attention (1982). Many more variations and additions to ARCH models have since been put out. Univariate models have received a lot of attention in this field; for example, see Bollerslev et al. [78], Palm [79], and Shephard [80]. Understanding the co-movements of financial returns is crucial for practical purposes even though modeling return volatility has received most of the focus. Therefore, it is critical to include multivariate GARCH (MGARCH) models in the considerations. When analyzing the impacts of volatility spillover on equity markets, multivariate GARCH (MGARCH) models have proven to be quite helpful.For example, [81], [82], [83], [84], and [85] used MGARCH models to study oil prices, electricity prices, and natural gas prices.

This chapter's econometric specification consists of two parts. First, the mean equation is estimated with an autoregressive moving average ARMA(p,q) process. Second, the time-varying variances and covariances are modeled using a dynamic conditional correlation (DCC) GARCH model. Moreover, DCC GARCH models also have two steps in the estimation process. In the first step, variances are estimated through univariate GARCH models. In the second step, correlations between two assets are obtained based on the standardized residuals from step one [51]. Therefore, ARMA(p,q) and DCC GARCH(i,j) specification can be described as follows:

Mean Equation:

$$r_t = e_t + \partial r_{t-1} + \varepsilon_t \tag{6.1}$$

where $r_t$ indicates the return series of each asset, $e_t$ denotes the conditional mean of the return series $r_t$. Moreover, $\varepsilon_t$ expresses the residuals.

Variance Equation:

$$h_t = a + \varphi \varepsilon_{t-1}^2 + \omega h_{t-1} \tag{6.2}$$

where $h_t$ is the conditional variance, a is the constant term of GARCH model, $\phi$ indicates the short-run persistence of the ARCH effect, while $\omega$ denotes the long-run persistence of the GARCH effect. The Eq. 6.2 is univariate GARCH(1,1) model and we construct this model for each of the series in the sample.

Dynamic Conditional Correlation, DCC(1,1) Equation:

$$\theta_t = (1 - \alpha - \beta)\underline{\theta} + \alpha \varepsilon_{t,1} \hat{\varepsilon}_{t-1} + \beta \theta_{t-1} \tag{6.3}$$

where $\theta_t$ defines the time-varying unconditional correlation matrix of the standardized residuals from the GARCH(1,1) equation and indicated by $\varepsilon t$. The $\alpha$ and $\beta$ parameters express the impacts of previous shocks and previous DCC on the current DCC respectively.

### 6.1.1 Dynamic Conditional Correlations Results

In this section, we present empirical findings of the DCC GARCH model. First, we provide $\alpha$ and $\beta$ outcomes from the DCC GARCH model and their interpretations. Subsequently, we demonstrate time-varying conditional correlation graphs of each pair of assets.

According to Table 6.1, $\alpha$ and $\beta$ coefficients are the dynamic correlation coefficients of the DCC-GARCH model. The coefficient of $\alpha$ indicates the impact of the standardized residuals of the previous period on the dynamic correlation coefficient, while the coefficient of $\beta$ represents the impact of the correlation coefficient of the previous period on the correlation coefficient of this period. Furthermore, the summation of $\alpha$ and $\beta$ $(\alpha + \beta)$ represents the attenuation coefficient of the model. In other words, their summation represents the persistence of the correlation between two time series or two assets. The higher value of the summation indicates stronger persistence of correlation or vice versa. In this regard, the $\alpha$ and $\beta$ values of TUPRS with all energy commodities are statistically significant and positive, indicating that there is an important time-varying change characteristic, and the correlation coefficient is mainly affected by both previous fluctuations and the correlation coefficient of the previous period. The summation of $\alpha$ and $\beta$ values represents shows that there is a strong persistence of correlation between TUPRS and fossil fuel energy commodities (crude oil, natural gas, and coal). For COSMO and three energy commodities, the $\alpha$ and $\beta$ coefficients are statistically significant and positive in the

Table 6.1: Dynamic conditional correlation (DCC) estimations

| **Pairs of assets** | **ARMA(p,q)** | **DCC ($\alpha$)** | **DCC ($\beta$)** |
|---|---|---|---|
| tuprs - oil | ARMA(10,10) | 0.02*** | 0.97*** |
| tuprs - gas | ARMA(10,10) | 0.01*** | 0.98*** |
| tuprs - coal | ARMA(5,5) | 0.07*** | 0.98*** |
| | | | |
| cosmo - oil | ARMA(9,10) | 0.00** | 0.99*** |
| cosmo - gas | ARMA(6,7) | 0.00 | 0.69* |
| cosmo - coal | ARMA(10,10) | 0.00 | 0.05 |
| | | | |
| ipeke - oil | ARMA(10,10) | 0.00** | 0.99*** |
| ipeke - gas | ARMA(8,9) | 0.00 | 0.45 |
| ipeke - coal | ARMA(9,10) | 0.00*** | 0.00 |
| | | | |
| trcas - oil | ARMA(9,9) | 0.02** | 0.97*** |
| trcas - gas | ARMA(10,10) | 0.01 | 0.98*** |
| trcas - coal | ARMA(10,10) | 0.01 | 0.29 |
| | | | |
| xelkt - oil | ARMA(9,8) | 0.03** | 0.94*** |
| xelkt - gas | ARMA(9,10) | 0.01* | 0.97*** |
| xelkt - coal | ARMA(9,10) | 0.00 | 0.01 |

Note: ARMA(p,q) column represents the optimal lags for the mean equation. To do this, lags selected based on AIC. DCC ($\alpha$) indicates the coefficients of $\alpha$ values estimated from the DCC GARCH model, while DCC ($\beta$) expresses the coefficients of $\beta$ values estimated from the DCC GARCH model. ***, **, * indicates significance at 1%, 5%, and 10% levels respectively.

cosmo-oil pair, implying that there is a time-varying change characteristic, and the correlation coefficient is mainly affected by both previous fluctuations and the correlation coefficient of the previous period. However, the correlation coefficient in the COSMO-GAS pair is mainly affected by the previous fluctuations since the $\beta$ is the only statistically significant asset in the model. For COSMO-COAL, we do not observe statistically significant $\alpha$ and $\beta$ coefficients, meaning that the correlation coefficient between these two assets does not affected by either the previous fluctuations or the correlation coefficient of the previous period. Therefore, the strongly persistent conditional correlation is recorded for only COSMO-OIL pair. Another energy stock of IPEKE and its dynamic correlation coefficients with fossil fuel energy commodities indicate that $\alpha$ and $\beta$ are both statistically significant and positive in IPEKE-OIL pair, and this is the strongest persistency among others. On the other hand, the $\alpha$ and $\beta$ coefficients are not statistically significant in the IPEKE-GAS pair, indicating no effects of previous fluctuations or the correlation coefficient of the previous period. In addition, the $\alpha$ is statistically significant and positive for IPEKE-COAL. This is the indication of the impact of the previous period's correlation coefficient on the current period. For trcas and fossil fuel energy commodities, the strongest persistency of correlation coefficient is obtained for TRCAS-OIL. The values of $\alpha$ and $\beta$ are also statistically significant in this pair, implying that there is an important time-varying change characteristic, and the correlation coefficient is mainly affected by both previous fluctuations and the correlation coefficient of the previous period. In the pair of TRCAS-GAS, the $\beta$ is statistically significant which is evidence of the impact of previous fluctuations on the current correlation coefficient between the two assets. However, the statistically significant $\alpha$ and $\beta$ coefficients are not obtained in the TRCAS-COAL pair. For the XELKT and fossil fuel energy commodities, XELKT-OIL and XELKT-GAS have statistically significant $\alpha$ and $\beta$ which indicates that there is an important time-varying change characteristic, and the correlation coefficient is mainly affected by both previous fluctuations and the correlation coefficient of the previous period for both pairs. On the other hand, the $\alpha$ and $\beta$ coefficients are not statistically significant for XELKT-COAL. Hence, the impact of previous fluctuations and the correlation coefficient of the previous period can not be considered for this pair.

Table 6.2 presents diagnostic tests for standardized residuals. According to the table, there is an ARCH effect at a 1% significance level for each series (except for COAL) in lag (5) and (10). However, COAL has also an ARCH effect in lag (20). In other words, all of the return series reveal conditional heteroskedasticity, indicating that ARCH effects should be taken into account in the estimation stage. Moreover, there is no evidence of serial correlation at 1%, 5%, or 10% levels based on Ljung-Box serial correlation tests.

Fig. 6.1-6.15 demonstrate the findings regarding time-varying conditional correlations for each pair of energy stocks with fossil fuel energy commodities based on the DCC model. According to the results, it can be seen that there is volatility clustering in each pair outcome. In addtion, these results can be evident for the importance of time-varying conditional correlation (DCC) since conditional correlation for each pair varies over time. For tuprs and three fossil fuel energy commodities, we found generally positive dynamic conditional correlations, reaching the highest level around 0.40 in the pair of TUPRS-OIL. Nevertheless, there are some negative correlation periods for these three pairs such as TUPRS-OIL, TUPRS-GAS, and TUPRS-COAL which is implying an opportunity for meaningful portfolio diversification. For instance, the period between 2013-2014 (corresponds to 1700th

Table 6.2: Diagnostic tests (conditional heteroskedasticity and autocorrelation) for standardized residuals.

| Variable | ARCH LM(5) | ARCH LM(10) | LBQ(5) | LBQ(10) |
|---|---|---|---|---|
| tuprs | 270.27*** (0.00) | 302.63*** (0.00) | 0.02 (1.00) | 0.06 (1.00) |
| cosmo | 303.58***(0.00) | 319.59***(0.00) | 0.00 (1.00) | 0.77 (1.00) |
| ipeke | 136.19***(0.00) | 141.74***(0.00) | 1.51 (1.00) | 4.28 (0.93) |
| trcas | 277.20***(0.00) | 287.04***(0.00) | 0.00 (1.00) | 0.53 (1.00) |
| xelkt | 271.97***(0.00) | 287.29***(0.00) | 0.02 (1.00) | 1.96 (0.99) |
| oil | 274.83***(0.00) | 417.81***(0.00) | 0.01 (1.00) | 11.58 (0.31) |
| gas | 63.00***(0.00) | 68.45***(0.00) | 0.01 (1.00) | 0.05 (1.00) |
| coal | 2.15 (0.83) | 2.95 (0.98) | 0.07 (1.00) | 0.44 (1.00) |

Note: The ARCH LM test is introduced by Engle (1982) for conditional heteroskedasticity. The LBQ refers to Ljung-Box Test for autocorrelation. For both tests, ***, **, * indicates significance at 1%, 5%, and 10% levels respectively.

