Agent-based modeling of de-risking instruments in renewable energy auctions

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ABSTRACT

We study renewable energy auctions in the presence of de-risking instruments using an agent-based model. A sealed-bid, pay-as-bid scheme with several rounds of auctions is considered. A certain fraction of the auctioned volume is guaranteed, and each bidder has then two costs, presenting two bids depending on whether the contract will be covered by the guarantee or not. We study the resulting dynamics, and identify a sharp phase transition depending on the competition level of the auction. The guarantee impacts throughout the program and contributes to a significant decrease of the final prices when the auction is competitive enough. However, in not competitive auctions, its impact becomes negligible, and does not depend on the guaranteed volume fraction. A novel differentiated ceiling price mechanism applied only to bids benefiting from the guarantee is then introduced and studied. In particular, a new phase transition appears when the auction is not competitive, showing that relatively low prices can still be obtained when the guaranteed volume is high enough. We use the German wind on-shore auction datasets to study the differentiated ceiling price and its impact.

JEL Classification: C53, C54, C57, C73, D44, Q21

1. Introduction

The 28th Conference of the Parties (COP28) concluded in December 2023 with a call for a just and equitable transition away from fossil fuels, and emphasized the need to triple global renewable energy (RE) capacity by 2030, see COP28 (2023a,b). This significant increase in RE is recognized as a critical pathway to limiting global warming to 1.5°C, while also enabling sustainable economic development, a particularly pressing concern for developing nations facing growing energy demands.

Renewable energies (RE) are playing a key role in meeting global energy demands. Driven by the various ecological and socio-economic benefits of RE, alongside decreasing technological costs, see Ilas, Ralon, Rodriguez and Taylor (2018); Wigand, Amazo, Lawson, Monteforte, Eisendrath, Gutierrez and Paz (2019)), RE sources accounted for 29% of the world's total electricity generation in 2020 IEA (2021). This shift is partially explained since RE is increasingly cost-competitive with conventional fossil fuels.

Several developing countries rely on RE to meet their increasing energy demand taking advantage of their natural resources. However, in light of the challenges of high externalities and uncertainty, governments have a critical role in supporting investments in green technologies by providing funding and risk sharing, lowering the risk premium and encouraging private participation (e.g., Stiglitz (1993)). De-risking green investments is particularly crucial for developing countries, where innovative renewable energy sources face high upfront costs, see Ondraczek, Komendantova and Patt (2015); Sweerts, Dalla Longa and van der Zwaan (2019); Taghizadeh-Hesary and Yoshino (2020); Waissbein, Glemarec, Bayraktar and Schmidt (2013). Thus, investments from private sources remain below its potential.

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There are different reasons explaining this, being the risks one of the most important. Investors' perceptions of risk and hedging mechanisms against them result in an added premium on the cost of capital in RE projects, thus leading to high energy prices.

Risks associated with renewable energy investments can be broadly categorized into two primary categories: financial and political risks, and geographical and technological risks. Financial and political risks encompass factors such as changes in regulations, liquidity problems, inflation, and sovereign default. Geographical and technological risks primarily involve a lack of infrastructure, including grid connections, transmission lines, and grid nodes, as well as natural hazards. While infrastructure investments can address geographical and technological risks, these same investments can be hindered by the presence of financial and political risks. De-risking instruments, such as guarantees from public entities like governments and international financial institutions, can be implemented to mitigate the first group of risks and attract private investors. (see Abba, Balta-Ozkan and Hart (2022); Đukan and Kitzing (2023)). For instance, according to Agora (2019), the cost of equity and debt in Serbia for the wind on-shore technology in 2018 was estimated as 14.5% and 4.6% respectively, whereas it was only of 5.4% and 1.6% in Germany. This large difference is mainly due to the impact of some specific risks which, adequately addressed, can be mitigated to reduce the cost of equity and debt to 7.9% and 2.3% (Agora (2019), pp 21-23). The impact of these risks on the Levelized Cost of Electricity (LCOE) is significant since it was estimated to 6.7 Euro cents/kWh without de-risking and to 5.4 Euro cents/kWh after de-risking, i.e., de-risking measures lead to a reduction of nearly 20% in the cost. Let us also mention the paper Sweerts et al. (2019) where the authors analyse the impact de-risking measures have on the Weighted Average Cost of Capital (WACC) of several African countries and the long-term implications concerning the penetration of renewable energies.

De-risking measures can take various forms depending on the risks to be mitigated and the characteristics of the stakeholders, see the reports Waissbein et al. (2013); Wuester, Jungmin and Lumijarvi (2016) for a general classification of risks and possible mitigation instruments. Let us mention as an example the case of RenovAr, the Argentine program of RE deployment held between 2016 and 2019. In spite of a highly volatile national economy, RenovAr attracted a large number of participants resulting in low energy prices. One of the reason of this success was the implementation of a guarantee scheme backstopped by the World Bank to mitigate the risk of payment default of the electricity market administrator to energy producers. We refer to the survey Menzies, Marquardt and Spieler (2019) for a detailed presentation and analysis of RenovAr.

In renewable energy (RE) auctions, typically a government entity acts as the auctioneer and seeks to procure a predetermined amount of RE capacity by offering to buy it from bidders. This competitive process, where bidders compete by offering the lowest price, is becoming the most widely used mechanism to allocate various RE sources, including solar photovoltaic, wind, geothermal, and hydro. Indeed, more than a hundred countries had used auctions at least once by the end of 2018, see IRENA (2019), and the European Union made auctions mandatory to grant support from member states since 2017, see Szabó, Bartek-Lesi, Dézsi, Diallo, Mezösi, Kitzing, Woodman, Fitch-Roy, del Rio, Resch, von Blücher, Wigand, Menzies and Anatolitis (2020).

