Encouraging Renewable Investment: Risk Sharing Using Auctions*

Konan Hara†

March 1, 2024

Job Market Paper

Link to the latest version

Abstract

Volatile wholesale electricity prices can discourage investors from building new renewable capacity because this volatility makes the investors' future revenue stream uncertain. Policymakers use power purchase agreements to take this wholesale market risk from renewable investors to support new projects. In achieving policymakers' renewable energy targets, policymakers face a trade-off between the risks they take and additional payments to investors because policymakers must compensate investors for the risk premium when the investors take the risk. I study this trade-off in the context of Brazilian wind energy auctions that award these purchase agreements for a share of production the winners bid into the auction. In these auctions, wind turbine investors make a portfolio choice to allocate their production across a risk-free purchase agreement and a risky wholesale market. I develop and estimate a structural auction model that separately recovers the investors' risk aversion and private costs. I find that investors are substantially risk averse: investors require an additional risk premium of \$20.16/MWh to accept the risk of selling all electricity into the wholesale market, where revenues have a standard deviation of \$5.44/MWh. For 3% of Brazil's generation capacity auctioned, the policymaker will expect to save \$20 billion by taking the entire wholesale market risk because of the investors' risk aversion.

*I am especially grateful to Ashley Langer, Hidehiko Ichimura, Derek Lemoine, Juan Pantano, and Matthijs Wildenbeest for their feedback, support, and guidance. I would also like to thank Christian Cox, Price Fishback, Yuki Ito, Stanley Reynolds, Eduardo Souza-Rodrigues, Evan Taylor, Tiemen Woutersen, Mo Xiao, and seminar participants at the University of Arizona and Arizona Workshop on Environment, Natural Resource, and Energy Economics for many useful comments and suggestions. The computations used the University of Arizona High Performance Computing (HPC) resources supported by the University of Arizona TRIF, UITS, and Research, Innovation, and Impact (RII) and maintained by the UArizona Research Technologies department. All errors are my own.

†Department of Economics, University of Arizona. Email: harakonan@arizona.edu

1 Introduction

In response to the threat of climate change, government policies have increasingly tried to encourage the construction of new renewable energy projects.[1] Yet, profits of renewable energy investors—who expect financial returns from sales of electricity produced from new renewable capacity—depend on revenues from wholesale electricity markets that typically have volatile prices. This volatility can discourage renewable investors from building new capacity and (IEA and OECD, 2008; Bürer and Wüstenhagen, 2009), as such, leads policymakers to consider policies to reduce investors' wholesale market risk exposure.

This paper studies renewable power purchase agreements, which are contracts that guarantee a certain electricity price regardless of the wholesale market price. Policymakers have advocated these purchase agreements as an investment-supporting scheme because purchase agreements enable *risk sharing* between investors and the policymaker (Farrell et al., 2017). To understand the value of these policies, I model contracts between policymakers and risk-averse renewable investors that share this electricity price risk. When the investor bears a larger risk, the policymaker must provide a larger upfront payment to compensate for the investor's risk premium and encourage the investor to move forward with a renewable energy project.[2] Conversely, the policymaker may choose to take on more of the electricity price risk in order to lower the up-front payment to the investor for the project. Thus, the policymaker faces a trade-off between the upfront payment of contracts and the risk she must take. The extent of this trade-off is determined by the investor's risk aversion and cost.

I exploit that certain auctions involve renewable investors' portfolio choices to identify their risk aversion and costs using a structural auction model. I further use my model to quantify the effectiveness of auctions, which are receiving growing attention as mechanisms to distribute these purchase agreements efficiently.[3] Auctions identify the lowest-cost investors, leading to lower contract prices without knowing investors' costs. Considering

[1] Nearly all countries have set renewable energy targets (REN21, 2023).
[2] In the extreme case where the investor bears all the risk, these policies are equivalent to subsidies.
[3] 106 countries have held auctions to distribute renewable power purchase agreements (IRENA, 2019).

investors' costs as unobservable is especially important in renewable technologies because of their rapid and unpredictable cost evolution.[4]

I study these trade-offs in the context of unique long-term purchase agreement auctions that allow bidders to have portfolio choices for wind energy in Brazil from 2011–2021. A defining feature of these auctions is that bidders with a new wind turbine project 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 of this share. The lowest-price bidders (or winners) commit to install the planned project capacity in exchange for the purchase agreement.

The winners secure a risk-free revenue stream for the share of their production that they bid into the auction since the purchase agreements cover the entire lifetime of the wind turbines. Consequently, bidders make a portfolio choice to allocate the total production across a risk-free purchase agreement and a risky electricity wholesale market. Notably, 58.2% of bidders make interior portfolio choices in my data. The fact that an appreciable proportion of bidders make interior portfolio choices suggests that the bidders are risk-averse, as first noted by Athey and Levin (2001) in the context of scaling auctions. In contrast to risk-averse bidders, risk-neutral bidders should only choose corner solutions to maximize the expected revenue. Risk-neutral bidders will allocate all of their production to either purchase agreements or the wholesale market, whichever gives them the higher expected revenue.

To uncover the bidders' risk aversion and costs, I specify and estimate a structural model of risk-averse bidders in these multi-unit procurement auctions using the share auction framework of Wilson (1979). Bidders with a common constant absolute risk aversion (CARA) utility function and heterogenous cost types choose their bid share and price to maximize their expected utility. I exploit the fact that bidders make portfolio choices in both of the auction formats observed—pay-as-bid auctions where the awarded purchase agreements have discriminatory prices and uniform-price auctions where the awards have a single market clearing price—to estimate their risk aversion. For pay-as-

[4]For instance, Wiser et al. (2021) show that, from 2015 to 2020, wind energy costs have declined far greater than experts predicted in 2015.

bid auctions, I employ an identification strategy analogous to Bolotnyy and Vasserman's (2023) scaling auction model that separates bidders' portfolio problems, subject to their "scores" that determine the winner, from their score optimization problems.

Leveraging the separability of the portfolio and bid price (the "score" in my setting) optimization problems in pay-as-bid auctions, I estimate the structural parameters in two steps. First, I use the solutions to bidders' portfolio problems for both pay-as-bid auctions and uniform-price auctions to estimate the risk aversion and the expected revenue in the wholesale market. In this step, to separate the risk aversion coefficient from the wholesale market risk premium, I assume bidders expect the variance (or risk) of the wholesale market revenue to come from a mean reverting process estimated using the history of spot market prices. Second, I infer the bidders' costs in pay-as-bid auctions from the solutions to their bid price optimization problems, following the insight of Guerre, Perrigne and Vuong (2000) in identifying bidders' values from their bid prices. For each bidder, the bidder's solution to the optimal bid price implies the bidder's cost equals the expected revenue net of the wholesale market risk premium and the auction markup, which can be calculated from the bid data and the first step estimates given the equilibrium winning probability functions. I specify and estimate a model underlying the equilibrium winning probability functions to calculate them.

I face the common issue of only having access to winners' bid data (Athey and Haile, 2002). This is a common situation in new renewable energy auctions, as policymakers may have concerns about the influence of making all bids publicly available on the future competitiveness of the market.[5] I show that information on the winners' bids and the number of auction participants—the information I have—is enough to identify the structural parameters using the order statistics inversion technique developed by Athey and Haile (2002).

I find that bidders are substantially risk averse. The average winner requires an additional risk premium of \$20.16/MWh (98.7% of the average winner's cost) to accept the

[5] Brazil's energy department raises this concern as the primary reason for not publicly making the auction participants' individual-level power generation cost estimates available (EPE, 2022).

risk of selling all electricity into the wholesale market, where revenues have a standard deviation (SD) of \$5.44/MWh. Additionally, the winners have, on average, \$8.35/MWh lower costs than all participants (whose SD of cost is \$4.56/MWh) for the median auction. Since the average winner only collects an auction markup of \$1.72/MWh, auctions efficiently allocate and price the purchase agreements.

I then simulate the policymaker's trade-off between her cost and risk to achieve the policymaker's renewable energy target. I consider an alternative pay-as-bid auction, which requires all bidders to bid in a share $\lambda \in [0,1]$ of their production, holding the total capacity of winning bidders constant. A high λ requires the policymaker to take on higher risk and lowers bidders' risk exposure. The expected policymaker's net expenditure is the highest with zero policymaker risk at $\lambda = 0$ and decreases with increasing risk as λ moves to 1. The zero policymaker risk scenario at $\lambda = 0$ is equivalent to generation subsidies, where the winners will receive a premium on top of the wholesale electricity price.

For 5.6 GW of generation capacity auctioned (3% of the entire capacity in Brazil), my model predicts that moving from $\lambda = 0$ to 1 lowers the expected policymaker's net expenditure by \$20 billion while increasing the SD of the policymaker's net expenditure from \$0 to \$5 billion. The policymaker can choose a λ that conforms with her risk preference and institutional/political constraints to maximize her expected utility. I propose a certainty equivalent of the policymaker's net expenditure as a measure of assessing the welfare consequences of risk-sharing contracts. For a given level of the policymaker's risk aversion, I define the certainty equivalent of the policymaker's net expenditure as the sum of the expected net expenditure and the risk premium for the net expenditure. Using this certainty equivalent measure, I illustrate that a risk-averse policymaker enjoys the benefit of risk sharing, while it works negatively for a risk-neutral policymaker because she is willing to accept all risks.

A growing body of literature has examined the effect of policy interventions on renewable investments.[6] I propose a framework integrating purchase agreements and subsidies

[6] For example: Alishahi, Moghaddam and Sheikh-El-Eslami (2012), Jenner, Groba and Indvik (2013), Ryan (2022) for purchase agreements; Metcalf (2010), Hughes and Podolefsky (2015), Johnston (2019),

to assess the trade-off of a policymaker's cost and risk from sharing electricity market risk between renewable investors and the policymaker.[7] Researchers have recognized the risk-sharing aspect of purchase agreements.[8][9] My paper is particularly novel in conducting out-of-sample counterfactuals using the estimates of investors' risk aversion and cost distribution to quantify the trade-off from risk sharing.[10]

The paper also builds on the literature on auctions with risk-averse bidders. Theoretical implications of risk-averse bidders have been extensively discussed.[11] However, the empirical identification of bidders' risk aversion has been challenging. Adopting the classical idea of identifying investors' risk aversion from their portfolio choices (e.g., Cohn et al., 1975), Athey and Levin (2001) use scaling auctions to demonstrate bidders' risk aversion, relying on the portfolio problem embedded in these auctions.[12] Bolotnyy and Vasserman (2023) extend this observation and estimate bidders' risk aversion in scaling auctions, exploiting the separability of bidders' portfolio problem and score optimization problem. I show that the separability also holds in a special case of multi-unit auctions and use that to identify bidders' risk aversion, as well as their cost distribution, from their revealed preference.

The next section presents a theoretical framework that illustrates the value of risk sharing. Section 3 explains the institutional context of new energy auctions in Brazil and

Pless and van Benthem (2019), Langer and Lemoine (2022), and Aldy, Gerarden and Sweeney (2023) for subsidies; Borenstein (2017) for a mix of purchase agreements and subsidies; Carley et al. (2018) and Greenstone and Nath (2021) for renewable portfolio standards; Gonzales, Ito and Reguant (2023) for grid expansions.

[7] Purchase agreements and subsidies are also called feed-in tariffs and feed-in premiums, respectively. I call them purchase agreements and subsidies throughout the paper.

[8] For example, Farrell et al. (2017), May and Neuhoff (2021), and Alcorta, Espinosa and Pizarro-Irizar (2023).

[9] There are several reasons why private financial markets may not function as a risk-sharing tool in the context of renewable investments. First, risk pooling may unravel due to the high correlation of the wholesale price risk across projects. Second, the policymaker intermediated power purchase agreements essentially subsidize renewable investors and crowd out private financial markets. Third, annual spot prices are positively correlated with GDP (correlation coefficient 0.38 from 2001–2022), which makes hedging more difficult.

[10] One paper that estimates renewable investors' cost distribution using long-term purchase agreement auctions is Ryan (2022).

[11] Early examples include Holt (1980), Cox, Smith and Walker (1982), and Matthews (1983).

[12] Perrigne and Vuong (2019) and Vasserman and Watt (2021) review identification strategies of auctions with risk-averse bidders.

introduces the data. Section 4 presents the model of new energy auctions. Section 5 discusses the identification and estimation approach. Section 6 shows estimation results, and Section 7 demonstrates counterfactuals. Section 8 concludes.

2 Theoretical Framework of Risk Sharing

To illustrate the value of risk sharing, I present a simple model of a policymaker and a renewable investor. 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 the risky wholesale market where he knows that the lifetime revenue r is distributed normally as $\mathcal{N}(\mu_r, \sigma_r^2)$. The investor has a standard CARA utility over profits from the project, π, with a risk aversion coefficient $\gamma \geq 0$,

$$u(\pi) = \begin{cases} 1 - \exp(-\gamma\pi) & \text{if } \gamma > 0 \\ \pi & \text{if } \gamma = 0 \end{cases}.$$

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. Under this contract, the investor is only responsible for selling a share of $1 - \lambda$ of the electricity to the wholesale market. Thus, the investor signs the contract when the contract payment ϕ satisfies

$$E[u(\phi + (1-\lambda)r - c)] \geq 0 \iff \underbrace{\phi + (1-\lambda)\mu_r}_{\text{Expected revenue}} \geq \underbrace{c}_{\text{Cost}} + \underbrace{(1-\lambda)^2 \cdot \frac{\gamma\sigma_r^2}{2}}_{\substack{\text{Wholesale market}\\ \text{risk premium}}}.$$

A non-negative expected utility from the contract is equivalent to the inequality on the right due to the CARA utility function. The investor signs the contract when the expected revenue is no less than the cost plus the risk premium for the wholesale market. The risk premium to account for the full wholesale market risk, $\gamma\sigma_r^2/2$, increases as the investor is more risk averse (larger γ) and the wholesale market is more volatile (larger σ_r^2).[13] The investor's wholesale market risk premium for this contract decreases as the policymaker takes a larger risk (larger λ).

I assume the policymaker always signs the contract by setting ϕ as the minimum amount necessary for the investor to sign. That is, ϕ is set so that the investor builds the new renewable capacity and earns a certainty equivalent of zero. The policymaker understands that she will sell the share λ of the electricity generated by the project into the wholesale market, which yields a revenue of λr. Since she pays for the contract price ϕ, her net expenditure is $C = \phi - \lambda r$. Substituting the value of ϕ and taking expectation and variance, I obtain the policymaker's cost-risk trade-off:

$$\begin{cases} E[C] = -\mu_r + c + (1-\lambda)^2 \cdot \frac{\gamma\sigma_r^2}{2} \\ \mathrm{Var}(C) = \lambda^2\sigma_r^2 \end{cases}. \tag{1}$$

The expected policymaker's net expenditure is the highest with variance zero at $\lambda = 0$ and decreases with increasing variance as λ moves to 1 (Figure 1). This formulation clarifies that if the investor is not risk-averse, $\gamma = 0$, the policymaker does not face the trade-off

[13]This form of risk premium relies on the normality of the revenue r. For a general random variable r, the risk premium can be expressed using a moment-generating function of r, which means that the third or higher-order moments of r come into the calculation of the risk premium. Thus, the normality assumption approximates the investor's behavior well if the investor considers the variance of the revenue, σ_r^2, as the primary driver of the risk premium.

between her expected net expenditure and risk: i.e., the expected net expenditure $E[C]$ is constant regardless of the level of risk sharing determined by λ.

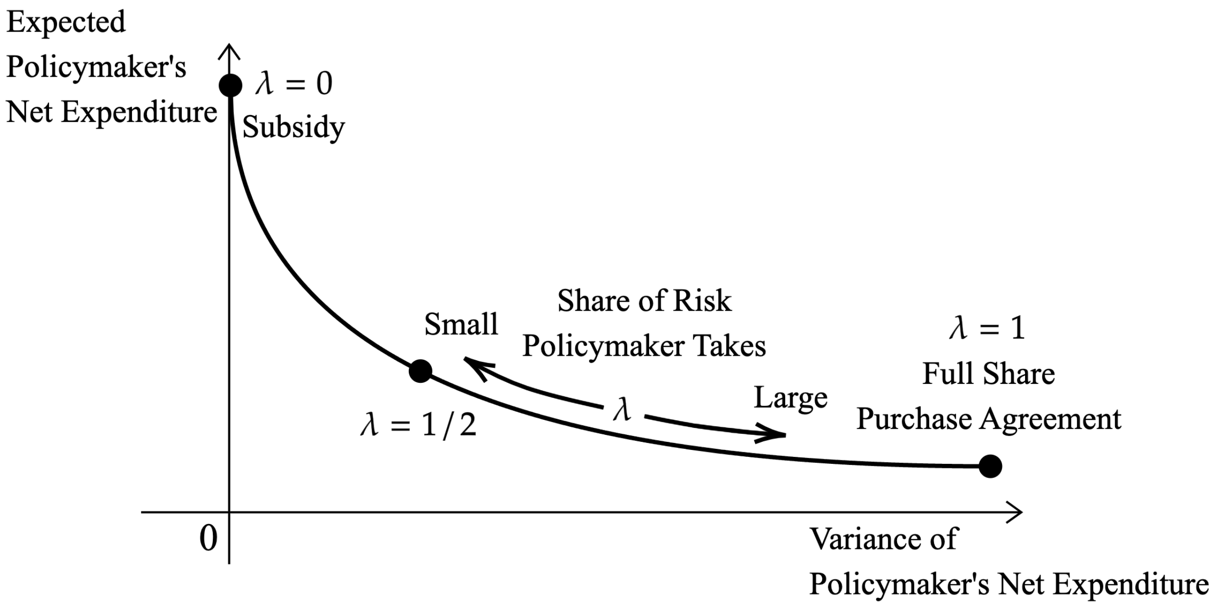


Figure 1: Policymaker's cost-risk trade-off from the risk-sharing contract

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 CARA utility, u_{PM}, over her budget surplus having a risk aversion coefficient $\gamma_{PM} \geq 0$. I assume she has a certain budget of B, defines the budget surplus as $B - C$, and knows that her net expenditure C is not too high so that $B - C$ is almost always positive. Without any constraints, she chooses λ to maximize the expected utility:

$$\max_{\lambda \in [0,1]} E[u_{PM}(B - C)] = u_{PM}\left(B - E[C] - \frac{\gamma_{PM}\,\mathrm{Var}(C)}{2}\right). \tag{2}$$

The equality is due to the CARA utility function and the normality of $C = \phi - \lambda r$. Plugging in the mean and variance in Equation (1), I obtain $\lambda = (1 + \gamma_{PM}/\gamma)^{-1}$ as the maximizer. This result indicates that if the policymaker is as risk averse as the investor (i.e., $\gamma_{PM} = \gamma$), the policymaker divides the share equally (i.e., $\lambda = 1/2$, the point indicated with the filled circle in Figure 1). If the policymaker is risk-neutral ($\gamma_{PM} = 0$), the policymaker takes all the risk ($\lambda = 1$), and if the policymaker is infinitely risk-averse ($\gamma_{PM} = \infty$), the policymaker avoids the risk entirely ($\lambda = 0$).

