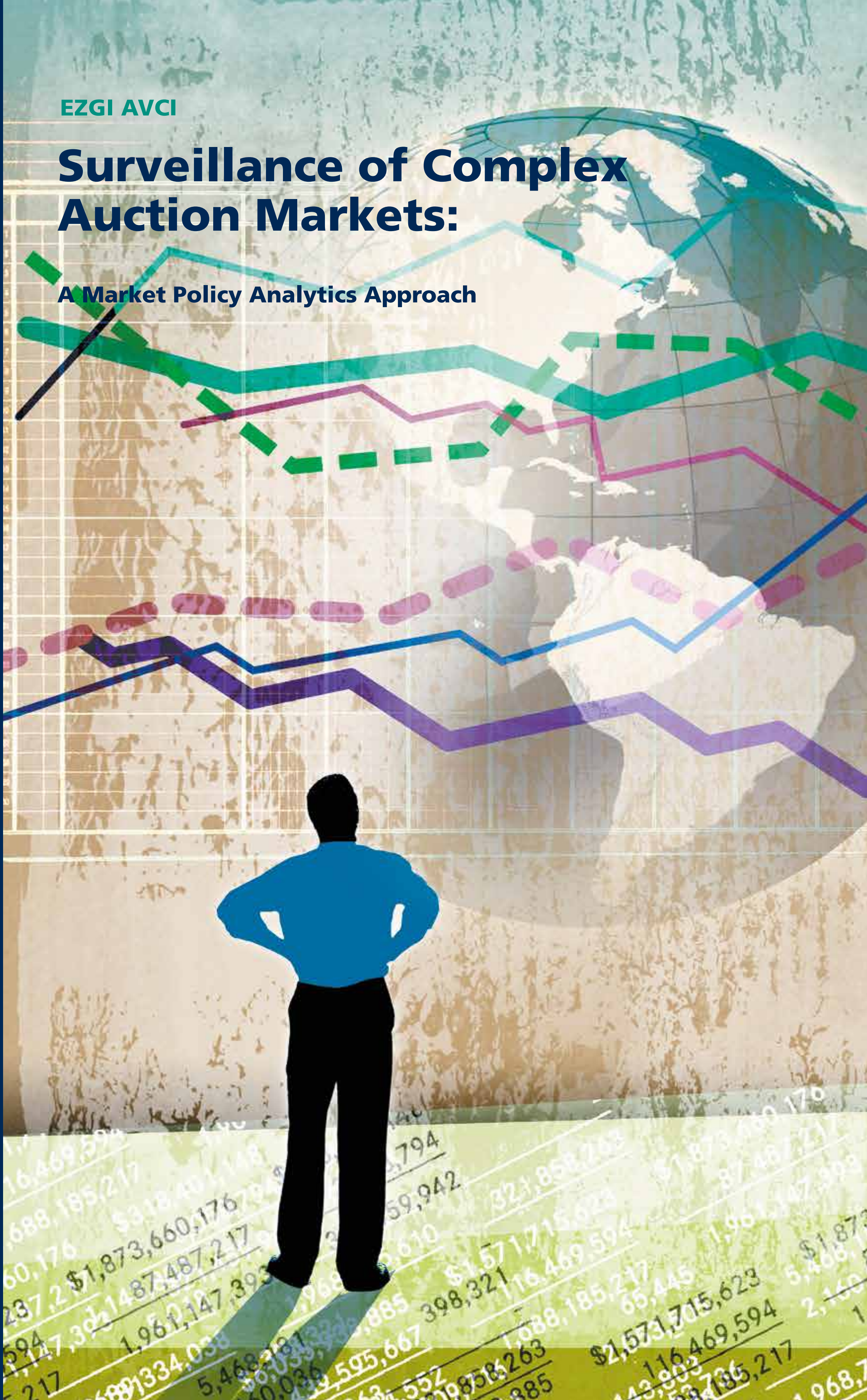
EZGI AVCI

Surveillance of Complex Auction Markets:

A Market Policy Analytics Approach



SURVEILLANCE OF COMPLEX AUCTION MARKETS: A MARKET POLICY ANALYTICS APPROACH

Surveillance of Complex Auction Markets: A Market Policy Analytics Approach

Toezicht op complexe veiling markten:
Een marktbeleid analytics benadering

Thesis

to obtain the degree of Doctor from the
Erasmus University Rotterdam
by command of the
Rector Magnificus

Prof.dr. H.A.P. Pols

and in accordance with the decision of the Doctorate Board.

The public defence shall be held on

Friday the 25th of May 2018 at 09:30 hrs

by

Ezgi Avci

born in Ankara, Turkey

Erasmus University Rotterdam

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Erasmus Research Institute of Management – ERIM
The joint research institute of the Rotterdam School of Management (RSM)
and the Erasmus School of Economics (ESE) at the Erasmus University Rotterdam
Internet: http://www.erim.eur.nl

ERIM Electronic Series Portal: http://repub.eur.nl/

ERIM PhD Series in Research in Management, 426
ERIM reference number: EPS-2018-426-LIS
ISBN 978-9058-92-514-5

Design: PanArt, www.panart.nl

This publication (cover and interior) is printed by Tuijtel on recycled paper, BalanceSilk®
The ink used is produced from renewable resources and alcohol free fountain solution.
Certifications for the paper and the printing production process: Recycle, EU Ecolabel, FSC®, ISO14001.
More info: www.tuijtel.com

Foreword

First of all, I would like to express my very great appreciation to my supervisors Prof. Wolfgang Ketter, Prof. Eric van Heck and Prof. Derek Bunn.

First, and foremost I would like to thank you, Wolf. If you weren't there at the first stage, when I got my Jean Monnet Scholarship, I could not start this wonderful journey at the Erasmus University. Thank you very much for your excellent scientific guidance, sharing your valuable insights and knowledge, continuous support, believing in me and giving me the space to develop my own work.

I feel so fortunate that Eric van Heck accepted to be one of my promoters. He is always the one wearing the pure IS glass and I learned a lot from him in terms of developing conceptual models, methodologies, and approaches. Eric, thank you very much for your high-level suggestions, excellent scientific guidance and encouraging me to pursue my own research interests.

Special thanks go to Prof. Derek Bunn, my promoter from London Business School, Management Science and Operations Department. Prof. Bunn, thank you very much for sharing your valuable insights and knowledge and helping me to polish different research ideas. You have always been very supportive and inspiring in many ways from the start of my Energy journey. I wouldn't have finished my dissertation timely and with such quality without your valuable suggestions, excellent scientific guidance and generous mentoring in every sense.

I would also like to thank the members of my thesis committee Prof. Robert Kaufmann, Prof. Schmuel Oren and Dr. Jan van Dalen for making it all the way from Singapore, Berkeley and Rotterdam to my defense. Thank you for your constructive feedback, support, and challenging questions.

I would also like to extend my special thanks to Prof. Kursat AYDOGAN (Bilkent University, Vice Rector), Selahattin CİMEN, PhD. (Deputy Undersecretary at the Ministry of Energy and Natural Resources (MENR), Doganbey AKGUL, PhD. (Head of Strategy Development Department at MENR), Yusuf YAZAR (Vice Head of Turkish Standards Institute, General Directorate of Renewable Energy at MENR), Zafer DEMIRCAN, PhD. (General Directorate of Energy Affairs General Directorate at MENR), Abdulkadir ONGUN (Member of Board at TEIAS), Fatih BAYTUGAN, MSc. (Head of Information systems at TEIAS), Erkan KALAYCI, PhD. (Head of Portfolio Optimization and Quantitative Analysis at Enerjisa), Fatih YAZITAS (Head of Market Surveillance Committee) and Baris SANLI (Lead Advisor of the Undersecretary of the MENR) for their support and invaluable comments throughout this study.

I would also like to thank Alp, Mehtap, Micha, Francesco, Mark, Rodrigo, Yashar, Jun and Kaveh for their valuable friendship and support. Ingrid, Cheryl, and Carmen thank you for all your administrative support. I am thankful for the comprehensive support I have received from the ERIM; Natalija Gersak, Kim Harte, Miho Izuka and Tineke van der Vhee.

Last but not least, I would like to thank my family for their unconditional love and support, making me the idealist and enthusiastic person today.

Finally, I greatly acknowledge financial support from Jean Monnet Scholarship in the area of energy funded by TR. Ministry for EU Affairs and TUBITAK under the project 114K601. I would also like to thank ERIM and the Erasmus Trustfonds for their financial support for my research visit, and the Oxford Institute for Energy Studies and London Business School for hosting me during my time in UK.

Disclaimer: It should be noted that the views in this thesis are entirely those of the author and do not represent those of the institutions with which she is/was affiliated with.

Oxford, December 2017

Ezgi Avci

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Chapter 1

Introduction

1.1. Motivation

As technology advances, the past two decades have seen an explosion of digital data and every sector of the global economy is being changed by the large amount of data available. This has enabled a different way of making decisions that involves more empirical evidence rather than personal experience, intuition, or belief. Such a new practice of "basing decisions on the analysis of data rather than purely on intuition" has been named *as data-driven decision making* (Provost and Fawcett, 2013). The revolution from data scarcity to large-scale data can be more thoroughly studied with the help of various *data analytics methods*. There is a desire to understand the methods and inquiry approaches that are used in organizations to achieve high quality, policy-relevant information (Kenett and Shmueli, 2017). What is needed is a framework for how large-scale data can be used to understand the impacts of different policies and the economic consequences of related decisions. As De Marchi et al. (2016) have stated, the analytics themselves are most useful for *evidence-based policy-making*, which ''helps people make well informed decisions about policies, programs and projects by putting the best available evidence from research at the heart of policy development and implementation" (Davies, 1999).

Auctions play a critical role in the modern society: governments use auctions to sell treasury bills, mineral rights and many other assets; firms use auctions to subcontract work, buy services and raw materials; individuals also participate in auctions of various consumer products such as art, antiques, cars, or even houses (Klemperer, 1999). The Internet has expanded the scope and reach of auctions tremendously: by breaking the physical limitations such as geography, time, and space, online auctions open up vast new opportunities for businesses of all sizes and become an indispensable part of the new economy (Bajari and Hortacsu, 2004). Over the past decades, Information Systems (IS) researchers have made significant contributions to *practical auction design* by investigating different bidding strategies and price dynamics in real-world auctions (e.g. Bapna et al., 2004; Kauffman and Wood, 2006; Goes et al., 2010; Bichler et al., 2010). Despite the great promise they hold, online auctions also pose many new challenges for practitioners and academics. For example, Bapna et al. (2001) point out that the behaviour of the different economic agents in auctions is heavily influenced by the online context in which they take place. Further, researchers have made considerable progress in the development of computational tools to facilitate decision making in complex auction markets (Adomavicius and Gupta, 2005; Adomavicius et al., 2009; Ketter et al., 2012; Mehta and Bhattacharya, 2006).

In this thesis we focus on the merits of data analytics for decision making in complex auction markets from the perspective of *Market Surveillance Committees (MSC)* whose main aim is to provide independent oversight and analysis of the auctions for the protection of consumers and bidders by the identification and reporting of market design flaws, potential market rule violations, and market abuse behaviour (CAISO, 2017). Duties of MSCs are review of market rules, performance and trends. More explicitly MSCs shall review existing and proposed market rules, tariff provisions, and market design elements and recommend proposed rule and tariff changes to the policy-maker/auctioneer. The MSC's review shall include but not limited to the identification of flaws in the overall structure of the related markets that may reveal undue concentrations of market power or other structural flaws. MSCs shall review and report on market trends and the performance of the wholesale markets to the policy-maker/auctioneer. MSCs shall identify and notify the enforcement staff of instances in which a market participant's behaviour or the behaviour of the auctioneer itself is suspected to constitute a market violation. In sum, the main activities of MSC can be summarized as follows: 1) Monitoring market efficiency (performance); 2) Monitoring market participants' behaviour through their activities and transactions (detection of attempts to exercise market power and fraudulent behaviour); and 3) Identification of market design flaws (Pinczynski and Kasperowicz, 2016).

With the proliferation of electronic trading, there are millions of events (orders, trades, price-quantity matches, etc.) per day and it is impossible for MSCs to detect suspicious activity manually. The standard way of dealing with such big data is to aggregate it and expressing it in summary form for the purpose of statistical analysis. Many market surveillance systems leverage these statistical techniques and technologies to quickly compare huge volumes of real-time data with historical data. Unfortunately, statistical analysis alone is not sufficient to fully understand what is happening amidst market complexity and why it is happening. When it is supplemented with behavioural analysis, MSCs can understand the intent behind strategic behaviour (NASDAQ, 2017, Behavioral Analysis in Market Surveillance Report).

Based upon the aforementioned recent developments in data analytics and the decision support needs of evidence-based policy-making, we raise the following research question:

How can the power of data analytics be leveraged to improve surveillance of complex auction markets?

1.2. Outline

The dissertation is structured as follows. This introduction is followed by a presentation of the research context in Chapter 2. In Chapter 3 we examine efficiency of the market by using parametric and semiparametric approaches for each time zone in a multi-time tariff setting. Then, in Chapter 4 we discuss how to manage price modelling risk via ensemble forecasts in a semi-transparent auction setting. In Chapter 5 we discuss how attitude and trading behaviour of bidders effect their price expectations in online double auctions with the existence of forward trading. Then, in Chapter 6 we discuss characterization, determinants and efficiency of strategic bidding in oligopolistic multi-unit auctions. Finally, we conclude our work in Chapter 7 and provide directions for future research. Figure 1.1 provides an overview of the structure of this dissertation.

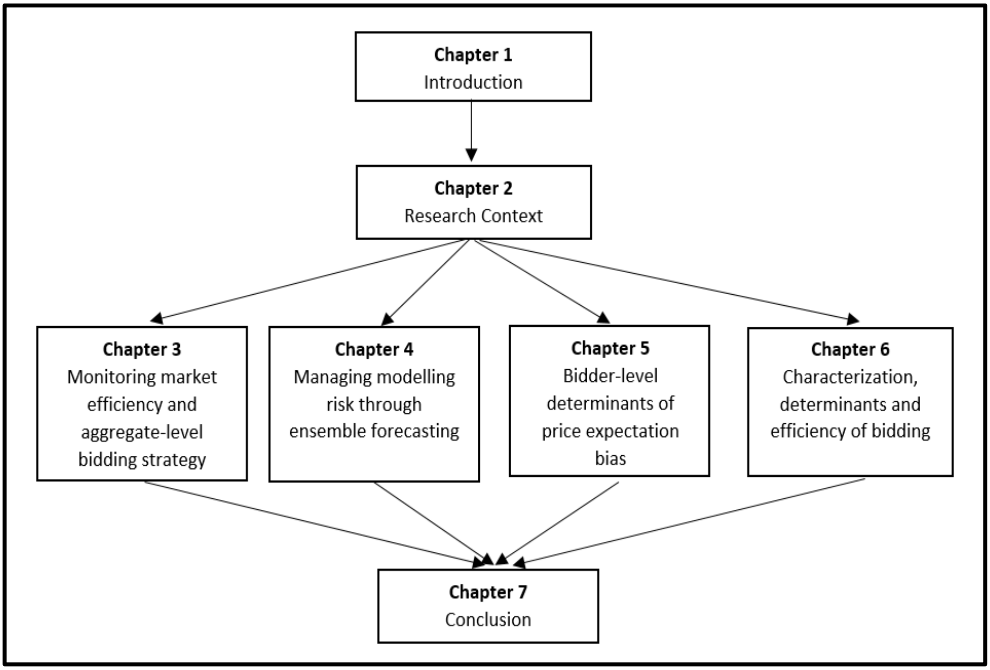

Fig. 1.1: Structure of the dissertation

In the following section we present a short description or a brief abstract of the contents of Chapters 2 through 7 of this dissertation.

Chapter 2 We explain the conceptual framework, auction mechanism and regulatory framework for surveillance of complex auction markets.

Chapter 3 - Abstract We examine the fractal dynamics of day-ahead electricity prices by using parametric and semiparametric approaches for each time zone in a multi-time tariff setting in the framework of bidding strategies, market efficiency and persistence of exogenous shocks. On the one hand, we find that electricity prices have long-term correlation structure for the first and third time zones indicating that market participants bid hyperbolically and not at their marginal costs, the market is not weak form efficient at these hours and exogenous shocks to change the mean level of prices will have a permanent effect and be effective. On the other hand, for the second time zone we find that the price series does not exhibit long-term memory. This finding suggests the weak form efficiency of the market in these hours and that marginal bidders bid at their marginal costs. Furthermore this indicates that exogenous shocks will have a temporary effect on electricity prices in these hours. These findings constitute an important foundation for policy-makers and market participants to develop appropriate electricity price forecasting tools and market monitoring indexes and to conduct ex-ante impact assessment.

Chapter 4 – Abstract There are two ways of managing market price risk in electricity day-ahead markets: forecasting and hedging. In emerging markets, since hedging possibilities are limited, forecasting becomes the most important tool to manage spot price risk. Despite the existence of a great diversity of spot price forecasting methods, due to the unique characteristics of electricity as a commodity, there are still three key forecasting challenges that a market participant must take into account: risk of selection of an inadequate forecasting method; transparency level of the market (availability level of public data); and country-specific multi-seasonality factors. We address these challenges by using detailed market-level data from the Turkish electricity day-ahead auctions, which is an interesting research setting in that it presents a number of challenges for forecasting. We reveal the key distinguishing features of this market in a quantitative way, which then allow us to propose individual and ensemble forecasting models that are particularly well suited to it. This forecasting study is pioneering for Turkey as it is the very first to focus specifically on electricity spot prices since the country's day-ahead market was established in 2012. We also discuss applicable policy and managerial implications for both regulatory bodies, market makers and participants.

Chapter 5 – Abstract In the presence of information asymmetry in imperfect auction markets, for an auctioneer it is of utmost importance to design a mechanism that gives robust price signals which in turn decreases bidders' uncertainty and thus increases auction performance. The traditional presumption that bidders form rational expectations by accurately processing all available information in the online trading environment and forming their expectations accordingly has found mixed support. In this study we aim to understand how the attitude and trading behaviour of bidders impact their price expectations in online double auctions with the existence of forward trading. We develop a research model that empirically tests the impact of bidders' attitudes on their price expectation through their

trading behaviour. Using a unique and extensive data set, we tested our hypotheses on real ex-ante forecasts, evaluated ex-post, in an electricity day-ahead auction context. This research is the first to take an information-based view to investigate the price expectation of bidders through their behaviour; with results that prompt further consideration of some of the conventional concepts.

Chapter 6 – Abstract We conduct an empirical investigation of bidder behaviour in a multi-unit uniform-price auction from a centralized product market, electricity auctions, with the existence of oligopoly. The susceptibility of these auctions to the exercise of unilateral market power makes them an ideal research setting to study the determinants of oligopolistic behaviour and productive efficiency. Since electricity auctions are regulated, they have detailed market surveillance rules that must be used by the auctioneer and define the feasible set of bidder behaviour. However with the proliferation of electronic trading, there are millions of orders per hour and it is impossible to manually detect market abuse behaviour. Leveraging the power of big data, we propose a behavioural analytics approach to address the cognitive and computational limitations of MSCs in their identification of diagnostic flags or signals of market manipulation.

Chapter 7 We revisit the most important conclusions and findings from Chapters 3 through 6, put them in perspective, and give an outlook on future work.

1.3. Declaration of Contribution

Chapter 1: This Chapter was written by the author of this thesis.

Chapter 2: This Chapter was written by the author of this thesis.

Chapter 3: This Chapter represents the joint work of the author of the thesis, Prof. Dr. K. Aydogan, and D. Akgul. The author of this dissertation is the first author of this Chapter and has done the majority of the work. The data collection, data analysis, programming, algorithm implementation, testing, and writing of the paper were done by the author of this thesis. The co-authors of this Chapter contributed by structuring the Chapter, providing significant guidance, and feedback. Without the co-authors this Chapter would not have been possible in its current form and quality.

Chapter 4: This Chapter represents the joint work of the author of the thesis, Prof. Dr. W. Ketter, and Prof. Dr. E. van Heck. The author of this dissertation is the first author of this Chapter and has done the majority of the work. The data collection, data analysis, programming, algorithm implementation, testing, and writing of the paper were done by the author of this thesis. The co-authors of this Chapter contributed by structuring the Chapter, improving modelling aspects of the paper, giving it more focus by rewriting parts of the Chapter, providing significant guidance, and feedback. Without the co-authors this Chapter would not have been possible in its current form and quality.

Chapter 5: This Chapter represents the joint work of the author of the thesis, Prof. Dr. W. Ketter, Prof. Dr. E. van Heck, and Prof. Dr. D. Bunn. The author of this dissertation is the first author of this Chapter and has done the majority of the work. The data collection, data analysis, programming, algorithm implementation, testing, and writing of the paper were done by the author of this thesis. The co-authors of this Chapter contributed by structuring the Chapter, improving modelling aspects of the paper, giving it more focus by rewriting parts of the Chapter, providing significant guidance, and feedback. Without the co-authors this Chapter would not have been possible in its current form and quality.

Chapter 6: This Chapter represents the joint work of the author of the thesis, Prof. Dr. W. Ketter, Prof. Dr. E. van Heck, and Prof. Dr. D. Bunn. The author of this dissertation is the first author of this Chapter and has done the majority of the work. The data collection, data analysis, programming, algorithm implementation, testing, and writing of the paper were done by the author of this thesis. The co-authors of this Chapter contributed by structuring the Chapter, improving modelling aspects of the paper, giving it more focus by rewriting parts of the Chapter, providing significant guidance, and feedback. Without the co-authors this Chapter would not have been possible in its current form and quality.

Chapter 7: This Chapter was written by the author of this thesis.

Chapter 2

Research Background

2.1. Introduction

In this Chapter, we first justify the choice of this empirical setting and then introduce this auction market in detail. All the empirical data used in this research were obtained from a complex auction market, namely, the Electricity Day-Ahead (EDA) auctions. The primary reason for choosing the EDA auctions as the research context is that they add real-world complications to the decision-making process in classical auction models. They are ideal research settings as they require detailed information-processing and these auctions clear through the actions of heterogeneous power bidders with expectations and strategies that have major effects on auction efficiency.

2.2. Electricity Auctions

Electricity wholesale markets are sequential clearing mechanisms which can be divided into four categories: day-ahead markets, intra-day markets, balancing and reserve markets, and forwards and futures markets. A day-ahead market determines the electricity prices for the delivery of electricity the next day, and this category of markets has a position of prominence. The prices coming from day-ahead markets are usually accepted as a *reference point* for the other electricity markets and bilateral contracts.

Day-ahead auctions represent a spot trading mechanism which takes place on one day for the delivery of electricity the next day (Figure 2.1). Market members submit their orders electronically, after which supply and demand are compared and the market price is calculated for each hour of the following day. The development of demand and supply on the market is completely determined by market parties themselves. Players are production and distribution companies, large consumers, industrial end-users, brokers and traders. All of these can be active as buyer or supplier. Making bids on the spot market is completely electronic. The bid from buyers and sellers must be made known one day in advance. After the closure of the day-ahead bidding, the auctioneer provides matching and sends the result to the bidders.

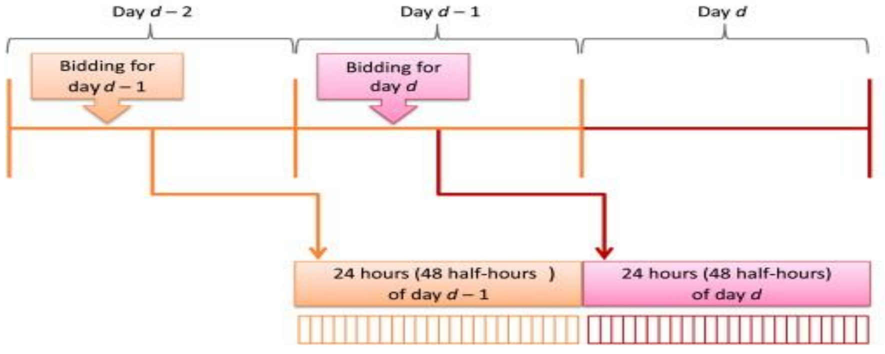

Fig. 2.1: Timeline of EDA auctions (Source: Weron, 2014)

2.3. The Auction Mechanism

Bidders can submit their orders for the next day every day until 11:30. Bids for the next day that are presented by bidders are used to determine the market clearing price (MCP) and market clearing quantity (MCQ) after collateral checking is performed and an adequate collateral amount is confirmed, in accordance with relevant procedures. Orders submitted to the auctioneer (market operator) are verified from 11:30 to 12:00. Verified orders are assessed between 12:00 and 13:00 using an optimization tool, and the MCP and MCQ are determined for every hour of that specific day. Trade confirmations, including quantities of bids or asks are announced to the relevant bidders each day at 13:00. Bidders can object to these notifications in the case of any errors regarding transactions between 13:00 and 13:30. The objections are evaluated from 13:00 and 13:30, and the results are then notified to bidders who made the objection. At 14:00, finalized prices and matched quantities for the 24 hours of the following day are announced. Bidders can submit their bilateral contract notifications between 00:00 and 16:00 each day. The processes described above are normal processes for EDA auctions and are illustrated in Figure 2.2. If any technical problems arise within the EDA auction system, emergency procedures are carried out by the auctioneer.

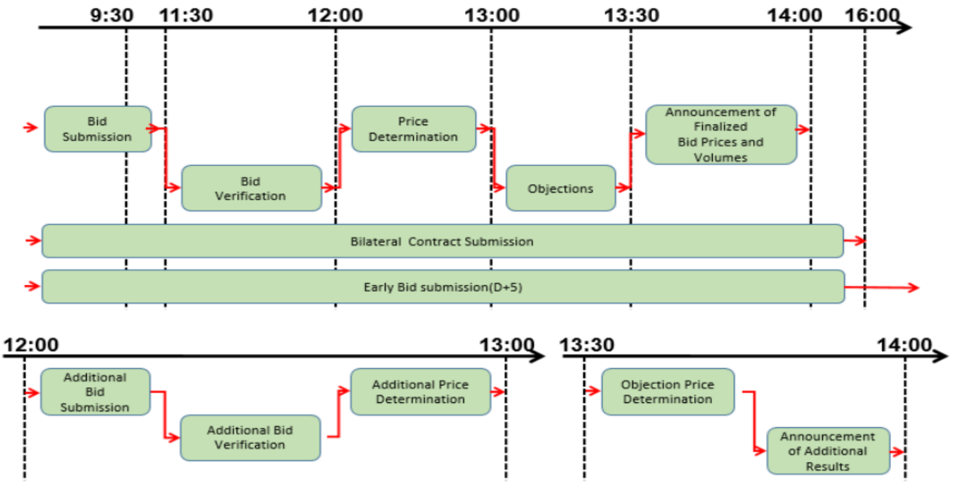

Fig. 2.2: Order submission timeline for EDA auctions

Bidders can submit orders hourly or daily for a particular hour or period of hours, or can make flexible orders. Orders are composed of quantity and price information that can change for different hours. Submitted order prices have centesimal sensitivity. Orders can be made in terms of Euro per MWh. Order volumes are submitted in terms of a Lot as an integer (one Lot is equivalent to 0.1 MWh). Orders can be submitted as bid and/or ask. Depending on the sign in front of the order quantity, the order is marked as either a bid or an ask (for instance, a 100 Lot indicates a bid, whereas a -100 Lot indicates an ask). A single order is a price and quantity schedule determined by the bidder. Basically, the bidders tell the auctioneer the price-quantity pair they are willing to trade for a particular hour of the next day. Table 2.1 demonstrates two single orders by a bidder for the first two periods of the day.

Table 2.1: An example for single orders

Hour	**Price (Euro)/MWh**					
	0	**50**	**80**	**120**	**200**	**2000**
0 – 1	600	400	0	-200	-500	-1000
1 – 2	300	300	200	0	-2000	-2000
…	…	…	…	…	…	…

For instance, in period 1, the bidder is willing to sell 200 MWh if the clearing price is above 120 Euro/MWh; and willing to buy 400 MWh if the clearing price is below 50 Euro/MWh. Each time period corresponds to an hour in the market. Single hourly orders have maximum 64 steps which contain 32 bids and 32 asks. The prices of single hourly orders must be listed in ascending order. In a single price step there cannot be valid single hourly orders for both bid and ask. During the formation of the supply-demand curve, the linear interpolation method is employed to interpolate values between two consecutive price/quantity steps. Minimum/maximum price limits and bid quantities are determined by the auctioneer. Depending on changing market circumstances, the auctioneer can update the minimum and maximum price limits and announce them to bidders.

2.4. The Auctioneers' Problem

The auctioneer's main goal is to plan, establish, develop, and manage the energy market within the market operation license in an effective, transparent, reliable manner that fulfils market requirements. The auctioneer aims to ensure the energy market management procures a reliable reference price without discriminating equivalent parties and maximizes the liquidity with an increasing number of market participants, product range and trading volume. In sum the auctioneer aims to create a *transparent mechanism which provides reliable reference price formation* and as a result actualize competitive conditions for investors and maximize the trading volume.

In the idealized theory, energy and related reserve scarcity prices would provide all that would be needed to support a market and capture the benefits of competition. In reality, there are many complications in achieving the theoretical results (Hogan, 2014). The characteristics of the product and the technology used to produce it make bid-based wholesale electricity markets extremely susceptible to the exercise of unilateral market power (Wolak, 2010). This situation raises the need for Market Surveillance Committees (MSCs) whose main objective is to provide independent oversight and analysis of the auctions for the protection of consumers and bidders by identifying and reporting market design flaws, potential market rule violations, and market abuse behaviour.

Market abuse behaviour on wholesale energy markets involves actions undertaken by persons that artificially cause prices to be at a level not justified by market forces of supply and demand, including actual availability of production, storage or transportation capacity. Certain types of behaviour such as; false/misleading transactions (trading, or placing orders to trade, which gives, or is likely to give, false or misleading signals as to the supply of, demand for, or price of wholesale energy products), price positioning (trading, or placing orders to trade, which secures or attempts to secure, by a person, or persons acting in collaboration, the price of one or several wholesale energy products at an artificial level, unless the person who entered into the transaction or issued the order to trade establishes that his reasons for doing so are legitimate and that transaction or order to trade conforms to accepted market practices on the wholesale energy market concerned), transactions involving fictitious devices/deception (trading, or placing orders to trade, which employs fictitious devices or any other form of deception or contrivance), dissemination of false and misleading information (giving out information that conveys a false or misleading impression about a wholesale energy product where the person doing this knows or ought to have known the information to be false or misleading) are considered as market manipulation (REMIT, 2011) and can amount to market abuse.

MSCs shall report possible market abuse behaviour to the auctioneer in a timely manner. Based on these expert reports, the auctioneer can influence the dynamics of auctions by controlling the key auction parameters including the number of bid steps, the minimum bid price or the maximum ask price. Further, the auctioneer can also influence the bidding competition by disclosing or withholding extra information about market states during an auction (level of market transparency).

Chapter 3

Monitoring Market Efficiency and Aggregate-level Bidding Strategy[1]

3.1. Introduction

In recent years most electricity markets have been restructured and in this setting, energy-based financial products and electricity price analysis become substantially important for both policy-makers and market participants. After the famous California blackout in 2000, a significant increase in the number of studies on price forecasting was observed. Preliminary studies focused on the basic characteristics of electricity differed from those of financial assets, namely; non-storability, seasonality and inelasticity of supply/demand (Zachmann, 2008; Lucia and Schwartz, 2002; Geman and Roncoroni, 2006; Sensfuss et al., 2008). Following studies focus on spikes, causing asymmetry in the underlying distribution; nonstationarity and mean reversion (Knittel and Roberts, 2005; Haugom et al., 2011; Janczura et al., 2013; Simonsen, 2003; Weron and Przybylowicz, 2000).

Considering security of supply, another crucial feature of electricity is the intraday volatility arising from demand fluctuations during the course of the day. Regulatory authorities usually oblige the system operators to adopt multi-time tariff mechanisms in order to manage peak-time volatility. In these tariff settings, different rates are applied for the consumption at defined time zones during the day. The bills of the subscribers under this setting are arranged by considering their consumptions at the defined time zones and the

[1] This Chapter is based on Avci-Surucu, Aydogan and Akgul (2016) published in *Energy Economics*, 54, 77-87. Parts of this Chapter appeared in the following conference proceedings: 55th EWGCF, Euro Working Group for Commodities and Financial Modelling Conference. Ankara, TURKEY and 4th Energy Finance Conference, Erice, ITALY.

rates for these time zones with the aim of shifting the load from peak time to off-peak time and thereby enable the end user to manage his energy costs and allow generators to operate efficiently. This situation results in different incentives on generators side. Generators, with the ability of flexible offering, tend to adopt different bidding strategies at super peak, peak and off-peak times.

Studies on analysing dynamics of day-ahead prices ignore the different characteristics of time zones in multi-time tariff settings and consider the daily average prices.[2] However daily average prices do not capture the microstructure of the day-ahead market since level of mean reversion and volatility structure are not constant throughout the day (Huisman et al., 2007). Other studies consider hourly prices as a stack and ignore the fact that day-ahead electricity prices are determined a day before the trading day for all 24 hours, that is traders cannot update their information set hourly. Under this setting, information set is not constant throughout the day and updates over the days. Applying a classic time series approach to hourly day-ahead prices can be misleading from a statistical point of view. Huisman et al. (2007) model each hour as a separate time series through a panel data methodology and find the mean reversion of day-ahead prices is significantly lower over the super-peak hours (18:00-22:00). Thus prices are less predictable in these hours. Moreover they show there exists clear blocks of cross-sectional correlation between specific hours. The first block appears in 24:00 – 06:00, second block shows up through 6:00 to 19:00 and also there is very high correlation between specific two adjacent hours (between hours 20 and 21; between hours 15 and 16). These findings reveal the different dynamics in hourly prices but similar characteristics in each time zone.

There are also emerging studies of applied mathematics in the field of electricity pricing and market modelling, especially, by the use of game theory, stochastic differential equations and mathematics supported data mining (Vasin et al., 2013; Vasin, 2014). However the literature on electricity price analysis focuses mostly on the features of autocorrelation, stochasticity and nonlinearity. Only a small number of studies analyse the presence and quantification of fractality (long-term correlation structure) and very few of

[2] For a comprehensive overview, see Huisman and Mahieu (2003), Eydeland and Wolyniec (2003) and Bunn and Karakatsani (2003).

them relate these findings to basic financial concepts; namely multi-time tariff mechanism, market efficiency, bidding structure or policy development.

Accurate measurement of fractality is crucial for correct statistical inference and forecast uncertainty (Lildholt, 2000). There are three reasons stimulating this fact. First, ignoring the long memory property in a series can lead to confidence intervals for a process mean that are too optimistic by orders of magnitude. Second, there are many important economic time series exhibiting long-term correlation structure (Beran, 1994). Moreover the potential for spurious regressions of stationary variables depend on the level of fractal noise (Tsay and Chung, 2000).

Economic intuition of the presence of long memory structure in electricity prices is important on several fronts. First, if electricity prices are stationary in levels, shocks to electricity prices will have only transitory effects. On the other hand, if electricity prices are nonstationary, shocks to electricity prices will have permanent effects. The nature of a shock has implications for transmission of that shock from electricity prices to other sectors of the economy. If shocks to electricity prices are permanent, then the probability of transmission of such a shock to other sectors of the economy, where energy prices have a substantial impact on expenditures, would be higher than the probability of transmission of a transitory shock.

Secondly, the presence of fractal noise in electricity prices can be used to capture the bidding strategies of market participants. In restructured electricity markets, the probability of setting the price each hour is not the same for all market participants, mostly because they have different marginal costs. Each hour, the market clearing price is determined by just one generator, called the marginal generator, whose bid is at the intersection of the supply and demand curves. Generators whose bids are higher in the merit order curve are called inframarginal generators. Each generator knows only the past market prices and their own bids. In this setting, the inframarginal generators' strategy is to not bid higher than the marginal generator's bid (Sapio, 2004). Thus, they observe and analyse past prices and offer their current bids according to past information. For off-peak hours, if marginal generators bid at their marginal costs, then there is no fractal noise. This observation allows for testing of firms' bidding behaviour based on marginal cost structures. For peak hours, if there exists a long-term correlation in prices, we can suggest that marginal generators use the prices of the day and week before, which means applying hyperbolic bidding rules. Moreover this observation is contrary to Fama's (1970) weak-form efficient market hypothesis (WEMH), which assumes the absence of long-term correlation between price increments for any time scale. If markets are weak-form efficient, then market participants cannot earn excess profits in the presence of trading rules based on past prices or returns (Farmer et al., 2006; Eoma et al., 2008; Mun et al., 2008). Such a WEMH can be tested using historical data through short- and long-range correlations (Lillo and Farmer, 2004; Couillard and Davidson, 2005).

Thirdly; considering the persistence of a series, the presence and degree of long-term correlation structure have policy implications.[3] Persistence is a measure of the speed at which a series returns to its mean level after a shock. In the context of this research, a shock can be a new policy design/regulation or the introduction of an innovation to the market. In this sense, when the degree of persistence is small, a shock tends to have more temporary effects. In the case of electricity prices, deviating from the mean level of the price is not easy. On the one hand, it is more costly and difficult to permanently affect electricity prices when persistence is low. On the other hand, if the degree of persistence is high, a shock tends to have a more long-lasting effect. Thus, the degree of persistence of electricity prices makes a difference in the effectiveness of energy policies/regulations. Therefore the results of this study can be an input for regulatory bodies and policy-makers to make "evidence-based ex-ante policy impact analysis" which has recently been a popular approach used by UNDP, EU, OECD and World Bank[4].

In this study, our aim is to investigate fractal phenomena in level electricity prices for each time zone separately. We focus on the essential statistical properties of fractal noise and identify appropriate instruments for measuring fractality in day-ahead electricity prices. Our paper contributes to the literature firstly by comprehensively discussing the theoretical characteristics of a fractal pattern and demonstrating the crucial steps of a fractal analysis approach adapted to capture the dynamics of electricity prices. We employ both parametric and semiparametric methods to benefit from their different statistical properties. Secondly,

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[3] For details, see Chen and Lee, 2007; Gil-Alana et al., 2010; Peraire and Belbuta, 2012; Apergis and Tsoumas, 2012.

[4]For details, see
http://ec.europa.eu/dgs/energy_transport/evaluation/activites/doc/reports/energie/intelligent_energy_ex_ante_en.pdf https://ec.europa.eu/energy/intelligent/files/doc/2011_iee2_programme_ex_ante_en.pdf
http://www.oecd.org/dac/povertyreduction/38978856.pdf
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prior studies have focused on hourly price differences or daily average price differences rather than on level prices. This first differencing approach is a natural fit for most financial assets because of their nonstationary dynamics. However, this property may not exist for electricity prices depending on the maturity of the market, the time interval, the technology mix and other contaminating factors. For instance; markets with low diversity of generation, low maturity or non-reservoir hydro-dependence may experience many spikes which can affect the evaluation of the long memory differencing parameter based on returns. As stated by Uritskaya and Uritsky (2015) using level prices is more consistent with the original formulation of the parametric long memory estimation methods, like DFA. Thus, studies on long memory for level prices can provide useful information to improve existing models and to assess limitations on prediction. Lastly, previous studies have investigated either daily average or hourly prices. However, Alvarez-Ramirez and Escarela-Perez (2010) and Erzgraber et al. (2008) show that fractal properties of electricity price vary over time. Accordingly we introduce a new time unit based on time zones in a multi-time tariff mechanism considering the fact that electricity market participants have different incentives, risk management and forecasting approaches for each time zone. With respect to this fact we expect different levels of predictability of prices, efficiency of the market, bidding structures of market participants and permanence of shocks for each time zone.

