Online Appendix to "Encouraging Renewable Investment: Risk Sharing Using Auctions"

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A Descriptive Evidence

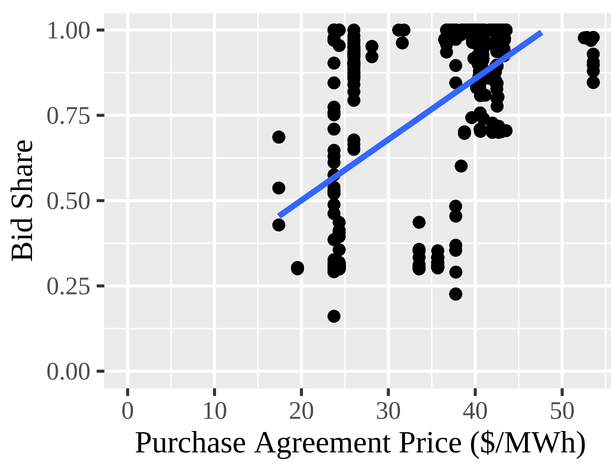

Figure A1: Relationship between bid shares and purchase agreement prices

B Equilibrium Bid Share-Price Relationship

Consider a bidder with an increasing concave utility function u and cost c in a pay-as-bid auction. I set the discount factor $\delta = 1$ for simplicity, though the following

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argument applies to general δ. The bidder's bid share decision problem is effectively the following portfolio optimization:

$$\max_{q} E[u(qb^* + (1-q)r - c)] = u(qb^* + (1-q)\mu_r - c - RP_r(1-q)),$$

where b^* is the bidder's equilibrium bid price, and $RP_r(1-q) \coloneqq RP_{(1-q)r}$ (defined in equation (1) in Section 2) is the bidder's risk premium for selling share $1-q$ of the electricity to the wholesale market. I assume the risk premium function is increasing, differentiable, and convex. The risk premium is zero when the bidder is not exposed to the wholesale market risk, i.e., $RP_r(0) = 0$.

The optimal bid share q^* satisfies $RP_r'(1-q^*) = \mu_r - b^*$ for $q^* \in (\underline{q}, 1)$. q^* balances the marginal risk premium and the marginal expected gain from the wholesale market relative to the purchase agreement. The optimal bid share implied by this equality, $q^* = 1 - (RP_r')^{-1}(\mu_r - b^*)$, is continuous and increasing with respect to b^*.

The counterfactuals of comparing risk-sharing contracts with different shares of risk the policymaker takes, λ, in Section 7 require the entire risk premium function, $RP_r(1-\lambda)$, $\forall \lambda \in [0,1]$. Consider auctions without a constraint on the possible bid share, i.e., $\underline{q} = 0$, first. The equilibrium bid share-price relationship $q^*(b^*)$ for all $q^* \in [0,1]$ is identified from the bid data, as in Section 5.1. Let b_0^* and b_1^* be the maximum and minimum equilibrium bid prices b^* that satisfy $q^*(b^*) = 0$ and 1, respectively. The expected wholesale price μ_r is identified as $\mu_r = b_1^*$ because

$$q^*(b_1^*) = 1 - (RP_r')^{-1}(\mu_r - b_1^*) \iff \mu_r = b_1^*.$$

Since the continuity and monotonicity of $q^*(b^*)$ are assured in $b^* \in [b_0^*, b_1^*]$, I obtain $b^*(q^*)$, $\forall q^* \in [0,1]$, by taking the inverse of $q^*(b^*)$ in $b^* \in [b_0^*, b_1^*]$. Given the initial condition of $RP_r(0) = 0$, I integrate out $RP_r'(1-q^*) = \mu_r - b^*(q^*)$ from $q^* = 1$ to 0 to recover the risk premium function $RP_r(1-q^*)$ for all $q^* \in [0,1]$. If the minimum possible bid share is non-zero (i.e., $\underline{q} > 0$), identifying the entire risk premium function ($RP_r(1-q^*)$ for all $q^* \in [0,1]$) requires some functional form restrictions to extend the risk premium function to the region outside the possible bid share, $q^* \in [0, \underline{q})$.

