Encouraging Renewable Investment: Risk Sharing Using Auctions*

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Abstract

Renewable energy investors face substantial risk because they sell intermittent electricity into volatile wholesale markets. High upfront capital costs of new renewable capacity can make investors risk-averse, resulting in a high risk premium to assume the wholesale market risk. Policymakers looking to encourage renewable investment can implement power purchase agreements that ensure a certain price to take the risk from investors. The value of policymaker risk-taking depends critically upon investors' risk premium. I develop and estimate a structural auction model that recovers investors' risk premium from their portfolio choices embedded in Brazil's long-term wind power purchase agreement auctions. To entice investors to install wind turbines costing \$12.2 billion, the policymaker would save \$4.4 billion by taking on 100% of the wholesale market risk, relative to the cost of a subsidy policy that left all the risk with the investors.

Keywords: Renewable energy investment, wholesale electricity markets, purchase agreement, risk-averse bidders, multidimensional bids

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1 Introduction

Widespread private sector investment in renewable energy is crucial in mitigating the impacts of climate change (REN21, 2023). Renewable energy investors expect financial returns from sales of electricity produced from new renewable capacity. However, wholesale electricity markets have volatile prices, and investors cannot shift their production schedule to avoid low prices because of the intermittency of renewable energy (Beiter et al., 2024). Moreover, renewable technologies are much more capital-intensive than fossil fuel-based plants, where fuel costs dominate the overall costs (Schmidt, 2014). High upfront capital costs of new renewable capacity can make investors substantially risk-averse to uncertain revenues (May and Neuhoff, 2021). The situation would worsen in low and middle-income countries with under-developed financial markets where handing off the risk to financial entities is costly (Ameli et al., 2021; Calcaterra et al., 2024). Therefore, policymakers' risk-sharing can be essential in promoting renewable investments unless private markets can absorb the risk at a modest cost (Schmidt, 2014; Beiter et al., 2024).

Policymakers have implemented two broad approaches to aid renewable investors financially (IRENA, 2019): power purchase agreements and generation subsidies.[1] Purchase agreements ensure a certain price regardless of wholesale prices, while subsidies pay a premium on top of wholesale prices. A critical difference between purchase agreements and subsidies is who bears the wholesale market risk (Farrell et al., 2017; Alcorta, Espinosa, and Pizarro-Irizar, 2023). With purchase agreements, policymakers take the risk from investors, while the risk remains on the investors' side with subsidies. Consequently, policymakers face a trade-off between taking the risk and paying investors to assume the risk, corresponding to investors' *risk premium*. I estimate investors' risk premium from their *portfolio choices* to quantify this trade-off, providing policymakers with a menu of possible cost-risk combinations to achieve the same renewable investments.

I study the trade-off using long-term wind power purchase agreement auctions, planned and administered by the Brazil Ministry of Mines and Energy (Ministério

[1] Purchase agreements and subsidies are also called feed-in tariffs and feed-in premiums. Also, my framework can handle upfront investment subsidies instead of generation subsidies. Policy implications of these two subsidy schemes will remain the same if there is no risk in the payout.

de Minas e Energia, MME) and Electricity Regulatory Agency (Agência Nacional de Energia Elétrica, ANEEL), respectively, from 2011–2021. MME calls for investors with a new wind turbine installation project to bid 1) a share of the production they will include in a purchase agreement and 2) a price for each unit of this share. The lowest bid prices win the purchase agreements where ANEEL guarantees payouts for 20 years—the wind turbines' lifetime. In exchange, winners commit to installing their planned capacity. Winners secure a purchase agreement for the share of the production they bid and sell the remaining into Brazil's wholesale market, consisting of a spot market reflecting the marginal hydroelectric and thermal fuel costs, short-term purchase agreements intermediated by ANEEL, and bilateral contracts with high-volume consumers (Hochberg and Poudineh, 2021). The short-term purchase agreements and bilateral contracts usually last up to 6 years (CCEE, 2024; Perez, 2024), and prices will be uncertain upon renewal. Moreover, ANEEL has been concerned about the transparency of price formation and counterparty risks in payouts in bilateral contracts (CCEE, 2012). The uncertain prices and counterparty risks motivated MME to provide long-term purchase agreements immune from these wholesale market risks to ease investors' upfront capital financing (Tolmasquim et al., 2021).

Bidders essentially make portfolio choices to allocate their total production across the risk-free purchase agreement and risky wholesale market. Portfolio choices embedded in auctions can hint at bidders' risk attitudes, as Athey and Levin (2001) have noted in scaling auctions. Risk-neutral bidders will allocate all of their allocatable production to either the purchase agreement or wholesale market, whichever gives them the higher expected price. However, 58% of bidders in my data make partial allocations. Risk-averse bidders explain these partial allocations because they diversify their portfolios to balance the expected price and price variability. Motivated by this observation, I develop a structural model of risk-averse bidders in these auctions to separately recover bidders' wholesale market beliefs—consisting of the expected price and risk premium—and private costs, following the share auction framework of Wilson (1979). I extend Bolotnyy and Vasserman (2023) and Luo and Takahashi (2024)'s identification strategies in scaling auctions to a different auction design involving bidders' portfolio choices more explicitly.[2]

[2]See Perrigne and Vuong (2019) and Vasserman and Watt (2021) for literature reviews on identifying bidders' risk aversion.

Bidders with a common wholesale market belief and heterogeneous cost types choose their bid share and price to maximize their expected utility of bidding. I show that the bid share decision boils down to a portfolio optimization across a risk-free purchase agreement and a risky wholesale market because bidders' bid shares do not affect their likelihood of winning the auction. Bidders only care about the expected utility conditional on winning—determined by their portfolio choices given their purchase agreement prices—in their bid share decisions, which reveal their wholesale market beliefs. Intuitively, the minimum purchase agreement price in which bidders allocate all production to the purchase agreement informs about the expected wholesale price because bidders strictly prefer a risk-free option to a risky alternative if the risk-free price is at least as high as the risky option's expected price. The risk premium is identified from how bidders trade-off between the expected price gain and the additional price variability in their portfolio choices for different purchase agreement prices. Leveraging on these identification strategies, I obtain a robust risk premium estimate *without* accurate wholesale market data, which is hard to collect because it involves private bilateral contracts.

I estimate the structural parameters from winning bids, assuming that bidders are symmetric. Only having access to winners' bids is common in new renewable energy auctions, as policymakers are concerned about the future competition impacts of making all bids public.[3] I first estimate bidders' wholesale market beliefs from their portfolio choices via indirect inference (Gourieroux, Monfort, and Renault, 1993). An auxiliary regression capturing the winners' portfolio choice-purchase agreement price relationship recovers the wholesale market belief that is common across winners and losers. I then infer bidders' private costs from their bid price decisions using participants' bid distribution in the spirit of Guerre, Perrigne, and Vuong (2000). The participants' bid distribution is recovered from the participants' bid price distribution estimated from winners' bid prices following Athey and Haile (2002) and the participants' portfolio decisions implied by the estimated wholesale market belief.

I find that wind turbine investors' wholesale market risk premium is high in Brazil. Their risk premium of selling all electricity into the wholesale market is \$7.38/MWh, which amounts to 35.6% of the average winner's cost of \$20.74/MWh. The risk pre-

[3]MME raises this concern as the primary reason for not making their auction participant generation cost microdata public (EPE, 2022).

mium estimate is comparable to May and Neuhoff (2021)'s estimate of 29% of the cost from the interview data on financing costs in the European Union. Nevertheless, obtaining significantly different risk premium estimates would not be surprising because they likely depend on local electricity price volatility and counterparty risks.

Policymakers can use my framework to understand their cost-risk trade-off from risk sharing with renewable investors using investors' risk premium estimated from investors' revealed preference in policymakers' jurisdiction. I simulate a policymaker seeking to entice investors to install the same wind energy capacities as in actual auctions, which amount to 3.4 GW, 1.9% of the overall generation capacity in Brazil in 2020 (Tolmasquim et al., 2021), and reach the simulated cost of $12.2 billion. Knowing that investors are risk-averse, the policymaker proposes taking a share $\lambda \in [0, 1]$ of the responsibility of selling the electricity to the wholesale market to support the investment. The policymaker implements this risk sharing using alternative auctions that require all bidders to bid in share λ of their production instead of allowing them to choose their shares individually. The policymaker's counterfactual net expenditure is the discounted sum of cash transfers to investors net of the wholesale market revenues during 20 years of support.

The expected net expenditure decreases from $5.0 billion ($\lambda = 0$, equivalent to subsidies) to $1.7 billion by taking half of the risk ($\lambda = 0.5$) and to $0.6 billion by taking the entire risk ($\lambda = 1$, full share purchase agreements). The difference of $4.4 billion between subsidies and full share purchase agreements would be able to cover additional costs of 1.1 GW of wind turbines. Nevertheless, the policymaker might be struck by high net expenditures by taking risks. The 97.5 percentile of net expenditure with full share purchase agreements is $2.0 billion higher than subsidies, with the wholesale market risk evaluated using historical spot prices. The policymaker can be more pessimistic and evaluate the wholesale price to have a 50% larger standard deviation. Then, that 97.5 percentile reaches twice the $5.0 billion subsidy. The policymaker can choose a λ—from the options encompassing purchase agreements and subsidies—to balance her expected net expenditure and her appetite to take risks. The policymaker's distaste for risks can depend on how she recoups the losses from risk-taking, often in the form of a surcharge on consumers' bills, as in Brazil

(Tolmasquim et al., 2021),[4] or direct tax (Beiter et al., 2024).

Researchers have estimated structural models of energy investors' behavior toward uncertainties involved in capital investments and inferred values associated with uncertainties, such as future product price volatility (Kellogg, 2014), counterparty risk (Ryan, 2022), and policy uncertainty (Gowrisankaran, Langer, and Zhang, 2024; Chen, 2024). These studies have exploited intertemporal or cross-sectional variations of uncertainties to sort out investors' behavior facing different levels of risk. Most relatedly, Ryan (2022) quantifies solar energy investors' risk premium for the counterparty risk of state governments relative to the trusted central government in India by comparing investors' costs inferred from their bid prices in long-term purchase agreement auctions intermediated by state and central governments.

I shed light on another novel way to study investors' risk evaluation using their portfolio choices embedded in auctions. Investors' portfolio decisions exposed to different prices of a risk-free option reveal investors' risk evaluation on the other risky option. Policymakers can observe investors' portfolio choices by asking investors to bid shares in addition to prices in long-term power purchase agreement auctions that have been held worldwide for various renewable technologies, including solar, onshore/offshore wind, biomass, hydro, and hydrogen (IRENA, 2019, 2024). The new hydrogen auctions launched by the European Commission allow investors to choose their shares (European Commission, 2024), providing an opportunity to uncover these investors' risk premium. My framework is also applicable to other markets in which investors put high risk premiums on uncertain returns from investments with positive externalities. For example, Germany and the U.S. Department of Energy have recently announced policies to share the risk of carbon markets and transmission line investments, respectively (Federal Government of Germany, 2023; DOE, 2023). Policymakers can use my framework to understand the trade-off from risk sharing in these growing contexts and investments in future technologies with relevant characteristics.

[4] A renewable energy surcharge is a common way to fund financial aid on renewable investments worldwide, including in Canada, China, Germany, Ireland, Italy, Japan, and the United Kingdom (Ming et al., 2013; Ansarin et al., 2022).

2 Theoretical Framework of Risk Sharing

I present a simple model of a policymaker and a renewable investor to illustrate the role of risk sharing between them. The investor has a potential renewable project that costs c and generates a certain amount of electricity during the lifetime. Absent risk sharing, the investor sells the electricity to a risky wholesale market to earn an exogenous lifetime revenue of r. The investor has a utility u over the project profit π. The utility increases with profits, $u'(\pi) > 0$, and is normalized as zero when there are no profits, $u(0) = 0$. A risk premium for profits π, $RP_\pi \geq 0$, satisfies

$$E[u(\pi)] = u(E[\pi] - RP_\pi), \tag{1}$$

which means that the certainty equivalent of profits π for the investor is the expected profits $E[\pi]$ net of the risk premium RP_π. A risk-neutral investor's risk premium is zero for any distribution of π. A risk-averse investor's risk premium increases with the volatility of π and is zero if and only if π is certain. Without the policymaker's support, the investor does not build this new renewable capacity and earns a certainty equivalent of zero.

