Bidding Farewell to Fossil Fuels

An Empirical Study of Auctions for Renewable Energy Support

Bachelor Thesis

Supervisor: Tommy Andersson

LUND UNIVERSITY, DEPARTMENT OF ECONOMICS

Sara Svensson

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Abstract

Using government auctions to distribute subsidies and locations for renewable energy sources is a good way to receive signals about the cost of renewables. My thesis studies the relationship between auction design and auction prices in Renewable Energy Support (RES) auctions in Europe. I empirically compare price outcomes of first-price and second-price auctions, as well as auctions with and without penalties or pre-qualifications. My empirical analysis finds that second-price auctions generate lower bids than first-price auctions, which in turn means lower subsidies. Studied from an auction theoretic perspective this could imply bidders in RES auction bid differently depending on how the auction is designed.

Key words: *Renewable energy auctions, first-price auctions, second-price auctions.*

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Abbreviations

RES Renewable Energy Support

AURES Auctions for Renewable Energy Support

PAB Pay-as-Bid

UP Uniform Price

PV Photovoltaic

FIT Feed-in-Tariff

FIP Feed-in-Premium

kWh Kilowatt-hour

ct Euro-cent

1 Introduction

While the world is dealing with climate change, energy demand is predicted to increase by 50 percent to 2050 and the energy sector stands for two-thirds of global emissions (International Energy Agency 2018, IRENA 2020). 170 billion US dollars were paid out as subsidies for renewable energy in 2019 worldwide. Meanwhile, subsidies for fossil fuels accounted for approximately the double amount (REN21. 2019). Building renewable energy sources plays a central role in coping with increasing energy demand and carbon emissions. However, many renewables projects still depend on government subsidies to be realised.

Auctions are thought to be the most efficient way to allocate renewable energy subsidies and receive signals about the true costs of renewables (AURES 2020). Learning the amount of subsidies energy companies need to build and operate renewable energy can help governments decide where to invest. In turn, efficient investments can help cope with the energy demand and climate change issues. During the last couple of years renewable energy support (RES) auctions have become increasingly popular. Governments auction out the energy source location in combination with the subsidies for building and operating it. Companies (bidders) compete for subsidies handed out by governments (the auctioneer), which award the subsidy to the lowest bidder. RES auctions have made use of many different types of auction design features to try to reach optimal outcomes in terms of prices and efficiency. (Tiedemann 2019). To find out if auction prices tell us something about the subsidies needed my thesis will attempt to answer the question: Do RES auction design features have an effect on awarded price outcomes?

To study the effect of auction design on price outcomes I empirically analyse data on RES auctions in Europe. My thesis will focus on price differences between two different kinds of pricing rules used in the renewables context, first-price and second-price auctions. In first-price auctions the company submitting the lowest bid wins the object and receives the subsidy he bids. In second-price auctions the company submitting the lowest bid wins the auction but does not receive the subsidy he bids, but the second-lowest bid (Krishna 2010). I also include empirical findings of auctions with or without penalties and with or without pre-financial qualification as these are the most effective way to increase efficiency in RES auctions according to earlier research (Matthäus 2020).

My thesis starts by explaining the theory behind first-price and second-price auction bidding behaviour and which effects they have on prices in section 2. Section 2 also discusses earlier research on RES auctions and other natural resource auctions. At the end of section 2 my hypotheses is presented based on the auction theoretical framework. Section 3 covers the data and method I use for the empirical analysis. Finally my results and analysis are presented in section 4 and section 5.

2 Background and Literature Review

In this section I describe how auctions for renewable energy support (RES) work and the auction theoretical background behind the auction design features I analyse. I start by explaining prices and valuation in the RES context to understand the elements that go into bidding. An auction theoretical background to auction designs' effects on price outcomes follows. Thereafter I discuss earlier research on natural resource auctions. Finally, I present my hypotheses based on the theory and research discussed.

2.1 Renewable Energy Support Auctions

RES auctions are a diverse group of auctions and have made use of many different design features. Each auction feature could potentially affect the outcome of the auction. Outcomes of auctions are often measured in revenue and efficiency, revenue being final prices and efficiency meaning the item is awarded to the most suitable buyer (Krishna 2010). In RES auctions the auctioneer takes both revenues and realisation rates (efficiency) into consideration when evaluating auction results. The realisation rate is the proportion of the project finished within the set time frame. Although the auctions sometimes include different types of energy sources in one auction, my thesis will examine RES auctions as homogeneous good auctions since the auctioned out good is measured in euros and capacity, not in the type of energy source auctioned out. The auction design features I study in my thesis are pricing rules and financial repercussions of not finishing the project. Below I present the meaning of auction prices in the RES context and describe how energy sources up for auction are valued.

2.1.1 Prices

In RES auctions energy companies bid on the location of the energy source project in combination with the subsidies to build and run it. Subsidies can be given out in different forms of support schemes which determine how the winners of the auction are paid. The most common support schemes are sliding one-way or two-way feed-in-premiums (FIP). FIPs are paid out in addition to the wholesale electricity price and either cover costs for when wholesale electricity prices (between producer and retailer) are below the award price or awarded on top of the wholesale market price. The aim of the RES auctions is to create competitiveness and transparency in prices for the support distributed. Feed-in-tariffs (FIT) are sometimes used for smaller installations or new technologies and are paid directly to the producer, as it does not itself sell energy on the market. (AURES 2020).