Equation (2) suggests that the policymaker's expected utility is the same when $E[C] + \gamma_{PM}\operatorname{Var}(C)/2$ is the same. I define $E[C] + \gamma_{PM}\operatorname{Var}(C)/2$ as the certainty equivalent of the policymaker's net expenditure C and use this certainty equivalent measure to assess the welfare consequences of risk-sharing contracts. Given the policymaker's risk aversion γ_{PM}, this certainty equivalent measure captures how the policymaker trade-off between the expected net expenditure, $E[C]$, and the risk premium for the net expenditure, $\gamma_{PM}\operatorname{Var}(C)/2$. The idea of using a certainty equivalent in welfare evaluation aligns with the recent proposal of the U.S. Office of Management and Budget to use the certainty equivalent to account for uncertainty in Federal activities (OMB, 2023).

To get a sense of the role of auctions in this context, I extend the model to include $i = 1, \ldots, N$ investors that all have the same risk aversion coefficient γ but with heterogenous costs c_i. The policymaker still wants one investor to sign the contract. As shown in Equation (1), the policymaker can lower her expected net expenditure $E[C]$ by selecting a lower-cost investor without changing the variance $\operatorname{Var}(C)$. Thus, the first best is to select the lowest-cost investor. An auction reveals the lowest-cost investor but potentially allows him to collect a positive markup, depending on the auction format and competitiveness.

Motivated by these theoretical insights, I empirically quantify the policymaker's cost-risk trade-off from risk sharing and the effectiveness of auctions using the estimates of investors' risk aversion and cost distribution. To do so, I use unique renewable energy auctions that embed bidders' portfolio choices and construct a structural model of risk-averse bidders in these auctions. I also discuss the pros and cons of auctions that allow bidders to have portfolio choices in contrast to auctions that require all bidders to bid in the same share.

3 Institutional Context and Data

3.1 Institutional Context of New Energy Auctions in Brazil

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

These new energy auctions award long-term power purchase agreements to investment projects for new generation capacity. I focus on wind energy auctions because these auctions attract 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, which still has a capacity share of 58.1% (Tolmasquim et al., 2021).

In these auctions, MME and ANEEL call 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 start of electricity supply, 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 in a qualification phase. The Energy Research Company (Empresa de Pesquisa Energética, EPE), a public research institute supporting the MME, assesses bidders in the qualification phase. The application documents required in the qualification phase include proofs of land use rights, environmental permits, and technical and financial feasibility. EPE evaluates the production amount bidders can stably provide according to their application and defines that as a basis for the bidder's share choice. I define the bidder's capacity as the amount of stable supply per hour.[14]

ANEEL uses the Chamber of Electric Energy Commercialization (Câmara de Comercialização de Energia Elétrica, CCEE), which is a nonprofit civil association that operates the Brazilian electricity market, to administer these auctions. 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. For instance, consider a bidder who chooses to bid a share of 80% and a price of \$40/MWh. If the bidder wins the auction, he will be awarded a purchase agreement for 80% of his production at \$40/MWh. CCEE awards purchase agreements to the lowest-price bidders until the total procurement capacity for the winners exceeds the auction's procurement capacity. EPE determines the procurement capacity considering the forecasted demand growth (Rosa et al., 2013). The procurement capacity is not disclosed before bidding to prevent collusive behavior.[15]

The auction format was initially pay-as-bid until 2015, at which point it switched to uniform-price. In pay-as-bid auctions, bidders submit sealed bids one time, and these bids determine the winners and the contents of the purchase agreements. In uniform-price auctions, bidders fix their bid shares at the beginning. CCEE then implements a descending clock iteration procedure wherein CCEE announces a tentative clearing price and lets bidders adjust their bid prices until the clearing price does not change. This descending clock iteration results in a uniform price because all winners are incentivized to align their bid prices to the clearing price.[16]

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

[15]I do not consider the possibility of collusion in this paper. In addition to the non-disclosure policy of the procurement capacity, the Brazilian wind energy auctions have large numbers of participants (400–600 bidders) and are competitive (proportions of winners are at most 20% out of the participants). Also, it is challenging to differentiate collusive and competitive behavior without information on losers' bidding behavior. The existing literature relies on both winners' and losers' bidding behavior to detect collusion in auctions. See Porter and Zona (1993, 1999) for the pioneering work and Chassang et al. (2022); Kawai and Nakabayashi (2022); Kawai et al. (2023) for more recent developments in this literature.

[16]In practice, the final winners' bid prices may not exactly align because the descending clock iteration

The winners sign a new energy contract composed of the purchase agreement and commitment to install the planned capacity for commercial operation by the designated date. Distribution companies, which provide distribution services to supply electricity to consumers, procure electricity through these purchase agreements. CCEE intermediates the contracts between the winners and distribution companies and implements several policies to ensure the revenue stream according to the purchase agreements. 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 cost of the purchase agreements in their consumers' bill, and the revenue collected from the consumers are directly passed to the winners to pay for the purchase agreements.

The winners sell the uncontracted electricity to the wholesale market. Brazil's electricity wholesale market includes a spot market, purchase agreement auctions, and bilateral contracts between sellers and consumers (Hochberg and Poudineh, 2021). In Brazil, a stochastic computer model automatically calculates hourly spot market prices that reflect the marginal cost of hydroelectricity, which is essentially the opportunity cost of stored water. Since the spot market is always an option, further purchase agreement auctions and bilateral contracts will be based on expectations over spot prices.

3.2 Data and Descriptive Evidence

I primarily use three publicly available data sources. First is the auction results database maintained by CCEE. The auction database gives the auction date, designated commercial operation date, winners' capacities, and winners' bid shares and prices. I calculate lead time as the difference between the commercial operation date and the auction date. Second is the auction registration and qualification reports provided by EPE. These reports give the number of auction participants that are qualified for bidding. Last is the electricity spot market prices provided by CCEE. I adjust prices for inflation using 2022

is implemented as a discrete process. CCEE sets a minimum decrement that must be lowered from the tentative clearing price when bidders adjust their bid prices (Hochberg and Poudineh, 2018).

as the base year and assume a 5 to 1 Brazilian Real to U.S. Dollar exchange rate.

I analyze 16 wind energy auctions with 476 winning bids totaling 5.6 GW of capacity from 2011–2021 (Table 1). The new energy auctions for wind energy started in 2011, and the length of purchase agreements was the wind turbine's expected lifetime, 20 years, until 2021.[17] There were 8 pay-as-bid auctions from 2011–2015 (296 winning bids) and 8 uniform-price auctions from 2017–2021 (180 winning bids). The auctions are competitive, with around 20–40 winners out of 400–600 participants. I define auctions' procurement capacities as the sum of winners' capacities allocated to the auction. The procurement capacities decreased in later periods, reflecting the fact that the growth of forecasted demand slowed down during this period.

Table 1: Summary statistics for 16 wind energy auctions from 2011–2021

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

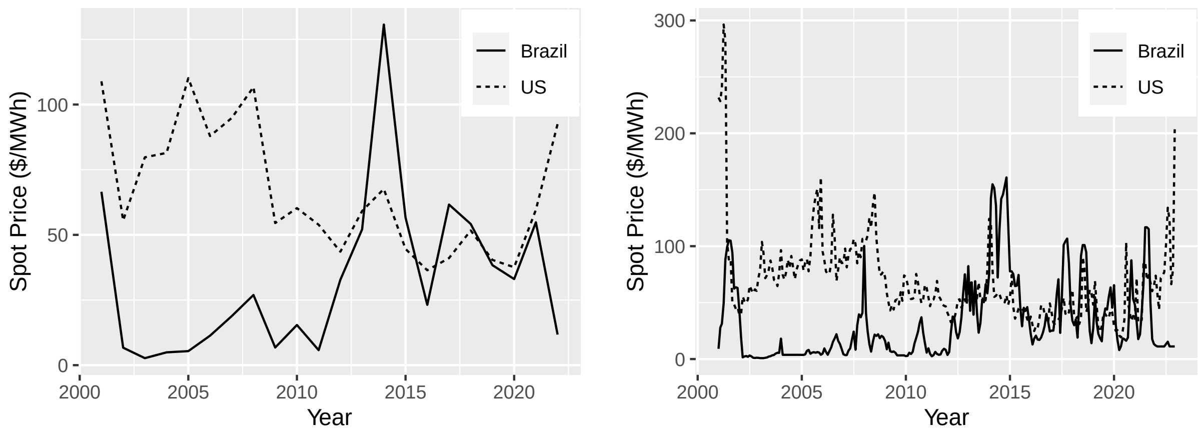
The median bid share of the 476 winning bids is 0.91, with an interquartile range (IQR) of $[0.64, 1.00]$. Overall, 58.2% of winners make interior portfolio choices.[18] The fact that an appreciable proportion of bidders make interior portfolio choices suggests that the bidders are risk-averse. The median purchase agreement price (the bid price for pay-as-bid auctions and the clearing price for uniform-price auctions) is \$39.27/MWh, with an IQR of \$26.03–\$40.97/MWh. The correlation coefficient between the bid share and the purchase agreement price is 0.55 (Figure A1(a) in Appendix A depicts the scatter plot of bids). Bidders optimize their portfolio by selecting larger shares when they expect the purchase agreements to be more attractive than the wholesale market.

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

[18] CCEE has required bidders to bid at least a share of 0.3 of their production into the auction since 2018. Bidders bid freely between 0 and 1 until 2017. I round off the endpoints to the nearest 0.01 in calculating the proportion of people making interior portfolio choices. For example, I count a bidder with a bid share from 0.29–0.31 after 2018 as not making an interior portfolio choice.

The average bid price of the 296 winning bids in pay-as-bid auctions is \$38.00/MWh initially in 2011, exceeds \$40/MWh after 2013, and is \$53.20/MWh in the last pay-as-bid auction in 2015 (Figure A1(b) in Appendix A depicts the trend of bid prices). This increasing trend suggests that wind energy costs also increased since the bid prices reflect the underlying costs. Tolmasquim et al. (2021) noted two factors contributing to this price hike. First, the wind technology costs barely decreased during this period (EPE, 2022), primarily because of the bankruptcy of a large local equipment provider. Second, Brazil's base interest rates hiked from 7% in 2013 to 14% in 2016 (Central Bank of Brazil, 2023), making financing the investments costly.

I use the spot market electricity prices to get a sense of the volatility of the wholesale market. Figure 2 compares the spot market prices in Brazil and the U.S.[19] The SDs of annual and monthly spot prices in Brazil are comparable to those in the U.S. In Brazil, the SD of spot prices is \$30.49/MWh across years and \$35.35/MWh across months, whereas in the U.S., they are \$24.41/MWh and \$38.48/MWh. Brazil's spot market looks more volatile than the U.S. if I consider the coefficient of variation (the SD divided by the mean) as a measure of volatility. In Brazil, the coefficient of variation of spot prices is 0.93 across years and 1.09 across months, whereas in the U.S., they are 0.37 and 0.56.



(a) Annual average

(b) Monthly average

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

[19] I use wholesale daily spot prices provided by the Intercontinental Exchange for the U.S. spot market prices. I average the five electricity hubs for which historical data are available from January 2001 (Mass Hub, PJM West, Mid-C, Palo Verde, and SP-15).

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 they will include in a long-term purchase agreement. Each bidder also bids one price per unit that applies to all units of the purchase agreement.[20] Risk-averse bidders optimize their portfolio by allocating their production to the risk-free purchase agreement and the risky wholesale market.[21]

An auctioneer holds procurement auctions that guarantee the purchase of electricity at a fixed price for the entire life of the 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 the minimum 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 auction.

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.[22] Bidder i specifies a share $q_i \in [\underline{q}, 1]$ and a price b_i in his bid. The auctioneer agrees to purchase $q_i \times Capacity_i \times H$ hours of electricity for each period at price b_i if bidder i wins the auction. 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 contract. The auctioneer awards these purchase contracts to the lowest-price bidders until the total bid

[20] Bidders do not bid price schedules. Ryan (2022) also models bidders as bidding one price applied to all awarded production in long-term purchase agreement auctions. In contrast to this paper, Ryan (2022) assumes that all bidders bid in the full share.

[21] Bolotnyy and Vasserman (2023) and Luo and Takahashi (2022) model risk-averse bidders facing a portfolio problem in the context of scaling auctions.

[22] There is also uncertainty about effective production hours H_{it} from weather, such as wind or solar irradiance variability. The structural parameters can still be identified, given the distribution of H_{it}. The bidders' risk premium will then represent the risk premium for the wholesale market relative to the purchase agreement.

capacity $\sum_i q_i Capacity_i$ for 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 $\mathbb{1}(\cdot)$ is an indicator function.

I assume that bidders are risk averse and have a CARA utility, u, over their per unit net present value (NPV), π. Having a concave utility over NPV is a standard choice in analyzing projects with uncertain cash flows in the field of decision analysis (Baucells and Bodily, 2022). I also assume that bidders have a common risk aversion coefficient $\gamma > 0$, i.e., $u(\pi) = 1 - \exp(-\gamma\pi)$.

When bidder i wins the auction, he invests an up-front fixed cost FC_i to start supplying electricity from $t = l$. Bidder i also pays a constant variable cost VC_i per unit of production during the purchase contract. Thus, bidder i's per unit NPV of winning with bid (q, b) is

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

where δ is a common discount factor. $Capacity_i HT$ is the total production over the lifetime of technology. The term in the curly brackets, $qb + (1 - q)r_t - VC_i$, is the per-period profit calculated as the sum of the purchase agreement and wholesale market revenues subtracted by the variable costs. The overall NPV inside the square brackets subtracts the fixed cost from the discounted sum of the per-period profits.

The NPV function can be rewritten as

$$\pi_i(q,b) = \underbrace{q \cdot \left(\frac{1}{T}\sum_{t=l}^{l+T-1}\delta^t b\right)}_{\text{Purchase agreement revenue}} + \underbrace{(1-q)\cdot\left(\frac{1}{T}\sum_{t=l}^{l+T-1}\delta^t r_t\right)}_{\text{Wholesale market revenue}} - \underbrace{c_i}_{\text{Cost}}, \tag{3}$$

where c_i is an average cost defined as

$$c_i := \frac{FC_i}{Capacity_i HT} + \frac{1}{T}\sum_{t=l}^{l+T-1} \delta^t VC_i.$$

The cost c_i comprises the fixed cost allocated across the entire production and the average discounted variable cost.

To capture the uncertainty of the wholesale market, I specify bidders' beliefs about future wholesale market prices. Since $T^{-1}\sum_t \delta^t r_t$ is the only term that involves future wholesale market prices in bidders' NPV (Equation (3)), I redefine this term as r and assume a common normally distributed belief for r:

$$r := \frac{1}{T}\sum_{t=l}^{l+T-1} \delta^t r_t \sim \mathcal{N}(\mu_r, \sigma_r^2). \tag{4}$$

The winners receive the expected utility from the NPV of building the planned capacity. Bidder i's expected utility conditional on winning the auction with a bid (q, b) is $E[u(\pi_i(q, b))]$, where the expectation is taken over the belief on the future wholesale market prices according to Equation (4). The expected utility can be written as

$$E[u(\pi_i(q,b))] = u\left(\underbrace{q\tilde{\delta}b + (1-q)\mu_r - c_i}_{\text{Expected NPV}} - \underbrace{(1-q)^2 \cdot \frac{\gamma\sigma_r^2}{2}}_{\substack{\text{Wholesale market}\\ \text{risk premium}}}\right), \tag{5}$$

where I denote $\tilde{\delta} = T^{-1}\sum_{t=l}^{l+T-1}\delta^t$ for conciseness. The wholesale market risk premium is larger, as the share of production planned to be sold to the wholesale market, $1-q$, the risk aversion coefficient γ, and the wholesale price uncertainty, σ_r^2, are larger. I assume that bidders earn a zero if they lose the auction.[23]

[23] Ryan (2022) also assumes that bidders earn zero profit when they lose in long-term purchase agreement auctions. The assumption can be relaxed to losers earning a certainty equivalent of a positive value π_{0i} 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, which is the bid (q_i, b_i). The introduction of π_{0i} changes the "cost" parameter identified by the model from c_i to $c_i + \pi_{0i}$, but the identification of the other structural parameters remains the same. Thus, it affects the interpretation of the revealed "cost," but the implications of counterfactuals do not change as long as the counterfactual does not affect c_i and π_{0i} differently. Therefore, I consider $\pi_{0i} = 0$ as a normalization as far as we do not model dynamic considerations.

