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Auctioning the Green Transition: A Quantitative Analysis of German Offshore Wind Auctions

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Abstract:

The study develops a model using auction theory and Monte Carlo simulations to estimate firms' cost and revenue parameters, to analyze non-pre-examined offshore wind auctions in Germany. By distinguishing between normal and aggressive bidders, the model examines how firm-specific strategies and assumptions about cost efficiencies influence bid levels. Implied hurdle rates, representing the minimum acceptable return expected by developers, are calculated to assess market sentiment. Results show that hurdle rates increased from 6.4%–8.72% in 2023 to 9.62%–10.42% in 2024, reflecting deteriorating industry conditions. The paper also finds that wake effects can explain a significant difference in willingness to pay of firms between auction sites. The methodology provides a framework for policymakers and industry stakeholders to better understand market sentiment, which can be used to improve bidding strategies and auction design.

Keywords: Offshore wind auctions, Auction theory, Monte Carlo simulation, Strategic Bidding

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List of Abbreviations

AV - Affiliated Values

BNetzA - Bundesnetzagentur

BSH - The German Federal Maritime and Hydrographic Agency

CAPEX - Capital Expenditures

COD - Commercial Operation Date

CV - Common Values

GW - giga-watt

IPV - Independent Private Values

IRENA - International Renewable Energy Agency

NPV - Net Present Value

OPEX - Operational Expenditures

RET - Revenue Equivalence Theorem

WACC - Weighted Average Cost of Capital

1 Introduction

Offshore wind is expected to be a key energy resource in Europe's green energy transition. In 2023, EU countries agreed on a renewed development plan for the technology, where 111 GW of offshore wind capacity is set to be built by 2030, a near doubling in capacity compared to the agreement it replaces; by mid-century, the goal is to have 317 GW of offshore wind capacity within the Union (European Commission, 2023). Policy-makers and industry are scrambling for methods to facilitate this historic expansion. An increasingly favored approach among European policymakers is the auctioning of development rights for offshore wind farms. Auction criteria vary both between and within countries, ranging from purely financial criteria to mixed models that incorporate both financial and qualitative factors. This paper analyzes the German non pre-examined auction sites, where financial bids are uncapped, meaning there is no limit to how high bids can be, thus ensuring that the sea lease is won by the developer with the largest financial bid.

The auction format was introduced in 2023 by the German Federal Network Agency (BNetzA), and capacity of 9.5 GW has been auctioned at the time of writing, resulting in total government revenue of 1,560 mEUR (Bundesnetzagentur, 2023; Bundesnetzagentur, 2024c), well above the bids seen in other European marekts. While the president of BNetzA hails the bid levels as proof of the attractiveness of German offshore wind investments, industry experts have grown increasingly wary, with a press-release from WindEurope (2024) accusing it of being a "long-term cost to society", due to increased costs in development. At the time of writing, more uncapped financial auctions are expected. The Danish government announced that their auctions for 2024 and 2025 worth 6 GW offshore wind capacity, will be purely based on financial criteria (Danish Energy Agency, 2024). Meanwhile, the German government has listed a total of 6 GW of non pre-examined sites to be auctioned in the coming three years on the Union Renewable Development Platform (European Commission, n.d.). The Dutch government held mixed criteria auctions, with financial criteria in 2024 (Government of the Netherlands, 2023). Jansen et al. (2022) estimate that auctions will account for 97% of global renewable energy procurements by 2030; this includes all types of auction. There are in other words reasons to believe that auctions are here to stay, with purely financial auctions likely to increase in prevalence as offshore wind technologies mature.

This paper exploits the fact that all willingness to pay information is disseminated into the bids in purely financial auctions, enabling a quantitative analysis of return expectations and market sentiment among German offshore wind farm developers. By incorporating auction theory on the final bid values and using data provided by the International Renewables Energy Agency (IRENA) and Aurora Energy Research, we construct an analysis of the underlying cost and revenue parameters used by developers in their project valuations. The underlying valuation parameters are estimated

using Monte Carlo simulations, where upper and lower boundaries for parameters depend on firm-side assumption on cost efficiencies. Due to an apparent asymmetry in bidding levels among the analyzed bidder population, we divide the firms into two types: normal and aggressive firms, where the former is assumed to exploit some degree of economies of scale in their forecast assumptions.

The main purpose of this paper is to analyze how industry participants' outlook on future revenues and costs, as well as internal strategies affects auction outcomes. Insights into market participants' investment outlook is valuable for policy makers and potential bidders. A recent Danish tender process received no bids (Jacobsen, 2024), underscoring the importance of accurately assessing market sentiment. According to Danish wind farm developer Orsted, they chose not to bid due to an unfavorable risk-reward balance and changing industry factors (Jacobsen, 2024). This highlights the need for policymakers to carefully evaluate market conditions when designing auctions. The methodology used in this paper can be used in other contexts too, assuming there is data on auction bids and revenue and cost forecasts. Offshore wind auctions in Germany provide an ideal case for such an analysis, due to their uncapped financial bids and the availability of cost and revenue data, which, combined with the importance of the market justifies the country as the research subject in this analysis.

The primary contribution of this paper is the development of the methodology for calculating the implied hurdle rates of the winning bid. Hurdle rates represent the lowest required yearly return of the bidders, thus giving indication of how firms assess the attractiveness of offshore wind farm investments. This approach can be extended to analyze offshore wind auctions in other markets too, provided the winning bid accurately reflects the true willingness to pay of the participants. Since most auctions are designed to ensure that bids reflect bidders' willingness to pay, it is likely that the methodology can be used outside the scope of Germany. To test the model and likewise analyze the German offshore wind auctions, we perform a quantitative analysis which calculates implied nominal hurdle rates, providing insight into how firm strategy differed in 2023 and 2024. The main finding is that implied hurdle rates were notably lower in 2023 than in 2024, indicating a worsening market environment. Hurdle rates were calculated as between 6.4% - 8.72% in 2023, and 9.62% - 10.42% in 2024. Another finding highlights the importance of wake losses, which can explain the perceived willingness to pay reduction for the N-9 auction sites.

The paper is organized in five sections. Section 2 includes a literature review and an institutional background on the German non pre-examined auction sites and their rules. The auction format and bidder strategies are modeled in section 3. Section 3 also presents the data and the parameter distributions that are used in the auction model. Section 4 presents the main findings of the model, which are discussed in greater detail in section 5. Finally, section 6 concludes.

2 Background

The purpose of this chapter is to give the reader insight into foundations of auction theory, how it has been applied to offshore wind auctions, and how the German offshore wind auctions are structured.

2.1 Literature Review

This subsection first covers core auction theoretical concepts, with a focus on the standard auction formats and the Revenue Equivalence Theorem (RET), as well as the effect of risk neutrality and asymmetric bidders. We will also explore the applied auction theory literature for offshore wind auctions, to see how these concepts can be modeled for real-world applications, which is the purpose of our paper.

2.1.1 Auction Theory

The application of game theory to auctions was first introduced by Vickrey (1961), thereby founding auction theory as a discipline. In the paper, Vickrey (1961) sought to analyze auction mechanisms and competitive bidding in imperfect markets, where he introduced the second-price auction mechanism: a novel auction format where the highest bidder win the auctioned object and pays the price of the second-highest bid. To analyze bidder strategies, he proposed that bidders' valuation of the auctioned object were drawn independently from a common value distribution. This is the first formulation of the later widely used independent private valuation (IPV) framework. He then applies the framework to show that English auctions, where prices increase gradually until only one bidder remains, produces the same expected revenue to the seller as the sealed-bid second-price auction. He likewise proves that Dutch auctions, where price gradually decrease until a bidder accepts to pay it, and sealed-bid first-price auctions are revenue equivalent. He would expand on the strategic aspect of the standard auctions under different circumstances in his 1962 paper, introducing mechanism design to the analysis of auctions (Vickrey, 1962).

Vickrey's (1961; 1962) foundational contributions to auction theory in general and the RET in particular were later expanded upon by Myerson (1981)) and Riley and Samuelson (1981). These two works, developed independently, generalized the RET beyond the four standard auction formats (first-price, second-price, English, and Dutch) to apply to broader classes of auction mechanisms. Riley and Samuelson (1981) prove that the expected revenues remain equivalent across auction formats as long as the assumptions of independent private values, symmetric bidders, risk neutrality, and efficient allocation hold (meaning the highest valuation bidder wins the auction). Myerson's (1981) proof of the RET uses optimal mechanism design and is more general. He shows that the

RET holds under any auction mechanism as long as it ensures incentive compatibility for participants and efficient allocation.

The early development of auction theory is not limited to the RET. Wilson (1969) introduced a common value (CV) framework, where bidders compete for an auctioned object that has the same *ex-post* value for all bidders. IPV and CV are model-wise polar opposites. In IPV, bidders have private valuations of the auctioned object, and are content winning the auction at any price lower than their valuation. The CV framework developed by Wilson (1969) posits that bidders have private valuations, but the true valuation of the auctioned good is unknown and equal for all bidders. The symmetrically distributed private value component of the object's value reflects the lack of information about its true value. Winning a CV auction is therefore often bad news, because it means you were the bidders to overvalue the object the most. Capen et al. (1971) were first to formally analyze the phenomenon, and found that the failure to account for the winner's curse could explain the low profits of oil companies on offshore tracts in the 1960's.

Milgrom and Weber (1982) would later introduce the affiliated values (AV) framework, and show that expected revenue differ due to differences in informational dissemination. The AV framework is essentially a hybrid between the CV and the IPV format. Affiliation implies that bidders valuations are correlated, meaning that if one bidder has a high valuation, other bidders are likely to have high valuations too. They show that the optimal auction depends on whether bidders' valuations are CV, IPV, or AV, implying that the RET does not always hold. Information dissemination, they show, explains why auctions under either CV or AV tends to produce higher revenue in English auctions, where much information about competitors' valuations is shared, given by the price where bidders decide to drop out of the auction. This is not the case, they point out, in sealed-bid auction formats, making bidders bid lower due to greater uncertainty of competitors' valuations.

The papers Vickrey (1961), Vickrey (1962), Myerson (1981), Riley and Samuelson (1981), Wilson (1969), and Milgrom and Weber (1982) define the theoretical underpinnings of auction theory, and later analysis delves deeper into how different dynamics in the auctioned object and bidder populations affects outcomes. Maskin and Riley (1984) analyze risk averse bidders, and find that first-price auctions produce greater revenue to the seller than second-price auctions. The reason being that risk-averse bidders weight the risk of losing the auction higher than the potential reduction in profit from bidding closer to ones valuation. It remains, however, a weakly dominant strategy to bid one's own valuation under the IPV framework. Maskin and Riley (1984) thus highlights the mechanism which makes the RET not hold under risk-averse bidders.

Matthews (1987) takes the bidder's perspective of risk aversion and shows that Maskin and Ri-

ley's (1984) finding does not necessarily imply that risk averse bidders prefer second-price auctions or English auctions. He highlights how the modeling decision for risk aversion determines bidder preferences of different auction formats, where bidders are indifferent between second-price auctions and first-price auction under *constant* absolute risk aversion. Bidders with *increasing* absolute risk aversion do, however, prefer second-price auctions, as argued by Maskin and Riley (1984).

Asymmetry in bidders' valuations is another fundamental aspect to auctions. Symmetry implies that bidders are drawn from the same value probability distribution, meaning that all bidders have a similar idea of the value of the auctioned object. This is obviously not always true in real life, where one type of bidder can systematically value an object higher than another type. Myerson (1981) introduced bidder asymmetry in his paper, when showing that any two auction designs that lead to the same allocation of the auctioned good yield the same expected revenue. Bulow and Roberts (1989) would later build a useful framework for analyzing the effect of asymmetric bidders, where they developed the relationship between marginal revenue of bidders and profit-maximizing sellers. They show that revenue-maximizing sellers allocate the object to the bidder with the highest marginal revenue, not necessarily the bidder with the highest valuation.

McAfee and McMillan (1989) make a similar finding to Bulow and Roberts (1989) in the context of government procurements. Asymmetric bidder does, in other words, not always ensure efficient allocation – where the highest valuation bidder wins – indicating that the RET does not hold in the context. The implication of asymmetry in the IPV framework is, as described by Maskin and Riley (2000), that low type bidders prefer sealed-bid first-price auctions, while strong bidders prefer English auctions. The major difference between the two auctions with asymmetry is that in the latter, it remains weakly dominant to bid ones' valuation. Weaker bidders will, on the other hand, bid more aggressively in first-price auctions due to having relatively higher marginal revenues (Klemperer, 2004).

