Agent-level determinants of price expectation formation in online double-sided auctions

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A B S T R A C T

For an auctioneer, it is of utmost importance to design an auction mechanism that gives robust price signals which in turn increases auction performance. Information architecture and forward trading platforms are the two main information sources that could generate these price signals. However the traditional presumption that agents form rational expectations by accurately processing all available information in the online trading environment and forming their expectations accordingly has found mixed support. We develop a research model that empirically tests the impact of agents' attitudes on their price expectation through their trading behaviour. Using a unique data set, we tested our hypotheses on real ex ante forecasts, evaluated ex post, in an electricity day ahead auction context. This paper is one of the first to take an information-based view to study the trading behaviour of agents and their price expectations, with results that suggest a re-consideration of some of the conventional concepts.

Key words: Auctions, Rational Expectations Hypothesis, Agent Informedness, Forward Trading, Forecasting, Smart Markets

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1 Introduction

The assumption that agents can (rationally) predict to some level of accuracy the values of market outcomes is frequently made in economic analysis (e.g. Jensen, 1987; Stoneman and Ireland, 1983; Choi and Tam, 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 market agents 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 auction context within which they take place, especially in the cases of online auctions (Bapna et al. 2001, Kambil and Van Heck, 2002).

In this paper we focus on an online *double auction* in the context of *forward trading*; namely the *Electricity Day Ahead (EDA)* auction. We aim 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?* We tested our hypotheses on real ex ante forecasts, evaluated ex post, using a unique and extensive data set consisting of 153 professional power market participants.

We contribute to the growing literature on (1) information transparency and revelation policies in online (Bloomfield, 1999; Zu 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 at 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 surprisingly 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 an 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 the 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 market transparency platforms (e.g. Arora et al., 2007; Greenwald et al., 2010) 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 the research hypotheses. Section 3 presents research methodology, Section 4 presents results and Section 5 concludes the paper with a summary of the findings, implications for practice, and suggestions for future research.

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, 2000) and depends critically on the expectations of bidders involved (Krishna and Perry, 1997) 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* (Li et al., 2014)). 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). Electricity day ahead 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 (Table A1, Fig. A1), 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 (Table A2). 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 (Keynes, 1930; Newbery and Stiglitz, 1981), there will usually be a substantial *behavioural* pricing component (beliefs) in electricity forward markets, as reflected by sustained risk premia (Redl and Bunn, 2011).

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 and 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 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 which 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).

2.1 Forecasting behaviour

We focus on the behavioural determinants of performance (forecast 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.*

2.2 Hedging (forward trading) 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, 2005), 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.*

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 and 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).

Information asymmetry is a crucial market imperfection (e.g. Clemens and Thatcher, 1997 a,b; Clemens, 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. Bloomfield, 1999; Zu 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 (Simon, 1991; 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 at al. 2009).

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., 2015). 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: *A power bidder's market informedness level is positively related to his/her 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); 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: *A power bidder’s risk aversion is positively related to his/her use of advanced forecasting techniques.*

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 (Hellwig, 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: *A power bidder's market informedness level is positively related to his/her 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); 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: A power bidder's risk aversion is not related to his/her use of hedging.

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 (1997 a,b) 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 (1997). 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 paper 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.

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, and 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.

3 Research Methodology

The above hypotheses were tested by analysing a sample of cross-sectional data 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 the Ministry of Energy and Natural Resources (MENR) and the 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 153 were fully completed, providing a satisfactory 30% response rate and a sufficiently large sample for testing the research hypotheses. This unique dataset 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.

3.1 Instrument Development

The 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. The 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.

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[1] 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 (1997) and Kalayci and

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

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 measuring the market informedness level of e-consumers about a new product, website etc. (e.g. Li et al. 2015). In this paper, 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. Sixteen 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, hydro 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, (3) interaction of size and portfolio diversity, and (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[2]) 3 (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 Table B1.

The major descriptive statistics for the variables are presented in Table 1. Even though the scales are ordinal, the summary measures indicate that a sufficiently reasonable spread was obtained to facilitate subsequent analysis.

Table 1: Descriptive Statistics

Variable	N	Range	Min	Max	Mean	Std. Dev.
(1)size	153	2	1	3	1.6	.9
(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	100	0	100	40.7	34.1
(8)use of advanced forecasting	153	3	0	3	2.27	.9
(9)forecast error	153	90	0	90	21.7	15.9

The Pearson correlations derived from the sample are summarized in Table 2 and here it is worth noticing the distinctly different intercorrelations for the use of advanced forecasting and hedging,

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

suggesting that they are indeed separate approaches to facing price risk uncertainty. This is very reassuring for the basic research motivation in this paper. Furthermore, market informedness is correlated both with size and portfolio diversity one might expect. More subtle analysis is undertaken by structural equation models, as described below.

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 difference. Thus, we conclude that our sample is not systematically biased and the results are generalizable to our population (e.g. Lindner et al., 2001; Sivo et al., 2006).

Table 2: Summary Statistics and Correlations

Variable	**(1)**	**(2)**	**(3)**	**(4.1)**	**(4.2)**	**(4.3)**	**(4.4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
(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	1.000

[1]Since *type of license* is a categorical variable with five levels and 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).

We used *structural equation models* 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 structural 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. The results of the SEMs are summarized in Table 3 and the results of testing each working hypothesis are summarized in Table 4.