I exemplify the identifying power of a functional form restriction by considering a risk premium that increases proportionally to the variance of the risk, as is the case with a CARA utility and normally distributed wholesale market price r in Section 4.

The risk premium function can be specified as $RP_r(1-q^*) = (1-q^*)^2 RP_r(1)$ because the variance of the bidder's risk is proportional to the square of the share of risk the bidder takes, $(1-q^*)^2$. Then,

$$\mu_r - b^*(q^*) = RP_r'(1-q^*) = 2(1-q^*)RP_r(1),$$

so, $RP_r(1)$, the bidder's risk premium for taking all wholesale market risks, is the difference between the expected wholesale price μ_r (identified as b_1^*) and the equilibrium bid price b^* at $q^* = 0.5$, i.e., $RP_r(1) = \mu_r - b^*(0.5)$. Moreover, the entire risk premium function is recovered as $RP_r(1-q^*) = (1-q^*)^2 RP_r(1)$ for all $q^* \in [0,1]$ because of the functional form specification. Therefore, the entire risk premium function is identified from the information on the equilibrium bid price at the equilibrium bid share of 100% (to identify μ_r) and 50% (to identify $RP_r(1)$).

C Estimation Procedures

C.1 Wholesale Market Variance

Consider an auction at year $t = 0$ with a lead time $l \geq 1$. I detail the wholesale market variance calculation as defined in Section 4, i.e., $\sigma_r^2 = \text{Var}(T^{-1}\sum_{t=l}^{l+T-1} \delta^t r_t)$. I consider integer-valued lead time and a mean reverting process for discrete time $t = 0, 1, \ldots$ in the model. I linearly interpolate σ_r^2 for lead times that are not integer-valued.

I specify a mean reverting process (or an AR(1) model with an intercept) of wholesale market prices as

$$r_t = A + \rho r_{t-1} + \xi_t, \xi_t \sim \mathcal{N}(0, \sigma_\xi^2),$$

where A is an intercept, ρ is an autocorrelation coefficient, and ξ_t is a residual independent across t. I use annual spot market prices to estimate the parameters (A, ρ, σ_ξ^2) by maximum likelihood estimation. As the mean reverting process implies

$$r_t = A \sum_{s=0}^{t-1} \rho^{t-s} + \rho^t r_0 + \sum_{s=0}^{t-1} \rho^s \xi_{t-s},$$

the wholesale market variance σ_r^2 can be calculated as

$$\sigma_r^2 = \frac{\sigma_\xi^2}{T^2}\left[\sum_{t=1}^{l}\left(\frac{\delta^l \rho^{l-t}(1-\delta^T\rho^T)}{1-\delta\rho}\right)^2 + \sum_{t=l+1}^{l+T-1}\left(\frac{\delta^t(1-\delta^{l+T-t}\rho^{l+T-t})}{1-\delta\rho}\right)^2\right].$$

C.2 Equilibrium Clearing Price Distribution

I detail the calculation of the uniform-price auction's equilibrium clearing price distribution. Let X be auction covariates, including auction date $t = s$, lead time l, and number of participants N. I specify the conditional distribution of equilibrium clearing price p^* given procurement capacity D as

$$f_{p^*|D}^X = \mathcal{N}(\beta_{pD0} + \beta_{pD1}D + \beta_{pD2}(s+l) + \beta_{pD3}N + \beta_{pD4}N^2, \sigma_{pD}^2).$$

I expect a low clearing price with a low procurement capacity D and a large number of participants N because a low bid price likely clears the auction. The operation start date, $s + l$, intends to capture the trend of bidders' costs parsimoniously. I use the parameters $(\beta_{pD0}, \beta_{pD1}, \beta_{pD2}, \beta_{pD3}, \beta_{pD4}, \sigma_{pD}^2)$ that maximize the likelihood.

I specify the procurement capacity distribution as

$$f_D^X = \mathcal{N}(\beta_{D0} + \beta_{D1}s + \beta_{D2}N, \sigma_D^2).$$

The term for auction date s intends to capture the change in the forecasted demand for new energy at different dates. The procurement capacity may also depend on the number of participants N since the policymaker may manipulate the procurement capacity after observing N to maintain the competitiveness of the auction. I use the parameters $(\beta_{D0}, \beta_{D1}, \beta_{D2}, \sigma_D^2)$ that maximize the likelihood.