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

I next characterize the equilibrium strategies for pay-as-bid and uniform-price auctions.

4.1 Pay-as-bid Auctions

In pay-as-bid auctions, bidders finalize the bids before the realization of the procurement capacity and the competitors' bids. The winning probability for bidder i choosing bid price b is the probability of the total bid capacity of competitors, $\sum_{j \neq i} q_j Capacity_j$, with a bid price lower than b is below the procurement capacity D:

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

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

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

$$\underbrace{W_i(b)}_{\text{Probability of winning with } b} \times \underbrace{u\left(q\tilde{\delta}b + (1-q)\mu_r - c_i - (1-q)^2 \cdot \frac{\gamma\sigma_r^2}{2}\right)}_{\text{Expected utility conditional on winning with } (q,b)}.$$

A pure-strategy Bayes Nash Equilibrium (BNE), $\{(q_i^*, b_i^*)\}_{i=1}^N$, satisfies, for all $i = 1, \dots, N$,

$$(q_i^*, b_i^*) = \underset{q \in [\underline{q}, 1], b}{\arg\max}\, W_i^*(b) \times u\left(q\tilde{\delta}b + (1-q)\mu_r - c_i - (1-q)^2 \cdot \frac{\gamma\sigma_r^2}{2}\right),$$

where

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

I prove that there exists a unique pure-strategy BNE in Appendix B.[24]

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

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

Figure 3(a) illustrates this risk-averse bidder's optimal portfolio choice when his 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 into the purchase agreement when the equilibrium bid price b_i^* is higher or equal to the expected wholesale market price μ_r because risk-averse actors strictly prefer a risk-free choice to a risky choice when the risk-free choice has a higher or equal expected price. The linear slope below $b_i^* = \mu_r$ results from the CARA utility specification. The bidder bids a 50% share when indifferent between the purchase agreement and the wholesale market. Thus, the difference between the wholesale market price μ_r and the equilibrium bid price b_i^* at the bidder's 50% share choice is the bidder's risk premium for the wholesale market, which equals $\gamma\sigma_r^2/2$. In contrast, a risk-neutral bidder discontinuously switches all of his shares from the purchase agreement to the wholesale market by comparing their expected prices (Figure 3(b)).

Notably, the bidder's private cost c_i and equilibrium winning probability function $W_i^*(\cdot)$ do not enter into his optimal portfolio decision. The bidder's equilibrium bid price b_i^* sufficiently captures the information on his cost and competitors' situation. Thus, in any equilibrium, each bidder solves the portfolio problem, conditional on the bidder's equilibrium bid price.[25] This property is crucial to use the bidders' portfolio choice and

[24] Note that bidder i does not change the strategy by $Capacity_i$ since it only affects the objective function through his cost type c_i.

[25] This property of a bidder's bid price being payoff-sufficient for his portfolio problem is analogous to

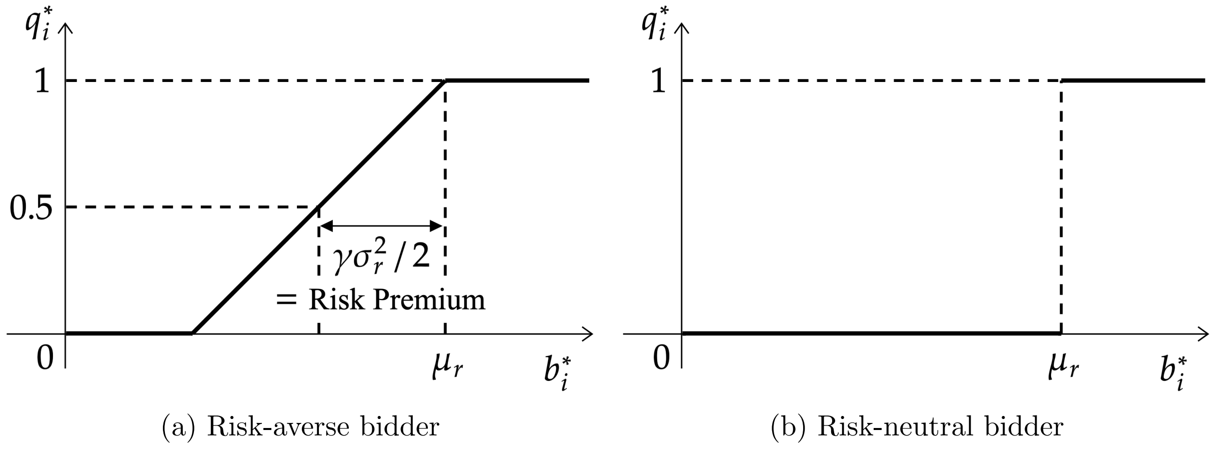


Figure 3: Optimal portfolio choice when $\delta = 1$ and $\underline{q} = 0$

bid price optimization decisions separately in identification and estimation.

Bidder i's optimal bid price b_i^* satisfies[26]

$$\underbrace{q_i^* \tilde{\delta} b_i^*}_{\substack{\text{Agreement}\\ \text{revenue}}} + \underbrace{(1-q_i^*)\mu_r}_{\substack{\text{Wholesale market}\\ \text{expected revenue}}} = \underbrace{c_i}_{\text{Cost}} + \underbrace{(1-q_i^*)^2 \cdot \frac{\gamma\sigma_r^2}{2}}_{\substack{\text{Wholesale market}\\ \text{risk premium}}} + \underbrace{\frac{1}{\gamma}\ln\left(-\frac{\gamma q_i^* \tilde{\delta} W_i^*(b_i^*)}{dW_i^*(b_i^*)/db} + 1\right)}_{\substack{\text{Auction}\\ \text{markup}}}. \tag{8}$$

The two terms on the left-hand side, the purchase agreement and the 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: the bidder's cost, wholesale market risk premium, and auction markup. The markup term is a decreasing function of the risk aversion coefficient γ. 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 probability does not change much by increasing their bid price.

Bolotnyy and Vasserman's (2023) observation of a bidder's score being payoff-sufficient for his choice of unit bids in scaling auctions.

[26] This equality converges to $b_i^* = c_i/\tilde{\delta} - W_i^*(b_i^*)/(dW_i^*(b_i^*)/db)$ as $\gamma \to 0$ and $q_i^* \to 1$, which matches the standard formula in empirical auctions with risk-neutral bidders (e.g., Athey and Haile, 2007).

4.2 Uniform-price Auctions

In uniform-price auctions, bidders finalize the bid share before the realization of the procurement capacity and the competitors' bids but can change the bid price afterward. The auction clears when the bidders no longer change their bids.

Define bidders' pseudo costs as the lowest bid price they can afford for a given bid share q. Bidder i's pseudo cost pc_i satisfies $E[u(\pi_i(q, pc_i))] = 0$ and is monotonically increasing with the cost type c_i for a fixed q. Bidders are sorted by their pseudo costs, and the bidders are awarded from the lowest until the realized procurement capacity D is filled. The winners finalize the bid price at the smallest pseudo cost among the losers, the clearing price p. I assume that bidders have a common normally distributed belief about the clearing price, $p \sim \mathcal{N}(\mu_p, \sigma_p^2)$, independent of the wholesale market belief.[27] Bidders decide on the bid share q to maximize the expected utility conditional on winning, $E[u(\pi_i(q, p))]$, where the expectation is now also taken over the distribution of the clearing price belief.

Bidder i's optimal bid share q_i^* satisfies

$$q_i^* = \min\left\{ \max\left\{ \underline{q}, \frac{1}{1 + \tilde{\delta}^2 \sigma_p^2 / \sigma_r^2} \cdot \left(1 - \frac{\mu_r - \tilde{\delta}\mu_p}{\gamma \sigma_r^2}\right) \right\}, 1 \right\}. \tag{9}$$

I highlight two changes from the optimal portfolio choice in pay-as-bid auctions (Equation (7)). First, the expected clearing price μ_p replaces the bid price b. Second, the uncertainty of the clearing price σ_p^2 makes the purchase agreement less attractive, resulting in a lower optimal bid share q_i^*. Since the optimal portfolio choice only depends on the elements common across bidders, bidders' equilibrium bid share is the same for all bidders within an auction. Consequently, the order of pseudo costs and cost types coincide because of

[27] The independence of the clearing price and wholesale market beliefs holds as long as their sources of uncertainties are independent. The competitors' costs and the procurement capacity are the sources of the clearing price uncertainty. In contrast, Brazil's wholesale market uncertainty stems from the rainfall and electricity demand since the wholesale market reflects the marginal cost of hydroelectricity. This independence assumption can be relaxed by introducing a covariance between the clearing price and wholesale market beliefs. Then, the covariance comes into the optimal bid share in Equation (9), and it must be assumed to be known for the identification of the uniform-price auction model in Assumption 3.

their monotonicity for a fixed bid share, and, therefore, bidders are awarded from the lowest cost type in the equilibrium.

5 Econometric Model

In this section, I demonstrate my identification results and then specialize the structural model to Brazil's new wind energy auctions for estimation.

5.1 Identification

I first show my baseline identification result for pay-as-bid auctions. I start from a setup in which an analyst observes bids (q^d_{ia}, b^d_{ia}) for all participants $i = 1, \dots, N$ for each pay-as-bid auction $a = 1, \dots, A$ with a fixed lead time l and minimum possible bid share $\underline{q}$. I assume that A is large with a fixed N. The structural parameters of interest are the risk aversion coefficient γ, the expected wholesale market revenue μ_r, and the bidders' cost types c_{ia}. The discount factor δ is prespecified.

I summarize the assumptions for the baseline identification result as follows.

Assumption 1 (Identification of the pay-as-bid auction model)**.**

1. *The equilibrium bid price b^*_{ia} is exactly observed, i.e., $b^d_{ia} = b^*_{ia}$, and it sufficiently varies across bidders.*

2. *The equilibrium bid share q^*_{ia}, evaluated at b^*_{ia}, as in the solution to the portfolio problem, Equation (7), is observed as q^d_{ia} with an idiosyncratic normal bid share shock, i.e., $q^d_{ia} = q^*_{ia} + \eta_{ia}$, $\eta_{ia} \sim \mathcal{N}(0, \sigma^2_\eta)$.*

3. *The variance of the wholesale market revenue σ^2_r is identified from the data.*

4. *The equilibrium winning probability functions $W^*_i(\cdot)$ are identified from the data.*

The first and fourth assumptions are standard in the literature following Guerre, Perrigne and Vuong (2000) to identify bidders' values from their bid prices. The second and third assumptions are essentially what Bolotnyy and Vasserman (2023) assume in the identification of scaling auctions, except for two differences. First, I specify a parametric distribution of the bid share shock to deal with the censoring nature of the bid share. Second, the expected wholesale market revenue μ_r is identified from bidders' bidding behavior.[28]

In practice, I make further assumptions to identify σ_r^2 and $W_i^*(\cdot)$ from the data. I assume bidders expect σ_r^2 to come from a mean reverting process for annual spot market price transitions. I use spot market price variation to measure bidders' expectations of sales price volatility since I do not observe wholesale prices.[29] I also specify a model underlying the equilibrium winning probability functions $W_i^*(\cdot)$.

The first three assumptions in Assumption 1 imply that the observed bid share q_{ia}^d conditional on the observed bid price b_{ia}^d has the following censored normal distribution:

$$q_{ia}^d = \min\left\{\max\left\{\underline{q}, 1 - \frac{\mu_r - \tilde{\delta} b_{ia}^d}{\gamma\sigma_r^2} + \eta_{ia}\right\}, 1\right\}, \eta_{ia} \sim \mathcal{N}(0, \sigma_\eta^2). \tag{10}$$

This result implies that the structural parameters $(\gamma, \mu_r, \sigma_\eta^2)$ are identified if the observed bid prices b_{ia}^d sufficiently vary across bidders. This equation makes clear that the analyst needs to identify the variance of the wholesale market revenue σ_r^2 outside the bid data to separate the risk aversion coefficient γ from the wholesale market risk premium, $\gamma\sigma_r^2/2$.

Given that the structural parameters γ and μ_r are identified, under Assumption 1, the analyst knows everything except for the bidder's cost type c_{ia} in the solution to the bidder's bid price optimization problem (Equation (8)). Therefore, each bidder's cost type c_{ia} is identified as in Guerre, Perrigne and Vuong (2000).

I next extend the identification result to the case where the analyst only has access to winners' bids with the following additional assumption.

[28] Assuming bidders' beliefs to be known is preferable in Bolotnyy and Vasserman's (2023) application, and, importantly, this assumption on bidders' beliefs makes it easier for them to identify the distribution of bidders' heterogeneous risk aversion. In contrast, it would be challenging to justify such an assumption about the expected wholesale market revenue μ_r in my application.

[29] I discuss how my structural estimates will change if bidders face more or less volatile prices in the wholesale market than the spot market in Section 6.

Assumption 2 (Additional assumption for identification with winners' bids)**.** *Bidders are ex-ante symmetric. That is, bidders independently draw their private types of cost c_i and $Capacity_i$ from a common distribution.*

The goal is to recover the equilibrium bid distribution $f(q^*, b^*)$ from winners' equilibrium bids. The baseline identification argument above follows once the analyst has $f(q^*, b^*)$. I decompose the distribution into two components as $f(q^*, b^*) = f(q^*|b^*)f(b^*)$ and analyze these two components separately.

The analyst obtains $f(b^*)$ from winners' equilibrium bid prices as in Athey and Haile (2002). From winners' equilibrium bid prices, the analyst, at least, has information on the lowest equilibrium bid price for each auction since the bidders having the lowest bid prices are selected as winners. Thus, the analyst knows the CDF for the first order statistic of N samples of equilibrium bid prices, $F^{1:N}(b^*)$. The analyst can recover $f(b^*)$ from $F^{1:N}(b^*)$ because there is a one-to-one relationship between $F^{1:N}(b^*)$ and the CDF for equilibrium bid prices, $F(b^*)$, given that the equilibrium bid price b_i^* is i.i.d. across bidders. Under Assumption 2, b_i^* is i.i.d. across bidders since bidders independently draw their types and employ symmetric strategy in the equilibrium (proof of symmetric strategy in Appendix C.1). The analyst also has $f(q^*|b^*)$ since whether winner or not does not change the bidder's optimal portfolio choice conditional on b^* (Equation (7)).[30]

In uniform-price auctions, the analyst observes a uniform clearing price p_a instead of bid prices b_{ia}^d. Bidders still make portfolio choices in uniform-price auctions. Thus, the analyst can identify the structural parameters related to portfolio choices, risk aversion coefficient γ and the expected wholesale market revenue μ_r, using uniform-price auctions. I adapt the first two assumptions in Assumption 1 to the case of uniform-price auctions as follows.

Assumption 3 (Identification of the uniform-price auction model)**.**

[30]This argument does not hold when an unobserved heterogeneity simultaneously affects portfolio choice and the "score" for the winner selection. For example, I cannot allow bidders to have heterogeneity in risk aversion.

1. *The clearing price belief is normally distributed, and the mean and variance parameters are identified from the data, i.e.,* $p_a \sim \mathcal{N}(\mu_{pa}, \sigma_p^2)$*, and the mean* μ_{pa} *sufficiently varies across auctions.*

2. *The equilibrium bid share* q_{ia}^**, evaluated at* μ_{pa}*, as in the solution to the portfolio problem, Equation (9), is observed as* q_{ia}^d *with an idiosyncratic normal bid share shock, i.e.,* $q_{ia}^d = q_{ia}^* + \eta_{ia}$*,* $\eta_{ia} \sim \mathcal{N}(0, \sigma_\eta^2)$*.*

3. *The variance of the wholesale market revenue* σ_r^2 *is identified from the data.*

I assume the bidders' clearing price belief is identified instead of the equilibrium bid prices observed in the first assumption. I apply the solution to the portfolio problem of uniform-price auctions in the second assumption. In practice, I further assume bidders believe the clearing price to be distributed so that it best rationalizes the observation to identify (μ_{pa}, σ_p^2) from the data.

Assumption 3 implies that the observed bid share q_{ia}^d has the following censored normal distribution:

$$q_{ia}^d = \min\left\{\max\left\{\underline{q}, \frac{1}{1+\tilde{\delta}^2\sigma_p^2/\sigma_r^2}\left(1 - \frac{\mu_r - \tilde{\delta}\mu_{pa}}{\gamma\sigma_r^2}\right) + \eta_{ia}\right\}, 1\right\}, \eta_{ia} \sim \mathcal{N}(0, \sigma_\eta^2). \quad (11)$$

This result implies that the structural parameters $(\gamma, \mu_r, \sigma_\eta^2)$ are identified if the expected clearing price μ_{pa} sufficiently varies across auctions.

5.2 Estimation

For each pay-as-bid auction, I observe auction covariates X_a, the procurement capacity D_a, and the bids (q_{ia}^d, b_{ia}^d) and $Capacity_{ia}$ for all winners. The auction covariates X_a include the auction date t_a, lead time l_a, the minimum bid share $\underline{q}_a$, and the number of participants N_a. For a uniform-price auction, I observe the clearing price p_a instead of the bid prices b_{ia}^d. I fix the annual discount factor to be $\delta = 0.95$.

My estimation approach closely follows my identification strategy in Section 5.1. I estimate the structural parameters using the portfolio problem and bid price optimization problem sequentially. I first use the solution to the portfolio problem to estimate the risk aversion coefficient γ and the expected wholesale market revenue μ_r. I then infer the bidders' cost types c_{ia} using the solution to the bid price optimization problem.