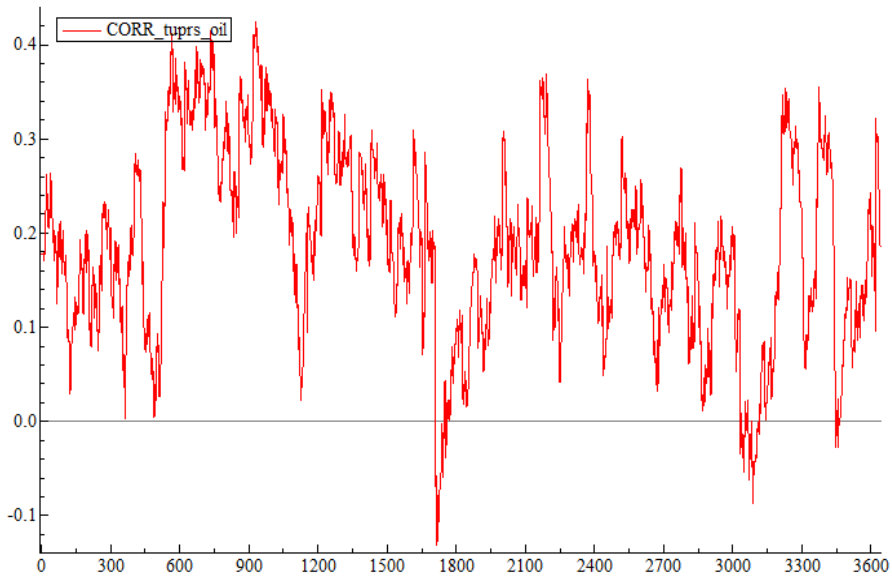



Figure 6.1: Time-varying conditional correlations for TUPRS-OIL based on DC model

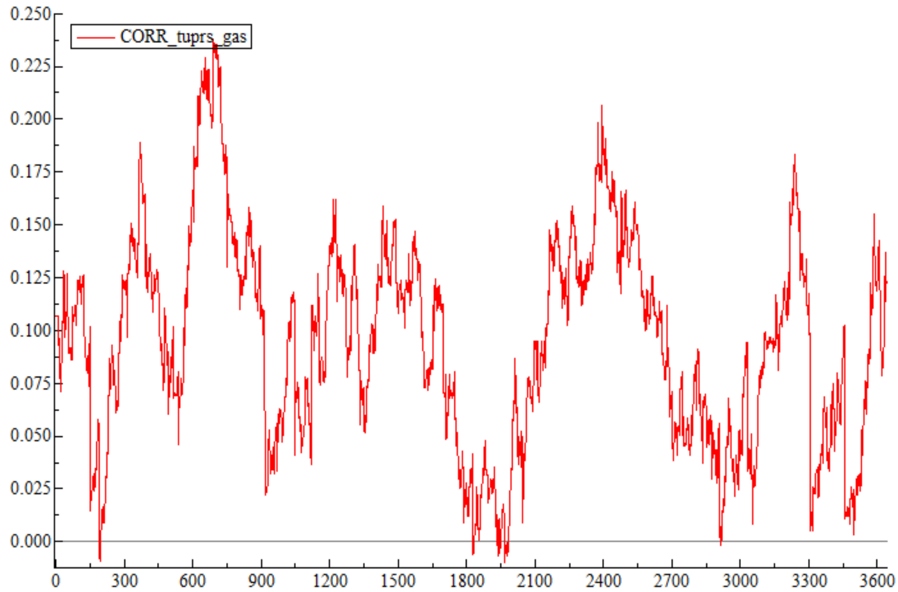


Figure 6.2: Time-varying conditional correlations for TUPRS-GAS based on DC model

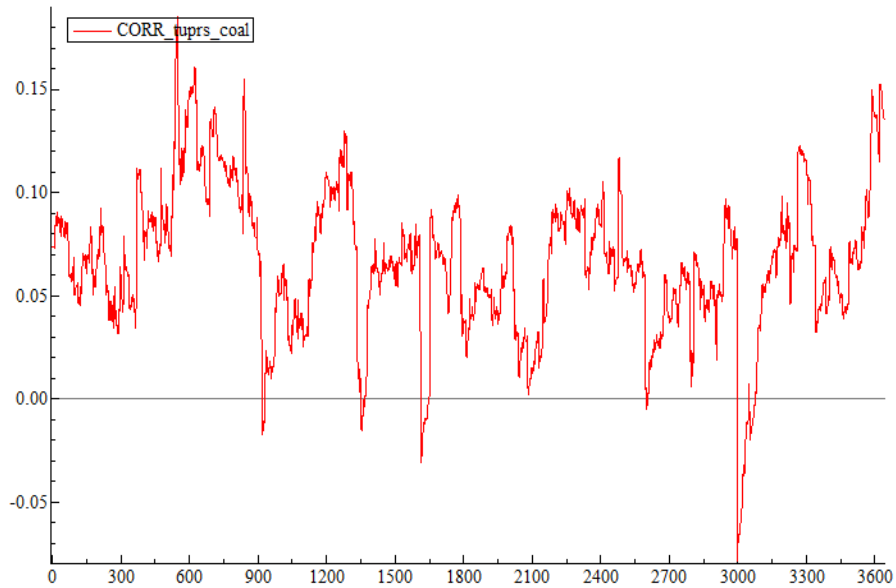


Figure 6.3: Time-varying conditional correlations for TUPRS-COAL based on DC model

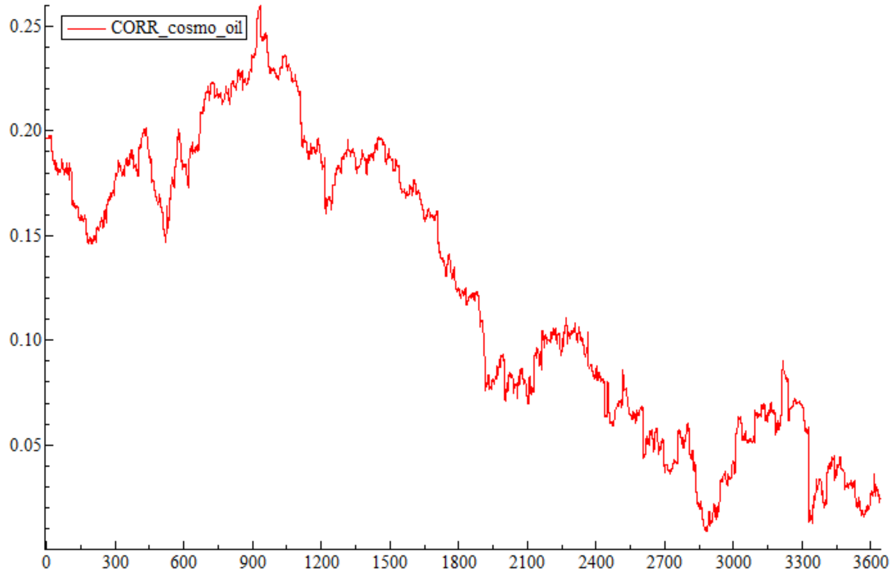


Figure 6.4: Time-varying conditional correlations for COSMO-OIL based on DC model

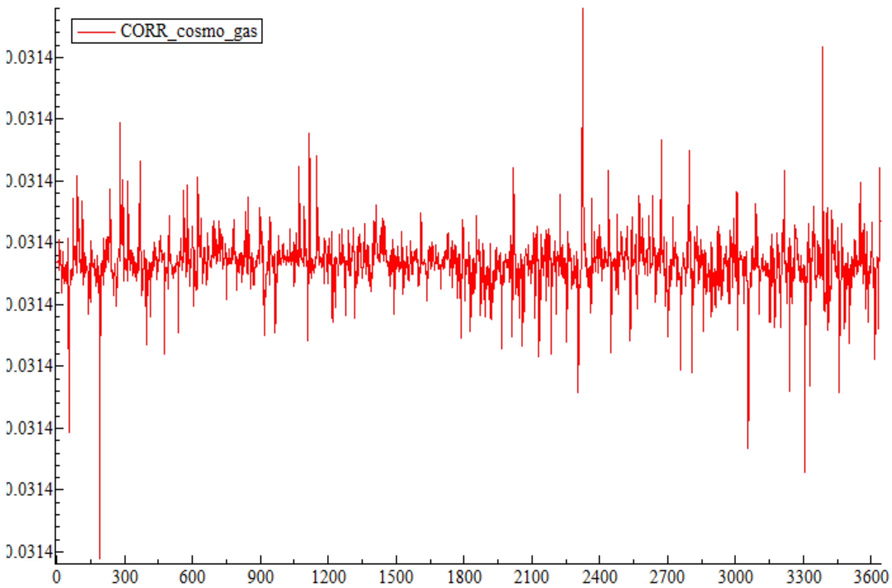


Figure 6.5: Time-varying conditional correlations for COSMO-GAS based on DC model

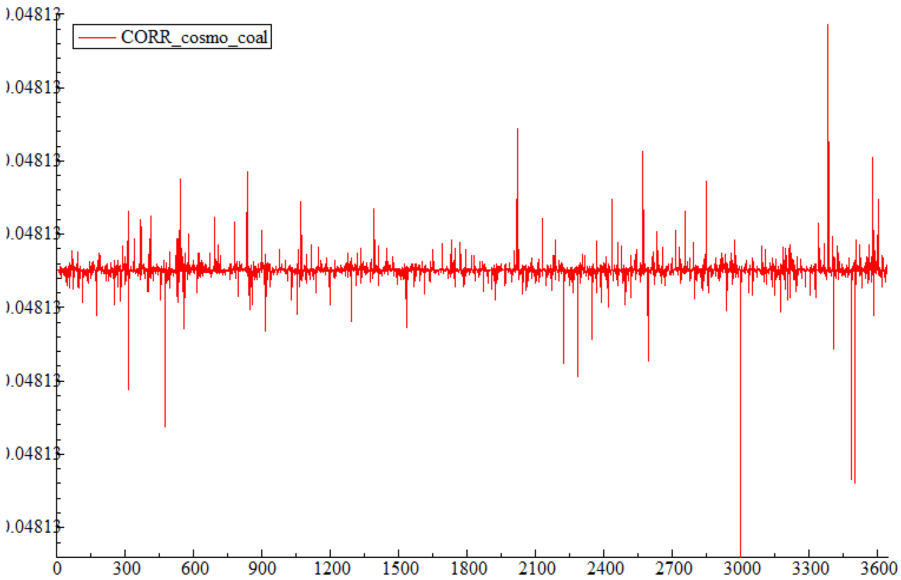



Figure 6.6: Time-varying conditional correlations for COSMO-COAL based on DC model

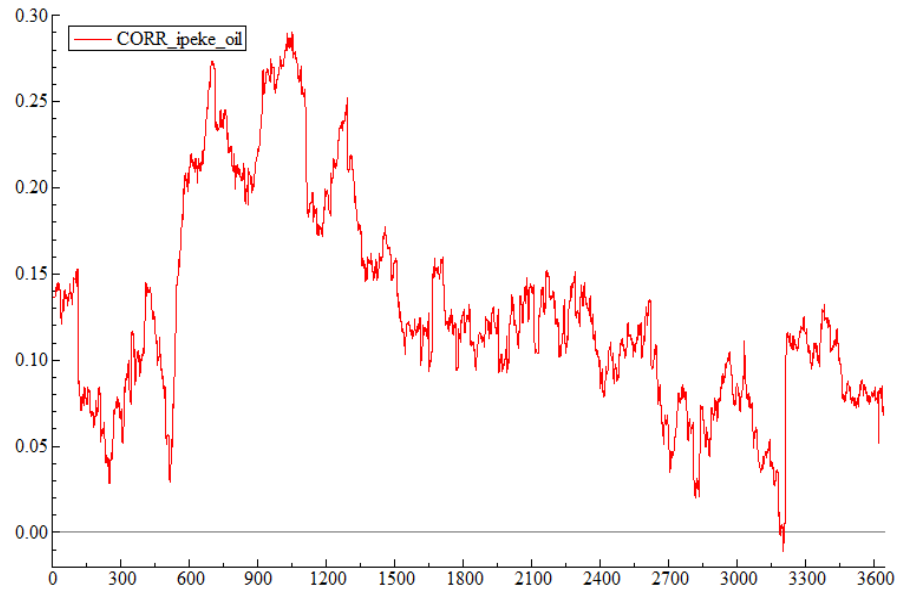



Figure 6.7: Time-varying conditional correlations for IPEKE-OIL based on DC model