The government (auctioneer) auctions out the support and the energy company (bidder) with the lowest bid wins the auction. In this way the government hopes to be able to pay out as little support as possible. The prices discussed in my thesis must be understood as the amount of subsidy energy companies receive from the government. The prices are given in euro-cents per kilowatt hour (ct/kWh). Many RES auctions have a dividable amount of capacity available and are multi-item auctions where several bidders can win capacity. In cases with several winners, each company submits how much capacity they want to build as well as their price. First the lowest bid is offered the amount of capacity they submit, afterwards the second lowest bid is offered their desired capacity and this sequence continues until all the auctioned out capacity is distributed. (Tiedemann 2019).

2.1.2 Valuation

Auctions are a market mechanism for allocating goods when the auctioneer is not aware of the good's market price (AURES 2020). If auctioneers were aware of exactly how each bidder valued the item, an auction would not be needed (Krishna 2010). Auctions can have different outcomes depending on the role information about the item plays in bidding behaviour. In auction theory, this is divided into different types of valuations; private value, common value and interdependent value auctions. Private value auctions are when each bidder has his own valuation of the item which is independent of other bidders valuations. Common value auctions are when all bidders value the item exactly the same, often exemplified by bidding on coins, as they are worth the same to everyone. Interdependent value auctions include both a private and a common value component. (Krishna 2010).

Kreiss, Ehrhart & Hanke (2013) conclude that RES auction bidders mainly base their bids on future wholesale market prices (which is identical for all bidders) and the costs for materials and building of the resource (which is available at similar prices for all bidders). This would indicate RES auctions include a common value component. However, their valuation can also be affected by the market share of the energy company, scale effects or other private values. Therefore, RES auctions include both common and private values and are, like most real-life auctions, interdependent value auctions. (Krishna 2010).

2.2 Auction Design

In order to create a good outcome in terms of revenue and efficiency the government is interested in getting each bidder to bid their true cost. The true cost is referred to as the subsidy the company needs to be able to invest in and realise the project. If the auction is designed in the right way bidders will have incentives to bid their true costs and the bids will equal the true cost ($b_i = c_i$). (Tiedemann 2019). In the description of the auction designs (b) will stand for bids and (c) for true costs.

2.2.1 First-Price Auctions

First-price auctions are discriminatory auctions which are often termed pay-as-bid auctions (PAB) in RES literature. All bidders submit a sealed bid and the winner is paid the bid they won the auction with (b_i). Bidders will try to maximise their profits by estimating their chances of winning, while still receiving a high subsidy. According to auction theory the dominant strategy in first-price auctions is not necessarily to bid ones true cost (c_i). Two possible scenarios could result from first-price auction bidders speculating instead of bidding their true costs. (Krishna 2010).

Scenario 1: $b_i > c_i$ Bidders intentionally overestimate their costs and increase their bid to receive a higher subsidy, potentially increasing their profits. If all bidders overestimate their bids, an overestimated bid will win the auction. As follows, the cost of the government will be higher than necessary and the government will not achieve its goal to pay optimal subsidies.

> *Example:* Two companies (i and j) are bidding for energy support and have calculated their true costs to c_i = 5ct/kWh and c_j = 6ct/kWh. Both companies want to increase their profits, as follows they increase their bids to b_i = 7ct/kWh and b_j = 8ct/kWh. The bid of 7ct/kWh wins the auction, as it is the lowest given bid which means the government pays higher subsidies than any of the companies need to execute the project.

Scenario 2: $c_i > b_i$. Bidders underestimate their costs (or overestimate their revenues) in order to win the auction. Instead of the bidder with the true lowest costs winning the auction, the bidder with the highest valuation of future electricity prices or willing to take the highest risk wins the auction. This is not necessarily the most efficient outcome and might lead to low realisation rates of the projects. This scenario is titled the winner's curse.

Example: Two companies (i & j) are bidding for energy support and have calculated their true costs to c_i = 5ct/kWh and c_j = 6ct/kWh. However, one of the companies (j) overestimates future electricity prices, and therefore believes it can afford to lower their bid in order to win the auction. The bids b_j = 4ct/kWh and b_i = 5ct/kWh result in company j winning the auction with their lower bid, even though company i would be able to build at a lower cost. This may lead to company j having too little financial capability to finish the project and less capacity being built than intended.

Table 1: Pricing Rule Scenarios

Pricing Rule	Scenario	True Costs	Bids	Average cost	Outcome
First-price	1: Overbidding	5 & 6	7 & 8	7.5	High prices, untrue bids
First-price	2: Underbidding	5 & 6	5 & 4	4.5	Low prices, untrue bids
Second-price	3: True bidding	5 & 6	5 & 6	6	Higher prices, true bids

Notes: A hypothetical example of bidding under different pricing rules. The scenarios have been created according to the auction theoretical background regarding bidding behaviour with two winners. It illustrates the potential outcomes in terms of cost of government and degree of truthfulness in bidding.