The use of RE auctions led to an overall significant decrease of the price of energy Ilas et al. (2018); IRENA (2019); Szabó et al. (2020); Wigand et al. (2019). Indeed, a well-designed auction can foster competition amongst energy producers thus capitalizing on technological cost reduction. Moreover, they ensure a transparent allocation process and can be tailored to each country specific needs. Thus, RE auctions contribute to a fair and inclusive economic growth, aligned with the COP28 agreement and the United Nations SDG7 and SDG8. On the other hand, a poorly designed auction scheme may lead to undesired outcomes such as high prices or a low realization rate of the awarded projects, thus jeopardizing the future deployment of renewable energy.

However, auctions are complex mechanisms to study. Firstly, because bidders compete against each others trying to maximise their profit with only partial information about their opponents and their bidding behaviour, and also about their own cost and future reward. Beyond the classical english or ascending auction widely used, where the auctioneer raises the price until only one participant remains and is declared the winner, there exist multiple auction formats specifying the bidding process, who wins, and how much the participants pay, presenting various pros and cons from the bidders' and the auctioneer's point of view. Notice also that bidders behavior is very sensitive to the design of the auction, and empirical studies of past auctions show that there is no one-fits-all design (see Del Río (2017); Szabó et al. (2020)).

Auction theory, which has been central to the work of several Nobel laureates in Economics, is a well-developed field (see, for example, Klemperer (2004) and Krishna (2002)). These laureates include W. Vickrey (1996), R. Myerson

(2007), and P. Milgrom and R. Wilson (2020). Bidders are assumed to bid rationally in order to maximize their expected utility, and the main questions are the existence of a Nash equilibrium (that is, how rational bidders are expected to bid), and the expected revenue of the auctioneer. However, experiments show that bidders do not always behave fully rationally, although when several rounds of an auction are held, bidders can learn from one round to another adapting their bidding behaviour, thus possibly resulting in bidders coordinating indirectly.

RE auctions may attract a large number of heterogeneous participants ranging from large national and international companies to small local producers. The possibly large number of participants and their heterogeneity make very difficult, or even impossible due to combinatorial complexity, to apply the theoretical results available in the classical game theory literature. To circumvent these difficulties, agent-based models (ABM) are being increasingly used to study some aspects of auctions, see Anatolitis and Welisch (2017); Azadeh, Ghaderi, Nokhandan and Sheikhalishahi (2012); Lundberg (2019); Welisch (2018). They are widely used to study complex socio-economic systems, since their bottom-up approach is well suited to aggregate microscopic behaviour of heterogeneous agents up to their macroscopic consequences, thus allowing to study the impact of the modelling parameters. In particular, see Castro, Drews, Exadaktylos, Foramitti, Klein, Konc, Savin and van den Bergh (2020) about the use of ABM to model climate-energy policies.

Using ideas from game theory and statistical physics, the authors in Saintier, Marenco, Kind and Pinasco (2023) proposed an ABM to model RE auctions where bidders can adapt their bidding behaviour from one round to the next in a myopic way, only reacting to their performance in the round. Numerical experiments show the resulting dynamic mainly depends on one parameter, namely the level of competition ρ of the round defined as the ratio of volume of energy offered by bidders over the volume the auctioneer wants to buy. This parameter has a critical impact on the prices in the sense they tend to go up when $\rho < 2$, and to go down when $\rho > 2$. Moreover, it was observed that bidders coordinate in the sense they end up bidding the same price for a given volume of energy. The model parameters were fit to reproduce with a good accuracy the results of the German solar and wind auctions, a program well studied in the literature and a standard benchmark for RE auctions models.

These numerical findings can be explained theoretically using tools from mathematical analysis, see Kind, Pinasco and Saintier (2023), where a system of ordinary differential equations was obtained to describe the trajectories of the agents in the space of bids. Also, a first-order, non local, nonlinear partial differential equation describes the behavior of this particle system, as in classical statistical mechanics. The validity of this approach, where bidders are dummy particles reacting only to their success or failure in auctions can be theoretically justified. Recently, in Crucianelli, Pinasco and Saintier (2024) it was proved that agents, following very simple dynamical rules, learn the Nash equilibrium for both first price and second price auctions.

We propose to use this framework to incorporate de-risking mechanisms and study their impact on prices. This is a non-trivial task since bidders now have two costs depending on whether de-risking instruments were applied to mitigate risks or not. They are thus expected to bid differently if they benefit from such instruments or not, thus resulting in a more complex dynamic. We consider a very simplified guarantee instrument, which will be modelled as a fraction of the total auctioned volume covered against default payment of the state (in the spirit of the RenovAr program mentioned earlier), although any other instrument impacting on the costs by reducing them can be considered in a similar way. A complete description of the model is given in Section §2, where we describe the dynamics of the agent-based model.

Then, in Section §3 we analyze through numerical simulations the impact of the competition level of the auction, and the fraction of auctioned volume covered by the guarantee. We observe a sharp transition at a competition level of 2, that is, when twice the auctioned volume is offered, and a positive impact of the guarantee only in competitive auctions. Hence, a novel policy mechanism is introduced in Section §4, namely a differentiated ceiling price applied only to bids benefiting from the guarantee.

