NBER WORKING PAPER SERIES

HOLDING UP GREEN ENERGY

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Working Paper 29154
http://www.nber.org/papers/w29154

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2021

Thank you to Rahul Banerjee, Sushanta Chatterjee, Jose Miguel Abito, Phil Haile, Bård Harstad, Jonas Hjort, Paul Joskow, Michael Kremer, Benjamin Olken, Katja Seim and Joe Shapiro for helpful comments and discussions. Thank you to seminar and conference participants at Berkeley/Harvard/Yale EEE, Colorado, Chicago, HKUST, NBER DEV, the Northeast Workshop on Energy Policy and the Zurich Conference on Public Finance in Developing Countries for comments. Thanks to Yashaswi Mohanty, Marie-Rose Tonguino, Andrew Wei and Tracy Zhou for excellent Research Assistance. All views and errors are my own. The views expressed herein are those of the author and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 29154
August 2021
JEL No. L14,O13,Q42

ABSTRACT

Green energy is produced by relationship-specific assets that are vulnerable to hold-up if contracts are not strictly enforced. I study the role of counterparty risk in the procurement of green energy using data on the universe of solar procurement auctions in India. The Indian context allows clean estimates of how risk affects procurement, because solar power plants set up in the same states, by the same firms, are procured in auctions variously intermediated by either risky states themselves or the central government. I find that: (i) the counterparty risk of an average state increases solar energy prices by 10%; (ii) the intermediation of the central government eliminates this risk premium; (iii) higher prices due to risk reduce investment, because state demand for green energy is elastic. The results suggest that the risk of hold-up places developing countries at a disadvantage in the procurement of green energy.

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1 Introduction

In order to bring down greenhouse gas emissions and mitigate global climate change, the world has begun to shift from brown energy, made by burning fossil fuels, to green energy, produced by renewable resources like wind and solar power. The pace and scale of this green energy transition will make it a revolution, for energy supply, comparable to the rise of coal in the first industrial revolution or of oil and electrification in the second. By one estimate, meeting greenhouse gas abatement targets will require \$131 *trillion* of investment in renewable energy (IRENA, 2021). If countries follow through on their abatement pledges, solar and wind are projected to overtake coal in global electricity production as soon as 2030 (IEA, 2021).

The green energy revolution has a special urgency in developing countries, where many people have yet to adopt the energy sources of the prior revolution. As countries grow, green energy serves both to head off increases in emissions and to meet rapid growth in energy demand (EIA, 2019; Wolfram, Shelef and Gertler, 2012). Figure 1 compares electricity supply in different parts of the world. Within the OECD, electricity produced from brown energy looks already to have reached an historic peak (Panel A). Outside the OECD, despite increases in renewable generation, brown energy use continues to grow (Panel B). Renewable energy investment will be most needed in developing countries, to meet their rising energy demand.

I conjecture that hold-up might hinder this revolution in the making. Weak contract enforcement puts developing countries at a disadvantage in the kinds of production that use relationship-specific assets (Nunn, 2007). Investments in power generation are known to be highly relationship-specific (Joskow, 1987). Weak contract enforcement and specificity create hold-up risk (Williamson, 1975; Klein, Crawford and Alchian, 1978). A private firm builds a power plant to connect to the grid and sell energy on contract. Once a plant is built, the firm loses all bargaining power if the contract does not hold, since the grid hosts few large buyers, or only one: a state-run utility. This counterparty risk has caused major renewable energy auctions around the world to be cancelled and contracts to be thrown out.[1] Ironically, technological progress in renewable energy, which pulls down costs over time, exacerbates the hold-up problem, since buyers of green energy can always buy it more cheaply from new projects than from old contracts, signed at yesterday's high prices.

The import of these forces is that green energy investments face a high degree of counterparty risk.

[1] There are many examples (IRENA, 2019*a*). Because power distribution is a natural monopoly, and many countries do not have well-developed wholesale markets, the buy side of the power sector tends to be thin and state-controlled. Mexico cancelled a large solar auction after the government decided to give the power generation business back to state firms (Deign, 2019). Turkey cancelled an auction when firms were scared off by the procuring government's weak finances (Bellini, 2019). South Africa scrapped solar contracts awarded at auction after its state utility went bankrupt and the government turned over (IRENA, 2018).