2.2.2 Second-Price Auctions

Second-price auctions are non-discriminatory auctions which are often titled uniform price (UP) auctions in the RES context. The auction is executed in the same way as a first-price auctions, and the lowest bid still wins the auction, but the awarded prices are set differently. In second-price RES auctions all winners receive the subsidy of the first losing bid, regardless of the value of their own bids. This means the awarded price is determined by another bidder with a higher bid. According to auction theory, a weakly dominant strategy for bidders is to bid their true cost since winners cannot affect their own awarded price (Krishna 2010). We assume bidder i knows his true cost c_i and cannot afford to build at any subsidy below this. He knows his awarded price (p_i) will be higher or equal to his bid ($p_i \geq b_i$) which gives him no incentive to bid anything else than his true cost, thus, $c_i = b_i$. This auction format is thought to mitigate the winner's curse or overbidding of first-price auctions. (Ausubel & Milgrom 2006, Krishna 2010).

2.2.3 Penalties and Pre-qualifications

If different pricing rules are for reaching efficient revenues, penalties and pre-qualifications are for reaching good realisation rates. In my thesis, financial repercussions will be used as a collective term for penalties and financial pre-qualifications. Below I will explain RES auction financial repercussions and how they can affect prices.

In RES auctions with penalties, fines are appointed to winning bidders that do not finish the project within the set time frame. The fines are appointed after the realisation period if an avoidable delay has taken place. Penalties are to prevent bidders from winning projects they have no intention of finishing. (Kreiss et al. 2017).

In RES auctions with financial pre-qualifications, a financial guarantee is required to participate in the auction. In case of non-realisation the payment is collected after the realisation period. According to Welisch (2018) this decreases the number of bids and competition. However, it aims to guarantee the seriousness of the bidders that do participate, before the auction takes place.

Although penalties and pre-qualification are not part of the pricing rule in RES auctions, they do involve potential extra costs for bidders. Therefore we can expect them to have an effect on the awarded prices. Financial repercussions also aim to influence the type of bidders participating in the auction, which could have an additional effect on prices. The aim of financial repercussions is to create costs for winning bids that do not finish the project. The cost makes the alternative to gamble on low subsidies in order to win the auction less attractive. Therefore penalties and pre-qualifications are thought to mitigate the winner's curse. (Tiedemann 2019).

Earlier research on penalties and pre-qualifications shows that including them in auctions has a positive effect on realisation rates, meaning they make sure more projects are finished on time (Matthäus 2020, Kreiss et al. 2017). However, financial repercussions effect on awarded prices have not been empirically researched. Bidders are thought to include the risk of financial repercussions into their bid, which should increase the all participating bids. Financial repercussions are also thought to prevent bidders without intentions of realising the project to participate in the auction, which reduces competition and presses up prices. However, this is the type of price increase auctions want to achieve with repercussions, since these bidders would not have been able to afford building the project. Kreiss et al. (2017) point out that higher prices are mainly the case with penalties, and suggest using only pre-qualifications to maintain efficiency in prices whilst still making sure projects are realised. In conclusion, we can expect average prices to increase when financial repercussions are included as an auction feature.

2.3 Earlier Research on Natural Resource Auction Design

Auctions to distribute support for renewable energy has only become a widespread way to finance renewables over the last couple of years. Previous literature on RES auctions is mainly constructed as case studies or computational simulations (Agent Based Modelling) since the data on the topic have been limited (Anatolitis & Welisch 2017, Kreiss et al. 2013). Below I present the research done on pricing rules in RES auctions as well as research on pricing rules in other natural resource auctions.

Matthäus (2020) has constructed one of the only empirical studies of RES auction efficiency to date. He has collected a unique dataset with auctions all around the world and tested auction design features' effect on realisation rates. No significant difference between the realisation rates of first-price and second-price RES auctions is found. As mentioned earlier financial repercussions are found to be the most effective way to increase realisation rates.

Anatolitis & Welisch (2017) use an agent based modeling approach to study changes in bidding behaviour over time in onshore wind power auctions in Germany. Their model includes several similar auctions over time, which according to their results, would mean that bidders learn their competitors bids over time and are able to lower their bids accordingly. They conclude this leads to second-price auction generating marginally higher prices than first-price auctions. The agent-based modelling approach is very different to an empirical approach studying existing data.

An AURES report by Haufe, Kreiss & Ehrhart (2017) report constructed an experiment on the difference in bidding behaviour of first-price and second-price RES auctions. The report could not find any significant difference in bidding behaviour through their comparison but could instead derive the differences in prices to degree of competition. However, they point out that the students in their experiment may not have understood the second-price auction system fully, since it is less intuitive according to Haufe et al. (2017). It is likely that energy companies spending time and money on a new investment get more engaged in bidding behaviour and have access to more advanced modelling systems to determine what to bid.

Kreiss et al. (2013) use a theoretical approach to analyse off-shore wind energy auctions in Germany which over the last couple of years have had some 0.0ct/kWh bids. These bids would insinuate off-shore wind is now competitive on the market. However, Kreiss et al. (2013) argue it is unlikely electricity prices will cover costs every month and conclude 0.0ct/kWh bids in first-price auctions may be underestimating costs and becoming victims of the winner's curse. They highlight the importance of auctioneers finding a balance between minimising costs and reducing the risk of non-realisation of the projects. As bidders have access to similar information before the auction they conclude the underbidding can be a result of the common value component present in RES auctions.