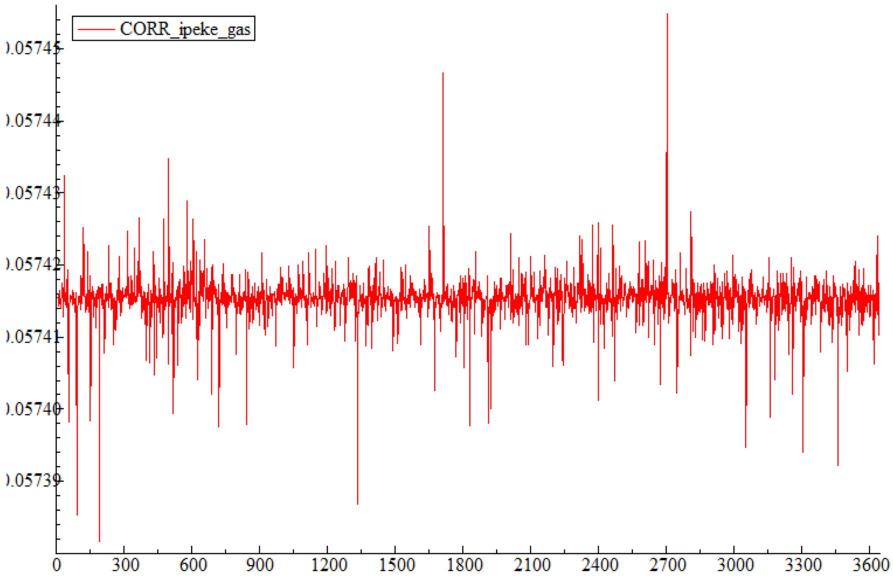



Figure 6.8: Time-varying conditional correlations for IPEKE-GAS based on DC model

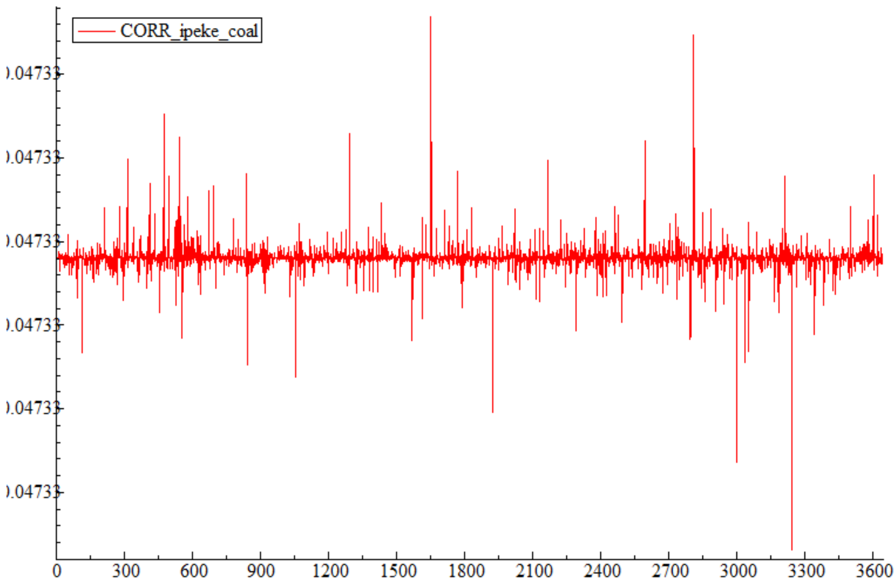



Figure 6.9: Time-varying conditional correlations for IPEKE-COAL based on DC model

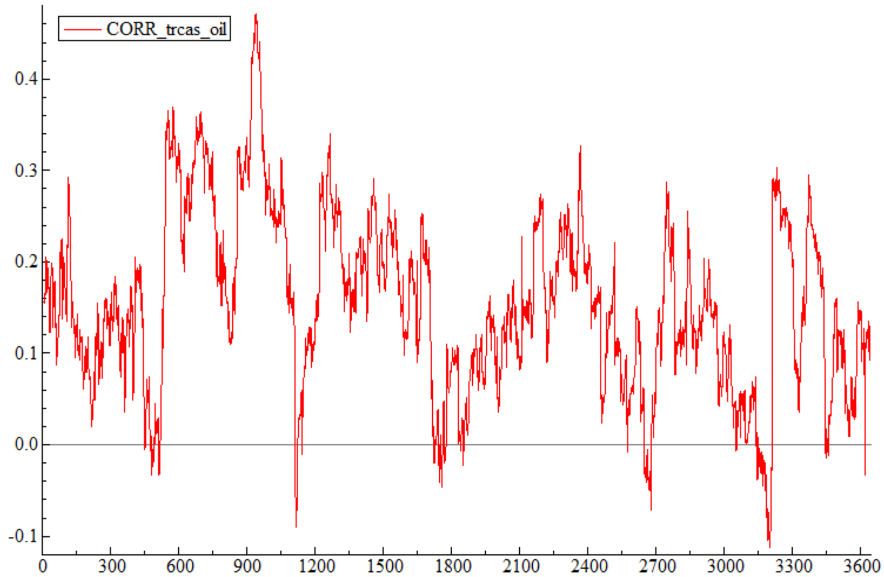



Figure 6.10: Time-varying conditional correlations for TRCAS-OIL based on DC model

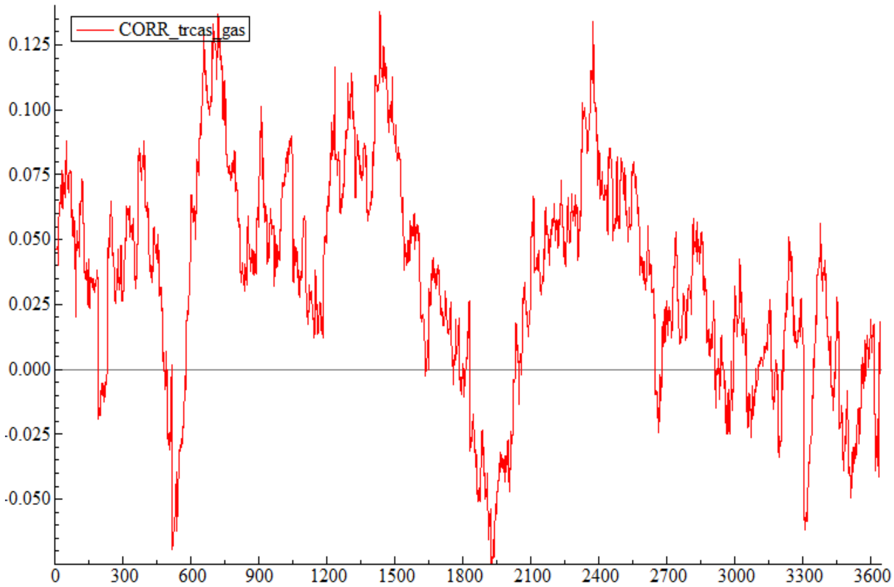



Figure 6.11: Time-varying conditional correlations for TRCAS-GAS based on DC model

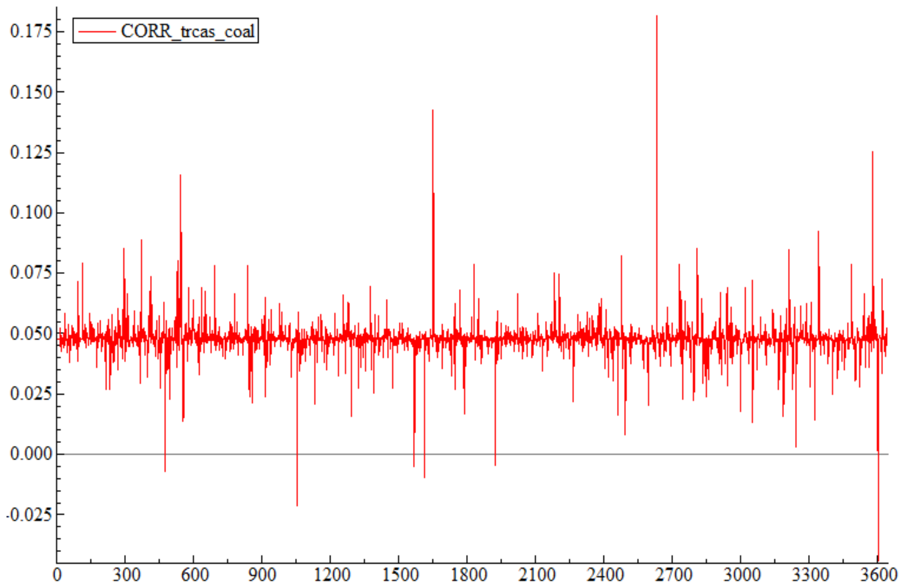



Figure 6.12: Time-varying conditional correlations for TRCAS-COAL based on DC model

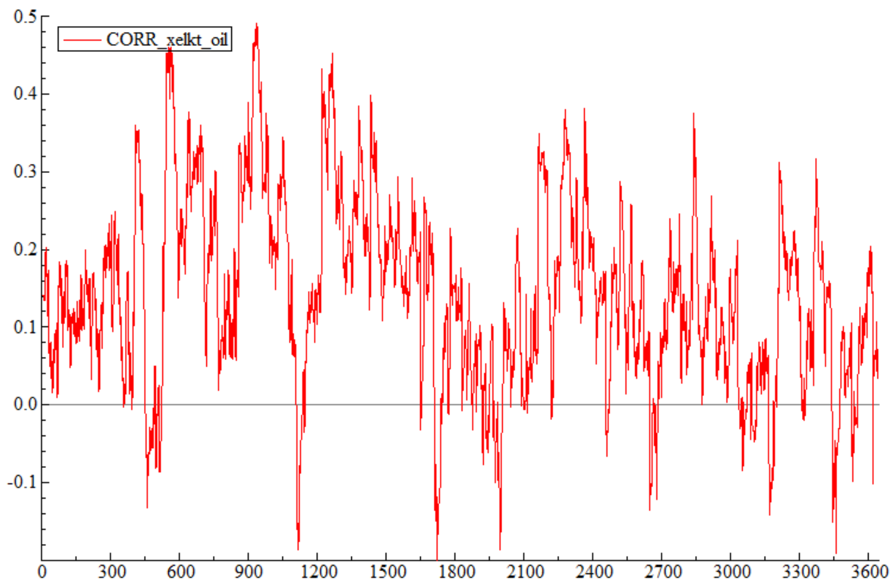



Figure 6.13: Time-varying conditional correlations for XELKT-OIL based on DC model