The policymaker values this new renewable project high enough and wants the investor to build the capacity. Knowing that the investor can be risk-averse, the policymaker considers a contract that shares the market risk between her and the investor to support the investment. This risk-sharing contract consists of three elements. First, the policymaker pays a certain amount ϕ to the investor. Second, the investor commits to building the planned renewable project. Third, the investor provides the policymaker with a share $\lambda \in [0, 1]$ of the lifetime electricity. This contract encompasses the two commonly adopted renewable supporting schemes, a full share purchase agreement at $\lambda = 1$ and a subsidy at $\lambda = 0$, as the two extremes.[5] Under the contract, the investor is only responsible for selling a share of $1 - \lambda$ of the electricity to the wholesale market. The investor signs the contract when it gives a non-negative

[5] Another common scheme, contracts for differences, which guarantee a minimum price, fall in-between as the policymaker takes a part of the wholesale market risk from the investor.

expected utility:

$$E[u(\phi + (1-\lambda)r - c)] \geq 0 \iff \underbrace{\phi + (1-\lambda)E[r]}_{\text{Expected revenue}} \geq \underbrace{c}_{\text{Cost}} + \underbrace{RP_r(1-\lambda)}_{\substack{\text{Wholesale market}\\ \text{risk premium}}}, \tag{2}$$

where $RP_r(1-\lambda) \coloneqq RP_{(1-\lambda)r}$ is the investor's risk premium for selling share $1-\lambda$ of the electricity to the wholesale market. A risk-averse investor's risk premium is zero when he does not sell electricity to the wholesale market, i.e., $RP_r(0) = 0$, and increases as the share of responsibility gets large, i.e., $RP_r'(1-\lambda) > 0$, because the revenue becomes uncertain.

The policymaker implements the first-best policy and signs the contract by setting the contract payment ϕ as the minimum amount necessary for the investor to sign. That is, ϕ is set to $\phi(\lambda)$—ϕ that satisfies the equality in equation (2)—so that the investor builds the new renewable capacity and earns a certainty equivalent of zero. The policymaker will sell share λ of the electricity to the wholesale market, yielding a revenue of λr. Since the policymaker pays for the contract price $\phi(\lambda)$, her net expenditure is $NE(\lambda) = \phi(\lambda) - \lambda r$. The policymaker evaluates the risk associated with the contract by the variance of the net expenditure. Substituting the value of ϕ and taking expectation and variance, I obtain the policymaker's cost-risk trade-off:

$$\begin{cases} E[NE(\lambda)] = c - E[r] + RP_r(1-\lambda) \\ \mathrm{Var}(NE(\lambda)) = \lambda^2 \,\mathrm{Var}(r) \end{cases} . \tag{3}$$

The expected net expenditure consists of a cost compensation (cost c exceeding the expected revenue $E[r]$) and the investor's risk premium $RP_r(1-\lambda)$ that depends on the risk the investor takes $(1-\lambda)$. The net expenditure variance commensurates with the risk the policymaker takes (λ). The net expenditure is expected to be the highest with variance zero at $\lambda = 0$ (subsidy) and decreases with increasing variance as λ moves to 1 (full share purchase agreement) if the investor is risk-averse (Figure 1). The difference in the expected net expenditure between the subsidy and full share purchase agreement corresponds to the investor's risk premium for selling all electricity to the wholesale market, $RP_r(1)$. This formulation clarifies that the policymaker does not face the cost-risk trade-off if the investor is risk-neutral ($RP_r(1-\lambda) = 0$ for any λ) since the expected net expenditure does not change with the level of risk sharing λ.

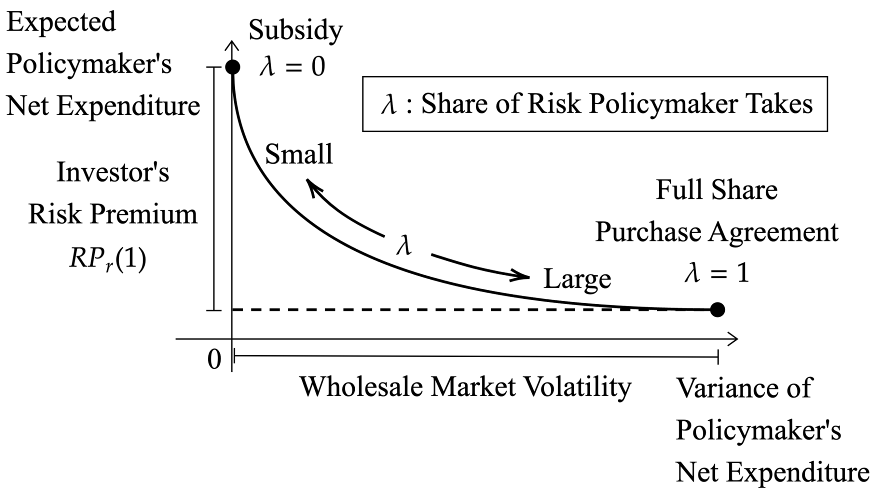


Figure 1: Policymaker's cost-risk trade-off from risk-sharing contracts

The policymaker can choose a λ—from the options encompassing a full share purchase agreement and a subsidy—to balance her expected net expenditure and risk that conforms with her risk preference and institutional/political constraints. To illustrate the policymaker's decision, I consider a policymaker with a certain budget of B and an increasing utility u^{PM} over her budget surplus $((u^{PM})'(B - NE) > 0)$. Without any constraints, she chooses λ to maximize the expected utility:

$$\max_{\lambda \in [0,1]} E[u^{PM}(B - NE(\lambda))] = u^{PM}\left(B - E[NE(\lambda)] - RP_r^{PM}(\lambda)\right), \tag{4}$$

where $RP_r^{PM}(\lambda) := RP_{\lambda r}^{PM}$ is the policymaker's risk premium for selling the contracted electricity to the wholesale market. The policymaker solves the problem using the expected net expenditure formula in equation (3). A risk-neutral policymaker ($RP_r^{PM}(\lambda) = 0$ for any λ) takes all risks ($\lambda = 1$) if the investor is risk-averse. To ensure a unique solution for a risk-averse policymaker, I assume that the risk premium functions for the policymaker and investor are increasing, differentiable, and convex. For instance, these conditions are satisfied if the risk premium increases proportionally to the wholesale market variance, $\mathrm{Var}(r)$, as with a constant absolute risk aversion (CARA) utility and normally distributed r that I use in my auction model (Section 4). We can see that the policymaker maximizes her expected utility at λ, balancing the marginal risk premiums of the policymaker and investor, as $(RP_r^{PM})'(\lambda) = RP_r'(1 - \lambda)$. If the risk premium function is the same for the policymaker and investor, the policymaker divides the share equally (i.e., $\lambda = 1/2$).

Equation (4) suggests that the policymaker's expected utility depends on the sum of the expected net expenditure $E[NE(\lambda)]$ and the policymaker's risk premium $RP_r^{PM}(\lambda)$. I define the sum, $E[NE(\lambda)] + RP_r^{PM}(\lambda)$, as the certainty equivalent of the policymaker's net expenditure and use it to assess the welfare consequences of risk-sharing contracts. It captures how the policymaker balances the expected net expenditure and associated risk premium. Using a certainty equivalent that incorporates risks in welfare evaluation aligns with the recent proposal of the U.S. Office of Management and Budget to account for uncertainty in Federal activities (OMB, 2023).

To get a sense of the role of auctions in this context, consider multiple investors having the same risk premium function but with heterogeneous costs. As equation (3) shows, the policymaker can decrease her expected net expenditure by selecting a low-cost investor without changing the net expenditure variance. Thus, the best is to select the lowest-cost investor, which requires the policymaker to know the investors' costs. Without the information on the investors' costs, the policymaker can hold an auction to reveal the lowest-cost investor. However, the auction allows the winner to collect a markup, depending on the auction format and competitiveness.

I use unique renewable energy auctions that embed investors' portfolio choices to estimate their risk premium and then empirically quantify the policymaker's cost-risk trade-off from risk sharing in the following sections.

3 New Energy Auctions in Brazil

MME and ANEEL have organized new energy auctions (Leilão de Energia Nova) for various electricity sources (e.g., hydro, biomass, wind, and solar) since 2005. Until then, Brazil mainly had met its electricity needs with hydropower, relying on its abundant hydroelectric resources. However, Brazil has moved forward to reduce its dependence on hydropower for several reasons (Werner and Lazaro, 2023). First, it was becoming increasingly difficult to build new large-scale hydroelectric capacity to meet the expanding demand for electricity to keep up the economic growth without affecting the Amazon rainforest ecology. Thus, expanding the renewable capacity beyond hydro was crucial to avoid shifting to fossil fuels while preserving forests. Second, consumers endured energy rationing in 2001 after a period of drought. This incident promoted the diversification of the electricity sources to ensure energy security via a good mix of sources.

MME plans new energy auctions that award long-term power purchase agreements to new generation capacity. I focus on wind energy auctions because these auctions have attracted the largest number of bids. Wind has grown to Brazil's second-largest energy source, with a capacity share of 10.2% as of 2020, after hydro, having a share of 58.1% (Tolmasquim et al., 2021). MME calls for bidders with a new investment project that will be available for commercial operation from a designated date. The period from the auction date to the commissioning date, called the lead time, ranges from 2 to 5 years. Upon participation, bidders register their planned capacity and need to prove that they are capable of completing the project. The Energy Research Company (Empresa de Pesquisa Energética, EPE), a public research institute supporting the MME, assesses the application documents, including proofs of land use rights, environmental permits, and technical and financial feasibility. EPE evaluates the production amount bidders can stably provide according to their application and defines that as a basis for the bidder's share choice. I define the bidder's capacity as the amount of stable supply per hour.[6]

The Chamber of Electric Energy Commercialization (Câmara de Comercialização de Energia Elétrica, CCEE), a nonprofit civil association operating the Brazilian electricity market, administers these auctions under ANEEL's supervision. Bidders specify two elements in their bids: 1) a share of the production they will include in a purchase agreement and 2) a price for each unit (MWh) of this share. CCEE awards purchase agreements to the lowest bid prices until the total procurement capacity for the winners exceeds the auction's procurement capacity. EPE determines the procurement capacity considering the forecasted demand growth (Rosa et al., 2013). The procurement capacity is not disclosed before bidding to prevent collusive behavior.[7]

[6]This capacity differs from the nameplate capacity, which is the maximum generation amount possible per hour.

[7]I do not consider the possibility of collusion in the Brazilian new wind energy auctions. Collusion is very unlikely in these auctions because they have large numbers of participants (400–600 bidders) and are competitive (proportions of winners are at most 20% of the participants) in addition to

The auction format was pay-as-bid until 2015, when it switched to uniform-price. In pay-as-bid auctions, the winners will receive a purchase agreement as specified in their one-shot sealed bid. For instance, a winner who bids a share of 80% and a price of $40/MWh will receive a purchase agreement for 80% of his production at $40/MWh. In uniform-price auctions, bidders fix their bid shares at the beginning. CCEE then implements a descending clock iteration procedure wherein CCEE announces a tentative clearing price and lets bidders adjust their prices until the clearing price does not change. This descending clock iteration yields a uniform price because all winners are incentivized to align their prices to the clearing price.[8]

Winners sign a new energy contract composed of the purchase agreement and commitment to install the planned capacity for commercial operation by the designated date. Distribution companies, which provide distribution services to supply electricity to consumers, procure electricity through these purchase agreements. ANEEL intermediates the contracts between winners and distribution companies and implements several policies to ensure the purchase agreement payouts (Tolmasquim et al., 2021). First, each winner contracts with a pool of distribution companies. Thus, each distribution company is responsible for only a fraction of a purchase agreement. Second, the distribution companies include the purchase agreement payments in their consumers' bills, and revenues collected are directly transferred to the winners to comply with the purchase agreements.

Winners sell the uncontracted electricity to the wholesale market, including a spot market, short-term purchase agreements intermediated by ANEEL, and bilateral contracts with high-volume consumers (Hochberg and Poudineh, 2021). CCEE holds short-term purchase agreement auctions similarly where the purchase agreement terms have been less than 6 years (CCEE, 2024). Investors and high-volume consumers negotiate their terms freely in bilateral contracts, usually lasting up to 6 years (Perez, 2024). Bilateral contracts' price formation is not transparent, and they also have counterparty risks in payouts (CCEE, 2012). ANEEL-intermediated

the non-disclosure of procurement capacity. Also, it is challenging to differentiate collusive and competitive behavior only with the winners' bids that I observe. The existing literature relies on both winners' and losers' bidding behavior to detect collusion in auctions (e.g., Porter and Zona, 1993; Chassang et al., 2022; Kawai and Nakabayashi, 2022).

[8] In practice, the final winners' prices may not align because the descending clock iteration is implemented as a discrete process. CCEE sets a minimum decrement that must be lowered from the tentative clearing price when bidders adjust their prices (Hochberg and Poudineh, 2018).

purchase agreements and bilateral contracts divide the overall demand by 70% and 30% (Perez, 2024). A stochastic computer model automatically calculates hourly spot prices reflecting the marginal hydroelectric and thermal fuel costs to clear the market mismatch (Hochberg and Poudineh, 2021; Perez, 2024). Since the spot market is always an option, short-term purchase agreements and bilateral contracts will be based on expectations over spot prices.