In Section §5 we first perform numerical experiments in this modelling framework with the German solar and wind on-shore programs datasets to study the results that some guarantee scheme and a differentiated ceiling price would have had on the prices had it been applied, assuming that the scheme can reduce the bidder's costs.

We conclude the paper with some policy recommendations and possible future works.

2. Description of the agent-based model

We consider a sealed-bid, pay-as-bid auction taking place in several rounds $t = 1, \dots, T$ involving the same N bidders. At each round a fraction $G \in [0, 1]$ of the auctioned volume is covered by the guarantee. We suppose for simplicity that G is the same in all the rounds. Bidders who can benefit from the guarantee thus do not have to hedge against the risk of a payment default, resulting in a lower cost. Each bidder i has then two costs $c_{i,with}$ and $c_{i,without}$ such that $c_{i,with} < c_{i,without}$ which will be used to define the bids and their profits.

A round t of the auction is organized as follows:

Step 1: Initialization.

The auctioneer publicly announces the total auctioned volume V_t and the ceiling price (or cap price) CP_t of the round, namely the maximum accepted value of a bid. Denote $V_{t,guaranteed} := G.V_t$ the auctioned volume covered by the guarantee.

Step 2: Bidding process.

Each bidder i submits two sealed bids $b_{i,without}$ and $b_{i,with}$, the price at which the bidder is willing to provide a volume v of energy depending on if he can benefits of the guarantee scheme or not. For simplicity, bidders are all assumed to submit the same volume v, and we suppose that the auctioned volume V_t is a multiple of v. There are then $N_{w,t} := V_t/v$ winners at round t.

The bids $b_{i,without}$ and $b_{i,with}$ are drawn at random from the normal distributions $N(\mu_{i,with}, \sigma^2)$ and $N(\mu_{i,without}, \sigma^2)$. Since $c_{i,with} < c_{i,without}$, we enforce $b_{i,with} < b_{i,without}$ exchanging both bids if needed. If bidder i's bid $b_{i,with}$ is greater than the ceiling price, i.e. $b_{i,with} > CP_t$, then to have an admissible bid, we put $b_{i,with} := CP_t$. Likewise, if $b_{i,with} < c_{i,with}$, then to have a profitable bid, we put $b_{i,with} := c_{i,with}$. The same truncation procedure is applied to $b_{i,without}$ if needed.

In case bidder's cost $c_{i,with}$ is higher than the ceiling price, bidder can not reasonably expect a positive gain by participating to the round and thus abandon it. If $c_{i,with} < CP_t < c_{i,without}$, bidder i can expect a positive gain only if he benefits of the guarantee. In that case we assume $b_{i,without} = +\infty$.

The mean bids $\mu_{i,with}$ and $\mu_{i,without}$ will change from round to round as explained in the learning step below. The bid variance σ^2 is assumed to be the same for all bidders through the whole auction.

Step 3: Determination of the winners.

The auctioneer sorts the $2N$ bids

$$b_{1,with}, b_{1,without}, ..., b_{N,with}, b_{N,without}$$

in ascending order. Say bidder i submitted the lowest bid, necessarily $b_{i,with}$. Then the volume v is discounted from the auctioned volume V_t and the guaranteed auctioned volume $V_{t,guaranteed} = GV_t$. Both i's bids $b_{i,with}$ and $b_{i,without}$ are then eliminated from the list of ordered bids. The auctioneer then awards the lowest bid of this new list and so on. This goes on until the guaranteed volume $V_{t,guaranteed}$ is exhausted. The remaining bids $b_{j,with}$ are then eliminated from the list and the auctioneer keeps on awarding bids until covering the auctioned volume V_t.

Step 4: Learning.

Each bidder i updates his parameters $\mu_{i,with}$ and $\mu_{i,without}$ to $\mu'_{i,with}$ and $\mu'_{i,without}$ in the following way. He first computes the expected *relative markups* as

$$rm_{i,with} := (\mu_{i,with} - c_{i,with})_+/(CP_t - c_{i,with})$$

and

$$rm_{i,without} := (\mu_{i,without} - c_{i,without})_+/(CP_t - c_{i,without})$$

which represent i's expected profit upon winning but scaled relatively to the maximum possible profit. Here $x_+ = max\{x, 0\}$ is the positive part of a real number x. Notice the relative markups belong to $[0, 1]$. Bidder i then updates them by adding $+\gamma$ to both if he won, or $-\gamma$ to both if he lost. Here, $\gamma > 0$ is the learning parameter, the same for every bidders and rounds. The updated relative mark-ups $rm'_{i,with}$, $rm'_{i,without}$ are truncated to remain in $[0, 1]$. Thus

$$rm'_{i,with} = \begin{cases} \min\{1, rm_{i,with} + \gamma\} & \text{if bidder } i \text{ won,} \\ \max\{0, rm_{i,with} - \gamma\} & \text{if bidder } i \text{ lost,} \end{cases}$$

with an analogous expression for $rm'_{i,without}$. Finally, bidder i computes $\mu'_{i,with}$ and $\mu'_{i,without}$ scaling the updated relative markups back to the interval $[c_{i,with}, CP_{t+1}]$ and $[c_{i,without}, CP_{t+1}]$, with CP_{t+1} the ceiling price of the next round:

$$\mu'_{i,with} := c_{i,with} + (CP_{t+1} - c_{i,with}) rm'_{i,with} \tag{1}$$

and

$$\mu'_{i,without} := c_{i,without} + (CP_{t+1} - c_{i,without}) rm'_{i,without}. \tag{2}$$

This rule models a myopic behaviour in the sense that bidders lower or increase their relative markups only taking into account how well they performed in the round, thus reinforcing good behaviour and penalizing bad ones. The reinforcement of actions leading to good outcomes is a robust property observed in experimental psychology on both human and animal learning, and which has been successfully used in games and economic literature, see the seminal paper Roth and Ido (1995). This idea is by now very popular in computer science and algorithmic game theory, see chapter 17 in Roughgarden (2016) and the classical book of Sutton Sutton and Barto (2018). It was recently applied in the context of auctions in Crucianelli et al. (2024).

