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How Do External Costs Affect Pay-As-Bid Renewable Energy Connection Auctions?

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Abstract: Renewable energy deployment costs comprise both internal generation costs and external location-related infrastructure, environmental and social costs. To minimise generation costs, competitive connection contract auctions are becoming increasingly common. Should external costs have considerable influence on site selection outside of the auction process, optimal bidding strategies may be affected by the resulting re-ranking of winning bids. This paper elicits the impact this may have on optimal bidding behaviour. Specifically, we address the impact internalisation of external costs may have on bidding strategy. With deterministic generation costs, optimal bidding strategies include a markup. The optimal markup is lower if external costs are internalised into the investment decision. If investors have the ability to appropriate rents, due to market dominance or asymmetric information, non-internalised external costs lower markup. Generation cost uncertainty may result in below-cost bidding. This is less likely when externalities are not internalised. For markets where bids are competitively priced, this paper provides evidence to suggest that methods to minimise externalities associated with renewables deployment should be integrated with competitive pay-as-bid auctions.

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1 Introduction

The ambition to achieve an environmentally sustainable, cost-effective and secure future energy supply has motivated greater use of renewable resources such as wind for electricity generation (E.C., 2007; DCENR, 2010; DECC, 2011). The total social cost of renewables investment may be split into the internal cost of generation and any external costs. Common external costs include infrastructural upgrade requirements (Hemmati et al., 2016; van der Weijde and Hobbs, 2012); social impacts such as visual disamenity (Azadeh et al., 2014; Ladenburg and Lutzeyer, 2012; Lang et al., 2014); and environmental/ecological impacts such as habitat destruction (Bright et al., 2008; Hötker et al., 2006). Efficient deployment requires the sum of these costs to be minimised (Baumol, 1972; Pigou, 1920).

Competitive auctions may minimise the internal cost of generation. Competitive auctions usually take the form of a pay-as-bid auction, where investors reveal the price at which they are willing to generate electricity and receive this price if successful. This price is a signal for policymakers to choose the least-cost schedule of deployment. Auction mechanisms have been receiving greater attention due to the increasing cost of wind deployment (Chawla and Pollitt, 2013; Farrell and Lyons, 2015; Kylili and Fokaides, 2015; Neuhoff et al., 2013) and have been implemented with success in France, the US, Taiwan, India (Kylili and Fokaides, 2015) and Brazil (Porrua et al., 2010).

Successful implementation has largely occurred in mature markets as implementation in immature markets has led to below-cost bidding. In such cases, investors faced uncertainty regarding their true investment cost and, combined with relative inexperience and the existence of speculators, winning bids were often unviably low (Kylili and Fokaides, 2015; Shrimali and Tirumalachetty, 2013). This occurred in Ireland, China and Cyprus (Kylili and Fokaides, 2015; O Gallachoir et al., 2006).

Alongside mechanisms to minimise internal generation costs, many approaches have been developed to both quantify and subsequently minimise external costs. Drechsler et al. (2011) show how choice models and spatial modelling can be used to optimise wind site selection such that external costs are minimised. Site selection to minimise externalities has also been advocated by means of a weighted checklist and/or ranking approaches (Chase et al., 2001; Azadeh et al., 2011), Data Envelopment Analysis (Azadeh et al., 2014) and ranking based on Geographic Information Systems (GIS) or geospatial optimisation techniques (Snchez-Lozano et al., 2014; Voivontas et al., 1998; Ramachandra and Shruthi, 2007; Baban and Parry, 2001; van Haaren and Fthenakis, 2011; Phillips and Middleton, 2012). For infrastructure upgrades, Transmission Expansion Planning (TEP) models have been used to efficiently upgrade a transmission system (e.g. Hemmati et al., 2016; van der Weijde and Hobbs, 2012; Ugranli and Karatepe, 2014). A number of transmission expansion planning models have considered investor-transmission planner interactions (van der Weijde and Hobbs, 2012; Ng et al., 2006; Tor et al., 2008; Sauma and Oren, 2006) in the pursuit of least cost generation expansion.

Despite the general concern surrounding external costs and methodologies to both quantify and minimise their prevalence, they have not been incorporated into competitive auction frameworks. It is the purpose of this paper to compare different methods for such integration. Two primary approaches may be taken. First, policymakers may employ a competitive auction to identify internal costs of generation. This data may then be used in conjunction with information on external costs such that both internal and external costs are minimised. Indeed, the methodologies for minimising external costs, outlined above, take internal generation costs as a primary input (e.g. Drechsler et al., 2011).

Alternatively, policymakers may calculate the external cost of deployment at each potential site and reveal this information to investors. Investors may then incorporate this information into their bidding strategy, thus internalising external costs into the competitive auction. This follows the theory of Pigouvian taxation and allows private investment strategies to be aligned with the social optimum (Baumol, 1972). Much literature exists to quantify environmental and social externalities associated with renewables deployment (Longo et al., 2008; Owen, 2004). Calculating external infrastructure upgrade costs is less advanced. Shirmohammadi et al. (1996) discuss a number of 'transmission pricing paradigms' that may be employed to internalise such costs, whilst Roustaei et al. (2014) gives an overview of the literature in this area. Adopting the concept of 'cost causality', Dupont et al. (2014) and Ortega et al. (2008) suggest that external transmission cost apportionment should reflect each site's benefit of long term incremental investment costs (Dupont et al., 2014; Commission, 2011; Hogan, 2011; Munasinghe and Warford, 1982; Roustaei et al., 2014; Shirmohammadi et al., 1996; Tabors, 1994). However, each site's benefit of long term incremental investment costs is determined by collective siting decisions, making ex-ante estimation difficult.

While this paper does not aim to quantify these externalities, it does seek to identify how best to treat them with respect to competitive contract auctions. In the pursuit of socially efficient renewables deployment, external costs may place a considerable constraint on site selection. Under such circumstances, techniques to minimise external costs may influence the probability of receiving a connection offer. This may re-rank successful bids in a way that is unknown to the investor. As a result, the investor's probability of bid acceptance and thus the investor's optimal bidding strategy may change. Indeed, even if externalities are not considered by the modeller, they may affect the probability of eventual deployment. Public opposition to any of the social, environmental and infrastructural externalities, following the competitive bidding process, may affect the probability of successful deployment (Cohen et al., 2014; Devine-Wright, 2005; Valentine, 2010; Warren et al., 2005; Wolsink, 2007). Thus, in the presence of social, environmental or infrastructural constraints, a least cost bid in a competitive auction may not necessarily be successful if it is likely to be affected by either ex-post opposition or ex-post modelling to minimise external costs. This paper seeks to identify whether the investor's optimal bidding strategy differs when external costs are internalised into the investment decision.

