Encouraging Renewable Investment: Risk Sharing Using Auctions*

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Abstract

Renewable energy's high upfront capital costs can make investors selling intermittent electricity into volatile wholesale markets substantially risk-averse. This paper quantifies the value of policymakers taking on the risk from investors through power purchase agreements that guarantee a certain price. I use an auction model to recover investors' risk premiums from their portfolio choices embedded in Brazil's long-term wind power purchase agreement auctions. I identify and estimate the joint distribution of risk aversion and cost from winning bids, revealing substantial heterogeneity in risk preferences and a weak negative correlation between risk aversion and cost. To entice investors to install wind turbines costing $27.0 billion, the policymaker would save $8.0 billion by taking on 100% of the wholesale market risk, relative to 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 premiums*. I estimate investors' risk premiums 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. Recent work highlights that private long-term purchase agreements can be constrained by counterparty and renegotiation risk, motivating a larger role for regulator-backed arrangements (Fabra and Llobet, 2025b,a).

[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.

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 de Minas e Energia, MME) and Electricity Regulatory Agency (Agência Nacional de Energia Elétrica, ANEEL), respectively, from 2009 to 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 indicate 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, 43.5% of bidders in the 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]

Bidders with heterogeneous risk aversion and cost types, sharing a common expected wholesale price belief, 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 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. Additionally, 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. Leveraging these identification strategies, I obtain a robust risk premium estimate *without* relying on detailed wholesale market data, which is difficult to collect because it typically involves private bilateral contracts.

I estimate the model using winners' bids, assuming symmetric bidders. 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] A key contribution of the paper is to show that winners' bids and attributes data identify the entire participants' distribution of bids and observable attributes when winners are selected on a one-dimensional ranking variable (bid price in this paper). The argument treats the ranking variable as an order statistic and exploits results on the *concomitants* of order statistics (Yang, 1977): under i.i.d. draws of bids and attributes implied by symmetric bidders, the conditional distribution of the concomitants (the remaining bid components and bidder attributes) given their paired order statistic (the ranking variable) coincides with the corresponding conditional distribu-

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

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

tion in the underlying participant population. This extends the classic order-statistics approach that recovers one-dimensional bid distributions from winners (Athey and Haile, 2002) to multidimensional settings by providing a way to reconstruct the entire joint distribution of bids and observable attributes from winners' bids and attributes. I show the identification for two auction formats observed in the data, sealed-bid and descending-clock auctions, using the properties of the concomitants.

Given these identification results, the estimation proceeds in two steps. First, I estimate the distribution of risk aversion coefficients and the expected wholesale price from the portfolio choices implied by the bid share optimality condition using the method of simulated moments. Second, I recover the cost distribution by combining the inferred participant bid and attribute distribution with the optimal bid price condition in the spirit of Guerre, Perrigne and Vuong (2000). I combine the data from two auction formats, sealed-bid and descending clock auctions, in the first stage, while I only use the sealed-bid auction data in the second stage since there is not much individual cost information in the descending clock auctions.

I find that the wind turbine investors' wholesale market risk premium is high in Brazil. The average winner's risk premium of selling all electricity into the wholesale market is \$7.09/MWh, which amounts to 29.5% of their cost of \$24.01/MWh. The risk premium estimate is comparable to May and Neuhoff (2021)'s estimate of 29% of the cost, based on financing-cost interview data from the European Union. Nevertheless, obtaining significantly different risk premium estimates would not be surprising, as they likely depend on local electricity price volatility and counterparty risk. The estimated joint distribution of risk aversion and cost for all participants reveals substantial heterogeneity in risk preferences across bidders, and a weak, statistically insignificant negative correlation between risk aversion and cost. The implied risk premium for an investor one standard deviation above the average is 2.1 times that of an investor one standard deviation below.

Policymakers can use my framework to understand their cost-risk trade-off from risk sharing with renewable investors using investors' risk premiums estimated from investors' revealed preference in policymakers' jurisdiction. For the winners included in the analysis (total capacity of 6.4 GW, 3.6% of the overall generation capacity in Brazil in 2020 (Tolmasquim et al., 2021)), the estimates imply that the winners' over-

all risk premium is $8.0 billion for wind turbines costing $27.0 billion on aggregate. In other words, to entice investors to install wind turbines costing $27.0 billion, the policymaker would save $8.0 billion by taking on 100% of the wholesale market risk, relative to a subsidy policy that left all the risk with the investors. The policymaker can choose a middle ground—among options encompassing purchase agreements and subsidies—to balance her expected net expenditure and her risk appetite. 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 premiums 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. Complementary to Ryan (2022)—who leverages variation in the contracting counterparty to isolate counterparty risk—my approach uses these portfolio choices to recover the premium investors require for bearing the bundle of residual risks in sales outside the long-term contract in a given market. In this way, the estimated risk premium can be interpreted as an overall premium for bearing this residual exposure—encompassing whatever risks are bundled in the wholesale market, such as spot market price volatility, contract-renewal uncertainty, and counterparty risk. This interpretation can be especially useful in practice when investors face multiple, jointly-

[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).

determined sources of risk and policymakers care about de-risking the overall revenue stream, as emphasized in discussions of long-run contracting and risk allocation in electricity markets (Fabra and Llobet, 2025b).

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.

The remainder of the paper proceeds as follows. Section 2 begins by presenting a simple model of a policymaker and a renewable investor to illustrate the role of risk sharing between them. Section 3 discusses relevant institutional details of the new energy auctions in Brazil and highlights descriptive features of the data. Section 4 presents the structural model of bidding a share and a price in these auctions by bidders with heterogeneous risk aversion and cost types, and Section 5 proceeds to identification and estimation of the model. Section 6 demonstrates the estimation results, and Section 7 concludes with a discussion of policy implications and future research directions.

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 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

[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.

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.

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:

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

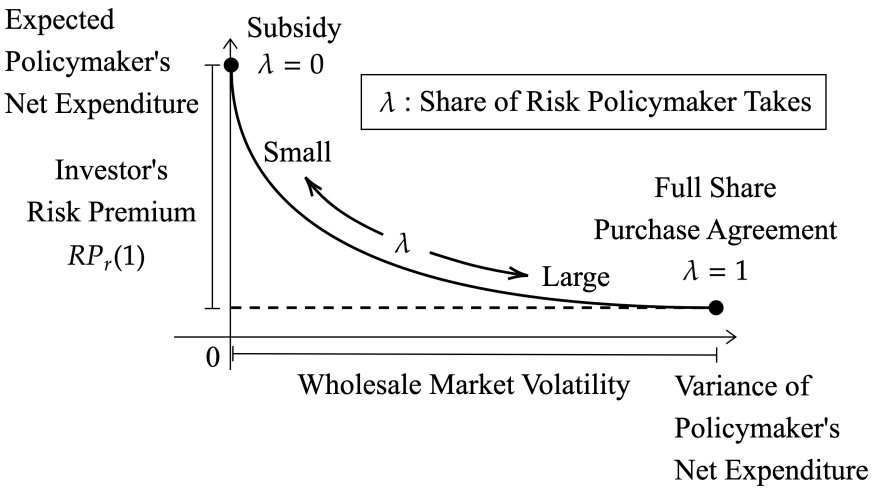


Figure 1: Policymaker's cost-risk trade-off from risk-sharing contracts

where $RP_r^{PM}(\lambda) \coloneqq RP_{\lambda r}^{PM}$ 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, $\text{Var}(r)$, 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 with heterogeneous risk premiums and costs. When the auction allows bidders to choose the share of production they include in the contract, the risk-sharing parameter becomes investor-specific, $\lambda = q_i$, reflecting investor i's portfolio allocation between the risk-free contract and the risky wholesale market. For investor i, equation (3) implies that the policymaker's expected net expenditure is

$$E[NE_i(q_i)] = c_i - E[r] + RP_{ri}(1 - q_i),$$

so heterogeneity in both costs and risk attitudes shapes the fiscal implications of contracting with different bidders. The policymaker evaluates these options based on her own preferences, and her relevant certainty-equivalent measure is $E[NE_i(q_i)] + RP_r^{PM}(q_i)$. While the risk-premium function RP_r^{PM} is fixed by the policymaker's preferences, its argument q_i varies with the investor's chosen share. Thus, investor heterogeneity indirectly affects the policymaker's evaluation by influencing the risk exposure she ultimately bears.

Because the policymaker does not observe either c_i or RP_{ri}, she cannot directly identify which investor minimizes her certainty-equivalent expenditure. Auctions help reveal this information, but the winning bidder typically earns an information rent, whose magnitude reflects both competition and the auction format. Under heterogeneous risk aversion, these information rents embed not only differences in technological costs but also differences in how investors value risk, which drive their choices of q_i and bid prices. As a result, auction outcomes reflect a blend of cost heterogeneity and risk-premium heterogeneity. This motivates the empirical strategy that uses bidders' portfolio-based share choices to infer heterogeneous risk premiums and to quantify the policymaker's cost–risk trade-off.

I use 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

Since 2005, MME and ANEEL have organized long-term power purchase agreement auctions to contract new renewable generation capacity across multiple auction types—New Energy Auctions (Leilão de Energia Nova), Alternative Sources Auctions (Leilão de Fontes Alternativas), and Reserve Energy Auctions (Leilão de Energia de Reserva)—covering hydro, biomass, wind, and solar. While Brazil had historically relied on abundant hydropower, expanding non-hydro renewables became essential for several reasons (Werner and Lazaro, 2023). First, it became increasingly difficult to build new large-scale hydroelectric capacity to meet the expanding demand for electricity and sustain economic growth without affecting the Amazon rainforest's 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 following a drought. This incident promoted diversification of electricity sources to ensure energy security through a balanced mix.

MME awards long-term power purchase agreements to new generation capacity through these auctions. I focus on wind energy auctions because they 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 based on their applications 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

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

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.[7] 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.[8]

The auction format was sealed-bid pay-as-bid until 2015, when it switched to a descending-clock pay-as-bid procedure. Both formats are pay-as-bid in settlement, so each winner's purchase agreement will be based on their final submitted bid. They differ only in the bidding procedure, and I therefore refer to these two auction formats as sealed-bid and descending-clock auctions throughout the paper. In sealed-bid auctions, winners receive a purchase agreement as specified in their one-shot sealed bids. For example, a winner who bids a share of 80% and a price of \$40/MWh receives a purchase agreement for 80% of his production at \$40/MWh. In descending-clock auctions, bidders fix their bid shares at the beginning, and CCEE runs an iterative descending clock: it announces a tentative clearing price and allows bidders to revise their prices downward until that price no longer changes. Theoretically, in the continuous-clock limit, this iteration leads the winners' final prices converge to a common clearing price. Deviations from exact alignment arise in practice because the clock is implemented in discrete steps with a minimum decrement (Hochberg and Poudineh, 2018).

