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Electricity Price Forecasting

Elektrik Fiyat Tahmini

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LIST OF ACRONYMS

ACF: Autocorrelation Function

ADF: Augmented Dickey-Fuller

AIC: Akaike Information Criterion

ARIMA: Autoregressive Integrated Moving Average

BPM: Balancing Power Market

BOO: Build-Operate-Own Model

BOT: Build-Operate-Transfer Model

BOTAS: Petroleum Pipeline Corporation

CAGR: Compound Annual Growth Rate

CBRT: Central Bank of the Republic of Turkey

CCGT: Closed-Cycle Gas Turbines

CPI: Consumer Price Index

D-PPI: Domestic Producer Price Index

EMRA: Energy Markets Regulator Authority

EUAS: Electricity Generation Corporation

EXIST: Energy Exchange Istanbul (EPIAS)

GDP: Gross Domestic Product

IDM: Intra-Day Market

MAE: Mean Absolute Error

MAPE: Mean Absolute Percentage Error

MENR: Ministry of Energy and Natural Resources

MSE: Mean Square Error

OPEC: The Organization of the Petroleum Exporting Countries

PACF: Partial Autocorrelation Function

PMUM: Electricity Market Financial Reconciliation Center

PPA: Power Purchase Agreement

PPP: Public Private Partnership

RMSE: Root Mean Square Error

SIC: Schwarz Information Criterion

TANAP: Trans-Anatolian Gas Pipeline

TEAS: Turkish Electricity Joint Venture (Generation & Transmission)

TEDAS: Turkish Electricity Distribution Corporation

TEIAS: Turkish Electricity Transmission Corporation

TEK: Turkish Electricity Institution

TETAS: Turkish Electricity Trade and Contract Corporation

TKI: Turkish Coal Enterprises

TOOR: Transfer of Operating Rights

TTK: Turkish Hard Coal Enterprises

TURKSTAT: Turkish Statistical Institute

TUSIAD: Turkish Industry and Business Association

YEKA: Renewable Energy Resources Zones

YEKDEM: Renewable Energy Resources Support Mechanism

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ABSTRACT

Electricity price forecasting is one of the key pillars that the industry players watch carefully in order to maximize their profits and hedge against any unexpected fluctuations in prices. Since Turkey lacks a deep electricity derivatives market, it is essential for the firms to make an accurate electricity price forecasting which is used in their strategic decision-making. Among all the studies on Turkish electricity market in the literature, many exogenous variables and frequently amended regulations were considered in this paper as well as use of a recent data differentiates it from the others. In order to make a monthly forecast of the electricity prices in the Turkish market, following the seasonal adjustments, Autoregression and several GARCH models were implemented. It was discovered that the best-fit model was EGARCH(1,2) with the lowest AIC value though the smallest error terms were acquired using EGARCH(1,1). In conclusion, it has recently got more difficult to forecast the electricity prices accurately due to the impact of fx rates fluctuations on the electricity prices through renewable energy resources support mechanism and Turkey's dependence on imported raw materials. The electricity demand growth vs installed capacity growth as well as any change in the merit order curve through YEKA, local coal auctions and the privatization deals will be the key follow-ups on the electricity prices in the near future while the impact of developments with regards to liberalization of electricity and natural gas markets on the electricity trade and supply will be watched closely.

Key words

Electricity Price Forecasting, Renewable Energy Resources Support Mechanism (YEKDEM), Autoregression, Heteroskedasticity, GARCH

ÖZET

Elektrik fiyat tahmini enerji sektöründeki firmaları tarafından kârlılık oranlarını maksimize etmek ve fiyatlardaki anî değişikliklere karşı korunmak için kullanılmaktadır. Türkiye'de fiyat değişikliklerine karşı korunmayı sağlayan türev araçlarının kısıtlı olması nedeniye doğru fiyat tahmini firmaların stratejik planlama yapmaları açısından büyük önem taşımaktadır. Türkiye elektrik piyasasına yönelik yapılan sınırlı sayıdaki elektrik fiyat tahmini çalışmaları arasında bu çalışma göz önünde bulundurulan çok sayıdaki girdi sayısı. güncel veri kullanımı ve son dönemde sıkca değiştirilen regülasyonların detaylı anlatımı açısından diğerlerinden ayrışmaktadır. Elektrik fiyatlarının mevsim etkilerinden arındırılmasının ardından elektrik Oto regresyon ve çeşitli GARCH modelleini kullanarak Türkiye elektrik piyasasında oluşan fiyatları aylık olarak tahmin etmeye çalıştık. En doğru sonucun en düşük AIC değerine sahip EGARCH(1,2) modeli olduğuna karar verdik. Diğer taraftan, EGARCH(1,1) modeli ise en küçük hatayla sonuçlanan model olarak öne çıktı. Son olarak, spot piyasada elektrik fiyatlarının tahmini yenilenebilir enerji kaynakları destekleme mekanizmasının döviz cinsi verilmesi ve Türkiye'nin elektrik üretiminde ithal hammadde kullanımına bağımlılığı nedeniyle döviz kurundaki dalgalanmalara yüksek hassasiyet göstermekte ve bu nedenle piyasada tahmin yapmak güçleşmektedir. Elektrik talep büyümesine karşın kurulu güçteki büyüme trendi ile YEKA, yerli kömür ihaleleri ve özelleştirmelerle ilgili gelişmelerin önümüzdeki dönemde merit order üzerindeki etkisi açısından elektrik fiyatlarının seyrinde etkili olacağı düşünülürken, doğal gaz piyasasının açılması elektrik ve doğal gaz piyasalarının serbestleştirilmesine yönelik çalışmaların elektrik ticareti ve tedariki üzerindeki etkisi yakından takip edilecektir.

Anahtar Sözcükler

Elektrik Fiyat Tahmini, Yenilenebilir Enerji Kaynakları Destekleme Mekanizması (YEKDEM), Otoregresyon, Heteroskedastisite, GARCH

INTRODUCTION

Electricity price forecasting is essential on both macro and micro levels for several reasons. To start with macro perspectives, the price of electricity is an important part of the calculation of inflation not only through the consumer price index basket but the pass-through impact of producer prices on the consumer inflation. The electricity prices constitute only around 2.4% of the consumer price index basket due mostly to political reasons such as the social welfare purpose of the government trying to keep the prices at low levels. The share of electricity prices in consumer inflation is actually higher when the calculation includes the producer inflation factor, which is intensely affected by a change in electricity prices for energy (electricity, natural gas, etc.) constitutes the highest share of manufacturing costs at most of the industrial sectors. It was calculated that 10% of increase in electricity prices pushes up the consumer inflation by 0.38 bps (TUSIAD & BCG, April 2018). On the other hand, the share of cost of electricity on minimum wage in Turkey is calculated as 5.9% (MENR, January 2017). It has been on a downward trend and is considered relatively low compared to most of the EU countries.

Additionally, considering raw materials used for electricity generations, Turkish electricity market is highly dependent on imported resources such as natural gas and coal. That's why the composition of raw materials used in electricity generation, which is one of the determinants of electricity prices, matters on macro levels due to its burden on Turkey's current account balance and foreign exchange needs. On micro levels, on the other hand, forecasting electricity prices is essential for the electricity generators to be able to make their investments and trade contracts accordingly in a way to maximize their profits. It is used for the electricity market players to schedule their maintenance and plan their budgeting accordingly. It also helps industrial and commercial electricity consumers plan their business processes in order to minimize their input electricity costs.

There have been many statistical and machine learning models that were used in the literature to forecast electricity prices. They differed not only in terms of the model implemented but the characteristics of the data used for estimations. Historical electricity prices have been the widely-used variable in the literature in order to calculate future electricity prices. However, there are certain things to be considered making calculations in Turkish electricity market due to its cost composition and specific market structure. Turkey generated around 37% of its electricity from natural gas while about 33% of it came from coal while the rest, 30% of it was derived from the renewables in 2017 (TEIAS, 2017). Turkey could only produce 0.2% of its natural gas demand in 2017 and it is highly dependent on imports of natural gas, especially from Russia (EMRA, 2017). Apart from natural gas, imported coal also occupies notable part of electricity generation. Being that much of dependent on imported raw materials makes Turkey very sensitive to changes in oil prices and volatilities in FX rates. In addition to that, Turkish energy firms are exposed to the currency risks since they carry FX loans and have their revenues in TRY terms. Because energy loans are generally financed in FX terms in Turkey, their financial burdens peaked in 2018 due to depreciation in TRY and rising interest rates not only in Turkey, but globally. Besides the effect of raw material and financial costs, it is very important to review the continuously evolving Turkish electricity market structure. The market liberalization was officially initiated as of 2001 and from then on, huge progresses have been made. The market has been fully privatized in distribution and retailing. The share of private sector in electricity generation and trade in 2017 was 84% and 60% respectively (TEIAS & TETAS, 2017). However, electricity transmission is still under the control of state owned TEIAS by 100%. How liberal the market is very essential in price determinations, which means the more liberal the market is the more competitive the prices are. Additionally, Turkish electricity market is structured in a way that depreciation in local currency marks up the spot electricity prices through the support mechanism for renewables as well as the factor of imported raw material costs. In an emerging country like Turkey where it is very difficult to forecast the FX rates, electricity price forecasting does not result in 100% accuracy.

Since electricity is a commodity market similar to stock exchange and FX markets, supply and demand are the real determinants of the prices. Installed capacity and market match volumes in the day-ahead market were included as supply variables. Availability of electricity installed capacity matters for electricity price forecasting such that electricity capacity above the level of demand suppresses the prices downwards. Electricity demand is also a big part of electricity price forecasting. For electricity is non-storable, it is generated as much as the amount of electricity consumption, excluding small amount of exports and imports. It is observed that there has been a downward trend at electricity demand growth in years despite the increase in demand growth in 2017, which was supported by the strong GDP growth last year. Turkey's gross electricity demand grew by around 6% last year (TEIAS, 2017). TEIAS, based on its base scenario, projects that the electricity demand growth will be 4.7% CAGR in the next 10 years.

Because the electricity market is highly regulated in Turkey, it is noteworthy to examine the government's energy policies and the frequent regulatory changes made in the sector. In 2017 MENR released a National Energy and Mining policy, which was based on supply security, localization and predictability. They have issued several regulations related to these priorities since then. Ministry of Treasury and Finance recently announced a New Economic Program 2019-2021, which also highlighted that the government will prioritize the energy sector in order to decrease Turkey's current account deficit. It was stated that they would do so supporting an increase in the share of renewables and local coal resources in electricity generation and localization of energy technologies via YEKA models.

Turkish spot electricity market became operational in September 2015. Because it is relatively new compared to other European markets, Turkey's historical electricity prices are limited to the time period as of December 2009. The data on the renewable energy support mechanism and its financials (YEKDEM costs) were added later to the publicly available market database as of January 2012. Due to the reason that we wanted to include supply and demand, cost factors and the data with regards to the market liberalization in the estimation as well as the fact that the related data is published in monthly basis, the monthly released data dated 2012-2018 was used in the estimation model of this paper. It was discovered that previous studies in the international literature weighed on hourly price forecasting, some of which took only the demand as an exogenous variable. They were based on the assumption that the future electricity price patterns would be similar to what was observed in the past. However, electricity prices show outliers, non-constant mean and variance. It means that one cannot explain the price trends by the trend of historical prices only. The monthly electricity prices, used in this paper for the estimation, show seasonality i.e., prices increase during the summer and winter, where electricity demand peaks. They were also found out to be non-stationary. Following the elimination of unit roots and seasonality, autoregressions were applied on the price series to see if there was a significant linear relation between the current prices and the previous ones. Afterwards, several GARCH models were implemented to forecast the volatility in the price series. Lastly, error terms of the models were checked for the accuracy of the estimation models.

This paper is organized as follows. Section I specifies the Turkish electricity market framework, recent developments and regulations in the market. Section II provides information on electricity price forecasting studies that were made both for international and Turkish markets. Section III informs on the original dataset and forecasting techniques used for the estimation in this paper. Section IV details the empirical methods such as unit-root tests, seasonality adjustments, AR terms and GARCH models followed by the accuracy checks using techniques such as RMSE, MAE and MAPE. Finally, the results of the proposed models and a comparison of forecasted day-ahead electric prices were placed in the Results part of this section.

1. TURKISH ELECTRICITY MARKET

1.1 Market History and Liberalization Processes:

The efforts to create a liberal electricity market started in 1984 in Turkey. State owned monopoly, TEK was divided into two institutions: TEAS and TEDAS in 1994. However, strong and applicable steps were taken as of 2001 with the Law No.4628. Energy regulatory institution, EMRA was founded during the same year and TEAS was divided into three: EUAS, TEIAS and TETAS. Privatization of 21 electricity distribution companies, previously belonged to TEDAS, was completed in 2013. Following the initial phases like reconciliation three times a day and Day-Ahead Planning before today's hourly reconciliation and Day-Ahead Market, the electricity spot market started operating in real terms as of September 2015.

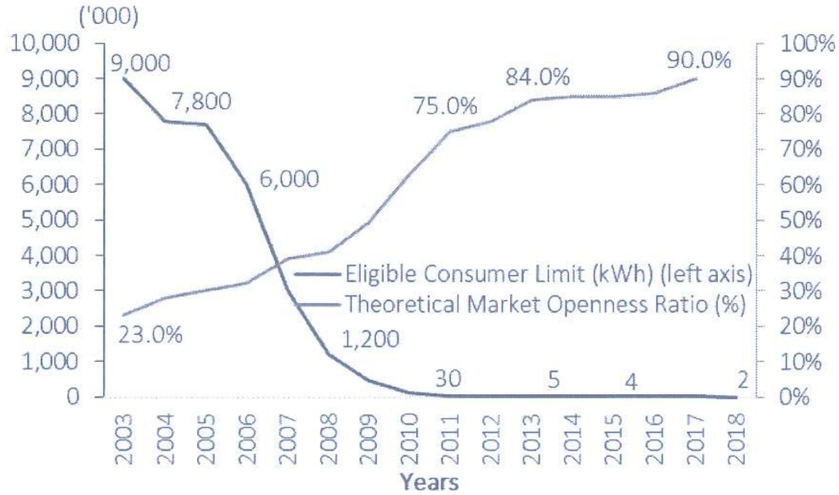
Table 1.1 Turkish Electricity Market in Chronology

2001	2004	2006	2009	2011	2013	Mar. 2015	Jul. 2015	Sept.2015
*Law No.4628	*Temporary Regulation on Balancing and Reconciliation	*Balancing Market (1st Phase) *Reconciliation on Day, Night and Peak Periods	*Day-Ahead Planning *Hourly Pricing and Reconciliation	*Day-Ahead Market *Guarantee and Advance Payments *Renewables Support Mechanism	*Law No.6446. Establishment o EPIAS was legalized.	*EPIAS was established.	*Intra-Day Market was established.	*EPIAS received the official license and permit to operate.

Source: TEIAS

The state institutions have created two different terms to measure the openness of the electricity market, which are theoretical and real openness ratios. These ratios are calculated using the number of eligible consumers. Eligible consumer is the electricity consumer, who consumes more electricity than the limit set by the government each year. If they can get over that limit, they gain the ability to receive electricity from traders participating at the spot market aside from the retailers, whose prices are determined by the government quarterly. The current consumption limit to be able to become an eligible consumer is 1,600 kWh/year in 2019. The government, in an effort to liberalize the market, lowers the limit in years. This low limit is now supposed to cover 90% of the market: nevertheless, some eligible consumers still prefer receiving electricity from the retailers. That's why it pushes down the real openness ratio, which was 55.5% in 2017 (EMRA, 2017). The topic of eligible consumers and retailers will be explained further in this paper detailing the Turkish market structure.