Generally auction theory shows bidding behaviour in first-price auctions is dependent on valuation and the information available to bidders. Milgrom & Weber (1982). Several studies have been constructed on the US government auctions of oil tracts. Hendricks & Porter (1988) study first-price sealed bid auctions and study the bidding behaviour of two groups of bidders, ones with access to more information and less information. The firms with more information all have access to the same information, including a common value component in the auction. They conclude that the winner's curse is more often present for firms with common value components, which has a negative effect on the bids. As Kreiss et al. (2013) point out, RES auctions also include a common value component and a similar effect could take place.

In contrast to earlier auction theory, Milgrom & Weber (1982) conclude first-price auctions and second-price auctions will lead to the same revenues for the auctioneer when bidders have interdependent valuations of the item. This is called the revenue-equivalance result and only holds if all bidders are risk-neutral. Milgrom & Weber (1982) exemplify with natural resource auctions, namely oil, gas and mineral rights auctions. In natural resource auctions there is often a common value component, but the estimation of the common value may differ. On average, this means the winner will have overestimated the value of the item, or underestimated costs. The prediction of Milgrom & Weber (1982) model is that second-price auctions will generate higher average prices than first-price auctions will as the bidder's estimates of values are dependent on their estimation of a common value. This result concers regular auctions which means it would have the opposite effect on RES auctions, second-price auctions generating lower average prices.

In conclusion, earlier research suggests there are both advantages and disadvantages with both pricing rules in terms of costs and efficiency. The final auction prices are important since they can tell us about renewables competitiveness on the market. Awarded prices act as a signal for the government which energy sources to subsidise or not, for an overall more efficient outcome. My thesis aims to find if there is any broader empirical relationship between different auction designs and the price outcome in RES auction which has not yet been empirically researched with this database.

2.4 Hypotheses

The overall hypotheses of my thesis is that different auction features affect auction prices. A conclusion of the auction theoretical framework presented in section 3.1 is auction pricing rules can affect outcome prices of auctions in different ways. The sub-hypotheses below will all be tested to see if there is any effect of auction design on average prices.

Hypothesis 1 First-price auctions generate higher bids than second-price auctions. As in first-price auction scenario 1 (see 2.2.1) bidders overestimate costs to receive higher remunerations.

Hypothesis 2 First-price auctions generate lower bids compared to second-price auctions. As in first-price auction scenario 2 (see 2.2.1) bidders underestimate costs or fall victims of the winners curse.

Hypothesis 3 Auctions with financial pre-qualifications or penalties will generate higher bids than auctions without financial repercussions.

3 Methodology

In this section I describe how the statistical analysis of auction design's effects on prices is constructed. First, I explain which data and which variables I use and why. I go on to present the limitations of the data and finally the statistical tests used for the results.

3.1 Data and descriptive statistics

3.1.1 Database

I use the D3.1., *AURES II auction database v1 1* (2019) from January 2020 constructed by Auctions for Renewable Energy Support (AURES), a European research project consisting of eleven public institutions and private firms. The database covers the design and outcomes of RES auctions in 19 EU countries. The database contains observations from 329 auctions in Europe during the time period 1990 - 2020. *AURES II auction database v1 1* (2019) is the first publicly available database combining auction design features, awarded prices and efficiency for a large amount of countries. Matthäus (2020) has hand-collected extensive RES auction data for his study on auction design and efficiency which he has kindly sent to me. However, as this covered other auctions than the AURES database, I have not been able to include it into my analysis. Within the time frame of my thesis, it has not been possible to hand-collect new data on auction results from every auction's individual source of information that would fit my research question. Therefore I have only used the AURES database covering auctions in Europe.

3.1.2 Variables

The variables I choose to include in my empirical study, depend both on the quality of the observations available through the *AURES II auction database v1 1* (2019) and the relevance to my thesis. My dependent variable, auction price outcome, can best be detected through the observations of *average price* (see table 2 notes). My independent variables, auction design features, are all categorical variables and are therefore converted into dummy variables. Dummy variables are used to give each category either the value one or zero and can be used to asses the average effects of an auction belonging to a category on the average prices.

Average Price The dependent variable *average price* is observed in euro-cents per kilowatt-hours (ct/kWh) and is the average of all the awarded bids in one auction. In first-price auctions the average price is different for all winners and in second-price auctions all winners receive the same price. The prices are the subsidy the bidder receives per kilowatt-hour of capacity and can come in different forms.

Pricing Rule The independent variable *pricing rule* is stored in a dummy variable taking the value one for the second-price auction rule and zero for the first-price auction rule.

Penalties The independent variable *penalties* is a dummy variable and takes the value one if penalties are used and zero if penalties are not used in the auction. Penalties refer to a sum of money the winner of the auction has to pay if the project is not finished within the set time frame.

Financial Pre-qualification The independent dummy variable pre-qualification takes the value one if pre-qualification is demanded and zero if not. Pre-qualifications refer to a sum of money the auctioneers have to garantuee they can pay before the auction if the project is not realised.

Remuneration Scheme The way the subsidy is paid out is added as a control variable, *remuneration scheme*, using dummy variables for one-way FITs, two-way FITs, fixed FITs or FIPs.