Asymmetry may introduce issues for modeling as there may not exist a unique Nash equilibrium in sealed-bid first-price auctions. Lebrun (1999) analyzes the existence of equilibria in first-price auction, and found that while pure strategy equilibria exist, they are not necessarily unique. Lebrun (2006) expands the analysis of asymmetric equilibria and shows that there can exist a unique monotonic equilibrium bidding strategy even in asymmetric settings, given specific assumptions on bidders' valuation distributions. Fibich and Gavious (2003) use perturbation analysis to estimate the difference between the symmetric Nash equilibrium, and asymmetric equilibria in sealed-bid first-price auctions. They found that the difference in outcome is small under weak asymmetry, highlighting the possibility of approximating the asymmetric Nash equilibrium using the symmetric Nash equilibrium.

Asymmetry's effect on auction outcomes is more pronounced under CV auctions, where bidders must avoid the winner's curse. Milgrom and Weber (1982) point out how the existence of the winner's curse forces bidders to shade their bids to minimize the risk of overbidding, and how the optimal strategies depends on how information is disseminated over the course of the auction. Klemperer (1998) shows how asymmetry in CV auctions strengthens the effect of the winner's curse in English auctions, since winning against a high value bidder is even worse news than winning the object under symmetry because it implies a greater overpay.

The auction theory literature is remarkably vast and it is impossible to cover all of it in a literature review, so we focused on the foundational theories applied in our thesis. The next subsection focuses on the application of auction theory to the more recent field of renewable energy auctions, and how it has been used to analyze outcomes and the underlying market structure, which is the purpose of this thesis.

2.1.2 Applications of Auction Theory to Offshore Wind Auctions

The use of auctions to distribute and facilitate the development of renewable energy resources such as offshore wind is a recent phenomenon, although one that is spreading rapidly. Jansen et al. (2022) predict that 97% of global renewable procurement will take place through auctions by 2030. Not all auctions are the same however, as tenders in more developed offshore wind markets are becoming less focused on subsidy schemes. A key reason behind the move from subsidy schemes to more general auction formats is most likely due to the decrease in costs seen within the offshore wind industry (International Renewable Energy Agency, 2023b; International Renewable Energy Agency, 2024). The non pre-examined German offshore wind auctions analyzed in this paper is a case in point, which includes both a subsidy component and a financial bid component (which will be discussed in greater detail in the institutional background).

Much of the literature on renewable energy auctions has focused on how the policy can be used to efficiently distribute development rights contracts and subsidies. Kitzing et al. (2012) explore the evolution of auction designs in response to market and policy changes. Their work highlighted the dynamic nature of auction mechanisms and the need for continuous adaptation to ensure their effectiveness. Jansen et al. (2020) provide an in-depth analysis of offshore wind auctions globally, focusing on auction design elements like contract length, revenue stabilization mechanisms, and grid connection responsibilities. They point out the challenges facing offshore wind bidders of high capital costs, lengthy project timelines, and location-specific risks are key drivers for auction outcomes.

There are also papers that analyze offshore wind auctions using frameworks from auction the-

ory. Kreiss et al. (2017) analyze renewable energy auctions using an IPV model to establish the importance of prequalifications to bid in auctions, and penalties for non-compliant winners, who fail to develop the resource. Winkler et al. (2018) investigate the role of strategic behavior in renewable energy auctions. They find that bidders with asymmetric cost structures or private information about project risks tend to behave more conservatively, which can influence auction outcomes. In the context of offshore wind, Haufe and Ehrhart (2018) examine the impact of bidder heterogeneity on competition, noting that larger developers often enjoy economies of scale, giving them a competitive edge.

The papers most similar to this thesis are Kell et al. (2023), and Malleret et al. (2024), who use Monte Carlo simulations to structure cost and revenue estimates in UK contracts for difference auctions. Their study focuses on contract for difference auctions in the UK, where bidders compete on the lowest fixed price they require to develop the wind farm. To do this, they applied a CV auction model, meaning all bidders value the object the same, with some individual differences due to firms' failure to accurately assess the true costs. There are to the best of our knowledge no papers that analyze the more recent development of financial auctions with dynamic bidding, where bidders pay for the right to develop a wind farm. Our paper aims to fill the knowledge gap and at the same time provide a methodology that can be expanded beyond the German context.

2.2 Institutional Background

Auctions have been a modus of resource allocation throughout civilized history. Ancient historian Herodotus reports of auctions in Babylon as early as 500 BC (Milgrom and Weber, 1982). Given its long history, it should come as no surprise that there are varying methods of auctioning objects. Economists have defined four standard auction methods based on key differentiating mechanisms: first price auctions, where the winner pays the value of the winning bid; second price auctions, where the winner pays the value of the second highest bid; Dutch auctions, where the price gradually falls until a bidder agrees to pay it; and finally the English auction, where the price gradually rises until only one bidder remains. The implications of the different auctions was reviewed in the previous subsection, and the purpose of the institutional background is to explore how the findings relate to the German offshore wind auctions.

The BNetzA deploys two different types of auctions for offshore wind in Germany: pre-examined auction sites and non pre-examined auction sites. We will focus on the latter, but it is worthwhile to explain the difference between the two. The pre-examined auction sites have been investigated by the Federal Maritime and Hydrographic Agency (BSH), who gathers data on marine environment, subsoil, wind, oceanographic conditions, and traffic suitability (Bundesnetzagentur, 2024c).

The auction criteria for these sites include a mix of qualitative criteria, including environmentally friendly foundation methods, green steel in construction, and financial bids (Bundesnetzagentur, 2024c). However, limited resources on behalf of the BSH and the ambitious renewable energy goals of the German government saw the necessity of introducing a second type of auction: the non pre-examined auction sites, where any site investigations have to be performed by the bidders themselves. The winner in non pre-examined auctions is entirely decided by the size of the financial bids. Unfortunately, criteria results are not published for the pre-examined auctions, making it difficult to analyze the outcomes. The winning bids are, however, announced in non pre-examined auctions. This transparency is the key reason why we focus our attention on the latter type.

2.2.1 Non Pre-examined Site Auction

Non pre-examined auctions are split into two stages: a subsidy auction and a dynamic, financial auction. In the first stage, participants bid the minimum subsidy level they require (Bundesnetzagentur, 2024a). If two or more zero-cent bids are made, the auction moves on to the second stage. All zero-cent bidders are invited to the dynamic auction, where the lease winner is decided by the highest financial bid (Bundesnetzagentur, 2024a). All non-developed auctions to date have progressed to the dynamic stage, and the German government have received over 1,500 mEUR for generation capacity worth 9.5 GW over the six auctions, indicating a high willingness to pay.

The dynamic auction mostly resembles an English auction, as prices rise gradually over time and bidders may drop out at any point. However, there are slight technical differences. Zero-cent subsidy bidders are invited by BNetzA to the dynamic bidding process, which takes place Monday to Friday, between 9 AM and 4 PM (unless there are national holidays). Prices rise by 30,000 EUR/MW in every round, unless there are only two bidders remaining; then the increment is reduced to 15,000 EUR/MW. The bidding process will continue until there is only one bidder remaining. Table 1 shows an example of a dynamic bidding process with 5 participants. A participant may make an intermediate bid if they do not agree to the incremented price required to advance to to the next round. The intermediate bid can be any value between the bid values of round n and $n+1$. Hence, every participant can bid precisely up to their preferred dropout price. Additionally, BNetzA informs participants of the number of active participants in the auctions they are active in.

Table 1: Dynamic Bidding Process

Round	Start Time	End Time	Increment (€/MW)	Bid Value (€/MW)	Bidders
1	9:00 AM	9:20 AM	30,000	30,000	5
2	9:30 AM	9:50 AM	30,000	60,000	5
3	10:00 AM	10:20 AM	30,000	90,000	4
4	10:30 AM	10:50 AM	30,000	120,000	4
5	11:00 AM	11:20 AM	30,000	150,000	3
6	11:30 AM	11:50 AM	30,000	180,000	3
Lunch Break					
7	12:30 PM	12:50 PM	30,000	210,000	3
8	1:00 PM	1:20 PM	30,000	240,000	3
9	1:30 PM	1:50 PM	15,000	255,000	2
10	2:00 PM	2:20 PM	15,000	270,000	2
11	2:30 PM	2:50 PM	15,000	285,000	2
12	3:00 PM	3:20 PM	15,000	300,000	2

The dynamic auction is a slightly unorthodox version of the traditional English auction. The combination of incremental bid increases and the possibility of intermediate bids means that participants can bid precisely up to their preferred drop out price. For the structure of the non-developed offshore wind auctions, it suffices to conclude that i) bidders are well-informed of the number of bidders remaining in each round, and at what price they drop out at, ii) a bidder may be active in multiple auctions simultaneously, iii) all bidders, except for the winner (who never reaches their dropout price), are unconstrained to bid up to their optimal dropout price, iv) re-entry is forbidden, as bidders who dropout fail to qualify to the next round, and v) anonymous bids mean that participants do not know who drops out at what price. As will be discussed in the auction model section, the winning bid yields information of the bidder with the *second-highest* highest valuation.

There is a clear trend of large European oil and gas companies winning the non pre-examined auctions in Germany. Notably, British Petroleum (BP) and French oil and gas giant TotalEnergies have won five of the six auctions, or 8.5 GW out of the 9.5 GW capacity auctioned, as shown in Table 2. Table 2 provides a summary of bid price, number of participants, and winner. The dominance of large international energy companies suggests that they have a greater willingness to pay than their competitors. We will elaborate more on the effect on the asymmetries in willingness to pay between international and regional energy companies for our model in the next section.

Table 2: Non Pre-Examined Offshore Wind Auction Results in Germany, 2023-2024

Year	Auction	Capacity (MW)	Winning Bidder	Bid Price (EUR/MW)	Participants
2023	N-11.1	2000	BP	1,830,000	8
2023	N-12.1	2000	TotalEnergies	1,875,000	8
2023	N-12.2	2000	BP	1,560,000	8
2023	O-2.2	1000	TotalEnergies	2,070,000	9
2024	N-11.2	1500	TotalEnergies	1,305,000	7
2024	N-12.3	1000	EnBW	1,065,000	8
2024	N.9.X*	4000	RWE	450,000	-

** N-9.X is N-9.1 and N-9.2 combined, which were auctioned in pre-examined offshore wind auctions. They are added here since RWE announced the winning bid price.*

Source: Bundesnetzagentur (2023; 2024).

3 Methodology

In this section, we take the information provided in the institutional background and apply the theoretical findings presented in the literature review, to model the auction and information structure which the bidders operate in. The section also describes the net present value (NPV) model used to approximate firms' valuation methods. Finally, the application of Monte Carlo simulations to estimate the winning bidders' cost and revenue parameters are discussed.

3.1 Auction Model

This section introduces the model on bidder strategies under the auction format used in German non pre-examined offshore wind. The ascending auction format used by the BNetzA resembles a hybrid between English auctions, where prices rise over time, and sealed-bid first-price auctions, where each bidder presents a single bid and the highest bidder wins. The hybrid characteristic is due to the round format, which splits every auction into several sub-auctions. Hence, each bidder is required to make a decision in every round of the auction, where their bidding strategy depends on their private valuation and bid amount required to qualify to the next round. We also show that the dynamic auction format enables the application of the Revenue Equivalence Theorem in the later rounds, allowing us to approximate the expected payment of the highest bidder.

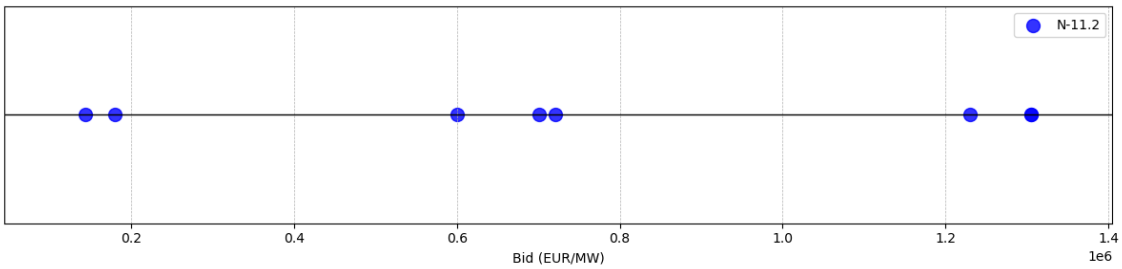
3.1.1 Key Assumptions

For the purpose of our model, we apply the IPV framework for bidders' valuations. The key implication of this assumption is that bidders' valuations are unaffected by the valuations of their competitors. The motivation for applying the IPV framework derives from an underlying assumption that each firm values the project based on internal cost and revenue assumptions. The internal valuations are then used by the agent(s) who represent the firm in the auction. We argue that

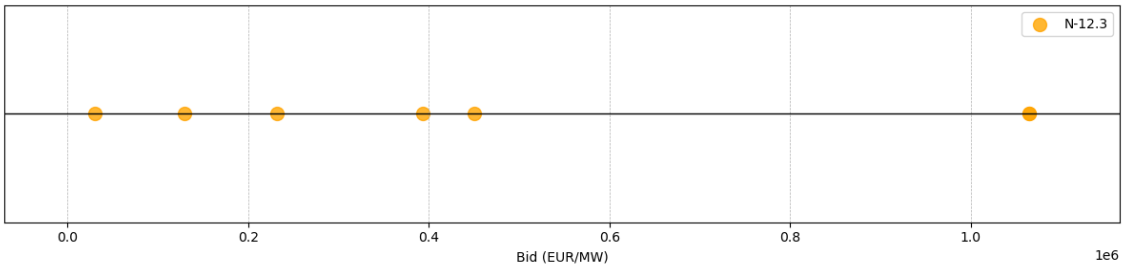
firm-specific strategies reduce the importance of the common value component, which is the value of the wind resource; the quality of the wind resource, is of course, the same for all bidders for any given auction site. The argument for IPV is supported by the low variance in auction winners, as shown in Table 2. Large oil and gas companies seemingly have a strategy profile that causes them to be systematically more aggressive in their valuations compared to their competitors, and this lends itself more to the IPV framework than the CV framework, where the underlying value is assumed to be the same for all bidders. Strategic decisions, such as portfolio diversification, mean that the same project and wind resource may not have the same value to all bidders.