When this risk cannot be contracted away, private firms will either be deterred from investing or be willing to supply energy only at a premium.

This paper studies the possible hold-up of green energy in the context of procurement auctions for large solar power plants in India. Investment in solar power is one of the main ways that India plans to meet its intended nationally-determined contribution under the Paris Climate Accord (Ministry of Environment, Forest and Climate Change, 2015). I use novel data on the universe of large-scale solar procurement auctions in India from 2012 to early 2020, basically the entire history of the Indian solar industry. In solar auctions, firms compete to be awarded long-term (typically 25-year) contracts to supply solar power to state utilities. The data depict a solar boom, in which prices fell by a factor of three and capacity exploded: India installed 32 GW of utility-scale solar capacity, more than a hundred-fold increase, to approach the level of utility-scale solar in the United States (37 GW, circa 2019).

The institutions of the Indian solar market create rich variation in counterparty risk with which to study the effects of hold-up on procurement. State-government-owned electricity distribution companies are the wholesale buyers of nearly all electricity in India. Many of these buyers are perenially bankrupt, with long track records of strategic renegotiation and default (Mathavan, 2008). The latent risk to green energy producers from signing long contracts to sell to these counterparties is therefore high. However, both individual states, with records of late payment and default, and the central Government of India, a trusted counterparty, run auctions to procure renewable energy. In *centrally-intermediated* auctions (hereafter "central auctions"), the ultimate buyers of power—risky state companies—are the same, but the central government acts as a pass-through, on paper, insulating power sellers from counterparty risk. It is therefore possible to compare the outcomes of procurement auctions for projects that are built with the same technology, by the same firms, in the same places, but which were subject to starkly different levels of counterparty risk. Figure 2 gives an example of two such projects, from the state of Andhra Pradesh.

The empirical analysis is in two parts. The first part of the analysis uses intermediation to estimate how counterparty risk affects bid prices. Counterparty risk is measured directly using ratings of state procurers from India's Ministry of Power. The empirical idea is to compare prices for auctions in high-risk versus low-risk states that are or are not intermediated. The risk premium is estimated as the relative increase in solar prices in risky states for non-intermediated auctions. This empirical strategy has the virtue of differencing out factors other than risk, like unobserved differences in the quality of infrastructure, that vary solar costs across states in both state-run and central auctions.

With this strategy, in the first part, I obtain three main findings. First, the counterparty risk of an average state increases solar bid prices by 10%, over what the central government would have paid. This risk premium is nearly two-thirds as large as the mean markup of bid prices over cost among winning bidders (16%). Alternately, we can benchmark the risk effect against the estimated effect of sunshine on bid prices. The increase in prices due to the average state risk is the same, by my estimates, as from moving a solar plant from the mean solar irradiance of Kentucky to that of New Hampshire.

Second, central intermediation mitigates counterparty risk entirely. I find that solar bid prices are 6% lower in central auctions relative to comparable state auctions.[2] Lower prices in central auctions are consistent with intermediation mitigating risk, but this estimate is not dispositive, since it is possible that central auctions have some other advantage in cost or competitiveness, not having to do with risk. However, I additionally find that in a centrally-intermediated auction, increasing counterparty risk—for the state buying the power, through the central intermediary—does not increase bid prices. Moreover, conditioning on explicit controls for risk eliminates the effect of central intermediation on bid prices. The lower prices in central auctions are therefore consistent with sellers adjusting their bids to account for the lower hold-up risk they bear when auctions in risky states are intermediated. I use a second data set, on solar contracts, rather than auction bids, to replicate closely and to extend these first two main findings on counterparty risk.

Third, the counterparty risk premium is due specifically to the risk of strategic default. Firms may face high risk from states with weak or unpredictable finances, even if those states do not *deliberately* hold up solar producers. I test for the importance of strategic default, as opposed to exogenous risk, using differences in bargaining power across firms. Green energy has high fixed costs but low variable costs. Green energy projects therefore earn a high surplus and have a weak bargaining position, once a plant is up and running, which may invite strategic renegotiation of power purchase contracts. I hypothesize that a firm that runs thermal power plants in the same state to which they are selling solar power will have a stronger bargaining position, because they can more credibly threaten to withhold power from their thermal plants if a contract is breached. I match solar firms to any thermal power plants they own around the country. I find that, indeed, the counterparty risk premium is large for solar-only firms but practically null for firms that hold thermal plants in the same states. (In a placebo test, owning thermal plants in *other* states makes no difference in solar bid prices, or slightly increases them.)

