MEASURING THE EFFECTIVENESS OF HEDGING STRATEGIES FOR FX RISK IN TURKISH ELECTRICITY MARKETS

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ABSTRACT

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Ph.D. Program in Finance

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The main purpose of this comprehensive study is to measure hedging effectiveness in the electricity revenue portfolio under the imbalance regulation of a wind power plant affected by exchange rate changes by finding the optimum hedge ratios and comparing different constant and dynamic hedging models. This study aims to find ways to better manage the exchange rate risk in the Turkish electricity market by using financial currency futures contracts available in the country and measuring the risk by using different risk measurement techniques. To achieve this goal, the optimal hedge ratios of futures contracts traded on the Borsa Istanbul (BIST), namely the US dollar–Turkish lira currency futures (USDTRY), are determined. The efficiency of hedge ratios for portfolios estimated through constant and time-varying econometric models, such as ordinary least squares (OLS), fully hedged, and diagonal VECH—a multivariate GARCH model—are compared under the minimum variance hedge ratio framework. The results indicate that the percentage of variance reduction improves highly for the dynamic GARCH model, compared to the static OLS and fully hedged model, for electricity portfolio. On the other hand, daily return VaR figures calculated by the parametric method and Monte Carlo simulation are closer. GARCH hedged portfolio has the lowest VaR(1%) and is consistent with the result found with the EHE minimum variance rule. Christoffersen backtesting results also suggest that all VaR values calculated through out-of-sample data for all hedged portfolios are acceptable.

Keywords: Minimum variance; Futures market hedging; Optimal hedge ratio; Diagonal VECH; BIST; VaR

ÖZET

TÜRK ELEKTRİK PİYASASINDA DÖVİZ RİSKİ KORUNMA STRATEJİLERİNİN ETKİNLİĞİNİN ÖLÇÜLMESİ

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Bu kapsamlı çalışmanın ana amacı Dengeleme ve Uzlaştırma Yönetmeliğine tabi bir rüzgar enerjisi santralinin elektrik gelir portföyü döviz riskinin optimum korunma oranları bulunarak ve sabit ve dinamik korunma stratejileri karşılaştırılarak korunma etkinliğinin ölçülmesidir. Bu çalışma ülkede bulunan finansal vadeli döviz sözleşmelerini kullanarak ve farklı risk ölçme teknikleriyle ölçerek Türk elektrik piyasasındaki döviz riskinin daha iyi yönetilmesinin yollarının bulunmasını hedeflemektedir. Bu hedefe ulaşmak için Borsa İstanbul (BIST)'da işlem gören Türk Lirası ABD Doları döviz vadeli işlem sözleşmelerinin optimum korunma oranları tespit edilmiştir. Portföylerin sabit ve dinamik yöntemlerden olan Sıradan En Küçük Kareler, tam korunma ve çok değişkenli bir GARCH modeli olan diagonal VECH yöntemleriyle hesaplanan korunma oranları Minimum Varyans Korunma Oranı Teorisi çerçevesinde karşılaştırılmıştır. Bulunan sonuçlar, varyansın yüzdesel azalımının dinamik GARCH modelinde, statik Sıradan En Küçük Kareler ve tam korunma oranının kullanıldığı yönteme göre daha fazla olduğunu göstermektedir.

Diğer taraftan parametrik yöntem ve Monte Carlo simülasyonuna göre hesaplanan günlük Riske Maruz Değerleri birbirine yakındır. GARCH yöntemiyle korunan portföyün %1'lik Riske Maruz Değeri hesaplanan en düşük değer olmakla birlikte EHE'nin minimum varyans modelinin sonucuyla da uyumludur. Christoffersen geriye dönük testi, korunan portföyler için örneklem dışı ve örneklem içi verileriyle hesaplanan bütün Riske Maruz Değerlerinin kabul edilebilir olduğunu göstermektedir.

Anahtar Kelimeler: Minimum varyans; Vadeli işlem sözleşmesi; Korunma etkinliği; Optimum korunma oranı; Diagonal VECH; BIST; Riske Maruz Değer

This thesis is dedicated to:

The memory of my late mother who really encouraged me to start my Ph.D. studies

and

My father, my wife and my daughter for their endless love and support

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CHAPTER 1: INTRODUCTION

1.1. Context and Motivation

Electricity is becoming more and more important in human beings' daily lives and has a direct effect on the quality of living. The type of sources that electricity is produced is also an important point considering its environmental issues. Most traditional fossil energy sources face the danger of depletion due to the increasing energy-consuming activities. These are oil, natural gas, and coal. On the other hand, global warming caused by the emissions of gases such as carbon dioxide and methane is becoming another critical issue. Therefore, the most popular subject of the past couple of years in the energy industry has been the growth of new renewable energy sources. Wind, solar, geothermal, and biofuel are among them.

Countries are increasing their investments in renewable energy sources. Even the big oil companies such as Shell, BP, and others are diversifying their energy investments into these clean, safe, cheap, and infinite energy sources. The share of global electricity production from renewables grew from 18% in 2009 to nearly 28% in 2020. With the new investments in this area, authorities believe that this number will surpass traditional energy sources soon.

With the liberalization of the electricity markets worldwide, electricity has become an asset that can be tradable in energy exchanges such as Nordpool in Europe and EXIST in Turkey. The price of the commodity has started to be determined through these exchanges with supply and demand factors. However, the liberalization of electricity trading has also led to a significant problem: electricity price volatility. Between different commodities, electricity has the highest volatility, and the price risk is relatively high for the related parties such as electricity producers, distributors, consumers. In addition to price risk, there is also foreign exchange risk (FX) in countries like Turkey, where electricity price guarantee is determined in USD but paid in Turkish lira in a determined lagged period. Therefore, an effective way of managing price and FX risk has become so important in the energy sector where the volatility is high.

In this thesis, hedging the FX risks in the renewable energy sector is analysed, alternative hedging techniques are discussed and compared in terms of their hedging effectiveness. For this purpose, the generation data of an active wind power plant located at the Aegean cost of Turkey is used and all the electricity revenue calculations are conducted according to the current YEKDEM (Renewable Energy Resources Support Mechanism) regulations in Turkey. This regulation and main concept of this mechanism is similar in most of the European and developing countries. Therefore, this study also represents a good example to countries where they might face FX risk due to currency volatility.

Foreign exchange volatility and currency risk management is an important topic for policy makers who are responsible for a well-functioning energy market. Therefore, the implications of findings of this thesis is not only important for investors in the energy market but also for regulators that should design an appropriate risk management environment.

1.2. Research Objective

The recent global financial crises have shown the importance of financial derivatives contracts, mainly for hedging purposes. It is increasingly evident that high volatility in financial markets has harmful effects on different industries, and the need to protect financial assets is becoming more urgent. Financial derivatives offer an efficient solution for hedging different kinds of risks. These are mainly currency, interest rate, and price risks. If appropriately used, these instruments provide benefits for both investors and firms in different industries such as energy.

Companies need to hedge their exposures with different derivatives contracts; the effectiveness of their hedge is the key to avoiding the effects of crises. A growing number of studies focus on the relationship between spot and future market price fluctuation to measure the hedging effectiveness of different underlying assets by using constant and dynamic hedging models. Kharbanda and Singh (2020) study currency futures in India and compare three models for evaluating the effectiveness of hedge. Chiou-Wei, Chen and Zhu (2020) analyse natural gas spot and future prices in terms of hedging effectiveness. Kumar and Bose (2019) investigate the hedging effectiveness of cross-listed Nifty Index futures and compare the performance of constant and dynamic hedging strategies. These studies find that the dynamic multivariate GARCH model outperforms the other static models and improves hedging effectiveness. On the other hand, Kumar and Bose (2019) observe that constant hedging models generate superior hedging effectiveness compared to the time-variant hedging model.

Currently, electricity trading is performed through spot and derivatives markets in Turkey. Derivatives contracts are financial contracts between two or more counterparties whose value is based on an-agreed underlying asset. These contracts might be used for hedging, speculation, and arbitrage purposes. Forwards, futures, options, swap contracts are the main derivatives contracts that are widely used in different industries, especially for risk management. Electricity price risk and FX risk can be eliminated by using these kinds of derivatives instruments.

In this respect, the main objective of this thesis is to measure hedging effectiveness in the electricity revenue portfolio of a wind power plant affected by currency volatility by finding the optimum hedge ratios and comparing different constant and dynamic hedging models. This study aims to find ways to better manage the exchange rate risk in the Turkish electricity market by using financial currency futures contracts available in the country under the new imbalance regulation and measure the risk by using different risk measurement techniques.

1.3. Scope and Research Methodology

The generation data of a wind power plant located in the Aegean Region of Turkey is used and analysed to achieve the objectives of this thesis. The power plant's exchange rate risk is hedged by using Borsa Istanbul VIOP's USDTRY future contracts.

For this purpose, the daily revenue of the power plant under YEKDEM regulation is calculated using hourly revenue data. Day-Ahead Market Revenue, Imbalance Cost/Revenue, and YEKDEM Incentives are calculated by using necessary

YEKDEM formulas. After obtaining daily revenue figures denominated in TRY, unhedged and hedged portfolios with different methods are formed, and hedging effectiveness and total ending balance of these electricity revenue portfolios are analysed.

Several studies were conducted on the hedging effectiveness of derivatives contracts traded on global derivatives exchanges using the unconditional constant and conditional dynamic hedge strategies. Past studies, especially starting with Ederington (1979), focused on the percentage reduction in the return variance of the hedged portfolio relative to the unhedged portfolio, which Ederington called "Ederington hedging effectiveness (EHE)." Many studies followed this approach. While the variance could be conditional or unconditional, EHE is always calculated based on an unconditional variance in empirical studies. Ederington considered only unconditional constant hedge strategies, but later studies also considered using the conditional variance.

In this study, different hedged and unhedged electricity revenue portfolios affected by the exchange rate fluctuations are formed for the sample wind power plant. Hedging effectiveness and ending balance of unhedged, fully hedged, and partially hedged with a constant hedge ratio calculated through OLS and the diagonal VECH, a multivariate GARCH model portfolios are calculated and compared.

In addition to that, daily Value at Risk (VAR) values of electricity portfolios are calculated by using different methods such as historical simulation, variance-covariance, and Monte Carlo simulation methods. Furthermore, all back testing of these values are performed through Christoffersen tests.

1.4. Contributions of the Thesis

This thesis is concerned with the implementations of different constant and dynamic hedge effectiveness measures. Different VaR models are also applied to hedged and unhedged portfolio returns to investigate the consequences of model selections. For this reason, this thesis makes several contributions to the current literature.

This study's main contributions are summarized as follows:

Firstly, as far as our knowledge, this is the first study that considered the FX risk in an electricity market under Ederington's variance reduction framework. The literature generally focuses on electricity price risk, the role of hedging effectiveness, and the protective role of electricity futures contracts. However, in a country like Turkey, where the currency volatility is high, FX risk is another crucial issue that renewable energy companies must consider. Turkey can be a good model for other developing countries where the share of renewable energy is growing steadily.

Secondly, it estimates the hedge ratios by using unconditional and conditional methods and compares the hedging effectiveness of these different methods to find the best hedging model for the electricity revenue portfolio.

Thirdly, the Borsa Istanbul (BIST) US dollar–Turkish lira (USDTRY) future contract is used for hedging the currency portion of the electricity revenue portfolio in this thesis. In 2018, USDTRY futures contracts were ranked the world's ninth most liquid currency futures contracts. To our best knowledge, it is thought that this the first to undertake a study on the hedging effectiveness of USDTRY currency futures contracts which are used in the electricity market.

The fourth contribution of this thesis is the comprehensive VaR and backtesting analysis for an active renewable power plant located at the Aegean cost of Turkey. The results provide some evidence on effectively controlling the revenue stream of the electricity generating plant. The modelling is conducted through applying both out-of-sample and in-sample approaches.

1.5. Thesis Structure

This thesis is divided into eight different chapters. The overall structure of the thesis is as follows:

The introduction chapter introduces the motivation and research objectives of the thesis, summarizes the research methods, and clarifies main contributions of the study.

Chapter 2 illustrates a comprehensive literature review on hedging effectiveness, energy hedging and VaR studies on energy markets.

Chapter 3 and Chapter 4 provides an overview of the current structure of the Turkish Power Market and focuses on financial risk management in electricity markets as well as current risks under YEKDEM environment, respectively.

Chapter 5 involves the data sources and preliminary data analysis covering the spot and future FX rates and electricity prices.

Subsequent chapter (Chapter 6) develops an understanding of methodologies used in this study especially on revenue generation, optimum hedge ratio computations, hedging effectiveness, VaR calculations and backtesting.

Chapter 7 includes empirical findings of the study and interpretations.

Moreover, final Chapter 8 concludes the research, points out the limitations and directs further studies.

CHAPTER 2: LITERATURE REVIEW

2.1 Literature review

The hedging effectiveness measure proposed by Ederington (1979), or the EHE, remains the most common criterion for evaluating the value of different hedging instruments. Ederington's fundamental idea originates from Johnson (1960) and Stein (1961), who introduced portfolio theory into the area of hedging. Most previous hedging theories consider only "naive" hedging, that is, trading a hedging instrument in the same amounts as the asset being hedged. Ederington shows that the hedge ratio, which is the ratio of the amount of the hedging instrument used relative to the amount of the asset hedged, must be adjusted to obtain maximum hedging effectiveness. To derive this result, Ederington demonstrates the existence of an optimal hedge ratio, which minimizes the variance of the portfolio value. Different hedging strategies and instruments have been compared in terms of the EHE. The strategy possessing the greatest EHE is deemed the most appropriate. Specifically, the EHE is the percentage reduction in the return variance of the hedged portfolio relative to the return variance of the unhedged portfolio. In empirical studies, the EHE is always calculated based on unconditional variance since Ederington considers only unconditional constant hedge strategies.

Further developments in the futures hedging literature focus on conditional dynamic hedging strategies. The EHE remains the primary criterion for evaluating the usefulness of these strategies; however, this approach is inappropriate because, although the conditional hedge strategy is constructed to minimize conditional variance, its usefulness is measured by unconditional variance. Without a linear relation between the conditional and unconditional variances, the EHE is unsuitable as a benchmark for evaluating a conditional hedge strategy.

Conditional heteroskedasticity in spot and futures price series has induced the wide use of the generalized autoregressive conditional heteroskedasticity (GARCH) methodology (Bollerslev, 1986) in the optimal hedge ratio literature. Most studies focus on the bivariate GARCH (B-GARCH) model, which utilizes information from both markets jointly throughout the variance-covariance matrix (Tokat and Tokat, 2010).

Many unconditional and conditional variance studies calculate optimal hedge ratios, as well as the EHE. We conclude that, in many studies, different GARCH models that allow for the calculation of conditional variances generally outperform the unconditional variance calculated by Ederington’s (1979) ordinary least squares (OLS). Ballie and Myers (1991) study US beef, corn, cotton, gold, and soybean markets using OLS, B-GARCH, and diagonal VECH models and find that GARCH hedge ratios perform best to reduce the conditional variance of the portfolio returns for all these commodities. Park and Switzer (1995) analyse Standard & Poor’s (S&P) 500 and Toronto 35 Index data and conclude that the B-GARCH model outperforms others.

Further support for various multivariate GARCH (M-GARCH) models—such as the modified Baba–Engle–Kraft–Kroner (BEKK), vector autoregressive (VAR)-M-GARCH, diagonal VEC (DVEC), B-GARCH, DCC-MGARCH—is provided by Bhaduri, Durai, and Raja (2008), Caldarelli and Souza (2011), Choudhry and Zhang (2013), Kumar and Bose (2019) Moschini and Myers (2001) and Kumar, Singh, and Pandey (2008). On the other hand, Alexander and Barbosa (2007), Gupta and Singh (2009), Gupta and Kaur (2019) and Park and Jei (2010) report that unconditional hedge ratios either outperform or are virtually identical to conditional hedge ratios, which are calculated by different conditional variance models.

Chunhachinda, Boyrie and Pavlova (2019) also used a multivariate GARCH model (DCC-GARCH) framework and showed that portfolios consisting of commodities and emerging market equities have higher hedging effectiveness than portfolios with commodities and developed market equities.

A few studies have focused on the hedging effectiveness s of the Turkish derivatives market. Aksoy and Olgun (2009) investigate static hedge strategies by using OLS, bivariate VAR, error correction model (ECM), and GARCH and M-GARCH models for ISE 30 stock index futures. They point out that the hedge ratio estimated by the M-GARCH model gives the best results in terms of hedging effectiveness criteria and outperforms other models’ estimates for both in- and out-of-sample data.

Olgun and Yetkiner (2011) aim to determine an optimal hedge strategy for ISE 30 stock index futures in Turkey by comparing the hedging performance of constant and time-varying hedge ratios under mean-variance utility criteria. They employ standard regression, the OLS method of Viswanath (1993), and the bivariate diagonal VECH GARCH framework of Bollerslev et al. (1988). They use the mean-variance utility criteria of variance reduction to compare constant and time-varying hedge ratios, respectively. Olgun and Yetkiner (2011) empirical results reveal that the dynamic hedge strategy outperforms static and traditional strategies.

Another study analysing the hedging effectiveness of BIST 30 equity futures contracts, conducted by Celik (2014), uses static methods, such as conventional OLS regression, a simple ECM, VECM, and ECM-GARCH models. Furthermore, time-varying hedge ratios are estimated using a multivariate GARCH (M-GARCH) model, such as VEC-constant conditional correlation (CCC) GARCH and VEC-Diagonal-BEKK. The dynamic models provide the best hedge ratios.

Gümrah and Gökbulut (2017) also show that optimal hedge ratios are not constant over time for BIST 30 equity index futures. The authors used a BEKK parameterization of the multivariate GARCH(1,1) model, which nests the hypothesis of the constancy of the ratio of conditional covariance into the conditional variance of one of the variables. They estimate a GARCH-BEKK model using daily data for the ISE 30 index. The optimum hedge ratio during the first year of the TurkDex was found to be highly volatile, implying informational inefficiency related to the structure of the new futures market. Lack of trade, in particular, can stem from the valuation of new information.

Evci and Kandir (2017) apply a linear regression model and several symmetric and asymmetric GARCH models to estimate the optimum hedge ratio for USDTRY futures contracts traded on BIST. They find that the best model for determining the hedge ratio is the generalized error distribution (GED)-EGARCH(1,2,2) model.

Xu and Lien apply generalized autoregressive score-driven (GAS) models to hedge natural gas and crude oil market price risk. They found that OLS strategy is not inferior to other time-varying GARCH models in volatility and VaR reduction.

In terms of VaR models, several studies analysed different VaR and backtesting methods to find out the best one. Yulling (2018) discusses different VaR estimation approaches and backtesting methods such as Kupiec's Unconditional Coverage and Christoffersen Test. He applied these methods to Apple stock and found out that the most effective method of VaR estimation is the filtered historical simulation method followed the historical simulation.

On the other hand, Linsen (2018) investigates whether a dynamic Value at Risk model can improve the accuracy of frequently used traditional models. For this reason, he constructed 60 different conditional forecasting models. He concluded that the dynamic VaR models produce forecasts which are better than traditional models. While the traditional and HAR models significantly underestimate risk, the applied dynamic VaR produces much better results.

Other than FX hedging, some studies focus on hedging the effectiveness of spot and future electricity markets. Madalena and Pinho (2010) applied the Ederington framework to German electricity spot and futures prices. They concluded that dynamic hedging strategies provided better results in hedging effectiveness in the German electricity market. On the other hand, Bystrom & Bystrom (2003) investigated Nordic Power Exchange (Nordpool) electricity future contracts to find the most effective hedging strategies. In contrast to Madalena and Pinho (2010), they found out that the hedging performance of the simple OLS hedge compared to the conditional hedges is slightly better.

Shamsi and Cuffe (2021) propose a model for wind power producers that offsets imbalance costs by taking opposite positions at the prediction markets. Prediction markets are exchange-traded markets where an outcome of an event is traded. In this case, the future value of wind power is traded opposite the spot electricity market. They show that this hedging model limits the loss values and has better risk measures.

Pineda and Conejo (2013) explore whether electricity option contracts might be used in addition to power forward contracts to reduce the uncertainties related to price and production. One of the main disadvantages of forwards contracts for power producers is that they are mandatory. Power producers must fulfil the requirements and sell the electricity at the agreed price at the settlement period. However, when the price is much higher on the delivery day, the power producer may experiment with a hedging loss. Electricity options give more flexibility since the power producer can choosewhether to exercise or not to exercise the option according to the availability of its generating units or the pool price behaviour.

Botterud, Kristiansen and Ilic (2009) analyse historical spot and futures prices at Nord Pool electricity market. They show that future electricity prices tend to be higher than spot prices, and there is a negative convenience yield that depends on the season and hydro reservoir storage levels. Their findings of negative convenience yield and risk premium contradict with many other commodity markets.

On the other hand, Liu and Wu (2007) combine the VaR analysis with risk management in power market. Their simulation results confirm that trading in multiple different markets such as spot, forward, and future markets is helping to reduce the risks. They find out that VaR provides a valuable approach to decide if the created trading portfolio is acceptable or not.

This research aims to find the best optimum hedge ratio, which gives the highest variance reduction level for the electricity revenue portfolio which is denominated in US dollars but paid in Turkish lira with a time gap. Our study, similar to those of Ballie and Myers (1991), Bhaduri, Durai, and Raja (2008), and Olgun and Yetkiner (2011), the optimal hedge ratio estimates are determined by a diagonal VECH model, which outperforms other constant and dynamic models in many studies. The VECH model is expected to be superior to other models because, in many studies, the optimal hedge ratios determined by this model are found to decrease portfolio variance the most effectively. Table 1 summarizes past studies where dynamic GARCH methods outperform static methods using similar underlying instruments.

Table 1: Empirical Evidence on Hedging Efficiency of Futures Markets

Author (Year of Study)	Asset Analyzed	Data Period	Data Freq.	Methodology Applied	Conclusion: Methods with Highest Hedging Effectiveness
Baillie and Myers (1991)	Beef, coffee, corn, cotton, gold and soybeans (USA)	In Sample: 1986 Out Sample: 1982 contract period	D	OLS, B-GARCH: Diagonal VECH	GARCH
Park and Switzer (1995)	S&P 500, Toronto 35 Index (USA/Canada)	June 8, 1988-December 18, 1991	W	OLS, OLS with Cointegration, B-GARCH	B-GARCH
Kumar, Singh and Pandey (2008)	S&P CNX Nifty, NCE Gold and NCE Soybean	S&P CNX Nifty index (January 1st, 2004-May 8th, 2008), Gold (22 July 2005-8 May 2008), Soybean (October 4, 2004-May 8, 2008)	D	Constant hedge ratio (OLS, VAR, and VECM); Dynamic hedge ratios (VAR-M-GARCH)	VAR-M-GARCH
Bhaduri, Durai and Raja (2008)	NSE Stock Index Futures, S&P CNX Nifty Index	September 4, 2000-August 4, 2005	D	OLS, Bivariate VAR, VECM, Multivariate GARCH (DVEC-GARCH)	DVEC-GARCH

Table 2 (continued): Empirical Evidence on Hedging Efficiency of Futures Markets

Author (Year of Study)	Asset Analyzed	Data Period	Data Freq.	Methodology Applied	Conclusion: Methods with Highest Hedging Effectiveness
Gupta and Singh (2009)	Nifty, BankNifty and CNXIT	January 1, 2003-December 31, 2006	D	OLS, GARCH (p,q), TARCH (p,q), EGARCH (p,q), VAR and VECM	VAR or VECM
Aksoy and Olgun (2009)	ISE30	May 2, 2005-April 30, 2009	D	OLS, Bivariate VAR, ECM, GARCH, M-GARCH	M-GARCH
Olgun and Yetkiner (2011)	ISE30	May 2, 2005-September 15, 2009)	D	OLS, B-GARCH	B-GARCH
Çelik (2014)	ISE30	February 2005-August 2013	D	Static Hedge Ratios: OLS, ECM, VECM, ECM-GARCH Dynamic Hedge Ratios: VEC-CCC-GARCH and VEC-Diag-BEK	ECM-GARCH
Gümrah and Gökbulut (2017)	ISE30	February 2, 2005-July 7, 2009	D	OLS, GARCH BEKK	GARCH-BEKK
Evci and Kandir (2017)	USDTRY	March 1, 2005-March 31, 2016	D	OLS, GED-EGARCH (1,2,2)	GED-EGARCH
Kumar and Bose (2019)	Nifty Index	July 15, 2010-July 15, 2016	D	OLS, Bivariate VAR, CCC and DCC-MGARCH	DCC-MGARCH
Chiou-Wei, Chen and Zhu (2020)	US Natural Gas	January 2000-December 2013	D, W	VECM, DCC-MGARCH	DCC-MGARCH
Kharbanda and Singh (2020)	USD, GBP, EURO and JPY against INR	February 2010-May 2017	D	OLS, VECM, DCC-MGARCH	DCC-MGARCH

CHAPTER 3: AN OVERVIEW OF THE TURKISH ELECTRICITY MARKET

3.1 Turkish electricity market liberalization

Different authorities governed activities such as generation, distribution and transmission of electricity in Turkey until 1970. In 1970, the Turkish Electricity Institution was established, and all of these activities were conducted by this state-owned institution from 1970 until 1984. With the 1984 Law No. 3096 on Authorization of Enterprises other than the Turkish Electricity Institution to Produce, Transmit, Distribute and Trade Electricity *(Official Gazette No. 18610 dated 19.12.1984)*, private capital were allowed to enter into the electricity market. We can say that this was the first step towards the deregulation of the electricity market in Turkey.

The Turkish government also took more actions to facilitate the privatization process. The demerge of the Turkish Electricity Institution into Turkish Electricity Generation and Transmission Company (TEAŞ). Turkish Electricity Distribution Company (TEDAŞ) in 1993, acceptance of the Law on Procurement of Certain Investments and Services through Build-Operate-Transfer Model (BOT) in 1994 and the law on Establishment and Operation of Electricity Production Facilities through Build-Operate Model (BO) and Regulation of Energy Sales in 1997 were among them. BOT and BO laws were enacted to attract investors, generate electricity and sell it to the government for a certain period. But even with the BOT and BO laws, state-owned companies still had great dominance in the electricity market.

These efforts led us to the acceptance of the Electricity Market Law (EML) No. 4628 which was *published at the Official Gazette No. 24335 dated 03.03.2001*. This was a major step in the Turkish electricity market liberalization process. With this law still in effect, the state acts only as a supervisory and administrative authority. On the other hand, it is preferred that private companies perform generation, distribution, and supply activities of the electricity. With this law, private investors were encouraged to invest in production activities.

To facilitate this privatization process, in 2001, TEAŞ was demerged into three different companies as Electricity Generation Corporation (EÜAŞ), Turkish Electricity Transmission Corporation (TEİAŞ), and Turkish Electricity Trading Corporation (TETAŞ). In addition to that, 21 different companies, which are authorized to deal with the distribution activities in their distribution areas, were formed under TEDAŞ.

We can say that EÜAŞ and TEDAŞ are the government-owned players in the Turkish electricity market, and private entities are engaged in electricity generation and distribution activities. The electricity transmission is still at the hand of TEİAŞ, which is the Turkish electricity transmission company.

With the acceptance of the EML in 2001, Energy Market Regulatory Agency (EMRA) was established to regulate and monitor electricity, natural gas, petroleum, and the liquid petroleum gas markets. EMRA, an independent regulatory power, is an autonomous public legal entity with administrative and financial authority. EMRA gives all the licenses for production, distribution and transmission. With the EML, different licenses that the EMRA can give are listed below:

- Production license
- Auto-producer license
- Auto-producer group license
- Distribution license
- Transmission license
- Wholesale license
- Retail license

To define the procedures and principles of activities related to real-time balancing and settlement of the current electricity demand and supply, “Electricity Market Balancing and Settlement Regulation (DUY)” had been accepted in 2004. This was a major step in electricity trading in Turkey and it opened the door to trades through bilateral agreements, which started in 2006.

Finally, in 2013 there was an amendment to EML, and The New Electricity Market Law No. 6446 has been enacted by the Turkish Parliament on 14 March 2013. Law No. 4628 is still in force, but its name has changed to the Law on the Organization and Duties of the Energy Market Regulatory Authority. Therefore, Law No. 4628 only regulates the duties and rights of EMRA, while the new EML regulates market activities.

With this new EML, a new license - the market operation license- was created, and EMRA issued it for Turkish Energy Exchange (EXIST) on 1 September 2015.

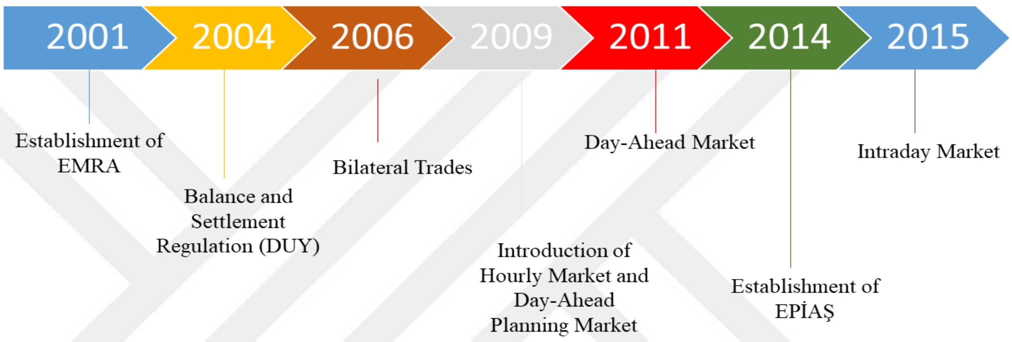

Figure 1: Steps Taken To A More Liberal Electricity Market in Turkey

3.2 Energy Exchange Istanbul (EXIST)

EXIST, which was established on March 12, 2015, is the market operator of the Turkish energy market. Currently, it operates Turkish electricity and natural gas markets. It is a corporation and jointly owned by TEİAŞ (representing 30% of the share capital), Borsa Istanbul (representing 30.83% of the share capital), and private entities (representing 39.17% of the share capital).

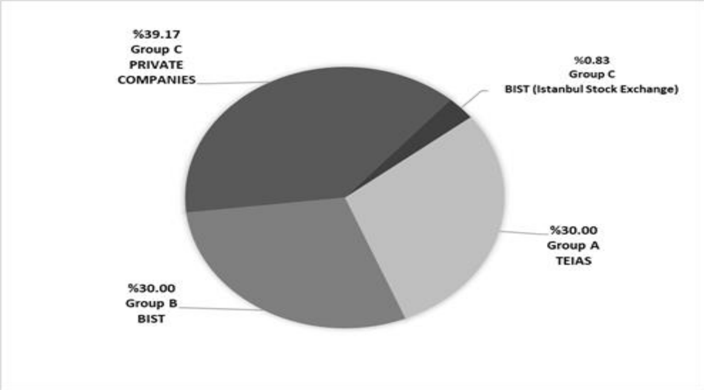

Figure 2: Shareholder Structure of EXIST (Source: EPİAŞ, 2021)

On the electricity side, three different markets are currently fully operational. These markets are the Day-Ahead market, Intraday market, and Future Physical Delivery Market.

3.2.1 Day-Ahead Market

The Day-Ahead market provides market participants with the opportunity to buy and sell electricity for the next day to balance their production or consumption requirements one day ahead. It provides the system operator with a better-balanced market and a market reference price for electricity trades.

Before the Day-Ahead market, the first step to a more liberal and competitive model at electricity trading was the transition to a monthly 3-period financial settlement system on 1 July 2006. Then Day-Ahead Planning system started on 1 December 2009 with the introduction of the hourly market. Finally, Day-Ahead market was established on 1 December 2011.

The most significant change that the Day-Ahead market brought to the market was the ability of the demand side to control its consumption according to price levels. With this new system, the demand side became much more active in the market and protected itself against future market prices.

Another novelty of the Day-Ahead market was the introduction of daily financial settlement/clearing of payables and receivables due to commercial transactions at next day after the date of the commercial transaction. With this, market participants started to collect their revenues daily rather than waiting until the end of the month.

The Day-Ahead market also secured a guarantee mechanism that protected market participants' receivables due to possible cash-flow problems. Thus reducing the effects of cash-flow problems at the electricity market.

General principles of the Day-Ahead market are listed below, and the market operation timeline is given in Figure 3:

- Day-Ahead Market transactions are conducted daily on an hourly basis. It starts from 00:00 am and ends at 00:00 am of the following day
- Participants can send their offers from the next day to 5 days later
- Market Clearing Prices (MCP) and volumes are calculated for each hour
- Advance payment notifications as results of clearing calculations for market participants based on their day-ahead balancing activities indicate payables to Market Operator and receivables from Market Operator for respective market participants, and these notifications are announced in a daily basis fashion by Market Operator to market participants via Central Clearing House
- Letters of guaranty are presented to Market Operator every day until 10:30 am. Collaterals other than letters of guaranty are presented to Central Clearing House every day until 11:00 am by market participants.
- For market participants to continue Day-Ahead Market activities during the weekend and official holidays; letters of guaranty must be presented on the previous working day until 10:30 am, and collaterals other than letters of guaranty must be presented on the previous working day until 11:00 am

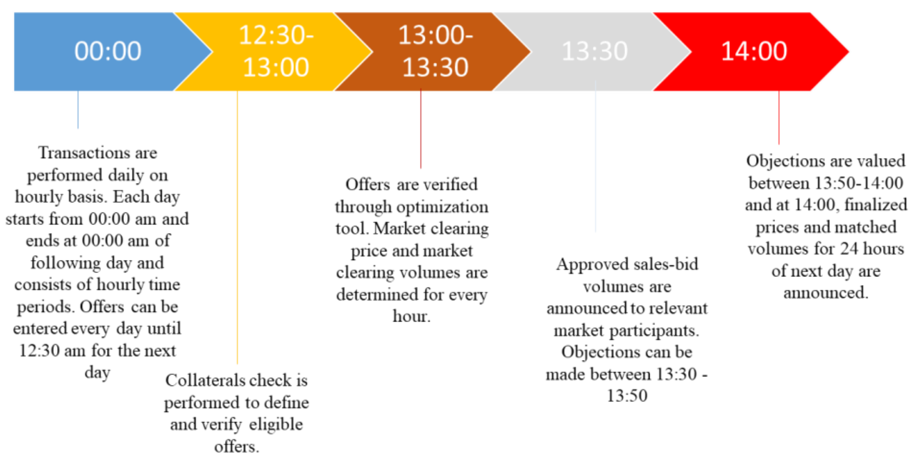

Figure 3: Day-Ahead Market Daily Market Operation Timeline (Source: EPİAŞ, 2021)

Market clearing price is determined through an optimization algorithm that uses a mathematical model. The software gets the bids from the market participants and returns the market clearing prices (MCPs) for each hour and quantities for each bid. The market operator determines matching quantities for each bid so that daily market surplus is maximized while total supply and demand are balanced at each period.