In the first step, I estimate the structural parameters related to portfolio choices, $(\gamma, \mu_r, \sigma_\eta^2)$, using pay-as-bid and uniform-price auctions by maximum likelihood approach.[31] I parameterize the structural parameters by auction covariates X_a. I assume the risk aversion coefficient and the bid share shock distribution to be the same across different auction covariates, i.e., $\gamma(X_a) = \gamma$ and $\sigma_\eta^2(X_a) = \sigma_\eta^2$ for all $X_a = x$. I also assume that bidders have a baseline belief about the expected wholesale market revenue, α_r, and discount it according to the lead time l_a, i.e., $\mu_r(X_a) = \delta^{l_a}\alpha_r$.[32]

Before this first step estimation, I prepare the variance of the wholesale market revenue σ_r^2 and the parameters in the clearing price belief for uniform-price auctions, (μ_{pa}, σ_p^2), outside the bid data. I use the spot market prices to gauge the volatility of the wholesale market revenue. I estimate a mean reverting process of annual spot market prices and then calculate σ_r^2 as it comes from the estimated process (Appendix C.2). I specify the parameters in the clearing price belief, (μ_{pa}, σ_p^2), so that they best rationalizes the observation (Appendix C.3).

With the estimated parameters in the first step, I infer the bidders' cost types c_{ia} using the solution to the bid price optimization problem, Equation (8), in the second step. The second step only applies to pay-as-bid auctions. I can recover c_{ia} from Equation (8) once I have the equilibrium winning probability functions $W_{ia}^*(\cdot)$ since the other variables/parameters are either observed, estimated in the first step, or prespecified. I

[31] Observed bid prices b_{ia}^d within pay-as-bid auctions do not have enough variation to estimate the structural parameters precisely.

[32] By the definition of the wholesale market belief in Equation (4), the mean $\mu_r(X_a)$ can be written as

$$\mu_r(X_a) = E\left[\frac{1}{T}\sum_{t=t_a+l_a}^{t_a+l_a+T-1} \delta^{t-t_a} r_t\right] = \delta^{l_a} \times \left(\frac{1}{T}\sum_{t=0}^{T-1} \delta^t E[r_{t_a+l_a+t}]\right).$$

Thus, the specification of the baseline belief α_r assumes that the discounted sum of the expected wholesale price is the same across different auction covariates.

detail the estimation of the equilibrium winning probability functions and then come back to the cost estimation.

Under Assumption 2, I have shown that the equilibrium winning probability functions are symmetric (Appendix C.1). Thus, I omit subscript i from the equilibrium winning probability functions hereafter. I prepare the distribution of the random variables included in the definition of the equilibrium winning probability function, Equation (6). These random variables are $Capacity_{ia}$, the equilibrium bid (q^*_{ia}, b^*_{ia}), and the procurement capacity D_a.[33] I model the distribution of the remaining random variables $Capacity_{ia}$, b^*_{ia}, and D_a since an equilibrium bid price b^*_{ia} uniquely determines the equilibrium bid share q^*_{ia} by solving the portfolio problem as in Equation (7). I assume that $Capacity_{ia}$, b^*_{ia}, and D_a are mutually independent conditional on auction covariates X_a.[34]

I estimate the distribution of $Capacity_{ia}$ specified as

$$Capacity_{ia}|X_a \sim \mathcal{N}(\beta_{Cap0} + \beta_{Cap1}(t_a + l_a), \sigma^2_{Cap}).$$

The average capacity is expected to increase by the operation start date, $t_a + l_a$, due to technological progress. The conditional independence of $Capacity_{ia}$ and b^*_{ia} implies that winners' capacities identify the entire bidders' capacity distribution since bidders' capacities are irrelevant to the selection of winners.

I next estimate the distribution of the equilibrium bid price b^*_{ia} specified as

$$b^*_{ia}|X_a \sim \mathcal{N}(\beta_{b0} + \beta_{b1}t_a + \beta_{b2}t^2_a + \beta_{b3}l_a + \beta_{b4}N_a, \sigma^2_b).$$

This parameterization intends to flexibly capture the time trend and the dependence on

[33]The distribution of $Capacity_{ia}$ and the equilibrium bid (q^*_{ia}, b^*_{ia}) is equivalent to that of competitors' $Capacity_{ja}$ and equilibrium bids (q^*_{ja}, b^*_{ja}) because the bidders are symmetric.

[34]One may think that a bidder with a large $Capacity_{ia}$ can have a low cost type c_{ia}, which leads to a low equilibrium bid price b^*_{ia}. However, I find no evidence that the winners' average capacity differs from the overall average capacity, which I calculate from the total capacity and number of participants observed in my data. Although extending the model to allow for correlation between $Capacity_{ia}$ and b^*_{ia} adds no theoretical complication, I need to assume this independence to overcome the problem of observing only winners' capacities in my application.

the lead time l_a. The equilibrium bid price can also depend on the competitiveness of the auction, proxied by the number of participants N_a. With the winners' equilibrium bid prices in hand, I can form a likelihood function using the distribution function of order statistics. The individual log-likelihood for bidder i is

$$\ln f_{b^*}(b^*_{ia}) + (brank_{ia} - 1)\ln F_{b^*}(b^*_{ia}) + (N_a - brank_{ia})\ln(1 - F_{b^*}(b^*_{ia})),$$

where $f_{b^*}(\cdot)$ and $F_{b^*}(\cdot)$ are the PDF and CDF for b^*_{ia} specified above and $brank_{ia}$ is the bid price rank of bidder i counted from the lowest in auction a.

Lastly, to obtain the procurement capacity distribution, I assume bidders believe the procurement capacity to be distributed such that it fits the observed procurement capacities (details in Appendix C.3). With the resulting distribution of $Capacity_{ia}$, (q^*_{ia}, b^*_{ia}), and D_a, I approximate the equilibrium winning probability function $W^*_a(\cdot)$ by simulation (details in Appendix C.4).

I use the observed winners' bids to infer their cost types. I also use the estimated equilibrium bid distribution to simulate the entire bidders' cost distribution. To get a sense of how cost has changed across auctions, I linearly project the simulated cost on a constant, t_a, t_a^2, and l_a. This linear projection intends to capture the time trend and the dependence on the lead time l_a similarly to the parameterization of the equilibrium bid price distribution.

6 Estimation Results

The estimation of the structural parameters proceeds in two steps. I first use the solution to the portfolio problem to estimate the risk aversion and the expected wholesale market revenue. I next use the solution to the bid price optimization problem to recover the bidders' cost distribution. The first step uses both pay-as-bid and uniform-price auctions while the second step only applies to pay-as-bid auctions. After presenting these estimation results, I demonstrate how structural parameter estimates are sensitive to the assumption of wholesale market volatility. My wholesale market risk premium estimate—which plays a central role in the counterfactual analysis of the policymaker's cost-risk trade-off—does not change in this sensitivity analysis because the risk premium is identified from the bid data without any wholesale market assumption. I also discuss whether other assumptions matter to the risk premium estimate.

Table 2 presents the structural parameter estimates. In the first step, I estimate the risk aversion coefficient γ and the expected wholesale market revenue parameter, $\alpha_r = \mu_r/\delta^l$, using the solution to the portfolio problem. The risk aversion coefficient γ of 1.36 implies that a bidder with a median project size would require a certain payment of \$0.3 million to accept a 50-50 lottery to either win or lose \$1 million.[35][36] The expected wholesale market revenue parameter α_r of \$27.91/MWh implies a long-run annual wholesale price, $E[r_t]$, of \$43.51/MWh, which is comparable with the average spot market price from 2011–2022, \$46.24/MWh.

Table 2: Structural parameter estimates for new wind energy auctions

First Step			Second Step		
Parameter	Coeff.	S.E.	Parameter	Coeff.	S.E.
Portfolio Problem			Capacity Type Distribution		
Risk Aversion, γ	1.358	(0.119)	Intercept, β_{Cap0}	10.592	(0.552)
E[Wholesale Revenue], α_r	27.914	(0.739)	Operation Start (year), β_{Cap1}	0.177	(0.119)
Bid Share Shock, σ_η^2	0.0886	(0.0044)	Variance, σ_{Cap}^2	11.214	(0.820)
			Equilibrium Bid Price Distribution		
			Intercept, β_{b0}	48.286	(0.204)
			Auction Date (year), β_{b1}	-0.861	(0.155)
			Auction Date Square, β_{b2}	0.977	(0.022)
			Lead Time (year), β_{b3}	-0.280	(0.064)
			# Participants, β_{b4}	-0.0135	(0.0007)
			Variance, σ_b^2	16.323	(0.823)

Notes: Standard errors are calculated using 200 auction-level block bootstrap replications, where I rerun the two-step estimation procedure.

[35] The dollar values in the model are scaled by \$/MWh. Since the total production of the median size project is 2.1 million MWh, γ of 1.36 is interpreted as dollar values scaled by \$2.1 million for the median project size bidder.

[36] Bolotnyy and Vasserman's (2023) estimate of risk aversion in the U.S. bridge construction and maintenance projects suggests a bidder would require a certain payment of \$3,000 to accept a 50-50 lottery to win or lose \$10,000. Since Brazil's wind turbine projects are 30 times larger than those bridge projects (median project value, \$60 million vs. \$2 million), the levels of risk aversion are comparable when we think that bidders are determining their risk behavior relative to the project size.

In this step, I use the SD of the wholesale market revenue σ_r ranging from \$4.94–\$5.82/MWh, which is estimated from annual spot market prices from 2001–2022. I use the clearing price belief with mean μ_p ranging from \$20.24–\$33.41/MWh and SD $\sigma_p =$ \$4.00/MWh. Results for the underlying model parameters are in Appendix D.

In the second step, I first estimate the equilibrium winning probability function $W^*(\cdot)$ for each pay-as-bid auction. I estimate two distributions for capacity type and the equilibrium bid price b_i^* in this step. Bidders draw their capacity type from a distribution with a mean of 10.59 MW and an SD of 3.35 MW if their wind turbines are planned to start operation at the beginning of 2011.[37] The average capacity type increases by 0.18 MW each year due to technological progress.

The parameter estimates for the equilibrium bid price distribution imply that bidders understand that the competitors' equilibrium bid prices follow a distribution with a mean of \$44.17/MWh and an SD of \$4.04/MWh in the first auction in 2011. The mean of the equilibrium bid price distribution changes depending on the auction's date, lead time, and number of participants. The mean ranges from \$42.64/MWh to \$60.07/MWh for the 8 pay-as-bid auctions from 2011–2015. I use the procurement capacity distribution with mean ranging from 277.9–488.8 MW and SD 244.8 MW (details in Appendix D).[38] Estimated equilibrium winning probability functions and actual winning bids are plotted in Figure D2 in Appendix D. The winning probabilities of the actual winning bids are in a plausible range for each auction.

I them recover the bidders' cost distribution. The average winner's cost, wholesale market risk premium, and auction markup are \$20.40/MWh, \$0.03/MWh, and \$1.72/MWh, respectively, for the median auction.[39] The average risk premium is near zero since the average share allocated to the wholesale market, $1 - q_i^*$, is very small, 0.03.

[37] The beginning of 2011 is set to date 0.

[38] The large SD of the procurement capacity distribution makes the procurement capacity to be non-positive with an appreciable level of probability. I interpret a non-positive procurement capacity as a case where the auction is canceled and truncate those cases in calculating the equilibrium winning probability functions. Brazil's new energy auctions are canceled about once every five years historically, and I omit the canceled auctions from the analysis.

[39] I define the median auction as the pay-as-bid auction having the median average winner's cost. I use the same median auction throughout the paper.

Absent risk sharing, the average winner's risk premium is \$20.16/MWh, so the investor requires the expected revenue to be at least \$40.56/MWh to cover the risk premium (\$20.16/MWh) in addition to his cost (\$20.40/MWh). Risk sharing halves the minimum expected revenue he chooses to invest because his risk premium falls from \$20.16/MWh to \$0.03/MWh.

The mean and SD of the entire bidders' costs are \$26.30/MWh and \$2.47/MWh in the median auction. Since the average winner has \$5.91/MWh lower cost than all participants and only collects an auction markup of \$1.72/MWh, auctions efficiently allocate and price the purchase agreements. The implied cost estimates are in a reasonable range compared to the engineering estimates.[40] Table 3 tabulates the linear projection of the entire bidders' costs on auction covariates. The average investor's cost is around \$31/MWh from 2011 to 2013, exceeds \$32/MWh after that, and becomes \$36/MWh in 2015, if the lead time is zero. Additionally, the coefficient on the lead time reflects the bidders' expected change in their costs over time. The lead time coefficient estimate implies that bidders expected the cost to decrease by \$2.07/MWh annually.

Table 3: Linear projection of the entire bidders' costs on auction covariates

Variable	Coeff.	S.E.
Intercept	31.242	(0.184)
Auction Date (year)	−1.667	(0.087)
Auction Date Square	0.703	(0.015)
Lead Time (year)	−2.069	(0.027)

Notes: Standard errors are calculated using 200 auction-level block bootstrap replications, where I rerun the two-step estimation procedure.

I use the spot market prices to gauge the variance of the wholesale market revenue, σ_r^2. I need the variance σ_r^2 to isolate the risk aversion coefficient γ from the wholesale market risk premium, $\gamma\sigma_r^2/2$, which is estimated from the bids. Thus, my risk premium estimate

[40] My estimates suggest the average winner's cost of \$13–\$29/MWh and the average bidder's cost of \$22–\$34/MWh for the auctions from 2011–2015. Brazil EPE's cost estimates imply the average bidder's cost of \$22–\$33/MWh over the same period (EPE, 2022). The International Renewable Energy Agency estimates the cost of \$37–\$67/MWh, on average, for wind turbines commissioned from 2014–2019 (IRENA, 2022). Note that my estimates are recovered from revealed preference and may include friction costs.

is not sensitive to the assumption of wholesale market volatility. However, overestimating (or underestimating) the variance σ_r^2 results in underestimating (or overestimating) the risk aversion coefficient γ and, consequently, affects the markup and cost estimates. In Table 4, I re-estimate the structural parameters, changing the variance σ_r^2 from 1/4 to 4 times the main analysis. For instance, when the variance σ_r^2 is halved (column 2), the risk aversion coefficient γ doubles to 2.72 since the risk premium is unchanged. As a result, the markup decreases from \$1.72/MWh to \$1.05/MWh. The cost then increases from \$20.40/MWh to \$21.06/MWh because the sum of the markup and cost stays constant.

Table 4: Sensitivity to the wholesale market variance assumption

	Wholesale Revenue Variance σ_r^2				
	$\times 1/4$	$\times 1/2$	Main	$\times 2$	$\times 4$
Parameter	(1)	(2)	(3)	(4)	(5)
Risk Aversion, γ	5.432	2.716	1.358	0.679	0.339
Average Winner Markup (\$/MWh)	0.629	1.048	1.716	2.755	4.305
Average Winner Cost (\$/MWh)	21.483	21.064	20.396	19.357	17.807

Notes: The average winner markup and cost are calculated for the median auction.

The wholesale market is likely less volatile than the spot market because of the opportunity to enter into other contracts. Thus, it is likely that the markup is overestimated and the cost is underestimated, though the estimates only change by \$1/MWh even if the variance σ_r^2 is four times smaller than the main analysis (column 1). There is also a possibility that the mean reverting process misspecifies the bidders' wholesale market belief and underestimates the variance σ_r^2. Then, the markup is underestimated and the cost is overestimated as in columns 4 and 5.

The risk premium estimate also stays the same for different assumptions on competitors' situation. Assumptions on competitors' situation are required to estimate the equilibrium winning probability function $W_i^*(\cdot)$ in the second step. The first step estimates do not change by how $W_i^*(\cdot)$ is estimated since it does not enter into the optimal portfolio choice conditional on the bidder's equilibrium bid price b_i^* (Equation (7)). Thus, I can relax the assumptions on competitors' situation, such as independent private costs and bidder symmetry, and still obtain the same risk premium estimate.

7 Counterfactuals

With the structural estimates, I conduct two counterfactual exercises where the policymaker has a goal to encourage a given amount of renewable capacity installation. To accomplish this goal, the policymaker calls for new energy agreements under which investors commit to building new renewable capacity in exchange for a risk-sharing contract, as defined in Section 2. With this risk-sharing contract, the policymaker pays a certain amount as the investor provides the policymaker with a share $\lambda \in [0, 1]$ of the production. The policymaker understands that she will sell her share of the electricity into the wholesale market, which follows the same belief over wholesale market prices as the bidders. Thus, λ can be interpreted as the share of risk the policymaker takes.

Importantly, the policymaker specifies the share λ and applies the same share to all investors instead of allowing investors to choose their shares individually. Moving from $\lambda = 0$ to $\lambda = 1$ traces out the policymaker's cost-risk trade-off that arises from the risk-sharing contracts, as illustrated in Section 2. In the first counterfactual, I simulate the policymaker's cost-risk frontiers for three scenarios, prespecified price, first-best, and pay-as-bid auctions, as ways to allocate these contracts to investors. I then use the simulated cost-risk frontiers to decompose the policymaker's utility gains from the actual Brazilian auctions that allow bidders to have portfolio choices. In the second counterfactual, I compare the two observed auction formats, pay-as-bid and uniform-price, in providing the risk-sharing contracts, focusing on the fact that the procurement capacity is not disclosed before bidding in this context. I formulate auctions that provide the risk-sharing contracts, which I call uniform share auctions, before proceeding to the details of the two counterfactuals.

7.1 Uniform Share Auctions

Uniform share auctions differ from the actual auctions defined in Section 4 in three ways. First, all bidders bid in a policymaker designated share λ of their production. Bidders cannot choose their shares. Second, the objective capacity $\widetilde{D}$ decides the winners based on their installation capacity rather than capacity allocated to the purchase agreement. Third, the auctioneer pays price per total production rather than production allocated to the purchase agreement. The latter two devices enable uniform share auctions to encompass subsidy auctions since the capacity or production allocated to the purchase agreement cannot be defined for subsidy auctions. The remaining concepts stay the same as the purchase agreement auctions defined in Section 4.