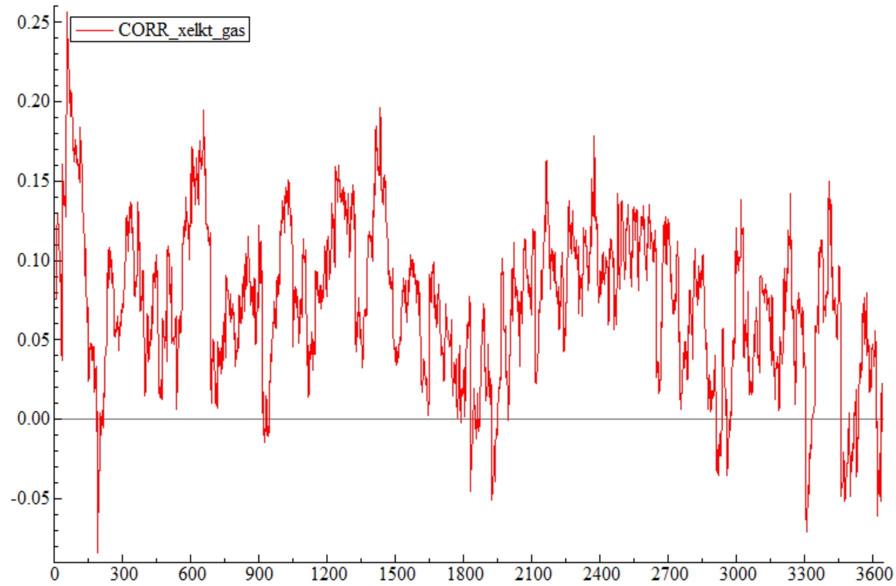


Figure 6.14: Time-varying conditional correlations for XELKT-GAS based on DC model

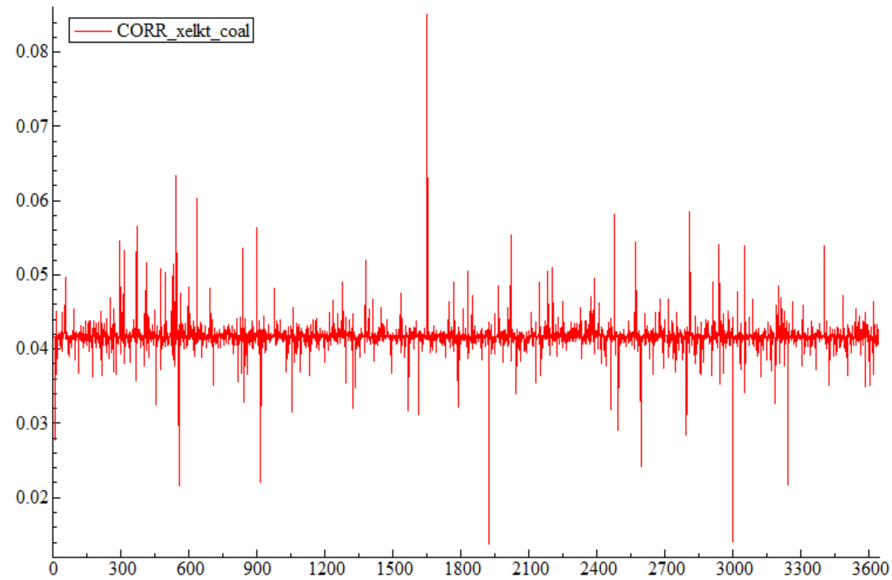


Figure 6.15: Time-varying conditional correlations for XELKT-COAL based on DC model

and 1800th observations in the graph) provides an opportunity for diversification between tuprs and oil since negative correlations are observed. We also found positive correlations between COSMO and three fossil fuel energy commodities. The strongest dynamic conditional correlation is observed for COSMO-OIL compared to COSMO-GAS and COSMO-COAL. This may be an indication that natural gas and coal have a better opportunity for portfolio diversification compared to oil. For the pairs of IPEKE-OIL, IPEKE-GAS, and IPEKE-COAL, we obtained positive dynamic conditional correlations over the period as well. The strongest correlation occurs between IPEKE and OIL (by reaching to 0.30) compared to natural gas and coal. The dynamic conditional correlation between TRCAS-OIL, TRCAS-GAS, and TRCAS-COAL provide more portfolio diversification opportunities. For instance, TRCAS-OIL have mainly five periods that show negative correlations. These periods are between 2007-2009, 2010-2011, 2013-2014, 2017-2018, and 2019-2020. For TRCAS-GAS and TRCAS-COAL, negative correlations are recorded in some periods as well. Hence, TRCAS has more opportunities for portfolio diversification with fossil fuel energy commodities compared to previous energy stocks. Lastly, the electricity index of XELKT has an opportunity for portfolio diversification with oil and natural gas for some periods as both pairs have negative correlation periods. However, a negative dynamic conditional correlation is not observed for the pair of XELKT-COAL, indicating a little scope for portfolio diversification.

To sum up, the enegy stocks of TUPRS and TRCAS, and the electricity index of XELKT have some negative dynamic conditional correlation periods with fossil fuel energy commodities. These negative correlation periods provide an opportunity for meaningful portfolio diversification, while positive correlation periods decreases the benefits of diversificaiton. We will provide optimal hedge ratios and optimal portfolio weights for our sample assets in the next sub-section and we believe that it will provide more insightful information for investors and their portfolio strategies.

## 6.2 Hedging Analysis

We extend the estimated findings from the previous section by calculating the optimal hedge ratios and optimal portfolio weights. According to Kroner and Sultan [86], we can use estimations of conditional volatilities to construct the hedge ratios. Moreover, we can also evaluate the hedging effectiveness of fossil fuel energy commodities against Turkish energy stocks. Following Kroner and Sultan [86], a long position in one asset (e.g. asset m) can be hedged with a short position in another asset (e.g. asset n). The formulation for the hedge ratio between assets m and n can be calculated as follows:

$$\beta_{mn,t} = \frac{h_{mn,t}}{h_{nn,t}} \tag{6.4}$$

Table 6.3 and Fig. 6.16-30 present full-sample and time-varying hedge ratios computed from the DCC model respectively. The lowest average value of the hedge ratio corresponds to COSMO/GAS and TRCAS/GAS, indicating the cheapest hedge among other pairs with 0.04. This hedge ratio is important in constructing a 1$ long position (buy) in COSMO (or TRCAS) and can be hedged for 4 cents with a short position (sell) in the natural gas market. However, the highest average value of the hedge ratio is achieved by the pair of IPEKE/OIL with 0.26. This hedge ratio indicates that this is the most expensive hedge by going long 1$ in IPEKE and short 26 cents in the crude oil market. For each pair of series, it can be seen from Fig. 6.16-30 that hedging ratios vary over time with sharp increases or decreases, implying that investors must sometimes take a short position or long position to minimize their risks. For TUPRS and three fossil fuel energy commodities (crude oil, natural gas,

Table 6.3: Summary statistics for hedge ratios.

| Long/Short | Mean | Max | Min | SD |
|---|---|---|---|---|
| TUPRS/OIL | 0.24 | 0.74 | -0.33 | 0.14 |
| TUPRS/GAS | 0.09 | 0.46 | -0.01 | 0.07 |
| TUPRS/COAL | 0.11 | 0.49 | -0.09 | 0.07 |
| COSMO/OIL | 0.23 | 1.44 | 0.02 | 0.15 |
| COSMO/GAS | 0.04 | 0.21 | 0.01 | 0.02 |
| COSMO/COAL | 0.12 | 0.44 | 0.01 | 0.06 |
| IPEKE/OIL | 0.26 | 2.28 | -0.02 | 0.16 |
| IPEKE/GAS | 0.08 | 0.48 | 0.01 | 0.05 |
| IPEKE/COAL | 0.13 | 0.76 | 0.01 | 0.06 |
| TRCAS/OIL | 0.22 | 1.02 | -0.36 | 0.16 |
| TRCAS/GAS | 0.04 | 0.37 | -0.08 | 0.05 |
| TRCAS/COAL | 0.09 | 0.92 | -0.04 | 0.05 |
| XELKT/OIL | 0.17 | 1.40 | -0.47 | 0.17 |
| XELKT/GAS | 0.06 | 0.50 | -0.09 | 0.06 |
| XELKT/COAL | 0.07 | 0.34 | 0.01 | 0.03 |