3.2.2 Intra-Day Market

In order to give market participants to balance their portfolios almost in real-time, the Intra-Day market was introduced in 2015. It allows market participants to buy and sell electricity in addition to their trades through bilateral agreements and Day-Ahead Market. Hourly System marginal prices (SMPs) are calculated at this market.

Intraday Market transactions are executed on an hourly basis every day. Trades can be performed until the door close time, which is one-hour prior physical settlement process. The Intraday market is a market where there is price and time priority at matching. It begins at 12:00 AM continuously and ends at 12:00 AM of next day. The market opening time is 6 PM.

3.3 Current and Targeted Structure of Turkish Power Market

Turkish Power Market is becoming more liberal, and privatization is the hot topic of the last decade. The current structure is summarized in Figure 4 below.

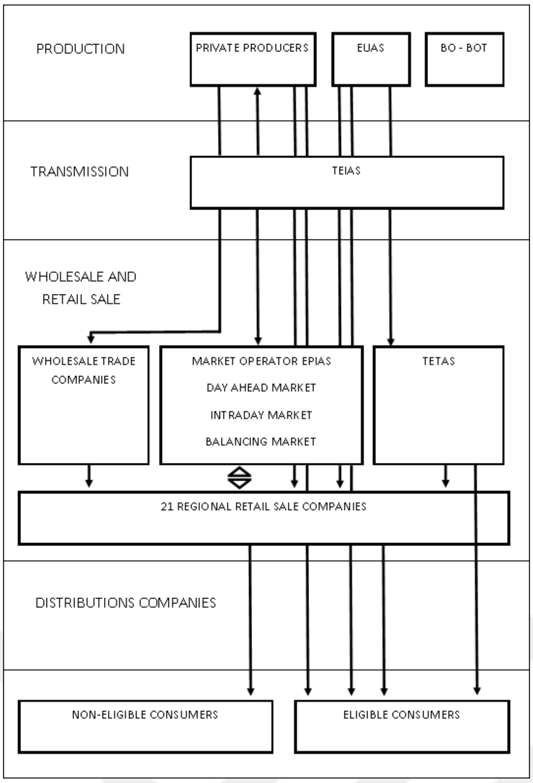

Figure 4: Current Structure of the Turkish Power Market (Source: Energy Trading Association of Turkey- Pure Energy-Energy Trading in Turkey Report, 2016)

With the targeted Turkish Power Market Structure the production will be handled mostly with the private sector and EUAS. There is also the issue of the privatization of TEIAS responsible for transmission of electricity in Turkey. In terms of power markets under EXIST, in addition to Borsa Istanbul's cash future contracts physically delivered futures contracts are already launched in 2021. On the other hand, the establishment of Turkey's first nuclear power plant is under construction.

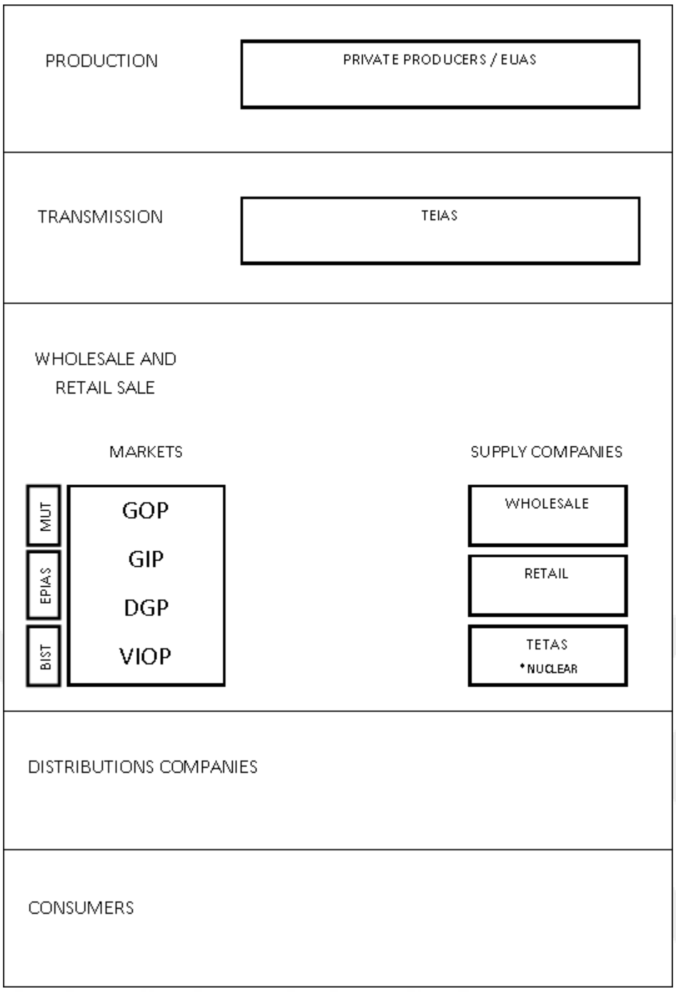

Figure 5: Targeted Structure of the Turkish Power Market (Source: Energy Trading Association of Turkey- Pure Energy-Energy Trading in Turkey Report, 2016)

3.4 Installed Capacity, Generation and Renewable Energy Sector in Turkey

Turkey has limited natural gas and oil reserves. However, most of the electricity production is supplied by these types of energy sources. That is why it relies mainly on foreign imports, which are denominated in dollars. Turkey imports 99,7% of its natural gas, %95 of fuel oil, and %50% of coal needs. This has a massive impact on the Turkish foreign account deficit.

On the other hand, Turkey is rich in terms of renewables. According to the Ministry of Energy and Natural Resources (MENR), Turkey has a potential capacity of 130 TWh/year in wind power, 140 TWh/year in hydropower, and 380 TWh/year in solar energy. Because of this reason, the renewable energy sector is developing so fast, and the percentage share of renewables in the total energy production is increasing year by year.

The installed capacity has reached 96GW at the end of 2020. Table 2 represents the installed capacity and production by resources for licensed and unlicensed power plants in Turkey. As specified in the table, hydropower is the most significant energy resource with a total share of 26% in 2020. Followed by natural gas and coal powered plants. However, the reliability of fossil-fuelled plants is still high and can be easily seen in Table 1. Even though the share is decreasing during the last couple of years, 55,7% of production is still supplied by fossil fuels in 2020.

In 2016 the new regulation on the Renewable Energy Resource Areas (YEKA) is adopted by EMRA. YEKA model became a unique model to Turkey and ensured a domestication rate higher than 65 percent, and encouraged research and development (R&D) in this area.

As a result of liberalization in the electricity market, declining costs, the support of renewable energy resources by the government, and YEKA model, renewable energy has increased its share in installed capacity remarkably during the last decade in Turkey. Total installed capacity has increased from 0.8 GW to 18 GW over the 2009-2020 period. While the share of wind power reached 8%, the solar, geothermal, and biomass energy sources increased their share to almost 9% at the end of 2020.

Table 3: Installed Capacity and Production by Resources at the End of 2020 (Source: EMRA Electricity Sector Report, 2020)

Resource Type	Total Installed Capacity (MW)	Share (%)	Total Production (GWh)	Share (%)
HYDRAULIC	30.983,90	32,3	78.114,95	25,6
NATURAL GAS	26.041,93	27,2	69.277,54	22,7
LIGNITE	10.119,92	10,6	38.163,85	12,5
IMPORT COAL	8.986,85	9,4	62.466,47	20,5
WIND	8.832,40	9,2	24.680,83	8,1
SOLAR	6.667,42	7,0	11.242,48	3,7
GEOTHERMAL	1.613,19	1,7	9.929,41	3,3
BIOMASS	1.115,59	1,2	5.501,94	1,8
HARD COAL	810,77	0,8	3.415,83	1,1
ASPHALTITE	405,00	0,4	2.222,88	0,7
FUEL OIL	305,93	0,3	313,04	0,1
NAPHTA	4,74	0,0	0,00	0,0
LNG	1,95	0,0	0,00	0,0
DIESEL	1,04	0,0	1,00	0,0
TOTAL	95.890,61	100,00	305.330,21	100,00

*Licensed and unlicensed power plants are included.

3.5 Renewable Energy Resources Support Mechanism ("YEKDEM")

YEKDEM is a support mechanism in Turkey for electricity manufacturers from renewable energy resources, which has been regulated in the "Regulation on Documentation and Support of Electricity Manufacturing from Renewable Energy Resources" which has entered into force in 2013. This mechanism which consists of feed-in tariffs for electricity manufacturing license holders and unlicensed electricity manufacturers producing electricity from renewables and other opportunities for renewable energy is valid until 2020. Wind energy, solar energy, geothermal energy, biogas, hydro-power, and biomass are energy sources that are subject to this regulation.

With this support mechanism, the retail companies assigned by EMRA are required to purchase the produced electricity from the electricity manufacturers, which are subject to this mechanism on the tariffs regulated by the legislation. These electricity manufacturers cannot sell the produced electricity to other companies under open market conditions. YEKDEM differentiates the amount of the fixed feed-in-tariffs depending on the technology as well as whether the plant components were produced in Turkey or not. For example, wind energy and hydro-power tariffs are 7.3 USD Cent/kWh and 12.3 USD Cent/kWh for solar energy.

In addition, the electricity manufacturer can benefit from the local equipment support, in where cases local equipment in the power plant is used. These prices are added to the feed-in tariffs and paid to the electricity manufacturer. As in the feed-in tariffs, the amount of local equipment support depends on the energy resource. For example, if local content is used, a bonus from 0.6 USD Cent/kWh to 3.7 USD Cent/kWh is given for wind energy. Similar bonuses with different amounts are also available for solar, hydro-power, etc.

Companies manufacturing electricity from renewable energy resources who are willing to benefit from support mechanism must submit their applications until the end of October of each year for the following calendar year. After reviewing and evaluating the applications, the appropriate applicants receive a notice within the first ten days of November. EMRA declares the final list for the upcoming year until the end of November 30^{th}.

3.5.1 *Advantages and Disadvantages of the YEKDEM*

The main aim of YEKDEM is to encourage investments in renewable energy. The feed-in tariffs provide a guarantee, especially for newly established electricity power plants. Therefore, the risks of financial instability are minimized due to this mechanism. On the other hand, the feed-in tariffs are determined based on foreign currency, and the currency risk might be considered either a risk or an advantage. However, in a country like Turkey where the local exchange rate depreciates significantly for the last couple of years, currency risk is a major threat to these new power generators. Moreover, the market prices may go much higher than feed-in tariffs, which can also constitute a price risk for these electricity manufacturers.

3.5.2 *How Long Will YEKDEM Last?*

The support mechanism had been regulated until 2015. Later in the past, these feed-in tariffs and additional payment for local equipments in the power plants have been extended until 2020. Due to the Covid-19 pandemic, the regulatory authority extended this period for power plants established until the end of June 2021. They will be able to benefit from this law until the end of 2030. It is unknown how YEKDEM will be regulated after 2021. Since there is no new declaration on this issue there is also a chance that a new legislation would change the feed-in tariffs and the new rates will apply after 2021. A support mechanism for electricity generators from renewable energy resources is vital for increasing the share of renewables in the electricity production industry.

3.5.3 *New Amendment on YEKDEM Law*

There was an amendment on YEKDEM law which was published into regulation on April 29th, 2016. With this law, some fundamental changes would apply to YEKDEM power generating companies in terms of feed-in tariffs received and the market structure.

The main change with this new regulation was that the plants became responsible for balancing thus have to incur costs associated with imbalances. So far, YEKDEM power plants were not responsible for balancing. In addition to that, the following new changes took effect:

- YEKDEM portfolio was abolished, and YEKDEM power generating plants were expected to sell their generation on the free market, including the bilateral market, the day-ahead market, and the intra-day market.
- The spread between the feed-in tariff and the hourly day-ahead market price (which is apparently the MCP) is to be paid to the plants separately (or paid by the plants if MCP>YEKDEM price).
- A tolerance co-efficient is introduced.
- Plants are subject to ancillary services requirements.

The balancing issue brought some uncertainty to the revenue of electricity-generating firms. With the new amendment, they were forced to manage their balancing much more efficiently by themselves. They were given a choice to be a part of a balancing group to avoid the costs arising from imbalances.

CHAPTER 4: FINANCIAL RISK MANAGEMENT IN ELECTRICITY MARKET

4.1 The Concept of Risk and Return

The simplest description of the risk concept is the "probability of having an unexpected event." But in finance, risk is often described as "the probability that an actual return on an investment will be lower than the expected return." This description is not good enough to give the true meaning of the risk concept. Maybe one word that can better define the concept of risk is: "Volatility"—the higher the volatility, the riskier the underlying asset.

Most of the time, risk and uncertainty concepts are confused. While uncertainty cannot be quantified, the risk of an asset can be measured through different statistical concepts such as standard deviation or variance.

Analyzing return and profit only does not give us the accurate picture most of the time. The risk profile of the investment and the return opportunities must be evaluated together to come up with an optimal and balanced portfolio.

Harry Markowitz first analyzed risk and return trade-off at his paper "Portfolio Selection (1952)". Markowitz introduced the "Modern Portfolio Theory (MPT)" which specified how risk-averse investors could construct portfolios to optimize or maximize expected return based on a given level of market risk, emphasizing that risk is an inherent part of higher reward. According to the theory, it is possible to construct an "efficient frontier" of optimal portfolios offering the maximum possible expected return for a given level of risk. The theory focused on the effects of investment on the overall portfolio's risk and return instead of focusing on the investment's risk and return characteristics alone.

Markowitz was later awarded a Nobel prize for developing the MPT. His theory was used as a base for the famous Capital Asset Pricing Model (CAPM), which was developed by Jack Treynor (1961, 1962), William F. Sharpe (1964), John Lintner (1965a,b), and Jan Mossin (1966) independently.

According to CAPM total risk of a portfolio is the sum of systematic risk and unsystematic risk. Systematic risk is the probability of a loss associated with the entire market or the segment, whereas unsystematic risk is associated with a specific industry, segment, or security. While systematic risk is non-diversifiable, unsystematic risk is diversifiable through portfolio diversification.

Interest rate risk, market risk (currency risk, price risk), and inflationary risk are among the risks that are classified as systematic risks. On the other hand, firm-specific risks such as management, credit risks are diversifiable risks. Derivatives instruments can be used as hedging tools to minimize or eliminate systematic risk. For this thesis, the emphasis will be on the systematic risk such as currency risk of the electricity revenue portfolio which is denominated in Turkish Lira.

4.2 Risk Management in Power Market

The US and European markets suffered due to speculative financial derivatives contracts during the 2008 crisis, while the damage to Turkey was much less extensive. Due to strict regulations taken after one of Turkey’s worst banking crises during 2000 and 2001, the Turkish banking sector became much more resilient to financial shocks. Turkish banks have tended to avoid derivatives instruments, especially for investment purposes, protecting the country from the worst effects of the 2008 crisis.

Between 2010 and 2018, the Turkish economy grew significantly and minimized the externalities of the 2008 global crisis. However, during quantitative easing—implemented by leading global central banks—due to stable exchange rates and low financing costs, most Turkish nonfinancial companies preferred to borrow in either US dollars or euros. This increased their short position in foreign currency, which reached 220 billion USD in 2017. A significant currency jump occurred in 2018, and during the first eight months of the year, the Turkish lira depreciated 74% against the US dollar and 68% against Euro. Due to high volatility caused by the Covid-19 pandemic, the Turkish lira depreciated another 30% against the US dollar and 36% against Euro during the first three quarters of 2020. These recent currency devaluations show that non-financial companies hold higher risk compared to the banking sector. Therefore, an effective hedging mechanism is vital for Turkish firms for reliable currency risk management.

On the other hand, the liberalization of the power industry introduced heightened volatility in price. In the past regulatory authority determined the price of the electricity so that market participants did not need to worry about its volatility. But with the introduction of the new electricity exchanges and more liberal power markets, the fluctuations of the electricity prices became an important issue for buyers and sellers. In a competitive market, the settlement price of electricity is determined by supply and demand function, and the price can change real-time.

In addition to price risk, currency risk can be easily an issue in countries like Turkey where the whole investments are made in foreign currencies such as American Dollar and Euro through bank credits, and revenues are in Turkish Lira.

Therefore, conducting an efficient financial risk management system became so essential to be able to survive under this highly volatile environment also for power companies.

4.2.1 Exchange-Traded and Over the Counter (OTC) Power Markets

Nowadays, electricity trading can be done through organized financial exchanges and bilateral agreements of the over-the-counter markets. On these markets, spot and derivatives electricity contracts such as futures, forwards, and options are listed.

New marketplaces where power can be traded in a standardized form, similar to how other traditional commodities like crude oil, corn, and wheat are traded, became the main channel of electricity trading. At these power exchanges, producers offer a predetermined supply of electricity (in megawatts) during one or more hours of the next day for a fixed price. On the other hand, buyers bid purchase of an equal amount of energy during the same time frame. These exchanges are matched to a power grid. Nordpool, EEX, Powernext, and EXIST in Turkey are some examples of such power markets.

Alongside the organized exchanges, the importance of the OTC platforms where trading volumes can be pretty significant should not be underestimated. Trayport, Tradition, ICAP are among these OTC platforms where bilateral agreements are conducted between electricity generating companies and electricity buyers such as industrial consumers and local distributing companies. Organized power markets and some OTC platforms are listed in Table 3.

Table 4*:* Organized Power Exchanges and OTC Electricity Markets

Organized Power Exchanges	OTC Markets
APX-Endex (ICE Endeks)	CIMD
CME Group	GFI
EXIST – Turkish Energy Exchange	Global Commodities
EEX – European Energy Exchange	ICAP
HUPX -Hungarian Power Exchange	OTCex
IDEX – Italian Derivatives Energy Exchange	Spectron
ICE – Inter-Continental Exchange	Tradition
NASDAQ OMX Commodities Europe	Tullet Prebon
Nordpoolspot and Derivatives	BGC Partners
OMIP – The Iberian Energy Derivatives Exchange	Trayport
Powernext	Matriks Terminal (Turkey)

Despite the standard contracts which are listed at the organized exchanges, OTC contracts are bilateral agreements where details of the contracts are negotiated between counterparties. Usually, the exchange-traded contracts are much more liquid and have more depth compared to OTC markets.

The clearinghouse guarantees the settlement and clearing of the trades at the exchange-traded electricity contracts. On the other hand, OTC contracts have credit risk, and if one of the counterparties cannot fulfill its obligation, there is a risk of default. In Turkey, all the electricity clearing transactions are conducted through

Takasbank, the Central Clearing Counterparty of Turkey (CCP). Takasbank uses a portfolio-based margining system called Standardized Portfolio Analysis of Risk (SPAN). All the initial margin of contracts, margin calls, and other risk checks are executed through SPAN, a post-trade risk management tool. In addition to that, there are also some pre-trade risk checks available at the Borsa Istanbul trading system.

4.2.2 Power Market Derivatives Contracts

Derivative contracts are contracts between two or more counterparties whose value depends on an agreed underlying asset. These underlying assets can be financial, such as equity index, currency and interest rate, or commodities such as wheat, corn, soybean, or energy such as electricity, natural gas, and crude oil. The most popular derivative contracts are futures, forwards, options, and swap contracts. While future contracts are traded at organized derivative exchanges, forward contracts are traded at the OTC platforms. Options can be traded in both environment.

There are several benefits of the usage of derivatives contracts at power trading:

- Derivative contracts can be used for hedging, speculation, and arbitrage purposes by both power companies and financial market players.
- Future, forward, or option electricity contracts traded at these exchanges give participants a way to reduce their risk exposure by minimizing the electricity price volatility.
- Power generating firms and power marketeers may seek certainty in their costs and revenues structure through hedging by using derivatives contracts
- Future markets can be used at price discovery. They can provide signals for investments in the power system infrastructure and contribute to an adequate development of supply and demand. Several studies support this. While Manogna & Mishra (2020) compare price discovery function by analyzing the nine most liquid agricultural commodities in spot and future markets in India, Yang & Wang (2020) focus on the eleven Chinese agricultural futures products. They all conclude that future markets are more efficient in price discovery compared to spot markets.

4.2.3 Borsa Istanbul VIOP Future Contracts

In 2013, the derivatives exchange of Turkey, VOB merged into Borsa Istanbul, and it continued its operation under the name VIOP which became the only derivatives exchange in Turkey. All the contracts traded at VOB and currency and electricity futures contracts were transferred to Borsa Istanbul during this merger.

According to trading volume data for 2019 from the Futures Industry Association, BIST's Futures and Options Market (VIOP) was ranked the 16th most liquid derivatives exchange globally, with a very impressive growth rate of 64% during that year. This growth rate is the third-highest after the Indian Commodity Exchange Ltd and the China Financial Futures Exchange. VIOP is a good role model of an emerging futures exchange for other countries.

USDTRY futures contracts are used by a variety of sectors, such as fund managers, exporters, and importers. In 2018, USDTRY futures contracts were ranked the world's ninth most liquid currency futures contracts, with an astonishing yearly volume growth rate of 42%, and were among the ten leading currency futures.

USDTRY future contract analysed is a cash-settled contracts such as Non-Deliverable Forward (NDF) contracts at the OTC market. With cash-settled future contracts, there is no physical delivery of the underlying asset for the buyer or seller; instead, the counterparties agree to accept the cash credit or debit resulting from their trade price relative to the settlement price of the futures contract. The exchange declares the daily settlement prices at the end of each day, and calculates profit/loss amounts for each account. If there is a profit, the investors might withdraw this excess cash over its required margin, and if there is a loss the amount is deducted from the account. All the required margin deposited to the Clearing House also earns daily interest. This is another positive aspect of the future market in Turkey, since the interest is rare in other developed and developing countries. Investors also have the choice of not accepting the interest for religious reasons.

In this thesis, USDTRY VIOP future contract is used for hedging currency exposure of a sample power wind plant. But since some power plants also use Euro-denominated debt, EURTRY future contract might also be used for hedging purposes. The contract details of the USDTRY and EURTRY currency future contracts are listed in Table 5 and Table 6.

On the other hand, the underlying asset of the based load electricity future contract is the basic arithmetic average of the Unconstrained Market Clearing Prices announced by Turkey Electricity Transmission Company for each hour of the contract month. Contract specifications of this contract are listed in Table 4:

Table 5: Borsa Istanbul Base Load VIOP Electricity Future Contract Details (Source: Borsa İstanbul, 2021)

Contract Size	Number of hours in the contract month x 0.1 MWh Number of hours in the contract month: Number of days in the contract month x 24.
Quotation	Price of 1 MWh electricity energy in TRY with two decimals
Tick Size	The minimum price tick is 0.10
Contract Months	7 months (The current contract month and the nearest 6 contract months shall be concurrently traded)
Daily Price Limit	The daily price limit is set as +/-10% of the base price, which is found by rounding the previous daily settlement price.
Last Trading Day	Last business day of each contract month. If domestic markets are closed for half day due to an official holiday, the last trading day shall be the preceding business day.
Settlement Type	Cash Settled
Final Settlement Price	The basic arithmetic average of the Unconstrained Market Clearing Prices announced by Turkey Electricity Transmission Company for each hour of the contract month.

Table 6: Borsa Istanbul VIOP USDTRY Currency Future Contract Details (Source: Borsa İstanbul, 2021)

Contract Size	1000 USD
Quotation	TRY with four decimals (6.1500)
Tick Size	0.0001 = 0.1 TRY
Contract Months	Cycle months are February, April, June, August, October and December. Six contracts whose expiration months are the current month, the next calendar month, the next three cycle month and December shall be concurrently traded. If there are less than six contracts, an extra contract with an expiration month of December of the next year shall be launched.
Daily Price Limit	The daily price limit is set as +/-10% of the base price which is found by rounding the previous daily settlement price.
Last Trading Day	Last business day of each contract month. In case domestic markets are closed for half day due to an official holiday, last trading day shall be the preceding business day.
Settlement Type	Cash Settled
Final Settlement Price	The average of US Dollar selling and buying rate announced by the CBRT at 15:30 of the last trading day. The Last Settlement Price shall be rounded to the nearest tick.
Settlement Period	T+1 Losses are deducted from the accounts at the end of T day, profits are added to the accounts on T day as well.

Table 7: Borsa Istanbul VIOP EURTRY Currency Future Contract Details (Source: Borsa İstanbul, 2021)

Contract Size	1000 EUR
Quotation	TRY with four decimals (7.1500)
Tick Size	0.0001 = 0.1 TRY
Contract Months	Cycle months are February, April, June, August, October and December. Four contracts whose expiration months are the current month, the next calendar month, the next cycle month and December shall be concurrently traded. If there are less than four contracts, an extra contract with an expiration month of December of the next year shall be launched.
Daily Price Limit	The daily price limit is set as +/-10% of the base price which is found by rounding the previous daily settlement price.
Last Trading Day	Last business day of each contract month. In case domestic markets are closed for half day due to an official holiday, last trading day shall be the preceding business day.
Settlement Type	Cash Settled
Final Settlement Price	The average of Euro selling and buying rate announced by the CBRT at 15:30 of the last trading day. The Last Settlement Price shall be rounded to the nearest tick.
Settlement Period	T+1 Losses are deducted from the accounts at the end of T day, profits are added to the accounts on T day as well.

4.2.4 *Electricity Hedging Example at VIOP (Electricity Generating Firm)*

It is November 2017, and a power plant that has a generating capacity of 20 MWh would like to hedge all of its upcoming January production by using VIOP electricity future contract. The price of the January base load electricity future is 240 TRY/MWh. There are 31 days in January. Therefore, the contract size of January is calculated as follow:

$$\text{Contract Size}=\text{Total Day of the Month}\times 24\text{hours}\times 0.1=31\times 24\times 0.1=74.4\text{MWh}$$

We assume that power plant hedge all of its January exposure by selling VIOP baseload future contracts (fully hedged). The total hedge amount and the number of contracts that power plant need to sell are calculated as follow:

$$\text{Total Hedge Amount}=\text{Hourly Capacity}\times 24\times 31=20\times 24\times 31=14{,}880\text{MWh}$$

$$\text{Number of Contracts Sold}=\frac{14{,}880}{74.4}=200\text{ contracts}$$

Generating power plant hedged all of its January production by selling 200 contracts at 240 TRY/MWh. The last settlement price of the future contract is the basic arithmetic average of the Unconstrained Market Clearing Prices announced by Turkey Electricity Transmission Company for each hour of the contract month. Whatever the settlement price at the end of January, the generating power plant guarantees the average 240 TRY/MWh as specified in Table 7.

Table 8: Hedging Electricity Generation with VIOP Baseload Electricity Future

Last Settlement Price as of January 31st 2018 (TRY/WHh)	Future Profit/Loss	Spot Sales of Electricity (TRY)	Net Revenue (TRY)	Net Sales Price (TRY/MWh)
260	-297.600	3,868,800	3,571,200	240
250	-148.800	3,720,000	3,571,200	240
240	0	2,232,000	3,571,200	240
230	+148.800	3,422,400	3,571,200	240
220	+297.600	3,273,600	3,571,200	240

4.2.5 Electricity Hedging Example at VIOP (Wholesale Electricity Distribution Company)

It is November 2017, and a wholesale power distributor would like to hedge all of its January sales by using VIOP electricity future contract. The wholesale company purchases an average of 15 MWh of energy during the whole month. The price of the January base load electricity future is 240 TRY/MWh. There are 31 days in January. Therefore, the contract size of January is calculated as follow:

$$\text{Contrat Size}=\text{Total Day of the Month}\times 24\text{hours}\times 0.1=31\times 24\times 0.1=74.4\text{MWh}$$

We assume that the power plant hedge all of its January exposure by buying VIOP baseload future contracts (fully hedged). The total hedge amount and the number of contracts that power plant need to buy are calculated as follow:

$$\text{Total Hedge Amount}=\text{Hourly Capacity}\times 24\times 31=15\times 24\times 31=11{,}160\text{MWh}$$

$$\text{Number of Contracts Bought}=\frac{11{,}160}{74.4}=150\text{ contracts}$$

Wholesale distributor hedged all of its January sales by buying 150 contracts at 240 TRY/MWh. The last settlement price of the future contract is the basic arithmetic average of the Unconstrained Market Clearing Prices announced by Turkey Electricity Transmission Company for each hour of the contract month. Whatever the settlement price at the end of January, the wholesale distributor guarantees the average 240 TRY/MWh purchasing price.

Table 9: Hedging Electricity Sales with VIOP Baseload Electricity Future

Last Settlement Price as of January 31st 2018 (TRY/MHh)	Future Profit/Loss	Spot Purchase of Electricity (TRY)	Net Revenue (TRY)	Net Purchase Price (TRY/MWh)
260	+223,200	-2,901,600	2,678,400	240
250	+111,600	-2,790,000	2,678,400	240
240	0	-2,678,400	2,678,400	240
230	-111,600	-2,566,800	2,678,400	240
220	-223,200	-2,455,200	2,678,400	240

4.2.6 EXIST Physically Delivered Power Futures Market (PFM)

In June 2021, a physically delivered power future market was launched by EXIST. In addition to cash settled future contracts traded at Borsa Istanbul, these contracts allow users to go to physical delivery at the end of the settlement period. In the PFM, the market participants can hedge the price risk (hedging) and see price prospects for the future (price discovery). EXIST is the central clearing counterparty in these transactions. Since counterparty risk is an essential issue in the OTC market in Turkey, this is very important development which might bring these OTC transactions to the organized market.

4.3 YEKDEM Specific Risks for Electricity Generating Firms

As mentioned previously in this chapter there are two types of risks related to the new YEKDEM regulation. The first one is related to the currency risk, and the second one is the price risk.

Price Risk: Price risk arises from the volatility of the spot electricity prices. In a broad view, when the market electricity prices (MCP) are high, the total revenue that the power plant will generate will also be high. However, when the prices are low, the total revenue decreases significantly. YEKDEM feed-in tariff prevents companies from suffering revenue loss due to low market prices. When the market price is lower than the feed-in tariff price (7.3 USD Cent/kWh for wind and hydro currently), companies receive the YEKDEM incentive difference. In fact, for the last couple of years, this was the case, and YEKDEM companies received this incentive regularly. Currently still the feed-in tariff price is much higher than the market settlement price (MCP).

Currency Risk:

Each day throughout the month, the renewable power plants enter their production forecasts for the next day to the day ahead market on an hourly basis. They sell their production hourly and receive a daily revenue in TRY according to the market settlement price (MCP). Each hour’s revenue is added together to calculate the daily sales revenue from the day-ahead market. This day-ahead market revenue is received daily regularly in Turkish lira.

At 45th day, the next calendar month the imbalance cost and YEKDEM incentive difference is calculated for the previous month by the regulator and net payment (the total of imbalance cost and YEKDEM incentive) is paid to the power plant in TRY on the 56^{th} day of this month.

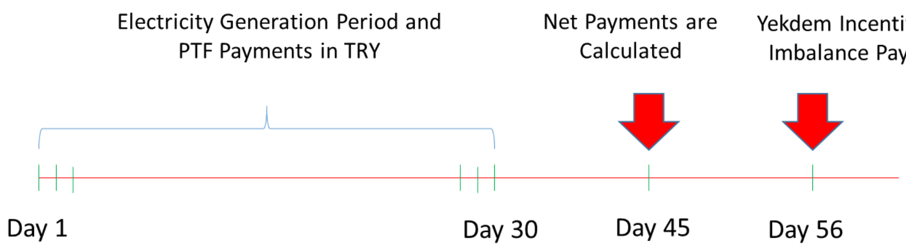

Figure 6: Payment Structure of YEKDEM Process

Since the energy-generating power plant receives the total revenue in Turkish lira from the regulator, the plant has currency risk. Day-ahead market revenue, imbalance cost, and YEKDEM incentive difference are all denominated in Turkish Lira. On the other hand, the YEKDEM incentive is calculated by multiplying the fixed incentive amount of 7,3 USD Cent/kWh by the related daily Turkish Lira versus USD exchange rate. When the Turkish lira depreciates, the total monthly revenue amount in USD that the power plant generates diminishes. Since most of these power plants were financed by using longer terms bank credits denominated in foreign currencies such as USD and Euro, it is becoming much more important to efficiently manage the currency risk.

In summary, YEKDEM power plants have currency and price risks. An effective hedging mechanism for these financial risks will prevent energy-generating plants from suffering from currency depreciation and price declines. In this thesis, only currency risk of the power plant is analyzed, and price risk remained the focus of another study.

CHAPTER 5: DESCRIPTIVE DATA ANALYSIS

5.1 Data Source and Preliminary Data Analysis

A local wind power plant located in the Aegean Region of Turkey is used to analyze the balancing process and plant's currency and electricity price risk. The power plant is an onshore wind farm with eight tribunes and an installed capacity of 20 MWe.