Integrating out the procurement capacity from the conditional equilibrium clearing price distribution yields the (marginal) equilibrium clearing price distribution: $f_{p^*}^X = \mathcal{N}(\mu_{p^*}, \sigma_{p^*}^2)$, where

$$\begin{cases} \mu_{p^*} = \beta_{pD0} + \beta_{pD1}(\beta_{D0} + \beta_{D1}s + \beta_{D2}N) + \beta_{pD2}(s+l) + \beta_{pD3}N + \beta_{pD4}N^2 \\ \sigma_{p^*}^2 = \sigma_{pD}^2 + \beta_{pD1}^2\sigma_D^2 \end{cases}.$$

C.3 Indirect Inference

I detail the indirect inference procedure. I first derive the equilibrium bid price distribution f_{b^*} in uniform-price auctions. Consider uniform-price auctions with number of participants N. Let realizations of procurement capacity and number of winners in a uniform-price auction a be D_a and M_a. Then, the equilibrium clearing price distribution conditional on D_a, $f_{p^*|D=D_a}$, can be seen as the distribution of $M_a + 1$th order statistic of N i.i.d. samples drawn from f_{b^*}. Since $f_{p^*|D=D_a}$ has been calculated for all uniform-price auctions as in Online Appendix C.2, I obtain the $M_a + 1$th order statistic distribution as $f_{b^*_{M_a+1:N}} = f_{p^*|D=D_a}$. I then calculate f_{b^*} using the monotone relationship between the CDFs of the equilibrium bid price distribution, F_{b^*}, and the $M_a + 1$th order statistic, $F_{b^*_{M_a+1:N}}$:

$$F_{b^*_{M_a+1:N}}(\tau) = \sum_{j=M_a+1}^{N} \binom{N}{j} [F_{b^*}(\tau)]^j [1 - F_{b^*}(\tau)]^{N-j}.$$

I then estimate the structural parameters $\theta = (\alpha_r, \gamma, \sigma_\eta^2)$ by indirect inference. Note that the expected wholesale price μ_r is parameterized as $\mu_r(\alpha_r) = \delta^l \alpha_r$ for an auction with lead time l. For pay-as-bid auctions, I use observed bid prices b_i^d to simulate bid shares q_i^z using the optimal bid share decision and drawing bid share shocks for each simulation $z = 1, \ldots, Z$. Given a candidate parameter value θ, I simulate bids (q_i^z, b_i^d) in pay-as-bid auction a as follows:

1. Draw $\eta_i^z \sim \mathcal{N}(0, \sigma_\eta^2)$ for $i = 1, \ldots, M_a$.

2. Calculate $q_i^z = \min\{\max\{\underline{q}, q^{**}(b_i^d; \alpha_r, \gamma) + \eta_i^z\}, 1\}$, where q^{**} is the unconstrained optimal bid share function for pay-as-bid auctions defined as

$$q^{**}(b; \alpha_r, \gamma) = 1 - \frac{\mu_r(\alpha_r) - \tilde{\delta} b}{\gamma \sigma_r^2}.$$

For uniform-price auctions, I use simulated winners' bid prices b_i^z to simulate bid shares q_i^z because I do not observe winners' bid prices. Each simulation z for uniform-price auction a with observed clearing price p_a^d involves the following:

1. Draw $b_i^z \sim f_{b^*}$ truncated from above at p_a^d for $i = 1, \ldots, M_a$.

2. Draw $\eta_i^z \sim \mathcal{N}(0, \sigma_\eta^2)$ for $i = 1, \ldots, M_a$.

3. Calculate $q_i^z = \min\{\max\{\underline{q}, q^{**}(b_i^z; \alpha_r, \gamma) + \eta_i^z\}, 1\}$, where q^{**} is the unconstrained optimal bid share function for uniform-price auctions defined as the solution to equation (9) in Section 4.2.