For this study we use a data set from Turkey where exists three time zones (T_i); T_1 (day): 6:00 – 17:00, T_2 (peak): 17:00 – 22:00 and T_3 (night): 22:00 – 6:00. There have been few empirical studies focusing on the statistical and fractal properties of electricity prices in Turkey because of the relative youth of electricity market restructuring. There are only two emerging studies on forecasting electricity prices of Turkey; Yıldırım et al. (2012) and Hayfavi and Talasli (2014). On the other hand Turkey has experienced the longest and most extensive "black out" on 31 March 2015 in the history of the Turkish Republic. This recent experience[5] has revealed the importance of bidding structures in electricity markets and

[5] Turkey has experienced the longest and most extensive blackout on 31 March 2015 in the history of the Turkish Republic. Turkish Transmission system collapsed for 10 hours due to positioning of generation plants mostly on the eastern part of Turkey. Nevertheless the basic reason is the formation of merit order curve and lack of management initiative. During the winter 2015 Turkey had high precipitation and thus the level of reservoirs became very high. On 30 March 2015, that is the day MOC(Merit Order Curve) was planned for 31 March 2015; the operators recognize that most of the hydropower enter the merit order curve, became marginal generators (as defined in the manuscript; marginal generators are the ones whose bid at the intersection of the supply and demand curves and thus determining the hourly market clearing price) and natural gas plants mostly located near

implementing hedging strategies. Thus we expect a rapid increase in the number studies on electricity price analysis and forecasting about the Turkish electricity market.

3.2. Related Work

Fractal noise has been found in most scientific fields, including physics, finance, biology and psychology (Hausdorf et al., 1996; Chen et al., 1997) and is still a hot topic (Barunik and Kristoufek, 2010; Yerlikaya-Ozkurt et al., 2014; Uritskaya and Uritsky, 2015). It is intermediate between white noise and brown noise and has both stability and adaptability properties (Bak et al., 1987). Different approaches to capture fractality exist. However, statistical characteristics of some nonfractal noise can resemble fractal noise, which may result in incorrect classification. Therefore, proper measurement of fractality in applied research is very difficult. One of the main objectives in measuring fractality is distinguishing between fractal and nonfractal noise for diagnostic checking (Stadnitski, 2012).

Fractality of electricity prices has been the subject of a number of recent studies. Pioneer studies mostly attempt to detect the unit root in a series through analysing the long memory differencing parameter. Some of them use level electricity prices to investigate the unit root in their series and show that the characteristics of electricity prices are very different from those of financial assets (DeVany and Walls, 1999; Leon and Rubia, 2001; Atkins and Chen, 2002; Rypdal and Lovsleten, 2013); most of them consider the characteristics of the electricity prices similar to financial assets and use returns as the main variable in their modelling and their results demonstrate that nonstationarity in electricity prices differs with respect to market and time framework (Weron and Przybylowicz, 2000; Weron, 2002; Simonsen, 2003; Norouzzadeh et al., 2007). Another branch of the literature focus on comparing several electricity markets in Europe and US based on their degree of long memory (Koopman et al., 2007; Park et al., 2006; Koopman et al., 2007; Alvarez-Ramirez and Escarela-Perez, 2010) and mainly find that the prices are nonstationary and that in some of them fractional differencing exists.

the Marmara region stay out of the MOC due to their relatively high marginal generation costs. Operators responsible for the realization of the merit order curve ignore the geographical location of the hydropower plants and accept / realize the output of the hourly MOCs for the next day to generate electricity at lower prices. On March 31, the electricity transmission system is collapsed due to the unbalancement in the transmission lines.

The literature most similar in spirit to ours are the ones focusing on testing basic finance theories through using long memory correlation structures. Uritskaya and Serletis (2008) compare the market efficiencies in Alberta and Mid-C markets using detrended fluctuation analysis and spectral exponents. Sapio (2004) finds that long-term correlation structure exists in electricity prices and that can be explained by bidding strategies of market participants. He notes that institutional setting is very important in shaping participants' behaviour and illuminates the relationship between bidding rules and ways of processing past information. In terms of considering time of the day, Erzgraber et al. (2008) study long-term memory in the Nord Pool market and find the memory parameter varies greatly with respect to the time of the day.

3.3. Hypothesis Development

Hypothesis-1: If marginal generators bid at their marginal costs, then the off-peak price does not display a fractal pattern.

The off-peak hour strategy for generators is to bid at marginal cost (Von der Fehr and Harbord, 1993). If generators use the off-peak strategy and marginal cost is constant, then marginal generators are assumed to have no long-term memory since their own cost information is constant. This situation is also an indicator for Fama's weak-form efficient market hypothesis. If the electricity market is efficient in weak form for each time zone, then prices should not have a long-term correlation structure. Hence, current prices cannot be predicted by using information on past prices.

Hypothesis-2: If marginal generators use hyperbolic bidding rules, then the peak-load price should be represented by a long memory process and the day-ahead market will not be efficient in weak form.

The peak-hour strategy for generators is to bid above marginal cost (Sapio, 2004), since the risk of not being selected is low due to high demand. Thus, at peak load, marginal generators are assumed to give hyperbolically decaying weights to information by considering past electricity prices.

Hypothesis-3: If shocks to electricity prices are permanent, then the price series for each time zone should exhibit the long memory property.

The presence of fractal patterns in each time zone has important implications for public policy design and effectiveness. First, given the strong influence of the energy sector on other sectors of the economy, if shocks to electricity prices are permanent, then such "innovations" may be transmitted to other sectors of the economy as well as to macroeconomic variables. Second, the fractal dynamics of electricity prices are crucial to the design and the effectiveness of public policies. In particular, if electricity prices exhibit long-term correlation structure, then related public policies will tend to have long-lasting effects. In contrast, if electricity prices do not suggest a fractal pattern, then such policies will have only transitory effects (Lean and Smyth, 2009; Gil-Alana et al., 2010; Pereira and Belbute, 2012; Apergis and Tsoumas, 2012).

Based on our hypothesis, we propose the research model in Figure 3.1.

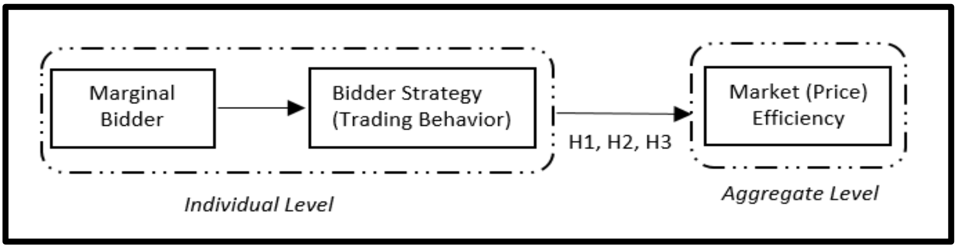

Fig. 3.1: Research Model

3.4. Data and Preliminary Analysis

The data used in this study consists of day-ahead prices from 00:00 on December 1, 2011 (establishment of the GOP), through 24:00 on April 15, 2014 from the electricity market in Turkey, taken from the market maker (PMUM). This gives us 857 observations for each time zone.

Most studies on analysing fractal dynamics of spot electricity prices take the daily average of hourly prices or returns. We thoroughly examine this approach by analysing the spectral density of hourly level electricity prices as illustrated in Figure 3.2 in which the most dominant cycles are observed to be approximately 8, 12, 24 and 48 hours. Thus, we propose to use average price of each time zone i (PTF_T_i) since 1) we do not want to lose information about the microstructure of day-ahead prices, as would be the case were we to use daily averaging 2) previous studies considering each hour separately concludes that there exists a block-structured cross-correlation structure between specific hours referring to the time zones 3) taking average with respect to each time zone is more intuitive in the sense that electricity market participants have different incentives and bidding strategies for each time zone.

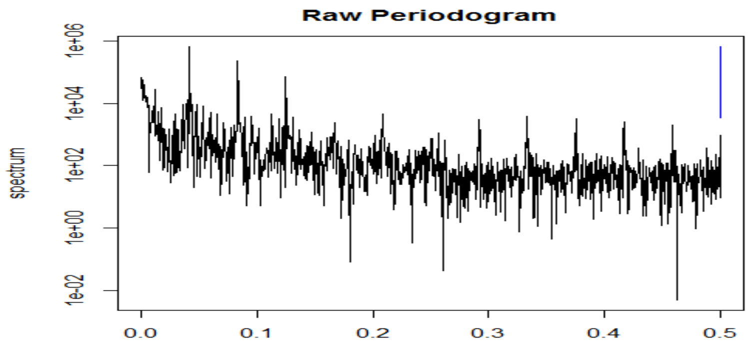

Fig. 3.2: Raw periodogram of hourly prices from 00:00 on December 1, 2011, to 24:00 on April 15, 2014 with bandwidth 0,000134

Logarithm of PTF_Ti (LNPTF_Ti) are presented in Figure 3.3 and its descriptive statistics and test results are illustrated in Table 3.1.

3.5. Methodology and Results

3.5.1. Fractal Parameters

The main characteristic of a fractal noise is to remain similar when viewed at different scales of time or space. This implies the following statistical properties: 1) a hyperbolically decaying ACF and 2) a specific relation between frequency (f) and size (S) of process variation. Hurst (H), differencing (d), power exponent (β) and scaling exponent (α) are the most commonly used fractal parameters. The Hurst coefficient is the probability that an event in a process is followed by a similar event, which measures the intensity of long-range dependence in a time series[6].

Broadly we can classify the differencing parameter estimation methods into two groups; parametric and semiparametric. In the parametric fractal analysis methods all the parameters are simultaneously estimated mostly through a likelihood function. Within the second group of estimators a periodogram based approach is used (Geweke and Porter-Hudak, 1983; Reisen, 1994; Robinson, 1995b).

3.5.2. Fractal Analysis Approach

As a general fractal analysis strategy, it is important to remember that none of the fractal parameter estimation procedures mentioned below is superior to the others (Stadnitski, 2012). Simulation studies on fractal analysis have demonstrated that the performance of the various methods depends very much on aspects such as the complexity of the underlying process or the parameterizations (Stadnytska and Werner, 2006). As a result, comprehensive strategies are required to correctly estimate fractality parameters. Firstly it is very important to distinguish between stationary and nonstationary processes since some fractal analysis approaches have stationarity assumption or are more efficient for stationary processes. Traditionally, researchers chose the differencing parameter, d, as an integer (generally 1) to guarantee that the resulting differenced series is a stationary process. In our fractal analysis approach, we propose to check the unit root by a combination of PP and KPSS tests as suggested in (Bailie et al., 1996) and look for indication of fractality since unit root tests

[6] It was first introduced by Hurst (1951) in hydrological analysis. For both white and brown noises the Hurst coefficient (H) is 0.5; for fractal noise, H=1. The differencing parameter is another fractal parameter, proposed by Granger and Joyeux (1980) and Hosking (1981, 1984). They show that if $-0.5<d<0.5$, then the process is covariance stationary and the moving average coefficients decay at a relatively slow hyperbolic rate compared with the stationary and invertible autoregresssive moving average (ARMA) process (Bailie et al., 1996). If $0<d<0.5$, then the process is stationary with a finite long memory property. If $0.5\leq d \leq 1$, then the series is nonstationary (Beran, 1994; Brockwell and Davis, 2002). The power exponent is determined by examining the spectral density function, which describes the amount of variance accounted for by each frequency that can be measured. The analysis of power distribution represents the analysis of variance (ANOVA) in the way that the overall process variance is divided into variance components due to independent cycles of different length (Stadnitski, 2012). If the power spectrum of a set of data is plotted on a log-log scale, the logarithmic power function of fractal noise is expected to follow a straight line with slope -1 for pink noise. The scaling exponent (α) represents the self-similarity of pink noise and fractality can be expressed by the following power low: $F(n) \propto n^{\alpha}$ with $\alpha=1$. If α is 1.5, then the process is brown noise. To summarize, the theoretical parameter values of pink noise are $d=0.5$, $\beta=1$, $\alpha=1$ and $H=1$ (Warner, 1998).

often lack the power to distinguish between a truly nonstationary (I(1)) series and a stationary series with a structural break. If the combination of unit root tests indicate fractal behaviour then visual detection methods can be used to ensure the existence of long memory in the data. After getting a first impression of long memory characteristics of the data visually, one can use appropriate parametric and semiparametric long memory estimation methods to find the degree of fractality in the data.

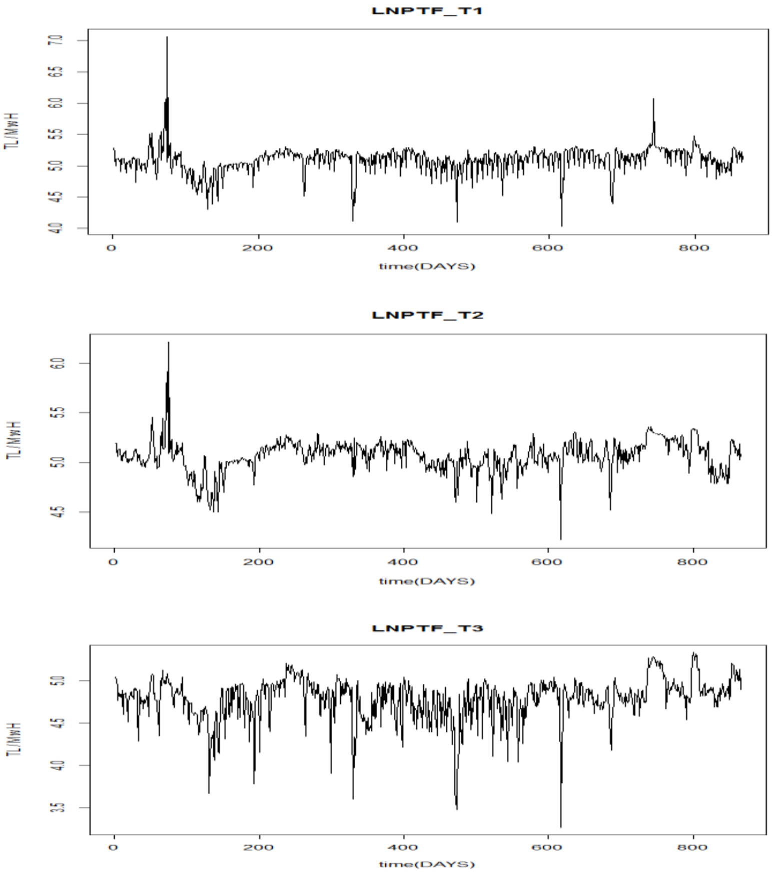

Fig. 3.3: Panel 1: Time series plot of LNPTF_T_1 from December 1, 2011, to April 15, 2014. Panel 2: Time series plot of LNPTF_T_2 from December 1, 2011, to April 15, 2014. Panel 3: Time series plot of LNPTF_T_3 from December 1, 2011, to April 15, 2014. Note: LNPTF_T_i is the logarithm of average price of time zone i.

Table 3.1: Descriptive statisticsand test results. Notes: JB is the value of the Jarque-Bera statistic of the price residuals. Q (20) and Q^2 (20) are Ljung-Box statistics for the price residuals and the squared price residuals for up to 20th-order serial correlation, respectively. *** indicates rejection of the null hypothesis at the 1% significance level. ** indicates rejection of the null hypothesis at the 5% significance level. * indicates rejection of the null hypothesis at the 10% significance level. $LNPTF\_T_i$ is the logarithm of average price of time zone i.

	$LNPTF\_T_1$	$LNPTF\_T_2$	$LNPTF\_T_3$
# of observ.	867	867	867
Mean	5.095	5.067	4.787
Min	4.029	4.22	3.268
Max	7.06	6.215	5.336
Std. dev.	0.1995	0.1591	0.2491
Skewness	0.277	-0.1777	-1.46
Kurtosis	18.18	8.764	7.742
JB	8330.139***	1204.967***	1120.507***
ARCH(10)	389.2607***	498.3533***	480.2928***
Q(20)	1433.03***	3497.096***	1918.531***
Q^2(20)	1362.056***	3408.895***	2087.08**

3.5.2.1. Unit Root Tests

There are three unit root tests commonly used to test the stationarity of a process: 1) the Augmented Dickey-Fuller (ADF) test, 2) the Phillips–Peron (PP) test and 3) the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. ADF (Dickey and Fuller, 1979) and PP (Philips, 1987; Philips and Peron, 1988) test the null hypothesis d=1 against d=0. However, Schwert (1987) noted that when the true generating process is an I(1) process with a large negative moving average coefficient, the performance of the ADF and PP tests is poor, due to their rejecting a unit root too often in favour of an I(0) stationary process. Thus, if we wish to test stationarity as a null and have strong priors in its favour, employing the ADF test may not be useful (Bailie et al., 1996). An empirical series with d close to 0.5 will probably be misclassified as nonstationary. In contrast, the KPSS test assumes that process is stationary (H_0: d=0) (Kwiatkowski, Philips, Schmidt and Shin, 1992).

Therefore, we use a combination of the PP and KPSS tests allowing us to determine the four possible outcomes of the series (Bailie et al., 1996): 1) if the PP is significant and the

KPSS is not, then the data are probably stationary with d ∈ (0;0.5)—strong evidence of a covariance stationary process; 2) if the PP is insignificant and the KPSS is significant, then the data may indicate having brown noise—a strong indicator of a unit root, i.e., an I(0) process; 3) if neither the PP nor the KPSS is significant, then the data are insufficiently informative regarding the long memory of the process; and 4) if both the PP and the KPSS are significant, then the data are not well described as either an I(1) or an I(0) process—d ∈ (0; 1).

Table 3.2 presents the unit root tests for logarithm of level prices without/with a trend. In Table 3.2, the p-values p_{pp} <0.01 and p_{KPSS} <0.01 are observed for the analysed series, indicating that the electricity price averages for each time zone are not well described as either an I(1) or an I(0) process which means the differencing parameter, d, is not an integer but between 0 and 1.

Table 3.2: Unit root tests for logarithm of level prices with and without a trend. Notes: *** indicates rejection of the null hypothesis at the 1% significance level. ** indicates rejection of the null hypothesis at the 5% significance level. * indicates rejection of the null hypothesis at the 10% significance level. LNPTF(T_i) is the logarithm of average price of time zone i.

	LNPTF(T_1)	**LNPTF(T_2)**	**LNPTF(T_3)**
KPSS (without trend)	0.74***	0.45***	1***
PP (without trend)	-427.77***	-231.55***	-240.98***
KPSS (with trend)	0.11***	0.24***	0.48***
PP (with trend)	-16.37***	-11.59***	-11.96***

3.5.2.2. Visual Detection of Long-term Correlation Structure

The second step in our proposed fractal analysis approach is to visually examine the rate of the series' autocorrelation function and logarithmic power spectrum. For fractal series, we expect a slower hyperbolic decay of autocorrelations in autocorrelation function (ACF) (Beran, 1994). Figure 3.4 illustrate the ACF of the LNPTF_T_i and squared-prices for each time zone. There is a slow decay of the autocorrelations, and they are positive and significant even at high lags, which is an indicator of the finite long memory typical of fractal noise. Only weekly seasonality (lags 7, 14, 28) appears in the data, which means that considering the average price of each time zone eliminates most of the intraday seasonality problem in both level prices and volatility.

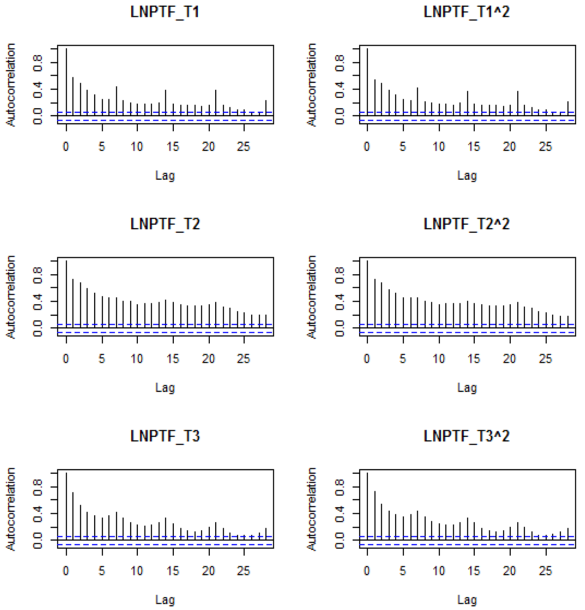

Fig. 3.4: Autocorrelation function of LNPTF_T_i and square of LNPTF_T_i for 28 lags. Note: LNPTF_T_i is the logarithm of average price of time zone i.

Figure 3.5 presents the autocorrelations of first differenced price series. After taking the first differences of the series, most of the autocorrelations at different lags are negative, which is an indicator of over differencing. This plot confirms the observation made above regarding the existence of long-term correlation structure in level prices. As a result we use level electricity prices instead of first differenced prices for the following reasons: 1) the results presented in Table 3.2, Figure 3.3 and Figure 3.4 provide evidence that the price series do not contain a unit root and would be over differenced if we used the first differenced series which is an indicator for fractal behaviour; 2) in a statistical sense, level prices are more informative than differenced prices; 3) in the case of electricity, there are in fact no actual returns (as a result of first differencing) because of the nonstorability of electricity; and 4) the Hurst coefficient might be biased due to the expected antipersistence of the first differenced series.

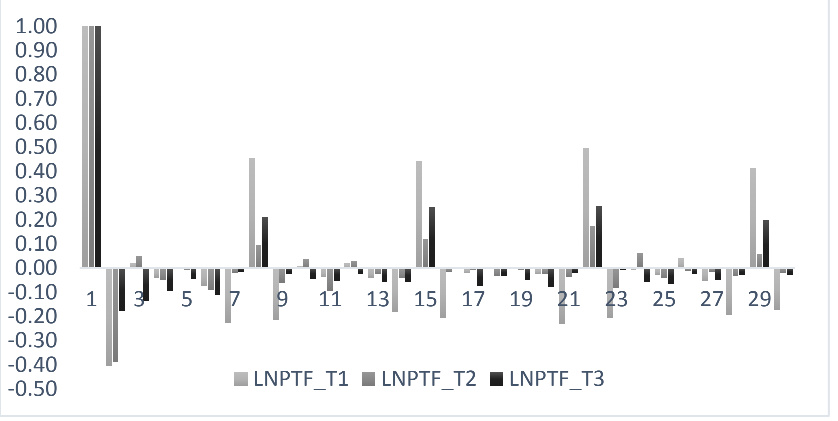

Fig. 3.5: Autocorrelation function of first differenced LNPTF_T$_i$. Note: LNPTF_T$_i$ is the logarithm of average price of time zone i.

However, studies show that the sample ACF should not be used as the only visual tool to detect fractality. Agiakoglu and Newbold (1992) have shown that a substantial part of the slow decaying pattern can originate from the slow rate of convergence of the sample mean. Thus we also use Rescaled range (R/S) and Power spectral density (PSD) analyses to ensure the existence of fractality in our data. Mandelbrot and Van Ness (1968) and Mandelbrot and Wallis (1969) extended Hurst's study and proposed R/S analysis. In a log-log R/S plot, if the slope of the straight line is more than 0.5, then the series has a long memory property. If the slope is less than 0.5, the series is antipersistent. R/S statistic can detect long memory in highly non-Gaussian time series with large skewness and kurtosis (Mandelbrot and Wallis, 1969). It has been pointed out by Lo (1991) that R/S analysis can be affected by non-stationarities and spurious short-term correlations. In this study we employ the R/S procedure suggested by Beran (1994), Taqqu and Teverovsky (1998) and Taqqu et al. (1995). Figure 3.6. illustrates the R/S analysis result of average electricity prices for time zone T_2.[7]

[7] Since the appearance of the figures for the other time zones are similar, they are omitted from the text.

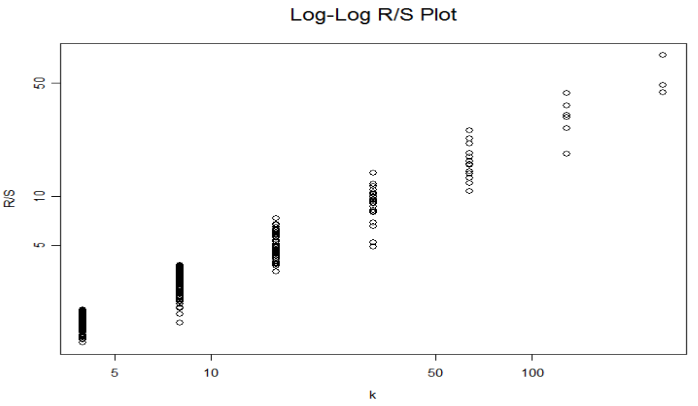

Fig. 3.6: Rescaled range analysis result of $LNPTF\_T_2$ **Note:** $LNPTF\_T_2$ is the logarithm of average price of time zone 2.

The slopes are far from 0.5, which is an indicator of long memory. To eliminate the sample size problem of R/S analysis, we investigate the electricity price data with least absolute deviation (LAD) regression integrated into the aforementioned procedure to get a robust estimate of the long memory parameter. The results using LAD regression are presented in Table 3.3 and are similar to those of least square (LS) regression. We can conclude that the long memory parameter estimates found by R/S analysis are robust to outliers in the data.

Table 3.3: Hurst coefficient estimates using R/S analysis**.** Note: $LNPTF\_T_i$ is the logarithm of average price of time zone i.

	$LNPTF\_T_1$	**$LNPTF\_T_2$**	**$LNPTF\_T_3$**
R/S estimate with LS	0.7616	0.8390	0.817
R/S estimate with LAD	0.7564	0.8308	0.830

PSD analysis is a periodogram based visualization technique which uses various data transformations such as detrending or filtering. The performance of PSD estimators thus depends greatly on the manipulations employed (Delignières et al., 2006; Stadnitski, 2012). If the negative slope is approximately 1 then this is an indicator for long memory. In addition to ACF and R/S, we apply PSD analysis to see if there is a difference between the results of trended and detrended data. The negative slopes $(\hat{\beta}_{PSD})$ are nearly 1 for all series. The logarithmic power spectrum of the series is presented in Figure 3.7 and seems to be compatible with the long memory property.

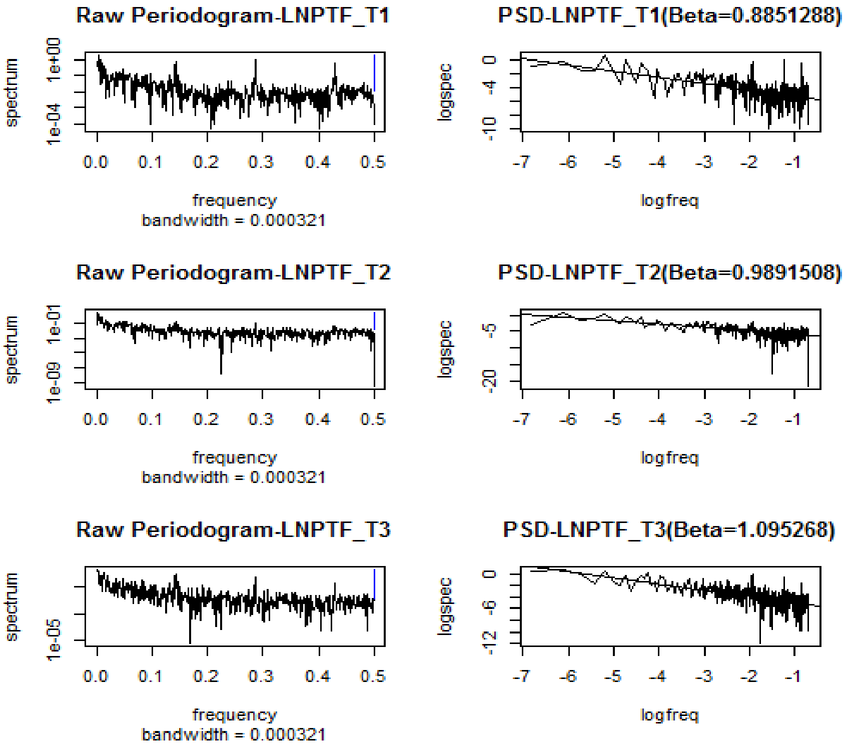

Fig. 3.7: Results of PSD analysis of all series. *Logfreq* denotes the logarithmic power spectrum of the series. **Note:** LNPTF_T$_i$ is the logarithm of average price of time zone i.

3.5.2.3. Fractal Parameter Estimation for Conditional Mean

Lastly, after visual detection of long-term correlation structure by ACF, R/S and PSD analysis, we ensure the existence and degree of fractality with respect to each time zone by using parametric and semiparametric estimation methods. In this study we estimate the differencing parameter for the conditional mean through Geweke–Porter-Hudak (GPH), Sperio estimator (FDSperio), local Whittle estimator (FDWhittle), Detrended Fluctuation Analysis (DFA) and Autoregressive Fractionally Integrated Moving Average (ARFIMA). We adopt these methods to benefit from their different statistical properties; namely GPH's common usage and comparability with the literature, FDSperio's usage of smoothed periodogram function instead of spectral density function, FDWhittle's parametric efficiency and consistency, DFA's performance for nonstationary series and ARFIMA's efficiency for series consisting both long and short memory characteristics. We use the algorithm of Taqqu et al. (1995) to estimate GPH, algorithms of Reisen (1994) and Taqqu and Teverovsky (1998) to estimate FDSperio and FDWhittle correspondingly. Besides we use the algorithm of Peng et al. (1994) to estimate DFA and fast and accurate algorithm of Haslett and Raftery (1989) to estimate d in ARFIMA.

The GPH, the oldest periodogram-based semiparametric estimator, is introduced by Geweke and Porter-Hudak (1983)**.** The GPH estimator is based on the regression equation, using the periodogram function as an estimate of the spectral density (Geweke and Porter-Hudak, 1983; Robinson, 1994; Taqqu et al., 1995; Lobato and Robinson, 1996).

The FDSperio is also a periodogram-based method and was proposed in order to improve the GPH estimator. It takes advantage of the Reisen (1994) algorithm to estimate the fractal parameter d in the ARFIMA (p,d,q) model. It is based on the regression equation, using the smoothed periodogram function as an estimate of the spectral density.

The FDWhittle is one of the most commonly used parametric periodogram-based Whittle estimators. It was proposed by Whittle (1953) and modified by Künsch (1987), Robinson (1995b) and Taqqu and Teverovsky (1998). One of the advances of the Whittle Estimator is that it is consistent and asymptotically normal for nonstationary and unit root cases (Phillips and Shimotsu, 2004). Whittle's method fits the parameters of a specified spectral density function(SDF) model to data by optimizing an appropriate function using an estimate of the SDF for an input time series.

Another method we use to detect long memory is DFA which was proposed by Peng et al. (1994) based on the relationship $F(n) \propto n^{\alpha}$. DFA analysis performs better for detecting the long memory property in nonstationary series.[8] Hu et al. (2001) focus on the effect of trends on DFA, while Kristoufek (2010) examines finite sample properties and confidence intervals of DFA. In DFA, if there is a straight line with slope 0.5, then the series is white noise. If the slope is greater than 0.5, then the series is persistent. If the slope is less than 0.5,

[8] See Grech and Mazur (2005) for a discussion of the statistical properties of old and new techniques in detrended fluctuation analysis of time series.

then the series is antipersistent. We apply the DFA estimator on both the trended and detrended data to investigate the effects of trends on detecting long memory.

ARFIMA is the most frequently used parametric method with the ability to estimate the short- and long-memory parameters jointly (Reisen et al., 2001; Sowell, 1992b). Its main disadvantages are that it is valid only for stationary series and needs a sufficiently large sample size for acceptable measurement accuracy (Stadnitski, 2012; Stadnytska and Werner, 2006). Its validness only for stationary series can lead to situations where nonstationary processes are classified as having long memory. The exact maximum likelihood (EML) method introduced by Sowell (1992a), the conditional sum of squares (CSS) approach proposed by Chung (1996) and the approximate method likelihood (AML) method introduced by Haslett and Raftery (1989) are commonly used to estimate the fractional differencing parameter in ARFIMA models.

Semiparametric estimates (PSD, DFA and HurstSpec) are converted to $\hat{d}$ to make the comparison of results clearer, and illustrated in Table 3.4. The estimates range from 0.40 to 0.7 depending on the tariff zone, except for those of the DFA. The interpretation of fractal dynamics is clearer for time zones T_1 and T_3 since the range of the parameters is between 0.4 and 0.6 for most of the estimators. However, the fractal estimates for time zone T_2 are in the critical region between fractional integration and nonstationarity. We take the first difference of the T_2 series for the sake of eliminating the potential nonstationarity in that series. As illustrated in Table 3.5, the T_2 series does not exhibit long memory after taking the first difference, which indicates that electricity prices in time zone T_2 do not have long memory.

The deficiency of the semiparametric methods is to overestimate fractality in time series that contain both long- and short-range components. Due to larger biases, the precision of semiparametric methods is distinctly inferior to that of the ARFIMA approaches. Since the values obtained for T_1 and T_3 are all smaller than 0.6, the preceding analyses do not allow rejecting the hypothesis of fractality for the T_1 and T_3 series. Therefore, ARFIMA analysis appears to be appropriate for the T_1 and T_3 series. The comparison of different ARFIMA models is analysed using Akaike information criteria (AIC); a summary of the results is presented in Table 3.6. T_1 and T_3 exhibit the long-term memory property using models ARFIMA (0, 0.4090, 0) and ARFIMA (1, 0.3202, 0) respectively. In summary, the time zones defined in the multi-time tariff mechanism are found to have different fractal dynamics.

Table 3.4: Long memory tests for log prices in converted measures. Notes: *** indicates rejection of the null hypothesis at the 1% significance level. ** indicates rejection of the null hypothesis at the 5% significance level. * indicates rejection of the null hypothesis at the 10% significance level. $LNPTF\_T_i$ is the logarithm of average price of time zone i.

		LM MEASURES					
	Vrb.	DFA	FDSperio	FDGPH	FDWhittle	HurstSpec	ModR/S
$LNPTF\_T_1$	**P_t**	0.5278	0.4692	0.5020	0.4145	0.5991	1.9054*
	P_t^2	0.5199	0.4569	0.4983	0.3959	0.5929	1.9164*
$LNPTF\_T_2$	**P_t**	0.6893	0.6675	0.5292	0.5240	0.5956	1.8218
	P_t^2	0.6846	1.1847	0.5341	0.5140	0.6020	1.8141
$LNPTF\_T_3$	**P_t**	0.5652	0.4489	0.4991	0.5643	0.5756	2.2477**
	P_t^2	0.5788	0.4637	0.5203	0.5725	0.5876	2.2541**

Table 3.5: Long memory tests for diff-$LNPTF\_T_2$ prices in converted measures. Notes: DIFF_LNPTF_T2 is the first differenced LNPTF_T2. $LNPTF\_T_i$ is the logarithm of average price of time zone i

		LM MEASURES					
	Vrb.	**DFA**	**FDSperio**	**FDGPH**	**FDWhittle**	**HurstSpec**	**ModR/S**
DIFF_LNPTF_T2	**P_t**	0.1181	-0.2073	-0.3668	-0.47160	-0.3855	1.0462

3.5.2.4. Fractal Parameter Estimation for Conditional Variance

Studies by De Lima and Crato (1994), Ding, Granger and Engle (1993) and Harvey (1993) all reported the apparent presence of long memory in the autocorrelations of squared returns of various financial asset prices. Long memory in volatility is an indicator of uncertainty and risk (Kasman and Torun, 2007; Kasman et al., 2009; Barkoulas et al., 2000; Ural and Kucukozmen, 2011). There are different approaches to measure the long memory in volatility. Some of the previous studies use the square of the returns of assets as an artificial variable and apply semiparametric methods to this variable to find the fractal parameter for process volatility. However, as noted by Wright (2002), the fractal parameter d is underestimated when using this approach. Thus we use the parametric fractionally integrated generalized autoregressive conditionally heteroskedastic (FIGARCH) estimator introduced by Bailie et al. (1996) to eliminate the deficiency of using square of the returns. Estimation results are illustrated in Table 3.7. Among the FIGARCH models, we chose for consideration the one with the lowest AIC. The volatility of T_1 and T_2 does not seem to exhibit long memory with significant (approximately 1) d estimates, which indicates that there is an I(1) process in volatility and that the T_3 series has a long memory property in volatility.

Table 3.6: Estimation results of the ARFIMA models. Notes: μ is the time series mean. ξ is the fractional differencing parameter. Ln (L) is the value of the maximized Gaussian likelihood**.** JB is the value of the Jarque-Bera statistic of the price residuals. Q (20) and Q^2 (20) are Ljung-Box statistics for the price residuals and the squared price residuals for up to 20th-order serial correlation, respectively. *** indicates rejection of the null hypothesis at the 1% significance level. ** indicates rejection of the null hypothesis at the 5% significance level. * indicates rejection of the null hypothesis at the 10% significance level. LNPTF_T_i is the logarithm of average price of time zone i.

	LNPTF_T1 (0, ξ, 0)	LNPTF_T3 (1, ξ, 0)
μ	5.083	4.79
α_1	-	0.33
ξ	0.40***	0.32***
ln(L)	361.74	292.39
AIC	-716.72	-571.26
Skewness	0.38	-1.16
Kurtosis	24.83	8.64
JB	17214.27***	1345.05***
Q(20)	305.07***	106.18***
Q^2(20)	114.70***	83.52***
ARCH(10)	95.71***	70.34***

Table 3.7: Estimation results of the FIGARCH models**. Notes:** μ is the time series mean. d is the fractional differencing parameter. ln (L) is the value of the maximized Gaussian likelihood**.** JB is the value of the Jarque-Bera statistic of the price residuals. Q (20) and Q^2(20) are Ljung-Box statistics for the price residuals and the squared price residuals for up to 20th-order serial correlation, respectively. *** indicates rejection of the null hypothesis at the 1% significance level. ** indicates rejection of the null hypothesis at the 5% significance level. * indicates rejection of the null hypothesis at the 10% significance level. $LNPTF\_T_i$ is the logarithm of average price of time zone i.