Competition The variable *competition* added as an additional control variables. *Competition* is calculated by dividing the submitted volume of kWh by the auctioned volume of kWh.

Table 2: Descriptive Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Average awarded price [ct/ kWh]	7.207	3.444	0	17.5	199
Highest given bid price [ct/kWh]	10.518	9.117	0.852	65.400	88
Lowest given bid price [ct / kWh]	6.654	6.091	0.07	53	93
Highest awarded price [ct / kWh]	7.962	3.752	0	18.03	151
Lowest awarded price [ct / kWh]	8.003	13.122	0	98.03	156
Median price [ct / kWh]	8.109	4.226	0	17.007	33
Number of submitted bids	85.189	100.022	0	598	74
Number of qualified bids	80.347	95.575	0	586	49
Competition	3.604	7.388	0.02	67.8	113
Support duration [years]	16.848	3.281	7	25	264
Realisation rate	0.804	0.146	0.35	1	63

Notes: The table shows us the approximate distribution of prices in RES auctions. Since average awarded price is the price with the most observations (N=199), this is the observation which will be used for further observations. It is also the most relevant to compare between auction designs. Adding competition as a control variable reduces the number of observations to 113.

3.1.3 Data Manipulation

The changes I make to be able to use the *AURES II auction database v1 1* (2019) for a statistical analysis are described below.

Most of the AURES II database is constructed in text-matter and the database is shaped to be useful for my estimations in the statistical software STATA/IC 15.1. I do this by converting all categorical and descriptive variables into to dummy variables. Auctions with unique designs within any of the independent variables are dropped since no conclusion can be made if comparing with an auction format with only one or two observations. I also drop all observations of auctions on biomass, waste or hydro-power since there are not enough observations to see if the differences in prices depended entirely on the technology or not. Thus, the technologies included in the observations are solar PV, onshore wind and off-shore wind.

Table 3 shows us the uneven distribution between observations in each category. This implies some of the variables with few observations from table 2 have almost no observations within a specific category. As my independent variables consist of the categorical variables they are the main focus of my analysis. Therefore, it makes more sense to be able to say a little more about the independent variables than adding another control variable which limits the data to a small sample size. One of the variables impaired by this is the

Table 3: Summary Statistics Categorical Variables

Variable	**Categories**	**Frequency**	**Percent**
Pricing rule	First-price	290	88.15
	Second-price	28	8.51
	Missing	11	3.34
Penalties	No	14	4.26
	Yes	177	53.80
	Missing	138	41.95
Pre-qualifications	No	133	40.43
	Yes	154	46.81
	Missing	42	12.77
Remuneration Scheme	FIP one-sided	79	24.01
	FIP two-sided	102	31.00
	FIT	35	10.64
	FIP fixed	8	2.43
	Missing	105	31.91

Notes: The table illustrates the distribution between the different categories. As we can see the distribution of pricing rules and penalties is skewed. One-sided and two-sided FIP refer to sliding feed-in-premiums.

variable *number of bids* which was at first included in my regressions to control for the effect of competition but limited the observations to 34 auctions (see appendix table 10). However, I have tried to capture this element in the model through the new variable *competition*. I generate the variable *competition* by dividing the submitted volume (by all bidders) by the awarded volume (to winning bidders).

I use the database as cross sectional data since the majority of observed auctions take place after 2015 and the analysis takes no regard to differences in time. A regression run on time and average prices show a very small and insignificant correlation (see appendix figure 3).

Although I make some modifications and assumptions of the data, there are still limitations left preventing an accurate analysis, these are discussed in the next section.

3.1.4 Limitations of the Data

The main limitation of the database is the restricted number of observations available. The major downside of the data for my thesis is the small number of second-price auctions (28 observations) which can be seen in table 3, a clear minority of the total observations. This implies a small number of observations for studying the effects of second-price auctions is available. The same problem is present for auctions without penalties, only adding up to 14 observations (table 3).

The large amount of missing variables in potential control variables, for example number of qualified bids (49 obs. table 2), implies they are seldom part of the same observations as the ones of the independent variables (with few observations in one category). In the regression I try to include a fair proportion of the total observations, unfortunately, at the expense of some control variables.

To truly study whether auction design features effects prices, one would need information from a large number of auctions within different auction design categories with all other factors equal. However, only a limited amount of each type of auction has taken place. The data include all RES auctions which have been completed within the EU which makes it a broad database, albeit missing observations within each auction.

To be able to link auction design features to auction theoretical bidding behaviour one would need more detailed information about the prices and volumes of each individual bid, both losing and winning ones. Unfortunately, individual bidding information is classified information and could not be found for the purpose of this thesis.

3.2 Statistical Analysis

I study the effects of auction design on pricing in two ways. First I compare the mean prices of different designs by t-tests. Thereafter, I use a regression with multiple variables to test the effects of different auction design features on prices.

3.2.1 T-test/Wilcoxon Signed Rank Test

One of the main observations important to my thesis is to see if there is a statistically significant difference in awarded auction prices between different pricing rules, pre-qualifications and penalties. To do this I use a simple two-way t-test. The null hypotheses are that no price differences are present between auctions with different design features. A Wilcoxon signed rank test is used to double check the differences in means without assuming normality.