Figure 1.1 Eligible Consumer Limit and Theoretical Openness

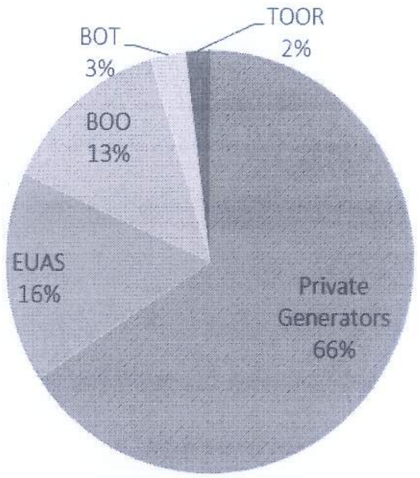


Source: EMRA

1.2 Market Structure:

An electricity market basically has three structures: generation, trade and retailing, distribution and transmission. It is exactly the same in Turkey. To be able to participate in the market, the entities have to hold a license for their activities like generation, auto-production, supply (trade and retailing), distribution and transmission. There are several electricity generators in terms of ownership: EUAS, institutions generating under the models BOO-BOT-TOOR, auto-producers and private sector electricity generators, including unlicensed producers. EUAS represents as the public sector and it is still the market leader by the market share of 16% in 2017 in generation. The government also created the PPP models like TOOR, BOT and BOO in order to attract private sector into invest in the energy sector. The institutions under these models were granted PPAs, which included that they could sell their electricity to TETAS, the state owned trade institution. Auto-producers are the ones generating heat/steam and other energies for their own use and convert them into other energies eventually. Market shares in electricity generation are as in the following graphs:

Figure 1.2 Market Shares in Electricity Generation in 2017



Source: EMRA

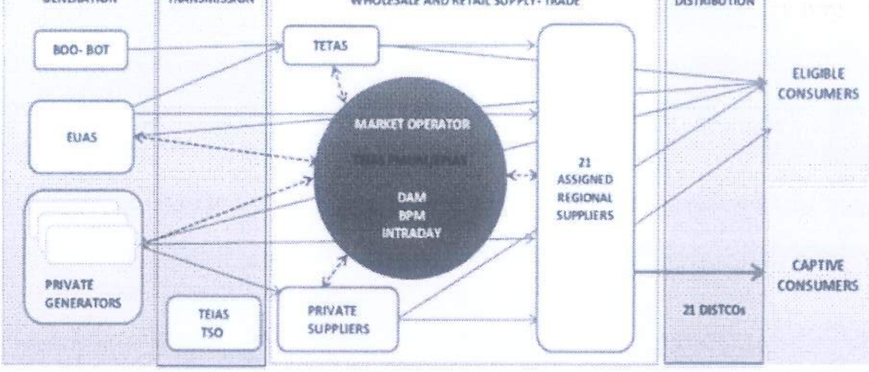
TEIAS controls Turkey's transmission lines by 100%. The reason why the public sector's dominance in the transmission still persists is explained both by the public sector's reluctance to make it privatized and investment into the transmission requires high financing needs.

Electricity trade market players are, on the other hand, TETAS, 21 regional electricity suppliers (both traders and retailers), private suppliers and EXIST. TETAS has the highest market share in electricity supply by 40% in 2017 due to its ongoing PPAs, which gives TETAS the requirement to purchase electricity from power plants operating under EUAS, as well as BOO, BOT and TOOR models. 21 regional suppliers are the partner companies of 21 regional distributors. They can operate both as retailers selling their electricity at a predetermined and regulated price by EMRA to non-eligible/captive consumers and as traders in which case they can sell electricity to eligible consumers all over the world. Since private trade companies can also sell to eligible consumers, they compete with 21 regional suppliers in this context. EXIST is the market place where the spot electricity prices, which are the prices to be forecasted in this paper, are hourly calculated. EXIST had a 32.3% share in electricity trading in 2017. It means that %67.7 of the electricity trade was made in bilateral agreements, most of which are between EUAS and TETAS.

Finally, there are 21 regional companies in electricity distribution. Their privatizations were completed in 2013. In the same year, they were separated into two different companies in order to comply with the competition law despite the fact that both retailer and distributor in one region still belong to the same mother company. By the law, the distributors cannot prioritize their retail partner company over another trade company in terms of delivering the electricity since a distributor must be neutral over electricity suppliers.

Turkish electricity market structure is detailed in the table below. The generated electricity is transmitted through TEIAS if its voltage is bigger than some amount or through distributors to suppliers to be delivered to customers. Some generation companies have their own private trade companies while 21 regional suppliers have their own power plants. It proves that there is a complex market structure here.

Table 1.2 Turkish Electricity Market Structure



Source: World Bank, 2015 *(TOORs are included in EUAS here).*

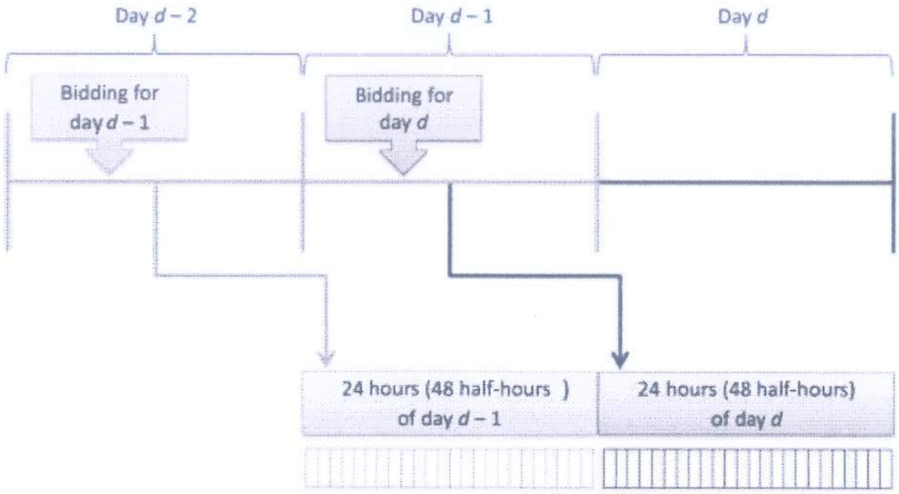
1.3 EXIST Market Operations:

Turkey's spot electricity market, EXIST was established in March 2015 and became operational as of September 2015. Before EXIST, there were PMUM and BPM operating under the authority of TEIAS. Once the spot market was activated, all the duties of TEIAS regarding the market operations were transferred to EXIST while BPM still operates under TEIAS. EXIST was structured in the following shareholder structure: 30% TEIAS, 30% Istanbul Stock Exchange and the final 40% electricity/gas market players.

There are basically three different electricity markets: DAM, IDM and BPM. There is also a platform where the market players make bilateral agreements. They agree on their needs at a determined price and this price/agreement is not published online to the public. In order to have an understanding of these markets, it might be helpful to see the shares of each market in electricity trade. Market shares of DAM, IDM, BPM and bilateral agreements were 27.5%, 0.4%, 4.5% and 66.7% in 2017 respectively (EXIST, 2017).

Since electricity is not stored, the market has to be in balance in physical flows. Today's electricity prices are determined at DAM a day earlier. If the there is a mismatch between supply and demand, there appear some market volume at IDM, though small one compared to DAM. Finally, BPM implements the balancing and reconciliation. The spot electricity prices, estimated in this paper, are the ones determined at DAM since most of the market volume is realized there. The operations of DAM and IDM are as in the following:

Table 1.3 EXIST Market Operations

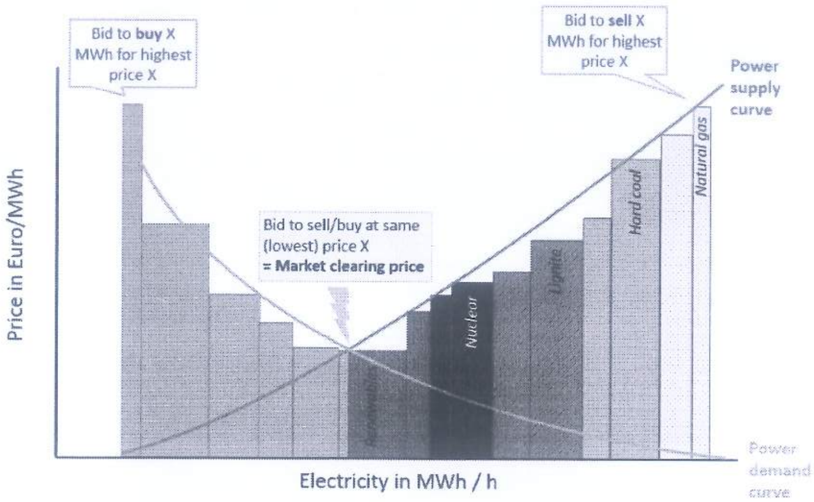


Source: Weron, 2014

At DAM, the market players can trade in hourly price-volume bundles and in blocks. Either the market is hourly cleared, generators and consumers are hourly matched at their related bundles or the market players make block sales/purchases. During the hourly trade, the lowest electricity price is granted to the supplier and higher prices follow it in order to provide fairness at EXIST. After all the demand of the electricity suppliers is covered, the generators are paid the hourly market clearing price determined at DAM. Secondly, the generators submit selling bids in blocks and their minimum selling prices while consumers submit buying bids in blocks and their maximum buying prices.

The spot electricity prices are calculated based on the supply-demand mechanism just as in the other commodities markets. Merit order is essential in terms of the level of the electricity prices. Merit order stands for the ranking of the sources used to produce electricity in a decreasing order of costs and electricity supply. It can be explained in a better way showing its graph below. The bids for generation is sorted in ascending order in order and the demands in descending order with the intersection between the two determining the traded quantity and the market price. All generators sell their electricity at this market price for more than or equal to their bid and all consumers buy electricity for less than or equal to their bid.

Figure 1.3 Merit Order Curve

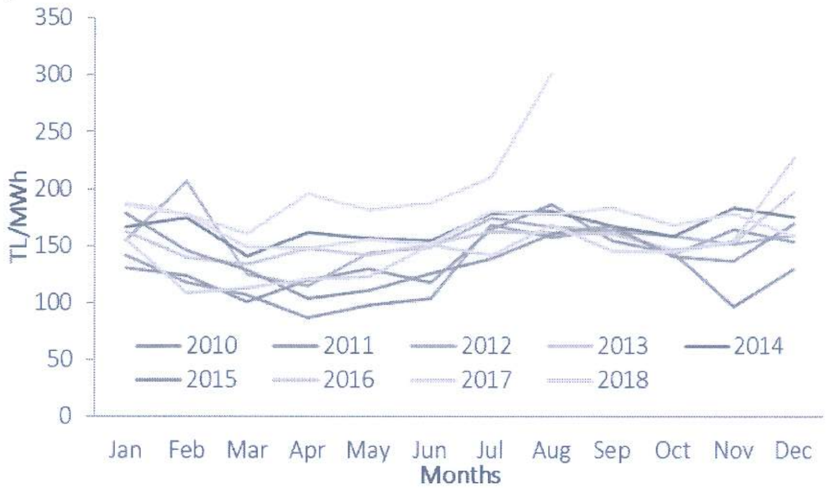


Source: EXIST

Clearly, electricity generated from fossil-fuel power plants is more costly than the renewables. On the other hand, the supply security requires that fossil-fuel plants should be actively operating as well. In Turkish electricity market, there are no nuclear plants, at least for now, to support the load in the merit order and there is still public dominance in the natural gas market. Despite the establishment of a new natural gas market as of September 2018 under the umbrella of EXIST, the gas market is still not entirely transparent. On the other hand, the government controls the biggest hydropower plants in Turkey, which are very essential at the shape of the merit order curve and the electricity price determination. Around 65% of EUAS's installed capacity is hydropower plants and that's the reason why rain and humidity received each month had better be considered in the price estimations. Nevertheless; we preferred not to include temporal indicators as exogenous variables for inadequate/missing forecasted data on the meteorology would lead to irrational and inaccurate forecasting. That's why it made more sense to plug YEKDEM and renewables, in general, into the modeling.

The trend of the DAM prices in Turkish currency in years is shown on the graph below. The prices indicate an increasing trend during the summer and winter months due to rising demand during that period. The peaked prices as observed apparently in December 2016 and at recent months are explained by unexpected developments such as issues related to gas imports from Iran and surge in USD/TRY respectively.

Figure 1.4 DAM Electricity Prices

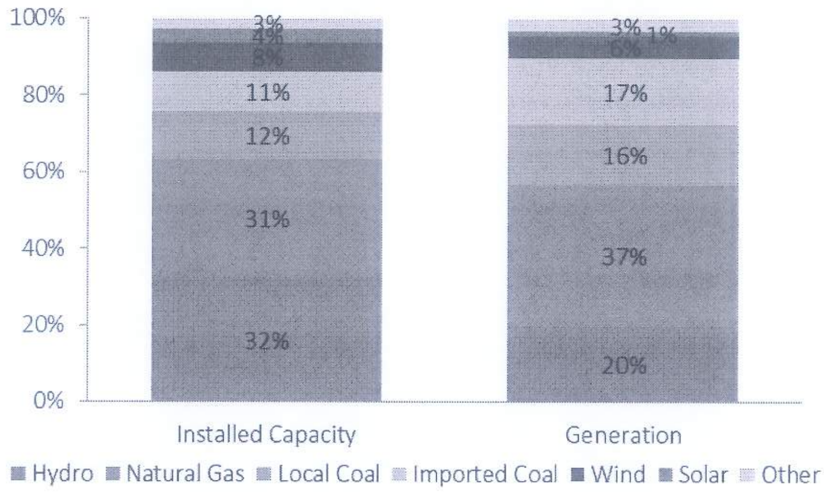


Source: EXIST

1.4 Turkish Electricity Market Today:

Electricity markets have two different supply indicators: installed capacity and electricity generation. The former indicates the availability of the power while the generation stands for what was actually produced. It means that not all the capacity might be used for the generation and only demanded amount of the electricity is generated since electricity is not stored. In order to take a closer look at Turkey's electricity supply mechanism, it is essential to understand the raw material compositions of both of the supply terms. As observed in the graph below, natural gas and hydropower plants have the highest shares in installed electricity capacity in 2017 while share of natural gas in generation is by far the largest in generation. Since renewables like hydro, wind and solar are dependent on weather conditions, fossil-fuel power plants which use materials such as natural gas, coal and oil are must-to-have in the electricity supply composition for the purpose of the supply security. It is observed that there is a great impact of the composition of electricity generation on the electricity prices since generation from renewables are cheaper than the fossil-fuel ones with huge raw material costs. It is also due to the fact that it is easier for the renewables to find financing to set up the plant. It is; however, obvious that it is getting more difficult to forecast the electricity prices since the composition of generation moves towards renewables and it is hard to predict weather conditions.

Figure 1.5 Compositions of Installed Capacity and Electricity Generation in 2017

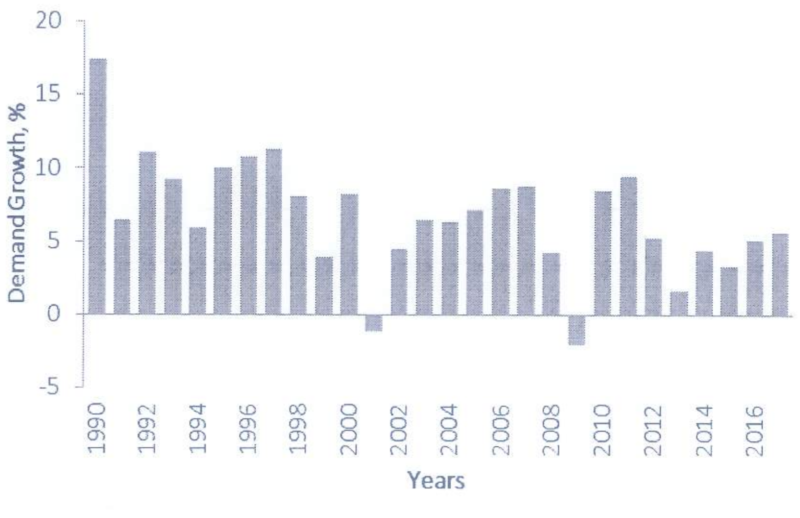


Source: EMRA *(Licensed and unlicensed power plants are included here).*

Turkey, in order to support the investments into renewables, initiated a mechanism called YEKDEM in 2012. The government promised not only purchase guarantees to the electricity generated from the hydro, wind, geothermal, biomass and solar power plants, but additional contribution to the plants which use locally produced equipment within the context of YEKDEM. All the support under YEKDEM has been granted in USD terms. It has moved up the renewables investments by a great extent; however, the government transferred these purchase payments to EXIST, which means that all market players have to share this payment burden. It has eventually led to a crisis at EXIST where peaks in USD/TRY surged the YEKDEM burden as well as imported raw material costs of the fossil-fuel plants, which finally were reflected on huge increases in spot electricity prices.

