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Innovative Applications of O.R.

Renewable auctions: Bidding for real options

David Matthäus, Sebastian Schwenen, David Wozabal*

TUM School of Management, Technical University of Munich, Munich 80333, Germany

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ABSTRACT

Procurement auctions for renewable energy support have become a standard policy instrument to stimulate investment in clean energy. Winning bidders have the right but not the obligation to realize their projects during a grace period following the auction. Currently, the nexus of award prices and the realization rate is not well understood in the literature. We combine auction theory and real options theory to model bidders who view the right to build subsidized renewable capacity as real option. Using asymptotic theory for multi-unit auctions, we derive optimal bidding strategies and analyze how auction design and bidder characteristics impact equilibrium bids, award prices, and realization rates. In particular, we show that bidders who value the flexibility of non-realization higher bid more aggressively and exhibit lower realization rates. We analyze determinants of these effects and illustrate how auction design can trade-off procurement cost and realization rates by adjusting pre-qualification payments and the grace period for construction. Finally, we test our results on real-world auctions in UK and Germany and show that our model explains auction outcomes and observed realization rates.

1. Introduction

Recent climate agreements stress the need for policies to mitigate global warming. In many regions, such as the US, Europe, or China, the dominant climate strategy is to decarbonize power markets using nuclear power or renewable generation. Even though costs of wind and solar generation have fallen drastically in the last decades, renewable technologies still depend on government support. In 2017 alone, worldwide subsidies amounted to $166 billion (Taylor, 2020).

Governments allocate a growing share of these subsidies in multi-unit procurement auctions for renewable capacity (*renewable auctions*) that gained strong momentum across the globe, e.g., in Brazil, California, China, Germany, India, or the UK. In renewable auctions, governments auction off contracts that guarantee subsidized remuneration to owners of renewable capacity for the electricity they produce (Buckman, Sibley, & Bourne, 2014; Mayr, Schmidt, & Schmid, 2014).

Auction prices have dropped in recent years and have decreased support costs far below expectations (del Río & Linares, 2014). Amid euphoria about the cost-efficiency of renewable auctions, there are concerns that winning bidders might have bid below their cost. Consequently, a large share of projects may not materialize, as witnessed in early renewable auctions in Great Britain (Mitchell, 2000). In a recent study, Matthäus (2020) investigates data on more than 90 renewable auctions all over the world and shows that non-realization is a major concern in auction design: the mean realization rate of the entire sample is below 75 % and about 70 % for auctions after 2010, implying that in most auctions a significant portion of the awarded projects is not developed. Furthermore, he shows that 20 % of the auctions persistently have realization rates below 50 %, clearly falling short of the desired targets.

While the extant literature explains low bids by the winner's curse and aggressive market entry (e.g., Gephart, Klessmann, & Wigand, 2017), we develop a real option approach to rationalize low bids in renewable auctions and in procurement auctions in general. To this end, we model the awarded right to build subsidized renewable energy capacity as a real option. To conceptualize how optionality changes bidding strategies, we introduce two archetypal bidders: option-based cost bidders (*OBC bidders*) who view awarded projects as real options to invest, and the benchmark case of bidders who employ traditional net present cost approaches instead (*NPC bidders*). In contrast to the NPC benchmark, OBC bidders assign a positive *option value* to the possibility to default on the project.

Our model draws from recent literature on multi-unit auctions with asymptotically large numbers of competitive bidders. Specifically, we rely on Swinkels (2001), Cripps and Swinkels (2006), Jackson and Kremer (2006), and analytically show that in typical

* Corresponding author.
E-mail addresses: david.matthaeus@tum.de (D. Matthäus), sebastian.schwenen@tum.de (S. Schwenen), david.wozabal@tum.de (D. Wozabal).

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renewable auctions all equilibria in bidding strategies converge to the truth-telling auction outcome for both uniform price and discriminatory auctions as the number of participants increases. This allows us to explicitly derive bidding strategies as well as comparative statics with respect to auction design and model primitives. We illustrate numerically that the (finite) number of bidders typically observed in renewable auctions justifies the assumption of truthful bidding as an accurate approximation of bidding behaviour.

Our results show that bidders with high option value act more aggressively independent of the auction format. Consequently, efficiency and realization rates decrease as these bidders undercut their rivals, who despite lower cost are not awarded projects. We show that pre-qualification measures and penalties can act as powerful enforcement mechanisms (Board, 2007; Spulber, 1990; Waehrer, 1995) that allow the auctioneer to influence auction prices and realization rates. For higher penalties of non-delivery, the option value decreases, and the bids of OBC bidders converge to those of NPC bidders. Higher penalties thus lead to less aggressive bids, and award prices rise. Hence, the auctioneer can use penalties to trade off the two competing goals of low realization rates and low award prices.

Moreover, we prove that for participating firms the value of flexibility, i.e., the option value, increases in the length of the grace period that the auctioneer grants winning bidders to develop their projects. Hence, bidders with a high option value are likely to drive down auction prices for long grace periods, which might in turn lead to low realization rates.

To put our theoretical results to the test, we discuss the outcomes of an early renewable auction in the UK and simulate equilibrium bidding strategies and auction outcomes for a recent German auction. Comparative statics of the UK auction qualitatively support our model intuition that auctioneers need to implement enforcement mechanisms to achieve reasonable realization rates. For the German auction, our simulation results are in line with observed bids and auction outcomes and we are able to numerically quantify the effects of the choice of pricing format, grace period, and pre-qualification on award prices and realization rates. We conjecture that auction outcomes were to a large extent driven by bidders with high option values and predict low realization rates for awarded projects. The simulation shows that expected realization rates drastically increase for higher financial pre-qualification, whereas deployment costs are only moderately affected.

Our paper relates to several strands of research. First, we connect to the literature on multi-unit procurement auctions. The extant literature considers models where bidders cannot default on awarded projects and hence do not consider the option value of projects. Bidding strategies are modelled either as continuous bid functions (e.g., Hortacsu & Puller, 2008; Klemperer & Meyer, 1989; Wilson, 1979) or as discrete bids (e.g., Ausubel, Cramton, Pycia, Rostek, & Weretka, 2014; Fabra, von der Fehr, & Harbord, 2006; Kastl, 2011; 2012; Schwenen, 2015). In models with discrete per-unit bids, equilibrium prices above competitive levels typically result from capacity constraints (e.g. Chaturvedi, 2015; Fabra et al., 2006). In models with continuous bid functions, bidders have a positive probability of impacting the market price and therefore strategic bidding may occur. However, for an increasing number of bidders all Bayes-Nash equilibria converge to the truth-telling auction outcome, i.e., strategic bidding vanishes in the limit (Cripps & Swinkels, 2006; Jackson & Kremer, 2006; Swinkels, 2001).

Building on the truth-telling equilibria in Swinkels (2001), Cripps and Swinkels (2006), Jackson and Kremer (2006), we add to this literature by incorporating real options valuation (Dixit & Pindyck, 1994) into the analysis of bidding strategies in multi-unit auctions. Previous works that are closest to our modeling approach are Cong (2018) and Schummer and Vohra (2003), who study single unit auctions where the awarded good is a real option. Our approach, in contrast, considers multi-unit auctions and models the valuation of the bidders as endogenous to the auction outcome. More specifically, the strike price of the option equals the auction price, tying the option value to the auction outcome. To the best of our knowledge, this paper is the first to integrate endogenous project valuation via option theory in a multi-unit auction framework.

In addition, we contribute to the extensive literature on the optimal design of support policies for renewable energy under different support schemes (e.g., Bigerna, Wen, Hagspiel, & Kort, 2019; Kök, Shang, & Yücel, 2018; Pineda, Boomsma, & Wogrin, 2018; Ritzenhofen, Birge, & Spinler, 2016; Siddiqui, Tanaka, & Chen, 2016). Flexibility and uncertainty have a decisive impact on the policy design (e.g., Boomsma, Meade, & Fleten, 2012; Bruno, Ahmed, Shapiro, & Street, 2016), but have to the best of our knowledge not been assessed in the context of renewable auctions. We particularly relate to the small but growing literature on renewable auctions, which comprises mostly of country studies and qualitative surveys (e.g., Buckman et al., 2014; Mitchell & Connor, 2004; del Río & Linares, 2014). The paper that is closest to our approach in the renewable auction literature is Kreiss, Ehrhart, and Haufe (2017), who model single unit auctions and do not capture the real option characteristics of the auctioned contracts.

Our results yield implications for policy makers, auctioneers, and participating firms. Optimal bidding strategies take the option not to realize the project into account and lead to more aggressive bidding. In turn, policy makers need to design auctions in order to manage the option value of awarded contracts by adjusting pre-qualification payments and the length of the grace period. Also, the choice of the pricing rule matters when considering the trade-off between deployment cost and realization rates. Uniform pricing results in higher deployment cost and comes at the benefit of higher realization rates. Thus, instead of increasing penalties or shortening the grace period, the auctioneer may alternatively switch to uniform pricing to increase realization rates. This choice comes with the benefit of fostering participation of small and potentially capital-constrained firms, thereby increasing competition. Hence, the pricing rule, the choice of penalties, and the length of the grace period become strategic substitutes for the auctioneer.

This paper is organized as follows. In Section 2, we discuss our assumptions, introduce the auction framework, and describe valuation approaches. In Section 3, we derive bidding strategies and conduct comparative statics for auction outcomes. In Section 4, we apply our model to two real-world case studies. Section 5 discusses policy implications and concludes.

2. Model

This section presents our multi-unit auction framework and describes bidders' valuation functions. We introduce two types of bidders who compete in procurement auctions to illustrate the effect of flexibility: net present cost bidders and option based cost bidders. Net present cost bidders conceptualize the extreme case of bidders that assign no value to the option of non-realization and thus value the project by its net present cost. In contrast, option based cost bidders value the flexibility not to invest, i.e., view the auction as a mechanism to allocate real options.

2.1. Auction setup

We consider N risk-neutral bidders in a multi-unit procurement auction with ex-ante uncertainty about other bidders' participation and therefore uncertainty about the number of competing bidders in the auction. Uncertain participation prevents degenerate equilibria that require bidders to have definite knowledge about participation such as in Noussair (1995). In particular, we follow Swinkels (2001) and Jackson and Kremer (2006) in making the following assumption.

Assumption 1 (Uncertain Participation)**.** Any given player is inactive with positive probability. Inactivity is independent across bidders.

The average participation probability of a bidder can be thought of as close to 1, implying that most bidders take part in the auction.

The auctioneer procures $K \in \mathbb{N}$ megawatt (MW) of renewable generation capacity. Each bidder i with $i = 1, \ldots, N$ may develop several projects $h = 1, \ldots, H^i$ of different capacity. Offered project sizes are multiples of a minimum increment of k kilowatt (kW), i.e., the maximal number of auctioned contracts equals $\left(\frac{K}{k}\right) \times 1,000$. For each project, bidders submit a bid that specifies the price per MWh of electricity generated from that project, resulting in a piece-wise constant bidding function mapping prices to offered capacity. Bids can thus be viewed as required *feed-in tariffs* for which bidders are ready to develop projects.