	$LNPTF\_T_1$	$LNPTF\_T_2$	$LNPTF\_T_3$
	FIGARCH (1,d,0)	FIGARCH (1,d,0)	FIGARCH (1,d,1)
μ = C	5.11***	5.10***	4.84***
ω =A	0.00***	0.00***	0.01***
α_1	-0.14***	-0.16***	0.11***
β_1	-	-	0.52***
d	0.99***	0.94***	0.47***
ln(L)	378.39	581.95	170.94
AIC	-748.79	-1155.91	-331.88
BIC	-729.73	-1136.85	-308.05
Skewness	-0.75	-0.51	-0.86
Kurtosis	5.65	7.27	5.61
JB	337.35***	697.37***	353.96***
Q(20)	1026.54***	1689.58***	956.45***
Q^2(20)	188.50***	8.14	15.2484
ARCH(10)	84.67***	3.36	5.9687

Results of our hypothesis tests are summarized in Table 3.8.

Table 3.8: Summary of Hypothesis Tests

	HYPOTHESES	**RESULTS**
H1	*If marginal bidders bid at their marginal costs, then the off-peak price does not display a fractal pattern.*	H1 is not supported.
H2	If market is efficient at peak time, then peak-load price does not display a fractal pattern.	H2 is supported.
H3	*If shocks to electricity prices are permanent, then the price series for each time zone should exhibit the long memory property.*	Shocks to electricity prices not permanent for T1 and T3, not permanent for T2.

3.6. Concluding Remarks

We empirically investigate three propositions considering the presence of long-term correlation in day-ahead electricity prices for each time zone in a multi-time tariff setting. The results obtained provide new information on the fractal behaviour of electricity prices considering different time zones. We have reached the following main conclusions:

Analysing the fractal dynamics of electricity prices is very complicated because of the unique characteristics of electricity, and requires elaborate strategies. Numerous procedures have been developed for estimating the fractal parameters β, α, H and d. Approaches aimed at detecting long memory in the conditional mean and variance have been developed independently of each other; however, long-term correlation structure is often observed in both the conditional mean and variance. Thus, we investigated the presence of the long memory property in both the conditional mean and variance for each time zone. Moreover the crucial steps of a fractal analysis approach customized to capture electricity price dynamics are demonstrated elaborately.

Considering time zones in electricity price analysis is very intuitive and important. Our results suggest that the fractal dynamics of electricity are different for each time zone. Long-memory parameters are found to be significantly different from zero for the conditional mean, indicating long-term dependence for time zone 1. This confirms the proposition that at peak load, marginal generators may give hyperbolically decaying weights to information by considering the prices of a day/week before. We also show that the T_3 price series has a long memory property in both level and volatility. T_2 price series, however, does not have long memory in either level or volatility. It is nonstationary but mean reverting.

Implications of the propositions can be different for each time zone. Positive and significant fractional differencing coefficients of the mean for the T_1 series suggest that marginal generators exhibit hyperbolic information processing, which supports Proposition 1. Further, since there exists long-term correlation structure, future prices are predictable from past prices, and the market is not efficient in weak form in the T_1 time zone. This structure also indicates that exogenous shocks/innovations can have permanent effects on prices. Thus, the effectiveness of price policies for T_1 is expected to be high.

Interpretation of the long-term correlation structure is different for the T_3 time zone, where the demand for and price of electricity is low. In this time zone, only the base load power plants (thermal, hydropower plants without dams, and renewable) offer to the market. To rank along the merit order curve, base load power plants are expected to offer at their marginal costs. Since demand is uncertain, participants face a trade-off between submitting a high but risky bid, and a safer but potentially less profitable low bid. If marginal generators bid at their marginal costs, they are expected not to bid hyperbolically and not to have long memory. However, we find that off-peak fractional differencing coefficients are significantly greater than zero, which can be taken as evidence that bidding above marginal cost occurs even off-peak. This finding further suggests that the market is not efficient in weak form and that future prices are predictable from past prices. Moreover, exogenous shocks can have permanent effects on prices.

T_2 is the peak-load time zone, where demand is very high and the probability of not being on the merit order curve is very low, even for high bids. Thus, at peak load, marginal generators would be expected to give hyperbolically decaying weights to information by considering the prices of a day/week before. However, our findings suggest that the T_2 price series does not display a long memory property in either level prices or volatility. This finding suggests that marginal generators do not consider past information in their bidding processes and offer at their marginal costs. Further, since long-term correlation structure does not exist, future prices are not predictable from past prices, and the market is weak-form efficient in T_2. This finding also indicates that innovations to the market can have temporary effect for the T_2 time zone.

3.7. Suggestions for Future Research

Developing approaches more robust to skewed distributions for the conditional mean would provide an opportunity on relaxing the normality assumption. Developing new electricity market monitoring indexes considering the time zones would result in interesting policy implications. Furthermore considering the fractal dynamics of electricity prices at different time scales, one would reduce the prediction confidence intervals.

Chapter 4

Managing Price Modelling Risk with Ensemble Forecasting[9]

4.1. Introduction

Electricity day-ahead (EDA) auctions play a central role for the sustainability of electricity markets since they reveal the *reference price* for all market participants. In emerging markets, since the number and variety of hedging tools are limited, for market participants accurate forecasting becomes the most essential tool for managing spot price risk. On the other hand designing a market with a proper transparency level is one of main responsibilities of the policy-makers to let market participants generate reasonable forecasts using public information.

Especially after the well-known California crisis in the 2000s, the number of studies on day-ahead price forecasting increased substantially, as the need for such studies became apparent (e.g. Borenstein, 2002; Borenstein and Bushnell, 2000; Borenstein et al., 2002). Since the storability of electricity is limited, electricity prices reveal characteristics that

[9]Parts of this Chapter appeared in the following conference proceeding:
Avci, E., Bunn, D.W., Ketter, W. & van Heck, E. (2017). An Ensemble Approach to Forecast Electricity Day Ahead Auction Prices: Experiences from the Turkish Market. Institute for Operations Research and the Management Sciences (INFORMS). Houston, Texas, United States.
Avci, E., van Heck, E. & Ketter, W. (2017). Forecasting prices in electricity day-ahead auctions: An overview of the Turkey market. In 5th International Symposium on Environment and Energy Finance Issues (ISEFI-2017), Paris, FRANCE.

differ from other commodities and present specific forecasting challenges. Studies focus first on the basic characteristics of electricity, namely non-storability and inelasticity of supply/demand (Geman and Roncoroni, 2006; Lucia and Schwartz, 2002), and then examine spikes, nonstationarity and mean reversion (Haugom et al., 2011; Knittel and Roberts, 2005). However there are still three challenges that needs to be dealt with in electricity price forecasting (Weron, 2014).

The first one is a methodological issue, the *risk of selection of an inappropriate forecasting model*. Although various individual forecasting methods are suggested in the literature, none of them has been proven to be superior (Chen and Bunn, 2010; Weron, 2014), and the performance of individual models depends on the periods being considered and the characteristics of market (Aggarwal et al., 2009). To compensate for the weaknesses of each individual method, the combined forecasting approach was developed (Crane and Crotty, 1967; Bates and Granger, 1969). The main advantage of combining forecasts is not that the ex-post performance of best ensembles are better than that of best individuals, but that it is less risky to ensemble forecasts than to select ex-ante one individual forecasting method (Hibon and Evgeniou, 2005). Although ensemble approach has been well-studied in other contexts (Stock and Watson, 2004; Timmerman, 2006), the number of combined forecasting studies relating to electricity markets is limited (Weron, 2014). The existing studies are mostly on electricity load forecasting (e.g. Bunn, 1975, 1977; Taylor, 2010). In the context of day-ahead price forecasting, leading point forecasting studies are, Bordignon et al. (2013) and Nowotarski et al. (2014), both of which are of mature electricity markets (the UK and Nord Pool). The recent few studies (e.g. Maciejowska et al., 2016; Gaillard et al., 2016; Maciejowska and Nowotarski, 2016) focus on probabilistic forecasting and are from the results of the GEF2014 probabilistic forecasting competition in which US zonal prices are used. One of the main findings of these papers is that analysis of different market conditions can provide important insights in terms of comparing individual and ensemble models.

Second challenge is a more market-specific one which is the *appropriate selection of exogenous variables* (e.g. Keles et al., 2016), since the quality and availability of public data (transparency level of the market) and their influence on price may differ depending on the market studied (Aggarwal et al., 2009; Von der Fehr, 2013). Including exogenous variables (e.g. demand) generally increases the accuracy of price forecasts. However, when the number of exogenous variables is increased, the probability of data quality issues and access problems can increase, and may lead to even worser price forecasts. Therefore, in devising a sound process for selecting variables the features of the market need to be taken into account.

The last challenge is catching market-specific *multi-seasonality* (e.g. Janczura et al., 2013) characteristics of the spot price. Multi-seasonality is defined as having simultaneously daily, weekly and annual components. The *annual seasonality* is more difficult to detect, as it is masked by more irregular patterns, and it is often ignored in studies as it is generally believed to add complexity to already parsimonious models (Weron, 2014; Nowotarski and Weron, 2016). The problem of *daily seasonality* is solved by either taking daily averages or modelling each hour separately (Misiorek et al., 2006; Karakatsani and Bunn, 2008, 2010). Since predictability level (and thus market efficiency) of electricity prices can change over the course of the day, choosing forecasting models by considering fractal properties is very important (Avci-Surucu et al., 2016). The *dual-calendar effect* is another factor that influences prices in countries which follow both the Hijri and Gregorian calendars for holidays (De Livera et al., 2011).

In this research our aim is to examine the performance of carefully selected individual and ensemble models in the emerging EDA market of Turkey. It provides several challenges for forecasters. First, since it is an emerging market, hedging possibilities are limited, forecasting becomes the foremost important tool to manage spot price risk for power agents. As stated in Hong (2015), even one percent decrease in short term price forecasting error could result in a hundred thousands of profit per year for a medium sized utility. Even worse, as in most of the emerging markets, there is no information transparency platform from which market participants can obtain relevant data easily and use them in order to decrease their forecast errors. This makes the Turkey DAM a *semi-transparent* one in terms of information dissemination[10]. Secondly, there is no nuclear power plant and therefore it will eases the horizontal shift of the base load in the hourly merit order curve. Third, there is no gas forward market as gas prices are regulated by the government, therefore it is more difficult to catch the trend seasonality by calculating the marginal costs of bidders. Fourth, the observance of multiple religious holidays in Turkey means that dual-calendar seasonal

[10] Details about the *transparency level* is given in Section 3.

effects can be found and this situation complicates modelling seasonality component. Lastly, bids by the state-owned hydropower plants (PP) have a crucial impact on the shape of the merit order curve, therefore appropriate selection of the exogenous variables relating to supply stack characteristics becomes vital. Thus, our main research question is *How to manage price modelling risk via ensemble forecasting in the Turkish EDA auctions'*. In sum, we aim to develop well-performing ensemble forecast models for an emerging market and compare their performance with alternative individual models. This will enable us to address some of the shortcomings of existing ensemble modelling studies, specifically the inadequate handling of trend seasonality component, the inappropriate selection of exogenous variables when one considers the relationships that exist between price and system constraints, and the methodological similarity of the individual models they have considered. We contribute to the energy economics literature on both theoretical and practical dimensions. Firstly, regarding the variety and type of individual models, ours is one of the first studies to include a long-term seasonality component for ensemble forecasts and to provide evidence of their performance. Secondly, since all of the previous ensemble forecasting studies of electricity price are from well-developed markets (such as the UK and Nord Pool) and ours is the first to look at a developing market with a semi-transparent structure, our findings may be informative for market participants and policy-makers in other developing markets with similar transparency features. Lastly, this forecasting study is also pioneering in terms of the Turkish electricity market since it is the very first to examine EDA auction prices after the establishment of the Day-Ahead Market (DAM) in 2012.

The remainder of the paper is organized as follows. In Section 2, we briefly explain the theoretical framework of the individual and ensemble models that we adopt for this study. Section 3 illustrates the conceptual background related to general processes and fundamental drivers of the clearing price in day-ahead auctions. Section 4 describes the data and its temporal properties, Section 5 explains the theoretical framework and presents the results, and Section 6 concludes the paper with a summary of the findings and suggestions for future research.

4.2. Theoretical Framework

We consider three classes of individual models; econometric time series, artificial neural networks and seasonality models; which are chosen by virtue of their suitability for catching the specific features of the price dynamics of EDA auctions and also for minimizing the methodological similarities between them guided by the previous literature. We aim to understand how their forecasting performance changes according to the particular electricity market. We derive our ensemble models by using *equally weighted means* which has been highly advocated (Makridakis et al., 1998; Stock and Watson, 2004). All the models (both individual and ensemble) are executed with a set of explanatory variables which are carefully selected from the literature due to their fundamental relation with auction mechanism of the day-ahead markets and their correlation with the clearing price (Karakatsani and Bunn, 2008; Nan, 2009).

4.2.1. Exogenous Variables Affecting Auction Prices

The selection of exogenous variables is a crucial step for developing forecasting models. Market characteristics, nonstrategic uncertainties, other stochastic uncertainties, behavioural indices, and temporal effects are main classes of input variables effecting electricity prices (Karakatsani and Bunn, 2008). *Historical electricity prices* (e.g. price lags of 1–7, 14, 21, 28 or 364 days) are the most extensively used variable. Due to its strong correlation with price, *demand* is the next most often used input variable. There are different approaches to using demand in the models, namely demand forecasts made by Independent System Operator (ISO) (e.g. Nan, 2009; Bordignon et al., 2013), in-house demand forecasts (e.g. Georgilakis, 2006; Mandal et al., 2006) and historical demand data (e.g. Weron, 2006). Since storage of electricity is limited, variables that indicate stochastic uncertainties (e.g. system constraints) can be very useful for modelling the spikes or extreme conditions. *Reserve margin* (the difference between available capacity and demand) (Eydeland and Wolyniec, 2003; Harris, 2006) and *reserve margin ratio* (the ratio of demand divided by available capacity, and is also an indicator of safe functioning of power system) (Anderson and Davison, 2008; Cartea et al., 2009; Davison et al., 2002; Maryniak, 2013; Maryniak and Weron, 2014) are two of the most commonly used system capacity constraint variables. Another possible explanatory variable is *temperature* as it is strongly correlated to demand (Mandal et al., 2006; Guo and Luh, 2003, 2004). However, if demand can be forecasted accurately, the explanatory power of temperature can be ignored considering the data quality and accessibility issues. The marginal costs of market participants affect their bidding strategies and shape (i.e., steepness) of the merit order curve. Thus *natural gas and oil prices* have also been used to explain prices (Guo and Luh, 2003, 2004; Gao et al., 2000; Zhang and Luh, 2005; Bordignon et al., 2013). Importance level of these exogenous variables for electricity prices may change according to the market design and characteristics, and their effect may be limited (Weron, 2014). For the UK market, for example, whilst Bordignon et al. (2013) find demand and gas price to have significant effects on the UK spot electricity prices. Maciejowska (2014) finds these fundamental variables to have only minor effects. Therefore optimal selection of exogenous variables depends on the characteristics of the market, the type of model used, data access[11], heuristics, and experience of the modeller[12].

In this research, to select the appropriate exogenous variables we follow the approach of Weron (2006, 2014), Karakatsani and Bunn (2008) and Bordignon et al. (2013), and use only publicly available explanatory data even though we also have access to insider information. We have three reasons for this; first, we are looking at how these methods are used by energy experts in the market and policy-makers; second, it allows us to compare our forecast accuracy results with the previous studies; and third, although we have access to insider information (the level of all dams with reservoirs, forecasted geospatial temperatures) we prefer not use these data, due to the data being of poor quality and not available until relatively late (usually not before the gate's closure in the day-ahead market). From these variables we chose the ones which have been most widely used in the literature and which are most relevant for the Turkish electricity market. We run each model with and without exogenous variables to see the effect of adding explanatory variables on performance. The exogenous variables (X) used in the models are summarized in Table 4.1.

[11] For a detailed discussion, see Weron (2014) and Aggarwal et al. (2009).
[12] For a detailed discussion, see Amjady and Hemmati (2006).

Table 4.1: Exogenous variables used in the models

Variables	Description	Notation and lags
Forecasted demand (d)	Day-ahead demand forecast published by the system operator	d_{t-j} (j=0, 1, 2, 3, 7, 14, 21, 28)
Margin (m)	Available capacity (generation, surplus) – demand forecast	m_{t-i} (i=0, 1, 2)
Day-specific dummy	Three dummy variables for Saturday, Sunday and Monday, separately	D_{sat}, D_{sun}, D_{mon}
Holiday dummy	Dummy variable for official and religious holidays	D_{hol}

4.2.2. Individual Forecasting Methods

In the following subsections, we briefly explain the parametric and nonparametric methods that are adopted in this reserach for generating individual forecast models.

4.2.2.1. Econometric Time Series Models

Econometric time series methods forecast the current price by using a mathematical combination of historical prices and/or historical or current values of exogenous variables. Although these methods are not good for spiky periods, they perform well in terms of capturing the general patterns in electricity price data (Weron, 2014).

(Seasonal) ARMA models (SARMA)

If the dependence on the past prices is likely to occur at certain seasonal lag s, it is appropriate to introduce autoregressive and moving average polynomials that identify with the seasonal lags. The resulting seasonal autoregressive moving average model is ARMA (P;Q)$_s$, which can be written as $\Phi_P(B^s)x_t = \Theta_Q(B^s)\omega_t$, where $\Phi_P(B^s)x_t = 1 - \Phi_1 \mathrm{B}^{\mathrm{s}} - \Phi_2 \mathrm{B}^{2\mathrm{s}} - \cdots - \Phi_p \mathrm{B}^{\mathrm{Ps}}$, and $\Phi_Q(B^s)x_t = 1 + \Phi_1 \mathrm{B}^{\mathrm{s}} + \Phi_2 \mathrm{B}^{2\mathrm{s}} + \cdots + \Phi_Q \mathrm{B}^{\mathrm{Qs}}$ are the seasonal autoregressive operator and the seasonal moving average operator of orders P and Q, respectively, with seasonal period s. SARIMA models are most often used as a benchmark in electricity price literature. The following AR formula gives a general expression of the model structure adopted in this study: $p_t = \emptyset_1 p_{t-1} + \emptyset_2 p_{t-2} + \emptyset_3 p_{t-3} + \emptyset_4 p_{t-7} + \emptyset_5 p_{t-14} + \emptyset_6 p_{t-21} + \emptyset_7 p_{t-28} + \psi_1 d_t + \psi_2 d_{t-1} + \psi_3 d_{t-2} + \psi_4 d_{t-3} + \psi_5 d_{t-7} +$

$\psi_6 d_{t-14} + \psi_7 d_{t-21} + \psi_8 d_{t-28} + \delta_1 m_t + \delta_2 m_{t-1} + \delta_3 m_{t-2} + \gamma_1 D_{sat} + \gamma_2 D_{sun} + \gamma_3 D_{mon} + \alpha_1 D_{hol}$ where p_{t-i} denotes the ith lag of the clearing price which represents the autoregressive effects of the previous days, d_{t-i} is for the ith lag of the demand forecast where i=0 represents the demand forecast for the next day. m_{t-1} is for the ith lag of margin variable where i=0 represents the planned margin for the next day. D_{sat}, D_{sun}, D_{mon} are dummy variables for days Saturday, Sunday and Monday to consider the weekly seasonality. The dummy variable D_{hol} refers to the official and religious holidays in the whole data set. The orders of our models are identified through Akaike Information Criterion (AIC) and investigation of the residual diagnostics.

4.2.2.2. Artificial Intelligence (AI) Models

AI methods model price processes using non-parametric approaches. Due to their flexibility and their ability to handle complexity and non-linearity they have been preferred by many authors (e.g. Catalao et al., 2007; Pino et al., 2008; Vahidinasab et al., 2008) for short-term price forecasting. Despite their popularity for individual modelling, there is still an open question for their performance in emsemble models (Keles et al., 2016) with and without exogenous variables. We use the *nonlinear autoregressive exogenous (NARX)* AI method which have been proposed by Lin et al. (1996). These recurrent networks also have very good learning capabilities and generalization performance (Weron, 2014) and have shown that they can greatly improve performance on long-term dependency problems. They relate the current value of a time series both to past values of the same series and to current and past values of the exogenous variables. NARX can be written implicitly as

$y_t = F\,(y_{t-1}, y_{t-1}, y_{t-3}, \cdots, u_t, u_{t-1}, u_{t-2}, u_{t-3}, \cdots) + \varepsilon_t,$

where u are the exogenous variables and ε is the error term. The function F is a neural network. An NAR $(p,P,k)_m$ model has inputs $(y_{t-1}, y_{t-2}, \cdots, y_{t-p}, y_{t-m}, y_{t-2m}, y_{t-pm})$ and k neurons in the hidden layer. For this model we use a *feed-forward single layer algorithm* NARX.

4.2.2.3. Seasonality Models

Adequate treatment of seasonality in electricity prices is of utmost importance for developing sound forecasting models (Janczura et al., 2013; Lisi and Nan, 2014) There are different approaches to modeling seasonality such as piecewise constant/sinusoidal functions and wavelets. A failure to acknowledge seasonality or to handle it appropriately can significantly reduce the accuracy of the model (Ketter et al., 2009; 2012; De Livera, 2011). For short term electricity price forecasting; although daily and weekly components have been taken into account, long-term component has been neglected due to the general belief that it adds unnecessary complexity to already parsimonious models (Weron, 2014). However, recently Nowotarski and Weron, 2016 have shown that taking the LTSC component into account in short term electricity price forecasting can significantly improve the model performance and create a natural opportunity to include them in ensemble forecasts. This can be done in a number of ways; polynomial and sinusoidal regression, polynomial kernel regression, linear regression and smoothing splines, filters, state space models etc. (for details see Hydman et al., 2002; De Livera, 2011; Lisi and Nan, 2014). After a thorough review of this extensive literature we adopt two of the recently developed, state space based models, namely *Exponential smoothing state space (ETS)* and *Trigonometric Box-Cox Transformed ARMA errored Seasonal (TBATS)* models, by virtue of their ability for handling complex seasonal patterns existing in electricity prices.

Hydman et al. (2002) have expanded earlier work by Ord et al. (1997) on special types of innovation state-space models which underlie exponential smoothing models and have developed a new and more general set of methods which bring exponential smoothing into the same class as ARMA models. These are known as exponential smoothing state-space models (ETS). For this research we utilise the algorithm of Hydman et al. (2002) to estimate the parameters of our ETS models.

Commonly used seasonality models, *single seasonal exponential smoothing* (Makridakis et al., 1982; Makridakis and Hibon, 2000; Snyder, Koehler, and Ord, 2002) and *second seasonal Holt–Winters* (Taylor, 2003) methods cannot catch complex seasonal patterns such as non-integer seasonality and calendar effects, or time series with non-nested seasonal patterns. The *nonlinear versions of the state space models* can be unstable, as they have infinite forecast variances beyond a certain forecasting horizon, and analytical results for the prediction distributions are not available (Akram et al., 2009). Thus we use the TBATS algorithm, introduced by De Livera et al. (2011), which is developed as an alternative estimation method to allow for non-integer seasonality and calendar effects, or time series with non-nested seasonal patterns; and handle a wider variety of seasonal patterns.

4.2.3. Ensemble models

The idea of ensemble forecasts was developed by Reid (1968, 1969) and Bates and Granger (1969), and has been extensively studied (e.g. Bunn, 1975, 1977; de Menezes et al., 2000; Timmermann, 2006; Altavilla and De Grauwe, 2010; Clark and McCracken, 2009). The idea behind ensemble forecasting techniques is straightforward: individual models have their own weaknesses and none of them is superior to the others. Ensemble forecasting enables us to compensate for the weaknesses of individual models. In general, an ensemble forecast including a set of K competing spot price predictors $(\hat{P}_t^{(1)}, \dots, \hat{P}_t^{(K)})$ can be written as: $\hat{P}_t^{(C)} = f\ (\hat{P}_t^{(1)}, \dots, \hat{P}_t^{(K)};\ \omega\ )$ where f is a generic function and ω is a parameter vector. Using linear functions, this expression can be written as $\hat{P}_t^C = \sum_{k=1}^{K} \omega_k\, \hat{P}_t^{(k)}$. In general, weights ω_k can be constant or time-varying, ω_{t-k}. Several studies have shown that, due to the effect of finite-sample error in estimating the combining weights, an equally weighted mean is often the best choice (Clemen, 1989; Makridakis and Winkler, 1983; Smith and Wallis, 2009; Stock and Watson, 2004). Although ensemble forecasts have generally been shown in theoretical studies to outperform the individual methods (e.g. Chen and Yang, 2007) they have not stood out in the context of electricity markets. The first ensemble forecasting studies in electricity markets were done by Bunn (1985) and Bunn and Farmer (1985), looking at load forecasting provided a theoretical discussion of the merits of ensemble modelling. Smith (1989) provides empirical evidence to show the superiority of forecast combinations of ARMA models over the individual ARMA models. Taylor and Majithia (2000) find that the performance of ensemble models differs with respect to the time of the day.

The literature on ensemble modelling for electricity price forecasting is very rare. As far we know, there have been only three studies; Nan (2009), Bordignon et al. (2013) and

Nowotarski et al. (2014). Nan (2009) is the pioneer study in this area. She examines the UK market prices and uses 19 individual models which are derived from four basic models; namely linear regression, ARMAX, time-varying regression and Markov regime switching models. The author then selects subsets of individual models through using model confidence set and encompassing approaches. Her ensemble models outperform the individual ones in most cases. In a follow up study, with the same data set, Bordignon et al. (2013) examine the performance of ensemble models against five individual models; linear regression, ARMAX, time-varying regression and two Markov regime switching models and conclude that most ensemble models perform better than individual ones. Nowotarski et al. (2014) as an extension of these two studies, increased the number of considered markets (to Nord Pool, EEX and PJM), time periods and individual models (to AR- and mean reversion based) and similarly find supporting evidence for the outperformance of ensemble models. However they show that the performance of combined forecasts may differ with respect to the market considered and periods.

In this study we aim to develop well-performing ensemble forecast models for an emerging market and compare their performances with competing individual models addressing some short comings of existing ensemble modelling studies. First, we increase the variety of considered individual models to minimize the methodological similarity between them. We extend the set of individual models to seasonality methods; which have not been considered by the prior literature; in virtue of their potential to describe some specific characteristics of electricity prices. We adopt ETS and TBATS seasonality models to take into account inadequate handling of trend-seasonality component and to deal with the complex multi-seasonality in electricity prices. Second we conduct the analysis following the literature which has found that price volatility, fractality, market efficiency, predictability of prices, costs and operational constraints differ for each hour/hour block during the course of a day (Shahidehour et al., 2002; Huisman et al., 2007; Avci-Surucu et al., 2016). Focus of the previous studies are on testing the performance of ensemble models for each hour separately (e.g. Huisman et al., 2007) or taking daily averages (e.g. Bunn, 2004; Bunn and Karakatsani, 2003) . We rather stayed focus on the market efficiency and predictability of prices in a day and provide important insights on the performance of our models considering three different tariff time-zones – namely T1 (day): 06:00–17:00, T2 (peak): 17:00–22:00, and T3 (night): 22:00–06:00, leading to three sets of parameters for each day. Third, most of the previous studies are from well-developed markets; namely UK, Nord Pool and PJM. We extend these studies to an emerging market which has different price characteristics in terms of seasonality, spikes and fractality level. Thus we believe that our findings can be informative for the market participants/policy-makers in other developing markets with similar characteristics (e.g. share of renewables, natural gas etc.). Lastly, while testing the additional gains from ensemble modelling approach we also test the additional benefit from including exogenous variables considering the fundamental relations between price and system constraints through using a complete and big data set.

4.3. Conceptual Background

4.3.1. General Principles of the Market

The general principles and processes of the DAM in Turkey is similar to most European electricity markets. Between 2012 and 2015 DAM was operated by Electricity Market Financial Reconciliation Centre (PMUM), and is currently operated by the Istanbul Energy Exchange (EXIST). Prices and volumes are determined each hour on a daily basis. Power plants are ranked on the basis of their bid prices, and a merit order curve is thus formed. The general shape of a supply stack in Turkey is demonstrated in Figure 4.1. In day-ahead auctions marginal generators are the ones that determine the clearing price. In Turkey, since the demand side is not actively managed, understanding the shape and order of plants in the supply stack is crucial for understanding price formation in this market.

4.3.2. Information Transparency Level of the Market

Until September 2015 information on the market-specific variables was made available by the Market Financial Settlement Centre (PMUM), then Istanbul Energy Exchange (EXIST) took over this responsibility and now disseminates both forecasted (ex-ante), real-time and realized (ex-post) data through its Market Transparency Platform in a timely manner. DAM related information revealed through the transparency platform and its details are illustrated in Tables 4.A.1 and Table 4.A.2. As can be observed from these tables, until the beginning of 2016 information transparency level of the market is low which can be defined as *semi-*

transparent. EDA prices in our sample (January 2012-December 2015) were comprised of aggregation of expectations of market participants making decisions in such a transparency level. Thus to imitate the real decision-making setting of power agents, we utilize from only public data released during that time period.

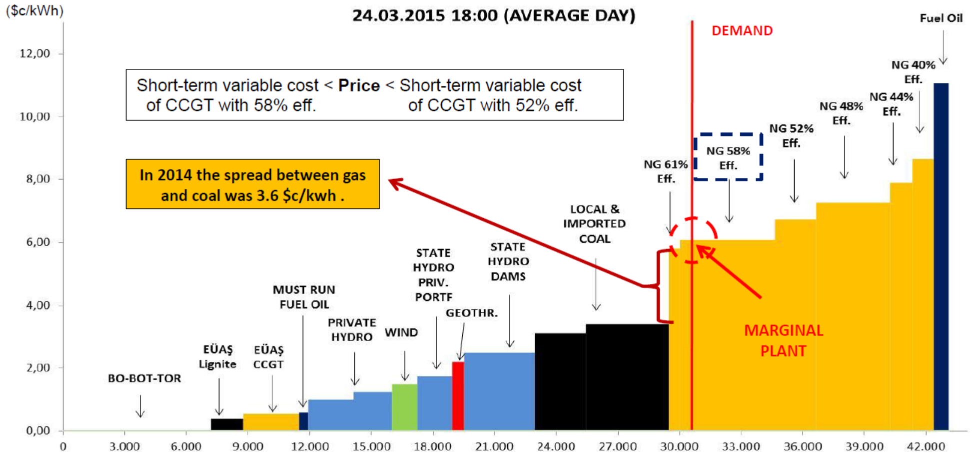

Fig. 4.1: Approximate supply stack on a sample day; 24/03/2015 (Source: Garanti Bank)[13]

4.3.3. Fundamental Drivers of EDA Clearing Price in Turkey

Changes in the supply and demand characteristics, market architecture and/or ownership structure can affect the dynamics of the clearing price in uniform-price auctions (Petrella and Sapio, 2012; Glachant and Saguan, 2007) and lead to structural breaks in the series. In this section we investigate these characteristics in the Turkish day-ahead market to understand whether there have been any structural breaks in the price series between 2012 and 2015. The capacity mix in Turkey is not particularly well balanced and is mostly based

[13] Transfer of operational rights (TOOR) provides for the transfer of operational rights relating to public assets (in this case the power generation and distribution assets of TEK, TEAŞ and TEDAŞ) to private management, along with new investment by the private sector, for the duration of the TOOR contract. Build, operate and transfer (BOT) provides for the transfer of the asset to the State at the end of the contract period. Build, Own and Operate (BOO) which includes the transfer of the power stations to TEAŞ at the end of the contract period was withdrawn in order to reduce legal uncertainties and thereby improve the bankability of the projects. Autoproduction provides for the ownership and operation of power plants by industrial companies, primarily for their own electricity needs.

on fossil fuels, which constituted 67.7% of the total generation in 2015. Natural gas is the major fuel in electricity generation (38.6%), followed by coal (28.3%), and some fuel oil (0.8%). The capacity mix in Turkey can change year on year, owing to the seasonality of hydroelectric supply and availability of old lignite plants. Currently, generation activities are carried out by three parties: EUAS, private generators and auto-producers. In 2012, the share held by EUAS and its affiliates was 42% of the total installed capacity. In 2015 this state-owned share decreased to 28% with a portfolio of hydroelectric and lignite power plants. IPPs and BOT, BOO and TOOR utilities are responsible for most of the power generation and hold 70% of the total capacity. The important issue here is that the privatized EUAS power plants were those that had not generally been marginal generators in the merit order curve. Therefore we can confidently state that there has not been any major change in industry structure that has led to a structural break in the price series.

4.3.4. Electricity Price Forecasting Studies in Turkey

There is an absence of substantial research on electricity price forecasting in Turkey and those studies that do exist are in the form of PhD theses or conference proceedings and represent the period before the day-ahead market was established. Hayfavi and Talasli (2014) model logarithmic daily average spot prices for electricity as the sum of a deterministic function and a multi-factor stochastic process. They do not use any exogenous variables. Their data interval runs from December 2009 to July 2011, which was the *Day-Ahead Plannning* period and does thus not reflect the market regulations and conditions of the day-ahead market currently operating in Turkey. Yildirim et al. (2012) use dynamic regression, CMARS and RCMARS to forecast the next day's electricity prices. They do not use any exogenous variables in their models. For their training data they use only one month of data because of the limitations in their RCMARS method, thus the validity of their results is questionable in the context of electricity markets. Kölmek and Navruz (2013) use ANN and AR methods to forecast the electricity prices with a training data interval running from December 2009 to November 2010. For the ANN model they use historical day-ahead prices, demand forecast, bilateral contact, and available capacity as exogenous variables, however, they do not use any exogenous variables for the AR model. The authors compared these two methods with respect to MAPE and conclude that performance of the ANN method is higher than that of the AR. This study is valuable in the sense that it is the first published paper which uses ANN for electricity price forecasting in Turkey. However, it has some deficiencies. First, their data is from the day-ahead planning period and does not represent the current electricity market conditions. Second, they compare these two methods, one with exogenous variables and one without. It is known that models with exogenous variables tend to perform better than the ones without them, thus the validity of their performance comparison is also questionable.

Unlu (2012) has studied the linear relationship between temperature and day-ahead electricity prices using a data set of 35 days. He investigate in particular the seasonality and predictability issue in temperature. In the final stage, in which linear models (AR and ARX) and 30 days training data are used, he attempts to predict the electricity price for the next five days. The drawback of this study is that it takes no account of the well-known nonlinear relationship between temperature and electricity prices, and thus concludes that there is no relationship between these two variables. From the studies undertaken up to now, it is very difficult to understand the general characteristics of electricity prices in Turkey and the driving factors behind them since all the studies use data sets from the day-ahead planning period, the training sets are not large enough for the results to be generalizable, and all have some methodological deficiencies.

Ozyıldırım and Beyazit (2014) forecast the day-ahead electricity prices using linear regression and radial basis function with a data set from the period 2010-2013. They found that the out-of-sample performance of RBF is slightly better than that of linear regression. They use hourly MCP without logarithmic transformation and integration. Their exogenous variables are MCP lags, temperature, square of temperature (to deal with the nonlinearity issue) and hourly, daily, monthly, and holiday dummies. By using graphs and descriptive statistics, they showed that hourly MCP have distinct clusters with respect to time zones.

As far as we know the only study that reflects current market conditions is Taysi et al. (2015). They forecast MCP using SARIMA and ANN methods with exogenous variables: historical prices and calendar dummies. They showed that the performance of these two methods is very similar. The crucial deficiency of this study is that it uses 1, 2, 3, 4 lagged MCP as exogenous variables. This issue has been well-studied in the energy economics literature and has been found to run counter to the electricity market mechanism. Thus the models in this study cannot be implemented in real life since bidders do not know the prices up to 24 hours ahead. Our examination of the literature on the Turkish electricity market shows that there are no electricity price forecasting studies that reflect current market conditions and mechanisms.

4.4. The Data

The data set used in this study consists of hourly day-ahead auction clearing price time series from the Turkey Electricity Market. The sample starts on 1 January 2012 and ends on 27 December 2015 providing a total of 34.944 hourly observations. This period covers the time after the DAM in Turkey was established and does not have any significant structural changes in the market mechanism and auction design, until the launch of the Market Transparency Platform at the EXIST. The time series data set were obtained from the General Directorate of Energy Affairs at the Ministry of Energy and Natural Resources without any missing values or doubled values. Although in the literature some studies (e.g. Weron 2006) advocate the substitution of outliers with arithmetic averages of some neighbour values or the general mean, we intentionally did not pre-process the data set in terms of outliers to see the real performance of the artificial intelligence and seasonality models.

4.4.1. Summary of Descriptives

We conduct our analyses considering three tariff time zones T1 (day): 06:00–17:00, T2 (peak): 17:00–22:00, and T3 (night): 22:00–06:00 where each time series has 1456 observations. Figure 4.2 illustrates plots of each series and Table 4.2 gives summary statistics for each time zone. T3 series has the highest standard deviation and skewness, but the lowest mean. T1 and T2 series have similar statistical characteristics.

4.4.2. Stationarity, Long-term Correlation and Predictability

We investigate stationarity and predictability level of price series through their fractal dynamics since accurate measurement of fractality is crucial for correct statistical inference and forecast uncertainty (Lildholdt, 2000). We adopt the approach of Baillie et al. (1996) to check the unit root by a combination of PP and KPSS tests and look for indication of fractality since unit root tests often lack the power to distinguish between a truly nonstationary (I(1)) series and a stationary series with a structural break. If the combination of unit root tests indicate fractal behaviour then one can use appropriate long memory estimation methods to find the degree of fractality in the data.

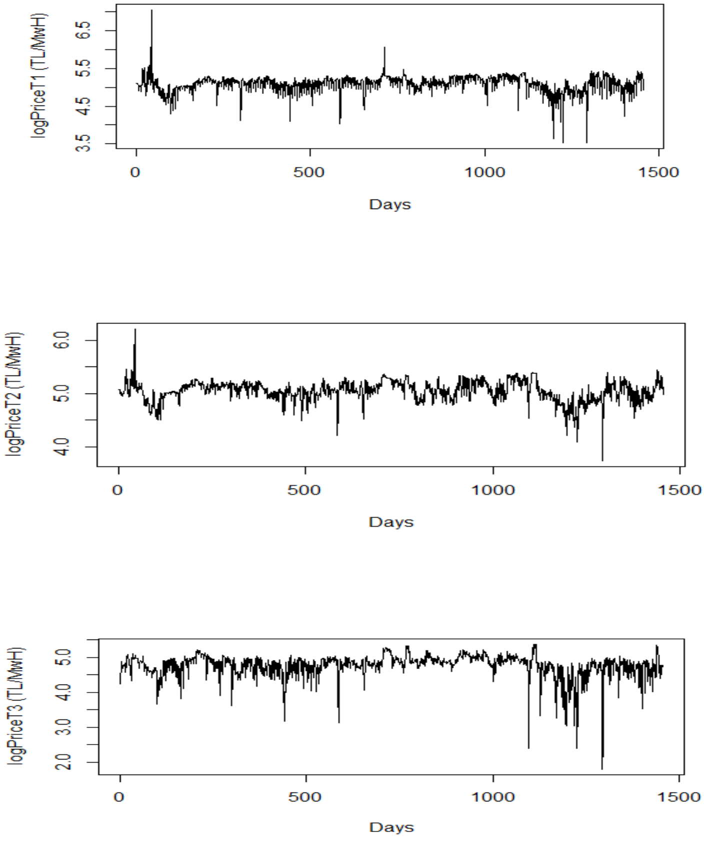

Fig. 4.2: Time series plot of market clearing price with respect to three tariff time zones

Table 4.2: Descriptive statistics for three tariff time zones

Variables	Min.	Max.	Range	Median	Mean	Var.	Std.dev	Skewn.	Kurt.
logPriceT1	3.53	7.06	3.53	5.13	5.09	0.05	0.22	-0.98	15
logPriceT2	3.74	6.21	2.47	5.06	5.05	0.04	0.19	-0.66	6.8
logPriceT3	1.79	5.38	3.58	4.82	4.75	0.11	0.33	-2.7	16

There are three unit root tests commonly used to test the stationarity of a process: 1) the AugmentedDickey-Fuller (ADF) test, 2) the Phillips– Peron (PP) test and 3) the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. However if we wish to test stationarity as a null and have strong priors in its favour, employing the ADF test may not be useful (Baillie et al., 1996). An empirical series with d close to 0.5 will probably be misclassified as nonstationary. Therefore, we use a combination of the PP and KPSS tests allowing us to determine the four possible outcomes of the series (Baillie et al., 1996): 1) if the PP is significant and the KPSS is not, then the data are probably stationary with $d \in (0;0.5)$—strong evidence of a covariance stationary process; 2) if the PP is insignificant and the KPSS is significant, then the data may indicate having brown noise—a strong indicator of a unit root, i.e., an I(0) process; 3) if neither the PP nor the KPSS is significant, then the data are insufficiently informative regarding the long memory of the process; and 4) if both the PP and the KPSS are significant, then the data are not well described as either an I(1) or an I(0) process—$d \in (0; 1)$.