Notice that no communication among bidders is allowed during the whole auction. Bids are sealed and bidders only know their own performance in the round, neither the awarded nor rejected bids are used in the learning process. Thus, they are only affected by the other bidders through the result of the auction.

In the next section we study the dynamics via agent-based simulations focusing on the evolution of the winning bids and the distribution of bidders' μ parameters. In particular we will be most interested in studying the impact of the competition level ρ_t of round t which can be expressed as

$$\rho_t = \frac{\text{offered volume}}{\text{auctioned volume}} = \frac{Nv}{V_t} = \frac{N}{N_{w,t}}. \tag{3}$$

To do so it will be convenient from a theoretical point of view to assume that the learning rate γ is small. Indeed, γ mainly fixes the time scale of the dynamic. Assuming it is small means that bidders are conservative changing their behaviour smoothly. Observable effects will then only appear when T is large. This is of course unrealistic but will prove very useful concerning the theoretical impact of the competition level.

3. Agent-based simulations and results

In this section we present agent-based simulations of the dynamics described in the previous section. In all the simulations we took $N = 1000$ bidders. Since we are mainly interested in the bidding dynamics, we suppose for simplicity that bidders have all the same cost 0 with guarantee and 0.3 without guarantee:

$$c_{i,with} = 0, \quad c_{i,without} = 0.3 \qquad i = 1, \dots, N.$$

We also suppose the ceiling price is $CP_t = 1$ for any round t.

Let us note that the interval between the minimal costs and the ceiling price can be mapped linearly to the interval $[0, 1]$. In that sense, we are assuming that costs taking in account the risks of the country starts at 0.3 after the transformation.

The updating rule (1)-(2) of bidders' μ parameter then simplifies to

$$\mu'_{i,with} := \begin{cases} (\mu_{i,with})_+ + \gamma & \text{if bidder } i \text{ won,} \\ (\mu_{i,with})_+ - \gamma & \text{if bidder } i \text{ lost.} \end{cases} \tag{4}$$

and

$$\mu'_{i,without} := \begin{cases} 0.3 + \Big(\frac{(\mu_{i,without} - 0.3)_+}{0.7} + \gamma \Big).0.7 \\ \qquad \text{if bidder } i \text{ won,} \\ 0.3 + \Big(\frac{(\mu_{i,without} - 0.3)_+}{0.7} - \gamma \Big).0.7 \\ \qquad \text{if bidder } i \text{ lost.} \end{cases} \tag{5}$$

Remember that $\mu'_{i,with}$ and $\mu'_{i,with}$ are implicitly truncated to remain in $[0, 1]$.

Bidders' initial relative mark-ups are drawn independently and uniformly at random between 0,1 and 0.5, from which bidders initial $\mu_{i,with}$ and $\mu_{i,without}$ parameters are then deduced. We set the learning rate to $\gamma = 0.001$.

We begin by taking $\sigma = 0$, so bidders bid exactly their μ. To assess the influence of the competition level ρ defined in (3) we assume it constant throughout the auction. We show in Figures 1 the evolution from round-to-round of the mean prices for different percentage of guaranteed volume and competition level. We can observe that the mean price eventually stabilizes either to the ceiling price 1 when $\rho = 1.5$, and, when $\rho = 2.5$, to some value between 0 and 1 which decreases to 0 as the percentage of guaranteed volume goes up to 100%.

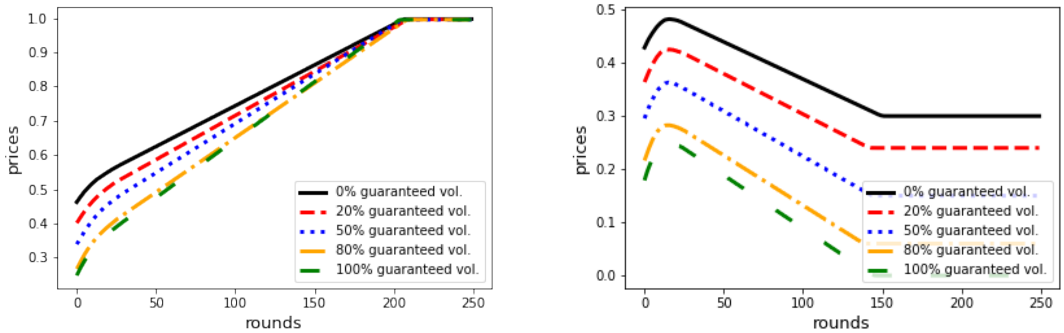

Figure 1: Final mean price for different percentage of guaranteed volume for a fixed competition level (Left: $\rho = 1.5$, Right: $\rho = 2.5$)

To better understand how the final mean price depends on the competition level ρ and the percentage of guaranteed volume G, we discretize the interval $[0, 1]$ of ρ values with a constant step size 0.01 resulting in the discretized values $\rho_k = 0.01 \times k$, $k = 0, \dots, 100$. The same is done for the interval $[0, 1]$ of G values by considering

$$G_k = 0.01 \times k,$$

for $k = 0, \dots, 100$. For each pair (G_i, ρ_j), $i, j = 0, \dots, 100$, we run 100 simulations of the model and record the average of the final mean price resulting in the heatmap shown in Figure 2 (Left). In the same Figure (Right) are displayed some vertical slices of the heatmap showing the final price in function of the competition level for different percentage of guaranteed volume.