Project costs are characterized by two attributes: the current cost of developing the project and future random variation of this cost. We represent the cost of a project by the *levelized cost of electricity* (LCOE). The LCOE measure the total cost per MWh of electricity production, taking into account fixed cost of development, variable cost, financial cost such as interest payments, taxes, and insurance, as well as structural properties of the project, e.g., expected life-time. If the developer of a project obtains the LCOE for every MWh of produced electricity, the project exactly breaks even (see İşlegen & Reichelstein, 2011; Kost, Shammugam, Jülch, Nguyen, & Schlegl, 2018).

The future evolution of LCOE depends on the random future changes of input costs. We account for this uncertainty by modeling LCOE of project h of firm i as a stochastic process $(L_t^{ih})_{t\geq 0}$. As is common in the real options literature (e.g., Broadie & Detemple, 2004; Cortazar, Schwartz, & Salinas, 1998; Dixit & Pindyck, 1994; McDonald & Siegel, 1986; Merton, 1977) and to ensure analytic tractability, we model $(L_t^{ih})_{t\geq 0}$ as a geometric Brownian motion

$$dL_t^{ih} = \mu^{ih} L_t^{ih} dt + \sigma^i L_t^{ih} dB_t^{ih}, \tag{1}$$

where μ^{ih} is the drift, σ^i is the volatility, and $(dB_t^{ih})_{t\geq 0}$ are the increments of a standard Brownian motion with an arbitrary correlation structure. The correlation captures the influence of a common market for components. Note, however, that our results are invariant to the exact specification of the correlation, since it turns out that bids, auction outcomes, and expected realization rates only depend on the marginal distributions of costs and not on the correlation between L_t^{ih}. To keep the formulas simple and focus on the relevant aspects of the problem, we do not explicitly model the joint distribution of L_t^{ih} for a given t.

We assume that prior to bidding at $t = 0$, each participating firm privately observes two signals: the current LCOE for each of its projects h, denoted by L_0^{ih}, and its volatility σ^i. Note that σ^i is firm-specific, i.e., constant for all projects of bidder i, while L_0^{ih} varies for each project. Firm-specific volatility in LCOE stems from heterogeneity in, e.g., labour cost for maintenance or learning curves that may vary at firm-level. All results in this paper remain valid for project specific volatilities. In line with classic auction theory (Myerson, 1981; Riley & Samuelson, 1981) we assume independent private values for L_0^{ih} and σ^i.

We use a risk-free approach to calculate project valuations. To that end, we define a constant risk-free interest rate r and a risk-free version of the LCOE process

$$dL_t^{ih*} = rL_t^{ih*} dt + \sigma^i L_t^{ih*} dB_t^{ih*}, \tag{2}$$

where $(dB_t^{ih*})_{t\leq 0}$ are the increments of the Brownian motion under the equivalent martingale measure $\mathbb{Q}$. The discounted process $e^{-rt}L_t^{ih*}$ is martingale under $\mathbb{Q}$, in particular, $\mathbb{E}_0^*(e^{-rt}L_t^{ih}) = L_0^{ih}$, where $\mathbb{E}_0^*$ is the expectation at time $t = 0$ with respect to $\mathbb{Q}$.

Assumption 2 (Independent Private Values)**.** Bidder i's signals L_0^{ih} and σ^i are i.i.d. continuous random variables. Realizations of L_0^{ih} and σ^i are private information of player i.

This assumption implies that, at the moment of bidding, the market situation, e.g., the range of prices for wind turbines, is common knowledge. All other aspects that influence the costs of bidders are idiosyncratic, i.e., private characteristics of bidders.

Furthermore, we assume that bidders act in a competitive environment.

Assumption 3 (Competitive Pressure)**.** There is an $\epsilon > 0$ such that the joint density $f_{L_0,\sigma}(x)$ is bounded below by ϵ, i.e., $f_{L_0,\sigma}(x) \geq \epsilon$ for all x in the support.

Assumption 3 ensures that any bidder expects other bidders with similar LCOE and volatility to be present if participation is large enough. Thereby, competitive pressure exists for any combination of signals.

Observing their own signals, bidders form expectations about their project-specific cost and the cost of competing participants based on the cumulative distribution functions F_L and F_σ. Based on this information, bidders submit their project-specific bids b^{ih}.

The auctioneer collects bids and selects winning bidders. The payment rule is announced ex-ante and may follow uniform or discriminatory pricing. All bids lower than or equal to the clearing price, i.e., the last accepted bid, are awarded and obtain permission for the construction of subsidized renewable energy capacity. With uniform pricing, all projects receive the clearing price p for generating electricity. With discriminatory pricing, each awarded project obtains payments p^{ih} according to the corresponding bid, i.e., $p^{ih} = b^{ih}$. The permission to build capacity is valid until time $t = T$, with the auction taking place at time $t = 0$. Bidders that do not develop their projects in the grace period from $t = 0$ to $t = T$ forgo the rights they win in the auction.

Auctioneers usually follow partially conflicting objectives when designing renewable auctions: They aim to minimize procurement costs, maximize the realization rates, and maximize efficiency ensuring that bidders with the lowest cost win the auction.

To incentivize high realization rates, auctioneers have various design options to enforce allocated contracts. Auctioneers can either charge *penalties* for non-realization of the projects or require bidders to complete *pre-qualification* measures ahead of the auction.

Penalties do not require payments or actions prior to maturity of the contract. Instead, awarded bidders pay a penalty if they do not fulfill their contracts within the grace period. Pre-qualification measures may be financial or physical. Financial pre-qualification is typically implemented as a non interest-bearing deposit posted to the auctioneer prior to the auction. In case a bidder decides to default on the contract or cannot fulfill requirements of the project within the grace period, the deposit is not refunded. Financial pre-qualifications are thereby comparable to penalties in their incentive structure. In fact, in the absence of credit risk and stochastic interest rates, penalties and financial pre-qualification are equivalent.

Physical pre-qualification comprises non-financial criteria which have to be met by bidders in order to participate in the auction. Common examples of physical pre-qualification measures are the attainment of building permits or completion of conduction studies previous to the auction (del Río & Linares, 2014). Physical pre-qualification can be considered as participation cost that ensures the capability of the winning bidders. However, bidders may have an information gain from completing requirements set by the auctioneer.

In the following, we restrict our attention to financial pre-qualifications, which are common in many auctions. We model financial pre-qualifications by a payment for each unit of capacity contracted but not supplied. In order to make pre-qualification payments comparable to LCOE, we scale them to a cost P per unit of energy (see Section 4 for details).

2.2. Net present cost bidders

As a benchmark, we introduce NPC bidders who determine their valuation according to net present cost. In particular, NPC bidders do not recognize the flexibility embedded in the awarded contracts.

The literature has demonstrated that in many instances, observed managerial decisions and market prices for assets seem to be consistent with real options theory (e.g., Bulan, Mayer, & Somerville, 2009; Cunningham, 2006; Kellogg, 2014; Moel & Tufano, 2002; Paddock, Siegel, & Smith, 1988; Quigg, 1993). However, a growing body of recent literature uses laboratory and field experiments to show that observed behavior is often not in line with predictions of real options theory (e.g., Morreale, Mittone, & Nigro, 2019). A significant portion of decision makers evaluates projects using simpler net present value (NPV) approaches, not taking into account the inherent option values of projects (e.g., Denison, Farrell, & Jackson, 2012; Holst, März, & Mußhoff, 2016; Ihli, Gassner, & Musshoff, 2018; Wang, Bernstein, & Chesney, 2012). Furthermore, surveys on senior managers provide ample evidence that real options valuation is used only in a minority of companies while the NPV approach seems to be more popular (e.g., Graham & Harvey, 2001). To include bidders with different strategic approaches, we introduce NPC bidders into our model. NPC bidders represent an extreme case and help us to trace out the impact of flexibility on bids, auction outcomes, and realization rates.

In the following, we drop indices i and h from the processes L_t and B_t and parameters L_0, σ, p, and b where no confusion can arise. Note that since we use risk-free pricing and L^*_t is a Martingale, $\mathbb{E}^*_0(e^{-rt}L_t) = L_0$ and it is inconsequential for NPC bidders at what time they develop a project. To facilitate a comparison with OBC bidders, we assume without loss of generality that NPC bidders develop their projects at $t = T$, i.e., that the right to develop the project is equivalent to a standard forward contract maturing at T with risk-free price $\mathbb{E}^*_0[L_T] = e^{rT}L_0$.

The expected NPV per MWh for an NPC bidder therefore equals the discounted difference between the price p the bidder receives and the expected LCOE at time T, i.e.,

$$\mathbb{E}^*_0[\mathrm{NPV}(L_0, p)] = e^{-rT}(p - e^{rT}L_0). \tag{3}$$

2.3. Option based cost bidders

Next, we investigate bidders who view projects as real options to develop subsidized renewable energy capacity. As opposed to NPC bidders, these bidders explicitly include the option to default on the awarded project into their ex-ante valuation. In the case of renewable auctions, unlike in the standard case of real option valuation, the possibility to realize the project has a last date T.

To deal with the resulting finite horizon problems, we use standard option pricing theory as used for pricing financial options (Black & Scholes, 1973). We calculate the value W^{ih} of the option to invest by modelling the investment opportunity as a European put option. More specifically, at maturity the option to sell electricity for the price p awarded in the auction has a payout profile of

$$\max(p - L_T, -P) \tag{4}$$

per unit capacity, where P is the pre-qualification payment that is lost if the option is not exercised. Note that unlike for standard put options, the pay-off may be negative and is bounded below by $-P$ rather than zero. The guaranteed price of electricity p resembles the strike price of a financial option while the grace period is the time to maturity. From the perspective of OBC bidders, the auction allocates real options among bidders who specify the strike price of the options as bids.

Conceptually, the option to invest in a project would be better captured by an American option because the exercise date is not restricted to the time of maturity T. However, it has been shown in the literature that differences in value between European and American put options are negligible (e.g., Brennan & Schwartz, 1977). Consequently, the right to exercise early is only of minor economic relevance and we use the classical framework for valuation of European options for analytical tractability. Based on these assumptions, we calculate the option value using standard arguments for risk neutral valuation. In the following lemma, we discuss the pricing formula as well as sensitivities, which will be required for the subsequent analysis.

Lemma 1 (Real Option Based Valuation)**.** *The value of the option with pre-qualification P and payout profile (4) at maturity is given by*

$$\begin{aligned} W(L_0, \sigma, p, P) = &-L_0\Phi(z) + e^{-rT}\Big((p+P)\Phi\big(z+\sigma\sqrt{T}\big) - P\Big),\\ z := &-\frac{\ln\frac{L_0}{p+P} + \left(r + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}, \end{aligned} \tag{5}$$

where Φ is the CDF of a standard normal distribution. The option value W

(a) *decreases in the underlying, i.e.,*

$$\frac{\partial W}{\partial L_0} = -\Phi(z) \leq 0. \tag{6}$$

(b) *increases in the volatility of the underlying, i.e.,*

$$\nu := \frac{\partial W}{\partial \sigma} = L_0 \cdot \varphi(z) \cdot \sqrt{T} \geq 0, \tag{7}$$

with $\varphi(x) = \Phi'(x)$ the density of the standard normal distribution.