It would also be reasonable to apply the AV framework, where bidders' valuations are correlated, essentially representing a hybrid between the IPV and the CV framework. Data constraints and difficulties in modeling sustainable Nash equilibria unfortunately hinder the usage of the framework. Hong and Shum (2003) presented a method for analyzing outcomes in asymmetric Nash equilibria, but the method requires the researcher to have access to all bids. Unfortunately, we only have access to all bids in the 2024 auctions, which constitutes $2/7$ of the auctions analyzed. Thus, we proceed with IPV for the rest of the analysis. The difference in modeling outcome between the AV and the IPV framework is that the expected revenue will be slightly higher, as bidders bids more cautiously in the former framework to avoid the winner's curse (Milgrom and Weber, 1982).

Due to the apparent asymmetry within our bidder population, as evidenced by the concentration of auction wins by few actors shown in the previous section, bidders are divided into high and low types. As the name suggests, the former's valuations are derived from a probability distribution function with relatively higher valuations, compared to low-type bidders. If symmetry was assumed, we would expect auction winners to be more evenly spread among participants, which Table 2 shows is not the case. Take the example of TotalEnergies. Under symmetry, the probability of winning an auction would be $1/N$ for every auction they participate in, which is the chance of drawing the highest valuation. The probability of TotalEnergies winning the three auctions under symmetric IPV translates into a probability of $\frac{1}{8} \times \frac{1}{9} \times \frac{1}{7} \approx 0.2\%$ (taken from Table 2). Figure 1 displays line plots of bids made in the two 2024 auctions. A notable property is that two or three participants place significantly higher bids than the rest. BNetzA unfortunately never uploaded such granular bid data for the 2023 auctions, so the figures cannot be replicated for the other auctions. Moving forward, we refer to high valuation bidders as *aggressive* bidders, and low valuation bidders as *normal* bidders.



(a) N-11.2 Plot



(b) N-12.3 Plot

Figure 1: All Auction Bids in 2024

To structure the analysis, we assume that each bidder i assigns a net present value (from here one simply valuation) v_i to the auctioned object from a random normal distribution V that is based on their costs, revenues, and strategy (this is further elaborated on in section 4.2), which represents their valuation and the highest price they are willing to pay. Under the assumption of rationality, bidders will maximize their expected profit. We assume that every valuation is independently and identically distributed in some non-negative number interval, $V \in [0, \omega]$ according to the increasing distribution function F_t, for type t, where ω is any valuation up to ∞.

In addition, we assume that F_t admits a continuous density $f_t \equiv F_t'$ and has full support. To allow normal firms to win auctions in the presence of aggressive firms, we assume the valuation distributions to have common support (meaning the probability distributions intersect), where the aggressive type's valuation distribution first-order stochastically dominates the normal type's distribution. Common support is added to ensure that auction results are not wholly represented by the aggressive type in the auction simulation, which we describe in greater detail in section 4.3. First-order stochastic dominance implies $F_{\text{aggressive}}(v) \leq F_{\text{normal}}(v)$, for the same valuation, v. Simply put, it means that aggressive types are more likely to have higher valuations than normal types.

Summarizing what the assumptions imply, we posit that valuations are continuous and non-negative. Within each distribution, a higher valuation implies that other competitors from the same type are more likely to have lower valuations. Finally, aggressive firms are likely to have higher valuations than normal firms due to the first-order stochastic dominance of their valuation distribution.

Continuing, we assume that every auction sells an indivisible good, with N potential buyers, and that the number of bidders is known among all auction participants in every bid round. This assumption is consistent with the auction format, where the number of bidders remaining is announced before every bid round. Another key assumption is that bidders are risk-neutral. The reason we make this assumption is further elaborated on in the next section, where we show that risk appetite is incorporated into the NPV model used to assign valuation distributions. Including risk-aversion in the auction model would cause us to double count it. Finally, we assume that bidders are unrestricted in terms of budget and liquidity constraints meaning that they can actually bid up to their valuation. Both assumptions are likely to hold for two reasons: bidders include financing costs in their net present valuation model (as will be shown in the next section), and there are financial penalties for failing to develop the project within the time frame set by BNetzA, as described in the Offshore Wind Energy Act (WindSeeG). Hence, valuations will reflect both budget and liquidity constraints, and there are clear disincentives to underestimate budgets, as any delay will lead to financial penalties.

The assumptions presented lay the foundation in defining bidder strategies. By adopting the IPV framework, we assume that bidders' valuations are derived independently, unaffected by competitors' valuations. This assumption aligns with the observed heterogeneity in bidder behavior, as evidenced by the dominance of certain large international firms in offshore wind auctions. The division of bidders into high and low valuation types reflects the asymmetry in the bidder population, providing a more realistic depiction of the prevailing auction dynamics. The assumption of risk-neutrality ensures that the model avoids double-counting risk preferences. Additionally, the assumption of continuous valuation distributions with full support allows for smooth and analytically tractable bidding strategies. The absence of liquidity and budget constraints implies that auction participants bid, and value their projects truthfully. These assumptions collectively establish a framework for analyzing bidder behavior and outcomes, which will be developed further in the next subsection.

3.1.2 Bidder Strategies

The institutional structure of the non pre-examined German offshore wind auctions described in section 2.2 highlights two key properties: bidders make decisions in every round, and participants will

drop out out over time as prices increase. In this subsection, we apply the structural assumptions presented in the previous subsection to model bidder strategies. Bidder strategies depend on the rules of the auction, and the ascending auction with bid rounds used by BNetzA creates important strategic considerations. With bidders forced to make decisions in each bid round, we will show that the strategy depends on their own valuation in relation to the *qualification price* - the bid amount required to qualify to the next bidding round. This subsection will also apply the RET to structure bidder decision-making, allowing us to make predictions of the Nash equilibrium at later bid rounds.

For clarity, we describe our bidder strategy formulation as if the bidders are symmetric. Bidder asymmetry has key implications for bidder behavior and the prevailing Nash equilibrium, but we will show that the rules of the ascending auction mitigate the effect of asymmetry at higher valuations, due to the bid round system. This set-up is sufficient since we are interested in the winning bid. The bid round system ensures that auction participants must place a bid in every auction round. If bidder i's valuation, v_i, is higher than the qualification price, they will simply place their bid to match it, as bidding lower would only decrease expected profit by greatly reducing the probability of winning. Equation 1 shows the expected profit of bidder i depending on if they win or lose the auction, where b_i is the *final* bid from bidder i. Note that the probability that two bidders have the same valuations, and therefore place the same bids, is zero due to the probability density functions values are drawn from is continuous.

$$E[\Pi_i] = \begin{cases} v_i - b_i \geq 0 & \text{if } b_i > \max(b_{j \neq i}) \\ 0 & \text{if } b_i < \max(b_{j \neq i}). \end{cases} \tag{1}$$

The reason we use expected profits is that bidders do not know the true value of the lease until after the wind farm's life-time. As expected, the bidder who submits the highest bid wins the auction, while all non-winners receive a profit of zero. Similarly, the expected profit of bidding one's valuation is zero. The actual, *ex post* profit may differ from zero in the case of winning, but bidders are making their decision on value projections, as represented by v_i.

Due to the bid round system, we must differentiate between round bids, z_{ir}, and the final bid, b_i, where r indexes the bid round. This distinction introduces the necessity of a piecewise bid strategy, $B(v_i, r)$, which gives an optimal bid strategy depending on which bid round the agent is in, and the resulting relation between the qualification price, δ_r, and v_i. Since bid amounts are accommodated by agent valuations, we assume that $B(v_i, r)$ is monotonically increasing in v_i. Equation 2 formalizes the relationship between bidding strategy and the size of valuation in relation

to the qualification price.

$$B(v_i, r) = \begin{cases} \beta^E(v_i) = \delta_r = z_{ir} & \text{if } v_i > \delta_r, \text{ for } r = 1, 2, \ldots, s_i, \\ \beta^F(v_i) = b_i & \text{if } \delta_{r-1} \leq v_i < \delta_r \text{ for } r = s_i + 1. \end{cases} \tag{2}$$

If a bidder's valuation is greater than the qualification price for round r, they bid according to the English auction Bayes-Nash strategy, $\beta^E(v_i)$, and if it is lower, the first-price sealed bid Bayes-Nash strategy, $\beta^F(v_i)$. Since δ_r depends on the bid round, we let s_i represents the highest round that bidder i will reach given their valuation. Note that the final round bid z_{is} can equal the final bid b_i if the bidder's valuation precisely matches the qualification bid from the prior round, or if no other bidder qualified to the last round, ie, $z_{is_i} = \delta_{s_i} = b_i$. The more general relationship between round bids for any round r and the final bid is of course $b_i \geq z_{is_i}$, as bidders can make incremental bids. Since incremental bids mean that a bidder bids below the qualification price for round $s_i + 1$, it is also the bidder's final bid, b_i. The implication of Equation 2 is that final bids and round bids have different strategic considerations. In their final bid round, s_i, a bidder's strategic consideration is the same as in a first-price sealed-bid auction, $\beta^F(v_i)$. In all other rounds, they bid as if participating in an English auction, $\beta^E(v_i)$.

Since the optimal bidding strategy for English auctions is simpler, we will begin by describing it. Milgrom and Weber (1982) describe the unique Nash equilibrium as a button game, where each bidder is assigned a random valuation, and prices increase continuously over time. Each bidder maximizes their expected profits, meaning they try to maximize the difference between their valuation and their bid price. By holding the button depressed, the player remains in the game, and if they release the button, they exit it. A player wins when all competitors have exited the game. Milgrom and Weber (1982) show that it is a weakly dominant strategy to stay in the game precisely until the price matches your valuation; exiting earlier ensures that you lose the auction, and staying after ones valuation ensures negative profits. A player that keeps the button depressed up until their valuation will at worst have a profit of zero, while having a non-zero chance of winning the auction at a price lower than their valuation. Thus, it is weakly dominant to stay until one's valuation. Their abstraction of the English auction succinctly highlights the unique Nash equilibrium in IPV English auctions, where it is weakly dominant to stay in the auction until expected profits reach zero.

For the bidding strategy described in Equation 2, this implies that a bidder will keep 'holding the button' until the qualification price exceeds their valuation. Bidding the qualification price in each round up to ones valuation is therefore strategically equivalent to the button game, although time is incremental rather than continuous: the only difference is that the increments force a bidder to 'release the button' at their highest obtainable bid round, s_i, instead of precisely at their

valuation. Hence, the incremental structure of the bid rounds means that $\beta^E(v_i)$ is only optimal up until δ_{s_i}. Note that the bidding strategy in English auctions is the same regardless of it having symmetric or asymmetric bidders, as the bid strategy is independent of competitors' valuations.

The more complicated decision is when bidders must place a final, intermediate bid, when they cannot qualify to the next round due to their valuation being lower than the qualification price. In other words, when $B(v_i, r) = \beta^F(v_i)$. In the bid round where bidders are forced to place their intermediate bids, the auction structure resembles that of a first-price sealed bid auction. A glance at Equation 1 suggests that bidding such that $v_i = b_i$ produces an expected profit of zero, the same as you are guaranteed if you lose, or do not enter the auction at all. Vickrey (1961) shows that there are unique Nash equilibrium strategies for symmetric IPV bidders in first-price sealed bid auctions, where bidders shade their bids (bid lower than valuation) to maximize expected profit. However, Lebrun (1999) shows that a unique Nash equilibrium is not guaranteed in the case of asymmetric bidders. A unique Nash equilibrium is necessary for modeling purposes, since it is otherwise impossible to predict the outcomes of the auction.