Table 10: Electricity Generating Wind Power Plant Information

Period	Installed Power (MWe)	Number of Tribune	Electricity Generated (MWh)
1.12.2017-30.11.2018	20	8	45,906

All the USDTRY spot and futures market data are obtained from a Matriks terminal, a local data provider for BIST. The sample period for the USDTRY spot and futures prices spans from December 1, 2017, to November 30, 2018, for a total of 250 observations. All the data for the futures contracts are near-month futures contracts.

Data for spot daily market clearing prices (MCP) and system marginal prices (SMP) for the same period are obtained from Energy Exchange Istanbul (EXIST)'s transparency platform. The data period for spot MCP and SMP prices are similar to USDTRY spot and future data. However, since the electricity market is also open during weekends, there are 364 daily observations. Out of these data, day-ahead market revenue, imbalance cost/revenue, and YEKDEM incentive difference are calculated for each hour.

Preliminary statistics for the Jarque–Bera (1980) normality test and Ljung–Box (1978) Q(36) statistics for the first 36 lags of the sample are used to find any serial correlation (see Table 10). All the data in the first lag are presented as the result of serial correlation, indicating that each day's price is derived from the previous day's. Neither spot returns nor future price returns exhibit a normal distribution.

In addition, Table 11 shows that all the return data are stationary, since all the *t*-values are lower than the critical value at the 1% significance level, according to augmented Dickey–Fuller tests.

Table 11: Summary Statistics of Return Series

Contract	Obs.	Mean	Med.	Max.	Min.	Std. Dev	Skewness	Kurtosis	JB	LB-Q(36)
USDTRY Spot	250	0.1146	-0.0065	14.56	-7.75	1.7490	1.9539	23.9345	4724.21 (0.0000)	(0.0000)
USDTRY Futures	250	0.1058	0.0473	14.46	-8.04	1.7655	2.2070	23.4933	4577.74 (0.0000)	(0.0000)
MCP Spot	364	0.1908	0.1723	58.39	-38.97	8.8955	0.9407	13.8696	1845.61 (0.0000)	(0.0000)
SMP Spot	364	0.1681	0.1591	59.12	-49.61	14.288	0.3236	5.6259	110.85 (0.0000)	(0.0000)

Table 12: Augmented Dickey–Fuller Test Results for Spot and Future Returns

Variables	t-Statistics	p-Value	Level of Significance	Critical Values
USDTRY Spot	-11.2864***	0.0000	1%	-3.4340
USDTRY Future	-11.9477***	0.0001	5%	-2.8631
MCP Spot	-14.2711***	0.0000	10%	-2.5676
SMP Spot	-14.2167***			

Note: In this table, *** indicates 1% significance level.

On the other hand, hourly expected day-ahead market sales (MWh) and actual electricity data for the power generating wind plant are taken from the plant operator for the period starting from December 1st, 2017, to November 30th, 2018 (including the weekends).

The data type, data unit, data range, and source of the data are summarized in Table 12.

Table 13: Data Information

Data Type	Data Unit	Data Range	Source
Day-Ahead Market Sales	MWh (hourly)	1.12.2017-30.11.2018	Wind Power Plant
Electricity Generation	MWh (hourly)	1.12.2017-30.11.2018	Wind Power Plant
MCP	TRY/MWh (hourly)	1.12.2017-30.11.2018	Energy Exchange Istanbul (EXIST)
SMP	TRY/MWh (hourly)	1.12.2017-30.11.2018	Energy Exchange Istanbul (EXIST)
USDTRY Spot	TRY per USD	1.12.2017-30.11.2018	Local Data Terminal (Daily Settlement Prices)
USDTRY Future	TRY per USD	1.12.2017-30.11.2018	Local Data Terminal (VIOP Daily Settlement Prices)

Since nearby future contracts are used, spot and future prices are very close to each other. The spread between them sometimes becomes very close, especially towards the end of the contract month. Daily USDTRY spot-future price and returns and MCP-SMP price and returns are displayed in Figure 7 and Figure 8.

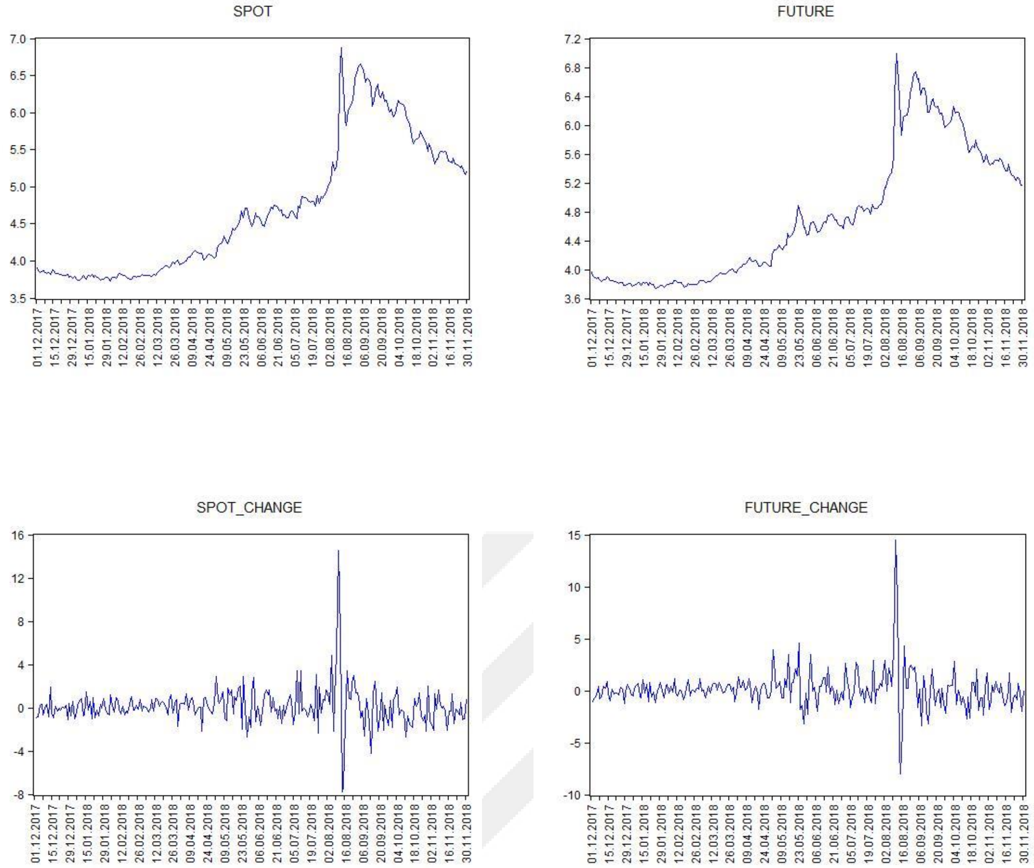

Figure 7: USDTRY Spot and Future Price and Returns (01.12.2017-30.11.2018)

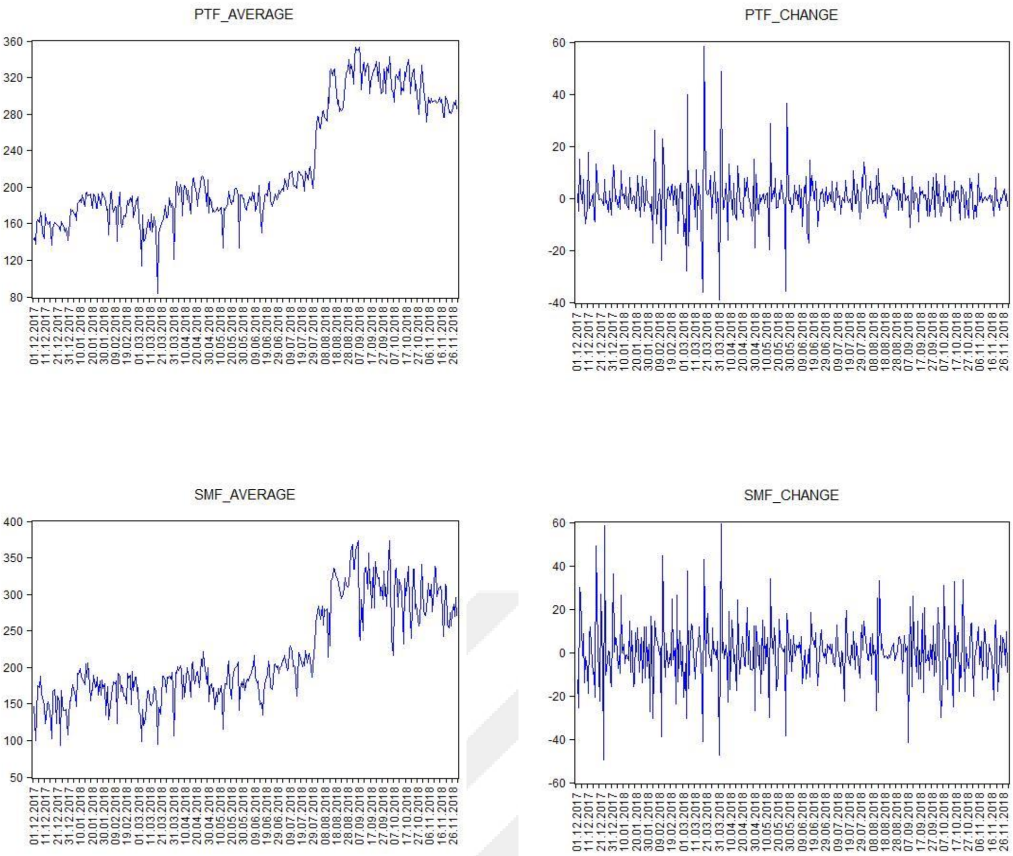

Figure 8*:* Electricity MCP/SMP Price and Returns (01.12.2017-30.11.2018)

The following chapter will discuss the imbalance cost structure of electricity market in Turkey and will focus on the theoretical framework for the calculation of electricity revenue portfolio. How hourly and daily day ahead market revenue is calculated when there is a lack of, or excess generation will be explained with the official formulas used by the system operator. This chapter will show the effect of YEKDEM incentives, the imbalance costs on the total system revenue and the details of the FX hedging model constructed. And furthermore, all the methodologies used for optimal hedge ratio calculation, hedging effectiveness, VaR computations and backtesting models will be explained in detail.

CHAPTER 6: METHODOLOGY

The share of renewable energy in Turkey grew significantly during the last decade. There are many new wind, solar and geothermal investments in the country and the government is supporting them with the YEKDEM and YEKA models that was previously explained in Chapter 3. These support mechanism encourage investors to construct new power plants and decrease the dependence on the fossil fuel sources. These new investments in the renewable industry raise the importance of another issue: How to actively manage YEKDEM supported electricity revenue portfolio of new power plants?

As mentioned in the previous sections of the thesis, currency risk and electricity price risk are two main financial risks that electricity-generating power plants face. In addition to that, with the new amendment at YEKDEM law, managing imbalances to avoid extra cost became much more critical. Out of different energy sources, the ones highly affected by this balancing issue are wind and hydro energy. Due to uncertainty in weather forecasting, it is getting much harder to manage the balancing process, especially in wind energy.

In investment management a portfolio manager must act diligently on behalf of its clients and need to give proper care to manage the portfolio effectively. Portfolio manager's aim is to bring the maximum profit to its client's portfolio considering the risk profile of its investors. With the acceptance of the new YEKDEM regulation in the energy sector the management of the electricity revenue portfolio became much more important for the electricity generating companies since these portfolios need to be managed actively twenty four hours a day and seven days a week.

The daily revenue data are used in this thesis to compute the hedging effectiveness and VaR values of alternative hedged and unhedged electricity portfolios. Therefore, at the beginning of this chapter, the theoretical framework for hourly and daily renewable energy electricity revenue calculations for an electricity generating firm according to YEKDEM law will be explained with the current YEKDEM formulas. And then currency hedge model constructed in this thesis will be described.

Subsequently, the methodologies for optimal hedge ratio calculations, hedging effectiveness, VaR computations and backtesting of VaR values will be addressed in this section.

6.1 Theoretical Framework for Renewable Energy Revenue Calculations

First, we will discuss the imbalance cost and YEKDEM incentives structure of electricity market in Turkey and focus on the theoretical framework for the calculation of electricity revenue portfolio. How hourly and daily day ahead market revenue is calculated when there is a lack of, or excess generation will be explained with the official formulas used by the system operator.

6.1.1 Calculation of System Revenue

The core concept of the new regulation in 2016 was the imbalance costs which was new to electricity power generating companies. With the new regulation there are three components of the revenue generated by a YEKDEM power generating plant in Turkey. The sum of these three gives us the total revenue:

- Day Ahead Market Revenue (+)
- Imbalance Cost (-/+)
- YEKDEM Incentive Difference (+)

Hourly System Revenue=Day Ahead Market Revenue+/-Imbalance Cost+YEKDEM Incentive (1)

Each day on an hourly basis total revenue of the power plant is calculated by adding these three components together by using the following formulas:

Day Ahead Market Revenue:

Day Ahead Market Revenue=Expected Sales Amount×MCP (2)

MCP: Market Clearing Price

Imbalance Cost/Revenue:

According to Article 110 of "Balancing and Settlement Regulation (DUY)" the imbalance cost is calculated as follow:

$$EDT_f = \sum_{t=1}^{m} \sum_{u=1}^{n} \left[\left(EDM_{f,t,u}(-) \times \max\left(SGÖF_{t,u}, SMP_{t,u}\right) \times (1+k) \right) + (EDM_{f,t,u}(+) \times \min(SGÖF_{t,u}, SMP_{t,u}) \times (1-l) \right] \quad (3)$$

EDT is the cost of imbalance.

EDM is the amount of imbalance (plus or minus)

SGÖF is the day-ahead market price (MCP).

SMP is the system marginal price (price occurred at the balancing power market).

k and l are coefficients set by EMRA to penalize imbalances (currently 0.03).

f is the counterparty who is responsible for the imbalance

t is the different offer region

u is the settlement period

m is the number of offer region number

n is the number of settlement period

As mentioned at the above formulas, there are two important price calculation performed for each hour by EXIST. These are Market Clearing Price and System Marginal Price. The first one is the equilibrium price found at the intersection of supply and demand curve and is determined and announced hourly for market participants at Day-Ahead Market. MCP is determined through an optimization algorithm that uses a mathematical model. The details of this method is mentioned in the previous Chapter 3 at section 3.2.1. The second one is calculated by taking into account the point of net instruction volume by starting from the lowest price of up regulation offer if there is energy deficit in system or the highest price of down regulation bid if there is energy surplus in the system. This price is calculated at the Balancing Power Market.

A “min-max” approach is used to prevent a possible arbitration between day-ahead and intraday market during the imbalance process. When settling the imbalances, power plants that need to buy (due to lack of generation) would be buying at the max(MCP), and power plants that need to sell (due to excess generation) would be selling at the min(MCP, SMP). This "buy expensive, sell cheap" approach regulator tries to prevent a possible arbitrage between the day-ahead and intra-day markets.

k and l coefficients which the EMRA Board sets, represent monetary penalties applied for the imbalances. Current k and l coefficients of 0.03 represent an imbalance cost increase of three percent of MCP or SMP price during the imbalance process.

YEKDEM Incentive Difference

$$\text{Realized Production}\times\lfloor 73\times\text{Exchange Rate}-(\text{Tolerance Coefficient}\times\text{PTF})\rfloor \qquad (4)$$

Tolerance Coefficient=0.98

Some examples of hourly electricity revenue calculations are given in Appendix B.1. and Appendix B.2. at the end of this thesis.

6.1.2 *Currency Hedge Model*

A new model is constructed for the wind power plant's currency hedging process, which is subject to YEKDEM law. This currency hedge strategy is implemented for December 1st, 2017, and November 30th, 2018.

Each hourly revenue figure for the power plant is found by calculating Day Ahead Market Revenue, Imbalance Cost/Revenue, and YEKDEM Incentive Difference. As mentioned before, the total of these three gives us the total hourly revenue.

All the hourly TRY revenue portfolio is added together hour by hour. Then the total daily balance is calculated.

$$\text{Hedged Amount}=\sum_{i=0}^{24} R_i \qquad (5)$$

R_i: Hourly Revenue

An example of this calculation for November 30th, 2018, is given in Table 33 Appendix B.3. The total revenue for the power plant is calculated as 123.475 TRY for that day.

Since the power plant is fully operational during the weekend days, the weekend revenue is added to Monday’s balance. It is assumed that daily revenue is added to the prior day’s total portfolio balance to develop the new daily total portfolio balance available for hedging during the whole hedging period. This amount is used to find the daily optimum hedging contract amount. Each day total TRY portfolio balance is hedged by using the nearby VIOP USD/TRY future contract. Table 34 in Appendix B.4. includes a daily portfolio revenue data for a sample month (December 2017) calculated through this model.

In addition to the unhedged portfolio balance, fully hedged (HR=1) and optimal hedged portfolio balances with GARCH model are also calculated for each day for the whole sample period. At the same time daily portfolio returns for these portfolios are calculated as well. All the GARCH model parameters and calculated optimum daily hedge ratio figures are listed in Table 28 Appendix A.

To find the daily portfolio returns, since each day a new electricity generation revenue is realized, this new balance is added to the total revenue balance of the prior's day. For the hedged portfolio, the total revenue balance is the cumulative revenue portfolio of each day which is the sum of previous days' portfolio, additional daily revenue of wind plant, daily future return, and daily spot return. This balance is compared with the previous day's portfolio balance to find the daily return of the portfolio. Since there is no use of futures contracts at the unhedged portfolio, the cumulative revenue portfolio is the sum of previous days' portfolio, additional daily revenue of wind plant, and daily spot return. Daily spot return in TRY is calculated in terms of the value change of the Turkish Lira against the American Dollar. It is assumed that when the TRY appreciates, the portfolio gains in value in TRY and when the TRY depreciates, the portfolio loses its value. An example of such calculation and the calculated optimum number of contracts for a sample month (December 2017) is given in Table 35 Appendix B.5.

When finding the optimum hedge ratios OLS and a multivariate GARCH model, diagonal VECH method is applied to the USDTRY spot and VIOP USDTRY future contracts' returns for the whole sample period. In addition to that, optimum contract number is also found for fully hedged portfolio for each day.

At the end of the sample period (30.11.2018) the ending portfolio balances which are in TRY are all converted into USD with the ending day's currency rate to evaluate the performance of different portfolios.

6.2 Optimal Hedge Ratio Calculation

It is possible to hedge a spot portfolio by shorting futures contracts in the futures market. The question is, how much spot exposure will be hedged by the futures contract? As Ederington (1979) suggests, the optimal hedge ratio is the proportion of futures to spot positions, which minimizes both the variance for the whole portfolio and price change risk.

First, we calculate the hedge ratio using constant and time-varying econometric models (e.g., Ballie and Myers, 1991; Bhaduri, Durai, and Raja, 2008; Olgun and Yetkiner, 2011). The hedging effectiveness of hedged, unhedged, and naively hedged portfolios are then compared. A naively hedged portfolio (i.e., where the hedge ratio equals one) is one for which the hedger takes an equal but opposite position in the futures contract.

As stated previously, two models are used to evaluate the optimal hedge ratio, namely, the conventional constant OLS and multivariate GARCH models. A constant hedge ratio is found using OLS, and a time-varying optimal hedge ratio is calculated using diagonal VECH, a multivariate GARCH model. Some studies (e.g., Aksoy and Olgun, 2009; Ballie and Myers, 1991; Park and Switzer, 1995) observe that optimal hedge ratios found through multivariate GARCH models, such as diagonal VECH, outperform constant and time-varying hedge ratio estimates. A sample portfolio is constructed with a certain amount of spot underlying and futures contracts. Short futures contracts are used to hedge the spot exposure. Hedging is implemented for the electricity portfolio balance, which is denominated in TRY. Daily spot and futures returns are calculated as follows:

$$R_s = \ln\left(\frac{S_t}{S_{t-1}}\right) \tag{6}$$

$$R_f = \ln\left(\frac{F_t}{F_{t-1}}\right) \tag{7}$$

where

R_s = daily spot return

R_f = daily futures return

S_t = spot price at time t

S_{t-1} = spot price at time t - 1

F_t = futures price at time t

F_{t-1} = futures price at time t - 1

The number of contracts to sell for hedging purposes is found by estimating the hedge ratio. The hedge ratio is calculated using the following two methods and can be applied throughout the entire hedging process.

$$\text{Daily Spot Return} = \ln\left(\frac{S_t}{S_{t-1}}\right) \tag{8}$$

$$\text{Daily Future Return} = \ln\left(\frac{F_t}{F_{t-1}}\right) \tag{9}$$

Where

S_t = Spot price at time t
S_{t-1} = Spot price at time t-1
F_t = Futures price at time t

F_{t-1}= Futures price at time t-1

The number of contracts to buy for hedging purposes was found by estimating the hedge ratio. The hedge ratio was calculated by using the following two different methods and used during the hedging process throughout the whole period:

6.2.1 Model 1: OLS

A conventional way of finding the constant optimum hedge ratio is employed, using the simple OLS methodology of Ederington (1979):

$$R_s=\alpha+b^*\times R_f+\varepsilon \tag{10}$$

where α and b^* are the regression parameters, ε is the error term, R_s (the dependent variable) is the spot market return, R_f (the independent variable) is the futures market return, and b^*, which is also the slope of the regression, represents the hedge ratio. For example, if the slope coefficient is one, then the hedge ratio is one, and the portfolio is naively hedged. In other words, one unit of a spot portfolio is hedged with exactly one unit of a futures portfolio.
Hedge effectiveness can be measured by R^2, which is the coefficient of

determination of the regression of futures price returns (the independent variable) on cash price returns (the dependent variable). The R^2 statistic is an indication of the maximum risk reduction potential of a hedge. In this case, R^2 represents the percentage reduction in the variance of unhedged cash price changes that is explained by futures price changes. A high R^2 value indicates better hedging effectiveness.

The constant hedge ratio is obtained first, using OLS for USDTRY and then applied to calculate the number of futures contracts that must be bought and sold each trading day.

6.2.2 *Model 2: Diagonal VECH*

Commodity prices are better represented with a time-varying covariance matrix, so the OLS assumption of homoscedasticity is not achieved; therefore, the B-GARCH model allows for a time-varying covariance matrix.

The time-varying hedge ratios are estimated using the following diagonal VECH model, a multivariate GARCH(p, q) model suggested by Bollerslev et al. (1988), which is applied to returns from the spot and futures markets:

$$Y_t=\mu+\delta(z_{t-1})+\varepsilon_t \tag{11}$$

$$\varepsilon_t|\Omega_{t-1}\sim N(0,H_t) \tag{12}$$

$$vech(H_t)=C+\sum_{i=1}^{p} A_i\, vech(\varepsilon_{t-i})^2+\sum_{j=1}^{q} B_j\, vech(H_{t-j}) \tag{13}$$

where $Y_t = (r_t^s, r_t^f)$ is a 2×1 vector containing returns from the spot and futures markets, H_t is a 2×2 conditional covariance matrix, C is 3×1 parameter vector of constants, A_i and B_j are 3×3 parameter matrices, and *vech* is the column stacking operator that stacks the lower triangular portions of a symmetric matrix. The error correction term (z_t) from the cointegration represents short-run deviations from a long-run relation between the spot price and the futures price. A significant positive coefficient (δ) on the error term implies that an increase in short-run deviations raises the logarithmic difference of spot and/or futures prices; if the error term coefficient is negative and significant, the opposite is true.

To make the estimation more manageable, Engle and Kroner (1995) suggest various restrictions on the parameters of the A_i and B_j matrices. A parsimonious representation can be achieved by imposing a diagonal restriction on the parameter matrices, so that each variance and covariance element depends only on its own past values and prediction errors. The following are the conditional variance equations for diagonal VECH B-GARCH(1,1):

$$H_{11,t}=C_1+A_{11}\left(\varepsilon_{1,t-1}\right)^2+B_{11}H_{11,t-1} \tag{14a}$$

$$H_{12,t}=C_2+A_{22}\left(\varepsilon_{1,t-1},\varepsilon_{2,t-1}\right)+B_{22(}H_{12,t-1)} \tag{14b}$$

$$H_{22,t}=C_3+A_{33}\left(\varepsilon_{2,t-1}\right)^2+B_{33}H_{22,t-1} \tag{14c}$$

Using the B-GARCH model, we compute the time-varying hedge ratio as

$$h_t^*=\frac{H_{12,t}}{H_{22,t}} \tag{15}$$

where $H_{12,t}$ is the estimated conditional covariance between the spot and futures returns and $H_{22,t}$ is the estimated conditional variance of futures returns. Since the conditional covariance is time varying, the optimal hedge will also be time varying. On the other hand, $H_{11,t}$ is the estimated conditional variance of spot returns. This formula is important because of the changes over time in the variance of futures price and the covariance between movements in the spot and futures prices.

We find a constant hedge ratio by using the OLS method. The time-varying optimal hedge ratios are calculated with the diagonal VECH B-GARCH model for USDTRY contracts. Different hedge ratios are found for each day for the whole period, and the numbers of contracts that need to be bought are calculated.

6.3 *Hedging effectiveness*

The hedging performance of each portfolio (hedged, unhedged, and naively hedged) is analyzed using the hedge ratios calculated with the OLS and diagonal VECH models. The total portfolio consists of the spot and futures exposures. The hedge ratios are used to calculate the number of futures contracts that must be sold and the total return of the whole portfolio for each day. The most effectively hedged portfolio is the one with the lowest variance; in other words, hedging effectiveness is calculated by reducing variance in the hedged portfolio compared to that of the unhedged portfolio. The aim is to balance the change in the spot portfolio with that in the futures portfolio by using the hedge ratio, as in Ederington's (1979) model.

The returns of unhedged and hedged portfolios are estimated by the following formulas, respectively:

$$R_{unhedged}=S_{t-1}-S_t \quad (16)$$

$$R_{hedged}=(S_{t-1}-S_t)+h_t^* \times (F_{t-1}-F_t) \quad (18)$$

where $R_{unhedged}$ is the daily return of the unhedged portfolio and R_{hedged} is the daily return of the hedged portfolio, using constant and time-varying optimum hedge ratios. The term h_t^* is the optimum hedge ratio calculated for day *t*.

The risk of the position is then defined in terms of the variance in the returns of the whole portfolio (hedged and unhedged):

$$var_u=\sigma_s^2 \quad (17)$$

$$var_h=\sigma_s^2+h_t^2\times\sigma_f^2-2h_t^*\times\sigma_{sf} \quad (18)$$

var_u = variance of the unhedged portfolio

var_h = variance of the hedged portfolio

σ_s^2 and σ_f^2 are the variances of the spot and futures price changes, respectively

σ_{sf} = covariance between spot and futures price changes

Ederington (1979) proposes the percentage reduction in the variances of the hedged and unhedged portfolios as a measure of hedging effectiveness. The following EHE formula is used:

$$\text{Hedging Effectiveness (HE)} = \frac{\text{var}_u - \text{var}_h}{\text{var}_u} \tag{19}$$

In addition, by employing the OLS methodology, we check that the coefficient of determination, R^2, determines the ex-post proportion of the variability of spot price changes that can be hedged successfully by employing the minimum variance hedge ratio, h_t^* .

6.4 Value at Risk (VaR) Calculations

VaR is a risk measurement model first developed in the banking sector back in the 1990s. It quickly became popular, especially among big banks, and started to be widely used to quantify risk. VaR's dominance stems from its computational appeal and the regulatory incentives in place at that period. In 1933, the Glass-Steagall Act divided commercial and investment banks, banning investment banks from providing investment-banking services to their customers. However, towards 1990s some commercial banks started to break this rule by offering some insurance products and merge with investment banks. Finally, in November 1999, the Financial Services Modernization Act was signed, repealing the Glass-Steagall Act. These developments increased the risks at the commercial bank side and introduced risk-adjusted capital requirements brought by the Banks for International Settlements (BIS). For this reason, many banks tried to develop their own proprietary internal risk measurement methods. JP Morgan came up with their model, which is called RiskMetrics^{TM}, a VaR-based risk measurement methodology.

Value at Risk is a measure of maximum potential change in the value of a portfolio of financial instruments over a pre-set horizon. VAR answers the question: how much I can lose with X% probability over a given horizon.

VaR method is relatively easy to calculate and interpret and is a probabilistic method of measuring the potential loss in portfolio value over a given period and for a given distribution of historical returns. VaR is the dollar or percentage loss in portfolio (asset) value that will be equaled or exceeded only X% of time in a given period such as one day, one week. In other words, if the period given is one day, there is an X% probability that the loss in portfolio value in one day will be equal to or greater than the VaR measure.

6.4.1 Methods of Calculating VaR

We can summarize the calculation of VaR process as below:

- Mark-to-market process of the existing portfolio
- The calculation of the volatility of risk factors
- Time horizon selection (1-10 days or 1 month)
- Confidence level selection (95%, 99%)
- Calculation of the VaR value at a determined confidence level

There are three different methods to compute VaR value of portfolios: Historical simulation, variance-covariance (parametric approach), and Monte Carlo simulation methods.

In this thesis VaR figures for daily electricity revenue returns of unhedged, fully hedged, and hedged with OLS and diagonal VECH method portfolios are calculated through the methods mentioned above.

In addition to the out-of-sample analysis, historical and parametric VaR figures are recalculated for a rolling window of a shorter period for in-sample analysis.

6.4.1.1 Historical Simulation

The historical simulation method considers past returns. The worst X% of the observation is calculated based on historical experience. For example, in this thesis, the last 252 days' daily return of the hedged and unhedged electricity revenue portfolio is calculated and compared to determine the worst 1% of the returns. In other words, daily VaR(1%) is calculated by using the past 252 daily returns.

6.4.1.2 Variance-Covariance Method (Parametric Approach)

It is a parametric method and is concerned primarily with the estimated daily potential loss under adverse circumstances. It is like the historical method. However, instead of actual data normal distribution curve is used.

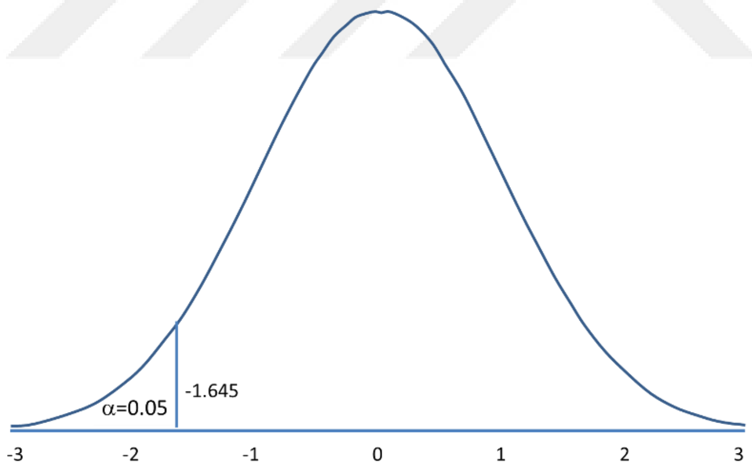

Figure 9*:* Standard Normal Distribution and Cumulative Probabilities

VaR value can be stated with the following formula:

$$VaR(X\%) = Z_{x\%} \times \sigma \tag{20}$$

where:

$VaR(X\%)$: the X% probability value at risk

$Z_{x\%}$: the critical z-value based on the normal distribution and the selected X% probability

σ: the standard deviation of daily returns on a percentage basis

The above formula gives us the percentage loss of the asset that would exceed X% of the time. For example, if we use 10% as the confidence interval, the critical z-value of -1.28 times the standard deviation of percent returns will give us the percentage loss that would exceed 10% of the time.

In order to calculate a dollar-based VaR we need to calculate the percentage based VaR with the total asset value:

$$\text{VaR}(\text{X}\%)_{\text{dollar basis}}=\text{VaR}(\text{X}\%)_{\text{percentage basis}}\times\text{asset value} \tag{21}$$

If the probability is 10%, this would represent the dollar loss in asset value that will only be exceeded 10% of the time.

If the daily standard deviation of a portfolio is 15% and the portfolio value is TRY 2 million with 5% probability we can say that there is 5% probability that, on a given day, the loss of the total portfolio will equal or exceed 495.000 TRY.

$$VaR(X\%)_{dollar\ basis} = -1.65 \times (0.15) \times 2.000.000 = -495.000TRY$$

If we would like to convert the daily VaR into weekly, monthly, semiannual or annual VaR we need to multiply the daily VaR by the square root of the related number of days such as 5-days, 20-days, 125-days and 250-days respectively:

For example weekly dollar VaR of the portfolio above can be calculated as follow:

$$VaR(5\%)_{5\text{-days(weekly)}}=VaR(5\%)_{1\text{-day}}\times\sqrt{5} \quad (22)$$

$$VaR(5\%)_{5\text{-days(weekly)}}=495.000\times\sqrt{5}=1.106.854TRY$$

Table 14: Pros and Cons of Variance-Covariance Method

Pros	Cons
It is a very simple method. Calculation of VaR is so easy.	Normal distribution assumption Estimation of Variance-Covariance matrix and volatilities of the risk factors are required Model is not sufficient for second order risk factors such as options It cannot be used in sensitivity analysis.

6.4.1.3 Monte Carlo Simulation

This simulation method uses more observations by simulating more data points that are consistent with actual recent experience. It creates multiple scenarios by consistently sampling values. With Monte Carlo simulation, a greater number of observations can be used. In this thesis, 100.000 random numbers are generated from the normal distributions of the hedged and the unhedged portfolios.

6.5 Christoffersen BackTesting Method

One of the most popular tests for validation of VaR models is Christoffersen's (1998) Markov independence test. It is based on the failure process and is a likelihood ratio test that checks for frequent consecutive exceedances. It searches instances when both ${}^{t-1}i = 1$ and ${}^{t}i = 1$ for some t. The test checks the probability of a VaR violation (failure) with a dependence on a VaR violation that occurred on the previous day.