(c) *decreases in the pre-qualification payment, i.e.,*

$$\frac{\partial W}{\partial P} = e^{-rT}\Big(\Phi\big(z+\sigma\sqrt{T}\big) - 1\Big) \leq 0. \tag{8}$$

(d) *and is convex and increasing in the award price, i.e.,*

$$\frac{\partial W}{\partial p} = e^{-rT} \cdot \Phi\big(z+\sigma\sqrt{T}\big) \geq 0 \tag{9}$$

and

$$\frac{\partial^2 W}{\partial^2 p} = \frac{L_0}{(p+P)^2} \cdot \frac{1}{\sigma\sqrt{T}} \cdot \varphi(z) \geq 0. \tag{10}$$

The proof of (5) is relegated to Appendix A. The calculation of the partial derivatives in (a) - (d) is tedious but straightforward.

3. Optimal bidding and auction outcomes

In this section, we illustrate that for auctions with a large number of bidders all equilibria are close to the competitive truth-telling equilibrium. Subsequently, we use truth-telling equilibria to analyze the impact of bidder characteristics and identify an advantage for bidders with a high option value. Finally, we derive comparative statics for auction outcomes and compare post-auction realization rates for different auction designs.

3.1. Truthful bidding

Typically, for any given and finite number of bidders multiple equilibria arise in multi-unit procurement auctions, and bidders profit with positive probability from marking-up their bid (e.g., Ausubel et al., 2014). However, Swinkels (2001), Cripps and Swinkels (2006), and Jackson and Kremer (2006) show that all auction outcomes converge to truth-telling equilibria as the number of bidders increases.[1]

Definition 1 (Truth-Telling Bid)**.** A bid for a project is truth-telling if it is equal to the bidder's reservation price for that project, i.e., the price for which the bidder is indifferent between entering the contract or not. Synonymously, we say that a bidder is truthful or submits a truthful bid if the bid is truth-telling.

To find the truth-telling bid b, we derive the minimal award price for which the bidder would be willing to enter the contract. For the NPC bidder, we solve

$$0 = \mathbb{E}_0^*[\mathrm{NPV}(L_0^{ih}, p)] = e^{-rT}(p - \mathbb{E}_0^*[L_T^{ih}]) = e^{-rT}\left(p - e^{rT}L_0^{ih}\right), \quad (11)$$

which yields a reservation price of $e^{rT}L_0^{ih}$. The reservation price makes the NPC bidder indifferent between entering the contract or not as it just covers cost. We denote the reservation price of a net present cost bidder as

$$\mathrm{NPC}(L_0^{ih}) := e^{rT}L_0^{ih}, \quad (12)$$

with NPC^{ih} as shorthand notation. Note that NPC^{ih} does not depend on the volatility of the LCOE process, i.e., $\frac{\partial}{\partial\sigma}\mathrm{NPC}^{ih} = 0$.

Similarly, we derive the truth-telling bid of an OBC bidder. Note that for $P > 0$, the value of the option can also be negative implying a positive reservation price. In particular, we define the reservation price $\mathrm{OBC}(L_0^{ih}, \sigma^i, P)$ of an option based cost bidder implicitly by

$$W^{ih}(L_0^{ih}, \sigma^i, \mathrm{OBC}(L_0^{ih}, \sigma^i, P), P) = 0, \quad (13)$$

with OBC^{ih} a shorthand notation. Where we do not need to differentiate between OBC^{ih} and NPC^{ih}, we simply write c^{ih} in the following. Note that OBC^{ih} exists and is unique since W^{ih} is continuous, convex, and increasing in p by Lemma 1 and $W^{ih}(L_0^{ih}, \sigma^i, 0, P) < 0$.

Having established the notion of truthful bidding, we start by analyzing the case of uniform price auctions, using results of Cripps and Swinkels (2006). They show that with an increasing number of players, the probability that a particular player is price setting decreases towards zero. As a result, the incentive to shade bids, i.e., to bid above reservation price, vanishes. Consequently, deviation from truthful bidding becomes less attractive and strategies converge to truthful bidding in the limit where the auction becomes perfectly competitive. We use these results to prove the following proposition.

Proposition 1 (Asymptotic Equilibrium in Uniform Price Auctions, Cripps and Swinkels (2006))**.** *For uniform price renewable auctions fulfilling Assumption 2, all Bayesian-Nash equilibrium strategies converge to the truth-telling strategy of bidding c^{ih} as the number of bidders goes to infinity.*

Proof. By Assumption 2, bidders have independent signals and hence z-independence as defined in Cripps and Swinkels (2006) holds. For the same reason, the costs of bidders c^{ih} are independent and fulfill Assumption 4 in Cripps and Swinkels (2006). The result on competitive bidding follows from Theorem 2 in Cripps and Swinkels (2006). □

[1] This result also holds in the linear supply function approach to uniform price auctions, where bid functions converge to the true costs as the number of bidders increases, see, e.g., the analytical solutions in Hortacsu and Puller (2005, 2008).

Note that Cripps and Swinkels (2006) in addition impose the two further conditions of no asymptotic gaps and no asymptotic atoms. These conditions ensure that the distribution of signals is sufficiently even for a large number of bidders, i.e., the support of the distribution does neither have gaps nor does the distribution have atoms. However, these conditions are not required for the convergence result, but merely to establish a certain rate of convergence.

To analyze discriminatory auctions, we use asymptotic results in Swinkels (2001) and Jackson and Kremer (2006).

Proposition 2 (Asymptotic Equilibrium in Discriminatory Auctions, Jackson and Kremer (2006))**.** *For discriminatory renewable auctions fulfilling Assumption 1-3, all Bayesian-Nash equilibrium strategies converge to the truth-telling strategy of bidding c^{ih} as the number of bidders goes to infinity.*

Proof. Because of Assumptions 1 – 3, Theorem 1 of Jackson and Kremer (2006) applies. It follows that all equilibria in large multi-unit discriminatory auctions with fixed auctioneer's demand converge to efficient allocations, and the auctioneer extracts the entire surplus. The combination of efficiency and full surplus extraction by the auctioneer implies a truth-telling equilibrium. □

Next, we demonstrate that typical renewable auctions have a sufficient number of bidders to use the above asymptotic results as a close approximation of reality. To this end, we assess convergence behaviour of equilibrium strategies towards truth-telling bids as characterized in Propositions 1 and 2. To illustrate how equilibrium bids converge to true costs as N increases, we use a characterization of optimal bidding behavior in discriminatory multi-unit auctions proposed by Swinkels (2001). He shows that the optimal strategy in a multi-unit discriminatory auction asymptotically is a natural generalization of the optimal strategy in a first-price single-unit auction. In our procurement setting this implies that bidders asymptotically bid the expectation of the next lowest cost conditional on that cost exceeding their own cost. Formally,

$$\left(b^{ih}(c^{ih}) - \mathbb{E}\left[Y_{h+1:\mathbb{E}[\mathcal{H}]} | Y_{h+1:\mathbb{E}[\mathcal{H}]} > c^{ih}\right]\right) \xrightarrow{N\to\infty} 0, \quad (14)$$

where $Y_{l:L}$ is the l-th order statistic of unit valuations c^{jk} for a sample size of L units, $\mathcal{H}$ is the overall random number of units offered by bidders, and $b^{ih}(c^{ih})$ is an equilibrium bid. Put differently, each bidder forms an expectation on the next highest competing bid and submits a bid marginally below to not be undercut by a rival project. This result allows us to use $\mathbb{E}\left[Y_{h+1:\mathbb{E}[\mathcal{H}]} | Y_{h+1:\mathbb{E}[\mathcal{H}]} > c^{ih}\right]$ to approximate bids for increasing N in order to numerically investigate the bidding behavior. If, for a large N, $\mathbb{E}\left[Y_{h+1:\mathbb{E}[\mathcal{H}]} | Y_{h+1:\mathbb{E}[\mathcal{H}]} > c^{ih}\right] \approx c^{ih}$, then (14) implies that equilibrium bids are close to true project costs.

We analyze the convergence speed to truth-telling bids by simulating a real-world example of German wind energy auctions (for details on the parametrization as well as the ratio of OBC and NPC bidders used, see Section 4). In particular, we compute the difference between the conditional expectation in (14) and the truth-telling bid for the 1st unit up to the 5th unit for randomly sampled OBC and NPC bidders for varying N resulting in different values for $\mathbb{E}(\mathcal{H})$. We compute the conditional expectations using numerical integration.

We repeat this process 100 times and report the average deviation of the truth-telling bid from $\mathbb{E}\left[Y_{h+1:\mathbb{E}[\mathcal{H}]} | Y_{h+1:\mathbb{E}[\mathcal{H}]} > c^{ih}\right]$ for the two bidder types in Fig. 1. We plot this deviation as a function of the expected number of bidders N. As can be seen, for auctions with more than 100 bidders, the bidding strategy proposed by Swinkels (2001) is within 1 % of the true costs for both bidder types.

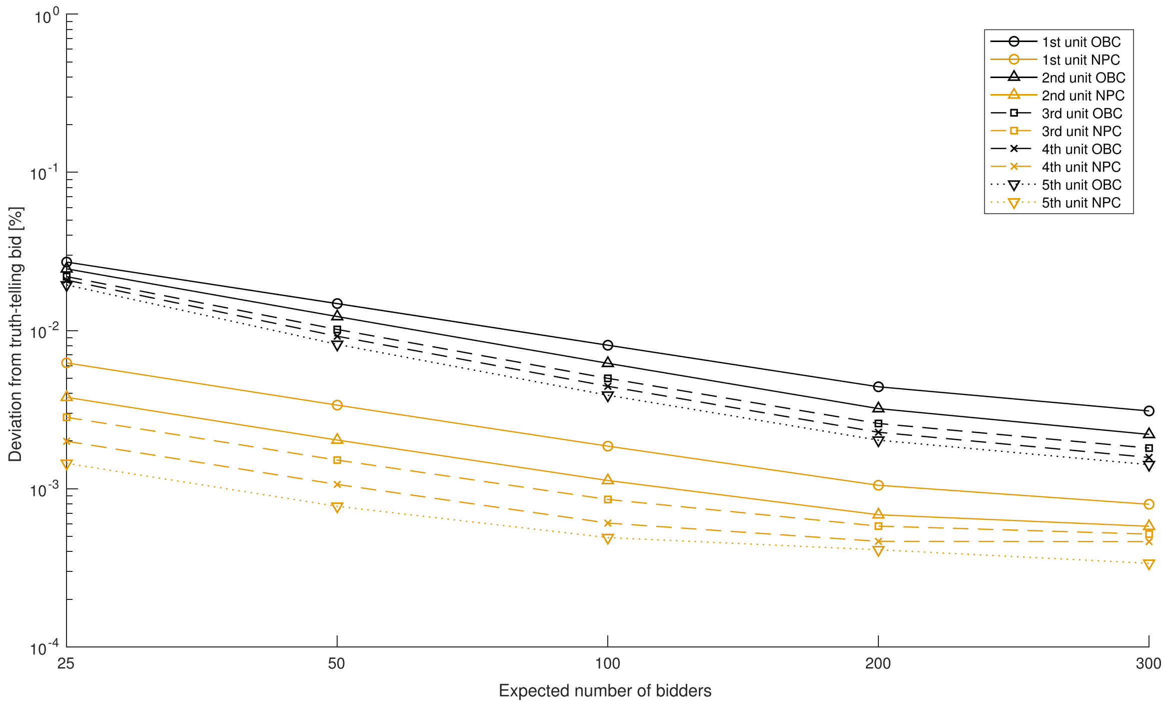

Fig. 1. Deviation of the bidding strategy for discriminatory auctions from truth-telling bids.