Bidder i specifies a bid price b_i. If bidder i wins the auction, for each period during the contract, the bidder provides $\lambda \times Capacity_i \times H$ hours of electricity, and the auctioneer pays $b_i \times Capacity_i \times H$. Bidder i sells the remaining production, $(1-\lambda) \times Capacity_i \times H$ hours, to the wholesale market at price r_t for each period t. Thus, bidder i's expected utility conditional on winning the auction with a bid b is

$$E\left[u\left(\tilde{\delta}b + (1-\lambda)r - c_i\right)\right] = u\left(\tilde{\delta}b + (1-\lambda)\mu_r - c_i - (1-\lambda)^2 \cdot \frac{\gamma\sigma_r^2}{2}\right).$$

There are two differences compared to auctions that allow bidders to have portfolio choices (Equation (5)). First, the policymaker designated share λ replaces the bidder-selected share q. Second, the revenue from the contract, $\tilde{\delta}b$, does not depend on the share λ since the contract payment is made per total production. The auction provides a full share purchase agreement when $\lambda = 1$ and a per-unit subsidy when $\lambda = 0$. The auctioneer awards these contracts to the lowest-price bidders until winners' total capacity $\sum_i Capacity_i$ exceeds the objective capacity $\widetilde{D}$.

With the pay-as-bid format, a pure-strategy BNE, $\{b_i^*\}_{i=1}^N$, satisfies, for all $i = 1, \ldots, N$,

$$b_i^* = \arg\max_b \widetilde{W}_i^*(b) \times u\left(\tilde{\delta}b + (1-\lambda)\mu_r - c_i - (1-\lambda)^2 \cdot \frac{\gamma\sigma_r^2}{2}\right),$$

where

$$\widetilde{W}_i^*(b) := \Pr\left(\sum_{j \neq i} Capacity_j \mathbb{1}(b_j^* \leq b) < \widetilde{D}\right).$$

I assume *ex-ante* symmetry (Assumption 2) to ease the calculation of the counterfactual equilibrium strategy. With *ex-ante* symmetry, I prove that a unique symmetric monotone pure-strategy BNE exists in Appendix E.1.

In the uniform-price format equilibrium, the auctioneer awards the lowest-cost bidders until the objective capacity $\widetilde{D}$ is filled. The winners finalize the bid price at the smallest pseudo cost among the losers.

7.2 Policymaker's Cost-Risk Trade-off

I consider three scenarios under which the policymaker allocates the risk-sharing contracts to investors to achieve a given amount of renewable capacity installation. Policymakers have allocated power purchase agreements at a prespecified price to support renewable investments (Fabra, 2021). The policymaker determines a technology-specific fixed price per unit of renewable electricity and calls for investors to sign a power purchase agreement at this prespecified price on a first-come, first-served basis. I adopt this prespecified price allocation in the first scenario. The policymaker sets the contract payment to the minimum amount necessary for the average cost investor to sign the risk-sharing contract and calls for investors at this prespecified contract payment amount. The policymaker needs to know the average investor's cost but not the investors' private costs in this prespecified price scenario.

The second scenario considers the first-best allocation, where the policymaker pays the minimum amount for each of the lowest-cost investors to sign. This scenario requires the policymaker to have full information about the investors' costs. Since the policymaker obtaining the full investor private cost information is impractical, the policymaker relies on auctions to lower contract payments without knowing investors' costs. Historically, policymakers have shifted from prespecified prices to auctions to allocate power purchase agreements (Fabra, 2021). In the third scenario, the policymaker implements uniform share auctions with the pay-as-bid format. I demonstrate how the uniform-price format can change the pay-as-bid format results in the second counterfactual in Section 7.3.

I simulate these three scenarios in the economic environment of the 8 actual pay-as-bid auctions from 2011–2015. I fix the number of winners and the capacities of the winners to the actual values to hold the total installation capacity constant. Figure 4 depicts the simulated cost-risk frontiers for a representative auction.[41] The prespecified price scenario (dashed line) uses the average bidder's cost to calculate the outcomes of interest: the expected policymaker's net expenditure (y-axis) and the variance of the policymaker's net expenditure (x-axis). For the other two scenarios, I draw investors' costs from their distribution and simulate the average outcomes. I detail the calculation of the equilibrium strategies in uniform share auctions with the pay-as-bid format in Appendix E.2.

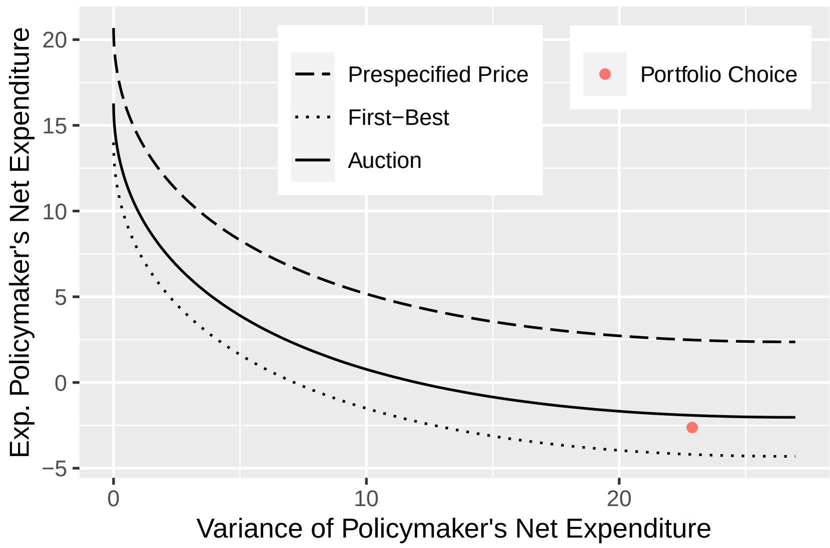


Figure 4: Simulated cost-risk frontiers for the policymaker's net expenditure ($/MWh)

Table 5 shows the mean and SD of the policymaker's net expenditure for different shares of production the investors provide the policymaker, λ, for the median auction. The policymaker's net expenditure is the contract payment net of the wholesale market revenue. The policymaker's contract payment covers the cost and markup of the share λ of

[41] Figure F1 in Appendix F contains the simulation results for all 8 auctions.

investors' production and the investors' wholesale market risk premium for the remaining share $1 - \lambda$ of it. As the policymaker sets a larger λ, the cost and markup component increases while the risk premium part decreases. Thus, the policymaker's contract payment does not change monotonically by λ. The first-best allocation has the lowest contract payment for a given share λ because the investors' markup is zero. Uniform share auctions with the pay-as-bid format allow the investors to collect a positive markup, resulting in the contract payment falling between the prespecified price and first-best scenarios. The mean and SD of the policymaker's wholesale market revenue increase as the share of electricity the policymaker sells to the wholesale market, λ, becomes larger.

Table 5: Counterfactual policymaker net expenditures

	Share of Risk Policymaker Takes			
	$\lambda = 0$	$\lambda = 1/2$	$\lambda = 1$	$\lambda = q^*$
Allocation Mechanism	(1)	(2)	(3)	(4)
Policymaker's Contract Payment (\$/MWh)				
Prespecified Price	23.76	20.34	26.99	25.95
First-Best	16.23	12.80	19.45	18.42
Auction: Uniform Share + Pay-as-Bid	18.89	15.46	22.11	21.08
Auction: Bidder Portfolio Choice + Pay-as-Bid	-	-	-	20.66
Policymaker's Wholesale Market Revenue				
Mean (\$/MWh)	0.00	11.69	23.38	22.29
Standard Deviation (\$/MWh)	0.00	2.72	5.44	5.19
Policymaker's Net Expenditure				
Mean (\$/MWh)				
Prespecified Price	23.76	8.65	3.61	3.67
First-Best	16.23	1.11	−3.93	−3.87
Auction: Uniform Share + Pay-as-Bid	18.89	3.77	−1.27	−1.21
Auction: Bidder Portfolio Choice + Pay-as-Bid	-	-	-	−1.63
Standard Deviation (\$/MWh)	0.00	2.72	5.44	5.19

Notes: The policymaker's net expenditure is the contract payment net of the wholesale market revenue. λ is the share of production the investors provide the policymaker. The policymaker understands that she will sell her share of the electricity into the wholesale market, which follows the same belief over wholesale market prices as the investors. $q^* = 0.95$ is the model-predicted equilibrium share in pay-as-bid auctions that allow bidders to have portfolio choices. Values are from the median winner cost auction.

Consequently, if the policymaker sets λ large, the expected policymaker's net expenditure decreases, and the SD of the policymaker's net expenditure increases. The SD is determined by the share λ and does not change by the allocation mechanism. My simulation predicts that moving from zero policymaker risk (column 1) to the highest risk (column 3) lowers the expected policymaker's net expenditure by \$20.16/MWh (98.7% of the average winner's cost) while increasing the SD of the policymaker's net expenditure from \$0/MWh to \$5.44/MWh. Absent risk sharing, the investors' wholesale market risk premium is \$20.16/MWh. Thus, the investors consider it worth \$20.16/MWh for the policymaker to take the full risk, where the policymaker will be exposed to an uncertain wholesale market revenue stream with an SD of \$5.44/MWh. For 5.6 GW of generation capacity auctioned (3% of the entire capacity in Brazil), these numbers are scaled up to \$20 billion and \$5 billion from \$20.16/MWh and \$5.44/MWh, respectively.

The policymaker achieves the expected net expenditure below zero by accepting enough risk for the first-best and uniform share auction scenarios. The simulated average of winners' costs (\$19.45/MWh) is lower than the estimated expected wholesale market revenue (\$23.38/MWh) for the median auction. The contract payment consists of the investor's cost and risk premium for the first-best allocation. Thus, the policymaker can offset the contract payment with the expected sales in the wholesale market if the risk the policymaker takes is large enough for the investors' risk premium to be smaller than \$3.93/MWh. The risk-averse investors value the policymaker taking a large risk, and the investors build the new renewable capacity with a certain electricity price below the average wholesale price. The uniform share auction also achieves the contract payment below the expected sales if the auction markup is sufficiently small. For example, suppose the policymaker takes all the risk (column 3), so the investors' risk premium is zero. In that case, the expected wholesale market revenue (\$23.38/MWh) covers the average winner's cost (\$19.45/MWh) and the auction markup (\$2.66/MWh) to make the expected policymaker's net expenditure to be −\$1.27/MWh.

I also simulate the average outcomes for the actual Brazilian auctions that allow bidders to have portfolio choices (red filled circle in Figure 4).[42] Column 4 in Table 5 shows the policymaker's contract payments, wholesale market revenue, and net expenditures for the model-predicted equilibrium share of production the bidders bid into the auction, $q^* = 0.95$. Allowing bidders to have portfolio choices leads to a \$0.43/MWh smaller policymaker's contract payment and expected policymaker's net expenditure than imposing the same share uniformly on bidders. The opportunity for portfolio optimization makes the auction more lucrative and induces more competitive bids. Conversely, the constraint of bidding in the designated share makes the auction less attractive and lets bidders charge higher markups than bidders having the opportunity for portfolio optimization.

To illustrate the usefulness of these predictions, I contrast two policymakers, one risk-neutral and the other as risk-averse as the bidders. I assume that the policymaker has a CARA utility with a risk aversion coefficient $\gamma_{PM} \geq 0$ as in Section 2. I use the certainty equivalent of the policymaker's net expenditure (defined in Section 2) for welfare evaluation.

Table 6 shows the certainty equivalent of the policymaker's net expenditure for different shares of production the investors provide the policymaker, λ, for the median auction. I define the full share purchase agreement (column 3) in the prespecified price scenario as the reference case and discuss the savings relative to this case. For the risk-neutral policymaker, the certainty equivalent of the net expenditure is the same as the expected net expenditure. The expected net expenditure of the optimal risk sharing policy (column 2) with the first-best allocation is $-$\$3.93/MWh, which achieves the maximum possible savings of \$7.53/MWh relative to the reference case (column 3, prespecified price, \$3.61/MWh).

[42] Using the estimated equilibrium winning probability functions, the first-order conditions in Equations (7) and (8) uniquely determine the equilibrium strategies in the actual auctions. Solving for the counterfactual equilibrium strategy in an auction that allows bidders to have portfolio choices is challenging unless the equilibrium winning probability functions are given. This feature is common with multi-unit auctions (e.g., Hortaçsu and McAdams, 2010; Ryan, 2022; Richert, 2023). As Richert (2023) suggests, one may think of an indirect inference approach by parameterizing the distribution of the equilibrium bid prices to find the parameters that comfort the ODEs in Appendix B. However, one-iteration of the parameter search is impractically slow since each iteration involves calculating an equilibrium winning probability function as in Appendix C.4.

Table 6: Counterfactual policymaker certainty equivalent net expenditure ($/MWh)

	Share of Risk Policymaker Takes			
	$\lambda = 0$	$\lambda = \lambda^*$	$\lambda = 1$	$\lambda = q^*$
Allocation Mechanism	(1)	(2)	(3)	(4)
Risk-Neutral Policymaker $\gamma_{PM} = 0$				
Prespecified Price	23.76	3.61	3.61	3.67
First-Best	16.23	−3.93	−3.93	−3.87
Auction: Uniform Share + Pay-as-Bid	18.89	−1.27	−1.27	−1.21
Auction: Bidder Portfolio Choice + Pay-as-Bid	-	-	-	−1.63
Risk-Averse Policymaker $\gamma_{PM} = \hat{\gamma} = 1.36$				
Prespecified Price	23.76	13.69	23.76	22.06
First-Best	16.23	6.15	16.23	14.52
Auction: Uniform Share + Pay-as-Bid	18.89	8.81	18.89	17.18
Auction: Bidder Portfolio Choice + Pay-as-Bid	-	-	-	16.76

Notes: λ is the share of production the investors provide the policymaker. The policymaker understands that she will sell her share of the electricity into the wholesale market, which follows the same belief over wholesale market prices as the investors. The policymaker's certainty equivalent net expenditure is defined as $E[C] + (\gamma_{PM}/2) \times \mathrm{Var}(C)$, where C is the policymaker's net expenditure. λ^* is the share that maximizes the policymaker's utility. $\lambda^* = 1$ for the risk-neutral policymaker and $\lambda^* = 1/2$ for the policymaker as risk-averse as the bidders. $q^* = 0.95$ is the model predicted equilibrium share in pay-as-bid auctions that allow bidders to have portfolio choices. γ_{PM} is the policymaker's risk aversion coefficient. $\hat{\gamma}$ is the estimated bidders' risk aversion coefficient. Values are from the median winner cost auction.

The pay-as-bid auction that allows bidders to have portfolio choices achieves $5.24/MWh of savings, 70.1% of the maximum possible. The $5.24/MWh savings can be decomposed into three effects: auction mechanism, risk sharing, and auction markup reduction stemming from bidders having the opportunity of portfolio choices. First, starting from the reference case (column 3, prespecified price, $3.61/MWh), distributing full share purchase agreements using an auction (auction scenario in row 3, −$1.27/MWh) saves $4.87/MWh. Second, shifting to the share of production the bidders bid into the auction (column 4, −$1.21/MWh) saves −$0.06/MWh (costs $0.06/MWh). Third, allowing bidders to have portfolio choices (column 4, −$1.63/MWh) saves $0.43/MWh for the same level of risk sharing. In terms of percentage points, 70.1% of savings consists of the savings from the auction mechanism, 64.8 pps ($4.87/MWh), and the markup reduction, 6.1 pps ($0.43/MWh), while losing 0.1 pps ($0.06/MWh) because of risk sharing. Risk sharing works negatively for the risk-neutral policymaker because she does not want to share the risk with the investors.

If the policymaker is as risk-averse as the investors, the policymaker is indifferent between subsidies (column 1) and full share purchase agreements (column 3) for the same allocation mechanism. The certainty equivalent net expenditure of the reference case of the full share purchase agreement (column 3) in the prespecified price scenario is \$23.76/MWh. The certainty equivalent net expenditure of the optimal risk sharing (column 2) with the first-best allocation is \$6.15/MWh, which achieves the maximum possible savings of \$17.61/MWh. The pay-as-bid auction that allows bidders to have portfolio choices saves \$7.01/MWh, 40.6% of the maximum possible. I can decompose this \$7.01/MWh (40.6%) savings similarly to the risk-neutral policymaker case: auction mechanism (\$4.87/MWh, 27.7 pps), risk sharing (\$1.71/MWh, 10.3 pps), and markup reduction (\$0.43/MWh, 2.6 pps). The risk-averse policymaker enjoys the benefit of sharing the risk with the investors.

7.3 Pay-as-bid and Uniform-price Auctions

In comparing pay-as-bid and uniform-price formats, I focus on the fact that the procurement capacity is not disclosed before bidding in the context of renewable energy auctions. Auction's expected (or realized) procurement capacity changes the expected (or realized) competitiveness of the auction. I consider scenarios where the realized competitiveness is not as expected by the bidders. To simplify the situation, I fix the bidders' capacities to be the same so that the numbers of bidders and winners determine the competitiveness.

I simulate the average winner's prices of uniform share auctions with share $\lambda = 1$ (full share purchase agreements) for different realizations of the number of winners when the bidders expect 50 bidders to win out of 500 for sure.[43] I fix the lead time to be $l = 1$ year and the average bidder's cost to be $\mu_c = \$30$/MWh. I use the estimated values for the risk aversion coefficient γ and the variance of the bidder's cost σ_c^2. I calculate counterfactual

[43] The bidders expecting 50 bidders to win for sure means that the distribution of the objective capacity $\widetilde{D}$ is degenerate.