[2] The estimated counterparty risk of an average state (10%) is larger than the estimated effect of intermediation (6%) because the average non-intermediated auction is held in a state of lower-than-average risk (such as Gujarat, which has high solar potential).

Does risk hold up investment? The counterparty risk premium could serve as adequate compensation for bearing risk, in which case it would have no bearing on investment. I argue, however, that the risk premium does cut green energy investment, because wholesale demand for green energy is elastic: states trade-off green energy against other power sources in order to hold down energy prices (Ministry of New and Renewable Energy, 2010). In my sample, elastic demand was made an explicit policy in the period from 2018 to 2020, when procurers widely adopted ceiling tariffs, maximum allowable prices on solar power bought at auction, to try to hold prices down. During the same period, the capacity awarded at auction fell far short of what buyers sought, and new investment in solar slowed (Figure 5).

The second part of the analysis uses a structural model to study this trade-off between counterparty risk and investment when demand for green energy is elastic. The model describes optimal bidding in a multi-unit procurement auction using the share auction framework of Wilson (1979). The main distinguishing feature of the model is that counterparty risk is treated as an observable payout shifter, known and common to all bidders in an auction. I show that this formulation is equivalent to bidder costs being inflated by the risk they face. The distribution of costs and counterparty risks are identified in this framework under the plausible assumption that central auctions pose no counterparty risk. I establish a new result on bid homogenization in a multi-unit auction and use it to adjust bid prices for auction observable characteristics, including risk. I then estimate the primitive distribution of costs in the model by simulating the residual demand faced by every bidder and inferring costs from the bid data and modeled optimal mark-ups (Kang and Puller, 2008; Hortaçsu and McAdams, 2010).

The model estimates allow me to trace out the aggregate supply curve for solar power that India would face under different levels of its own counterparty risk. I trace the supply curve, for a given level of risk, by varying ceiling tariffs and recording the set of equilibrium prices and quantities that would result. Any given ceiling price reduces participation from potential solar bidders with costs too high meet the ceiling. It also changes bids, for those firms whose costs are low enough to bid beneath the ceiling. I use the model estimates of the distribution of costs to simulate auction equilibria accounting for both of these effects. I find that the all-India solar supply curve would shift inwards by 37% if the whole country moved from the level of risk of the central government to that of a high-risk (75th-percentile) state.

I apply the model to study the foregone solar investment caused by the widespread adoption of ceiling prices from 2018 to 2020 (Figure 5). I find that this policy reduced capacity procured by 16%. Risky states set ceiling prices, in imitation of the central government, to try to match the low prices that the central government had obtained at auction. I find that the ceiling policy did not meet this goal: for the actual level of risk in the data, the ceiling prices imposed are estimated to lower the price of solar energy procured by a mere 1%. The model shows why the reduction in prices is so small: ceiling prices reduce participation, so that the remaining bidders in an auction respond by raising their markups, pushing bid prices towards the ceiling. Risky states therefore face an extreme trade-off where any attempt to suppress the risk premium will sharply decrease investment at little gain in lower procurement costs.

The results suggest that developing countries with weaker institutions for contract enforcement may be at a competitive disadvantage in the procurement of green energy. The prospect of strategic default creates counterparty risk. Higher counterparty risk increases bid prices. When the demand for renewable energy is elastic, whether due to ceiling tariffs or other policy choices, this risk will feed back to reduce investment.