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 electric-

[7]Before 2018, the marginal project was fully contracted, even if it pushed contracted capacity above the procurement capacity; afterward, it could receive only a capped partial contract or withdraw. I exclude marginal projects subject to partial contracts (11 out of 783 winners) from the analysis because the observed final quantity may not reflect the original bid choice.

[8]I do not consider collusion. Collusion is unlikely in these auctions given the large number of qualified participants (typically 400–600), low winner shares (at most 20%), and the non-disclosure of procurement capacity. Moreover, because I observe only winners' bids, I cannot reliably distinguish collusive from competitive behavior; standard detection approaches typically require both winners' and losers' bids (e.g., Porter and Zona, 1993; Chassang et al., 2022; Kawai and Nakabayashi, 2022).

ity to consumers, procure electricity through these purchase agreements.[9] 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 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.

3.1 Data

I primarily use three publicly available data sources. First is the auction results database maintained by CCEE (CCEE, 2022). The auction database gives the auction

[9]The purchase agreements use two remuneration schemes: quantity contracts (quantidade de energia) and availability contracts (disponibilidade de energia). Under quantity contracts, generators commit to a fixed average energy supply and are paid according to actual generation. Under availability contracts, generators commit to make capacity available and are remunerated through a fixed payment regardless of actual generation. Across the 24 auctions analyzed, 11 used quantity contracts and 13 used availability contracts, with a mix over time. I use both auction types jointly in the estimation since my model abstracts from generation fluctuations and therefore delivers identical implications under either remuneration scheme. See also footnote 12 for a related discussion about generation fluctuations.

date, designated commercial operation date, winners' capacities, and winners' bid shares and prices. Second, the auction registration and qualification reports provided by EPE, including the number of participants and the total capacities qualified for bidding (EPE, 2022a). Last is the electricity spot prices provided by CCEE (CCEE, 2023). Additionally, I collect ten-year forecasts of the marginal cost of operation of the Brazilian power system (Custo Marginal de Operação) from EPE's Ten-Year Energy Expansion Plan (EPE, 2026). All prices used in the analysis are adjusted for inflation using 2022 as the base year and are converted to U.S. dollars assuming a 5-to-1 Brazilian Real to U.S. Dollar exchange rate.

I analyze 24 wind energy auctions with 772 winning bids totaling 9.3 GW of capacity from 2009 to 2021. New wind energy auctions began in 2009, and the length of purchase agreements was set at the wind turbine's expected lifetime, 20 years, until 2021.[10] There were 16 sealed-bid auctions from 2009 to 2015 (600 winning bids) and 8 descending-clock auctions from 2017 to 2021 (172 winning bids).

Table 1 reports auction-level summary statistics. The number of participants is missing for two sealed-bid auctions. Consequently, I use all auctions to recover bidders' wholesale-market beliefs from their bid choices, but I drop these two auctions in the cost-estimation step: estimating the winning probability function requires the number of participants, and without it, I cannot map bids back to costs. The auctions are competitive, typically selecting a few dozen winners from several hundred qualified participants or several hundred MWs of capacity from the order of 10 GW of qualified capacity. I define an auction's procurement capacity as the sum of the winners' capacities allocated to that auction. Procurement capacities are smaller in later years, consistent with a slowdown in forecasted demand growth.

Table 2 summarizes the distribution of the 772 winning bids. In sealed-bid auctions, bid shares are tightly concentrated near full allocation (mean 0.94; interquartile range $[0.93, 1.00]$; 5th–95th percentile range $[0.71, 1.00]$). In contrast, descending-clock auctions display much greater variation in shares (mean 0.56; interquartile range $[0.30, 0.90]$), with many bids falling well below the upper boundary. This difference is crucial for estimation. In sealed-bid auctions, bid prices rarely reach the low-price regions that would induce shares to meaningfully depart from one. Consequently, the

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

Table 1: Summary statistics of 24 wind energy auctions

	N	Mean	SD	Range
16 Sealed-Bid Auctions (2009–2015)				
Lead Time (years)	16	2.9	0.8	[2.0, 4.4]
Number of Participants	14	341	123	[172, 577]
Participants Total Capacity (GW)	14	8.6	3.0	[3.9, 14.2]
Number of Winners	16	38	24	[3, 97]
Procurement Capacity (MW)	16	414.4	244.9	[29.7, 989.6]
8 Descending-Clock Auctions (2017–2021)				
Lead Time (years)	8	4.0	1.1	[2.5, 5.3]
Number of Participants	8	565	211	[315, 829]
Participants Total Capacity (GW)	8	16.7	5.8	[8.9, 24.1]
Number of Winners	8	23	21	[2, 49]
Procurement Capacity (MW)	8	180.9	248.2	[15.2, 691.8]

Notes: Procurement capacity is the sum of the winners' capacities allocated to the auction. N is the number of auctions with non-missing values used for each variable's calculation. SD stands for standard deviation.

share-price relationship lacks variation exactly where it is most informative about risk aversion. Descending-clock auctions, however, exhibit rich variation in interior share choices. I therefore combine data from both auction formats, using the structural model to justify their joint usage. By linking observed share choices to the relevant purchase agreement prices, the model allows the two formats to jointly discipline wholesale-market beliefs. Capacity levels remain relatively stable across formats, averaging roughly 12 MW per winning bid.

3.2 Descriptive Evidence

Overall, 43.5% of winners partially allocate their allocatable production to the auction, consistent with portfolio behavior in which investors trade off expected revenues against revenue risk. Risk-averse bidders make partial allocations to balance the expected revenue and revenue variability. Figure 2 shows a binned scatter plot of bid shares against purchase agreement prices. The relationship is highly non-linear and exhibits a clear boundary pattern: at high purchase agreement prices, bid shares are mostly stuck at one (full allocation), while shares begin to decline as purchase agree-

Table 2: Summary statistics of 772 winning bids

	N	Mean	SD	IQR	[P5, P95]
16 Sealed-Bid Auctions (2009–2015)					
Bid Share	600	0.94	0.10	[0.93, 1.00]	[0.71, 1.00]
Purchase Agreement Price ($/MWh)	600	45.5	8.9	[39.4, 53.3]	[36.3, 63.6]
Capacity (MW)	600	11.7	4.0	[9.4, 14.1]	[5.0, 16.3]
8 Descending-Clock Auctions (2017–2021)					
Bid Share	172	0.56	0.28	[0.30, 0.90]	[0.30, 0.97]
Purchase Agreement Price ($/MWh)	172	25.2	3.3	[23.5, 26.0]	[21.0, 33.2]
Capacity (MW)	172	11.8	7.2	[4.8, 16.4]	[1.8, 19.8]

Notes: SD stands for standard deviation. N is the number of bids with non-missing values used for each variable's calculation. IQR reports the interquartile interval [Q1, Q3]. [P5, P95] reports the 5th and 95th percentiles.

ment prices move into the low-price region. This is exactly the qualitative pattern implied by the model's optimal portfolio rule: when the purchase agreement price is sufficiently attractive, bidders optimally allocate all production to the purchase agreement; when it becomes less attractive, bidders shift exposure toward the wholesale market and bid smaller shares (cf. the model-implied share schedule in Figure 4(a)).

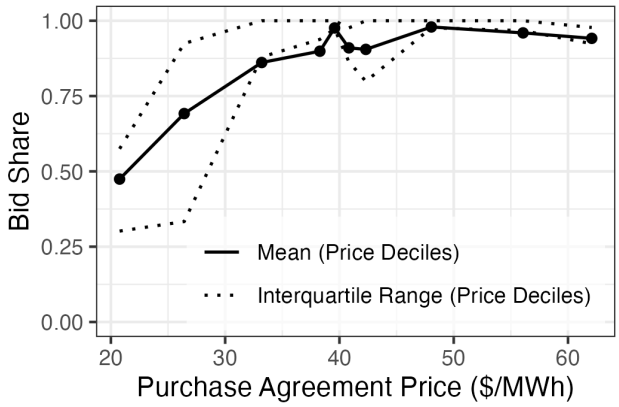


Figure 2: Relationship between bid shares and purchase agreement prices

Table 3 reports regressions of bid shares on covariates. The estimated price coefficient remains positive and statistically significant at 5% level after including additional auction and bidder controls. I use the average of the 6th to 10th years of the ten-year forecasts of the marginal cost of power system operation to create a

variable reflecting future wholesale-market conditions (variable "Forecasted Marginal Cost of Electricity"). The forecasted marginal cost at the time of auction enters negatively, consistent with interpreting it as a proxy for future wholesale-market conditions: when wholesale prices are expected to be higher, bidders optimally allocate more electricity to the wholesale market and bid smaller shares into the purchase agreement.

Capacity enters positively: larger projects allocate relatively more to the purchase agreement, i.e., they leave less electricity to be exposed to wholesale-market risk. This capacity pattern is informative for modeling. In the baseline portfolio-choice logic written in per-capacity terms, two bidders facing the same prices and having the same risk-aversion parameter would choose the same share. The positive capacity–share relationship therefore motivates allowing risk aversion to vary systematically with capacity in the heterogeneous-risk extension. Conceptually, this bridges two polar benchmark specifications: CARA defined over total profits tends to push large projects toward higher contract shares (because total risk exposure scales with size), whereas CARA defined over profits per unit of capacity implies size-invariant portfolio shares. Allowing the risk-aversion coefficient to depend on capacity captures an empirically relevant middle ground while preserving the tractability of the CARA-based portfolio rule.