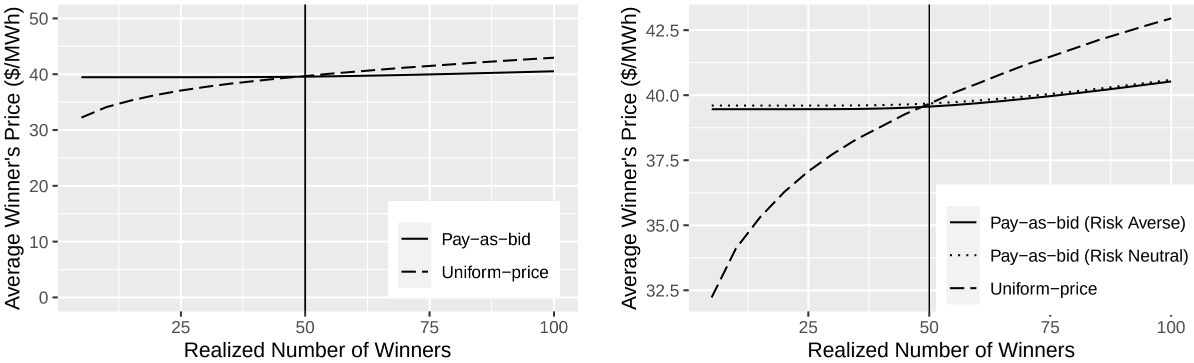
equilibrium strategies for the pay-as-bid format as detailed in Appendix E.3.[44]

Figure 5(a) compares the simulated average winner prices in pay-as-bid and uniform-price auctions for different realizations of the number of winners. The solid vertical line indicates the expected number of winners, 50. Auction's expected (or realized) number of winners changes the expected (or realized) competitiveness of the auction. The price curve of pay-as-bid auctions is flatter than uniform-price auctions across different realizations of competitiveness. The average winner's price in pay-as-bid auctions changes little by the realized competitiveness because the expected competitiveness, fixed across the simulations, forms pay-as-bid auction's bid prices. On the other hand, the average winner's price in uniform-price auctions changes more because the realized competitiveness determines uniform-price auction's clearing prices. If the auction is as competitive as bidders expected, the pay-as-bid and uniform-price formats result in comparable average winner prices. Uniform-price auctions reduce average winner prices if the auction is more competitive than expected, and vice versa. Figure 5(b) also plots the simulated average winner prices for risk-neutral bidders, having $\gamma = 0$, in pay-as-bid auctions.[45] Risk-neutral bidders yield the same results as risk-averse bidders but with slightly higher average winner prices. Thus, bidders' risk aversion is not the primary driving force of the differences between pay-as-bid and uniform-price auctions in this counterfactual.

I change the auction's designated share λ to depict the cost-risk frontiers in Figure F2 in Appendix F. I fix the expected wholesale market revenue to be the same as the average bidder's cost, $\mu_r = 30$, and use the estimated values for the variance of wholesale market revenue σ_r^2. The simulated cost-risk frontiers confirm that the pay-as-bid and uniform-price auctions obtain comparable outcomes if the auction is as competitive as bidders expect, and uniform-price auctions reduce the expected policymaker's net expenditure if the auction is more competitive than expected.

[44]The equilibrium strategy calculations are much more manageable with bidders having the same capacity and a degenerate distribution of the number of winners because the winning probability function can be derived analytically.

[45]The outcome of uniform-price auctions with share $\lambda = 1$ (full share purchase agreements) does not change by whether the bidders are risk averse or risk neutral.



(a) Risk-averse bidders (b) Risk-averse and risk-neutral bidders

Figure 5: Comparison of pay-as-bid and uniform-price auctions

8 Conclusion

I propose a structural framework of policymakers using contracts that share the wholesale electricity price risk to support risk-averse investors' new renewable energy projects. Investors' risk aversion gives rise to the policymaker's cost-risk trade-off associated with these risk-sharing contracts. These contracts encompass the two commonly adopted renewable supporting schemes as the two extremes: full share purchase agreements when the policymaker bears all the risk with the lowest expected net expenditure, and subsidies when the investors bear all the risk with the highest expected policymaker's net expenditure. If the investors are risk-neutral, full share purchase agreements and subsidies have the same expected net expenditure for the policymaker.

To empirically assess this trade-off, I study Brazilian long-term power purchase agreement auctions that embed bidders' portfolio choices. I build and estimate a structural model of risk-averse bidders in these multi-unit procurement auctions to uncover bidders' risk aversion and the distribution of their private costs. I find that bidders are substantially risk averse, and consequently, volatile wholesale electricity prices considerably increase the minimum expected revenue under which bidders choose to invest compared to if they were risk neutral. Additionally, the recovered winners' costs are much lower than the average bidder, and the winners collect modest auction markups. These results suggest that the auctions efficiently allocate and price the purchase agreements in Brazil.

With the structural estimates, I quantify the policymaker's cost-risk trade-off to achieve the policymaker's renewable energy target. For 3% of Brazil's generation capacity auctioned, full share purchase agreements will be expected to cost $20 billion less than subsidies because of the renewable investors' risk premium. Whether this is a good deal depends on the policymaker's risk preference. I propose the certainty equivalent of the policymaker's net expenditure as a measure of assessing the welfare consequences for a given level of the policymaker's risk aversion. How policymakers should decide on an appropriate level of risk aversion is a reasonable normative question to ask in future research.

Auctions with risk-sharing devices may facilitate competition by inducing more risk-averse bidders' entry if bidders have heterogeneity in risk aversion and auctions have positive entry costs. With the bids and covariates of all participating bidders and information on potential participants, extending the proposed estimation procedure to incorporate heterogeneous risk aversion and positive entry costs is straightforward, analogously to what Bolotnyy and Vasserman (2023) have demonstrated in scaling auctions. However, estimating heterogeneous risk aversion in a computationally tractable way is challenging without losers' information. I leave this for future research agenda.

References

Alcorta, Peio, Maria Paz Espinosa, and Cristina Pizarro-Irizar, "Who Bears the Risk? Incentives for Renewable Electricity under Strategic Interaction between Regulator and Investors," *Resource and Energy Economics*, 2023, *75* (July), 101401.

Aldy, Joseph E., Todd D. Gerarden, and Richard L. Sweeney, "Investment versus Output Subsidies: Implications of Alternative Incentives for Wind Energy," *Journal of the Association of Environmental and Resource Economists*, 2023, *10* (4), 981–1018.

Alishahi, E., M. Parsa Moghaddam, and M.K. Sheikh-El-Eslami, "A System Dynamics Approach for Investigating Impacts of Incentive Mechanisms on Wind Power Investment," *Renewable Energy*, 2012, *37* (1), 310–317.

Athey, Susan and Jonathan Levin, "Information and Competition in U.S. Forest Service Timber Auctions," *Journal of Political Economy*, 2001, *109* (2), 375–417.

_ **and Philip A. Haile**, "Identification of Standard Auction Models," *Econometrica*, 2002, *70* (6), 2107–2140.

_ **and** _ , "Nonparametric Approaches to Auctions," in "Handbook of Econometrics," Vol. 6 2007, pp. 3847–3965.

Baucells, Manel and Samuel E. Bodily, "The Discount Rate for Investment Analysis Applying Expected Utility," Technical Report, Available at SSRN 4195050 2022.

Bolotnyy, Valentin and Shoshana Vasserman, "Scaling Auctions as Insurance: A Case Study in Infrastructure Procurement," *Econometrica*, 2023, *91* (4), 1205–1259.

Borenstein, Severin, "Private Net Benefits of Residential Solar PV: The Role of Electricity Tariffs, Tax Incentives, and Rebates," *Journal of the Association of Environmental and Resource Economists*, 2017, *4* (S1), S85–S122.

Bürer, Mary Jean and Rolf Wüstenhagen, "Which Renewable Energy Policy is a Venture Capitalist's Best Friend? Empirical Evidence From a Survey of International Cleantech Investors," *Energy Policy*, 2009, *37* (12), 4997–5006.

Carley, Sanya, Lincoln L. Davies, David B. Spence, and Nikolaos Zirogiannis, "Empirical Evaluation of the Stringency and Design of Renewable Portfolio Standards," *Nature Energy*, 2018, *3* (9), 754–763.

Central Bank of Brazil, "Basic interest rates - History (in Portuguese)," 2023. Data retrieved May 25, 2023, https://www.bcb.gov.br/controleinflacao/historicotaxasjuros.

Chassang, Sylvain, Kei Kawai, Jun Nakabayashi, and Juan Ortner, "Robust Screens for Noncompetitive Bidding in Procurement Auctions," *Econometrica*, 2022, *90* (1), 315–346.

Cohn, Richard A., Wilbur G. Lewellen, Ronald C. Lease, and Gary G. Schlarbaum, "Individual Investor Risk Aversion and Investment Portfolio Composition," *The Journal of Finance*, 1975, *30* (2), 605–620.

Cox, James C., Vernon L. Smith, and James M. Walker, "Auction Market Theory of Heterogeneous Bidders," *Economics Letters*, 1982, *9* (4), 319–325.

EPE, *Power Generation Costs Report 2021*, No.EPE-DEE-RE-089/2021-r1, Empresa de Pesquisa Energética, Brazil, 2022.

Fabra, Natalia, "The Energy Transition: An Industrial Economics Perspective," *International Journal of Industrial Organization*, 2021, *79*, 102734.

Farrell, Niall, Mel T. Devine, William T. Lee, James P. Gleeson, and Sean Lyons, "Specifying An Efficient Renewable Energy Feed-in Tariff," *The Energy Journal*, 2017, *38* (2), 53–75.

Gonzales, Luis E., Koichiro Ito, and Mar Reguant, "The Investment Effects of Market Integration: Evidence From Renewable Energy Expansion in Chile," *Econometrica*, 2023, *91* (5), 1659–1693.

Greenstone, Michael and Ishan Nath, *Do Renewable Portfolio Standards Deliver Cost-Effective Carbon Abatement?*, Working Paper, 2021.

Guerre, Emmanuel, Isabelle Perrigne, and Quang Vuong, "Optimal Nonparametric Estimation of First-price Auctions," *Econometrica*, 2000, *68* (3), 525–574.

Hochberg, Michael and Rahmatallah Poudineh, *Renewable Auction Design in Theory and Practice: Lessons from the Experiences of Brazil and Mexico* 2018.

_ **and** _ , "The Brazilian electricity market architecture: An analysis of instruments and misalignments," *Utilities Policy*, 2021, *72*, 101267.

Holt, Charles A., "Competitive Bidding for Contracts under Alternative Auction Procedures," *Journal of Political Economy*, 1980, *88* (3), 433–445.

Hortaçsu, Ali and David McAdams, "Mechanism Choice and Strategic Bidding in Divisible Good Auctions: An Empirical Analysis of the Turkish Treasury Auction Market," *Journal of Political Economy*, 2010, *118* (5), 833–865.

Hughes, Jonathan E. and Molly Podolefsky, "Getting Green with Solar Subsidies: Evidence from the California Solar Initiative," *Journal of the Association of Environmental and Resource Economists*, 2015, *2* (2), 235–275.

IEA and OECD, *Deploying Renewables Principles for Effective Policies: in Support of the G8 Plan of Action*, Paris: OECD/IEA, 2008.

IRENA, *Renewable Energy Auctions: Status and Trends Beyond Price*, Abu Dhabi: International Renewable Energy Agency, 2019.

_ , *Renewable Power Generation Costs in 2021*, Abu Dhabi: International Renewable Energy Agency, 2022.

Jenner, Steffen, Felix Groba, and Joe Indvik, "Assessing the Strength and Effectiveness of Renewable Electricity Feed-in Tariffs in European Union Countries," *Energy Policy*, 2013, *52*, 385–401.

Johnston, Sarah, "Nonrefundable Tax Credits versus Grants: The Impact of Subsidy Form on the Effectiveness of Subsidies for Renewable Energy," *Journal of the Association of Environmental and Resource Economists*, 2019, *6* (3), 433–460.

Kawai, Kei and Jun Nakabayashi, "Detecting Large-Scale Collusion in Procurement Auctions," *Journal of Political Economy*, 2022, *130* (5), 1364–1411.

_ , _ , Juan Ortner, and Sylvain Chassang, "Using Bid Rotation and Incumbency to Detect Collusion: A Regression Discontinuity Approach," *The Review of Economic Studies*, 2023, *90* (1), 376–403.

Langer, Ashley and Derek Lemoine, "Designing Dynamic Subsidies to Spur Adoption of New Technologies," *Journal of the Association of Environmental and Resource Economists*, 2022, *9* (6), 1197–1234.

Luo, Yao and Hidenori Takahashi, *Bidding for Contracts under Uncertain Demand: Skewed Bidding and Risk Sharing*, Working Paper, 2022.

Matthews, Steven A., "Selling to Risk Averse Buyers With Unobservable Tastes," *Journal of Economic Theory*, 1983, *30* (2), 370–400.

May, Nils and Karsten Neuhoff, "Financing Power: Impacts of Energy Policies in Changing Regulatory Environments," *The Energy Journal*, 2021, *42* (4), 131–151.

Metcalf, Gilbert E., "Investment in Energy Infrastructure and the Tax Code," *Tax Policy and the Economy*, 2010, *24* (1), 1–34.

Office of Management and Budget, *Guidelines and Discount Rates for Benefit-Cost Analysis of Federal Programs*, Proposed Update to OMB Circular No. A-94, Washington, DC: Executive Office of the President, Office of Management and Budget, 2023.

Perrigne, Isabelle and Quang Vuong, "Econometrics of Auctions and Nonlinear Pricing," *Annual Review of Economics*, 2019, *11* (1), 27–54.

Pless, Jacquelyn and Arthur A. van Benthem, "Pass-Through as a Test for Market Power: An Application to Solar Subsidies," *American Economic Journal: Applied Economics*, 2019, *11* (4), 367–401.

Porter, Robert H. and J. Douglas Zona, "Detection of Bid Rigging in Procurement Auctions," *Journal of Political Economy*, 1993, *101* (3), 518–538.

_ and _ , "Ohio School Milk Markets: An Analysis of Bidding," *The RAND Journal of Economics*, 1999, *30* (2), 263.

Rackauckas, Christopher and Qing Nie, "DifferentialEquations.jl – A Performant and Feature-Rich Ecosystem for Solving Differential Equations in Julia," *Journal of Open Research Software*, 2017, *5* (1), 15.

REN21, *Renewables 2023 Global Status Report Collection, Global Overview*, Paris: REN21 Secretariat, 2023.

Richert, Eric, *Indirect Inference Techniques as an Alternative to Direct Computation of Equilibrium Bid Distributions*, Working Paper, 2023.

Rosa, Luiz Pinguelli, Neilton Fidelis da Silva, Marcio Giannini Pereira, and Luciano Dias Losekann, "The Evolution of Brazilian Electricity Market," in "Evolution of Global Electricity Markets," Elsevier, 2013, pp. 435–459.

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

Teschl, Gerald, *Ordinary Differential Equations and Dynamical Systems*, American Mathematical Society, 2012.

Tolmasquim, Maurício T., Tiago de Barros Correia, Natália Addas Porto, and Wikus Kruger, "Electricity Market Design and Renewable Energy Auctions: The Case of Brazil," *Energy Policy*, 2021, *158*, 112558.

Vasserman, Shoshana and Mitchell Watt, "Risk Aversion and Auction Design: Theoretical and Empirical Evidence," *International Journal of Industrial Organization*, 2021, *79*, 102758.

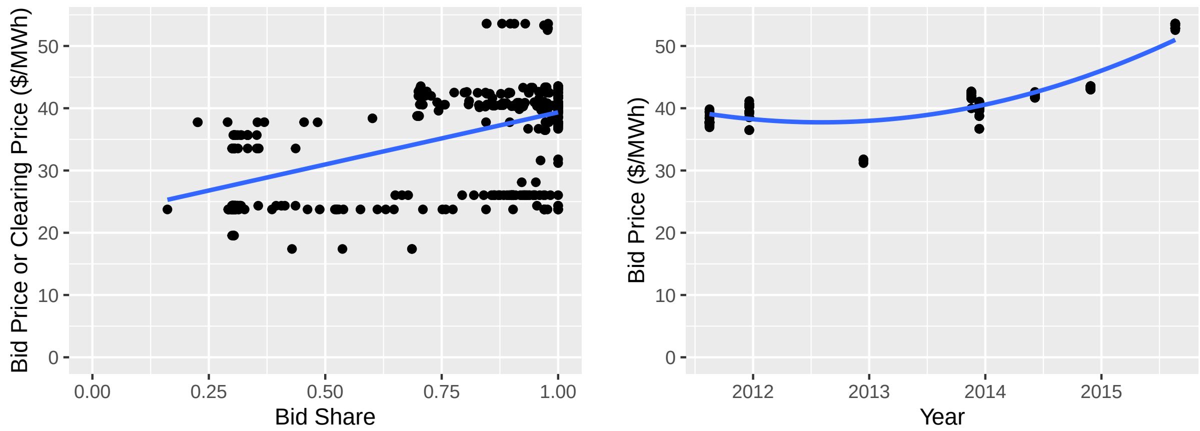
Werner, Deborah and Lira Luz Benites Lazaro, "The Policy Dimension of Energy Transition: The Brazilian Case in Promoting Renewable Energies (2000–2022)," *Energy Policy*, 2023, *175* (January), 113480.

Wilson, Robert, "Auctions of Shares," *The Quarterly Journal of Economics*, 1979, *93* (4), 675.

Wiser, Ryan, Joseph Rand, Joachim Seel, Philipp Beiter, Erin Baker, Eric Lantz, and Patrick Gilman, "Expert Elicitation Survey Predicts 37% to 49% Declines in Wind Energy Costs by 2050," *Nature Energy*, 2021, *6* (5), 555–565.