Lebrun (2006) extends the analysis of unique equilibria in asymmetric first-price auctions where he shows that a unique Nash equilibrium exists under specific conditions: bidders' valuation probability distributions have common support, their support is bounded, and they are log-concave (such as the normal distribution). All requirements hold for the bidders' valuation distributions in our analysis. The common support assumption for bidder valuation distributions makes the first condition hold, while the Central Limit Theorem ensures that the valuation distributions are normally distributed, meaning the probability distribution function is log-concave. Finally, the support of any valuation distribution is bounded because the underlying cost and revenue parameters are bounded – this is further discussed in the next subsection. The existence of a unique Nash equilibrium highlights the possibility of applying the RET to estimate $\beta^A(v_i)$ using the well-defined bidding strategy of $\beta^E(v_i)$.

Our analysis focuses on the winning bids, and we argue that asymmetry will become weaker the longer an auction progresses due to the bid rounds system, which essentially divides the auction into several sub auctions. Under weak asymmetry we find that weaker bidders bid more aggressively in relation to their valuation compared to the stronger bidders (Klemperer, 2004). Normal bidders are thus, in our application, expected to place more aggressive bids than aggressive firms in relation to their valuation (aggressive bidders have aggressive valuations, not aggressive bid strategies), which affects the Nash equilibrium outcome; but this effect will be subdued at higher bid rounds since the probability of normal bidders reaching that far is low. Taken together, we argue that there will be either symmetry or weak asymmetry at high bid rounds, allowing us to posit that the RET will approximately hold in the bid round where the winning bid is placed.

Riley and Samuelson (1981) highlight that the RET holds under the following conditions: i) bidders are risk neutral, ii) the expected payment from a bidder with a zero valuation is zero, and iii) bidder valuations are IPV and symmetric. The first two assumptions will always hold in our auction model. Since our model is based on an NPV model (which is introduced in greater detail in section 3.2) with strategic hurdle rates that incorporate risk, applying risk aversion to agent's bidding behavior would double count it. Bidders will therefore bid as if they are risk neutral. As for the second requirement, bidders with a zero valuation in our auction model are never required to pay anything, as there is no auction mechanism that forces bidders to pay unless they win. Since a zero valuation bidder will never bid anything, their payment is always zero, meaning the second requirement holds.

The third requirement is obviously problematic, since we have already established that bidders are asymmetric. While bidders are IPV within types, the asymmetry assumption causes RET to not hold in general. However, as shown by Fibich and Gavious (2003), the weak asymmetry Nash equilibrium closely approximates the symmetric Nash equilibrium. This means that it is possible to apply the RET at the final bid round with a slight measurement error if there is asymmetry. The process of auction simulation, which we discuss in section 3.3, means that the simulated auctions will contain a mix of symmetric and weakly asymmetric final bids. The expected winning bid, estimated from 100,000 auctions, will help mitigate the measurement error, as simulated auctions with weak asymmetry are a subset of the total number of simulated auctions. Hence, the measurement error from applying the RET to calculate final bids is expected to be small, meaning that the auction model's calculated bid value is similar between the English auction bid strategy, and the first price sealed-bid strategy, ie, $\beta^E(v) \approx \beta^F(v)$. In other words, we approximate the *winning* bid using the well-defined, unique Nash equilibrium strategy of English auctions, where the winning bid is estimated under $B(v_i, r) = \beta^E(v_i)$.

The bidding strategy of the winning bid, $\beta^E(\max(v))$ can thus be defined as the optimal strategy employed in symmetric IPV, English auctions. For ease of notation, we write the highest valuation, $\max(v)$ as v^* going forward. As stipulated by Vickrey (1961), an English auction is strategically equivalent to a second-price auction; it is weakly dominant to bid one's valuation in both, $\beta^E(v_i) = v_i$. English auctions are therefore commonly referred to as second-price auctions. Since the Bayes-Nash strategy is to bid truthfully, the winning bid is entirely decided by the realized valuations of the N participants, where the highest valuation bidder wins and pays the valuation of the second-highest bidder. The resulting expected payment for bidder i, with any valuation v_i is defined by $m(v_i)$ in Equation 3, where Y is the second highest valuation, and $G(v_i) = F(v_i)^{N-1}$ is the probability that bidder i has drawn a valuation from the cumulative distribution function F that is greater than all other bidders' valuation.

$$
\begin{aligned}
m(v_i) &= \text{Prob[Win]} \times E[\text{2nd highest bid} \mid v_i \text{ is the highest bid}] \\
&= \text{Prob[Win]} \times E[\text{2nd highest value} \mid v_i \text{ is the highest value}] \\
&= \text{Prob}[v_{j \neq i} < v_i] \times E[Y \mid v_{j \neq i} < v_i] \\
&= G(v_i) \times E[Y \mid Y < v_i]. \qquad (3)
\end{aligned}
$$

The first equality in Equation 4 is given by the fact that in second-price auctions, the highest bidder pays the value of the second highest bid. In English auctions, this is implicit since the highest-valuation bidder never gets to bid truthfully - the auction ends as soon as the second highest-valuation bidder drops out. The second equality holds because bidders bid truthfully. Equality three simply defines the likelihood of winning as the probability of having the highest valuation, and that the expected payment is Y, conditional on having the highest valuation. After all, only the winner makes a payment. Finally, equality four defines the expected payment as the probability of drawing the valuation from the cumulative distribution function $F(\cdot)$, as defined by $G(\cdot)$. It is obviously the case that the highest valuation is greater than the second-highest valuation, as formalized by the condition in $E[Y \mid Y < v_i]$.

Our analysis only focuses on the winning bids because they define the highest willingness to pay among German offshore wind auction participants, and since RET only holds at late bid rounds. By definition, the highest bid v^* will have $G(v^*) = 1$, and $v^* > Y$, meaning the winning bid is $E[Y]$. We can therefore assume that the winning bid approximately equals the valuation of the second-highest bidder, $m(v^*) \approx v^{2:N}$. This fact is useful when performing the auction simulations, which are presented in subsection 4.3.

3.2 Agent Simulation

Our analysis deploys a NPV model to represent firm valuations. The NPV framework is simple and incorporates key economic and decision variables, allowing us to calculate the value of the investment at the time of the auction. The reasons for using this model are twofold. Firstly, the value drivers of an offshore wind project can be divided into revenue and cost estimates, for which there are forecasts. The availability of data for key parameters enables a quantitative analysis of project valuation using Monte Carlo simulations, which is used to estimate the input parameters used by bidders. The benefit of the Monte Carlo simulations is that while the true parameter estimates that bidders apply in their valuations remain unknown, they should lie within boundaries that are reasonable given the market outlook at any point in time.

Secondly, although the bidding firms likely have more complex valuation models than the one presented in this section, we argue that more detailed aspects of a firm's valuation are implicitly captured in the strategic component of the hurdle rate. Financing costs, operational expenses (OPEX), capital expenses (CAPEX), prices, and capacity factors are quasi-exogenous to the firm, as they are determined by financial markets and the physical realities of harnessing energy from wind. A firm may have specific beliefs about these factors based on its own experience and forecasting assumptions, but we assume that any such beliefs are well-anchored in economic reality.

For example, a firm could internally argue that a project's CAPEX costs will be zero, allowing its valuation — and thereby bids — to be higher, but such unrealistic assumptions will likely lead to overbids and, if they win, negative profits. A profit maximizing firm is therefore incentivized to ensure that all valuation parameters are realistic. It is common within the renewable energy industry to benchmark internal cost and revenue assumptions with external forecasts to minimize the risk of over- and undershooting parameter values. The prevalence of benchmarking suggests that forecasts from major energy consultancies can be used to approximate the internal forecasts of firms. Even if there are firms that produce internal forecasts without benchmarking it to external forecasts, it is likely that resulting forecasts vary within a reasonable range from consultancies' forecasts since the same underlying parameters will have to be analyzed. To generate the distributions for bidder types and ensure sufficient density, valuation draws are iterated 200,000 times per type. Each auction analyzed has unique bidder valuations generated for it depending on the auction's characteristics.

3.2.1 Net Present Value Model

Equation 4 presents the NPV model that is used to estimate bidder valuations. V_i represents bidder valuation, R_{it} is revenue, O_{it} is OPEX, C_{it} is CAPEX, and H_{it} is hurdle rate. A hurdle rate is the minimum required rate of yearly return that the firm expects. $R_{it} - O_{it}$ represents the cashflow over the wind farms operation period, T, and H_i is the rate that the cashflow is discounted with. Financing starts roughly two years before the commercial operation date, when capital expenditures are incurred. For simplicity and ease of notation, we calculate all capital expenditures as occuring in the first year of operation. Since the same NPV model is applied to all auctions, we defer notation for any individual auction. However, the input values change depending on the auction. Walgern et al. (2023) found that it is profitable to extend the life-time of existing offshore wind farms beyond 25 years in over 80% of cases. This statistic is likely higher for future wind farms due to technological progress, meaning we assume that all bidders assume a ten-year life extension in their valuations (as allowed by the BNetzA). Hence, $T = 34$, by adding the allowed ten-year extension to the 25-year lease.

$$V_i = \sum_{t=0}^{T} \frac{R_{it} - O_{it}}{(1 + H_i)^t} - C_i \tag{4}$$

The parameters used in our analysis are slightly more involved than what Equation 4 suggests. Starting with revenue, the parameter is a function of the transmission capacity assigned by BNetzA, Z, locational wake effects, μ_{it} from surrounding wind farms that deteriorate nearby wind resources, and the capacity factor, CF_{it}, which represents the difference between actual production and maximal production. The capacity factor is essentially an estimate of wind energy's intermittency, since wind levels are not always optimal for the turbines' power generation. Multiplying net power generation by price forecasts, $P_{it} + G_{it}$, where P_{it} is wholesale price and G_{it} is Guarantee of Origin (GoO), yields undiscounted revenue:

$$R_{it} = \mu_{it} \times CF_{it} \times Z \times (P_{it} + G_{it}).$$

If we subtract the undiscounted OPEX from the undiscounted revenue, we get the undiscounted operational earnings, $R_{it} - O_{it}$, which we discount over the hurdle rate to calculate discounted earnings. The overwhelming majority of European renewable energy projects are financed off-balance sheet using project financing (International Renewable Energy Agency, 2023b). The popularity of project financing implies the existence of project-specific discount rates, which we argue can be split into two components: a purely financial component, the weighted average cost of capital (WACC), W_i, and a strategic component, σ_i, which incorporates potential benefits that the project

contributes that cannot be directly attributed to the profitability of the project itself.

An example of such a benefit is portfolio diversification, a factor that cannot reasonably be modeled as either revenues, OPEX, or CAPEX for the project in question, but affects the firm's valuation nonetheless. The revenue diversifying firm would hence apply a relatively low or even negative value to the strategic component. In contrast, a firm with several potential investments may instead have greater opportunity costs, which can be accounted for by applying a high, positive value to the strategic component. Finally, the strategic component can also be zero, which means that the hurdle rate equals WACC. A combination of the strategic component and WACC produces the following equation for hurdle rates.

$$H_i = \sigma_i + W_i$$

Each inputted parameter in the NPV model comes from predefined distributions, that are slightly different based on whether the agent is a normal or aggressive type. We then simulate valuations according to the NPV model 100,000 times to generate the valuation distributions of the winning bid. The resulting valuation distributions are normally distributed, as stipulated by the Central Limit Theorem, and the support is given by the differences in inputs defined by bidders type. How the parameters and their distributions are defined is assessed in detail in the next section. Figure 2 presents a high-level illustration of how the valuations are calculated, where each input parameter is randomized over a pre-defined statistical probability distribution.