The main contribution of this paper to the literature is to provide sharp estimates of how hold-up risk changes prices and investment. It is hard empirically to separate hold-up risk from other factors that may affect firm costs. The frontier of the empirical literature compares firm investment, integration or costs across countries or states with differing contract enforcement in industries that are more or less reliant on contract-intensive inputs (i.e., inputs produced with relationship-specific investments) (Nunn, 2007; Acemoglu, Johnson and Mitton, 2009; Boehm and Oberfield, 2020; Amirapu, 2021). This approach assumes that unobservable factors that shape investment in contract-intensive industries, for example input quality, do not covary with contract enforcement. I take a complementary approach with a within-industry study of the solar power industry, in the tradition of Joskow's canonical validation of transactions cost theory.[3] This approach has the advantage that solar production costs are well-understood and fairly homogenous so that contractual risk becomes an important determinant of solar prices. The Indian setting allows clean estimates of the value of counterparty risk using the interaction of risk with contract intermediation.

This main contribution connects the paper to work in development economics, industrial organization and energy economics. I contribute to the literature in development economics on contract enforcement. A main theme of this literature is how reputation or relational contracts may substitute for formal contracts (McMillan and Woodruff, 1999; Banerjee and Duflo, 2000; Macchiavello and Morjaria, 2015, 2021). The present analysis is most closely related to work that measures the economic costs of weak contract en-

[3] Joskow (1987) finds that greater asset specificity is associated with longer contracts, akin to integration. In the Joskow (1987) case, specificity for power plants is due to fuel supply relationships, on the input side, rather than from constrained output markets as I emphasize here. Contracting solves the hold-up problem when contracts can be specified and enforced, as in the US energy market (Joskow, 1988, 1990). Contracts may not achieve efficiency when projects are complex and contracting is therefore costly (Bajari and Tadelis, 2001) or when contracts are not strictly enforced (Ryan, 2020).

forcement, renegotiation or default (Stroebel and Van Benthem, 2013; Blouin and Machiavello, 2019; Ryan, 2020).[4] Counterparty risk has been hard to estimate but is perhaps the greatest single concern for private investors in many developing economies (Collier and Pattillo, 2000). My findings offer an unusually direct, revealed preference estimate of hold-up risk from the imperfect enforcement of formal contracts.

The role of contract enforcement has received less attention in the industrial organization literature on procurement.[5] This paper is closest to a small set of empirical papers on procurement when ex post performance is not contractible (Bajari, Houghton and Tadelis, 2014; Lewis and Bajari, 2014; Bhattacharya, Ordin and Roberts, 2020). In these papers, the main contracting failure is due to the bidding firm's ex post cost of adaptation or effort (Bajari and Tadelis, 2001). My contribution is to show that the counterparty risk posed by the *buyer* affects bidding and investment. This finding implies that public procurement costs depend not only on market structure, or the firm's performance, but also on a state's ability to commit.

The paper also contributes to a fast-growing literature on the green energy revolution, by measuring the determinants of green energy prices and investment in a major developing economy. The economics literature on renewable energy in developed countries has focused on how wholesale markets adapt to intermittent renewable generation and the efficiency of green energy subsidies.[6] A small body of empirical research connects green energy investment in developing countries to policy choices.[7] I argue that hold-up risk is a fundamental yet overlooked determinant of green energy prices and investment.

The paper goes on as follows. Sections 2 and 3 describe the context and data. Section 4 estimates how counterparty risk affects solar prices. Section 5 lays out a model of bidding in the presence of counterparty

[4]Blouin and Machiavello (2019) provide evidence of strategic default in the international coffee market. Wholesale coffee sellers are more likely to default on a forward sales contract when spot prices rise after the contract is signed. The same logic may help explain why counterparty risk appears on the sell side of India's market for power from coal but the buy side of the solar market. Ryan (2020) measures the efficiency cost of the renegotiation of contracts for electricity supply by large coal plants. In the coal power market, input costs rose, moving against selling firms. I find that power sellers renegotiate the terms of contracts with procurers, rather than vice versa. In the solar market, input costs have fallen, lowering spot output prices and making it more likely that buyers would renegotiate. Structural differences between the markets also give more bargaining power to coal firms.

[5]A large literature studies the efficiency of procurement auctions. Empirical work has studied procurement auctions with collusion (Porter and Zona, 1993; Conley and Decarolis, 2016), endogenous entry (Li and Zheng, 2009; Bhattacharya, Roberts and Sweeting, 2014), and bidder asymmetry and preference policies (Krasnokutskaya and Seim, 2011; Nakabayashi, 2013). Tadelis (2012) studies mechanism choice in procurement and calls explicitly for more research on procurement under incomplete contracts.