Table 4.3 presents the unit root tests for logarithm of prices. As can be observed from the PP and KPSS values, price series for each time zone are not well described as either an I(1) or an I(0) process which means the differencing parameter (d) is not an integer but between 0 and 1. We estimate this differencing parameter through *Geweke–Porter-Hudak (GPH)* and *Local Whittle estimator (Whittle)*. We adopt these methods to benefit from their different statistical properties; namely GPH's common usage and comparability with the literature, Whittle's parametric efficiency and consistency. As can be seen from Table 4.3, each price series has different fractal dynamics. T1 tariff zone has the lowest differencing average value (0.372) which indicates that it has the highest long-term correlation and prices in this tariff zone are the most predictable. T3 price series has the highest fractal value demonstrating that predictability level of prices in this tariff zone are the lowest. This confirms the proposition that at peak load (here T1 and T2), marginal generators give hyperbolically decaying weights to information by considering the prices of a day/week before (Sapio, 2004). At off-peak load, if marginal generators bid at their marginal costs, then there is no fractal noise, as we observed in the night tariff time zone T3.

Table 4.3: Unit Root results for logarithm of prices in three tariff time zones. Notes: PP null hypothesis: non-stationary, KPSS null hypothesis: stationarity. *Avr. Fract.value* is the average of the PP, KPSS, GPH and Whittle estimates for the corresponding row. *** indicates rejection of the null hypothesis at the 1% significance level. ** indicates rejection of the null hypothesis at the 5% significance level. * indicates rejection of the null hypothesis at the 10% significance level.

Variables	PP	KPSS	GPH	Whittle	Avr.Fract.value
logPriceT1	-1259.6**	0.302*	0.450	0.295	0.372
logPriceT2	-440.81**	0.476*	0.428	0.492	0.460
logPriceT3	-345.2**	0.857**	0.477	0.567	0.522

4.4.3. Multi-seasonality

Multi-seasonality and complexity of the long-term correlation structure in electricity prices are two of the most important challenges for forecasters. Multi-seasonality is mainly shaped by the variation in demand. The daily cycle refers to variations between day and night and during the different points in the day. This daily variation in prices reflects the working habits of the population. To remove *intra-day seasonality*, it is possible to model each hour (or half-hour) of the day separately, as different commodities (Ramanathan et al., 1997; Guthrie and Videbeck, 2002) or by taking daily averages. However it has been shown that daily average prices do not capture the microstructure of the day-ahead auctions since the level of mean reversion, volatility structure and predictability (fractality) level in clearing prices are not constant throughout the day (Huisman et al., 2007; Avci-Surucu et al., 2016). Following the approaches of the aforementioned studies, for our modelling purposes we use the average price for each tariff time zone since first, we do not want to lose information about the microstructure of day-ahead prices, as would be the case were we to use daily averaging. Second, previous studies that have considered each hour separately conclude that there is a block-structured correlation between specific hours resembling the time zones. Third, taking average with respect to each time zone is more intuitive in the sense that electricity market participants have different incentives and bidding strategies for each time zone.

The *intra-week variability* is also non-negligible. The load profile for Saturday and Sunday is generally lower than for the weekdays; this feature is called the *weekend effect*. Similar to the findings of Weron (2006), our results indicate that price characteristics for

Monday are different from those of other weekdays. There are two approaches in the literature to eliminate the intra-week seasonality; omitting the weekends and developing models only for weekdays (e.g. Bordignon et al., 2013) or introducing dummies for the weekends (and some of the days which have different characteristics from those of the rest of weekdays) (e.g. Weron and Misiorek, 2008). We follow the approach of the latter studies and introduce daily dummy variables for Saturday, Sunday and Monday.

Electricity prices also contain strong *seasonal fluctuations (annual cycle)*, reflecting the use of lighting and heating in winter and the growing use of air conditioning in summer. To consider the effects of different profiles on official and religious holidays (*calendar effects*), we include holiday dummies for each of these days. This approach is commonly used in the electricity price forecasting literature as an alternative to removing these days.

4.4.4. Selection and Description of Exogenous Variables

Historical market clearing prices are the lagged values of MCP which are determined by means of the ACF and PACF graphs of electricity prices with respect to time zones. *Forecasted demand* is the hourly demand forecasts published each day by TEIAS for the next physical day. The prices strongly reflect the level of demand with very high peaks in winter and summer, especially during high-demand load periods. In the literature, for the demand variable, there are different approaches. Some researchers (e.g. Bordignon et al., 2013) use forecasted demand published by the TSO and its lagged values, while others (Weron, 2006) use the forecasted demand by the TSO for the next day's demand and take the realized load values for the lagged values. There are three types of information published on the webpage of the National Load Dispatch Centre: historical load data, forecasted load schedule and real-time load consumption. Since market participants are making their price forecasts based on forecasted demand and the merit order curves are aggregations of individual price expectations, we would expect there to be a higher correlation between price and forecasted demand. When we analyse the training data, as presented in Table 4.4, the correlation between price and forecasted demand is 0.604, which is slightly higher than the correlation between price and realized demand. Thus we choose to use forecasted demand data and its lagged values as one of the exogenous variables. *Reserve Margin* is the difference between the demand forecast and the *Daily Production Program* (The generation values with respect to the settlement delivery point which a settlement aggregation entity (SAE) expects to realize in the following day and notifies the market operator at the beginning of day-ahead balancing stage, according to the obligations of the balance responsible party to which the SAE is attached). It can be seen from Table 4.4 that there is a significant relationship between margin and MCP, with a correlation level of 0.151. *Natural gas prices* have been used as an exogenous variable especially for markets in which there are natural gas exchanges and the share of natural gas in electricity production is high. Some of the previous studies utilize the daily forward gas as the forecasted gas price. However, when we analyse the training data, the price of natural gas has increased very slightly. Also there is no natural gas market in Turkey, and the price of natural gas is regulated by the government rather than randomly determined by a liberalized market. Thus we do not use the price of natural gas as an exogenous variable.

Table 4.4: Correlation table for the exogenous variables. Notes: **Correlation is significant at the 0.01 level (two-tailed).

	MCP	For. Demand	Margin	Demand
MCP	1			
Forecasted Demand	.604**	1		
Margin	-.151**	-.515**	1	
Demand	.602**	.987**	-.476**	1

4.5. Results

4.5.1. Data Partition

For model validation purposes, the whole data set (January 1, 2012–December 31, 2015) is divided into two parts. The first part, *training (in-sample) set*, covering the period January 1, 2012–December 31, 2014, is used only for regressor selection and model building. The remaining period, *test set*, (January 1, 2015– December 30, 2015) is used for *out-of-sample* forecast evaluation. Following the previous literature (e.g. Weron and Misiorek, 2008) all the series (clearing prices and exogenous variables) are considered using a logarithmic scale to obtain a more stable variance and have the opportunity to make our results comparable with the previous studies.

4.5.2. Experimental Framework for Comparing Forecast Accuracies

4.5.2.1. Accuracy Measure

We adopt the most commonly used accuracy measure (Weron, 2014) in the electricity pricing literature; the mean absolute percentage error (MAPE);

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{p_t - \widehat{p_t}}{p_t}\right|$$

to compare the results of our models since we do not have any negative prices in our data set. It is important to note that we also got the results with Mean Square Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Error(MAE), however since results are similar, we omit them to save from space.

4.5.2.2. Criteria for Comparing Model Performance

We compare performance of the models according to *three criteria*. In the first criteria we adopt an *ex-post* approach in which we use out-of-sample MAPE values to compare the models. In this criteria, we take ARMA as the benchmark model and compare the performance of the individual and ensemble models within themselves. In the *second criteria*, we compare the *ex-post* performance of the *best individual (BI)* model with that of the *best ensemble (BE)* based on their out-of-sample MAPE values. Although this criteria has been commonly used in the literature, it has also been criticized for not being a realistic forecasting setting. In the *third criteria*, we adopt a more realistic approach and decide the BI and BE based on in-sample MAPE values (*ex-ante*), then compare their performances using their out-of-sample MAPEs.

4.5.2.3. Test for Statistical Significance

To evaluate competing forecasting models, we use the *Diebold-Mariano* (DM) (Diebold and Mariano, 1995) test which verifies the existence of statistical significant difference between forecasting accuracy of two models. The test statistic is based on the loss differential d_t which we take in this study as week-ahead forecast errors. The two-sided DM test evaluates the accuracy of the competing forecasting models by testing the null hypothesis, ($H_0 : d_t = 0$), indicating there is no statistical significant difference between the compared two forecasting models. The alternative hypothesis is that the two forecasts have different levels of accuracy.

4.5.3. Forecast Accuracy Comparison According to Criteria-1

4.5.3.1. Accuracy Comparison of Individual Models

Our findings are summarized in Tables 4.5 and 4.6. Table 4.5 presents the summary of individual models with the lowest forecast errors according to *in-sample MAPE* values. NARX outperforms other competing individual models in most of the cases (96%). T3 and T1 tariff time zones have the highest and lowest MAPE values, respectively. This is an expected result and can be explained by T3 having the lowest long-term correlation and T1 having the highest.

Table 4.6 illustrates summary of individual models with the lowest forecast errors according to *out-of-sample MAPE* values and their related DM test statistics according to Criteria-1. As can be observed from the table, especially for T2 and T3 series, dominant outperformance of NARX is replaced by ARMA-based and seasonality models. Similar to the results of Table 4.4, in most of the cases T3 has the highest MAPE values. Performance of ARMA is the one of the worst among the other competing individual models. Its MAPE value is the lowest in only 5 out of 48 cases (11%). NARX model has the lowest MAPE value in 14 out of 48 cases (30%) (mostly in T1 time zone), however accuracy difference is statistically significant in only 2% of them. ARMAX is the second best performer and outperformed the other individual models in 26% of the cases with a 5% ratio of significant cases. ETS, NAR, ARMA and TBATS are the following outperforming models with 15%, 12%, 11% and 6% outperforming cases respectively. In sum, according to DM test, ARMA can be outperformed significantly in 15% of the cases. Models with exogenous variables generally perform better than models without exogenous variables. This finding is in line with the previous literature and arises because of the high cross-correlation between demand, margin and price. Further this result also shows the appropriate selection of our input variables.

Table 4.5: Summary of individual models with best performance according to *in-sample MAPE*

WEEK NO	T1 training	MAPE (in)	T2 training	MAPE (in)	T3 training	MAPE (in)	MAX MAPE (in)	MIN MAPE (in)
Winter1	NARX	0. 145	NARX	0.250	NARX	0.449	T3	T1
Winter2	NARX	0.149	NARX	0.257	NARX	0.467	T3	T1
Winter3	NARX	0.138	NARX	0.248	NARX	0.451	T3	T1
Winter4	NARX	0.133	NARX	0.237	NARX	0.445	T3	T1
Spring1	NARX	0.139	NARX	0.219	NARX	0.481	T3	T1
Spring2	NARX	0.135	NARX	0.240	NARX	0.453	T3	T1
Spring3	NARX	0.135	NARX	0.220	NARX	0.477	T3	T1
Spring4	NARX	0.130	NARX	0.223	NARX	0.476	T3	T1
Summer1	NARX	0.172	NARX	0.265	NARX	0.496	T3	T1
Summer2	NARX	0.178	NARX	0.275	NARX	0.593	T3	T1
Summer3	NARX	0.180	NARX	0.285	NARX	0.309	T3	T1
Summer4	NARX	0.180	NARX	0.279	NARX	0.310	T3	T1
Autumn1	NAR	0.074	NARX	0.325	NARX	0.636	T3	T1
Autumn2	NARX	0.192	NARX	0.312	NARX	0.660	T3	T1
Autumn3	NAR	0.123	NARX	0.315	NAR	0.182	T2	T1
Autumn4	NARX	0.180	NARX	0.285	NARX	0.676	T3	T1

4.5.3.2. Accuracy Comparison of Ensemble Models

Table 4.7 presents the summary of ensemble models with the lowest forecast errors according to *in-sample MAPE* values. ARMAXNARX outperforms other competing ensemble models in all of the cases (100%). T3 and T1 tariff time zones have the highest and lowest MAPE values, respectively. This is an expected result and can be explained by T3 having the lowest long-term correlation and T1 having the highest.

Table 4.6: Summary of individual models with best model performance (*out-of-sample MAPE*) and Diebold-Marino statistics and p values (second row) according to Critera-1. Notes: *** indicates rejection of the null hypothesis at the 1% significance level. ** indicates rejection of the null hypothesis at the 5% significance level. * indicates rejection of the null hypothesis at the 10% significance level.

WEEK NO	T1 Test	MAPE (OUT)	DMSTAT	T2 Test	MAPE (OUT)	DMSTAT	T3 Test	MAPE (OUT)	DMSTAT	MAX MAPE (out)	MIN MAPE (out)
Winter1	NARX	0.856	1.3283 0.232	NAR	0.728	0.900 0.402	**ARMA**	4.364	-	T3	T2
Winter2	NARX	0.966	1.039 0.338	NARX	1.107	0.252 0.809	**ARMA**	3.321	-	T3	T1
Winter3	ARMAX	0.632	**3.263**** 0.017	ETS	0.994	0.612 0.562	ARMAX	1.307	1.927 0.102	T3	T1
Winter4	NAR	1.182	0.944 0.424	NARX	0.696	**2.246*** 0.065	ARMA	1.277	-	T3	T2
Spring1	NAR	1.179	1.122 0.304	NARX	1.669	1.174 0.284	NARX	4.563	**2.727**** 0.034	T3	T1
Spring2	NAR	1.272	0.789 0.459	NARX	1.189	0.627 0.553	NAR	7.832	0.824 0.441	T3	T2
Spring3	NARX	1.447	1.329 0.232	ETS	1.792	**3.079**** 0.021	TBATS	4.789	-0.949 0.379	T3	T1
Spring4	NARX	1.348	1.027 0.343	TBATS	1.463	1.810 0.120	NARX	8.898	0.150 0.885	T3	T1
Summer1	NARX	1.685	0.802 0.453	**ARMA**	0.897	-	ETS	4.971	1.672 0.145	T3	T2
Summer2	ARMAX	1.340	0.891 0.407	ARMAX	1.344	0.956 0.375	**ARMA**	4.851	-	T3	T1
Summer3	ARIMAX	1.413	1.149 0.294	NARX	1.136	-1.221 0.267	ARMAX	4.355	**2.414*** 0.052	T3	T2
Summer4	ETS	1.559	1.122 0.304	ETS	0.985	0.539 0.609	ETS	1.028	**1.943*** 0.099	T1	T2
Autumn1	ARMAX	0.745	**2.360*** 0.056	ARMAX	1.917	1.748 0.130	NAR	3.227	-0.441 0.674	T3	T1
Autumn2	ARMAX	0.833	1.546 0.173	**ARMA**	3.109	-	ARMAX	3.819	0.901 0.402	T3	T1
Autumn3	ARMAX	1.181	1.232 0.263	ARMAX	2.203	0.156 0.880	NARX	3.313	0.095 0.927	T3	T1
Autumn4	NARX	3.203	1.131 0.300	TBATS	2.170	0.727 0.494	ETS	8.807	0.749 0.481	T3	T2

Table 4.8 illustrates summary of ensemble models with the lowest forecast errors according to *out-of-sample MAPE* values and their related DM test statistics according to Criteria-1. As can be observed from the table, especially for T2 and T3 series, dominant outperformance of ARMAXNARX is replaced by ensemble seasonality models such as ARMAXETS and ARMAXTBATS. Similar to the results of Table 4.7, in most of the cases T3 has the highest MAPE values. According to DM test results, these accuracy differences

are statistically significant in only in 9 out of 48 cases (19%). 45% of these cases are in the T3 zone indicating that for T3 price series, usage of ensemble seasonality models could be useful to increase forecast accuracy.

Table 4.7: Summary of ensemble models with best model performance (according to *in-sample MAPE*)

WEEK NO	T1-training	MAPE (in)	T2-training	MAPE (in)	T3-training	MAPE (in)	MAX MAPE (in)	MIN MAPE (in)
Winter1	ARMAXNARX	0.605	ARMAXETS	0.049	ARMAXNARX	1.326	T3	T2
Winter2	ARMAXNARX	0.603	ARMAXNARX	0.715	ARMAXNARX	1.344	T3	T1
Winter3	ARMAXNARX	0.591	ARMAXNARX	0.710	ARMAXNARX	1.342	T3	T1
Winter4	ARMAXNARX	0.578	ARMAXNARX	0.704	ARMAXNARX	1.332	T3	T1
Spring1	ARMAXNARX	0.578	ARMAXNARX	0.698	ARMAXNARX	1.324	T3	T1
Spring2	ARMAXNARX	0.574	ARMAXNARX	0.698	ARMAXNARX	1.322	T3	T1
Spring3	ARMAXNARX	0.575	ARMAXNARX	0.700	ARMAXNARX	1.343	T3	T1
Spring4	ARMAXNARX	0.578	ARMAXNARX	0.704	ARMAXNARX	1.350	T3	T1
Summer1	ARMAXNARX	0.674	ARMAXNARX	0.780	ARMAXNARX	1.566	T3	T1
Summer2	ARMAXNARX	0.672	ARMAXNARX	0.783	ARMAXNARX	1.624	T3	T1
Summer3	ARMAXNARX	0.685	ARMAXNARX	0.791	ARMAXNARX	1.499	T3	T1
Summer4	ARMAXNARX	0.687	ARMAXNARX	0.791	ARMAXNARX	1.493	T3	T1
Autumn1	ARMAXNARX	0.696	ARMAXNARX	0.835	ARMAXNARX	1.745	T3	T1
Autumn2	ARMAXNARX	0.692	ARMAXNARX	0.839	ARMAXNARX	1.751	T3	T1
Autumn3	ARMAXNARX	0.700	ARMAXNARX	0.847	ARMAXNARX	1.762	T3	T1
Autumn4	ARMAXNARX	0.699	ARMAXNARX	0.834	ARMAXNARX	1.749	T3	T1

ARMAXNARX model has the lowest MAPE value in 12 out of 48 cases (25%) (mostly in T1 time zone), however accuracy difference is statistically significant in only 16% of them. ARMAXETS is the second best performer and outperformed the other individual models in 21% of the cases with a 2% ratio of significant cases. ARMAXTBATS, ARMANAR, TBATSNAR and ETSNAR are the following outperforming models with 15%, 11%, 11% and 8% outperforming cases respectively. In sum, according to DM test with 5% significance level, ARMA can be outperformed significantly in 19% of the cases, mostly for the T3 time zone. Models with exogenous variables generally perform better than models without exogenous variables.

Table 4.8: Summary of ensemble models with best model performance (*out-of-sample MAPE*) and Diebold Marino statistic and p values (second row) according to criteria1. Notes: *** indicates rejection of the null hypothesis at the 1% significance level. ** indicates rejection of the null hypothesis at the 5% significance level. * indicates rejection of the null hypothesis at the 10% significance level.

WEEK NO	T1-Test	MAPE (out)	DMSTAT	T2_Test	MAPE (out)	DMSTAT	T3_Test	MAPE (out)	DMSTAT	MAX MAPE	MIN MAPE
Winter1	ARMAXTBATS	0.960	1.826 0.117	ARMANAR	0.876	-0.716 0.500	ARMAETS	4.900	-1.821 0.118	T3	T2
Winter2	ARMAXETS	0.418	1.876 0.109	ETSNAR	1.091	0.412 0.694	ARMANAR	3.573	-0.782 0.463	T3	T1
Winter3	ARMAXTBATS	0.753	**2.803**** 0.031	TBATSNAR	0.974	0.3602 0.731	ARMAXTBATS	1.567	**2.542**** 0.043	T3	T1
Winter4	ARMAXNARX	0.293	1.482 0.188	ARMAXNARX	0.650	**2.799**** 0.031	ARMANAR	0.914	1.165 0.287	T3	T1
Spring1	TBATSNAR	1.395	1.222 0.267	TBATSNAR	1.741	1.454 0.196	ETSNAR	6.038	**3.203**** 0.018	T3	T1
Spring2	ARMAXNARX	1.269	1.013 0.350	ARMANAR	1.165	0.847 0.429	ARMAXNARX	7.909	0.976 0.366	T3	T2
Spring3	ARMAXNARX	1.455	1.367 0.220	ARMAXETS	2.224	**2.090*** 0.081	ARMAXTBATS	4.795	0.373 0.721	T3	T1
Spring4	ETSNNAR	1.294	1.282 0.247	ARMAXETS	1.247	1.643 0.151	ETSNAR	8.345	0.721 0.497	T3	T2
Summer1	ARMAXNARX	1.192	0.991 0.359	ARMATBATS	1.139	-0.283 0.786	ARMAXETS	4.504	1.258 0.254	T3	T2
Summer2	TBATSNAR	1.121	1.155 0.291	ARMAXETS	1.818	0.392 0.708	ARMAXTBATS	8.806	**-7.670***** 0.0002	T3	T1
Summer3	ARMAXNARX	1.081	**2.169*** 0.073	ARMAXNARX	1.377	-0.212 0.838	ARMAXETS	6.334	1.161 0.289	T3	T1
Summer4	ARMAXETS	1.213	1.146 0.295	ARMAXETS	0.824	1.438 0.200	ETSNAR	1.453	**2.810**** 0.030	T3	T2
Autumn1	ARMAXTBATS	0.537	**2.589**** 0.041	ARMAXNARX	1.981	-0.447 0.670	TBATSNAR	3.699	-1.062 0.328	T3	T1
Autumn2	ARMAXTBATS	1.046	1.808 0.120	ARMATBATSETS	3.104	0.437 0.677	ARMAXETS	3.804	0.853 0.426	T3	T1
Autumn3	ARMAXNARX	1.202	1.236 0.262	ARMAXETS	2.181	0.501 0.634	ARMANAR	3.205	-0.406 0.698	T3	T1
Autumn4	ARMAXNARX	2.823	1.127 0.302	ARMATBATS	2.161	0.796 0.455	ARMAXNARX	8.289	0.634 0.549	T3	T2

4.5.4. Forecast Accuracy Comparison According to Criteria-2

Our findings according to Criteria-2 are summarized in Table 4.9. In order to interpret the table, for example in T1-Winter1, ‘4-12’ means comparing the BI model 4 with BE model 12. As can be observed from the table, the difference between the BI and BE is statistically significant in 9 out of 48 cases (19%). 70% of these significant cases are in the T2 zone. However BE model outperforms the BI in only 3 out of 9 significant cases (30%). These results indicate that, looking from an ex-post performance evaluation, using ensemble models does not increase price forecast accuracy significantly. On the contrary for the peak time load time (T2), in most of the cases, BI models significantly outperforms BEs.

Table 4.9: Summary of ensemble models with best model performance (*out-of-sample MAPE*) and Diebold Marino statistic and p values (second row) according to criteria2. Notes: Model no (1)ARMA (2)ARMAX (3)NAR (4)NARX (5) ETS (6)TBATS (7)ARMANAR (8)ARMAXNARX (9)ARMAETS (10)ARMAXETS (11)ARMATBATS (12)ARMAXTBATS (13)ETSNAR (14)TBATSNAR (15)ARMATBATSETS (16)ARMATBATSNAR (17)HYBRIDALL. *** indicates rejection of the null hypothesis at the 1% significance level. ** indicates rejection of the null hypothesis at the 5% significance level. * indicates rejection of the null hypothesis at the 10% significance level.

WEEK NO	T1	DMTEST	T2	DMTEST	T3	DMTEST
Winter1	4-12	-0.536 0.610	3-7	**-3.693***** 0.000	1-9	-1.821 0.118
Winter2	4-10	1.881 0.108	4-13	-0.539 0.590	1-7	-0.782 0.463
Winter3	2-12	-0.696 0.512	5-14	0.806 0.421	2-12	-0.665 0.530
Winter4	3-8	**2.521**** 0.045	4-8	0.015 0.987	1-7	1.165 0.287
Spring1	3-14	-0.888 0.408	4-14	**-3.452***** 0.001	4-13	-1.926 0.102
Spring2	3-8	0.839 0.433	4-7	1.615 0.110	3-8	0.752 0.480
Spring3	4-8	-0.909 0.398	5-10	**-5.712***** 0.001	6-12	0.692 0.514
Spring4	4-13	-0.195 0.851	6-10	**4.451***** 0.001	4-13	1.220 0.268
Summer1	4-8	0.011 0.991	1-11	-0.602 0.552	5-10	0.712 0.502
Summer2	2-14	0.624 0.555	2-10	-1.229 0.264	1-12	**-7.670***** 0.000
Summer3	2-8	1.007 0.352	4-8	**2.767**** 0.0325	2-10	**-2.718**** 0.034
Summer4	5-10	1.113 0.308	5-10	0.668 0.528	5-13	-0.225 0.829
Autumn1	2-12	0.734 0.469	2-8	**-2.192**** 0.037	3-13	-1.436 0.201
Autumn2	2-12	-0.616 0.56	1-15	0.437 0.677	2-10	-0.952 0.377
Autumn3	2-8	-0.522 0.619	2-10	0.227 0.827	4-7	0.021 0.984
Autumn4	4-8	0.417 0.690	6-11	1.314 0.236	5-8	0.205 0.843

4.5.5. Forecast Accuracy Comparison According to Criteria-3

Our findings according to Criteria-3 are summarized in Table 4.10. As can be observed from the table, the difference between the BI and BE is statistically significant in 18 out of 48 cases (38%). 45% of these significant cases are in the T2 zone. BE model outperforms the

BI in 14 out of 18 significant cases (75%). These results indicate that, looking from an ex-ante performance evaluation, using ensemble models increase price forecast accuracy significantly in 30% of the cases. In the remaining 70% of the cases, there is no statistical significant difference between forecast accuracies of BI and BEs. Thus for a power market participant, looking from a more realistic ex-ante decision-making approach, using ensemble forecasting is useful to manage electricity price modelling risk.

Table 4.10: Summary of ensemble models with best model performance (*in-sample MAPE*) and Diebold Marino statistic and p values (second row) according to criteria3. Note: Model no (1)ARMA (2)ARMAX (3)NAR (4)NARX (5) ETS (6)TBATS (7)ARMANAR (8)ARMAXNARX (9)ARMAETS (10)ARMAXETS (11)ARMATBATS (12)ARMAXTBATS (13)ETSNAR (14)TBATSNAR (15)ARMATBATSETS (16)ARMATBATSNAR (17)HYBRIDALL. *** indicates rejection of the null hypothesis at the 1% significance level. ** indicates rejection of the null hypothesis at the 5% significance level. * indicates rejection of the null hypothesis at the 10% significance level.

WEEK NO	T1	DMTEST	T2	DMTEST	T3	DMTEST
Winter1	4-8	-1.2854 0.246	4-10	**6.405***** 0.001	4-8	-1.247 0.258
Winter2	4-8	1.2982 0.241	4-8	**-7.252***** 0.001	4-8	-0.129 0.901
Winter3	4-8	**4.1369***** 0.006	4-8	**6.819***** 0.001	4-8	0.766 0.472
Winter4	4-8	**2.1307*** 0.077	4-8	0.015 0.987	4-8	**1.992*** 0.093
Spring1	4-8	-0.727 0.494	4-8	**-3.585***** 0.001	4-8	**-2.610**** 0.040
Spring2	4-8	0.272 0.794	4-8	**-5.305***** 0.001	4-8	-0.265 0.799
Spring3	4-8	-0.90 0.398	4-8	-1.402 0.165	4-8	1.843 0.115
Spring4	4-8	0.011 0.991	4-8	-0.116 0.908	4-8	-0.065 0.950
Summer1	4-8	0.011 0.991	4-8	**2.373**** 0.025	4-8	0.234 0.822
Summer2	4-8	1.873 0.110	4-8	**2.767**** 0.032	4-8	**4.004***** 0.007
Summer3	4-8	1.458 0.195	4-8	**2.767**** 0.032	4-8	**2.878**** 0.028
Summer4	4-8	1.796 0.122	4-8	1.272 0.250	4-8	**4.779***** 0.003
Autumn1	3-8	**2.684**** 0.012	4-8	1.220 0.232	4-8	**3.089**** 0.021
Autumn2	4-8	0.684 0.519	4-8	1.256 0.255	4-8	1.501 0.183
Autumn3	3-8	**2.736**** 0.034	4-8	0.762 0.474	3-8	0.387 0.711
Autumn4	4-8	0.417 0.690	4-8	1.001 0.355	4-8	0.261 0.802

4.6. Conclusion and Suggestions for Future Work

In this Chapter we examine the relative forecasting performances of six promising individual models and ensemble models derived from them through equal weighting scheme in a semi-transparent EDA market. Although ensemble models are well studied in other contexts, the number of these studies are very limited for the electricity markets. Previous studies are from mature electricity markets (UK, Nord Pool and PJM) and variety of individual methods used for the ensemble models in them are limited. Following the main findings of these studies; namely performance of ensemble models are different for different market conditions, time periods and model combinations; we develop well-performing ensemble forecast models for an emerging market, Turkey, and compare their performance with alternative individual models according to three benchmark criteria. This enables us to address three forecasting challenges which have been encountered in the previous ensemble modelling studies, specifically the inadequate handling of trend seasonality component and varying market power over the course of a day, the inappropriate selection of exogenous variables when one considers the relationships that exist between price and system constraints, and the methodological similarity of the individual models they have considered.

We addressed the following research question: *How to manage price modelling risk via ensemble forecasting in the Turkish EDA auctions?*

We compare performance of the models according to three criteria. In the first criteria, we take ARMA as the benchmark model and compare the performance of the individual and ensemble models within themselves according to both in-sample and out-of-sample MAPE values. In the second criteria, we compare ex-post performance of the best individual (BI) model with that of the best ensemble (BE) based on their out-of-sample MAPE values. In the third criteria, we adopt a more realistic approach and decide the BI and BE based on in-sample MAPE values (ex-ante), then compare their performances using their out-of-sample MAPEs.

According to Criteria-1, regarding the individual models, we find that although NARX outperforms other competing individual models in most of the cases (96%) with respect to in-sample MAPE; for out-of-sample MAPE, dominant outperformance of NARX is replaced by ARMA-based and seasonality models. However, according to DM test with 5% significance level, ARMA can be outperformed significantly in only 15% of the cases.

Regarding the ensemble models, considering in-sample MAPE, ARMAXNARX outperforms other competing ensemble models in all of the cases (100%). For out-of-sample MAPE, dominant outperformance of ARMAXNARX is replaced by ensemble seasonality models such as ARMAXETS and ARMAXTBATS. According to DM test with 5% significance level, ARMA can be outperformed significantly in only 19% of the cases, mostly for the T3 time zone. According to Criteria-2, the difference between the BI and BE is found to be statistically significant for 19% of cases. 75% of these significant cases are in the T2 zone. These results demonstrate that, looking from an ex-post performance evaluation, using ensemble models does not increase price forecast accuracy significantly. According to Criteria-3, which is the most realistic decision-making setting among the other two criteria, we find that the difference between the BI and BE is statistically significant for 30% of the cases. BE model outperforms the BI for 65% of these significant cases. These results indicate that, looking from an ex-ante performance evaluation, using ensemble models increase price forecast accuracy significantly in 30% of the cases. In the remaining 70% of the cases (after subtracting BI significant cases), there is no statistical significant difference between forecast accuracies of BI and BEs. Thus for a power agent, looking from a more realistic ex-ante decision-making approach, using ensemble models can be very useful to manage price modelling risk. Thus our findings support the additional benefits of ensemble forecasts especially according to an ex-ante (more realistic) decision-making setting and in line with the previous findings indicating ensemble modelling is less uncertain and more accurate than the ex-ante best individual model.

4.6.1. Managerial and Policy Implications

For a power agent, using ensemble models can be useful to manage electricity market price risk and lead to better decisions on corporate risk management.

Electricity price forecasts are used by power agents as one of the main input variables for evaluating their corporate risk levels (Conejo et al., 2010; Shahidehpour et al., 2002). In forecasting, uncertainty is reflected in the forecast error and the source of risk arises from the unobservability of full information set underlying the individual forecasts which could be differently affected by statistical properties of the related price series (Timmerman, 2006).

Therefore using ensemble forecasting could mitigate this risk related to decision making of a power agent (Bunn, 1985).

Considering fractal dynamics of price could improve decision making of power agents.

We find that for both individual and ensemble models, in most of the cases T3 (night tariff time zone) has the highest MAPE values. This can be explained by the lower predictability level of this price series compared to T1 and T2, and the stronger impact of seasonality factors on demand during the night. Thus if fractal dynamics of price is prominently different for some time zones during the course of a day, ensemble modelling is less risky than individual models in terms of the risk of selection of an inappropriate individual forecasting model. Further, choosing ensemble models based upon the fractal dynamics of each time zone could improve power agents forecast accuracy.

Increasing transparency level of the market through disseminating data on primary resource based available installed capacity and planned generation schedules could enhance predictability level of prices, especially for off-peak load periods.

We find that models with exogenous variables generally perform better than models without exogenous variables. This finding is in line with the previous literature and arises because of the high cross-correlation between demand, margin and price. Further this result also shows the appropriate selection of our input variables. On the other hand we find that T3 price series has lowest level of predictability and no long-term correlation indicating that marginal bidders bid at their marginal costs (Sapio, 2004). This means if a power agent attempts to forecast the prices for off-peak hour, s/he needs prior information on *primary resource based available installed capacity* (the active power capacity that a generation unit can provide to the system) and *final daily production program* (firm-level) to understand the possible future supply stack for each hour and estimate technology of the marginal generator.

4.6.2. Suggestions for Future Work

In emerging markets, from which most of them are semi-transparent, since market data is very limited for price forecasting, market participants tend to utilize from international data provider consultancy firms to get information which is not public. The type of data they seek for is usually on the planned generation schedules of large firms, dam level of some state-owned hydropower plants (for Turkey case), primary resource based available installed capacity and final daily production program (firm-level) and matching quantities(ex-post) on the hourly merit order curve. We call this type of data private (not insider) since it does not include any firm-level *confidential* data. Since most of the market participants do not have this information, the ones that have it can make a more fundamental analysis of the market, improve their forecast accuracies and beat the market. Based on this point of view, it would be interesting to examine the worth of this information to market participants considering the improvement in forecast accuracy of models (both individual and ensemble).

Appendix 4.A.

Table 4.A.1: Data related to day-ahead auctions in Turkey. Note: Settlement aggregation entity (UEVCB): Active electric energy generating or consuming entities which are defined by market participants so that the settlement calculations can be made for each market participant.

Class	Type	Name	Abbr.	Definition
Gen.	Planning	Daily production program	DPP	The generation values with respect to settlement delivery point which a settlement aggregation entity anticipates to realize in the following day and notifies the market operator at the beginning of day-ahead balancing stage, according to the obligations of the balance responsible party to which it is attached.
		Final daily production program	FDPP	The generation or consumption values which a settlement aggregation entity expects to realize in the following day and notifies the system operator at the opening of the balancing power market according to the obligations of the balance responsible party to which it is attached and the result of day-ahead balancing
		Available installed capacity	AIC	The active power capacity that a generation unit can provide to the system
	Real-time	Real-time generation	RGT	Hourly resource-based power generation
	Ex-post	Injection quantity (settlement volume)	IQ	Hourly injection of aggregate energy of the injection units (UEVCB)[1] through a settlement period (In terms of the settlement delivery point, the reading values of the meters in the settlement aggregation entity configuration will be used as a basis in settlement calculations)
Demand	Forecast	Demand forecast	DemFor	The hourly consumption forecasts published on a daily basis for the next physical day
	Real-time	Consumption		Hourly real-time consumption
	Ex-post	Withdrawal quantity		Hourly withdrawal of aggregate energy of withdrawal units through a settlement period
		Eligible customer withdrawal quantity (settlement withdrawal volume)		-
		Withdrawal quantity under supply liability		-
Price	Planning	Interim market clearing price	IMCP	Temporary hourly energy price which is determined within the objection period with respect to bids that are cleared according to total supply and demand
	Real-time	Market clearing price	MCP	Hourly energy price that is determined with respect to bids that are cleared according to total supply and demand
	Ex-post	Trade value		Hourly aggregate of cleared bids and offers
		Price independent offer		Hourly aggregate of offer quantity at 0 TL/MWh

	Price independent bid		Hourly aggregate of bid quantity at 2,000 TL/MWh
	Supply/demand	MOC	Hourly merit order curve
	Bid quantity		Hourly and block bid(purchase) quantity at 0 TL/MWh
	Offer quantity		Hourly, block and flexible offer(sale) quantity at 2,000 TL/MWh
	Block bids		Aggregate quantity of cleared block bid that covers a minimum of 4 to a maximum of 24 hours
	Block offers		Aggregate quantity of cleared block bid that covers a minimum of 4 to a maximum of 24 hours
	Matching quantity		Hourly aggregate quantity of cleared bids

Table 4.A.2: Dissemination details for day-ahead auction data

Name	Responsible Institution	Period of Time	Publish Time	Detail	Public from
DPP	TEIAS	Hourly	D-1	Firm[1]-level	Aggregate-level: 2011 Firm-level: 2016
FDPP	TEIAS	Hourly	D-1	Firm-level	Aggregate-level: 2011 Firm-level: 2016
AIC	TEIAS	Hourly	D-1	Firm-level	Aggregate-level: 2011 Firm-level: 2016
RGT	TEIAS	Hourly	Real-time	Primary-resource-based	2016
IQ	TEIAS	Hourly	D+1	Primary-resource-based	Aggregate-level: 2011 Primary-resource-based:2016
Demand Forecast	TEIAS	Hourly	D-1	Aggregate	2011
Consumption	TEIAS	Hourly	Real-time	Aggregate	2016
Withdrawal quantity	TEIAS	Hourly	D+S	Aggregate	2016
Interim Market Clearing Price	EXIST	Hourly	D-1	Aggregate	2016
Market Clearing Price	EXIST	Hourly	D-1	Aggregate	2011
Trade value	EXIST	Hourly	D-1	Aggregate	2011
Price independent offer	EXIST	Hourly	D-1	Aggregate	2016
Price independent bid	EXIST	Hourly	D-1	Aggregate	2016
Supply/Demand	EXIST	Hourly	D-1	Aggregate	2014
Bid quantity	EXIST	Hourly	D-1	Aggregate	2016
Offer quantity	EXIST	Hourly	D-1	Aggregate	2016
Block bids	EXIST	Hourly	D-1	Aggregate	2016
Block offers	EXIST	Hourly	D-1	Aggregate	2016
Matching Quantity	EXIST	Hourly	D-1	Aggregate	2014

[1]Firm represents the settlement aggregation entity in the day-ahead auctions.