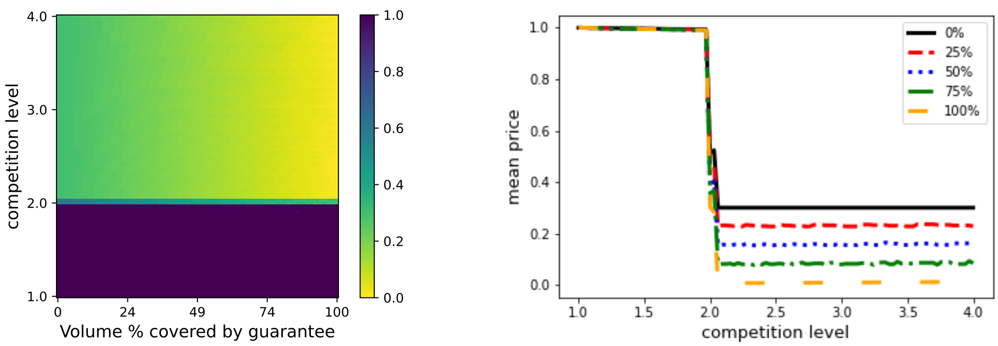

Figure 2: Left: Heatmap of the final mean price in function of the competition level and the percentage of guaranteed volume. Right: Final mean price in function of the competition level for different percentage of guaranteed volume $G = 0\%, 25\%, 50\%, 75\%, 100\%$.

Two zones with completely different behaviour of the final mean price can be observed, namely $\rho < 2$ and $\rho > 2$. Indeed, when $\rho < 2$, the final mean price is 1 (the ceiling price, after rescaling) regardless of the guaranteed volume.

On the other hand, when $\rho > 2$, the final mean price is independent of ρ and, as the fraction of guaranteed volume goes to 100%, decreases linearly from 0.3, bidders' cost in absence of guarantee, down to 0, bidders' cost with guarantee (see Figure 2 (Right)).

This behavior can be understood by looking at the evolution of bidders μ parameters μ_{with} and $\mu_{without}$ shown in Figure 3. Indeed, we can observe that bidders coordinate in the sense that they tend to have all the same value of the μ_{with} and $\mu_{without}$ parameters (up to negligible random fluctuations). This is quite surprising since, as mentioned before, no explicit communication between bidders is allowed in our model: the model shows that simple reinforcement behaviours can produce implicit collusion. Then, these common values converge either both to the ceiling price 1 when $\rho = 1.5$, or, when $\rho = 2.5$, to the costs 0 and 0.3.

Numerical experiments varying the competition level ρ and the fraction of guaranteed volume show this behaviour holds for all values of $\rho < 2$ or $\rho > 2$ respectively. Since we assumed no noise on the bids, bidders' bids are thus eventually all equal to 1 when $\rho < 2$ resulting a final mean price of 1 in agreement with the heatmap Figure 2. When $\rho > 2$, bidders eventually bid their costs 0 or 0.3. Noticing there are GV/v and $(1-G)V/v$ winners with and without guarantee, the sum of winning bids is $0 \times GV/v + 0.3 \times (1-G)V/v$. Dividing by the number of winners, V/v, results in a mean winning bid of $0 \times G + 0.3 \times (1-G)$ independently of the particular value of competition level $\rho > 2$. This is the final mean price shown in Figure 2 (Right) when $\rho > 2$.

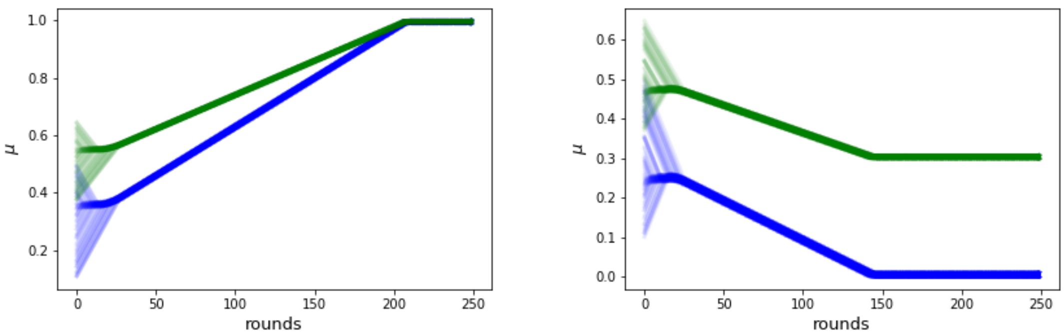

Figure 3: Evolution from round to round of bidders μ parameters μ_{with} (blue) and $\mu_{without}$ (green) with 80% guaranteed volume and competition level $\rho = 1.5$ (Left) and $\rho = 2.5$ (Right).

Adding a noise σ on the bids does not significantly modify the qualitative behaviour observed previously when $\sigma = 0$. Indeed simulations show bidders still coordinate sharing asymptotically the same μ value. As a consequence the mean prices stabilize to a value which, as in the case without noise, is either close to the ceiling price or close to the cost 0 and 0.3. As shown in Figure 4, the phase transition at $\rho = 2$ persists in the presence of the noise, and when $\rho > 2$, the final mean price still linearly decreases from 0.3 to 0 as the percentage of guaranteed volume grows from 0 to 100%. However, when $\rho < 2$, the noise gives some room to the guarantee to impact and produce a slight decrease of the prices. Notice that the more intense the noise, the more significant the impact of the guarantee.