The electricity generators make their investments into the capacity according to their estimation of Turkey's electricity demand growth. It actually grew by around 6% in 2017. It is observed that this growth figure is less than Turkey's past demand growth trend though more than growth figures in some of the emerging countries. Electricity demand growth estimation is very important for the firms to be able to make their feasibility studies accordingly. They take several indicators such as industrial production index, number of working days/official holidays, GDP % growth etc. into consideration. While more than expected demand growth is expected to increase the electricity prices, demand growth vs installed capacity growth is effective on the spot prices as well.

Figure 1.6 Electricity Demand Growth in Turkey



Source: TEIAS

The electricity prices in Turkey differ among regions and they are up to some transmission congestions. To give you an example, electricity is mostly generated in the east side of Turkey while consumed mostly in the west side. It means that the prices would be much cheaper in the east than in the west if they were to be calculated region-wise. TEIAS announces its transmission investment program each year; however, there are often deviations from its current program since it requires huge investments and financing needs. There are public institutions like TEIAS, which estimated domestic demand growth based on this transmission program. Nevertheless, the transmission-related issues were ignored in this paper for ease of work.

Electricity price forecasting is hard to accomplish in Turkey for several reasons. First, historical data of hourly electricity prices goes only back to December 2009. Second, the market deepness requires improvement from the side of eligible consumers; although most of the electricity generators are actively operating under the umbrella of EXIST. Eligible electricity consumers, who are allowed to purchase power from EXIST are mostly residential consumers now considering that the government has lowered the limit in years. It is essential that residential consumers must be trained to be able to negotiate for the lowest possible market price. This is also important for market development competition purposes.

Additionally, unlike European markets, which are well-established and transparent, Turkish electricity market needs more liberalization. Despite the developments, the public sector's high dominance in price settings has a big impact on the market electricity prices as well. The market suffers from frequent changes in regulations. EXIST is relatively new and it requires EMRA's frequent interferences which hurts the market competition and predictability. The regulated electricity prices offered to captive customers are tried to be kept low for political and social welfare reasons. It sometimes might be lower than the spot prices that eligible consumers move to receive the regulated prices, which is a big risk for market competition.

On the other hand, electricity generation in Turkey is highly dependent on natural gas and coal. CCGTs and coal-fired power plants had around 70% of share in Turkey's electricity generation in 2017 (EMRA, 2017). However, there are problems with the regular announcement of the publicly available data for the related commodities. The exact monthly prices of gas and coal used at power plants and which amount of the production/imported amount is used for electricity generation, etc. are not known for most of the time. MENR, in order to increase transparency in the natural gas sector, made the spot gas market effective as of September 2018 under EXIST. Although it is a big step, the natural gas sector is still under the dominance of state owned gas importer/supplier BOTAS. Besides that, the natural gas supply is mostly dependent on Russia, which puts the supply security at stake for Turkey.

Lastly, volatility in the electricity prices spurs the market players to trade electricity at derivatives markets in some countries so that they hedge the risks of electricity market changes. In Turkey, the derivatives market for electricity is very shallow and there are not many future contracts to trade. It also points to a low predictability and a huge volatility in Turkish electricity prices.

1.5 Incentives & Recent Changes in Regulations:

Turkish electricity market has encountered several problems during the recent years. EMRA has made frequent changes in regulations to solve the issues. MENR also announced the National Energy and Mining policy, which prioritized supply security, localization and predictable markets. In this context, they focused on increasing the share of local product use and renewables in electricity generation. The recent developments at the Turkish electricity market were discussed one by one in chronological order and the stories behind them were given in details. First, what has recently happened in the natural gas market was explained. It was followed by the coal market, renewables and changes in the electricity pricing/market structure.

Natural gas is a big part of electricity generation in Turkey and 38.1% of the gas consumption was made at the CCGTs in 2017, the gas and electricity markets are quite interrelated (EMRA, 2017). Since there is only a small amount of domestic gas production in Turkey, it is considered to be dependent on imports to meet its gas needs in the long term. Turkey made 51.9% of its gas imports from Russia in 2017 while it was followed by Iran and Azerbaijan by the share of 16.7% and 11.9% respectively (EMRA, 2017). After the incident of Turkey's downing a

Russian warplane in November 2015, Turkish government was reminded of supply security and more attention was given to pipeline projects to import gas from other countries like Azerbaijan. TANAP was completed and started operating as of June 2018. The government has made efforts to build new gas storage units, LNG terminals and floating storage regasification units. Turkey's spot LNG imports showed a clear increase in 2017 (EMRA, 2017). The spot natural gas trade system became operational as of September 2018; thus; more data on the natural gas industry became publicly available. Following easing tensions between Turkey and Russia, Turkish Stream gas pipeline project was kicked off in mid-2017 in order to import gas from Russia and for Turkey to be a transit country to supply energy to European countries.

Turkey's state-owned natural gas importer and supplier BOTAS works in a way that it subsidizes the domestic market. It means that BOTAS tries to keep the gas prices low in order not to reflect the cost increases on to the consumers for social welfare. However, BOTAS came to the point where it could not subsidize the gas market and announced on July 31, 2018 that its prices would be in USD terms and the prices would be updated based on the current USD/TRY parity (BOTAS, 2018). It is due to the fact that following the production cuts of OPEC and rising demand pushed the oil prices upwards during the first ten months of 2018 (Bloomberg HT). While that moved the international natural gas prices up, huge depreciations in TRY against USD during the same period also surged the import costs of the natural gas. Overall, that caused a great pain for CCGTs for a while - Later in August, BOTAS fixed the USD/TRY parity at 6.5 in order to prevent more cost increases- since their raw material costs showed a huge increase while rise-ups in electricity prices were not enough to cover their expenses. Some of the CCGTs were closed down since their operations were not feasible anymore. MENR intervened at this point and released a new regulation called "Capacity Mechanism" on the Official Gazette in January 2018. By that regulation, fossil-fuel power plants such as CCGTs and coal fired power plants, which meet the required conditions like efficiency, installed capacity size and availability of this capacity, would be paid monthly through TEIAS as of April 2018. Hydropower plants were decided to be added to this mechanism as of 2019 by the regulation released in November 2018 (The Official Gazette, 2018). The payment would be made to the power plants of which unit electricity generation cost is higher than the market electricity price. Hence, MENR wanted to ensure that the power plants, which are high in the ranking of the merit order curve like CCGTs, will be financially supported to remain operating. Some consider the amount payed to the CCGTs under the capacity mechanism as little providing their huge raw material costs.

Turkish government, in order to take the foreign trade deficit under control wants to incentivize the production of raw materials, machinery and equipment used for electricity generation in Turkey. That's why the construction of local coal fired and renewable energy power plants are supported by the government prominently. The renewables were restated in the paper later on while the coal was first discussed here. Since the government wanted to limit the rising coal imports, 15 USD/ton of additional duty was implemented on imported coal in August 2016; however, it later was amended and eased not to create a price-up in electricity prices. There were also some speeches made by the government officials at the end of 2016 pointing out that they would like to stop granting new generation licenses to imported coal fired power plants (Dunya Gazetesi, 2016).

MENR initiated several support mechanisms for local coal fired power plants. First of all, electricity purchase guarantee for the electricity generated from local coal fired plants were extended. It was 130 TL/MWh for 2016 and 185TL/MWh for 2017 for a limited amount. Both prices were higher than the weighted average of DAM electricity prices at the time. Lastly, the purchase guarantee agreements were amended in December 2017 such that the first price was set at 201.35 TL/MWh for a period of 7 years for half of their installed capacities (The Official Gazette, 2017). The price was entitled to change based on the changes in CPI every 3 months. The purchase price right now is a bit higher than the DAM electricity prices. The fact that it is higher or lower than the market price is actually up to volatilities in USD/TRY parity. On the other hand, MENR announced an auction model in order to transfer the coal mines, managed by the public institutions such as TKI and TKK, to the private sector (Isbank, 2017). The auction, not only required the extraction of the coal but the construction of a local coal fired power plant near the mine. The first auction was realized for Cayirhan area in Ankara in February 2017. The selling price at the auction was determined as 6.04 USDcent/kWh which is higher than the DAM electricity price of 4.9 USDcent/kWh (Isbank, 2017). Since the government pledged a guarantee to purchase the electricity that will be generated from the power plant to be built in Cayirhan for 15 years, it is expected that these circumstances will cause financial imbalances in the public sector. If there comes a point where the public institutions are no longer able to subsidize the industry, then the market may encounter price-ups due to the cost factors as in the case of BOTAS, discussed above. Besides that, it is a worrying fact that it is getting more difficult to find financing for coal fired power plants due to global efforts to transfer dynamics to clean energy. It is however expected that Cayirhan-like auctions will continue to be implemented in the near future.

The recent developments in the renewables part of the electricity market are very important and considered to be effective for the electricity price forecasting purposes. The share of electricity generation in the context of YEKDEM was 17.1% of overall electricity generation in Turkey while YEKDEM's additional unit cost was calculated as 23.84 TL/MWh in 2017, 14.2% of the DAM prices (EMRA, 2017). As stated earlier, YEKDEM costs are reflected on the DAM prices and since the incentives are given in USD terms, an increase in the USD/TRY parity moves up the DAM prices through YEKDEM costs. According to a speech made by the Energy Minister at the end of 2017, YEKDEM will be finalized 2020 year-end and MENR will focus on YEKA projects (Dunya Gazetesi, 2017). Since YEKDEM was designed to support the renewable energy generation for 10 years, even if a renewable project was offered YEKDEM in 2020, it will be valid till the end of 2030. The noteworthy thing here to consider is how the market will proceed after YEKDEM and the impact of YEKA in the

DAM prices. YEKA auctions indicated that the market players have expected the cost of generating renewable energy will keep going down in the medium term.

YEKA are defined as the large zones located on the public or private properties assigned for large-scale renewable energy power plants provided that locally produced machinery and equipment are used at the power plants. YEKA will grant the winner of the auction a PPA at the price determined for 15 years (PwC, 2017). The winner will not receive the additional local production contribution under YEKDEM (Encon-Consult, 2017). The first YEKA auction was made in March 2017 for the construction of a solar power plant in Karapinar, Konya with an installed capacity of 1.000 MW. The selling price was determined as 6.99 USDcent/kWh at the auction where the opening price was 8 USDcent/kWh (Dunya Gazetesi, 2017). The second auction for the construction of a solar power plant with the same installed capacity is expected to be held in 2019. This time, the auction requires the winner to build a storage system as well. It has been planned that the project will be located in in three different cities: 500 MW of it in Sanliurfa, 200 MW in Hatay and 300 MW in Nigde. The opening price for the second auction was announced as 6.5 USDcent/kWh (Enerji Gunlugu, 2018). On the other hand, the first YEKA auction in order to set up a wind power plant took place in August 2017. The electricity price at the auction was determined to be a lot lower than the market expectations, 3.48 USDcent/kWh (Enerji Gunlugu, 2017). Although the winner explained it in a way that they would like to use a new technology and will make the related investments thanks to the cheap financing from an official export credit agency, the very low price at the auction hinted that the cost of the renewables has been moving downwards (Ekonomist, 2017). It has been planned that the power plants will be built in 5 different locations with a total installed capacity of 1.000 MW: 406 MW in Kirklareli, 294 MW in Edirne, 250 MW in Sivas and 50 MW in Eskisehir (Yesil Ekonomi). Moreover, it has recently been publicly released that the second YEKA auction to construct a wind power plant will be located in four different cities: Balikesir, Canakkale, Aydin and Mugla, each of them with a 250 MW of installed capacity. The opening price for the auction was decided as 5.5 USDcent/kWh (Yesil

Ekonomi). Lastly, the government announced its plans to establish the world's biggest offshore wind power plant in one location through one auction in Turkey under the YEKA mechanism. It was announced that the initial price at the auction will be 8 USDcent/kWh. The plant will be located either in Saros, Kiyikoy or Gelibolu with a total installed capacity of 1.200 MW (Enerji Gunlugu, 2018).

Although Turkey has a huge potential in terms of wind energy, it only represented 6.1% of the electricity generation in Turkey in 2017 out of transmission issues (EMRA, 2017). It is obligatory for TEIAS to make investments in order to connect the newly established plants to the national transmission line. Since TEIAS has a limited newly available capacity, it organizes capacity auctions in order to deliver the capacity to the lowest-price submitter. The reason why these capacity auctions were mentioned here is that there were surprisingly negative prices submitted at the auctions held in June 2017 for the capacity of 710 MW and in December 2017 for 2.1 GW. Negative prices mean that these plants, which could receive the capacity, will not take any YEKDEM support and sell their electricity at a price in USD terms, which is lower than the USD terms of the DAM electricity price for the first 10 years of their operations. It is considered that these investors assume that electricity prices will keep increasing in order to compensate the negative prices in the first 10 years with the higher prices later on.

The final points to be discussed here are related to the recent changes in Turkish electricity pricing/market structure. Following the crisis regarding the rising imported raw material and YEKDEM costs, it was getting very difficult for the electricity traders to supply electricity at a competitive price than the regulated retail prices, which is subsidized by the government. Rising electricity market prices made it very impossible for the electricity traders to make a profit. That's why a plenty of traders cancelled their agreements with the eligible consumers without reaching the due date of the agreements. It has led to a downfall in the number of eligible consumers as seen on the graph below and number of electricity traders in the market. Since that was a huge threat against the market competition, EMRA decided to take action and released a new regulation named as the last resource supply mechanism to be effective as of April 2018. Consumers, which were within the eligible consumer limits, but do not receive their electricity from the traders, became subjected to the last resource supply mechanism (The Official Gazette, 2018). Hence, it was initiated that they were forced to receive cost-oriented prices, which were actually quite high compared to their previous prices. The limit for that mechanism was initially set as 50 million kWh for 2018. Since they were mostly organized industrial zones, which could get over this electricity consumption limit, the electricity costs of these big industrial increased remarkably. The formula behind the mechanism is as follows where SKTT stands for the last resource supply price and KBK is the coefficient determined by the EMRA which was 1.128 for 2018.

$$SKKT_d = \left(DAM_d + YEKDEM_d\right) * KBK$$

Figure 1.7 Number of Eligible Consumers and Price Comparison

Source: EXIST, EMRA *(Industrial: Medium voltage daytime, Residential: Low voltage one time prices were used. SKTT was calculated from the equation above).*

On the other hand, EMRA has implemented several price-ups in the regulated prices since the end of 2017 due to the rises in oil prices and volatility in USD/TRY parity. Even EMRA had to announce the regulated prices a month earlier than its quarterly scheduled data release time and published the new regulated prices in September instead of October in 2018. Despite the consecutive and frequent price-ups, the price under the last resource supply mechanism was still higher than the regulated prices. This was a good move in order to reflect the costs in prices for a transparent electricity market; however, it was only big consumers, who were paying these high prices. Eventually, the limit for the last resource supply mechanism was lowered to 10 million kWh in November 2018 as of 2019 year-beginning.

Lastly, TETAS and EUAS were united under the umbrella of EUAS in July 2018 while TETAS was shut down permanently. As of the related date, EUAS has been the responsible public institution not only for electricity generation but trade and supply related issues. It is considered that this way the loss of TETAS was transferred to EUAS where the loss compensation would be handled in a better way via blending several duties in one hand.

All of these changes in regulation and recent unexpected developments in the sector have required making a recent electricity price forecasting study necessary. The cost-factor analysis was needed due to the volatility in foreign exchange rates and commodity prices. The structural market analysis was required in order to understand how the new mechanism would affect the DAM electricity prices eventually.