Chapter 5

Agent-Level Determinants of Price Expectation Bias in Online Double-Sided Auctions[14]

5.1. Introduction

Information Systems researchers have made significant contributions to practical auction design (e.g. Kauffman and Wood, 2000; Bapna et al., 2001; Goes et al., 2012) and the development of computational tools to facilitate decision making in complex auction markets (Adomavicius and Gupta, 2005; Adomavicius et al., 2009; Ketter et al., 2012; Mehta and Bhattacharya, 2006). This body of work has given rise to the interdisciplinary research area of *smart markets* (McCabe et al., 1991). The primary goal of smart market research is to develop theoretically guided computational tools to understand the characteristics of a complex trading environment and to facilitate decision making in these settings (Bichler et al., 2010). Although information technology has been one of the most crucial drivers of smart market development, research containing the behavioural elements of economic agents participating in these markets, with policy implications for well-functioning real sector markets, has been slow to appear.

[14] Parts of this Chapter appeared in the following conference proceedings:
Avci, E., Bunn, D.W., Ketter, W. & van Heck, E. (2017). Managing Market Price Risk through Forecasting and Hedging: The effects of Market Informedness and Risk Aversion. In Commodity and Energy Markets Conference, Oxford, UK.
Avci, E., Bunn, D.W., Ketter, W. & van Heck, E. (2017). Price Forecast Accuracy of Trading Agents in Electricity Markets: The Role of Market Informedness, Risk Aversion, and Trading Behavior. In 40th IAEE International Conference, Singapore.
Avci, E., Bunn, D.W., Ketter, W. & van Heck, E. (2018). Determinants of Price Expectation Bias in Online Double Auctions Commodity Markets Winter Workshop, Nantes, France.

The assumption that agents can (rationally) predict the values of market outcomes is frequently made in economic analysis (e.g. Stoneman and Ireland, 1983; Choi and Thum, 1998), but how these economic agents obtain their knowledge or form their expectations are issues which are usually out of scope in these theoretical contexts. However, the expectations and the behaviour of bidders have crucial roles in creating actual market outcomes (e.g. Shapiro and Varian, 1999; Au and Kauffman, 2003; Easley et al., 2010) and these expectations in real markets are heavily influenced by the online auction context within which they take place (Bapna et al., 2001; Kambil and Van Heck, 2002). Imperfections in the auction design can distort the price signals and alter the trading behaviour of market participants so that they will seek a satisfactory solution instead of an optimal one. *Information asymmetry* is a crucial market imperfection (e.g. Clemons and Thatcher, 1997; Clemons, 2007; Dawson et al., 2010) which may be reduced by means of well-functioning institutional information-aggregation and -dissemination mechanisms, i.e. *information feedback platforms*.

Previous research has shown the importance of the presence of information feedback mechanisms (e.g. Zhu, 2002, 2004; Arora et al., 2007; Soh et al., 2006; Adomavicious et al., 2012; Strecker, 2010) and the type/amount of information that is provided to bidders through transparency platforms (e.g. Koppius, 2002; Granados et al., 2005, 2008, 2010; Watson et al., 2010) on bidders' expectations. However, the traditional presumption that bidders form rational expectations by *accurately* processing *all available information* in the online trading environment and forming their expectations accordingly (Muth, 1961) has found mixed support in the empirical literature since in practice *boundedly rational bidders* experience limits in processing information (Tisdel, 1996). Thus, whilst a market regulator can make an online auction *fully transparent* by publishing all transaction-level data in a Transparency Platform making it costless to the bidders, nevertheless they may not use all the information in this platform. They value information based on their preferences (Helwig, 1980) which are mostly shaped by their risk aversion levels (Lavella, 1968; Hilton, 1981; Bickel, 2008; Abbas et al., 2013). This practical fact leads us to make a distinction between *information transparency level (of a market)* and *informedness (of a bidder)*:

Information transparency, defined as the availability and accessibility of market information to its participants (Zhu, 2004), is usually deemed to be valuable for the whole supply chain. This is because it helps improve its allocative efficiency (e.g. Cachon and Fisher, 2000; Lee et al., 2000; Patnayakuni et al., 2006). In contrast, various studies demonstrate that more information transparency is not always better (e.g. Koppius, 2002; Von der Fehr, 2013; Yang et al., 2015) since there can be a form of information saturation, after which more information to bidders does not further increase the auction performance. Also, it could enhance behavioural biases or confuse agents by adding complexity to relevant information. And furthermore, requiring bidders to reveal private information may lead to behaviour which is intended to conceal or distort information, or alternatively facilitate collusive behaviour in repetitive contexts.

Informedness, on the other hand, is the degree to which bidders know and have access to complete, reliable, and timely information (Li et al., 2014). We add one more aspect to this definition which is the *usage level* of this accessible information for predicting the related market outcome. That is, since bidders in most of the online auctions (B2B, B2C, multi-unit, combinatorial etc.) are highly heterogeneous (e.g. Bapna et al., 2004; Adomovicious et al., 2012; Lu et al., 2016), their utilisation (trading behaviour/strategy) of accessed information may be different. In fact, this diversity of information processing and expectations has motivated the widespread use of prediction markets in many applications of forecasting (e.g. Forsythe et al., 1991; Chen and Plott, 2002; Wolfers and Zitzewitz, 2006; Van Bruggen et al., 2010) and the informational role of forward trading (Grossman 1977, 1978; Helwig, 1980; Friedman, 1982; Forsythe et al., 1984; Admati, 1991; Antoniou and Holmes, 1995; Redl et al., 2009).

In this Chapter we focus on an online *double auction* in the context of *forward trading*; namely the *Electricity Day-Ahead (EDA)* auction. EDA auctions provide an ideal research setting, as they require detailed information-processing and these auctions clear through the actions of heterogeneous bidders with expectations that have major effects on auction performance and efficiency. We draw upon the behavioural finance literature on predicting expectations from behaviours and behaviours from attitudes (Ajzen and Fishbein, 1970) and upon the judgement and decision-making literature for understanding expectation biases in markets (Kahneman and Tversky, 1979), in order to provide an *evidence-based* analysis. We develop a research model to empirically test the impact of bidders' attitudes (informedness and risk aversion) on their price expectations (forecast accuracy) through their trading behaviour (forecasting and forward trading). Furthermore, situational factors such as the type of company and its strategic position would also impact these effects. The research theme in general is therefore to understand the determinants of price expectation formation by market participants in online auctions that provide forward trading platforms. Simply put, we attempt to address various aspects of the general question: *How does the attitude and trading behaviour of market participants influence their price expectations in online auctions, as revealed through their forecasts and trading?* We tested our hypotheses on real ex-ante forecasts, evaluated ex-post, using a unique and extensive data set consisting of 158 professional power market participants.

We contribute to the growing literature on (1) information transparency and revelation policies in online (Zhu, 2002, 2004; Arora et al., 2007; Soh et al., 2006; Adomavicious et al., 2012; Strecker, 2010) and specifically, in day-ahead auctions (Ray and Cashman, 1999; van der Fehr, 2015); (2) the effect of amount of information feedback (Granados et al., 2005, 2008, 2010; Watson et al., 2010; Yang et al., 2015) and bidders' heterogeneity/behaviour (Bapna et al., 2004; Adomovicious et al., 2012; Lu et al., 2016) on their trading decisions/strategies; and (3) informational role of forward/prediction markets (Grossman, 1977, 1978; Forsythe et al., 1984; Antoniou and Holmes, 1995; Redl et al., 2009; Chen and Plott, 2002; Wolfers and Zitzewitz, 2006; Van Bruggen et al., 2010).

We show that the informational role of forward trading is the most important factor that decreases bidders' expectation biases and that more information does not always lead to more rational (less biased) expectations. Further our results indicate that risk aversion does not play a major role in the trading decisions of power bidders. On the other hand, our control variables, including bidder type and strategic positioning in the market, had significant impacts, particularly on forecast accuracy and forward trading. This suggests that in monitoring and promoting efficient and competitive market outcome, regulators may need to look at more subtle measures of auction design than simple concentration metrics.

In summary, this study reveals that whilst informedness level does not have a directly significant impact on price forecast accuracy and as a consequence a policy of making more data public (or complete information policy) via the market transparency platforms (e.g. Arora et al., 2007) may not increase agents' understanding of price formation; rather, it is more crucial to improve the functioning and depth of the forward markets.

The structure of the paper is organized as follows. In Section 2, we discuss previous research and develop some research hypothesis. Section 3 presents empirical results and

Section 4 concludes the paper with a summary of the findings, implications for practice and suggestions for future research.

5.2. Theoretical Background and Hypothesis Development

After various well-publicised market failures, it is evident that a well-functioning market needs to go beyond an appropriate auction design (Borenstein, 2002) and depends critically on the expectations of bidders involved (Krishna and Perry, 1998) since market price is the aggregation of bidders' individual expectations. Whilst the rational expectations theory implies that bidders should use all the information available to them in forming their price expectations, translating this into an efficient auction design usually assumes homogeneity in availability and thereby often ignores bidders' different levels of *informedness* (Muth, 1961). Further, as a pure economic theory without behavioural aspects, this theory is silent about the effect of bidders' *risk attitude* and *cognitive biases* in their price expectations. However, in seeking to develop empirical insights from real auctions we cannot assume that all bidders are risk-neutral, homogenous and cognitively unbiased. Furthermore, to investigate expectations (cognitive biases) through revealed behaviour, we need an appropriate construct and for this we focus upon trading activities. We characterize trading by *forecasting* and *hedging* (through forward contracts).

Because of the distinctive characteristics of electricity (e.g. limited storability and physical delivery requirements), price expectation formation and trading behaviour in EDAs are complex and challenging (Borenstein, 2002; Bunn, 2004). EDA auctions and forward markets are the two main online auction places in which the formation of reference prices occurs. Day-Ahead auctions provide a *spot* trading mechanism which takes place on one day for the delivery of electricity the next day. Participants with bids and offers submit their orders electronically into order books, after which aggregate supply and demand are compared and the auction clearing price is calculated for each hour of the following day by the auctioneer. Forward trading, in contrast, is generally undertaken through brokers as "over-the-counter".

Electricity spot price dynamics create high price volatility (Stoft, 2002) and so, as a consequence, bidders will generally seek to achieve accurate price forecasting and/or use forward contracts to hedge the risk. To the extent that forward markets in theory manifest an equilibrium in expectations and risk aversion amongst bidders with heterogeneous needs for hedging spot price uncertainty, there will usually be a substantial *behavioural* pricing component (beliefs) in electricity forward markets, as reflected by sustained risk premia (Redl and Bunn, 2013).

In the general forecasting literature there are a multitude of studies on identifying factors influencing forecast accuracy. Some of them examined the effects of different company characteristics such as firm size (Small, 1980; White, 1986; Dalrymple, 1987), firm age (Dalrymple, 1975) and industry (Rothe, 1978; Mentzer and Cox, 1984; Peterson, 1990); some of them focus on the characteristics of the forecasting process such as the time horizon (Small, 1980; Mentzer and Cox, 1984), forecast level (White, 1986), team based forecasting (Kahn and Mentzer, 1994), technique (Dalrymple, 1975; Small, 1980), sophistication of techniques (Mentzer and Cox, 1984b), number of forecasting methods used (Small, 1980; West, 1994), use of forecast combinations (Dalrymple, 1987) and use of consultants (Dalrymple, 1987). The majority of surveys found that larger firms achieved more accurate forecasts than smaller firms (Small, 1980; White, 1986; Dalrymple, 1987). Firms that utilised a greater number of forecasting techniques (Small, 1980; West, 1994) and prepared their forecasts for more applications (McHugh and Sparkes, 1983) also reported a better forecast performance. Adoption of more sophisticated techniques resulted in accuracy gains (Mentzer and Cox, 1984b). Pan et al. (1977) found that firms which desired greater accuracy utilised techniques that they thought were more sophisticated. A final stream of literature has looked at what can be done to improve/assist the forecasting task. Sanders (1992) and Sanders and Manrodt (1994) indicate better data, greater management support and better training improves the forecasting process. Better data about the industry, customers, competition and the economy were also identified in the study conducted by Rothe (1978).

5.2.1. Forecasting Behaviour

We focus on the behavioural determinants of performance (accuracy) by power market participants whose fundamental inputs for their decisions may change according to the forecasting approach they use (Bunn, 2004; Eydeland and Wolyniec, 2003; Weron, 2006).

The advanced use of forecasting techniques is one of the critical selection/specification issues in the forecasting process, and it usually affects the expectation bias (Ketter et al., 2012). Since the related literature (Mentzer and Cox, 1984b; Small, 1980; West, 1994) mostly finds a positive relation between the sophistication of the forecasting methods and forecast accuracy (as measured for example ex-post by mean absolute error, or mean absolute percentage error), we propose as a working hypothesis that:

H1: *Power bidders' use of advanced forecasting techniques is positively related to their forecast accuracy.*

5.2.2. Hedging Behaviour

The *forward curve* derives future prices from the balance of observable trades in the forward market. In general, forward curves result from the willingness-to-contract by traders today for power to be produced or delivered in the future. For a storable energy commodity such as oil or gas, there is a theoretical link between spot prices and forwards through the cost of carry and convenience yield (Geman, 2006), but with electricity having limited storability, the conventional view is that forward prices result from market expectations adjusted by a market risk premium (Redl and Bunn, 2013). This is another reason why the choice of electricity for this study on expectations is particularly appropriate. Furthermore, in immature ("incomplete") power markets the risk premium may also incorporate some illiquidity risk, as manifest by high bid-ask spreads, and concerns about insufficient market depth to transact substantial spot trades. With this in mind, we have chosen to analyse an important, well-functioning, but still maturing power market, that of Turkey, to feature this distinction between forecasting and forward hedging, whereupon market informedness is likely to be influential.

Related literature regarding the informational role of forward trading began with Grossman's studies (Grossman, 1975, 1977, 1978) which defined forward markets as places where information is exchanged and where people who collect and analyse information about future states of the world can gain an advantage in information gathering. He finds that for commodities with forward markets, the volume of forward trading (extent of hedging) is directly related to how poorly current and futures prices predict the future spot price, relative to how well various exogenous variables (available information) predict the future spot price. Danthine (1978) examines the informational role of forward prices and the relationship between forward and spot prices in a setting in which not all relevant information is contained in the past data but some can be obtained through forward prices. Foryste et al. (1984) show that a forward market can increase the speed with which information is made public through price transactions and this increases market efficiency.

The informational role of forward trading is even more important in electricity markets since bidders who are actively trading on the forward/OTC markets have a better understanding of the price for forward power. Forward curves are related to various fundamentals (fuel market prices, demand, regulations, technology mix, plant outages, etc.) and as a synthesis of market insight on these underlying factors, the forward curve is often considered the best forecast (EFET, 2015). Thus, it is critical to consider the informational role of forward trading on price expectation formation. Based on the discussion above we propose that:

H2: *Power bidders' advanced use of forward trading is positively related to their forecast accuracy.*

5.2.3. Factors Affecting Forecasting Behaviour

Although considerable empirical research has focused on the bidder-level determinants of forecasting practices, not all issues have received equal attention. While variables such as size (Small, 1980; White, 1986; Dalrymple, 1987) and industry type (Rothe, 1978; Mentzer and Cox, 1984b; Peterson, 1990) have been systematically linked to some aspects of forecasting practice (e.g. use of consultancy, sophistication of methods, diversity of forecasting techniques), information-based linkages (e.g. data sources utilised) have been left unexplored (Winklhofer et al., 1996).

Market informedness is a key issue in the functioning of electricity markets, as with any smart market. Previous research on electricity markets has focused much more on market mechanisms (Borenstein and Bushnell, 2000; Joskow and Kahn, 2002; Bushnell et al., 2008) and incentives (Hogan, 1998; Micola et al., 2008; Ito, 2014). Research related to market informedness in electricity markets is scarce and has only recently started to gain importance after the introduction of advanced trading platforms and the electronic dissemination of relevant, large-scale data (Ketter et al., 2016). As far as we know the only study on this theme is by Von der Fehr (2013) which approaches the issue from a regulatory perspective and discusses the possible effects of the EU Regulation on the Submission and Publication of Data in Electricity Markets (SPDEM) and on wholesale energy market integrity and transparency (REMIT). He argues that, for market performance, more information is not always better; indeed, more information may undermine market performance by facilitating behaviour that is not cost efficient, and/or aims at exercising market power and/or establishes and maintains collusion. Moreover, he emphasizes that ensuring accurate price forecasts and sound reference price signals does not require general access to information at a very detailed level or with a high degree of immediacy. As far as we know, there is no study related to behavioural and attitudinal determinants of power bidders' price expectations. If the more informed bidders exercise this advantage on the spot market, then it is plausible that they would use more advanced forecasting methods. Thus, we test that;

H3A: *Power bidders' market informedness level is positively related to their use of more advanced forecasting techniques.*

The research investigating the role of bidders' risk perceptions on the forecasting process is mainly informed by prediction markets which can be defined as designed futures markets to predict outcomes. Manski (2004, 2006) analyses the relationship between the bidders' expectations and the realized price with risk neutral traders in a prediction market. He finds that there can be substantial forecast errors, but when risk aversion is taken into the formulation, as in Gjerstad (2005), the forecasts do not differ significantly from the realized market prices. Wolfers and Zitzewitz (2006) provide a formal model that includes Manski's (2006) as a special case. They show that while prediction market prices typically aggregate participants' information into useful forecasts, several features may undermine the efficacy of these forecasts, with the extent of risk aversion being one of them. The theoretical models of Gjerstad (2005) and Ottaviani and Sørensen (2005, 2007) also support a view that the participant's degree of risk aversion and beliefs are key parameters driving the equilibrium price in prediction markets. These findings indicate that the interpretation of prices in prediction markets (that is price forecast accuracy) requires knowledge on participants' risk preferences.

On the other hand, studies show that risk aversion can also affect individual's information gathering behaviour since this activity can be considered as a close substitute for hedging against certain types of risks (Willinger, 1989). However, the sign of the relationship has not been well-determined. In situations where hedging opportunities are restricted (e.g. liquidity constraints of the forward market), more risk averse bidders can have a tendency to gather more information. On the other hand if information gathering also involves risks and uncertainties, then risk aversion may decrease information gathering behaviour (Freixas and Kihlstrom, 1984). We note from studies in prediction markets that risk averse bidders tend to gather more information, and therefore based on the discussion above we test that:

H3B: *Power bidders' risk aversion is positively related to their use of advanced forecasting techniques.*

5.2.4. Factors Affecting Hedging Behaviour

Prior empirical studies tend to assume that all market participants have access to the same information. In Grossman's models (Grossman, 1976, 1978), the aggregation of information into price formation depends only on the statistical properties of the information vector and is independent of bidders' preferences. However, how information is processed is known to be a subjective process (Helwig, 1980). Following von der Fehr (2013), we consider the *market informedness* of a bidder as a factor related to hedging behaviour. For the case of electricity markets, it is not self-evident that greater informedness will lead to more hedging activity, since bidders may use this to act more profitably on the spot market where market power effects can be greater. We explore this in the next working hypothesis:

H4A: *Power bidders's market informedness level is positively related to their use of advanced hedging.*

There is a substantial literature on the determinants of the hedging behaviour of trading firms. However, this literature focuses mainly on the relation between firm value and the extent of hedging in the framework of the classic Modigliani Miller paradigm, with its many extensions. Pioneering studies on this include Stulz (1984), Smith and Stulz (1985), Froot, Scharfstein, and Stein (1993), and Nance, Smith, and Smithson (1993). Stulz (1984) studied the effect of managers' risk aversion on the usage of hedging instruments and found that risk averse managers are more likely to use hedging. Tufano (1996) examines hedging activities in the gold mining industry and finds that the use of commodity derivatives is negatively related to the number of instruments and positively related to the value of stock held by managers and directors. In an empirical asset market, Michailova (2010) investigates the effect of risk aversion on trading behaviour and find no significant relation.

For electricity markets, Sanchez et al. (2009) examine theoretically the strategy selection of heterogeneous power bidders and find that with risk aversion on the demand side, hedging is a response to spot price volatility. However, Lien (2001) examines the effect of risk aversion on hedging through a modified constant-absolute-risk-aversion utility function and finds that risk aversion has no effect in an unbiased forward market. Similarly, Mattos et al. (2006) find that the impact of risk aversion on hedging decisions appears to be small, and it diminishes as risk aversion increases. Thus, we test the null hypothesis that;

H4B: *Power bidders' risk aversion is not related to their use of hedging.*

5.2.5. Factors Affecting Risk Aversion

Kahneman and Tversky's (1979) prospect theory has become one of the most important concepts in analysing the behaviour of bidders in today's markets. According to prospect theory, the larger the disutility of a loss compared to the utility of an equivalent gain forces decision makers to weight losses more than gains. Many studies confirm this hypothesis (Payne et al., 1984; Arkes and Blumer, 1985; Tversky and Kahneman, 1991; Shefrin and Statman, 1985). Olsen (1997a, 1997b) examines the results of surveys of professional investment managers' risk perceptions and finds that managers do exhibit loss aversion in practice. Following this, Kalayci and Basdas (2010) find that Swiss power bidders were even more loss averse compared to the investment portfolio managers in Olsen (1997b). While these studies have enhanced our understanding of prospect theory, both attempt to explain the differences in bidders' risk attitude through demographic variables such as gender, age, professional experience and influence. However, in this Chapter we take a more corporate perspective and consider, as control variables, the bidders' strategic positioning in the market namely; size, portfolio diversity, market power and type of participation license, as possible factors affecting their attitude.

5.2.6. Control Variables

Power bidders are very heterogeneous with respect to their strategic positioning in the market and thus they may have different incentives for their trading behaviour and attitude. Therefore, we included the most important strategic positioning variables in our models to account for these effects. Those variables include size, portfolio diversity, interaction of size and portfolio diversity, and type of participation license.

A number of studies investigated the effect of *size* on decision making. In the forecasting literature; Dalrymple (1987), Peterson (1990), and Sanders and Manrodt (1994) examined the differences between the adoption of forecasting techniques by small vs. large firms. They find small firms use subjective and extrapolation methods more than large firms, whereas large companies use more sophisticated quantitative techniques more often. In the literature there are different definitions of firm size. Since our focus is on electricity price expectations we define the size of a bidder as their daily electricity trading volume. Here it is important to distinguish a bidder's size and its market power. A large-sized bidder may not necessarily be a bidder with market power. For example, a generator with substantial baseload facilities may not be engaged in price setting. Nevertheless, as a control variable, firm size may be important for the hypotheses related to market informedness and risk aversion.

In electricity markets bidders have different *types of power plants* in their portfolio, namely; river type, canal type, reservoir, dam, wind, solar, natural gas, biogas, biomass, fuel oil, lignite, imported coal, anthracite, geothermal, nuclear, landfill gas, naphtha. Bidders with *less diversified portfolios* may have less private information about the fundamental drivers of future electricity prices; while bidders with *more diversified portfolios* may have more *insider information* about the underlying supply situations such as water constraints, weather effects, impending plant outages, etc. Thus, bidders with more diversified portfolios are expected to be more informed and less risk averse.

We use the control variable *interaction of size and diversity* as a proxy for *market power* since if a generator has both high trading volumes and high diversity, the probability of having market power is very high. In imperfect electricity markets, if players have market power, there will be information asymmetry, and therefore each bidder's expectation for the spot may differ. Thus, consistent with the existing literature we consider a bidder to have more market power if it is more diversified. The case is not so obvious with risk aversion since risk aversion can increase with increasing volume, but decrease with increasing diversity. Further if market informedness is linked to market power, then dominant players may prefer to exercise it in the spot market.

5.3. Research Methodology

Based on the discussion above we conceptualised the research constructs and influences for testing as the Proposed Conceptual Model shown in Figure 5.1. "Market Informedness" and "Risk Aversion" are considered to be two attitudinal properties of bidders, which may influence how they approach market risk through their trading behaviour by relying upon "Forecasting" or "Hedging", and this in turn may affect the forecast accuracy of their price expectations.

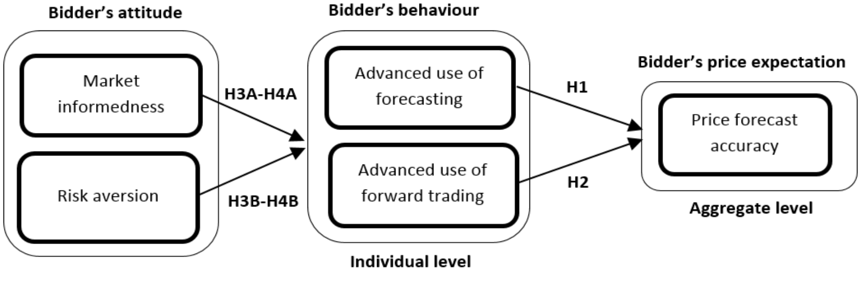

Fig. 5.1: Proposed Conceptual Model

The above hypotheses were tested by analysing a sample of cross-sectional data (Appendix 5.A) from the Turkish Electricity Market which is a large, liberalized, technologically diversified and liquid market attracting substantial investment and operating a day-ahead auction in a way that is similar to most power exchanges around the world. Furthermore, it suits our research purposes in several respects because substantial quantities of power are traded both on the spot and forward markets, and there is a diversity of market participants in terms of experience and potential informedness due to it being a relatively new market and not having an official transparency platform at the time we conducted this study. The energy exchange in Turkey, Energy Exchange Istanbul (EXIST), operates the wholesale power markets (day-ahead and intraday) and provides the settlement services for the transactions made in these markets. The Transmission System Operator (TEIAS) operates the real-time balancing power and ancillary services markets. Trading and risk management instruments are developed and operated by Borsa Istanbul (BIST). The day-ahead market operated by EXIST now covers about 30% of Turkey's electricity supply, and like most spot markets, provides the underlying reference price for derivatives including the forward contracts.

For this study, we acquired the support of Ministry of Energy and Natural Resources (MENR) and Turkish Electricity Transmission Company (TEIAS). We targeted the whole population of firms *actively* trading in the day-ahead market having obtained the contact details of the relevant trading mangers through an official request by the MENR. We undertook the survey via a web-link. We received 258 surveys, of which 158 were fully completed, providing a satisfactory 30% response rate and a sufficiently large sample for testing the research hypotheses. This unique data set gives us the ability to research a maturing market in a detailed fashion. Using this unique data set, this study is the first to take an information-based view to study the trading behaviour of bidders and their price expectations in a real sector market.

5.3.1. Instrument Development

A self-administered questionnaire was designed on the basis of the framework discussed in the previous section and in consultation with official administrators and executives in some of the leading private companies. The instrument was validated in three stages. In the first stage, semi-structured interviews were conducted with 22 traders and the dimensions of the construct were determined. Then in the second stage 33 traders provided interviews and preliminary questionnaire responses. This information together with indications from the research literature resulted in the construction of an initial set of 30 questions that reflected various aspects of the factors affecting the behaviour of power traders. In the final stage, 33 responded to the pilot study. To guarantee content validity (Cronbach, 1971: Smith, 1996), we asked these respondents to screen the 30 questions for those that did not appear consistent with the construct and identified dimensions. This permitted us to eliminate five that were either ambiguous or unreliable resulting in an instrument with 25 questions. Then, 20 energy experts from the Ministry evaluated this reduced set. Particularly, the dimensions were explained to 10 of the energy experts, who were asked to evaluate the questions for their applicability to the respective dimensions. The other 10 experts were presented with the items but were not given an explanation of the dimensions. They indicated for each question, what the perceived item would measure. Questions that were misclassified were eliminated. As a result, 24 questions remained.

There were eight parts in the survey. The introduction outlined the objectives of the study, possible benefits / risks of participating to the study and how the participant’s personal information would be used. Then, the first survey part is about the bidder-level information which includes the license type, ownership structure, type of plants in firm’s portfolio, average daily trading volume, types of risk they consider while determining firm strategies and the risk management practices in their firm. The second part attempts to measure the risk attitude of the respondent, in our case the person who is responsible for electricity trading in the firm. Third part is about general risk management operations of the firm regarding the day-ahead market, electricity price forecasting, OTC market, bilateral agreements, intraday market and demographic information of respondent. The respondents were asked to answer to five-point Likert scales mostly ranging from “very unimportant” (coded as 1) to “very important” (coded as 5), and a few ranging from “very useful” to “not useful at all”. We also collected participant and demographic data about the respondents and their firms. Although such information could perhaps have revealed the identity of the firm or respondent, we informed the respondents that all of their information and company’s information would be kept confidential at every phase of this research and that all responses would only be presented in aggregated form and only for academic research purposes.

5.3.2. Measurement of Variables

A bidder's price expectation formation has been defined and measured in many different ways. In this research we are interested in price forecast accuracy as measured by a single item[15] in which the respondents were asked at the end of 2015 what their yearly average electricity price forecast would be for the next year (2016) and this was then compared to the actual outcome price at the end of 2016. Thus, we waited a full year to evaluate the results and thereby ensure a valid ex-ante forecast and ex-post accuracy measure.

Bidders' trading behaviour is characterized in two dimensions: (1) hedging and (2) price forecasting behaviour. In the previous studies *hedging behaviour* has been defined and measured in different ways. We are interested in the *extent of forward trading* that bidders use for electricity trading. This variable was measured by a single item which asked respondents the percentage of electricity they hedged via forward trading for electricity sale/purchase. Accordingly, it was coded as 1 (0%-25%) to 4 (75%-100%). For the *price forecasting behaviour*, six items from the survey were used to construct a categorical variable. Respondents were asked to rate each of the methods listed in terms of their usefulness in forecasting electricity prices. The listed methods are independent forecasts (from consultancy firms), forecasts from internal modelling, and OTC/Forward Curves. Each item is on a 4-point Likert scale, 1=very useful, 4=not useful at all. This measure is used as a proxy for *advanced use of forecasting techniques* and calculated as the sum of dummy variables assigned for each item.

Bidders' attitude has been measured in two dimensions: (1) risk aversion and (2) market informedness. The measurement of risk aversion was adopted from Olsen (1997b) and Kalayci and Basdas (2012). Thus, we use six items from the survey to construct a categorical variable to measure the risk aversion of power traders. Respondents were asked to rate each of the risk attitudes listed in terms of their importance. The listed risk attitudes are the chance of incurring a large loss relative to what is expected, the chance that the portfolio will earn less than the minimum needed to meet the performance target, the overall variability in the portfolio return over time, the chance that the portfolio will earn less than what is expected, the chance that the portfolio will earn less than it has historically and the chance of having the same portfolio value. Each item is on a 5-point Likert scale, 1=not important at all, 5=very important. Market informedness has been defined and measured in different ways in previous studies, especially in the e-commerce literature through

[15] A single item measure is acceptable if the construct is unambiguous, unidimensional and directly accessible to respondents (Wanous et al., 1997).

measuring the market informedness level of e-consumers about a new product, website etc. (e.g. Li et al., 2014). In this research, we are interested in the market informedness level of bidders about a product whose demand is inelastic and for which the price depends much more on the environmental factors. In this case the information level of a power bidder (or is forecasting algorithm) would be crucial for the forecast performance. 16 items (which were chosen by thorough literature review and expert views) were used to construct a categorical variable. Respondents were asked to indicate their usage of the listed variables and rate them in terms of their importance to develop a reasonable price forecast for their electricity contracts. The listed variables are market clearing price, system marginal price, hourly load, hourly Bilateral Agreement (BA) amounts, system purchase amount, system sale amount, exact daily production plan, weather forecasts, wind power forecasts, solar power forecasts, hydropower reservoir quotas, river flow rates, cost of delay, out of order/ in maintenance plant information, hourly merit order curve, BA prices learned from the market, BA prices of large producers, OTC forward price curve, hourly electricity prices in the neighbour countries and exchange rate. Each item is on a 5-point Likert scale, 1=not important at all, 5=very important.

The strategic positioning of the bidders has been characterized in four dimensions: (1) size (2) portfolio diversity and (3) interaction of size and portfolio diversity (4) type of license. *Size* was measured by a single item in the survey from which the respondents were asked how much electricity they trade daily. For measuring the *portfolio diversity*, respondents were asked what kind of plants they have in their portfolio. Respondents who have one type of facility in their portfolio are coded as 1 (undiversified), up to three technologies are coded as 2 (semi-diversified) and more than three technologies are coded as 3 (highly diversified). *Type of license* has been measured by a single item from which the respondents were asked under what type of electricity market participation licence they operate. The listed license types and coding are: 1 (generator) 2 (auto producer[16]) 3

[16] The auto producer category refers the ownership and operation of power plants by industrial companies, primarily for their own electricity needs. Although there had been auto producer plants in Turkey before 1984, they were used mostly in state-owned sugar factories and cogeneration plants and were governed through special regulations. The 1984 law, and subsequent regulations in 1994–99 allowing companies to set up jointly-owned plants, triggered widespread investment in auto production facilities. About 2,300 MW of auto-generation capacity was installed by 2001. Although not envisioned at the time of the 1984 Law, these plants played an important role in the development of Turkey's electricity market two decades later. Later they started selling their

(incumbent retailer) 4 (distributor) 5 (retailer). Since type of license is a categorical (nominal) variable, it is encoded into four dummy variables with the reference type being retailer. The variables' names and measures are summarized in Appendix 5.A.

The major descriptive statistics for the variables are presented in Table 5.1. Even though the scales are ordinal, the summary measures indicate that a sufficiently reasonable spread was obtained to facilitate subsequent regression analysis.

Table 5.1: Descriptive Statistics

Variable	N	Range	Minimum	Maximum	Mean	Std. Dev.
(1)size	153	2	1	3	1.6	.8
(2)portfolio diversity	153	2	1	3	1.7	.9
(3)size * portfolio diversity	153	8	1	9	3.2	2.8
(5)risk aversion	153	4	1	5	3.7	.7
(6)market informedness	153	99	0	99	64.8	18.4
(7) use of advanced hedging	153	3	0	3	2.3	.9
(8)use of advanced forecasting	152	100	0	100	40.4	33.9
(9)forecast error	153	90	0	90	21.7	15.9

The Pearson correlations derived from the sample are summarized in Table 5.2 and here it is worth noticing the distinctly different intercorrelations for the use of advanced forecasting and hedging, suggesting that they are indeed separate approaches to facing price risk uncertainty. This is very reassuring for the basic research motivation in this Chapter. Furthermore, risk aversion and market informedness are significantly correlated as postulated and indeed market informedness is correlated both with size and portfolio diversity one might expect. More subtle analysis is undertaken by multivariate regressions, as described below.

5.4. Data Analysis and Results

Non-response bias was checked by four tests (Straub and Nance, 1990). In the first three tests, size, portfolio diversity, and type of utility characteristics of the group were compared for the full mail-out targets and respondents. No significant differences were found. In a further test, early and late respondents were compared and again there were no significant

generation in the market and bought electricity for their own use from distribution companies at the lower, government-controlled tariff.

difference. Thus, we conclude that our sample is not systematically biased and the results are generalizable to our population.

Table 5.2: Summary Statistics and correlations. Notes: *** Correlation is significant at the 0.001 level (2-tailed). **. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

Variable	(1)	(2)	(3)	(4.1)	(4.2)	(4.3)	(4.4)	(5)	(6)	(7)	(8)
(1)size	1.000										
(2)portfolio diversity	**.375****	1.000									
(3) size*portfoliodiv.	**.787****	**.812****	1.000								
(4.1)D_Generator[1]	**-243****	-.009	-.130	1.000							
(4.2)D_AutoProd.[1]	**-.058**	-.068	-.066	**-.183***	1.000						
(4.3)D_IncumRet[1]	**.221****	.033	.138	**-.290****	-.054	1.000					
(4.4) D_Discom[1]	**.291****	.103	**.207***	**-.233****	-.043	-.069	1.000				
(5)risk aversion	.014	.017	.012	.097	-.121	.012	-.043	1.000			
(6)market informedness	.098	**.235****	**.176***	-.077	-.106	.088	.114	**.160***	1.000		
(7) use of advanced hedging	**.329****	**.235****	**.366****	**-.358****	-.024	.108	.123	-.103	.109	1.000	
(8)use of advanced forecasting	.015	.070	.058	-.074	**-.273****	.048	.062	.085	**.375****	**.196***	1.000
(9)forecast error	-.129	-.135	**-.170***	**.195***	.084	-.073	-.035	.076	.083	**-.288****	-.121

[1]Since *type of license* is a categorical variable with five levels and it is encoded into four dummy variables.

We used *ordinary least squares (OLS) regression*[17] to test our hypotheses and estimate the model for bidders' forecast accuracy, trading behaviour, market informedness and risk aversion. We encoded the type of participation license into four dummy variables since it is a five category variable. To understand the effect of the control variables (bidders' strategic positioning) we estimated all models in two phases. In the first phase, only control variables were entered into the model. In the second phase, all variables were entered into the model. For models 4 and 5 since we used only control variables as independent variables, we constructed one model for each dependent variable (risk aversion and market informedness). For the other models, the first model is the one with only the control variables taken as independent variables; and the second model is constructed with the independent variables taken according the relevant hypothesis. Through this approach we can discriminate the effect of control variables from attitudinal and behavioural ones. We

[17] We used OLS regression since it is a *limited-information* statistical method which estimates each parameter equation separately. Thus, it is relatively robust to misspecification. On the other hand, structural equation modelling including classical path analysis is a *full information* technique which has the advantage that the estimation of each parameter utilizes the information provided by the entire system (Long, 1983) but the disadvantage that estimation of each parameter can be affected by mis-specification in other parts of the model. Thus, we aim to make our study robust to mis-specification issues through using the less structured nature of OLS multiple regression.

constructed the models 5 to 1 sequentially by following the logical flow implied our Proposed Conceptual Concept (Figure 5.1). The results of the regression estimations are summarized in Table 5.3 and the results of testing each working hypothesis are summarized in Table 5.4.