Appendix

A Descriptive Evidence Figures



(a) Scatterplot of bid shares and prices for 476 winning bids in 16 auctions from 2011–2021

(b) Time trend of bid prices for 296 winning bids in 8 pay-as-bid auctions from 2011–2015

Figure A1: Descriptive evidence from bid data

B Equilibrium Strategy in Pay-as-bid Auctions

In this section, I show that a unique pure-strategy BNE exists in pay-as-bid auctions in Section 4.1. Bidder i's bid price strategy function $\omega_i : [\underline{c}, \bar{c}] \mapsto \mathbb{R}$ maps the cost type c onto the bid price. A bid price strategy ω_i uniquely determines a bid share strategy as $q^*(\omega_i(c))$, where

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

solves the portfolio problem for a given bid price b as in Equation (7). Thus, characterizing the equilibrium bid price strategy suffices to prove the statement about the equilibrium bid strategy.

The key observation is that the winning probability function can be reformulated as a function of the bidder's cost type c_i and competitors' bid price strategy ω_{-i}:

$$H_i(c_i, \omega_{-i}) \coloneqq \Pr\left(\sum_{j \neq i} \{q^*(\omega_j(c_j)) Capacity_j\} \mathbb{1}(\omega_j(c_j) \leq \omega_i(c_i)) < D\right).$$

Bidder i's expected utility of bidding $(q^*(b), b)$ given his cost type c is

$$\mathrm{EU}_i(b|c) \coloneqq H_i(\omega_i^{-1}(b), \omega_{-i}) \times u(\mathrm{CE}(q^*(b), b|c)),$$

where

$$\mathrm{CE}(q, b|c) = q\tilde{\delta}b + (1-q)\mu_r - c - (1-q)^2 \cdot \frac{\gamma\sigma_r^2}{2}.$$

Differentiating with respect to b and plugging in $b = \omega_i(c)$, I obtain the first-order condition that characterizes the equilibrium bid price strategy:

$$\frac{d\mathrm{EU}_i(\omega_i(c)|c)}{db} = 0.$$

Observe that, for any $c \in [\underline{c}, \bar{c}]$,

$$\begin{aligned} \frac{d\mathrm{EU}_i(\omega_i(c)|c)}{db} &= \frac{dH_i(\omega_i^{-1}(\omega_i(c)), \omega_{-i})}{db} \times u(\mathrm{CE}(q^*(\omega_i(c)), \omega_i(c)|c)) \\ &\quad + H_i(c, \omega_{-i}) \times \frac{du(\mathrm{CE}(q^*(\omega_i(c)), \omega_i(c)|c))}{db}, \end{aligned}$$

where

$$\begin{aligned} \frac{dH_i(\omega_i^{-1}(\omega_i(c)), \omega_{-i})}{db} &= \frac{\partial H_i(\omega_i^{-1}(\omega_i(c)), \omega_{-i})}{\partial c} \times \frac{1}{\omega_i'(\omega_i^{-1}(\omega_i(c)))} \\ &= \frac{\partial H_i(c, \omega_{-i})}{\partial c} \times \frac{1}{\omega_i'(c)}, \end{aligned}$$

$$\frac{du(\mathrm{CE}(q^*(\omega_i(c)), \omega_i(c)|c))}{db} = u'(\mathrm{CE}(q^*(\omega_i(c)), \omega_i(c)|c)) \times \frac{d\mathrm{CE}(q^*(\omega_i(c)), \omega_i(c)|c)}{db},$$

and, for all b,

$$\begin{aligned}\frac{d\mathrm{CE}(q^*(b),b|c)}{db} &= \frac{\partial \mathrm{CE}(q^*(b),b|c)}{\partial b} + \frac{\partial \mathrm{CE}(q^*(b),b|c)}{\partial q}\cdot\frac{dq^*(b)}{db}\\ &= q^*(b)\times\tilde{\delta}.\end{aligned}$$

Then, the first-order condition can be seen as a system of ordinary differential equations (ODEs): for all $i = 1,\dots,N$,

$$\omega_i'(c) = -\frac{(\partial H_i(c,\omega_{-i})/\partial c)\times u(\mathrm{CE}(q^*(\omega_i(c)),\omega_i(c)|c))}{H_i(c,\omega_{-i})\times u'(\mathrm{CE}(q^*(\omega_i(c)),\omega_i(c)|c))\times q^*(\omega_i(c))\times\tilde{\delta}}. \tag{12}$$

A solution to this system of ODEs is a BNE bid price strategy profile $\{\omega_i^*\}_{i=1}^N$. Applying the Picard-Lindelöf theorem (e.g., Teschl, 2012, Theorem 2.2), I conclude the existence and uniqueness of the strategy profile $\{\omega_i^*\}_{i=1}^N$ under a suitable boundary condition since the functions involved in the ODEs are all continuous in their arguments. The boundary condition can be a zero expected utility conditional on winning at the highest cost type $\bar{c}$: i.e., for all $i = 1,\dots,N$,

$$u(\mathrm{CE}(q^*(\omega_i^*(\bar{c})),\omega_i^*(\bar{c})|\bar{c})) = 0.$$

C Econometric Details

C.1 *Ex-ante* Symmetric Bidders

I show that bidders' equilibrium strategies are symmetric if bidders are *ex-ante* symmetric (Assumption 2). I use the notations in Appendix B. Symmetric bid strategy is equivalent to symmetric bid price strategy since a bid price strategy uniquely determines a bid share strategy as shown in Appendix B.

Consider a symmetric bid price strategy ω, i.e., $\omega_i = \omega$ for all i. Then, the winning probability function becomes symmetric as

$$H_i(c_i, \omega) = \Pr\left(\sum_{j \neq i} \{q^*(\omega(c_j))Capacity_j\} \mathbb{1}(\omega(c_j) \leq \omega(c_i)) < D\right)$$

is the same for all bidders due to *ex-ante* symmetry, i.e., bidders independently draw their types $(c_i, Capacity_i)$ from a common distribution. Denote the symmetric winning probability function as $H(\cdot, \cdot)$.

Consequently, ODEs that characterize the BNE (Equation (12)) also become symmetric: for all $i = 1, \ldots, N$,

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

There exists a solution ω to this ODE by the Picard-Lindelöf theorem under a suitable boundary condition as in Appendix B. Since the uniqueness of BNE has been shown in Appendix B, this symmetric strategy ω is the unique BNE strategy if bidders are *ex-ante* symmetric.

C.2 Variance of the Wholesale Market Revenue

Consider an auction at year $t = 0$ with a lead time $l \geq 1$. I detail the calculation of the variance of the wholesale market revenue defined in (4),

$$\sigma_r^2 = \mathrm{Var}\left(\frac{1}{T}\sum_{t=l}^{l+T-1} \delta^t r_t\right).$$

I proxy wholesale market prices r_t by spot market prices and use r_t to denote spot market prices in this section. I assume the lead time is integer-valued below and consider a mean reverting process for discrete time $t = 0, 1, \ldots$. I linearly interpolate the variance σ_r^2 for lead times not integer-valued.

I specify a mean reverting process (or an AR(1) model with an intercept) for annual spot market price transitions as

$$r_t = A + \rho r_{t-1} + \xi_t,$$

where A is an intercept, ρ is an autocorrelation coefficient, and $\xi_t \sim \mathcal{N}(0, \sigma_\xi^2)$ is a normally distributed residual independent across t. I use time-series data of spot market prices to estimate the parameters (A, ρ, σ_ξ^2) by maximum likelihood estimation.

I derive an analytic formula to calculate the variance of the wholesale market revenue σ_r^2 given the parameters in the following. The mean reverting process specification implies

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

Then, observe

$$\begin{aligned} \mathrm{Var}\left(\sum_{t=l}^{l+T-1} \delta^t r_t\right) &= \mathrm{Var}\left(\sum_{t=l}^{l+T-1} \delta^t \left(A \sum_{s=0}^{t-1} \rho^{t-s} + \rho^t r_0 + \sum_{s=0}^{t-1} \rho^s \xi_{t-s}\right)\right) \\ &= \mathrm{Var}\left(\sum_{t=l}^{l+T-1} \delta^t \sum_{s=0}^{t-1} \rho^s \xi_{t-s}\right) \end{aligned}$$

and

$$\sum_{t=l}^{l+T-1} \delta^t \sum_{s=0}^{t-1} \rho^s \xi_{t-s} = \sum_{t=1}^{l} \frac{\delta^l \rho^{l-t}(1-\delta^T \rho^T)}{1-\delta\rho} \cdot \xi_t + \sum_{t=l+1}^{l+T-1} \frac{\delta^t (1-\delta^{l+T-t} \rho^{l+T-t})}{1-\delta\rho} \cdot \xi_t.$$

Thus,

$$\begin{aligned} \sigma_r^2 &= \mathrm{Var}\left(\frac{1}{T} \sum_{t=l}^{l+T-1} \delta^t r_t\right) \\ &= \frac{1}{T^2}\left[\sum_{t=1}^{l} \left(\frac{\delta^l \rho^{l-t}(1-\delta^T \rho^T)}{1-\delta\rho}\right)^2 \mathrm{Var}(\xi_t) + \sum_{t=l+1}^{l+T-1} \left(\frac{\delta^t (1-\delta^{l+T-t} \rho^{l+T-t})}{1-\delta\rho}\right)^2 \mathrm{Var}(\xi_t)\right] \\ &= \frac{\sigma_\xi^2}{T^2}\left[\sum_{t=1}^{l} \left(\frac{\delta^l \rho^{l-t}(1-\delta^T \rho^T)}{1-\delta\rho}\right)^2 + \sum_{t=l+1}^{l+T-1} \left(\frac{\delta^t (1-\delta^{l+T-t} \rho^{l+T-t})}{1-\delta\rho}\right)^2\right]. \end{aligned}$$

C.3 Distributions of Procurement Capacity and Clearing Price

I parameterize the procurement capacity distribution as

$$D_a|X_a \sim \mathcal{N}(\beta_{D0} + \beta_{D1}t_a + \beta_{D2}N_a, \sigma_D^2).$$

The term for auction date t_a intends to capture the change in the forecasted demand for new energy during this period. The procurement capacity may also depend on the number of participants N_a since the government may manipulate the procurement capacity after observing N_a to maintain the competitiveness of the auction. I use the parameters $(\beta_{D0}, \beta_{D1}, \beta_{D2}, \sigma_D^2)$ that best fit the data, separately for pay-as-bid auctions and uniform-price auctions.

I parameterize the conditional distribution of clearing price p_a given a realized procurement capacity D_a in uniform-price auctions as

$$p_a|D_a, X_a \sim \mathcal{N}(\beta_{p0} + \beta_{p1}D_a + \beta_{p2}(t_a + l_a) + \beta_{p3}N_a, \sigma_{pD}^2).$$

I expect a low clearing price with a low procurement capacity D_a and a large number of participants N_a because a low-cost bidder likely clears the auction. The operation start date, $t_a + l_a$, intends to capture the trend of bidders' costs parsimoniously. I use the parameters $(\beta_{p0}, \beta_{p1}, \beta_{p2}, \beta_{p3}, \sigma_p^2)$ that best fit the uniform-price auction data.

Integrating out the procurement capacity yields the marginal distribution of clearing price: $p_a|X_a \sim \mathcal{N}(\mu_{pa}, \sigma_p^2)$, where

$$\begin{cases} \mu_{pa} = \beta_{p0} + \beta_{p1}(\beta_{D0} + \beta_{D1}t_a + \beta_{D2}N_a) + \beta_{p2}(t_a + l_a) + \beta_{p3}N_a \\ \sigma_p^2 = \sigma_{pD}^2 + \beta_{p1}^2\sigma_D^2 \end{cases}.$$

The clearing price distribution takes into account that the procurement capacity D_a is not disclosed before bidders bid, but they know the other auction covariates X_a.

C.4 Computation of the Equilibrium Winning Probability Function

Consider an auction with N participants and distributions for the capacity type, $Capacity_i \sim F_{Cap}$, the equilibrium bid price, $b_i^* \sim F_{b^*}$, and the procurement capacity, $D \sim F_D$. I approximate the equilibrium winning probability function $W^*(b)$ of this auction, defined in Equation (6) and shown to be the same for all bidders in Appendix C.1, by the following simulation procedure:

1. For $s = 1, \ldots, S$, draw competitors' capacity types, $Capacity_j^s \sim F_{Cap}$, and bid prices, $(b_j^*)^s \sim F_{b^*}$, independently for $j = 1, \ldots, N-1$.

2. For $s' = 1, \ldots, S_D$, draw a procurement capacity, $D^{s'} \sim F_D$.

3. Compute the equilibrium winning probability function $W^*(b)$ as

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

   where $\hat{q}^*(\cdot)$ is defined as

$$\hat{q}^*(b) := \min\left\{ \max\left\{ \underline{q}, 1 - \frac{\hat{\mu}_r - T^{-1}\sum_{t=l}^{l+T-1} \delta^t b}{\hat{\gamma}\sigma_r^2} \right\}, 1 \right\}, \tag{13}$$

   and $\hat{\gamma}$ and $\hat{\mu}_r$ are the estimates from the first step of the structural parameter estimation in Section 5.2.

I smooth the indicator functions in the last step using a normal CDF, denoted Φ, following Ryan (2022): i.e., an indicator function $\mathbb{1}(x_0 < x)$ is smoothed as $\Phi((x - x_0)/h)$, where I set the bandwidth parameter to be $h = \$2$/MWh, about 1/30 of the level of a typical bid. I calculate $\hat{W}^*(b)$ for a grid of b with \$0.10/MWh increments and linearly interpolate between the grid points. I numerically differentiate $\hat{W}^*(b)$ to obtain the derivative function $d\hat{W}^*(b)/db$.

D Estimation Results

Table D1 tabulates parameter estimates for the mean reverting process in Appendix C.2. As depicted in Figure D1, the estimated variance of the wholesale market revenue σ_r^2 decreases by lead time l_a because of the discount for the further future and the stability of the further future prices in the mean reverting process.

Table D1: Parameter estimates of the mean reverting process

Parameter	Coeff.	S.E.
Intercept, A	17.7	(16.4)
AR(1) Coefficient, ρ	0.397	(0.327)
Variance, σ_ξ^2	729.0	(197.1)

Notes: Annual spot market prices from 2001 to 2022 are used in the estimation. Standard errors are calculated with the outer product approximation method for maximum likelihood estimation.

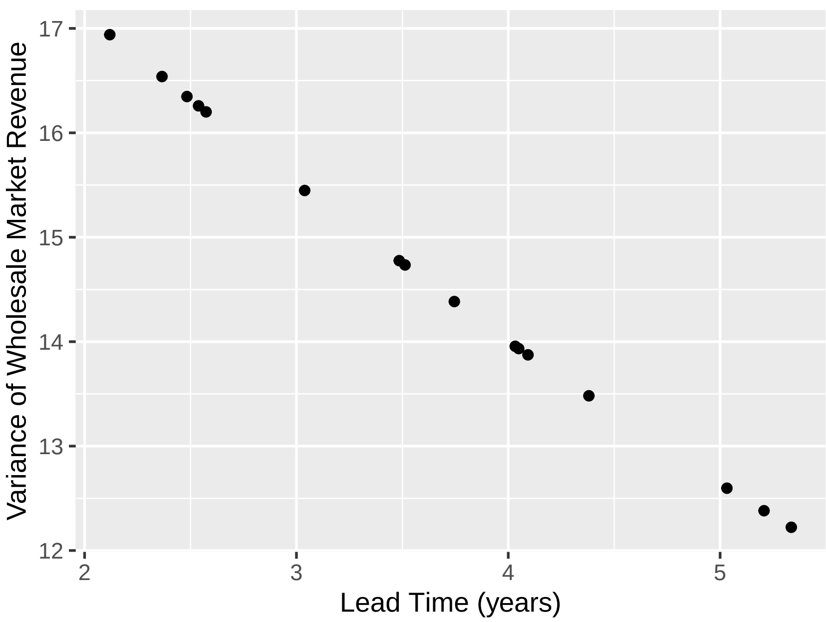


Figure D1: Relationship between the estimated variance of the wholesale market revenue and lead time for 16 auctions

Table D2 reports the fitted parameters of the procurement capacity and clearing price models in Appendix C.3. For pay-as-bid auctions, the procurement capacity is expected to drop by 34 MW each year and by 67 MW if there are 100 fewer participants. For uniform-price auctions, the procurement capacity is expected to drop by 23 MW each year and by 82 MW if there are 100 fewer participants. The variance of the procurement capacity is larger for the earlier period (pay-as-bid auctions from 2011–2015) than for the later period (uniform-price auctions from 2017–2021).

Table D2: Fitted parameters for procurement capacity and clearing price models

Parameter	Pay-as-bid	Uniform-price
Procurement Capacity Distribution		
Intercept, β_{D0}	230.2	−95.13
Auction Date (year), β_{D1}	−34.43	−23.14
# Participants, β_{D2}	0.667	0.824
Variance, σ_D^2	59912.6	17564.8
Clearing Price Distribution		
Intercept, β_{p0}		6.86
Procurement Capacity, β_{p1}		0.0278
Operation Start (year), β_{p2}		3.25
# Participants, β_{p3}		−0.0461
Variance, σ_{pD}^2		2.31

Notes: 8 pay-as-bid auctions from 2011–2015 and 8 uniform-price auctions from 2017–2021 are used.

The clearing price is expected to drop by \$2.78/MWh for 100 less MW of procurement capacity and by \$4.61/MWh if there are 100 more participants. A year-late operation starting date increases the clearing price increases by \$3.25/MWh. From the fitted parameters of the procurement capacity and clearing price models for uniform-price auctions, the mean and SD of the clearing price distribution are calculated as $\mu_p = \$20.24–\$33.41/\text{MWh}$ and $\sigma_p = \$4.00/\text{MWh}$. The variance of the marginal clearing price distribution, $\sigma_p^2 \approx 16$, is much larger than the conditional clearing price distribution, $\sigma_{pD}^2 \approx 2$, which reflects the uncertainty bidders face because of the non-disclosure policy of the procurement capacity.