A comparison with real-world renewable auctions shows that number of bidders in most auctions therefore is sufficiently large to render the errors made by the assumption of truthful bidding negligible: In Germany, the number of issued bids was on average 198 (maximum 281, minimum 111) for auctions of onshore wind energy and 110 (maximum 170, minimum 62) for auctions of photo-voltaic systems (see Bundesnetzagentur, 2018a; 2018b). NFFO auctions in UK and RAM auctions in California showed comparable numbers of participants (see del Río & Linares, 2014).

Since uniform price auctions foster more aggressive bidding than discriminatory auctions (Ausubel et al., 2014), the differences between players bids and reservation price in Fig. 1 serve as an upper bound for the case of uniform auctions.[2] In sum, this investigation indicates that our assumption of truth-telling bids is reasonable for the majority of renewable auctions.

We conclude this section by a discussion on the difference between uniform price and discriminatory price auctions. Jackson and Kremer (2006) prove asymptotic revenue equivalence between uniform and discriminatory auction formats for limited supply (see Jackson & Kremer, 2006, Theorem 1). Intuitively, this result can be explained as follows: In the limit there are enough bidders with very low cost signals to satisfy demand. Full demand is awarded close to the minimum cost resulting in a convergence of cost for the two auction formats.

However, evidence from our simulations reveals that there is a difference in procurement cost between discriminatory and uniform auctions (see Table 1 in Section 4). This difference is driving a wedge between the result of asymptotic truthful bidding and asymptotic revenue equivalence: While truthful bidding is a close approximation of reality in renewable auctions as argued above, revenue equivalence seems to require an unrealistically large number of bidders. The result of asymptotic revenue equivalence is therefore not applicable for renewable auctions, implying that the choice of the auction format matters.

3.2. The value of flexibility

In this section, we show that bidders who value the embedded flexibility in the auctioned contract have an advantage in renewable auctions and analyze the determinants of this effect. We start by showing that a project is more valuable for OBC bidders than for NPC bidders, independent of the clearing bid. Consequently, OBC bidders issue lower bids than NPC bidders, if both bid truthfully.

Proposition 3 (Value of Flexibility)**.** *The option value of each bidder is always above the expected NPV for any award price p^{ih}, i.e.,*

$$W(L_0^{ih}, \sigma^i, p^{ih}, P) > \mathbb{E}_0^*[\mathrm{NPV}(L_0^{ih}, p^{ih})] \tag{15}$$

and a truthful OBC bidder always bids lower than a truthful NPC bidder with the same signals in uniform price and discriminatory price auctions.

Proof. The option value is the expected payoff with respect to the risk neutral measure, i.e.,

$$W(p) = \mathbb{E}_0^*\left[e^{-rT}\max(-P, p - L_t)\right] \geq \mathbb{E}_0^*\left[e^{-rT}(p - L_t)\right] = \mathbb{E}_0^*[\mathrm{NPV}(L_0^{ih}, p^{ih})],$$

which establishes the claim.

It follows that the project value of an OBC bidder is ceteris paribus larger than the project value of an NPC bidder. Since bidders bid truthfully in uniform price auctions (Proposition 1) as well as discriminatory price auctions (Proposition 2), the second part of the result follows. □

In order to optimize auction outcomes, regulators can influence the value of flexibility Γ in the auctioned contracts, where

$$\Gamma(L_0, \sigma, p, P) = W(L_0, p, \sigma, P) - \mathbb{E}_0^*[\mathrm{NPV}(L_0, p)] = L_0[1 - \Phi(z)] + e^{-rT}(P + p)\left[\Phi\left(z + \sigma\sqrt{T}\right) - 1\right]$$

[2] For uniform price auctions, expression (14) can serve as an approximation of the pivotal bid: the marginal and price setting bidder must submit a bid below the next highest bid to remain among the winning bidders and set the uniform clearing price, and hence must bid below the expected next highest project costs (i.e., the lowest losing bid).

Table 1
Simulated results of auction outcomes for different settings based on a 10,000 sample Monte Carlo simulation for the status quo, low cost scenario, and high cost scenario. Standard deviations are reported in brackets and actual outcomes of the auction are displayed in the last column.

	status quo		low cost		high cost		
	uniform	pay-as-bid	uniform	pay-as-bid	uniform	pay-as-bid	ONWA17
Minimal bid [€ /MWh]	28.56 (1.16)		26.60 (1.15)		32.69 (1.34)		35.00
Maximal bid [€ /MWh]	69.49 (1.93)		69.48 (1.94)		67.92 (1.84)		64.50
Maximal award price [€ /MWh]	42.67 (0.92)		41.04 (1.05)		45.35 (0.67)		42.90
Weighted award price [€ /MWh]	42.67 (0.92)	37.72 (0.75)	41.04 (1.05)	35.86 (0.79)	45.35 (0.67)	41.35 (0.58)	42.80
Expected realization rate [%]	49.36 (4.07)	27.55 (2.60)	40.08 (4.15)	18.47 (1.91)	64.86 (3.38)	43.03 (2.92)	

the difference between the reservation price of an OBC and an NPC bidder with the same signals. In the following proposition, we assess the effect of volatility σ, financial pre-qualification P, award price p, and duration of the grace period T on Γ.

Proposition 4 (Drivers of the Value of Flexibility)**.** *The value of flexibility Γ ...*

(a) *vanishes monotonically for high financial pre-qualification, i.e., $\lim_{P\to\infty}\Gamma = 0$.*
(b) *vanishes monotonically for high awarded bids, i.e., $\lim_{p\to\infty}\Gamma = 0$.*
(c) *decreases with decreasing σ, i.e., $\frac{\partial\Gamma}{\partial\sigma} \geq 0$ and the optimal OBC bid converges to the optimal NPC bid.*
(d) *decreases with decreasing duration of the grace period T, i.e., $\frac{\partial\Gamma}{\partial T} \geq 0$*

Proof. The results follow from straightforward calculations of limits. Note that for (a) and (c) only the value of the option changes, while the expected NPV stays constant. Due to the exponential structure of Φ, $\lim_{p\to\infty}\Gamma = \lim_{P\to\infty}\Gamma = 0$. Partial derivatives show that the limit is reached monotonically:

$$\frac{\partial\Gamma}{\partial p} = \frac{\partial\Gamma}{\partial P} = \frac{\partial W}{\partial P} = e^{-rT}\left(\Phi\left(z+\sigma\sqrt{T}\right) - 1\right) \leq 0, \tag{16}$$

proving (a) and (b). The partial derivative with respect to volatility is

$$\frac{\partial\Gamma}{\partial\sigma} = \frac{\partial W}{\partial\sigma} = L_0 \cdot \varphi(z) \cdot \sqrt{T} \geq 0, \tag{17}$$

proving the first part of (c).

To prove the second part of (c), observe that the truthtelling bid p for an OBC bidder fulfills

$$0 = W^{ih}(L_0^{ih}, \sigma^i, p, P) = -L_0\Phi(z) + e^{-rT}\left((p+P)\Phi\left(z+\sigma\sqrt{T}\right) - P\right),$$

which is equivalent to

$$P = (p+P)\Phi\left(z+\sigma\sqrt{T}\right) - e^{rT}L_0\Phi(z). \tag{18}$$

Now suppose that optimal bid fulfilling (18) is such that

$$p \leq L_0e^{rT} - P. \tag{19}$$

Since Φ is Lipschitz, there exists $L > 0$ such that

$$\Phi(z+\sigma\sqrt{T}) - \Phi(z) \leq L\sigma\sqrt{T}, \quad \forall z \in \mathbb{R}.$$

It follows that for a given T and $\epsilon > 0$, there is a $\sigma_0 > 0$ such that

$$\Phi(z+\sigma\sqrt{T}) - \Phi(z) < \epsilon, \quad \forall z \in \mathbb{R}.$$

Using assumption (19), we estimate

$$\begin{aligned} P &= (p+P)\Phi(z+\sigma\sqrt{T}) - e^{rT}L_0\Phi(z) \\ &\leq e^{rT}L_0(\Phi(z+\sigma\sqrt{T}) - \Phi(z)) < \epsilon L_0 e^{rT}. \end{aligned}$$

Since $\epsilon > 0$ is arbitrary, this leads to a contradiction for a fixed $P > 0$. We conclude that (19) leads to a contradiction and for truth-telling bids, we always have $p > L_0e^{rT} - P$ which implies that $-\ln\frac{L_0}{p+P} - rT > 0$. Thereby, $\lim_{\sigma\to 0} z = \infty$ as the enumerator is positive. Consequently, we have $\lim_{\sigma\to 0}\Gamma = 0$, as stated in (c).

Furthermore, we infer from $\lim_{\sigma\to 0} z = \infty$ that

$$\begin{aligned} \lim_{\sigma\to 0} W(L_0, \sigma, p, P) &= \lim_{\sigma\to 0} -L_0\Phi(z) + e^{-rT}\left((p+P)\Phi\left(z+\sigma\sqrt{T}\right) - P\right) \\ &= -L_0 + pe^{-rT}. \end{aligned}$$

For truthful bidding as in (13), we have that in the limit OBC $= L_0e^{rT}$. Recalling the definition of NPC in (12), we have OBC = NPC, proving the last part of (c).

The partial derivative with respect to maturity is

$$\frac{\partial\Gamma}{\partial T} = e^{-rT}r(p+P)(1 - \Phi(z+\sigma\sqrt{T})) + \varphi(z)L\frac{\sigma}{2\sqrt{T}} \geq 0, \tag{20}$$

proving (d). □

It follows from Proposition 4(a) that a high penalty P decreases the advantage of option bidders by making the non-realization option less attractive. Since P can be directly influenced by the auctioneer, it is one of the main tools to steer the value of flexibility and thereby the realized prices and realization rates. In situations with large award prices, the advantage of OBC bidders is small (see Proposition 4(b)) as the non-realization option does not matter much. The positive sign of the derivative in Proposition 4(c) also implies that, ceteris paribus, bidders with higher σ, i.e., larger uncertainties in production cost, assign higher value to contracts and therefore submit lower bids. Bidders with a lower option value thus bid higher and have a disadvantage in the auction. Since valuation of OBC bidders converges to the valuation of NPC bidders, this finding extends the result in Proposition 3. Finally, in auctions with a long grace period, the value of flexibility tends to be high (see Proposition 4(d)).