Data. I primarily use three publicly available data sources. First is the auction results database maintained by CCEE. The auction database gives the auction date, designated commercial operation date, winners' capacities, and winners' bid shares and prices. Second is the auction registration and qualification reports provided by EPE, including the number of participants and total capacities qualified for bidding. Last is electricity spot prices provided by CCEE. The prices are adjusted for inflation using 2022 as the base year and converted to U.S. dollars, assuming a 5 to 1 Brazilian Real to U.S. Dollar exchange rate.

I analyze 16 wind energy auctions with 476 winning bids totaling 5.6 GW of capacity from 2011–2021 (Table 1). New wind energy auctions started in 2011, and the length of purchase agreements was the wind turbine's expected lifetime, 20 years, until 2021.[9] There were 8 pay-as-bid auctions from 2011–2015 (296 winning bids) and 8 uniform-price auctions from 2017–2021 (180 winning bids). The auctions are competitive, with around 20–40 winners out of 400–600 participants. I define auctions' procurement capacities as the sum of winners' capacities allocated to the auction. The procurement capacities decreased in later periods, reflecting the fact that the growth of forecasted demand slowed down during this period.

Descriptive Evidence. The median bid share of the 476 winning bids is 0.91, with an interquartile range (IQR) of $[0.64, 1.00]$. Overall, 58.2% of winners partially allocate their allocatable production to the auction.[10] Risk-averse bidders make partial allocations to balance the expected revenue and revenue variability. The median purchase agreement price (bid prices in pay-as-bid auctions and clearing prices in uniform-price auctions) is \$39.27/MWh, with an IQR of \$26.03–\$40.97/MWh. A positive correlation exists between bid shares and purchase agreement prices (corre-

[9]The purchase agreement length has shortened to 15 years after this period.

[10]CCEE has required bidders to bid at least 30% of their production into the auction since 2018. Bidders freely choose shares between 0 and 1 until 2017.

Table 1: Summary statistics of 476 winning bids in 16 wind energy auctions

	8 Pay-as-Bid (2011–2015)			8 Uniform-Price (2017–2021)		
	Mean	SD	Range	Mean	SD	Range
Lead Time (years)	3.2	0.9	$[2.1, 4.3]$	3.9	1.0	$[2.4, 5.3]$
Number of Participants	376.5	143.5	$[205, 577]$	565.0	210.9	$[315, 829]$
Number of Winners	37.0	27.6	$[3, 97]$	22.5	20.5	$[2, 48]$
Procurement Capacity (MW)	389.9	275.5	$[35.6, 989.6]$	176.3	237.7	$[15.2, 655.8]$

Notes: SD stands for standard deviation.

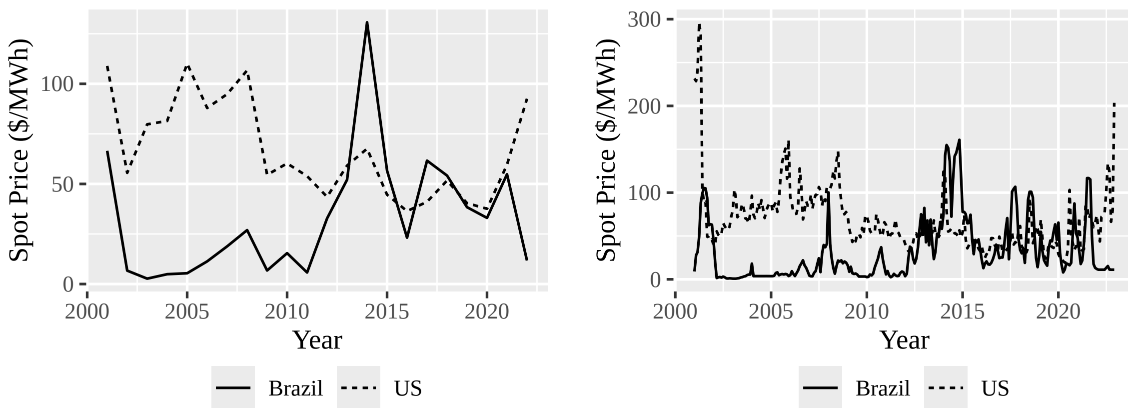
lation coefficient 0.55; Figure A1 in Online Appendix A for a scatter plot). Bidders optimize their portfolios by allocating a large share to the purchase agreement when they expect it to have a high price.

I use spot market electricity prices to get a sense of the wholesale market volatility. Figure 2 compares the spot prices in Brazil and the U.S.[11] The SDs of Brazil's annual and monthly spot prices are comparable to the U.S. In Brazil, the SD of spot prices is \$30.49/MWh across years and \$35.35/MWh across months, whereas in the U.S., they are \$24.41/MWh and \$38.48/MWh. Brazil's spot market looks more volatile than the U.S. if I consider the coefficient of variation (the SD divided by the mean) as a measure of volatility since Brazil has lower average prices than the U.S. In Brazil, the coefficient of variation of spot prices is 0.93 across years and 1.09 across months, whereas in the U.S., they are 0.37 and 0.56.

4 Structural Model of New Energy Auctions

I model bidders participating in a multi-unit procurement auction following the share auction framework of Wilson (1979). The distinguishing feature of the model is that bidders bid a share of production, which they will include in the awarded long-term purchase agreement. Risk-averse bidders essentially optimize their portfolios by allocating certain production to the risk-free purchase agreement and a risky wholesale

[11]The U.S. spot prices average the five hubs (Mass Hub, PJM West, Mid-C, Palo Verde, and SP-15) for which historical data are available from January 2001 in the Intercontinental Exchange.



(a) Annual average

(b) Monthly average

Figure 2: Electricity spot prices in Brazil and the U.S. from 2001–2022

market.[12] Each bidder also bids one price per unit, which applies to all units of the purchase agreement.[13]

An auctioneer holds procurement auctions that guarantee the purchase of electricity at a fixed price for the entire life of a renewable technology, T. An auction at time $t = 0$ is characterized by a lead time l, a number of participants N, a procurement capacity D, and a minimum possible bid share $\underline{q} \in [0, 1]$. Qualified bidders, $i = 1, \ldots, N$, each with a new investment project, compete for the procurement capacity D. The procurement capacity is not disclosed before bidding, which makes the procurement capacity a random variable from the bidders' perspective. Bidders are required to allocate at least a share of $\underline{q}$ of their total production to the purchase agreement.

The purchase agreement spans discrete time $t = l, l + 1, \ldots, l + T - 1$ since the electricity supply begins at time $t = l$ and lasts for T. Bidder i stably produces $Capacity_i$ hours of electricity per hour throughout the purchase agreement period, where each time t consists of H hours. Bidder i specifies a share $q_i \in [\underline{q}, 1]$ and a price b_i in his bid. If bidder i wins the auction, the auctioneer agrees to purchase

[12] The production amount and purchase agreement price can be uncertain at the time of bidding because of intermittency and counterparty risk, respectively. The model can incorporate these uncertainties by specifying their distribution. The bidder's risk premium will then represent the risk premium for the wholesale market relative to the purchase agreement, and the bidder's cost will reflect the price he expects to get, as in Ryan (2022).

[13] The model is a special case of multi-unit auction model because one price is applied to all units rather than bidding a price schedule along each share.

$q_i \times Capacity_i \times H$ hours of electricity for each period at price p_i, which is determined as a function of participants' bid prices $b_1, \ldots, b_N$ as specified in the auction format. Bidder i sells the remaining production, $(1 - q_i) \times Capacity_i \times H$ hours, to the wholesale market at price r_t for each t during the purchase agreement. The auctioneer awards these purchase agreements to the lowest bid prices until the total bid capacity $\sum_i q_i Capacity_i$ of winners exceeds the procurement capacity D. Thus, bidder i wins when the total bid capacity of competitors, $\sum_{j \neq i} q_j Capacity_j$, with a bid price lower than b_i is below the procurement capacity D, i.e., $\sum_{j \neq i} \{q_j Capacity_j \cdot \mathbb{1}(b_j \leq b_i)\} < D$, where $\mathbb{1}$ is an indicator function.

I assume risk-averse bidders having a common CARA utility, u, over their per unit net present value (NPV) π, i.e., $u(\pi) = 1 - \exp(-\gamma\pi)$, where $\gamma > 0$ is the risk aversion coefficient. A concave utility over NPV in terms of rate is a viable option in analyzing projects with uncertain cash flows in the field of decision analysis (Hazen, 2009). When bidder i wins the auction, he invests upfront fixed costs FC_i to start supplying electricity from $t = l$. Bidder i also pays constant variable costs VC_i per unit of production during the purchase agreement. Thus, bidder i's per unit NPV of winning is

$$\pi_i := \frac{\sum_{t=l}^{l+T-1} Capacity_i H \delta^t \{q_i p_i + (1 - q_i) r_t - VC_i\} - FC_i}{Capacity_i HT},$$

where δ is a common discount factor. $Capacity_i HT$ in the denominator is the total production over the technology lifetime. The curly brackets encapsulate per-period profits as the sum of the purchase agreement and wholesale market revenues net of variable costs. The overall NPV subtracts fixed costs from the discounted sum of per-period profits.

Bidder i's expected utility conditional on winning the auction is

$$E[u(\pi_i)] = u\Bigg(\underbrace{q_i \tilde{\delta} p_i + (1 - q_i)E[r] - c_i}_{\text{Expected NPV}} - \underbrace{RP_r(1 - q_i)}_{\text{Risk premium}}\Bigg), \tag{5}$$

where $r := T^{-1} \sum_{t=l}^{l+T-1} \delta^t r_t$ summarizes the future wholesale prices, $RP_r(1 - q_i) := RP_{(1-q_i)r}$ (defined in equation (1)) is the bidder's risk premium for selling share $1 - q_i$ of the electricity to the wholesale market, c_i is the average cost that comprises the fixed costs allocated across the entire production ($FC_i / Capacity_i HT$) and average variable costs ($T^{-1}\sum_{t=l}^{l+T-1}\delta^t VC_i$), and $\tilde{\delta} = T^{-1}\sum_{t=l}^{l+T-1}\delta^t$ for conciseness. Bidders earn a certainty equivalent of zero if they lose the auction.[14]

I assume an exogenous wholesale price process and that bidders have a common normally distributed belief for the summary of their future wholesale prices, i.e., $r \sim \mathcal{N}(\mu_r, \sigma_r^2)$, to make the risk premium function tractable. The CARA utility with a normal r implies that the risk premium is proportional to the wholesale market variance: $RP_r(1-q_i) = (1-q_i)^2 \cdot \gamma\sigma_r^2/2$. The risk premium becomes high with the wholesale market share, $1-q_i$, risk aversion coefficient γ, and wholesale market variance, σ_r^2. The CARA utility and normality of r should capture the bidders' behavior well so long as the wholesale market variance is the bidders' primary concern in their risk premium evaluation.

Before the auction, bidders form a common belief for future wholesale prices. Upon participating in the auction, bidders independently draw their private types of cost, $c_i \in [\underline{c}, \bar{c}]$, and $Capacity_i \in \mathbb{R}_+$ from a publicly known distribution. Bidders observe the number of participants N and a publicly known distribution of procurement capacity D before they bid. Bidders bid, the procurement capacity D realizes, and the auction concludes the purchase agreement prices according to the auction format. I next characterize the equilibrium strategies in pay-as-bid and uniform-price auctions.

4.1 Pay-as-Bid Auctions

Winners receive purchase agreements at their bid prices, i.e., $p_i = b_i$, in pay-as-bid auctions. Bidder i chooses bid (q, b) to maximize the expected utility of bidding:

$$\underbrace{W_i(b)}_{\text{Winning probability with } b} \times \underbrace{u\left(q\tilde{\delta}b + (1-q)\mu_r - c_i - RP_r(1-q)\right)}_{\text{Expected utility conditional on winning with } (q,b)},$$

where the winning probability is the probability of the total bid capacity of competitors, $\sum_{j\neq i} q_j Capacity_j$, with a bid price lower than b is below the procurement

[14] Ryan (2022) also assumes that bidders earn zero profit when they lose in long-term purchase agreement auctions. I can extend the model to incorporate losers earning a certainty equivalent of $\pi_{0i} > 0$ that does not depend on their bid (q_i, b_i). Note that I am still ruling out dynamic considerations; π_{0i} cannot be a function of the bidder's action or bid (q_i, b_i). My framework will then identify the cost inclusive of the reservation value $c_i + \pi_{0i}$ from pay-as-bid auction bids, but will not identify c_i and π_{0i} separately. Thus, policy implications will not change as long as the counterfactual does not affect c_i and π_{0i} differently.

capacity D,

$$W_i(b) \coloneqq \Pr\left(\sum_{j\neq i}\{q_j Capacity_j \cdot \mathbb{1}(b_j \leq b)\} < D\right). \tag{6}$$

I assume the winning probability is strictly between 0 and 1 for all possible bid prices.