3.2.2 Regression Analysis

I use a regression analysis to understand which effects auction features have on differences in prices. Since price is a continuous variable a standard ordinary least squares (OLS) estimator is used for the regression. To create consistent estimates I have used an estimator with robust standard errors. It is noteworthy that Matthäus (2020) has constructed one of the only empirical studies of RES auctions thus far, and has used the same estimator with the dependent variable efficiency. To check for potential flaws with the OLS estimator I perform a few tests.

Equation 1: OLS Estimation: Average Price

$$Average\,Price = \beta_0 + \beta_1 * Auction\,Features_i + \beta_2 * Control\,Variables_i + \epsilon_i \tag{1}$$

Equation 1 is the regression used to check for effects of auction features on average price, the dependent variable. The independent variables, auctions features include the dummy variables *pricing rule*, *penalties* and *financial pre-qualification*. The control variables include *competition* and the dummy variable *remuneration scheme*. The beta (β) coefficients will tell us how average price is effected by the different variables.

4 Results

In this section I illustrate and describe the empirical findings gathered from the statistical analysis of the *AURES II auction database v1 1* (2019).

4.1 Pricing Rules

The two-way t-test shows significant price differences between auction feature categories. Prices in first-price auctions have a significantly higher mean price (7.37ct/kWh) compared to second-price auctions (4.05ct/kWh). This is in line with the theoretical expectations from hypothesis 1 (see 2.2.1). As the data is not entirely normally distributed the two-way t-test is complemented with a Wilcoxon signed-rang test which confirms the findings from the two-way t-test.

Table 4: Average Price Two-Sample T-Test

Auction feature	**Num.obs**	**Mean**	**Std. Err**	**T-value**
First-price	265	7.37	0.247	3.29**
Second-price	28	4.05	1.055	3.29**
Penalty	177	7.56	0.33	-3.7**
No Penalty	14	3.35	1.16	-3.7**
Prefinance	154	6.62	0.35	-0.94
No Prefinance	133	7.12	0.35	-0.94

Notes: A two-way t-test constructed in STATA for each auction design category. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In order to find out if the auction features are what contribute to the differences in prices observed in the two-way t-test I regress *average price* on the dummy variables *pricingrule*, *penalties* and *financial pre-qualification* and control for *competitions* in an OLS estimator with robust standard errors. The results are presented in table 5. The test has been run with robust standard errors to compensate for heteroskedasticity. As my main independent variable is *pricing rule* I have started by running the regression only on average prices and added one control variable after the other to see how this effects the pricing rule coefficient and

R_2. R_2 and adjusted R_2 describe the amount of variation in price described by the model and takes a value between one and zero.

As observed in table 5 the coefficient of the dummy variable *pricing rule* takes a negative value of -2.78 when all my control variables are added to the model, suggesting awarded subsidies in second-price auctions are on average 2.78ct/kWh lower, if all other variables are held constant. This result is statistically significant at the 5 percent level. This result is in line with the theory of overbidding from hypothesis 1.

Penalties have a positive coefficient of 3.007 which would imply awarded subsidies for auctions with penalties for non-realisation are on average 3ct/kWh higher than auctions without penalties, all else constant. Financial pre-qualifications have a negative coefficient of -0.512 which would mean awarded subsidies in auctions with financial pre-qualifications were 0.5ct/kWh lower than the awarded subsidies without financial pre-qualifications. However, neither of these results are statistically significant, and we cannot conclude a difference in price for auctions with or without penalties or with or without financial pre-qualifications.

After running the full model I end up with an R_2 value of 0.26 (adjusted R_2=0.175) which means the proportion of the variance in the dependent variable explained by the model is approximately 26 percent. This is fairly low, but can still tell us something about explaining average prices.

I have controlled for the variable *competition* as this could have an effect on bidding behaviour according to auction theory, however we cannot conclude any significant effect of competition on awarded subsidies. The other control variable remuneration scheme (a dummy-variable for which type of subsidy is used) has coefficients of 6.8 and 7.3 which implies one-sided and two-sided sliding feed-in-premiums have a significant positive effect on awarded subsidies at the one percent level.

Observing the results from the OLS regression used we must also consider the limitations of the database discussed in section 3. To eliminate common problems that can appear in OLS regressions I have run a few tests. To check for normality I have made a histogram of the residuals which to check if they are distributed normally around zero. There is fair evidence they are distributed around zero, but they are not entirely normally distributed.

Table 5: Estimation Results: Average Price

Variables	**Regression coefficients average price**				
	(1)	(2)	(3)	(4)	(5)
Pricing rule	-3.317**	-2.779*	-2.549	-2.742*	-2.778*
	(1.046)	(1.129)	(1.379)	(1.339)	(1.371)
Competition		0.0234	0.112	0.107	0.117
		(0.0476)	(0.237)	(0.245)	(0.240)
Penalties			2.748	3.006	3.007
			(2.584)	(2.905)	(2.963)
Financial Pre-Qualification				-0.862	-0.512
				(1.430)	(1.470)
FIP one-sided					6.837***
					(0.530)
FIP two-sided					7.379***
					(0.523)
FIP fixed					0
					(.)
Constant	7.375***	7.101***	4.066	4.618	-2.426
	(0.249)	(0.377)	(2.896)	(2.643)	(2.564)
Observations	195	92	60	60	59
R^2	0.053	0.074	0.164	0.170	0.260
Adjusted R^2	0.048	0.054	0.120	0.110	0.175

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The OLS regression of all the variables included. Dummy pricing rule 0=First-Price Auction and 1=Second-Price Auction. Dummy penalty: No=0 Yes=1. Dummy pre-qualification 0=No 1=Yes.