These results have important implications in auctions for technologies whose future cost developments are uncertain. These auctions are likely to be dominated by inexpensive OBC bidders, which may result in rather low realization rates of projects if the development of the LCOE turns out to be unfavorable (see Section 3.3). In this setting, the auctioneer might consider high penalties to decrease the value of flexibility and consequently attract more bidders with small σ that bid close to NPC.

Proposition 4 (d) shows that the value of flexibility decreases as the time to maturity of the option goes to 0. This is intuitively clear, since the value of the option approaches its intrinsic value as $T \to 0$. Similar to the penalty P, the length of the grace period can be directly controlled by the auctioneer and therefore represents an important policy instrument to control the value of flexibility.

3.3. Equilibrium prices and post auction realization rates

Next, we analyze realization rates $\frac{K_r}{K}$, where K_r denotes realized capacity at time T. We determine the ex-ante probability of realization ρ^{ih} for each project h of bidder i and use the expected realization rate $\frac{\mathbb{E}[K_r]}{K}$ to measure effectiveness of the auction.

At time T, winning bidders decide whether they want to realize the project. A bidder—independent of the type—will realize the project if the difference between feed-in tariff and LCOE is larger than the pre-qualification payment per unit, i.e., if $p^{ih} - L_T^{ih} \geq -P$. In particular, given an award price and an LCOE, there is no difference between NPC bidders and OBC bidders in their propensity to develop the project. Thus, the difference is merely in the ex-ante anticipation and valuation of this option.

For uniform pricing, we obtain a realization probability of

$$\rho^{ih} = \mathbb{P}(p^{ih} - L_T^{ih} \geq -P) = F_{L_T^{ih}}(P + p^{ih}), \tag{21}$$

where $p^{ih} = p$ for all units across all bidders. Based on the properties of the stochastic process (1), we can calculate these probabilities using the log-normal distribution of L_T^{ih} (see Appendix A, Proof of Proposition 1). Given the auction outcome, it is thus straightforward to calculate the expected total realization of renewable capacity

$$\mathbb{E}[K_r] = \sum_{i=1}^{N} \sum_{h=1}^{H^i} \rho^{ih} k^{ih} \mathbb{1}_{\{\text{project } h \text{ of bidder } i \text{ wins}\}}, \tag{22}$$

with k^{ih} the capacity of bidder i's project h and $\mathbb{1}_A$ the indicator function of the event A.

Realization probabilities depend on the award price, which is determined by issued bids. Clearly, ceteris paribus, the realization probability for projects of OBC bidders is lower than or equal to the realization probability for projects of NPC bidders by Proposition 3. Bids of NPC bidders are independent of volatility and financial pre-qualification and only affected by LCOE, while bids of OBC bidders depend on all of those parameters. In the following proposition, we derive comparative statics for truth-telling bids of OBC bidders and discuss their effects on realization probabilities.

Proposition 5 (Comparative Statics for Bids and Realization Probabilities)**.**

(a) *For the truth-telling bid* OBC^{ih} *of an OBC bidder it holds that*

$$\frac{\partial \mathrm{OBC}^{ih}}{\partial \sigma^i} \leq 0, \; \frac{\partial \mathrm{OBC}^{ih}}{\partial L_0^{ih}} \geq 0, \; \frac{\partial \mathrm{OBC}^{ih}}{\partial P} \geq 0, \; \frac{\partial^2 \mathrm{OBC}^{ih}}{\partial^2 P} \leq 0. \tag{23}$$

Thus, for higher financial pre-qualification or higher initial values of LCOE, OBC bidders submit higher bids, while they submit lower bids for increasing volatility. Furthermore, the marginal effect of financial pre-qualification is diminishing.

(b) *For both bidder types, the realization probability increases for higher financial pre-qualification with a diminishing marginal effect.*

Proof.

(a) By invoking the implicit function theorem on the OBC condition $W(L_0, \mathrm{OBC}, \sigma, P) = 0$, we determine the partial derivatives of OBC w.r.t. L_0, σ, and P. For the first case, using (6) and (9) yields

$$\frac{\partial \mathrm{OBC}}{\partial L_0} = -\frac{\partial W / \partial L_0}{\partial W / \partial p} = e^{rT} \frac{\Phi(z)}{\Phi\left(z + \sigma\sqrt{T}\right)} \; \geq 0. \tag{24}$$

Analogously, using Eqs. (7),(8) and (9) we obtain

$$\frac{\partial \mathrm{OBC}}{\partial \sigma} = -e^{rT}\sqrt{T} L_0 \frac{\varphi(z)}{\Phi\left(z + \sigma\sqrt{T}\right)} \; \leq 0, \tag{25}$$

$$\frac{\partial \mathrm{OBC}}{\partial P} = \frac{1}{\Phi\left(z + \sigma\sqrt{T}\right)} - 1 \; \geq 0. \tag{26}$$

Taking the partial derivative again yields

$$\frac{\partial^2 \mathrm{OBC}}{\partial^2 P} = -\frac{\varphi(z + \sqrt{\tau})}{\Phi\left(z + \sigma\sqrt{T}\right)^3 \sigma\sqrt{\tau}(\mathrm{OBC} + P)} \leq 0. \tag{27}$$

(b) For the case of *NPC bidders*, we take the partial derivative of the realization probability yielding

$$\frac{\partial F_{L_T}(P + \mathrm{NPC})}{\partial P} = f_{L_T}(P + \mathrm{NPC}) \geq 0. \tag{28}$$

The second partial derivative reveals the diminishing marginal effect of P on the realization probability for NPC-bidders

$$\begin{aligned}\frac{\partial^2 F_{L_T}(P+\mathrm{NPC})}{\partial^2 P} &= -\frac{\varphi(z+\sigma\sqrt{T})}{(b+P)\sigma\sqrt{T}}\left(1 + \frac{z+\sigma\sqrt{T}}{\sigma\sqrt{T}}\right) = \\ &= -f_{L_T}(P + \mathrm{NPC}) \cdot \left(2 + \frac{z}{\sigma\sqrt{T}}\right) \leq 0.\end{aligned} \tag{29}$$

For the case of *OBC bidders*, we establish a positive relation of increasing penalties and realization probability by using (26),

$$\frac{\partial F_{L_T}(P + \mathrm{OBC})}{\partial P} = f_{L_T}(P + \mathrm{OBC}) \frac{1}{\Phi(z + \sigma\sqrt{T})} \geq 0. \tag{30}$$

The second partial derivative reveals the diminishing marginal effect of P on the realization probability for OBC-bidders

$$\frac{\partial^2 F_{L_T}(P + \mathrm{OBC})}{\partial^2 P} = -\frac{f_{L_T}(P + \mathrm{OBC})}{\Phi(z + \sigma\sqrt{T})^2} \cdot \left(f_{L_T}(P + p) + \frac{2 + \frac{z}{\sigma\sqrt{T}}}{(P + \mathrm{OBC})}\right) \leq 0. \tag{31}$$

□

Note that the auctioneer's goals of minimal procurement cost and high post-auction realization rates are partially conflicting as lower award prices lead, ceteris paribus, to lower realization rates. The above result sheds light on this trade-off. Auctioneers may favor bidders with low option value for their higher realization rates and design the auction accordingly. Yet, OBC bidders with high σ potentially deploy projects with low need for subsidies, especially if LCOE develops favorably. For this reason, financial pre-qualifications are an important tool for policy makers to navigate this trade-off. In contrast, LCOE and the volatility σ are largely outside the control of auctioneers.

The increase in realization probability from increasing financial pre-qualification discussed in Proposition 5(b) comes at the price of increasing deployment cost due to increasing bids of OBC bidders, see Proposition 5(a). Intuitively, the value of the non-realization option shrinks due to a higher pre-qualification payment and thereby the bids increase.

As opposed to Kreiss et al. (2017), we identify a diminishing marginal effect of P on the realization probability of both bidder types in Proposition 5(b). Thus, increasing financial pre-qualification is helpful in pushing realization rates to a certain level, but the marginal effect wears off. Furthermore, we find that increasing P increases OBC bids and that the marginal increase is diminishing as well (see Proposition 5(a)).

Note that while increasing financial pre-qualification does increase realization probability for all bidders, see Proposition 5(b), it does not increase bids of NPC bidders. Therefore increasing financial pre-qualification increases realization rates through two channels: First, it decreases the share of OBC bidders with a high σ that win the auction (see Proposition 4(a)) and, second, it raises the realization probabilities for all winning bidders.

The above argument only holds if there is a sufficient number of bidders. If this is not the case, auctioneers need to take into account bidder diversity and participation when setting financial pre-qualification levels. In particular, if auctioneers wish to enable participation of a broad range of firms, they should avoid high deposits that push smaller, less liquid bidders out of the market.

4. Case studies

In this section, we use our model to analyze two real-world renewable auctions. First, we discuss our results qualitatively and consider the case of an onshore wind auction under the England and Wales Non-Fossil Fuel Obligation (NFFO3). While we lack detailed data on bids and underlying cost parameters, this early auction presents a good case in point, because the grace period has passed and realization rates are fully observable. We hence use our results on comparative statics and discuss the outcomes of this auction with a focus on realization rates. Second, we illustrate that our model is able to numerically replicate equilibrium outcomes in renewable auctions. To that end, we simulate bids of the German auction for onshore wind energy in August 2017 (ONWA17), where more detailed information is available. Simulations are performed with MATLAB R2017b. Both auctions have sufficiently many participants to assume truth-telling bids as discussed in Section 3.1.

4.1. United Kingdom — NFFO3

England and Wales have supported renewable energy generation since 1990 via the Non-Fossil Fuel Obligation, conducting five renewable auctions between 1990 and 1998. The total commissioned volume of 1500 MW equaled 3 % of UK electricity supply (Mitchell, 2000). As part of the implementation of the NFFO, subsidies for a variety of technologies such as wind energy, hydro power, as well as municipal and industrial waste power plants were awarded to producers. Our discussion centers on the results of the wind band of NFFO3, which was held in 1994.

Total capacity auctioned off was 165 MW with a grace period of 4 years for the option to build. Bidders were separated into two groups ("sub-bands") for onshore wind: one sub-band for plants below 1.6 MW and one sub-band for larger plants. In total, about 150 wind projects were offered and allocated in a pay-as-bid design. A crucial detail in auction design was the absence of financial pre-qualification or fines for non-realization. As discussed in Section 3, this rendered the non-realization option very valuable to investors, since defaulting bidders only had to bear cost of bid preparation and the reputational cost of non-realization.