In addition to the real life market analysis, theoretical and statistical analysis was completed for forecasting in the electricity markets. The academic papers as well as some key studies for Turkish electricity market were examined for both international and domestic markets in order to see which kind of data and econometric models have been used in the past.

2. LITERATURE REVIEW

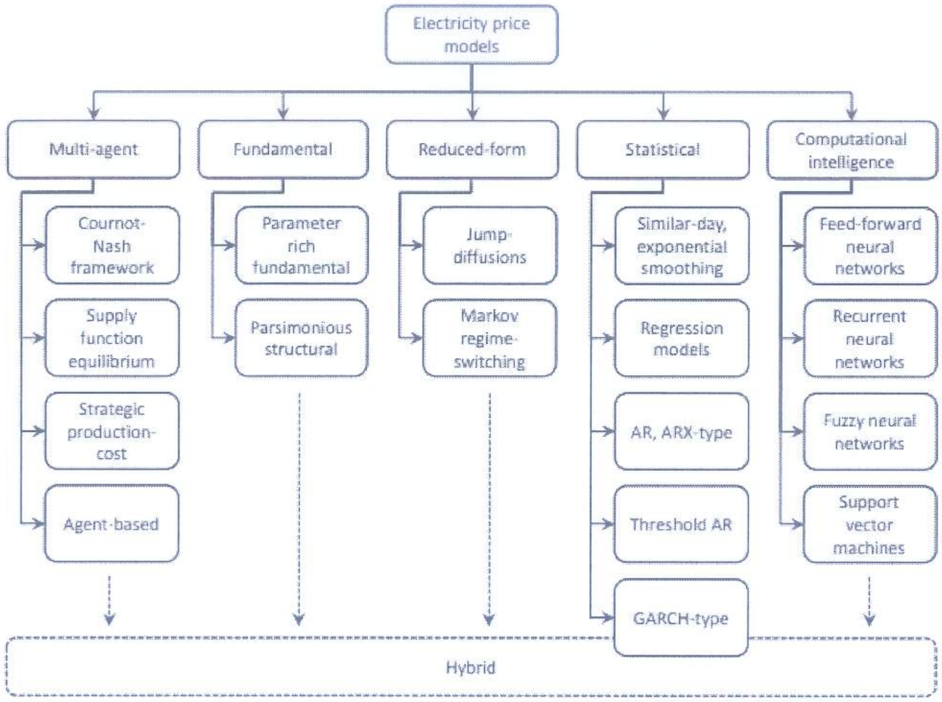
2.1 Electricity Price Forecasting:

Electricity spot prices are calculated within supply-demand working mechanism as any other commodities. There are temporal indicators such as wind power, temperature and number of rainy/sunny days as well as calendar effects such as number of working days and holidays to directly increase/decrease electricity demand. Since electricity has a specific structure that it cannot be stored and it is generated as much as demanded excluding the international electricity trade. It has an inelastic supply-demand function. The specific properties of electricity require analysts to use the most appropriate model and data to be able to get the most accurate results. There are a plenty of models that are used to forecast day-ahead electricity prices. The performance of the econometric model to forecast electricity prices were discovered to be data specific, i.e. information regarding which time period is used in forecasting and the frequency of the data are effective on the accuracy of forecasting.

Previous articles about electricity price forecasting used mostly the data from the developed countries such as UK and Australia where the electricity market is quite old and developed compared to Turkey. Most of them focused more on the electricity load forecasting rather than price forecasting. Besides, there are various articles on the electricity price forecasting, which were mostly written in the context of Global Energy Forecasting Competition initiated in 2012. The first competition, which was mostly on load and wind power forecasting, was followed by the others held in 2014 and 2017. The articles, written for the following competitions, were also mainly on energy demand/load forecasting using data from the US electricity market.

Electricity price forecasting can be made using several methods as the graph shows below:

Table 2.1 Electricity Price Forecasting Models



Source: Weron, 2014

Multi-agent modeling uses supply-demand fundamentals of the market and considers if the price is higher than the marginal cost for a power plant to keep operating. This modeling is considered to be used widely for qualitative issues. Fundamental modeling takes some economic and physical factors as assumptions to forecast the electricity prices. It is therefore very responsive to changes in the related assumptions. Reduced-form modeling; on the other hand, is a more quantitative and statistical model compared to the others and uses the past trend of prices in order to make estimations for the future. That's why it is not fully dedicated to finding the correct future price, but finding what is right considering the historical prices. Computational intelligence modelling works in a similar way as artificial intelligence methods. They use machine learning models to solve complex trends. Finally, statistical modeling, also used in this paper, has been mostly implemented in the past for electricity load forecasting. It uses econometrical and theoretical methods to calculate future prices. Since every method mentioned above has its own pros and cons. It has been recommended by the previous researchers to take advantage of all the methods by creating a hybrid models which cover all or some of the following modellings like dynamic regression model, neural artificial model, transfer function, Bayesian techniques, Monte Carlo simulation, other time-series methods, etc.

Use of ARIMA makes the forecasting outcome more effective for several reasons. First of all, it is good enough to create accurate results for electricity price forecasting. It gives powerful outcomes and could be used for non-stationary dataset such as electricity prices. Although recent studies were mainly focused on using artificial neural networks, ARIMA methods are much simpler to implement compared to machine learning methodology. ANNs are considered not intuitive and they do not provide an easy interpretation (Weron & Misiorek, 2005). They are flexible in terms of use of exogenous variables and dealing with data with unit roots and seasonality. Since they give outcomes of a linear regression, they are not good with forecasting volatility. That's why we wanted to combine GARCH models with AR terms to make better-fit estimations.

2.2 Academic Literature History:

Researchers have so far been implemented various ARIMA and GARCH models as well as a hybrid ARIMA-GARCH model to make forecasting. There are many sample articles in the literature combining ARIMA and GARCH models, similar to what were implemented in this paper. Some were dedicated to forecast indices/returns in bond and stock markets, prices in commodity markets and for exchange rate forecasting. The articles differ in terms of the characteristics of the data used to forecast such as the frequency, time interval or consideration of calendar/seasonality effects. There are also review articles elaborating on the econometrical methods used in the literature to make forecasting, among which this paper focused on the Weron's. Lastly, the articles, in which the related models were implemented and which the implementation was made on Turkish electricity market, were examined. Overall, we wanted to exemplify each of the above to have a wide understanding of the past research in order to make a more accurate modeling and forecasted results for our paper.

ARIMA-GARCH hybrid model was applied to Dow Transportation, S&P 500 and VIX returns retrieved from indices and good indicators were received from the models which was applied on 10 years of historical daily data to forecast for the next 10 days (Sun, 2017). After testing for the stationarity, AR and MA terms were calculated based on whose AIC was lower. Since ARIMA assumes that error process is homoscedastic over time, ARCH test was implemented on the residuals in order to see if there is an ARCH effect needed to be modeled. ARCH and GARCH terms were discovered based on the lowest AIC values. Since the fitness of the model was based on the simulations, it was explained that the accuracy of the forecasting needed some improvements. It was also considered important to combine this hybrid model to an ANN model in the upcoming studies.

Yaziz, Azizan, Zakaria and Ahmad also implemented a hybrid ARIMA and GARCH model in order to forecast gold prices in 2013. They used 40 daily prices to forecast the gold prices in the next 5 days and the hybrid model resulted in 1% of significance level. Out of 40 possible hybrid model combinations, the model with the lowest AIC was chosen as the best fit. The accuracy of the hybrid model was checked via MAE and MSE forecast evaluation criteria which gave quite low prediction errors.

In his review paper he wrote on electricity price forecasting in 2014, Weron touched a bunch of issues at international electricity markets. He underlined that the popularity of electricity price forecasting-related articles has risen since 2006 when he published a book on electricity price forecasting. Stating how the DAM operates and how the spot prices are created, Weron noted that it is important to know the details of the electricity market used for forecasting since each has its own structures and working mechanism. He also discussed that the data availability in the electricity market carves the way to make medium term forecasting rather than short-term since it takes some time for us to reach some of the market data. It was argued that the accountability of the statistical models is dependent on the quality of the estimated data and the statistical program used for forecasting. Even if there are more variables than the past electricity prices to be considered in the estimation, the existence of spikes in electricity prices makes it difficult to forecast very accurately. Additionally, it was stated that linear regression models, a statistical model also used in this paper, are still the most popular in the literature despite rising number of different models for electricity price forecasting. Explaining ARIMA models, Weron elaborated on the different techniques combining ARIMA model to others such as wavelet transform, exponential smoothing, GARCH, TARCH and ANN etc. since ARIMA is not able to forecast relationships other than linear ones. Referring to the future of electricity price forecasting, it was added that more analysis on point and density forecasting as well as more use of electricity market-related data such as reserve margins and national demand forecasts etc. will be observed in the upcoming period.

In a conference paper authored by Weron and Misiorek in 2005, ARMA and ARMAX models were calibrated and implemented on data series with/without an independent value of system loads to forecast electricity prices. The dataset was from Californian electricity market where the hourly prices and loads as well as DAM load forecasts were taken into consideration. They claimed that it would be wise to apply single stochastic models on price series to see their particular impact of the models for the reason that there are many studies on hybrid models taking various independent variables into consideration. Hourly price forecasting was achieved by using the prices from the same hour a day before and a week before as well as a function of all hourly prices from a day before. They used daily dummy variables for the days with high seasonality, Monday, Saturday and Sunday. Applying several models like seasonal ARIMA, ARIMA with an exogenous variable of loads, dynamic regression and transfer function, they ensured for the accuracy of their forecasts through checking for the daily and weekly prediction error terms.

In the paper written by Nogales, Contreras, Conejo, Espinola in 2002, time series regressions such as dynamic regression and transfer function models were implemented on the hourly electricity price and demand data from Spanish and Californian electricity market and the results were compared. They needed several fine-tuners to increase the forecast quality such as logarithmic transformation, outlier detection and mean elimination of unbiasness before taking its exponential to transform it to the original series. The same authors and some members of the organization called International Electrical and Electronics Engineers (IEEE), discussed electricity price forecasting in another paper using the ARIMA model in 2003. They concluded that they received more accurate price forecasts in the previous 5 hours in Spain and in the previous 2 hours in California applied on non-spiky prices since Spanish market prices are more volatile than California. It would contribute to the bidding strategy of the electricity traders in two different markets. Finally, in a different paper authored by Conejo, Plazas, Espinola, Molina and some members of IEEE in 2005, wavelet transforms and the ARIMA model was implemented on the price data from the year of 2002 and from the Spanish market. The dataset was divided into wavelets and then inverse wavelets were applied. No explanatory variables were used in the model since the paper mostly focused on the use of wavelets. Four weekly data from four different seasons were used to check for the accuracy of the model. Although the data was from four different periods, low prediction errors were received due to the fact that each group had similar internal features.

The Box and Jenkins method of autoregressive models were widely used in the literature review of electricity price forecasting. Jakasa, Androcec and Sprcic implemented ARIMA models on the daily spot electricity prices from the European Energy Exchange which operates as the electricity market for France, Germany, Switzerland and Austria. They used massive data for the period 2000-2011 from Germany's electricity market. They tested the stationarity of the data by autocorrelation and partial autocorrelation to find the best fitting ARIMA model. Finally, they tested the accuracy of the model via MAPE tests, which shows how far the forecasted dependent series differ from the predicted model.

MAPE gave a value of 3.55%. Besides, some calendar effect-related outliners were found out and added to the model on SPSS.

Joshi, Pandya, Bhavsar and Shah on a paper written in 2016 implemented seasonal ARIMA models on the Indian hourly electricity price data dated between 1st June 2013 and 31st May 2014 to forecast the prices a week later. Identifying the best fitted ARIMA model, they used ACF and PACF and they tested the accuracy of the right ARIMA model via residuals. They ensured that the residual ACF and PACF were white noise for the best fitted model. They stated that they received the best ARIMA model and the lowest MAPE value (4.457%) using the data dated between 1st December 2013 and 31st May 2014. They concluded that the difference between the actual and the predicted prices are explained through uncertainty in demand caused by the temporal and calendar effects.

On another IEEE Transactions on Power Systems paper, Garcia, Contreras, Akkeren, Garcia and some members of IEEE used some weeks of a time window (21 weeks for Spain and 15 weeks for California) in order to forecast the next 24 hours in the Spanish and Californian electricity market. To do so, they first applied an AR term for each day and hour. They used maximum likelihood function for estimating unobservable parameters. They applied GARCH and ARIMA models in the hourly price data on Spanish market for the year 1999 and Californian market for the year 2000. They considered electricity demand as an exogenous variable for the GARCH model. They concluded that GARCH model performed better than ARIMA model. Only in the months when the volatility was low, ARIMA performed a bit better. They additionally wanted to catch the price peak which occurred in the Californian market in 2000 through their estimation. A related study was completed by Li and Zhang for the Californian market and similar results were discovered via use of GARCH and ARMA models (2007).

According to a paper written by Tan, Zhang, Wang and Xu in 2010, wavelet transform model was combined with ARIMA-GARCH hybrid models. They differentiated their data as to use market clearing price for Spanish market in 2002 and locational marginal price for PJM market in 2006. They detailed that use of locational price was derived from possible transmission congestions happening in the US. The wavelet transforms they applied to the prices divided the dataset into parts; hence, to forecast the future prices in parts accordingly. They decided on AR and MA terms based on ACF and PACF plots and then checked if the residuals are white noise i.e. showing a flat pattern. They highlighted the clear difference between the MAPE of their proposed model and other previously used models in the literature to prove that use of wavelets and hybridization of ARIMA and GARCH grant more accurate forecasts.

Since it is believed that heteroscedasticity is a problem for the simple least square analysis, GARCH is considered helpful in order to overcome this issue (Hua & Li & Li-Zi, 2005). Based on the analysis they made on different electricity markets, they came up to the decision that electricity prices are not Gaussian and they possess fat tails i.e. they are heteroskedastic. Implementing GARCH(1,1), AR(1) and ANN models on hourly system marginal prices at English electricity market in 1999 to forecast 48 hourly prices, they received lower MAPE values for GARCH(1,1) model since they stated that it is better at catching volatility in the price dataset.

Reviewing the academic articles on forecasting in the Turkish electricity market, it was found that electricity price/load/demand forecasting has been achieved through the use of ANN models and fuzzy logic (Bilgic & Girep & Aslanoglu & Aydinalp-Koksal, 2010) (Cunkas & Altun, 2010). On the other hand, the combination of Autoregression with GARCH models has mainly been applied to gold prices, exchange rates or stock exchange indices (Gencer & Musoglu, 2014) (Akgul & Sayyan, 2008).

Next, the relevant articles on Turkish electricity market, which was considered helpful for our paper, were elaborated.

2.3 Publications by Institutions:

There are many variables to help explain the changes in electricity prices. Electricity demand, installed capacity, costs of raw materials such as natural gas, coal and the determinants of how much electricity is produced from renewable sources like air temperature, number of sunny/rainy days, water level at dams, wind force, etc. is supposed to be considered to create a detailed study on electricity price forecasting. There are other factors that need consideration to forecast electricity prices such as failures leading to the withdrawal of capacity i.e. planned outages for maintenance or transmission/distribution congestions. Although it is possible to create a forecasting model through the historical dataset of the variables, it is not easy to forecast on weather temperatures and transmission line problems. Additionally, when pricing is locational, transmission congestion can have a sudden and hard to predict effect although if the inclusion of new plants into the transmission grids is publicly announced beforehand, it can be included in the price calculation. Finally, when competition is less than perfect, some generators have the ability to influence prices to suit their own objectives. In Turkey's case, this dominant player is EUAS.

Since Turkish EXIST is new compared to the ones in Europe and there are still rooms for improvement in terms of transparency and liberalization, it is important to consider the forecasts made by the local organizations on Turkish electricity market. Since the market became operational around 3 years ago, the articles on Turkish electricity price forecasting is relatively new compared to the ones in Europe and the USA. Turkey's public transmission institution, TEIAS each year publishes its electricity demand forecasts for the next 10 years and its projections for Turkey's installed capacity for the next 5 years (TEIAS, 2018). These figures are used by the market players not only to compare with the actual demand figures but also to come up with some business outcomes in terms of how the electricity prices will evolve in the medium and long term.