A pure-strategy Bayes Nash Equilibrium (BNE), $\{(q_i^*, b_i^*)\}_{i=1}^N$, maximizes the expected utility for all i under the equilibrium winning probability functions $W_i^*(b)$, which replaces $\{(q_j, b_j)\}_{j\neq i}$ with $\{(q_j^*, b_j^*)\}_{j\neq i}$ in equation (6). A monotone pure-strategy BNE exists because the model satisfies the single crossing condition for games of incomplete information in Athey (2001).[15] Moreover, a unique symmetric monotone pure-strategy BNE exists when bidders are *ex-ante* symmetric, i.e., bidders independently draw their private types (cost c_i and $Capacity_i$) from a common distribution. I prove the existence and uniqueness of the equilibrium by formalizing the strategy as a solution to an ordinary differential equation following the procedure in Hubbard and Paarsch (2014). Proofs are in Appendix A.1.

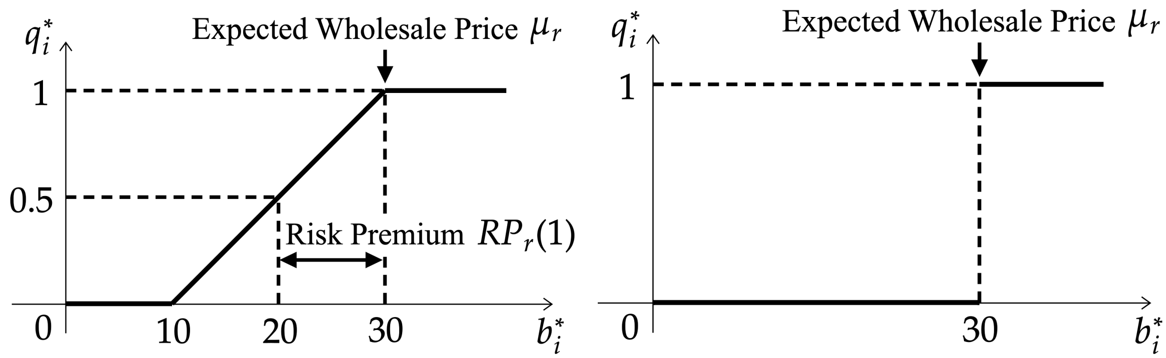
The optimal bid share and price characterize the equilibrium bid strategy. Bidder i's optimal bid share q_i^* satisfies

$$q_i^* = \min\left\{\max\left\{\underline{q}, 1 - \frac{\mu_r - \tilde{\delta} b_i^*}{\gamma\sigma_r^2}\right\}, 1\right\}. \tag{7}$$

Figure 3(a) illustrates the optimal bid share decision when the discount factor δ is 1 (i.e., $\tilde{\delta} = 1$), and there is no constraint on the possible bid share (i.e., $\underline{q} = 0$). The bidder bids 100% share when the equilibrium bid price b_i^* is at least as high as the expected wholesale price μ_r of 30 because he strictly prefers a risk-free option to a risky one if the risk-free price is at least as high as the risky option's expected price. As b_i^* becomes below μ_r, the bidder starts to partially allocate his production into the wholesale market because he considers the additional price variability worth the expected price gain. The difference between μ_r $(= 30)$ and b_i^* at the bidder's 50% share choice $(= 20)$ corresponds to the bidder's risk premium ($RP_r(1) = \gamma\sigma_r^2/2 = 30 - 20 = 10$) as if he is indifferent between the purchase agreement and the wholesale market. The linear slope below μ_r and the bidder's behavior of acting as if the options

[15] Note that bidders' strategies are a function of their cost types because the capacity type only affects the expected utility of bidding through their cost types.

are indifferent at his 50%/50% portfolio division results from the specification of risk premium to be proportional to the wholesale market variance. In contrast, a risk-neutral bidder allocates all production into the purchase agreement (resp. wholesale market) if b_i^* is higher (resp. lower) than μ_r of 30 to maximize his expected price (Figure 3(b)).



(a) Risk-averse bidder

(b) Risk-neutral bidder

Figure 3: Bidders' optimal bid shares when $\delta = 1$ and $\underline{q} = 0$

Bidders determine their bid shares as if they only care about the expected utility conditional on winning because their bid shares do not affect their winning probability. As a result, bidder i chooses the bid share to optimize his portfolio upon winning by comparing his equilibrium bid price b_i^* and wholesale market belief about the expected price and risk premium in any equilibrium.[16] The equilibrium winning probability function W_i^* and private cost c_i do not enter his optimal bid share decision because they are irrelevant to his portfolio optimization. This observation is crucial for using bidders' bid share and price decisions separately in identification and estimation.

Bidder i's optimal bid price b_i^* satisfies

$$\underbrace{q_i^* \tilde{\delta} b_i^* + (1 - q_i^*)\mu_r}_{\text{Expected revenue}} = c_i + \underbrace{(1 - q_i^*)^2 \cdot \frac{\gamma \sigma_r^2}{2}}_{\text{Risk premium}} + \underbrace{\frac{1}{\gamma} \ln \left(- \frac{\gamma q_i^* \tilde{\delta} W_i^*(b_i^*)}{dW_i^*(b_i^*)/db} + 1 \right)}_{\text{Markup}}. \quad (8)$$

The two terms on the left-hand side, the purchase agreement and expected wholesale market revenues, comprise the bidder's expected revenue. The bidder optimizes the

[16]This observation is analogous to Bolotnyy and Vasserman (2023)'s observation of a bidder's score being payoff-sufficient for his choice of unit bids in scaling auctions.

bid price by balancing the expected revenue with the three terms on the right-hand side: cost, risk premium, and markup. The markup decreases with the risk aversion coefficient γ because more risk-averse bidders cut markups for fear of the possibility of losing the auction. Additionally, bidders collect higher markup when the auction is less competitive since their winning probabilities decrease little by increasing their bid prices. The equality converges to $b_i^* = c_i/\tilde{\delta} - W_i^*(b_i^*)/(dW_i^*(b_i^*)/db)$ as the bidders become risk-neutral ($\gamma \to 0$ and $q_i^* \to 1$), coinciding with the standard optimal bid price formula for risk-neutral bidders (e.g., Athey and Haile, 2007).

4.2 Uniform-Price Auctions

I analyze uniform-price auctions in line with Milgrom and Weber (1982)'s English auction model. In uniform-price auctions, bidders decide the lowest price they are willing to accept as "bid price" b_i. Winners receive purchase agreements at the lowest bid price among the losers, i.e., $p_i = p \coloneqq b_{M+1:N}$, where M is the number of winners and $b_{M+1:N}$ indicates the $M+1$th lowest bid price of N bid prices. I assume the clearing price is distributed normally, $p \sim \mathcal{N}(\mu_p, \sigma_p^2)$, independent of the wholesale price r.[17] Derivations of the statements in this section are in Appendix A.2.

Bidder i chooses bid (q, b) to maximize the expected utility of bidding:

$$\int \underbrace{\mathbb{1}(b < p)}_{\text{Winning at } p} \times \underbrace{u\left(q\tilde{\delta}p + (1-q)\mu_r - c_i - RP_r(1-q)\right)}_{\text{Expected utility conditional on winning at } p} f_p(p)dp.$$

The bidder takes expectation of what he expects to earn over the clearing price p. A pure-strategy BNE maximizes the expected utility for all bidders under the equilibrium clearing price distribution f_{p^*}, where p^* is the $M+1$th order statistic of N equilibrium bid prices, i.e., $p^* \coloneqq b^*_{M+1:N}$. A monotone pure-strategy BNE exists because the model satisfies the single crossing condition in Athey (2001).

Bidder i's optimal bid share satisfies $q_i^* = \min\left\{\max\left\{\underline{q}, q^{**}(b_i^*)\right\}, 1\right\}$, where $q^{**}(b)$

[17] Clearing and wholesale market prices are independent if they have independent sources of uncertainty. Clearing prices vary by the wind energy's cost distribution. In contrast, Brazil's wholesale market uncertainty stems from the marginal hydroelectric and thermal fuel costs.

is an unconstrained optimal bid share function implicitly defined as the solution to

$$q^{**} = \left(\frac{1}{1 + \tilde{\delta}^2 \sigma_{p^*}^2 / \sigma_r^2} \right) \left(1 - \frac{\mu_r - \tilde{\delta} \tilde{\mu}_{p^*}(q^{**}, b)}{\gamma \sigma_r^2} \right). \tag{9}$$

$\tilde{\mu}_{p^*}(q, b)$ is the effective expected equilibrium clearing price for choosing bid (q, b),

$$\tilde{\mu}_{p^*}(q, b) = \mu_{p^*} + \sigma_{p^*} \Lambda \left(\frac{\mu_{p^*} - b}{\sigma_{p^*}} - q \gamma \tilde{\delta} \sigma_{p^*} \right),$$

where Λ is the inverse Mills ratio for a standard normal. For a risk-neutral bidder ($\gamma \to 0$), $\tilde{\mu}_{p^*}$ is the mean of the equilibrium clearing price distribution truncated from below at b. A risk-averse bidder effectively moves up the truncation point to $b + q\gamma\tilde{\delta}\sigma_{p^*}^2$ because he appreciates the truncation more than the risk-neutral bidder, as it reduces the risk of getting the purchase agreement at a low price. Bidders' optimal bid prices are the price at which the expected utility conditional on winning is zero.

I highlight several features of the optimal bid share decision. First, the equilibrium bid share q_i^* continuously increases with the equilibrium bid price b_i^* as in pay-as-bid auctions in Figure 3(a), though the relationship is now nonlinear. Second, a large equilibrium clearing price variance $\sigma_{p^*}^2$ has two counteracting effects. It lowers q_i^* because the purchase agreement becomes unattractive relative to the wholesale market (channel through the term $\tilde{\delta}^2 \sigma_{p^*}^2 / \sigma_r^2$ in equation (9)). On the other hand, the effective expected equilibrium clearing price $\tilde{\mu}_{p^*}$ can increase because of the truncation. Third, the effect of the risk aversion coefficient γ is unclear because both purchase agreement and wholesale prices are uncertain at the time of bidding.

5 Econometric Model

I demonstrate my identification results and then specialize the structural model to Brazil's new wind energy auctions for estimation. The discount factor δ is prespecified to be the annual rate of 0.95.

5.1 Identification

Pay-as-Bid Auctions. I start from a setup where all bids (q^d_{ia}, b^d_{ia}) are observed for $i = 1, \ldots, N$ participants in $a = 1, \ldots, A$ identical pay-as-bid auctions. Intuitively, the relationship between the bid share q^d_{ia} and price b^d_{ia} traces out the optimal bid share function $q^*_{ia} = q^*(b^*_{ia})$, which identifies the bidders' wholesale market beliefs, consisting of the expected price μ_r and risk premium $RP_r(1)$, as illustrated in Figure 3(a). Once I have $q^*(b)$, μ_r will be the lowest bid price that makes the bid share 100%, and $RP_r(1)$ will be the difference between μ_r and the bid price that gives 50% bid share.[18] I make the following assumptions to justify the procedure of tracing out $q^*(b)$.

Assumption 1. *The optimal bid share in equation (7), evaluated at the equilibrium bid price b^*_{ia}, is observed as a censored normal regression model, i.e.,*

$$q^d_{ia} = \min\left\{\max\left\{\underline{q}, 1 - \frac{\mu_r - \tilde{\delta} b^*_{ia}}{\gamma\sigma^2_r} + \eta_{ia}\right\}, 1\right\}, \eta_{ia} \sim \mathcal{N}(0, \sigma^2_\eta),$$

where η_{ia} is a bid share shock that is i.i.d. across bidders and auctions. Additionally, b^*_{ia} is exactly observed, i.e., $b^d_{ia} = b^*_{ia}$.

Bolotnyy and Vasserman (2023) also make a similar assumption in the identification of their scaling auction model but without a parametric assumption on the exogenous shock. In my case, the parametric assumption of the bid share shock η_{ia} deals with the censoring nature of the bid share. To regard the equilibrium bid price b^*_{ia} to be observed is standard in the literature following Guerre, Perrigne, and Vuong (2000) to identify bidders' values from their bid prices.

Assumption 1 implies that the bid share q^d_{ia} follows a censored normal regression model linear in the bid price b^d_{ia}, which traces out the optimal bid share function $q^*(b)$ if b^d_{ia} sufficiently varies. Moreover, I can trace out $q^*(b)$ from winners' bids because whether the winner or not does not change the bidder's optimal bid share decision given his equilibrium bid price (see equation (7)).[19]

[18] I show that $q^*(b)$ is a continuously increasing function as long as the bidder's risk premium function $RP_r(1 - q^*_i)$ is increasing, differentiable, and convex in Online Appendix B. In this more general setting, the shape of $q^*(b)$ informs about the marginal risk premium for each $(1 - q^*_i)$.