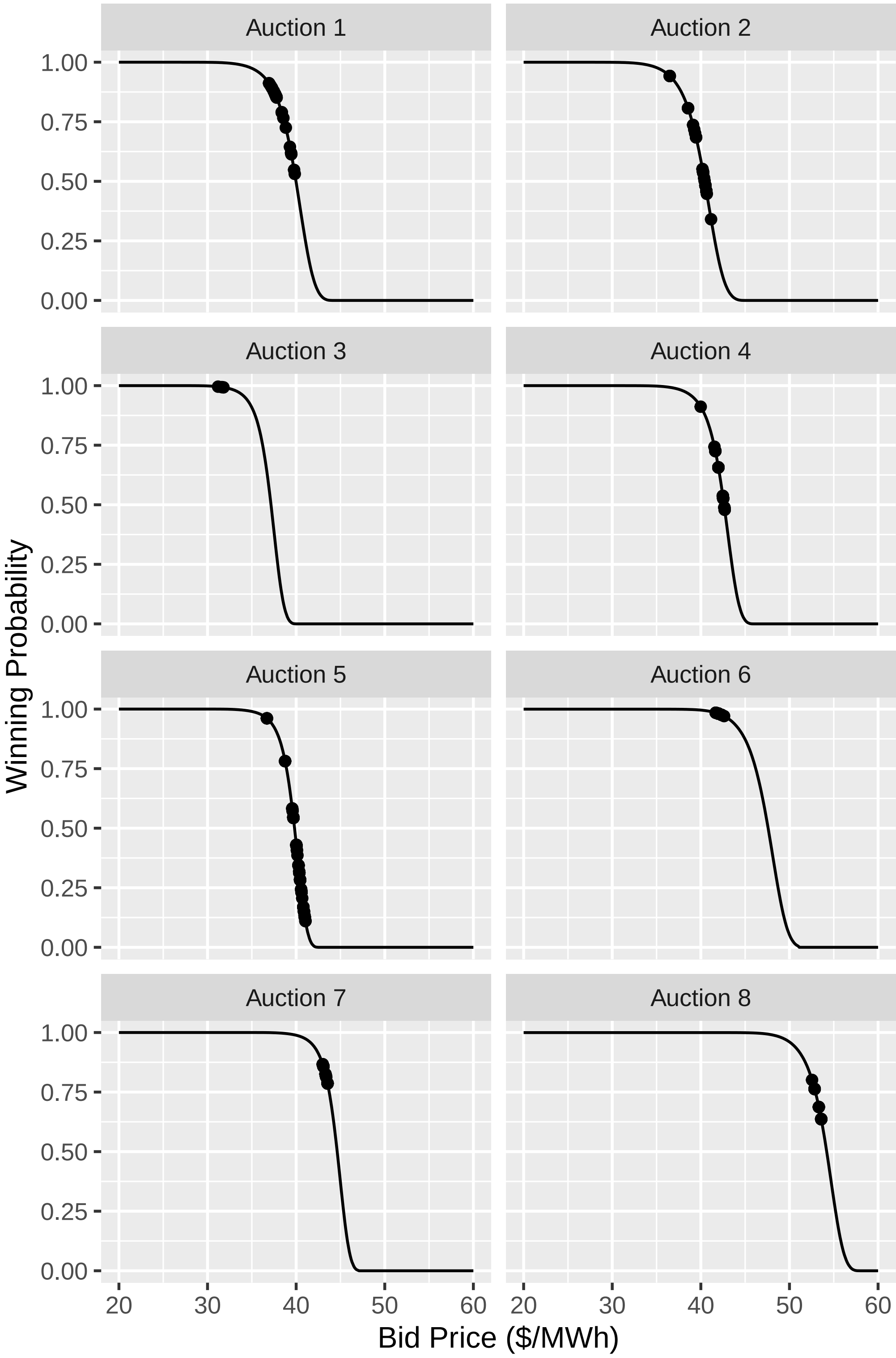


Figure D2: Estimated equilibrium winning probability functions and actual winning bids

E Equilibrium Strategy in Uniform Share Auctions With the Pay-as-bid Format

In this section, I detail the calculation of the counterfactual equilibrium strategy in uniform share auctions with the pay-as-bid format in Section 7.1.

E.1 General Framework

I first show that a unique symmetric monotone pure-strategy BNE exists under *ex-ante* symmetry (Assumption 2). Following the same argument as in Appendix B, I can show that a unique pure-strategy BNE exists without *ex-ante* symmetry. Then, with *ex-ante* symmetry, consider a monotonically increasing symmetric bid price strategy $\omega : [\underline{c}, \bar{c}] \mapsto \mathbb{R}$. The monotonicity of ω implies that the winning probability function can be reformulated as a function of the bidder's cost type c_i:

$$\begin{aligned}\widetilde{H}_i(c_i) &:= \Pr\left(\sum_{j\neq i} Capacity_j \mathbb{1}(\omega(c_j) \leq \omega(c_i)) < \widetilde{D}\right) \\ &= \Pr\left(\sum_{j\neq i} Capacity_j \mathbb{1}(c_j \leq c_i) < \widetilde{D}\right). \qquad (14)\end{aligned}$$

Additionally, this winning probability function is symmetric due to *ex-ante* symmetry, so I denote it as $\widetilde{H}(\cdot)$.

Following the same argument as in Appendix B, I obtain an ODE that characterizes the equilibrium bid price strategy:

$$\omega'(c) = -\frac{\widetilde{H}'(c) \times u(\widetilde{\mathrm{CE}}(\omega(c)|c))}{\widetilde{H}(c) \times u'(\widetilde{\mathrm{CE}}(\omega(c)|c)) \times \tilde{\delta}}, \qquad (15)$$

where

$$\widetilde{\mathrm{CE}}(b|c) = \tilde{\delta} b + (1-\lambda)\mu_r - c - (1-\lambda)^2 \cdot \frac{\gamma \sigma_r^2}{2}.$$

A solution to this ODE is a BNE bid price strategy ω^*, which exists due to the Picard-Lindelöf theorem under a suitable boundary condition. Since the winning probability function $\widetilde{H}(c)$ is monotonically decreasing according to Equation (14), the ODE in Equation (15) implies $\omega'(c) > 0$. Thus, I conclude that a monotonically increasing symmetric equilibrium strategy ω^* exists. Since the uniqueness of BNE has been shown at the beginning of this section, this monotonically increasing symmetric strategy is the unique BNE strategy if bidders are *ex-ante* symmetric.

I define the boundary condition as a zero expected utility conditional on winning at the highest cost type $\bar{c}$: i.e.,

$$u(\widetilde{\mathrm{CE}}(\omega^*(\bar{c})|\bar{c})) = 0. \tag{16}$$

Therefore, once I have the winning probability function $\widetilde{H}(c)$ and the structural parameters, I can calculate the equilibrium strategy ω^* by solving the ODE in Equation (15) with the boundary condition in Equation (16). Importantly, since $\widetilde{H}(c)$ does not depend on strategy ω, I do not need to recalculate $\widetilde{H}(c)$ while searching for the equilibrium strategy ω^*. I detail the calculation of $\widetilde{H}(c)$ in my counterfactuals in the rest of Appendix E. I solve the ODE using the ODE solvers implemented by Rackauckas and Nie (2017).

E.2 If the Actual Auctions Were Uniform Share Auctions

Given the winning probability function $\widetilde{H}(c)$ in Equation (14), the equilibrium strategy can be calculated as in Appendix E.1. Thus, this section aims to calculate $\widetilde{H}(c)$ for the uniform share auctions in the same economic environment as the actual auctions.

Consider an actual auction with a lead time l, N participants, a wholesale market belief $r \sim \mathcal{N}(\mu_r, \sigma_r)$, distributions for the capacity type, $Capacity_i \sim F_{Cap}$, the equilibrium bid price, $b_i^* \sim F_{b^*}$, the cost type, $c_i \sim F_c$, and the procurement capacity, $D \sim F_D$, and the minimum bid share $\underline{q}$. I convert the procurement capacity D to the objective capacity $\widetilde{D}$ in uniform share auctions in the calculation of $\widetilde{H}(c)$. I approximate $\widetilde{H}(c)$ by the following simulation procedure:

1. For $s = 1, \ldots, S$, draw participants' capacity types, $Capacity_i^s \sim F_{Cap}$, and bid prices, $(b_i^*)^s \sim F_{b^*}$, independently for $i = 1, \ldots, N$.

2. For $s' = 1, \ldots, S_D$, draw a procurement capacity, $D^{s'} \sim F_D$.

3. For each combination of s and s', simulate an auction that allows bidders to have portfolio choices. Bidder i wins when

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

where $\hat{q}^*(\cdot)$ is defined in Equation (13). Let the set of the simulated winners be $Winner^{s,s'}$ and the bidder with the lowest bid price among the simulated losers be $i = k^{s,s'}$.

4. For each combination of s and s', recover the objective capacity $\widetilde{D}^{s,s'}$ by adding up the capacity of $Winner^{s,s'}$. I linearly interpolate the residual of $D^{s'}$ to smooth $\widetilde{D}^{s,s'}$ as follows:

$$\widetilde{D}^{s,s'} = \sum_{i \in Winner^{s,s'}} Capacity_i^s + \frac{D^{s'} - \sum_{i \in Winner^{s,s'}} (\hat{q}^*((b_i^*)^s) \times Capacity_i^s)}{\hat{q}^*((b_{k^{s,s'}}^*)^s) \times Capacity_{k^{s,s'}}^s} \times Capacity_{k^{s,s'}}^s.$$

5. For $s = 1, \ldots, S$, draw competitors' cost types, $c_j^s \sim F_c$, independently for $j = 1, \ldots, N-1$.

6. Compute the winning probability function $\widetilde{H}(c)$ as

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

Similarly to the calculation of the equilibrium winning probability function in Appendix C.4, I smooth the indicator functions in the last step using a normal CDF Φ with a bandwidth parameter $h = \$2$/MWh. I calculate $\widetilde{H}(c)$ for a grid of c with \$0.10/MWh increments and linearly interpolate between the grid points. I numerically differentiate $\widetilde{H}(c)$ to obtain the derivative function $d\widetilde{H}(c)/dc$.

E.3 If Bidders Had the Same Capacity

Given the winning probability function $\widetilde{H}(c)$ in Equation (14), the equilibrium strategy can be calculated as in Appendix E.1. Thus, this section aims to calculate $\widetilde{H}(c)$ when all bidders have the same capacity, $Capacity_j = Capacity$ for all j. I only consider the cases where the objective capacity $\widetilde{D}$ is a multiple of $Capacity$, i.e., the number of winners is $\#Winner = \widetilde{D}/Capacity$.

Let $F_c^{k:n}$ and $f_c^{k:n}$ be the CDF and PDF for the kth order statistic of n samples drawn from the distribution of the cost type c_i. Then, Equation (14) reduces to

$$\begin{aligned}
\widetilde{H}(c_i) &= \Pr\left(\widetilde{D} - \sum_{j\neq i} Capacity\mathbb{1}(c_j \leq c_i) > 0\right) \\
&= \Pr\left(\#Winner - \sum_{j\neq i} \mathbb{1}(c_j \leq c_i) > 0\right) \\
&= 1 - F_c^{\#Winner:N-1}(c_i).
\end{aligned}$$

As a consequence, I obtain the derivative of the winning probability function $\widetilde{H}(c)$ as

$$\widetilde{H}'(c) = -f_c^{\#Winner:N-1}(c).$$

F Counterfactual Results

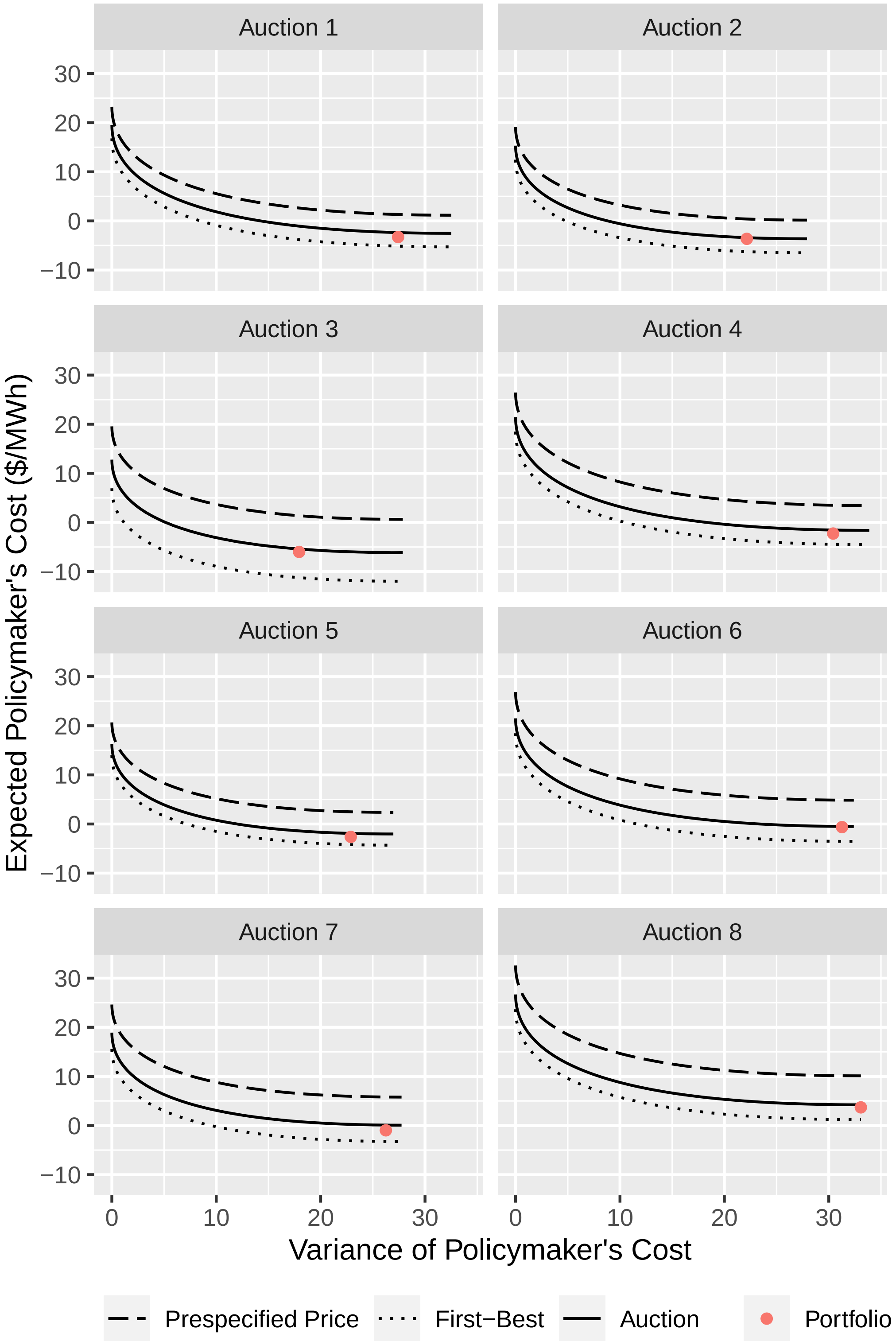


Figure F1: Simulated cost-risk frontiers for the 8 actual pay-as-bid auctions

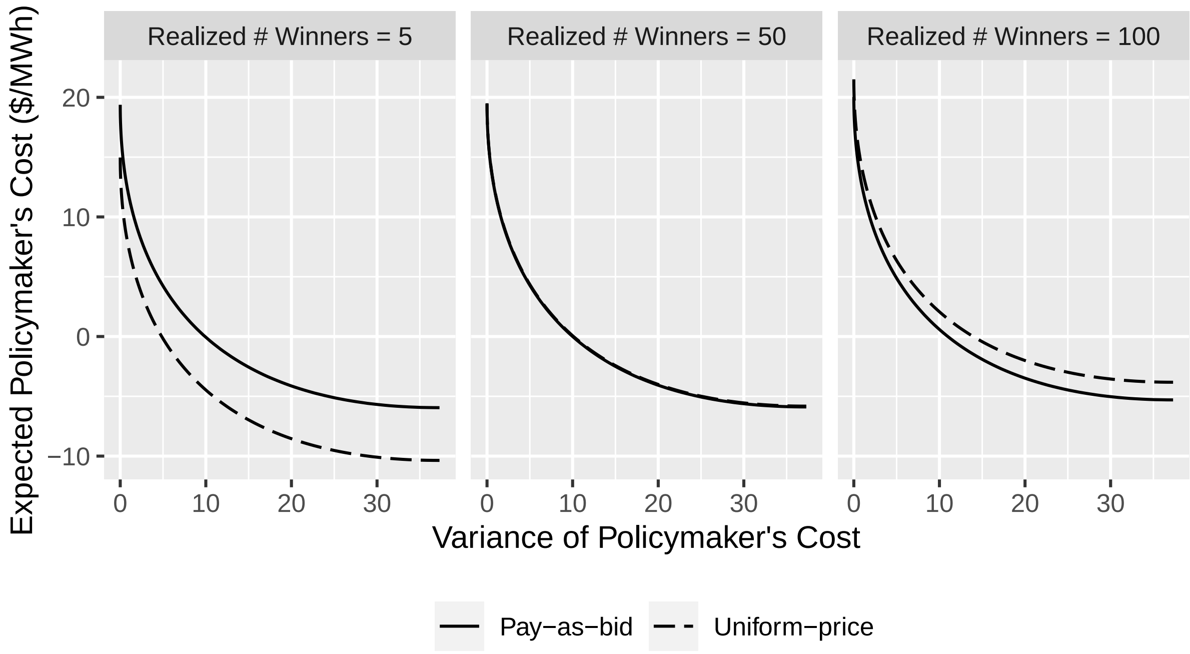


Figure F2: Simulated cost-risk frontiers for pay-as-bid and uniform-price auctions when the expected number of winners is 50