The failure function is defined as follows:

$$I_t(q)=\begin{cases} 1;\ r_{pt}\leq F^{-1}_{rp,t}(q) \text{ if a violation occurs} \\ 0;\ r_{pt}>F^{-1}_{rp,t}(q) \text{ if no violation occurs} \end{cases} \tag{23}$$

The null hypothesis is:

$$H_0{:}\hat{q}=q \tag{24}$$

This test statistics is based on the following likelihood ratio and it is asymptotically chi-square distributed with one degree of freedom.

$$LR_{uc}=-2\ln\left(\frac{(1-q)^{T_0}q^{T_1}}{(1-\hat{q})^{T_0}\hat{q}^{T_1}}\right)\sim\chi_1^{\ 2} \tag{25}$$

where;

$$\hat{q}=\frac{T_1}{T_o+T_1}, \qquad T_1=\sum_{t=1}^{T} I_t(q), \quad T_o=T-T_1 \tag{26}$$

The formula for the Christoffersen test which examines the independence of exceptions, is given below:

$$LR_{ind}=-2\ln\left(\frac{(1-\bar{q})^{T_{00}+T_{10}}\bar{q}^{T_{01}+T_{11}}}{(1-\hat{q}_{01})^{T_{00}}\hat{q}_{01}^{T_{01}}(1-\hat{q}_{11})^{T_{10}}\hat{q}_{11}^{\ T_{11}}}\right)\sim\chi_1^{\ 2} \tag{27}$$

where;

$$\hat{q}_{ij}=\frac{T_{ij}}{T_{io+}T_{i1}},\ \bar{q}=\frac{T_{01}+T_{11}}{T_{00+}T_{01}+T_{10+}T_{11}} \tag{28}$$

T_{ij} is a number of i values followed by a j value in the failure series.

With the Christoffersen test, our null hypothesis becomes like this:

$$H_0:\hat{q}_{01}=\hat{q}_{11}=\bar{q} \tag{29}$$

This is based on the likelihood ratio of serial independence against the alternative of the first order Markov dependence. This checks if the likelihood of VaR violations depends on whether or not a VaR violation occurred on the previous day.

Christoffersen proposed the mixed approach where unconditional coverage and independence property of the failure sequence are handled together.

$$LR^1_{mix}=LR_{uc}+LR_{ind}\sim\chi_2{}^2 \tag{30}$$

As mentioned before, the Christoffersen test relies on the frequency with which consecutive failures are experienced. As these are inherently rare events, the test has limited power. Also, the test is not specified when there is no consecutive failures at all, which is possible. Christoffersen cannot handle this situation. In some cases, it may be acceptable to accept the null hypothesis when there are no consecutive exceedances. To address this issue, when there are no consecutive exceedances, the null hypothesis is accepted in this study.

In this thesis, backtesting of unhedged and hedged portfolio VaR figures are conducted through the Christoffersen test. Unusual frequent consecutive exceedances of VaR values are calculated for four different portfolios.

The following chapter will describe the empirical findings obtained as a result of all the methodologies mentioned in this section of the thesis. First optimum hedge ratios calculated through different models such as OLS and diagonal VECH model are given and then hedging effectiveness of portfolios formed through these models as well as naively hedged portfolio are compared under Ederington’s EHE framework. In addition to that, VaR values calculated by different models for these portfolios are also shown in this chapter including the backtesting results.

CHAPTER 7: EMPRICAL FINDINGS AND INTERPRETATIONS

7.1 Hedge Ratio Calculations

First the constant and time-varying hedge ratios for the USDTRY are found by applying the OLS and diagonal VECH methods, respectively. Using these hedge ratios, we then find the variance of naively hedged and model-based hedged electricity revenue portfolios to obtain Ederington's (1979) minimum variance portfolio.

To find hedge ratios and optimum contract amounts for each day, first spot and future daily logarithmic returns of USDTRY spot and future contracts are calculated. Then by using these daily returns OLS as well as time-varying hedge ratios according to the bivariate GARCH model are calculated for each day.

7.1.1. OLS Regression Results:

According to OLS, hedge ratio which is the coefficient of daily future returns (R_f) for the period December 1st, 2017 to November 30th is calculated as 0.83. On the other hand, the statistical significance of estimated coefficients is also checked through standard error, t-statistics, and p-values. The coefficient representing the hedge ratio (b^*) is found significant at 1% significance level, contrary to the constant parameter (α) of the model.

This constant hedge ratio is used in determining the optimum number of VIOP USDTRY contracts to hedge the total portfolio of the wind power plant. Furthermore, R-squared, which is the percentage of the response variable variation that the linear model explains, is 0.71 for USDTRY. The details of the linear regression between spot and future daily returns are reported in Appendix C.

Table 15: OLS Constant Hedge Ratios (CHR) and R-Squared Values

Period	USDTRY	
	CHR	R-squared
1/12/2017-30/11/2018	0.83	0.71

7.1.2. Multivariate GARCH Results:

Figures 10 illustrates the time-varying hedge ratios based on the diagonal VECH model. Since a dynamic method is used, different hedge ratios for each day are observed for the related period. The time-varying hedge ratios calculated through the diagonal VECH method for USDTRY range from 0.16 to 0.99.

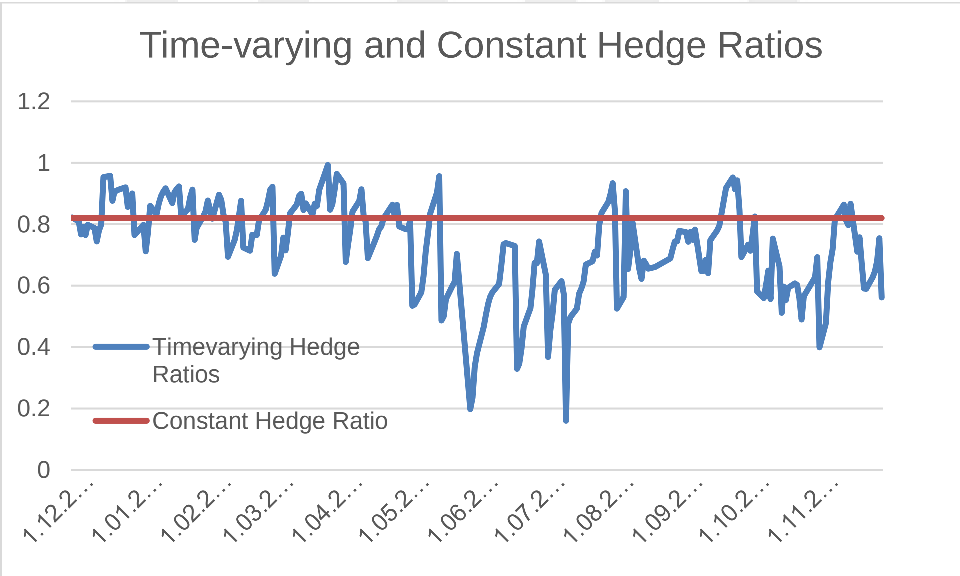

Figure 10: Time-varying and Constant Hedge Ratios for USDTRY

7.2. Hedging Effectiveness of Electricity Revenue Portfolios

According to Ederington (1979), a hedging strategy is effective only if it reduces a significant portion of the variance with respect to its unhedged strategy. In this respect, the mean return, standard deviation, and risk-adjusted return of portfolios are calculated by using the above optimum hedge ratios (estimated by both the OLS and GARCH models). These measures are then compared with those of the unhedged and naively hedged portfolio. Table 15 shows this comparison, and Table 16 provides the variances and hedging effectiveness ratios of each portfolio for the corresponding period.

Table 16: Mean Return and Standard Deviation for USDTRY Portfolio

	Period (1/12/2017-30/11/2018)		
	Mean	Std. Dev.	Risk-Adjusted Returns (*100)
USDTRY			
Unhedged	-0.1455	1.8228	-0.0798
GARCH Hedged	-0.0021	0.8225	-0.0026
Naively Hedged	0.0042	0.9848	0.0043
OLS Hedged	-0.0171	0.8469	-0.0202

This table compares the realized risk-adjusted returns of unhedged and hedged portfolios, measured by calculating the ratio of each portfolio's mean to its standard deviation.

When we analyze the risk-adjusted return of the four portfolios it is obvious that unhedged portfolio is the most fragile portfolio out of these four, with a Sharpe ratio of -0.08. The Sharpe ratio which is developed by William Sharpe is a popular measure of risk-adjusted return in the investment analysis. It is designed to measure the expected return per unit of risk (standard deviation) for an investment strategy. Since our aim is to minimize the variation of mean return of the electricity revenue portfolio mean returns of the hedged portfolios are close to 0 at full hedge and

GARCH hedge portfolios, contrary to others which have negative returns which is higher than 1%. Therefore, we can conclude that full hedge and GARCH hedge portfolio give us the highest Sharpe ratios.

The results in Table 15 show that hedging the spot portfolio by using USDTRY futures contracts improves the risk-adjusted return ratio, calculated as the ratio of the mean return to its standard deviation. More importantly, this result holds for almost all the models considered. There are four cases, and for all, the hedged portfolio’s risk-adjusted return is higher than that of the unhedged portfolio. The naively hedged portfolio provides a positive risk-adjusted return and is the best in four cases, followed by the GARCH hedged model, which prevails in two of the four cases.

On the other hand, GARCH hedged portfolio has the lowest standard deviation compared to other portfolios. It is analyzed that, in general, the hedged portfolios' standard deviation is much lower than the unhedged ones. While the standard deviation of the unhedged portfolio is 1.82, the GARCH hedge portfolio has a standard deviation of 0.82. On the other hand, the fully hedged portfolio and OLS hedge portfolio’s standard deviations are 0.98 and 0.85.

Table 17: % Variance Reduction Compared to Unhedged Portfolio

	Period (1/12/2017-30/11/2018)	
	Variance	Hedging Effectiveness (%)
USDTRY		
Unhedged	3.3224	
GARCH Hedged	**0.6765**	**54.8739**
Naively Hedged	0.9697	45.9734
OLS Hedged	0.7171	53.5389

This table reports the portfolio variance and hedge effectiveness ratios, computed using Eq. (13). Numbers in boldface indicate the hedged portfolio with the highest variance reduction.

In addition to the improved risk-adjusted returns in Table 15, we conclude that hedging through USDTRY currency futures contracts also helps lower the variance of portfolios and increase hedging effectiveness. As Table 16 indicates, we observe substantial variance reduction and hedging effectiveness for hedged electricity revenue portfolio. The GARCH hedged portfolio outperforms the other methods, with variance reductions of 55%. Optimum hedge ratios estimated by the multivariate GARCH model produced the best result for the corresponding period. On the other hand, OLS hedge model was also close to GARCH model with a 54% variance reduction. The variance reduction was lowest at fully hedge portfolio with a reduction of 46%.

Our finding is similar to Aksoy and Olgun's (2009) findings that the multivariate GARCH method is superior to other methods. On the other hand, this contradicts Alexander and Barbosa's (2007) study, which provides no evidence that complex econometric models such as GARCH are superior to simpler models such as OLS and naively hedged portfolios. They found out that no single method can be considered superior to the other two since the variance reductions are almost equal, whether constant or dynamic.

In this thesis, the OLS regression R^2 value is 0.71. This measure represents the proportion of the variance for a dependent variable (daily spot change) explained by an independent variable (daily future change) or variables in a regression model. This value might also be considered as another way of measuring the hedging effectiveness of the related strategy. Although the OLS hedge model's variance reduction is closer to the GARCH model, the calculated R^2 value isn't that high.

7.3. VaR Results

In addition to Ederington's variance reduction analysis, a VaR analysis is also conducted for the unhedged, OLS hedged, GARCH hedged and fully hedged electricity revenue portfolio returns to find out the portfolio with the minimum loss at a given confidence level.

First, an out-of-sample analysis is applied to the whole data set, and then an in-sample analysis is executed on a rolling window of 50 observations in order to generate VaR forecasts. These obtained VaR vales are referred to as “dynamic VaR values” as Linsen (2018). A model averaging technique is applied to construct the dynamic VaR forecasts on a 99% confidence level.

7.3.1. Out-of-Sample VAR with Historical Simulation Results

As mentioned before and displayed in Table 17, past 250 daily return data are used to calculate the daily percentage VaR value for the unhedged, fully hedged, GARCH hedged and OLS hedged portfolios for the out-of-sample period. The actual distributions for the data are being used, so it does not depend on any assumption. The shape of the conditional distribution is estimated based on historical data. Correlogram analysis of daily portfolio returns is given in Appendix D.

Table 18: Daily Historical Returns of Hedged/Unhedged Portfolios

Date	Unhedged Portfolio Return (%)	Fully Hedged Portfolio Return (%)	GARCH Hedged Return (%)	OLS Hedged Return (%)
1.12.2017				
4.12.2017	0.97	-0.10	0.10	0.10
5.12.2017	0.80	0.09	0.23	0.22
6.12.2017	-0.21	-0.65	-0.54	-0.57
7.12.2017	-0.32	0.12	0.03	0.04
8.12.2017	0.68	-0.07	0.11	0.07
-	-	-	-	-
-	-	-	-	-
-	-	-	-	-
-	-	-	-	-
26.11.2018	0.64	-0.32	0.04	-0.16
27.11.2018	-0.50	0.25	-0.01	0.13
28.11.2018	1.06	0.81	0.85	0.85
29.11.2018	1.00	-1.05	-0.43	-0.72
30.11.2018	-0.84	-0.74	-0.74	-0.76

The hedged portfolio obtains the portfolio with the lowest standard deviation with the GARCH model. While this portfolio has a standard deviation of 0.82%, the unhedged portfolio has a standard deviation of 1.82%. OLS hedged, and fully hedged portfolios have a standard deviation of 0.84% and 0.98%, respectively. On the other hand unhedged portfolio has the lowest mean return of -0.15%, and the fully hedged and GARCH hedged portfolio produced mean returns of close to 0. GARCH hedged model also has the lowest skewness and kurtosis figures of 0.50 and 6.66, respectively. Based on this skewness value, we can conclude that the GARCH hedged portfolio’s return distribution is approximately symmetric. Although the GARCH hedged portfolio represents a leptokurtic distribution (kurtosis > 3), it has the lowest kurtosis between all other hedged and unhedged portfolios. All these results are displayed in Table 18.

Table 19: Basic Statistics of Past Daily Electricity Returns

	Unhedged	Fully Hedged	GARCH Hedged	OLS Hedged
Mean	-0.1455	0.0042	-0.0021	-0.0171
Std.Dev	1.8264	0.9867	0.8242	0.8486
Skewness	-3.1020	1.3104	0.5051	0.9971
Kurtosis	31.0121	8.9034	6.6615	9.7145

According to the historical simulation method, daily VAR(1%) level for the unhedged, fully hedged, GARCH hedged, and OLS hedged portfolios are calculated as -5.14%, -2.78, -2.23%, and -2.21%, respectively. In other words, we can say that there is a 1% probability that, on a given day, the loss of the total portfolio will equal or exceed 5.14% for the unhedged portfolio, -2.78% for the fully hedged portfolio, -2.23% for the GARCH Hedged portfolio and -2.21% for the OLS Hedged portfolio.

Table 20: Daily Percentage Historical Simulation VaR Values for Unhedged and Hedged Portfolios

Probability	Unhedged	Fully Hedged	GARCH Hedged	OLS Hedged
0.01	-5.14070	-2.78288	-2.23250	-2.21328
0.99	3.33013	3.51611	2.48002	2.81004

In Table 19, it can be seen that GARCH Hedged portfolio produces the lowest VAR values with a 99% confidence level.

7.3.2. Out-of-Sample VaR with Parametric Approach (Variance-Covariance Method)

In this thesis first, parametric VaR values are calculated by using the unconditional constant variance for the out-of-sample data series with 250 observations. Table 20 lists these VaR values. According to Table 20, we can say that there is a 1% probability that, on a given day, the loss of the total portfolio will equal or exceed -4.39% for the unhedged portfolio, -2.29% for the fully hedged portfolio, -1.92% for the GARCH Hedged portfolio and -1.99% for the OLS Hedged portfolio. GARCH produces the lowest VAR values with 99% confidence level Hedged portfolio with a value of -1.92%.

Table 21: Daily Percentage Parametric VaR Values for Unhedged and Hedged Portfolios by Using Unconditional Variance

Probability	Unhedged	Fully Hedged	GARCH Hedged	OLS Hedged
0.01	-4.39436	-2.29124	-1.91942	-1.99113
0.99	4.10327	2.29973	1.91522	1.95695

Second, in estimating daily parametric VaR values, ARMA(1,1)-GARCH(1,0) model is applied for hedged portfolios and ARMA (4,0)-GARCH)(1,1) model for unhedged portfolio. In other words, conditional volatility for a log return times series (electricity hedged and unhedged revenues) is modeled by implementing a conditional heteroskedastic GARCH model. In order to forecast the one step ahead VaR value, these GARCH models are used in a rolling window estimation on 250 observations. To find the goodness-of-fit of these models to data all the statistical tests are implemented, and its results are given in Appendix E.

By using the parametric VaR formula mentioned in previous sections and by applying the ARMA(4,0)-GARCH(1,1) for unhedged and ARMA(1,1)-GARCH(1,0) model for hedged portfolios we found the following VAR (1%) values.

All the parametric daily VaR values are given in Figures from 11 to 14, and it is observed that GARCH hedged portfolio has the lowest mean VaR figures. All the parametric VaR values are listed in Appendix F.

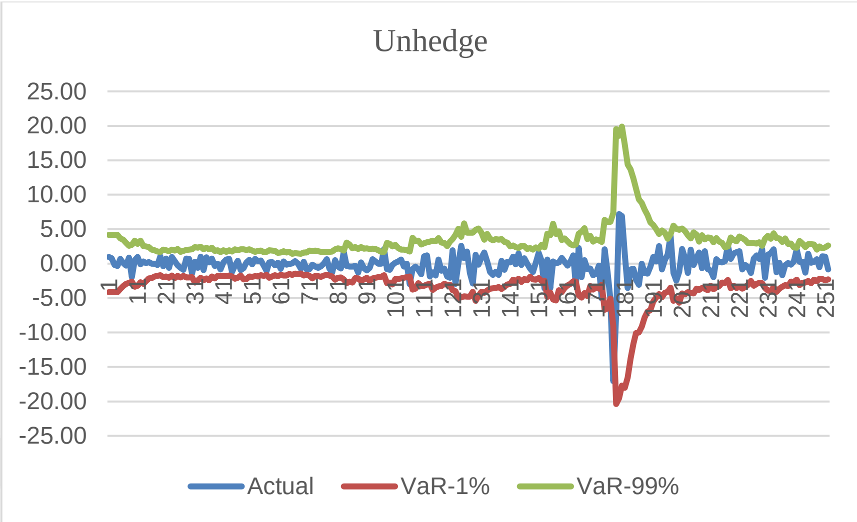

Figure 11: Daily Parametric % VaR Values of Unhedged Portfolio

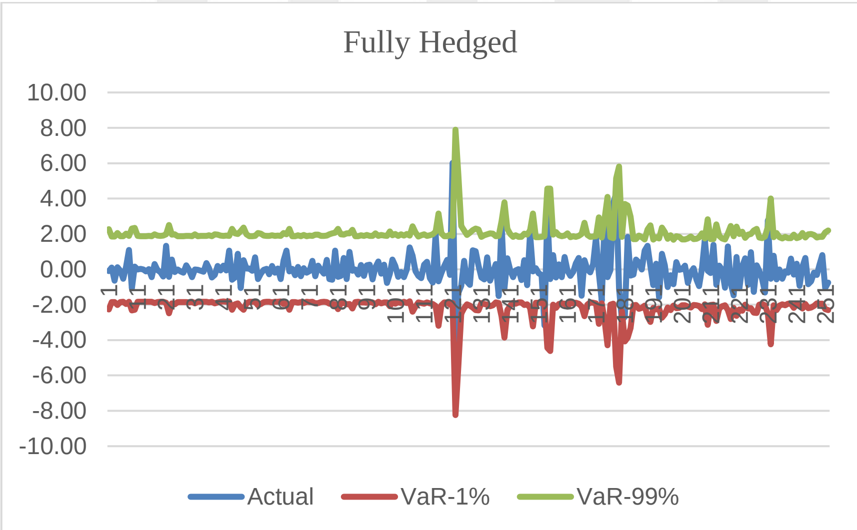

Figure 12: Daily Parametric % VaR Values of Fully Hedged Portfolio

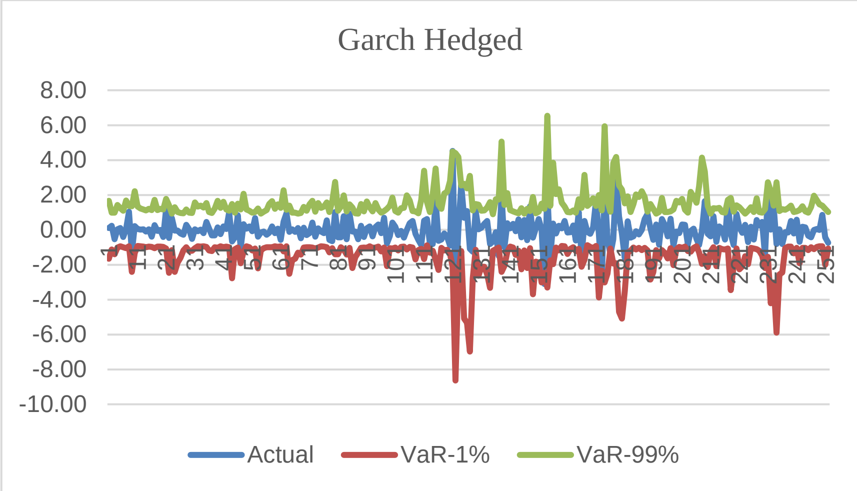

Figure 13: Daily Parametric % VaR Values of GARCH Hedged Portfolio

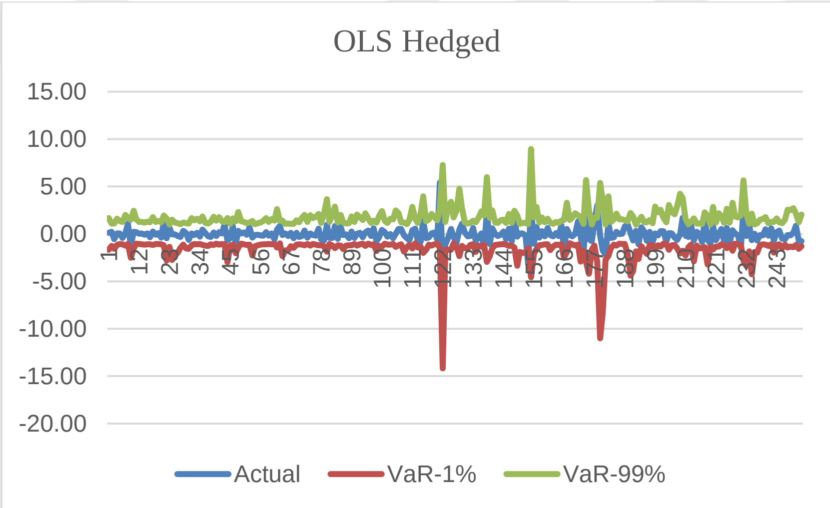

Figure 14: Daily Parametric % VaR Values of OLS Hedged Portfolio

7.3.3. Out-of-Sample VaR with Monte Carlo Simulation

100.000 random numbers generated from the normal distribution of the time daily return time series, and the new parametric VaR figures are calculated. According to this, we can say that there is a 1% probability that, on a given day, the loss of the total portfolio will equal or exceed -4.40% for the unhedged portfolio, -2.30% for the fully hedged portfolio, -1.91% for the GARCH Hedged portfolio and -2.01% for the OLS Hedged portfolio. GARCH produces the lowest VaR values with 99% confidence level Hedged portfolio with a value of -1.91%.

Table 22: Daily Percentage Monte Carlo VAR Values for Unhedged and Hedged Portfolios

Probability	Unhedged	Fully Hedged	GARCH Hedged	OLS Hedged
0.01	-4.4011	-2.2992	-1.9128	-2.0109
0.99	4.0917	2.3017	1.9164	1.9631

7.3.4. Comparison of VaR Values Found with Different Methods

Table 23: Comparison of Daily VaR Values with Different Methods

Method	Probability	Unhedged	Fully Hedged	GARCH Hedged	OLS Hedged
Historical Simulation	0.01	-5.1407	-2.7828	-2.2325	-2.2132
Parametric	0.01	-4.3943	-2.2912	-1.9194	-1.9911
Monte Carlo	0.01	-4.4011	-2.2992	-1.9128	-2.0109

As shown in Table 22, VaR figures calculated by parametric method and Monte Carlo simulation are closer. On the other hand, the lowest VaR(1%) value is obtained using the GARH Hedged portfolio. This result is consistent with the result found with the EHE minimum variance rule analyzed in the previous section and parametric VaR figures found by using the conditional variance.

7.3.5. In-Sample Analysis of VaR Values

In addition to out-of-sample analysis, a dynamic 50-day rolling window approach is applied for the in-sample analysis. VaR values calculated with historical and parametric methods are used to forecast in-sample future VaR values.

Since the out-of-sample period includes 250 observations, the first forecasted VaR value starts with the 51st observations, and this dynamic process is repeated until the entire period is forecasted.

Actual portfolio returns and forecasted in-sample VaR values for different portfolios with historical simulation method are given in Figures from 15 to 18:

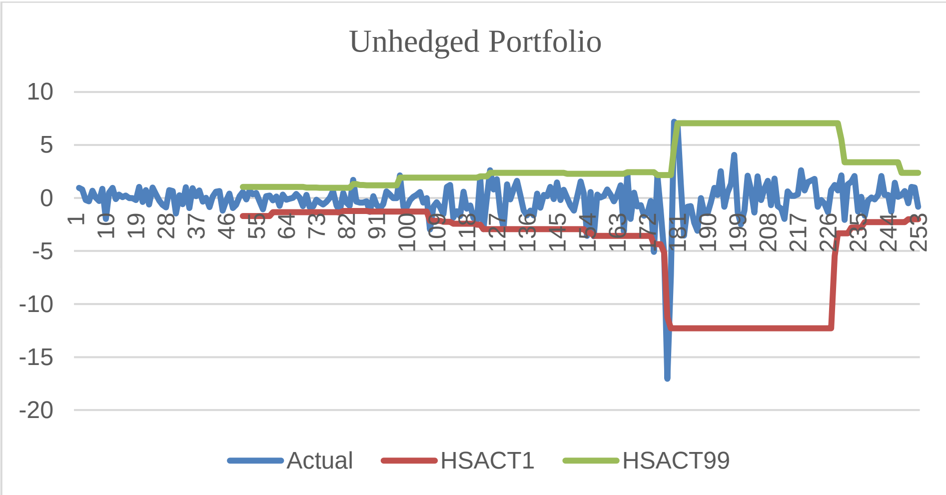

Figure 15: Daily Historical % VaR Values of Unhedged Portfolio-In Sample

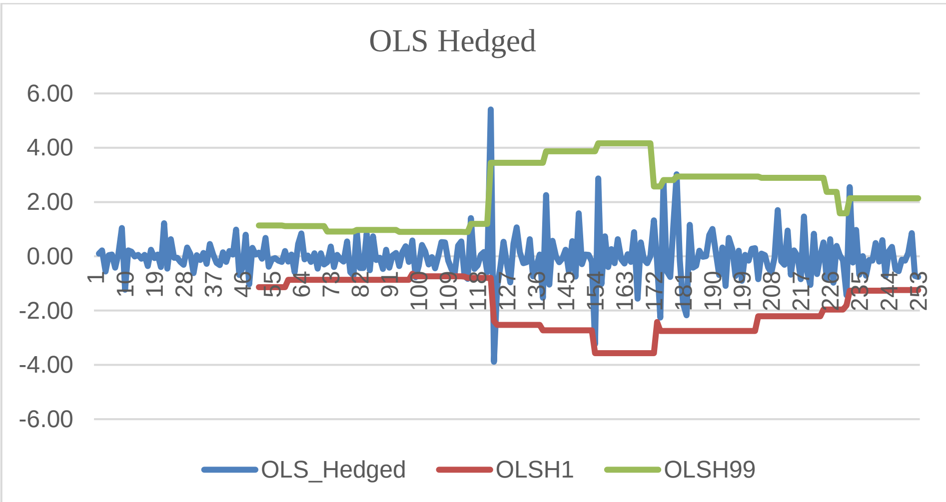

Figure 16: Daily Historical % VaR Values of OLS Hedged Portfolio-In Sample

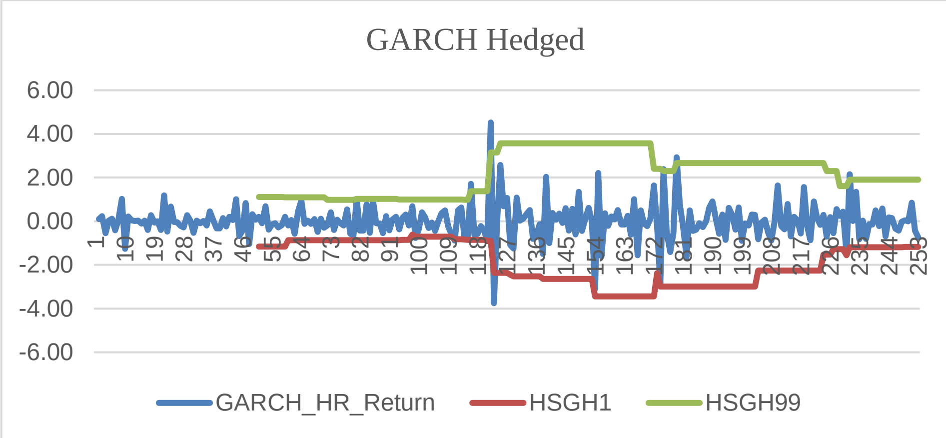

Figure 17: Daily Historical % VaR Values of GARCH Hedged Portfolio-In Sample

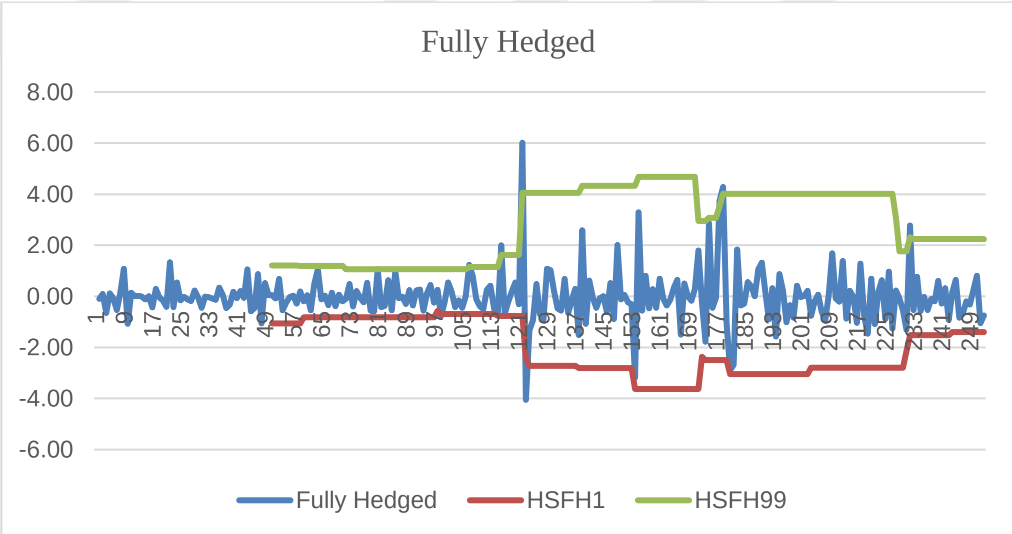

Figure 18: Daily Historical % VaR Values of Fully Hedged Portfolio-In Sample

According to the shape of VaR curves at the historical simulation model, we can see that they are at a fixed level for a long time. This characteristic is unique for the historical simulation method. At the historical simulation method, the given quantile of historical returns is utilized as a negative VaR estimation. This quantile is determined by significance level. For this reason, the VaR value might be the same for a while. From Figures from 18 to 21, we observe that big volatility happened on August 10, 2018, when the Turkish lira depreciated significantly due to political turmoil in Turkey.