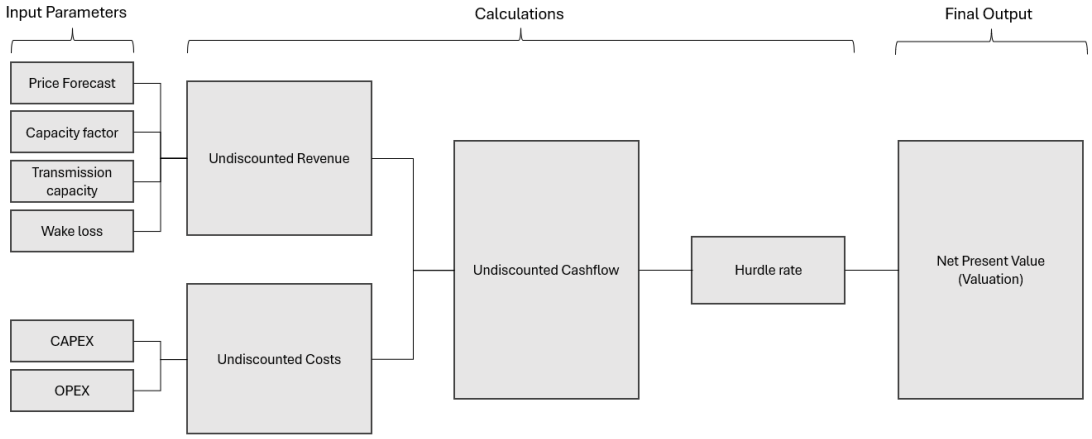


Figure 2: Net Present Value Model

3.2.2 Net Present Value of Bid

We also have to account for the net present value of the winning bid, which is made in nominal terms. Only 10% of the bid amount is paid the year after winning the auction. The rest of the bid payment is made over 20 years, starting at the commercial operation date (COD). If we take an auction in 2023 as an example, where the COD is 2030 (Bundesnetzagentur, 2023), a significant amount of the value in NPV terms will have been lost. By applying a NPV to the bid's payment structure, we estimate the actual value of the bid that bidders use in their valuation. The payment structure means that the sum of payments in real terms is in total worth 26.1% less than if the entire bid payments was made within a year of the auction, assuming 2% inflation. If we were to apply a nominal discount rate of 8%, the net present value of the bid decreases by 64.96%. When we calculate the implied hurdle rates of the winning bid, we multiply the bid amount by each winning bidder's hurdle rate, $1 - H_i$, thus internalizing the bid payments into operating cashflow, which is natural since bid payments essentially represents a rent payment to the German government.

3.3 Data and Parameter Distributions

In previous sections, we defined how the valuations of the bidder population is drawn from asymmetric distributions, which we divided into aggressive and normal types. We have also shown that bids ultimately depend on valuations, which are derived from the NPV model. This section expands on the sources of asymmetry, and how it inputted into the model to derive the type-specific valuation distributions. Not all parameters are likely to differ between the types: we assume that

aggressive and normal types do not systematically disagree over price forecasts, the value of the wind assets, or wind turbine capacity factors. Kreiss et al. (2017) point out that all bidders are subject to the same future wholesale prices and component costs, which implies that firms' costs and revenues estimates lie within a reasonable boundary; that is not to say that their estimates turn out to be correct, just that robust analysis of the underlying market dynamics should result in parameter estimates that do not systematically depart from each other. Furthermore, we argue that aggressive bidders rely on economies of scale assumptions, and potentially lower hurdle rates to justify their relatively higher valuations, which could be reflected by higher risk appetite, lower financing costs, or firm strategy in general.

The choice of parameter distributions is an important consideration when performing simulations. Since all parameters are determined by either financial markets or physics, we will mostly rely on triangular probability distributions due to its simplicity, allowing us to reduce the risk of results being driven by values drawn from the tails of the distribution. The resulting winning bids in the auction simulation would then be driven by highly unlikely parameter estimates. A profit-maximizing turbine producer would, for example, not sell their products at a massive discount to one wind farm developer over another, and minimizing the effect of tail-driven outcomes allows the model to produce more realistic parameter estimates. Similarly, a developer is unlikely to increase their generation by 50% over their industry competitors, using the same equipment, which is constrained by the physical reality of harnessing power from wind. We therefore opt for triangular distributions to allow bidders' value forecasts to vary within realistic boundaries. Another benefit of the triangular distribution is that the mode input can be different between the bidder types, allowing us to give aggressive firms more optimistic outlooks on costs from economies of scale.

The triangular distribution is often used when the function parameters are taken by experts, since the parameter assigns a most likely scenario as well as upper- and lower scenarios (Back et al., 2000). In our model, the triangular distribution is used to produce estimates for firm's forecasts of the parameters that they use in their valuations, and not necessarily the actual future values. The estimates used in this report are taken from IRENA, and Aurora Energy Research, the former being a well-respected international NGO, and the latter a major energy consultancy, although we only present data for the former for copyright purposes. We also make use of three different power price providers to estimate the boundaries for the price forecasts. As previously mentioned, it is common practice among energy companies to benchmark their internal estimates (which they base their valuation on) to well-respected external sources, which implies that IRENA, Aurora, and the power price providers' estimates can be used to construct the triangular distributions we use to construct firm's internal forecasts. In the following subsections, we describe the parameter data and how it is modeled in the agent simulation.

3.3.1 Revenue

Revenue is the value of the total power generated by the wind farm. In our model, we divided it into total gross capacity, Z, capacity factor, CF_{it}, prices, P_{it}, and wake loss, μ_{it}. Since we have no reason to suspect aggressive firm advantages among the bidder population in terms of revenue, we let the parameter distributions and their mode/mean be identical across bidder types. The underlying reason for symmetric assumptions in revenue is that the sources of it are mostly exogenous to the firms. While gross capacity is set by the BNetzA, as determined by their areal assessments and transmission capacity. Wake loss estimates are provided by the BSH, and due to the costs involved, no firm has incentives to perform tests of their own. Wake loss estimates are therefore likely to be similar, or even the same, across bidders. The estimates used in the agent simulations are displayed in Table 3. Assumptions on future prices and capacity factors are, on the other hand, an active decision by the firms.

Table 3: Generation Loss due to Wake Effects per Area

Area	Wake loss (%)
N-9	39.6%
N-11	25.3%
N-12	28.1%
O-2*	25.0%

** O-2 has no centralized estimate for wake loss, so we apply 25%.*

Source: Vollmer and Dörenkämper (2023), Vollmer and Dörenkämper (2024) provided full-load hours, which we converted to percentages.

We begin by describing capture price, which is the product of capacity factors and prices, $CF_{it} \times P_{it}$. The capture price reflects the intermittency of wind energy production. A wind farm will not be able to produce at full capacity due to the nature of wind energy, and the capacity factor represent the share of actual production compared to maximal production. The capacity factor is, in other words, a measure of the wind resource quality and the wind farm design. Since bidders compete over the same wind resource, and areal wind quality data is given by BSH for neighboring sea leases, it is reasonable to assume that bidders use the data in their valuations. (A key difference between pre-examined and non-examined wind farm auctions, except for the auction rules, is that BSH provide wind resource estimates for the former.) Therefore, doing your own investigations has low marginal benefit, especially when considering the costs and uncertainty of you even winning the development rights.

IRENA provides historical capacity factor of newly constructed offshore wind farms for 2022 and 2023, and their upper and lower bounds. In Europe, these bounds differed from the average esti-

mate by ±7% in 2022 (International Renewable Energy Agency, 2023a), and roughly ±10% in 2023 (International Renewable Energy Agency, 2024). Hence, the boundaries we apply to the triangular distribution for capacity factor forecasts are ±10%. To apply realized capacity factors boundaries to forecasted capacity factors is admittedly not perfect, but it gives insight into how capacity factors generally are distributed, which should be reflected in the firms' forecasts we aim to reproduce.

With intermittent sources like wind and solar taking greater share of total electricity production, the variance of electricity prices is expected to increase. The risk introduced by higher revenue variance is commonly mitigated by Power-Purchasing Agreements (PPA), where a power producer and a power consumer agree on a set price for an agreed quantity over a specified time period. Since buyers and sellers may have different internal projections of future electricity prices, it is common to consult third-party sources. Figure 3 illustrates the average price forecast (red) for Germany, and the actual forecasts from the three providers (grey). All prices are in real 2022 terms. In this analysis, we take forecasts from the three providers and average them, and let their projections vary over a defined percentage range. We then apply the *highest* average difference recorded for our price assumption boundaries, to ensure that price assumptions are allowed to vary within realistic ranges. The highest difference from the average among forecast providers was 5.4% in 2023, and 7.6% in 2024. Hence, we set the price forecast boundaries used by firms for revenue estimation as ±8% from the average forecast price.

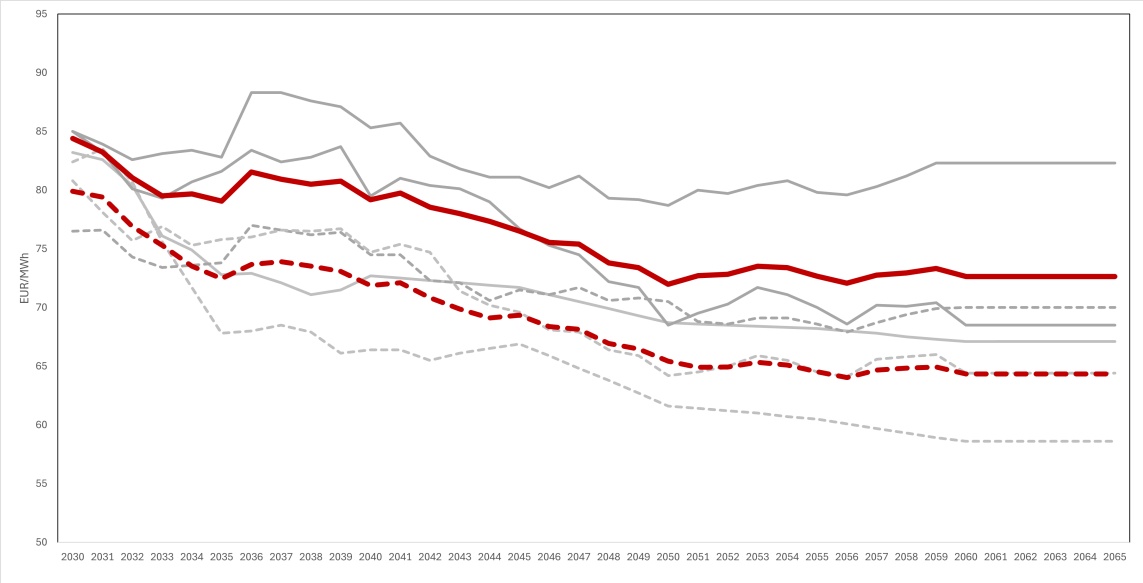


Figure 3: Provider Power Price Projections for Germany, 2023 and 2024

Note: The figure illustrates price projections from three different providers, from 2023 and 2024. Dashed lines indicate that the projection is from 2023, and whole lines for 2024. The red line is the average price projections for the corresponding years.

Revenue for offshore wind is driven to a lesser degree by the market for Guarantee of Origin (GoO), which is the added value of electricity produced from renewable sources. The average value of GoO's is low compared to the wholesale price of electricity: the value of GoO prices are between 1.5% and 2.0% of the value of their forecasted wholesale prices. Since GoO's will not produce meaningful variance in firm valuation, we use the average of the estimates between the price forecast providers. This simplification allows us to decrease model complexity with little downside.

3.3.2 Expenditures

Expenditures in offshore wind farm is commonly divided into two main categories: operational expenditures (OPEX), and capital expenditures (CAPEX). The former describes costs to maintain production during operation, and is therefore incurred after COD. The latter category refers to costs before and during construction, to procure equipment and developed the wind farm. OPEX accounts for approximately 30% of the levelized cost of energy for offshore wind (Walgern et al., 2023), with CAPEX accounting for the rest. In the analysis we assume that CAPEX costs are incurred during the two years before COD, and OPEX over the entirety of the project's commercial lifetime. Figure 4 illustrates the timeline of expenditures, revenues, and bid payments. Project financing typically begins during the development phase, when CAPEX costs are incurred.

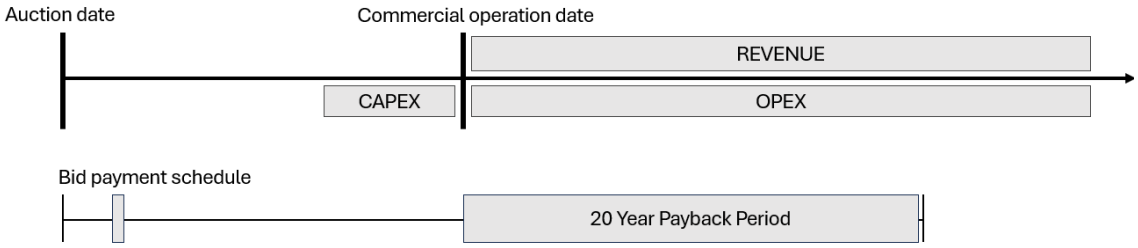


Figure 4: Stylized Project Cashflow Timeline

Bidders' valuations are based on forward-looking projections, due to the time difference between the auction date and the commercial operation date. As such, we assume that bidders' estimates for CAPEX are based on their expected value at two years before COD. Firms often include turbine generators that have yet to launch beyond the prototype stage when developing their business case (Sieler, 2021). Forecasts for costs are difficult in general, as they are sensitive to macroeconomics and commodity prices, and are expected to decrease over time due to efficiency gains. Wiser et al. (2021) explore the historical cost reductions for offshore wind globally, and use expert elicitation to predict the rate of future cost reductions. The yearly cost efficiency gains they find most likely is 14%, but they point out their previous 2015 study on the matter greatly underestimated the learning rate. Learning rates represent the expected decrease in costs due to efficiency gains and learning by doing. A recent study from Kost et al. (2024) uses a learning rate of 7% for German offshore wind, which seems more likely given the relative maturity of the German offshore wind industry. Applying the learning rate used in Kost et al. (2024) to IRENA's German estimates for CAPEX, we get the predictions displayed in Table 4. To allow agents to be more and less optimistic about cost reductions, we also compute the estimates for $\pm 2\%$ of 7%.