In conclusion, the above numerical experiments suggest the sharp transition at $\rho = 2$ already observed in Saintier et al. (2023) in absence of guarantee scheme persists in the presence of a guarantee independently of the intensity of the noise on the bids. When the auction is not competitive enough ($\rho < 2$), the guarantee impacts but only while bidders are not completely coordinated, and has almost no effect on the final prices which is close to the ceiling price regardless of the amount of guarantee. On the other side, when the auction is competitive ($\rho > 2$), the guarantee allows to reduce final prices down to bidders costs. This confirms the critical role of the competition level in the success of a tender previously observed Kind et al. (2023).

4. Differentiated ceiling price

According to the simulations shown in the previous section (see Figure 2), when the auction is not competitive (i.e., when the level of competition ρ is less than 2), the guarantee scheme cannot prevent prices from going up to the ceiling price. Bidders winning with the guarantee thus get the highest possible price while at the same time benefitting from the cost reduction resulting from the guarantee. The cost of the guarantee borne by the auctioneer is thus not

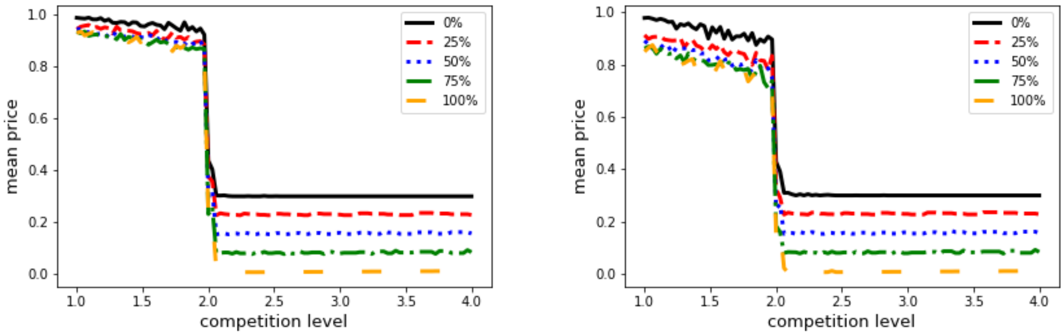

Figure 4: Final mean price in function of the competition level for different percentage of guaranteed volume $G = 0, 25\%, 50\%, 75\%, 100\%$ when bids are drawn at random from a normal with standard deviation $\sigma = 0.1$ (Left) and $\sigma = 0.2$ (Right).

followed by a reduction in energy prices. It seems thus reasonable from the auctioneer's point of view to introduce a second ceiling price specific for the bids under the guarantee scheme, obviously lower than the original ceiling price which applies now only to the bids without guarantee.

Up to the authors knowledge, a differentiated ceiling price has never been implemented in real auctions nor has it been considered theoretically. We propose to study such mechanism in the framework of our model. To do so we simulate our model with the same parameters as in the previous section keeping the original ceiling price to 1 and introducing a ceiling price of 0.9 for the bids under the guarantee. The dependency of the final mean price with respect to the competition level and the fraction of guaranteed volume is shown in Figure 5 (Left).

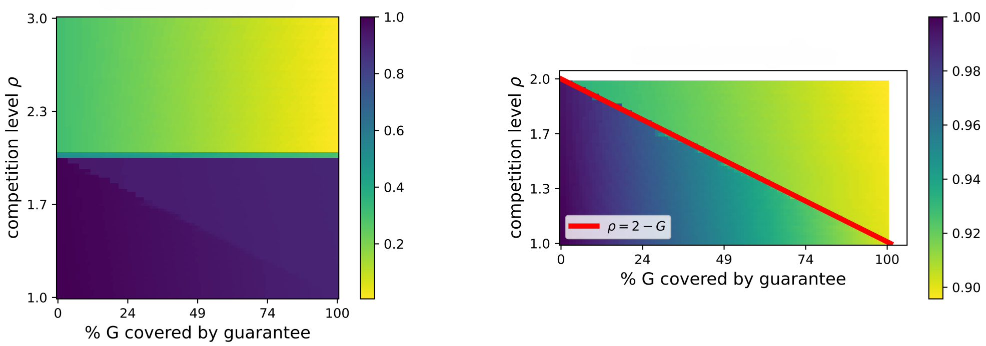

Figure 5: Left: Final mean price in function of the competition level and the percentage of guaranteed volume when there are two ceiling price 0.9 and 1 for bids with and without guarantee. Right: Zoom in the region $\{\rho < 2\}$.

Comparing with the heatmap in Figure 2 (Left) with the same ceiling price for all the bids, we first observe that the behaviour of the final price is identical when the level of competition is greater than 2 (upper half of the plot), namely prices decrease linearly with G from 0.3 to 0 independently of ρ. However, when the level of competition is less than 2 (lower half of the plot), we can observe a strong difference between the two heatmaps. Indeed with a differentiated ceiling price, the final price is not equal to 1 whatever the amount of guarantee but instead it varies abruptly along the diagonal line $\rho = 2 - G$. To better appreciate this transition, a zoom of the region $\{\rho < 2\}$ is shown in Figure 5 (Right) where the red line is $\rho = 2 - G$. The second ceiling price thus allows now the guarantee to impact on the prices but only when it is high enough with respect to the level of competition, more precisely only when $G > 2 - \rho$.