Table 3: Results of SEM of Research Hypotheses

	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 4.1	Model 5.1
(1)size	0.132	0.046	-0.195	-0.243	-0.178	-0.174	0.097	0.109
(2)div.	0.057	-0.088	-0.032	-0.204	-0.248	-0.264	**0.429***	0.073
(3)size*div.	-0.099	-0.027	0.061	0.099	**0.228***	**0.229***	-0.088	-0.038
(4.1)D_Gen	**0.443***	0.297	-0.272	-0.217	**-0.696*****	**-0.674*****	-0.119	0.168
(4.2)D_Auto	0.667	0.517	**-1.663*****	**-1.467*****	-0.411	-0.437	-0.530	-0.579
(4.3)D_IncR	0.043	-0.039	0.038	-0.060	-0.164	-0.170	0.276	0.073
(4.4)D_Disc	0.185	0.113	0.157	0.022	-0.119	-0.154	0.390	-0.174
(5)risk av.	-	0.035	-	0.009	-	-0.089	-	-
(6)inform.	-	**0.193***	-	**0.367*****	-	0.049	-	-
(7)adv.hedg	-	**-0.198***	-	-	-	-	-	-
(8)adv.fore	-	-0.114	-	-	-	-	-	-
(9)prederr	-	-	-	-	-	-	-	-
Adj.R^2	SEM-1 **Adj.R^2** 0.145				SEM-2 **Adj.R^2** 0.111			

[1]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).

Our results (Table 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= -.198 at $P<0.05$). Hedging activity uses the forward curve as a 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= .367 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.

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= .367 at $P<0.001$), which relates to the use of advanced forecasting. Thus, 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= -1.467, $P<0.001$) 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=.442, $P<0.05$). 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, hydro 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. 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= -.674, $P<0.001$) 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, in Model 3.2, show that there is a significant and positive relation between the control variables size*diversity and use of advanced hedging (coefficient= .229, $P<0.05$). 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 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 Summary and Conclusion

5.1. Summary

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.

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 (1997) on prospect theory.

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.

5.2. Implications and Future Research

This paper makes several contributions to the research on online auction design through investigating how behavioural perspectives inform the design of IT artifacts that are embedded in economic systems. 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. Thus, this paper is one of the first to take an information-based view to study trading behaviour of bidders and highlights the role of informedness. 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.

Considering energy policy and auction design research, 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 (e.g. 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. Our methods by themselves are generic and they could be applied to other auction trading markets, such as flower markets as well. Since prices at the Dutch flower auctions, similar to electricity auctions, are extremely volatile; good price forecasts can improve decision making on space allocation; what species to plant; the timing of harvesting (Steen and Gjolberg, 1999). Reductions in information available due to an IT-enabled process discontinuity creates new information seeking or trust-generation costs. Market designers can respond to these requirements by allowing more information gathering by different stakeholders (buyers and sellers) (Kambil and Van Heck, 1998). To respond to the needs of larger buyers, a Mediation Office was established with the role of an auction employee who acts as an agent for the growers and negotiates between growers and buyers. The mediation office is useful for the sale of large lots to large buyers like supermarkets for the occasion's market. From a regulatory point of view, this bilateral trading arrangement is not considered a trading facility because it is not multilateral (although it is highly automated). Dealers have direct communication lines (phone, email, web) between themselves and other dealers. A quick series of such calls can give an investor a view of the market that is not entirely different from a view obtained by observing a multilateral negotiating process. Based on our findings and Kambil and Van Heck, 1998; Gebhart, 2014; and Steen, 2014 we propose the formation of an electronically brokered OTC market through the use of an electronic brokering platform that create a multilateral trading environment and will bring efficiency for price discovery and improve forecasting.

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Appendix A. General Information about EDA auctions

Table A1.
A sample (single) hourly order with few steps from a Dam Hydro bidder (Bidder Z). Note: QZ is the installed capacity of Bidder Z and P is the market clearing price on day xx/xx/2012 at hour 17:00.

Date	Hour	Type	Ask	Bid	Price
xx/xx/2012	17	Hourly	0	(0.03) Q_Z	0
xx/xx/2012	17	Hourly	0	(0.03) Q_Z	P-65.37
xx/xx/2012	17	Hourly	(0.08) Q_Z	0	P-65.36
xx/xx/2012	17	Hourly	(0.08) Q_Z	0	P+40.16
xx/xx/2012	17	Hourly	(0.60) Q_Z	0	P+40.17
xx/xx/2012	17	Hourly	(0.60) Q_Z	0	2000

Fig. A1. EDA Order Book screen for entering Price&Quantity orders

Table A2.
Clearing the market by the EDA auctioneer on a sample day and hour

Price	44.99	45.00	49.99	50.00	54.99	55.00	55.01	2000.00
Bidder A	40	40	40	40	40	40	20	20
Bidder B	20	20	20	20	20	20	20	20
Bidder C	-40	-60	-60	-60	-60	-120	-120	-120
Bidder D	20	0	0	-100	-100	-100	-100	-100
Bid	80	60	60	60	60	60	40	40
Ask	-40	-60	-60	-160	-220	-160	-220	-220

MCP=47.50

Appendix B. Measurement of Variables

Table B1.
Measurement items and coding for 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 -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)	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
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	Count the total number of plants in their portfolio Coded as 1 (undiversified), up to three utilities are coded as 2 (semi-

	-Reservoir -Dam -Wind -Natural Gas -Biogas -Fuel oil -Lignite -Imported coal -Anthracite -Geothermal -Landfill gas -Naphtha -Other (Please indicate)	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

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