[6]Research has gathered around several disparate themes, including: how the intermittency of renewable generation affects its social value (Joskow, 2011; Cullen, 2013; Novan, 2015; Gowrisankaran, Reynolds and Samano, 2016); how the growth of green energy changes prices and market conduct in wholesale electricity markets (Ito and Reguant, 2016; Bushnell and Novan, 2018); and, the efficiency of policies that subsidize green energy investment, especially residential investment (Borenstein, 2012; Bollinger and Gillingham, 2012; Borenstein, 2017; Pless and van Benthem, 2019).

[7]Declines in prices are due mainly to huge falls in capital input costs, as for solar panels. Falling prices have also been attributed, in part, to policy changes like a move from feed-in tariffs to procurement auctions (Eberhard and Kåberger, 2016; Bose and Sarkar, 2019; Shrimali, Konda and Farooquee, 2016). Working against this trend, Probst et al. (2020) find, in the Indian solar market, that domestic content requirements, mandating that some projects use domestically-made solar panels, increase solar prices.

risk. Section 6 estimates the model and Section 7 presents counterfactual results. Section 8 concludes.

2 Institutional context

2.1 Renewable energy policy in India

India has set ambitious goals for growth in renewable energy to meet its intended nationally-determined contribution under the Paris Climate Accord: 100 GW of installed solar capacity and 60 GW of wind by 2022 (Ministry of Environment, Forest and Climate Change, 2015). These goals have grown with the solar market. In 2010, the Government of India launched the "Jawaharlal Nehru National Solar Mission" (JNNSM). The mission sought "to scale-up deployment of solar energy and to do this keeping in mind the financial constraints and affordability challenge in a country where large numbers of people still have no access to basic power and are poor and unable to pay for high cost solutions" (Ministry of New and Renewable Energy, 2010). The JNNSM set an initial target of 20 GW of solar capacity addition by 2022, which was met with skepticism, given the high cost of solar at the time (Deshmukh, Gambhir and Sant, 2011). Nevertheless, with the cost of solar falling, a new Government in 2015 quintupled the prior target.

Investment in green energy raises an institutional tension between the central government and the various states. The central government has national and international goals in developing a renewable energy industry and reducing greenhouse gas emissions intensity, yet the central government does not own electricity distribution companies and buys little electricity itself. The states, via wholly state-owned electricity distribution companies (discoms), buy nearly all electricity in the country, and care mainly about keeping down the cost of procurement, rather than the broader goals laid out at the central level. The central government therefore supports renewables through policy instruments such as tax expenditures and subsidies.[8] While these policies are an important sign of the Government's commitment to solar power, the subsidies they represent are small relative to the value of the solar market. I argue below that such policy support for solar has been less important than the Government's direct intervention in the market.

[8]The central government lowers capital costs for renewable energy projects by exempting renewable energy capital from import duties and by allowing accelerated depreciation of capital investments in renewable production. The government also offered capital subsidies, for certain projects, in the form of "viability gap funding" (VGF), which pays for the estimated difference in procurement costs between green energy and brown energy projects, to encourage states to buy green power.

2.2 Counterparty risk in the sale of power to state buyers

Renewable energy in India is sold only through long-term contracts, which entail counterparty risk. The main buyers of power are state-owned and run distribution companies. These state discoms have a long track record of strategic default against private power generators (Mathavan, 2008). For many states, discom defaults lead to an accumulation of debt and ultimately precipitate central government bailouts, including, most recently, in 2020, 2015, 2012 and 2002 (see Appendix B). The cycle of default, debt and bailouts has continued in spite of structural reforms like the creation of state electricity regulators (Kumar and Chatterjee, 2012).

Data from the Ministry of Power makes it possible to measure just how risky state distribution companies are as counterparties. The Ministry of Power issues letter grades of state discoms to rate their financial condition and credit risk (Ministry of Power, 2013). It has also created a database of late and disputed payments, in order to shame state discoms into paying generators for the electricity they deliver (See Section 3 and Appendix A for a description of these data). Figure 3 plots the mean share of payments from state distribution companies to generators that are late or in dispute against the distribution company rating. Late payment and non-payment increase for lower-rated companies. Companies rated "A+" have barely any late or disputed payments; companies rated "C" have roughly a quarter of their payments late or disputed.