Table 4: Learning Rate and Real CAPEX

CAPEX (EUR/kW)	9%	7%	5%
2023	2396.4	2730.3	3102.1
2024	2180.7	2539.2	2947.0

Note: The table displays real CAPEX estimates based on different learning curve assumptions. The base values are from IRENA (2023b). The calculations are: base estimate $\times$ (1 $-$ learning rate)^6. The exponent is the number of years between auction year and construction start, which we assume is two years before the commercial operation date.

The upper and lower values shown in Table 4 are the boundaries used in the CAPEX triangular distributions, meaning that all values lie within that range with non-zero probability. Furthermore, to account for scale advantages that the larger firms are likely to have, we set the mode of large firms to be biased toward the lower boundary. The mode is set such that it is 5% higher than the lower bound for strategic firms, and 5% lower than the upper bound for non-strategic firms. Figure 5 shows an example of the asymmetric cost assumptions applied in the model, using inputs for the N-11.1 auction site.

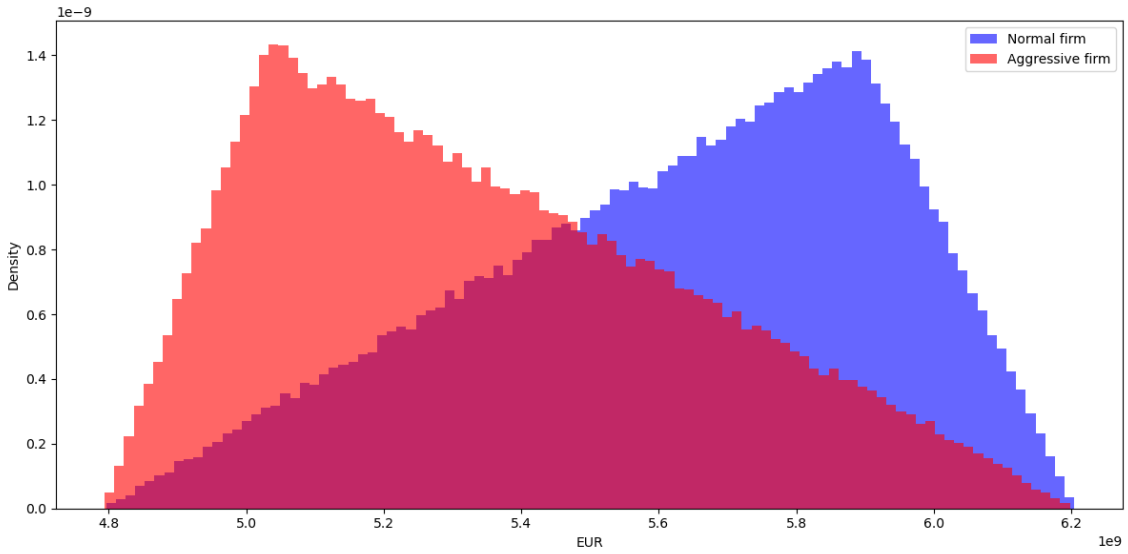


Figure 5: Triangular Distribution for CAPEX estimates, N-11.1

In their cost-analysis of offshore wind, International Renewable Energy Agency (2024) point out that estimates for OPEX are hard to come by, due to its less transparent nature compared to other

costs. Both financing costs and CAPEX costs are determined on financial markets, but OPEX is by its nature localized to the area of operation. All German offshore wind projects are in the North Sea and the Baltic Sea, where the majority of current and planned capacity being in the former. Considering the aggressive goals set in the German Offshore Wind Energy Act (WindSeeG), with at least 30 GW set to be in operation by 2030, and 70 GW by 2045, one can expect notable agglomeration effects for offshore wind farm development and maintenance.

A study by the inter-European wind energy consortium, North Sea Wind Power Hub Consortium (2021), provide guidance on intergovernmental policies to facilitate agglomeration, further highlighting the importance of industry clustering in the region. The more aggressive developers are therefore likely to expect efficiency gains from having several, large wind farms in the same area. Sieler (2021) notes that cooperation is likely, where developers buy and sell services for maintenance and operation, thus decreasing OPEX across industry. While OPEX likely will decrease over time, the pace of progress is less clear. A study by Ruijgrok et al. (2019) on offshore wind cost evaluations in the North Sea after 2030 assumes OPEX to range by $\pm 25\%$. If we input International Renewable Energy Agency (2024) OPEX estimates assuming a learning rate of 7%, and uncertainty of $\pm 2\%$, we likewise get estimates varying by up to 25% within the expected range.

Due to the uncertainty in OPEX estimates and the expected efficiency gains from agglomeration and scale effects, we use a similar triangular distribution to CAPEX, where large firms are assumed to have a slight scale advantage. Hence, we set OPEX boundaries to vary by up to 25%, and let the mode for large firms be biased to lower cost estimates. It is difficult to estimate yearly OPEX values over a project's life cycle, as two cost factors pull in opposite directions: efficiency gains of the maintenance procedures will tend to decrease costs over time, while the need for maintenance increases as a wind farm ages. However, maintenance is often contracted to the suppliers of the equipment, meaning there is some price rigidity and potential for market power abuse. Taking all of the effects together, it is unclear in what direction the end result is in. For the analysis, we therefore apply $\pm 7\%$, with uncertainty of $\pm 2\%$, using International Renewable Energy Agency (2024) estimates as baseline. The resulting estimates, and the corresponding boundaries are seen in Table 5.

3.4 Auction Simulation

The auction simulation uses the auction rules and expected outcomes formulated in the institutional background and the auction model to simulate bidding rules and strategy. Agents are first randomly assigned a type in the simulated auction, aggressive or normal, and are then drawn from the respective valuation distributions. As discussed in the previous subsection, an aggressive firm is

Table 5: Learning Rate and Real OPEX

OPEX (EUR/kW/year)	9%	7%	5%
2023	43.7	49.8	56.6
2024	37.0	43.1	50.0

Note: The table displays real OPEX estimates based on different learning curve assumptions. The base values are from IRENA (2023b). The calculations are: base estimate $\times$ $(1 - \text{learning rate})^6$. The exponent is the number of years between auction year and construction start, which we assume is two years before the commercial operation date.

more likely to have lower OPEX and CAPEX assumptions. Figure 1 suggests that there are more normal than aggressive types in the auctions, so we give a probability of being large to 25%, and 75% for the normal type. The winning bid of any auction depends on the number of participants, as an additional draw from the distributions increases the chances of a high valuation. In the 2023 and 2024 auctions, the number of participants varied between 7 and 9. Hence, we let the number of participants be a randomly drawn integer within the range, $[7, 9] \in \mathbb{Z}$.

The purpose of the auction simulations is to approximate the environment in which winning bids in the German non pre-examined site auctions were made, allowing us to compare our simulated agent draws and their underlying decision parameter with the observed, historical auction results. The programming of the auction is simple: from the pool of 200,000 agent simulations per type, the auction simulation randomly draws valuations and their underlying decision parameters, where the second-highest valuation equals the winning bid, as defined in subsection 4.1. The same auction is performed 100,000 times to ensure that the winning bid converges to the expected value, as given by the Law of Large Numbers. After the simulation, we have estimation for winning bids and their corresponding parameter inputs, which have also experienced some degree of convergence, allowing us to estimate the difference between our simulated results and the actual results.

The key benefit to the auction simulation is that the simulated bids provide information on the underlying parameter values, as each winning bid represents a simulated agent. We can therefore deconstruct the winning bid valuation into the inputted parameters, allowing us to calculate implied hurdle rates of the winning bid. The input parameters used to calculate the implied hurdle rate of the winning bid is given by the values of the second-highest valuation bidder. The results of the auction simulations and the calculated parameter values are presented in the next section.

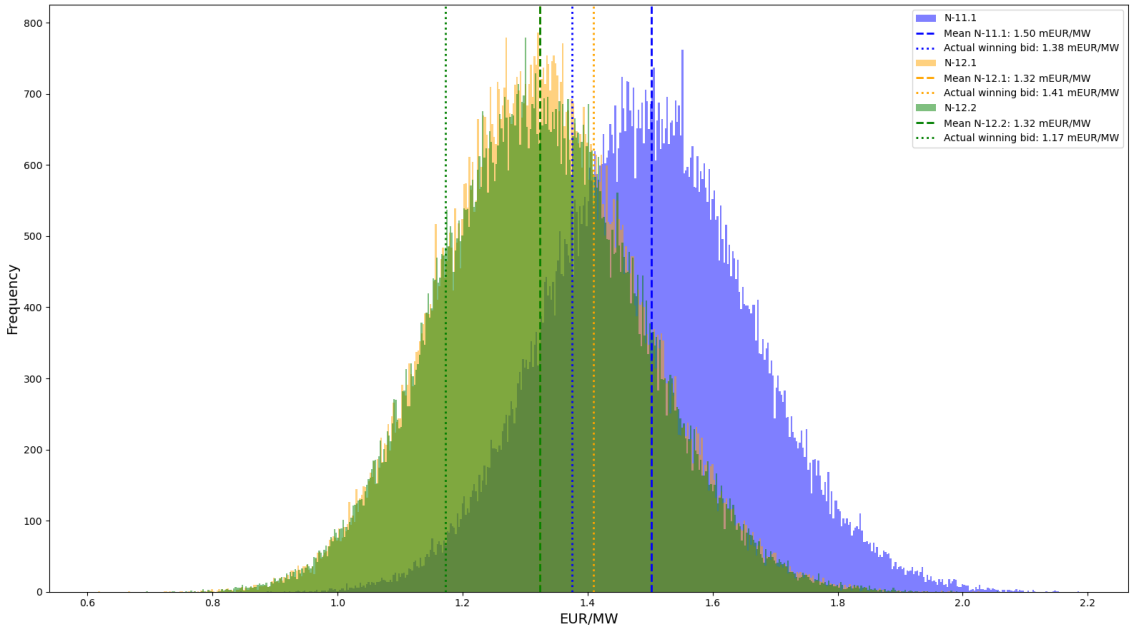
4 Results and Analysis

In this section, we explore the finding from the estimates-based simulated valuations and auction results to the actual auction results. As expressed in the model section, the cost and revenue drivers are determined by economics and the physical realities of harnessing energy from wind, and should not vary significantly between firms. To account for differences in outlook, we let the parameter values vary within bounds determined as realistic, which we described in the previous section, where our aggressive firm type see advantages in cost reduction due to economies of scale. Since discount rates are partly driven by cost of capital and partly driven by firm strategy in the model, we run the agent and auction simulations with different discounting, to allow us to analyze the most likely ranges. Finally, we calculate the most likely discount rates by internalizing the bid value into the valuation, meaning that firms discount the bid value to the same extent as operating earnings. In doing this, we are able to calculate a most likely discount rate given the cost and revenue parameter distributions assigned.