Award prices of the onshore wind auction were surprisingly low, ranging from 39.8 £/MWh to 59.9 £/MWh with an average price of 45.3 £/MWh. For comparison, in 2011, feed-in-tariffs for onshore wind in UK (in 1994-£) were still ranging from 39.37 £/MWh to 165.88 £/MWh for comparable turbine classes and up to 305.66 £/MWh for turbines with capacity lower than 1.5 kW according to the Office of Gas and Electricity Markets (Ofgem).[3] After the grace period, it turned out that realization rates were rather low as only 27 % of auctioned capacity was built (see Mitchell, 1995; 2000).

These auction results are in line with our model predictions. In particular, a setting with low financial pre-qualification increases the value of flexibility (see Proposition 4(a)). As a result, bidders that assign a high value to the option of non-realization bid more aggressively and drive down award prices (see Propositions 3 and 4(c)). This effect was further aggravated by the state of wind energy technology at the time of the auction. Being a immature technology in 1994, the cost of wind energy and its future cost development was rather volatile. High volatility increases the value of flexibility even further (see Proposition 4(c) and Lemma 1), guaranteeing a high share of winning OBC bidders with high option values. This induces an increased risk of non-realization, which is further amplified by non existing financial pre-qualification (see Proposition 5(b)). The low realization rates of about 27 % can thus be explained by the interaction of these effects.

4.2. Germany — ONWA17

Until recently, Germany supported renewable electricity generation via feed-in tariffs per unit of generated electricity. In 2014, the German government switched from feed-in tariffs to an auction system to reduce support costs. Auction schemes have been applied to award feed-in premiums for photovoltaics, onshore wind energy, offshore wind energy, energy production from biomass, and combined heat and power generation. The awarded feed-in premia are a slight modification of the feed in tariffs used in this paper. For our modeling, we disregard this difference.

We simulate outcomes of the auction for onshore wind energy held in August 2017 (ONWA17). Our analytic setup requires data on the regulatory framework (auction format, P, K, T), data concerning bidders (N, L_t, σ), and data on the surrounding economic environment (r).

Information on the regulatory framework is directly obtained from German legislation (Deutscher Bundestag, 2014). Total capacity to be auctioned off in ONWA17 is 1000 MW with a bid cap of 70 €/MWh.

The auction design recognized two types of bidders: commercial bidders and non-commercial bidding groups (NCBG, the term "Brgerwindgesellschaften" is used in German legislation). NCBGs had several advantages compared to commercial bidders including a longer grace period of 4.5 years, instead of 2.5 years, and a lower financial pre-qualification of 15,000 € /MW, as compared to 30,000 € /MW. Additionally, NCBGs were awarded subsidies based on uniform pricing, while commercial bidders were subject to discriminatory pricing. As the data shows that about 81 % of participating and 99 % of winning bidders are NCBGs (see Bundesnetzagentur, 2018b), we disregard commercial bidders and set up the auction using the parameters for NCBGs.

We convert pre-qualification payments to a per MWh payment assuming a life time of the plant of 25 years, an output of 2721 full load hours a year (see Kost et al., 2018), and discount the payments using a risk-free rate of 1.17 %, which was the average yield of a German 30-year bond in 2017. This results in a pre-qualification payment of 0.2443 € /MWh.

In ONWA17, 281 bids with capacities between 750 kW and 24.4 MW were submitted. For our simulation, we randomly generate bid sizes in a two step procedure: first we simulate in which range of nameplate capacity the project falls, where capacity ranges and their probabilities are defined according to the data published in Bundesnetzagentur (2018b). Second, we draw the exact capacity from a uniform distribution on the possible project sizes in the chosen range. We simulate 150 bidders, each offering either 1, 2, or 3 projects (with equal probability), implying an expected number of 300 bids.

LCOE for onshore wind energy in Germany at the time of the auction ranged from 39.9 € /MWh to 82.3 € /MWh depending on the construction site (Kost et al., 2018). To sample from the distribution of LCOE, we follow the approach in Heck, Smith, and Hittinger (2016), who sample LCOE for wind energy by treating the inputs of the LCOE calculation as random (see Appendix B for details).

As discussed in Section 2, we sample LCOE per unit, but use only one volatility per bidder. However, our results are robust when simulating volatility for each unit. We assume that the volatilities σ_i and the initial LCOE L_0^{ih} are independent for every

[3] See https://www.ofgem.gov.uk/environmental-programmes/fit/.

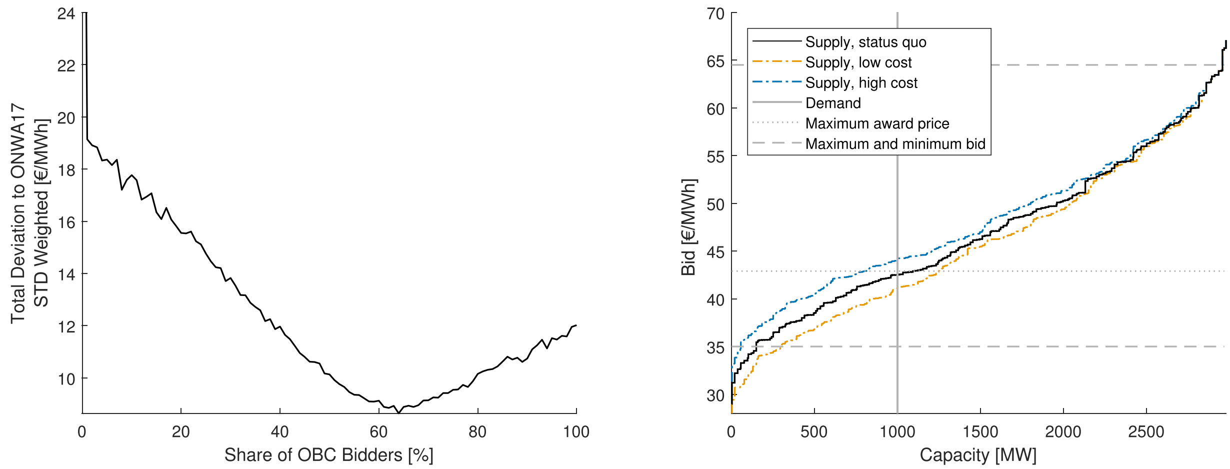

Fig. 2. Calibration error for varying share of OBC bidders (left). Simulation result for the supply curve in ONWA17 for different levels of financial pre-qualification and maturity (right).

bidder i and every project h. Volatility ranges between 0 % and 15 % according to Kost et al. (2018), and we assume a symmetric triangular distribution for our simulation.

To conceptualize the difference between bidders with high and low option values, we assume that NPC and OBC bidders with varying σ participate in the auction. As the split-up between the two bidder types cannot be directly inferred from publicly available data, we calibrate the share of OBC bidders to the results of the auction. In particular, using the parameters discussed above, we conduct Monte Carlo analyses varying the share of OBC bidders between 0 % and 100 % in one percent increments. For each setting, we simulate 2000 auctions and compute the absolute distance between our results and main auction outcomes of ONWA17 (minimal bid, maximal bid, and maximal award price, see Table 1). To compute a single number for the aggregate error, we sum the absolute distances weighted by the respective standard deviations resulting from the Monte Carlo sample and plot the result in Fig. 2 (left). The graph suggests that roughly two thirds (65 %) of the bidders pursue the OBC approach, while the remaining third bids their NPC.

We note that we do not make any claims on the actual prevalence of bidder types from the above analysis. The presence of NPC bidders in the model serves as a way to model a deviation from a competitive equilibrium in risk-neutral OBC bids. While, as we have argued in Section 2.2, it is plausible that at least some bidders employ NPC bidding, we acknowledge that there are other factors such as risk-aversion or strategic bidding which we do not capture in our model and which might explain the deviation from risk-neutral, competitive OBC bidding.

Yet, our simulation shows a good fit to the data published by German authorities, as presented in Fig. 2 (right), which displays the outcome of a single simulation run. The published information comprises minimal/maximal bid (grey dashed lines), maximal award price (grey dotted line), and capacity weighted award price.

In the following, we focus our attention on the auction results of ONWA17. However, to validate our calibration, we simulate the two subsequent auctions for wind energy in Germany in November 2017 (ONWN17) and February 2018 (ONWF18). We use a share of 65 % of OBC bidders, as calibrated in Fig. 2 for ONWA17, and assume auction and technology specifications as present in ONWN17 and ONWNF18, respectively. The results are presented in Appendix C. The model yields a good fit for these additional auctions, showing that our parameterization is robust across auctions.

We analyze three setups of ONWA17: the status quo, a low cost case with penalties of 7500 € /MW (50% of the status quo), and a high cost case with penalties of 30,000 € /MW and a shorter grace period of 2.5 years corresponding to the conditions faced by commercial bidders in ONWA17.

For the status quo, the simulated clearing price of the auction at the intersection of the black supply curve and the vertical grey line is rather close the observed clearing price of 42.90 € /MWh. The simulated maximum and minimum bids are more extreme than the values observed in ONWA17. However, the latter statistics are driven by the most extreme bids and therefore have a higher variability. In accordance with our comparative statics, the simulations for the high (low) cost regime yield a strictly higher (lower) supply curve, depicted by the upper (lower) dashed supply curve, and consequently yield higher (lower) award prices.

To make the results robust with respect to idiosyncratic sampling bias, we conduct a Monte Carlo analysis with 10,000 simulations of the auction and report average values and standard deviations of effects on bids, expected realization rates, award prices, and deployment cost for both auction formats in Table 1.

In the status quo, simulated bids range from from 28.56 € /MWh to 69.49 € /MWh and result in a maximal award price of 42.67 € /MWh. Comparing these numbers with the auction outcomes, the simulation reveals a close match with reality as was already observed for a single simulation in Fig. 2.

Realization probabilities are calculated with a drift of $\mu = -1.7\,\%$ for the LCOE process, based on forecasts presented by Wiser et al. (2016). The expected realization rate of 49.36 % in the status quo is in the lower range of observed realization rates in renewable auctions until now. Note, however, that *expected* realization rates are only a prediction for final results. In states of the world with stronger reduction of LCOE, realization rates will be substantially higher. However, the predicted low rates are in accordance with the fact that at time of writing only 15 out of 67 projects with a capacity of 53.4 MW have been built, yielding a realization rate of 5% three years after the auction.[4]

A visual representation of the connection between penalty, marginal OBC bid, and realization probability is given in Fig. 3. We vary volatility and initial LCOE of the base case (solid black line) by $\pm 20\%$. Due to their effects on option value demonstrated in Lemma 1, an increase in both σ and L_0 increases bids of OBC bidders and therefore decreases realization probability due to a higher share of winning OBC bidders (see Proposition 5(a)).

[4] For the database on registration of power plants in Germany (Marktstammdatenregister), see https://www.marktstammdatenregister.de.