[19] The bid share decisions of winners and losers will be observationally different when an unobserved

I then follow Guerre, Perrigne, and Vuong (2000) to identify the cost distribution. The idea is to recover each bidder's cost type c_{ia} from his bid (q^d_{ia}, b^d_{ia}) using the solution to the optimal bid price decision (equation (8)). Given the assumptions and identification results so far, the remaining pieces are the risk aversion coefficient γ and equilibrium winning probability functions $W^*_i(b)$ to recover c_{ia} from equation (8). I assume that the wholesale market variance σ^2_r is identified from the data to separately identify γ from the wholesale market risk premium, $RP_r(1) = \gamma\sigma^2_r/2$. Winners' equilibrium bid prices b^*_{ia}, observed as b^d_{ia}, identify $W^*_i(b)$ because each bid price's winning probability can be calculated. Thus, all bidders' cost types are identified if all bids are observed.

I can still identify the cost distribution when only accessing winners' bids, assuming symmetric bidders (i.e., *ex-ante* symmetric bidders that employ a symmetric strategy). The goal is to identify the equilibrium bid distribution f_{q^*,b^*} from winners' equilibrium bids since the cost distribution can be recovered from f_{q^*,b^*} using the solution to the optimal bid price decision (equation (8)). I can recover f_{q^*,b^*} from the equilibrium bid price distribution f_{b^*} because the optimal bid share function $q^*(b)$, which maps the equilibrium bid price onto the equilibrium bid share, is identified from winners' bids. I obtain f_{b^*} from winners' equilibrium bid prices and the number of auction participants N as in Athey and Haile (2002). At least, I have information on the lowest equilibrium bid price for each auction since the bidders with the lowest bid prices are selected as winners. Thus, I observe the distribution of the first order statistic of N samples of equilibrium bid prices, $f_{b^*_{1:N}}$. I identify f_{b^*} from $f_{b^*_{1:N}}$ given that equilibrium bid prices b^*_i are i.i.d. across bidders because there is a one-to-one relationship between a distribution and a distribution of an order statistic of a fixed number of i.i.d. samples from that distribution. Equilibrium bid prices are i.i.d. across bidders since bidders independently draw their types from a common distribution and employ a symmetric strategy.

Uniform-Price Auctions. I closely follow the identification strategy for pay-as-bid auctions and highlight the differences. I start from a setup in which the equilibrium clearing price p^*_a is always observed as the clearing price in data, p^d_a, and, at least, some bid pairs (q^d_{ia}, b^d_{ia}) are observed. The equilibrium clearing price distribution

heterogeneity simultaneously affects bid share and price decisions since bid prices determine winners. Heterogeneity in the wholesale market beliefs is an example of such heterogeneity.

parameters $(\mu_{p^*}, \sigma^2_{p^*})$ are identified from $p^d_a = p^*_a$. With assumptions analogous to Assumption 1, the bid share q^d_{ia} follows a censored normal regression model that is nonlinear in the bid price b^d_{ia} through the unconstrained optimal bid share function $q^{**}(b^d_{ia})$ defined as the solution to equation (9). Then, I obtain the optimal bid share function $q^*(b)$ if I observe bid pairs (q^d_{ia}, b^d_{ia}) and their bid prices b^d_{ia} sufficiently vary because bidders' optimal bid share decisions given their equilibrium bid prices are the same for all bidders (see equation (9)). Nevertheless, I cannot identify the wholesale market risk premium, $RP_r(1) = \gamma\sigma^2_r/2$, from $q^*(b)$ without assuming that the wholesale market variance σ^2_r is identified because the purchase agreement price is also uncertain. Assuming that σ^2_r is identified, I identify the expected wholesale price μ_r and the risk aversion coefficient γ from $q^*(b)$ because $(\mu_{p^*}, \sigma^2_{p^*})$ are already identified above.

Assuming symmetric bidders, I can identify the optimal bid share function $q^*(b)$ from winners' bid shares q^d_{ia} and the clearing price p^d_a. No bid pairs (q^d_{ia}, b^d_{ia}) are observed since p^d_a is the lowest bid price among losers. Symmetric bidders imply the equilibrium bid price b^*_i to be i.i.d. across bidders. Thus, again, following Athey and Haile (2002), I obtain the equilibrium bid price distribution f_{b^*} from the equilibrium clearing price distribution since the clearing price is the $M_a + 1$th order statistic of N i.i.d. samples from f_{b^*}, where M_a is the number of winners in auction a. Then, I have the winners' equilibrium bid price distribution as f_{b^*} truncated from above at the equilibrium clearing price $p^*_a = p^d_a$. The relationship between the winners' equilibrium bid price distribution and winners' observed bid shares q^d_{ia} across different p^*_a traces out $q^*(b)$.

5.2 Estimation

The estimation procedure applies the optimal bid share and price decisions sequentially. I first use the solution to the bid share decision, equivalent to the portfolio optimization, to estimate the expected wholesale price μ_r and risk aversion coefficient γ. I then infer the bidders' cost types c_{ia} using the solution to the bid price optimization problem. I assume symmetric bidders because I only observe winners' bids, as discussed in Section 5.1. Further details about the estimation procedures are in Online Appendix C.

I prepare the wholesale market variance σ_r^2 and uniform-price auctions' equilibrium clearing price distributions $f_{p^*} = \mathcal{N}(\mu_{p^*}, \sigma_{p^*}^2)$ to sort out the risk aversion coefficient γ in the first step. I check the sensitivity of my structural estimates to changes in σ_r^2 and $(\mu_{p^*}, \sigma_{p^*}^2)$ from those specified here in Section 6. I estimate a mean reverting process of annual wholesale prices using time-series data of spot prices. I then calculate each auction's σ_r^2 with the future wholesale prices r_t following the estimated mean reverting process. I model the equilibrium clearing price distribution conditional on the procurement capacity D, $f_{p^*|D}$, with auction covariates, including auction date, lead time, and number of participants. I then integrate it out by the procurement capacity distribution f_D to obtain f_{p^*} because D is not disclosed at the time of bidding. I specify the parameters in $f_{p^*|D}$ to those that best rationalize the observed clearing prices and D. I also model f_D with auction covariates and specify the parameters to fit the observed D.

In the first step, I estimate the expected wholesale price μ_r, risk aversion coefficient γ, and the bid share shock variance σ_η^2 using the optimal bid share decision by indirect inference (Gourieroux, Monfort, and Renault, 1993). I apply indirect inference because I do not observe bid pairs (q_{ia}^d, b_{ia}^d) and can only trace out the optimal bid share function $q^*(b)$ via simulations in uniform-price auctions. I define auxiliary parameters as the coefficients and residual variance of regressing bid shares on purchase agreement prices (i.e., pay-as-bid auctions' bid prices and uniform-price auctions' clearing prices). Intuitively, the regression coefficients capture the shape of $q^*(b)$, which recovers μ_r and γ, and the residual variance captures the variance around $q^*(b)$, which corresponds to σ_η^2. The estimators of $(\mu_r, \gamma, \sigma_\eta^2)$ minimize the distance between the auxiliary parameter estimates from data and simulated datasets.

For pay-as-bid auctions, I use observed bid prices to simulate bid shares using the optimal bid share decision and drawing bid share shocks. For uniform-price auctions, I use simulated winners' bid prices instead to simulate bid shares because I do not observe winners' bid prices. I derive the equilibrium bid price distribution f_{b^*} to simulate winners' bid prices. For a uniform-price auction a with realizations of procurement capacity D_a and number of winners M_a, 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^*}, where N is the number of participants. Thus, I use the monotone relationship between their CDFs, F_{b^*} and $F_{b^*_{M_a+1:N}} = F_{p^*|D=D_a}$, to calculate f_{b^*} from $f_{p^*|D}$. I then simulate winners' bid prices using f_{b^*} by drawing bid prices conditional on being below the clearing price. I specify the risk aversion coefficient γ and bid share shock variance σ^2_η to be the same across auctions with different covariates. Additionally, I assume that bidders have a stationary belief about the expected wholesale price, denoted α_r, and discount it according to the auction's lead time l to calculate its expected wholesale price μ_r, i.e., $\mu_r = \delta^l \alpha_r$.[20]

In the second step, I infer bidders' cost types c_{ia} using the optimal bid price decision. I do not pursue estimating the cost distribution in uniform-price auctions because I only observe 8 clearing prices that inform about it. I first prepare the pay-as-bid auction's equilibrium winning probability functions W^*_i. W^*_i is symmetric for symmetric bidders, i.e., $W^*_i = W^*$ for all i, as shown in Appendix A.1. I model the joint distribution of $Capacity_{ia}$, the equilibrium bid price b^*_{ia}, and the procurement capacity D_a with auction covariates to simulate W^* according to equation (6). Modeling the distribution of b^*_{ia}, f_{b^*}, is enough to get the distribution of (q^*_{ia}, b^*_{ia}), f_{q^*,b^*}, because b^*_{ia} uniquely determines the equilibrium bid share q^*_{ia} as the solution to the bid share decision (equation (7)). I assume that $Capacity_{ia}$, b^*_{ia}, and D_a are mutually independent across bidders and auctions therein.[21] I can estimate the participants' capacity distribution from the observed winners' capacities since capacities and the determinant of winners, bid prices, are independent. I estimate f_{b^*} from winners' bid prices using the likelihood function for the order statistics. I specify the procurement capacity distribution parameters to fit the observed procurement capacities. I then infer winners' cost types from their observed bids using the solution to the bid price decision in equation (8). I also recover the participants' cost distribution from the estimated f_{q^*,b^*} by simulation. I linearly project the simulated costs on the auction dates and lead times to understand the cost trend.

[20] μ_r in an auction at date $t = s$ with lead time l can be written as $\delta^l \times T^{-1} \sum_{t=0}^{T-1} \delta^t E[r_{s+l+t}]$. Thus, a stationary wholesale price process justifies summarizing the term after δ^l as a constant α_r.

[21] I assume the independence of $Capacity_{ia}$ and b^*_{ia} because I find no evidence of the winners' average capacity being different from the participants' average capacity. Although extending the model to allow for covariance between $Capacity_{ia}$ and b^*_{ia} adds no theoretical complication, the independence makes it easier to overcome the problem of observing only winners' capacities.

6 Structural Estimates

I estimate the risk aversion coefficient γ and expected wholesale price parameter α_r from the bid share decisions in pay-as-bid and uniform-price auctions from 2011–2021 (Table 2, left column). γ of 0.50 indicates that the certainty equivalent price of a 50-50 chance of a wholesale market having a fixed price of \$30/MWh and \$40/MWh is \$31.38/MWh, while the expected price is \$35/MWh. Nonetheless, γ needs to be interpreted with caution because its estimate heavily relies on the specification of the wholesale market volatility, which fundamentally differs from the risk premium estimate I discuss below. For instance, bidders would be less risk averse, and the 50-50 lottery's certainty equivalent price would be closer to the expected price if the true wholesale market variance σ_r^2 is larger. This is because γ changes reciprocally to σ_r^2 according to their relationship to the risk premium, $RP_r(1) = \gamma\sigma_r^2/2$, since the risk premium estimate is robust to the misspecification of the wholesale market variance, as shown in the sensitivity analysis (Table 3). α_r of 24.99 implies a stationary expected wholesale price of \$38.95/MWh, which is reasonable given that the average spot price from 2001–2022 was \$32.75/MWh and the prices were higher during the relevant period (2011–2022 average, \$46.24/MWh) than the earlier period (2001–2010 average, \$16.55/MWh).[22]

I then recover the bidders' cost distribution from the bid price decisions in pay-as-bid auctions from 2011–2015. The capacity-weighted average of the winners' costs and markups are \$20.74/MWh (s.e., 0.06) and \$1.54/MWh (0.05), respectively. Winners' risk premium of selling all electricity into the wholesale market amounts to 35.6% of the cost, \$7.38/MWh (0.02). The participants' cost distribution has a mean and SD of \$25.89/MWh (0.08) and \$2.66/MWh (0.07), respectively. The cost estimates are in a reasonable range compared to the engineering estimates.[23]

I linearly project the participants' cost distribution on the time variables to un-

[22]The stationary expected wholesale price implied by the mean reverting process of annual spot prices from 2001–2022 is \$29.41/MWh, much lower than that implied by the bids, \$38.95/MWh. This discrepancy results from the high spot prices during the relevant period compared to the earlier period and supports the importance of expected wholesale price estimation using bids.

[23]Brazil EPE's engineering cost estimates imply the participants' cost distribution having a mean and SD of \$21.86/MWh and \$2.75/MWh, respectively, over the same period (EPE, 2022). My cost estimates from revealed preference could be higher than engineering estimates because the revealed preference estimates may include costs other than engineering costs, such as friction costs.