This analysis is carried out for mature markets where costs are known, and immature markets where costs are uncertain and investors are averse to losing the auction. Hao (2000) has shown that investors exhibit rent-seeking behaviour with respect to their optimal strategy in first-price sealed bid auctions. Similar rent-seeking has been shown to occur in different types of electricity market pay-as-bid auctions (e.g. Nicolaisen et al., 2001; Rassenti et al., 2003). We thus analyse the impact external costs may have on such rent-seeking under different degrees of market competitiveness. With an increasing concern surrounding the cost of renewables deployment, these findings will be of increasing importance as renewables deployment progresses. This contribution proceeds as follows. Section 2 discusses the methodology employed. Section 3 presents the data used in this analysis. Results are presented in Sections 4 and 5 and some concluding comments are offered in Section 6.

2 Methodology

The allocation of wind connection contracts is carried out by a policymaker who wishes to minimise the total societal cost of achieving a renewables target. This total cost includes both internal generation and any external costs. This may be carried out by connection contract auction to identify internal costs, followed by a separate cost optimisation procedure that takes into account external costs. Such external costs may include transmission upgrades, environmental impacts and/or social impacts such as visual disamenity. Alternatively, policymakers may identify the incremental external cost incurred by investment at a given site and insist that investors pay this cost if deployment occurs at that location. In this way, site-specific external costs are internalised into their bids. Conditional on either of these connection contract allocation strategies, the bidder will construct a bidding strategy. The policymaker's objective will now be formally outlined.

2.1 Policymaker's objective

Policymakers wish to deploy a q capacity of wind deployment such that they meet a Q_I deployment target, while minimising the discounted sum of total social costs, TC. An a spatial arrangement must be chosen to carry this out. As a different spatial arrangement of wind deployment results in different sites being chosen and thus different investment and external costs, a is the control variable that the policymaker may alter to minimise costs, with a being an element of the set of feasible actions A. This deployment decision may be formally represented as:

$$\min_{a \in A} \{TC(a)]\}, \tag{1}$$

subject to the constraint

$$q = Q_I. \tag{2}$$

TC may be formally represented by equation (3):

$$TC = \sum_{i}^{I} c_i + D(a), \tag{3}$$

where c_i represents the discounted sum of deployment costs incurred by investor at site i for one MW of capacity (i.e. $q_i = 1$) and D is the external cost determined by the a spatial pattern of wind capacity installed. To facilitate internalisation of these external costs, policymakers must disaggregate total external costs according to the external cost attributable to deployment at each site i. Under such circumstances, D may be disaggregated to d_i components such that

$$\sum_{i}^{I} d_i = D. \tag{4}$$

To determine the optimal schedule a, the policymaker must quantify the cost of deployment, both internal costs and external costs, for each potential arrangement. To carry this out, the policymaker puts in place a pay-as-bid auction. Investors bid the €/MWh price which they require to invest at site i. This bid may include or exclude their share of incremental external cost. Policymakers minimise TC by choosing the least cost combination of bid and external costs. Bidding strategies under each auction specification will now be outlined.

2.2 Investor bidding strategies in a pay-as-bid auction

In a competitive pay-as-bid auction, investors bid the k_i price they are willing to receive per unit of electricity generated should they win a connection contract. Policymakers choose the combination of sites from these bids that facilitates cost-minimisation. As the policymaker will offer connection contracts to the combination of sites that minimises total cost, a lower bid signals lower cost at that site and thus increases the probability of acceptance for the investor. However, a higher bid will increase the potential revenue, conditional on acceptance, as the investor will receive a higher price per unit of electricity generated. As Naert and Weverbergh (1978) and Hao (2000) discuss, rational bidders will seek to maximise utility derived from profits based on their private information, including their perception of how others will bid. Bidders may thus seek a markup by bidding in excess of their private breakeven costs. A Nash equilibrium will result when each bidder chooses a strategy and no bidder wishes to change their strategy (Hao, 2000).

We consider bidding in risk-neutral and risk-averse settings. When uncertainty surrounds the cost of the renewable energy installation, this affects the value of winning the auction for the investor. The empirical and experimental literature indicates that risk aversion is an important component of bidder behaviour under such circumstances (Guerre et al., 2009; Hayashi and Yoshimoto, 2015; Holt and Sherman, 2014) and has been used to explain the frequently observed overvaluation of winning the bid (Cox et al., 1988; Guerre et al., 2009). Guerre et al. (2009) give an overview of the literature in this field. In such cases, bidders are faced with uncertainty surrounding a key parameter determining the value of their bid and thus bidders prefer to raise probabilities of winning at the cost of lowering the value of remuneration, conditional on winning (Hayashi and Yoshimoto, 2015). As Guerre et al. (2009) discuss, risk aversion is generally modelled by parameterising a bidder's utility function. To accommodate this, we assume investors wish to maximise their utility according to a utility function U [1]. For the purposes of this paper, investors' utility is modelled using a power law utility function, where we model risk aversion based on the utility of profit alone. Should the risk aversion parameter be zero, the utility maximisation procedure is the same as profit maximisation.

[1] The purpose of this analysis is to compare risk aversion with risk neutrality and a single tractable utility function is chosen. Preliminary analyses have found that the general conclusions of this analysis are not sensitive to the utility function chosen and for the purposes of this paper, investors' utility is modelled using a power law utility function

$$U_i^s = \begin{cases} \left(\frac{1}{1-\alpha}\right)(\pi_i^s)^{1-\alpha} & if \;\; \alpha \neq 1, \\ ln(\pi_i^s) & if \;\; \alpha = 1, \end{cases} \tag{5}$$

where π_i^s represents the profit earned by investor i in cost scenario s as follows:

$$\pi_i^s = k_i g_i - c_i^s, \tag{6}$$

where g_i and c_i^s are the level of generation and costs associated with at site i respectively. Following Bushnell and Oren (1994) we focus primarily on investment in risk-neutral settings for the majority of this analysis and thus the risk aversion parameter $\alpha = 0$. When markets are mature and investors know with certainty the costs that they will face, then the assumption of risk neutrality (i.e. $\alpha = 0$) is appropriate. Positive risk aversion is most appropriate when the technology is immature and there is uncertainty surrounding cost and thus the underlying value of item being auctioned (Guerre et al., 2009). Investors may be averse to risk of losing the auction created by uncertainty (Holt and Sherman, 2014). Under such circumstances the parameter c_i^s is stochastic and $\alpha > 0$.

