Encouraging Renewable Investment: Risk Sharing Using Auctions[*]

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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 contracts that share this electricity price risk between the policymaker and renewable energy investors to support new projects. I model these contracts and show that the policymaker faces a trade-off between her cost and risk when the investors are risk-averse. I study this trade-off in the context of Brazilian wind energy auctions that award these risk-sharing contracts for a share of production the winners bid into the auction. In these auctions, bidders make a portfolio choice to allocate their production across a risk-free revenue stream assured by the risk-sharing contract and a risky electricity wholesale market. I develop and estimate a structural model of risk-averse bidders making portfolio choices in these auctions to uncover the bidders' risk aversion and private costs. I find that risk sharing strongly incentivizes investors due to their risk aversion: risk sharing halves the minimum expected revenue under which the average auction winner chooses to invest. The estimated model predicts that, by taking all risk, the policymaker can reduce her expected cost by \$20.48/MWh, 97.1% of the average winner's cost, compared to zero policymaker risk contracts while increasing the standard deviation of her cost up to \$5.49/MWh, for the median auction. I apply the predicted cost-risk trade-off to decompose the policymaker's utility gains from the actual Brazilian auction into three effects: auction mechanism, risk sharing, and auction markup reduction stemming from bidders having the opportunity of portfolio choices.

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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 cost 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

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[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, the fact that bidders make interior portfolio choices in my data suggests that 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 one of the two extremes of the range of possible shares to maximize the expected revenue. For instance, if the purchase agreement price is higher than the expected wholesale market price, risk-neutral bidders will allocate all of their production to the purchase agreement.

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-bid auctions, I employ an identification strategy analogous to Bolotnyy and Vasserman's

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[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.

(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 three 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 estimate the equilibrium winning probability functions for pay-as-bid auctions. Lastly, 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 first-order condition for the 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 estimates in the previous two steps.

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 the risk-sharing aspect of purchase agreements strongly incentivizes bidders due to their risk aversion. Absent risk sharing, the average winner requires the expected revenue to be twice his cost to cover the risk premium in addition to the cost, and risk sharing halves the minimum expected revenue under which he chooses to invest for the

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[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).

median pay-as-bid auction. Additionally, the winners have, on average, \$8.35/MWh lower costs than all participants (whose standard deviation [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. 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 cost is the highest with zero policymaker risk at $\lambda = 0$ and decreases with increasing risk as λ moves to 1. My model predicts that moving from $\lambda = 0$ to 1 lowers the expected policymaker's cost by \$20.48/MWh (97.1% of the average winner's cost) while increasing the SD of the policymaker's cost up to \$5.49/MWh, for the median auction. The policymaker can choose a λ that conforms with her risk preference and institutional/political constraints to maximize her utility.

I apply the predicted cost-risk trade-off to decompose the policymaker's utility gains from the actual Brazilian auction into three effects: auction mechanism, risk sharing, and auction markup reduction from bidders having the opportunity of portfolio choices. Bidders decrease their auction markup because the opportunity for portfolio optimization makes the auction more lucrative and induces more competitive bids. My back-of-the-envelope calculations suggest that, without any constraints, a risk-neutral policymaker implementing the actual median pay-as-bid auction gains 70.1% of the maximum attainable, which can be decomposed into auction mechanism (63.5 percentage points [pps]), risk sharing (−0.1 pps) and markup reduction (6.8 pps). In contrast, a policymaker who is as risk-averse as the bidders gains 37.2% of the policymaker's maximum, breaking down into auction mechanism (29.3 pps) risk sharing (4.7 pps) and markup reduction (3.3 pps).[6] The risk-averse policymaker enjoys the benefit of risk sharing, while it works negatively

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[6]Policymakers can be risk-averse. For instance, the U.S. Office of Management and Budget has proposed the usage of the certainty equivalent to account for risk, which implies its risk aversion (OMB, 2023).

for the risk-neutral policymaker because she is willing to accept all risks.

I also compare the two auction formats, pay-as-bid and uniform-price, when the procurement capacity is not disclosed before bidding, which is a common practice in these renewable energy auctions to prevent collusive behavior.[7] Importantly, the expected (or realized) procurement capacity affects the auction's expected (or realized) competitiveness. My simulations reveal that if an auction is as competitive as bidders expected, both auction formats result in comparable policymaker costs. In contrast, the uniform-price format reduces policymaker's costs compared to the pay-as-bid format if an auction is more competitive than expected and the other way around if it is less competitive. These results are because the expected competitiveness determines bid prices in the pay-as-bid format, while the realized competitiveness determines clearing prices in the uniform-price format. I also show that bidders' risk aversion is not the primary driving force of these results. Risk-neutral bidders yield the same results but with slightly higher pay-as-bid prices.

A growing body of literature has examined the effect of policy interventions on renewable investments.[8] I propose a framework integrating purchase agreements and subsidies to assess the trade-off of a policymaker's cost and risk from sharing electricity market risk between renewable investors and the policymaker.[9] Researchers have recognized the risk-sharing aspect of purchase agreements (e.g., Farrell et al., 2017).[10] 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.[11]

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[7]Generally, ranking these two auction formats in multi-unit auctions is ambiguous, and the question of which is better can often only be answered empirically (Hortaçsu and McAdams, 2018).

[8]For example: Farrell et al. (2017), Ye, Rodrigues and Lin (2017), Ryan (2022) for purchase agreements; Metcalf (2010), Hughes and Podolefsky (2015), Johnston (2019), 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.

[9]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.

[10]Private financial markets may not work as a risk-sharing tool in the context of renewable investments since risk pooling unravels due to the high correlation of the wholesale price risk across projects.

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

The paper also builds on the literature on auctions with risk-averse bidders. Theoretical implications of risk-averse bidders have been extensively discussed.[12] 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.[13] 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 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. I assume that actors are infinitely patient, with a discount factor $\beta = 1$ to simplify the model. 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

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

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

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 may be risk averse, the policymaker considers a contract that shares the market risk between her and the investor to support the investment. The contract pays a certain amount ϕ in exchange for the investor providing 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 risk-sharing 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

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

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 cost is $C = \phi - \lambda r$. Substituting the value of ϕ and taking

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expectation and variance, I obtain the policymaker's cost-risk trade-off:

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

The expected policymaker's cost 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 between her expected cost and risk: i.e., the expected cost $E[C]$ is constant regardless of the level of risk sharing determined by λ.
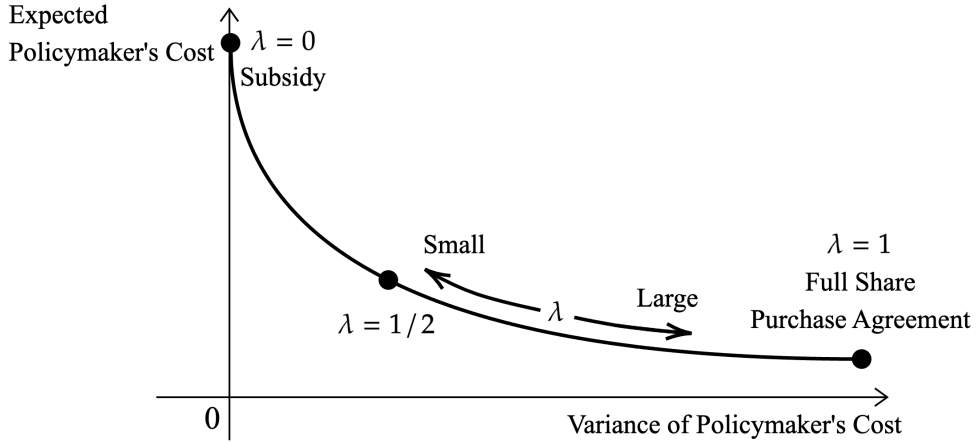

Figure 1: Policymaker's cost-risk trade-off

The policymaker can choose a λ—from the options encompassing a full share purchase agreement and a subsidy—to balance her expected cost 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 cost C is not too high so that $B - C$ is almost always positive. Without any constraints, she chooses λ to maximize the expected utility:

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

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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 less risk averse than the investor (i.e., $\gamma_{PM} < \gamma$), then the policymaker prefers bearing a larger share of the risk (i.e., $\lambda > 1/2$), and vice versa.

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 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 cost $E[C]$ by selecting a lower-cost investor without changing the variance $\text{Var}(C)$. 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

Brazilian consumers endured energy rationing in 2001 because Brazil had experienced a drought and primarily met its electricity needs with hydroelectric generation. To ensure energy security via a good mix of sources, the Brazilian energy departments, the Ministry of Mines and Energy (Ministério de Minas e Energia, MME) and the Electric-

ity Regulatory Agency (Agência Nacional de Energia Elétrica, ANEEL) have organized new energy auctions (Leilão de Energia Nova) for various sources (e.g., hydro, biomass, wind, and solar) since 2005. 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 capacity as this amount of stable supply per hour in my model and empirical application.[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. 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

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

disclosed before bidding to prevent collusive behavior.

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.[15]

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

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

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 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.[16] 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 average bid share of the 476 winning bids is 0.78 with an SD of 0.27. The fact

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

that bidders make interior portfolio choices suggests that the bidders are risk-averse.[17] The average purchase agreement price (the bid price for pay-as-bid auctions and the clearing price for uniform-price auctions) is \$35.66/MWh with an SD of \$8.26/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. I employ all 476 bids to estimate structural parameters relevant to the portfolio choice and quantify the bidders' risk aversion.