Table 2: Structural parameter estimates for new wind energy auctions

Bid Share Decision		Cost Distribution (Linear Projection)	
Risk Aversion, γ	0.498 (0.001)	Intercept	31.00 (0.12)
E[Wholesale Price], α_r	24.99 (0.02)	Auction Date (year)	−1.61 (0.07)
SD(Bid Share Shock), σ_η	0.375 (0.031)	Auction Date Square	0.70 (0.01)
		Lead Time (year)	−2.06 (0.02)

Notes: The bid share decision parameters are estimated using the pay-as-bid and uniform-price auction data from 2011–2021. The cost distribution is estimated using the pay-as-bid auction data from 2011–2015. Auction Date is 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.

derstand the cost trend (Table 2, right column). The average participant's cost was \$30–31/MWh from 2011 to 2013, exceeded \$32/MWh in 2014, and rose rapidly to \$36/MWh in 2015 (values calculated setting the lead time to zero). Two factors account for the price hike from 2013–2015 (Tolmasquim et al., 2021). First, a large local equipment provider went bankrupt in 2014. Second, Brazil's base interest rates hiked from 7% in 2013 to 14% in 2015 (Central Bank of Brazil, 2023), making investment financing costly. The lead time coefficient may reflect the participants' expectations about future cost changes. However, the participant's (perceived) cost decreases mechanically by the lead time because the wind turbine cost will be incurred further in the future. After adjusting for this mechanical discount, the participants still expected the cost to decrease by \$0.87/MWh annually,[24] even though the cost mostly increased from 2011–2015, which implies that the wind turbine cost inflation was unexpected to the investors. The estimated winning probability functions yield plausible winning probabilities for the observed bids (Figure D2 in Online Appendix D plots the predicted winning probabilities for each auction). All other parameter values are summarized in Online Appendix D.

Table 3 demonstrates how risk premium and cost estimates are sensitive to the specifications of the wholesale market volatility (SD, σ_r) and uniform-price auction's equilibrium clearing price distribution (mean, μ_{p^*}, and SD, σ_{p^*}). The risk premium estimate is expected to be robust to their misspecification because the risk premium

[24] I undiscount the cost distribution by the lead time and rerun the linear projection.

is identified without these specifications in pay-as-bid auctions, which account for 62% of the bid data. Quantifying how risk premium estimates may change by also using uniform-price auction bids is important since the estimated risk premium plays a central role in the policymaker's counterfactual cost-risk trade-off from risk sharing. Panel A and C change the main specification of σ_r = \$4.94–\$5.82/MWh (varies across auctions according to their lead time) and σ_{p^*} = \$2.55/MWh to 50%–150% of them. Panel B reduces/increases the main specification of μ_{p^*} = \$19.92–\$34.33/MWh (varies across auctions according to their covariates) by 1–2 SD of σ_{p^*} = \$2.55/MWh.

Table 3: Sensitivity analysis: Winners' average risk premium and cost

	Change from the Main Specification				
A. Wholesale Price SD, σ_r	−50%	−25%	Main	+25%	+50%
Risk Premium (\$/MWh)	7.14	7.34	7.38	7.39	7.39
Cost (\$/MWh)	21.49	21.09	20.74	20.42	20.15
B. Clearing Price Mean, μ_{p^*}	−2SD	−1SD	Main	+1SD	+2SD
Risk Premium (\$/MWh)	6.53	7.17	7.38	7.14	6.51
Cost (\$/MWh)	20.65	20.72	20.74	20.71	20.65
C. Clearing Price SD, σ_{p^*}	−50%	−25%	Main	+25%	+50%
Risk Premium (\$/MWh)	8.55	8.09	7.38	6.47	5.42
Cost (\$/MWh)	20.83	20.80	20.74	20.65	20.52

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

I highlight several findings in the sensitivity analysis. First, the risk premium estimate is fairly robust to the wholesale market volatility misspecification. It only changes from \$7.38/MWh to \$7.14–\$7.39/MWh with a wide range of alternative specifications. Second, the clearing price distribution misspecification affects the risk premium estimate more than the wholesale market volatility misspecification because it substantially changes the attractiveness of purchase agreements in uniform-price auctions. Third, however, the clearing price distribution misspecification barely changes the cost estimates in pay-as-bid auctions. Online Appendix E contains further sensitivity analyses of 1. how markup estimates are sensitive to the misspecification and 2. combinations of different wholesale market volatility and clearing price distribution specifications.

7 Counterfactual Analysis

I consider a policymaker seeking to entice investors to install the same amount of wind turbines as in the 8 pay-as-bid auctions from 2011–2015, where the full structural parameters are estimated. The policymaker calls for risk-sharing contracts (Section 2) to accomplish this goal. With risk-sharing contracts, the policymaker takes a share $\lambda \in [0, 1]$ of the responsibility for selling the electricity to the risky wholesale market. The policymaker specifies the share λ and applies the same share to all investors instead of allowing investors to choose their shares individually. I simulate the policymaker's net expenditure of auctioning the risk-sharing contracts with λ moving from 0 to 1 to trace the policymaker's cost-risk trade-off and discuss welfare consequences. Wholesale prices will not change by the policymaker's choice of λ since the same amount of electricity will be supplied to the wholesale market regardless of λ. I formulate risk-sharing contract auctions before proceeding to counterfactual simulations.

7.1 Risk-Sharing Contract Auctions

In risk-sharing contract auctions, all bidders bid in a policymaker-designated share λ of their production. Bidders cannot choose their shares. I make two adjustments in the auction model that allows bidder share choices introduced in Section 4 to encompass subsidy auctions. First, an objective capacity $\widetilde{D}$ decides the winners based on their installation capacity, not only the capacity allocated to the auction. Second, bidders bid a price per total production rather than a price per production allocated to the auction. I consider counterfactual pay-as-bid auctions where winners receive risk-sharing contracts at their bid prices.

If bidder i wins with a bid price b_i, for each period during the contract, the bidder provides $\lambda \times Capacity_i \times H$ hours of electricity, and the auctioneer pays $b_i \times Capacity_i \times H$, which yields an expected utility of $u(\tilde{\delta} b_i + (1-\lambda)E[r] - c_i - RP_r(1-\lambda))$. Note that the (discounted) revenue from the contract, $\tilde{\delta} b_i$, does not depend on the share λ since the contract payment is made per total production (see equation (5) for a comparison).

The auction provides a (pure) generation subsidy when $\lambda = 0$ and a full share purchase agreement when $\lambda = 1$. The auctioneer awards these contracts to the lowest bid prices until the total capacity $\sum_i Capacity_i$ of winners exceeds the objective capacity $\widetilde{D}$. I can easily compute a unique counterfactual equilibrium strategy by solving an ordinary differential equation because the counterfactual winning probability function does not depend on the competitors' strategies, assuming symmetric bidders (details in Appendix A.3).

7.2 Policymaker's Counterfactual Cost-Risk Trade-off

I draw participants' costs from the estimated cost distribution and simulate bid prices if the 8 pay-as-bid auctions from 2011–2015 were to offer risk-sharing contracts. I fix the number of winners and winners' capacities to the actual values. I run simulations for each $\lambda = 0, 0.01, \ldots, 0.99, 1$. The policymaker's counterfactual net expenditure is the total contract payment according to the winners' simulated bid prices, net of the revenue from the wholesale market of selling the contracted electricity determined by λ.

The expected net expenditures are \$5.0 billion with subsidies ($\lambda = 0$) and \$0.6 billion with full share purchase agreements ($\lambda = 1$) to make bidders commit to installing wind turbines that cost \$12.2 billion.[25] The excess of \$4.4 billion with full share purchase agreements relative to subsidies would be able to cover the additional costs of 1.1 GW of wind turbines. However, the policymaker must bear all wholesale market risks over 20 years with full share purchase agreements.

The policymaker examines the distribution of her possible net expenditures to assess whether taking the wholesale market risk is worth the expected net expenditure saving. I illustrate the net expenditure variability with 50% share purchase agreements ($\lambda = 0.5$) and full share purchase agreements in Table 4 and Figure 4. The expected net expenditure decreases from \$5.0 billion to \$1.7 billion by taking half the risk and to \$0.6 billion by taking all. The net expenditures of the purchase agreements will likely be lower than the subsidy if the policymaker evaluates the wholesale market

[25] The policymaker is expected to pay \$6.9 billion more with subsidies than full share purchase agreements to make bidders commit to installing 5.6 GW of wind turbines if the simulations include the 8 uniform-price auctions from 2017–2021. However, I do not have cost estimates for uniform-price auctions and cannot quantify the level of net expenditures.

variance using the historical spot prices in the same way as in my main specification in the structural model estimation (Baseline Wholesale Risk). The probabilities of half and full share purchase agreements having net expenditures higher than subsidies are only 2.1% and 8.7%. Nevertheless, the policymaker might be struck by high net expenditures by taking risks. For instance, the 97.5 percentile of the net expenditure with full share purchase agreements is $2.0 billion higher than subsidies.

Table 4: Counterfactual net expenditures by risk the policymaker takes (Billion $)

		Percentile					
	Mean	p60	p70	p80	p90	p95	p97.5
Subsidy ($\lambda = 0$)	5.004 (0.014)	-	-	-	-	-	-
Baseline Wholesale Risk							
50% Purchase Agreement ($\lambda = 0.5$)	1.701 (0.021)	2.112	2.551	3.066	3.779	4.368	4.879
100% Purchase Agreement ($\lambda = 1$)	0.600 (0.023)	1.421	2.300	3.329	4.756	5.934	6.956
1.5 Times Wholesale Risk							
50% Purchase Agreement ($\lambda = 0.5$)	1.701 (0.021)	2.317	2.976	3.748	4.818	5.701	6.468
100% Purchase Agreement ($\lambda = 1$)	0.600 (0.023)	1.832	3.151	4.694	6.834	8.601	10.134

Notes: Subsidy's net expenditure is certain and does not depend on the wholesale market risk. Baseline Wholesale Risk uses the wholesale market standard deviation evaluated using the historical spot prices, and 1.5 Times Wholesale Risk uses 1.5 times it. λ is the share of risk the policymaker takes. Values are the average of 200 simulations for each λ. The total installation capacity is fixed across all simulations. Standard errors (in parentheses) are calculated using 200 auction-level block bootstrap replications.

Policymakers can evaluate the wholesale market risk differently. My framework allows the policymaker to have her risk evaluation since the investors' risk premium estimate—which drives the expected net expenditure changes by the policymaker's risk-taking—is robust to the wholesale market volatility misspecification. If the policymaker evaluates the wholesale price to have a 50% larger SD than my main specification (1.5 Times Wholesale Risk), the probabilities of the net expenditures with half and full share purchase agreements to be higher than subsidies increase to 8.7% and 18.3%. Moreover, the 97.5 percentile of the net expenditure with half share purchase agreements is $1.5 billion higher than subsidies, and that with full share purchase agreements reaches twice the $5.0 billion subsidy.

The policymaker may consider how much of a burden it would be if the net expenditure were passed through to electricity consumers as a surcharge on top of their bills. Brazil's average resident pays $17.87 monthly for electricity in 2019 (EPE, 2021).

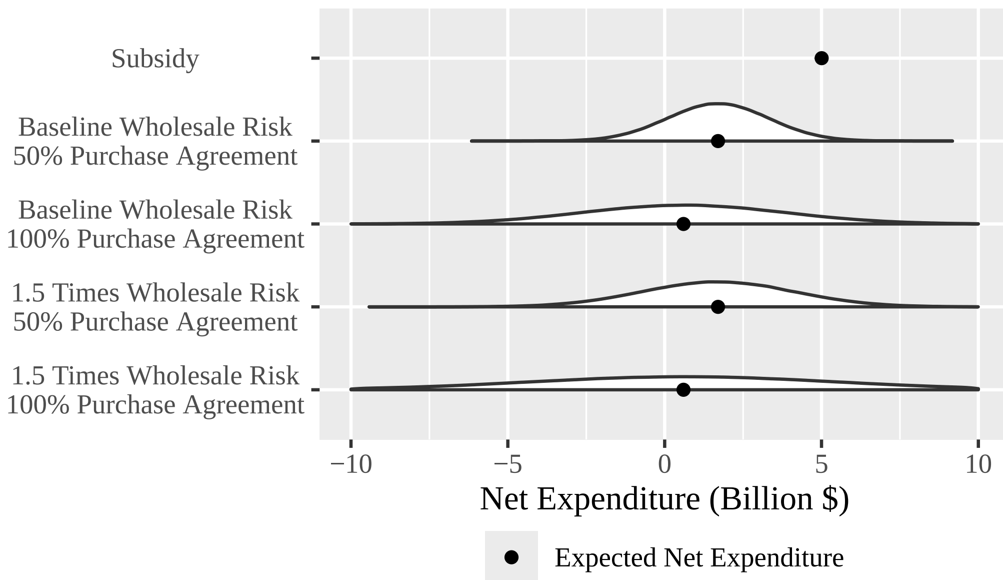


Figure 4: Net expenditure variability by taking the wholesale market risk

Wind energy subsidies, which accounts for 1.9% of the entire generation capacity, increase the monthly bill by 16 cents (undiscounted 20-year average) when the net expenditure is distributed across all end-users in Brazil. 16 cents increase has the same burden of 0.9% electricity price inflation. Full share purchase agreements decrease the expected surcharge to 2 cents. However, consumers might be struck by a higher surcharge due to the wholesale market volatility. The 97.5 percentiles of the full share purchase agreement surcharges are 22 and 32 cents—equivalent to 1.2% and 1.8% electricity price inflation—with the wholesale market variance evaluated using the historical spot prices and 50% larger SD of it, respectively.