The origin of the transition along the line $\rho = 2 - G$ can be explained as follows. First, numerical experiments show that as before bidders coordinate tending to share the same μ_{with} and $\mu_{without}$ parameters with $\mu_{with} < \mu_{without}$. Since $\rho < 2$, μ_{with} is then equal to the ceiling price for the bids with guarantee, denoted cp_{with}. Being the cheapest, these bids are adjudicated first until covering the guaranteed volume GV. It thus remains to adjudicate the volume $V - GV$

among the remaining offered volume $\rho V - GV$. Thus it is as if the bids without guarantee were participating to an auction with the competition level $\rho^* = (\rho V - GV)/(V - GV)$, i.e., $\rho^* = (\rho - G)/(1 - G)$. Prices then go up or down depending on whether $\rho^* < 2$ or $\rho^* > 2$. Rewriting $\rho^* > 2$ as $G > 2 - \rho$ gives the result.

Moreover when $\rho^* < 2$, i.e., $\rho < 2 - G$ (below the red line), this secondary auction is not competitive so that the final bid without guarantee is the ceiling price without guarantee, denoted $cp_{without}$. Recalling that bidders offer all the same volume v, there are then GV/v winners with guarantee and $(V - GV)/v$ winners without, leading to a total revenue of $cp_{with}GV/v + cp_{without}(V - GV)/v$. Dividing by the total number of winners V/v gives the final mean price $cp_{with}G + cp_{without}(1 - G)$, i.e., $cp_{without} - G(cp_{without} - cp_{with})$. In the numerical simulations presented here, $cp_{without} = 1$ and $cp_{with} = 0.9$ yielding a final mean price $1 - 0.1G$. This corresponds to the price below the red line which decreases linearly from 1 on the left to 0.9 on the right.

5. Assessing the impact of guarantee scheme in real auctions: solar and wind auctions in Germany

In this section we consider real auctions and use our model to assess the impact on prices a guarantee scheme would have had if it had been implemented. We focus on the datasets of the Germany RE program which is determined by auctions since 2015, with approximately three rounds by technology per years. German RE auctions program has been the subject of an intense research activity in the last years (see e.g. (Anatolitis and Welisch (2017); Batz Liñeiro and Müsgens (2021); Grashof, Berkhout, Cernusko and Pfennig (2020); Kácsor (2021); Lundberg (2019); Sach, Lotz and von Blücher (2019); Szabó et al. (2020); Welisch (2018); Welisch and Kreiss (2019))) and is a standard benchmark for RE auctions analysis due to the large amount of data publicly available in the web-page of the German government Federal Ministry for Economic Affairs and Climate Action. We are taking the data as a synthetic dataset of a risky country, where the costs can be reduced by implementing some guarantee scheme.

We consider the solar PV and wind on-shore auctions which are presented and analyzed in detail in Sach et al. (2019); Lundberg (2019). It was observed in Saintier et al. (2023) that, in absence of guarantee, the model presented here can be fitted to reproduce the trends of the mean prices in these two programs (we refer to Saintier et al. (2023) for a detailed description of the parameters values used). We show in Figure 6 the evolution from round to round of the ceiling price (green dotted), the real mean prices (solid blue), the level of competition (grey background) and the simulated price in absence of guaranteed (solid brown) using the German solar and wind on-shore auctions datasets. Notice the solar auctions (Left) were competitive ($\rho > 2$) and accordingly prices were going down. The wind on-shore auctions (Right) on the other hand was competitive mainly during the first three rounds where prices were going down quickly. Then the level of competition dropped below 2 and prices started going up until sticking to the ceiling price.

To assess the possible impact a guarantee mechanism would have had on the prices, supposing for the moment the same ceiling price applies to all the bids, we simulated our model for different percentage G of guaranteed volume while maintaining the parameters as in Saintier et al. (2023), bidders cost there becoming their cost without guarantee. Bidders cost with guarantee was taken equal to their cost without guarantee minus 2 Euro cents/kWh. The results are shown in Figure 6.

We can first notice that the guarantee impacts throughout the solar program leading to lower prices, the reduction being higher as the percentage of guaranteed volume becomes higher. On the other hand, in the wind on-shore program, the guarantee leads to a significant price reduction only in the first rounds, where the level of competition was greater than 2. Its impact then becomes negligible as the prices go up to the ceiling price, regardless the fraction of guaranteed volume.

Eventually, we assess the impact of a differentiated ceiling price on the (non-competitive) wind auction. We consider that the real ceiling price applies to the bids without guarantee, and fix a new ceiling price on the bids under guarantee equal to the real ceiling price minus one. The result prices are shown in the Figure 7. We can appreciate that the presence of the second ceiling price leads to a significant price reduction whose value depends strongly on the competition level. More precisely, in the case $G = 50\%$, we can observe abrupt variations when it crosses the value 1.5, which is exactly the critical value $2 - G = 2 - 0.5$ found in the previous section.

It thus seems that the conclusion drawn in the previous section in an idealized setting still hold in the context of a real auctions, namely the guarantee significantly impacts on the prices when the auction is competitive enough, i.e., when the competition level is greater than 2, and a differentiated ceiling price can lead to a significant decrease of the prices in a non competitive auctions.