The auxiliary regression model is

$$q_i = \begin{cases} \beta_0 + \beta_1 p_a^d + e_i & \text{in uniform-price auctions} \\ \beta_0 + \beta_1 b_i^d + e_i & \text{in pay-as-bid auctions} \end{cases}, e_i \sim \mathcal{N}(0, \sigma_e^2),$$

where $\beta = (\beta_0, \beta_1, \sigma_e^2)$ are the auxiliary parameters. I obtain the auxiliary parameter estimates $\hat{\beta}$ from data using the observed bid shares q_i^d as the dependent variable q_i and the simulated auxiliary parameter estimates $\hat{\beta}^z(\theta)$ using the simulated bid shares q_i^z as q_i for each z. The indirect inference estimator minimizes the objective function defined as

$$Q(\theta) = \left(\hat{\beta} - \frac{1}{Z}\sum_{z=1}^{Z} \hat{\beta}^z(\theta)\right)' W \left(\hat{\beta} - \frac{1}{Z}\sum_{z=1}^{Z} \hat{\beta}^z(\theta)\right),$$

where W is a weighting matrix. I estimate $\mathrm{Var}(\hat{\beta})$ using 200 auction-level block bootstrap replications and use $W = [\mathrm{Var}(\hat{\beta})]^{-1}$ as the weighting matrix. I simulate $Z = 200$ times.

C.4 Equilibrium Winning Probability Function

I detail the calculation of the pay-as-bid auction's equilibrium winning probability function. Let X be auction covariates, including auction date $t = s$, lead time l, and number of participants N. I estimate the capacity distribution specified as

$$f_C^X = \mathcal{N}(\beta_{C0} + \beta_{C1}(s + l), \sigma_C^2).$$

The average capacity is expected to increase by the operation start date, $s + l$, due to technological progress.

I estimate the equilibrium bid price distribution specified as

$$f_{b^*}^X = \mathcal{N}(\beta_{b0} + \beta_{b1}s + \beta_{b2}s^2 + \beta_{b3}l + \beta_{b4}N, \sigma_b^2).$$

The parameterization intends to flexibly capture the time trend and the dependence on lead time l. The equilibrium bid price can also depend on the competitiveness of the auction, proxied by the number of participants N. I form a likelihood using the distribution of order statistics. The individual log-likelihood for bidder i in auction a to have the observed bid price b_{ia}^d and bid price rank counted from the lowest, $brank_{ia}$, is

$$\ln f_{b^*}^X(b_{ia}^d) + (brank_{ia} - 1)\ln F_{b^*}^X(b_{ia}^d) + (N - brank_{ia})\ln(1 - F_{b^*}^X(b_{ia}^d)),$$

where $F_{b^*}^X$ is the CDF for the equilibrium bid price distribution. I specify the procurement capacity distribution in the same way as for uniform-price auctions in Online Appendix C.2.

I then compute the (symmetric) equilibrium winning probability function W^* by simulation. Consider a pay-as-bid auction with lead time l, N participants, and distributions for the capacity type, equilibrium bid price, and procurement capacity given as f_C, f_{b^*}, and f_D, respectively. The following simulation procedure computes W^* in this auction according to the definition of the winning probability function in equation (6) in Section 4.1:

1. For $z = 1, \ldots, Z$, draw competitors' capacity types, $Capacity_j^z \sim f_C$, and bid prices, $(b_j^*)^z \sim f_{b^*}$, independently for $j = 1, \ldots, N-1$.

2. For $z' = 1, \ldots, Z_D$, draw a procurement capacity, $D^{z'} \sim f_D$.

3. Compute the equilibrium winning probability function as

$$\hat{W}^*(b) = \frac{1}{Z_D}\sum_{z'=1}^{Z_D}\frac{1}{Z}\sum_{z=1}^{Z}\mathbb{1}\left\{\sum_{j=1}^{N-1}(\hat{q}^*(b_j^z) \times Capacity_j^z)\mathbb{1}(b_j^z < b) < D^{z'}\right\},$$

   where $\hat{q}^*$ is the optimal bid share function as in equation (7) in Section 4.1 with structural estimates from the portfolio decision (Section 5.2):

$$\hat{q}^*(b) := \min\left\{\max\left\{\underline{q}, 1 - \frac{\delta^l\hat{\alpha}_r - \tilde{\delta}b}{\hat{\gamma}\sigma_r^2}\right\}, 1\right\}. \tag{1}$$