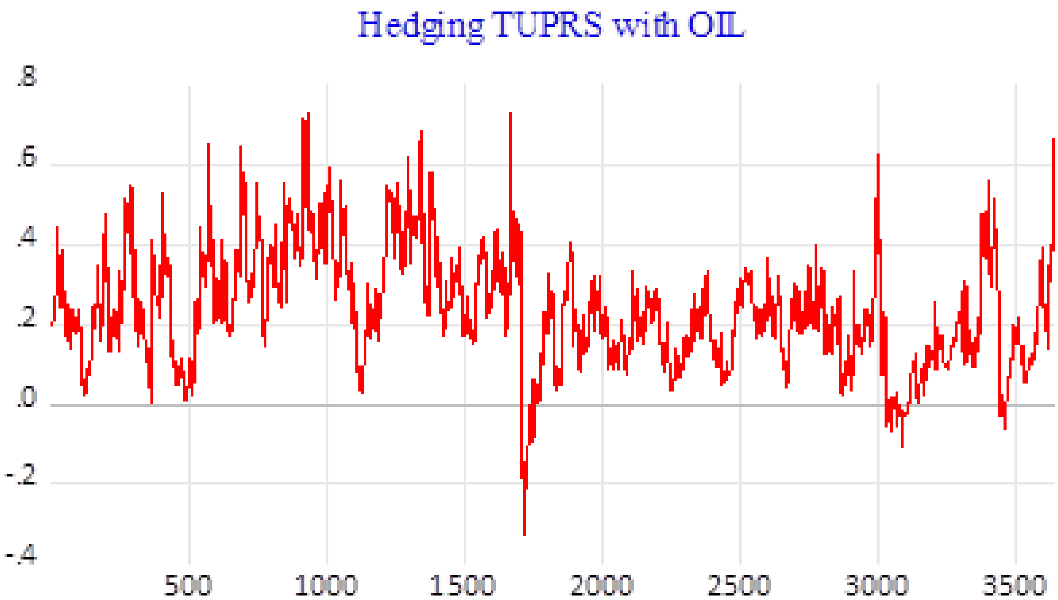


Figure 6.16: Time-varying hedge ratios for TUPRS-OIL

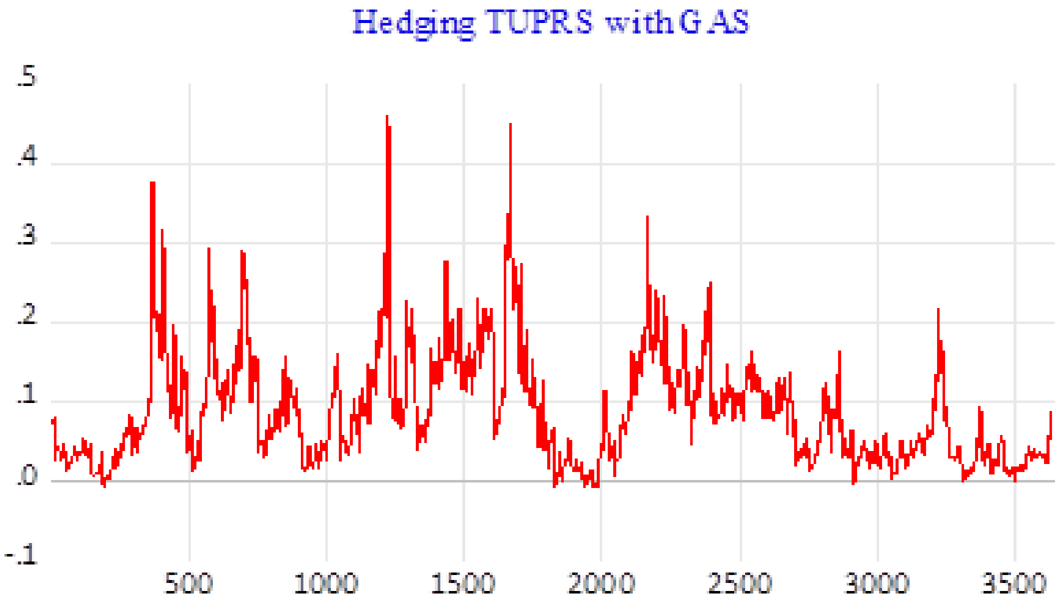


Figure 6.17: Time-varying hedge ratios for TUPRS-GAS

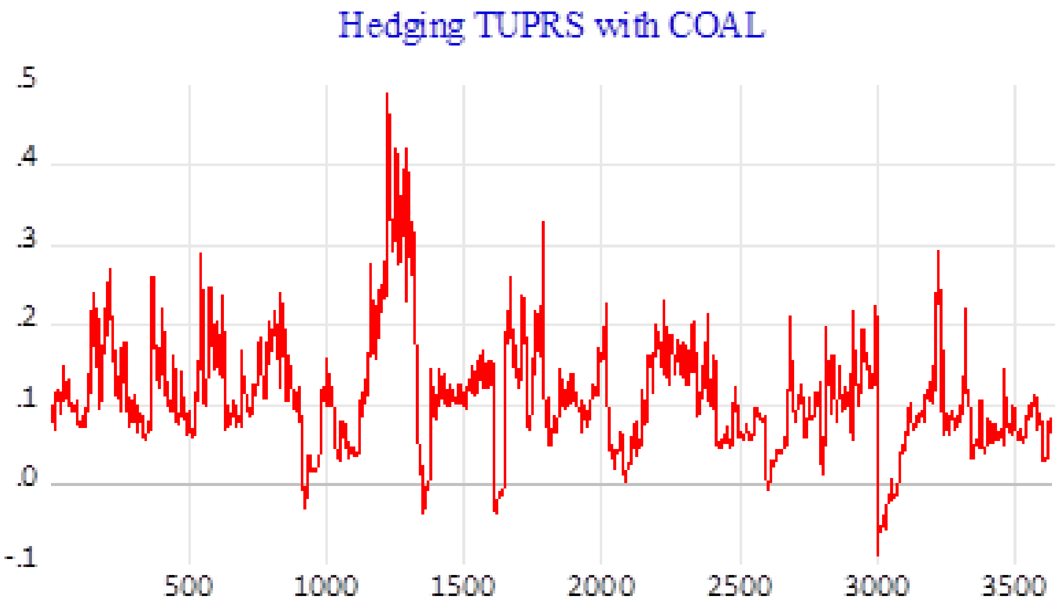


Figure 6.18: Time-varying hedge ratios for TUPRS-COAL

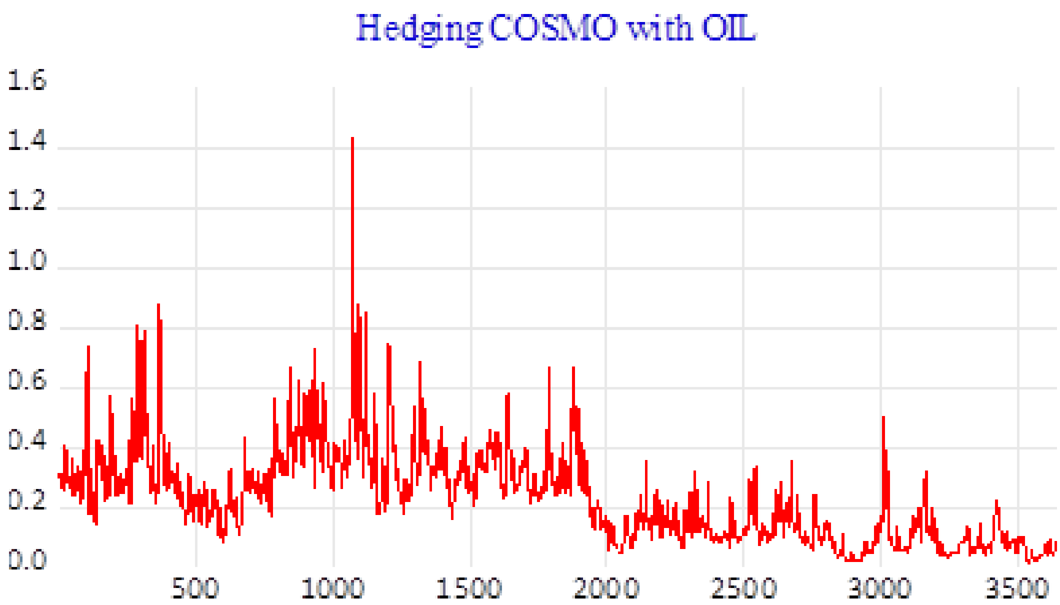



Figure 6.19: Time-varying hedge ratios for COSMO-OIL

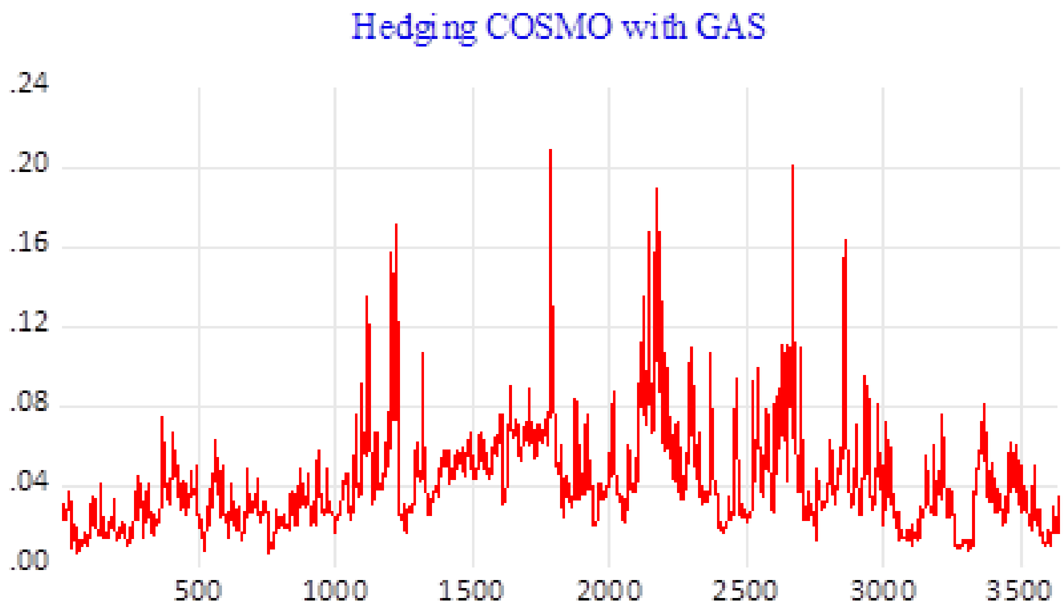



Figure 6.20: Time-varying hedge ratios for COSMO-GAS

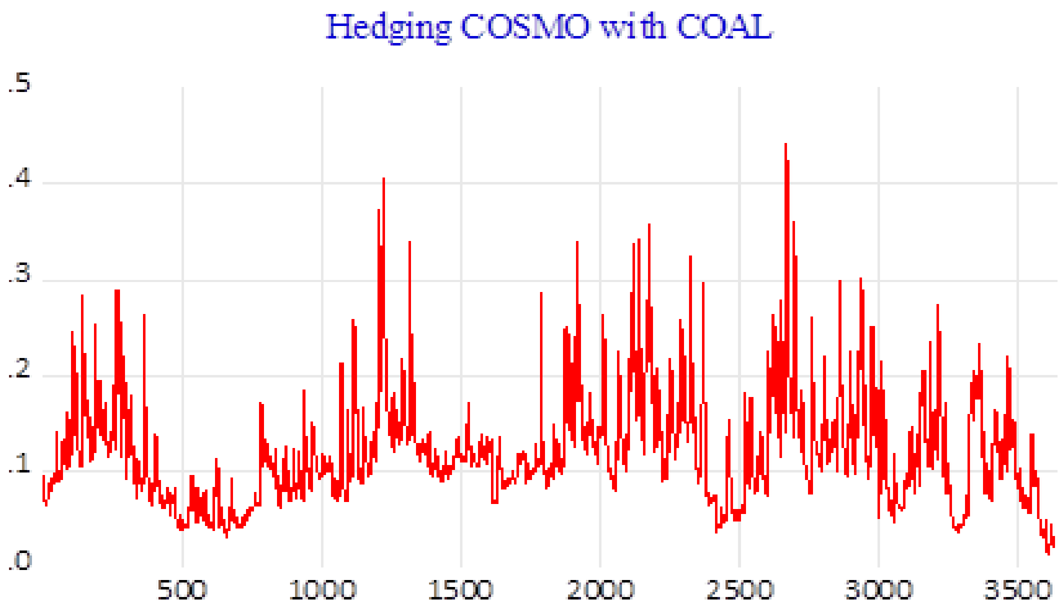


Figure 6.21: Time-varying hedge ratios for COSMO-COAL

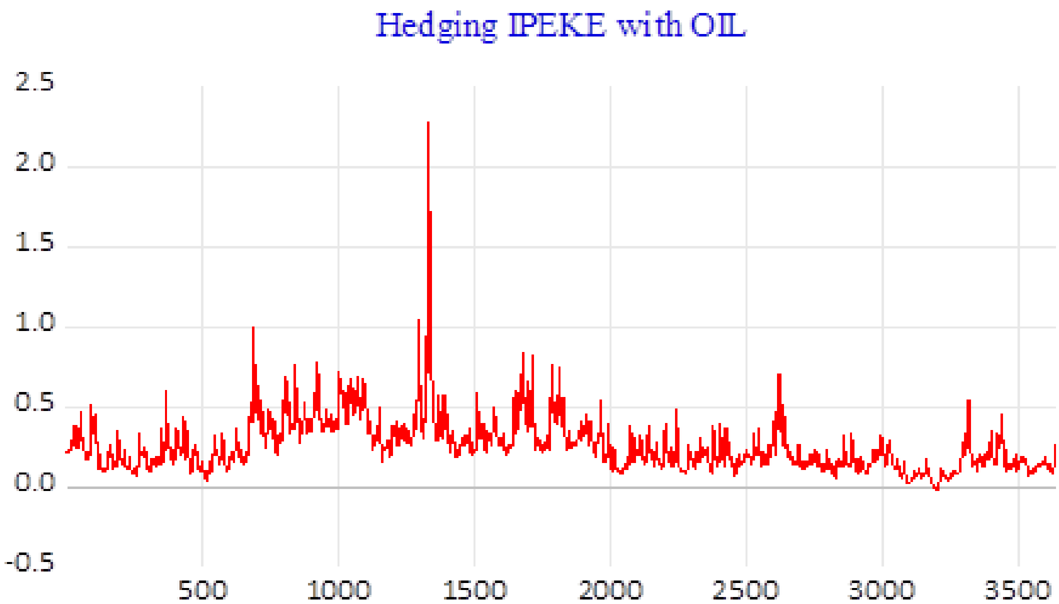


Figure 6.22: Time-varying hedge ratio for IPEKE-OIL

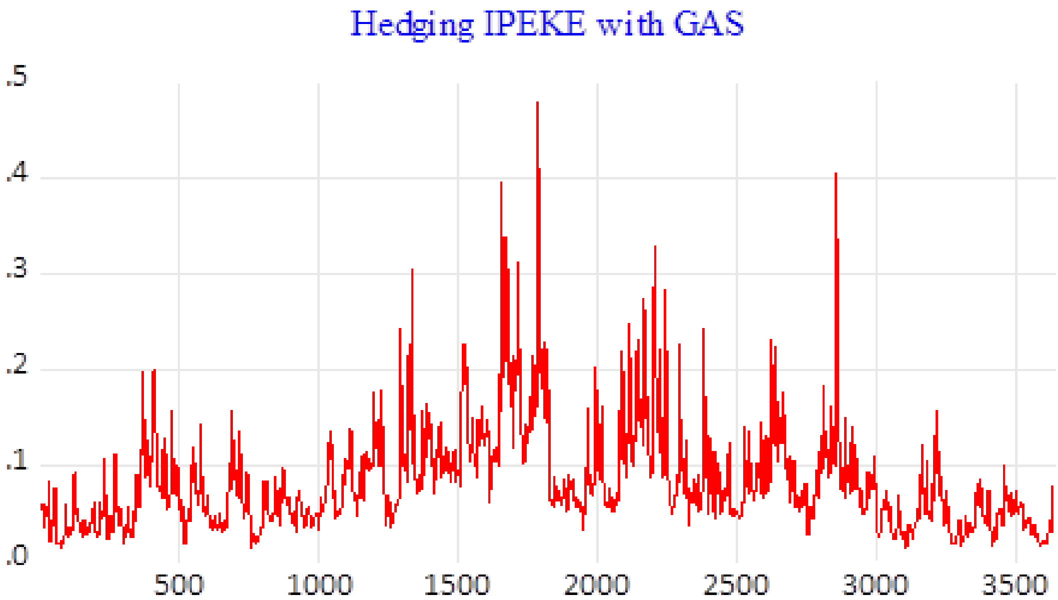


Figure 6.23: Time-varying hedge ratios for IPEKE-GAS

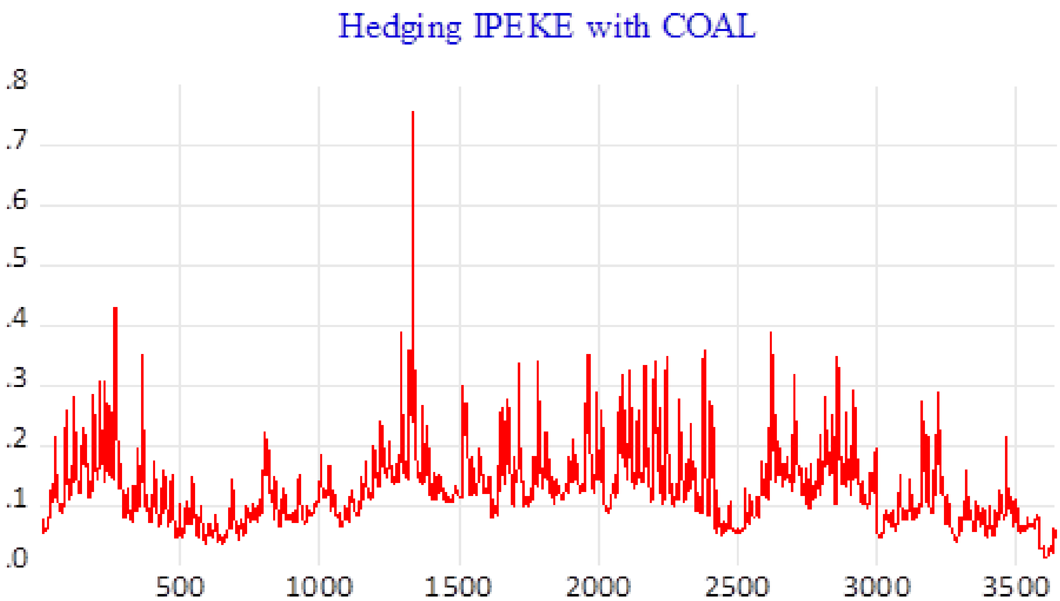


Figure 6.24: Time-varying hedge ratios for IPEKE-COAL

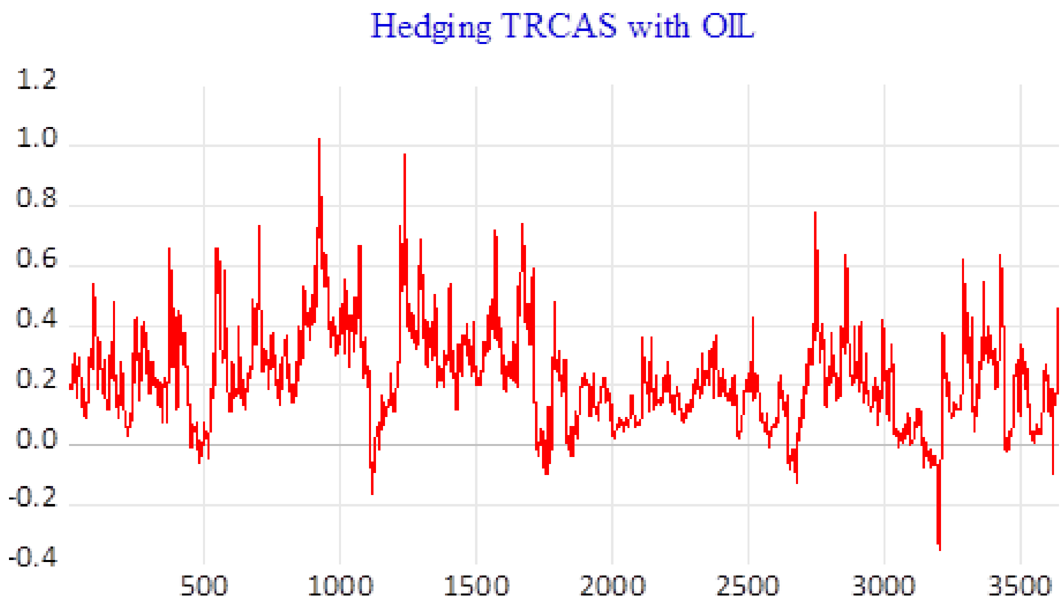


Figure 6.25: Time-varying hedge ratios for TRCAS-OIL

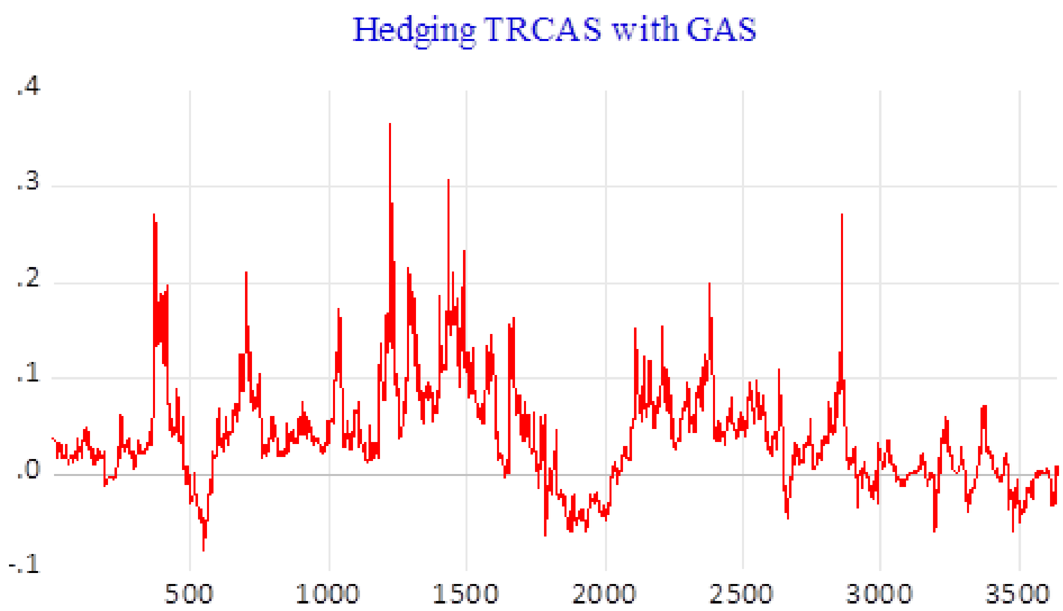


Figure 6.26: Time-varying hedge ratios for TRCAS-GAS

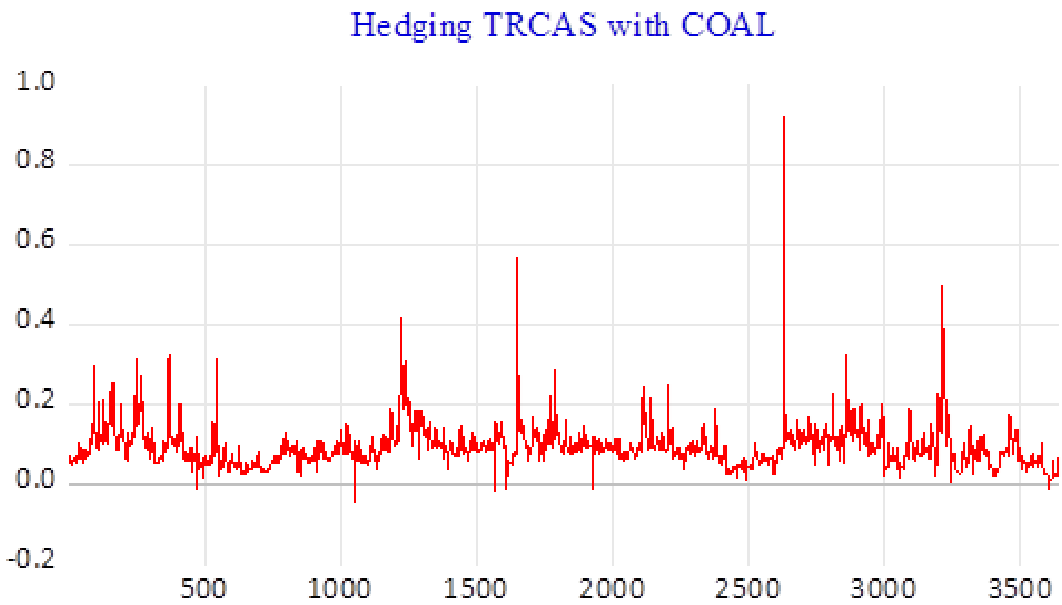


Figure 6.27: Time-varying hedge ratios for TRCAS-COAL

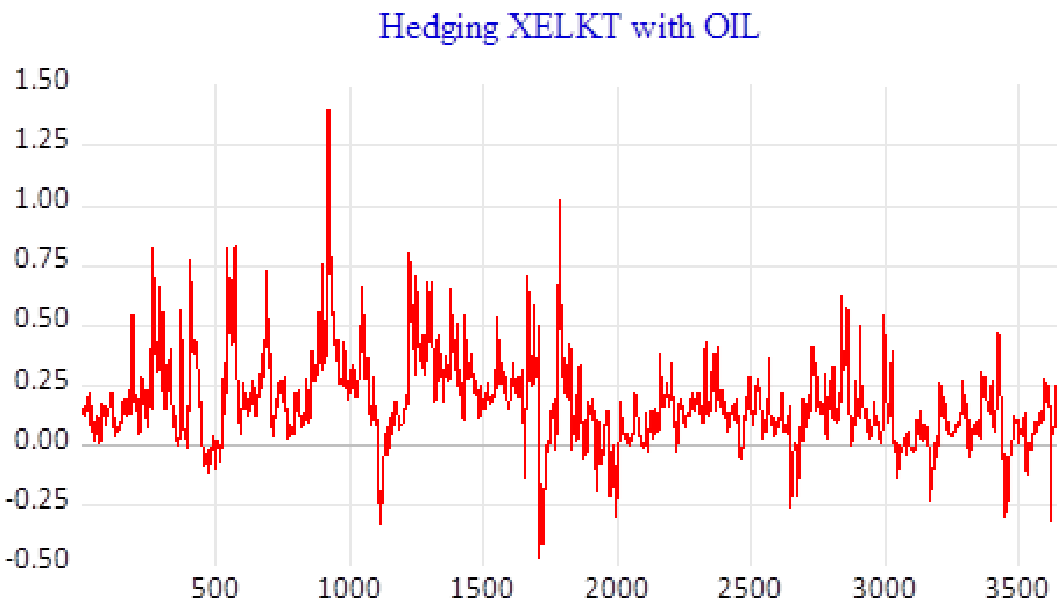


Figure 6.28: Time-varying hedge ratios for XELKT-OIL

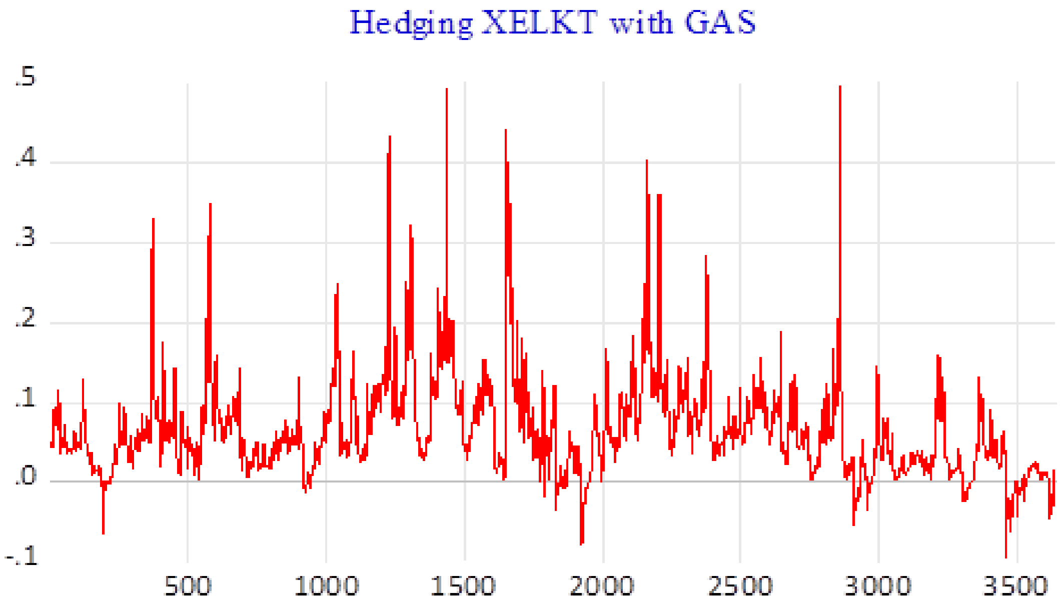


Figure 6.29: Time-varying hedge ratios for XELKT-GAS

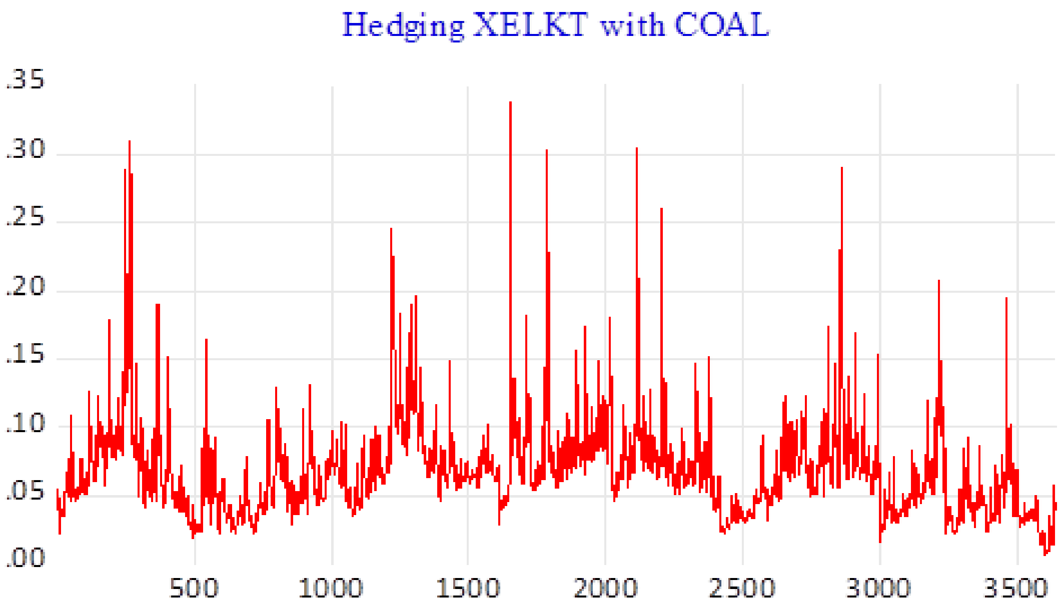


Figure 6.30: Time-varying hedge ratios for XELKT-COAL

and coal), the most expensive hedging is with OIL since the hedge ratio records its highest value, around 0.68. Hence, hedging TUPRS with OIL will be costly and not useful for investors as expected from the previous findings of DCC analysis. The cheapeast hedge can be obtained in periods when hedge ratios record the highest negative values. Similarly, other Turkish energy stocks also have the highest hedge ratio with the oil market including the BIST electricity index. This is an indication that hedging strategy with oil is the most costly way for investors to minimize their risks. Nevertheless, there are some periods when the hedge ratios decrease, thus, investors need to follow these dynamics including in the oil market to invest their money. Even though it will be costly because of higher transaction costs, investors in the Turkish energy market may follow an active portfolio strategy and rearrange their portfolios according to the circumstances in the energy market [87].