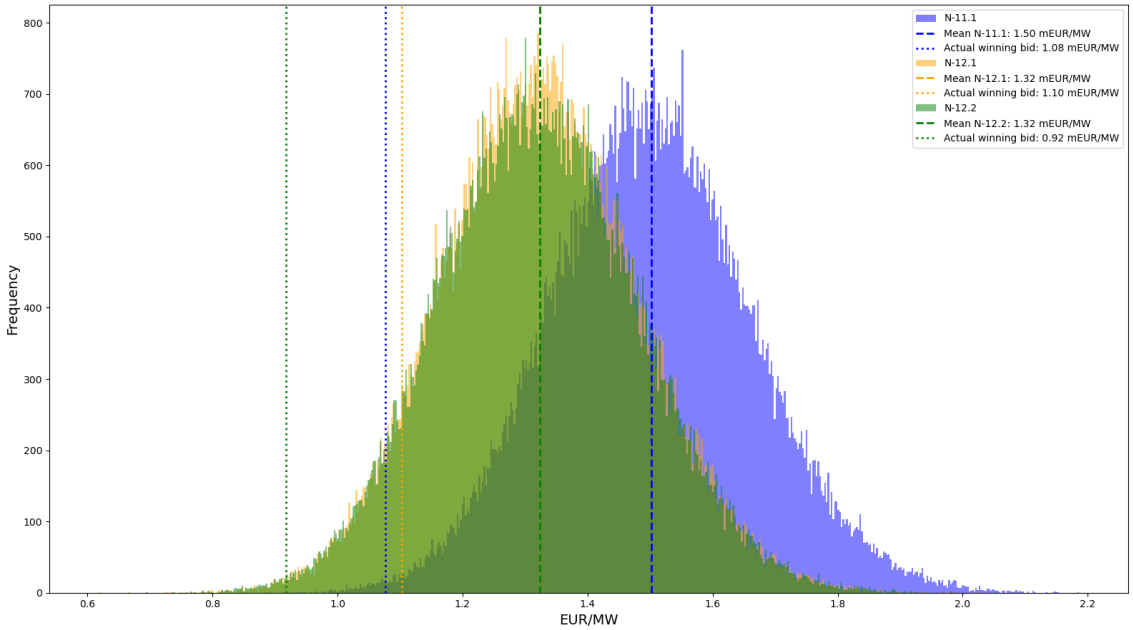
To see the effect of different discount rates, we begin by applying the same discount rate to all simulated agents. Since the sea leases vary slightly in output due to locational wake losses and different capacities, we produce estimates for every auction. Note that the auctions for N-12.1 and N-12.2 will have identical parameter input distributions, as they are part of the same sea-lease area meaning they have the same estimated wake loss, while already having the same capacity and being auctioned in the same year. The decision parameters between the two auctions is therefore identical. Similarly, the auction for N-11.1 will have the same inputs as the two aforementioned auctions, but with a slightly higher expected output due to a 2.7 percentage points lower wake loss effect. Combining the three auctions, we get winning bid valuation estimates for similar auctions, which can be directly compared to the actual auction results.

Figure 6 shows the difference between actual winning bids and estimated winning bids, when we discount the bid payments over inflation and the nominal risk-free rate of 3.88%. The operational cashflow is discounted over the risk-free rate in both subplots. Figure 7 performs the same exercise but uses 6% as the nominal discount rate for the operational cashflow. The dashed lines represent the most likely outcome based on the model, and the dotted lines the actual observed winning bids. Hence, the difference between the two lines represents the estimate error of the model for a given discount rate. The first subplot in the figures, meaning Subplot 6a and Subplot 7a, indicate the scenario when the bid payment is discounted over inflation, and the project cashflow is over the risk-free rate and 6%, respectively. Subplots 6b, and 7b show the results when project cashflow and bid payments are discounted over the same discount rate, which essentially shifts the present value of the historical bids to the left.

The predictions yielded by the auction model with inflation as the discount factor for bid payments in Figure 6a is quite similar to the bids levels estimated in the model, as indicated by the fact that the dashed lines and the dotted lines are relatively close. It is however highly unlikely that a rational wind farm developer would develop a project for billions of EUR if expected return equals the risk-free rate. Given the payment schedule of the auctions for the winning bid and the fact that the bids themselves essentially represent a rent payment to the German government, it is instead likely that the bid payments are discounted as if operating expenditure. The implication of this is that the bid payments are discounted at the same rate as operating cash flow, and not inflation as we assumed in Figure 7. The scenario when both bid payments and operating cashflow are discounted at the same rate is seen in subplots 6b, and 7b.

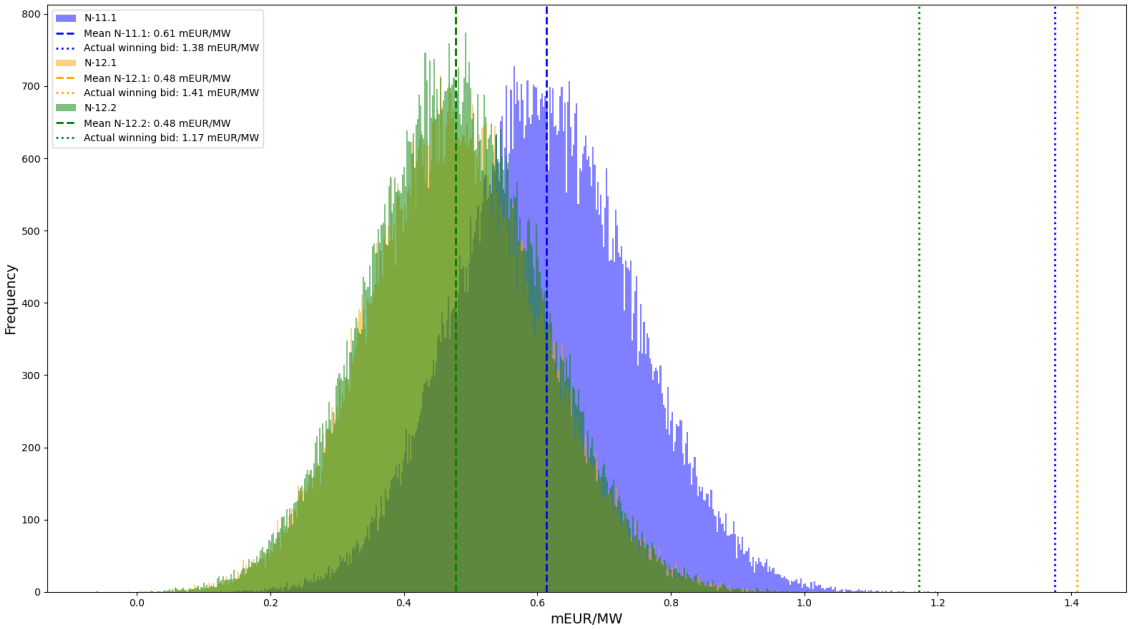


(a) Discounting Bid Payment with Inflation (2%)

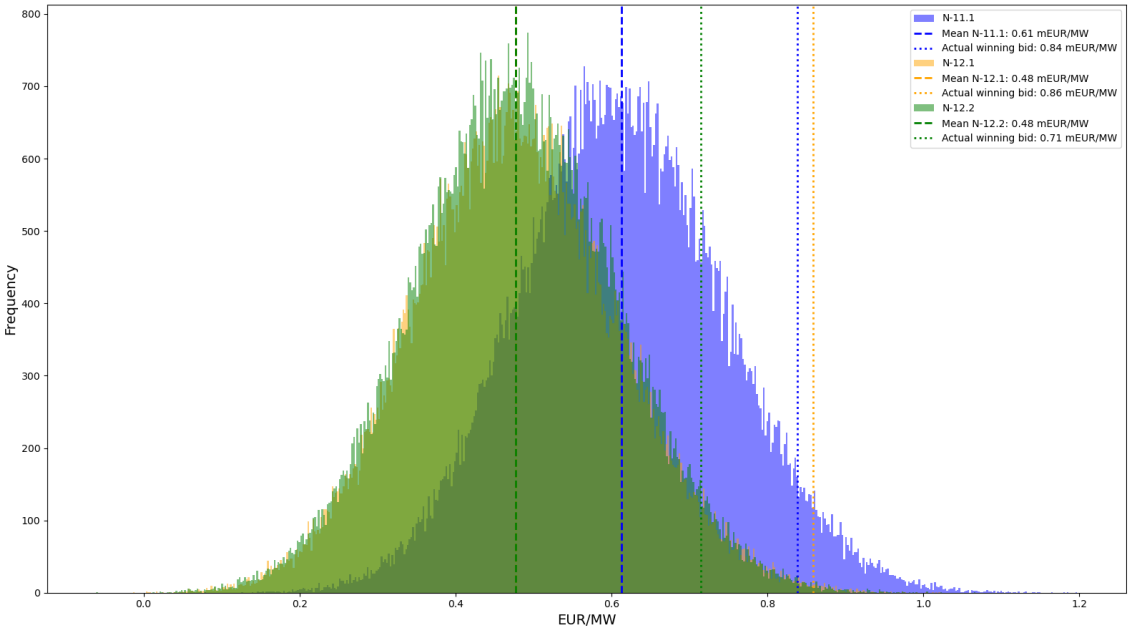


(b) Discounting Bid Payment with Risk-free Rate

Figure 6: Model Estimated (dashed) and Actual (dotted) Winning Bid, when Discounting Operating Cashflow over Risk-free Rate (3.88%).



(a) Discounting Bid Payments with Inflation (2%)



(b) Discounting Bid Payments with 6% Discount Rate

Figure 7: Model Estimated (dashed) and Actual (dotted) Winning Bid, when Discounting Operating Cashflow over 6%.

In the two figures, we can see that when discounting bid payments as if regular cashflow, the relative value of the bid payments decrease. The closeness of the estimated winning bids and the actual winning bids in Figure 6a is, as we pointed out, flawed: the risk-return requirement associated with offshore wind farm development is not similar to 30-year US treasuries. When looking at Figure 6b and 7b, it seems as if the actual nominal discount rate lies between the risk-free rate and 6%. Since we posit that bid payments will be discounted at the same rate as operational cashflow, we can calculate the discount rate which makes the model's estimated winning bid and the actual winning bid the same.

Our auction model distributes the development rights for any auction to the highest valued bidder at the price of the second-highest bidder's valuation. Hence, we can determine an *implied* hurdle rate of the second-highest bidder, who stayed in the auction until their valuation equaled their valuation. The implied hurdle rate of the winning bid is the discount rate that precisely makes the second-highest bidder's expected profit zero, which is when bidders are predicted to drop out of the auction. We can then solve for the internal rate of return that makes this hold, ie, when $v - b = 0$. The implied hurdle rate is, in other words, the lowest rate of return that a developer would find developing the wind farm profitable. These calculations are our main results, and are displayed in Table 6.

Table 6: Calculated Hurdle Rates and Bid Prices

Year	Auction	IRENA + Learning Rate (%)	Aurora (%)	Bid Price (EUR/MW)
2023	N-11.1	4.68	7.56	1,830,000
2023	N-12.1	3.62	6.36	1,875,000
2023	N-12.2	4.76	7.76	1,560,000
2023	O-2.2	5.76	8.72	2,070,000
2024	N-12.3	10.42	10.42	1,305,000
2024	N-11.2	10.38	10.36	1,065,000
2024	N-9.X*	9.62	9.62	112,500

** N-9.X is N-9.1 and N-9.2 combined, and the calculations only use the financial criteria of the auctions.*

Note: The table displays calculated hurdle rates in nominal terms for CAPEX and OPEX based on cost projections from Aurora and IRENA. For the IRENA projection, we applied learning rates to historical cost estimates to predict future costs.

The resulting hurdle rates are noticeably different in 2023 for the IRENA-based cost estimates, where we apply learning rates to historical costs, and Aurora's cost projections. Hurdle rates are however strikingly similar in 2024, with the calculated rate only departing by a trivial amount for N-11.2. Aurora data is not described in detail for copyright purposes, but the main difference

between their cost projections and our projections using IRENA data is CAPEX-related. Regardless of which cost estimates you apply, a difference between implied hurdle rates can be observed between the auction years.

British Petroleum (BP) won two of the auctions in 2023, N-11.1 and N-12.2, and they announced the same year that the expected return on their renewable investments is 6-8% on an unlevered basis (British Petroleum, 2023b), which fits the implied hurdle rates using Aurora's cost estimates quite well. TotalEnergies' CEO announced in 2024 that they expect their German OFW fleet to generate returns of at least 12% (Chetwynd, 2024), suggesting strong earnings assumptions compared to the data used in our analysis. If we apply a hurdle rate of 12% to the auctions that TotalEnergies has won, we can calculate the size of the 'missing' earnings to make the hurdle rate profitable. Using Aurora's cost projections, the calculated yearly earnings gap from our model to TotalEnergies' earnings predictions are 265 mEUR, 118 mEUR, and 166 mEUR in real 2022 EUR terms, for N-12.1, O-2.2, and N-11.2, respectively. No other winning firm have made statements on return expectations, and one should be wary that publicly expressed return requirements may not be the same as the return requirements applied in project valuations.

Another data point of interest is the case of N-9.X, which has a hurdle rate roughly in line with other auctions in 2024, despite having a bid price a tenth the size of the second lowest bid price that year. The development rights for N-9.1 and N-9.2 - the two auctions we refer to as N-9.X due to only their combined price being announced - were auctioned in pre-examined auctions, meaning there were both financial and qualitative criteria. Table 6 only displays the financial criteria, which accounts for 60 of the total 100 points used to determine the winner (Bundesnetzagentur, 2023). Despite these facts, we find an implied hurdle rate in line with the other, non-examined auctions. The biggest value difference between N-9.X and other wind farms in development is the level of expected wake loss in the N-9 area, which can be seen in Table 3. All other inputs are equivalent, thus highlighting the importance of wake effects in auction outcomes. Since N-9.X was auctioned using mixed criteria that included requirements for green steel and marine life protection, it is likely that costs are slightly higher than the cost distributions we applied to the non-examined auctions in our model, meaning that hurdle rates are slightly underestimated for the n-9.X projects. It is therefore probable that N-9.X's hurdle rate is actually closer to the other observed 2024 auctions' hurdle rates than what the value in Table 6 indicates.