Firms selling to these counterparties on long contracts face hold-up risk because the value of their plants is relationship-specific. India's power market has lately become more physically integrated, lessening long-standing transmission constraints across states and regions (Ryan, 2021). Yet power plants built to supply on long-term contracts still face narrow output markets. The market for the resale of long-term contracts is thin. Despite regulations for open access to the power grid, to sell across states, various "tariff and non-tariff constraints" hinder trade and create large differences between the in-state and out-of-state prices of wholesale electricity (Forum of Regulators, 2019).

Solar power projects may be especially vulnerable to hold-up, for three reasons. First, lending for the construction of new renewable energy plants is contingent on selling under a long-term contract. A firm that lost its power purchase contract would likely have its loan called in. Second, the profile of project cost and payments. The investment in a solar project is up-front and the tariff payments over a long horizon, typically 25 years. Ex post, once a project is built, the variable costs of supplying power are low, which creates on ongoing variable surplus for the solar firm and an incentive for the buyer to renegotiate. Third, technological change: because renewable power prices have been declining, the outside option of states, to break a contract and buy renewable power at lower current rates, has been improving. These risks are not hypothetical in the Indian solar market. While most contracts are in their early years, several states have already taken advantage of falling prices by renegotiating solar tariffs initially set at auction, making the argument that old prices were not in line with today's market (Chandrasekaran, 2017; Bihar Electricity Regulatory Commission, 2019).

2.3 Intermediation in solar procurement auctions

To attempt to mitigate counterparty risk, the central government intervenes in the market for solar power by serving as an intermediary between sellers and buying states.

There are three main ways solar procurement is done. First, states can negotiate bilateral contracts to procure energy (a "state bilateral"). Second, state discoms can buy power through procurement auctions (a "state auction"). In both of these methods, states act on their own; selling firms can draw on central tax exemptions and other policies, but the central government is not otherwise involved. Third, states can buy power via an auction run by a central government entity, either SECI or NTPC (a "central auction").[9] The central government's role in these auctions is purely *intermediation*. In central auctions, the true buyer of power is still a state or a collection of states. The solar power is produced with the same technology, by many of the same firms, as for state auctions.

Figure 2 shows an example of how similar projects can be, regardless of whether their procurement was intermediated. The left-hand panels (A and C) show a solar power plant bought in a central auction. The right-hand panels (B and D) show a solar power plant bought in a state auction. The two projects are of the same scale, in the same district of Andhra Pradesh, and have strikingly homogeneous physical layouts.

The salient economic difference between state and central auctions is that in central auctions the central government assumes the counterparty risk faced by solar firms. If the distribution companies later do not pay for solar power bought at a central auction, those payments are made by the central agency.[10] Low solar

[9]The Solar Energy Corporation of India (SECI), is a central-government-owned company, controlled by the Ministry of New and Renewable Energy, that was established in 2011 to implement the JNNSM. The National Thermal Power Corporation (NTPC) is an incumbent, central-government-owned generation company with a large portfolio of power plants. Both of these companies run solar auctions for the central government to procure power on behalf of the states.

[10]This guarantee was initially implicit. Astute market watchers noted that counterparty risk, "virtually absent in projects bid out by SECI and NTPC, exists mostly in projects bid out by state agencies" (Aggarwal and Dutt, 2018). In 2016, the Government of India formalized this absorption of counterparty risk by changing the terms of SECI contracts, so that the central agency was not only an auctioneer, but a formal intermediary party to the power purchase contract, which was obligated to pay solar firms if states did not. States, in turn, were obligated to compensate the central agency on a "back to back" basis. This intermediation arrangement would later be tested when solar power sellers sought an increase in contract prices from SECI to offset an unexpected

tariffs in recent years have been attributed in part to this guarantee: “It is understood that this fall in solar tariffs is the result of combination of various factors, most important being the decision of the Government of India to cover solar power by SECI … against defaults by State distribution companies” (Market Screener, 2017). The empirical analysis in Section 4 will provide evidence on how central intermediation affects bidding in solar procurement auctions.