The average winner's price 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 rely on the structural auction model to recover the costs from these 296 bids in pay-as-bid auctions.

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.[18] 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

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[17]CCEE has required bidders to bid at least a share of 0.3 of their production into the auction since 2018. Otherwise, bidders could bid freely between 0 and 1.

[18]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).

0.93 across years and 1.09 across months, whereas in the U.S., they are 0.37 and 0.56.
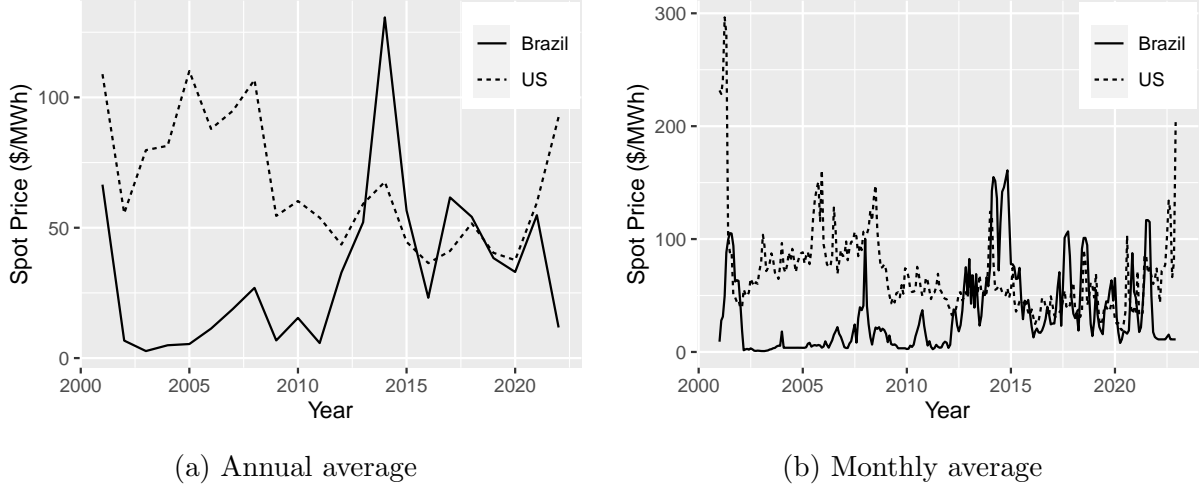

(a) Annual average

(b) Monthly average

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

Renewable energy investors are likely exposed to less price volatility in the wholesale market than what is reflected in the spot market because of the opportunity to contract with distribution companies and consumers. I interpret the resulting volatility estimates as the largest possible wholesale market volatility that the bidders may consider. I discuss how my structural estimates will change if bidders face less volatile prices in the wholesale market in Section 6.

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.[19] Risk-averse bidders optimize their portfolio by allocating their production to the risk-free purchase agreement and the risky wholesale market.[20]

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[19]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.

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

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. 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 procurement capacity $\sum_i q_i \times Capacity_i$ for winners exceeds the procurement capacity D: bidder i wins the auction when the residual capacity is positive, i.e.,

$$D - \sum_{j \neq i}(q_j \times Capacity_j)\mathbb{1}(b_j \leq b_i) > 0,$$

where $\mathbb{1}(\cdot)$ is an indicator function.

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 profit of winning with bid (q, b) is

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

where β is a common discount factor. $Capacity_i \times HT$ 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 profit inside the square brackets subtracts the fixed cost from the discounted sum of the per-period profits.

The profit function can be rewritten as

$$\pi_i(q, b) = q \times \left(\frac{1}{T} \sum_{t=l}^{l+T-1} \beta^t b \right) + (1-q) \times \left(\frac{1}{T} \sum_{t=l}^{l+T-1} \beta^t r_t \right) - c_i, \tag{3}$$

where c_i is an average cost defined as

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

The average discounted bid price, $T^{-1} \sum_t \beta^t b$, and wholesale market price, $T^{-1} \sum_t \beta^t r_t$, summarize the revenues from the purchase agreement and the wholesale market, respectively. The average cost c_i comprises the fixed cost allocated across the entire production and the average discounted variable cost, $T^{-1} \sum_t \beta^t VC_i$.

To capture the uncertainty of the wholesale market, I assume that bidders have beliefs about the future wholesale market prices. For bidders, the sufficient statistic of a path of future wholesale market prices $\{r_t\}_t$ is the average discounted wholesale market price, $T^{-1} \sum_t \beta^t r_t$. Thus, I assume that bidders have a common normally distributed belief for this sufficient statistic:

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

When determining the bid, bidders believe that they draw a sample path of wholesale market prices such that the sufficient statistic of the path, $T^{-1} \sum_t \beta^t r_t$, follows a normal distribution with mean μ_r and variance σ_r^2.

Before the auction, bidders form a common belief for the future wholesale market

prices. Upon participating in the auction, bidders draw their private types of a cost, $c_i \in [\underline{c}, \bar{c}]$, and $Capacity_i \in \mathbb{R}_+$ independently 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 assume that bidders are risk averse and have a CARA utility function with a common risk aversion coefficient $\gamma > 0$, $u(\pi) = 1 - \exp(-\gamma\pi)$, where π is the per unit profit defined in Equation (3). The winners receive the expected utility from the profit 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). Bidder i's certainty equivalent of a per unit profit $\pi_i(q, b)$ given the bidder's cost type c_i can be written as

$$\mathrm{CE}(q, b|c_i) = \underbrace{q \times \left(\frac{1}{T} \sum_{t=l}^{l+T-1} \beta^t b \right) + (1-q) \times \mu_r - c_i}_{\text{Expected profit}} - \underbrace{(1-q)^2 \cdot \frac{\gamma \sigma_r^2}{2}}_{\substack{\text{Wholesale market} \\ \text{risk premium}}}. \tag{5}$$

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 γ, and the wholesale price uncertainty, σ_r^2, are larger. I assume that bidders earn a certainty equivalent of zero if they lose the auction.[21]

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

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[21]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.

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

$$W_i(b) \coloneqq \Pr\left(D - \sum_{j \neq i}(q_j \times Capacity_j)\mathbb{1}(b_j \leq b) > 0 \right),$$

where (q_j, b_j), for $j \neq i$, is the competitors' bids. 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:

$$\max_{q \in [\underline{q},1],b} W_i(b) \times u(\text{CE}(q,b|c_i)).$$

The first-order conditions for the bid share and price characterize the bid strategy. Note that bidder i does not change the strategy by his capacity type since $Capacity_i$ only affects the objective function through his cost type c_i.

The first-order condition for the bid share q yields

$$q = 1 - \frac{\mu_r - \tilde{\beta}b}{\gamma \sigma_r^2} \quad \text{subject to} \quad q \in [\underline{q}, 1], \tag{6}$$

where I denote $\tilde{\beta} = T^{-1}\sum_{t=l}^{l+T-1} \beta^t$ for conciseness. Notably, bidders do not take the winning probability function $W_i(b)$, which summarizes the competitors' situation, into account in deciding their bid share q. The equilibrium bid share solves the portfolio problem, considering the bid price b as the sufficient statistic for competitors' situation.[22] Bidders allocate more to the auction when the purchase agreement is more attractive relative to the wholesale market: lower expected wholesale revenue μ_r; more risky wholesale market (larger σ_r^2); higher purchase agreement revenue b; and larger risk aversion γ.

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[22]This property of the bid price working as a sufficient statistic is analogous to Bolotnyy and Vasserman's (2023) observation of the bidder's score being payoff-sufficient in scaling auctions and is crucial to separately use the bidders' portfolio problem and score optimization problem in the estimation.

The first-order condition for the bid price b yields

$$\underbrace{q\tilde{\beta}b}_{\substack{\text{Agreement} \\ \text{revenue}}} + \underbrace{(1-q)\mu_r}_{\substack{\text{Wholesale market} \\ \text{expected revenue}}} = \underbrace{c_i}_{\text{Cost}} + \underbrace{(1-q)^2 \cdot \frac{\gamma\sigma_r^2}{2}}_{\substack{\text{Wholesale market} \\ \text{risk premium}}} + \underbrace{\frac{1}{\gamma}\ln\left(-\frac{\gamma q\tilde{\beta}W_i(b)}{dW_i(b)/db} + 1\right)}_{\substack{\text{Auction} \\ \text{markup}}}. \quad (7)$$

The left-hand side is bidder i's expected revenue. The equilibrium bid price balances the expected revenue with the three terms on the right-hand side. The markup term is a decreasing function of risk aversion γ. More risk-averse bidders cut markups for fear of the possibility of losing.

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

$$(q_i^*, b_i^*) = \arg\max_{q \in [\underline{q}, 1], b} W_i^*(b) \times u(\text{CE}(q, b|c_i)),$$

where

$$W_i^*(b) := \Pr\left(D - \sum_{j \neq i}(q_j^* \times Capacity_j)\mathbb{1}(b_j^* \leq b) > 0\right). \quad (8)$$

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

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 $\text{CE}(q, pc_i|c_i) = 0$ 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.[23] Bidders decide on the bid share q to maximize the expected utility conditional on winning, $E[u(\mathrm{CE}(q, p|c_i))]$, where the expectation is taken over the distribution of the clearing price belief.