Actual portfolio returns and forecasted in-sample VaR values for different portfolios with the parametric method are given in Figures from 19 to 22:

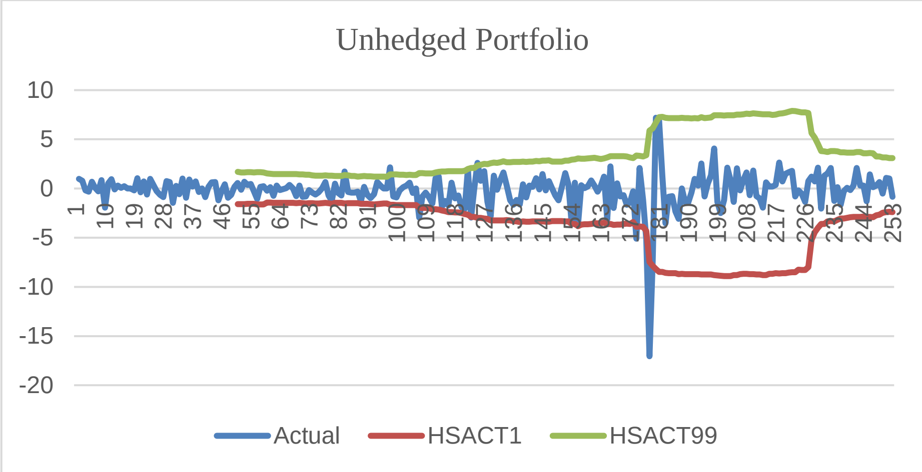

Figure 19: Daily Parametric % VaR Values of Unhedged Portfolio-In Sample

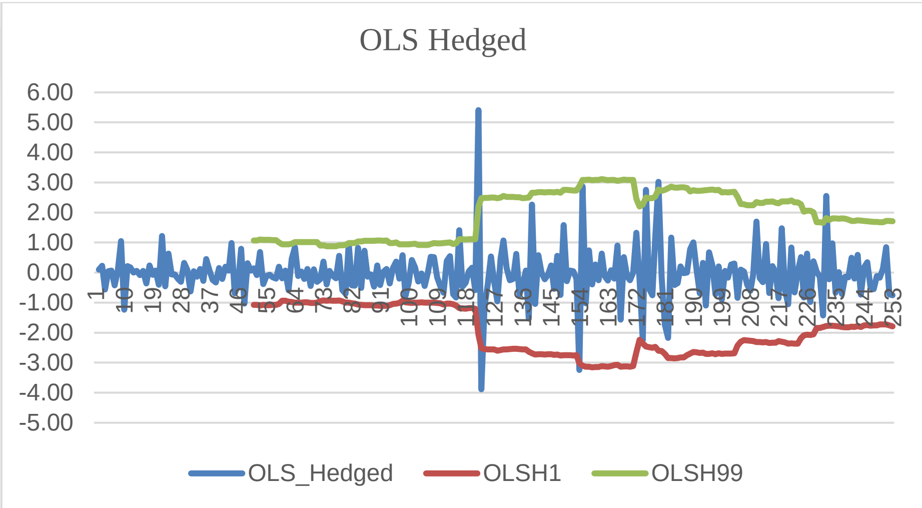

Figure 20: Daily Parametric % VaR Values of OLS Hedged Portfolio-In Sample

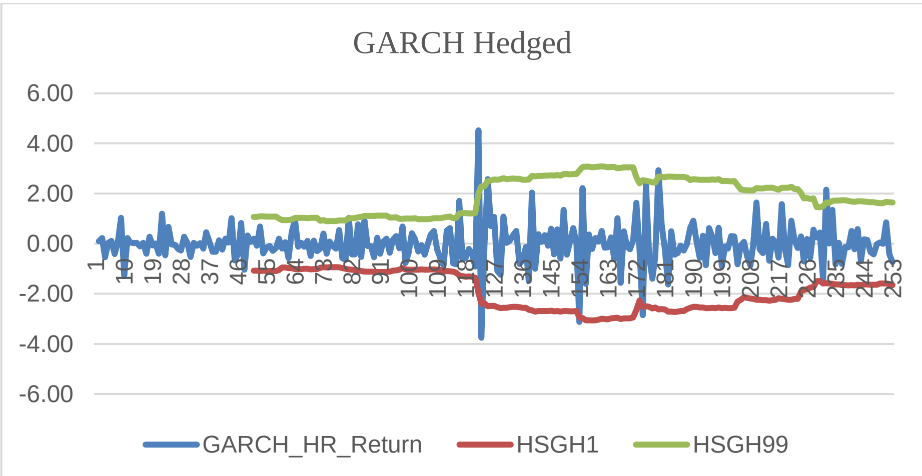

Figure 21: Daily Parametric % VaR Values of GARCH Hedged Portfolio-In Sample

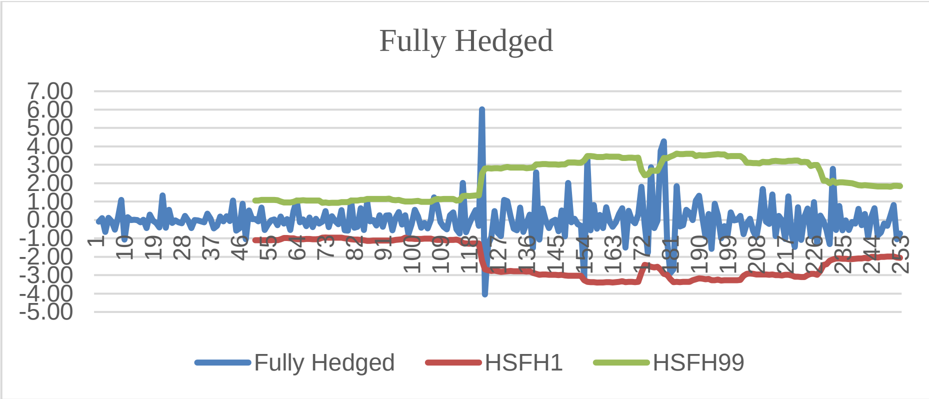

Figure 22: Daily Parametric % VaR Values of Fully Hedged Portfolio-In Sample

7.4. Christoffersen Backtesting Results for Calculated VaR Values

According to the Christoffersen test, all the VaR models are accepted except for the in-sample unhedged portfolio, where there are seven exceedances and one consecutive exceedance. All the other hedged portfolios have lower exceedances than the unhedged portfolio, they don't have any consecutive exceedance and all VaR models are accepted. The lowest exceedance value is obtained through fully hedged portfolio followed by the OLS and GARCH hedged portfolios. Table 23 summarizes the exceedances obtained through Christoffersen Backtesting Method, and Figures from 23 to 34 display visually all the exceedances for out-of-sample and in-sample data. Detailed results of Christoffersen Backtesting Method is given in Appendix G in Table 27.

Table 24: Exceedances Obtained Through Christoffersen Backtesting Results

Portfolio	Out-of-Sample	In-Sample	
		Historical	Parametric
Undhedged	6	7	5
OLS Hedged	3	3	2
GARCH Hedged	4	4	3
Fully Hedged	2	2	1

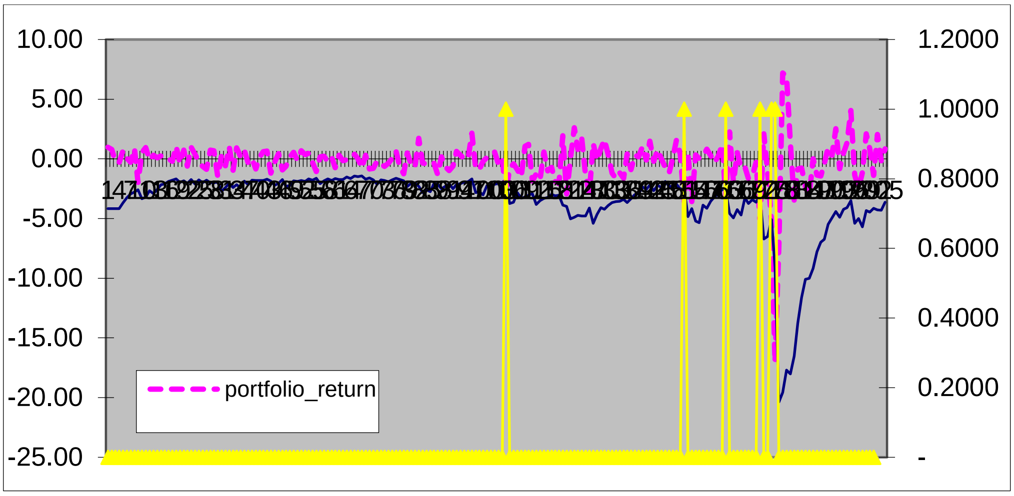

Figure 23: Christoffersen Test Result Unhedged Portfolio-Out-of-Sample

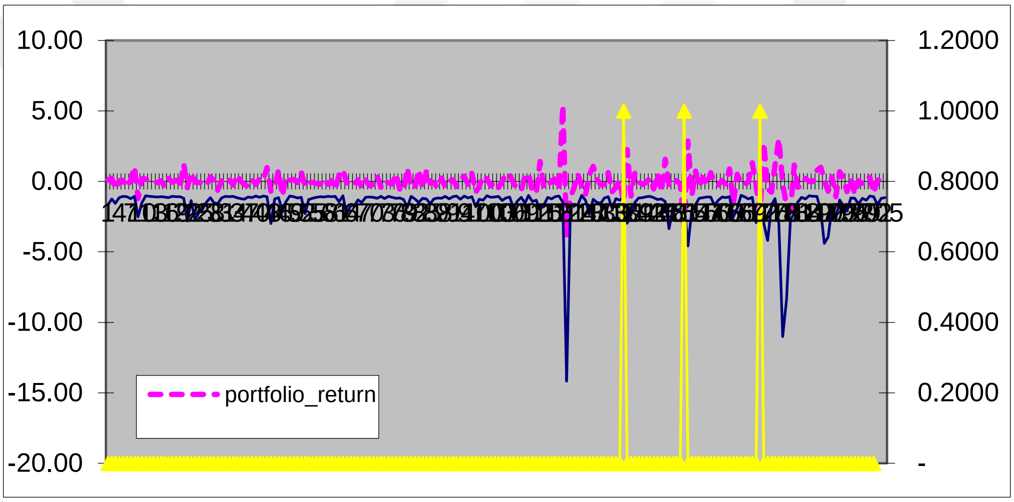

Figure 24: Christoffersen Test Results OLS Hedged Portfolio-Out-of-Sample

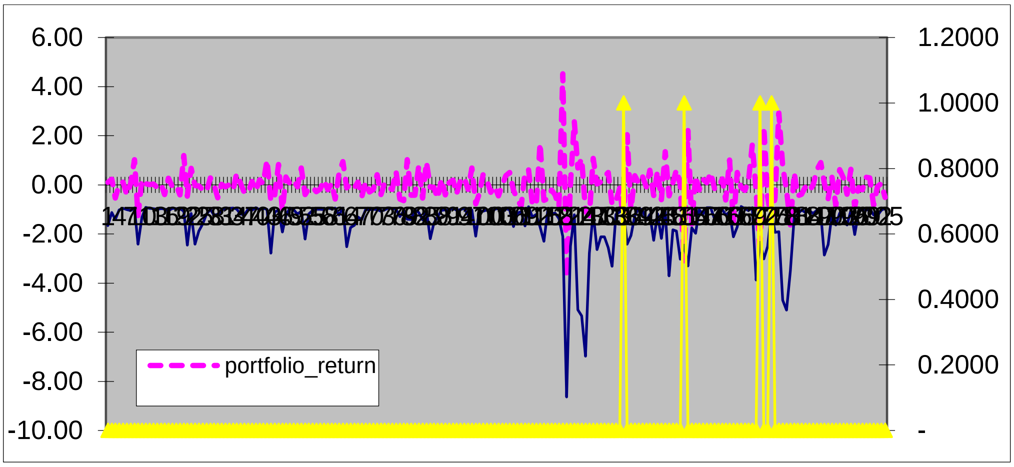

Figure 25: Christoffersen Test Results GARCH Hedged Portfolio-Out-of-Sample

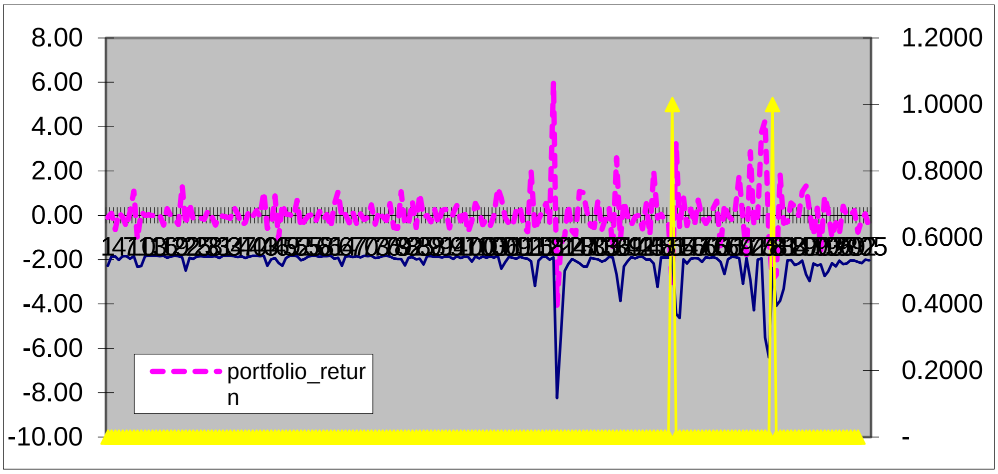

Figure 26: Christoffersen Test Results Fully Hedged Portfolio-Out-of-Sample

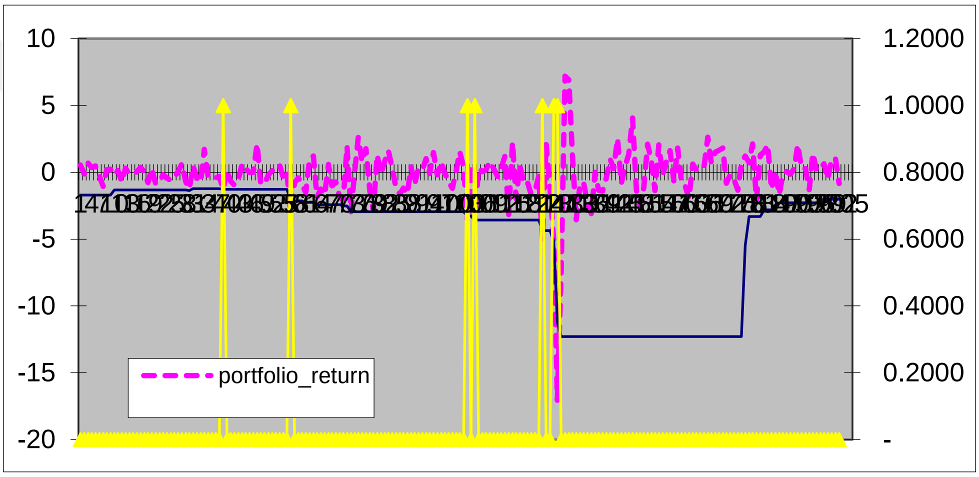

Figure 27: Christoffersen Test Results Unhedged Portfolio-In-Sample (Historical)

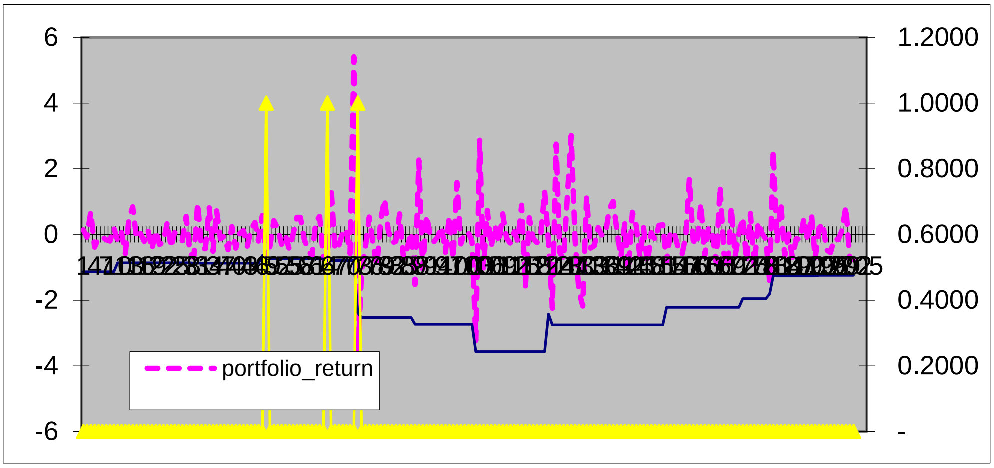

Figure 28: Christoffersen Test Results OLS Hedged Portfolio-In-Sample (Historical)

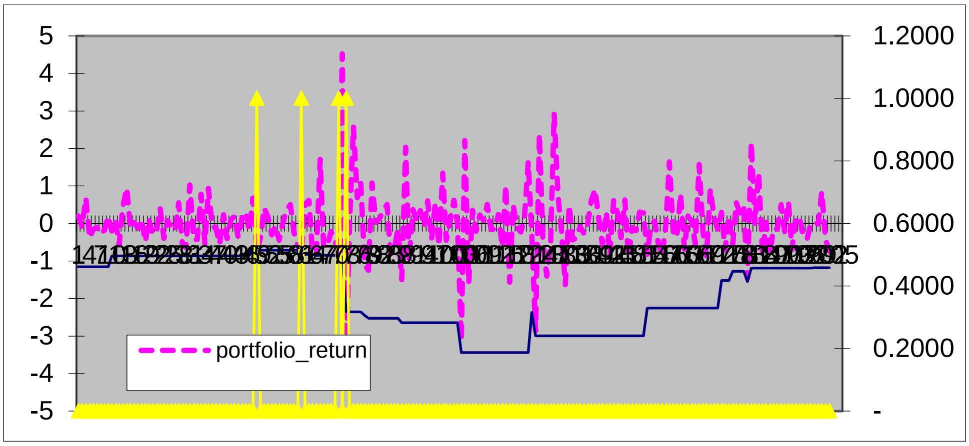

Figure 29: Christoffersen Test Results GARCH Hedged Portfolio-In-Sample (Historical)

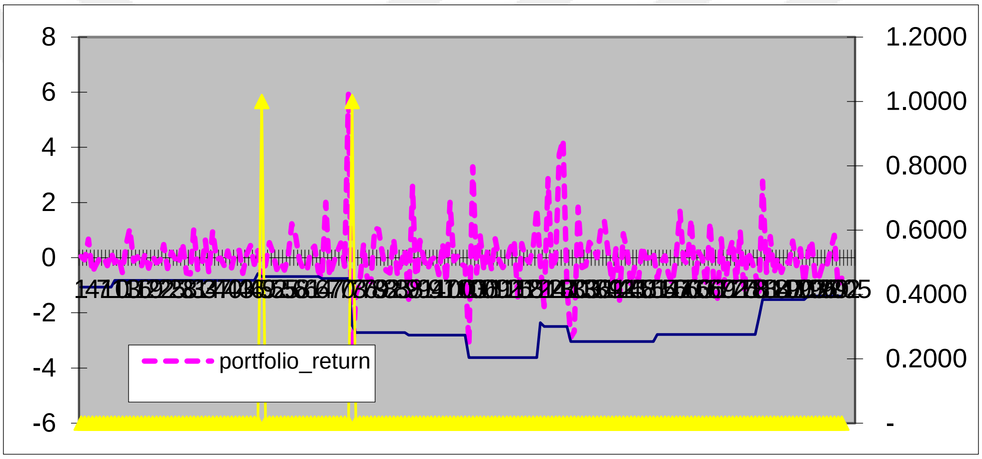

Figure 30: Christoffersen Test Results Fully Hedged Portfolio-In-Sample (Historical)

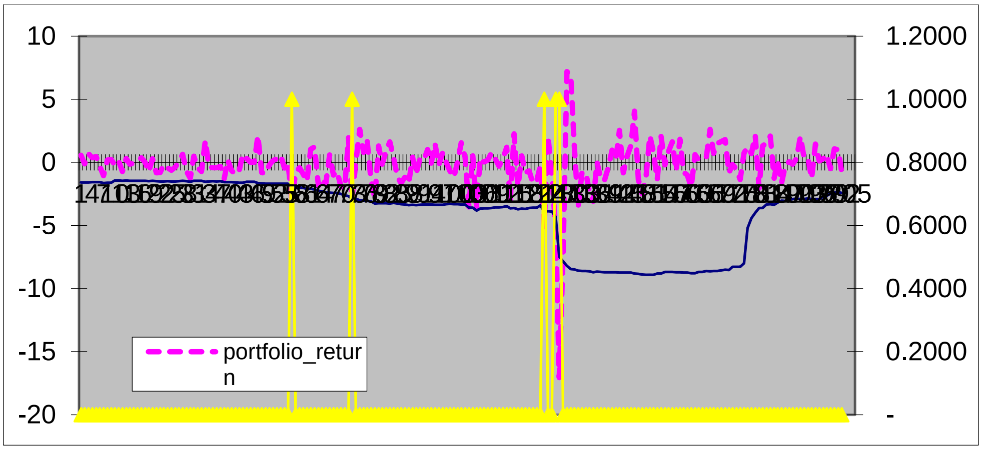

Figure 31: Christoffersen Test Results Unhedged Portfolio-In-Sample (Parametric)

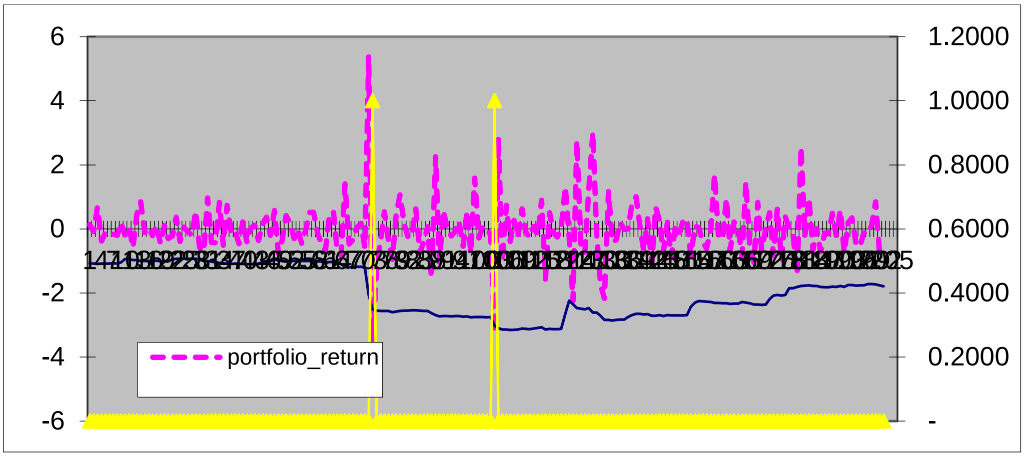

Figure 32: Christoffersen Test Results OLS Hedged Portfolio-In-Sample (Parametric)

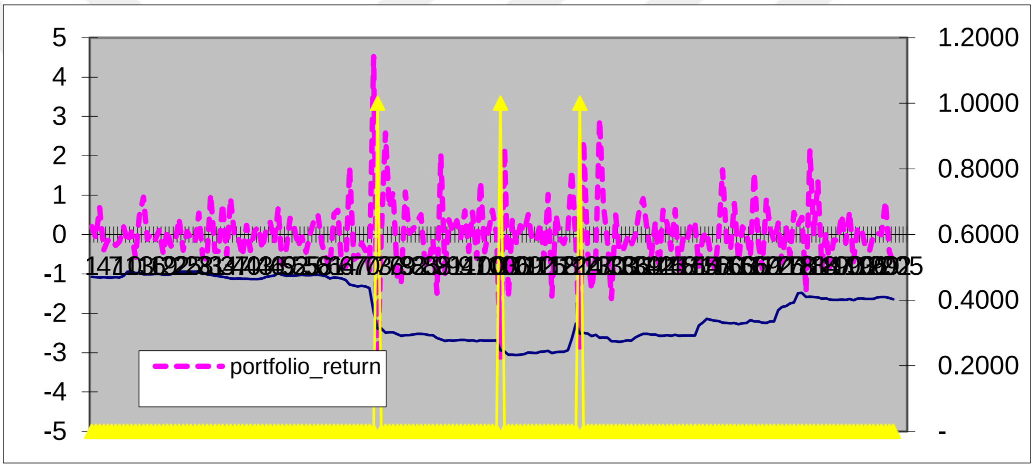

Figure 33: Christoffersen Test Results GARCH Hedged Portfolio-In-Sample (Parametric)

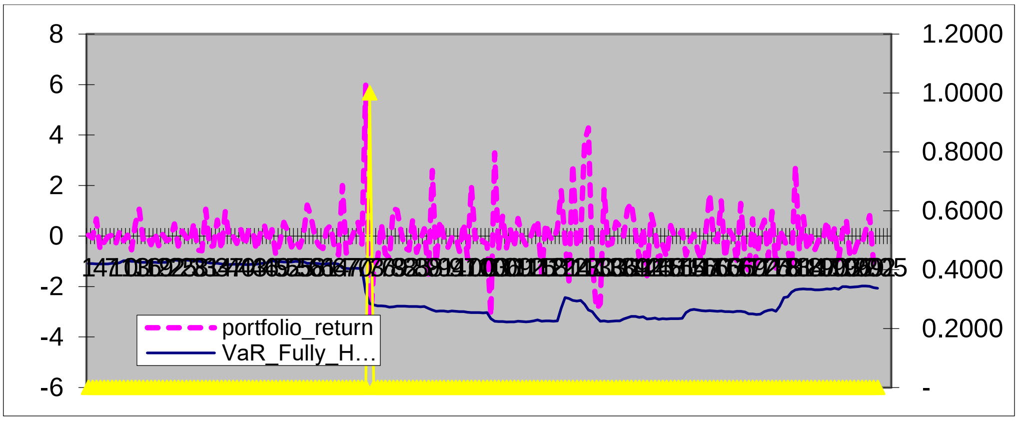

Figure 34: Christoffersen Test Results Fully Hedged Portfolio-In-Sample (Parametric)

7.5. Total Hedge Gains Obtained with Different Hedging Models

In addition, to obtain a portfolio with the minimum variance, it is also worthwhile to check and compare the revenue stream created with different unhedged and hedged electricity portfolios with different hedge ratios during the observed period. For this reason, the total ending period portfolio balances at 30.11.2018 are calculated and converted into USD as displayed in Table 24.

According to this analysis, it is observed that the maximum portfolio balance is obtained through the GARCH hedged portfolio. The total ending period balance of GARCH hedged portfolio reaches TRY17,039,287 (USD3,268,865), while the ending balance of unhedged portfolio is TRY15,261,686 (USD2,927,845). With the GARCH hedged portfolio a saving of USD341.020 is provided. This represents a total hedge gain of 12% in USD terms for the observed period. As of November 30th, 2018 one US dollar equals to 5,21 Turkish Lira.

Table 25: Final Portfolio Balances and Total Hedge Gains

	Date	Unhedged	Fully Hedged	GARCH Hedged	OLS Hedged
Portfolio Balance (TRY)	30.11.2018	15,261,686	16,931,964	17,039,287	16,631,671
Portfolio Balance (USD)	30.11.2018	2,927,845	3,248,276	3,268,865	3,190,667
Hedge Gain (USD	30.11.2018	-	320.431	**341.020**	262.822
Hedge Gain (%)	30.11.2018	-	10.94	**11.65**	8.97

Note: The ending TRY portfolio balances are converted into USD with the USDTRY exchange rate of 30.11.2018 (TRY5.2126).

In this analysis, the interest rate effect is ignored. In other words, electricity revenue portfolio is also earning an overnight interest rate in TRY if deposited in a bank account. Considering the high-interest rates in Turkey, the total ending portfolio balance would be much higher if this amount is deposited into an overnight earning interest rate account.

The detailed daily calculation of the ending balance of hedged and unhedged portfolios are given in Tables from 25 to 27:

Table 26*:* Daily Portfolio Balance of Unhedged and Fully Hedged Portfolio

Date	Revenue (TRY)	Portfolio Balance Unhedged (TRY)	Spot USD Rate	Future Price	Hedge Ratio	Optimum Contract	Future Return	Total Portfolio
1.12.2017	107,403	107,403	3.9133	3.9615	1	27	-1.148	107,403
4.12.2017	236,570	343,973	3.8753	3.919	1	88	-2.438	342,826
5.12.2017	41,027	385,001	3.8443	3.8913	1	99	-1,683	381,415
-	-	-	-	-	-	-	-	-
-	-	-	-	-	-	-	-	-
-	-	-	-	-	-	-	-	-
-	-	-	-	-	-	-	-	-
29.11.2018	133,819	15,138,211	5.1695	5.1614	1	2,933	-16,962	16,807,902
30.11.2018	123,475	15,261,686	5.2126	5.1616	1	2,957	-291,840	16,931,964
		2,927,845 USD						**3,248,276 USD**

Table 27: Daily Portfolio Balance of Unhedged and GARCH Hedged Portfolio

Date	Revenue (TRY)	Portfolio Balance Unhedged (TRY)	Spot USD Rate	Future Price	Hedge Ratio	Optimum Contract	Future Return	Total Portfolio
1.12.2017	107,403	107,403	3.9133	3.9615	0.82	22		107,403
4.12.2017	236,570	343,973	3.8753	3.919	0.80	71	-935	343,038
5.12.2017	41,027	385,001	3.8443	3.8913	0.76	76	-1,967	382,099
-	-	-	-	-	-	-	-	-
-	-	-	-	-	-	-	-	-
-	-	-	-	-	-	-	-	-
29.11.2018	133,819	15,138,211	5.1695	5.1614	0.75	2213	-198,554	16,915,369
30.11.2018	123,475	15,261,686	5.2126	5.1616	0.56	1659	443	17,039,287
		2,927,845 USD						**3,268,865 USD**

Table 28: Daily Portfolio Balance of Unhedged and OLS Hedged Portfolio

Date	Revenue (TRY)	Portfolio Balance Unhedged (TRY)	Spot USD Rate	Future Price	Hedge Ratio	Optimum Contract	Future Return	Total Portfolio
1.12.2017	107,403	107,403	3.9133	3.9615	0.82	22		107,403
4.12.2017	236,570	343,973	3.8753	3.919	0.82	72	-935	343,038
5.12.2017	41,027	385,001	3.8443	3.8913	0.82	81	-1,994	382,071
-	-	-	-	-	-	-	-	-
-	-	-	-	-	-	-	-	-
-	-	-	-	-	-	-	-	-
29.11.2018	133,819	15,138,211	5.1695	5.1614	0.82	2,405	-239,309	16,507,715
30.11.2018	123,475	15,261,686	5.2126	5.1616	0.82	2,425	481	16,631,671
		2,927,845 USD						**3,190,667 USD**

CHAPTER 8: CONCLUSIONS

Financial markets are becoming more volatile, and the consequent risks are becoming a great challenge for investors and corporations alike. Futures contracts offer an effective hedging mechanism to eliminate financial risks, such as currency, interest rate, and commodity risks. Many derivatives exchanges worldwide, including BIST and EXIST, offer futures contracts on different underlying instruments.

On the other hand, the liberalization of electricity trading has also led to an important problem: the price volatility of electricity. Between different commodities, electricity has the highest volatility, and the price risk is high for the related parties such as electricity producers, distributors, consumers. In addition to price risk, there is also foreign exchange risk (FX) in countries like Turkey where electricity price guarantee is determined in USD. Therefore, an effective way of managing price and FX risk has become so important in the energy sector where the volatility is high.

In this respect, hedging effectiveness in the electricity revenue portfolio of a wind power plant that is affected by FX rate changes in Turkey is analyzed by finding the optimum hedge ratios. In this study, different constant and dynamic hedging models are used. This study aims to find ways to better manage the exchange rate risk in the Turkish electricity market by using financial currency future contracts available in the country under the new imbalance regulations and measure the risk by using different risk measurement techniques.

The Borsa Istanbul (BIST) US dollar–Turkish lira (USDTRY) future contract is used for hedging the currency portion of the electricity revenue portfolio. To our best knowledge, it is thought that this is the first to undertake an analysis of the hedging effectiveness of currency futures contracts on the electricity market under Ederington’s (1979) hedging effectiveness (EHE) framework.

First, USDTRY future contracts on BIST are analyzed to find out dynamic hedge ratios. Then these ratios are used to hedge the FX risk of the daily electricity revenue portfolio. Then a constant OLS, naively hedged and a dynamic diagonal methodology is used to test hedging effectiveness under the EHE methodology.

It is found out that hedging the spot portfolio using USDTRY futures contracts improves the risk-adjusted return ratio, calculated as the ratio of the mean return to its standard deviation. More importantly, this result holds for almost all the models considered. The naively hedged portfolio provides a positive risk-adjusted return and is the best in four cases, followed by the GARCH hedged model, which prevails in two of the four cases.

On the other hand, GARCH hedged portfolio has the lowest standard deviation compared to other portfolios. It is analyzed that, in general, the hedged portfolios' standard deviation is much lower than the unhedged ones.

One of the striking finding of this thesis is the substantial variance reduction and hedging effectiveness for all hedged electricity revenue portfolios. In addition to the improved risk-adjusted returns, it is concluded that hedging through USDTRY currency futures contracts helps lower the variance of portfolios and increase hedging effectiveness. The GARCH hedged portfolio slightly outperforms the other methods, with variance reductions of 55%. Optimum hedge ratios estimated by the multivariate GARCH model produced the best result for the corresponding period. On the other hand, OLS hedge model was also close to GARCH model with a 54% variance reduction. The variance reduction was lowest at fully hedge portfolio with a reduction of 46%.

The finding of this thesis is similar to Aksoy and Olgun's (2009) findings that the multivariate GARCH method is superior to other methods. On the other hand, this contradicts Alexander and Barbosa's (2007) study, which provides no evidence that complex econometric models such as GARCH are superior to simpler models such as OLS and naively hedged portfolios. They found out that no single method can be considered superior to the other two, since the variance reductions are almost equal, whether constant or dynamic.

Furthermore, VaR values are also calculated each day through different models such as historical simulation, parametric approach and Monte Carlo Simulation for the unhedged, fully hedged, GARCH hedged and OLS hedged portfolios by using the out-of-sample data. In this respect, additional findings related to VaR values have emerged from the results. According to that, VaR figures calculated by the parametric method and Monte Carlo simulation are closer. On the other hand, the lowest VaR(1%) value is obtained using the GARH Hedged portfolio. This result is consistent with the result found with the EHE minimum variance rule, which was also in favor of the GARCH method.

An in-sample analysis with a dynamic 50 day rolling window approach have also conducted in addition to the out-of-sample analysis. VaR values are calculated with historical and parametric methods and are used to forecast in-sample future VaR values. The findings also favor the dynamic GARCH method used in the thesis.

According to the Christoffersen test, all the VaR models are accepted except for the unhedged portfolio with seven exceedances and one consecutive exceedance. All the other hedged portfolios have lower exceedances than the unhedged portfolio and they do not have any consecutive exceedance. The lowest exceedance figure is obtained through a fully hedged portfolio followed by the OLS and GARCH hedged portfolios. This backtest also supports the validity of the VaR models and suggests that hedging the electricity revenue portfolio decreases the volatility of the portfolio significantly with all the models used.

Another finding of this thesis is related to the revenue amount that power firms obtain through electricity generation. The revenue stream created with different unhedged and hedged electricity portfolios with different hedge ratios during the observed period is also analyzed in this thesis to obtain a portfolio with the minimum variance. For this reason, the total ending period portfolio balances are calculated and converted into USD. According to this analysis, it is observed that the maximum portfolio balance is obtained through the GARCH hedged portfolio, which represents a total hedge gain of 12% in USD terms for the observed period.