I smooth the indicator functions in the last step using a normal CDF, denoted Φ, following Ryan (2022): i.e., an indicator function $\mathbb{1}(x_0 < x)$ is smoothed as $\Phi((x - x_0)/h)$, where I set the bandwidth parameter to be $h = \$2/\text{MWh}$, about 1/20 of the level of a typical bid. I calculate $\hat{W}^*(b)$ for a grid of b with \$0.10/MWh increments and linearly interpolate between the grid points. I numerically differentiate $\hat{W}^*(b)$ to obtain the derivative $d\hat{W}^*(b)/db$. I simulate $Z = Z_D = 200$ times.

D Other Parameter Values

Wholesale market volatility. Table D1 tabulates the parameter estimates for the mean reverting process of annual wholesale prices in Online Appendix C.1. The estimated wholesale market standard deviation (SD) ranges from $\sigma_r = \$4.94$–\$5.82/MWh across 16 auctions. σ_r decreases by the lead time because of the discount for the further future and the stability of the further future prices in the mean reverting process (Figure D1).

Table D1: Annual wholesale price process parameter estimates

Parameter	Estimate
Intercept, A	17.7 (16.4)
AR(1) Coefficient, ρ	0.398 (0.327)
SD(Residual), σ_ξ	27.0 (14.0)

Note: Annual spot prices (\$/MWh) from 2001 to 2022 are used in the estimation. Standard errors (in parentheses) are calculated using the outer product approximation method for maximum likelihood estimation. SD stands for standard deviation.

Procurement capacity distribution. Table D2 reports the fitted parameter values of the procurement capacity model in Online Appendix C.2. The fitted procurement capacity models for pay-as-bid and uniform-price auctions are used to calculate the equilibrium winning probability function (Online Appendix C.4) and equilibrium clearing price distribution (Online Appendix C.2), respectively. In pay-as-bid auctions (resp. uniform-price auctions), the procurement capacity is expected to drop by 34 MW (resp. 23 MW) each year and by 67 MW (resp. 82 MW) if there are 100 fewer participants. The procurement capacity SD is larger for the earlier period (pay-as-bid auctions from 2011–2015) than for the later period (uniform-price auctions from 2017–2021). The expected procurement capacity ranges from 277.9–488.8

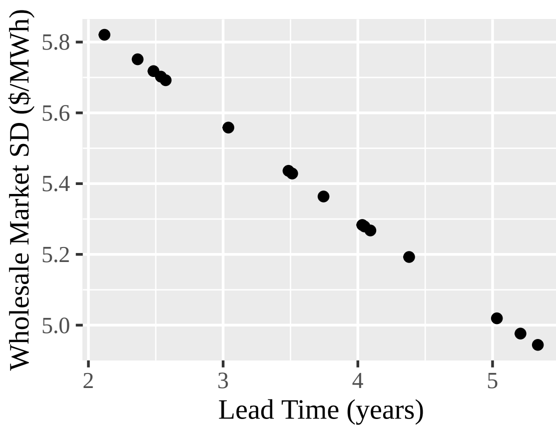

Figure D1: Relationship between the wholesale market SD and lead time

MW across 8 pay-as-bid auctions and −76.3–410.9 MW across 8 uniform-price auctions. The fitted procurement capacity distribution yields a non-positive procurement capacity with an appreciable probability, which I interpret as a case where the auction is canceled. Brazil's new energy auctions have been canceled about once every five years historically, and I do not include the canceled auctions in the analysis. I use procurement capacity distributions truncated from below at 0 in calculating the pay-as-bid auction's equilibrium winning probability function.

Table D2: Procurement capacity distribution parameter values

Parameter	Pay-as-Bid Auctions	Uniform-Price Auctions
Intercept, β_{D0}	230.3	−95.1
Auction Date (year), β_{D1}	−34.4	−23.1
100 Participants, β_{D2}	66.8	82.4
SD(Residual), σ_D	244.8	132.5

Note: The parameter values best rationalize the observed procurement capacities (MW) in pay-as-bid (2011–2015) and uniform-price (2017–2021) auctions, respectively. Auction Date is defined as the year since the beginning of 2011. SD stands for standard deviation.