TEIAS's electricity demand forecasts figures are published based on three different scenarios: low, base and high. They implement the following methods to make demand forecasting: sectoral regression model, a model in software named LEAP, artificial neural network & regression (monthly demand model) and flexibility models. According to the forecasted figures, which were based on the studies of MENR taking the GDP growth, population, calendar effects, temperature, electrical vehicles, energy efficiency, transmission loss and domestic consumption into consideration, Turkey's electricity demand is forecasted to grow by 4.7% CAGR between 2018-2027 according to the base scenario. It is expected to grow by 5.7% and 4.0% respectively based on high and low scenarios. Turkey's electricity demand showed a strong growth by 5.6% in 2017 due to the strong economic growth last year. Taking the base scenario as the main indicator, it is expected that Turkey's demand growth will slow down. Despite the fact that this effect will put a pressure on the electricity prices, it will be very dependent on the relation between supply and demand. According to TEIAS forecasts, Turkey will demand around 458 GWh of electricity by 2027 and it is approximately 55% more than the current electricity demand. It means that Turkey will need to keep receiving huge investments in electricity installed capacity in the upcoming periods to compensate its demand figures. This argument is detailed in Garanti Bank's projections.

Garanti Bank's Project Finance team released their electricity market projections in 2015 and has updated them yearly. However, there is only one report dated 2015, which is publicly available. Their forecast model considers many variables such as demand and installed capacity growth, raw material costs, technical details, temporal conditions, privatizations, regulations etc. Based on several assumptions, they calculated demand, supply and merit orders as well as EBITDA figures of power plants to decide if the plant can financially survive or not. Their prominent and differentiated outcomes are that renewables and local-sourced power plants will keep being financed by banks since they are covered by power purchase agreements. Share of natural gas will keep declining though their existence in the installed capacity mix will keep being important. Privatizations will have a pressuring impact on the prices since it is expected that the privatized plants will be operated more efficiently and their capacity factor will increase. The share of hydropower plants will keep being important in determination of the electricity prices: however, CCGTs will keep being the marginal plants in the merit order curve to decide the level of prices in the future. Finally, they determined that oil prices will be the determinant of prices in the long term. This study is a detailed analysis of Turkish electricity market and includes estimation of many indicators that are effective on the electricity prices. They made the price forecasting in USD terms excluding the fx rate fluctuations. On the other hand, it lacks use of an econometric model and bases some of the arguments on several assumptions. It is also difficult to make an accurate forecasting for weather conditions which also put the study in jeopardy in terms of calculating the correct prices.

To sum up the two related studies explained briefly above, unpredicted prices are only expected to occur in case of unexpected developments in supply and demand figures such as a troubles with acquiring raw materials, operations of power plants like plant closure for a long time due to maintenance, conditions with hydraulic conditions, financing new investments such as a switch in financing of thermal to renewables, the initial operation date of power plants and feasible operations of CCGTS. These are all the independent indicators influencing the prices, but difficult to estimate very accurately.

3. DATA & METHODOLOGY

There are many indicators to take into consideration forecasting electricity prices such as the factors related to electricity demand and supply since electricity prices are determined at the intersection of the supply and demand curve. Additionally, electricity is traded as any other commodity by traders and that's why trade-related factors should be taken into consideration to forecast prices as well. These include market estimates for electricity demand and load. There are also historical prices, weather conditions, calendar effects and transmission congestions etc. that might be considered for electricity price forecasting. Due to the reasons specific to Turkish electricity market discussed previously, exchange rates and exchange rate-related parameters should also be taken into account. Since the most important factors having an impact on electricity prices such as demand, installed capacity, YEKDEM costs etc. are published monthly, we wanted to consider as many as possible monthly-released exogenous variables in the modeling to see how effective they are on the prices.

At the beginning of the study, demand, industrial production index, DAM match volumes, installed capacity were plugged in the estimation as the variables important to determine the prices. Later on, monthly prices of imported coal and natural gas as well as domestic producer price index of local coal and natural gas distribution were added as variables which are cost-wise effective on the price-setting. Since YEKDEM costs as discussed earlier, are added up to the DAM prices, it was a must to take them into our estimation. Moreover, USD/TRY parity was included in the estimation for its impact on total imported raw material costs and YEKDEM costs, granted in USD terms. Several indicators like share of renewables and of private sector in electricity generation as well as share of eligible consumers in electricity extraction from EXIST and number of eligible consumers were also tried to use for modeling. A rise in the share of renewables in generation is expected to suppress the prices for the reason that it is cheaper to generate electricity utilizing renewable sources. The share of private sector and parameters with regards to eligible consumers are worthwhile considering the fact that Turkish electricity market has been liberalized and the dominance of eligible consumers mean that the prices are set in a more competitive environment.

Electricity demand figures were withdrawn from TEIAS. Industrial production index was also plugged into the equation as a demand indicator to see whose impact reflected more on the prices. In light of the fact that Turkey's electricity demand is mostly equal to the supply i.e. the amount of international trade is relatively low, monthly DAM physical match volume was also withdrawn from EXIST . Installed capacity figures, also published by TEIAS, were taken as a supply parameter. It is essential to note that this figure is released as cumulative data compared to other figures published as monthly data independent from one another. As the total addition to installed capacity was taken into the estimation, it would be also helpful to add the composition of installed capacity since each source used to generate electricity has different cost structure and diverse impact on prices. However, the publicly available composition dataset was not comprehensive enough for the estimation. Available installed capacity and reserve margins are taken seriously by several studies on electricity price forecasting. Available installed capacity is considered when a power plant is closed due to maintenance or a renewable plant does not operate if the temporal conditions are not met. Even though it is a very useful indicator to calculate prices, the data is only available yearly, not monthly. Reserve margin, on the other hand, is the surplus generation usually represented as capacity minus demand. If the reserve margin is X%, it means that the system has X% more capacity than the expected peak demand. Since it is not easy to evaluate and make a comment on this indicator, we did not want to add it to our econometric model. Paying close attention to electricity trading, it is traded in the market based on the market estimates for supply and demand. There are publicly available demand forecasts released by TEIAS as mentioned earlier and load forecasts also released by TEIAS (National Load and Dispatch Center under the control of TEIAS). Load forecasts are short term and demand forecasts are long term though demand forecasts are updated each year with upgraded datasets. That's why demand forecasts signal more about the market estimates for electricity prices for the upcoming year. In this paper, only past values of the demand figures were included into the estimation due to the requirements of the modeling used in this paper. TEIAS's demand estimates were placed in this paper later on in detail.

Cost factors are considered to have a big share in a plant's price determination. Reviewing the composition of electricity generation in Turkey, thermal plants still have a prominent share. Though a rise in the share of renewables, thermal plants are crucial in terms of their high ranks in the merit order. Natural gas and coal are two imported raw materials whose prices are determined differently based on the market specific facts and agreements between power plants and raw material exporter. Since Turkey's imported costs of natural gas and coal are not publicly available, European natural gas prices and South African coal prices released by World Bank were used in this paper. We wanted to add Colombian coal prices instead of South African prices for Turkey imports considerable amount of coal from Colombia. However, World Bank has recently stopped releasing the Colombian prices. As detailed earlier, the dominant natural gas supplier of Turkey, BOTAS did not act on the transparent pricing mechanism till lately (They started implementing transparent pricing at mid-2018 as discussed previously). Although there became a clear rise in international natural gas prices, it was possible for CCGTs not to experience any rise in their gas costs since BOTAS was not reflecting the rise in costs on the power plants for social welfare purposes. It is a known fact that a change in international natural gas prices is reflected in 6-9 months in lags by BOTAS (Isbank, 2017). The impact of the 6-month-lagged imported gas prices on the forecasting was also reviewed; nevertheless, it did not give statistically more significant results than the original imported prices. Overall, it was wise to take domestic producer prices of natural gas distribution published by TURKSTAT as they can be considered close to BOTAS's supplying prices. Use of producer price index instead of consumer price index made more sense since producer prices give a better signal on regarding power plants while consumer prices reflect the residential natural gas consumption. Local coal producer price index was also marked as an exogenous variable in the estimation.

YEKDEM costs were withdrawn from EXIST. There is a unit YEKDEM cost indicator published by EXIST as well. Because both of the indicators show identical patterns, we decided to take only the total YEKDEM costs, named YEKTOB, into our estimation. YEKDEM costs are related to the share of renewables in electricity generation as well. They are directly related; however, their impacts on electricity prices are inversely related. It was also necessary to add USD/TRY parity into the estimation model to observe its impact on electricity prices through YEKDEM costs and costs of imported raw materials. As mentioned previously in this paper, DAM prices have shown a significant increase due to the depreciation of TRY against USD. The parity also matters because of its effect on the merit curve since a rise in imported natural gas costs leads to a situation where the DAM prices are lower than the plants' marginal costs and shutdowns in some CCGTs.

Market liberalization is considered critical in price determination since a more liberal and competitive market brings more competitive prices. That's the reason why the share of private sector and eligible consumers-related indicators were added in the estimation model. The share of private sector in electricity generation was withdrawn from TEIAS while data on eligible consumers from EXIST.

For the sake of simplicity and clear comparison, the indicators such as transmission congestion or bank loans on energy sector were no covered in this paper though they have an impact on the prices as well. If the transmissionary data was to be used, it would be a must to consider locational prices that would make the forecasting complex and difficult. On the other hand, we needed to know the composition of bank loans in terms of renewables, thermals etc. that is data not published publicly. Besides that, temporal data is hard to retrieve and forecasting them monthly would not give accurate results. That's why weather-related indicators were excluded from the modeling.

Following the literature reviews and focused study on data characteristics, Autoregressions were used in order to forecast the linear trend between past and future prices and GARCH models were implemented in order to predict volatilities in our dataset. Since electricity prices in general show seasonality and possess unit roots, first it was necessary to check the seasonality via Correlogram and eliminate it via monthly dummy variables. Then, the non-stationary data was turned into stationary through logarithmic differencing. The dataset was split into two as Jan. 1, 2012 to Dec. 31, 2016 being the sample set and Jan. 1, 2017 to Aug. 31, 2018 being used to check if the sample test is forecasted accurately.

3.1 Seasonality Adjustment:

First of all, it was realized that electricity prices peak during winter and summer months meaning that it shows seasonality. To check for the seasonality of the data, ACF and PACF patterns on Correlogram were uncovered and examined. In addition to that, a dummy variable was created for each month to check how significant the seasonality of each month is and to eliminate the seasonality eventually.

ACF and PACF are explained statistically as in the following equation on E-views where $\bar{Y}$ is the sample mean and ACF stands for the correlation coefficient for Y and the value of Y k period earlier:

$$\tau_k = \frac{\sum_{t=k+1}^{\bar{}} ((Y_t - \bar{Y})(Y_{t-k} - \bar{Y}_{t-k}))(T-K)}{\sum_{t-1}^{T} (Y_t - \bar{Y})^2 / T}$$

PACF; on the other hand, is the regression coefficient at the period k when Y is regressed on a constant and it is the correlation between Y and Y k periods earlier excluding the effects of intermediate Ys. It is shown statistically as below on E-views:

τ_k is the estimated correlation at the period k and $\Phi_{k,j} = \Phi_{k-1,j} - \Phi_k \Phi_{k-1,k-j}$

$$\Phi_k = \tau_1 \text{ For k=1}$$

$$\Phi_k = \frac{\tau_k - \sum_{j=1}^{k-1} \Phi_{k-1,j}\tau_{k-j}}{1 - \sum_{j=1}^{k-1} \Phi_{k-1,j}\tau_{k-j}} \quad \text{For k>1}$$

The results from the ACF and PACF came as follows where ups and downs were observed on the Correlogram indicating some seasonality patterns.

Table 3.1 ACF and PACF Analysis of DAM Electricity Prices

Date: 11/29/18 Time: 12:16
Sample: 2012M01 2018M08
Included observations: 80

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.459	0.459	17.528	0.000
		2	0.252	0.052	22.886	0.000
		3	0.132	-0.003	24.360	0.000
		4	0.121	0.066	25.634	0.000
		5	0.063	-0.025	25.977	0.000
		6	0.102	0.082	26.896	0.000
		7	0.112	0.046	28.017	0.000
		8	0.033	-0.071	28.119	0.000
		9	0.052	0.056	28.369	0.001
		10	0.047	0.004	28.574	0.001
		11	0.230	0.247	33.625	0.000
		12	0.202	0.017	37.543	0.000
		13	0.141	-0.034	39.478	0.000
		14	-0.040	-0.164	39.638	0.000
		15	-0.100	-0.090	40.640	0.000
		16	-0.088	0.012	41.431	0.000
		17	-0.068	-0.029	41.919	0.001
		18	-0.052	-0.037	42.209	0.001
		19	-0.036	0.011	42.352	0.002
		20	-0.065	-0.058	42.820	0.002
		21	-0.217	-0.180	48.077	0.001
		22	-0.132	0.004	50.046	0.001
		23	-0.036	0.044	50.196	0.001
		24	0.065	0.096	50.696	0.001

Looking at the table above, it can be said that there is non-stationary where the ACF has a descending order at the beginning of the dataset and a unit root test was applied to identify the non-stationary later on.

To be able to check how significant months are in terms of seasonality, a dummy variable was appointed for each month as explained below:

γ_1 if t=January	γ_5 if t=May	γ_9 if t=September
γ_2 if t=February	γ_6 if t=June	γ_{10} if t=October
γ_3 if t=March	γ_7 if t=July	γ_{11} if t=November
γ_4 if t=April	γ_8 if t=August	γ_{12} if t=December

Afterwards, following regressions, where y_t is the explained (dependent) variable while y_{t-1} and dummy variables are the explanatory (independent) variables, were used to prove and eliminate the monthly seasonality:

$$y_t = \sum_{i=1}^{S} \alpha_i D_{it} + \beta y_{t-1} + e_t$$

Following the check for the seasonality using the dummy variables, it was observed that all monthly dummy variables, except the month 3, were statistically significant. Once the existence of the monthly seasonality was ensured, they were eliminated via the dummies as in the equation below where C stands for the estimated coefficients for each dummy:

$$mpnew = mp - D1*C(1) - D2*C(2) - D3*C(3) - D4*C(4) - D5*C(5) -$$
$$D6*C(6) - D7*C(7) - D8*C(8) - D9*C(9) - D10*C(10) - D11*C(11) - D12*C(12)$$

Table 3.2 Seasonality Check Using Dummies

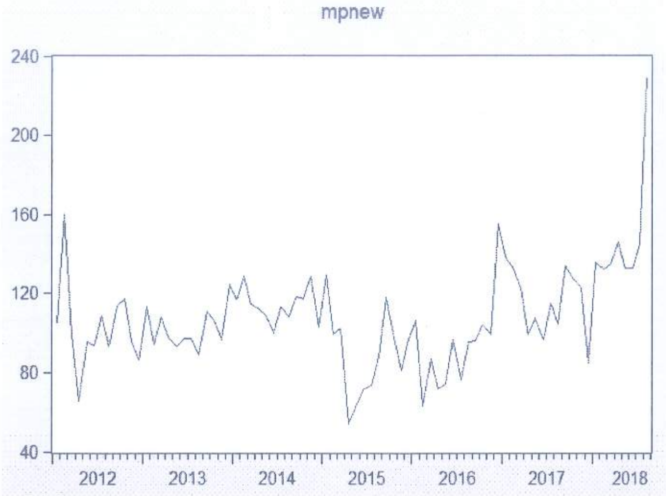
Dependent Variable: MP
Method: Least Squares
Date: 11/24/18 Time: 22:25
Sample (adjusted): 2012M02 2018M08
Included observations: 79 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MP1	0.680312	0.124731	5.454233	0.0000
DUMMY9	49.62275	22.91723	2.165303	0.0340
DUMMY8	72.94233	22.70821	3.212157	0.0020
DUMMY7	65.55377	20.78876	3.153327	0.0024
DUMMY6	54.66516	19.82666	2.757154	0.0075
DUMMY5	48.28983	19.48316	2.478542	0.0158
DUMMY4	49.36397	18.80339	2.625270	0.0107
DUMMY3	25.61850	21.76872	1.176849	0.2435
DUMMY2	45.66380	22.78818	2.003837	0.0492
DUMMY12	72.80513	21.80058	3.339595	0.0014
DUMMY11	55.47613	21.05630	2.634657	0.0105
DUMMY10	40.88503	22.39975	1.825244	0.0725
DUMMY1	49.56384	24.30744	2.039040	0.0455

R-squared	0.514315	Mean dependent var	160.1344
Adjusted R-squared	0.426009	S.D. dependent var	28.75531
S.E. of regression	21.78565	Akaike info criterion	9.149701
Sum squared resid	31324.57	Schwarz criterion	9.539610
Log likelihood	-348.4132	Hannan-Quinn criter.	9.305911
Durbin-Watson stat	1.977603		

As observed on the graph which shows the seasonality eliminated data series below, there is an upward trend at the end of the electricity price time series and there are volatilities in the time series. It means that the variance of the dataset is non-constant. Our new dataset was named as mpnew:

Figure 3.1 Seasonality Eliminated DAM Prices



3.2 Unit Root Test:

Since autoregression models require using stationary data as inputs, it was necessary to check for the stationarity of the dataset and convert the non-stationary data to stationary if it does not comply with it. The stationary data means that mean and variance of the data is constant over time. In order to check if the dataset was stationary or not, a unit root test called Augmented Dickey-Fuller test on E-views was used though it was already known from ACF and PACF analysis that the price dataset was non-stationary.