The first-order condition for the bid share q yields

$$q = \frac{1}{1 + \tilde{\beta}^2 \sigma_p^2 / \sigma_r^2} \cdot \left(1 - \frac{\mu_r - \tilde{\beta}\mu_p}{\gamma \sigma_r^2}\right) \quad \text{subject to} \quad q \in [\underline{q}, 1]. \tag{9}$$

I highlight two changes from the first-order condition for pay-as-bid auctions in Equation (6). 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 bid share q. Since this first-order condition 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 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 adapt the structural model to Brazil's new wind energy auctions and present my estimation approach. I introduce a subscript a to indicate the parameters and variables in an auction a.

For each pay-as-bid auction, I observe auction covariates X_a, the realized 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 and lead time l_a and the number of participants N_a. For

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[23]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 first-order condition in Equation (9), and it must be assumed to be known for the identification of uniform-price auctions in Assumption 2.

a uniform-price auction, I observe the realized clearing price p_a instead of the bid prices b_{ia}^d. I first present an estimation approach, assuming that I observe the bids (q_{ia}^d, b_{ia}^d) and $Capacity_{ia}$ for all bidders, and show that information on winners and the number of participants suffices to identify the structural parameters at the end of the section.

The structural parameters of interest are the risk aversion coefficient γ_a, the expected wholesale market revenue μ_{ra}, and the bidders' cost types c_{ia}. I fix the annual discount factor to be $\beta = 0.95$. The minimum bid share $\underline{q}_a$ was 0 until 2017 and 0.3 after 2018.

I summarize the assumptions to identify the structural parameters using the data from pay-as-bid auctions as follows.

Assumption 1 (Identification of pay-as-bid auctions).

1. *The equilibrium bid price b_{ia}^* is directly observed, i.e., $b_{ia}^d = b_{ia}^*$.*

2. *The equilibrium bid share q_{ia}^*, evaluated at b_{ia}^*, as in the first-order condition for the portfolio problem, Equation (6), is observed as q_{ia}^d with an idiosyncratic normal measurement error $\eta_{ia} \sim \mathcal{N}(0, \sigma_{\eta a}^2)$.*

3. *The variance of the wholesale market revenue σ_{ra}^2 is known.*

4. *The equilibrium winning probability functions $W_{ia}^*(\cdot)$ 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 measurement error to deal with the censoring nature of the bid share. Second, I do not assume the expected wholesale revenue μ_{ra} to be known.[24] I specify a model underlying the equilibrium winning probability functions $W_{ia}^*(\cdot)$ below in Section 5.2 to identify them from the data.

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[24]Assuming bidders' beliefs to be known is preferable in Bolotnyy and Vasserman's (2023) application, and, importantly, this assumption allows them to identify the distribution of bidders' heterogeneous risk aversion. In contrast, it would be challenging to justify the assumption about the expected wholesale revenue μ_{ra} in my application.

I can also identify the risk aversion γ_a and the expected wholesale revenue μ_{ra} under suitable parametric restrictions across auctions using the data from uniform-price auctions. I assume the following in this case:

Assumption 2 (Identification of uniform-price auctions)**.**

1. *The clearing price belief $\mathcal{N}(\mu_{pa}, \sigma_{pa}^2)$ is known.*

2. *The equilibrium bid share q_{ia}^*, evaluated at μ_{pa}, as in the first-order condition for the portfolio problem, Equation (9), is observed as q_{ia}^d with an idiosyncratic normal measurement error $\eta_{ia} \sim \mathcal{N}(0, \sigma_{\eta a}^2)$.*

3. *The variance of the wholesale market revenue σ_{ra}^2 is known.*

I adapt the first two assumptions in Assumption 1 to the case of uniform-price auctions. I assume the bidders' clearing price belief is known instead of the equilibrium bid prices observed in the first assumption. In the second assumption, I apply the first-order condition for the portfolio problem of uniform-price auctions.

In practice, I make further assumptions to obtain the values of the variance of the wholesale market revenue σ_{ra}^2 and the distribution of the clearing price belief, $\mathcal{N}(\mu_{pa}, \sigma_{pa}^2)$. First, I assume bidders expect the variance of the wholesale market revenue σ_{ra}^2 to come from a mean reverting process for annual spot market price transitions. I use annual spot market prices from 2001–2022 to estimate the mean reverting process. The resulting SD, σ_{ra}, ranges from \$4.94–\$5.82/MWh for the 16 auctions in the analysis. Details are in Appendix C.1. Second, I assume bidders believe the clearing price to be distributed so that it best rationalizes the observation. The resulting mean μ_{pa} ranges from \$20.24–\$33.41/MWh and the SD σ_{pa} is \$4.00/MWh for the 8 uniform-price auctions. See Appendix C.2 for details.

With these identification assumptions in mind, I estimate the structural parameters in three steps using the portfolio problem and bid price optimization problem in separate steps. First, I use the first-order condition for the portfolio problem to estimate the risk

aversion γ_a and the expected wholesale revenue μ_{ra}. Second, I estimate the equilibrium winning probability functions of pay-as-bid auctions to prepare for the last step. Lastly, I infer the bidders' cost types c_{ia} using the first-order condition for the bid price optimization problem in pay-as-bid auctions. I detail the estimation procedure for each step below.

5.1 Usage of the Portfolio Problem

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 in a pay-as-bid auction has the following censored normal distribution:

$$q_{ia}^d = \max\left\{\min\left\{\underline{q}_a, 1 - \frac{\mu_{ra} - \tilde{\beta}_a b_{ia}^d}{\gamma_a \sigma_{ra}^2} + \eta_{ia}\right\}, 1\right\}, \eta_{ia} \sim \mathcal{N}(0, \sigma_{\eta a}^2). \tag{10}$$

This result implies that I can identify the parameters $(\gamma_a, \mu_{ra}, \sigma_{\eta a}^2)$ for each pay-as-bid auction unless the observed bid prices, b_{ia}^d, are the same across bidders.

In a uniform-price auction, Assumption 2 implies that the observed bid share q_{ia}^d has the following censored normal distribution:

$$q_{ia}^d = \max\left\{\min\left\{\underline{q}_a, \frac{1}{1 + \tilde{\beta}_a^2 \sigma_{pa}^2/\sigma_{ra}^2}\left\{1 - \frac{\mu_{ra} - \tilde{\beta}_a \mu_{pa}}{\gamma_a \sigma_{ra}^2}\right\} + \eta_{ia}\right\}, 1\right\}, \eta_{ia} \sim \mathcal{N}(0, \sigma_{\eta a}^2). \tag{11}$$

In contrast to pay-as-bid auctions, I cannot separately identify the risk aversion γ_a and the expected wholesale revenue μ_{ra} within auction a since the expected clearing price μ_{pa}, which replaces the observed bid price b_{ia}^d in pay-as-bid auctions, is the same across bidders. Thus, to identify the parameters $(\gamma_a, \mu_{ra}, \sigma_{\eta a}^2)$, I need to impose parametric assumptions and use the variation of the expected clearing price μ_{pa} across auctions.

I restrict the parameters $(\gamma_a, \mu_{ra}, \sigma_{\eta a}^2)$ across auctions and estimate them using both pay-as-bid and uniform-price auctions by maximum likelihood estimation.[25] I assume the risk aversion γ_a and the measurement error distribution to be the same across auctions,

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[25]I do not have enough variation of bid prices, b_{ia}^d, within each pay-as-bid auction or even within all 8 pay-as-bid auctions combined.

i.e., $\gamma_a = \gamma$ and $\sigma_{\eta a}^2 = \sigma_\eta^2$ for all a. I also parameterize the expected wholesale revenue as $\mu_{ra} = \beta^{l_a} \delta_r$. The bidders have a constant baseline level δ_r of the expected wholesale revenue and discount it according to the lead time l_a.[26]

5.2 Estimating the Equilibrium Winning Probability Function

This section explains my approach to estimating the equilibrium winning probability functions of pay-as-bid auctions. To make the estimation tractable, I assume that bidders' strategies are symmetric. This assumption is a natural choice since the participating bidders are *ex-ante* symmetric, i.e., the bidders draw heterogeneous types from a common distribution. I show that the equilibrium winning probability functions are the same for all bidders within an auction as a result of the symmetric strategy in Appendix C.3. Thus, I omit subscript i from the equilibrium winning probability functions and denote $W_a^*(b)$ hereafter.

I prepare the joint distribution of the random variables included in the definition of the equilibrium winning probability function, Equation (8). These random variables are $Capacity_{ia}$, the equilibrium bid (q_{ia}^*, b_{ia}^*), and the procurement capacity 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 (6), I model the joint distribution of the remaining random variables $Capacity_{ia}$, b_{ia}^*, and D_a. I assume that these three random variables are mutually independent conditional on auction covariates X_a.[27]

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[26]By the definition of the wholesale market belief in Equation (4), the mean μ_{ra} can be written as

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

Thus, the specification of the constant baseline level δ_r assumes that the discounted sum of the expected wholesale price is the same across auctions.

[27] 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}^*. I assume the independence of $Capacity_{ia}$ and b_{ia}^* since I find no evidence that the overall average capacity differs from the winners' average capacity 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.