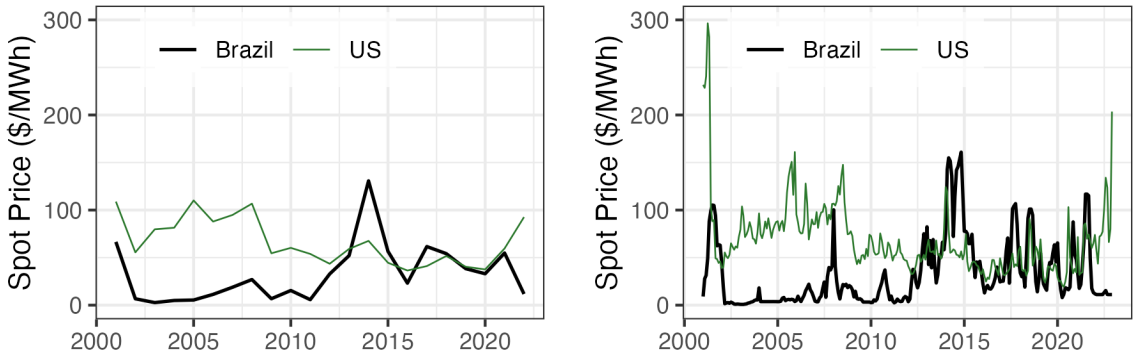
I use spot market electricity prices to get a sense of the wholesale market volatility. Figure 3 compares the spot prices in Brazil and the U.S.[11] The standard deviations (SDs) of Brazil's annual and monthly spot prices are comparable to the U.S. In Brazil, the SD of spot prices is \$30.49/MWh across years and \$35.35/MWh across months, whereas in the U.S., they are \$24.42/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 (mean divided by SD) 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.

[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 (EIA, 2024). The prices are adjusted for inflation using the Consumer Price Index, with 2022 as the base year (BLS, 2023).

Table 3: Bidder regressions using bid shares as the dependent variable

	(1)	(2)	(3)
Purchase Agreement Price ($/MWh)	0.0100	0.0134	0.0134
	(0.0037)	(0.0039)	(0.0036)
Forecasted Marginal Cost of Electricity ($/MWh)		−0.0144	−0.0146
		(0.0068)	(0.0065)
Capacity (MW)			0.0098
			(0.0042)
Number of observations	772	772	772
Number of auctions	24	24	24
R^2	0.27	0.34	0.39

Notes: Standard errors (in parentheses) are clustered at the auction level. The forecasted marginal cost of electricity is the average of the 6th to 10th years of the ten-year forecasts of the marginal cost of operation of the Brazilian power system (Custo Marginal de Operação) at the time of the auction, collected from EPE's Ten-Year Energy Expansion Plan (EPE, 2026).



(a) Annual average

(b) Monthly average

Figure 3: Electricity spot prices in Brazil and the U.S. from 2001–2022

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 make portfolio choices to allocate their total production across the risk-free purchase agreement and risky wholesale

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 $q_i \times Capacity_i \times H$ hours of electricity for each period at price p_i, which is determined as a function of participants' bid prices $b_1, \ldots, b_N$ according to 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 CARA utility, u, over their per unit net present value (NPV) π with heterogenous risk aversion, i.e., $u_i(\pi) = u(\pi|\gamma_i) = (1 - \exp(-\gamma_i \pi))/\gamma_i$, where $\gamma_i > 0$ is the risk aversion coefficient. A concave utility over

[12] The production amount and purchase agreement price can be uncertain at the time of bidding due to 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 receive, 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.

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 variable costs VC_{it} per unit of production for each t during the purchase agreement. Thus, bidder i's per unit NPV of winning is

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

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 can be written as

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

where $r := T^{-1} \sum_{t=l}^{l+T-1} \delta^t r_t$ summarizes the future wholesale prices, $RP_r(1-q_i|\gamma_i)$ 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 ($T^{-1} \sum_{t=l}^{l+T-1} \delta^t VC_{it}$), 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: $RP_r(1-q_i|\gamma_i) = (1-q_i)^2 \cdot \gamma_i \sigma_r^2/2$. The risk premium becomes high with

[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 sealed-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.

the wholesale market share, $1 - q_i$, risk aversion coefficient γ_i, 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 risk aversion, $\gamma_i \in [\underline{\gamma}, \bar{\gamma}] \subset \mathbb{R}_+$, cost, $c_i \in [\underline{c}, \bar{c}]$, and $Capacity_i \in [\underline{C}, \bar{C}] \subset \mathbb{R}_+$ 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 sealed-bid and descending-clock auctions.

4.1 Sealed-Bid Auctions

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

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

where the winning probability is the probability that 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 capacity D,

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

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). I derive a sufficient condition for the existence of a monotone pure-strategy BNE by applying Reny (2011) in Online Appendix A.1. Under the same condition, a symmetric monotone pure-strategy BNE exists when bidders are *ex-ante* symmetric, i.e., bidders independently

draw their private types (risk aversion γ_i, cost c_i, and $Capacity_i$) from a common distribution.

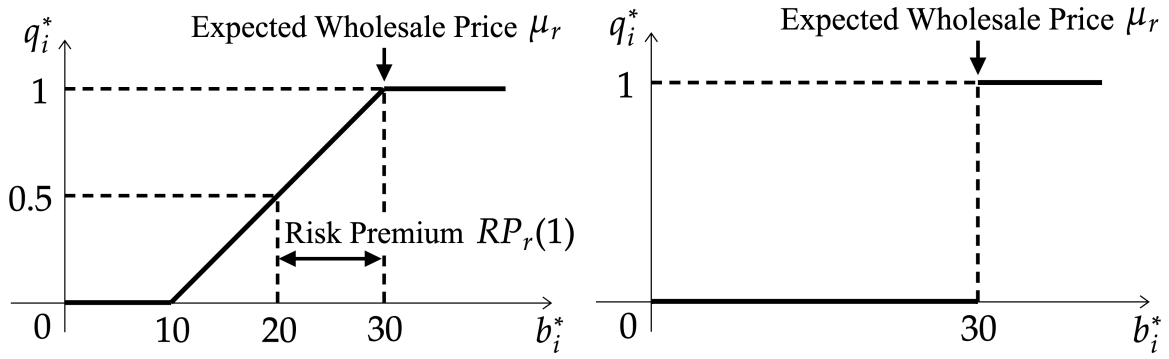
The optimal bid share and price characterize the equilibrium bid strategy. Bidder i's optimal bid share satisfies $q_i^* = \min\left\{\max\left\{\underline{q},\ q^{**}(b_i^* \mid \gamma_i)\right\},\ 1\right\}$, where $q^{**}(b \mid \gamma_i)$ is an unconstrained optimal bid share function defined as

$$q^{**}(b \mid \gamma_i) = 1 - \frac{\mu_r - \tilde{\delta} b}{\gamma_i \sigma_r^2}. \tag{7}$$

Figure 4(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 of selling all electricity to the wholesale market, $RP_r(1 \mid \gamma_i) = \gamma_i \sigma_r^2 / 2 = 30 - 20 = 10$, 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 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 4(b)).

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, given his own risk aversion γ_i, in any equilibrium.[15] 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

[15] 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.



(a) Risk-averse bidder (b) Risk-neutral bidder

Figure 4: Bidders' optimal bid shares when $\delta = 1$ and $\underline{q} = 0$

once b_i^* is fixed. 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

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

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 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 bidder's risk aversion coefficient γ_i 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 ($\gamma_i \to 0$ 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 Descending-Clock Auctions

I analyze descending-clock auctions in line with Milgrom and Weber (1982)'s English auction model. Institutionally, these auctions are implemented as a discrete descending-clock, pay-as-bid procedure, but, for tractability, I treat them as the

continuous-clock limit in which the outcome is equivalent to a uniform-price auction: bidders choose a cutoff—the lowest price they are willing to accept—as their "bid price" b_i, and winners would be paid a common clearing price pinned down at the margin, i.e., $p_i = p \coloneqq b_{M+1:N}$, where M is the number of winners and $b_{M+1:N}$ denotes the $(M+1)$th lowest of N bid prices.[16] Derivations and proofs of the statements in this section are in Online Appendix A.2.

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

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

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., $p^* \coloneqq b^*_{M+1:N}$. To keep the equilibrium analysis tractable, I assume f_{p^*} is normally distributed, $\mathcal{N}(\mu_{p^*}, \sigma^2_{p^*})$, and independent of the wholesale price r.[17] Under an additional condition that I detail in Online Appendix A.2, by Reny (2011), a monotone pure-strategy BNE exists, and a symmetric monotone pure-strategy BNE exists when bidders are *ex-ante* symmetric.

Bidder i's optimal bid share satisfies $q^*_i = \min\left\{\max\left\{\underline{q},\ q^{**}(b^*_i \mid \gamma_i)\right\},\ 1\right\}$, where $q^{**}(b \mid \gamma_i)$ is an unconstrained optimal bid share function implicitly defined as the solution to

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

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

[16] In the actual discrete-clock implementation, winners' final submitted prices may not coincide, and the equality $p_i = p$ may not hold exactly because bids adjust in discrete steps with a minimum decrement. I examine the robustness of this continuous-clock approximation by varying the equilibrium clearing price distribution around values implied by winners' observed final submitted prices in Section 6.

[17] Independence is reasonable if the main drivers of the clearing price and wholesale prices differ: clearing prices move with the distribution of wind-project costs, while Brazil's wholesale-price uncertainty is primarily driven by marginal hydroelectric and thermal fuel costs.

given risk aversion γ_i,

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

where Λ is the inverse Mills ratio for a standard normal. For a risk-neutral bidder ($\gamma_i \to 0$), $\tilde{\mu}_{p^*}$ 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 $b + q\gamma_i\tilde{\delta}\sigma^2_{p^*}$ 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 sealed-bid auctions in Figure 4(a), though the relationship is now nonlinear. Second, a large equilibrium clearing price variance $\sigma^2_{p^*}$ has two counteracting effects. It lowers q_i^* because the purchase agreement becomes unattractive relative to the wholesale market (channel through the term $\tilde{\delta}^2\sigma^2_{p^*}/\sigma^2_r$ 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_i is unclear because both purchase agreement and wholesale prices are uncertain at the time of bidding. Intuitively, the risk from the clearing price uncertainty becomes more salient than the risk of the wholesale market when the bidder puts most of his electricity into the purchase agreement, which makes more risk-averse bidders move away from the purchase agreement once the bid share gets close enough to 1.

5 Econometric Model

I present my identification results and then specialize the structural model for estimation using Brazil's new wind energy auctions.