In this case, the null hypothesis is that data is not stationary, possessing a unit root and alternative hypothesis is data is non-stationary as shown below where α and σ represent the parameters to be estimated and x_t represents exogenous variables:

$$\Delta Y_t = \alpha Y_{t-1} + x_t^{'}\sigma + \varepsilon_t$$

$$H_0 : \alpha = 0$$
$$H_1 : \alpha < 0$$

Table 3.3 ADF Test of Seasonality Eliminated DAM Electricity Prices

Null Hypothesis: MPNEW has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.963485	0.3022
Test critical values:	1% level	-3.516676	
	5% level	-2.899115	
	10% level	-2.586866	

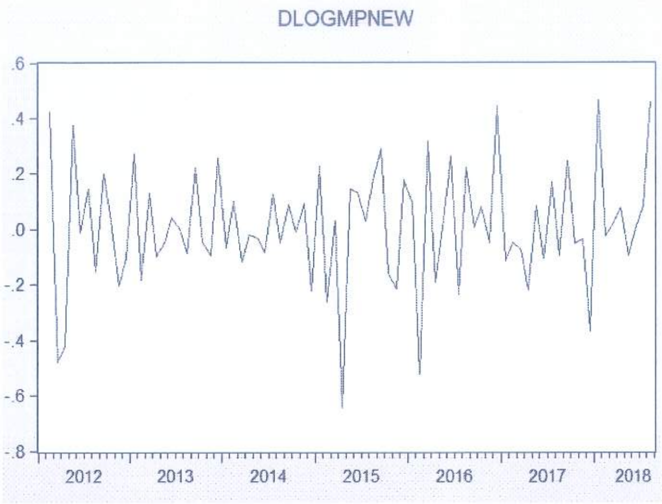
Applying the ADF test where only the 'intercept' was considered and not the 'trend', the null hypothesis could not be rejected at 5% level since the probability was higher than 5% and the absolute value of the t-statistics is lower than 5% t-statistics level. It means that the dataset has a unit root and is not stationary. Implementing the ADF test on each independent variable, it was discovered that it is only the share of the renewables in generation which showed a stationarity pattern. For the other non-stationary data, logarithmic differencing was used to make them stationary.

The logarithmic differencing is shown as below where *mp* stands for the DAM electricity prices:

$$d\log(mp) = \log(mp) - \log(mp(-1))$$

Following the logarithmic differencing, it was observed that probability and t-statistics came to the significant levels on a second ADF test. Therefore, the model was carried on using the latest, the logarithmic differentiated and seasonality eliminated data. The trend of the DAM prices after taking the logarithmic differencing is shown as on the following figure:

Figure 3.2 Log-Differenced and Seasonality Eliminated DAM Electricity Prices



4. EMPIRICAL STUDY

Before starting to work on this study, we wanted to make a price forecasting using ARIMA modeling. However, it made more sense not to use moving average terms but only autoregression terms since the errors and volatilities would already be used during GARCH modeling anyway. That's why we only took AR terms into account during GARCH modeling in order to use them to model linear relations. First, several autoregression models were implemented on the dataset with the use of different ARCH and GARCH modeling. Afterwards, RMSE and other error terms were checked in order to see the forecast accuracy.

4.1 Autoregression:

Autoregressive integrated moving average (ARIMA) method, as one of the ARIMAX models, is derived from ARMA, the combination of autoregression (AR) and moving average (MA). ARIMAX (p, d, q) is shown as below where p is the form of the dependent variable, d is the level of differencing and q is the number of AR and MA terms.

$$D(y_t, d) = \beta X_t + v_t$$
$$v_t = \rho_1 v_{t-1} + \rho_2 v_{t-2} + \ldots \rho_p v_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q}$$

Considering the seasonality and unit roots prior to ARIMA forecasting, our *d* value is considered 0 already since there is no longer need for differencing. *p* and *q* values are determined based on the ACF and PACF patterns and the most visible cut-offs are essential in determination of number of lags in autoregression. Use of the Correlogram to determine the number of AR and MA terms is explained on the table below:

Table 4.1 ACF and PACF Patterns for AR and MA terms

Model	ACF Pattern	PACF Pattern
AR (p)	Exponential decay, damped sine wave pattern	Significant spikes through first lag
MA (q)	Significant spikes through first lag	Exponential decay
ARMA (p,q)	Exponential decay	Exponential decay

Looking at the ACF and PACF pattern of the logarithmic-differenced and seasonality-eliminated sample dataset below, it was seen that there were similarities between ACF and PACF patterns which showed a cutoff at the first lag and had a descending order in higher lags. Since only the first orders were significant, it was rational to consider AR(1) model for forecasting. The other alternatives were to use AR terms up to the 4th lag, AR(1), AR(2), AR(3) and AR(4) terms and plug them into volatility modeling.

Table 4.2 ACF and PACF Patterns of the New Sample Dataset

Date: 11/29/18 Time: 13:12
Sample: 2012M01 2016M12
Included observations: 59

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.360	-0.360	8.0623	0.005
		2	-0.036	-0.191	8.1444	0.017
		3	0.056	-0.033	8.3493	0.039
		4	0.004	0.011	8.3503	0.080
		5	-0.132	-0.138	9.5102	0.090
		6	-0.005	-0.133	9.5117	0.147
		7	0.002	-0.098	9.5119	0.218
		8	0.051	0.015	9.6972	0.287
		9	-0.035	-0.012	9.7862	0.368
		10	-0.034	-0.081	9.8690	0.452
		11	0.064	-0.013	10.181	0.514
		12	0.069	0.094	10.544	0.568
		13	-0.015	0.097	10.561	0.648
		14	-0.059	-0.021	10.837	0.699
		15	0.029	-0.028	10.904	0.759
		16	-0.011	-0.012	10.915	0.815
		17	0.015	0.067	10.935	0.860
		18	-0.069	-0.022	11.358	0.879
		19	0.092	0.043	12.111	0.881
		20	-0.101	-0.096	13.052	0.875
		21	-0.024	-0.100	13.107	0.905
		22	-0.021	-0.095	13.148	0.929
		23	0.013	-0.079	13.164	0.948
		24	0.065	0.026	13.593	0.955

As detailed in the following section, the model with the smaller AIC value was taken as a better fit one. It was also important to check the R squared value and residual squared errors. R^2 value was supposed to be big enough to explain the impact of independent values on the dependent value. Since electricity demand, imported natural gas prices, industrial production, installed capacity, local coal prices, share of private sector in generation and total YEKDEM costs were also added as the exogenous variables into the estimation, it was necessary to check for their significance in the 5% significance level. No matter the constant value was significant, we added the constant to the equation anyway in order not to get a zero forecasted value. One can also say that the regression constant is generally not worth interpreting.

4.2 GARCH Modeling:

Since autoregression is good to estimate a linear trend, a GARCH model was necessary in order to model for the high variance/volatility in our dataset. The long form of GARCH is Generalized Autoregressive Conditional Heteroscedasticity. Heteroscedasticity is when the standard deviation and variance of a time series is not constant over time and conditional heteroscedasticity happens when you cannot specify the volatility of the time series in the future. GARCH models were introduced by Tim Bollerslev in 1986 as the developed version of ARCH first explained by Engle in 1982. GARCH is derived of ARCH, which is a model used to define the variance of error terms a function of historical error. While unconditional variance is constant, ARCH models make it possible for the conditional variance to differ over time as a function of historical errors. That sometimes leads to problems such as high volatility caused by the high standard deviation of previous values. GARCH models, on the other hand, are considered more flexible in terms of its lag structure compared to the ARCH model. They allow a large range of and persistent volatility (Bollerslev, 1986).

q stands for the order of autoregressive GARCH terms and p is the order of moving average ARCH terms at GARCH(q, p). ARCH is a special form of GARCH where GARCH(0,1) is an ARCH model. They work similar to AR and MA terms as discussed at the ARMA modeling earlier. Number of terms for GARCH modeling is also calculated using the same logic as on the Table 4.1.

There are three elements of an ARCH model, which are conditional mean equation, conditional variance and conditional error distribution. They are statistically shown as on the example of GARCH(1,1) below where the mean equation is a function of independent variables with an error term and the conditional variance equation is a function of the lagged values of squared residuals, which is derived from the mean equation, lagged values of variance and the constant term.

Conditional mean equation: $Y_t = X'_t\theta + \varepsilon_t$

Conditional variance equation: $\sigma^2_t = \omega + \propto\varepsilon^2_{t-1} + \beta\sigma^2_{t-1}$

On the conditional variance equation above, $\propto$ represents ARCH terms and β GARCH terms where if $\propto + \beta$ is close to 1, it means that the volatility is persistent and is vanished slowly.

The variance of GARCH(q, p) is in full form indicated as on the following equation:

$$\sigma^2_t = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \propto_i \varepsilon_{t-i}^2$$

For the third element of the ARCH model, E-views require us to assume for the conditional distribution of error terms and choose between some terms. The normal (Gaussian) distribution was selected and the estimation of ARCH models was made via maximum likelihood method, which requires that all the information must be available in the distribution and is shown for Gaussian distributions as below:

$$\text{Log-likelihood}_t = -\frac{1}{2}\log(2\pi) - \frac{1}{2}\log\sigma^2_t - \frac{1}{2}(y_t - X'_t\theta)^2 / \sigma^2_t$$

GARCH models were developed later on and new models such as Exponential GARCH (EGARCH), Integrated GARCH (IGARCH), Threshold GARCH (TGARCH), Power ARCH (PARCH) and Component GARCH (CGARCH) were created for different scenarios. In our estimation, we wanted to make use of EGARCH in order to see the effects of negative and positive developments on the volatility. EGARCH model was developed by Nelson in 1991. The conditional variance of EGARCH model is statistically shown as below on E-views:

$$\log(\sigma^2_t) = \omega + \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j}^2) + \sum_{i=1}^{p} \propto_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{k=1}^{r} \gamma_k \left|\frac{\varepsilon_{t-k}}{\sigma_{t-k}}\right|$$

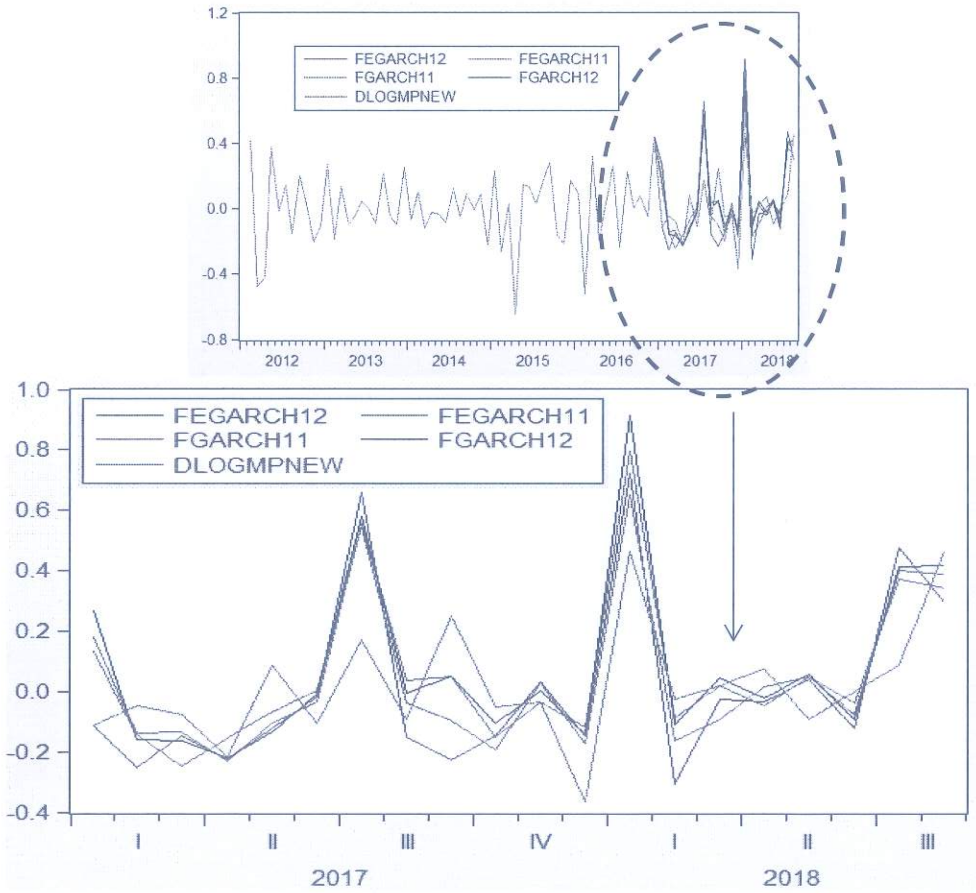
Since the conditional variance is represented as in its logarithmic term, it means that it can never be nonnegative. It is observed as the multiplicative representation of the lagged innovations rather than the additive representation of lagged errors at standard GARCH models. EGARCH also gives us the opportunity to choose an asymmetry order, which was chosen as '0' to understand the impact of good and bad news on the volatility.

4.3 Proposed Models:

As observed on the Correlogram of our seasonality-eliminated and logarithmic-differenced price series, there are significant cut-offs at the first lags. That's why we checked several GARCH models with one or two GARCH terms and zero or one ARCH terms like GARCH(1,0), GARCH(2,0), GARCH(1,1) and EGARCH(1,1) and with a combination of AR terms up to the 4^{th} lag in order to see how significant those AR terms are for GARCH modeling. Selecting the Gaussian distribution, we went on utilizing the fewest model parameters as resulting significant by the GARCH model. Only the following exogenous variables were taken into our estimation rather than all: demand, industrial production, installed capacity, share of private sector in generation, YEKDEM costs, imported natural gas prices and local coal D-PPI. Overall, the results of the estimated models were shown on the Appendices section. It was concluded that use of AR terms is significant in our estimation. More significant outcomes were received for the GARCH(1,1) and EGARCH (1,1) modeling. Thus, we kept on comparing the results of the following models: GARCH (1,1), GARCH(1,2), EGARCH(1,1) and EGARCH(1,2) using again different combinations of AR terms of which the maximum lag is 4. The results of these estimated models were also placed in the Appendices section. The best outcomes were received for GARCH (1,1), GARCH(1,2) and EGARCH(1,2) taking AR(1) and AR(2) terms into the estimation model, for EGARCH(1,1) using AR(1) term only.