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

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

Due to technological progress, the average capacity is expected to increase by the operation start date, $t_a + l_a$. I also estimate the distribution of the equilibrium bid price b_{ia}^* specified as

$$b_{ia}^*|X_a \sim \mathcal{N}(\delta_{b0} + \delta_{b1}t_a + \delta_{b2}t_a^2 + \delta_{b3}l_a + \delta_{b4}N_a, \sigma_b^2).$$

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

To obtain the procurement capacity distribution, I assume bidders believe the procurement capacity to be distributed such that it fits the observed procurement capacities. I use the resulting mean that ranges from \$278–\$489/MWh and the SD of \$245/MWh for the 8 pay-as-bid auctions (Appendix C.2).[28] With the resulting joint distribution, I approximate the equilibrium winning probability function $W_a^*(b)$ by simulation. Computation details are in Appendix C.4.

5.3 Usage of the Bid Price Optimization Problem

Given the estimates of the risk aversion γ_a and the expected wholesale revenue μ_{ra} in Section 5.1 and Assumption 1, I can recover bidders' cost types c_{ia} using their first-order conditions for the bid price optimization problem in Equation (7). Using the recovered

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[28]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.

bidders' costs, I estimate their distribution specified as

$$c_{ia}|X_a \sim \mathcal{N}(\delta_{c0} + \delta_{c1}t_a + \delta_{c2}t_a^2 + \delta_{c3}l_a, \sigma_c^2).$$

Similarly to the parameterization of the equilibrium bid price distribution, this specification intends to capture the time trend and the dependence on the lead time l_a. I assume the cost types are normally distributed, and the variance does not change across auctions.

5.4   Incomplete Bid Problem

In this section, I show that information on winners and the number of auction participants N_a are enough to identify the structural parameters. The key distributions used to identify the portfolio problem parameters in Section 5.1 are Equations (10) and (11) for pay-as-bid and uniform-price auctions, respectively. These distributions are the same for the winners and losers since the residual term η_{ia} is i.i.d. across bidders, and η_{ia} is irrelevant to the selection of winners.[29] Thus, winners' bids identify the same parameters as all bidders' bids.

In Section 5.2, I estimate the distributions of $Capacity_{ia}$ and the equilibrium bid price b_{ia}^* to calculate the equilibrium winning probability functions. First, I assume that $Capacity_{ia}$ is independent of the cost type c_{ia} to overcome the problem of observing only winners' capacities.[30] Assuming this independence, winners' capacities and the entire bidders' capacities identify the same capacity distribution since bidders' capacities are irrelevant to the selection of winners.

Second, given that the bid prices determine winners, I can identify the distribution of the entire bidders' bid prices by the winners' bid prices and the number of participants N_a using the order statistics inversion technique in Athey and Haile (2002). An important

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[29]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.

[30]The fact that I find no evidence that the overall average capacity is different from the winners' average capacity in my data supports the independence of $Capacity_{ia}$ and c_{ia}. See also footnote 27.

assumption to justify the usage of this technique is that the equilibrium bid price b_{ia}^* is i.i.d. across bidders for each auction, which holds when the bidders are *ex-ante* symmetric, employ symmetric strategies, and draw their types independently. I can then form the individual log-likelihood for bidder i as

$$\ln f_b(b_{ia}^*; \theta) + (brank_{ia} - 1) \ln F_b(b_{ia}^*; \theta) + (N_a - brank_{ia}) \ln(1 - F_b(b_{ia}^*; \theta)),$$

where $f_b(\cdot; \theta)$ and $F_b(\cdot; \theta)$ are the PDF and CDF for b_{ia}^* parameterized by θ and $brank_{ia}$ is the bid price rank of bidder i counted from the lowest in auction a. Using this technique, I can also estimate the entire bidders' cost distribution in Section 5.3 using the recovered winners' costs and the number of participants N_a.

6   Estimation Results

Table 2 presents the structural parameter estimates. I first estimate the risk aversion γ and the expected wholesale revenue, $\mu_{ra} = \beta^{l_a} \delta_r$, using the portfolio problem. The risk aversion 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.[31][32] The expected wholesale revenue parameter δ_r of 27.91 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.

I next estimate the equilibrium winning probability function $W_a^*(b)$ of pay-as-bid auctions. I estimate two distributions for $Capacity_{ia}$ and the equilibrium bid price b_{ia}^* as a preparation. A year-late operation starting date increases the average project capacity

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[31]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.

[32]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.

Table 2: Structural parameter estimates for new wind energy auctions

Parameter	Coeff.	S.E.	Equilibrium Winning Probability Function		
			Parameter	Coeff.	S.E.
Portfolio Problem			Capacity Distribution		
Risk Aversion, γ	1.36	(0.11)	Intercept, δ_{Cap0}	10.59	(0.55)
E[Wholesale Revenue], δ_r	27.91	(0.73)	Operation Start (year), δ_{Cap1}	0.177	(0.119)
Measurement Error, σ_η^2	0.0886	(0.0044)	Variance, σ_{Cap}^2	11.21	(0.82)
Cost Distribution			Equilibrium Bid Price Distribution		
Intercept, δ_{c0}	30.90	(0.20)	Intercept, δ_{b0}	48.28	(0.20)
Auction Date (year), δ_{c1}	-1.66	(0.08)	Auction Date (year), δ_{b1}	-0.861	(0.155)
Auction Date Square, δ_{c2}	0.736	(0.015)	Auction Date Square, δ_{b2}	0.977	(0.022)
Lead Time (year), δ_{c3}	-1.76	(0.02)	Lead Time (year), δ_{b3}	-0.280	(0.064)
Variance, σ_c^2	20.82	(1.51)	# Participants, δ_{b4}	-0.0135	(0.0007)
			Variance, σ_b^2	16.32	(0.82)

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

by 0.18 MW. The average bid prices show a quadratic increase from 2011–2015.[33] One year longer lead time decreases the bid price by \$0.28/MWh, and 100 more participants reduce \$1.35/MWh, reflecting that competition drives prices down. Estimated equilibrium winning probability functions and actual winning bids for the 8 pay-as-bid auctions are plotted in Figure D1 in Appendix D. The winning probabilities of the actual winning bids are in a plausible range for each auction.

I lastly recover the costs, c_{ia}, of the winners in pay-as-bid auctions. 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. The average risk premium is near zero since the average share allocated to the wholesale market, $1 - q_{ia}^*$, is very small, 0.03. As, absent risk sharing, the average winner's risk premium is \$20.16/MWh, he requires the expected revenue to be at least $\sim$\$40/MWh to cover the risk premium ($\sim$\$20/MWh) in addition to his cost ($\sim$\$20/MWh). Risk sharing halves the minimum expected revenue he chooses to invest because his risk premium falls from $\sim$\$20/MWh to almost zero.

I estimate the entire bidders' cost distribution from the recovered winners' costs. The

[33]The beginning of 2011 is set to auction date $t = 0$.

mean and SD of the bidders' costs are \$28.75/MWh and \$4.56/MWh in the median auction. Since the average winner has \$8.35/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 cost estimates are in a reasonable range compared to the engineering estimates.[34]

I estimate the expected wholesale revenue μ_{ra} from the bids. However, I use the spot market prices to gauge the variance of the wholesale revenue, σ_{ra}^2. Estimating the wholesale market risk premium does not require the variance σ_{ra}^2. It comes in when I isolate the risk aversion γ from the risk premium. Overestimating the variance σ_{ra}^2 results in underestimating the risk aversion γ. Since the wholesale market is likely less volatile than the spot market because of the opportunity to enter into other contracts, I interpret the risk aversion estimate as a lower bound. As a sensitivity check, I re-estimate the structural parameters with the variance σ_{ra}^2 half that of the main analysis. As expected, the risk premium stays the same, while the risk aversion γ doubles to 2.72. Nevertheless, the cost and auction markup do not change much: the average winner's cost and markup become \$21.06/MWh and \$1.05/MWh for the median auction. Higher risk aversion leads to lower markups and, thus, results in higher recovered costs, given that risk premiums stay the same.

7   Counterfactuals

With the structural estimates, I conduct two counterfactual exercises where the policy-maker has a goal for the amount of renewable technology 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. The policymaker understands that she will sell her share of the electricity into

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[34]My estimates suggest the average winner's cost of \$13–\$29/MWh and the average bidder's cost of \$25–\$37/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.

the wholesale market, which follows the same belief as the bidders.

In the first counterfactual, I simulate the policymaker's cost-risk trade-off that arises from these risk-sharing contracts. I consider three scenarios as ways to distribute these contracts: no private cost information, first-best, and pay-as-bid auctions. I then use the simulated cost-risk frontiers to decompose the policymaker's utility gains from the actual Brazilian auctions. In the second counterfactual, I compare the two auction formats, pay-as-bid and uniform-price, in providing these risk-sharing contracts, focusing on the fact that the procurement capacity is not disclosed before bidding.

I formulate auctions that provide the risk-sharing contracts, which I call uniform share auctions, before proceeding to the details of the two counterfactuals. A uniform share auction at time $t = 0$ is characterized by a share λ, a lead time l, a number of participants N, and an objective capacity $\widetilde{D}$. All bidders bid in a share λ of their production. Bidders cannot choose their shares in contrast to an actual auction that allows bidders to have portfolio choices. Another difference is that the objective capacity $\widetilde{D}$ decides the winners based on their installation capacity rather than the procurement capacity D selecting the winners based on their capacity bid into the auction. The remaining concepts stay the same as the actual auctions defined in Section 4.