The policymaker uses a certainty equivalent of net expenditure to evaluate her welfare consequences (Section 2):

$$\text{Certainty equivalent of net expenditure}(\lambda) = E[\text{Net expenditure}(\lambda)] + RP_r^{PM}(\lambda),$$

where $RP_r^{PM}(\lambda)$ is the policymaker's risk premium of taking share λ of the wholesale market risk. The certainty equivalent crucially depends on the policymaker's risk premium evaluation. I illustrate the certainty equivalent for two policymakers, risk-neutral and risk-averse. The risk-neutral policymaker evaluates the risk premium as zero for any risk she takes. The risk-averse policymaker evaluates the risk premium in the same way as the investors.

Rows Risk-Sharing Contract Auction in Table 5 and the solid lines in Figure 5 demonstrate the cases where the policymakers auction off risk-sharing contracts. The risk-neutral policymaker prefers to take all risks ($\lambda = 1$), whereas the risk-averse policymaker prefers to share risks by half and half ($\lambda = 0.5$), as I have shown analytically in Section 2. The policymakers' net expenditures are \$5.0 billion with subsidies ($\lambda = 0$) regardless of the policymakers' risk evaluation since there is no uncertainty. The risk-neutral policymaker saves \$3.3 billion by taking half the risk and \$4.4 billion by taking all because she only cares about the expected net expenditure. In contrast, the risk-averse policymaker saves \$2.2 billion by taking half the risk but taking risks any further will cost her—the risk-averse policymaker benefits from sharing risks with investors.

Table 5: Counterfactual certainty equivalent net expenditures (Billion \$)

	Share of Risk Policymaker Takes (λ)			
Allocation Mechanism	$\lambda = 0$	$\lambda = 0.5$	$\lambda = 1$	$\lambda = q^*$
Risk-Neutral Policymaker, $RP_r^{PM} = 0$				
Risk-Sharing Contract Auction	5.004 (0.014)	1.701 (0.021)	0.600 (0.023)	0.603 (0.023)
First-Best	4.061 (0.040)	0.759 (0.040)	−0.342 (0.040)	−0.340 (0.040)
Bidder Share Choice Auction	-	-	-	0.782 (0.021)
Risk-Averse Policymaker, $RP_r^{PM} = \widehat{RP}_r$				
Risk-Sharing Contract Auction	5.004 (0.014)	2.802 (0.018)	5.003 (0.014)	4.848 (0.022)
First-Best	4.061 (0.040)	1.860 (0.039)	4.061 (0.040)	3.904 (0.046)
Bidder Share Choice Auction	-	-	-	5.033 (0.021)

Notes: RP_r^{PM} is the policymaker's risk premium function. $\widehat{RP}_r$ is the estimated investors' risk premium function. $q^* = 0.98$ is the capacity-weighted average model-predicted equilibrium share in bidder share choice auctions. Values are the average of 200 simulations for each allocation mechanism and λ. The total installation capacity is fixed across all simulations. Auctions are in pay-as-bid format. Standard errors (in parentheses) are calculated using 200 auction-level block bootstrap replications.

Policymakers' first-best is to pay the minimum amount necessary for each of the lowest-cost investors selected in auctions to sign their risk-sharing contracts (rows First-Best in Table 5 and the dotted lines in Figure 5).[26] The auctions cost \$0.9 billion more than the first-best, which can be interpreted as the cost of selecting the lowest-cost investors without any information on their costs.

[26] Negative values imply the average cost is below the expected wholesale price (equation (3)).

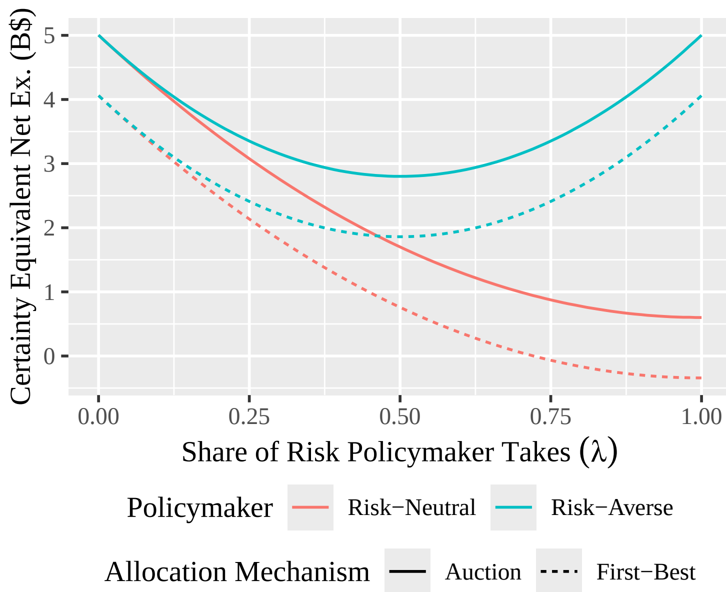


Figure 5: Certainty equivalent net expenditures by policymaker's risk attitude

I also simulate the certainty equivalent net expenditures of the actual auctions that allow bidders to choose their shares (rows Bidder Share Choice Auction in Table 5). I compute their equilibrium strategies using the estimated equilibrium winning probability functions. The average model-predicted equilibrium share is $q^* = 0.98$. Compared to the risk-sharing contract auctions with the same share of risk the policymaker takes (column $\lambda = q^*$), allowing bidders to choose their shares costs the policymakers \$0.2 billion more. The opportunity for share (or portfolio) choices should make the auction more lucrative and induce more competitive bids. Nonetheless, 74.5% of the simulated winners bid full shares to the auction. Those constrained to bidding full shares would not benefit from portfolio optimization and may make looser bids because more intense competition among unconstrained bidders can ease the competition around the constrained bidders' bid prices.

8 Conclusion

I propose a structural framework for policymakers to share wholesale electricity price risks with risk-averse renewable investors to support them in building new capacities. Renewable investors' high risk premium for wholesale markets because of volatile prices, compounded by intermittency and high upfront capital costs, motivates policymakers to take some risks. Policymakers face a trade-off between taking the risk and paying to cover investors' risk premium. Policymakers can use my framework to estimate renewable investors' risk premium from their revealed preference in portfolio choices embedded in long-term renewable energy purchase agreement auctions. The risk premium estimate helps policymakers to make an accurate assessment of their cost-risk trade-off from risk sharing. Estimating investors' risk premium is particularly important in low and middle-income countries with under-developed financial markets where the risk premium is expected to be high (Ameli et al., 2021; Calcaterra et al., 2024).

In fact, in Brazil, wind turbine investors' wholesale market risk premiums reach 36% of their cost. For 2% of Brazil's generation capacity auctioned from 2011–2015, the policymaker is expected to save \$4.4 billion by taking the entire risk from investors compared to not taking any risks. However, the policymaker must bear the future wholesale market risk over 20 years. Thus, whether taking the risk is worth the expected saving depends on the policymaker's risk evaluation. If the policymaker evaluates the wholesale market risk using historical spot prices, as in the paper, the 97.5 percentile of the policymaker's net expenditure of taking the entire risk is \$2.0 billion higher than not taking any risks. If the policymaker is more pessimistic and evaluates the wholesale price to have a 50% larger standard deviation, that value becomes \$5.0 billion rather than \$2.0 billion.

The framework proposed in this paper provides policymakers with a menu of possible cost-risk combinations for supporting a given amount of renewable investments. Policymakers may want to choose the cost and risk that conforms with their risk preference. A risk-neutral policymaker, evaluating her risk premium as zero regardless of her risk, would only care about the expected net expenditure and prefer taking all risks to save \$4.4 billion. In contrast, a risk-averse policymaker, evaluating her risk premium as the same as the investors, would balance her expected net expenditure and risk premium. As a result, she would prefer taking half the risk to save \$2.2 billion in terms of the certainty equivalent of net expenditure, which is the sum of the expected net expenditure and risk premium. How policymakers *should* decide on the appropriate amount of risk they take is a reasonable normative question to ask in future research. One direction is quantifying the policymakers' risk premium to translate their risk to monetary values. Policymakers can then evaluate their welfare of risk-taking using the certainty equivalent of net expenditure, as illustrated in this paper. The normative answer may also depend on the marginal externality benefits of policymakers taking additional risks and how policymakers recoup the losses from risk-taking analogously to the marginal value of public funds framework (Hahn et al., 2024).

Extending the auction model to incorporate bidder risk premium heterogeneity would be useful for analyzing the selection on risk premium. Low risk premium bidders will bid competitively if policymakers avoid taking risks. As policymakers take risks, high risk premium bidders will be able to compete with low risk premium bidders. Consequently, risk-sharing policies may facilitate fairness if, for example, small investors have high risk premiums. Moreover, separately identifying bidders' heterogeneous beliefs about their expected returns and risk premiums may be of independent interest in the context of investors' portfolio decisions (Egan, MacKay, and Yang, 2023). If we observe all participants' bids, extending the structural estimation to incorporate these additional heterogeneities would be straightforward. However, estimating these heterogeneities in a tractable way would be challenging without losers' bids.

A Equilibrium Strategy

A.1 Pay-as-Bid Auctions

A monotone pure-strategy BNE exists in pay-as-bid auctions in Section 4.1 because the auction model satisfies the single crossing condition for games of incomplete information (Athey, 2001). I show the single crossing condition to conclude the proof. A bid price b uniquely determines the optimal bid share as in equation (7):

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

Thus, the bid price is effectively the only action bidders consider. Bidder i's expected utility of action b, given his cost type c, is $\mathrm{EU}_i(b|c) := W_i(b) \cdot u(\mathrm{CE}(q^*(b), b|c))$, where

CE is a certainty equivalent function defined as

$$\mathrm{CE}(q, b|c) \coloneqq q\tilde{\delta}b + (1-q)\mu_r - c - RP_r(1-q).$$

The expected utility satisfies the single crossing of incremental returns as

$$\frac{\partial^2 \mathrm{EU}_i(b|c)}{\partial b \partial c} = -W_i'(b) \cdot u'(\mathrm{CE}(q^*(b), b|c)) - W_i(b) \cdot u''(\mathrm{CE}(q^*(b), b|c)) \cdot q^*(b)\tilde{\delta} > 0.$$

Symmetric Bidders. I assume *ex-ante* symmetric bidders and show that a unique symmetric monotone pure-strategy BNE exists in pay-as-bid auctions in Section 4.1. Let $\omega : [\underline{c}, \bar{c}] \mapsto \mathbb{R}$ be a monotonically increasing symmetric bid price strategy that maps the cost type c onto the bid price. A bid price strategy ω uniquely determines a bid share strategy as $q^*(\omega(c))$. Thus, characterizing the equilibrium bid price strategy suffices to prove the statement about the equilibrium bid strategy.

I analyze the equilibrium bid price strategy in line with the procedure in Hubbard and Paarsch (2014). The winning probability function can be reformulated as follows:

$$H_i(\omega^{-1}(b)|\omega) \coloneqq \Pr\left(\sum_{j \neq i} \{q^*(\omega(c_j)) Capacity_j\} \mathbb{1}(c_j \leq \omega^{-1}(b)) < D\right).$$

The winning probability function is the same for all bidders due to *ex-ante* symmetry, i.e., bidders independently draw their types $(c_i, Capacity_i)$ from a common distribution. Thus, I drop the subscript i from the winning probability function. Bidder's expected utility of action b given his cost type c is $\mathrm{EU}(b|c) \coloneqq H(\omega^{-1}(b)|\omega) \cdot u(\mathrm{CE}(q^*(b), b|c))$.

I obtain the first-order condition that characterizes the equilibrium bid price strategy by differentiating the expected utility with respect to b and plugging in $b = \omega(c)$: i.e., $d\mathrm{EU}(\omega(c)|c)/db = 0$. Noting $d\omega^{-1}(b)/db = 1/\omega'(c)$ when $b = \omega(c)$, the first-order condition can be seen as the following ordinary differential equation (ODE):

$$\omega'(c) = -\frac{H'(c|\omega) \cdot u(\mathrm{CE}(q^*(\omega(c)), \omega(c)|c))}{H(c|\omega) \cdot u'(\mathrm{CE}(q^*(\omega(c)), \omega(c)|c)) \cdot q^*(\omega(c))\tilde{\delta}}.$$

A solution to the ODE is a BNE bid price strategy ω. Applying the Picard-Lindelöf theorem (e.g., Teschl, 2012, Theorem 2.2), I conclude the existence and uniqueness of the strategy ω under a suitable boundary condition since the functions involved in the ODEs are all continuous in their arguments.