Equilibrium clearing price distribution. Table D3 reports the fitted parameter values of the conditional equilibrium clearing price model for uniform-price auctions in Online Appendix C.2. The expected clearing price drops by $1.84/MWh for 100 MW less procurement capacity and decreases at a diminishing rate as the number of participants increases, reflecting the competitiveness of the auction. The fitted conditional clearing price distribution and uniform-price auction's procurement capacity distribution yield (marginal) clearing price distributions with a mean ranging from μ_{p^*} = \$19.92–\$34.33/MWh (across 8 uniform-price auctions) and SD of σ_{p^*} = \$2.55/MWh. The SD of σ_{p^*} = \$2.55/MWh is larger than that of the conditional clearing price distribution, σ_{pD} = \$0.76/MWh, reflecting the uncertainty bidders face because the procurement capacity is not disclosed at the time of bidding.

Table D3: Equilibrium clearing price distribution parameter values

Parameter	Value
Intercept, β_{pD0}	26.50
Procurement Capacity (100 MW), β_{pD1}	1.84
Operation Start (year), β_{pD2}	3.04
100 Participants, β_{pD3}	−11.75
100 Participants Square, β_{pD4}	0.70
SD(Residual), σ_{pD}	0.76

Note: The parameter values best rationalize the observed clearing prices (\$/MWh) in uniform-price auctions from 2017–2021. Operation Start is defined as the year since the beginning of 2011. SD stands for standard deviation.

Equilibrium winning probability function. I estimate the capacity and equilibrium bid price distributions to calculate the equilibrium winning probability function for each pay-as-bid auction as in Online Appendix C.4. Table D4 shows the parameter estimates for the capacity and equilibrium bid price distribution models. The average capacity increases by 0.2 MW each year, 1.5% of the overall average of 11.5 MW from 2011–2015. Bidders understand that the competitors' equilibrium bid prices follow a distribution with a mean ranging from \$42.64/MWh–\$60.07/MWh (across 8 pay-as-bid auctions) and SD of \$4.04/MWh. Figure D2 plots the predicted winning probabilities of the observed winners' bid prices in each pay-as-bid auction. Most predicted winning probabilities drop on the steep slope of the equilibrium winning probability functions, meaning the predicted probabilities are reasonably far from the two extremes, 0 and 1, as expected.

Table D4: Equilibrium winning probability function parameter estimates

Capacity Distribution		Equilibrium Bid Price Distribution	
Intercept, β_{C0}	10.41 (0.78)	Intercept, β_{b0}	48.29 (0.21)
Operation Start (year), β_{C1}	0.18 (0.12)	Auction Date (year), β_{b1}	-0.86 (0.17)
SD(Residual), σ_C	3.35 (0.89)	Auction Date Square, β_{b2}	0.98 (0.02)
		Lead Time (year), β_{b3}	-0.28 (0.06)
		100 Participants, β_{b4}	-1.35 (0.07)
		SD(Residual), σ_b	4.04 (0.91)

Note: The parameters are estimated using the pay-as-bid auction data from 2011–2015. Operation Start and Auction Date are defined as the year since the beginning of 2011. Standard errors (in parentheses) are calculated using 200 auction-level block bootstrap replications. SD stands for standard deviation.