## 6.3 Portfolio Weights

To construct optimal portfolio weights, the conditional variance and covariances obtained from the MGARCH model can be used. In this regard, we can acquire the optimal proportion of Turkish energy stocks and fossil fuel energy commodities which is important for average rational investors while establishing their portfolios. Following Kroner and Ng (1998) [76], and Arouri et al. (2011) [42] optimal portfolio weights for holding two assets can be found as follows:

$$W_{mn,t} = \frac{h_{nn,t} - h_{mn,t}}{h_{mm,t} - 2h_{mn,t} + h_{nn,t}} \tag{6.5}$$

$$W_{mn,t} = \begin{cases} 0, \text{ if } W_{mn,t} < 0 \\ W_{mn,t} \text{ if } 0 \leqslant W_{mn,t} \leqslant 1 \\ 1, \text{ if } W_{mn,t} > 1 \end{cases} \tag{6.6}$$

where $W_{mn,t}$ represents the weight of the first asset in a 1\$ portfolio of two assets (i.e. asset m and n) at time t. As explained earlier, $h_{mn,t}$ indicates the conditional covariance between these two assets, while $h_{nn,t}$ is the conditional variance of the asset n. To calculate the weight of second asset, 1- $W_{mn,t}$ can be used.

Table 6.4 Summary statistics for portfolio weights.

| **Long/Short** | **Mean** | **Maximum** | **Minimum** | **Std. Dev.** |
|---|---|---|---|---|
| TUPRS/OIL | 0.39 | 1.02 | 0.04 | 0.20 |
| TUPRS/GAS | 0.59 | 0.99 | 0.04 | 0.23 |
| TUPRS/COAL | 0.30 | 0.98 | 0.02 | 0.17 |
| COSMO/OIL | 0.25 | 0.89 | -0.01 | 0.17 |
| COSMO/GAS | 0.44 | 0.96 | 0.02 | 0.23 |
| COSMO/COAL | 0.19 | 0.93 | 0.01 | 0.15 |
| IPEKE/OIL | 0.22 | 0.93 | -0.01 | 0.16 |
| IPEKE/GAS | 0.41 | 0.95 | 0.01 | 0.24 |
| IPEKE/COAL | 0.17 | 0.94 | 0.00 | 0.14 |
| TRCAS/OIL | 0.33 | 0.98 | -0.01 | 0.20 |
| TRCAS/GAS | 0.53 | 0.99 | 0.01 | 0.23 |
| TRCAS/COAL | 0.26 | 0.97 | 0.00 | 0.16 |
| XELKT/OIL | 0.43 | 0.99 | -0.06 | 0.20 |
| XELKT/GAS | 0.62 | 1.01 | 0.01 | 0.23 |
| XELKT/COAL | 0.33 | 0.98 | 0.01 | 0.19 |

Regarding the full sample period, the mean values of optimal portfolio weights for each pair of series are provided in Table 6.4. In this regard, the mean value of the pair TUPRS/OIL is found 0.39, indicating that for a \$1 TUPRS-OIL portfolio, 39 cents should be invested in TUPRS, and the remaining 0.61 cents should be invested in OIL. The mean value of TUPRS/GAS weight is 0.59, suggesting that 59 cents should be invested in TUPRS, while the rest of 41 cents should be invested in GAS. The average weight for TUPRS/COAL is 0.30, implying that 30 cents should be invested in TUPRS and 70 cents in COAL. For a 1\$ COSMO-OIL portfolio, the average weight is 0.25, meaning that 25 cents should be invested in COSMO, and 75 cents in OIL. For COSMO-GAS, the average weight is 0.44, indicating that 44 cents should be invested in COSMO, and the remaining 56 cents should be invested in GAS. The average weight for COSMO/COAL suggests that 19 cents should be invested in