A.2 Uniform-Price Auctions

I first derive the optimal bid share decision in uniform-price auctions in Section 4.2. A bidder with cost c chooses his bid (q, b) to maximize

$$E[u(q\tilde{\delta}p^* + (1-q)r - c)], \text{ where } p \sim \mathcal{TN}(\mu_{p^*}, \sigma_{p^*}^2, b, \infty), r \sim \mathcal{N}(\mu_r, \sigma_r^2).$$

$\mathcal{TN}(\mu_{p^*}, \sigma_{p^*}^2, b, \infty)$ is a truncated normal that truncates $\mathcal{N}(\mu_{p^*}, \sigma_{p^*}^2)$ from below at b. The certainty equivalent of NPV, $q\tilde{\delta}p^* + (1-q)r - c$, is

$$\mathrm{CE}(q, b|c) \coloneqq K_{p^*}(-\gamma q\tilde{\delta}; b) + K_r(-\gamma(1-q)) + \gamma c,$$

where $K_Y(\tau) \coloneqq \log E[\exp(\tau Y)]$ is a cumulant of a random variable Y. Thus, the optimal bid share satisfies equation (9) in Section 4.2 as

$$\frac{\partial \mathrm{CE}(q, b|c)}{\partial q} = 0 \iff q = \left(\frac{1}{1 + \tilde{\delta}^2\sigma_{p^*}^2/\sigma_r^2}\right)\left(1 - \frac{\mu_r - \tilde{\delta}\tilde{\mu}_{p^*}(q, b)}{\gamma\sigma_r^2}\right)$$

because, for any τ,

$$K'_{p^*}(\tau; b) = \mu_{p^*} + \sigma_{p^*}^2\tau + \sigma_{p^*}\Lambda\left(\frac{\mu_{p^*} - b}{\sigma_{p^*}} + \sigma_{p^*}\tau\right),$$

where Λ is the inverse Mills ratio for a standard normal. The unconstrained optimal bid share function $q^{**}(b)$ is defined as a solution of q to equation (9) for a given b.

I next show $dq^{**}(b)/db > 0$. Differentiating both sides of equation (9) with respect to b, I obtain

$$\frac{dq^{**}(b)}{db} = -\frac{\tilde{\delta}\Lambda'\left(\frac{\mu_{p^*}-b}{\sigma_{p^*}} - q\gamma\tilde{\delta}\sigma_{p^*}\right)}{\gamma\left\{\sigma_r^2 + \left(1 + \Lambda'\left(\frac{\mu_{p^*}-b}{\sigma_{p^*}} - q\gamma\tilde{\delta}\sigma_{p^*}\right)\right)\tilde{\delta}^2\sigma_{p^*}^2\right\}} > 0$$

since $\Lambda' \in (-1, 0)$ for any argument. Thus, the equilibrium bid share continuously increases with the equilibrium bid price.

Lastly, I show the single crossing condition (Athey, 2001) to prove that a monotone pure-strategy BNE exists. Similarly to pay-as-bid auctions in Appendix A.1, the bid price is effectively the only action bidders consider because the bid price uniquely determines the optimal bid share through the optimal bid share function q^*. Thus, the expected utility of action b for a bidder with cost c is $u(\mathrm{CE}(q^*(b), b|c))$, and it satisfies the single crossing of incremental returns as

$$\frac{\partial^2 u(\mathrm{CE}(q^*(b), b|c))}{\partial b \partial c} = \gamma u''(\mathrm{CE}(q^*(b), b|c)) \cdot \frac{1}{\sigma_{p^*}} \left(\Lambda \left(\frac{\mu_{p^*} - b}{\sigma_{p^*}} \right) - \Lambda \left(\frac{\mu_{p^*} - b}{\sigma_{p^*}} - q\gamma\tilde{\delta}\sigma_{p^*} \right) \right) > 0$$

since Λ is a decreasing function.

A.3 Risk-Sharing Contract Auctions

I detail the counterfactual equilibrium strategy calculation in risk-sharing contract auctions in Section 7.1. I can show that a unique symmetric monotone pure-strategy BNE exists with symmetric bidders following the same argument as in the "Symmetric Bidders" part of Appendix A.1. I highlight the differences. The counterfactual winning probability function and ODE become

$$H(\omega^{-1}(b)) := \Pr\left(\sum_{j \neq i} Capacity_j \mathbb{1}(c_j \leq \omega^{-1}(b)) < D \right)$$

and

$$\omega'(c) = -\frac{H'(c) \cdot u(\mathrm{CE}(\omega(c)|c))}{H(c) \cdot u'(\mathrm{CE}(\omega(c)|c)) \cdot \tilde{\delta}},$$

where $\mathrm{CE}(b|c) := \tilde{\delta} b + (1-\lambda)\mu_r - c - RP_r(1-\lambda)$.

I calculate the counterfactual equilibrium strategy ω^* by solving the ODE with the estimated structural parameters and a boundary condition. I calculate the counterfactual winning probability function $H(c)$ from the estimated structural parameters (details in Online Appendix F). Importantly, I do not need to recalculate $H(c)$ while searching for the counterfactual equilibrium strategy ω^* since $H(c)$ does not depend on strategy ω. I define the boundary condition as a zero expected utility conditional on winning at the highest cost type $\bar{c}$, i.e., $u(\mathrm{CE}(\omega^*(\bar{c})|\bar{c})) = 0$. I use the ODE solvers implemented by Rackauckas and Nie (2017).

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Online Appendix

A Descriptive Evidence

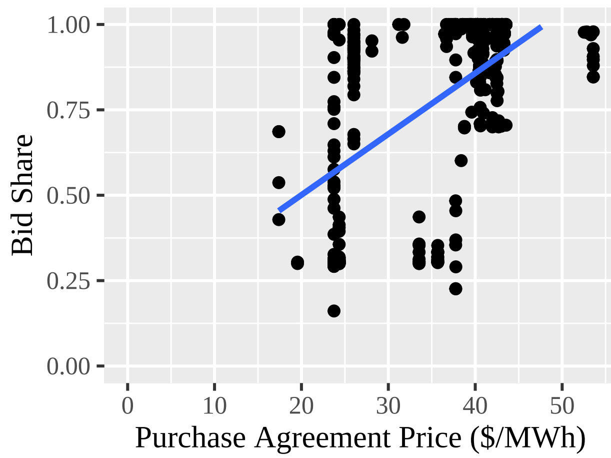

Figure A1: Relationship between bid shares and purchase agreement prices

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. Let the discount factor $\delta = 1$ for simplicity. 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 $RP'_r(1-q^*) = \mu_r - b^*$ in $(\underline{q}, 1)$. Thus, q^* balances the marginal risk premium and the marginal expected gain from the wholesale market relative to the purchase agreement. The optimal bid share $q^* = 1 - (RP'_r)^{-1}(\mu_r - b^*)$ 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. I then identify the equilibrium bid share-price relationship $q^*(b^*)$ for all $q^* \in [0,1]$ 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 $b^*(q^*)$, $\forall q^* \in [\underline{q}, 1]$, 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 $q^* \in [0,1]$. 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, $q^* \in [0, \underline{q})$, if the minimum possible bid share is non-zero (i.e., $\underline{q} > 0$).

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

$$f^X_{p^*|D} = \mathcal{N}(\beta_{pD0} + \beta_{pD1}D + \beta_{pD2}(s+l) + \beta_{pD3}N + \beta_{pD4}N^2, \sigma^2_{pD}).$$

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 $(\beta_{pD0}, \beta_{pD1}, \beta_{pD2}, \beta_{pD3}, \beta_{pD4}, \sigma^2_{pD})$ that maximize likelihood.

I specify the procurement capacity distribution as

$$f^X_D = \mathcal{N}(\beta_{D0} + \beta_{D1}s + \beta_{D2}N, \sigma^2_D).$$

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 $(\beta_{D0}, \beta_{D1}, \beta_{D2}, \sigma^2_D)$ that maximize likelihood.

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

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

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

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

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 $q_i^z = \min\{\max\{\underline{q}, q^{**}(b_i^z) + \eta_i^z\}, 1\}$, 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 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):

$$\hat{q}^*(b) := \min\left\{\max\left\{\underline{q}, 1 - \frac{\hat{\mu}_r - \tilde{\delta}b}{\hat{\gamma}\sigma_r^2}\right\}, 1\right\}. \tag{10}$$

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/MWh, about 1/30 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)

Notes: 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.

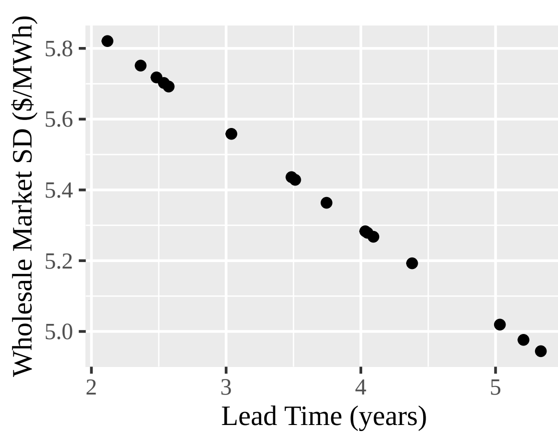

Figure D1: Relationship between the wholesale market SD and lead time

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 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

Notes: 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 \$3.04/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, $\sigma_{pD} = \$0.76$/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}	3.04
Operation Start (year), β_{pD2}	1.84
100 Participants, β_{pD3}	-11.75
100 Participants Square, β_{pD4}	0.70
SD(Residual), σ_{pD}	0.76

Notes: 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 in Online Appendix C.4. 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.

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 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)

Notes: 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.

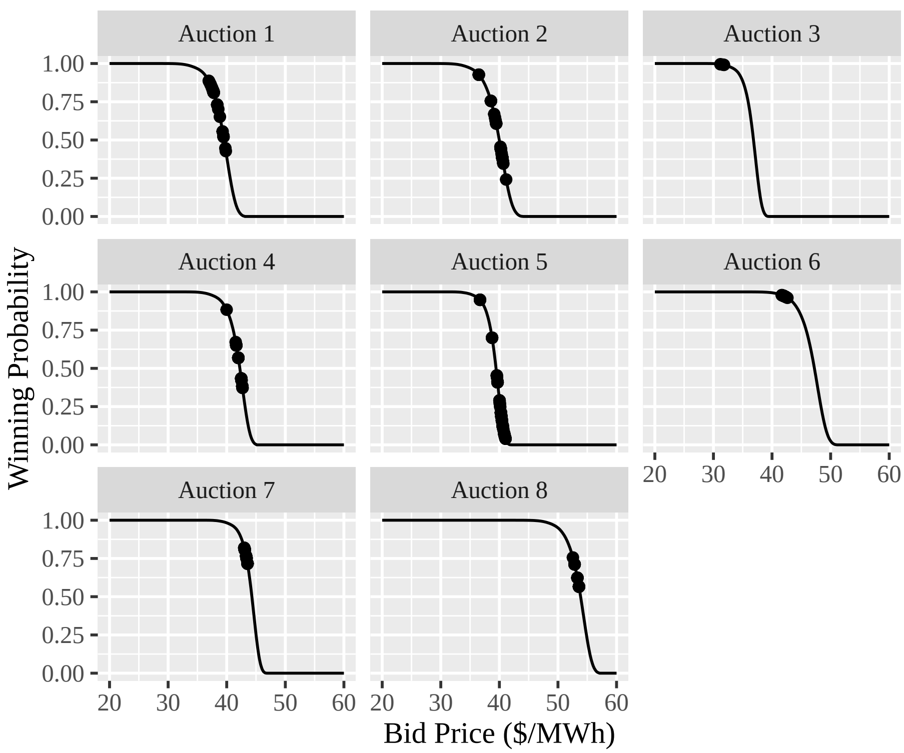

Figure D2: Estimated equilibrium winning probability functions and winners' bids

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 $\sigma_r =$ \$4.94–\$5.82/MWh, $\mu_{p^*} =$ \$19.92–\$34.33/MWh, and $\sigma_{p^*} =$ \$2.55/MWh to 75%–125%,

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	$+1$SD	$+2$SD
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

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

-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.

Table E2: Sensitivity analysis: Combinations of different specifications

	Change from the Main Specification								
Clearing Price Mean, μ_{p^*}	-1SD			Main			$+1$SD		
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

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

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 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 $i = 1, \ldots, N$.

2. For $z' = 1, \ldots, Z_D$, 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 (equation (10) 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.