Table 5.3: Results of regression analyses of research hypotheses. Notes: Since type of license is a categorical variable with five levels, it is encoded into four dummy variables. *** Correlation is significant at the 0.001 level (2-tailed). **Correlation is significant at the 0.01 level (2-tailed). *Correlation is significant at the 0.05 level (2-tailed).

	Method: OLS							
	Dep.vrb (9) Forecast error		**Dep.vrb. (8) Use of advanced forecasting**		**Dep.vrb. (7) Use of advanced hedging**		**Dep.vrb.(6) Market Inform.**	**Dep.vrb.(5) Risk aversion**
Variables	Model 1.1	Model 1.2	Model 2.1	Model 2.2	Model 3.1	Model 3.2	Model 4	Model 5
(1)size	-.087	-.037	-.001	-.033	-.010	-.010	.011	-.001
(2)portfolio div.	-.133	-.070	.052	-.030	-.096	-.096	**.235****	-.021
(3)size*div.	-.147^{b}	-.073	.040	-.020	**.327*****	**.327*****	-.045	-.017
(4.1)D_Generator	**.195***	.104	-.128	-.094	**-.317*****	**-.317*****	-.075	.110
(4.2)D_Autoproducer	.124	.077	**-.273****	**-.236****	-.063	-.063	-.091	-.105
(4.3)D_IncumbentRet	-.018	-.042	.034	.005	-.031	-.031	.081	-.002
(4.4)D_Discom	.011	.001	.050	.012	-.020	-.020	.090	-.062
(5)risk aversion	-	.047	-	.001	-	-.076	**.155***	-
(6)market informedness	-	.114	-	**.350*****	-	.019	-	-
(7)use of advanced hedging	-	**-.288*****	-	-	-	-	-	-
(8)use of advanced forecasting	-	-.067	-	-	-	-	-	-
(9)forecast error	-	-	-	-	-	-	-	-
R square	.038	.083	.075	.185	.233	.233	.055	.025
Adj. (or Pseudo) R square	.032	.077	.069	.196	.223	.223	.049	.019

Our results (Table 5.3) reveal significant findings in the context of information systems, behavioural finance and energy policy. In particular, it has identified surprising but plausible relationships between trading bidders' attitudes, behaviour and price expectations.

H1& H2: Firstly, we hypothesized that bidders' price forecast error is negatively related to their advanced use of forecasting techniques and hedging. Quite surprisingly, our results (Model 1.2) indicate that power bidders' advanced use of forecasting techniques is not related to their spot price forecast accuracy. Therefore H1 is not supported. Our categorical measure for advanced use of forecasting is defined as the sum of three dummy variables which is encoded for internal modelling, consultancy and OTC/Forward curve usage. Based upon this result, we made further analysis for each of the dummy variables and find a significant relation only between the OTC/Forward curve usage and forecast accuracy which supports our second hypothesis related to informational efficiency of forward trading. This finding is in line with the studies comparing the results of prediction market results which have demonstrated that prediction (electronic) markets can provide better forecasts than even the most popular forecasting companies (e.g. Forsythe et al. 1991; Chen, Fine, and Huberman, 2003; Pennock et al., 2002). This indicates the information power of prediction markets which is a similar market aggregator to forward markets. Thus, although individuals have biased expectations (cognitive biases) about the future prices, in aggregate most of the biases will be eliminated through averaging and thereby reflected on the forward curve. It follows, therefore, that if individuals use the forward curve then their expectations should be more accurate. Thus, we observe that the advanced use of hedging is indeed negatively related to price forecast error supporting H2 (Model 1.2, coefficient= -.288 at $P<0.001$). Hedging activity uses the forward curve as reference and this provides a consistent interpretation.

H3: We hypothesize in H3A that a power bidder' market informedness level is positively related to his/her use of more advanced forecasting techniques. Our results indicate that, from Model 2.2, that market informedness has indeed a significant positive impact on advanced use of forecasting techniques (coefficient= .350 at $P<0.001$). But, H3B proposes that higher risk aversion is associated with more advanced use of forecasting techniques. We do not find significant support for this. Risk aversion itself, in Model 5, is not related with any of the control variables. On the other hand we can observe from Model 4 that marked informedness is positively and significantly related to risk aversion. So, the implications could be that more risk averse bidders are more informed. But market informedness is the more significant driver in the use of advanced forecasting techniques.

H4: For forward trading we found no significant relation with either market informedness or risk aversion. It is quite plausible that more informed power bidders do not engage in forward trading because they prefer to exercise their informational advantage by forecasting prices for the spot market. This is consistent with a positive significant coefficient for market informedness in model 2.2 (coefficient= .350 at $P<0.001$), which relates to the use of advanced forecasting. Thus, risk aversion appears to increase marked informedness (Model 4, coefficient=.155, $P<0.05$) and the market informedness can increase the use of advanced forecasting for spot price activity (but in the end does not apparently increase forecast accuracy).

Finally, we observe some participant specificities. Firstly, the dummy variable for auto-producer has a significant negative coefficient (Model 2.2, coefficient= -.236, $P<0.01$) suggesting that they use less advanced forecasting techniques compared to retailer-bidders. This is quite intuitive since auto-producers are the power plants that generate electricity for their own holdings and do not trade on the spot very frequently.

We observe surprisingly that there is a significant and positive relationship between the control variable dummy for generator and spot price forecast error (Model 1.1, coefficient=.195, $P<0.05$). That is, generator-bidders have less accurate price forecasts compared to retailer-bidders. One possible special explanation for this could be that in our population there exist some generators with public ownership. These generators can be thermal, hydroelectric or natural gas and they sell their electricity directly to TETAS (Electricity Trading and Contracting Corporation of Turkey) for a predetermined fixed price. Thus, they do not need to forecast the prices. The existence of these type of generators may have decreased the overall forecast accuracy of the generators in the sample. Furthermore, we also see in Model 3.2 that there is a significant and negative relation (coefficient=.327, $P<0.001$) between being a generator-bidder and use of advanced hedging; and well – in other words they are less inclined to hedge. This seems to support an explanation that some of them are insulated against the market. It could also be suggested that by having these arrangements they are behaving like hedging companies, albeit through public ownership.

Our results show that there is a significant and positive relation between the control variables size*diversity and use of advanced hedging. One possible interpretation is that these are large companies with predefined corporate risk limits and therefore their risk management and compliance requirements may necessitate extensive hedging, or it may be that these generators are better able to engage in specially tailored forward contracts to meet market needs through OTC trading.

Table 5.4: Summary of Results

Hypothesis	Hypothesis Description	Expected Sign	Results
H1	Advanced use of forecasting → forecast accuracy	(+)	Not Supported
H2	Advanced use of forward trading → forecast accuracy	(+)	Supported
H3A	Market informedness → Advanced use of forecasting	(+)	Supported
H3B	Risk aversion → Advanced use of forecasting	(+)	Not Supported
H4A	Market informedness → Advanced use of hedging	(+)	Not Supported
H4B	Risk aversion → Advanced use of hedging	(.)	Supported

5.5. Summary and Conclusions

5.5.1. Theoretical Implications

In considering the use of market information to confront future price risks, either by acting upon more accurate forecasts or by hedging through forward contract, we have sought to identify the effects of informedness and risk aversion. Based on the empirical results, a revised conceptual model of influences is displayed in Figure 5.2, which has several subtle new insights beyond the initial considerations displayed in Figure 5.1.

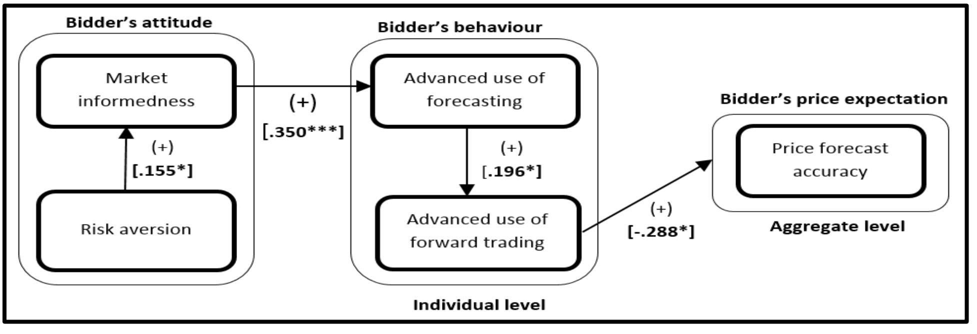

Fig.5.2: Revised Conceptual Model

The key findings are as follows:

Informational role of forward trading is the most important factor that decreases bidders' expectation biases.

We characterized power bidders' price expectation by their price forecast accuracy and trading behaviour by the advanced use of forecasting and forward trading. As summarized in Table 2, forecast error is most significantly and negatively related to the advanced use of forward trading, and surprisingly the advanced use of forecasting techniques has no significant relationship with the accuracy. These findings indicate the importance of the informational role of forward trading on decreasing bidders' expectation biases in online auctions.

More information does not always lead to more rational (less biased) expectations.

Bidders' informedness is positively and significantly related to their use of more advanced forecasting techniques; however, surprisingly, informedness is not significantly related to forecast accuracy. This suggests that in situations where forward trading is possible and effective, more information does not always lead to better electricity price forecasts. This appears to have some implications for the value of increased transparency initiatives and is consistent with the doubts expressed by von der Fehr (2013).

Risk aversion does not play a major role in trading decisions of power bidders

The effect of power bidders' risk aversion levels on their forecasting or forward trading behaviour is not significant, and this is in line with the previous empirical studies. This suggests that risk aversion does not play a major role in trading decisions of power bidders. On the other hand, our study suggests that bidders are risk averse, supporting the findings of Kalayci and Basdas (2010) and Olsen (1997b) on prospect theory, and risk aversion is positively influential on informedness.

In addition, our control variables, including bidder type and strategic positioning in the market, had significant impacts, particularly on forecast accuracy and forward trading. This suggests that in monitoring and promoting efficient and competitive market outcome, regulators may need to look at more subtle measure of auction design than simple concentration metrics.

More generally, this Chapter makes several contributions to the research on online auction design, behavioural finance and energy. With regard to the behavioural literature on examining price expectation formation and rational expectations hypothesis in experimental and real markets, we empirically test the impacts of a bidder's trading behaviour on their price expectations. Our studies provide evidence suggesting the informational efficiency of forward trading on decreasing the biases in price expectations. Bidders using advanced hedging, and trading frequently on the forward markets, can develop more rational and accurate forecasts. With regard to the conventional research theme that mainly seeks to explain trading behaviour via risk-aversion and prospect theory, we extend these studies by adding the bidder informedness variable. Furthermore, the indication from our results is that whilst bidder informedness is dependent upon risk aversion, it is bidder informedness that more significantly influences the use of advanced forecasting. Thus, the research presented in this Chapter is among the first to take an information-based view to study the trading behaviour of bidders and highlights the role of informedness.

5.5.2. Managerial Implications

With regard to its energy policy and auction design research contributions, the incorporation of behavioural elements into the analysis of auction design, beyond the usual market structure considerations, is an important theoretical contribution and reveals a more accurate description of the relationship between auction design and bidders' expectations. Market makers employ various interventions to respond to the market imperfections that occur when bidders are mis-/under informed or unsophisticated. An increasing number of *market transparency platforms* are recent examples of these attempts (eg REMIT in EU electricity trading). "Regulating for rationality", i.e. intervening to cure or overcome cognitive error, has novel challenges for regulators (Schwartz, 2015), but difficulties exist because cognitive-based regulatory interventions are often poorly-grounded. A particular concern is that bidders suffer from numerous cognitive biases, but not every bidder suffers from the same ones. Current market theory cannot prescribe how these biases interact within a bidder and how markets aggregate differing biased bidders' expectations. Nevertheless, by providing a better understanding of bidders' expectation biases, research will help policy-makers design more effective policy instruments to promote the design of efficient forward markets in particular. For *energy regulatory bodies*, in particular, developing an understanding of power bidders' expectations and trading behaviour may assist them to initiate interventions which improve the allocation of resources to better disseminate high quality market information. This study reveals that whilst informedness level does not have a direct significant impact on price forecast accuracy and therefore making more data public via the market transparency platforms may not increase bidders' understanding of price formation; rather, it is more crucial to improve the functioning and depth of the forward markets.

Finally, as with all empirical research, there are questions of generalizability and replication. Whilst the details and control variables have been specific to an electricity market, the conceptual model can in principle be applied to other smart markets. The key elements of forecast accuracy, forward contracting, market informedness and risk aversion are quite general.

Appendix 5.A. Measurement of Variables

	Variables	Measurement Items	Coding
Bidders' performance	Bidders' predictive accuracy	What is your yearly average electricity price forecast for the next year? (2016)	Coded as the difference between the predicted price and the actual yearly (2016) avr price. Variable type: numeric
Bidders' behaviour	Hedging behaviour	What percentage of electricity usage do you hedge by OTC/Forward markets?	Coded as extent of hedging Variable type: numeric
	Forecasting behaviour	Please rate each of the methods listed below in terms of their usefulness in forecasting electricity prices: -Independent forecasts(From consultancy firms) -Forecasts from internal modelling -OTC and derivative price curves	Each item is on a 4-point likert scale, 1=very useful, 4=not useful at all Coded as sum of the dummy variables corresponding to each item Variable type: categorical
Bidders' attitude	Risk aversion	Please rate each of the risk attitudes listed below in terms of their importance on a scale of 1-7 Risk Attitudes: -The chance of incurring a large loss relative to what is expected. -The chance that the portfolio will earn less than the minimum needed to meet the performance target -The overall variability in the portfolio return over time. -The chance that the portfolio will earn less than what is expected. -The chance that the portfolio will earn less than it has historically. -The chance of having the same portfolio value	Each item is on a 7-point likert scale, 1 = not important at all, 7 = very important Measured as the average of six items Variable type: categorical
	Market informedness	To develop a reasonable view of market price for electricity contracts, please indicate your usage of the below variables and rate them in terms of their importance to your company. Variables: -MCP -SMP -Hourly Load -Hourly BA(Bilateral Agreement) Amounts -System Purchase Amount -System Sale Amount -Exact Daily Production Plan -Temperature Forecasts -Wind Power Forecasts -Solar Power Forecasts	Each item is on a 5-point likert scale, 1 = not important at all, 5 = very important 6= cannot access/get this data Coded as sum of the used variables Variable type: numeric

		-Hydro Reservoir Quatos -River flow rates -Cost of delay (COD) -Out of order/ In maintenance plant info. -Hourly Merit Order Curve -BA Prices learned from the market -BA prices of large producers -OTC forward price curve -Hourly electricity prices in Balkans -Exchange rate -Other (Please indicate)	
Strategic positioning	Size	How much electricity do you trade daily?	Coded as 1: small 2: medium 3: large
	Portfolio diversity	What kind of plants are in your portfolio? [Please tick all relevant boxes] -River type -Canal type -Reservoir -Dam -Wind -Natural Gas -Biogas -Fuel oil -Lignite -Imported coal -Anthracite -Geothermal -Landfill gas -Naphtha -Other (Please indicate)	Count the total number of plants in their portfolio Coded as 1 (undiversified), up to three utilities are coded as 2 (semi-diversified) and more than three utilities are coded as 3 (highly diversified)
	Type of licence	What is your type of participation license in the Turkish Electricity Market? [Please tick all relevant boxes]. -Generator -Auto producer -Incumbent retail -Distributor -Retailer	Coded as (1) Generator (2)Auto producer (3) Incumbent retail (4)Distributor (5)Retailer Encoded into four dummy variables with retailer variable being the benchmark case

Chapter 6

Characterization, Determinants and Efficiency of Bidding in Electricity Auctions[18]

6.1 Introduction

With advancements in information technologies, online auction markets have been introduced (Kambil and van Heck, 2002) providing the necessary institutional framework to facilitate online trading. Bidder-level data has revealed the existence of significant heterogeneity in bidders' strategies (e.g. Kauffman and Wood, 2006; Hortacsu and Puller, 2008; Bapna et al., 2004, 2009; Goes et al., 2010, 2012; Lu et al., 2016) leading to different economic consequences. Those studies have raised the need for more complex stylization of supply function equilibrium models and have given rise to theory-driven empirical work on auctions (Hortacsu, 2011). Further they introduced large and complex trading-data sets at the bidder level which brings challenges, particularly for auctioneers, on understanding the *determinants and productive efficiency of observed trading behaviour/strategy* (Engelbrecht-Wiggans, 2000). In this chapter we focus on an online multi-unit uniform-price auction with the existence of oligopoly; namely the *Electricity Day-Ahead (EDA)* auctions. The susceptibility of these auctions to the exercise of unilateral market power makes them

[18] Parts of this Chapter are accepted for the following conferences:
Avci, E. (2018). Characterization, Determinants and Efficiency of Strategic Behavior in Multi-unit Auctions: Evidence from Electricity Markets. In 41st IAEE International Conference, Groningen, the Netherlands.
Avci, E. (2018). Understanding strategic bidding in oligopolistic multi-unit auctions. In SCECR (Statistical Challenges in E-Commerce) 2018, Rotterdam, the Netherlands.

an ideal research setting to study the determinants of oligopolistic behaviour and productive efficiency (Wolak, 2010). Since electricity auctions are regulated they have detailed *market surveillance rules* that must be used by the auctioneer specifying precisely how market-clearing prices are determined and defining the feasible set of market participant actions, i.e. *accepted market practices* (REMIT, 2011). Thus there are Market Surveillance Committees (MSCs) whose main aim is to provide independent oversight and analysis of auctions for the protection of consumers and bidders by the identification and reporting of market design flaws, potential market rule violations, and market abuse behaviour (CAISO, 2017). Market abuse behaviour in electricity auctions involves actions undertaken by persons that artificially cause prices to be at a level not justified by market forces of supply and demand, including actual availability of production, storage or transportation capacity (REMIT, 2011).

With the proliferation of electronic trading, there are millions of events (orders, trades, price-quantity matches etc.) per day (big data sets) and it is impossible to detect suspicious activity manually. The standard way of dealing with such big data is to aggregate it and expressing it in summary form for statistical analysis. Many market surveillance systems leverage these statistical techniques and technologies to quickly compare huge volumes of real-time data with historical data. Unfortunately, statistical analysis alone is not sufficient to fully understand what is happening amidst market complexity and why it is happening. When it is supplemented with *behavioural analytics*, MSCs can understand the *intent* behind these strategic behaviours (NASDAQ, 2017, Behavioural Analysis in Market Surveillance Report).

The goal of the research presented in this Chapter is to demonstrate how a behavioural analytics approach can be used to address the cognitive and computational limitations of MSCs in their detection of manipulative behaviour.

We adopt a *three-stage analysis approach* (Bapna et al., 2004). In the first stage, we use an *inductive, data-driven approach* to characterize strategic behaviour. We develop initial constructs before developing our hypotheses. The initial challenge was to identify *observable* classification variables that could be obtained from our EDA auction data set. In addition, we want to work with extrinsic variables that could subsequently be used by the MSC to monitor the market abuse behaviour. Therefore, we are not interested in measuring intrinsic bidder attributes like risk profile that could not be altered by modifying the mechanism. We introduce five hourly classification variables- *number of orders (for both bid and ask), maximum bid price, minimum ask price, ask price and supply withholding ratio*- to characterize bidders' behaviour in double sided multi-unit auctions. Note that the introduction of these hourly classification variables is a novel contribution to the characterization of bidding strategies in multi-unit uniform-price auction markets. Given that bidders participating in EDA auctions differ by size, forward commitment, generation technology and portfolio diversity, our novel classification variables can help us to better relate the observed bidding behaviour with the business profiles and needs of different bidders. The second stage is intended to explain why bidders choose different bidding strategies through using an econometric model. Drawing upon prior literature related to firm behaviour in electricity auctions, we identify four bidder-level factors that are critical to bidders' strategic choices: forward commitment, size, type and diversity. To test our hypotheses, we develop an explanatory model of bidders' strategic choices, using multinomial logistic regression (MNL). In the last stage, we analyse outcome efficiency and winning likelihood of each strategy.

The research presented in this Chapter makes several important contributions. Firstly, it is the first to characterize bidding strategies adopted by professional bidders in oligopolistic multi-unit auction markets. As such, it complements two previous studies by Bapna et al. (2004) and Lu et al. (2016) that empirically investigate bidder heterogeneity through applying the three-stage analysis to B2B and B2C auctions. In particular, our finding that despite bidders' extensive experiences there are still theoretically meaningful and empirically robust clusters of bidding strategies challenges the conventional view that bidders' strategies will eventually converge as they gain experience over time. Second, while most of the auction research in information systems and marketing has looked into bidding behaviour in online spot markets without the existence of oligopoly and forward markets. We investigate a centralized product market with the existence of oligopolistic firm behaviour and forward markets. This allows us to empirically test the effects of size and forward commitment on firm's choice of strategy, complementing and supporting the findings of Wolfram (1998), Wolak (2003), Hortacsu and Puller (2008), Bunn et al. (2015) and Hortacsu et al. (2017). Our study also contributes to the literature on how electricity supplier-bidders formulate their offers (e.g. Fabra and Reguant, 2014). Fourth, by analysing the economic impacts of bidding strategies, our study sheds new light on price dispersion in auction markets. Finally, this work relates to the literature that studies differences in productivity across firms (e.g. Syverson, 2004; Hsieh and Klenow, 2009).

6.2. Theoretical Background

6.2.1. Bidder Heterogeneity

Traditionally, auctions have largely been studied from the game-theory perspective. Bidders are assumed to be homogeneous and adopt the Bayesian-Nash equilibrium strategy (McAfee and McMillan, 1987; Milgrom, 1989; Myerson, 1981). When studying auctions, researchers use a Bayesian Nash model of bidding to "invert" bids to estimate valuations and then conduct counterfactual experiments to predict market outcomes under alternative auction formats (Hortacsu et al., 2017). However with the proliferation of electronic trading, the availability of bidder-level big data sets have made the assumptions behind these strategic equilibrium models questionable (Ariely and Simonson, 2003; Bajari and Hortacsu, 2004). This highlights the necessity of further developing explanaitons of real-life bidding behaviour. For example, using transaction data from Yankee auctions, Bapna et al. (2004) identify five different bidding strategies that result in different winning likelihoods and consumer surplus. They also discuss the promises of such bidder taxonomy in guiding the development of user-centric bidding agents and facilitating real-time auction calibration. A more recent study by Lu et al. (2016) extends the research on bidder taxonomy to B2C auctions and finds that bidders' choice of bidding strategies is contingent on their budget constraints, demand and transaction cost. However, most of the empirical research on bidding behaviour has exclusively focused on B2C and B2B auctions where bidding activities are predominantly associated with willingness-to-pay (WTP) in a one-sided demand elastic context. A natural question arises: does the observed heterogeneity in B2B and B2C auctions still exists in an oligopolistic multi-unit auction setting and lead to bidders' having an incentive to overstate their costs associated with providing a large quantity of the good (Wilson, 1979; Back and Zender, 1993; Ausubel and Cramton, 1998) or withholding their good from the market (Cramton, 2004)?

6.2.2. Strategic Bidding in EDA Auctions

After the well-known California blackout in the 2000s, it is understood that some of the bidders were able to exercise strategic bidding and this led to abundant research to improve the understanding of bidder strategies leading to such million-dollar losses for the government and consumers. The first stream of studies (between 1996 and 2004) can be divided into two in terms of defining market power, as described below.

(1) *Identifying strategic bidding at market-level*: finding evidence of strategic bidding through analysing the actual market outcome (market clearing price (MCP), or in some studies, system marginal price) and estimating a competitive market counterfactual by considering the technological specificities of suppliers in the supply stack (e.g. Wolfram, 1999). This approach is less vulnerable to the arguments of coincidence, bad luck, or ignorance that may be directed at analysis of the actions of a specific generator (Borenstein et al., 2002). However it is less informative about the specific manifestations of non-competitive bidding behaviour for different bidders (Tashpulatov, 2015). Also it captures all inefficiencies in the market, some of which may not be due to market power, including bad judgment and confusion on the part of some generators or market making institutions. For example, if low-cost generators are systematically held out of the merit order curve due to an inefficient dispatch algorithm, then that would impact the estimate of market power.

(2) *Identifying strategic bidding at bidder level*: finding evidence of strategic bidding through analysing the bid price and the estimated marginal cost of each bidder to detect behaviour that can affect MCP (e.g. Wolfram, 1998; Bushnell and Wolak, 1999; Wolak, 2003; Puller, 2001; Borenstein et al., 2002). Keeping in mind that our main objective is not understanding strategic bidding at the market level, our study is in line with the second approach due its possible merits in terms of behavioural market monitoring. The most influential study in this stream is Wolfram (1998) which was one of the first to consider strategic bidding and heterogeneity in EDA auctions. She finds evidence of strategic bidding by comparing bidders' bid price and their estimated marginal cost (composed of fuel price and efficiency index) and shows that significant heterogeneity exists within bidders through using *mark up* (the difference between MCP and bid price (not bid function)) as a *dependent variable* and *available MWh below, unit capacity (declared installed capacity), bid impact, daily average predicted demand* as independent variables in her ordinary least squares (OLS)

regression equations. She finds the larger supplier submits higher bids for similar plants. The (previous) Chair of the California MSC authored the first study to provide a direct link between the observed pattern of balancing prices and the bidding behaviour that produced those prices by examining information available to the MSC (Sheffrin, 2001). She examines bid data in the balancing auctions of the ISO and aims to understand whether bidders' behaviour was responsible for raising prices above competitive levels. Her data set includes individual offer functions, bilateral and power exchange schedules from generation units and unit specific heat-rates for generation-level scheduled outages. She observed five bidding strategies: (1) no withholding; (2) full output at high mark-up; (3) physical withholding with no mark-up for bids submitted; (4) physical withholding used in combination with significant bid mark-ups; and (5) economic withholding. The similarity between these two empirical settings is the presence of large suppliers and the lack of liquidity in the market.

The main drawback of these studies is that all of them ignore the functionality properties of the bid function but rather focus on the bid price. Thus they are not very informative in terms of the characterization of bidders' behaviour. Further, bidders are very few in number and there is little generation diversity of bidders in their considered markets which precludes observing a real heterogeneity. In addition they consider markets where bidders are required to report their start-up costs and marginal costs with their bid price which makes calculating mark up (the difference between MCP and bid price) straightforward and unbiased. However in most of the EU power markets, bidders submit only bid functions without any requirement for reporting marginal costs. This type of bidding necessitates novel identification approaches which are based only on the *observed (realized) bid function*.

6.2.3. Importance of Characterizing the Bid Function for Understanding Strategic Bidding

The other group of studies which consider the realized *bid functions* as actual market outcomes (Wolak, 2003; Hortacsu and Puller, 2008) consider strategic bidding as bidding above *best response bidding* and attempt to find evidence of oligopolistic firm behaviour through comparing *realized bid function,* and *optimal bid function* based on ex-post estimated marginal costs. Wolak (2003) investigates bidding behaviour in the Australian

EDA auctions (in which most of the participants in this market own multiple generators), through using *cost function recovering* techniques. He finds increasing, convex, marginal cost curves and argues that this may be the result of generators' having sold significant amounts of forward contracts and thus hedging against unit outages. Because of the enormous financial risk associated with losing a single generator in real time combined with the inability to quickly bring up another unit in time to meet this contingency, generation unit owners apply a large and increasing opportunity cost to *the last one third* to *one quarter of the capacity* of each single generator (*Partial Bidding*). This study is one of the first that emphasizes the importance of partial bidding and forward commitments on market outcomes. Hortacsu and Puller (2008) is the first to investigate heterogeneity among a considerable number of bidders (30 bidders). Their data set is from the Texas balancing energy market (ERCOT) and they develop benchmark bid functions that maximize profits based on a distribution of realizations of residual demand and a firm's generation costs. They find that smaller bidders submit bids at offer prices higher than optimal (steeper bids). They suggest that this could be the result of institutional complexities in entering the auction, and fixed cost of establishing a sophisticated trading system which inhibits small bidders from constructing informed bid functions (less steep bid functions). However these two studies suffer from rationality and mutually consistency assumptions which may break down in real auction markets since bidders that compete in the same market can vary substantially along a number of dimensions such as size, sophistication and management staff. A very recent study, Hortacsu et al. (2017), using the same data in Hortacsu and Puller (2008), use a cognitive hierarchy model that allows for bounded rationality of bidders and find that there is significant heterogeneity across firms in terms of strategic sophistication (closeness of a bidder's offer function to the assumed best response offer function) and larger bidders have higher levels of sophistication (indeed, in other words, larger firms submit less steep functions) confirming the results of Hortacsu and Puller (2008).

6.2.4. Data-driven Approaches

Hu et al. (2005) adopt a *graphical approach* to analyse the shapes of bids in the Australian National EDA. They find diversity in bidders' bidding strategies, partially related to their generation technologies, sizes and locations. They find that large suppliers have the ability to set and/or push market prices higher and display tendencies to withhold their capacities during peak periods. Zhang (2009) investigates generators' bidding behaviour in the New York EDA auction through *manually* dividing the generators into clusters based on the *highest price of their bid*. She finds that grouping choices are persistent, and generators in higher-priced groups tend to withhold their capacity strategically to push up market prices. Bosco et al. (2012) investigate strategic bidding in the Italian EDA auctions (13+ bidders). They find that forward contract commitments strongly improve the adaptability of existing theoretical models of bidding behaviour to the data generated in electricity markets. Bunn et al. (2015) examines the offer prices submitted to the British market by four coal-fired plants. They used bid data with *price* (*lowest offer price*) as a dependent variable and *demand, reserve margin, system buy price, gas and coal price, dark spread, closing price of the day ahead market, loss of load probability, a measure of uncontracted output* as exogenous variables. They show that among the factors affecting this heterogeneity (size, vertical integration, portfolio asset management and information asymmetry) only *size* is statistically significant.

All of the data-driven studies in EDA auctions have many drawbacks. First, their sample is not representative in terms of diversity of firms. All of them focus on only suppliers ignoring the other types of players in the market. Second, since they consider suppliers, they can only analyse the offer curve. However day-ahead markets are well known for their double auction mechanism. That is a generator can have incentive to buy electricity up to a certain price level (i.e., maximum bid price). Thus analysing only offer prices of suppliers is like telling half of the story. Third, the number of firms/bidders are very limited due to lack of data or complexity of querying big data sets. Fourth, they conduct their analyses by taking the multi-dimensional bid function as a single point such as lowest offer price or maximum offer price. Therefore they are missing the rich shape of the bid function.

Data-driven literature in other auction markets (e.g. Bapna et al., 2004; Goes et al., 2012; Lu et al., 2016) show that bidder heterogeneity is best determined by considering different aspects of shape of bid function such as total number of order steps, number of bid/ask steps, maximum/minimum bid price/quantity, maximum/minimum offer price/quantity, bid-ask spread etc. Therefore to eliminate these drawbacks, we adopt the empirical research framework of Bapna et al. (2004), Goes et al. (2012) and Lu et al. (2016).

6.3. Conceptual Background

Electricity wholesale markets are sequential clearing mechanisms which can be divided into four categories: day-ahead markets, intra-day markets, balancing and reserve markets, and forwards and futures markets. Among electricity markets, the day-ahead market, which determines the electricity prices for the delivery of electricity the next day, has a position of prominence. The prices coming from day-ahead markets are usually accepted as a reference point for the other electricity markets and bilateral contracts.

Bidders can submit orders hourly or daily for a particular hour or period of hours, or they can make flexible orders. Orders are composed of quantity and price information that can change for different hours. Submitted order prices have centesimal sensitivity. Orders can be made in terms of Turkish Lira per MWh. Order volumes are submitted in terms of a Lot as an integer (one Lot is equivalent to 0.1 MWh). Orders can be submitted as bid and/or ask. Depending on the sign in front of the order quantity, the order is marked as either a bid or an ask (for instance, a 100 Lot indicates a bid, whereas a -100 Lot indicates an ask). A *single order* is a price and quantity schedule determined by the bidder. Basically, the bidders tell the auctioneer the price-quantity pair they are willing to trade for a particular hour of the next day. Table 6.1 demonstrates two single orders by a bidder for the first two periods of the day.

TABLE 6.1: An example for single orders

Hour	**Price (TRY)/MWh**					
	0	**50**	**80**	**120**	**200**	**2000**
0 – 1	600	400	0	-200	-500	-1000
1 – 2	300	300	200	0	-2000	-2000
…	…	…	…	…	…	…

For instance, in period 1, the bidder is willing to sell 200 MWh if the clearing price is above 120 TRY/MWh; and willing to buy 400 MWh if the clearing price is below 50 TRY/MWh. Each time period corresponds to an hour in the Turkish market. Single hourly orders have a maximum of 64 steps which contain 32 bids and 32 asks. The prices of single hourly orders must be listed in ascending order. In a single price step there cannot be valid single hourly orders for both bid and ask. During the formation of the supply-demand curve, the linear interpolation method is employed to interpolate values between two consecutive price/quantity steps. Minimum and maximum price limits are determined by the auctioneer and settled in the Turkish market as 0 TRY and 2,000 TRY respectively. Depending on changing market circumstances, the auctioneer can update the minimum and maximum price limits and announce them to bidders. Minimum and maximum bid quantities are determined by the market operator as ±100.000 Lot.

6.4. Empirical Strategy

We use a unique and complex data set from Turkey EDA auctions which contains details of hourly single orders each bidder submits to the EDA auctions from January 2, 2011 to March 31, 2012 (90 auction days). Details of the raw data set can be seen in Table 6.2. In total we have 9,170 hourly forward transactions, corresponding to 89,243 single hourly orders. There are 721 registered bidders in the Turkish EDA auctions of which 252 are active of which 132 give regular hourly bids during our empirical time framework.

Table 6.2: Raw data for bidder-5B78C87D1D37958150FBEXSTSJDSAP for hour-17 on January 27, 2012

Date	**Hour**	**Bidder ID**	**Order Type**	**Ask Price**	**Bid Price**	**Quantity**
27-1-2012	17	5B78C87D1D37958150FBEXSTSJDSAP	Hourly	0	1010	0
27-1-2012	17	5B78C87D1D37958150FBEXSTSJDSAP	Hourly	0	1010	109
27-1-2012	17	5B78C87D1D37958150FBEXSTSJDSAP	Hourly	0	510	109,01
27-1-2012	17	5B78C87D1D37958150FBEXSTSJDSAP	Hourly	0	510	110
27-1-2012	17	5B78C87D1D37958150FBEXSTSJDSAP	Hourly	0	0	110,01
27-1-2012	17	5B78C87D1D37958150FBEXSTSJDSAP	Hourly	0	0	128,99
27-1-2012	17	5B78C87D1D37958150FBEXSTSJDSAP	Hourly	240	0	129
27-1-2012	17	5B78C87D1D37958150FBEXSTSJDSAP	Hourly	240	0	154,74
27-1-2012	17	5B78C87D1D37958150FBEXSTSJDSAP	Hourly	1020	0	154,75
27-1-2012	17	5B78C87D1D37958150FBEXSTSJDSAP	Hourly	1020	0	2000

6.4.1. Schematic Evidence on Bidder Heterogeneity

Analysing bidders' shapes of bids can give important insights about their approximate marginal cost and market and revenue expectations since there is a trade-off between volume of generation and MCP. As can be clearly observed from Figure 6.1, there are significant differences in bidding strategies of large portfolio bidders. Five of the bidders (bidders 3, 4, 5, 11, and 16) commit all their capacities at very low price bands, indicating that they are following an inframarginal strategy. The offer of bidder-5 is even price-independent. The number of their bid steps are a few. They are happy to offer all their capacity at whatever the market price would be since they do not want to take the risk of being out of the merit order curve at the peak hour (when MCP is likely to be highest). The strategies of two state-owned utilities seem to be very similar. The number of their order steps is highest, indicating their strategic sophistication. Bidders 2, 7, and 14 follow a physical withholding strategy in which they withhold approximately 40% of their capacity to commit at very high price bands (MCP+700 TRY).

Table 6.3 presents representative order books submitted by a sample of individual (not portfolio) bidders with different generation technologies; fuel oil, natural gas, canal type hydropower, hydro dam, wind, imported coal, and lignite. We use the word 'representative' on purpose in the previous sentence since large proportion of bidders does not change their bidding strategies for the whole month as also observed in Zhang (2009) in Australian EDA auction bidders. There can be two possible explanations for this persistent behaviour (Heckman, 1981): (1) bidders' past bidding behaviour can have a direct effect on current bidding behaviour, that is, if a bidder tests a certain strategy for a time and finds out that it is a profitable one, then he/she can keep the same strategy as long as expected market conditions are the same; and (2) bidders' bidder-specific and time-invariant heterogeneity can lead to *spurious state dependence*.

6.4.2. Identification of Strategic Variables: A Conceptual Perspective

Unlike Bapna et al. (2004), we cannot observe when a bidder enters an auction and drops out since EDA auctions are hourly and they are conducted one day before the physical delivery day. Each bidder is free to give bid/ask orders anytime until 11:00 on the physical delivery day. Therefore the time of the order (TOE in Bapna et al., 2004) is not a strategic decision for bidders. Instead, since electricity is a good with very limited storage capability and electricity wholesale markets are sequential auctions, one of key decisions in the EDA auction is to decide *how much to bid/offer to the market*. If, for example, a bidder offers all their hourly available capacity to the EDA auction and the outcome price is very low, then the bidder would lose the opportunity to bid in the balancing market in which the system marginal price could be higher. Another example could be given for a hydro dam bidder which have a fixed water storage capacity and water value. This type of bidder is a flexible one and can give more opportunistic orders to maximize value of its water. Further EDA auctions are double sided in which a bidder can give bid and ask orders in the same function. That is we can observe *willingness to sell* (WTS) as well as *willingness to pay* (WTP). Also due to being a multi-unit auction, bidders can give different ask prices for different quantity levels of the good. That is a bidder's WTS price may be very low (even zero), but their price ladder above the WTS price may be opportunistic. Therefore for an EDA bidder, determining the withholding ratio and average ask price is one of the key decisions. These variables are also very important for revealing/monitoring EDA bidders' strategies.