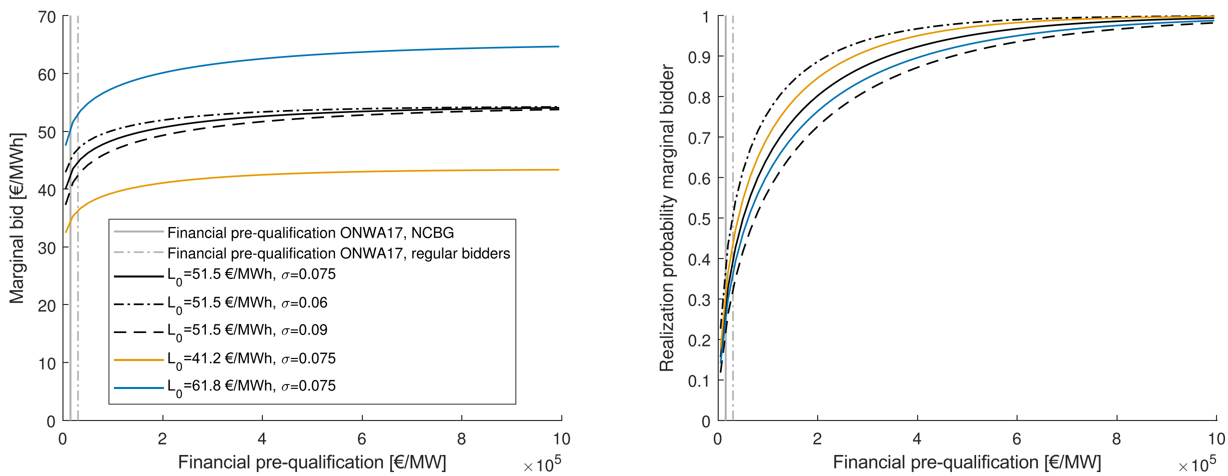

Fig. 3. Marginal bid (left) and corresponding realization probability (right) of hypothetical marginal OBC bidder with varying financial pre-qualification. Grey lines indicate current financial pre-qualification in ONWA17 for NCBGs (dashed) and regular bidders (solid).

Fig. 3 yields an argument for higher financial pre-qualification. For low pre-qualification payments both marginal bid and realization probability are quite sensitive. However, while realization rates stay sensitive to an increase of pre-qualification payments even for higher values like 100,000 € /MW, bids become almost fully inelastic after some point. Hence, one takeaway of our simulation which is not readily apparent from the comparative statics analysis in Proposition 5 is that drastically increasing penalties can considerably increase realization rates while only moderately increasing prices.

As expected, for the low cost scenario minimal bid and award prices are lower than in the status quo as can be seen in Table 1. This comes at the cost of decreasing expected realization rates which drop by about 10 percentage points in both auction formats. For the high cost scenario, the option value decreases relative to the status-quo which results in higher minimal bids and higher award prices. Corresponding to the less aggressive bidders, the expected realization rates significantly improve to 64.86% and 43.03% in the uniform price and discriminatory auctions, respectively. Considering the moderate increase of about € 2.50/MWh in weighted average award price, the German government might see this option as more attractive than the status quo. This observation is partially supported by the fact that in more recent auctions the advantages for NCBG bidders were severely restricted (Deutscher Bundestag, 2018).

We also note that the choice of the auction format matters. Firstly, realization rates are higher for the uniform auction, since award prices are ceterus paribus higher (see Proposition 4(b)). Secondly, we observe that simulated weighted award prices differ, i.e., there is no revenue equivalence between the two formats as discussed in Section 3.1.

5. Conclusion

In this paper, we propose a framework for the analysis of multi-unit procurement auctions in which winning bidders have the option but not the obligation to deliver the service or good. We use real options theory to model the value of flexibility embedded in an awarded contract and derive closed form valuation functions for projects. To derive bidding strategies, we employ asymptotic theory on multi-unit auctions and argue that, with a moderate number of bidders, it is reasonable to assume that auctions result in efficient truth-telling equilibria.

Based on these findings, we derive equilibrium bidding behaviour and comparative statics, e.g., on parameters of the auction design or bidder characteristics. We use our theoretical framework to analyze real-world cases of renewable auctions in the UK and in Germany and show that our model is able to explain and replicate observed auction outcomes.

Our results show that option based bidders with a high value of flexibility are likely to dominate the auctions. This effect decreases with advancing technology and less uncertainty about future costs, driving option values down. Consequently, while the literature has proposed winner's course and aggressive market entry to explain low bids witnessed in many real-world renewable auctions, our findings indicate that auction prices can be driven by the value of flexibility, which decreases bids below the net present value of projects. Thus, when migrating renewable energy support from fixed feed-in tariffs to auction based mechanisms—as many countries have done in the recent years—policy makers should bear in mind that auction prices are not directly comparable to prices of fixed feed-in tariffs set by the government.

Our model provides policy makers with a tool to balance the trade-offs of auction design. In particular, calibrating the pre-qualification payments and the grace period to develop projects allows the auctioneer to weigh procurement costs and realization rates: Procurement costs tend to decrease for long grace periods and low pre-qualification requirements. In turn, expected realization rates are likely to increase if grace periods are short and pre-qualification payments are high.

Increasing pre-qualification payments would be even more effective, if the required pre-qualification was physical, i.e., consists of certain non-financial criteria which have to be met by bidders. This would reduce the perceived future variability of the project value, since bidders learn about uncertain elements of the project. Reduced variability would in turn further decrease the option value and lead to higher realization rates. Moreover, certain requirements in physical pre-qualification, such as acquisition of construction permits, allow the auctioneer to further reduce the grace period, which can additionally benefit realization rates.

Given the relatively low levels of pre-qualification in renewable auctions worldwide, we show in our case study that cost of deployment rise only moderately with higher pre-qualification payments, while realization rates increase drastically. Yet, regulators need to bear in mind that high financial pre-qualification and challenging physical pre-qualification can pose entry barriers for smaller companies and less solvent bidders.

The choice of auction format, i.e., uniform pricing versus pay-as-bid pricing, also plays a role in the trade-off between deployment cost and realization rates. Both formats asymptotically lead to truth-telling equilibria. However, cost equivalence between the auction formats does not hold and hence uniform price auctions result in higher deployment cost. In turn, higher deployment costs come at the benefit of higher realization rates as confirmed in our simulations.

Another finding of our work concerns the efficiency of the allocation: As bidders with the highest valuation win the auction, truth-telling equilibria are efficient ex-ante but can be inefficient ex-post once costs are revealed at the end of the grace period. This is because option based bidders with a high valuation for flexibility and mediocre projects might outbid bidders with intrinsically better projects but low valuation for flexibility. Consequently, the ex-post allocation of subsidies is likely to be inefficient if bidders with heterogeneous option values participate in the auction.

Renewable electricity generation is pivotal in mitigating climate change and current international commitments mandate certain levels of renewable generation. We therefore conclude that auctioneers should seek to minimize the value of flexibility which ensures high realization rates and makes a commitment to quantity goals for renewable energy generation possible.

While this paper explores the trade offs of auction design and provides guidance to policy makers, we do not explicitly identify *optimal* auction designs. A more ambitious approach in this regard, which would be an interesting topic for future research, could be based on a bi-level model in which the auction design is the upper-level decision anticipating the investors' response at the lower level.

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Appendix A. Appendix – Proof of Proposition 1

We use an approach similar to Black and Scholes (1973) and follow Duffie (2010) in the presentation. In addition to the process L_t, we introduce a bond modelled by the process

$$d\beta_t = r\beta_t dt, \text{ and } \beta_0 > 0. \tag{A.1}$$

We construct a self-financing portfolio which replicates the price process Y_t of the option to invest. Duffie (2010) shows that one can infer

$$Y_t = a_t L_t + b_t \beta_t \tag{A.2}$$

from the existence of a self-financing strategy (a, b) with $Y_T = a_T L_T + b_T \beta_T$ and the assumption of an arbitrage free market. Assume in the following that $Y_t = W(L_t, t) \in C^{2,1}(\mathbb{R} \times [0, T))$. Applying Itō's lemma yields for $t < T$

$$dY_t = \left[W_x(L_t, t)\mu L_t + W_t(L_t, t) + \frac{1}{2}W_{xx}(L_t, t)\sigma^2 L_t^2\right]dt + W_x(L_t, t)\sigma L_t dB_t, \tag{A.3}$$

and on the other hand we have from the self-financing strategy that

$$dY_t = a_t dL_t + b_t d\beta_t = (a_t \mu L_t + b_t \beta_t r)dt + a_t \sigma L_t dB_t. \tag{A.4}$$

Comparing coefficients of dB_t, we have

$$a_t = W_x(L_t, t) \tag{A.5}$$

and from (A.2) we infer with $Y_t = W(L_t, t)$:

$$b_t = \frac{1}{\beta_t}[W(L_t, t) - W_x(L_t, t)L_t]. \tag{A.6}$$

Equating the coefficients of dt in (A.3) and (A.4) results in the equation

$$-rW(L_t, t) + W_t(L_t, t) + rL_t W_x(L_t, t) + \frac{1}{2}\sigma^2 L_t^2 W_{xx}(L_t, t) = 0. \tag{A.7}$$

Therefore, we need to solve the PDE

$$-rW(x, t) + W_t(x, t) + rxW_x(x, t) + \frac{1}{2}\sigma^2 x^2 W_{xx}(x, t) = 0 \tag{A.8}$$

on the region $(x, t) \in (0, \infty) \times [0, T)$ with boundary condition $W(x, t) = \max(p - x, -P)$.

Next we introduce a equivalent risk neutral measure $\mathbb{Q}$ with $d\mathbb{Q} = Z_T d\mathbb{P}$. Here, $\mathbb{P}$ denotes the natural measure and $dZ_t = (\mu - r)\sigma^{-1} Z_t dB_t$. Girsanov theorem yields $dB_t = -(\mu - r)\sigma^{-1}dt + dB_t^{\mathbb{Q}}$, and therefore $dL_t = rL_t dt + \sigma L_t dB_t^{\mathbb{Q}}$.

Having established the risk-neutral valuation of the underlying process and noting that μ, σ, r, $W(x_T, T)$ are continuous, we can solve the PDE (A.8) by applying the Feynman–Kac formula. A solution is given by

$$\begin{aligned} W(L_t, t) &= \mathbb{E}^*\left[\exp\left(-\int_t^T r\, ds\right)\max(p - L_t, -P)\right] \\ &= e^{-rT}\Bigg[\underbrace{b\int_{-\infty}^{b+P} dF(L_T)}_{A} - \underbrace{\int_{-\infty}^{b+P} L_T\, dF(L_T)}_{B} - \underbrace{P\int_{b+P}^{\infty} dF(L_T)}_{C}\Bigg]. \end{aligned} \tag{A.9}$$

In the following, we compute the integrals A,B, and C. For that purpose note that if $Y \sim \mathcal{N}(\omega, \psi^2)$ and $X = e^Y$, then the distribution of X is

$$F_X(x) = \Phi\left(\frac{\ln x - \omega}{\psi}\right), \tag{A.10}$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution. Furthermore, the curtailed expected value of X is given by

$$\mathbb{E}[X | X < x] = \exp\left(\omega + \frac{\psi^2}{2}\right)\Phi\left(\frac{\ln x - \omega - \psi^2}{\sigma}\right). \tag{A.11}$$

and

$$\ln L_T \sim \mathcal{N}\left(\ln L_t + (r - \frac{\sigma^2}{2})T, \sigma^2 T\right) \tag{A.12}$$

under the risk-neutral measure $\mathbb{Q}$.