The triangular distribution used to simulate CAPEX and OPEX data reflects linearly increasing and decreasing probabilities under the pre-defined boundaries, with the highest likelihood at the mode. While the distribution is useful under uncertainty, it may underestimate the likelihood of the scale effects that aggressive bidders can have. Therefore we make the same calculations with

truncated log-normal distributions, which assigns greater density around the mode compared to the triangular distribution. The distributions are however truncated at the same boundaries as the triangular distribution. The main difference between the distributions is that aggressive bidders are more likely to assume scale effects, than what is predicted using the triangular distribution. The calculated hurdle rates using log-normal cost estimates are insignificantly different from the values calculated using cost estimates derived from the triangular distribution. The estimated hurdle rates using log-normal cost estimates can be seen in Table A1 in the appendix.

Another robustness test is displayed in Table 7, where we test for the differences in calculated hurdle rates based on the probability of agents being assigned the aggressive type. The table uses cost estimates from Aurora and triangular distributions to simulate CAPEX and OPEX. While the share of aggressive bidders clearly affects the estimates, the effect is small. Our results are in other words not driven by how bidder types are assigned.

Table 7: Calculated Hurdle Rates (%) by Auction and Share of Aggressive Type

Year	Auction	50% Aggressive	33% Aggressive	25% Aggressive
2023	N-11.1	7.78%	7.56%	7.50%
2023	N-12.1	6.58%	6.36%	6.30%
2023	N-12.2	7.98%	7.76%	7.70%
2023	O-2.2	8.92%	8.72%	8.64%
2024	N-12.3	10.66%	10.42%	10.36%
2024	N-11.2	10.60%	10.38%	10.30%
2024	N-9.X	9.88%	9.62%	9.54%

Note: The table displays calculated hurdle rates in nominal terms using triangular cost estimates and Aurora projections. The share of bidders not covered by the aggressive bidder type is assigned as normal type.

5 Discussion

The purpose of this section is to discuss the methodology and the estimates it produced for German offshore wind auctions.

5.1 Methodological Limitations

The auction model proposed in this paper builds on auction theory and includes a number of assumptions to ensure that the simulated auctions produce a predictable outcome, with the underlying assumption that bidders are rational. While rationality should hold broadly, given the maturity of the bidders and the investments required for the winner, it is unclear if bidders actually are willing to spend their entire net present value, as assumed under English auctions. It would therefore be tempting to model the bidders as risk-averse, but as discussed in Riley and Samuelson (1981), RET then no longer holds, meaning that we cannot estimate the resulting Nash equilibrium. We also include risk aversion in the valuation via the hurdle rate, making it difficult to determine what share of an agent's risk aversion should be modeled into the valuation model and bidder strategy, respectively. More importantly, without a Nash equilibrium, we lose all predictability, rendering the model useless. If bidders indeed shade their bids even in English auctions, our results would tend to overestimate the true hurdle rates.

A related issue with the valuation process is that bidders are IPV. While independence between bidder valuations is likely due to differences in firm strategy, it is also possible that the presence of benchmarking of cost and revenue assumptions from external sources introduces correlation between firm valuations. We note however that the effect of this seems subdued, given the clear asymmetry in valuations between firms, as shown in Table 2. The effect of firm strategy is seemingly stronger, which suggests that the actual firm valuations are closer to IPV auctions than CV auctions. There are auction models that allow bidders' valuation to depend partly on the observed signals of competitors, such as the one deployed by Hong and Shum (2003) in their analysis of asymmetric English auctions, where bidders alter their reservation bid (highest bid they are willing to place) depending on the prices where competitors drop out. Such models rely on all bids being observable by the researcher however, which unfortunately is not the case for all of the auctions analyzed in this paper. Only the auctions in 2024 include all bids, which can be seen in Figure 1. If BNetzA continues to publish all bids going forward, an analysis using the AV framework is warranted in the future. Given the current data constraints, IPV is the most fitting valuation model to apply.

In the introduction, we mention how the model used in this paper may be applied to other markets, under the assumption that the auctions are efficient. This statement is generally true, but the

asymmetry assumption may be local to Germany, or at the very least different in other markets. For the RET to hold, it is required that bidders are symmetric, and the bid round system allowed us to approximate symmetry at the final bid round. The RET will however not hold in auctions where the bid population cannot be assumed to be symmetric, and bid rounds are absent. In that case, the auction model can only be used if the auction is a pure English auction (like in the button model from Milgrom and Weber (1982)), or if the auction-method used is efficient, bidders are symmetric and risk-neutral, and the auction has no entry payments; in other words, when RET holds. What this paper does contribute with is a methodology that allows researchers to estimate bidder hurdle rates from winning bids, but the underlying bidding strategies and auction model depends on the auction format that the bids were made under.

5.2 Results

The results presented in the previous section indicate a noticeable difference between hurdle rates in 2023 and 2024, where bidders seemingly have more aggressive valuations in the former. Based on the analysis in this paper, it is impossible to discern what the reason behind this is, but we will in this subsection present plausible explanations. The first explanation relates to how competitive bidding work in English auctions, where the final bid price depends on the valuation of the second-highest bidder. Hence, if there are several aggressive bidders, prices will increase significantly compared to if there is only one aggressive bidder. If there are fewer aggressive bidders in 2024 than in 2023, the expected result is that the final bids are lower. This effect will be more pronounced if there are two very aggressive bidders, and one bidder decides to not part-take in the next years auctions. Similarly, if a very aggressive bidder has satisfied their strategic goal for offshore wind in their portfolio, they may apply more conservative return requirements in future auctions. Both of these factors could explain the increase in hurdle rates in 2024.

Another plausible explanation to the difference in hurdle rates between the auction years is the outlook for interest rates. The risk-free interest rate we applied in this paper were 30-year US treasuries, since they effectively set a lower bound for risk-return expectations, and have a similar investment time frame to the wind farms. The risk-free rates applied in this analysis was 3.88% for the 2023 auction, and 4.08% for the 2024 auction. Both rates were taken from first non-bank holiday day in January. On a similar token, estimates from IRENA indicated that the after-tax real WACC had increased from 2.92% in 2022, to 4.29% in 2023 (International Renewable Energy Agency, 2023b; International Renewable Energy Agency, 2024). Both reports were released after the auction dates, meaning the most recent data point for firms in 2023 were the estimates for 2022, and 2023 for the 2024 auctions. The general outlook for wind farm financing was in other words negative, which may have caused valuations to be lower in 2024.

A related explanation to the high bids of the oil and gas majors in particular are the elevated oil prices following the Russian invasion of Ukraine, meaning that firms such as BP and TotalEnergies had significant boosts in profitability, enabling cheaper finaning. The financial statements of TotalEnergies indicates that adjusted profits increased to 18.1 billion EUR in 2021, compared to 11.8 billion EUR in 2019 (ignoring 2020 due to covid-19's short-term effect on oil prices), and doubled in 2022 to 36.2 billion EUR (TotalEnergies, 2019; TotalEnergies, 2021; TotalEnergies, 2023). BP's financial statements are less positive due to its exposure to Rosneft and the Russian economy, causing a net loss of 1.2 billion GBP in 2022 (British Petroleum, 2022). Profit in 2023 and 2021 were 15.2 billion GBP and 7.6 billion GBP, respectively (British Petroleum, 2021; British Petroleum, 2023a). The presented income statements suggests that TotalEnergies in particular can finance the auction bids via built up money reserves, lowering the share of financing and thereby financing costs for the wind farm projects; the general health of the balance sheet would also enable lower financing costs due to lower risks for lenders. Lowering financing costs could therefore explain the relatively high valuations of TotalEnergies, and maybe also of BP.

Another potential explanation to the aggression of some bidders compared to others is firm exposure to EU's cap and trade market for CO-2 emission rights. Since emission rights decrease gradually over time, prices of emissions in the electricity and heat industry is set to increase. This dynamic will increase costs for firms operating within the EU in emission-intensive industries. A likely effect is therefore that the opportunity costs for fossil fuel extraction and related industries is higher, making renewable investments more attractive. High emission firms reducing their exposure to the emission rights market could therefore explain why firms that are heavily exposed to the cap and trade market are relatively more aggressive in bidding for OFW farms; they have strong incentives to reduce their exposure to fossil-fuels, and are therefore likely to look into investments in renewable energies, such as offshore wind.

More generally, the results highlight the changes in market sentiment for offshore wind investments, and this has important implications to how policymakers design offshore wind auctions going forward. This point is highlighted by the December 2024 Danish offshore wind tender, where no bids were made. The Danish auction format did not include any subsidies, indicating that since no developer seemingly had a business case with a valuation over zero (or else they would have made a bid), no offshore wind farm will be developed, to the detriment of the green transition. Policymakers that are adamant in facilitating the green transition through auctions must ensure that the auction design reflects the underlying market conditions, so that investments are made under both beneficial and hostile market conditions. The methodology developed in this paper is therefore useful for policymakers, as it allows them to analyze market outlook, which is important

formulate auction criteria that both facilitates the green transition and ensures that wind farm development rights are distributed to the most efficient developer.

6 Conclusion

This paper sought to develop a methodology to analyze firm behavior in German offshore wind auctions, using forecast data and winning bid prices to calculate return hurdle rates. The implied hurdle represents the lowest IRR that the second highest valuation bidder would expect, meaning that actual valuations of winners is higher. However, considering that the same bidder did not win every auction, it is reasonable to assume that the realized winner's hurdle rate is within the region of the second-highest valuation bidder's hurdle rate. The key finding is that hurdle rates were systematically lower in 2023 compared to 2024. While the difference depends on whether learning rates-based forecasts or Aurora's forecasts were used, an increase using either data source indicates that investment outlook changed from 2023 to 2024. Another finding is that wake loss can explain the slump in bid values for N-9.1 and N-9.2 (called N-9.X in the analysis), as calculated hurdle rates remain in line with other projects auctioned in 2024, where the only major difference being higher wake loss effects.

The paper's main focus is on developing a methodology to analyze market outcomes and the underlying market sentiment in the offshore wind industry. Hence, the goal of the paper is more-so to produce a tool to analyze market sentiment rather than to produce policy advice. Concurrent developments such as the failure of the Danish 2024 offshore wind tender to produce bids does nevertheless introduce considerations for policymakers. Given offshore wind's importance in facilitating the green transition, as indicated by the EU's development plan for the technology, it is clear that policymakers must accurately assess the underlying market sentiment when constructing methods to distribute development rights for the technology to avoid auctions hindering, rather than facilitating offshore wind build-out. Recent developments, such as lowered willingness to pay in the German auctions and the failure to produce bids in Denmark, indicates that subsidies should still be considered when designing auction formats if the policy goal is to support the green transition.

This thesis contributes to both the auction and renewable energy literature, helping industry participants and policymakers to better understand auction outcomes. Auction models are developed to analyze specific auction formats, and the model developed in this paper is no exception. While the general methodology of using forecasts and Monte Carlo simulations to predict forward-looking project valuations can be applied to any Nash equilibrium outcome, it is the auction format that dictates bidder strategies, which ultimately assigns the winning bid. Hence, there is ample room for future research, where the lowest hanging fruit is to expand the analysis to other markets where data exists.

Another possible future research area is to estimate each cost area in greater granularity, allowing for better cross-country comparisons. Governments have different and varying degrees of subsidies for offshore wind farms, and if estimates exist for the costs on the component level, it is possible to estimate willingness to pay in one market based on the outcomes in another. Developers in Germany are for example not required to sustain the costs for transmission cables, but developers in Denmark are. Higher granularity would then enable researchers to apply transmission cable costs to Danish projects, and estimate a projected willingness to pay there. The same would of course apply to all other components.

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A Appendix

Table 8: Comparison of Calculated Hurdle Rates with IRENA and Aurora Projections for Auctions with Truncated Log-Normal Cost Distributions (2023-2024)

Year	Auction	IRENA (%)	Aurora (%)
2023	N-11.1	5.0	8.0
2023	N-12.1	4.0	6.8
2023	N-12.2	5.0	8.2
2023	O-2.2	6.0	9.0
2024	N-12.3	10.8	10.8
2024	N-11.2	10.6	10.8
2024	N-9.X*	10.0	10.2

** N-9.X is N-9.1 and N-9.2 combined, and the calculations only use the financial criteria of the auctions.*

Note: The table displays calculated hurdle rates in nominal terms for CAPEX and OPEX based on cost projections from Aurora and IRENA. For the IRENA projection, we applied learning rates to historical cost estimates to predict future costs.