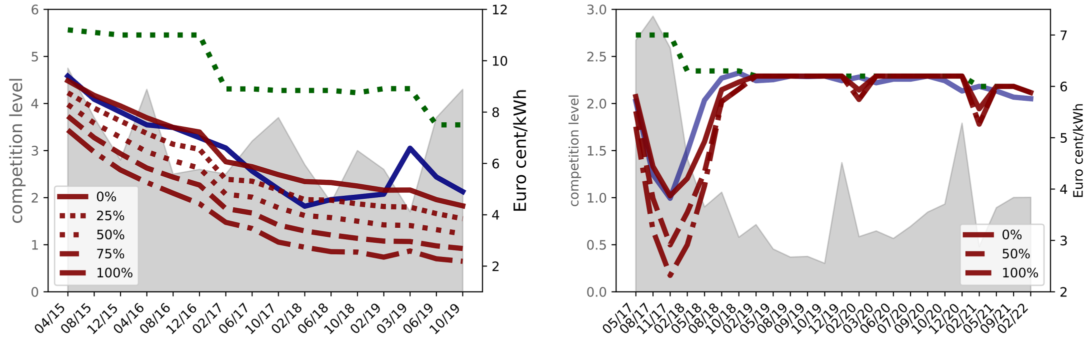

Figure 6: Evolution from round to round of the ceiling price (green dots), the competition level (grey background), the mean prices (solid blue) and the simulated mean prices (brown) if a guarantee scheme had been implemented with $G = 0$, 25%, 50%, 75%, 100% using the Germany solar (Left) and wind on-shore (Right) program dtasets.

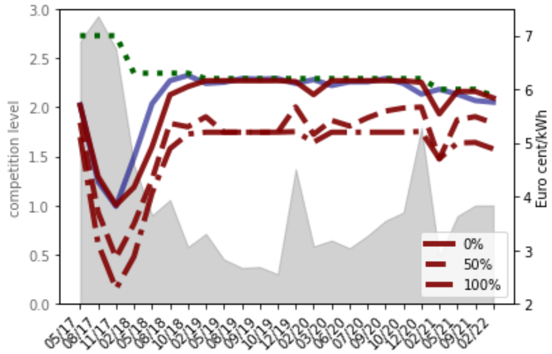

Figure 7: Simulations with the Germany wind on-shore auction dataset with two ceiling prices for different percentage of guaranteed volume $G = 0\%, 50\%, 100\%$.

6. Conclusion and policy recommendations

Renewable energy are one of the main path toward mitigation of climate changes while sustaining the fast economic growth of developing countries; thus contributing significantly to the realization of the United Nations SDG-7 and SDG-8. They are by now mainly allocated trough auctions due to their flexibility and efficiency. Designing reliable auctions scheme in developing countries is thus crucial but also challenging in view of the possible economic, social, political, financial instability they may present. In this context, de-risking mechanisms are crucial to lower bidders cost and ensure affordable energy prices. The present paper aims at providing a simple and flexible modelling framework to assess how a guarantee mechanism impacts on prices.

We proposed a simple model of procurement auction when a de-risking mechanism is implemented so as to guarantee a given fraction of the auctioned volume against default payment. Bidders are characterized by two costs and present two bids at each round depending on whether the volume they offer will be covered or not by the guarantee. They adapt from a round to the next one their bidding behaviour by raising (respectively, lowering) their relative markup by a constant increment if they won (resp., lost) the round.

Agent-based simulations in a simplified settings show that bidders coordinate, and prices undergo a sharp transition as the level of competition is less or greater than 2. When it is greater than 2, prices decreases up to a point determined by the fraction of guaranteed volume. When it is less than 2, prices go up to the ceiling price whatever the fraction of guaranteed auctioned volume, though the guarantee impact as long as bidders are not fully coordinated.

It thus seems that a guarantee scheme impact prices significantly when the auction is competitive enough, i.e., when the level of competition is at least 2, in which case it can drive the prices to low values. However, when the auction is not competitive, the guarantee scheme cannot prevent prices rising up, if it cannot attract bidders prior to the beginning of the auction program. The guarantee instrument is thus of secondary importance when compared to the level of competition which seems to be the main driver of the price evolution.

To mitigate this effect, a novel differentiated ceiling price mechanism has been considered, namely a second ceiling price applying only to bids benefiting from the guarantee was introduced. To the best of the authors' knowledge, such mechanism has never been considered before, neither in real auctions nor in theoretical works. Agent-based simulations show the presence of a new phase transition when the auction is not competitive, which was investigated using simulations. Moreover, this differentiated ceiling price can lead to a significant decrease of the price. When applied to the dataset of the wind on-shore German auctions, which was mostly non-competitive, this new mechanism has a strong impact on the prices. Guarantee scheme in conjunction with a differentiated ceiling price thus seems to be an effective way of obtaining low prices even in a non-competitive auctions.

A guarantee mechanism coupled with a differentiated ceiling price thus seem to be an interesting way of obtaining relatively low prices even in non-competitive auctions. Cares must be taken however in the practical implementation of such a novel design especially regarding the ceiling price on the bids benefiting from the guarantee. To avoid negative perception, the relative difference between the two ceiling prices should reflect the relative decrease of bidders cost induced by the guarantee, which requires a deep analysis of how the risk mitigated by the guarantee impacts on the cost. Otherwise, the differentiating ceiling price might undermine the positive effect the guarantee scheme has on the auction attractiveness. Our modelling framework could be extended to incorporate a functional dependence of the participation, and thus of the competition level ρ, on the fraction of volume G covered by the guarantee. More precisely, once defined a function $\rho = \rho(G)$, the energy prices could be studied to obtain finer prices estimates.

Declarations

Credit authorship contribution statement: all the authors contributed on the conceptualization of the problem, its modeling, computational simulations, and writing, reviewing and editing of the manuscript.

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