We consider a bidding strategy that is increasing continuous and differentiable function of investment cost. Investor i will submit a bid k_i to maximise expected utility, as outlined in Equation (7):

$$\max_{k_i} \;\; EU_i = \max_{k_i} \;\; \int_{-\infty}^{\infty} U_i^s pc_i^s pa_i(k_i) ds. \tag{7}$$

where pc_i^s represents the probability investor i associates with cost scenario s and pa_i represents the probability of investor i's bid being accepted. When costs are deterministic, there is a single cost scenario s. When costs are stochastic, there are S scenarios. It should be noted that pa_i is a function of investor i's bid k_i relative to all other bids and is assumed independent of the distribution of costs. The optimal bid is obtained when:

$$\frac{\partial EU_i}{\partial k_i} = 0. \tag{8}$$

When investor i is assumed to be risk-neutral optimal (i.e., $\alpha = 0$) k_i may be split into two parts as follows:

$$k_i = \frac{1}{g_i} \int_{-\infty}^{\infty} pc_i^s c_i^s ds - \left[\frac{\partial pa_i}{\partial k_i}\right]^{-1} pa_i. \tag{9}$$

The first section of equation (9) represents the expected breakeven cost per unit of electricity, with the second term representing the markup. Assuming that there is a negative change in the probability of acceptance with an increase in bid k_i, then this markup will be positive. Furthermore, a greater rate of change in the probability of acceptance due to a change in k_i bid results in a higher markup. Similarly, a higher probability of acceptance results in a higher markup, assuming a negative $\frac{\partial pa_i}{\partial k_i}$.

The profit π_i^s may be comprised of private installation costs alone (f_i) or private installation costs in addition to site i's share of external costs $(f_i + d_i)$. Bidding strategies for either case will now be derived.

2.2.1 Policy cost and bidding strategy: internalised externality

If π_i includes site i's share of the total externality, then being the n^{th} smallest bid or smaller guarantees a successful bid and thus the probability of being the n^{th} smallest bid or smaller is equal to the probability of success. Under this scenario, where external costs are incorporated into each investor's bid, policy cost will comprise

$$TC = \sum_{i}^{I} k_i g_i(q_i). \tag{10}$$

where k_i is as defined in (9), where $c_i = f_i + d_i$, with f_i corresponding to the internal cost for site i and d_i corresponding to the incremental connection cost apportioned to site i. In this way, external costs are now internalised into the bid.

Characterising the optimal bid by each investor requires information on the costs faced by bidder i and the distribution of all other bids. Following the literature, we assume all other bids are drawn from a distribution with a probability density function $f(K)$ and Cumulative Distribution Function $CDF(k)$ (Hao, 2000).

The probability that generator i's bid is less than the bid of one of these other bids is

$$Pr(k_i \leq k_j) = 1 - CDF, \tag{11}$$

where k_j represents the bid from another investor j. Similarly, the probability that generator i's bid is greater than the bid of one of these other bids is

$$Pr(k_i \geq k_j) = CDF. \tag{12}$$

Assuming there are N independent bids in total, the probability that there is exactly $n-1$ bids less than generator i's bid and $N-1-(n-1)$ bids greater is

$$\binom{N-1}{n-1}(CDF)^{n-1}(1-CDF)^{N-1-(n-1)}. \tag{13}$$

Furthermore the probability that there is $n-1$ or less bids less than generator i's bid is

$$\begin{aligned} ps_i(k_i) = & \binom{N-1}{n-1}(CDF)^{n-1}(1-CDF)^{N-1-(n-1)} \\ & + \binom{N-1}{n-2}(CDF)^{n-2}(1-CDF)^{N-1-(n-2)} \\ & \vdots \\ & + \binom{N-1}{1}(CDF)^{1}(1-CDF)^{N-1-(1)} \\ & + \binom{N-1}{0}(CDF)^{0}(1-CDF)^{N-1-(0)}, \end{aligned} \tag{14}$$

which is equal to

$$pa_i(k_i) = \sum_{l=0}^{n-1} \binom{N-1}{l} (CDF)^l (1 - CDF)^{N-1-l}. \tag{15}$$

Equation (15) gives us the probability that k_i is the nth smallest bid or smaller. To specify the parameters of equation (8), the partial derivative of equation (15) with respect to k_i is required which is

$$\frac{\partial pa_i}{\partial k_i} = \sum_{l=0}^{n-1} \binom{N-1}{l} \frac{\partial CDF}{\partial k_i} \Big[l(CDF)^{l-1}(1-CDF)^{N-1-l} - (N-1-l)(CDF)^l (1-CDF)^{N-2-l} \Big]. \tag{16}$$

2.2.2 Policy cost and bidding strategy: externality not internalised

If pa_i does not include site i's share of external costs, then being the n^{th} smallest bid or smaller does not guarantee a successful bid. Under this scenario, policy costs comprise

$$TC = \sum_{i}^{I} k_i g_i(q_i) + d_i(a), \tag{17}$$

where k_i is determined by equation (9). When the externality is not internalised, $c_i = f_i$. f_i is the internal generation cost for site i and d_i is the incremental connection cost apportioned to site i.

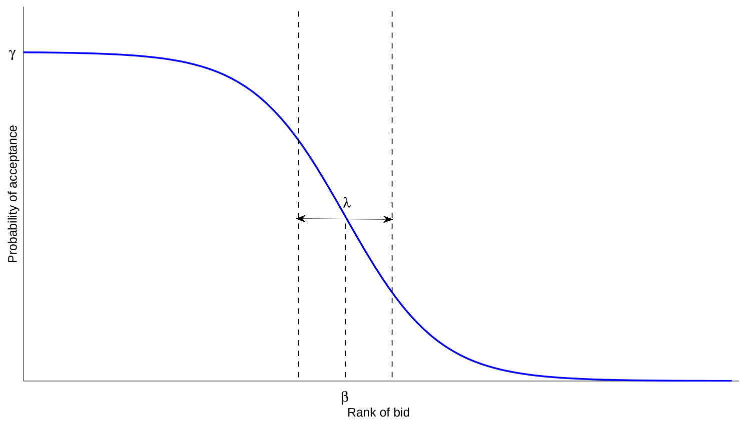
As being the n^{th} lowest bid might not necessarily mean your bid gets accepted we follow a procedure similar to Brock and Durlauf (2001) and represent the probability that generator i's bid will be accepted given there are l bids lower than theirs (i.e., given the rank of their bid) by a hyperbolic tangent function:

$$pr_i(l) = \frac{\gamma}{2}(1 - \tanh(\frac{l-\beta}{\lambda})). \tag{18}$$

This function models the probability of acceptance given the rank of bid such that for low values of l there is a high probability of acceptance and similarly for high values of l there is a low probability of acceptance. A shift from the high probability regime to the low probability regime occurs over a range of magnitude λ, centered at $l = \beta$. The parameter γ ensures that the probabilities are normalised such that the expected total number of bids accepted is n, i.e., $\sum_l pr_i(l) = n$. See Figure 1 for a schematic of equation (18).