Bidder i specifies a bid price b_i. If bidder i wins the auction, the auctioneer agrees to purchase $\lambda \times Capacity_i \times H$ hours of electricity by paying $b_i \times Capacity_i \times H$ for each period, $t = l, l+1, \ldots, l+T-1$. Bidder i sells the remaining production, $(1-\lambda) \times Capacity_i \times H$ hours, to the wholesale market at price r_t for each t during the contract. Thus, bidder i's certainty equivalent of a per unit profit at bid price b given the bidder's cost type c_i is

$$
\text{CE}(b|c_i) = \frac{1}{T} \sum_{t=l}^{l+T-1} \beta^t b + (1-\lambda)\mu_r - c_i - (1-\lambda)^2 \cdot \frac{\gamma \sigma_r^2}{2}.
$$

There are two differences compared to the certainty equivalent of an actual auction that allows bidders to have portfolio choices, Equation (5). First, the designated share λ replaces the bidder-selected share q_i. Second, the first term, which is the revenue from the

contract, does not depend on the share since the contract payment is made per total production rather than procurement 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, bidder i chooses bid b to maximize the expected utility of bidding:

$$\max_b \widetilde{W}_i(b) \times u(\text{CE}(b|c_i)), \text{ where } \widetilde{W}_i(b) := \Pr\left(\widetilde{D} - \sum_{j \neq i} Capacity_j \mathbb{1}(b_j \leq b) > 0\right).$$

I adopt BNE as an equilibrium concept similar to the actual pay-as-bid auctions in Section 4.1. I consider a symmetric monotone pure strategy to ease the calculation of the counterfactual equilibrium strategy (details 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.

7.1 Policymaker's Cost-risk Trade-off

I consider three scenarios under which the policymaker distributes the risk-sharing contracts. In the first scenario, I assume that the policymaker only knows the mean of the investors' cost distribution and does not observe the investors' private costs. The policymaker calls for investors on a first-come, first-served basis, with the minimum contract payment necessary for the average cost investor to sign the contract. The second scenario assumes the policymaker has full information about the investors' costs. The policymaker realizes the first-best by paying the minimum amount for the lowest-cost investors to sign. In the third scenario, the policymaker implements uniform share auctions with the pay-as-bid format.

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 3 depicts the simulated cost-risk frontiers for a representative auction.[35] The no-information scenario (dashed line) uses the average bidder's cost to calculate the outcomes of interest: the expected policymaker's cost (y-axis) and the variance of the policymaker's cost (x-axis). For the other two scenarios, I draw bidders' costs from their distribution and simulate the average outcomes. I detail the calculation of the equilibrium strategies in the pay-as-bid auction scenario in Appendix E.2. My simulation predicts that moving from zero policymaker risk (subsidies, $\lambda = 0$) to the highest risk (full share purchase agreements, $\lambda = 1$) lowers the expected policymaker's cost by \$20.48/MWh (97.1% of the average winner's cost) while increasing the SD of the policymaker's cost up to \$5.49/MWh, for the median auction.
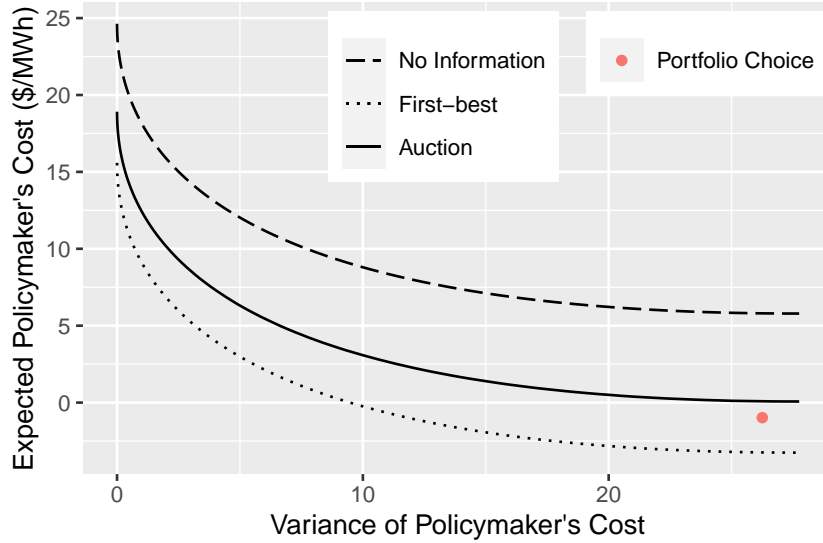

Figure 3: Simulated cost-risk frontiers for an actual pay-as-bid auction

I also simulate the average outcomes for the actual auctions that allow bidders to have portfolio choices (red filled circle in Figure 3). Using the estimated equilibrium winning probability functions, the first-order conditions in Equations (6) and (7) uniquely determine the equilibrium strategies in the actual auctions.[36] Allowing bidders to have

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

[36]Solving for the counterfactual equilibrium strategy in an auction that allows bidders to have portfolio

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portfolio choices lead to an outcome below the cost-risk frontier of comparable uniform share auctions. The opportunity for portfolio optimization makes the auction more lucrative and induces more competitive bids. In contrast, the constraint of bidding in the designated share makes the auction less attractive and lets bidders charge higher markups. I find that allowing bidders to have portfolio choices makes the expected policymaker's cost \$0.66/MWh smaller than otherwise for the same variance of the policymaker's cost.

To illustrate the usefulness of these predictions, I decompose the policymaker's utility gains from the actual Brazilian auctions. I contrast two policymakers, one risk-neutral and the other as risk-averse as the bidders, both without any institutional and political constraints. Assuming a policymaker with a CARA utility u_{PM} having a risk aversion $\gamma_{PM} \geq 0$ as in Section 2, the policymaker's utility maximization problem in Equation (2) implies the following indifference curves on the space of the mean and variance of the policymaker's cost C:

$$E[C] + \frac{\gamma_{PM}}{2} \times \text{Var}(C) = Const.$$

The left-hand side can be interpreted as the certainty equivalent of the policymaker's cost C.

Figure 4 illustrates my decomposition exercise when the policymaker is as risk-averse as the bidders. There are five indifference curves, and the policymaker's utility increases as the indifference curve lowers. The maximum possible gains are the difference between the two indifference curves at the top and bottom. The top line goes through the full share purchase agreements ($\lambda = 1$) in the no private cost information scenario,[37] and the bottom line is tangent to the policymaker's cost-risk frontier in the first-best scenario.

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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.

[37] If the policymaker is as risk-averse as the investors, the policymaker is indifferent between full share purchase agreements ($\lambda = 1$) and subsidies ($\lambda = 0$) on the same cost-risk frontier.

I find that the risk-neutral and risk-averse policymakers' maximum possible gains are $8.72/MWh (41.6% of the average winner's cost) and $18.93/MWh (90.3%), respectively, in the economic environment of the median actual pay-as-bid auction.
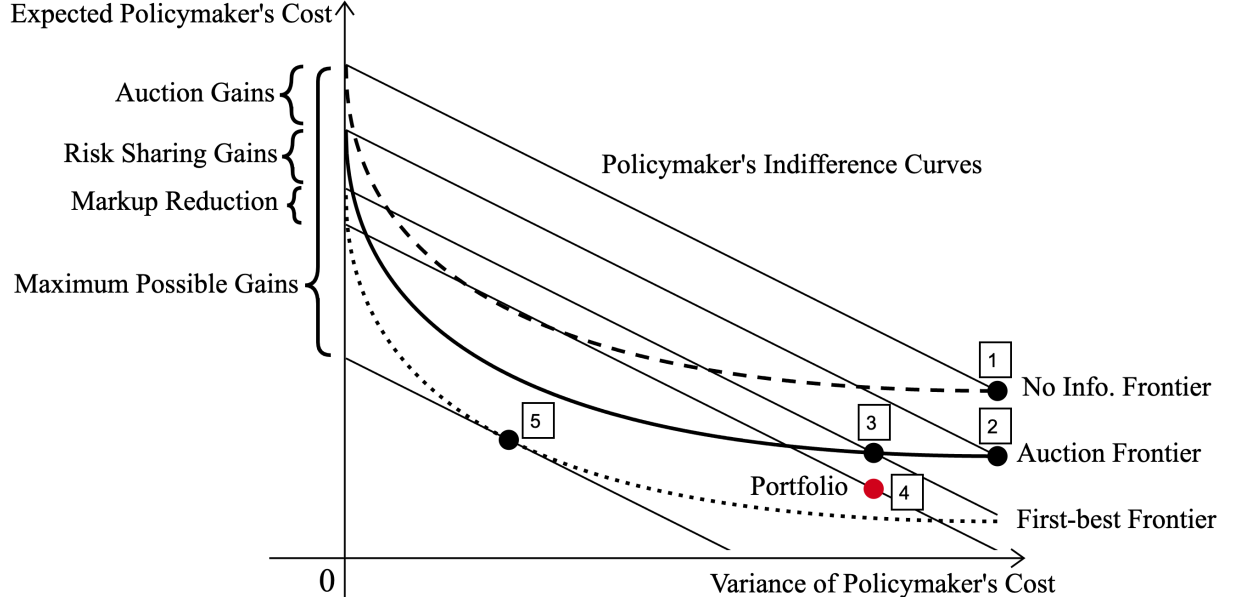

Figure 4: Decomposition of the policymaker's utility gains using the cost-risk frontiers

The policymaker's utility gains by implementing an auction that allows bidders to have portfolio choices (depicted as filled circle 4 in Figure 4) are the difference between the two indifference curves at the top and second from the bottom. I decompose these gains into three effects: auction mechanism, risk sharing, and auction markup reduction stemming from bidders having the opportunity of portfolio choices. The auction mechanism brings down the top indifference curve to the second, which goes through the full share purchase agreements in the auction scenario. Risk sharing then moves down to the third indifference curve that goes through the point with the same variance as the auction that allows bidders to have portfolio choices but on the cost-risk frontier in the auction scenario. Lastly, allowing bidders to have portfolio choices brings down to the fourth indifference curve because more competitive bids result in less winner markups.