5.1 Identification

I observe the joint distribution of winners' bids (shares and prices) and the capacities selected based on the bid prices. The challenge is to recover the joint distribution of equilibrium bids and capacities, $f_{q^*,b^*,C}$, from their distribution of winners. I assume the bids and capacities, $(q_i^*, b_i^*, Capacity_i)$, $i = 1, \ldots, N$, are independently drawn from $f_{q^*,b^*,C}$ (i.e., i.i.d.). They are i.i.d. when the bidders are symmetric (i.e., *ex-ante* symmetric and follow a symmetric equilibrium strategy). If we arrange the bid prices in ascending order to obtain the order statistics, $b_{1:N}^* \leq \cdots \leq b_{N:N}^*$, then the bid shares and capacities paired with them, $q_{[1:N]}^*, \cdots, q_{[N:N]}^*$ and $Capacity_{[1:N]}, \cdots, Capacity_{[N:N]}$, are called the *concomitants* of the order statistics (Yang, 1977). I extend the idea of using order statistics to identify the entire participants' one-dimensional bid distribution from winning bids in Athey and Haile (2002) to multidimensional bids, where winners are selected by one dimension of the bids. I build on the statistics literature of the concomitants to connect the joint distribution of concomitants and order statistics to the original distribution from which they are drawn. Particularly, I rely on the fact that the conditional distribution of a concomitant $Y_{[k:N]}$ given its paired order statistic $X_{k:N}$ equals that of the original distribution, i.e., $f_{Y_{[k:N]}|X_{k:N}} = f_{Y|X}$ for any $k = 1, \ldots, N$, if the draws are i.i.d. (Yang, 1977). Intuitively, the conditional relationship is preserved as the pairs are kept the same while sorting them based on the order statistics.

I identify the joint distribution of bidders' risk aversion coefficients γ_i and costs c_i. I also identify the expected wholesale price μ_r in sealed-bid auctions. I assume that the number of participants N, the distribution of procurement capacity D, and the wholesale market variance σ_r^2 at the time of the auction are observed for each auction. The discount factor δ is prespecified.

Sealed-Bid Auctions. I observe the joint distribution of the pairs of concomitants and order statistics, $f_{q_{[k:N]}^*, b_{k:N}^*, C_{[k:N]}}$, for winners, $k = 1, \ldots, M$, where $1 \leq M \leq N$ is the number of winners. I identify the original distribution as

$$f_{q^*,b^*,C} = f_{q^*,C|b^*} f_{b^*} = f_{q_{[k:N]}^*, C_{[k:N]}|b_{k:N}^*} f_{b^*}$$

since there is a one-to-one relationship between f_{b^*} and $f_{b_{k:N}^*}$ when the draws are i.i.d. (Athey and Haile, 2002), and $f_{q_{[k:N]}^*, C_{[k:N]}|b_{k:N}^*}$ and $f_{b_{k:N}^*}$ are observed for any k up to

M.

Bidders allocate all production to the risk-free purchase agreement when their discounted bid price $\tilde{\delta} b_i^*$ is higher than the expected wholesale price μ_r, regardless of their types. Thus, the bids with 100% bid share identify μ_r as the lowest bid price at which 100% bid share occurs: $\mu_r = \tilde{\delta} \cdot \inf\{b : \Pr(q^* = 1 \mid b) > 0\}$. Once I have μ_r, I can pin down γ_i of those who bid q_i^* in the interior of the possible bid share $[\underline{q}, 1]$ by their optimal bid share decisions (equation (7)) since c_i does not affect the decision on top of b_i^*. I then recover c_i using the solution to the optimal bid price decision (equation (8)) with μ_r and γ_i, as Guerre, Perrigne and Vuong (2000), by calculating the equilibrium winning probability function using $f_{q^*,b^*,C}$.

Note that the types (γ_i, c_i) are point identified only for those who bid q_i^* in the interior of $[\underline{q}, 1]$. Any $\gamma_i > 0$ can justify the bid share of 100%, and the bid share of $\underline{q}$ only provides an upper bound for γ_i. In principle, I can point identify (γ_i, c_i) if I have sufficient variation in the observed bid shares for each i. I make parametric assumptions to point identify the distribution of γ_i, f_γ, in estimation. Once f_γ is identified, I can point identify the distribution of c_i as well. Alternatively, I can evaluate the lower bound on the bidders' total wholesale market risk premium, which is a relevant measure for the policymaker, by setting the risk premiums of those with unidentified γ_i to zero. Somewhat surprisingly, c_i is partially identified without the identification of γ_i because the markup term in the optimal bid price decision is bounded as

$$0 < \frac{1}{\gamma_i} \ln\left(-\frac{\gamma_i \tilde{\delta} W_i^*(b_i^*)}{dW_i^*(b_i^*)/db} + 1\right) < -\frac{\tilde{\delta} W_i^*(b_i^*)}{dW_i^*(b_i^*)/db} \text{ for } \gamma_i \in (0, \infty),$$

and this can be narrowed down by an upper bound on γ_i for those bidding $\underline{q}$ share.

Descending-Clock Auctions. I observe the joint distribution of the winners' concomitants and the lowest order statistics among the losers, $f_{Y_{[1:N]},\ldots,Y_{[M:N]},b^*_{M+1:N}}$, where $Y_{[k:N]} = (q^*_{[k:N]}, C_{[k:N]})$.[18] $b^*_{M+1:N}$ is observed as the equilibrium clearing price p^*. As in sealed-bid auctions, the key is to identify the conditional distribution $f_{Y|b^*}$

[18] To be precise, I do not observe the ordering of the winners' concomitants since the winners' bid prices are unobserved. However, the following argument does not require that ordering because I only use the points that the concomitants are all tied, $Y_{[1:N]} = \cdots = Y_{[M:N]}$, to prove the identification. The ordering information can improve the efficiency of the estimation, since the latent bid price distribution for each winner can be inferred more accurately from it.

from the observed joint distribution since f_{b^*} is identified from the order statistic distribution I observe, $f_{b^*_{M+1:N}}$. The observed joint distribution can be expressed using the conditional distribution as follows (Yang, 1977):

$$f_{Y_{[1:N]},\ldots,Y_{[M:N]}|b^*_{M+1:N}}(y_1,\ldots,y_M|b_{M+1}) = \int^{b_{M+1}} \cdots \int^{b_2} \prod_{k=1}^{M} f_{Y_{[k:N]}|b^*_{k:N}}(y_k|b_k) f_{b^*_{1:N},\ldots,b^*_{M:N}|b^*_{M+1:N}}(b_1,\ldots,b_M|b_{M+1}) d(b_1,\ldots,b_M). \tag{10}$$

Since $f_{Y_{[k:N]}|b^*_{k:N}} = f_{Y|b^*}$ for all $k = 1,\ldots,M$, and the joint distribution of the order statistics $f_{b^*_{1:N},\ldots,b^*_{M:N}|b^*_{M+1:N}}$ can be calculated from f_{b^*}, the structure of the identification problem becomes similar to nonparametric instrumental variable models (Newey and Powell, 2003). Following that literature, I show the identification of (bounded) $f_{Y|b^*}$ under bounded completeness of certain conditional distributions in Appendix A. Bounded completeness admits very general families of distributions, and its sufficient conditions and testing procedures are extensively discussed (e.g.,Blundell, Chen and Kristensen, 2007; Hu and Schennach, 2008; Freyberger, 2017).

I cannot identify the expected wholesale price μ_r as in sealed-bid auctions since the bidders' risk aversion type γ_i always affects their optimal bid share decision (equation (9)), because both the purchase agreement and the wholesale prices are uncertain at the time of bidding. Thus, I assume that μ_r is identified from the data for descending-clock auctions. In the empirical application, I extrapolate the μ_r identified in sealed-bid auctions by parameterization.

I can then identify f_γ from bidders' bid share decisions, together with the observed clearing price distribution f_{p^*}. Because winners' bid prices b_i^* are unobserved in descending-clock auctions, I cannot identify each bidder's γ_i from a single observed share choice. Instead, identification of f_γ uses (i) the model-implied mapping from (b_i^*, γ_i) to q_i^* (equation (9)) and (ii) the implied distribution of winners' latent bid prices b_i^* conditional on the observed clearing price p^*, i.e., $f_{b^*|(b^*<p^*)}$. Variation in observed bid shares across auctions with different clearing price realizations, together with this truncation relationship, disciplines f_γ. Once f_γ is identified, I can identify the distribution of c_i by combining the equilibrium relationship that b_i^* is a cutoff at which his expected utility from winning is zero and $f_{b^*|(b^*<p^*)}$.

5.2 Estimation

The estimation procedure applies the optimal bid share and price decisions sequentially. I index an auction by a. I first use the solution to the bid share decision, equivalent to the portfolio optimization, to estimate the distribution of the risk aversion coefficient distribution γ_{ia}, f_{γ_a}, and the expected wholesale price μ_{ra}. I then infer the distribution of the cost types c_{ia}, f_{c_a}, using the solution to the bid price optimization problem. I do not pursue estimating f_{c_a} in descending-clock auctions because I only observe 8 clearing prices that inform about it. I assume symmetric bidders because I only observe winners' bids, as discussed in Section 5.1. I maintain the following assumption for estimation:

Assumption 1. *The optimal bid share, evaluated at the equilibrium bid price b^*_{ia}, is observed as a censored normal model with the unconstrained optimal bid share function q^{**} (defined in equations (7) and (9) for sealed-bid and descending-clock auctions, respectively), i.e.,*

$$q^d_{ia} = \min\left\{\max\left\{\underline{q}, q^{**}(b^*_{ia} \mid \gamma_{ia}) + \eta_{ia}\right\}, 1\right\}, \eta_{ia} \sim \mathcal{N}(0, \sigma^2_{\eta a}),$$

where q^d_{ia} is the observed bid share, and η_{ia} is a bid share shock that is independent across bidders and auctions.

Bolotnyy and Vasserman (2023) also make a similar assumption similar in their scaling auction model estimation, 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.

Prespecified Parameters. I prespecify the wholesale market variance σ^2_{ra}. I estimate a mean reverting process of annual wholesale prices using time-series data of spot prices. I then calculate each auction's σ^2_{ra} with the future wholesale prices r_t following the estimated mean reverting process.

I also prespecify descending-clock auctions' equilibrium clearing price distributions $f_{p^*_a} = \mathcal{N}(\mu_{p^*a}, \sigma^2_{p^*a})$. Although Section 5.1 shows the identification of $f_{p^*_a}$, I do not estimate it because I only observe 8 clearing prices. I model the equilibrium clearing price distribution conditional on the procurement capacity D_a, $f_{p^*_a|D_a}$, with auction covariates, including auction date, lead time, forecasted marginal cost of electricity

at the time of auction, and number of participants. I then integrate it out by the procurement capacity distribution f_{D_a} below to obtain $f_{p_a^*}$ because D_a is not disclosed at the time of bidding. I prespecify the parameters in $f_{p_a^*|D_a}$ to those that maximize the likelihood of the observed clearing prices and D_a.