As $\lambda \to 0$, equation (18) tends towards a stepwise linear function where the probability of acceptance is equal to one when $l \leq n$ and zero when $l > n$ which results in the same situation as described in Section 2.2.1 where external costs are internalised. As $\lambda \to \infty$, equation (18) tends towards a uniform distribution such that all values of l ($0 \leq l \leq N-1$) have equal probability.

Fig. 1: Probability of acceptance given the rank of bid



Using this conditional probability, the probability that generator i's bid is accepted is

$$pa_i(k_i) = \sum_{l=0}^{N-1} \frac{\gamma}{2}(1 - \tanh(\frac{l-\beta}{\lambda}))\binom{N-1}{l}(CDF)^l(1-CDF)^{N-1-l} \tag{19}$$

Equation (19) gives us the probability of acceptance when external factors affect the ranking of successful bids. To specify the parameters of equation (8), the partial derivative of equation (19) with respect to k_i is required and this is specified in equation (20):

$$\frac{\partial pa_i}{\partial k_i} = \sum_{l=0}^{N-1} \frac{\gamma}{2}(1 - \tanh(\frac{l-\beta}{\lambda}))\binom{N-1}{l}\frac{\partial CDF}{\partial k_i}\Big[l(CDF)^{l-1}(1-CDF)^{N-1-l} \\ -(N-1-l)(CDF)^l(1-CDF)^{N-2-l}\Big] \tag{20}$$

Given the complex nature of the problem formulation, analytical results are not possible. We solve the problem numerically to give insight into the optimal bidding strategy (9) when employing the specification of equations (15), (16), (19) and (20). An application to wind energy deployment in Ireland is chosen and the parameters for this application are outlined in the following section.

3 Data

3.1 Investment data

This auction framework may be applied to many contexts such as the deployment of wind, wave and solar technologies. For the purposes of this paper, we apply the framework to a wind energy example, taking installation data representative of an Irish case study. We consider scenarios of 10 bidders in a market. Following Hao (2000) we assume that each investor i has homogeneous expectations regarding the distribution of all other bids, where all other bids (k_j) follow a uniform distribution according to the parameters of Table 1. This is predicated on different capital investment costs, which are uniformly distributed about a mean of €1.76m/MW, following Doherty and O'Malley (2011) and Farrell et al. (2013). All other wind investment parameters are outlined in Table 1. It is important to note that, for the presented simulations, total costs incurred by investors under each scenario are the same (i.e. c_i is the same, regardless of whether upgrade costs are internalised or not). This allows for greater transparency as the only factor influencing bidding behaviour is a difference in the probability of acceptance.

Table 1: Numerical application: parameters

Parameter	Value
Internal investment cost parameters	
Capital Cost (Wind, per MW)	€1.408m-2.112m
Annual Operations & Maintenance Cost	2% of capital cost
Annual Generation (g)	2912.7 MWh[a]
Discount Rate (r)	0.06
Risk-aversion parameters	
α: risk neutral scenario	0
α: risk aversion scenario	0.8

[a] Assumes a capacity factor of 0.35 and availability factor of 0.95

3.2 Market concentration and probability of acceptance

Bidding strategy is influenced by the extent of competition in the market (market concentration) and the degree with which externalities affect the probability of acceptance. We consider two scenarios of market concentration and three scenarios through which the probability of acceptance is affected. 10 bidders are present in both scenarios of market concentration. For low concentration, three bidders of ten are successful (i.e. the market is competitive). For high concentration, seven bidders of ten are successful (i.e. the market is uncompetitive).

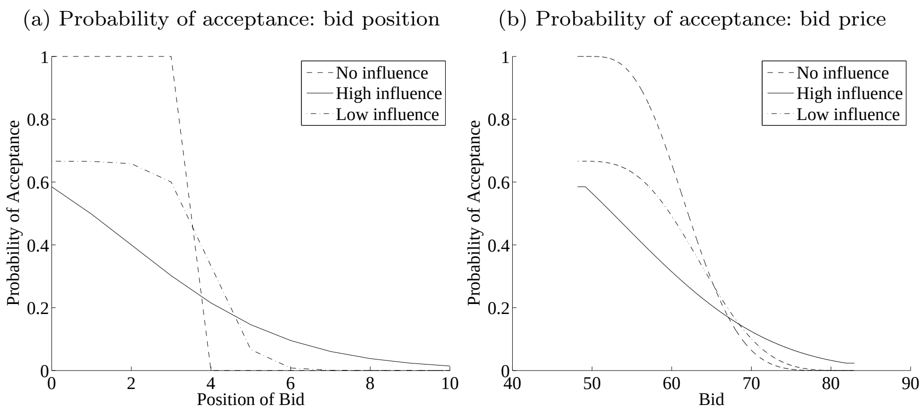
When analysing the probability of acceptance, we first consider the situation where costs are fully internalised and there is no external effect impacting the probability of acceptance. When external factors affect the probability of acceptance, we consider impacts of high or low influence. The parameters that define such high and low influence and the resulting effect on acceptance probability are illustrated in figures 2 and 3. When no external factors affect the probability of acceptance, bid ranking is the sole determinant of acceptance. This is shown in Figure 2(a) where we see that being within the lowest $n = 3$ bids gives a 100% probability of being issued with a connection contract. This falls to 0 as soon as a bid is ranked 4 or higher.

As figures 2(a) and 2(b) show, bid ranking still leads to a considerable difference in the probability of acceptance, however this is not the sole determinant of acceptance. When external factors have a low influence, bids that are ranked below n still have a considerably high probability of acceptance, but normalisation of probabilities has reduced this considerably to allow for the greater probability of acceptance in the neighbourhood of n. We see the most change around the neighbourhood of bid n. Increasing the influence of external factors lessens the sharp decline in acceptance probability in the neighbourhood of n. Thus, bid position still influences acceptance probability, but this influence is lessened with the influence of external factors on the policymaker's decision process.

The most notable difference between scenarios where external factors have low or high influence is that the decline in acceptance probability is less steep with a greater degree of uncertainty, with bids of different rankings having closer probabilities of acceptance. Figures 2(b) 3(b) shows how this affects the probability of acceptance for each bid value, where we see that this translates into a lower probability of acceptance for lower bids and a higher probability of acceptance for higher bids.

These scenarios are first analysed in the presence of deterministic internal costs, representing mature markets where investors are certain of their generation costs. Alongside this, these scenarios are analysed under stochastic generation costs to represent an immature market where investors are uncertain as to their true internal costs. When investors are uncertain as to their investment costs, we assume that they are averse to losing the auction, following observed behaviour when pay-as-bid auctions have been implemented in immature markets (Kylili and Fokaides, 2015).