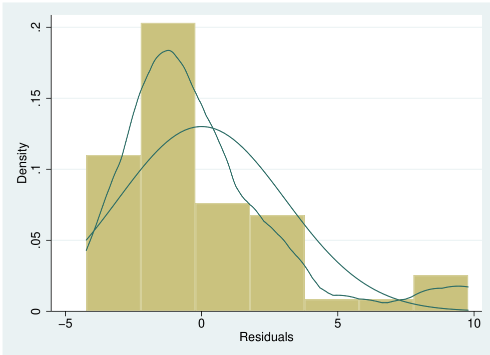

Figure 1: Histogram of residuals

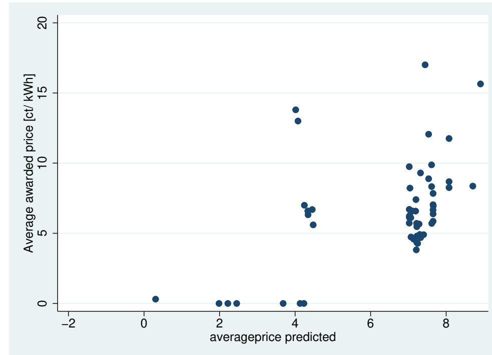

Figure 2: Observed & predicted

In figure 2 I have plotted the model from the regression in table 5 and the observed values. If the model was correct, the pattern in the data in figure 2 should have 45 degree pattern as the y-axis is the observed data and x-axis the predicted data. In this case the model seems to be doing a so-so job with predicting the data, which can also be observed in the R_2 value from table 5.

Table 6: Cross-correlation regression variables

	Average price	Pricing rule	Penalties	Pre-qualification	Competition
Average Price	1				
Pricing Rule	-0.231**	1			
Penalties	0.339***	-0.222**	1		
Pre-qualification	0.0714	-0.0703	0.146*	1	
competition	0.0493	-0.0131	-0.308**	-0.0961	1

Significance in stars * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The numbers in the cross-correlation table go from -1 to 1 where values close to 1 means strong correlation and negative values mean an inverse relationship. We can observe that there is no strong correlation between any of my independent or control variables. This is good news, since this would mean multi-correlation was present.

I also run a breusch-pagan to test for hetereoskedasticity which shows heteroskedasticity is present. This has been coped with by adding robust standard errors. The VIF test run also shows there is no multicollinearity present (see appendix). Finally, I have checked for endogeneity by regressing the the residuals of the regression with the variables in my model, which showed endogeneity should not be a problem.

In conclusion, the main significant finding are that first-price auctions generate higher prices than second-price auction with a 5 percent significance level. They do however not explain the main variation in prices.

5 Analysis

In this section I analyse the empirical findings with help of the theoretical background found in section 2. I also evaluate whether there is enough evidence to confirm any of the hypotheses presented in section 2 and what the results could imply.

Auction theory shows the auction price outcomes can vary depending on how the auction is designed, what kind of good is auctioned, how bidders valuate the good and what information about the good is accessible to bidders. Earlier research on RES auctions is somewhat divided about exactly how bidders behave in relation to auction design features and AURES (2020) state the importance of customizing auctions to suit the unique circumstances in each country and case. No earlier wider empirical study has been done on the effect of pricing rules in RES auction on final prices. The agent-based modelling study shows there is no significant difference in prices, although second-price auction prices were somewhat more volatile and a little higher (Anatolitis & Welisch 2017).

The results from my empirical study suggest auction results are affected by pricing rules. Although my empirical results show pricing rules do not explain the majority of variation between awarded prices, it does answer the question whether auction design affects awarded prices. Having a second-price auction system where all winners are paid the last winners bid, makes the final subsidies approximately 2.8 ct/kWh less than having a first-price auction, if all other factors of the auction are kept the same. This may not seem intuitive, since every winner beside the highest is paid more than they bid. However, if hypothesis one is correct, and first-price auctions generate overbidding, second-price auctions generate lower awarded prices, and lower government costs.

According to auction theory, this could be due to RES auctions containing common value components (Kreiss et al. 2013) which increases the risk of bidding untruthfully in first-price auctions according to Milgrom & Weber (1982). Earlier literature also shows this has been the case for many other natural resources, for example oil and timber auctions (Milgrom & Weber 1982, Hendricks & Porter 1988). However, my thesis has not evaluated the valuation of auctions empirically and can only speculate that the valuation components play a role in bidding behaviour. Further research could try to find out exactly how RES auction bidders determine their prices.

For future auctions, my findings would suggest second-price auctions can be more suitable for auctioning out renewable energy support. My empirical results combined with auction theory imply second-price auctions generate both lower subsidies and a higher degree of true cost bidding than first-price auctions in the RES auctions in Europe. However, we have to take into consideration there might not be enough observations available to predict if this will be the case for all auctions as there are many other variables affecting RES auctions.