The median actual pay-as-bid auction achieves 70.1% of the maximum possible gains for the risk-neutral policymaker. The gains of this auction consist of the gains from the auction mechanism, 63.5 pps, and the markup reduction, 6.8 pps, while losing 0.1 pps

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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. In contrast, the median auction achieves 37.2% of the risk-averse policymaker's maximum, and these gains can be decomposed into auction mechanism, 29.3 pps, risk sharing, 4.7 pps, and markup reduction, 3.3 pps. The risk-averse policymaker enjoys the benefit of sharing the risk with the investors.

7.2 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.[38] 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 γ and the variance of the bidder's cost σ_c^2. I calculate counterfactual equilibrium strategies for the pay-as-bid format as detailed in Appendix E.3.[39]

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 real-

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

[39]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.

izations 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.[40] 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.
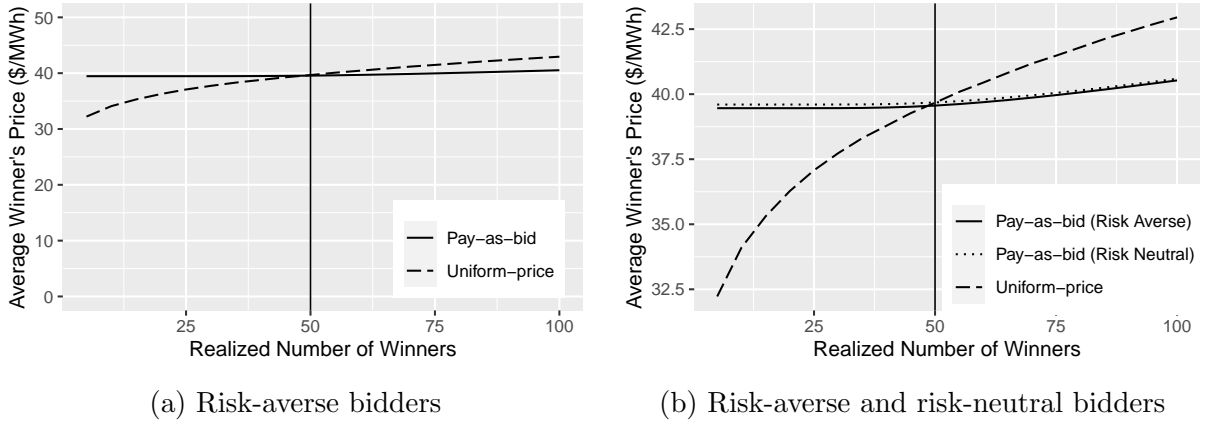

(a) Risk-averse bidders

(b) Risk-averse and risk-neutral bidders

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

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 revenue to be the same as the average bidder's cost, $\mu_r = 30$, and use the estimated values for the variance of wholesale 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 cost if the auction is more competitive than

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[40]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.

expected.

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 cost, and subsidies when the investors bear all the risk with the highest expected policymaker's cost. If the investors are risk-neutral, full share purchase agreements and subsidies have the same expected cost 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.

I quantify the policymaker's cost-risk trade-off from auctioning off the risk-sharing contracts using the structural estimates. By taking all risk, the policymaker can reduce her expected cost by \$20.48/MWh, 97.1% of the average winner's cost, compared to zero policymaker risk contracts while increasing the standard deviation of her cost up to \$5.49/MWh, for the median auction. The policymaker can choose a point on the cost-risk frontier that conforms with her risk preference and institutional/political constraints to

maximize her utility. To illustrate the usage of the simulated cost-risk frontiers, I apply them to decompose the policymaker's utility gains from the actual Brazilian auction into three effects: auction mechanism, risk sharing, and auction markup reduction stemming from bidders having the opportunity of portfolio choices. My simulations also demonstrate that, in the context of this paper, the pay-as-bid and uniform-price formats cost the policymaker differently depending on the relationship between the expected and realized competitiveness of auctions. If the auction is more competitive than bidders expected, the uniform-price format reduces the policymaker's costs, while the pay-as-bid format reduces the policymaker's costs if otherwise.

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. Extending the proposed structural auction model to incorporate heterogeneous risk aversion and endogenous entry would require the bids and covariates of all participating bidders and information on potential participants, analogously to what Bolotnyy and Vasserman (2023) demonstrate in scaling auctions. I leave this for future work.

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Appendix

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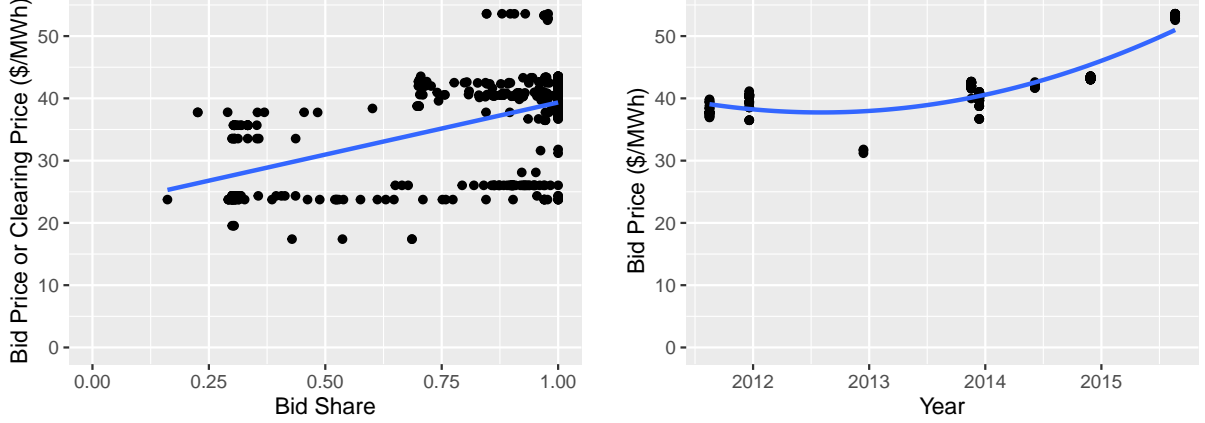
(a) Scatterplot of bid shares and prices for 476 winning bids in 16 auctions from 2011–2021

(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 there exists a unique pure-strategy Bayes Nash Equilibrium (BNE) 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

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

solves the portfolio problem for a given bid price b as in Equation (6). 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}:

$$H(c_i, \omega_{-i}) \;\; := \;\; \Pr\left(D - \sum_{j \neq i} (q^*(\omega_j(c_j)) \times Capacity_j) \mathbb{1}(\omega_j(c_j) \leq \omega_i(c_i)) > 0 \right).$$

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

$$\mathrm{EU}(b|c) := H(\omega_i^{-1}(b), \omega_{-i}) \times u(\mathrm{CE}(q^*(b), b|c)).$$

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:

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

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

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

where

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

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

and, for all b,

$$\frac{d\mathrm{CE}(q^*(b), b|c)}{db} = \frac{\partial \mathrm{CE}(q^*(b), b|c)}{\partial b} + \frac{\partial \mathrm{CE}(q^*(b), b|c)}{\partial q} \cdot \frac{dq^*(b)}{db}$$

$$= q^*(b) \times \frac{1}{T} \sum_{t=l}^{l+T-1} \beta^t.$$

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

$$\omega_i'(c) = -\frac{(\partial H(c, \omega_{-i})/\partial c) \times u(\mathrm{CE}(q^*(\omega_i(c)), \omega_i(c)|c))}{H(c, \omega_{-i}) \times u'(\mathrm{CE}(q^*(\omega_i(c)), \omega_i(c)|c)) \times q^*(\omega_i(c)) \times T^{-1} \sum_{t=l}^{l+T-1} \beta^t}.$$