Fig. 2: Competitive market: acceptance probabilities



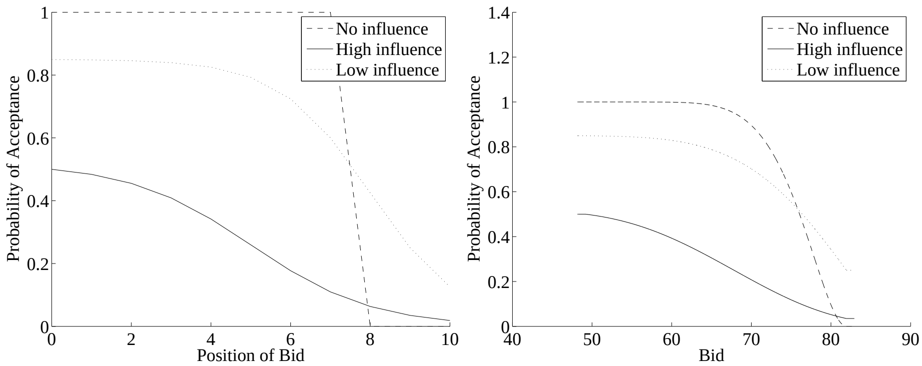
Parameters: High influence: $\beta = 2$, prob = 0.8; Low influence: $\beta = 4$, prob = 0.6

4 Results I: Mature technology

Assuming the considered renewable technology is mature, costs are deterministic and thus investors are risk-neutral in the formulation of their bidding strategy.

Fig. 3: Uncompetitive market: acceptance probabilities

(a) Probability of acceptance: bid position (b) Probability of acceptance: bid price



Parameters: High influence: $\beta = 5$, prob = 0.55; Low influence: $\beta = 5$, prob = 0.7

This section identifies the impact uncertainty of bid acceptance has on the optimal bidding strategy in that scenario. This is carried out for the scenarios outlined in Section 3.

4.1 High level of competition for bid acceptance and expectation of competitive bid price

We first consider the case of a competitive market where all investors have similar costs in the range of +/-10% around the mean value given in Table 1. Each investor has the same level of information regarding the costs faced by other competitors, with expected bid values uniformly distributed in the range of €49/MWh to €82/MWh. This range covers breakeven bids expected by investors, ranging from €50 to €72/MWh, whilst also incorporating the expectation that other bidders may incorporate a markup into their strategy.

Table 2 shows the bids for all investors in this scenario. First, we see that, under all scenarios, all investors place a markup on their breakeven costs, following the expected bidding practice found by Hao (2000). This markup is lowest when external costs have zero influence, and greatest under the scenario where external costs have greatest influence. As all investors face a concave profit function the bid chosen is the optimal strategy given their expectations regarding the bidding behaviour of all other investors. As such, a Nash equilibrium exists.

External factors do not affect bid rank when each bidder's expectation is influenced to the same extent. However, if investors have differing expectations, then the ranking of potential outcomes will change. To illustrate, if investor 1 expected that external factors would have a high degree of influence on the probability of acceptance, while investor 2 expected a low degree of influence, then the ranking of received bids would change. Thus, non-internalised external costs may yield an inefficient selection of sites should investors have heterogeneous expectations regarding their influence.

Table 2: Optimal bids: High level of competition for bid acceptance and expectation of competitive bid pricing

		Bid: influence of external factors		
Investor	Breakeven Cost	None	High	Low
1	60.31	64.88	69.43	66.12
2	61.62	65.76	70.41	66.93
3	62.93	66.67	71.40	67.76
4	64.24	67.60	72.40	68.63
5	65.55	68.57	73.42	69.53
6	66.87	69.56	74.45	70.45
7	68.18	70.57	75.48	71.39
8	69.49	71.60	76.53	72.35
9	70.80	72.64	77.59	73.34
10	72.11	73.70	78.66	74.33

These results allow for the merits of a pay-as-bid auction to be compared to a centrally-planned connection allocation. While investors seek a markup, this markup is relatively low and potentially lower than any bias likely to result from policymaker estimation. In Table 2, costs are between 2-8% greater under a competitive framework when external costs exert no influence on bidding strategy. A greater level of rent seeking exists for sites with lower costs. To put this rent-seeking into perspective, misspecifying an investor's capacity factor by 1% results in a difference of 3% in the required breakeven FiT. Given this high degree of sensitivity, it is highly likely that bias due to policymaker estimation may exceed the potential deviation due to market-based rent-seeking.

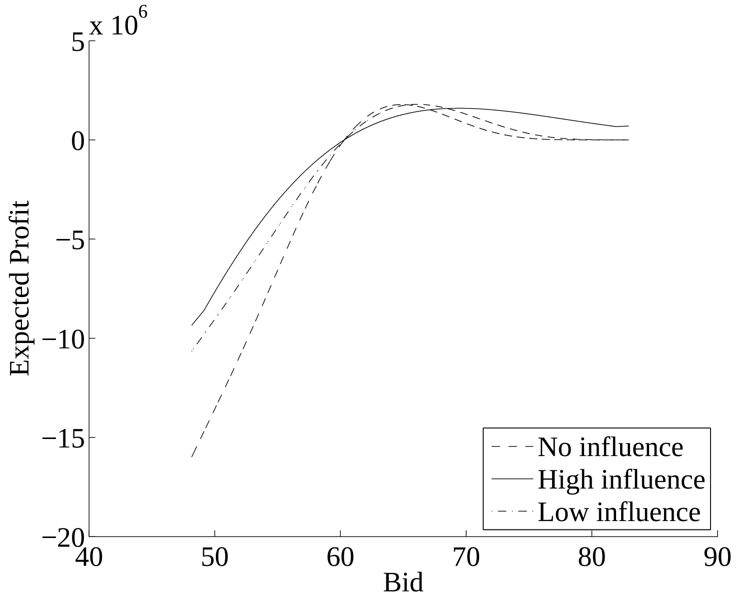
Figure 4 gives insight into the effect external factors have on the optimal bidding strategy under this competitive environment. Externalities increase the probability of acceptance for bids ranked $\geq n+1$, while also lowering the probability of acceptance should a bid be ranked $\leq n$. Given this change in acceptance probability, the expected profit for higher bids is raised by a small amount and thus the optimal bid is raised. This higher optimal point is shown in Figure 4 and is greater with a greater degree of externality influence as there is a higher probability of success for higher bids. As investors can no longer identify with great precision the point at which their probability of being accepted is maximised, there is an incentive for investors to seek a higher markup. This is a Nash equilibrium as this maximises expected profit and thus there is no incentive to change.