These findings carry some important implications for investors and policy makers in energy market. Since YEKDEM, in other words guaranteed payment in USD by the government will be over soon, the management of the exchange risk will be much more critical for the newly established power plants. These power plants that are mostly financed by loans denominated in USD or EUR will face the exchange rate risk since they will have income in TRY and expenditure in foreign currencies. As specified in the thesis, the exchange rate risk will also affect the already established power plants under YEKDEM regulation.

On the other hand, policy makers might consider new rules on the management of the exchange rate risk for energy companies since a local currency crisis might have adverse impacts on the financial conditions of these companies that are vital for the country. The findings of this thesis might also help them on the decision making process when revising the YEKDEM regulation.

The findings of this thesis might also be applied to other power plants located in Turkey as well as power plants located in other countries with similar renewable energy regulations. Since the regulations and the structure of energy markets in most of the other developed and emerging countries are similar, the hedging models and methods used in this thesis will also be valuable for these countries.

One potential avenue for further research is to add different GARCH models to find out the dynamic volatilities and time-varying hedge ratios for underlying instruments analyzed in this thesis. Such a study could contribute to the differentiation of the hedging effectiveness of hedged portfolios through alternative dynamic econometric models. In addition to that, electricity price risk might also be analyzed using Borsa Istanbul's cash electricity future or EXIST's physical delivery futures. This can be the subject of another study.

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APPENDICES

Appendix A. B-GARCH Model Results

Table 29: B-GARCH Model Time Varying Hedge Ratio Parameters

obs	GARCH_01	GARCH_01_02	GARCH_02	HR_GARCH
1.12.2017	1.064935	0.870094	1.058903	0.8216938
4.12.2017	0.91112	0.753021	0.930932	0.8088894
5.12.2017	1.035112	0.866707	1.129906	0.7670612
6.12.2017	1.045279	0.873908	1.102975	0.792319
7.12.2017	0.878216	0.763839	0.998683	0.7648463
8.12.2017	0.772105	0.702331	0.880331	0.7978033
11.12.2017	0.819206	0.742354	0.94275	0.7874346
12.12.2017	0.724166	0.690304	0.92779	0.7440304
13.12.2017	0.661326	0.644593	0.826588	0.7798238
14.12.2017	0.814821	0.586948	0.734352	0.7992734
15.12.2017	1.468471	0.767097	0.804701	0.9532696
18.12.2017	1.248331	0.735101	0.767481	0.95781
19.12.2017	1.258498	0.831106	0.948556	0.8761802
20.12.2017	1.022201	0.741281	0.819235	0.9048454
21.12.2017	0.89461	0.699074	0.768587	0.9095574
22.12.2017	0.777505	0.650363	0.712426	0.912885
25.12.2017	0.715272	0.623186	0.677308	0.9200925
26.12.2017	0.649154	0.592958	0.692432	0.8563411
27.12.2017	0.603648	0.561129	0.642713	0.8730631
28.12.2017	0.573125	0.540472	0.600177	0.900521
29.12.2017	0.848379	0.749968	0.981196	0.7643407
2.01.2018	0.757817	0.675229	0.846566	0.7976094
3.01.2018	0.828314	0.567758	0.798137	0.7113541
4.01.2018	0.786974	0.551578	0.71312	0.7734715
5.01.2018	0.958914	0.621171	0.722665	0.8595559
8.01.2018	0.863672	0.628567	0.754453	0.8331427
9.01.2018	0.755459	0.592986	0.68355	0.8675093
10.01.2018	0.739987	0.595904	0.668174	0.8918396
11.01.2018	0.802201	0.633532	0.698828	0.9065636
12.01.2018	0.861194	0.669631	0.730477	0.9167037
15.01.2018	0.877299	0.712502	0.820411	0.8684696
16.01.2018	1.164351	0.832606	0.920435	0.9045788
17.01.2018	0.984324	0.761626	0.832071	0.9153378
18.01.2018	0.889351	0.72257	0.782871	0.9229745
19.01.2018	1.04028	0.854379	1.034555	0.825842
22.01.2018	1.031688	0.845639	0.995349	0.8495904
23.01.2018	1.096179	0.853719	0.961163	0.8882146
24.01.2018	0.926859	0.767632	0.841323	0.9124106

Table 30 (continued): B-GARCH Model Time Varying Hedge Ratio Parameters

obs	GARCH_01	GARCH_01_02	GARCH_02	HR_GARCH
25.01.2018	0.943622	0.850099	1.135232	0.7488328
26.01.2018	0.819436	0.7524	0.954814	0.7880069
29.01.2018	0.721452	0.681638	0.824588	0.8266407
30.01.2018	0.782327	0.706139	0.838492	0.8421535
31.01.2018	0.706937	0.650067	0.74101	0.8772716
1.02.2018	0.750518	0.685076	0.808838	0.8469879
2.02.2018	0.800107	0.602127	0.736023	0.8180818
5.02.2018	0.971745	0.651944	0.727287	0.8964054
6.02.2018	0.831401	0.59966	0.681616	0.8797622
7.02.2018	0.787114	0.543255	0.653429	0.831391
8.02.2018	0.854611	0.498872	0.61895	0.8059973
9.02.2018	0.811059	0.576525	0.83129	0.6935305
12.02.2018	0.726849	0.558971	0.745992	0.7492989
13.02.2018	0.749496	0.596964	0.762917	0.7824757
14.02.2018	0.671315	0.566148	0.686916	0.8241881
15.02.2018	0.751537	0.556088	0.63426	0.8767509
16.02.2018	0.7157	0.600967	0.830143	0.7239319
19.02.2018	0.718766	0.637969	0.894115	0.7135201
20.02.2018	0.65747	0.600848	0.784658	0.7657451
21.02.2018	0.815057	0.7079	0.925325	0.7650285
22.02.2018	0.732158	0.671577	0.878262	0.7646659
23.02.2018	0.680818	0.628805	0.773663	0.8127634
26.02.2018	0.627573	0.588747	0.69505	0.847057
27.02.2018	0.599031	0.567507	0.647545	0.8763978
28.02.2018	0.658571	0.551715	0.604512	0.9126618
1.03.2018	0.643599	0.528658	0.573339	0.9220688
2.03.2018	0.598812	0.524976	0.822239	0.6384713
5.03.2018	0.567275	0.513401	0.735502	0.698028
6.03.2018	0.548107	0.505631	0.668396	0.7564842
7.03.2018	0.580143	0.554024	0.77469	0.7151557
8.03.2018	0.556373	0.534138	0.694486	0.7691127
9.03.2018	0.637872	0.545499	0.653096	0.8352509
12.03.2018	0.626452	0.546665	0.633007	0.8636002
13.03.2018	0.710639	0.586835	0.657896	0.8919875
14.03.2018	0.757225	0.61926	0.688563	0.8993513
15.03.2018	0.677745	0.589083	0.696337	0.845974
16.03.2018	0.645057	0.555908	0.640402	0.868061
19.03.2018	0.662854	0.590151	0.709878	0.8313414
20.03.2018	0.629696	0.569939	0.657505	0.8668208
21.03.2018	0.591654	0.552905	0.643006	0.8598753
22.03.2018	0.685452	0.556358	0.610054	0.9119816
23.03.2018	0.709028	0.537256	0.576243	0.9323428
26.03.2018	0.941354	0.608937	0.613402	0.9927209

Table 30 (continued): B-GARCH Model Time Varying Hedge Ratio Parameters

obs	GARCH_01	GARCH_01_02	GARCH_02	HR_GARCH
27.03.2018	0.877388	0.535103	0.631724	0.8470519
28.03.2018	0.785972	0.514406	0.594893	0.8647034
29.03.2018	0.784449	0.523662	0.575048	0.9106405
30.03.2018	1.44992	0.814962	0.84577	0.963574
2.04.2018	1.16961	0.717049	0.768764	0.9327297
3.04.2018	0.987338	0.720085	1.064103	0.6767061
4.04.2018	0.859433	0.668918	0.913222	0.7324813
5.04.2018	0.758275	0.626297	0.801804	0.7811098
6.04.2018	0.994415	0.731141	0.869284	0.8410842
9.04.2018	0.856014	0.667744	0.7625	0.8757298
10.04.2018	0.815418	0.631041	0.69035	0.9140885
11.04.2018	0.887894	0.72251	0.874647	0.826059
12.04.2018	0.8234	0.711979	0.880227	0.8088584
13.04.2018	0.841162	0.787595	1.141705	0.6898411
16.04.2018	0.769919	0.724886	0.975488	0.7431009
17.04.2018	0.686852	0.65778	0.863536	0.7617285
18.04.2018	0.629455	0.616244	0.786953	0.783076
19.04.2018	1.748725	1.208495	1.524367	0.7927848
20.04.2018	1.475544	1.012135	1.23512	0.8194629
24.04.2018	1.316639	0.935482	1.083246	0.8635915
25.04.2018	1.064943	0.828943	1.002679	0.8267282
26.04.2018	0.898734	0.740854	0.858428	0.8630357
27.04.2018	0.807022	0.719537	0.907186	0.7931527
30.04.2018	0.809357	0.736397	0.94038	0.7830845
2.05.2018	0.739649	0.663374	0.817945	0.8110252
3.05.2018	2.396156	2.153031	4.025096	0.5349018
4.05.2018	1.918462	1.871492	3.47339	0.5388085
7.05.2018	1.500704	1.525527	2.637742	0.5783458
8.05.2018	1.33228	1.296666	2.055028	0.6309724
9.05.2018	1.517588	1.240883	1.739372	0.7134086
10.05.2018	1.49171	1.17637	1.525747	0.7710125
11.05.2018	1.572128	1.150205	1.375672	0.8361041
14.05.2018	1.915344	1.245523	1.378785	0.9033482
15.05.2018	1.773318	1.094326	1.143568	0.95694
16.05.2018	1.942987	1.710821	3.514776	0.4867511
17.05.2018	1.596055	1.525855	3.050074	0.5002682
18.05.2018	1.444286	1.334558	2.399086	0.5562777
21.05.2018	1.236564	1.179734	1.970499	0.5986981
22.05.2018	1.697067	1.515121	2.477559	0.6115378
23.05.2018	2.164252	1.614636	2.295958	0.7032515
24.05.2018	2.611809	-0.014009	6.290579	-0.002227
25.05.2018	3.669492	-0.676064	5.527354	-0.1223124
28.05.2018	2.688791	-0.356919	4.627209	-0.0771348

Table 30 (continued): B-GARCH Model Time Varying Hedge Ratio Parameters

obs	GARCH_01	GARCH_01_02	GARCH_02	HR_GARCH
29.05.2018	3.720969	1.169656	5.904861	0.1980836
30.05.2018	2.898464	1.032857	4.398063	0.2348436
31.05.2018	2.951526	1.543778	4.583877	0.3367843
1.06.2018	2.537996	1.306206	3.436655	0.3800806
4.06.2018	3.529145	2.410235	5.177897	0.4654853
5.06.2018	3.031061	1.954989	3.862215	0.5061834
6.06.2018	2.245529	1.581903	2.921274	0.5415113
7.06.2018	1.907634	1.486711	2.639772	0.5631967
8.06.2018	2.141247	1.76004	3.042993	0.5783911
11.06.2018	1.669348	1.417029	2.342945	0.6048068
12.06.2018	1.573057	1.222744	1.837834	0.665318
13.06.2018	1.76045	1.283967	1.748399	0.7343673
14.06.2018	1.627499	1.264224	1.71252	0.7382244
18.06.2018	1.792623	1.0082	1.382645	0.7291821
19.06.2018	1.44719	0.717128	2.177008	0.3294099
20.06.2018	1.299693	0.603732	1.746343	0.3457122
21.06.2018	1.082963	0.555905	1.410217	0.3941982
22.06.2018	0.915552	0.546621	1.170234	0.467104
25.06.2018	1.070757	0.764379	1.448885	0.5275636
26.06.2018	0.892748	0.69123	1.180294	0.5856422
27.06.2018	1.336005	0.953224	1.413314	0.6744602
28.06.2018	1.078462	0.823441	1.222913	0.6733439
29.06.2018	1.063538	0.765815	1.029581	0.7438123
2.07.2018	0.889488	0.705675	1.111121	0.6351018
3.07.2018	0.850299	0.868125	2.358676	0.3680561
4.07.2018	1.006338	0.893158	1.972122	0.4528919
5.07.2018	0.857444	0.792019	1.559205	0.5079634
6.07.2018	1.36917	1.123855	1.915294	0.5867794
9.07.2018	1.152382	1.015255	1.651226	0.6148492
10.07.2018	3.47031	0.765012	1.336115	0.5725645
11.07.2018	2.646959	0.434536	2.716774	0.1599456
12.07.2018	4.530157	1.566631	3.281665	0.4773891
13.07.2018	3.317803	1.263615	2.539174	0.4976481
16.07.2018	2.446467	1.075782	2.049345	0.5249394
17.07.2018	1.859611	0.923289	1.609584	0.5736196
18.07.2018	1.61765	0.972043	1.644713	0.5910107
19.07.2018	1.300986	0.82736	1.347578	0.6139608
20.07.2018	1.062212	0.740659	1.106773	0.6692059
23.07.2018	0.912505	0.707763	1.041633	0.6794744
24.07.2018	1.15983	0.886717	1.248734	0.7100928
25.07.2018	2.936285	2.013509	2.883249	0.6983472
26.07.2018	3.469112	2.096225	2.626433	0.7981262
27.07.2018	3.31223	1.694167	2.024056	0.8370159

Table 30 (continued): B-GARCH Model Time Varying Hedge Ratio Parameters

obs	GARCH_01	GARCH_01_02	GARCH_02	HR_GARCH
30.07.2018	2.520541	1.387821	1.591509	0.8720158
31.07.2018	2.00441	1.213887	1.35116	0.8984036
1.08.2018	1.615245	1.051281	1.12635	0.933352
2.08.2018	1.804899	1.252574	1.489413	0.840985
3.08.2018	1.795589	1.60727	3.062135	0.5248854
6.08.2018	1.400651	1.317388	2.340105	0.5629611
7.08.2018	6.162133	2.508065	2.763685	0.9075075
8.08.2018	5.507759	1.605073	2.452972	0.6543381
9.08.2018	4.207012	1.371706	1.925686	0.7123207
10.08.2018	8.326599	3.767988	4.678893	0.8053161
13.08.2018	52.73224	33.16627	50.70662	0.6540817
14.08.2018	46.68882	33.34203	53.5835	0.6222443
15.08.2018	46.09837	31.74277	46.58098	0.6814535
16.08.2018	44.55845	32.7331	48.82777	0.6703788
17.08.2018	31.35091	25.37951	38.7404	0.6551174
20.08.2018	24.25686	21.08198	31.9099	0.6606721
27.08.2018	17.01154	15.86915	23.04887	0.6885001
28.08.2018	11.99154	11.97914	16.68838	0.7178132
29.08.2018	9.49076	9.702289	13.04401	0.7438118
31.08.2018	8.595139	8.339331	10.71664	0.7781666
3.09.2018	6.431535	6.687432	8.637426	0.774239
4.09.2018	4.979948	5.536122	7.448836	0.7432197
5.09.2018	3.61319	4.269905	5.511545	0.7747202
6.09.2018	2.899841	3.574458	4.769717	0.7494067
7.09.2018	2.18728	2.786661	3.563156	0.7820766
10.09.2018	3.274229	3.573218	5.522004	0.6470872
11.09.2018	2.53131	2.932634	4.526178	0.6479272
12.09.2018	1.97596	2.326045	3.395664	0.6850045
13.09.2018	1.987673	2.301683	3.59084	0.6409873
14.09.2018	5.693076	3.931925	5.25808	0.7477872
17.09.2018	4.428187	3.049444	3.91352	0.7792075
18.09.2018	4.435779	3.086228	3.883072	0.7947903
19.09.2018	3.460293	2.523641	3.021674	0.8351798
20.09.2018	3.66401	2.514916	2.867883	0.8769242
21.09.2018	2.876599	2.062323	2.247851	0.9174643
24.09.2018	2.498111	1.669836	1.752624	0.9527634
25.09.2018	2.942703	1.928175	2.110344	0.9136781
26.09.2018	2.186233	1.561775	1.655534	0.9433663
27.09.2018	1.858764	1.469042	1.735501	0.8464657
28.09.2018	2.106924	1.796105	2.591531	0.6930671
1.10.2018	1.680759	1.497091	2.040009	0.7338649
2.10.2018	2.156455	1.156969	1.621899	0.7133422
3.10.2018	1.74677	1.022777	1.336239	0.7654147

Table 30 (continued): B-GARCH Model Time Varying Hedge Ratio Parameters

obs	GARCH_01	GARCH_01_02	GARCH_02	HR_GARCH
4.10.2018	1.538794	0.93682	1.134566	0.8257078
5.10.2018	1.966431	1.54998	2.668534	0.5808358
8.10.2018	1.625012	1.433182	2.563074	0.5591653
9.10.2018	1.294894	1.192368	1.978652	0.6026163
10.10.2018	1.064891	1.022208	1.576057	0.6485857
11.10.2018	0.933289	0.97913	1.760436	0.5561861
12.10.2018	2.534486	1.150375	1.526291	0.7537062
15.10.2018	2.04601	1.152906	1.73974	0.6626887
16.10.2018	2.145359	1.643696	3.21625	0.5110598
17.10.2018	2.333917	1.528814	2.560332	0.5971155
18.10.2018	2.59425	2.020489	3.65191	0.5532691
19.10.2018	2.06203	1.70535	2.878324	0.5924802
22.10.2018	1.578317	1.402869	2.309574	0.6074146
23.10.2018	1.284996	1.130396	1.87812	0.6018763
24.10.2018	1.388495	1.316813	2.348248	0.560764
25.10.2018	1.269007	1.349786	2.754806	0.489975
26.10.2018	1.417146	1.290426	2.279549	0.5660883
30.10.2018	1.273373	1.172609	1.908171	0.6145199
31.10.2018	2.181224	1.801241	2.872764	0.6270063
1.11.2018	2.4864	1.534895	2.214727	0.6930403
2.11.2018	2.308237	0.933382	2.340582	0.398782
5.11.2018	2.352819	1.285383	2.691293	0.477608
6.11.2018	2.869587	1.428471	2.338603	0.6108224
7.11.2018	2.435657	1.251855	1.850595	0.6764608
8.11.2018	1.844279	1.062446	1.478768	0.718467
9.11.2018	1.966174	1.080918	1.324733	0.8159516
12.11.2018	1.516071	0.927355	1.089379	0.8512694
13.11.2018	1.204986	0.821094	0.950302	0.8640348
14.11.2018	0.986003	0.738967	0.909235	0.8127349
15.11.2018	0.868338	0.709871	0.890079	0.7975371
16.11.2018	1.835157	1.14268	1.3182	0.8668487
19.11.2018	1.450598	1.043682	1.469519	0.7102201
20.11.2018	1.185136	0.910257	1.201632	0.7575173
21.11.2018	1.286574	1.082784	1.613437	0.671104
22.11.2018	1.577177	1.427027	2.41597	0.5906642
23.11.2018	1.251516	1.213061	2.056775	0.5897879
26.11.2018	1.048076	1.056185	1.684547	0.6269846
27.11.2018	0.996344	1.014363	1.571335	0.6455422
28.11.2018	0.879324	0.912422	1.341395	0.6802038
29.11.2018	1.061146	0.839651	1.112681	0.7546197
30.11.2018	1.155342	1.078859	1.922454	0.5611885

Appendix B. Daily Revenue and Optimum Hedge Ratio Calculations

Appendix B.1. Total Revenue Calculation for a Power Generating Plant (Lack of Generation)

Let us assume the following hourly information for a power plant which needs to buy electricity due to lack of generation.

Table 31: Hourly Information for a Power Generating Plant

Date and Time	30/11/2018 12:00
MCP	308.64
SMP	313.0
USD/TRY Exchange Rate	5.1649
Day-Ahead Market Sales (Expectation)	13.1 MWh
Generation	12.68 MWh
k and l coefficients	0.03
Tolerance coefficient	0.98

With the data given in Table 13, we can calculate the total revenue of this power plant for this given hour as 4,852.85 TRY.

Table 32: Total Revenue of the Power Generating Power Plant

Day-Ahead Market Revenue	$13.1 \times 308.64 = 4{,}043.18\,TRY$
Imbalance Cost	
Imbalance:	$12.68 - 13.1 = -0.42MWh$
Imbalance Price:	$MAX(PTF; STF) \times (1 + 0.03)$ $= MAX(308.64; 313) \times 1.03$ $= 322.39TRY$
Imbalance Cost:	$-0.4212 \times 322.39 = -135.79\,TRY$
YEKDEM Incentive Difference	$12.68[73 \times 5.1649 - (0.98 \times 308.64)]$ $= 945.46TL$
Total Hourly Revenue	$4{,}043.18 - 135.79 + 945.46 = 4{,}852.85\,TRY$

Appendix B.2. Total Revenue Calculation for a Power Generating Plant (Excess Generation)

Let us assume the following hourly information for a power plant, which needs to sell electricity due to excess generation.

Table 33: Total Revenue Calculation for a Power Generating Plant (Excess Generation)

Date and Time	30/11/2018 13:00
MCP	307.85
SMP	322.8
USD/TRY Exchange Rate	5.1649
Day-Ahead Market Sales (Expectation)	13 MWh
Generation	14.54 MWh
k and l coefficients	0.03
Tolerance coefficient	0.98

With the data given in Table 15, we can calculate the total revenue of this power plant for this given hour as 5,557.42 TRY.

Table 34: Total Revenue of the Power Generating Power Plant

Day-Ahead Market Revenue	$13 \times 307.85 = 4{,}002.05\ TRY$
Imbalance Cost	
Imbalance:	$14.54 - 13 = 1.54MWh$
Imbalance Price:	$MIN(PTF; STF) \times (1 - 0.03) = MIN(307.85; 322.8) \times 0.97 = 298.61\ TRY$
Imbalance Cost:	$1.54 \times 298.61 = 459.86\ TRY$
YEKDEM Incentive Difference	$14.54[73 \times 5.1649 - (0.98 \times 307.85)] = 1{,}095.51TL$
Total Hourly Revenue	$4{,}002.05 + 459.86 + 1{,}095.51 = 5{,}557.42\ TRY$

Appendix B.3. Hourly System Revenue Calculation

Table 35: Hourly Revenue Calculation According to the DUY Regulation

Date	MCP (TRY/MWh)	SMP (TRY/MWh)	USDTRY Rate	Day-Ahead Sales Forecast (MWh)	Day-Ahead Sales Revenue (MWh)	Realized Production (MWh)	Imbalance (MWh)	Imbalance Price (TRY/MWh)	Imbalance Revenue/Loss (TRY)	Day Ahead +Imbalance Revenue (TRY)	Total Revenue (TRY)
30.11.2018 00:00	297	310	5.1649	-13	3,892	19	6	288	1,817	5,709	7,376
30.11.2018 01:00	284	300	5.1649	-13	3,722	13	0	309	-118	3,603	4,857
30.11.2018 02:00	174	189	5.1649	-13	2,297	10	-4	195	-715	1,582	3,549
30.11.2018 03:00	174	174	5.1649	-13	2,314	10	-3	179	-526	1,788	3,928
30.11.2018 04:00	160	160	5.1649	-13	2,144	16	3	155	409	2,553	6,084
30.11.2018 05:00	254	234	5.1649	-14	3,461	16	3	227	623	4,084	6,169
30.11.2018 06:00	281	276	5.1649	-14	3,880	14	0	268	62	3,942	5,366
30.11.2018 07:00	300	300	5.1649	-14	4,144	16	2	291	634	4,779	6,100
30.11.2018 08:00	306	256	5.1649	-14	4,224	16	2	248	586	4,810	6,056
30.11.2018 09:00	311	311	5.1649	-14	4,262	17	3	302	850	5,112	6,305
30.11.2018 10:00	312	313	5.1649	-14	4,210	15	2	302	593	4,803	5,907

Table 36 (continued): Hourly Revenue Calculation According to the DUY Regulation

Date	MCP (TRY/MWh)	SMP (TRY/MWh)	USDTRY Rate	Day-Ahead Sales Forecast (MWh)	Day-Ahead Sales Revenue (MWh)	Realized Production (MWh)	Imbalance (MWh)	Imbalance Price (TRY/MWh)	Imbalance Revenue/Loss (TRY)	Day Ahead +Imbalance Revenue (TRY)	Total Revenue (TRY)
30.11.2018 11:00	314	314	5.1649	-13	4,144	12	-2	323	-535	3,608	4,410
30.11.2018 12:00	309	313	5.1649	-13	4,043	13	0	322	-136	3,907	4,853
30.11.2018 13:00	308	323	5.1649	-13	4,002	15	2	299	459	4,461	5,557
30.11.2018 14:00	312	327	5.1649	-13	4,028	15	3	303	779	4,807	5,906
30.11.2018 15:00	312	326	5.1649	-13	4,019	15	2	302	698	4,717	5,808
30.11.2018 16:00	313	313	5.1649	-13	4,000	16	3	303	968	4,968	6,100
30.11.2018 17:00	313	328	5.1649	-12	3,847	16	4	303	1,198	5,045	6,191
30.11.2018 18:00	310	313	5.1649	-13	4,153	16	3	301	808	4,961	6,140
30.11.2018 19:00	305	275	5.1649	-12	3,750	16	4	267	957	4,707	5,951
30.11.2018 20:00	304	196	5.1649	-11	3,369	11	0	313	-111	3,258	4,113
30.11.2018 21:00	303	196	5.1649	-10	2,877	8	-1	312	-334	2,544	3,220
30.11.2018 22:00	293	190	5.1649	-8	2,432	6	-3	302	-788	1,644	2,155
30.11.2018 23:00	292	222	5.1649	-8	2,193	4	-4	301	-1,152	1,041	1,373
											123,475

Appendix B.4. Daily and Monthly System Revenue Calculation

Table 37: A Sample Month for Daily Electricity Revenue Portfolio Balance

Date	Revenue (TRY)	USD Equivalent	Portfolio Balance (TRY)
1.12.2017	107,403	27,446	107,403
4.12.2017	236,570	61,046	343,973
5.12.2017	41,027	10,672	385,001
6.12.2017	24,293	6,306	409,294
7.12.2017	-125	-32	409,169
8.12.2017	16,921	4,408	426,089
11.12.2017	199,642	52,046	625,731
12.12.2017	22,171	5,764	647,902
13.12.2017	5,301	1,390	653,203
14.12.2017	50,371	12,959	703,574
15.12.2017	57,695	14,919	761,268
18.12.2017	247,449	64,603	1,008,717
19.12.2017	7,801	2,035	1,016,519
20.12.2017	20,934	5,477	1,037,453
21.12.2017	26,425	6,919	1,063,878
22.12.2017	51,336	13,476	1,115,213
25.12.2017	192,739	50,594	1,307,952
26.12.2017	21,733	5,705	1,329,685
27.12.2017	88,561	23,202	1,418,247
28.12.2017	95,385	25,259	1,513,631
29.12.2017	100,648	26,553	1,614,279

Appendix B.5. Daily Optimum Contracts Number Calculations

Table 38: Daily Electricity Revenue Portfolio (Fully Hedged)

Date	Revenue (TRY)	USD Equivalent	Portfolio Balance (TRY)	Spot USD Rate	Future Price	Hedge Ratio	Optimum Contract	Future Return (TRY)	Total Portfolio (excluding spot P&L)
1.12.2017	107,403	27,446	107,403	3.9133	3.9615	1	27		107,403
4.12.2017	236,570	61,046	343,973	3.8753	3.9190	1	88	-1,148	342,826
5.12.2017	41,027	10,672	385,001	3.8443	3.8913	1	99	-2,438	381,415
6.12.2017	24,293	6,306	409,294	3.8522	3.8743	1	106	-1,683	404,026
7.12.2017	-125	-32	409,169	3.8646	3.8914	1	105	1,813	405,713
8.12.2017	16,921	4,408	426,089	3.8383	3.8620	1	110	-3,087	419,547
11.12.2017	199,642	52,046	625,731	3.8359	3.8392	1	163	-2,508	616,681
12.12.2017	22,171	5,764	647,902	3.8464	3.8554	1	168	2,641	641,492
13.12.2017	5,301	1,390	653,203	3.8131	3.8638	1	169	1,411	648,204
14.12.2017	50,371	12,959	703,574	3.8871	3.8983	1	180	5,831	704,406
15.12.2017	57,695	14,919	761,268	3.8671	3.8841	1	196	-2,556	759,544

Appendix C. USD/TRY Spot Future Daily Return Regression Results

USD/TRY Spot-Future Daily Return Regression:

Method: Least Squares

Date: 05/27/19 Time: 16:29

Sample (adjusted): 2 251

Included observations: 250 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.026051	0.059346	0.438969	0.6611
FUTURE_CHANGE	0.837304	0.033619	24.90538	0.0000

R-squared	0.714377	Mean dependent var	0.114679
Adjusted R-squared	0.713225	S.D. dependent var	1.749064
S.E. of regression	0.936647	Akaike info criterion	2.714947
Sum squared resid	217.5723	Schwarz criterion	2.743119
Log likelihood	-337.3684	Hannan-Quinn criter.	2.726286
F-statistic	620.2780	Durbin-Watson stat	2.797371
Prob(F-statistic)	0.000000		

Appendix D. Correlogram Analysis of Daily Portfolio Returns

Series: UNHEDGE Workfile: TOLGA_UYSAL_TEZ::Tolga_uysal_tez\

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Correlogram of UNHEDGE

Date: 01/07/19 Time: 14:13
Sample: 12/04/2017 11/30/2018
Included observations: 252

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.247	0.247	15.533	0.000
		2	-0.128	-0.201	19.730	0.000
		3	-0.235	-0.163	33.898	0.000
		4	0.040	0.140	34.318	0.000
		5	0.103	0.000	37.066	0.000
		6	0.004	-0.058	37.069	0.000
		7	0.006	0.086	37.079	0.000
		8	0.061	0.060	38.048	0.000
		9	0.095	0.046	40.405	0.000
		10	-0.025	-0.038	40.571	0.000
		11	0.036	0.114	40.909	0.000
		12	0.079	0.060	42.561	0.000
		13	0.110	0.054	45.777	0.000
		14	0.053	0.066	46.538	0.000
		15	-0.074	-0.067	48.035	0.000
		16	-0.004	0.056	48.040	0.000
		17	0.044	0.021	48.566	0.000
		18	0.027	-0.045	48.769	0.000
		19	-0.133	-0.134	53.625	0.000
		20	-0.086	-0.021	55.647	0.000
		21	0.049	0.026	56.310	0.000
		22	0.166	0.063	63.973	0.000
		23	0.036	-0.034	64.340	0.000
		24	-0.023	0.049	64.485	0.000
		25	-0.011	0.004	64.520	0.000
		26	-0.061	-0.105	65.564	0.000
		27	-0.022	0.035	65.705	0.000

Series: FULLYHEDGE Workfile: TOLGA_UYSAL_TEZ::Tolga_uysal...

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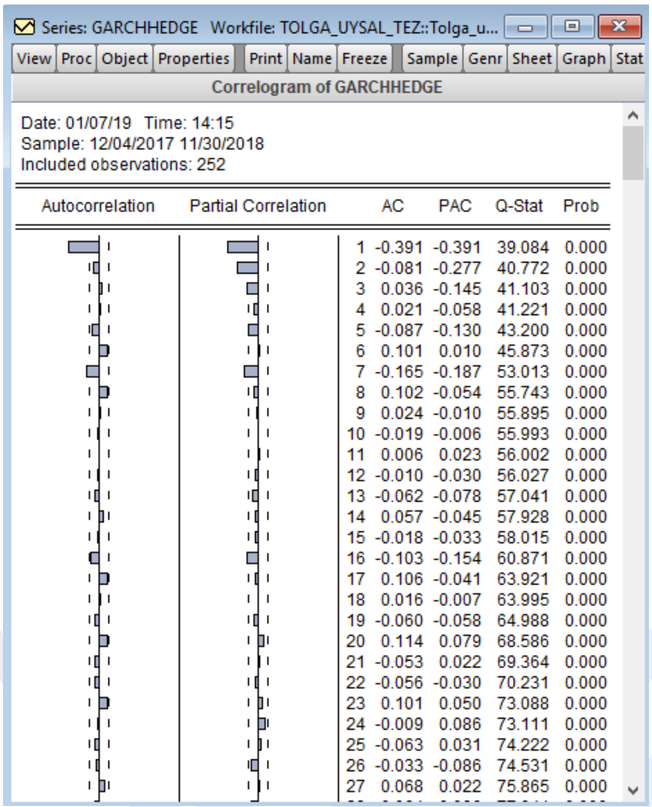
Correlogram of FULLYHEDGE

Date: 01/07/19 Time: 14:14
Sample: 12/04/2017 11/30/2018
Included observations: 252

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.235	-0.235	14.057	0.000
		2	-0.081	-0.144	15.717	0.000
		3	-0.061	-0.126	16.670	0.001
		4	0.003	-0.064	16.671	0.002
		5	-0.096	-0.147	19.061	0.002
		6	0.083	0.001	20.842	0.002
		7	-0.086	-0.112	22.790	0.002
		8	0.097	0.037	25.240	0.001
		9	-0.085	-0.084	27.165	0.001
		10	0.071	0.024	28.482	0.002
		11	0.014	0.036	28.532	0.003
		12	-0.019	-0.019	28.627	0.004
		13	0.025	0.056	28.789	0.007
		14	0.042	0.047	29.253	0.010
		15	-0.017	0.056	29.331	0.015
		16	-0.083	-0.076	31.191	0.013
		17	0.084	0.081	33.099	0.011
		18	-0.022	0.004	33.234	0.016
		19	-0.065	-0.064	34.411	0.016
		20	0.062	0.046	35.485	0.018
		21	-0.031	-0.052	35.750	0.023
		22	-0.003	0.004	35.753	0.032
		23	0.122	0.104	39.918	0.016
		24	-0.043	0.025	40.429	0.019
		25	-0.091	-0.088	42.773	0.015
		26	-0.024	-0.062	42.942	0.020
		27	0.061	0.038	44.014	0.021


Series: GARCHHEDGE Workfile: TOLGA_UYSAL_TEZ::Tolga_u...