Then, the forecasting process was initiated here where there was a selection between dynamic or static forecasting. The dynamic forecasting uses previously forecasted values in order to make forecasts for the future while static forecasting uses actual values to make forecasts, Since static forecasting considers actual values, it was considered that it would give more accurate outcomes for our forecast sample, which is dated 2017M01-2018M08. As seen on the forecasted sample, each four model was successful to catch the volatility at the beginning of 2018 and mid-2018. Differences are more visible when the volatility is relatively low. However, there appeared a high volatility in the forecasted samples at the beginning of 2017 though there was a comparatively low volatility in the actual dataset. The details of the fluctuations were discussed on the Results section after ensuring the best-fit model.

Figure 4.1 Forecasted Values of Each Model and Actual Values



(It is important to note that we had to use 2017M02-2018M08 as the forecast sample for EGARCH(1,2) because of its compatibility with static forecasting as there are 2 ARCH terms here)

4.4 Model Validation:

Akaike's Information Criterion (AIC) and Schwarz Criterion (SC) are used to find the best-fit forecasting model. The lower the AIC/SC is, the better-fit the model is.

According to the outcomes of the each model, the lowest AIC/SC values belonged to the EGARCH(1,2) model as shown on the Table 4.3.

Akaike Info Criterion: -2(*l/T*) + 2(*k/T*)

Schwarz Criterion: -2(*l/T*) + *klog(T)/T*

Table 4.3 Evaluation of Each Model using AIC/SC

	GARCH(1,1)	GARCH(1,2)	EGARCH(1,1)	EGARCH(1,2)
AIC	*-0.949412*	*-0.958152*	*-0.994629*	*-1.449939*
SC	*-0.479241*	*-0.451814*	*-0.564513*	*-0.943601*

However, in order to get the most accurate results, it was necessary to receive the lowest value of AIC/SC with lowest value of error terms. E-views offer four different methods in order to check for the accuracy of the forecast. They are RMSE, MAE, MAPE and the Theil Inequality Coefficient. RMSE, MAPE and MAE are shown as below where h is the number of periods in the forecast sample, T is the number of periods in the full sample and fy_t is the forecasted value of y at the time of t:

$$\text{Root Mean Squared Error} = \sqrt{\sum_{t=T+1}^{T+h} (fy_t - y_t)^2 / h}$$

$$\text{Mean Absolute Percentage Error} = 100 \sum_{t=T+1}^{T+h} \left| \frac{fy_t - y_t}{y_t} \right| / h$$

$$\text{Mean Absolute Error} = \sum_{t=T+1}^{T+h} |fy_t - y_t| / h$$

The results of the error terms of the proposed models were put into comparison. Although EGARCH (1,2) granted the smallest AIC/SC values, the RMSE value appeared the lowest for EGARCH(1,1).

Table 4.4 Error Terms of Each Model

	GARCH(1,1)	GARCH(1,2)	EGARCH(1,1)	EGARCH(1,2)
RMSE	*0.183976*	*0.206034*	*0.180899*	*0.228727*
MAPE	*1252.03*	*1493.684*	*740.9445*	*2112.001*
MAE	*0.145679*	*0.158862*	*0.15526*	*0.183402*

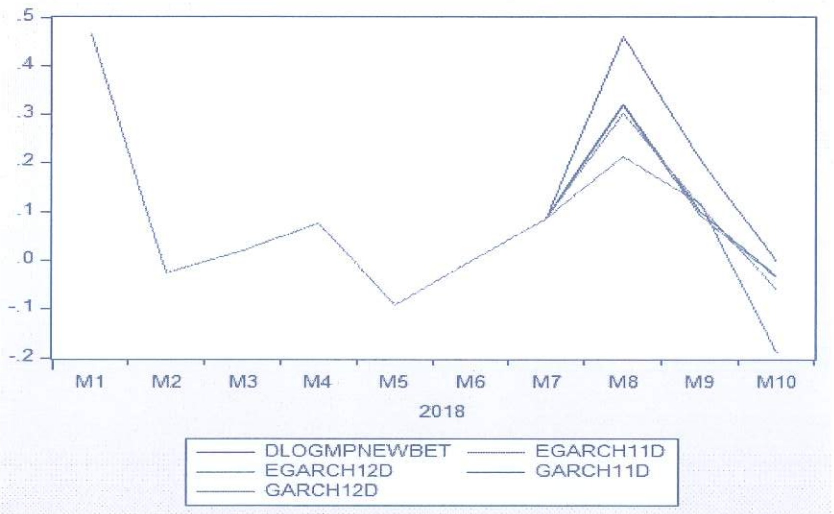
Additionally, EGARCH models were resulted with all coefficients being statistically significant while there appeared several insignificant independent variables for GARCH models. The absolute value of coefficients of installed capacity and local coal price index appeared the greatest among other independent variables.

In order to test the validity of the GARCH models, it was necessary to implement the following three tests, Ljung-Box Q statistics, normality and heteroscedasticity, on the residuals. Hence, it was ensured if the models were compatible with these requirements. The test results were placed on the Appendices. Correlogram squared residuals were checked to see if there is any autocorrelation left. ACF and PACF patterns of the models flat and probabilities were bigger than 5% significance level which is not enough to reject the null hypothesis that there is no serial correlation. Checking for the normality, Jarque-Bera statistics were applied to the residuals. For the reason that the Jarque-Bera statistics were realized as higher than the 5% significance level, the null hypothesis that the residuals are normally distributed could not be rejected. Finally, heteroscedasticity/ARCH LM (Lagrange multiplier) test was used to ensure for the heteroscedasticity. The probability of the test results was insignificant meaning that it was not in the 5 % significance level to reject the null hypothesis that there was no ARCH effect. Although it means that our residuals did not have an ARCH effect, we were able to use GARCH models since the residuals in our estimation models show a pattern where the high volatility is followed by the high volatility as shown on the Appendices section of this paper.

4.5 Multi-Step Ahead Forecasting:

Following the comparison of the actual dataset with the forecasted series, we wanted to see the multi-step ahead results of these proposed models. For the reason that the forecasted price was unknown at that time, dynamic forecasting was applied on the full dataset this time to find the prices for 2018M09-10. Since dynamic forecasting requires plugging all the exogenous variables for these two months, everything but the dependent variable was taken into the estimation for 2018M09 and M10. Because the prices for these two months were already publicly available, we had a chance to evaluate the results of the multi-step forecasting as well. We applied all four models on the dataset, 2012M01-2018M08 to forecast for the next two months. The forecasted prices were resulted quite close to its actual values as shown on the graph below. The error terms of GARCH(1,1) (RMSE: 0.140765) and EGARCH(1,1) (RMSE: 0.142235) ended up quite close to one another while they were resulted lower than the other two models.

Figure 4.2 Multi-Step Ahead Forecasting For Each Models



4.6 Results:

The comparison of forecasted samples using all the models and the actual data were indicated on the Figure 4.1. GARCH modeling helped determine the volatility in the electricity price dataset though EGARCH performed better than the regular GARCH models. When paying attention to only EGARCH(1,1) and EGARCH(1,2), which were resulted as statistically better-fits, the models were quite successful to catch the general trend of the actual prices. Use of AR terms also seemed logical as statistically significant outcomes were received when they were included. The EGARCH models were excellent at detecting the volatility at 2017M07, 2017M12, 2018M01, 2018M02 and the surging trend at the end of the forecasted sample. Moreover, it was later on discovered that use of all the proposed models was quite good to catch the downward trend in prices during these two months. However, it was clear that EGARCH(1,1) provided lower error terms compared to EGARCH(1,2) for multi-step forecasting as well.

On the other hand, EGARCH models were not enough to forecast some of the volatile points which would be explained precisely by the changes in the variables, previously excluded from the estimation due to their statistically insignificant levels. However, the addition of these variables had reduced the overall quality econometric model. Installed capacity and local coal price index appeared to have the biggest coefficients at both EGARCH models. When a change in actual prices was not explained mostly by changes in neither of these variables, it means that the estimated prices differentiated from the actual prices during that period. There are several times when neither of the forecasted models was very good at catching the actual data series. The most obvious of them are the peak points which occurred in 2017M02, 2017M05-M06, 2017M09 at the actual data, but were not realized at the estimated data as well as the peak point, which occurred in 2018M07 at the estimated data, but did not take place at the actual data.

When reviewed in details, a rise in DAM electricity price was observed in 2017M02 though variables other than the local coal price and industrial production index supported a decline in the price. The reason why the DAM price increased in February 2017 might be related to a decrease in share of renewables in the generation and rise in the local natural gas price, which were not included in the estimation model due to their statistically insignificance levels. In 2017M05-M06, there was a clear small up and down in the DAM prices, though the prices at the forecasted models kept increasing. This move might be related to the fact that USD/TRY parity showed a decline in that period pushing down the YEKDEM costs as well as the fall in the international natural gas prices in June 2017. Although YEKDEM costs and international natural gas prices were already included in our estimation model, their decreasing effect was not reflected on the forecasted prices. This might be due to the reason that the indicators like installed capacity and local coal price index with bigger numbers of coefficients did not show an observable change and industrial production index indicated a slight growth. Probably the most diverse forecasted data from the actual was realized in 2017M09 when the actual price data showed a clear peak while the estimated prices could not catch the volatility here. It was observed that demand figures were realized as greater than the same months in previous years. The electricity demand was around 14% higher in September 2017 compared to the same months in the last 3 years (TEIAS, 2018). Besides the strong demand, there was a significant growth in international natural gas and imported coal price, all of which might have supported a rise in prices. Nevertheless, TRY appreciated against USD during this period and it marked down the YEKDEM cost which would press down the prices. Although the absolute value of YEKDEM cost coefficient is lower than that of the demand, we still observed a downward price here. Actually, it is surprising that during this period the estimated price series using GARCH models were resulted more similar to the actual price series compared to EGARCH models. It might be due to the fact that the volatility here might have shown a more symmetrical trend than asymmetrical since EGARCH models are actually better-off to estimate asymmetrical reactions to both negative and positive shocks. Finally, the estimated prices peaked in 2018M07 and dropped in the next month. This is the period when Turkey started encountering wide fluctuations in the local currency. According to CBRT's database, USD/TRY parity surged by 20.7% in August 2018. This coincided with the BOTAS's announcement of a new pricing strategy. BOTAS initiated a more transparent pricing mechanism in August 2018 through which it released a current USD/TRY parity to calculate its selling price to its customers. Despite all these price increasing effects, the reason why the forecasted prices fell in 2017M08 might be related to the decrease in industrial production index and the fact that there were more additions made to the installed capacity compared to previous months.

Forecasting electricity prices, there was a great need to consider merit order, financial and regulatory limitations all together in the analysis. In Turkey's scenario, the merit order curve is expected to change in the upcoming period due to the reason that some of the CCGTs keep closing, the investments have been focused on renewables and the privatization deals on local coal fired power plants and a nuclear power plant is expected to be operative as of 2023. The merit order of Turkey's electricity market shows that the market is highly reliant on the marginal costs of natural gas prices. Since CCGTs in this case are able to reflect any changes in their costs to their selling electricity prices and BOTAS has started using transparent pricing mechanism for CCGTs, it means that the electricity prices will be dependent on the changes in the oil prices and fx rates. The recently introduced capacity mechanism will be much important for CCGTs to survive. It is not expected that new CCGTs and imported coal fired power plants will be built. The ministry has recently announced that they wanted to replace the installed capacity from imported coal with local coal by 10% in the near future. The investments are expected to be focused on local coal and renewables to which the government incentivizes. It is considered that YEKDEM will continue this time in TRY terms after 2020 that will decrease the fx risk burden on the market players. The nuclear power has a lower marginal cost than CCGTs in the merit order curve; however, the initial date of operation will be important on how the prices will move. Futhermore, the government's effort to increase the market competition will be watched closely in 2019. It is expected that the limit for the last resource supply mechanism is expected to get lower as of January 2019. It means that the regulated prices are expected to increase for the consumers whose electricity consumption is above that limit. It is aimed that the market competition is intensified again while the eligible consumers will consider being transferred back to the electricity traders. On the other hand, the government put a 10% decrease in regulated electricity prices for the resident consumers and small enterprises as of January 2019.

Despite the effects mentioned above that would be decreasing the prices in the future, the DAM prices are actually expected to be higher in 2019 for several reasons (Garanti Bank, 2018). First of all, it will take some years to complete all of the stated ongoing projects above. Although electricity demand % change yoy is expected to have declined in 2018, the projections for the installed capacity indicate that the installed capacity growth might decrease as well. The electricity market has been in the situation where the installed capacity was growing bigger than the demand. However, it is expected that the installed capacity growth will not be that fast in the next 2 years while demand growth is projected to be around 4.5-5%. On the other hand, the BOT, TOOR and BOO plants under the umbrella of TETAS, now EUAS, are expected to be privatized in the upcoming years and it is estimated that it will take time for them to compete with the low level of market prices since they have high marginal costs. Besides that, the oil prices are projected to recover from today's 55 USD/barrel levels to the levels above 60 USD/barrel. Nonetheless, it is expected that Turkey might receive some discounts on the price of natural gas imported from Russia due to long-lasting contracts with them. It is yet unknown to what extent these discounts will be reflected on the domestic market by BOTAS.

Changes in market dynamics are worth stating here since they are projected to affect the prices in the long run. Electrical vehicles (EV) are rising in popularity and use of blockchain is declining internationally. Additionally, Turkish government has recently released a guideline for energy efficiency projects. Electrical vehicles (EV) are expected to create demand starting from internally in cities to outside. It will keep the investment demand high in the distributed transmission network. Although the demand for EVs are surging, it is expected that it will take time to create widespread and sufficient numbers of charge stations to create a big burden on transmission networks. Lastly, public officials claim that regulations related to energy efficiency will help suppress the increase in electricity prices. They estimate that there will be 10.9 billion USD of investment in energy efficiency till 2023 and it will create 30.2 billion USD of savings up to 2033.

CONCLUSION

Making an accurate electricity price forecasting has recently become more essential in a country like Turkey where there is a current account deficit problem due mostly to energy imports. Additionally, Turkey's high dependence on imports has led to vulnerability in the country against fx rates. Turkey uses imported natural gas and coal in order to generate electricity and the share of imported raw materials was 54.1% in 2017. Electricity price have a considerable impact in inflation figures as well. Although the share of electricity in consumer price basket is relatively low, the share is considered higher taking the pass-through effect of producer prices. Considering the imported raw materials to generate electricity, electricity market has huge impact on the macroeconomic factors. Moreover, the energy sector has one of the highest shares among bank loans. Since energy investments are financed in USD terms, the volatility in fx rates make the market dynamics unpredictable. This situation has led policymakers grant some of energy incentives like YEKDEM in USD terms as well. These are the reasons why the electricity price forecasting requires considering the factors directly affected by changes in fx rates and the international commodity prices.

International articles focusing on the electricity price forecasting mostly used the data from comparatively old markets such as California and Spain. The price forecasting was mainly made using the hourly price series and for a short period time. Some of them only used electricity demand as the independent variable while most of them lacked any exogenous variables. Due to the fact that Turkey's electricity market is relatively new and is not as deep as the European and American electricity markets, there were not many studies in the literature on Turkey's electricity price forecasting. The ones in the literature were primarily concentrated on hourly prices to which artificial neural networks and fuzzy logic models were applied. The purpose of our study was to recognize the impacts of plentiful independent variables on the price determination. That required us to use monthly data, which was not widely implemented in the literature review.

Electricity prices show monthly and daily seasonality. They are mostly non-stationary. The elimination of these two issues and how to eliminate them were also discussed heavily and using several different methods in the literature review. In this paper, monthly dummy variables and logarithmic differencing were implemented for the related matters. Since it was already known that the Turkish electricity market has had huge fluctuations in recent months, use of GARCH models was rational. However, it was discovered that inclusion of AR terms to the model gave significant outcomes as well. Following a series of different GARCH and AR terms with them, EGARCH(1,1), with the lowest error terms, and EGARCH(1,2), with the highest estimation quality, were the better-fit models for our estimation. The models were strong to catch the big volatilities in the dataset and the general price trend accurately. However, some points were in the forecasted sample were missed due to the unpredictable market conditions. Even if this issue would be explained by other variables not included in the model or change in the EGARCH model, overall outcomes of the new models would not result in statistically significant ways. It is recommended that this study would be improved using hourly and daily price dataset with publicly available hourly and daily independent variables using the same models. The further study would be done for a period when the prices showed clear volatility and when the prices were mainly flat in order to see the impact of the proposed model on the original hourly frequency of the DAM prices. The studies would be updated once more numbers of independent variables are made publicly available.