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 $i = 1, \ldots, N$,

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

C   Econometric Details

C.1   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),

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

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

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

and

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

Thus,

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

Table C1 tabulates parameter estimates for the mean reverting process. As depicted in Figure C1, the estimated variance σ_{ra}^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 C1: 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.
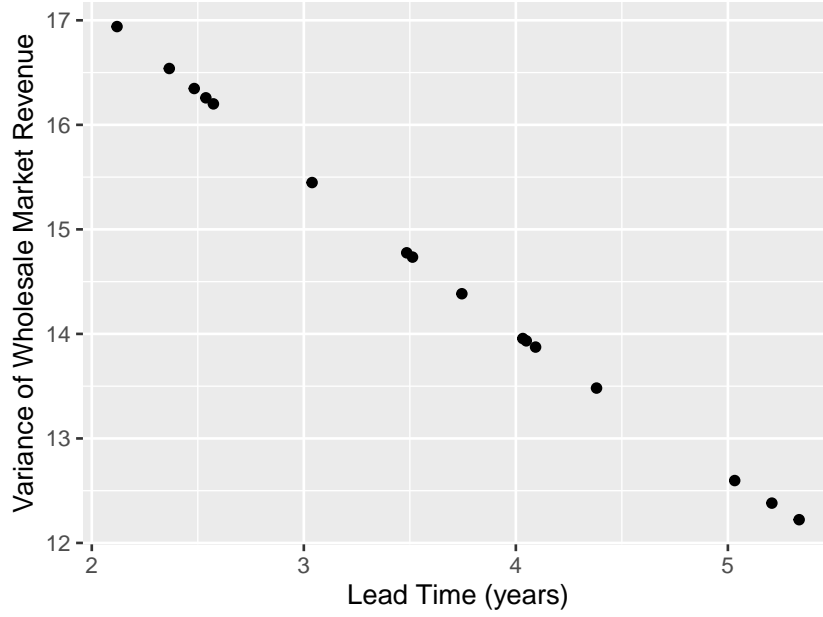

Figure C1: Relationship between the estimated variance of the wholesale market revenue and lead time for 16 auctions

C.2 Distributions of Procurement Capacity and Clearing Price

I parameterize the procurement capacity distribution as

$$D_a | X_a \sim \mathcal{N}(\delta_{C0} + \delta_{C1} t_a + \delta_{C2} N_a, \sigma_C^2).$$

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 $(\delta_{C0}, \delta_{C1}, \delta_{C2}, \sigma_C^2)$ 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

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

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 $(\delta_{p0}, \delta_{p1}, \delta_{p2}, \delta_{p3}, \sigma_p^2)$ that best fit the uniform-price auction data.

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

$$\begin{cases} \mu_{pa} = \delta_{p0} + \delta_{p1}(\delta_{C0} + \delta_{C1} t_a + \delta_{C2} N_a) + \delta_{p2}(t_a + l_a) + \delta_{p3} N_a \\ \sigma_{pa}^2 = \sigma_{pC}^2 + \delta_{p1}^2 \sigma_C^2 \end{cases}.$$

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.

Table C2 reports the fitted parameters of the procurement capacity and clearing price

models. 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).

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 $\mu_{pa} =$ \$20.24–\$33.41/MWh and $\sigma_{pa} =$ \$4.00/MWh. The variance of the marginal clearing price distribution, $\sigma_{pa}^2 \approx 16$, is much larger than the conditional clearing price distribution, $\sigma_{pC}^2 \approx 2$, which reflects the uncertainty bidders face because of the non-disclosure policy of the procurement capacity.

Table C2: Fitted parameters for procurement capacity and clearing price models

Parameter	Pay-as-bid	Uniform-price
Procurement Capacity Distribution		
Intercept, δ_{C0}	230.2	−95.13
Auction Date (year), δ_{C1}	−34.43	−23.14
# Participants, δ_{C2}	0.667	0.824
Variance, σ_C^2	59912.6	17564.8
Clearing Price Distribution		
Intercept, δ_{p0}		6.86
Procurement Capacity, δ_{p1}		0.0278
Operation Start (year), δ_{p2}		3.25
# Participants, δ_{p3}		−0.0461
Variance, σ_{pC}^2		2.31

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

C.3   Consequence of Symmetric Bid Strategy

I show that if bidders' strategies are symmetric, then the equilibrium winning probability functions are the same for all bidders within an auction. 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. Assuming that the bid price strategy is symmetric, i.e., $\omega_i = \omega$ for all i, the equilibrium winning probability function $W_i^*(b)$ can be written as

$$W_i^*(b) = \Pr\left(D - \sum_{j \neq i} (q^*(\omega^*(c_j)) \times Capacity_j) \mathbb{1}(\omega^*(c_j) \leq b) > 0 \right).$$

We can see that $W_i^*(b)$ is the same for all bidders given that bidders are *ex-ante* symmetric: bidders draw their types $(c_i, Capacity_i)$ independently from a common distribution.

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 (8) and shown to be the same for all bidders in Appendix C.3, 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

$$\hat{q}^*(b) := \max\left\{\min\left\{\underline{q}, 1 - \frac{\hat{\mu}_r - T^{-1}\sum_{t=l}^{l+T-1}\beta^t b}{\hat{\gamma}\sigma_r^2}\right\}, 1\right\}, \tag{12}$$

and $\hat{\gamma}$ and $\hat{\mu}_r$ are the estimates from the first step of the structural parameter estimation in Section 5.1.

I smooth the indicator functions in the last step using a normal CDF, denoted Φ, following Ryan (2022): i.e., an indicator function $\mathbb{1}(x_0 < x)$ is smoothed as $\Phi((x - x_0)/h)$, where I set the bandwidth parameter to be $h = \$2/\text{MWh}$, about 1/30 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 $d\hat{W}^*(b)/db$.
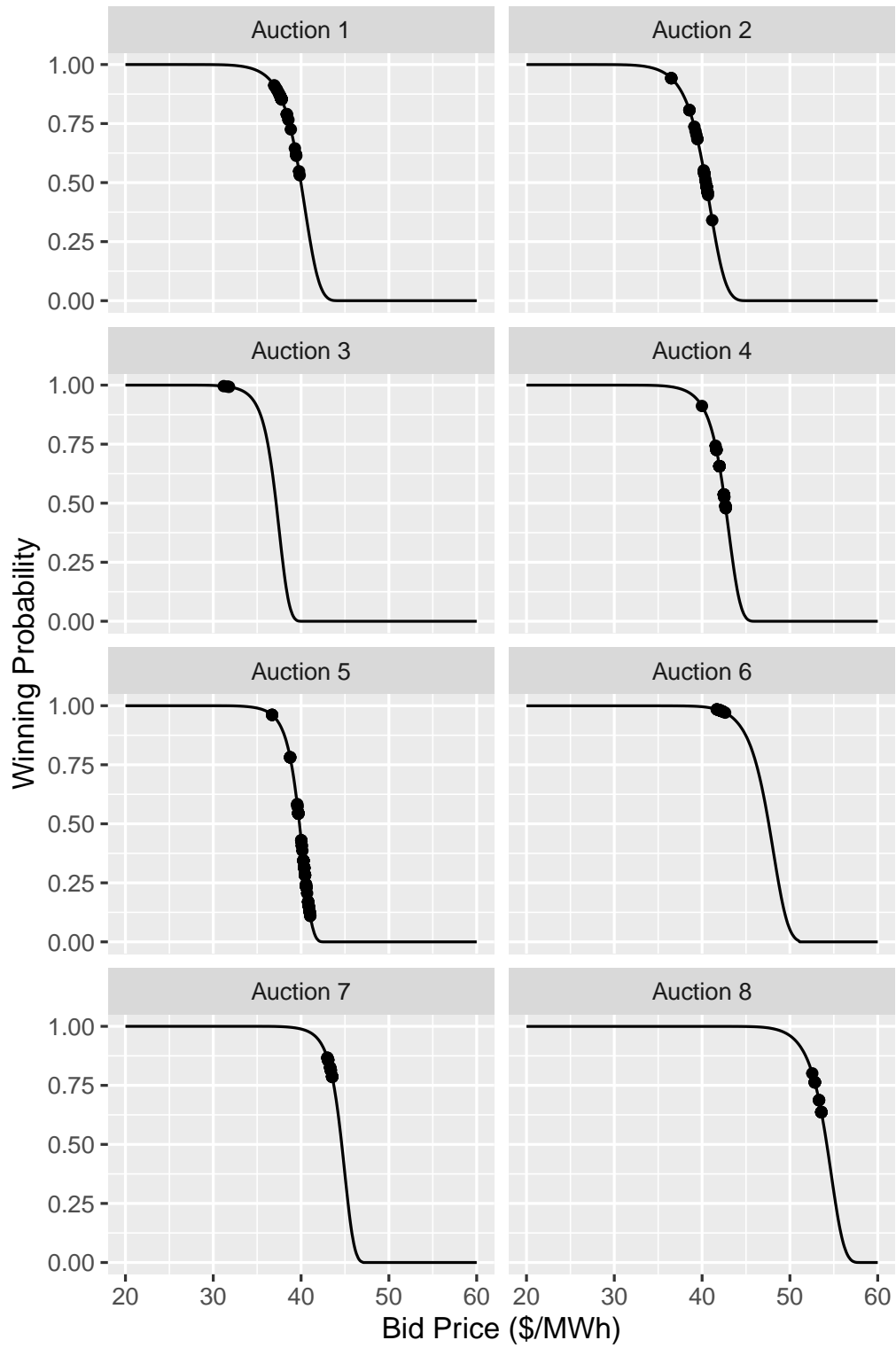
D   Estimation Results

Figure D1: Estimated equilibrium winning probability functions and actual winning bids

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

E.1   General framework

In this section, I detail the calculation of the counterfactual equilibrium strategy in uniform share auctions with the pay-as-bid format. I assume that the symmetric bid price strategy function $\omega : [\underline{c}, \bar{c}] \mapsto \mathbb{R}$ is monotonically increasing.