I model f_{D_a} with auction covariates and prespecify the parameters to maximize the likelihood of the observed D_a, separately for sealed-bid and descending-clock auctions. f_{D_a} for sealed-bid auctions is used to calculate the winning probability function in the second step of estimation. f_{D_a} for descending-clock auctions is used to obtain $f_{p_a^*} = f_{p_a^*|D_a} f_{D_a}$. Prespecified parameter values are summarized in Online Appendix C. The discount factor δ is prespecified to be the annual rate of 0.95.

First Step. I estimate winners' risk aversion coefficient γ_{ia}, the expected wholesale price μ_{ra}, and the bid share shock variance $\sigma^2_{\eta a}$ by method of simulated moments using the moment conditions implied by Assumption 1. I allow heterogeneous γ_{ia} across bidders with different capacities as $\gamma_{ia} = \exp(\alpha_{\gamma 0} + \alpha_{\gamma 1} \log(Capacity_i))$. The heterogeneity relaxes the per-capacity portfolio-choice implication that bidders facing the same prices and having the same risk parameter choose the same share. This specification captures the observed positive capacity–share pattern in Table 3 by letting effective risk tolerance vary systematically with project size, which can be interpreted as an intermediate case between CARA preferences defined over total profits and preferences defined over per-capacity payoffs, while keeping the CARA-normal portfolio mapping tractable.

I specify $\mu_{ra} = \delta^{l_a}(\alpha_{r0} + \alpha_{r1} m_a)$, where l_a is the lead time and m_a is forecasted marginal cost of electricity at the time of auction a. I include m_a to capture time variation in bidders' expected wholesale prices. The descriptive regressions in Table 3 show that m_a is negatively associated with bid shares, which is consistent with interpreting m_a as a proxy for more favorable wholesale-market conditions: when wholesale prices are expected to be higher, bidders shift exposure toward the wholesale market and bid smaller shares. Additionally, the expected wholesale price is discounted according to the auction's lead time l_a. I assume $\sigma^2_{\eta a}$ to be the same across auctions.

Simulation is necessary because I do not observe winners' equilibrium bid prices in descending-clock auctions. For each winner in descending-clock auctions, I draw their

latent equilibrium bid prices b^*_{ia} from the equilibrium bid price distribution conditional on being below the observed final bid price b^d_{ia}, $f_{b^*_a|(b^*_a \leq b^d_{ia})}$, which is calculated from the equilibrium clearing price distribution $f_{p^*_a}$ using the one-to-one relationship between $f_{b^*_a}$ and $f_{p^*_a} = f_{b^*_{M_a+1:N_a}}$. I compute the moments for each draw and average them to form the simulated individual moments. In sealed-bid auctions, I use observed bid prices, assuming they are equilibrium bid prices, to form the individual moments without simulation.

Second Step. I estimate the cost distribution f_{c_a} in sealed-bid auctions. To evaluate the winning probability and invert bids into costs, I recover the participants' joint distribution of $(\gamma_{ia}, Capacity_{ia}, b^*_{ia})$ from their winners' information, following the order-statistics and concomitants arguments in Section 5.1. First, I estimate $f_{b^*_a}$ from winners' bid prices using the likelihood function for the order statistics. $f_{b^*_a}$ is assumed to be normally distributed with auction-specific mean and common variance across auctions.

Second, I recover the conditional capacity distribution $f_{C_a|b^*_a}$ from winners, which is justified by the property of concomitants: under i.i.d. draws, the conditional distribution of a concomitant given its paired order statistic equals the original conditional distribution. So, the conditional distribution of winners' capacities given their bid prices equals that of participants. $f_{C_a|b^*_a}$ is assumed to be log-normally distributed with the mean parameterized by b^*_{ia} and auction fixed effects, and common variance across auctions. Combining these gives the joint distribution $f_{C_a,b^*_a} = f_{C_a|b^*_a} f_{b^*_a}$. Given my parameterization of the deterministic relationship between γ_{ia} and $Capacity_{ia}$ in the first step, f_{C_a,b^*_a} directly implies f_{γ_a,C_a,b^*_a}.[19]

I next compute the sealed-bid auction's equilibrium winning probability functions W^*_{ia} using f_{γ_a,C_a,b^*_a}. W^*_{ia} is symmetric for symmetric bidders, i.e., $W^*_{ia} = W^*_a$ for all i. f_{γ_a,C_a,b^*_a} implies f_{C_a,q^*_a,b^*_a} because b^*_{ia} uniquely determines the equilibrium bid share q^*_{ia} as the solution to the bid share decision conditional on γ_{ia}. Assuming the independence of f_{C_a,q^*_a,b^*_a} and the prespecified procurement capacity distribution f_{D_a}, I simulate $W^*_a(b)$ according to equation (6) using these two distributions.

I finally 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

[19]Even if γ_{ia} were not deterministically tied to $Capacity_{ia}$, the same logic would recover $f_{\gamma_a,C_a|b^*_a}$ from their winners' information and then construct $f_{\gamma_a,C_a,b^*_a} = f_{\gamma_a,C_a|b^*_a} f_{b^*_a}$.

from the estimated $f_{\gamma_a, q_a^*, b_a^*}$ by simulation.

6 Structural Estimates

I first estimate the bidders' risk aversion and expected wholesale prices from bid share decisions using all 16 sealed-bid and 8 descending-clock auctions from 2009 to 2021. I then recover the bidders' cost distribution using 14 sealed-bid auctions (with the number of participants data) from 2009 to 2015. I describe the summary statistics of the distribution of risk aversion coefficients γ_i based on the estimates from the 14 sealed-bid auctions used in the cost estimation to make them compatible with those of the cost distribution. Additionally, all summary statistics are capacity-weighted averages across auctions.

Table 4 shows estimates for the risk aversion parameters α_γ and expected wholesale price parameters α_r. The estimates imply winners' average risk aversion coefficient γ_i of 0.46 (s.e., 0.01). The estimate indicates that bidders are risk averse when selling electricity into the wholesale market. A bidder with γ_i of 0.46 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 \$31.50/MWh, while the expected price is \$35/MWh. Nonetheless, γ_i 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, if the true wholesale market variance σ_r^2 is larger than the current specification, bidders would be less risk averse, and the 50–50 lottery's certainty equivalent price would be closer to the expected price. This is because γ_i changes reciprocally to σ_r^2 according to their relationship to the risk premium, $RP_r(1|\gamma_i) = \gamma_i \sigma_r^2/2$, and the risk premium estimate is robust to the misspecification of the wholesale market variance.

According to the log-log specification of γ_i and $Capacity_i$, 1% increase of capacity is associated with 0.95% increase in γ_i approximately. Thus, larger projects are estimated to be more risk averse per unit of capacity and reduce their exposure to the wholesale market more by bidding higher shares. This result is consistent with the positive capacity–bid share pattern in Table 3 and conforms with the idea that heterogenous risk aversion allows the model to be the middle ground between ho-

Table 4: First stage structural parameter estimates from bid share decisions

Parameter	Estimate
Log Risk Aversion Coefficient, $\log(\gamma_i)$	
Intercept, $\alpha_{\gamma 0}$	−3.235 (0.064)
Log Capacity (MW), $\alpha_{\gamma 1}$	0.952 (0.027)
Discounted Expected Wholesale Price (\$/MWh), μ_r	
Intercept, α_{r0}	22.15 (0.19)
Forecasted Marginal Cost of Electricity (\$/MWh), α_{r1}	0.109 (0.005)
Standard Deviation of Bid Share Shock, σ_η	0.088 (0.001)

Notes: The parameters are estimated using all 16 sealed-bid and 8 descending-clock auctions from 2009 to 2021. The forecasted marginal cost of electricity is the average of the 6th to 10th years of the ten-year forecasts of the marginal cost of operation of the Brazilian power system (Custo Marginal de Operação) at the time of the auction, collected from EPE's Ten-Year Energy Expansion Plan (EPE, 2026). Standard errors (in parentheses) are calculated using 200 auction-level block bootstrap replications.

mogenous CARA preferences defined over per-capacity payoffs and over total profits.

The estimated α_r implies expected wholesale prices ranging from \$39.50/MWh to \$42.62/MWh across all auctions from 2009 to 2021. These expected wholesale prices are comparable to the average spot price since 2009 (to 2022), \$41.22/MWh. The stationary expected wholesale price implied by the mean reverting process of annual spot prices from 2001 to 2022, \$29.41/MWh, is close to the average spot price from 2001 to 2022, \$32.75/MWh, but is much lower than these expected wholesale prices implied by the bids. This discrepancy underscores the importance of the estimation of the expected wholesale prices using bids. The model predicted optimal bid shares from the estimated α_γ and α_r fit the observed bid shares reasonably well (Figure 5).

Given these first stage estimates, I estimate the winning probability functions and then infer costs from bid price decisions in sealed-bid auctions. The estimated winning probability functions yield plausible winning probabilities for the observed bids (Figure D1 in Online Appendix D plots the predicted winning probabilities for each auction). The estimated equilibrium bid price and capacity distributions used to calculate the equilibrium winning probability function are summarized in Online Appendix D.

The estimated winners' average cost and markup are \$24.01/MWh (s.e., \$0.13/MWh)

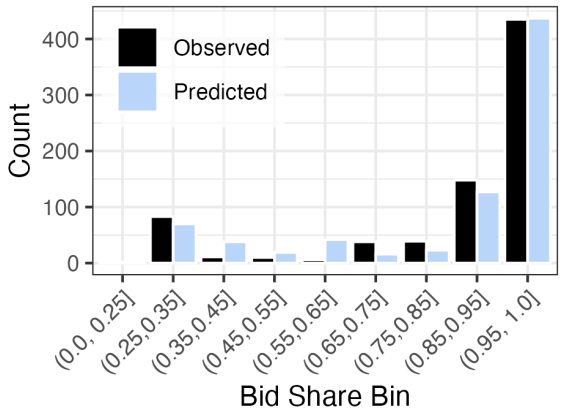


Figure 5: Observed and model predicted bid shares of all 772 bidders used in the first stage estimation

and \$1.03/MWh (s.e., \$0.09/MWh), respectively. Winners' average risk premium of selling all electricity into the wholesale market amounts to 29.5% of the cost, \$7.09/MWh (s.e., \$0.23/MWh). For the 549 winners included in the second stage estimation (total capacity of 6.4 GW, 3.6% of the overall generation capacity in Brazil in 2020 (Tolmasquim et al., 2021)), these estimates imply that the winners' overall risk premium is \$8.0 billion for wind turbines costing \$27.0 billion on aggregate. In other words, to entice these investors to install wind turbines costing \$27.0 billion, the policymaker would save \$8.0 billion by taking on 100% of the wholesale market risk, relative to a subsidy policy that left all the risk with the investors.