This is evidence to suggest that integrating external costs into pay-as-bid renewables connection auctions reduces rent-seeking and thus the cost of deployment for consumers. However, there are some scenarios where this may not prevail. These will now be analysed.

4.2 High level of competition for bid acceptance and expectation of uncompetitive bid price

Section 4.1 has shown how bidders use information asymmetries with respect to cost to extract informational rents. In this section, we consider how this rent-seeking is affected when further information asymmetries exist. In particular, we consider the scenario whereby the expected range of bids is considerably higher

Fig. 4: Investor 1 bid: high level of competition for bid acceptance and expectation of competitive bid pricing



Note: Influence refers to the degree of influence external factors have on the probability of bid acceptance

than investor cost, thus resulting in an added opportunity to seek informational rents.

A number of factors may lead to this occurring. First, there may be a sudden change in technological development, where investors are aware of lower costs but preceding auctions and prevailing market prices suggest bids will be in a higher range. This is similar to the step change in renewables costs that were experienced in Spain and Germany due to technological developments. When this occurred, prevailing Feed-in Tariff prices remained at higher levels, resulting in investor costs being much less than received prices (del Rio and Mir-Artigues, 2014; Poser et al., 2014). Secondly, an information asymmetry may arise where an individual investor's costs are less than all other competitors and thus the expected range of bids is greatly in excess of their breakeven costs. Such investors may have a cost advantage derived from factors such as economies of scale or experience, however, given cost constraints, all other investors are expected to bid within a higher range.

Table 3 shows the optimal bidding strategies for a bidder in either of these scenarios. Each bidder expects bids to be in the range specified in Section 4.1, however, breakeven cost values are considerably diminished. Once again, we see that investors seek a markup, with a higher markup for those with lower costs. However, a number of differences exist.

First, we find that the optimal bid strategy varies relatively little with respect to the underlying cost value. As predicted by (Swider and Weber, 2007), all participants bid close to what they expect the *a priori* unknown marginal bid will be. Bids are similar as the profit-maximising bid is no longer constrained by internal generation costs. When external factors influence acceptance probability to a small extent, investor markup increases, similar to that predicted by Section 4.1. This is to a much lesser magnitude, by 1.7% to 2.3% in Table 3.

The markup is lower under a scenario of high external influence than when no influence is present. This may be explained by comparing the bid functions of Figures 4 and 5. As costs are much lower for the scenario represented by Figure 5, we find that a change in bid results in a much greater change in profit and thus the expected profit when weighted by probability of occurrence. For a scenario of high external influence, the rate of change of expected profit with respect to a change in bid is very high. As such, when bid price is increasing, the reduction in probability outweighs the additional potential revenue, and expected profit falls. This results in the profit maximising bid being lower than under a scenario of no uncertainty.

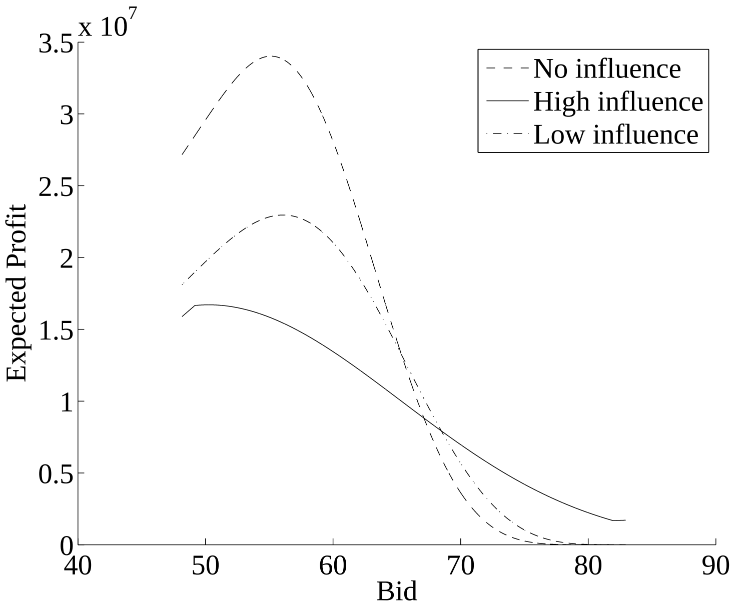
Table 3: Optimal bids: High level of competition for bid acceptance and expectation of uncompetitive bid pricing

		Bid: influence of external factors		
Investor	Breakeven Cost	None	High	Low
1	27.53	55.13	50.26	56.08
2	28.84	55.26	50.79	56.24
3	30.16	55.39	51.34	56.42
4	31.47	55.54	51.91	56.60
5	32.78	55.69	52.50	56.79
6	34.09	55.86	53.12	56.99
7	35.40	56.04	53.75	57.21
8	36.71	56.23	54.41	57.45
9	38.02	56.44	55.09	57.70
10	39.33	56.67	55.79	57.96

The findings of this analysis give insight into how policymakers may wish to treat external costs when they expect one or more bidders to extract excessive informational rents due to the reasons cited above. We see that the rent-reducing effects of external cost influence are greater when a greater cost difference is present. Also, only high levels of external influence induce a lower markup.

Whether it is worthwhile to retain this external influence is predicated on the expected market environment. When there is one player with a low cost, uncertainty will decrease the markup sought by the low cost bidder and increase the markup for investors with higher costs (as outlined in Table 2). Introducing uncertainty thus redistributes economic rents by eroding the rent-seeking for dominant, low-cost market participants and enhancing the rent-seeking for market players bidding in the neighbourhood of their breakeven costs. Comparing the magnitude of markups sought under Tables 2 and 3, the sum total of investor rents may increase with uncertainty under such a scenario. However, should there be a considerable number of investors with costs much lower than the range of expected bids, instigated by factors such as historical precedent, adding uncertainty may lower the sum total of investor rents. Thus, non-internalisation of external costs is only likely to yield an efficiency gain when the majority of market participants enjoy a cost advantage relative to the expected range of bids.

Fig. 5: Investor 1 bid: High level of competition for bid acceptance and expectation of uncompetitive bid pricing



Note: Influence refers to the degree of influence external factors have on the probability of bid acceptance

4.3 Low level of competition for bid acceptance

The second scenario analysed in this paper is related to the number of competitors in the market relative to the number of successful bids. Once again, we consider a scenario of 10 bidders, but this time there are 7 successful bids. As there are 7 winners of 10, this market is less competitive than the preceding analyses when only 3 bids were successful.