The monotonicity of ω implies that the winning probability function can be reformulated as a function of the bidder's cost type c_i:

$$
\begin{aligned}
\widetilde{H}(c_i) &:= \Pr\left(\widetilde{D} - \sum_{j \neq i} Capacity_j \mathbb{1}(\omega(c_j) \leq \omega(c_i)) > 0 \right) \\
&= \Pr\left(\widetilde{D} - \sum_{j \neq i} Capacity_j \mathbb{1}(c_j \leq c_i) > 0 \right).
\end{aligned}
\tag{13}
$$

Importantly, the winning probability function $\widetilde{H}(c)$ does not depend on the strategy ω. Thus, I do not need to recalculate $\widetilde{H}(c)$ while searching for the equilibrium strategy.

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

$$
\omega'(c) = -\frac{\widetilde{H}'(c) \times u(\text{CE}(\omega(c)|c))}{\widetilde{H}(c) \times u'(\text{CE}(\omega(c)|c)) \times T^{-1} \sum_{t=l}^{l+T-1} \beta^t}.
\tag{14}
$$

A solution to this ODE is a BNE bid price strategy ω^*, which exists and is unique 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 (13), the ODE in Equation (14) implies $\omega'(c) > 0$. Thus, I conclude that a unique monotone pure equilibrium strategy ω^* exists.

I define the boundary condition as a zero expected utility conditional on winning at

the highest cost type $\bar{c}$: i.e.,

$$u(\text{CE}(\omega^*(\bar{c})|\bar{c})) = 0. \tag{15}$$

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 (14) with the boundary condition in Equation (15). 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 (13), 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 $T^{-1} \sum_t \beta^t r_t \sim \mathcal{N}(\mu_r, \sigma_r)$, 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 (12). 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 $h = \$2/\text{MWh}$. I calculate $\widetilde{H}(c)$ for a grid of c with $\$0.10/\text{MWh}$ 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 (13), 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 (13) reduces to

$$\widetilde{H}(c_i) \;\; = \;\; \Pr\left(\widetilde{D} - \sum_{j \neq i} Capacity \mathbb{1}(c_j \leq c_i) > 0\right)$$

$$= \;\; \Pr\left(\#Winner - \sum_{j \neq i} \mathbb{1}(c_j \leq c_i) > 0\right)$$

$$= \;\; 1 - F_c^{\#Winner:N-1}(c_i).$$

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

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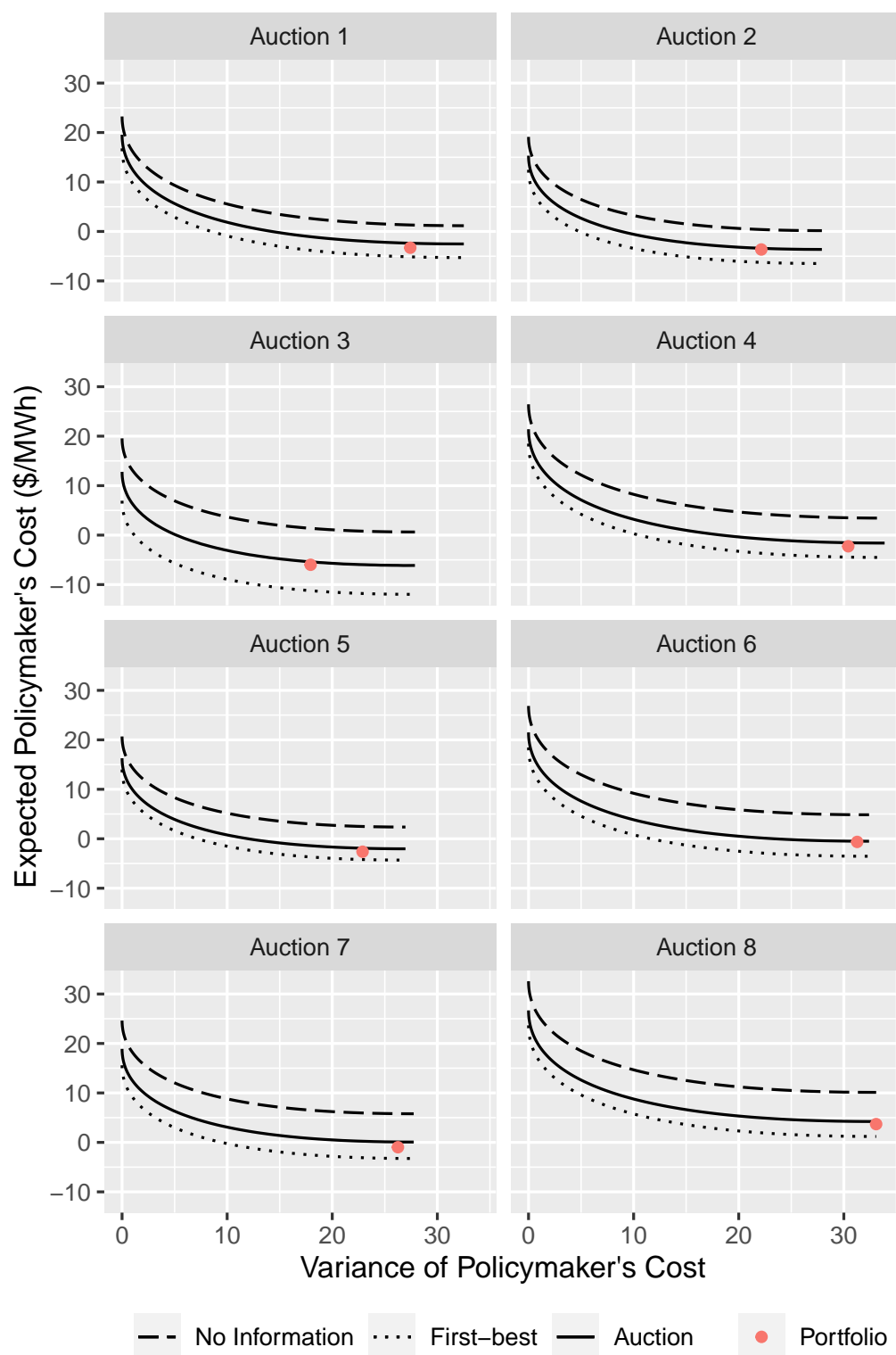
F   Counterfactual Results

Figure F1: Simulated cost-risk frontiers for the 8 actual pay-as-bid auctions
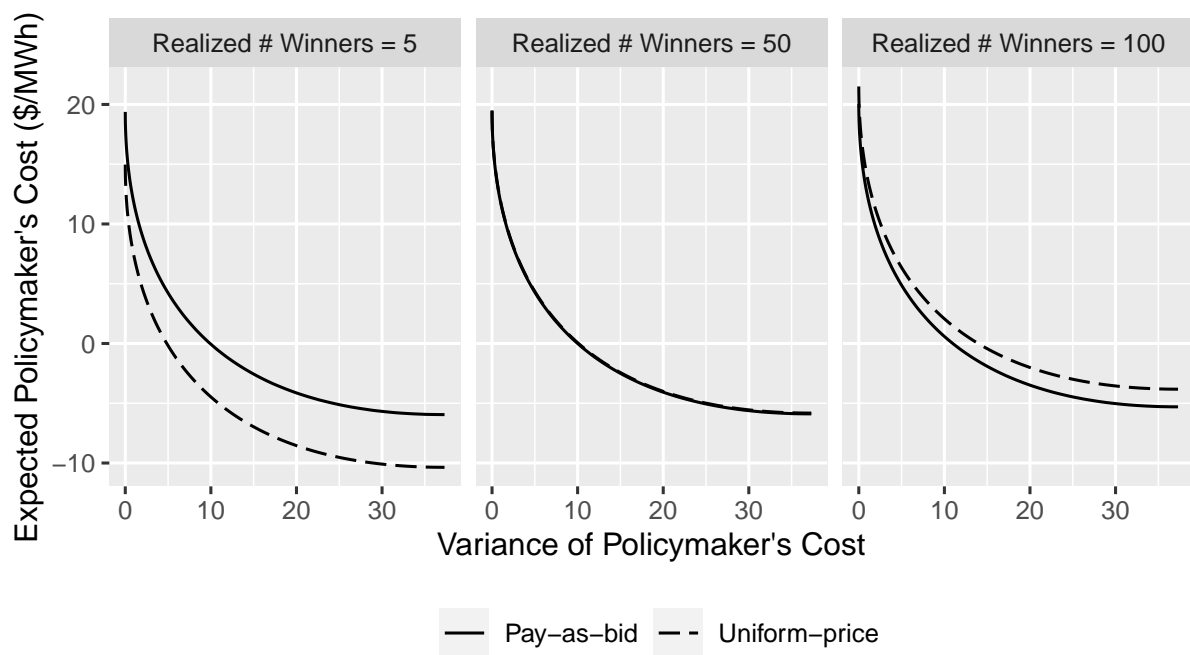
Figure F2: Simulated cost-risk frontiers for pay-as-bid and uniform-price auctions when the expected number of winners is 50