COSMO, and 81 cents in COAL. For 1$ IPEKE-OIL, IPEKE-GAS, and IPEKE-COAL portfolios separately, investors should invest in IPEKE around 22 cents and the rest in OIL, 41 cents in IPEKE and the rest in GAS, and 17 cents in IPEKE and the rest in COAL. For TRCAS-OIL, the average weight indicates that 33 cents should be invested in TRCAS, and the remaining 67 cents in OIL. In TRCAS-GAS, 53 cents should be invested in TRCAS, and the rest should be invested in GAS. In TRCAS-COAL, 26 cents should be invested in TRCAS, and 74 cents in COAL. For a 1$ XELKT-OIL portfolio, investors should invest around 43 cents in XELKT, and 57 cents in OIL. For the 1$ XELKT-GAS portfolio, approximately 62 cents should be invested in XELKT, and 38 cents in GAS. Lastly, in the XELKT-COAL portfolio, 33 cents should be invested in XELKT, and the remaining 67 cents in COAL.

Overall, we can conclude that Turkish energy stocks have the highest conditional correlation with crude oil, however, crude oil can be used as a hedging instrument for some periods. Hence, investors should follow the patterns of the interaction between Turkish energy stocks and fossil fuel energy commodities actively to make useful investment strategies.

# Chapter 7

# CONCLUSION

In this thesis, we investigated volatility spillovers among publicly Turkish-listed firms in the energy sector (TUPRS, COSMO, IPEKE, TRCAS), BIST Electricity Index (XELKT), and main fossil fuels futures markets (Brent crude oil, natural gas, and coal). To do this, we used daily prices (in US$) from 07/18/2006–12/31/2021 considering important global economic and political events such as the 2008 GFC, the 2011 Arab spring, the Syrian civil war, the 2014 international crude oil crisis, the 2016 increase in coal and natural gas prices, the 2016 Brexit event, the 2016 OPEC announcements about supply cut policies, and the 2020 COVID-19 pandemic by employing time and frequency domain approaches (Diebold and Yilmaz, 2012; Barunik and Krehlik, 2018). Finally, we calculate dynamic conditional correlations (DCC-GARCH), hedge ratios and portfolio weights of Turkish energy stocks, the electricity index, and fossil fuel commodities for global investors in the energy market.