With these formulas at hand, we can progress and calculate the integrals in (A.9). Substituting the parameters of (A.12) into (A.10) and by using the identity $\Phi(-x) = 1 - \Phi(x)$, we receive for integral A:

$$\begin{aligned} \int_{-\infty}^{b+P} dF(L_T) = F_{L_T}(p + P) &= \Phi\left(-\frac{\ln \frac{L_t}{p+P} + \left(r - \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}\right) \\ &= \Phi\left(-\frac{\ln \frac{L_t}{p+P} + \left(r + \frac{\sigma^2}{2}\right)T - \sigma^2 T}{\sigma\sqrt{T}}\right) = \Phi(z + \sigma\sqrt{T}), \end{aligned} \tag{A.13}$$

where we defined $z := -\frac{\ln \frac{L_t}{p+P} + \left(r + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}$. Using (A.11) and (A.12), we calculate integral B:

$$\begin{aligned} \int_{-\infty}^{p+P} dF(L_T) = \mathbb{E}[L_T | L_T < p + P] &= L_t e^{rT}\Phi\left(-\frac{\ln \frac{L_t}{p+P} + \left(r + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}\right) \\ &= L_t e^{rT}\Phi(z). \end{aligned} \tag{A.14}$$

Table B.2
Inputs for LCOE simulation of wind.

Input	Distribution	Range	Mean	STD	Source
Capital expenditure [€ /kW]	Normal	1500-2000	1750	350	(Heck et al., 2016; Kost et al., 2018)
WACC [%]	Constant	3.5 %			(Kost et al., 2018)
Loan period [y]	Constant	25			(Bundesnetzagentur, 2018b; Kost et al., 2018)
Fixed O&M [€ /kW]	Triangular	12-48	30		(Heck et al., 2016; Kost et al., 2018)
Variable O&M [€ /kWh]	Constant	0.005[a]			(Kost et al., 2018)
Capacity factor [%]	Normal	28.53-41.10	31.06	7	(Heck et al., 2016; Kost et al., 2018)[b]

[a] Heck et al. (2016) assume a log normal distribution. However, we use the constant value reported in Kost et al. (2018)
[b] We exclude the most unprofitable category of capacity factors reported in Kost et al. (2018) from our simulation, as wind sites in this category are not cost competitive and thereby avoid auction settings.

Similarly, we calculate the value of integral C:

$$\int_{p+P}^{\infty} dF(L_T) = 1 - \Phi\left(z + \sigma\sqrt{T}\right). \quad (A.15)$$

Collecting the solutions in (A.13)–(A.15) and inserting into (A.9) provides the complete formula for the value of the option, as seen in Proposition 1, Eq. (5)

$$W(L_t, \sigma, b, P) = -L_t\Phi(z) + e^{-rT}\left((p+P)\Phi\left(z+\sigma\sqrt{T}\right) - P\right),$$
$$z := -\frac{\ln\frac{L_t}{p+P} + \left(r + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}. \quad (A.16)$$

Appendix B. Appendix – Simulation of LCOE

Heck et al. (2016) propose to use probability distributions of LCOE rather than using point values in simulations. In their work, they propose a framework for major generation technologies, including wind energy. Their basic LCOE formula for wind energy, given in (B.1) comprises an annualized annual payment P, associated with initial capital expenditure, fixed operation and maintenance cost $O\&M_F$, a capacity factor C_f of the plant, and variable operation and maintenance cost $O\&M_V$.

$$\text{LCOE} = \frac{P + O\&M_F}{8760 \cdot C_f} + O\&M_V \quad (A.1)$$

The annualized payment P is given in (B.2) and depends on the weighted average cost of capital w, the capital expenditure of the cost C_c, and the number of payments n, assumed to be the lifetime in years of the plant.

$$P = C_c\left[w + \frac{w}{(w+1)^n - 1}\right] \quad (A.2)$$

Further, they propose probability distribution and ranges for the input parameters. We adapt their setting and include recent data from the German market. The parameters used in the simulation are presented in Table B.2.

Appendix C. Appendix – Additional Simulations

We use our calibration of the share of auction bidders from ONWA17 to simulate the two subsequent auctions for onshore wind energy in Germany in November 2017 (ONWN17) and February 2018 (ONWF18). We use a share of 65 % of OBC bidders, as calibrated in Fig. 2, and assume LCOE specifications as in ONWA17 since technology and investment environment has not changed substantially from August 2017 to February 2018. We adapt the auction specific parameters (e.g., number of bidders, interest rates) to the respective setting.

In ONWN17, total auctioned capacity is 1000 MW with a bid cap of 70 € /MWh. Similar to ONWA17, 89 % of the participating and 99 % of the winning bidders are NCBGs (see Bundesnetzagentur, 2018b). Thus, we disregard commercial bidders and use financial pre-qualification of 15,000 € /MW and a grace period of 4.5 years. The risk free rate based on German 30-year bond is 1.17 % in 2017. To match the 210 bids with capacities between 750 kW and 23.8 MW submitted in the auction, we simulate 110 bidders as explained in Section 4.

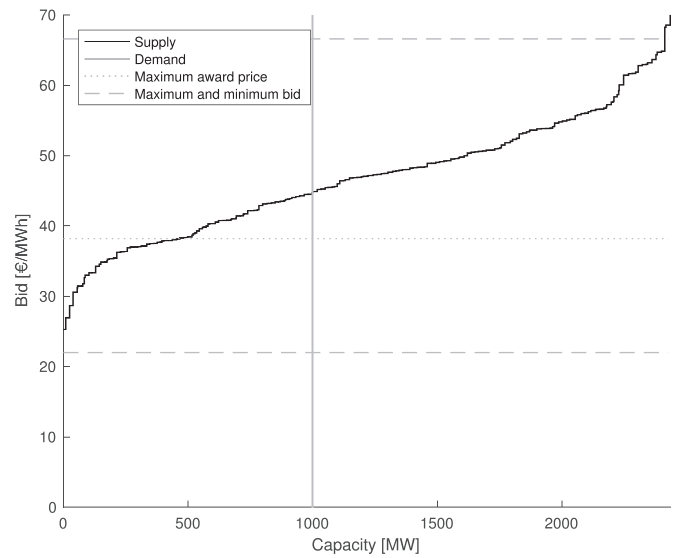

Fig. C.4. Simulation result for the supply curve in ONWN17 based on the calibrated share of OBC bidders in ONWA17.

In ONWF18, total auctioned capacity is 700 MW with a bid cap of 6,30 € /MWh. In contrast to previous auctions, only 19 % of the participating and 21 % of the winning bidders are NCBGs (see Bundesnetzagentur, 2018b). Thus, we disregard NCBGs for ONWF18 and use specifications for commercial bidders, i.e. financial pre-qualification of 30,000 € /MW and a grace period of 2.5 years. We still report weighted award price for discriminatory (commercial bidders) and uniform (NCBGs) auction format. Note that the observed weighted award price sits between our values as expected. The risk free rate based on German 30-year bond is 1.17 % in 2018. To match the 132 bids with capacities between 750 kW and 24.4 MW submitted in the auction, we simulate 70 bidders as explained above.

For ONWN17 and ONWF18, we present the simulated bid curve of a single auction in Figs. C.4 and C.5, respectively. The calibration of the share of OBC bidders in ONWA17 allows to predict the outcomes of ONWN17 and ONWF18 reasonably well. To account for the idiosyncratic sampling bias of a single auction, we conduct Monte Carlo analyses with 10,000 simulations of both auctions and report average values and standard deviations of effects on bids, expected realization rates, award prices, and deployment cost for a uniform and a discriminatory auction setup in Tables C.3 and C.4.

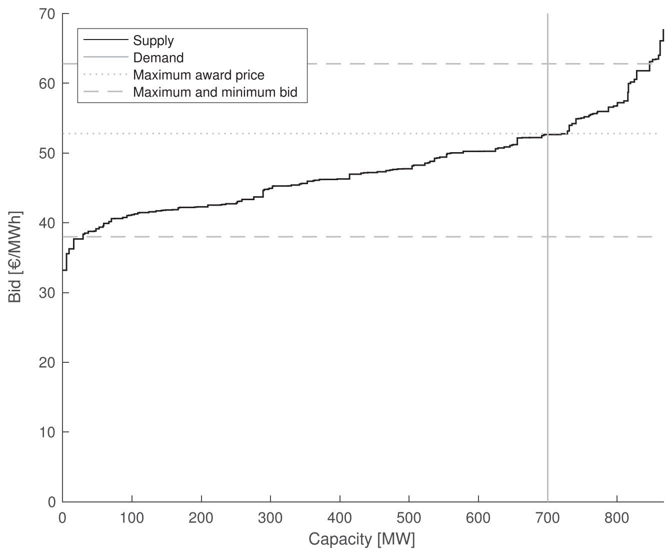

Fig. C.5. Simulation result for the supply curve in ONWF18 based on the calibrated share of OBC bidders in ONWA17.

Table C.3
Simulated results of auction outcomes in ONWN17 based on a 10,000 sample Monte Carlo simulation. The share of OBC bidders is based on our calibration for ONWA17. Standard deviations are reported in brackets and actual outcomes of the auction are displayed in the last column.

	simulation		
	uniform	pay-as-bid	ONWN17
Minimal bid [€/MWh]	28.32 (1.46)		22.00
Maximal bid [€/MWh]	68.86 (2.08)		66.60
Maximal award price [€/MWh]	43.95 (1.04)		38.2
Weighted award price [€/MWh]	43.95 (1.04)	38.39 (0.83)	42.80
Expected realization rate [%]	55.49 (4.56)	30.98 (3.23)	

Table C.4
Simulated results of auction outcomes in ONWF18 based on a 10,000 sample Monte Carlo simulation. The share of OBC bidders is based on our calibration for ONWA17. Standard deviations are reported in brackets and actual outcomes of the auction are displayed in the last column.

	simulation		
	uniform	pay-as-bid	ONWN17
Minimal bid [€/MWh]	33.64 (1.58)		38.00
Maximal bid [€/MWh]	66.57 (2.20)		62.80
Maximal award price [€/MWh]	51.28 (1.58)		52.80
Weighted award price [€/MWh]	51.28 (1.58)	44.76 (0.96)	47.30
Expected realization rate [%]	79.23 (4.34)	50.35 (3.86)	

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