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APPENDICES

Table A.1 The Comparison of Different Best-Fit Models between GARCH(1,0), GARCH(2,0), GARCH(1,1) and EGARCH(1,1)

Dependent Variable: DLOGMPNEW
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 12/06/18 Time: 13:26
Sample (adjusted): 2012M03 2016M12
Included observations: 58 after adjustments
Convergence achieved after 19 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(9) + C(10)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.028235	0.030298	-0.931896	0.3514
DLOGDEMAND	0.760775	0.280372	2.713453	0.0067
DLOGPRIVSHA	-1.275544	0.742722	-1.717390	0.0859
DLOGYEKTOB	-0.157237	0.086778	-1.811953	0.0700
DLOGINDPROD	0.900398	0.350519	2.568757	0.0102
DLOGINSTCAP	-13.40143	7.419037	-1.806357	0.0709
DLOGEURGAS	0.683029	0.248187	2.752078	0.0059
DLOGLOCCOAL	9.345287	2.522383	3.704944	0.0002
Variance Equation				
C	0.006753	0.005286	1.277474	0.2014
GARCH(-1)	0.622260	0.269798	2.306394	0.0211

R-squared	0.439254	Mean dependent var	-0.000595
Adjusted R-squared	0.360750	S.D. dependent var	0.216672
S.E. of regression	0.173236	Akaike info criterion	-0.692917
Sum squared resid	1.500530	Schwarz criterion	-0.337668
Log likelihood	30.09458	Hannan-Quinn criter.	-0.554540
Durbin-Watson stat	1.802981		

Dependent Variable: DLOGMPNEW
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 12/06/18 Time: 13:29
Sample (adjusted): 2012M03 2016M12
Included observations: 58 after adjustments
Failure to improve likelihood (non-zero gradients) after 77 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(9) + C(10)*GARCH(-1) + C(11)*GARCH(-2)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.046283	0.018289	-2.530675	0.0114
DLOGDEMAND	0.745458	0.156998	4.748206	0.0000
DLOGPRIVSHA	-0.986856	0.514006	-1.919929	0.0549
DLOGYEKTOB	-0.075984	0.067450	-1.126520	0.2599
DLOGINDPROD	1.255730	0.217118	5.783626	0.0000
DLOGINSTCAP	-11.31393	5.138798	-2.201669	0.0277
DLOGEURGAS	0.712519	0.160790	4.431352	0.0000
DLOGLOCCOAL	10.16039	1.215637	8.358079	0.0000
Variance Equation				
C	0.001095	0.000218	5.025242	0.0000
GARCH(-1)	1.625663	0.054544	29.80488	0.0000
GARCH(-2)	-0.698683	0.042659	-16.37831	0.0000

R-squared	0.371858	Mean dependent var	-0.000595
Adjusted R-squared	0.283918	S.D. dependent var	0.216672
S.E. of regression	0.183351	Akaike info criterion	-0.881700
Sum squared resid	1.680879	Schwarz criterion	-0.490927
Log likelihood	36.56931	Hannan-Quinn criter.	-0.729486
Durbin-Watson stat	1.642775		

Dependent Variable: DLOGMPNEW
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 12/06/18 Time: 13:34
Sample (adjusted): 2012M04 2016M12
Included observations: 57 after adjustments
Failure to improve likelihood (non-zero gradients) after 26 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(10) + C(11)*RESID(-1)^2 + C(12)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.008361	0.027055	-0.309015	0.7573
DLOGDEMAND	0.724519	0.321143	2.256059	0.0241
DLOGPRIVSHA	-1.536335	0.940063	-1.634289	0.1022
DLOGYEKTOB	-0.166578	0.080267	-2.075291	0.0380
DLOGINDPROD	0.702561	0.397874	1.765790	0.0774
DLOGINSTCAP	-16.04255	11.23496	-1.427913	0.1533
DLOGEURGAS	0.647447	0.246665	2.624806	0.0087
DLOGLOCCOAL	7.882899	2.362594	3.336544	0.0008
AR(1)	-0.332566	0.183544	-1.811912	0.0700
Variance Equation				
C	0.009178	0.004003	2.292948	0.0219
RESID(-1)^2	-0.109628	0.025670	-4.270598	0.0000
GARCH(-1)	0.600698	0.233201	2.575876	0.0100

R-squared	0.440910	Mean dependent var	0.007811
Adjusted R-squared	0.347728	S.D. dependent var	0.208839
S.E. of regression	0.168665	Akaike info criterion	-0.919921
Sum squared resid	1.365500	Schwarz criterion	-0.489805
Log likelihood	38.21775	Hannan-Quinn criter.	-0.752763
Durbin-Watson stat	1.622902		

Dependent Variable: DLOGMPNEW
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 12/06/18 Time: 14:09
Sample (adjusted): 2012M06 2016M12
Included observations: 55 after adjustments
Failure to improve likelihood (non-zero gradients) after 92 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(12) + C(13)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(14)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.001015	0.002720	-0.373277	0.7089
DLOGDEMAND	0.649273	0.002167	299.6787	0.0000
DLOGPRIVSHA	-3.927513	0.049764	-78.92267	0.0000
DLOGYEKTOB	-0.029925	0.016169	-1.850764	0.0642
DLOGINDPROD	0.142585	0.043844	3.252140	0.0011
DLOGINSTCAP	-17.30969	1.611841	-10.73908	0.0000
DLOGEURGAS	0.434581	0.042309	10.27156	0.0000
DLOGLOCCOAL	4.518134	0.313114	14.42969	0.0000
AR(1)	-0.197017	3.8E-103	-5.2E+101	0.0000
AR(2)	-0.248250	0.019096	-12.99978	0.0000
AR(3)	-0.118016	0.019684	-5.995535	0.0000
Variance Equation				
C(12)	-2.711638	8.6E-103	-3.1E+102	0.0000
C(13)	-2.755514	5.9E-103	-4.7E+102	0.0000
C(14)	-0.066780	0.010359	-6.446734	0.0000

R-squared	0.348744	Mean dependent var	0.008876
Adjusted R-squared	0.200731	S.D. dependent var	0.198280
S.E. of regression	0.177266	Akaike info criterion	-1.302939
Sum squared resid	1.382616	Schwarz criterion	-0.791982
Log likelihood	49.83083	Hannan-Quinn criter.	-1.105348

Table B.1 The Comparison of Different Best-Fit Models between GARCH(1,1), GARCH(1,2), EGARCH(1,1) and EGARCH(1,2)

Dependent Variable: DLOGMPNEW
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 12/06/18 Time: 16:05
Sample (adjusted): 2012M05 2016M12
Included observations: 56 after adjustments
Failure to improve likelihood (non-zero gradients) after 49 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(11) + C(12)*RESID(-1)^2 + C(13)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.021494	0.027005	-0.795912	0.4261
DLOGDEMAND	0.897928	0.357265	2.513340	0.0120
DLOGPRIVSHA	-1.462800	0.848206	-1.724581	0.0846
DLOGYEKTOB	-0.127768	0.067357	-1.896870	0.0578
DLOGINDPROD	0.977920	0.386663	2.529129	0.0114
DLOGINSTCAP	-11.50343	9.749935	-1.179847	0.2381
DLOGEURGAS	0.652020	0.017151	38.01623	0.0000
DLOGLOCCOAL	8.208664	2.332522	3.519222	0.0004
AR(1)	-0.247671	0.154793	-1.600013	0.1096
AR(2)	-0.273561	0.154076	-1.775494	0.0758
		Variance Equation		
C	0.008015	0.011702	0.684977	0.4934
RESID(-1)^2	-0.089931	0.144389	-0.622838	0.5334
GARCH(-1)	0.603601	0.680463	0.887045	0.3751

R-squared	0.576370	Mean dependent var	0.015450
Adjusted R-squared	0.493485	S.D. dependent var	0.202534
S.E. of regression	0.144143	Akaike info criterion	-0.949412
Sum squared resid	0.955753	Schwarz criterion	-0.479241
Log likelihood	39.58353	Hannan-Quinn criter.	-0.767128
Durbin-Watson stat	1.798565		

Dependent Variable: DLOGMPNEW
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 12/09/18 Time: 20:17
Sample (adjusted): 2012M05 2016M12
Included observations: 56 after adjustments
Failure to improve likelihood (non-zero gradients) after 34 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(11) + C(12)*RESID(-1)^2 + C(13)*RESID(-2)^2 + C(14)
*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.023015	0.031797	-0.723811	0.4692
DLOGDEMAND	0.873994	0.337941	2.586238	0.0097
DLOGPRIVSHA	-1.503856	0.923017	-1.629283	0.1033
DLOGYEKTOB	-0.149725	0.076472	-1.957903	0.0502
DLOGINDPROD	0.795030	0.391393	2.031283	0.0422
DLOGINSTCAP	-11.45784	8.756495	-1.308496	0.1907
DLOGEURGAS	0.745890	0.275475	2.707654	0.0068
DLOGLOCCOAL	9.145444	2.514977	3.636393	0.0003
AR(1)	-0.114479	0.001897	-60.36258	0.0000
AR(2)	-0.244977	0.179548	-1.364405	0.1724
		Variance Equation		
C	0.010676	0.012685	0.841681	0.4000
RESID(-1)^2	-0.011341	0.224855	-0.050436	0.9598
RESID(-2)^2	-0.119588	0.249116	-0.480049	0.6312
GARCH(-1)	0.513363	0.730906	0.702366	0.4825

R-squared	0.580475	Mean dependent var	0.015450
Adjusted R-squared	0.498394	S.D. dependent var	0.202534
S.E. of regression	0.143443	Akaike info criterion	-0.958152
Sum squared resid	0.946491	Schwarz criterion	-0.451814
Log likelihood	40.82827	Hannan-Quinn criter.	-0.761846

Dependent Variable: DLOGMPNEW
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 12/09/18 Time: 20:22
Sample (adjusted): 2012M04 2016M12
Included observations: 57 after adjustments
Failure to improve likelihood (non-zero gradients) after 206 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(10) + C(11)*ABS(RESID(-1)/@SQRT(GARCH(-1))) +
C(12)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.003629	0.009550	0.379980	0.7040
DLOGDEMAND	0.690177	0.148262	4.655127	0.0000
DLOGPRIVSHA	-2.223412	0.310216	-7.167312	0.0000
DLOGYEKTOB	-0.119087	0.034590	-3.442776	0.0006
DLOGINDPROD	0.647543	0.152209	4.254315	0.0000
DLOGINSTCAP	-13.65979	2.340282	-5.836815	0.0000
DLOGEURGAS	0.421476	0.212883	1.979848	0.0477
DLOGLOCCOAL	6.589302	1.167232	5.645236	0.0000
AR(1)	-0.213057	0.066708	-3.193876	0.0014
		Variance Equation		
C(10)	-0.664336	0.005770	-115.1305	0.0000
C(11)	-1.150324	0.003965	-290.1282	0.0000
C(12)	0.620924	0.001501	413.5798	0.0000

R-squared	0.438198	Mean dependent var	0.007811
Adjusted R-squared	0.344565	S.D. dependent var	0.208839
S.E. of regression	0.169074	Akaike info criterion	-0.994629
Sum squared resid	1.372123	Schwarz criterion	-0.564513
Log likelihood	40.34692	Hannan-Quinn criter.	-0.827471

Dependent Variable: DLOGMPNEW
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 12/09/18 Time: 19:07
Sample (adjusted): 2012M05 2016M12
Included observations: 56 after adjustments
Failure to improve likelihood (non-zero gradients) after 82 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(11) + C(12)*ABS(RESID(-1)/@SQRT(GARCH(-1))) +
C(13)*ABS(RESID(-2)/@SQRT(GARCH(-2))) + C(14)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.041051	0.003050	-13.46127	0.0000
DLOGDEMAND	1.273430	0.069208	18.40014	0.0000
DLOGPRIVSHA	-2.268207	0.003742	-606.1779	0.0000
DLOGYEKTOB	-0.076218	0.016545	-4.606650	0.0000
DLOGINDPROD	0.733889	0.035423	20.71808	0.0000
DLOGINSTCAP	-12.99731	0.418349	-31.06806	0.0000
DLOGEURGAS	0.482382	0.059244	8.142337	0.0000
DLOGLOCCOAL	7.916582	5.8E-101	1.4E+101	0.0000
AR(1)	-0.144229	0.031117	-4.634992	0.0000
AR(2)	-0.287071	0.005429	-52.87315	0.0000
		Variance Equation		
C(11)	-2.244898	2.3E-103	-9.7E+102	0.0000
C(12)	-1.203854	0.009957	-120.9103	0.0000
C(13)	-2.718714	0.014350	-189.4637	0.0000
C(14)	-0.118621	0.015427	-7.689369	0.0000

R-squared	0.496162	Mean dependent var	0.015450
Adjusted R-squared	0.397585	S.D. dependent var	0.202534
S.E. of regression	0.157198	Akaike info criterion	-1.449939
Sum squared resid	1.136709	Schwarz criterion	-0.943601
Log likelihood	54.59830	Hannan-Quinn criter.	-1.253633

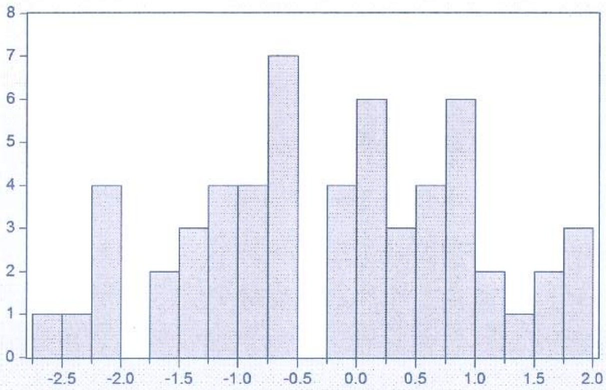
Table C.1 GARCH Modeling Test Results for EGARCH(1,1)

Correlogram – Q statistics

Date: 12/17/18 Time: 17:08
Sample: 2012M01 2016M12
Included observations: 57
Q-statistic probabilities adjusted for 1 ARMA term

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.111	-0.111	0.7410	
		2	-0.155	-0.169	2.2053	0.138
		3	-0.015	-0.056	2.2199	0.330
		4	0.160	0.130	3.8527	0.278
		5	-0.229	-0.214	7.2373	0.124
		6	-0.024	-0.034	7.2749	0.201
		7	0.000	-0.070	7.2749	0.296
		8	0.007	-0.051	7.2779	0.401
		9	-0.062	-0.024	7.5450	0.479
		10	0.101	0.046	8.2720	0.507
		11	-0.080	-0.094	8.7412	0.557
		12	0.050	0.045	8.9314	0.628
		13	0.004	-0.008	8.9327	0.709
		14	-0.062	-0.105	9.2345	0.755
		15	-0.087	-0.059	9.8416	0.774
		16	0.127	0.047	11.162	0.741
		17	-0.115	-0.131	12.271	0.725
		18	-0.096	-0.096	13.074	0.731
		19	0.093	0.037	13.838	0.740
		20	0.195	0.113	17.281	0.571
		21	-0.160	-0.066	19.675	0.478
		22	-0.022	-0.035	19.722	0.539
		23	0.133	0.060	21.470	0.492
		24	-0.036	-0.062	21.600	0.544

Histogram – Normality Test



Series: Standardized Residuals
Sample 2012M04 2016M12
Observations 57

Mean	-0.198837
Median	-0.000153
Maximum	1.920610
Minimum	-2.740865
Std. Dev.	1.184629
Skewness	-0.156283
Kurtosis	2.237850
Jarque-Bera	1.611604
Probability	0.446730

ARCH – LM Test

Heteroskedasticity Test: ARCH

F-statistic	0.768030	Prob. F(1,54)	0.3847
Obs*R-squared	0.785307	Prob. Chi-Square(1)	0.3755

Table D.1 Graph of Residual, Actual and Fitted Values for EGARCH(1,1) Model