We first consider the optimal bidding strategy when expected bids are in a similar range to breakeven costs. Table 4 shows that a higher markup results, relative to the results of Table 2, as investors have a greater probability of acceptance with higher bids. A marginally higher markup occurs when external costs have low influence, with Figure 6 showing that this is due to a shift in the bid curve. This shift is due to a greater probability of acceptance at higher bid prices.

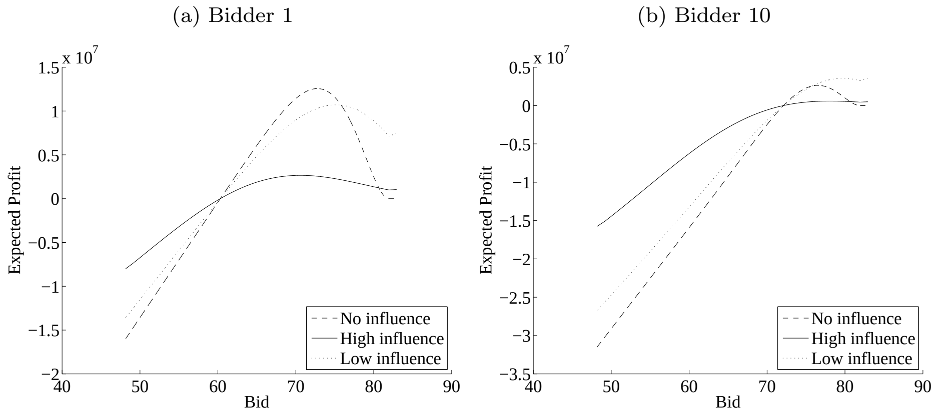
If external factors have a high degree of influence, bidder markup varies by their place on the expected distribution of bids. Relative to the no uncertainty scenario, we see that bidders with costs in the lower portion of the expected range add a lesser markup to their bids, while investors with costs in the higher portion of the distribution add a greater markup. For sites with lower costs, investors maximise their profits at a lower bid as the greater probability of acceptance at lower bids, coupled with the relatively greater profitability relative to higher cost bids, results in a more profitable bid. For higher costs, investors do not have this great degree of profitability at lower bids and thus it is optimal to seek a higher markup to compensate for the lower profit margin, at the expense of a lower probability of acceptance. This is displayed in Figure 6 where we see that under high uncertainty, the optimal bid is considerably different for bidder 1 (low cost) than it is for bidder 10 (high cost).

Table 4: Optimal bids: Low level of competition for bid acceptance and expectation of competitive bid pricing

	Bid: influence of external factors		
Investor	None	High	Low
1	72.76	70.60	75.17
2	73.07	71.35	75.61
3	73.41	72.12	76.07
4	73.76	72.91	76.54
5	74.15	73.72	77.02
6	74.56	74.55	77.53
7	75.00	75.39	78.06
8	75.47	76.26	78.60
9	75.98	77.14	79.16
10	76.53	78.04	82.94

Table 5 shows bidding strategies when costs much lower than the range of expected bids and seven bidders of ten are successful. We see a similar impact on the optimal bidding strategy as that observed in Table 4 when low levels of uncertainty are present, with low cost bidders reducing their markup and high cost bidders increasing their markup, relative to a no uncertainty scenario. Under a high uncertainty scenario, investors lower their bids for all cost values. The bid curve of Figure 7 shows a similar pattern to Figure 5, albeit more pronounced, where high levels of uncertainty result in a steeper decline in expected profit as bids are increased. Because of this, the optimal bid is lower under a high uncertainty case than under a case of no uncertainty, when prices and expectations are uncompetitive.

Fig. 6: Comparing bidder 1 and bidder 10: Low level of competition for bid acceptance and expectation of competitive bid pricing



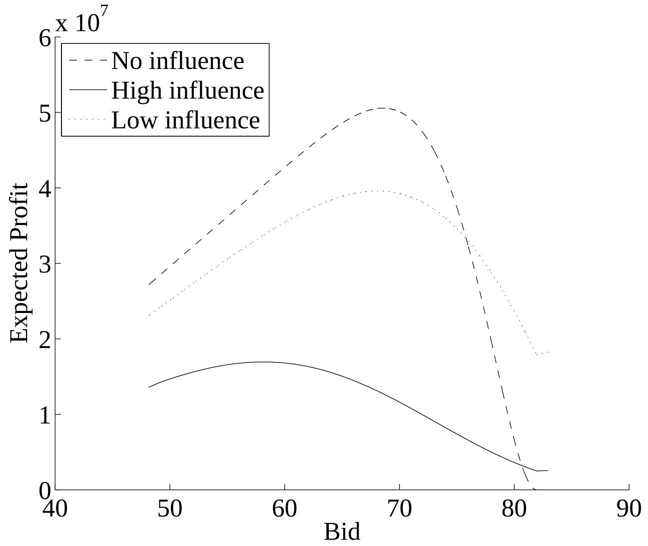
Note: Influence refers to the degree of influence external factors have on the probability of bid acceptance

Thus, should policymakers be faced with an uncompetitive market, external costs have potential to lower investor markup and thus the total societal cost. When the expected bid price range is competitive with breakeven costs, external factors with high levels of influence have the potential to lower bids for costs in the lower portion of the expected distribution. As those in the lower portion are winners of the auction, this is more likely to yield a reduction in policy cost. For scenarios of uncompetitive market prices and uncompetitive expectations, high levels of uncertainty result in reductions in rent-seeking across all bidders and thus a greater reduction in rent-seeking and policy cost.

Table 5: Optimal bids: Low level of competition for bid acceptance and expectation of uncompetitive bid pricing

	Bid: influence of external factors		
Investor	None	High	Low
1	68.57	58.15	68.07
2	68.67	58.45	68.25
3	68.77	58.77	68.45
4	68.87	59.10	68.65
5	68.98	59.45	68.85
6	69.09	59.81	69.06
7	69.20	60.18	69.28
8	69.32	60.56	69.50
9	69.45	60.97	69.74
10	69.58	61.38	69.97

Fig. 7: Investor 1 bid: Low level of competition for bid acceptance and expectation of uncompetitive bid pricing



Note: Influence refers to the degree of influence external factors have on the probability of bid acceptance

5 Results II: Immature technology and risk-averse investors

Results presented so far have assumed deterministic costs and risk neutrality on the part of the investor. Such assumptions are relevant for mature markets where costs and acceptance probabilities can be reliably estimated. However, in immature markets, costs are subject to uncertainty and investors have displayed aversion to losing the auction (Guerre et al., 2009; Hayashi and Yoshimoto, 2015; Holt and Sherman, 2014; Kylili and Fokaides, 2015; O Gallachoir et al., 2006; Shrimali and Tirumalachetty, 2013). As such, this section repeats the analysis of Section 4.1 and characterises the optimal bidding strategies when costs are assumed stochastic, in the region of +/-25% around each breakeven cost value, and investors are risk averse, with a risk aversion parameter of $\alpha = 0.8$ [2].