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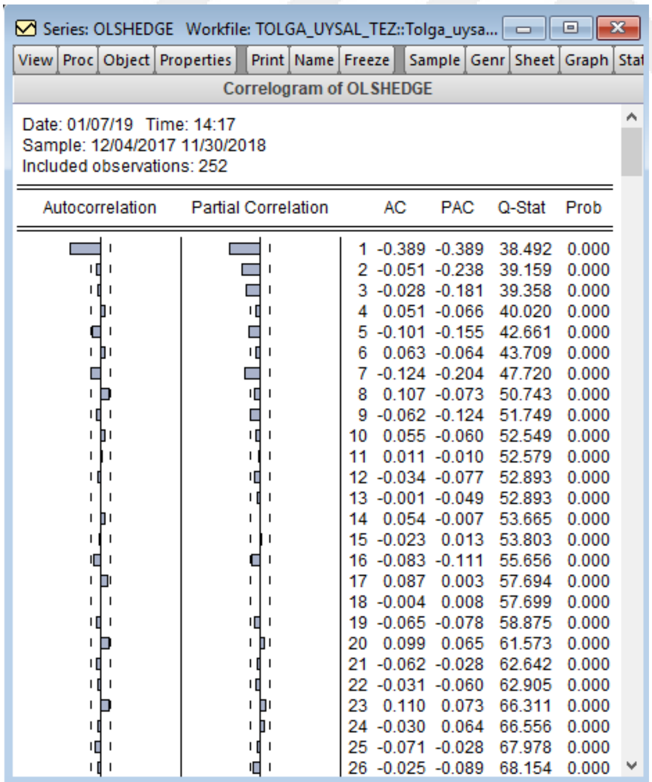
Correlogram of GARCHHEDGE

Date: 01/07/19 Time: 14:15
Sample: 12/04/2017 11/30/2018
Included observations: 252

Lag	AC	PAC	Q-Stat	Prob
1	-0.391	-0.391	39.084	0.000
2	-0.081	-0.277	40.772	0.000
3	0.036	-0.145	41.103	0.000
4	0.021	-0.058	41.221	0.000
5	-0.087	-0.130	43.200	0.000
6	0.101	0.010	45.873	0.000
7	-0.165	-0.187	53.013	0.000
8	0.102	-0.054	55.743	0.000
9	0.024	-0.010	55.895	0.000
10	-0.019	-0.006	55.993	0.000
11	0.006	0.023	56.002	0.000
12	-0.010	-0.030	56.027	0.000
13	-0.062	-0.078	57.041	0.000
14	0.057	-0.045	57.928	0.000
15	-0.018	-0.033	58.015	0.000
16	-0.103	-0.154	60.871	0.000
17	0.106	-0.041	63.921	0.000
18	0.016	-0.007	63.995	0.000
19	-0.060	-0.058	64.988	0.000
20	0.114	0.079	68.586	0.000
21	-0.053	0.022	69.364	0.000
22	-0.056	-0.030	70.231	0.000
23	0.101	0.050	73.088	0.000
24	-0.009	0.086	73.111	0.000
25	-0.063	0.031	74.222	0.000
26	-0.033	-0.086	74.531	0.000
27	0.068	0.022	75.865	0.000


Series: OLSHEDGE Workfile: TOLGA_UYSAL_TEZ::Tolga_uysa...

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Correlogram of OLSHEDGE

Date: 01/07/19 Time: 14:17
Sample: 12/04/2017 11/30/2018
Included observations: 252

Lag	AC	PAC	Q-Stat	Prob
1	-0.389	-0.389	38.492	0.000
2	-0.051	-0.238	39.159	0.000
3	-0.028	-0.181	39.358	0.000
4	0.051	-0.066	40.020	0.000
5	-0.101	-0.155	42.661	0.000
6	0.063	-0.064	43.709	0.000
7	-0.124	-0.204	47.720	0.000
8	0.107	-0.073	50.743	0.000
9	-0.062	-0.124	51.749	0.000
10	0.055	-0.060	52.549	0.000
11	0.011	-0.010	52.579	0.000
12	-0.034	-0.077	52.893	0.000
13	-0.001	-0.049	52.893	0.000
14	0.054	-0.007	53.665	0.000
15	-0.023	0.013	53.803	0.000
16	-0.083	-0.111	55.656	0.000
17	0.087	0.003	57.694	0.000
18	-0.004	0.008	57.699	0.000
19	-0.065	-0.078	58.875	0.000
20	0.099	0.065	61.573	0.000
21	-0.062	-0.028	62.642	0.000
22	-0.031	-0.060	62.905	0.000
23	0.110	0.073	66.311	0.000
24	-0.030	0.064	66.556	0.000
25	-0.071	-0.028	67.978	0.000
26	-0.025	-0.089	68.154	0.000

Appendix E. Goodness-of-Fit-Tests Results for ARMA-GARCH Models

Dependent Variable: UNHEDGE
Method: ARMA Generalized Least Squares (Gauss-Newton)
Date: 01/07/19 Time: 14:19
Sample: 12/04/2017 11/30/2018
Included observations: 252
Convergence achieved after 3 iterations
Coefficient covariance computed using outer product of gradients
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.294587	0.062861	4.686347	0.0000
AR(2)	-0.127987	0.064369	-1.988329	0.0479
AR(3)	-0.197648	0.064420	-3.068093	0.0024
AR(4)	0.148957	0.062920	2.367383	0.0187
R-squared	0.135800	Mean dependent var		-0.145545
Adjusted R-squared	0.125346	S.D. dependent var		1.826388
S.E. of regression	1.708092	Akaike info criterion		3.925609
Sum squared resid	723.5592	Schwarz criterion		3.981632
Log likelihood	-490.6267	Hannan-Quinn criter.		3.948151
Durbin-Watson stat	1.999184			
Inverted AR Roots	.49	.22-.67i	.22+.67i	-.62

Dependent Variable: UNHEDGE
Method: ML ARCH - Normal distribution (OPG - BHHH / Marquardt steps)
Date: 01/07/19 Time: 14:24
Sample: 12/04/2017 11/30/2018
Included observations: 252
Convergence achieved after 66 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.051006	0.057693	-0.884092	0.3766
Variance Equation				
C	0.050459	0.025873	1.950206	0.0512
RESID(-1)^2	0.236194	0.025879	9.126893	0.0000
GARCH(-1)	0.781596	0.030426	25.68846	0.0000
R-squared	-0.002690	Mean dependent var		-0.145545
Adjusted R-squared	-0.002690	S.D. dependent var		1.826388
S.E. of regression	1.828843	Akaike info criterion		3.350679
Sum squared resid	839.5111	Schwarz criterion		3.406702
Log likelihood	-418.1856	Hannan-Quinn criter.		3.373221
Durbin-Watson stat	1.500311			

Dependent Variable: UNHEDGE

Method: ML ARCH - Normal distribution (OPG - BHHH / Marquardt steps)
Date: 01/07/19 Time: 14:28
Sample (adjusted): 12/08/2017 11/30/2018
Included observations: 248 after adjustments
Failure to improve likelihood (non-zero gradients) after 486 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	0.185969	0.102568	1.813127	0.0698
AR(2)	-0.029098	0.096360	-0.301975	0.7627
AR(3)	-0.212495	0.111387	-1.907725	0.0564
AR(4)	0.135632	0.129456	1.047707	0.2948
		Variance Equation		
C	2.096789	3.264833	0.642235	0.5207
RESID(-1)^2	0.042865	0.044366	0.966151	0.3340
GARCH(-1)	0.492865	0.780028	0.631855	0.5275

R-squared	0.119859	Mean dependent var	-0.152872
Adjusted R-squared	0.109037	S.D. dependent var	1.838727
S.E. of regression	1.735589	Akaike info criterion	3.937383
Sum squared resid	734.9940	Schwarz criterion	4.036553
Log likelihood	-481.2355	Hannan-Quinn criter.	3.977305
Durbin-Watson stat	1.798776		

Inverted AR Roots	.47	.20+.62i	.20-.62i	-.68

Dependent Variable: UNHEDGE
Method: ML ARCH - Normal distribution (OPG - BHHH / Marquardt steps)
Date: 01/07/19 Time: 14:42
Sample (adjusted): 12/08/2017 11/30/2018
Included observations: 248 after adjustments
Failure to improve likelihood (non-zero gradients) after 247 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	0.102803	0.093195	1.103098	0.2700
AR(2)	-0.047086	0.055087	-0.854758	0.3927
AR(3)	-0.153758	0.071770	-2.142377	0.0322
AR(4)	0.071850	0.085471	0.840636	0.4006
		Variance Equation		
C	2.396068	0.299544	7.999041	0.0000
RESID(-1)^2	0.339353	0.071977	4.714749	0.0000

R-squared	0.094806	Mean dependent var	-0.152872
Adjusted R-squared	0.083677	S.D. dependent var	1.838727
S.E. of regression	1.760117	Akaike info criterion	3.624129
Sum squared resid	755.9150	Schwarz criterion	3.709131
Log likelihood	-443.3920	Hannan-Quinn criter.	3.658348
Durbin-Watson stat	1.638533		

Inverted AR Roots	.36	.17+.56i	.17-.56i	-.59

Dependent Variable: FULLYHEDGE
Method: ARMA Generalized Least Squares (Gauss-Newton)
Date: 01/07/19 Time: 17:12
Sample: 12/04/2017 11/30/2018
Included observations: 252
Convergence achieved after 16 iterations
Coefficient covariance computed using outer product of gradients
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.434953	0.122538	3.549531	0.0005
MA(1)	-0.750350	0.090410	-8.299428	0.0000

R-squared	0.108409	Mean dependent var	0.004245
Adjusted R-squared	0.104843	S.D. dependent var	0.986734
S.E. of regression	0.933576	Akaike info criterion	2.709298
Sum squared resid	217.8911	Schwarz criterion	2.737310
Log likelihood	-339.3716	Hannan-Quinn criter.	2.720570
Durbin-Watson stat	1.997927		

Inverted AR Roots	.43
Inverted MA Roots	.75

Dependent Variable: FULLYHEDGE
Method: ML ARCH - Normal distribution (OPG - BHHH / Marquardt steps)
Date: 01/07/19 Time: 14:31
Sample: 12/04/2017 11/30/2018
Included observations: 252
Convergence achieved after 87 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Variance Equation		
C	0.028516	0.012481	2.284678	0.0223
RESID(-1)^2	0.208638	0.056374	3.700985	0.0002
GARCH(-1)	0.812921	0.040177	20.23350	0.0000

R-squared	-0.000019	Mean dependent var	0.004245
Adjusted R-squared	0.003950	S.D. dependent var	0.986734
S.E. of regression	0.984783	Akaike info criterion	2.576990
Sum squared resid	244.3892	Schwarz criterion	2.619007
Log likelihood	-321.7008	Hannan-Quinn criter.	2.593897
Durbin-Watson stat	2.467203		

Dependent Variable: FULLYHEDGE
Method: ML ARCH - Normal distribution (OPG - BHHH / Marquardt steps)
Date: 01/07/19 Time: 14:38
Sample (adjusted): 12/05/2017 11/30/2018
Included observations: 251 after adjustments
Failure to improve likelihood (non-zero gradients) after 380 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 12/04/2017
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	0.421770	0.114451	3.685150	0.0002
MA(1)	-0.772772	0.068644	-11.25774	0.0000
Variance Equation				
C	0.655449	0.022529	29.09291	0.0000
RESID(-1)^2	0.187067	0.051742	3.615380	0.0003

R-squared	0.107010	Mean dependent var	0.004650
Adjusted R-squared	0.103423	S.D. dependent var	0.988684
S.E. of regression	0.936163	Akaike info criterion	2.573922
Sum squared resid	218.2239	Schwarz criterion	2.630104
Log likelihood	-319.0272	Hannan-Quinn criter.	2.596531
Durbin-Watson stat	1.925426		

Inverted AR Roots	.42
Inverted MA Roots	.77

Dependent Variable: GARCHHEDGE
Method: ARMA Generalized Least Squares (Gauss-Newton)
Date: 01/07/19 Time: 17:17
Sample: 12/04/2017 11/30/2018
Included observations: 252
Convergence achieved after 23 iterations
Coefficient covariance computed using outer product of gradients
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.207200	0.089719	2.309429	0.0217
MA(1)	-0.785578	0.056801	-13.83034	0.0000

R-squared	0.258258	Mean dependent var	-0.002102
Adjusted R-squared	0.255291	S.D. dependent var	0.824177
S.E. of regression	0.711236	Akaike info criterion	2.166855
Sum squared resid	126.4643	Schwarz criterion	2.194866
Log likelihood	-271.0237	Hannan-Quinn criter.	2.178126
Durbin-Watson stat	2.008461		

Inverted AR Roots	.21
Inverted MA Roots	.79

Dependent Variable: GARCHHEDGE
Method: ML ARCH - Normal distribution (OPG - BHHH / Marquardt steps)
Date: 01/07/19 Time: 17:17
Sample (adjusted): 12/05/2017 11/30/2018
Included observations: 251 after adjustments
Convergence not achieved after 500 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 12/04/2017
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	0.193309	0.086957	2.223037	0.0262
MA(1)	-0.822050	0.042638	-19.27989	0.0000
		Variance Equation		
C	0.426733	0.050313	8.481596	0.0000
RESID(-1)^2	0.151809	0.052022	2.918187	0.0035

R-squared	0.255215	Mean dependent var	-0.002510
Adjusted R-squared	0.252223	S.D. dependent var	0.825798
S.E. of regression	0.714102	Akaike info criterion	2.048293
Sum squared resid	126.9753	Schwarz criterion	2.104475
Log likelihood	-253.0607	Hannan-Quinn criter.	2.070902
Durbin-Watson stat	1.901990		

Inverted AR Roots	.19
Inverted MA Roots	.82

Dependent Variable: OLSHEDGE
Method: ARMA Generalized Least Squares (Gauss-Newton)
Date: 01/07/19 Time: 14:34
Sample: 12/04/2017 11/30/2018
Included observations: 252
Convergence achieved after 10 iterations
Coefficient covariance computed using outer product of gradients
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.267667	0.077039	3.474421	0.0006
MA(1)	-0.878276	0.039035	-22.49986	0.0000

R-squared	0.284081	Mean dependent var	-0.017089
Adjusted R-squared	0.281218	S.D. dependent var	0.848558
S.E. of regression	0.719416	Akaike info criterion	2.191176
Sum squared resid	129.3900	Schwarz criterion	2.219187
Log likelihood	-274.0882	Hannan-Quinn criter.	2.202447
Durbin-Watson stat	2.017033		

Inverted AR Roots	.27
Inverted MA Roots	.88

Dependent Variable: OLSHEDGE
Method: ML ARCH - Normal distribution (OPG - BHHH / Marquardt steps)
Date: 01/07/19 Time: 14:35
Sample: 12/04/2017 11/30/2018
Included observations: 252
Convergence achieved after 90 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Variance Equation		
C	0.393406	0.028126	13.98711	0.0000
RESID(-1)^2	0.571274	0.102100	5.595227	0.0000

R-squared	-0.000407	Mean dependent var	-0.017089
Adjusted R-squared	0.003563	S.D. dependent var	0.848558
S.E. of regression	0.847045	Akaike info criterion	2.317524
Sum squared resid	180.8064	Schwarz criterion	2.345536
Log likelihood	-290.0081	Hannan-Quinn criter.	2.328795
Durbin-Watson stat	2.772796		

Dependent Variable: OLSHEDGE
Method: ML ARCH - Normal distribution (OPG - BHHH / Marquardt steps)
Date: 01/07/19 Time: 14:33
Sample (adjusted): 12/05/2017 11/30/2018
Included observations: 251 after adjustments
Failure to improve likelihood (non-zero gradients) after 155 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 12/04/2017
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	0.311921	0.113658	2.744386	0.0061
MA(1)	-0.900232	0.038118	-23.61720	0.0000
		Variance Equation		
C	0.447096	0.037000	12.08360	0.0000
RESID(-1)^2	0.145182	0.073422	1.977366	0.0480

R-squared	0.282904	Mean dependent var	-0.017558
Adjusted R-squared	0.280024	S.D. dependent var	0.850221
S.E. of regression	0.721425	Akaike info criterion	2.143557
Sum squared resid	129.5929	Schwarz criterion	2.199739
Log likelihood	-265.0164	Hannan-Quinn criter.	2.166166
Durbin-Watson stat	2.063072		
Inverted AR Roots	.31		
Inverted MA Roots	.90		

Appendix F. Parametric VaR Results

Table 39: Parametric VaR Results

	Parametric VaR ARMA(4,0)-GARCH(1,1) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution		
	Unhedge			FullyHedge			GarchHedge			OLSHedge		
Date	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%
4.12.2017	0.97	-4.155639	4.155639	-0.10	-2.268750	2.268750	0.10	-1.659635	1.659635	0.10	-1.684344	1.684344
5.12.2017	0.80	-4.155639	4.155639	0.09	-1.855984	1.861280	0.23	-1.129123	0.991533	0.22	-1.253463	1.104906
6.12.2017	-0.21	-4.155639	4.155639	-0.65	-1.857983	1.858185	-0.54	-1.406281	0.978465	-0.57	-1.562300	1.100568
7.12.2017	-0.32	-4.155639	4.155639	0.12	-2.019081	2.054424	0.03	-1.024617	1.419359	0.04	-1.163682	1.586522
8.12.2017	0.68	-3.686983	3.676418	-0.07	-1.844575	1.873438	0.11	-0.950524	1.236335	0.07	-1.058900	1.379420
11.12.2017	0.06	-3.249486	3.454909	-0.53	-1.841294	1.874042	-0.41	-1.002165	1.086713	-0.42	-1.081793	1.271909
12.12.2017	-0.27	-2.938205	3.019087	0.15	-1.955276	2.016805	0.06	-1.045538	1.675057	0.07	-1.230372	2.022036
13.12.2017	0.86	-2.788599	2.585015	1.09	-1.833715	1.887246	1.03	-0.937749	1.375607	1.05	-1.061319	1.664758
14.12.2017	-1.96	-2.586394	2.733091	-1.07	-2.315632	2.310049	-1.27	-2.410848	1.357994	-1.23	-2.520606	1.512879
15.12.2017	0.51	-3.344726	3.354022	0.15	-2.294378	2.347157	0.22	-1.336063	2.213167	0.21	-1.525505	2.443879
18.12.2017	0.95	-3.202265	2.863764	0.00	-1.838793	1.883484	0.04	-0.917305	1.330110	0.17	-1.026207	1.532847
19.12.2017	-0.09	-2.678476	3.317540	0.02	-1.832180	1.876827	0.01	-0.950329	1.226513	0.00	-1.071751	1.272935
20.12.2017	0.31	-2.918738	2.522527	-0.01	-1.832507	1.876082	0.03	-0.966679	1.171884	0.05	-1.088890	1.270294
21.12.2017	0.08	-2.552194	2.476421	-0.12	-1.832693	1.876666	-0.10	-0.989651	1.112551	-0.09	-1.117677	1.205037
22.12.2017	0.25	-2.164955	2.388667	0.01	-1.838411	1.888991	0.03	-0.969194	1.210101	0.05	-1.090570	1.294756
25.12.2017	0.00	-2.109061	2.053257	-0.44	-1.829389	1.879391	-0.40	-0.979851	1.132751	-0.36	-1.111056	1.214942

Table 40 (continued): Parametric VaR Results

	Parametric VaR ARMA(4,0)-GARCH(1,1) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution		
	Unhedge			FullyHedge			GarchHedge			OLSHedge		
Date	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%
26.12.2017	0.00	-1.884040	1.945184	0.29	-1.912690	1.986443	0.27	-1.053985	1.723296	0.24	-1.159650	1.780011
27.12.2017	-0.20	-1.794969	1.762631	-0.04	-1.855280	1.913085	-0.06	-0.961079	1.138878	-0.07	-1.068208	1.268352
28.12.2017	1.06	-1.664975	1.698614	-0.15	-1.826542	1.886621	0.00	-0.967045	1.200518	0.07	-1.076398	1.358820
29.12.2017	-0.38	-1.967564	2.017876	-0.41	-1.835501	1.903946	-0.40	-0.971715	1.159904	-0.40	-1.093078	1.245554
2.01.2018	0.73	-1.850582	1.948103	1.33	-1.895820	1.986345	1.19	-1.065917	1.771819	1.22	-1.203269	1.932536
3.01.2018	-0.62	-2.045578	1.820411	-0.42	-2.491801	2.509871	-0.46	-2.458134	1.402073	-0.46	-2.804526	1.649036
4.01.2018	0.99	-1.740660	2.028958	0.55	-1.917600	1.958702	0.68	-1.163086	0.936205	0.63	-1.366136	1.009370
5.01.2018	0.38	-2.103359	1.905436	-0.16	-1.972276	1.983551	-0.03	-2.409391	1.295875	-0.06	-2.753576	1.505254
8.01.2018	-0.25	-1.752799	2.108313	-0.02	-1.856331	1.876082	-0.05	-1.882960	1.020878	-0.06	-2.222075	1.190723
9.01.2018	-0.63	-2.002790	1.711178	-0.12	-1.844287	1.864918	-0.20	-1.596387	0.959493	-0.21	-1.957568	1.120160
10.01.2018	-0.88	-1.793280	1.845453	-0.18	-1.848235	1.875245	-0.28	-1.186709	0.945040	-0.31	-1.465429	1.027163
11.01.2018	0.74	-1.989335	2.002875	0.23	-1.853575	1.890590	0.28	-0.994487	1.174806	0.32	-1.142698	1.207362
12.01.2018	0.67	-2.000699	2.054217	-0.04	-1.861649	1.886351	0.03	-1.224997	0.987084	0.09	-1.527214	1.113767
15.01.2018	-1.45	-1.935054	2.087398	-0.44	-1.842073	1.868853	-0.53	-1.197495	0.964027	-0.62	-1.584881	1.080258
16.01.2018	0.26	-2.733652	2.388357	-0.01	-1.921256	1.972021	0.03	-1.044329	1.573768	0.04	-1.186057	1.658242
17.01.2018	-0.59	-2.409483	2.320137	-0.03	-1.829203	1.880418	-0.08	-0.941624	1.336420	-0.13	-1.054951	1.417978
18.01.2018	1.01	-2.044549	2.433772	-0.08	-1.829291	1.882152	0.01	-0.957483	1.395880	0.12	-1.090449	1.611561
19.01.2018	-0.94	-2.400613	2.096326	-0.13	-1.830804	1.887965	-0.19	-0.946011	1.284500	-0.28	-1.054135	1.347001
22.01.2018	0.92	-2.153501	2.336203	0.35	-1.833733	1.897995	0.45	-0.985854	1.526598	0.45	-1.155035	1.828271
23.01.2018	0.19	-2.420930	2.099724	0.06	-1.877512	1.922725	0.08	-1.186386	1.011488	0.08	-1.219959	1.152831
24.01.2018	0.73	-1.873381	2.326523	-0.45	-1.833845	1.875896	-0.32	-1.214697	0.965651	-0.24	-1.275906	1.095430

Table 40 (continued): Parametric VaR Results

	Parametric VaR ARMA(4,0)-GARCH(1,1) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution		
	Unhedge			FullyHedge			GarchHedge			OLSHedge		
Date	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%
25.01.2018	-0.34	-2.160862	1.867350	-0.32	-1.921931	1.988718	-0.32	-0.991454	1.228264	-0.33	-1.107998	1.300736
26.01.2018	0.01	-1.787894	1.958432	0.18	-1.869592	1.953972	0.14	-1.031053	1.669683	0.15	-1.162336	1.818779
29.01.2018	-0.86	-1.813210	1.680865	-0.07	-1.826119	1.900556	-0.24	-0.933628	1.264396	-0.21	-1.040484	1.404554
30.01.2018	0.16	-1.805749	1.954578	0.21	-1.820271	1.898391	0.20	-1.004531	1.601203	0.20	-1.130711	1.770793
31.01.2018	0.61	-1.814629	1.691560	-0.05	-1.833885	1.900705	0.05	-0.952513	1.167363	0.07	-1.049029	1.328850
1.02.2018	0.67	-1.709987	1.928371	1.06	-1.822896	1.892638	1.01	-0.995407	1.100539	0.99	-1.093086	1.245825
2.02.2018	-1.19	-1.868828	1.767708	-0.58	-2.278385	2.290573	-0.67	-2.776501	1.478323	-0.69	-2.988830	1.665507
5.02.2018	-0.27	-2.205146	2.094024	-0.46	-1.983651	2.027376	-0.43	-1.111666	0.975375	-0.43	-1.241581	1.077967
6.02.2018	0.43	-2.047992	1.922539	0.88	-1.924395	1.993267	0.83	-1.015828	1.489115	0.79	-1.145180	1.629624
7.02.2018	-0.94	-1.740359	2.101111	-1.05	-2.143395	2.164674	-1.04	-1.923994	1.175242	-1.03	-2.055060	1.314156
8.02.2018	-0.64	-2.296515	2.100781	0.52	-2.277278	2.355899	0.33	-1.251778	2.065882	0.31	-1.438151	2.302800
9.02.2018	0.16	-2.228485	1.983436	0.05	-1.932576	1.982868	0.07	-0.944776	1.163487	0.07	-1.031877	1.344427
12.02.2018	0.56	-1.850972	2.071475	0.04	-1.830611	1.878384	0.20	-1.002448	1.088487	0.14	-1.084013	1.266198
13.02.2018	-0.12	-1.889806	1.886830	-0.08	-1.831771	1.877170	-0.09	-1.188353	0.983826	-0.08	-1.181198	1.143289
14.02.2018	0.68	-1.819425	1.705747	0.68	-1.834014	1.883571	0.68	-1.066234	1.019215	0.68	-1.121544	1.212575
15.02.2018	0.35	-1.885403	1.839780	-0.55	-2.035185	2.047775	-0.39	-2.201484	1.230768	-0.38	-2.285156	1.360059
16.02.2018	0.47	-1.687762	1.890364	-0.24	-1.968491	2.010827	-0.15	-1.189446	0.928676	-0.11	-1.300541	1.040982
19.02.2018	-0.27	-1.780145	1.682307	-0.03	-1.858403	1.914000	-0.09	-1.043841	1.043001	-0.07	-1.190701	1.126364
20.02.2018	-1.06	-1.611342	1.690466	0.04	-1.827107	1.884105	-0.28	-0.993695	1.122699	-0.16	-1.137599	1.184688
21.02.2018	0.18	-2.073160	1.959098	-0.29	-1.826809	1.881831	-0.18	-0.993095	1.482283	-0.20	-1.087940	1.370974
22.02.2018	0.22	-1.846157	1.915618	0.19	-1.863507	1.934080	0.20	-1.003036	1.645517	0.19	-1.109893	1.662781

Table 40 (continued): Parametric VaR Results

	Parametric VaR ARMA(4,0)-GARCH(1,1) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution		
	Unhedge			FullyHedge			GarchHedge			OLSHedge		
Date	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%
23.02.2018	-0.22	-1.673286	1.856095	-0.19	-1.834804	1.895144	-0.20	-0.942234	1.197244	-0.19	-1.068443	1.275715
26.02.2018	0.14	-1.810095	1.581506	0.04	-1.840888	1.911513	0.06	-0.977886	1.455680	0.06	-1.096635	1.570231
27.02.2018	-0.73	-1.639035	1.620927	-0.55	-1.820161	1.888471	-0.58	-0.944475	1.249850	-0.58	-1.054797	1.388460
28.02.2018	0.31	-1.734642	1.784381	0.49	-1.954157	2.052222	0.47	-1.235203	2.274133	0.46	-1.442287	2.599845
1.03.2018	-0.15	-1.738759	1.632111	1.06	-1.905751	1.977158	0.95	-0.943437	1.150621	0.84	-1.008733	1.368722
2.03.2018	-0.06	-1.506044	1.689551	-0.12	-2.277090	2.290931	-0.12	-2.517136	1.379819	-0.11	-2.331126	1.407846
5.03.2018	0.02	-1.640268	1.428973	0.04	-1.851875	1.872482	0.03	-1.739877	0.974692	0.03	-1.721966	1.062184
6.03.2018	0.37	-1.440928	1.523751	-0.34	-1.845287	1.863918	-0.12	-1.649580	0.981017	-0.21	-1.731865	1.090555
7.03.2018	0.01	-1.479743	1.489284	0.14	-1.890642	1.927725	0.11	-1.307283	0.930882	0.12	-1.313998	1.052140
8.03.2018	-0.76	-1.428657	1.442697	-0.38	-1.846098	1.875650	-0.49	-1.416247	0.961803	-0.45	-1.482967	1.077625
9.03.2018	0.29	-1.712406	1.597403	0.06	-1.900171	1.950537	0.12	-1.009910	1.309882	0.11	-1.130098	1.434016
12.03.2018	-0.84	-1.607481	1.634123	-0.19	-1.831566	1.878429	-0.30	-1.001850	1.086762	-0.31	-1.104399	1.220754
13.03.2018	-0.80	-1.769836	1.889559	-0.10	-1.846280	1.903419	-0.19	-0.993707	1.468133	-0.22	-1.132906	1.689168
14.03.2018	-0.17	-2.135906	1.821591	0.48	-1.830304	1.892723	0.41	-1.007999	1.659117	0.36	-1.190491	2.018580
15.03.2018	-0.41	-1.758612	1.902754	-0.39	-1.924908	1.961399	-0.40	-1.069098	1.040562	-0.40	-1.061341	1.265456
16.03.2018	-0.63	-1.819339	1.779937	0.20	-1.901420	1.959300	0.08	-1.018071	1.536715	0.06	-1.216234	1.986082
19.03.2018	-0.38	-1.918965	1.729871	-0.05	-1.844825	1.891631	-0.09	-0.941491	1.257537	-0.11	-1.064238	1.668423
20.03.2018	0.03	-1.747536	1.724508	-0.24	-1.831937	1.881380	-0.19	-0.956992	1.339358	-0.19	-1.120358	1.818271
21.03.2018	0.65	-1.626827	1.643829	0.53	-1.854167	1.916475	0.55	-0.991838	1.567527	0.55	-1.209979	2.115072
22.03.2018	-0.70	-1.721827	1.721398	-0.56	-1.948759	1.982190	-0.58	-1.295886	1.017289	-0.58	-1.181954	1.175800
23.03.2018	-1.26	-1.846006	1.776747	-0.58	-1.967445	2.031148	-0.64	-1.061481	1.622958	-0.70	-1.300332	2.155081

Table 40 (continued): Parametric VaR Results

	Parametric VaR ARMA(4,0)-GARCH(1,1) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution		
	Unhedge			FullyHedge			GarchHedge			OLSHedge		
Date	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%
26.03.2018	0.49	-2.330986	2.077972	1.06	-1.973232	2.068728	1.03	-1.400699	2.740628	0.96	-1.856528	3.661102
27.03.2018	-0.43	-2.041152	2.229912	-0.43	-2.258425	2.296182	-0.43	-1.405871	1.094447	-0.43	-1.068442	1.262415
28.03.2018	-0.72	-1.989497	2.113706	-0.37	-1.912163	1.973047	-0.43	-1.002016	1.332916	-0.43	-1.237328	2.042634
29.03.2018	1.72	-2.297857	1.890712	0.64	-1.887386	1.968641	0.78	-1.120974	1.973729	0.82	-1.505558	2.870111
30.03.2018	-0.35	-2.822749	3.048747	-0.55	-1.986587	2.033285	-0.53	-1.428455	1.060216	-0.52	-1.199246	1.201404
2.04.2018	-0.43	-2.594527	2.765250	0.98	-1.961086	2.037706	0.93	-1.027615	1.457537	0.73	-1.246034	2.010143
3.04.2018	-0.42	-2.744835	2.223209	-0.07	-2.211352	2.234743	-0.10	-2.197616	1.272889	-0.13	-1.592542	1.194485
4.04.2018	-0.31	-2.090713	2.418876	0.00	-1.843881	1.871226	-0.10	-1.574006	0.949128	-0.06	-1.247195	1.087244
5.04.2018	-1.30	-2.146473	2.112807	-0.29	-1.840647	1.868243	-0.55	-1.306890	0.933806	-0.47	-1.187636	1.130354
6.04.2018	0.18	-2.499611	2.394559	0.25	-1.875178	1.918709	0.23	-1.031796	1.475008	0.24	-1.190710	1.827699
9.04.2018	-0.65	-2.286239	2.179373	-0.36	-1.863164	1.893073	-0.41	-1.022294	1.062995	-0.41	-1.062584	1.280379
10.04.2018	-0.97	-2.070800	2.236232	0.23	-1.894036	1.943724	0.09	-1.035501	1.626387	0.03	-1.234218	2.041011
11.04.2018	-0.60	-2.511843	2.124064	0.26	-1.855199	1.892302	0.20	-0.935949	1.295630	0.12	-1.086350	1.770432
12.04.2018	0.64	-2.135929	2.183181	-0.56	-1.870462	1.893178	-0.37	-1.030654	1.055048	-0.36	-1.040629	1.476214
13.04.2018	0.31	-2.071797	2.131729	0.12	-1.973250	2.026599	0.16	-1.013092	1.534002	0.15	-1.264983	2.187287
16.04.2018	0.00	-1.956450	1.959924	0.44	-1.835152	1.881840	0.31	-0.955814	1.167837	0.36	-1.043848	1.641184
17.04.2018	0.00	-1.919022	1.708814	-0.25	-1.920506	1.943313	-0.19	-1.234535	0.988966	-0.20	-1.169331	1.165022
18.04.2018	2.14	-1.671940	1.730463	0.26	-1.866319	1.902503	0.68	-1.022868	1.075696	0.58	-1.092500	1.391593
19.04.2018	-0.81	-2.822930	3.014752	-0.77	-1.869208	1.891407	-0.77	-2.085486	1.196009	-0.77	-1.797285	1.205966
20.04.2018	-0.90	-2.754976	2.871776	-0.23	-2.081242	2.145111	-0.36	-1.054004	1.383167	-0.35	-1.262580	1.878155
24.04.2018	-0.20	-3.021705	2.486560	0.54	-1.848267	1.924898	0.41	-1.077314	1.845404	0.42	-1.326480	2.394355