Although governments should be interested in getting bidders to submit low bids, this is not the only component of RES auctions that is important. A major goal of RES policy is also the realisations rate, in other words, we want the project to be built well and on time. I have not found any significant effects of penalties and pre-qualifications on awarded prices, but earlier empirical research has found a significant positive relation between penalties, pre-qualifications and realisation rate (Matthäus 2020). Further research could try to combine empirical study of realisation rates and average prices to determine which auctions are most suitable in the RES context.

6 Conclusion

In the introduction of my thesis I ask the question if auction design features affect price outcomes in RES auctions. Below I conclude which answers I find and which conclusions can be made based on the findings.

The auction theory presented gives us two potential outcomes of first-price auctions, underbidding and overbidding. Earlier research on natural resource auctions tells us the probability of untruthful bidding increases if the auction contains a common value component, which research suggest RES auctions do. Auction theory also concludes bidding ones true cost is a weakly dominant strategy in second-price auctions. We also expect auctions with financial repercussions to generate higher awarded prices.

To see if there is any difference in awarded prices between first-price auctions and second-price auctions I use a database covering all the RES auctions in Europe. A simple two-way t-test shows first-price auctions generate significantly higher awarded prices than second-price auctions. This measure also shows us auctions with penalties generate higher awarded prices than auctions without penalties. A linear regression run on several auction design features and competition show us only pricing rule and type of support scheme have a significant effect on awarded prices. Having a second-price auction decreases the final awarded price compared to a first-price auction. However, more complete data is needed to check for other differences between auctions and be certain pricing rules are determining this difference.

The answer to the question would therefore be that auction design can effect price outcomes in RES auctions. More specifically, second-price auctions have generated lower bids, thus lower subsidies. However, we have no insight into energy companies individual bids, and cannot determine if second-price auctions necessarily make bidders submit their true cost to a higher degree than first-price auctions.

At the end of the day, governments are giving out subsidies to assist companies in the development of more renewable energy. The RES auctions are thought to be the most effective way to do this. Low average prices enable governments to invest in more projects but making sure the projects are realised is also key.

6.1 Further research

For further empirical research on auction prices it would be necessary to have more data on every auction design feature so one could check for every difference between the auctions. One could then combine empirically studying realisation rates and average prices, which are both important components of building renewable energy. It would also be interesting to study identical auctions with different pricing rules and compare the results to see which generate the best outcomes in terms of efficiency and price outcomes. As RES auctions are used in many different countries it would also be relevant to check if there are differences in how energy companies bid and function between countries. All in all, as RES auctions continue to develop more data will be available and future research can draw more conclusions with a broader database.

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Appendix

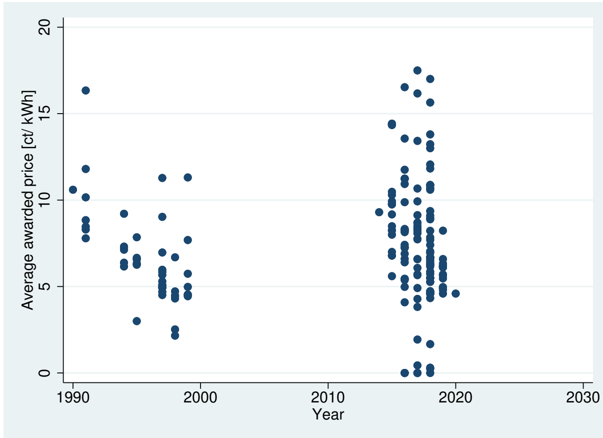

Figure 3: Average Price over time

Table 7: Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

chi2(6)	39.31
Prob > chi2	0.0000

Table 8: Variance Inflation Factor (VIF)

Variable	VIF
pricing rule	1.34
Penalties	1.38
Pre-qualifications	1.34
Competition	1.13
Remuneration 1	0.09
Remuneration 2	0.09

Table 9: Average Price Regression table

	(1) Average awarded price [ct/ kWh]
Remuneration scheme=1	3.647*
	(1.653)
Remuneration scheme=2	5.516**
	(1.684)
Remuneration scheme=3	5.352*
	(2.094)
Remuneration scheme=4	0
	(.)
Constant	2.880
	(1.599)
Observations	131
Adjusted R^2	0.088

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Effect of Auction Features on Average Price including nbids

	(1)	(2)	(3)	(4)
Pricing rule [1, 0]	0.800			0.995
	(1.084)			(0.610)
Competition	-0.414	-0.896**	-0.181	-0.556*
	(0.251)	(0.318)	(0.240)	(0.263)
Number of submitted bids	-0.00769	-0.00288	-0.00557	0.00240
	(0.00583)	(0.00555)	(0.00580)	(0.00563)
Penalties [0=no/1=yes]		-6.325***		-7.708***
		(0.604)		(0.435)
financial prequalification			-3.088**	-3.999***
			(1.067)	(0.891)
Constant	7.973***	14.17***	10.14***	17.85***
	(0.827)	(0.247)	(0.757)	(0.951)
Observations	44	34	44	34
Adjusted R^2	0.092	0.570	0.222	0.783

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$