Table 5 summarizes the estimated joint distribution of the risk aversion coefficient γ_i and cost c_i of the entire participant pool. The average γ_i is lower than that of the winners (participants, 0.43 vs. winners, 0.46), although the difference is small relative to its standard deviation of 0.15. This standard deviation demonstrates substantial heterogeneity in risk aversion across participants. The implied risk premium for the 1 standard deviation above the average investor would be 2.1 times the 1 standard deviation below the average investor.

The average cost of participants is \$2.63/MWh higher than that of winners. Thus, the average winner has 1.6 standard deviations lower cost than the average participant. The cost estimates are in a reasonable range compared to the engineering estimates.[20] The correlation between the participants' risk aversion coefficient and

[20]EPE's engineering cost estimates imply the participants' cost distribution having a mean and

Table 5: Summary statistics of the estimated risk aversion coefficient γ_i and cost c_i distribution

Statistic	Risk Aversion	Cost ($/MWh)
Mean	0.43 (0.03)	26.64 (0.12)
Standard Deviation	0.15 (0.01)	1.64 (0.10)
Correlation	−0.03 (0.09)	

Notes: The joint distribution is estimated using the 14 sealed-bid auctions (with the number of participants and participants' total capacity data) from 2009 to 2015. The values are total capacity-weighted averages across auctions. Standard errors (in parentheses) are calculated using 200 auction-level block bootstrap replications.

cost is weak. Still, the negative correlation is consistent with the idea that bidders with a larger capacity might have lower costs.

I linearly project the participants' cost distribution on the time variables to understand the cost trend (linear projection coefficients tabulated in Table D2 in Online Appendix D). The inferred average participant cost exhibits a marked U-shaped pattern over 2009–2015 (values are calculated setting the lead time to zero). Average costs fall steeply from $42/MWh in 2009 to a trough of $27/MWh in 2012 ($15/MWh, 35% decline), then reverse and rise persistently to $38/MWh by 2015 ($11/MWh, 40% increase from the trough). Two factors account for the price hike from 2013 to 2015 (Tolmasquim et al., 2021). First, a large local equipment provider went bankrupt in 2014. Second, Brazil's base interest rates hiked from an annual average of 8% 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 $0.53/MWh annually,[21] even though the cost increased from 2012 to 2015, which implies that the wind turbine cost inflation was unexpected to the investors.

standard deviation of $23.22/MWh and $3.06/MWh, respectively, from 2010 to 2015 (EPE, 2022b). This engineering cost mean is close to the estimated average cost calculated for the same period (2010–2015), $22.67/MWh.

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

7 Conclusion

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

In fact, in Brazil, wind turbine investors' wholesale market risk premiums reach 29.5% of their costs. For 3.6% of Brazil's generation capacity auctioned from 2009 to 2015, the policymaker is expected to save $8.0 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.

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 $8.0 billion. In contrast, a risk-averse policymaker, evaluating her risk premium as the same as the average investor, would balance her expected net expenditure and risk premium. As a result, she would prefer taking half the risk to save $4.0 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).

A key contribution of this paper is to develop and estimate a framework with joint heterogeneity in bidders' risk premiums and costs, using portfolio choices embedded in auctions. This heterogeneity naturally implies selection effects: policies that leave risk with investors tend to favor low-risk-premium bidders, while greater public risk absorption can expand the set of competitive bidders and shift the composition of winners—with potential distributional implications if risk premiums vary systematically across investor types (e.g., smaller developers). An important next step is to quantify these selection and distributional channels in counterfactual exercises that recompute equilibrium bidding and allocation under alternative risk-sharing rules. Implementing such counterfactuals is generally nontrivial in multidimensional bidding environments, and recent work such as Richert (2024) provides a useful template for conducting counterfactual auction analysis when strategic responses are multidimensional. More broadly, separately identifying heterogeneity in beliefs about expected returns versus heterogeneity in risk premiums remains of independent interest for understanding portfolio choices (Egan, MacKay and Yang, 2023).

A Identification of Descending-Clock Auctions

I assume the following bounded completeness and show the identification of bounded $f_{Y|b^*}$ under this assumption.

Assumption 2 (Bounded completeness of conditional order statistic distributions)**.** *For $k = 1, \ldots, M$, and any bounded function h on the space of bid price b^*,*

$$\int^{b_{k+1}} h(b_k) f_{b^*_{k:N}|b^*_{k+1:N}}(b_k|b_{k+1}) db_k = 0 \text{ for all } b_{k+1} \text{ implies } h(b_k) = 0 \text{ a.s.}$$

Proof. I can transform the joint distribution of the order statistics into a sequence of conditional distributions using the Markov property of order statistics (e.g., Arnold,

Balakrishnan and Nagaraja, 2008):

$$\begin{aligned} f_{b^*_{1:N},\ldots,b^*_{M:N}|b^*_{M+1:N}} &= f_{b^*_{1:N},\ldots,b^*_{M-1:N}|b^*_{M:N},b^*_{M+1:N}} f_{b^*_{M:N}|b^*_{M+1:N}} \\ &= f_{b^*_{1:N},\ldots,b^*_{M-1:N}|b^*_{M:N}} f_{b^*_{M:N}|b^*_{M+1:N}} \quad (\because \text{Markov property}) \\ &= \cdots = f_{b^*_{1:N}|b^*_{2:N}} f_{b^*_{2:N}|b^*_{3:N}} \cdots f_{b^*_{M:N}|b^*_{M+1:N}}. \end{aligned} \tag{11}$$

Consider two observationally equivalent conditional distributions $f^A_{Y|b^*}$ and $f^B_{Y|b^*}$. Equations (10), (11), and Assumption 2 imply $\prod_{k=1}^M f^A_{Y|b^*}(y|b) = \prod_{k=1}^M f^B_{Y|b^*}(y|b)$ for any y and b. Thus, $f^A_{Y|b^*} = f^B_{Y|b^*}$, which concludes the proof. □

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Online Appendix

A Equilibrium Strategy

A.1 Sealed-Bid Auctions

I demonstrate a sufficient condition for the existence of a monotone pure-strategy BNE in sealed-bid auctions in Section 4.1 using Reny (2011). Bidder i's bid price b uniquely determines his optimal bid share given his risk aversion type γ as in equation (7):

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

Thus, the game satisfies conditions (i) and (ii) of Proposition 3.1 in Reny (2011) because the support of the two-dimensional type space is compact and the bid price is effectively the only action bidders consider.

Bidder i's expected utility of action b, given his risk aversion type γ and cost type c, is $\mathrm{EU}_i(b|\gamma, c) \coloneqq W_i(b) \cdot u(\mathrm{CE}(q^*(b|\gamma), b|\gamma, c)|\gamma)$, where CE is a certainty equivalent function defined as

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

By Corollary 4.2 of Reny (2011), a monotone pure-strategy BNE exists if this expected utility satisfies $\partial^2\mathrm{EU}_i(b|\gamma, c)/\partial b\partial c \geq 0$ and $\partial^2\mathrm{EU}_i(b|\gamma, c)/\partial b\partial\gamma \geq 0$ for all b, γ, and c in the support for every monotone pure-strategy BNE of competitors. I show when these conditions hold below.

Define $\mathrm{CE}_b \coloneqq \mathrm{CE}(q^*(b|\gamma), b|\gamma, c)$ for brevity. Note

$$\frac{\partial\mathrm{EU}_i(b|\gamma, c)}{\partial b} = W_i'(b) \cdot u(\mathrm{CE}_b|\gamma) + W_i(b) \cdot u'(\mathrm{CE}_b|\gamma) \cdot q^*(b|\gamma)\tilde{\delta}.$$

First,

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

However, the direction of

$$\begin{aligned}\frac{\partial^2 \mathrm{EU}_i(b|\gamma,c)}{\partial b \partial \gamma} = W_i'(b) \cdot \left\{ -u'(\mathrm{CE}_b \,|\, \gamma) \cdot \frac{\partial RP_r(1-q^*(b|\gamma) \mid \gamma)}{\partial \gamma} + \frac{\partial u(\mathrm{CE}_b \mid \gamma)}{\partial \gamma} \right\} \\ - W_i(b) \cdot u''(\mathrm{CE}_b \,|\, \gamma) \cdot \frac{\partial RP_r(1-q^*(b|\gamma) \mid \gamma)}{\partial \gamma} \cdot q^*(b|\gamma)\tilde{\delta} \\ + W_i(b) \cdot \left\{ \frac{\partial u'(\mathrm{CE}_b \mid \gamma)}{\partial \gamma} \cdot q^*(b|\gamma)\tilde{\delta} + u'(\mathrm{CE}_b \,|\, \gamma) \cdot \frac{\partial q^*(b|\gamma)}{\partial \gamma}\tilde{\delta} \right\}.\end{aligned}$$

may depend on γ, though all terms are nonnegative except the term involving $\partial u'(\mathrm{CE}_b|\gamma)/\partial\gamma$. Thus, a monotone pure-strategy BNE exists if the right hand side is nonnegative.

Additionally, if the bidders are *ex-ante* symmetric, a symmetric monotone pure-strategy BNE exists under the same condition by Theorem 4.5 of Reny (2011).

A.2 Descending-Clock Auctions

I first derive the optimal bid share decision in descending-clock auctions in Section 4.2. A bidder with risk aversion type γ and cost type c chooses his bid (q, b) to maximize

$$(1 - F_{p^*}(b)) \cdot E[u(q\tilde{\delta}p_b^* + (1-q)r - c|\gamma)],$$

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

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

where $K_Y(\tau) \coloneqq \log E[\exp(\tau Y)]$ is a cumulant of a random variable Y. Note, for any τ,

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

where Λ is the inverse Mills ratio for a standard normal. Then, the optimal bid share satisfies equation (9) in Section 4.2 as

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

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

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

The unconstrained optimal bid share function $q^{**}(b|\gamma)$ is defined as a solution of q to equation (9) for a given b.