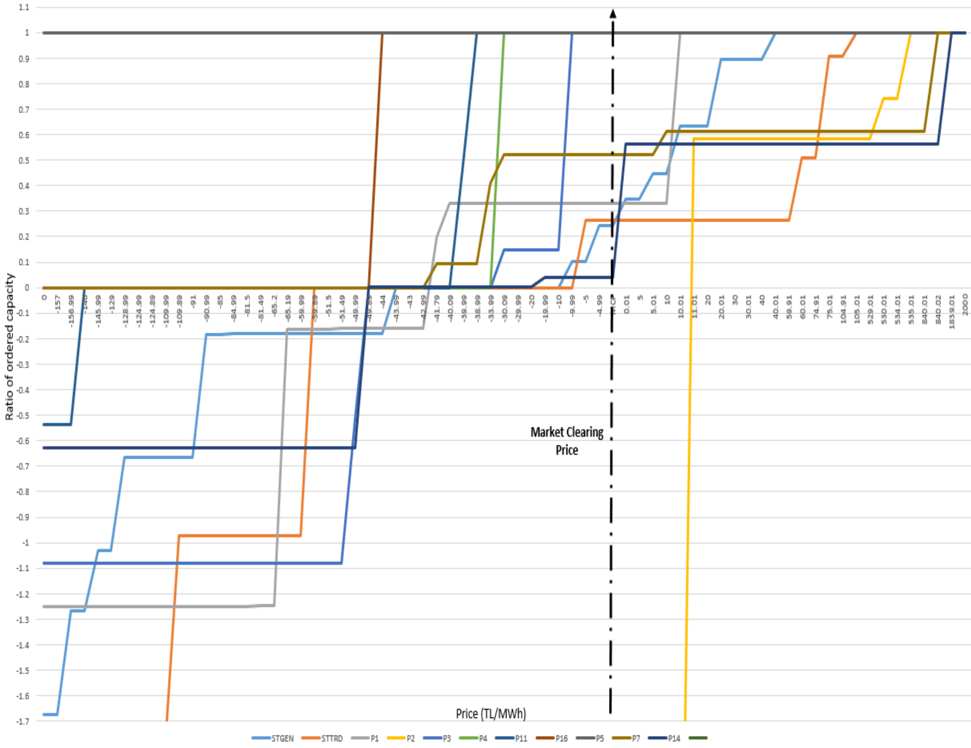

Fig. 6.1: Bid functions of large portfolio bidders on day X at hour 17:00 [Note: Y-axis: Ratio of ordered capacity is calculated as (order quantity/installed capacity)/ (DAM max. offer capacity on day X at hour 17:00)]

As a result, we introduce five hourly classification variables- *number of orders, willingness to pay, willingness to sell, ask price and withholding ratio*- to characterize bidders' behaviour in double sided multi-unit auctions. Note that the introduction of these hourly classification variables is a novel contribution to the characterization of bidding strategies in multi-unit auctions. Given that bidders participating in EDA auctions differ with respect to their size, forward commitment, generation technology and portfolio diversity; our novel classification variables can help better relate the observed bidding behaviour with the business profiles and needs of different bidders. In this section, we describe how we construct each of these classification variables.

Number of orders (NOO)

NOO is the total number of orders a bidder submits hourly. With the existence of bidding and monitoring costs in the auction setting, NOO is an indicator of bidder's sophistication (Bapna et al., 2004). In EDA auctions, there is no cost for bidding; that is, a bidder is not paying more when he increases his number of orders. Thus NOO is related only to monitoring costs by which we mean the money spent by bidders to understand the auction pricing mechanism such as hiring market analysts, subscribing to large energy databases in order to be able reach private information and/or buying expensive forecast software or consultancy. Therefore we take it as a proxy for the value of bidders' sophistication.

Willingness to pay (WTP)

WTP is the highest price that a buyer (i.e., bidder) is willing to pay for a good/part of a good. This corresponds to the standard economic view of buyer reservation price. It is usually referred to simply as the bid price or bid in Internet auctions and stock exchanges. According to the constructive preference view, consumer WTP is a context-sensitive construct, that is, a consumer's maximum WTP for a product depends on the concrete decision context. Many methods to measure WTP are presented in the literature (Breidert et al., 2006). The approaches to measure WTP differ according to whether they measure WTP directly or indirectly and whether they measure hypothetical or actual WTP (Miller et al., 2011). In practice, some researchers favour the direct approach, asking consumers directly to state their WTP for a specific product through, for example, an open-ended question format. Others prefer an indirect approach, such as choice-based conjoint analysis, in which WTP is calculated on the basis of consumers' choices among several product alternatives and a 'none' choice option. However, neither method is fool proof. A direct approach to elicit actual WTP is a mechanism that Becker, DeGroot, and Marschak (1964) propose (Becker–DeGroot–Marschak method), in which a participant is obligated to purchase a product if the price drawn from a lottery is less than or equal to his or her stated WTP (Wertenbroch and Bernd, 2002). However, an actual WTP generated with these methods may not always be accurate, because it may differ from the WTP shown in real consumer purchases. In EDA auctions context, bidders WTP mostly depends on the optimal bidding strategies. That is, an EDA bidder can pay for electricity as long as its generation cost is higher than the WTP price. Therefore, *minimum ask price* can be taken as the *actual* WTP in EDA auctions.

TABLE 6.3: Representative order books submitted by individual bidders. Note: IC is the installed capacity of the related bidder, P is the MCP at hour 17:00 on the day these order books submitted.

Bidder Type	Hour	Order Type	Ask	Bid	Price
Bidder X Fuel Oil (only seller)	17	Hourly	0	0	0
	17	Hourly	IC_X	0	P+190
	17	Hourly	IC_X	0	2000
Bidder Y Imported Coal (only seller)	17	Hourly	(0.52) IC_Y	0	0
	17	Hourly	(0.52) IC_Y	0	P-40
	17	Hourly	(0.52) IC_Y	0	P-25
	17	Hourly	(0.52) IC_Y	0	P-15
	17	Hourly	(0.93) IC_Y	0	P-10
	17	Hourly	(0.93) IC_Y	0	2000
Bidder Z Hard Coal (both buyer and seller)	17	Hourly	0	(0.10) IC_Z	0
	17	Hourly	0	(0.10) IC_Z	P-60.01
	17	Hourly	0	0	P-60
	17	Hourly	0	0	P-30.01
	17	Hourly	(0.14) IC_Z	0	P-30
	17	Hourly	(0.14) IC_Z	0	2000
Bidder T Lignite (only seller)	17	Hourly	(1.40) IC_T	0	0
	17	Hourly	(1.40) IC_T	0	2000
Bidder K Natural Gas (both buyer and seller)	17	Hourly	0	(0.05) IC_K	0
	17	Hourly	0	(0.05) IC_K	P-31
	17	Hourly	(0.25) IC_K	0	P-30.01
	17	Hourly	(0.93) IC_K	0	P-25.01
	17	Hourly	(0.93) IC_K	0	2000
Bidder L Canal type bidder (only seller)	17	Hourly	(0.85) IC_L	0	0
	17	Hourly	(0.85) IC_L	0	2000
Bidder M Hydro bidder (only seller)	17	Hourly	(0.90) IC_M	0	0
	17	Hourly	(0.90) IC_M	0	2000
Bidder N Dam Hydro bidder (both buyer and seller)	17	Hourly	0	(0.40) IC_N	0
	17	Hourly	0	(0.40) IC_N	P-65.37
	17	Hourly	(0.08) IC_N	0	P-65.36
	17	Hourly	(0.08) IC_N	0	P+40.16
	17	Hourly	(0.60) IC_N	0	P+40.17
	17	Hourly	(0.60) IC_N	0	2000
Bidder U Wind (only seller)	17	Hourly	(0.85) IC_U	0	0
	17	Hourly	(0.85) IC_U	0	2000
Bidder V Portfolio (only buyer)	17	Hourly	0	(0.60) IC_V	0
	17	Hourly	0	(0.40) IC_V	P-10.01
	17	Hourly	0	(0.40) IC_V	P-10
	17	Hourly	0	(0.20) IC_V	P+19.99
	17	Hourly	0	(0.20) IC_V	P+20
	17	Hourly	0	(0.10) IC_V	2000

Willingness to sell (WTS)

WTS is the lowest price a seller (i.e., bidder) is willing to accept for a good/part of a good. It is usually referred to simply as the *ask price* or *ask* in single-unit Internet auctions and stock exchanges. In the general auction literature, WTS is defined as the opportunity cost of producing that unit of output, since sellers would not sell that unit below the cost of producing it, but would sell if the price was greater than their marginal cost. That is, WTS is usually taken as a proxy for the seller's marginal cost which includes the supplier's marginal production cost, but also includes opportunity costs, such as the sale into a higher priced market. Since electricity is sold in a sequence of related markets, the opportunity costs are especially important and give the bidders bid above marginal cost a supplier decides to produce less than is economically feasible at a given price level, because the higher price level associated with the lower output maximizes the supplier's profits (Cramton, 2004). This is an indicator for economic withholding. Further, being a uniform price auction market, bidders have an incentive to bid 'untruthfully' by overstating their costs (Wilson, 1979; Ausubel and Cramton, 2002).

Ask price (ASKP)

A multi-unit auction allows participants to partially fulfil their orders, for accepted orders that are below MCP. Thus each bid is not an `all-or-nothing' proposition, but rather will have portions that are accepted and rejected. Therefore almost all equilibriums in a multi-unit auction contain some strategic bidding (Wang and Zender, 2002). Each rational bidder in multi-unit auctions sets the offer at each quantity at the point where the marginal gain from offering a little bit more (a higher price on the quantity sold) exactly balances the marginal loss (failure to get the spread between the offer and marginal cost on the expected available quantity that will go unsold as a result of the higher bid). This introduces non-convexities in the supplier's cost function that it is unable to express in its offer function (Cramton, 2004) and leads to physical withholding behaviour in EDA auctions. To capture this behaviour, we adopted a bid price formula used by the UK National Grid Company in order to calculate the bid price as a function of output from the unit. This bid price is also commonly used in the empirical literature starting from Wolfram (1998) and using the UK Pool data. We modified the above formula as presented in Equation (1):

$$Ask\ Price = \frac{Min.Ask\ Price * Min\ Ask\ Quantity + \sum_{i=1}^{k} Ask\ Price_i * Elbow_i}{Output\ (Max.Ask\ Quantity)} \quad (1)$$

Where $Min.Ask\ Quantity$ is the quantity (Lot=0.1 MW) offered at the WTP price; $Ask\ Price_i$ is the offer price in TRY/Lot of the $Elbow_i$ and $Elbow_i$ is the Lot (0.1 MW) offer of $Elbow_i$. Our definition of $Ask\ Price$ can be thought as a *weighted average* of ask prices multiplied by the corresponding increments in quantity offered.

Withholding ratio (WR)

We define a bidder's WR as follows in Equation (2):

$$Witholding\ Ratio = \frac{Output(Max.Ask\ Quantity) - Min.Ask\ Quantity}{Output\ (Max.Ask\ Quantity)} \quad (2)$$

where $Min.Ask\ Quantity$ is the quantity (0.1 MW) offered at the WTP price. This ratio indicates the percentage of quantity that the bidder withholds for strategic bidding after guaranteeing to sell the $Min.Ask\ Quantity$ at WTS price.

6.4.3. Classification Methodology

We use an efficient K-means clustering algorithm developed by Hartigan and Wong (1979). A key factor in choosing this method was its proficiency in handling large data sets like ours. Our bidder data point is a vector of five variables: NOO, WTP, WTS, ASKP and WR. If heterogeneity exists along these five dimensions, we expect the data vectors to form several clusters in the five-dimensional space. Well-formed clusters are characterized by small intra-cluster distance and large inter-cluster distance. The algorithm aims to partition the points into K disjoint groups such that the sum of squares from points to the assigned cluster centres is minimized. At the minimum, all cluster centres are at the mean of their Voronoi sets (the set of data points which are nearest to the cluster centre). A potential limitation of this approach is the a priori specification of the number of clusters, K. In our context, we do not know in advance how many different bidding strategies exist.

Given the exploratory nature of this research, we followed the procedure suggested by Koehly (2001) and started with a hierarchical clustering to examine the cluster structure at different levels. Next, we repeated K-means clustering with a range of different values of K (Kmin = 2, Kmax = 10). According to the Calinski-Harabasz criterion (Milligan and Cooper, 1985), the optimal number of clusters is five. We compared the cluster centres under hierarchical clustering and K-means clustering (K = 5), and found the results were very consistent. Note that good scores on an internal criterion (e.g. Calinski-Harabasz criterion) do not necessarily translate into the effectiveness of K-means clustering. An alternative, and perhaps better evaluation, is to look at the interpretability of the clustering results. This is often referred to as external validity. In our case, we used ANOVA to test whether there are significant differences between the cluster centroids. As shown in Table 6.4 the differences between the five clusters from K-means clustering are statistically significant.

TABLE 6.4: ANOVA results for each cluster

Variable	Cluster Mean Square	Error Mean Square	F	Significance
NOO	6122.9	28.8	212.42	.000
WTP	236391961	208279	1135	.000
WTS	408190	9741	41.91	.000
ASKP	4361454	13770	316.7	.000
WR	2.8361	0.0906	31.3	.000

Further, we also conducted a robustness test on the clustering results using cross validation. Specifically, we randomly split the observations into two parts, one with two thirds of the observations (training set) and the other with one third of the observations (test set). We applied K-means clustering (K = 5) to the training set and used the identified cluster centres to label the observations from the test set. We then checked whether the labels of the observations in the test set are the same as the ones resulting from the K-means clustering on the whole data set. We repeated this process 100 times and found that 99.9 percent of the observations from the test set have the same label. This confirms that our clustering results are very stable.

6.4.4. Bidder Strategy Analysis

This section discusses the strategic implications of different bidder behaviours as represented by the five clusters. Table 6.5 contains the classification results. The values present mean of the data in each cluster. We name each class of bidders based on the unique characteristics conveyed by the corresponding parameter values.

TABLE 6.5: Cluster Centres

Cluster Name	Cluster Dimension				
	NOO	**WTP**	**WTS**	**ASKP**	**WR**
Inframarginal	2.52	7.95	1.92	1.92	0
Physical Withholder	2.87	0	0.05	180.83	0.18
Economic Withholder	8.34	64.87	148.62	163.19	0.31
Opportunists	5.44	6.85	332.52	504.11	0.24
Risk Averse	2.2	2000	0	0	0

The first cluster is *inframarginal.* These bidders mostly place *price independent ask orders* (that is minimum ASKP is zero) with only two order steps, reflecting their willingness to offer to the spot market at any price. Their WTP is very low near to zero. Such low prices have not been observed in the Turkish EDA market indicating that these bidders give bid orders near to zero only for a hypothetical situation. We can say that bidders in this cluster are only sellers. Another interesting thing is that their WR is zero reflecting their aversion to strategic bidding. The second cluster is *physical withholders* who are only sellers (since WTP is zero) with a WTS close to zero. This cluster differs from inframarginals in terms of its ASKP which indicates that although these bidders are willing to guarantee selling *a part of* their supply, they withhold on the average 0.18% of their supply for strategic bidding. In fact the difference between ASKP and WTS also reflects the steepness of these bidders' bid function. The third cluster is *economic withholders* which have the highest number of orders indicating they are the most sophisticated bidder type. They are able to construct (sophisticated) profit maximizing bid functions. Also they give both bid and ask orders that is they are both buyers and sellers. They have the highest WR but this cluster differs from physical withholders in that their average WTS is 148 compared to physical withholders' zero WTS, reflecting the less steep supply function of economic withholders. The fourth cluster is *opportunists* with the highest WTS and ASKP. Their WR is also one of the highest.

Bidders in this group may have the highest marginal costs, therefore they have to operate at only peak hours (even mostly in crisis times, their annual working hours are very low). The last cluster is *risk averse bidders* who only buy from the spot market to close their positions in the forward market. Their WTP is at the market price cap 2,000 TL reflecting their eagerness to buy from the spot at any price. Their WTS and ASKP is zero indicating that they do not offer to the spot market. Given that all bidders in the EDA auctions are professionals and have more than sufficient bidding experience, the existence of these distinctive bidding strategies challenges the popular view that bidders' strategies will converge as they gain experience.

6.4.5. Determinants of Bidders' Strategy Choice

Drawing upon prior literature, we identify four bidder-level factors that are critical to bidders' strategic choices: forward commitment, size, type and diversity.

Forward commitment

Institutional complexities in electricity wholesale markets make the incentives for bidding in day-ahead auctions more complicated. In electricity wholesale markets, most of the electricity is traded through bilateral forward contracts between producers and users of electricity. These contract obligations determine the bidders' net buy or net sell positions in the spot market, and therefore affect bidding incentives (Hortacsu and Puller, 2008). Since a bidder with a high forward commitment ratio has to supply a large proportion of its maximum available capacity to its retail customers, it has an effectively smaller position on the spot market and less incentive to give high offer prices (Bushnell et al., 2008). Similarly, the findings of Allaz and Vila (1993) lead to the expectation that with greater forward commitments, we would see lower spot prices, at least in a short run. Wolak (2003) analyses the Australia NEM1 day-ahead auctions to find the impact of forward contracts on bidding behaviour. He shows that if a bidder's forward contract quantity is a large enough fraction of this bidder's expected offer quantity into the market, this can cause this bidder to find it optimal to offer at low prices. Consistently, the risk-neutral generators modelled by Sioshansi and Oren (2007) and Hortaçsu and Puller (2008) submit offer prices closer to marginal costs, the larger their forward commitments. Wolak (2000) and Bushnell et al.

(2008) also point out that forward contract positions are important determinants of bidding behaviour. Many other industries, in the presence of long-term fixed- price contracts, are likely to influence the bidding strategies in the spot market. This raises the question of why some companies have larger forward commitments than others. The agent-based simulation analysis by Sanchez et al. (2009), allowing learning and risk aversion in a supply function competition model, shows that the larger players prefer to exercise market power in the balancing market, while smaller companies prefer the security of contracting forward. This suggests an indirect effect of bidder' size on offer strategies. Therefore, we hypothesize:

H1a: Bidders with high forward commitment ratios are more likely choose the inframarginal strategy over the physical withholding strategy (Allaz-Villa Hypothesis)

H1b: Bidders with high forward commitment ratios are more likely choose the inframarginal strategy over the economic withholding strategy (Supply Function Gaming)

H1c: Bidders with high forward commitment ratios are more likely to choose the risk averse strategy over other strategies.

Size

Size is the available offer capacity which a company can bring to the spot market at short notice. It is expected to be associated with market power and market leadership. Wolfram (1998) found that larger bidders submited higher offer prices (corresponding to ASKP in the present research) for similar plants. Bunn et al. (2015) find that the mean of the smallest bidders offer prices (corresponding to WTS in the present research) were significantly lower. The largest one, a portfolio company, gave higher offer prices. Therefore, we hypothesize:

H2a: Large bidders are more likely choose the economic withholding strategy over either the inframarginal or risk averse strategy.

H2b: Large bidders are more likely choose the physical withholding strategy over other strategies.

Hortacsu and Puller (2008) find that large firms in the balancing market performed close to the theoretical benchmark of static profit maximization. However, smaller firms submitted excessively steep offer functions significantly deviating from this benchmark and resulting in a very high surplus. Therefore, we hypothesize:

H2c: Small bidders are more likely choose the opportunist strategy over other strategies.

Type

Type of a bidder is the generation technology written in its generation license. There are generally six types of bidders in day-ahead auctions, namely natural gas, hydro dam, canal, wind, conventional and portfolio. The institutional complexity of electricity wholesale markets and heterogeneity in marginal costs of different types of bidders affects bidders' strategy choice. One of the most important institutional complexities in electricity wholesale markets is the sequential clearing of related markets which raises opportunity costs for bidders with storage capacities. For a hydrodam bidder, fed from a limited pool of water, offering in the day-ahead market today can imply less available offer capacity for tomorrow or for the balancing market. Therefore, even if today's price is above the hydroelectric generator's variable cost (zero), the generator has an incentive to bid at least their opportunity cost based on their prediction of future and balancing prices. Therefore, we hypothesize:

H3a: Hydrodam bidders are more likely to choose the physical withholding strategy over other strategies.

Since bidders without storage capacities (and with marginal cost near to zero) do not have any opportunity costs for trading in the sequential markets, most optimal strategy for them would be to follow either the price independent offer (inframarginal) or risk averse strategy. Therefore, we hypothesize:

H3b: Canal and wind bidders are more likely to choose either the inframarginal or risk averse strategy over other strategies.

Conventional bidders (hard coal, imported coal and fuel oil) have high marginal costs thus they are more likely to offer at peak hours with high prices. Therefore, we hypothesize:

H3c: Conventional bidders are more likely to choose the opportunist strategy over other strategies.

One of the merits of day-ahead auction mechanism is letting bidders make *portfolio bidding* (the opportunity to submit bids/offers on a portfolio basis) so that bidders can balance their own portfolios before the trading day starts so that they have an incentive to follow less aggressive strategies in day-ahead market like inframarginal or risk averse strategies. Therefore, we hypothesize:

H3d: Portfolio bidders are more likely to choose either the inframarginal or risk averse strategy over other strategies.

Diversity

Bidders with more diversified portfolios can take advantage of short-term inelasticities in the supply and demand schedules to earn greater profits (EFET, 2010). Therefore, we hypothesize:

H4: More diversified bidders are more likely to choose physical withholding, economic withholding and opportunist strategies over inframarginal and risk averse strategies.

6.4.6. Explanatory Model of Bidders' Choice of Bidding Strategies

To test our hypotheses, we develop an explanatory model of bidders' strategic choices, using MNL, which has been used to model individual choice in a variety of social, economic, and political contexts (Greene, 2008). The MNL model relies on the assumption of independence of irrelevant alternative (IIA), which could be troublesome in practice, especially if some of the choices are close substitutes (McFadden, 1973). However, since the five identified bidding strategies form a partition of bidders' strategic choice space, IIA is less of an issue in our case. In our case, we model the log odds of a bidder choosing strategy i relative to a baseline strategy on a given day as a linear combination of four explanatory variables that reflect bidders' forward commitment, size, type, and diversity. The generic model is specified as follows in Equation (3):

$$\boldsymbol{log}\left(\frac{\boldsymbol{p}\,(\boldsymbol{strategy}=\boldsymbol{i})}{\boldsymbol{p}\,(\boldsymbol{reference\ strategy})}\right) = \boldsymbol{\beta}_{\mathbf{0},i} + \boldsymbol{\beta}_{\mathbf{1},i}\boldsymbol{Forward\ Commitment} + \boldsymbol{\beta}_{\mathbf{2},i}\boldsymbol{Size} + \boldsymbol{\beta}_{\mathbf{3},i}\boldsymbol{Type} + \boldsymbol{\beta}_{\mathbf{4},i}\,\boldsymbol{Diversity} \tag{3}$$

In Equation (3), $\boldsymbol{Forward\ Commitment}$ is a numeric variable which is calculated by dividing the bidder's forward committed quantity over its installed capacity. $\boldsymbol{Size}$ is a categorical variable which takes the value 1, 2, 3, 4, or 5 for bidders corresponding to *very small* (x<10 MW), *small* (10 MW <x<50 MW), *medium* (50 MW <x<150 MW), *large* (150 MW <x<300 MW), or *very large* (x>300 MW). $\boldsymbol{Type}$ is a categorical variable which takes the value 1, 2, 3, 4, 5, or 6 corresponding to auctions of *natural gas, hydro dam, canal, wind, conventional (hard coal, imported coal, fuel oil), portfolio*. $\boldsymbol{Diversity}$ is a categorical variable which takes the value 1, 2, or 3 corresponding to bidders who are *undiversified* (has one type of utility), *semi-diversified* (has up to three types of utilities), or *highly diversified* (has more than three types of utility). The coefficients $\boldsymbol{\beta_{0,i}}$, $\boldsymbol{\beta_{1,i}}$, $\boldsymbol{\beta_{2,i}}$, $\boldsymbol{\beta_{3,i}}$, $\boldsymbol{\beta_{4,i}}$ can be interpreted as the increase in log odds of choosing strategy i over the reference strategy resulting from a one-unit increase in $\boldsymbol{Forward\ Commitment}$, $\boldsymbol{Size}$, $\boldsymbol{Type}$ and $\boldsymbol{Diversity}$ respectively, given the other variables are held constant. We run the MNL model with different reference strategies. The parameter estimates are reported in Table 6.6.To begin with, we can see that when a bidder has a high forward commitment ratio, he/she is more likely to choose the risk averse strategy over other strategies (estimates coefficients are 17.846, 15.462, 19.521, 16.472 for inframarginal, physical withholding, economic withholding and opportunist), while other conditions are kept constant. This finding supports H1b and H1c. H1a is not supported since bidders with high forward commitments are more likely to adopt physical withholding over the inframarginal strategy. This finding can be explained by the indirect effect of size on forward commitment ratio as stated by Sanchez et al. (2009) who find that smaller companies prefer the security of contracting forward more than large ones.

Further we find that, compared to very small sized bidders, very large sized bidders (bidders with market power) are more likely to choose the physical and economic withholding strategies over the inframarginal strategy which supports H2a, H2b, and H2c. The least preferred strategy by this type of bidders is the risk averse strategy, indicating that these bidders try to exercise their power in the spot market rather than in the forward market. However, large sized bidders, compared to very small sized firms, are more likely to adopt the risk averse strategy over other strategies. This indicates that although these bidders are large, since they do not have any power on the market they prefer safer bilateral agreements. Medium sized bidders, compared to very small sized bidders, are more likely to choose the physical withholding strategy over other strategies similar to the very large sized bidders. Small sized bidders, compared to very small sized bidders, are more likely to adopt the opportunist strategy over other strategies (risk averse, inframarginal, economic withholding, and physical withholding), supporting H1c.

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We also find that hydro dam bidders, compared to natural gas bidders are more likely to adopt the physical withholding strategy over other strategies, supporting H3a. We can also see that log odds of a bidder choosing the risk averse strategy over physical withholding increases significantly if moving from type=natural gas to type=canal. Canal type bidders are more likely to adopt the risk averse strategy over other strategies. Log odds of a bidder choosing the inframarginal strategy over risk averse increases significantly if moving from type=natural gas to type=wind. Wind type bidders are more likely to adopt the inframarginal strategy over others. Conventional bidders are more likely to adopt the opportunist strategy over the inframarginal strategy compared to natural gas bidders. Portfolio bidders are more likely to use the inframarginal and risk averse strategies over the physical withholding, economic withholding and opportunist strategies compared to natural gas bidders.

Further we find that log odds of a bidder choosing the physical and economic withholding strategies over other strategies increases significantly if moving from an undiversified to semi-diversified bidder. Similarly, highly diversified bidders are more likely to adopt the physical withholding and economic withholding strategies over other strategies compared to undiversified bidders. Table 6.7 provides a summary of our findings.

TABLE 6.6: Parameter Estimates

		Reference Strategy			
Strategy	**Variable**	**Inframarginal**	**Physical Withholders**	**Economic Withholders**	**Opportunists**
Physical Withholders	Intercept	-2.858***			
	ForwardCR	2.383***			
	Size2 (small)	-0.370			
	Size3 (medium)	0.467*			
	Size4 (large)	-1.214***			
	Size5(very large)	3.270***			
	Type2(HydDam)	34.775***			
	Type3(Canal)	2.363***			
	Type4(Wind)	-34.507***			
	Type5(Conv)	-21.713***			
	Type6(Portfolio)	-26.288***			
	Diversity2	1.381***			
	Diversity3	24.462***			
Economic Withholders	Intercept	2.083***	4.941***		
	ForwardCR	-1.674***	-4.058***		
	Size2 (small)	-0.439**	-0.068		
	Size3 (medium)	-0.226	-0.694**		
	Size4 (large)	0.667**	1.881***		
	Size5(very large)	3.668***	0.398***		
	Type2(HydDam)	30.665***	-4.110		
	Type3(Canal)	-30.836***	-46.800		
	Type4(Wind)	-45.743	-6.731		
	Type5(Conv)	-2.868***	33.836***		
	Type6(Portfolio)	-2.474***	20.235		
	Diversity2	0.538*	-0.611		
	Diversity3	0.560*	-20.322		

Opportunists	Intercept	-18.668***	-16.773***	-27.163***	
	ForwardCR	1.373*	-1.010*	3.048***	
	Size2 (small)	16.549***	17.882***	23.400***	
	Size3 (medium)	-4.842***	-0.613***	-5.642***	
	Size4 (large)	-1.874**	2.710***	-13.577***	
	Size5(very large)	-4.743***	-11.812***	-14.796***	
	Type2(HydDam)	32.971***	-1.803***	2.306***	
	Type3(Canal)	-16.844***	-17.511***	-9.309***	
	Type4(Wind)	-26.980***	5.350***	-1.791***	
	Type5(Conv)	2.924***	39.629***	5.793***	
	Type6(Portfolio)	-16.295	4.298*	-20.257***	
	Diversity2	0.721	-1.267	-2.997***	
	Diversity3	16.386***	-7.527***	12.041***	
Risk Averse	Intercept	-47.961***	-49.871***	-63.474***	-37.942***
	ForwardCR	17.846***	15.462***	19.521***	16.472***
	Size2 (small)	-0.102	0.268	0.337	-17.006***
	Size3 (medium)	-22.598***	-17.752***	-25.733	-28.053***
	Size4 (large)	2.934***	4.149***	2.267**	7.749***
	Size5(very large)	-17.764***	-27.483***	-20.251***	-8.362***
	Type2(HydDam)	43.484***	-8.487	11.288***	4.627***
	Type3(Canal)	34.676***	37.082	70.661***	71.024***
	Type4(Wind)	-7.328***	35.862***	42.850	36.287***
	Type5(Conv)	15.791	62.278***	8.011***	1.814
	Type6(Portfolio)	30.316***	57.795	46.220***	71.610***
	Diversity2	-0.421	-1.571**	-0.960*	0.558**
	Diversity3	-11.817***	-27.966	-10.587***	-29.446

6.5. Discussion

6.5.1. Analysis of Winning Percentage

We first determine whether the strategies differ in the winning percentage they yield to their adopters. To do so, we tested the following hypothesis using single-factor ANOVA with five levels representing the different types of bidders.

H1: All bidding strategies have similar likelihoods of winning, as reflected in the proportion of winners versus losers.

TABLE 6.7: Summary of Hypothesis Test

	HYPOTHESIS	Result
H1a	*Bidders with high forward commitment ratios are more likely to choose the inframarginal strategy over the physical withholding strategy (Allaz-Villa Hypothesis)*	H1a is not supported
H1b	*Bidders with high forward commitment ratios are more likely to choose the inframarginal strategy over the economic withholding strategy (Supply Function Gaming)*	H1b is supported
H1c	*Bidders with high forward commitment ratios are more likely to choose the risk averse strategy over other strategies.*	H1c is supported
H2a	*Large bidders are more likely to choose the economic withholding strategy over either the inframarginal or risk averse strategy.*	H2a is supported
H2b	*Large bidders are more likely to choose the physical withholding strategy over other strategies*	H2b is supported
H2c	*Small bidders are more likely to choose the opportunist strategy over other strategies.*	H2c is supported
H3a	*Hydro dam bidders are more likely to choose the physical withholding strategy over other strategies.*	H3a is supported
H3b	*Canal and wind bidders are more likely to choose either the inframarginal or risk averse strategy over other strategies.*	H3b is supported
H3c	*Conventional bidders are more likely to choose the opportunist strategy over other strategies.*	H3c is supported
H3d	*Portfolio bidders are more likely to choose either the inframarginal or risk averse strategy over other strategies.*	H3d is supported
H4	*More diversified bidders are more likely to choose physical withholding, economic withholding and opportunist strategies over inframarginal and risk averse strategies.*	H4 is supported

Table 6.8 displays the summary results from the ANOVA test. The significant F-values indicate that we can reject the null hypothesis of equality of mean winning percentage among the different bidder classes.

TABLE 6.8: ANOVA-Winning Proportions

Source of Variation	SS	Df	MS	F	Significance
Between Groups	38.122	4	9.5304	177.6	.000
Within Groups	171.018	3187	0.0537		

Subsequently, to compare the bidding strategies with each other, we performed pairwise hypothesis tests on the differences between winning proportions. To deal with the inflation problem associated with pairwise comparisons, we used the *Bonferroni adjustment*. Table 6.9 summarizes the results of hypothesis tests. Values of .000 imply that the null hypothesis of equality of two means is rejected with a p-value of zero (for value 1, vice versa). The average winning percentage indicates what fraction of a certain bidding strategy resulted in a win. Inframarginal and physical withholders have significantly higher winning proportions than economic witholders, opportunists and risk averse.

TABLE 6.9: Pairwise Comparison - Difference of winning proportions

	Cluster Name			
(Average Winning Percentage %)	**Risk Averse** (100%)	**Economic withholders**	**Inframarginal**	**Physical Withholders**
Economic withholders (86%)	.000	-	-	-
Inframarginal (99%)	1	.000	-	-
Physical Withholders (98%)	1	.000	1	-
Opportunists (45%)	.000	.000	.000	.000

6.5.2. Analysis of Productive Efficiency

In auction markets, bidders develop offer curves, which normally have higher prices bid for higher quantities of output offered. These bidders will choose their offer curves so as to maximize their profits, which will entail making independent decisions trading off marginal gains from a higher bid curve against marginal losses from foregone output. This is the essential profit maximizing decision expected of each supplier acting independently in bid-based electricity markets. This profit maximizing behaviour results in offer curves above marginal cost, some supply being unsold.

We calculate a bidder's surplus as in Equation (4):

$$Surplus = \frac{Output(Max.Ask\ Quantity) - Sold\ Quantity\ at\ MCP}{Output\ (Max.Ask\ Quantity)} \tag{4}$$

The analysis is similar to the analysis of winning percentage. We use ANOVA to test the overall equality of means. If ANOVA suggests significant differences in the mean loss of surplus, we conduct pairwise tests to compare the bidder classes with each other. Our initial hypothesis is

H2: All bidding classes have the same level of loss of surplus.

Table 6.10 presents the summary results from a single-factor ANOVA. As before, the single factor has five levels representing the different types of bidders. There is a significant difference in the mean residual surplus among the five bidding strategies.

TABLE 6.10: ANOVA- Surplus

Source of Variation	SS	Df	MS	F	P-value
Between Groups	77.847	4	19.4618	244.94	.000
Within Groups	253.222	3187	0.0795		

Subsequently, to compare the bidding strategies with each other, we performed pairwise hypothesis tests on the differences between surpluses. To deal with the inflation problem associated with pairwise comparisons, we used the *Bonferroni adjustment*. Table 6.11 summarizes the results of hypothesis tests. Values of .000 imply that the null hypothesis of equality of two means is rejected with a p-value of zero (for value 1, vice versa). The average surplus percentage indicates what fraction of a certain bidding strategy resulted in a surplus.

TABLE 6.11: Pairwise Comparison- Difference of surplus

Average Surplus %	**Cluster Name**			
	Risk Averse (0%)	**Economic Withholders**	**Inframarginal**	**Physical Withholders**
Economic Withholders (27%)	.000	-	-	-
Inframarginal (2%)	1	.000	-	-
Physical Withholders (16%)	.000	.000	.000	-
Opportunists (70%)	.000	.000	.000	.000

The results indicate that inframarginal bidders and risk averse are best at minimizing surplus. However, the interpretation for risk averse is different in terms of surplus, such that; since risk averse do not offer to the spot market, they do not have any spot market-surplus. Since inframarginal traders offer their supply at very low prices, they are able to sell all their supply reserved for the spot market. The next best are physical withholders, followed by economic withholders. On average, opportunists have the largest losses of surplus.

In sum, we propose a research model as presented in Figure 6.2.

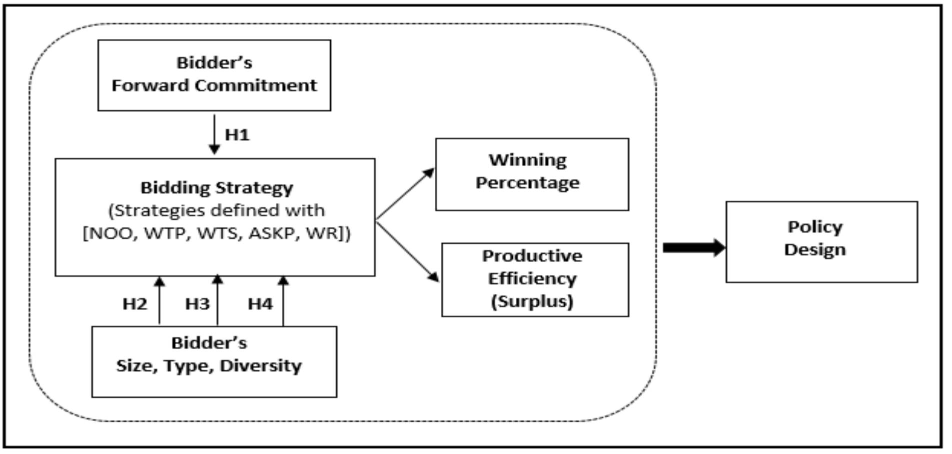

Fig. 6.2. A Research Model of Bidders' Strategy and Outcome Analysis

6.6. Conclusions

We have empirically analysed an oligopolistic multi-unit auction for electricity. Our analysis is motivated by important market surveillance issues that have been introduced by large and complex trading data sets at the bidder level which brings challenges, particularly for the auctioneers, on profiling traders, and understanding the determinants and productive efficiency of observed trading behaviour/strategy. Electricity auctions are regulated and they have detailed market surveillance rules that must be approved, with the auctioneer specifying precisely how MCPs are determined and defining the feasible set of market participant behaviour. The behavioural analytics approach we proposed and empirical results presented are useful to address the cognitive and computational limitations of MSC members in their detection of manipulative behaviour. In fact the results of our work are being considered by the Turkish government to facilitate and improve the daily operations of MSCs and evaluate the potential changes to the auction clearing price determination algorithm. Our analysis highlights the importance of considering the bidders' strategic behaviour and their market positions when detecting manipulative behaviour and evaluating the intent behind it. Using a unique and extensive data set from Turkish electricity auctions, we apply a three-stage analysis approach.

Firstly, we introduce five novel classification variables- NOO, WTP, WTS, ASKP and WR; and through applying a clustering algorithm, we find five different strategic behaviours: inframarginal; economic withholding; physical withholding; opportunist; and risk averse.

Secondly, we explain why bidders choose different strategies through using an econometric model. We identify four bidder-level factors that are critical to bidders' strategic choices: forward commitment, size, type and diversity. Using a multinomial logistic regression model, we demonstrate that bidders with high forward commitment ratios are more likely choose the inframarginal strategy over economic withholding and opportunist strategies, however not over physical withholding. They are also more likely to choose the risk averse strategy over other strategies. On the one hand, larger bidders are more likely choose the economic witholding strategy over either the inframarginal or risk averse strategy. They are also more likely choose the physical withholding strategy over other strategies. On the other hand, small bidders are more likely choose the opportunist strategy. Hydro dam bidders are more likely to choose the physical withholding strategy over other strategies. Canal and wind bidders are more likely to choose either the inframarginal or risk averse strategy over other strategies. Conventional bidders are more likely to choose the opportunist strategy. Portfolio bidders are more likely to choose either the inframarginal or risk averse strategy over other strategies. More diversified bidders are more likely to choose physical withholding, economic withholding and opportunist strategies over inframarginal and risk averse strategies.

In the last stage, we show that different strategies, in aggregate, lead to different winning likelihoods and productive efficiency. Inframarginal and physical withholders have significantly higher winning proportions than economic withholders, opportunists and risk averse. Our results show that the inframarginal bidders and risk averse are best at minimizing surplus. The next best are physical withholders, followed by economic withholders. On average, opportunists have the largest losses of surplus.