When external impacts do not influence acceptance probability, and bidders are averse to losing the auction, we find that investor's optimal bids are in the region of the breakeven cost. However, we find that a negative markup exists. This is because investors are averse to losing the auction and thus maximising the probability of acceptance takes greater weight. This is evidenced by the fact that investors with higher costs shade their bid by a greater extent, as the influence of

[2] For brevity, a single risk aversion parameter is chosen to illustrate the effect risk aversion has on bids. The general conclusions concerning the impact of risk aversion holds for all risk aversion parameters, although the magnitude of effect will differ as discussed.

Table 6: Optimal bids for risk averse investors

Investor	Expected Breakeven Cost	Bid: influence of external factors		
		None	High	Low
1	60.31	59.87	67.57	65.96
2	61.62	60.34	68.65	66.87
3	62.93	60.66	68.53	66.63
4	64.24	61.07	69.63	67.25
5	65.55	61.83	70.41	67.87
6	66.87	62.12	71.60	68.15
7	68.18	62.46	71.81	68.61
8	69.49	63.33	72.46	68.68
9	70.80	63.56	73.05	69.40
10	72.11	64.28	73.75	69.45

Note: Investors expect cost values to be in the range of +/-25% of each breakeven value. Risk aversion parameter (α) of 0.8 assumed. High level of competition for bid acceptance and expectation of competitive bid pricing also assumed.

maximising acceptance probability erodes profitability to a greater extent when higher internal costs are present. Thus, investors place greater weight on low cost outcomes when constructing their utility maximising bid. These utility maximising bids are below those when costs are known for certain under a risk neutral setting (Table 2).

This presents the possibility of an unviably low bid if investors win with a shaded bid and the eventual cost is similar to the expected breakeven level. This is similar to the pattern of bidding observed in many markets such as Ireland, China and Cyprus when unviably low bids occurred due to cost uncertainty and loss aversion amongst bidders (Kylili and Fokaides, 2015; O Gallachoir et al., 2006). While Table 6 represents findings in relation to a single assumed degree of risk aversion and cost uncertainty, the magnitude of bid shading will increase with the level of risk aversion and cost uncertainty. The degree to which this occurs must be considered by policymakers when implementing a pay-as-bid auction.

Policymakers must also consider the prevalence of loss aversion. Should all bidders have the same degree of loss aversion, then the relative ranking of bids will be unaffected, however, winning bids have a considerable risk of being unviably low. Should loss aversion be heterogeneous, the degree of bid shading will vary and this may result in a re-ordering of winning bids with unviable bids being accepted, along with many that are not amongst the least cost sites.

As has been observed in the deterministic analyses of Section 4, we find that the markup is greater when external factors influence investor bidding strategy. The extent to which external factors influence bidding strategy determines the additional markup sought, and, for the presented example, influence of a high magnitude results in all bids being viable.

Thus, when pay-as-bid auctions are introduced to immature markets with heterogeneous levels of risk aversion amongst market participants, potential exists for unviable bids to become accepted by a pay-as-bid auction. This occurs when high cost investors are risk-averse and indulge in 'bid shading', resulting in a re-ranking of successful bids to include unviably low winning bids. As bid shading is more prevalent amongst bidders at the upper end of a potential cost distribution, heterogeneity of risk aversion presents the possibility of high cost sites submitting unviably low bids and winning the auction ahead of sites with a lower true cost. The influence of external factors counteracts this potential for bid shading. Should policymakers consider the possibility of accepting unviable bids to be of greater concern than the possbility of investors seeking a markup, the influence of external factors may thus have desirable effects.

6 Discussion and Conclusion

With an increasing level of renewables deployment comes an increasing focus on the design of efficient market mechanisms. Competitive pay-as-bid auctions are becoming increasingly widespread. Alongside this, many methodologies exist to quantify and minimise external costs. To date, separate methodologies have been proposed to analyse each of these costs. It is the purpose of this paper to explore the impact that the use of separate methodologies may have on competitive wind connection contract auctions. Insight is given into how policymakers should treat external costs in the pursuit of minimising bid markup and ensuring that viable bids are successful.

In accordance with the findings in the literature to date, we find that scope for rent-seeking exists in competitive pay-as-bid auctions. However, the magnitude of rent-seeking is found to be small compared to the potential magnitude of cost misspecification on foot of policymaker estimation. This suggests that, even in imperfect markets, competitive auctions for renewable energy connection contracts can yield efficiency gains.

Of primary interest is the impact that acceptance uncertainty, due to non-internalised externalities, may have on bidding strategy. We show that the internalisation of externalities is important for total cost minimisation when internal costs are known with certainty and expected bids are competitive with breakeven cost. This is the primary finding of this paper. This is evidence to suggest that integrating external costs into pay-as-bid renewables connection auctions reduces rent-seeking and thus the cost of deployment for consumers.

However, there are some scenarios where internalisation may not be preferable and these have been explored by this paper. When investors have potential to earn a high markup, introducing uncertainty has the beneficial effect of reducing the markup sought. This potential may be brought about by a relatively low number of competitors or when the majority of market participants enjoy this power, perhaps when a step change in technology has occurred and expected bid prices are likely to be greatly in excess of breakeven costs due to information asymmetries. Introducing uncertainty is also found to be beneficial when markets are immature and bid shading is likely to occur. In such circumstances, costs are uncertain and investors are averse to losing the auction.

While this paper has focussed on the impact on the optimal bidding strategy, the influence this may have on the eventual portfolio of investment is determined by the heterogeneity of expectations surrounding uncertainty and risk aversion. If expectations are homogeneous, the impact of uncertainty is to affect the total cost of deployment, the ranking of successful bids being the same. Should investors have heterogeneous expectations, not dealing with the influence of external costs in the optimal way outlined can result in an ordering of successful bids such that additional economic rents are offered to investors, at the expense of the policy-maker/consumer. In immature markets, this may result in unviable bids being successful, resulting in the potential for missed deployment targets. Should policy-makers consider the possibility of accepting unviable bids to be of greater concern than the possbility of investors seeking a markup, the influence of external factors may thus have desirable effects.

This paper has provided evidence to suggest that integrating external cost-minimisation strategies with pay-as-bid auctions can lead to less rent-seeking by investors, and thus minimise the social cost of renewables deployment. Given the increasing levels of renewables deployment and the greater attention being paid to the cost of achieving energy and environmental policies, the findings of this paper will be of increasing importance as the pursuit of efficient renewables deployment grows.

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