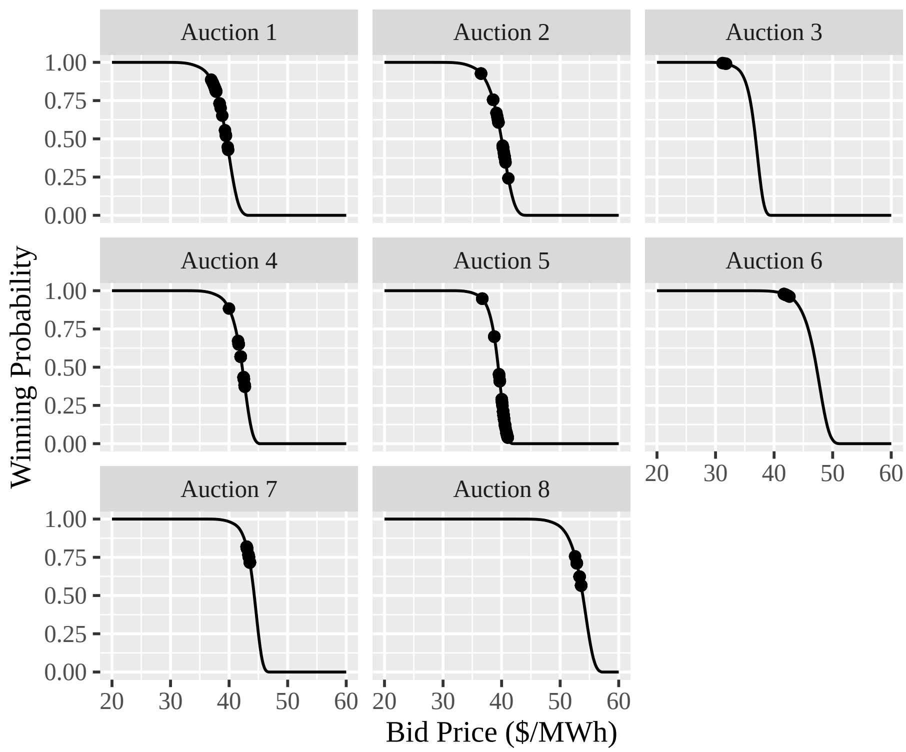

Figure D2: Estimated equilibrium winning probability functions and winners' bids

E Further Sensitivity Analyses

Table E1 reports the markup estimates by different specifications of the wholesale market volatility (SD, σ_r) and equilibrium clearing price distribution in uniform-price auctions (mean, μ_{p^*}, and SD, σ_{p^*}), analogous to Table 3 in Section 6. The clearing price distribution misspecification (Panel B and C) barely affects the markup estimates in pay-as-bid auctions, similar to the cost estimates in Table 3, because they are both estimated from bidders' bid price decisions.

Table E1: Sensitivity analysis: Winners' average markup

	Change from the Main Specification				
A. Wholesale Price SD, σ_r	−50%	−25%	Main	+25%	+50%
Markup ($/MWh)	0.79	1.19	1.54	1.85	2.13
B. Clearing Price Mean, μ_{p^*}	−2SD	−1SD	Main	+1SD	+2SD
Markup ($/MWh)	1.64	1.56	1.54	1.56	1.63
C. Clearing Price SD, σ_{p^*}	−50%	−25%	Main	+25%	+50%
Markup ($/MWh)	1.44	1.48	1.54	1.64	1.79

Note: Values are the capacity-weighted average of the pay-as-bid auction winners. SD stands for standard deviation.

Table E2 tabulates the risk premium, cost, and markup estimates from combinations of different wholesale market volatility and clearing price distribution specifications. It contains all combinations of changing the main specification of σ_r = \$4.94–\$5.82/MWh, μ_{p^*} = \$19.92–\$34.33/MWh, and σ_{p^*} = \$2.55/MWh to 75%–125%, -1–+1 SD of σ_{p^*} = \$2.55/MWh, and 75%–125% of them, respectively. Overall, the risk premium, cost, and markup estimates range from \$5.70–\$8.27/MWh, \$20.27–\$21.16/MWh, and \$1.12–\$2.03/MWh, respectively, across various alternative specifications.

F Counterfactual Winning Probability Function

I compute the counterfactual winning probability function H in Appendix A.3 for the 8 pay-as-bid auctions from 2011–2015. Consider an auction with lead time l, N participants, and distributions for the capacity type, equilibrium bid price, cost type, and procurement capacity, f_C, f_{b^*}, f_c, and f_D, respectively. The following simulation procedure computes H of this auction:

1. For $z = 1, \ldots, Z$, draw participants' capacity types, $Capacity_i^z \sim f_C$, and bid prices, $(b_i^*)^z \sim f_{b^*}$, independently for $i = 1, \ldots, N$.