I next show $\partial q^{**}(b|\gamma)/\partial b > 0$. Differentiating both sides of equation (9) with respect to b, I obtain

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

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

$$\frac{\partial q^{**}(b|\gamma)}{\partial \gamma} = \frac{\mu_r - \tilde{\delta}\tilde{\mu}_{p^*}(q^{**}(b|\gamma),b|\gamma) - q^{**}(b|\gamma)\gamma\tilde{\delta}^2\sigma_{p^*}^2\Lambda'\left(\frac{\mu_{p^*}-b}{\sigma_{p^*}} - q^{**}(b|\gamma)\gamma\tilde{\delta}\sigma_{p^*}\right)}{\gamma^2\left\{\sigma_r^2 + \left(1+\Lambda'\left(\frac{\mu_{p^*}-b}{\sigma_{p^*}} - q^{**}(b|\gamma)\gamma\tilde{\delta}\sigma_{p^*}\right)\right)\tilde{\delta}^2\sigma_{p^*}^2\right\}}$$

can be negative if q^{**} is close enough to 1. Intuitively, the risk from the clearing price uncertainty is more salient than the risk of the wholesale market when the bidder puts most of his electricity into the purchase agreement, which makes more risk-averse bidders move away from the purchase agreement.

Lastly, I show a sufficient condition for the existence of a monotone pure-strategy BNE using Reny (2011), similarly to sealed-bid auctions in Online 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 game satisfies conditions (i) and (ii) of Proposition 3.1 in Reny (2011).

The expected utility of action b for a bidder with risk aversion type γ and cost type c is $\mathrm{EU}(b|\gamma,c) \coloneqq (1-F_{p^*}(b))\cdot u(\mathrm{CE}(q^*(b|\gamma),b|\gamma,c)|\gamma)$. Define

$$\Delta_\Lambda(b|\gamma) \coloneqq \frac{1}{\sigma_{p^*}}\left[\Lambda\left(\frac{\mu_{p^*}-b}{\sigma_{p^*}}\right)-\Lambda\left(\frac{\mu_{p^*}-b}{\sigma_{p^*}}-q^*(b|\gamma)\gamma\tilde{\delta}\sigma_{p^*}\right)\right],$$

and $\mathrm{CE}_b \coloneqq \mathrm{CE}(q^*(b|\gamma),b|\gamma,c)$ for brevity. $\Delta_\Lambda(b|\gamma) < 0$ since Λ is a decreasing function. Note $\partial u(\mathrm{CE}_b|\gamma)/\partial b = -\gamma^{-1}u'(\mathrm{CE}_b|\gamma)\cdot\Delta_\Lambda(b|\gamma)$. First,

$$\frac{\partial^2\mathrm{EU}(b|\gamma,c)}{\partial b\partial c} = f_{p^*}(b)\cdot u'(\mathrm{CE}_b|\gamma)+(1-F_{p^*}(b))\cdot\gamma^{-1}u''(\mathrm{CE}_b|\gamma)\cdot\Delta_\Lambda(b|\gamma) \;>\; 0.$$

However, the direction of

$$\begin{aligned}\frac{\partial^2\mathrm{EU}(b|\gamma,c)}{\partial b\partial\gamma} &= -f_{p^*}(b)\cdot\left[u'(\mathrm{CE}_b|\gamma)\cdot\frac{\partial\mathrm{CE}_b}{\partial\gamma}+\frac{\partial u(\mathrm{CE}_b|\gamma)}{\partial\gamma}\right]\\ &+(1-F_{p^*}(b))\cdot\left[\Delta_\Lambda(b|\gamma)\cdot\left\{\gamma^{-2}u'(\mathrm{CE}_b|\gamma)-\gamma^{-1}\left(u''(\mathrm{CE}_b|\gamma)\cdot\frac{\partial\mathrm{CE}_b}{\partial\gamma}+\frac{\partial u'(\mathrm{CE}_b|\gamma)}{\partial\gamma}\right)\right\}\right.\\ &\left.-\gamma^{-1}u'(\mathrm{CE}_b|\gamma)\cdot\frac{1}{\sigma_{p^*}}\Lambda'\left(\frac{\mu_{p^*}-b}{\sigma_{p^*}}-q^*(b|\gamma)\gamma\tilde{\delta}\sigma_{p^*}\right)\times\left(\gamma\frac{\partial q^*(b|\gamma)}{\partial\gamma}+q^*(b|\gamma)\right)\tilde{\delta}\sigma_{p^*}\right]\end{aligned}$$

may depend on γ. The first line is positive, and the last line is also non-negative, as

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

The terms in the curly bracket can be rewritten as

$$\gamma^{-2}\left(1+\gamma\mathrm{CE}_b+\gamma^2\cdot\frac{\partial\mathrm{CE}_b}{\partial\gamma}\right)\exp(-\gamma\mathrm{CE}_b),$$

which will be positive unless the bidders are sufficiently risk averse to make $\gamma^2\partial\mathrm{CE}/\partial\gamma$ negative enough. Therefore, the expected utility satisfies the conditions in Corollary 4.2 of Reny (2011) when the bidders are not too risk averse.

As in sealed-bid auctions, if the bidders are *ex-ante* symmetric, a symmetric monotone pure-strategy BNE exists under the same conditions by Theorem 4.5 of Reny (2011).

B Estimation Procedures

B.1 Wholesale Market Price 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., $\sigma_r^2 = \mathrm{Var}(T^{-1} \sum_{t=l}^{l+T-1} \delta^t r_t)$. 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

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

B.2 Equilibrium Clearing Price Distribution

I detail the calculation of the descending-clock auction's equilibrium clearing price distribution. I specify the conditional distribution of equilibrium clearing price p^* given procurement capacity D as

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

where s is the auction date, l is the lead time, m is the forecasted marginal cost of electricity at the auction date, and N is the number of participants. 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 sum of the auction date and the lead time, $s + l$, is the scheduled operation start date, which intends to capture the trend of bidders' costs parsimoniously. Forecasted marginal cost of electricity m proxies the expected wholesale price, which affects the bidding decision. I use the parameters $(\beta_{pD0}, \beta_{pD1}, \beta_{pD2}, \beta_{pD3}, \beta_{pD4}, \sigma^2_{pD})$ that maximize the likelihood.

I specify the log procurement capacity ($\log D$) distribution similarly,

$$f_{\log D} = \mathcal{N}(\beta_{D0} + \beta_{D1}(s + l) + \beta_{D2}m + \beta_{D3}N, \sigma^2_D), \tag{12}$$

and use the parameters $(\beta_{D0}, \beta_{D1}, \beta_{D2}, \beta_{D3}, \sigma^2_D)$ that maximize the likelihood. Integrating out the procurement capacity from the conditional equilibrium clearing price distribution yields the (marginal) equilibrium clearing price distribution: $f_{p^*} = \mathcal{N}(\mu_{p^*}, \sigma^2_{p^*})$, where

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

and $\mu_D = \beta_{D0} + \beta_{D1}(s + l) + \beta_{D2}m + \beta_{D3}N$.

B.3 Equilibrium Winning Probability Function

I detail the calculation of the sealed-bid auction's equilibrium winning probability function. First, I estimate the log capacity ($\log C$) distribution, conditional on the equilibrium bid price b^*, specified as

$$f_{\log C|b^*} = \mathcal{N}(\beta_C b^* + \delta_a, \sigma^2_C),$$

where δ_a is the auction fixed effects, by maximum likelihood estimation (MLE), regarding the observed bid price b_i as the equilibrium bid price b^* for bidder i.

Next, I estimate the equilibrium bid price distribution specified as

$$f_{b^*} = \mathcal{N}(\delta_a, \sigma^2_b)$$

by MLE. I form a likelihood using the distribution of order statistics. The individual log-likelihood for bidder i to have the observed bid price b_i and bid price rank counted from the lowest within the auction, $brank_i$, is

$$\ln f_{b^*}(b_i) + (brank_i - 1)\ln F_{b^*}(b_i) + (N - brank_i)\ln(1 - F_{b^*}(b_i)),$$

where F_{b^*} is the CDF for the equilibrium bid price distribution. I specify the procurement capacity distribution in the same way as for descending-clock auctions in equation (12) in Online Appendix B.2.

I then compute the (symmetric) equilibrium winning probability function W^* by simulation. Consider a sealed-bid auction with lead time l, N participants, minimum possible bid share $\underline{q}$, forecasted marginal cost of electricity m, and distributions for the conditional capacity type, equilibrium bid price, and procurement capacity given as $f_{\log C|b^*}$, 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 each $z = 1, \ldots, Z$, draw the following variables independently: a procurement capacity, $D^z \sim f_D$; for $j = 1, \ldots, N-1$, competitors' bid prices, $(b_j^*)^z \sim f_{b^*}$; and, for $j = 1, \ldots, N-1$, competitors' capacity types conditional on their bid price draws, $Capacity_j^z \sim f_{\log C|(b_j^*)^z}$.

2. Calculate the risk aversion coefficient $\hat{\gamma}_j^z$ for each competitor j using the estimated structural parameters from the first step in Section 5.2, as

$$\hat{\gamma}_j^z = \exp(\hat{\alpha}_{\gamma 0} + \hat{\alpha}_{\gamma 1}\log(Capacity_j^z)).$$

3. Compute the equilibrium winning probability function as

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

where $\hat{q}^*$ is the optimal bid share function as in Section 4.1 with the first step

estimates:

$$\hat{q}^*(b|\gamma) \coloneqq \min\left\{\max\left\{\underline{q}, 1 - \frac{\delta^l(\hat{\alpha}_{r0} + \hat{\alpha}_{r1}m) - \tilde{\delta}b}{\gamma\sigma_r^2}\right\}, 1\right\}.$$

I smooth the indicator functions in the last step using a normal CDF, denoted Φ, following Ryan (2022). The indicator function for the bid price, $\mathbb{1}(b' < b)$, is smoothed as $\Phi((b - b')/h_b)$, where I set the bandwidth parameter to be $h_b = \$2$/MWh, about 1/30 of the level of a typical bid. The indicator function for the procurement capacity, $\mathbb{1}(D' < D)$, is smoothed as $\Phi((D - D')/h_D)$, where I set the bandwidth parameter to be $h_D = 15$ MW, about 1/30 of the level of a typical procurement capacity. I calculate $\hat{W}^*(b)$ for a grid of b with \$0.20/MWh increments and linearly interpolate between the grid points. I simulate $Z = 2000$ times and numerically differentiate $\hat{W}^*(b)$ to obtain the derivative $d\hat{W}^*(b)/db$.

C Prespecified Parameter Values

Wholesale market volatility. Table C1 tabulates the parameter estimates for the mean reverting process of annual wholesale prices in Online Appendix B.1. The estimated wholesale price standard deviation (SD), σ_r, ranges from \$4.94/MWh to \$5.85/MWh across 24 auctions (16 sealed-bid and 8 descending-clock 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 C1 demonstrates that σ_r decreases by the lead time approximately linearly across 24 auctions used in the analysis.