6.7. Policy Implications and Future Research

Our approach to examining bidder behaviour in online auctions reveals significant empirical regularities, which lead to our taxonomy of bidding behaviour. The taxonomy identifies five distinct bidding strategies in electricity auctions. This result can be viewed as a micro-segmentation of bidder strategies in these oligopolistic auction settings and has interesting practical applications in improving decision-making process of MSCs who are responsible for the surveillance of these auctions. In addition, knowledge of any domain-specific strategy dominance can be embedded within policy simulation platforms.

At the time of writing this Chapter, the Turkish MSC was attempting to identify possible market manipulators manually and to introduce some MCP mitigation procedures considering the specific supply stack characteristics of the Turkish market. In particular, they were revising the Market Surveillance Regulation and they were seeking systematic, evidence-based approaches to identify market manipulation and measure its effect on the clearing price before the announcement of the final MCP at 14:00. Since there is only one hour between the interim MCP and final MCP, it was impossible to ex-ante evaluate the effect of withholding bidders on the final MCP. With our approach they can find the economic/physical withholders and opportunists in milliseconds and evaluate the *level of artificial price increase* caused by these bidders and make informed decisions which in the end effect social welfare of all consumers.

In the end, we have proposed a behavioral analytics framework (Figure 6.3) to automate detection, investigation and analysis of potentially abusive or disorderly trading, to help improve the overall efficiency of the surveillance operations and reduce cost, even as market complexity and new regulations increase.

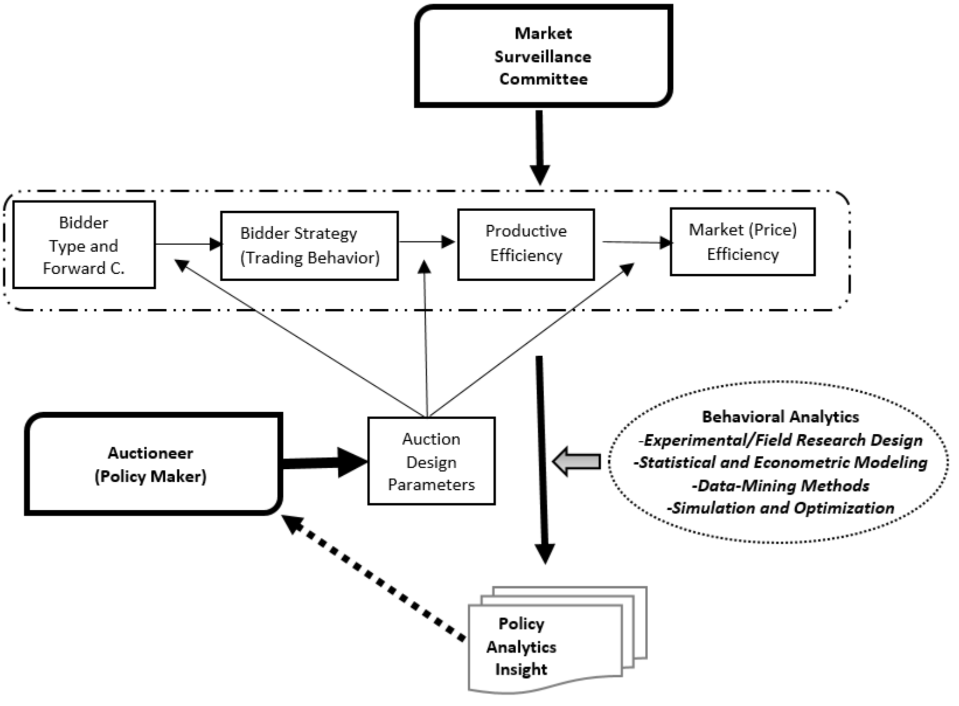

Fig. 6.3: A behavioural analytics framework for surveillance of complex auction markets

The identification of distinctive strategic behaviour in the EDA auction challenges the conventional view that bidders' strategies will converge as they gain experience from repeated participation in the competition. Thus it calls for a dynamic behavioural view in developing agent-based models (e.g. Power TAC, Ketter et al., 2013). There is a substantial modelling risk due to the possible lack of realism in definitions of the players, their potential strategies, the ways in which they interact, and the set of payoffs (Weron, 2014). In this sense, our findings, which map bidders' choices of strategies to their bidder-level (demographic) characteristics, indicate the average winning percentage and surplus (i.e., risk of the strategy) could provide valuable inputs for developing more realistic multi-agent models for policy simulations of power markets. We are now working on integrating our findings to Power TAC competitive simulation platform.

6.8. Acknowledgements

The corresponding author greatly acknowledge financial support from the Erasmus University PhD Fund and Research Visit Scholarship from Erasmus Research Institute of Management and Erasmus Thrust Funds for funding her Research Visit at UK, London Business School and Oxford Institute of Energy Studies.

The authors are grateful to Fatih BAYTUGAN (Head of Information systems at TEIAS), Baris SANLI (Advisor to the Undersecretary at the Ministry of Energy and Natural Resources) and Fatih YAZITAS (Chair of Market Surveillance Committee at Energy Exchange Istanbul) for their valuable comments, insights and encouragement.

Chapter 7

Conclusions, Implications, and Limitations

In this Chapter, we first summarize the findings from the four specific studies and then continue with a discussion of their theoretical contributions and managerial implications. Finally, we reflect on the limitations of the current research and present an outline for future work.

7.1. Main Findings

Our central research question is how to leverage the power of data analytics to improve surveillance of complex auction markets. We address this question by systematically examining the interplay of different informational, strategic, technological and regulatory factors in four specific studies.

7.1.1. Market Efficiency

In Chapter 3 we analyse the fractal dynamics of day-ahead electricity prices by using parametric and semiparametric approaches for each time zone in a multi-time tariff setting in the framework of bidding strategies, market efficiency and persistence of exogenous shocks. On the one hand, we find that electricity prices have long-term correlation structure for the first and third time zones indicating that market participants bid hyperbolically and not at their marginal costs, the market is not weak form efficient at these hours and exogenous shocks to change the mean level of prices will have a permanent effect and be effective. On the other hand, for the second time zone we find that the price series does not exhibit long-term memory. This finding suggests the weak form efficiency of the market in these hours and that marginal bidders bid at their marginal costs. Furthermore this indicates that exogenous shocks will have a temporary effect on prices in these hours.

7.1.2. Price Predictability

Despite the great diversity of spot price forecasting methods, due to the unique characteristics of electricity as a commodity, there are still three key forecasting challenges that a market participant must take into account: risk of selection of an inadequate forecasting method; transparency level of the market (availability level of public data); and country-specific multi-seasonality factors. In Chapter 4, we address these challenges by using detailed market-level data from the Turkish Electricity Day-Ahead (EDA) auctions, which is an interesting research setting in that it presents a number of challenges for forecasting. We reveal the key distinguishing features of this market quantitatively which then allow us to propose individual and ensemble forecasting models that are particularly well suited to it. We compare the performance of the models according to three criteria. According to Criteria-3, which is the most realistic decision-making setting of the three, we find that using ensemble models increases price forecast accuracy significantly in 30% of the cases. In the remaining 70% of the cases, there is no statistically significant difference between forecast accuracies of best individual model and the best ensemble model. Thus our findings support the additional benefits of ensemble forecasts especially according to an ex-ante (more realistic) decision-making setting and in line with previous findings indicating ensemble modeling is less uncertain and more accurate than the ex-ante best individual model.

7.1.3. Information Feedback Mechanisms

In Chapter 5 we aim to understand how attitude and trading behaviour of bidders effect their price expectations in online double auctions in the existence of forward trading. We develop a research model that empirically tests the impact of bidders' attitudes on their price expectation through their trading behaviour. Using a unique and extensive data set, we tested our hypotheses on real ex-ante forecasts, evaluated ex-post, in an EDA auction context. We find that the informational role of forward trading is the most important factor that decreases bidders' expectation biases. More information does not always lead to more rational (less biased) expectations. Risk aversion does not play a major role in trading decisions of power bidders. In addition, our control variables, including bidder type and strategic positioning in the market, had significant impacts, particularly on forecast accuracy and forward trading.

7.1.4. Bidder Heterogeneity

Traditionally, auctions have largely been studied from the game-theoretic perspective and bidders are assumed to be homogeneous. The availability of bidder-level big data sets have made this assumption questionable and highlights the necessity of developing more realistic models to explain real-life bidding behaviour. In Chapter 6, we use an inductive, data-driven approach to characterize bidder heterogeneity in oligopolistic multi-unit auctions. We introduce five hourly classification variables- number of orders (for both bid and ask), maximum bid price, minimum ask price, ask price, and supply withholding ratio, and find five distinct bidding behaviours: inframarginal, physical withholding, economic withholding, opportunists and risk averse. This result can be viewed as a micro-segmentation of bidder strategies in these oligopolistic auction settings and has interesting practical applications in improving decision-making process of Market Surveillance Committees (MSCs) who are responsible for the surveillance of these auctions. In addition, knowledge of this domain-specific strategy dominance can be embedded within policy simulation platforms.

7.1.5. Productive Efficiency

In Chapter 6 we focus on a multi-unit uniform-price auction setting in a centralized product market and show that different bidding strategies, in aggregate, lead to different winning likelihoods and productive efficiency. Specifically, we find that the inframarginal and physical withholding strategy have significantly higher winning proportions than the economic withholding, opportunist and risk averse. This result reflects that opportunist and economic withholding strategies have brought less profit to their adopters. Our results show that the inframarginal bidders and risk averse are best at minimizing surplus. For the inframarginals since they offer their supply at very low prices, they are able to sell all their supply reserved for the spot market. Next best are physical withholders, followed by economic withholders. On average, opportunists have the largest losses of surplus.

Overall, we have illustrated and quantified the benefits of using data analytics to improve surveillance of complex auction markets.

7.2. Scientific Contributions

This dissertation makes valuable contributions to the surveillance of complex auction markets. First of all, the four specific studies (Chapters 3, 4, 5, and 6) together have greatly improved our understanding of evidence-based policy development in complex auction markets. To the best of our knowledge, this is the first research that systematically examines the interplay of informational and strategic factors in oligopolistic multi-unit auctions.

Further, it contributes to the literature of smart markets (Bichler et al., 2010). In particular, the analysis approach proposed in Chapter 3 serves as a useful tool for monitoring market efficiency and ex-post evaluation of policies on predictability of prices and aggregate-level bidder strategy. In addition, ensemble models developed in Chapter 4 can be used by the auctioneer to understand the transparency level of prices using only publicly available data which can be very useful for agent-based simulation models. Moreover, in Chapter 5 we developed a qualitative monitoring framework to understand determinants of bidders' price expectation bias which is a prerequisite for the customization of information feedback mechanisms in smart markets. Chapter 6 presents a micro segmentation of bidders which serves as a useful starting point for the development of real-time decision support systems for policy-makers.

Finally, our research makes an important methodological contribution. Specifically, in Chapter 3 we extended the existing market monitoring and surveillance methodologies by using a long memory (fractal) model to measure the efficiency level of the market. In Chapter 4, we used long-term seasonal models ensemble with econometric and machine learning methods in order to manage price modeling risk, especially in semi-transparent settings. In Chapter 5, we developed a qualitative market monitoring methodology to be able to measure the effect of bidders' attitude and trading behaviour on their price expectations. In Chapter 6 we introduced a novel market surveillance method (combining machine learning techniques with statistical methods) to monitor oligopolistic auction markets.

7.3. Policy Implications

Our research demonstrates the merits and great promise of data analytics to facilitate the surveillance and monitoring of complex auction markets. In order to address the cognitive and computational limitations of MSCs in their ex-ante and ex-post decision-making process, we suggest:

- Considering the fractal dynamics of spot prices is an effective way to monitor market efficiency in terms of the aggregate-level bidding behavior of the marginal bidders in complex auction markets.
- In semi-transparent markets, using ensemble forecasts can be effective in managing market price modelling risk.
- The informational role of forward trading is a factor that decreases bidders' expectation biases in complex auction markets.
- More information does not always lead to more rational (less biased) expectations. Therefore auctioneers have to be careful when deciding on the information transparency level of the market.
- Bidders in oligopolistic auctions adopt trading strategies with respect to their size, type, forward commitment, and portfolio diversity. These strategies lead to different productive efficiencies in the market. Big data and advances of data analytics will lead to more accurate description and prediction of participants' behaviour and intent under different market settings.
- While theory provides useful principles to understand market performance in different auction settings, we need data-driven (evidence-based) approaches for surveillance of complex auction markets.

As a result, we propose to augment expert judgement with data analytics insights which is presented as a Market Monitoring and Surveillance Framework in Figure 7.1 where bidder attitude, such as risk aversion, is a learned tendency to evaluate things in a certain way. Bidder type is strategic position of the bidder in market, for example, size, portfolio diversity, and technology. Bidder expectation is the price expectation of the bidders. Market outcome refers to the transactions that result from the market process. Information feedback mechanisms include transparency and forward/over the counter trading platforms. Auction design parameters include regulations such as price caps, bid types, bid increments, time delays between sequential auctions etc. Data analytics refers to the practice of collecting, evaluating and analysing data to inform decision makers.

7.4. Limitations and Future Work

In Chapter 3, developing approaches that are more robust to skewed distributions for the conditional mean would provide an opportunity on relaxing the normality assumption. Developing new electricity market monitoring indexes considering the time zones would result in interesting policy implications. Furthermore considering the fractal dynamics of electricity prices at different time scales, one would reduce the prediction confidence intervals.

In Chapter 4, most emerging markets are semi-transparent since market data is very limited for price forecasting. Market participants tend to use international data provider consultancy firms to get information which is not public. The type of data they seek for is usually on the planned generation schedules of large firms, dam level of some state-owned hydropower plants (for Turkey case), primary resource-based available installed capacity and final daily production program (firm-level) and matching quantities(ex-post) on the hourly merit order curve. We call this type of data private, rather than insider, since it does not include any firm-level *confidential* data. Since most of the market participants do not have this information, the ones that have it can make a more fundamental analysis of the market, improve their forecast accuracies and beat the market. Based on this point of view, it would be interesting to examine the worth of this information to market participants considering the improvement in the forecast accuracy of individual and ensemble models.

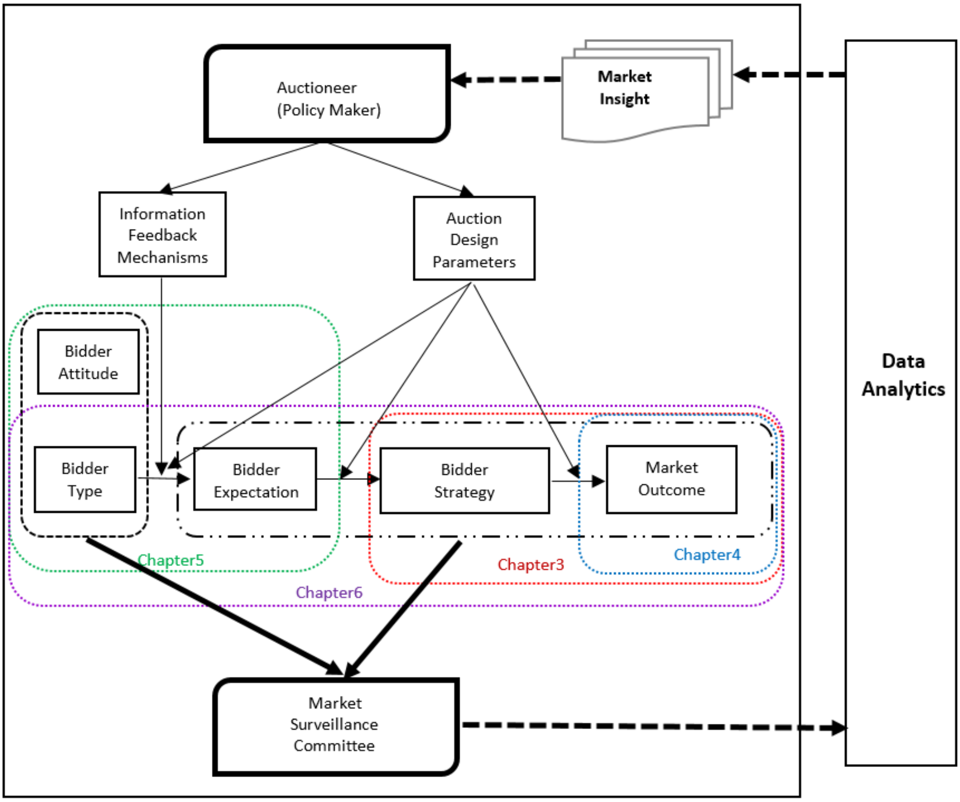

Fig. 7.1: A conceptual model of data-driven surveillance of complex auction markets

In Chapter 5, as with all empirical research, there are questions of generalizability and replication. Whilst the details and control variables have been specific to an electricity market, the conceptual model can in principle be applied to other smart markets. The key elements of forecast accuracy, forward contracting, market informedness, and risk aversion are quite general.

In Chapter 6, the identification of distinctive strategic behaviour in the EDA auction challenges the conventional view that bidders' strategies will converge as they gain experience from repeated participation in the competition. Thus, it calls for a dynamic behavioural view in developing agent-based models (ABM) (e.g. Power TAC, Ketter et al., 2013). In this sense, our findings, which map bidders' choices of strategies to their bidder-level (demographic) characteristics; average winning percentage and surplus (i.e., risk of the strategy) could provide valuable inputs for developing more realistic multi-agent models for policy simulations of power markets. We are now working on integrating our findings to Power TAC competitive simulation platform.

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Summary

As technology advances, the past two decades have seen an explosion of digital data and every sector of the global economy is being changed by the large amount of data available. This has enabled a different way of making decisions that involves more empirical evidence rather than personal experience, intuition, or belief. In this thesis we focus on the merits of using data analytics for decision making in complex auction markets from the perspective of policy-makers. More specifically we propose a Data-Driven Market Surveillance Framework enabling Market Surveillance Committees to establish recommendations or assessments by processing information from relevant data using appropriate tools to make important inferences and discover useful insights.

In first study (Chapter 3) we examine the fractal dynamics of spot market prices by using parametric and semiparametric approaches in a multi-time tariff setting. We find that that prices have long-term correlation structure for the first and third time zones indicating that marginal bidders bid hyperbolically and not at their marginal costs, market is not weak form efficient at these hours and exogenous shocks to change the mean level of prices will have permanent effect and be effective. On the other hand, for the second time zone we find that price series does not exhibit long-term memory. This finding suggests the weak form efficiency of the auction in these hours and that marginal bidders bid at their marginal costs. Furthermore this indicates that exogenous shocks will have temporary effect on prices in these hours. These findings constitute an important foundation for MSCs to understand level of market efficiency for specific trading periods, develop appropriate monitoring indexes and conduct ex-ante impact assessment.

In the second study (Chapter 4) we address three key forecasting challenges; risk of selection of an inadequate forecasting method and transparency level of the market (availability level of public data) and market-specific multi-seasonality factors in complex auction markets; and reveal the key distinguishing features of this auction quantitatively which then allow us to propose individual and ensemble forecasting models that are

particularly well suited to it. We find that using ensemble forecasts can be useful to manage market price modelling risk in semi-transparent market settings.

In the third study (Chapter 5), we demonstrate how attitude and trading behaviour of bidders effect their price expectations in complex auction markets with the existence of forward trading. We develop a research model that empirically tests the impact of bidders' attitudes on their price expectation through their trading behaviour. Using a unique and extensive data set, we tested our hypotheses on real ex-ante forecasts, evaluated ex-post. This study is the first to take an information-based view to investigate price expectation of bidders through their behaviour; with results that suggest a re-consideration of some of the conventional concepts.

In the fourth study (Chapter 6), we investigate characterization, determinants, and efficiency of bidding in an oligopolistic multi-unit auction. We find that there is significant heterogeneity across bidders in terms of bidding behaviour. Through introducing novel classification variables, we identify five distinct bidding strategies. Then we demonstrate bidder's choice of these strategies is associated with their forward commitment, size, generation technology, and diversity. In addition, we show that different strategies, in aggregate, lead to different winning likelihoods and productive efficiency. Finally, we demonstrate how our analysis approach and findings can be used to enhance behavioural monitoring of Market Surveillance Committees.

Overall, we have illustrated the merits of data analytics to improve the operations of Market Surveillance Committees in complex auction markets.

Nederlandse Samenvatting (Summary in Dutch)

Mede door de continue ontwikkeling van technologie heeft er in de laatste twee decennia een explosie van digitale data plaatsgevonden en elke sector van de wereldeconomie is aan het veranderen door de grote hoeveelheid van beschikbare data. Dit heeft het mogelijk gemaakt om op een andere manier beslissingen te nemen; op basis van empirisch bewijs in plaats van persoonlijke ervaring, intuïtie, of overtuiging. In deze dissertatie richten we ons op de voordelen van het gebruik van data analytics voor het nemen van beslissingen in complexe veilingen vanuit het perspectief van beleidsmakers. Specifiek presenteren wij een raamwerk voor data gedreven market toezicht dat markttoezicht commissies in staat zal stellen om aanbevelingen en inschattingen te geven door informatie uit relevante data te verwerken, gebruikmakend van de juiste hulpmiddelen, om daarmee belangrijke conclusies te trekken en nuttige inzichten te ontdekken.

In de eerste studie (Hoofdstuk 3) onderzoeken we de fractal dynamica van spot market prijzen door gebruik te maken van parametrische en semi-parametrische benaderingen in een multi-tijdzone tarief context. We vinden dat prijzen een lange termijn corrlatie structure hebben voor de eerste en derde tijdzone, wat aangeeft dat marginale bieders hyperbolisch bieden en niet gebaseerd op hun marginale kosten. De markt heeft niet een zwakke vorm of efficiency tijdens deze uren en de exogene schokken die de gemiddelde prijsniveaus veranderen zullen permanente effecten hebben en effectief zijn. Daarentegen vinden we voor de tweede tijdzone dat prijsreeksen geen lange-termijn geheugen vertonen. Deze bevinding geeft aan dat de veiling in deze uren een zwakke vorm van efficiency hebben en dat marginale bieders hun marginale kosten bieden. Tevens geeft dit aan dat exogene schokken een tijdelijk effect op prijzen zullen hebben in deze uren. Deze bevindingen vormen een belangrijke basis voor MSCs om het niveau van markt efficiëntie te begrijpen voor specifieke handelsperioden, passende monitoring indexen te ontwikkelen en ex-ante effectinschattingen uit te voeren.

In de tweede studie (Hoofdstuk 4) adresseren we drie belangrijke voorspellingsuitdagingen (het risico van het selecteren van een ontoereikende voorspellingsmethode, het transparantie niveau van de markt (mate van beschikbaarheid van publieke data) en markt-specifieke seizoensfactoren in complexe veilingen) en leggen we kwantitatief de belangrijkste onderscheidende kenmerken van deze veilingen bloot. Het stelt ons vervolgens in staat stelt om individuele en ensemble voorspellingsmodellen te ontwikkelen voor te stellen die goed bruikbaar zijn. We vinden dat het gebruik van ensemble voorspellingen nuttig kan zijn om market prijs risico's te modelleren en te managen in semi-transparante markten.

In de derde studie (Hoofdstuk 5) demonsteren we hoe attitude en handelsgedrag van bieders effect hebben op hun prijsverwachtingen in complexe veilingen met voorwaartse handel. We ontwikkelen een onderzoeksmodel dat empirisch de invloed test van de attitude van bieders op hun prijsverwachtingen door middel van hun handelsgedrag. Gebruikmakend van een unieke en uitgebreide dataset, testen we onze hypotheses op echte ex-ante voorspellingen die ex-post geëvalueerd worden. Dit is de eerste studie die een informatie-gebaseerde benadering gebruikt om prijsverwachtingen van bieders te onderzoeken door te kijken naar hun gedrag. De resultaten suggereren dat sommige traditionele concepten heroverwogen dienen te worden.

In de vierde studie (Hoofdstuk 6) onderzoeken we de karakteristieken, determinanten en efficiëntie van biedprocessen in een oligopolische multi-unit veiling. We vinden dat er een significante heterogeniteit is onder bieders met betrekking tot hun biedgedrag. Door middel van het introduceren van nieuwe classificatie variabelen identificeren we vijf unieke biedstrategieën. Vervolgens demonstreren we dat de strategiekeuze van bieders gerelateerd is aan hun voorwaartse commitment, grootte, generatie technologie en diversiteit. We laten ook zien dat verschillende strategieën, over het geheel genomen, leiden tot verschillende winkansen en productieve efficiëntie. Tot slot, demonstreren we hoe onze analyse aanpak en bevindingen gebruikt kunnen worden om het gedrag te monitoren door markttoezicht commisies te verbeteren.

Gezamenlijk hebben we met deze studies de voordelen geïllustreerd van data gedreven besluitvorming om de werkzaamheden van markttoezicht commisies in complexe veilingen te verbeteren.

About the Author

Ezgi Avci was born on August 11, 1983 in Ankara, Turkey. She received her Industrial Engineering (M.Sc.) and Statistics (B.Sc.) degrees both with honours from Middle East Technical University, Ankara, Turkey. She has 10+ years of industry and government experience as a project executive and consultant on the following research areas: auction market design, big data analytics, energy information systems, data-mining methods, machine learning algorithms, predictive analytics (Short/Mid/Long Term), sustainability modelling, market surveillance, utility analytics, market balancing and settlement, strategy development, regulatory impact assessment, market efficiency analytics, monitoring and surveillance of markets. Her work has appeared in the proceedings of various prestigious conferences such as IAEE International Conference, European Conference on Operational Research, Commodity and Energy Markets Conference, International Symposium on Environment and Energy Finance Issues, Operations Research and Industrial Engineering Congress, Euro Working Group for Commodities and Financial Modelling Conference, and published in the journal *Energy Economics*.

During her PhD study, she supervised 30 Master theses students, was co-instructor of Business Information Management Master elective ‘Big Data and Data Analytics’. In her business life, she has given over 80 professional trainings to Turkish Industry and Public Organizations, providing recommendations about measurement, analysis and improvement of the firms/organizations' management systems. Ezgi won several awards and grants including: *Jean Monnet* Research Scholarship, *Scientific and Technological Research Council of Turkey* research grant and *World Bank*, Energy and Extractives Global Practice technical assistance grant. During her PhD for six months Ezgi was also a Visiting Research Fellow at London Business School and the Oxford Institute for Energy Studies.

Author's Portfolio

RESEARCH

Publications

Journal Publications

- Avci-Surucu, E., Aydogan, K., Akgul, D., (2016). Bidding structure, market efficiency and persistence in a multi-time tariff setting. *Energy Economics*, 54, 77-87.

Papers Under Review

- Avci, E., Bunn, D.W., Ketter, W. and van Heck, E. (2017). Bidder-level determinants of price expectation formation in auction markets (under review)

- Avci, E., Ketter, W. and van Heck, E. (2017). Managing market price modelling risk through ensemble forecasting in a semi-transparent setting (under review)

- Avci, E., Bunn, D.W., Ketter, W. and van Heck, E. (2018). Characterization, determinants and efficiency of bidding in oligopolistic multi-unit auctions (under review)

Conference Proceeding Publications (peer-Reviewed)

- Avci, E., Bunn, D.W., Ketter, W. and van Heck, E. (2017). An Ensemble Approach to Forecast Electricity Day Ahead Auction Prices: Experiences from the Turkish Market. *INFORMS*, Houston, Texas, United States.

- Avci, E., Bunn, D.W., Ketter, W. and van Heck, E. (2017). Managing Market Price Risk through Forecasting and Hedging: The effects of Market Informedness and Risk Aversion. In *Commodity and Energy Markets Conference*, Oxford, UK.

- Avci, E., Bunn, D.W., Ketter, W. and van Heck, E. (2017). Price Forecast Accuracy of Trading Agents in Electricity Markets: The Role of Market Informedness, Risk Aversion, and Trading Behaviour. In *40th IAEE International Conference*, Singapore.

- Avci, E., van Heck, E. and Ketter, W. (2017). Forecasting prices in electricity day-ahead auctions: An overview of the Turkey market. In *5th International Symposium on Environment and Energy Finance Issues* (ISEFI-2017), Paris, FRANCE.

- Avci, E. (2015). A note on Electricity Market Monitoring Indexes. In *27th European Conference on Operational Research, Energy Markets / Systems Modelling*, Glasgow, SCOTLAND.

- Avci, E. (2015). Developing efficient energy market surveillance tools. In *35th Operations Research and Industrial Engineering Congress*, Ankara, TURKEY.

- Avci, E., Aydogan, K. and Akgul, D. (2015). Bidding structure, market efficiency and persis-tence in multi time tariff zones. In *55th EWGCF, Euro Working Group for Commodities and Financial Modelling Conference*, Ankara, TURKEY.

- Avci, E., Aydogan, K. and Akgul, D. (2014). Analysing Fractal Dynamics of Day Ahead Electricity Prices for Multi-time Tariff Zones: An Indicator for Market Efficiency in Electricity Markets. In *4th Energy Finance Conference*, Erice, ITALY.

- Avci, E. (2014). On the Sustainability of Electricity Market Development Strategies: Evidence from an Emerging Market. In *54th EWGCF, Euro Working Group for Commodities and Financial Modelling Conference*, Milano / ITALY.

Participation to International Events

- Workshop/ Focus Group Meeting on “Europe as a Global Actor” H2020 Call, Warsaw, POLAND
- 3rd International Symposium on Energy and Finance Issues, 20/03/2015, Paris, FRANCE
- H2020 – Societal Challenge-6 Project Market, 26/02/2015, Brussels, BELGIUM

Grants and Awards

- The Scientific and Technological Council of Turkey (TÜBİTAK) 3001 Grant, 2014-2016
- WORLD BANK Technical Assistance Grant, 2014-2016
- The Scientific and Technological Council of Turkey (TÜBİTAK) International Travel Grant, Brussels, BELGIUM, 2013
- The Scientific and Technological Council of Turkey (TÜBİTAK) International Travel Grant, Warsaw, POLAND, 2014

Projects Participated

Director

- Quantitative Modelling of Electricity Markets: A Case of Turkey. TUBİTAK-3001 Grant. No: 114K601. 2014-2016
- Modelling Financial and Operational Sustainability of Electricity Distribution Utilities in Turkey. World Bank Technical Assistance Grant. 2014-2016.

Expert

- ES-İS (Establishment of a Monitoring System of Energy Markets and Strategies). 2012-2015
- Strategic Management and Restructuring Programme of TSE. 2006-2008

Consultant

- Management Consultancy. SPAC Six Sigma Consultancy. 2005-2006.

TEACHING

Academic Teaching

Co-Instructor
Big Data and Data Analytics

- Business Information Management Elective course

Instructor (Full Responsibility)
Statistical Methods

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Quantitative Decision Methods

- Ankara Etlik İhtisas Hospital
- Turkish Statistics Institute
- General Directorate of Post, Telegraph and Telephone
- Dr.Nafiz Körez Sincan Public Hospital
- General Directorate of State Airports Authority
- Turkish Standards Institute Standardization Head Department
- General Directorate of Protection and Control
- Provincial Directorate of Health
- Eskisehir Small Medium Sized Enterprise (Group)
- Konya Water and Sewerage Administration
- Kardemir Karabuk Iron&Steel Industry and Trade Company Inc.
- ADOCIM Cement Factory
- Kırıkkale Maternity and Child Care Hospital
- 3. Main Maintenance Center
- Ankara Local Health Authority
- ETI Aliminium Inc.
- Mechanical and Chemical Industry Institution
- Ministry of National Education

Risk Management
- Provincial Directorate of Health
- Servergazi State Hospital
- SAKARYA TOYOTASA Emergency Hospital
- Mechanical and Chemical Industry Institution
- Ankara Local Health Authority
- ETI Aliminium Inc.

Survey Analysis
- Petroleum Pipeline Company (BOTAS) General Directorate
- General Directorate of Security Affairs
- Rize Chamber of Commerce and Industry
- Dr.Nafiz Körez Sincan Public Hospital
- General Directorate of Post, Telegraph and Telephone
- University of Sakarya
- Sigma Cement Factory
- General Directorate of Highways

Customer Satisfaction Analysis
- Cankiri State Hospital
- Ministry of Labor and Social Security
- Suleyman Demirel University Hospital
- General Directorate of Post, Telegraph and Telephone

Problem Solving Techniques
- General Directorate of State Airports Authority
- General Directorate of Civil Population and Citizenship Affairs
- Ankara Chamber of Industry
- Mechanical and Chemical Industry Institution
- General Directorate of Turkish State Railways
- CAYKUR Manufacturing General Directorate
- General Directorate of Post, Telegraph and Telephone

Six Sigma
- Ankara Chamber of Industry
- Konya Chamber of Industry
- Ordu State Hospital
- Antalya Chamber of Commerce and Industry
- General Directorate of Turkish State Railways
- TSE Infrastructure Laboratory
- Ministry of Economy

Thesis Supervision

Msc Theses

- Wiedenhof, D. ‘Stepwise Superior Predictive Ability for Futures Trading’ **Principal Advisor: E. Avci**. Co-advisor: Asst. Prof. M.I.Sandu.

- Tran, Y. ‘Effect of mining process, transaction costs, and arbitrage opportunities on cryptocurrency prices’. **Principal Advisor: E. Avci.** Co-advisor: Prof. R. Belo

- Grigoriadis, I. ‘Prediction of prices in balancing auctions for the energy markets of Germany & Turkey. **Principal Advisor: E. Avci**. Co-advisor: Asst. Prof. C.P. Belo.

- Paklaci, S. ‘Firm characteristics and stock manipulation’. **Principal Advisor: E. Avci.** Co-advisor: Prof. R. Belo

- Kogeler, B. ‘Monitoring Market Abusive Behavior in the German Commodity Market’. **Principal Advisor: E. Avci.** Co-advisor: Asst. Prof. Y. Ghiassi-Farrokhfal.

- Kiessling, N. ‘Forecasting Stock Indexes using ARIMA, SVR, ANN, Deep Belief Networks, Combined and Hybrid Forecasting Models : The cases of S&P 500, FTSE 100, BIST 100 and TAIEX’ . **Principal Advisor: E. Avci**. Co-advisor: Asst. Prof. C.P. Belo.

  Barry, A.J. ‘BI Reporting and Decision Making Style for Project Success: How BI Reporting affects Project Success with the moderating role of Decision Making Style’. **Principal Advisor: E. Avci.** Co-advisor: Prof. T. Li.

- Artique, P. ‘Predicting financial distress using ANN, SVM, Probit, and MDA: An application of the European banking industry’. **Principal Advisor: E. Avci.** Co-advisor: Asst. Prof. Y. Ghiassi-Farrokhfal.

- Deschamps, A.’Developing a Decision Support System for increasing sales of *HappytoServe* using Google Analytics Big Data’. **Principal Advisor: E. Avci.** Co-advisor: Asst. Prof. T. Brandt.

- Gang, N. ‘Understanding the effect of decentralized energy generation (limited to residents) on energy consumption and subsequent offering of demand response programs’. **Principal Advisor: E. Avci.** Co-advisor: Asst. Prof. Y. Ghiassi-Farrokhfal.

- Haaften, W. ‘Towards a standardized Management System for the Port of Rotterdam’. Principal Advisor: E. Avci. Co-advisor: Asst. Prof. H. Vries.

- Bueno de Mesquita, N. ‘Forecasting electricity load for upper-middle income and high income countries’. **Principal Advisor: E. Avci**. Co-advisor: Asst. Prof. T. Brandt.

- Colic, A. ‘The effect of smart metering rollout in Finland on Finnish spot prices in the Nord Pool electricity market’. **Principal Advisor: E. Avci**. Co-advisor: Asst. Prof. T. Brandt.

- Gast, M. ‘Improving stock index prediction using a deep learning approach’. **Principal Advisor: E. Avci**. Co-advisor: Asst. Prof. Y. Ghiassi-Farrokhfal.

- Hagedorn, H. ‘Forecasting the balancing premium in the German electricity market’ **Principal Advisor: E. Avci**. Co-advisor: Asst. Prof. Y. Ghiassi-Farrokhfal.

- Wu, C.Y. ‘Measuring Market Efficiency via Long-memory Models’ Ching Yun. **Principal Advisor: E. Avci.** Co-advisor: Dr. B. Bode.

- Hirsch, L. ‘Developing a Forecasting Decision Support System for Tactical Behavior on the Electricity Day-ahead and Balancing Market in Austria’. **Principal Advisor: E. Avci.** Co-advisor: Asst. Prof. Y. Ghiassi-Farrokhfal.

- Stoitsova, D. ‘Customer and merchant adoption of blockchain-based payment solutions for IoT’. Principal Advisor: Assoc.Prof. Ting Li. **Co-advisor: E. Avci**.

- Lefevre, L. ‘How to create the best blended learning environment. The students' perception’ Principal Advisor: Asst. Prof. R. Belo. **Co-advisor: E. Avci**.

- Hagen, S. ‘Using Blockchain to Secure Items in the Physical World’ Principal Advisor: Asst.Prof. R. Belo. **Co-advisor: E. Avci**.

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- Knappstein, C. ‘Data Management and Organizational Decision Making’. Principal Advisor: Prof. T. Li. **Co-advisor: E. Avci.**

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Organizational Activities

- Chair (Invited Session): 35th Operations Research and Industrial Engineering Congress, Energy Markets, 9-11 September 2015, Ankara, TURKEY
- Co-chair (Session): 27th European Conference on Operational Research, Energy Markets / Systems Modelling, 12-15 July 2015, Glasgow, SCOTLAND

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Journal
- Energy Economics
- Energy Policy
- Business & Information Systems Engineering

Conference
- Erasmus Energy Forum 2017 “Accelerating the energy transition – paths to zero carbon energy” - Energy Informatics & Management (EIM 2017)

- 35th Operations Research and Industrial Engineering Congress, Energy Markets, 9-11 September 2015, Ankara, TURKEY

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Dissertations in the last four years

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Promotors: Prof. L.G. Kroon & Prof. A.P.M. Wagelmans, EPS-2014-325-LIS,
http://repub.eur.nl/pub/76927

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The dissertation consists of four essays that investigates the merits of big data-driven decision-making in the surveillance of complex auction markets. In the first essay, Avci and her co-researchers examine the aggregate-level bidding strategies and market efficiency in a multi-time tariff setting by using parametric and semi parametric methods. In the second essay, they address three key forecasting challenges; risk of selection of an inadequate forecasting method and transparency level of the market and market-specific multi-seasonality factors in a semi-transparent auction market. In the third essay, they demonstrate the effect of information feedback mechanisms on bidders' price expectations in complex auction markets with the existence of forward contracts. They develop a research model that empirically tests the impact of bidders' attitudes on their price expectation through their trading behavior and tested their hypotheses on real ex-ante forecasts, evaluated ex-post. In the fourth essay, they investigate characterization of bidding strategies in an oligopolistic multi-unit auction and then examine the interactions between different strategies and auction design parameters. This dissertation offers important implications to theory and practice of surveillance of complex auction markets. From the theoretical perspective, this is, to our best knowledge, the first research that systematically examines the interplay of different informational and strategic factors in oligopolistic multi-unit auction markets. From the policy perspective, Avci's research shows that integration of big data analytics and domain-specific knowledge improves decision-making in surveillance of complex auction markets.

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