Our study is the first, to the authors' best knowledge, to investigate the volatility spillovers using the energy market considering crude oil, natural gas, and coal together and firm-level data from energy stocks in an emerging market, Turkey. We believe that taking three main energy commodities will allow us to see the complete picture in terms of volatility interlinkage between the fossil fuel commodities and energy stocks. We also believe that analyzing individual energy stocks at the firm level enables us to examine heterogeneity among firms, and examining individual countries will shed more light on the volatility connectedness among energy stocks and the fossil fuel energy market. To do this, we investigated both static and time-varying effects on the volatility connectedness between markets based on Diebold and Yilmaz (2012). The most remarkable findings of our study are as follows. First, we found a total volatility spillover index of 25% in the static analysis, indicating an interdependence between volatilities. In the fossil fuel energy market, crude oil has the highest volatility spillover to TUPRS, which is not surprising given tuprs is the largest oil importer in Turkey with 75% refinery capacity in the country. It is also the 7th largest refining company in Europe and 30th largest in the world [73]. When this is the case, tuprs may be more responsive to volatility in crude oil, which will be caused by geopolitical issues such as sanctions on oil producer/exporter countries or supply concerns owing to OPEC policies. Moreover, coal transmits the highest volatility to TUPRS, whereas natural gas transmits the highest volatility spillover to TRCAS. We explained this finding as follows. In the case of supply cuts and price increases for crude oil because of global tensions, countries may tend to increase their demand for other energy commodities such as natural gas or coal to meet their energy needs. Hence, countries that are heavily dependent on energy such as Turkey may begin to be more affected by the volatility of these energy commodities. Second, we needed to capture the impacts of cyclical trends and extreme events that change over time. Hence, we examined the volatility connectedness in a time-varying manner. Regarding the findings of dynamic analysis, we noticed that there are many fluctuations and sharp increases owing to extreme events around the world. In other words, the highest volatility spillovers among Turkish energy stocks, the electricity index, and fossil fuel energy commodities are observed during the COVID-19 pandemic, followed by the 2008 GFC. Therefore, the volatility connectedness among these markets during the COVID-19 outbreak in 2020 exceeded the 2008 GFC. Overall, we can conclude that Turkish individual energy stocks, the electricity index, and the fossil fuel energy market have a significant volatility interaction, and this is greatly affected by extreme events such as financial meltdown and price fluctuations of energy commodities. Third, we examined directional volatility spillovers among markets and found that the highest volatility spillovers from crude oil to other markets are observed during the COVID-19 pandemic and 2008 GFC. The volatility of spillovers from others to crude oil varies significantly over time, and the highest level of spillovers is recorded during the 2008 GFC. Natural gas has the highest volatility transmission to others during the COVID-19 pandemic. The volatility transmission of coal to other markets intensified during the 2008GFC. Overall, it can also be seen that Turkish energy stocks transferred significant volatility to all three fossil fuel energy commodities over the period. Although it is surprising that an emerging economy such as Turkey's energy stocks affect global energy markets, the possible explanation for this is that Turkish energy stocks may have the same dynamics as the largest international energy companies, which have a significant influence on oil markets or possibly predict their future movements [54]. Fourth, according to Barunik and Krehlik (2018), the highest performance is recorded in the long horizon compared to short and medium horizons, implying that the impact of volatility spillover transmission from one market to others is persistent (long-lasting).

We can also give some recommendations to investors and policymakers. We conclude that Turkish energy stocks and the fossil fuel energy markets have high interdependencies, and these are greatly affected by global political, financial, and extreme events. Given global tensions will never end, Turkey needs to have an energy policy road map concerning reduced dependence on imported crude oil, natural gas, and coal. To do this, alternative options such as domestically produced energy sources may be considered. For instance, improving and utilizing renewables may be an important alternative for power generation. According to our empirical results, volatility transmission spreads in the long-term frequency as well as intensifying volatility spillovers during extreme events. Hence, we can suggest to investors that they should be aware of intensifying volatility spillovers during global crisis periods. This will lead to higher oil prices and, as a result, higher oil prices will decrease stock prices. Moreover, natural gas and coal are alternative inputs for crude oil, and their volatilities affect each other. As a result, this will also decrease stock prices. Hence, investors should monitor extreme events carefully and their impacts on fossil fuel energy commodities to take action for their portfolio diversification strategies. Regarding policy decisions, the Turkish government can decrease uncertainties about tax rates and regulations related to the energy sector since this leads to energy price volatility at the retail level, and the government can implement policies to limit exchange rate volatility which increases domestic energy price volatility [46].

The limitation of our study is that we used only four energy firms in the Turkish energy sector owing to the limited number of publicly traded energy companies in Turkey. Hence, future researchers can follow new publicy traded companies in Turkey and expand sample firms to achieve better representation of the Turkish energy sector.

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# APPENDIX

Abstract for the publication that is used to construct this thesis is published in the Resources Policy and the title is Volatility Spillovers between Turkish Energy Stocks and Fossil Fuel Energy Commodities based on Time and Frequency Domain Approaches. **AUTHORS**: Merve Coskun and Nigar Taspinar. Department of Banking and Finance, Eastern Mediterranean University, Famagusta, Turkey (Accepted 22 August 2022).

**ABSTRACT**: In this paper, we investigate the volatility spillovers among major energy stocks, the electricity index, and fossil fuel energy commodities (crude oil, natural gas, and coal) using firm-level data in an emerging market, Turkey over the period July 18, 2006–December 31, 2021, which covers important economic events worldwide. To do this, we employ Diebold and Yilmaz's (2012) approach to examine both time-varying and invarying volatility spillovers among markets. Our findings reveal that Turkish energy stocks and the fossil fuel energy markets have high interdependencies, which are significantly affected by global political, financial, and extreme events. The volatility spillovers among markets during the COVID-19 outbreak in 2020 exceeded the 2008 global financial crisis. We also examine the volatility connectedness between markets based on frequency domain using various frequency bands (short term, medium term, long term). To do so, we adopt Barunik and Krehlik's (2018) approach and find that the highest performance is recorded in the long horizon compared to short and medium horizons, implying that the impact of volatility spillover transmission from one market to others is persistent (long-lasting) in the Turkish market. Finally, we discuss policy implications for global investors and policymakers based on our results. **Keywords**: Volatility Spillovers, Crude Oil, Natural Gas, Coal, Electricity, Stock Markets **JEL Classification**: C5, F3, G10, G15, Q40, Q43

Table A.1 ADF and PP unit root tests results for variables

| Statistics (Level) | tuprs | lag | cosmo | lag | ipeke | lag | trcas | lag | xelkt | lag |
|---|---|---|---|---|---|---|---|---|---|---|
| TT (ADF) | -12.336*** | (9) | -19.409*** | (4) | -19.969*** | (4) | -18.823*** | (4) | -18.811*** | (4) |
| TM (ADF) | -9.320*** | (13) | -18.923*** | (4) | -19.957*** | (4) | -18.823*** | (4) | -18.679*** | (4) |
| T (ADF) | -3.422*** | (13) | -4.166*** | (16) | -4.933*** | (13) | -3.291*** | (16) | -3.675*** | (16) |
| TT (PP) | -63.470*** | (32) | -52.712*** | (30) | -55.652*** | (29) | -60.625*** | (33) | -62.533*** | (34) |
| TM (PP) | -64.255*** | (33) | -53.670*** | (31) | -55.697*** | (29) | -60.619*** | (33) | -62.965*** | (34) |
| T (PP) | -59.766*** | (41) | -53.429*** | (40) | -59.408*** | (40) | -58.554*** | (41) | -62.545*** | (42) |
| Statistics | | | | | | | | | | |
| (First Difference) | tuprs | lag | cosmo | lag | ipeke | lag | trcas | lag | xelkt | lag |
| TT (ADF) | -27.401*** | (13) | -24.780*** | (15) | -26.083*** | (13) | -26.224*** | (15) | -25.631*** | (15) |
| TM (ADF) | -27.403*** | (13) | -24.783*** | (15) | -26.085*** | (13) | -26.225*** | (15) | -25.631*** | (15) |
| T (ADF) | -27.405*** | (13) | -24.786*** | (15) | -26.089*** | (13) | -26.227*** | (15) | -25.634*** | (15) |
| TT (PP) | -760.042*** | (232) | -913.253*** | (501) | -1217.643*** | (990) | -504.512*** | (106) | -532.668*** | (114) |
| TM (PP) | -760.085*** | (232) | -913.532*** | (500) | -1189.360 | (987) | -504.517*** | (106) | -532.508*** | (114) |
| T (PP) | -760.107*** | (232) | -905.366*** | (500) | -1175.472 | (988) | -504.586*** | (106) | -532.690*** | (114) |

Note: T stands for the most restricted model without a drift and trend, TT for the most general model with a drift and trend, TM for the model with a drift but no trend, and TT for the model with a drift but no trend. The lag lengths in brackets are utilized in the ADF test to eliminate serial correlation from the residuals. Numbers in brackets indicate Newey-West Bandwith when utilizing the PP test (as determined by Bartlett-Kernel). By removing trend and intercept throughout the models, unit root tests were carried out in both the ADF and PP tests, going from the most general to the least specific model. ***, ** and * represent rejection of the null hypothesis at the 1%, 5%, and 10% significance levels respectively.

Table A.2 ADF and PP unit root tests results for variables (continued)

| Statistics (Level) | oil | lag | gas | lag | coal | lag |
|---|---|---|---|---|---|---|
| TT (ADF) | -8.588*** | (10) | -4.736*** | (19) | -5.960*** | (19) |
| TM (ADF) | -8.588*** | (10) | -4.633*** | (19) | -5.903*** | (19) |
| T (ADF) | -3.177*** | (16) | -1.354 | (20) | -3.594*** | (19) |
| TT (PP) | -71.943*** | (39) | -69.561*** | (35) | -64.761*** | (31) |
| TM (PP) | -71.945*** | (39) | -69.589*** | (35) | -64.830*** | (31) |
| T (PP) | -60.672*** | (42) | -69.499*** | (41) | -76.594*** | (39) |
| Statistics | | | | | | |
| (First Difference) | oil | lag | gas | lag | coal | lag |
| TT (ADF) | -25.233*** | (15) | -23.828*** | (19) | -32.063*** | (18) |
| TM (ADF) | -25.237*** | (15) | -23.808*** | (19) | -32.064*** | (18) |
| T (ADF) | -25.240*** | (15) | -23.797*** | (19) | -32.069*** | (18) |
| TT (PP) | -746.183*** | (290) | -730.940*** | (647) | -683.998*** | (169) |
| TM (PP) | -745.927*** | (290) | -653.965*** | (656) | -685.258*** | (169) |
| T (PP) | -746.043*** | (290) | -637.503*** | (660) | -685.092*** | (169) |

Note: T stands for the most restricted model without a drift and trend, TT for the most general model with a drift and trend, TM for the model with a drift but no trend, and TT for the model with a drift but no trend. The lag lengths in brackets are utilized in the ADF test to eliminate serial correlation from the residuals. Numbers in brackets indicate Newey-West Bandwith when utilizing the PP test (as determired by Bartlett-Kernel). By removing trend and intercept throughout the models, unit root tests were carried out in both the ADF and PP tests, going from the most general to the least specific model. ***, ** and * represent rejection of the null hypothesis at the 1%, 5%, and 10% significance levels respectively.