Table 40 (continued): Parametric VaR Results

	Parametric VaR ARMA(4,0)-GARCH(1,1) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution		
	Unhedge			FullyHedge			GarchHedge			OLSHedge		
Date	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%
25.04.2018	0.12	-2.237765	2.711651	0.19	-1.944557	1.991596	0.18	-1.014537	1.073581	0.18	-1.016881	1.356023
26.04.2018	0.30	-2.235579	2.251229	-0.43	-1.848206	1.885032	-0.31	-1.180689	0.983234	-0.30	-1.137146	1.179057
27.04.2018	0.57	-2.125217	2.023967	-0.16	-1.912517	1.972482	-0.06	-0.987996	1.245031	-0.03	-1.119234	1.603487
30.04.2018	-0.44	-2.040841	2.039077	-0.45	-1.836034	1.904552	-0.45	-0.958255	1.252442	-0.45	-1.066974	1.547143
1.05.2018	0.00	-1.955496	1.938650	0.00	-1.912347	2.005339	0.00	-1.124819	1.975333	0.00	-1.368601	2.461512
2.05.2018	-2.96	-1.849958	1.759847	1.23	-1.808785	1.901778	0.37	-0.980912	1.675713	0.52	-1.186135	2.164971
3.05.2018	-0.80	-3.751790	3.758617	0.78	-2.400534	2.426556	0.50	-1.012167	1.074203	0.52	-1.106091	1.213816
4.05.2018	-0.41	-3.628553	3.266552	-0.10	-2.113214	2.096963	-0.23	-1.700327	1.065527	-0.15	-1.879597	1.212683
7.05.2018	-0.90	-2.828640	3.312830	-0.38	-1.863745	1.853103	-0.58	-1.156854	0.954563	-0.46	-1.409133	1.039603
8.05.2018	-1.52	-3.278819	2.795414	-0.50	-1.911621	1.921479	-0.88	-1.082079	1.715102	-0.67	-1.134738	1.487205
9.05.2018	1.04	-3.202922	2.968856	0.26	-1.949385	1.986465	0.52	-1.675758	3.394102	0.39	-1.547259	2.849330
10.05.2018	1.22	-3.038037	3.081478	0.42	-1.869571	1.892464	0.62	-0.887389	1.583363	0.55	-1.000266	1.592578
11.05.2018	-1.86	-2.915820	3.200879	-0.50	-1.928211	1.928410	-0.78	-1.311159	1.027842	-0.72	-1.426816	1.145645
14.05.2018	-1.26	-3.828219	3.321832	-0.74	-1.952444	1.979908	-0.82	-1.200065	2.040099	-0.83	-1.326602	2.146229
15.05.2018	-1.71	-3.505011	3.239705	2.01	-2.065913	2.133731	1.71	-1.712697	3.522220	1.41	-1.995792	3.951722
16.05.2018	0.58	-3.310540	3.692725	-0.67	-3.190075	3.148832	-0.63	-2.302025	1.441168	-0.47	-1.671248	1.336341
17.05.2018	-1.02	-3.237727	3.038221	-0.21	-2.040590	2.035758	-0.57	-1.031774	1.197047	-0.34	-1.140812	1.537231
18.05.2018	-0.71	-2.950998	3.029175	0.19	-1.870923	1.877604	-0.21	-1.177077	2.087658	0.05	-1.233196	2.090661
21.05.2018	-1.88	-3.086356	2.531709	0.54	-1.872065	1.868401	-0.41	-1.145175	2.183227	0.16	-1.084230	1.781057
22.05.2018	-2.07	-3.056661	3.189239	-0.31	-2.000895	1.967855	-0.91	-1.377749	2.792370	-0.58	-1.037214	1.419551
23.05.2018	1.95	-3.877447	3.550413	6.02	-1.902077	1.886039	4.52	-2.096715	4.495848	5.41	-1.464772	2.665718

Table 40 (continued): Parametric VaR Results

	Parametric VaR ARMA(4,0)-GARCH(1,1) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution		
	Unhedge			FullyHedge			GarchHedge			OLSHedge		
Date	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%
24.05.2018	-2.94	-3.994825	4.186785	-4.05	-8.239135	7.896028	-3.75	-8.635725	4.400431	-3.89	-14.181084	7.256878
25.05.2018	0.04	-5.015716	5.034335	-1.33	-5.445853	5.322928	0.03	-2.492985	4.173901	-1.12	-1.718683	1.265670
28.05.2018	2.61	-4.903151	3.913670	-0.93	-2.506334	2.455500	2.58	-1.214589	2.541934	-0.39	-1.672091	2.927385
29.05.2018	0.80	-4.727749	5.826354	0.48	-2.197230	2.196933	0.69	-5.081206	2.630200	0.53	-1.684989	3.386513
30.05.2018	1.77	-4.784299	4.483294	-0.70	-1.971706	1.945135	1.07	-5.328482	2.379799	-0.31	-0.987805	1.724586
31.05.2018	-1.35	-4.797818	4.472032	-0.88	-2.053986	2.065544	-1.09	-6.978465	3.100841	-0.96	-1.339226	2.458670
1.06.2018	-2.86	-4.105554	4.490385	1.08	-2.154973	2.214402	-1.25	-2.779275	1.107104	0.47	-2.344869	4.761486
4.06.2018	1.30	-5.407903	4.929145	1.03	-2.308124	2.308592	1.08	-1.141566	1.487396	1.07	-1.274922	2.751146
5.06.2018	-0.14	-4.642466	5.092345	0.20	-2.314501	2.259131	0.03	-2.638873	1.443091	0.15	-1.501537	1.241524
6.06.2018	0.86	-4.095596	4.490905	-0.47	-1.911094	1.844831	0.12	-2.115054	1.094117	-0.26	-1.537253	1.085745
7.06.2018	1.62	-4.228261	3.486399	-0.56	-1.958708	1.917783	0.33	-2.112613	1.108986	-0.22	-1.171043	1.149581
8.06.2018	0.33	-3.888777	4.326257	0.68	-1.988262	1.977765	0.51	-2.562804	1.285890	0.63	-1.093973	1.393406
11.06.2018	-1.20	-3.646807	3.600882	-0.65	-2.082920	2.035361	-0.81	-3.320148	1.582077	-0.73	-1.893452	1.237264
12.06.2018	-1.64	-3.583011	3.380559	-0.17	-2.030619	2.018238	-0.66	-1.203311	0.893659	-0.40	-1.217510	1.715695
13.06.2018	-1.18	-3.540195	3.582866	0.29	-1.867815	1.864543	-0.14	-1.103464	1.753761	0.06	-1.327838	2.365734
14.06.2018	-1.63	-3.399927	3.490334	-1.51	-1.903384	1.884156	-1.49	-1.015045	1.735760	-1.53	-1.117965	1.952924
18.06.2018	0.41	-3.666471	3.567781	2.59	-2.664004	2.726899	2.04	-2.417508	5.048692	2.26	-2.962598	5.972643
19.06.2018	-0.91	-3.336994	3.158184	-1.07	-3.858872	3.780758	-1.00	-2.062150	1.422005	-1.05	-2.357527	1.711208
20.06.2018	0.29	-3.003174	3.075591	0.63	-2.301039	2.281178	0.37	-1.255993	2.103283	0.58	-1.493013	2.461837
21.06.2018	0.17	-2.947753	2.511261	-0.04	-2.058085	2.004188	0.08	-0.956606	1.137079	-0.01	-1.166774	1.183847
22.06.2018	1.03	-2.349504	2.635434	-0.44	-1.880186	1.828639	0.35	-1.020907	1.064525	-0.22	-1.142858	1.174766

Table 40 (continued): Parametric VaR Results

	Parametric VaR ARMA(4,0)-GARCH(1,1) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution		
	Unhedge			FullyHedge			GarchHedge			OLSHedge		
Date	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%
25.06.2018	-0.10	-2.549996	2.402011	-0.07	-1.946781	1.919424	-0.08	-1.434996	0.997418	-0.07	-1.093299	1.444680
26.06.2018	1.48	-2.193063	2.289019	0.01	-1.867478	1.843829	0.60	-1.201320	0.952317	0.24	-1.071297	1.495257
27.06.2018	-0.20	-2.671714	2.587580	-0.61	-1.866600	1.842414	-0.43	-2.255701	1.233209	-0.54	-1.146258	1.172761
28.06.2018	0.77	-2.218333	2.533620	0.52	-2.006052	2.014932	0.57	-1.179013	0.930308	0.56	-1.278828	2.107224
29.06.2018	0.00	-2.406074	2.132092	-0.89	-1.983070	1.963555	-0.60	-2.185924	1.206416	-0.75	-1.246602	1.158936
2.07.2018	-0.70	-1.888015	2.262467	2.01	-2.165592	2.194422	1.35	-1.053446	1.073663	1.58	-1.429523	2.457535
3.07.2018	-1.19	-2.280723	2.051349	-0.12	-3.233169	3.152791	-0.44	-3.702061	1.874944	-0.29	-3.346924	1.926526
4.07.2018	0.12	-2.333456	2.346777	0.06	-1.894089	1.820180	0.08	-1.827954	0.941700	0.07	-1.917387	1.067351
5.07.2018	1.56	-2.106357	2.156708	-0.23	-1.896818	1.819818	0.62	-1.875308	1.038283	0.05	-2.018291	1.159497
6.07.2018	0.40	-2.531973	2.738810	-0.31	-1.903355	1.838894	0.01	-3.023949	1.495129	-0.20	-1.989950	1.148900
9.07.2018	-3.57	-2.447426	2.349813	-3.18	-1.913208	1.865625	-3.12	-2.459992	1.195819	-3.24	-1.488727	1.028396
10.07.2018	0.57	-4.838763	4.366633	3.29	-4.443920	4.568953	2.22	-3.302565	6.537428	2.87	-4.576429	8.952274
11.07.2018	-3.59	-4.167175	4.137313	-0.56	-4.626544	4.572602	-1.60	-1.754311	1.362002	-1.02	-2.058864	1.738063
12.07.2018	0.33	-5.216627	5.802685	0.81	-1.991096	1.967496	0.36	-1.974054	3.843473	0.74	-1.619417	2.841588
13.07.2018	0.04	-5.342668	4.307825	-0.47	-2.175157	2.107527	-0.21	-1.008415	2.043863	-0.39	-1.189642	1.193285
16.07.2018	0.20	-3.870288	4.700344	0.28	-1.959859	1.917678	0.22	-1.186434	2.320845	0.27	-1.158164	1.740270
17.07.2018	0.81	-4.140422	3.424235	-0.44	-1.924798	1.867261	0.08	-0.925918	1.544737	-0.25	-1.097479	1.220487
18.07.2018	0.28	-3.543538	3.662189	0.69	-1.948244	1.914828	0.50	-0.934852	1.326651	0.63	-1.109245	1.593097
19.07.2018	-0.31	-3.176621	3.227015	-0.08	-2.106872	2.035859	-0.15	-1.387319	1.016017	-0.11	-1.689703	1.192668
20.07.2018	0.25	-2.934742	2.818128	-0.36	-1.888510	1.821760	-0.14	-1.091671	0.997001	-0.27	-1.334653	1.057372
23.07.2018	1.20	-2.557405	2.644050	-0.13	-1.926464	1.879356	0.25	-0.999037	1.119018	0.08	-1.119071	1.266077

Table 40 (continued): Parametric VaR Results

	Parametric VaR ARMA(4,0)-GARCH(1,1) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution		
	Unhedge			FullyHedge			GarchHedge			OLSHedge		
Date	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%
24.07.2018	-3.16	-2.591293	2.798105	0.33	-1.879348	1.839192	-0.62	-1.224668	0.983238	-0.20	-1.149390	1.166640
25.07.2018	2.26	-4.580567	4.370135	0.65	-1.939831	1.881546	1.02	-1.096542	1.750642	0.89	-1.091610	1.408890
26.07.2018	-1.98	-4.934096	4.644459	-1.49	-2.099074	2.005679	-1.56	-2.119917	1.263571	-1.57	-2.514238	1.478488
27.07.2018	0.51	-4.261417	5.148941	0.51	-2.650427	2.638207	0.50	-1.708842	3.147211	0.51	-1.902734	3.293012
30.07.2018	-0.80	-4.708682	3.560275	0.00	-1.991372	1.951557	-0.11	-0.880392	1.371656	-0.12	-0.983084	1.475972
31.07.2018	-0.68	-3.257298	4.050942	-0.17	-1.874397	1.834562	-0.23	-0.972761	1.523048	-0.25	-1.105867	1.727468
1.08.2018	-1.66	-3.752780	3.180262	0.30	-1.880231	1.849812	0.13	-1.044958	1.805045	0.00	-1.236388	2.164445
2.08.2018	-1.44	-3.414205	3.507461	1.80	-1.921964	1.875351	1.63	-0.927401	1.365311	1.32	-1.131278	1.958799
3.08.2018	-0.28	-3.633740	3.397597	-0.23	-3.084376	2.940014	-0.23	-3.873617	1.992006	-0.24	-2.923713	1.712660
6.08.2018	-5.08	-3.089848	3.155094	-1.78	-1.931400	1.799451	-2.86	-2.334928	1.114410	-2.25	-1.787357	1.050826
7.08.2018	2.09	-6.703073	6.332565	2.87	-2.916384	2.880955	2.38	-3.018208	5.938314	2.76	-2.997771	5.669917
8.08.2018	-1.17	-6.508017	6.028246	-0.44	-4.286948	4.095694	-0.50	-2.508283	1.629465	-0.55	-4.193180	2.511005
9.08.2018	-5.20	-5.070246	6.092674	-0.04	-1.992271	1.825086	-1.40	-1.065001	1.033247	-0.76	-1.680717	0.980594
10.08.2018	-17.05	-9.079925	7.313169	3.75	-1.937518	1.772630	-0.53	-1.933261	3.829525	1.17	-1.221286	1.713437
13.08.2018	-7.33	-20.379038	19.521925	4.28	-5.511448	5.142734	2.93	-1.908577	4.184016	3.02	-3.000934	1.709186
14.08.2018	7.19	-19.567712	18.570397	-1.07	-6.406105	5.804772	0.76	-4.698725	2.545118	-0.16	-11.010441	5.390734
15.08.2018	6.91	-17.683490	19.895489	-2.89	-2.377038	1.833639	-0.22	-5.096147	2.301173	-1.73	-8.369993	3.580469
16.08.2018	1.33	-18.022373	17.260122	-2.68	-4.078576	3.692371	-1.63	-3.502131	1.517769	-2.18	-2.730422	1.004759
17.08.2018	-3.54	-16.522853	14.387056	1.83	-3.852807	3.612220	0.49	-1.310102	1.921687	1.16	-2.294840	3.966597
20.08.2018	-0.84	-13.788639	13.672457	-0.35	-3.320169	2.979905	-0.44	-1.193793	1.015635	-0.41	-1.474546	1.254099
27.08.2018	-0.77	-11.620946	12.321973	-0.29	-2.030334	1.709358	-0.38	-1.016203	1.475398	-0.35	-1.132035	1.546955

Table 40 (continued): Parametric VaR Results

	Parametric VaR ARMA(4,0)-GARCH(1,1) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution		
	Unhedge			FullyHedge			GarchHedge			OLSHedge		
Date	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%
28.08.2018	-2.32	-10.083359	10.901525	0.55	-2.014401	1.709092	-0.08	-1.126136	2.020532	0.20	-1.246415	2.131922
29.08.2018	-3.09	-10.008910	9.307981	0.40	-2.238111	1.902687	-0.27	-1.040435	1.884029	-0.02	-1.027703	1.521074
30.08.2018	0.00	-9.173244	8.791654	0.00	-2.174136	1.817063	0.00	-1.165603	2.221139	0.00	-1.063453	1.529825
31.08.2018	-1.35	-7.794455	7.859947	1.06	-2.047371	1.690298	0.62	-1.028531	1.890819	0.78	-1.059213	1.476907
3.09.2018	-1.43	-6.968570	7.050035	1.32	-2.665757	2.251063	0.91	-1.180521	1.032086	1.01	-2.099475	1.323584
4.09.2018	-0.42	-6.732627	5.962528	0.17	-2.965543	2.478985	0.08	-2.852714	1.486800	0.10	-4.393391	2.209078
5.09.2018	0.97	-5.484766	5.609658	-0.90	-2.177486	1.681875	-0.57	-2.421192	1.195441	-0.69	-3.937829	1.833011
6.09.2018	0.30	-4.941911	4.994379	0.32	-2.264338	1.817778	0.31	-1.157971	0.934080	0.32	-1.843212	0.977365
7.09.2018	2.53	-4.416099	4.324756	-1.58	-2.218243	1.754134	-0.86	-1.632190	1.021687	-1.10	-2.654621	1.406322
10.09.2018	-0.82	-4.901352	4.818037	0.88	-2.742315	2.364029	0.62	-1.154682	1.829327	0.68	-1.308035	1.809547
11.09.2018	0.49	-4.225650	4.494533	0.23	-2.530396	2.104415	0.28	-1.322150	1.027660	0.26	-1.767781	1.217517
12.09.2018	1.35	-4.094247	3.625698	-1.00	-2.161981	1.723412	-0.38	-1.633628	1.016150	-0.72	-2.102154	1.220998
13.09.2018	4.06	-3.489041	4.242088	-0.34	-2.310036	1.926086	0.63	-1.044308	1.057496	0.21	-1.175450	1.451801
14.09.2018	-1.35	-5.391469	5.501784	-0.83	-2.047285	1.681944	-0.90	-2.024505	1.170009	-0.90	-1.197937	1.138388
17.09.2018	-2.49	-5.006906	5.069904	0.41	-2.197676	1.877496	-0.11	-1.120156	1.655710	0.05	-1.607075	2.880332
18.09.2018	-1.15	-5.687844	4.891324	-0.02	-2.170893	1.828208	-0.19	-0.978043	1.562224	-0.16	-1.207995	2.274747
19.09.2018	2.11	-4.340396	5.091536	0.01	-2.034769	1.693432	0.31	-1.033170	1.776780	0.27	-1.332859	2.531781
20.09.2018	0.84	-4.462549	4.735579	0.22	-2.039610	1.697876	0.29	-0.955647	1.144861	0.30	-1.031300	1.704361
21.09.2018	-1.37	-4.135110	4.110947	-0.76	-2.098279	1.744815	-0.82	-1.226504	0.987616	-0.84	-1.078490	1.244712
24.09.2018	2.05	-4.280900	3.638012	-0.19	-2.161254	1.849236	-0.06	-1.250282	2.184279	0.10	-1.655621	3.047464
25.09.2018	-0.19	-4.312859	4.564139	0.07	-2.005663	1.703936	0.07	-1.038248	1.887940	0.04	-1.208139	2.308489

Table 40 (continued): Parametric VaR Results

	Parametric VaR ARMA(4,0)-GARCH(1,1) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution		
	Unhedge			FullyHedge			GarchHedge			OLSHedge		
Date	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%
26.09.2018	0.84	-3.636288	4.206959	-0.59	-2.029646	1.724023	-0.52	-0.950949	1.555136	-0.40	-1.156732	2.085820
27.09.2018	1.62	-3.829731	3.214588	-0.95	-2.076633	1.803085	-0.88	-1.295106	2.494221	-0.61	-1.529178	2.955874
28.09.2018	-0.66	-3.538017	4.123334	0.05	-2.248031	2.026239	-0.04	-1.951229	4.130561	-0.05	-2.060773	4.238174
1.10.2018	1.82	-3.617152	3.503591	1.68	-1.977632	1.753354	1.64	-1.501065	3.330688	1.70	-1.765150	3.790022
2.10.2018	-0.78	-3.872697	3.778516	-0.08	-3.141778	2.826081	-0.22	-2.134287	1.376559	-0.18	-2.265183	1.563842
3.10.2018	-0.99	-3.223149	3.746165	-0.21	-2.012394	1.701240	-0.37	-1.245436	0.927971	-0.32	-1.402260	1.037124
4.10.2018	-1.96	-3.711983	3.112898	1.39	-2.005593	1.706029	0.79	-0.996070	1.247647	0.95	-1.124539	1.268327
5.10.2018	0.62	-3.436575	3.726489	-0.87	-2.918731	2.543666	-0.68	-2.087229	1.214666	-0.68	-2.895519	1.623222
8.10.2018	0.21	-3.253915	3.187805	0.22	-2.222103	1.894500	0.20	-1.035335	1.259499	0.22	-1.230920	1.091938
9.10.2018	0.19	-2.752734	3.008573	-0.02	-2.088867	1.749526	0.05	-1.099226	1.011620	0.01	-1.540051	1.097320
10.10.2018	0.36	-2.809212	2.352354	-1.04	-2.033228	1.695116	-0.55	-1.127462	0.988229	-0.85	-1.465601	1.060165
11.10.2018	2.63	-2.367885	2.480829	1.29	-2.311802	2.029968	1.57	-1.078106	1.719883	1.47	-1.394702	2.285993
12.10.2018	0.71	-3.592886	3.787087	-0.79	-2.803438	2.451614	-0.22	-3.452052	1.822779	-0.58	-3.236255	1.860437
15.10.2018	1.50	-3.232864	3.448613	-1.47	-2.173126	1.864144	-0.86	-2.071251	1.039444	-1.05	-1.367787	0.995672
16.10.2018	1.65	-3.521087	3.227912	0.69	-2.637779	2.408571	0.91	-1.070395	1.408887	0.83	-1.627481	2.846834
17.10.2018	1.81	-3.359175	3.931705	-1.08	-2.263494	1.996786	0.14	-2.265743	1.291032	-0.66	-1.321959	1.188789
18.10.2018	-0.82	-3.630585	3.714003	0.16	-2.332211	2.124293	-0.17	-2.092817	1.105925	0.02	-1.323333	2.179422
19.10.2018	-0.18	-3.375014	3.423420	0.63	-1.995541	1.778660	0.29	-1.510137	0.930732	0.51	-1.100997	1.838959
22.10.2018	-0.52	-3.085629	2.968665	-0.88	-2.213893	1.962836	-0.71	-1.973408	1.098695	-0.83	-1.246787	1.152654
23.10.2018	-1.35	-2.531591	2.980350	0.97	-2.201762	1.998664	0.18	-1.038858	1.292863	0.63	-1.514368	2.657600
24.10.2018	0.75	-3.192607	2.948557	-1.27	-2.448916	2.193111	-0.55	-1.070578	1.025819	-0.97	-1.122108	1.209793

Table 40 (continued): Parametric VaR Results

	Parametric VaR ARMA(4,0)-GARCH(1,1) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution		
	Unhedge			FullyHedge			GarchHedge			OLSHedge		
Date	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%
25.10.2018	1.21	-2.911697	2.921329	0.23	-2.467942	2.280953	0.56	-1.100033	1.814746	0.38	-1.776523	3.296208
26.10.2018	0.70	-2.809670	3.108114	-0.08	-2.002346	1.802686	0.25	-1.207617	1.022127	0.04	-1.033757	1.837162
30.10.2018	2.13	-2.850513	2.592973	-0.55	-1.952094	1.756823	0.44	-1.482030	0.988544	-0.14	-1.080613	1.747890
31.10.2018	-2.05	-3.528407	3.620300	-1.32	-2.026828	1.861216	-1.47	-2.198916	1.189052	-1.43	-1.163084	1.972734
1.11.2018	1.30	-3.920829	4.048484	2.78	-2.500877	2.406805	2.16	-1.541769	2.725585	2.55	-2.804467	5.640985
2.11.2018	1.54	-3.973401	3.612609	-0.54	-4.242023	3.997065	0.01	-4.201480	2.212201	-0.22	-3.388396	2.151835
5.11.2018	2.08	-3.397061	4.388774	0.77	-2.039166	1.823384	1.34	-3.023283	1.386188	0.97	-1.837531	1.062206
6.11.2018	-1.27	-4.084308	3.700789	-0.57	-2.305335	2.047874	-0.82	-5.902619	2.725005	-0.67	-4.280761	2.155772
7.11.2018	0.12	-3.640525	3.667477	-0.01	-2.053134	1.826427	0.03	-2.551387	1.080050	0.01	-1.897957	0.990306
8.11.2018	-1.67	-3.341088	3.133592	-0.54	-1.971861	1.745878	-0.81	-2.438263	1.192488	-0.71	-1.957277	1.132895
9.11.2018	-0.25	-3.130001	3.667428	-0.11	-2.032763	1.835892	-0.14	-1.057509	1.151608	-0.13	-1.176321	1.485312
12.11.2018	0.06	-3.278426	2.873204	-0.20	-1.949759	1.759006	-0.15	-0.969194	1.236462	-0.16	-1.084962	1.558395
13.11.2018	-0.14	-2.595912	2.926893	0.60	-1.948933	1.768803	0.50	-0.966542	1.392140	0.49	-1.121188	1.775891
14.11.2018	0.30	-2.638437	2.371651	-0.29	-2.168539	1.955675	-0.22	-1.350116	1.012800	-0.20	-1.280198	1.143722
15.11.2018	2.07	-2.345372	2.294582	0.32	-1.968005	1.770825	0.59	-1.035158	1.058277	0.59	-1.107670	1.279597
16.11.2018	0.28	-3.110018	3.302903	-0.92	-2.041146	1.826436	-0.69	-1.918468	1.133180	-0.73	-1.970026	1.250242
19.11.2018	0.28	-2.816057	2.909467	0.16	-2.218627	2.054004	0.17	-1.039232	1.344384	0.18	-1.203917	1.645371
20.11.2018	-1.29	-2.731180	2.426410	0.64	-1.966831	1.793692	0.14	-1.033349	1.052212	0.34	-1.094727	1.229676
21.11.2018	1.44	-2.534918	2.806674	-0.83	-2.188542	1.980394	-0.34	-1.165292	0.983498	-0.48	-1.501550	1.115763
22.11.2018	0.12	-2.840527	2.828096	-0.67	-2.164402	2.001489	-0.42	-0.989750	1.305249	-0.55	-1.138212	1.498671
23.11.2018	0.28	-2.333872	2.755684	-0.20	-2.072112	1.945874	-0.02	-1.113242	1.947757	-0.12	-1.421017	2.556241

Table 40 (continued): Parametric VaR Results

	Parametric VaR ARMA(4,0)-GARCH(1,1) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution			Parametric VaR ARMA(1,1)-GARCH(1,0) under normal distribution		
	Unhedge			FullyHedge			GarchHedge			OLSHedge		
Date	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%	Actual	VaR-1%	VaR-99%
26.11.2018	0.64	-2.545640	2.053531	-0.32	-1.920120	1.804518	0.04	-0.986187	1.689941	-0.16	-1.316572	2.510468
27.11.2018	-0.50	-2.175914	2.482948	0.25	-1.934180	1.835860	-0.01	-0.944555	1.464651	0.13	-1.390360	2.703035
28.11.2018	1.06	-2.256645	2.242437	0.81	-1.949480	1.837813	0.85	-0.946663	1.383891	0.85	-1.155558	2.145381
29.11.2018	1.00	-2.415378	2.371457	-1.05	-2.247690	2.092052	-0.43	-2.006254	1.201548	-0.72	-1.583759	1.214334
30.11.2018	-0.84	-2.290113	2.651525	-0.74	-2.296740	2.198308	-0.74	-1.076247	1.011775	-0.76	-1.290754	2.024761

Appendix G. Christoffersen BackTesting Results

Table 41: Christoffersen Backtesting Results (Out-of-Sample)

Unhedged Portfolio: α=0.01					
T_0	T_1	T_{00}	T_{01}	T_{10}	T_{11}
245	6	240	5	5	1
π	π_{01}	π_{11}	$LRuc$	$LRInd$	$LRcc$
0.2390	0.0204	0.1666	3.5269	2.4375	3.9645
Chi-test (1%)	Exceedance	RMSE	$LRuc$	$LRInd$	$LRcc$
6.634897	6	4.5823	Do Not Reject	Do Not Reject	Do Not Reject

OLS Hedged Portfolio: α=0.01					
T_0	T_1	T_{00}	T_{01}	T_{10}	T_{11}
248	3	245	3	3	0
π	π_{01}	π_{11}	$LRuc$	$LRInd$	$LRcc$
0.0119	0.0120	0	0.0909	0	0
Chi-test (1%)	Exceedance	RMSE	$LRuc$	$LRInd$	$LRcc$
6.634897	3	2.0981	Do Not Reject	Do Not Reject	Do Not Reject

GARCH Hedged Portfolio: α=0.01					
T_0	T_1	T_{00}	T_{01}	T_{10}	T_{11}
244	4	240	4	4	0
π	π_{01}	π_{11}	$LRuc$	$LRInd$	$LRcc$
0.0161	0.0163	0	0.7937	0	0
Chi-test (1%)	Exceedance	RMSE	$LRuc$	$LRInd$	$LRcc$
6.634897	4	1.9352	Do Not Reject	Do Not Reject	Do Not Reject

Fully Hedged Portfolio: α=0.01					
T_0	T_1	T_{00}	T_{01}	T_{10}	T_{11}
249	2	247	2	2	0
π	π_{01}	π_{11}	$LRuc$	$LRInd$	$LRcc$
0.0079	0.0080	0	01125	0	0
Chi-test (1%)	Exceedance	RMSE	$LRuc$	$LRInd$	$LRcc$
6.634897	2	2.5052	Do Not Reject	Do Not Reject	Do Not Reject

Table 42: Christoffersen Backtesting Results (In-Sample-Historical)

Unhedged Portfolio: α=0.01					
T_0	T_1	T_{00}	T_{01}	T_{10}	T_{11}
195	7	189	6	6	1
π	π_{01}	π_{11}	$LRuc$	$LRInd$	$LRcc$
0.0346	0.0307	0.1428	7.5644	1.4976	7.0620
Chi-test (1%)	Exceedance	RMSE	$LRuc$	$LRInd$	$LRcc$
6.634897	7	6.6500	Reject	Do Not Reject	Do Not Reject

OLS Hedged Portfolio: α=0.01					
T_0	T_1	T_{00}	T_{01}	T_{10}	T_{11}
199	3	196	3	3	0
π	π_{01}	π_{11}	$LRuc$	$LRInd$	$LRcc$
0.0148	0.0150	0	0.4178	0	0
Chi-test (1%)	Exceedance	RMSE	$LRuc$	$LRInd$	$LRcc$
6.634897	3	2.2744	Do Not Reject	Do Not Reject	Do Not Reject

GARCH Hedged Portfolio: α=0.01					
T_0	T_1	T_{00}	T_{01}	T_{10}	T_{11}
198	4	194	4	4	0
π	π_{01}	π_{11}	$LRuc$	$LRInd$	$LRcc$
0.0198	0.0202	0	1.5252	0	0
Chi-test (1%)	Exceedance	RMSE	$LRuc$	$LRInd$	$LRcc$
6.634897	4	2.2841	Do Not Reject	Do Not Reject	Do Not Reject

Fully Hedged Portfolio: α=0.01					
T_0	T_1	T_{00}	T_{01}	T_{10}	T_{11}
200	2	198	2	2	0
π	π_{01}	π_{11}	$LRuc$	$LRInd$	$LRcc$
0.0099	0.01	0	0.0002	0	0
Chi-test (1%)	Exceedance	RMSE	$LRuc$	$LRInd$	$LRcc$
6.634897	2	2.5052	Do Not Reject	Do Not Reject	Do Not Reject

Table 43: Christoffersen Backtesting Results (In-Sample-Parametric)

Unhedged Portfolio: α=0.01					
T_0	T_1	T_{00}	T_{01}	T_{10}	T_{11}
197	5	193	4	4	1
π	π_{01}	π_{11}	$LRuc$	$LRInd$	$LRcc$
0.0247	0.0203	0.2	3.1480	2.7659	3.9140
Chi-test (1%)	Exceedance	RMSE	$LRuc$	$LRInd$	$LRcc$
6.634897	5	5.1520	Do Not Reject	Do Not Reject	Do Not Reject
OLS Hedged Portfolio: α=0.01					
T_0	T_1	T_{00}	T_{01}	T_{10}	T_{11}
200	2	198	2	2	0
π	π_{01}	π_{11}	$LRuc$	$LRInd$	$LRcc$
0.0099	0.01	0	0.0002	0	0
Chi-test (1%)	Exceedance	RMSE	$LRuc$	$LRInd$	$LRcc$
6.634897	2	2.2871	Do Not Reject	Do Not Reject	Do Not Reject
GARCH Hedged Portfolio: α=0.01					
T_0	T_1	T_{00}	T_{01}	T_{10}	T_{11}
199	3	196	3	3	0
π	π_{01}	π_{11}	$LRuc$	$LRInd$	$LRcc$
0.0148	0.0150	0	0.4178	0	0
Chi-test (1%)	Exceedance	RMSE	$LRuc$	$LRInd$	$LRcc$
6.634897	3	2.2341	Do Not Reject	Do Not Reject	Do Not Reject
Fully Hedged Portfolio: α=0.01					
T_0	T_1	T_{00}	T_{01}	T_{10}	T_{11}
201	1	200	1	1	0
π	π_{01}	π_{11}	$LRuc$	$LRInd$	$LRcc$
0.0049	0.0049	0	0.6389	0	0
Chi-test (1%)	Exceedance	RMSE	$LRuc$	$LRInd$	$LRcc$
6.634897	1	2.6527	Do Not Reject	Do Not Reject	Do Not Reject