Table E2: Sensitivity analysis: Combinations of different specifications

	Change from the Main Specification								
Clearing Price Mean, μ_{p^*}	−1SD			Main			+1SD		
Clearing Price SD, σ_{p^*}	−25%	Main	+25%	−25%	Main	+25%	−25%	Main	+25%
Wholesale Price SD, σ_r, −25%									
Risk Premium ($/MWh)	8.24	7.04	5.70	8.13	7.34	6.34	7.61	7.22	6.53
Cost ($/MWh)	21.16	21.07	20.95	21.15	21.09	21.01	21.11	21.08	21.03
Markup ($/MWh)	1.12	1.21	1.36	1.13	1.19	1.29	1.16	1.20	1.26
Wholesale Price SD, σ_r, Main									
Risk Premium ($/MWh)	8.27	7.17	5.94	8.09	7.38	6.47	7.51	7.14	6.55
Cost ($/MWh)	20.81	20.72	20.59	20.80	20.74	20.65	20.75	20.71	20.66
Markup ($/MWh)	1.46	1.56	1.71	1.48	1.54	1.64	1.53	1.56	1.63
Wholesale Price SD, σ_r, +25%									
Risk Premium ($/MWh)	8.27	7.23	6.04	8.06	7.39	6.53	7.46	7.10	6.54
Cost ($/MWh)	20.51	20.41	20.27	20.49	20.42	20.33	20.43	20.39	20.33
Markup ($/MWh)	1.77	1.87	2.03	1.79	1.85	1.95	1.85	1.88	1.95

Note: Values are the capacity-weighted average of the pay-as-bid auction winners. SD stands for standard deviation.

2. For $z' = 1, \dots, Z_D$, draw a procurement capacity, $D^{z'} \sim f_D$.

3. For each combination of z and z', simulate an auction that allows bidders to choose their shares. Bidder i wins when

$$D^{z'} - \sum_{j \neq i} (\hat{q}^*((b_j^*)^z) \times Capacity_j^z) \mathbb{1}((b_j^*)^z \leq (b_i^*)^z) > 0,$$

where $\hat{q}^*$ is the estimated optimal bid share function that depends on l (equation (1) in Online Appendix C.4). Let the set of simulated winners be $Winner^{z,z'}$ and the index of the bidder with the lowest bid price among the simulated losers be $i = k^{z,z'}$.

4. For each combination of z and z', calculate an implied objective capacity $\widetilde{D}^{z,z'}$ by adding up the simulated winners' capacities as follows:

$$\widetilde{D}^{z,z'} = \sum_{i \in Winner^{z,z'}} Capacity_i^z + \frac{D^{z'} - \sum_{i \in Winner^{z,z'}} (\hat{q}^*((b_i^*)^z) \times Capacity_i^z)}{\hat{q}^*((b^*_{k^{z,z'}})^s) \times Capacity^z_{k^{z,z'}}} \times Capacity^z_{k^{z,z'}},$$

where the bidder with the lowest bid price among the losers, $i = k^{z,z'}$, contributes proportionally to the residual of $D^{z'}$ to smooth $\widetilde{D}^{z,z'}$.

5. For $z = 1, \ldots, Z$, draw competitors' cost types, $c_j^z \sim f_c$, independently for $j = 1, \ldots, N-1$.

6. Compute the counterfactual winning probability function as

$$H(c) = \frac{1}{Z_D} \sum_{z'=1}^{Z_D} \frac{1}{Z} \sum_{z=1}^{Z} \mathbb{1} \left\{ \sum_{j=1}^{N-1} Capacity_j^z \mathbb{1}(c_j^z < c) < \widetilde{D}^{z,z'} \right\}.$$

Steps 1–4 convert procurement capacity D to objective capacity $\widetilde{D}$. f_c is simulated numerically using the estimated equilibrium bid distribution and the solution to the bid price decision in equation (8) in Section 4.1. Similarly to the equilibrium winning probability function computation in Online Appendix C.4, I smooth the indicator functions in the last step using a normal CDF with a bandwidth parameter $h =$ \$2/MWh. I calculate $H(c)$ for a grid of c with \$0.10/MWh increments and linearly interpolate between the grid points. I numerically differentiate $H(c)$ to obtain the derivative $dH(c)/dc$. I simulate $Z = Z_D = 200$ times.

References

Ryan, Nicholas, "Holding Up Green Energy," Working Paper 2022.