Procurement capacity distribution. Panel A of Table C2 reports the fitted parameter values of the log procurement capacity model in Online Appendix B.2. The fitted procurement capacity models for sealed-bid and descending-clock auctions are used to calculate the equilibrium winning probability function (Online Appendix B.3) and equilibrium clearing price distribution (Online Appendix B.2), respectively. Note that most of the following analysis requires the number of participants, which is not available for 2 sealed-bid auctions. So, the following analysis uses 14 sealed-bid and 8 descending-clock auctions with the number of participants data unless otherwise

Table C1: Annual wholesale price process parameter estimates

Parameter	Estimate
Intercept, A	17.7 (16.4)
AR(1) Coefficient, ρ	0.40 (0.33)
Standard Deviation of Residual, σ_ξ	729.1 (197.1)

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.

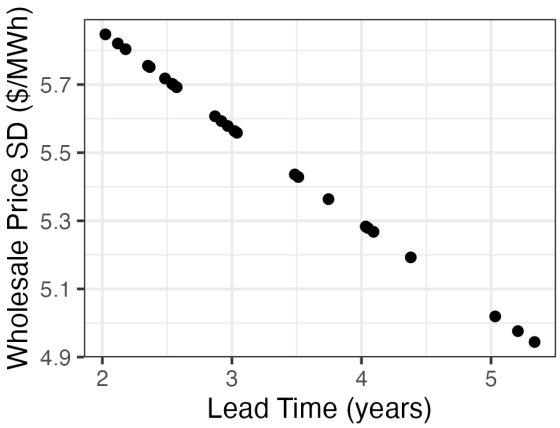


Figure C1: Relationship between the estimated wholesale price standard deviation (SD) and lead time across 24 auctions used in the analysis

noted.

The procurement capacity is expected to decline due to a later operation start date, a higher forecasted marginal cost, and fewer participants. The expected procurement capacity ranges from 18.3 MW to 631.4 MW across 14 sealed-bid auctions and 92.2 MW to 617.6 MW across 8 descending-clock auctions.

Equilibrium clearing price distribution. Panel B of Table C2 reports the fitted parameter values of the conditional equilibrium clearing price model for descending-clock auctions in Online Appendix B.2. The expected clearing price drops with less procurement capacity and a larger number of participants, reflecting the auction's competitiveness. The fitted conditional clearing price distribution and descending-clock auction's procurement capacity distribution yield (marginal) clearing price distributions with a mean, μ_{p^*}, ranging from $20.73/MWh to $35.62/MWh (across 8

Table C2: Prespecified auction distribution parameter values

Parameter	Sealed-Bid	Descending-Clock
A. Log Procurement Capacity (MW) Distribution		
Intercept, β_{D0}	8.51	7.38
Operation Start (year), β_{D1}	−0.40	−0.06
Forecasted Marginal Cost ($/MWh), β_{D2}	−0.06	−0.20
100 Participants, β_{D3}	0.52	0.75
Standard Deviation of Residual, σ_D	0.58	0.50
B. Equilibrium Clearing Price ($/MWh) Distribution		
Intercept, β_{pD0}	-	−1.33
Log Procurement Capacity (MW), β_{pD1}	-	5.08
Operation Start (year), β_{pD2}	-	2.61
Forecasted Marginal Cost ($/MWh), β_{pD3}	-	−0.09
100 Participants, β_{pD4}	-	−4.70
Standard Deviation of Residual, σ_{pD}	-	0.82

Notes: The parameter values maximize the likelihood of the observed log procurement capacities (MW) for Panel A, and the observed clearing prices ($/MWh) for Panel B. The forecasted marginal cost is the average of the 6th to 10th years of the ten-year forecasts of the marginal cost of operation of the Brazilian power system (Custo Marginal de Operação) at the time of the auction, collected from EPE's Ten-Year Energy Expansion Plan (EPE, 2026). The operation start is defined as the year since the beginning of 2010.

descending-clock auctions) and SD, σ_{p^*}, of \$2.69/MWh. The SD of \$2.69/MWh is larger than that of the conditional clearing price distribution, $\sigma_{pD} = \$0.82$/MWh, reflecting the uncertainty bidders face because the procurement capacity is not disclosed at the time of bidding.

D Other Structural Estimates

I estimate the equilibrium bid price and capacity distributions to calculate the equilibrium winning probability function for each sealed-bid auction as described in Online Appendix B.3. Table D1 shows the parameter estimates for the equilibrium bid price distribution and the conditional log capacity distribution given the bid price. Bidders understand that the competitors' equilibrium bid prices follow a distribution with a mean ranging from \$37.57/MWh to \$66.87/MWh (across 14 sealed-bid auctions) and

SD of \$2.71/MWh. The capacity distribution is estimated using all 16 sealed-bid auctions since it does not require the number of participants data.

Table D1: Equilibrium bid price and log capacity distributions parameter estimates

Parameter	Bid Price	Log Capacity
Bid Pirce (\$10/MWh)	-	−0.02 (0.13)
Auction Fixed Effects		
Auction 1	66.87 (0.15)	2.46 (0.79)
Auction 2	55.50 (0.34)	2.66 (0.63)
Auction 3	59.05 (0.25)	2.63 (0.69)
Auction 4	41.82 (0.25)	2.42 (0.48)
Auction 5	42.19 (0.26)	2.59 (0.48)
Auction 6	43.54 (0.21)	2.56 (0.49)
Auction 7	37.57 (0.37)	2.78 (0.39)
Auction 8	42.04 (0.22)	2.33 (0.50)
Auction 9	46.66 (0.28)	2.25 (0.53)
Auction 10	43.93 (0.22)	2.44 (0.50)
Auction 11	46.69 (0.28)	2.64 (0.53)
Auction 12	-	2.44 (0.57)
Auction 13	48.30 (0.30)	2.55 (0.55)
Auction 14	59.86 (0.37)	2.76 (0.67)
Auction 15	58.38 (0.31)	2.69 (0.66)
Auction 16	-	2.78 (0.74)
Standard Deviation of Residual	2.71 (0.17)	0.36 (0.01)

Notes: The log capacity distribution is estimated using all 16 sealed-bid auctions, while the bid price distribution is estimated using 14 sealed-bid auctions with number of participants data. Standard errors (in parentheses) are calculated using 200 auction-level block bootstrap replications.

The expected capacity drops by about 2% (though not statistically significant) when the bid price increases by \$10/MWh (large considering the bid price distribution's SD of \$2.71/MWh). The negative correlation between capacity and bid price is consistent with the idea that bidders with a larger capacity might have lower costs and thus bid more aggressively. The expected capacity ranges from 8.6 MW to 14.8 MW (calculated across 14 sealed-bid auctions plugging in the estimated expected bid price for each auction).

Figure D1 plots the predicted winning probabilities of the observed winners' bid prices in each sealed-bid auction. Most predicted winning probabilities drop on the

steep slope of the equilibrium winning probability functions, meaning the predicted probabilities are reasonably far from the two extremes, 0 and 1, as expected.

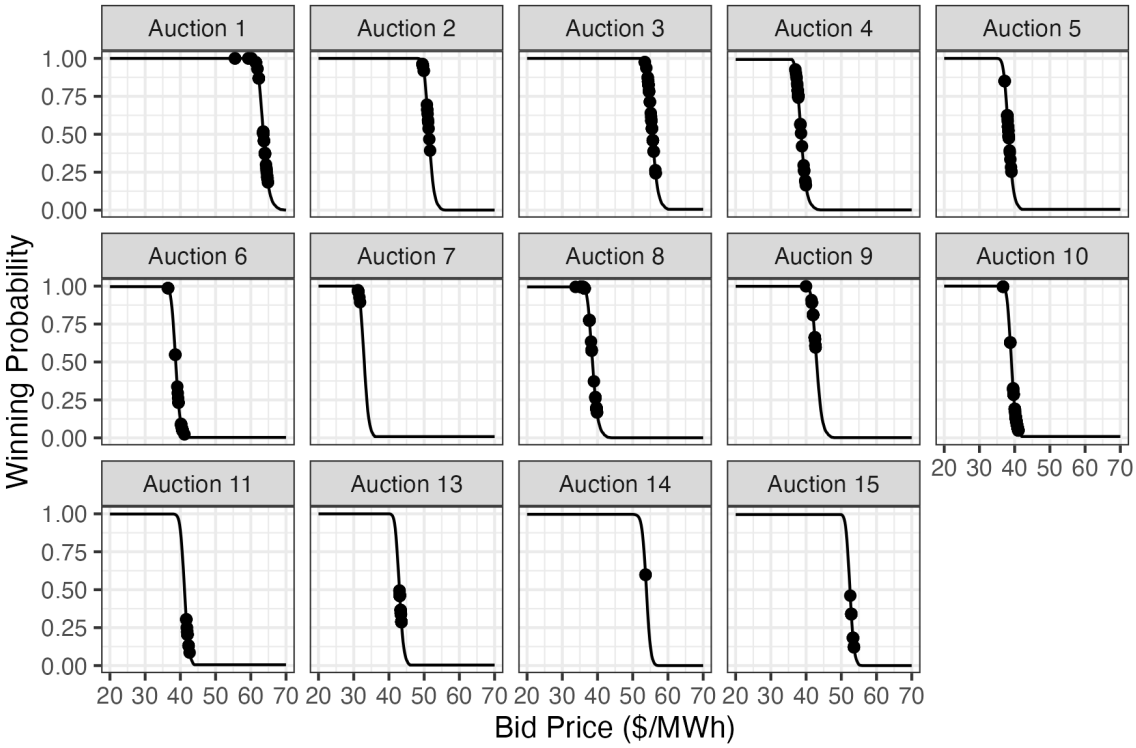


Figure D1: Estimated equilibrium winning probability functions and the predicted winning probabilities of the observed winning bids

Table D2: Linear projection of the estimated cost distribution

Variable	Main Specification	Undiscounted
Intercept	41.07 (0.11)	43.26 (0.12)
Auction Date (year)	−10.96 (0.12)	−12.62 (0.13)
Auction Date Square	2.37 (0.04)	2.75 (0.05)
Auction Date Cubic	−0.094 (0.005)	−0.111 (0.006)
Lead Time (year)	−1.71 (0.02)	−0.53 (0.02)

Notes: The values are estimated using the 14 sealed-bid auctions (with the number of participants data) from 2009 to 2015. The main specification column uses the estimated cost distribution, and the undiscounted column undiscounts the cost distribution by the lead time before the linear projection. The auction date is defined as the year since the beginning of 2010. Standard errors (in parentheses) are calculated using 200 auction-level block bootstrap replications.