3 Data and summary statistics

This section introduces the data sources and describes the recent transformation of the Indian solar market.

3.1 Data sources

The main data sources cover all utility-scale solar procurement auctions and solar projects in India.[11] There are two distinct databases, on solar auctions and on solar projects.

The *auction* database gives the date, procurer, tendering authority, capacity sought and capacity awarded for each auction. The tendering authority refers to the party that runs an auction and assumes the payment obligation for power procured through that auction, which may be either a state or a central agency (see Section 2). The tendering authority is often *not* the final buyer of power; in central auctions, for example, SECI might be the tendering authority even if the power procured at auction is being bought by a state distribution company in Andhra Pradesh. I impose sample restrictions to produce a set of homogenous auctions: an auction is retained if it seeks more than 5 MW of power from ground-mounted solar photovoltaic plants. The restrictions yield a sample of 232 auctions with 1264 bids totaling 124 GW of capacity bid (see Appendix A). I link auction-level data to the bids in each auction. Most analyses of bid prices and costs are further restricted by requiring that data be available on all individual bids in an auction.[12]

A second database on solar *projects* tracks investment in solar power plants rather than bids at auction. There are two main differences in coverage, relative to the auction data. First, the solar prices in the project

increase in taxes. SECI argued that solar power buyers themselves should be responsible for any increase. However, in a series of rulings, India's apex electricity regulator asserted that SECI, the central agency, was indeed liable in its role as contract intermediary (though solar buyers were also liable to the agency, in turn) (CERC, 2020*a*,*b*,*c*).

[11] Utility-scale refers to installations above a minimum size of 1 MW that are connected to the transmission grid (as opposed to small-scale, rooftop solar projects connected to the distribution network). These data were purchased from Bridge to India, a consulting firm that provides data and analysis on renewable energy in India. Bridge to India in turn gathers data on renewable auctions from public documents of the utilities and central agencies that procure power.

[12] A total of 102 auctions have data on *all* bids, whether winning or not, and 31 have data on some bids. Most bids are priced per unit of energy. A minority of bids are priced per unit capacity or have capital subsidies per unit capacity; in those cases, I calculate per unit energy equivalent prices to make prices comparable across all bids (Appendix A).

data are the prices of power purchase contracts, not of offered bids. The projects database therefore does not include any data on bids that lost at auction, which do not yield any contract or investment. Second, the projects database includes solar plants and contracts procured through means other than auctions. In particular, utilities also buy power directly through bilateral contracts signed at negotiated prices. The projects database includes variables on the procurer, the selling firm, the contract price, and plant capacity, state, district and commissioning date.

In addition to these main data, I also gather sundry data sources to measure solar irradiance and other determinants of solar power costs (see Appendix A for a complete description). The most important such data source is that used to measure counterparty risk. The Ministry of Power, Government of India rates distribution companies on their financial positions with letter grades, on an academic scale from F to A+ (Ministry of Power, 2013). I use a normalized version of the Ministry of Power rating to measure state-level counterparty risk in the empirical analysis. Let $GPA_s \in [0, 4.3]$ be the GPA equivalent of the state's letter grade from the Ministry of Power in 2012, at the start of the auction sample. I define counterparty risk as:

$$CounterpartyRisk_s = \frac{4.3 - GPA_s}{4.3 - \overline{GPA_s}}. \tag{1}$$

This measure is normalized so that zero represents no risk (a grade of A+, $GPA_s = 4.3$) and one represents a state of average risk. Figure 3, discussed above, validates this risk measure by showing that higher risk (a lower letter grade) is associated with more late or disputed payments.

3.2 Summary statistics

Table 1 presents summary statistics on the two main datasets, on solar procurement auctions and solar power projects. Panel A gives summary statistics in the auction data at the auction level, separately for all auctions, central auctions and state auctions. Panel B shows statistics in the auction data at the bid level. Panel C shows summary statistics at the project level. As noted above, projects are distinct from auctions: an auction may yield one or multiple projects, depending on the number of successful bids that then lead to signed contracts and plants, while the power from a project may have been procured without an auction.

The main finding with respect to the auction data is that there is a broad overlap in the characteristics of central and state-run auctions. Central auctions have fewer bidders on average than state auctions and seek to procure somewhat more capacity (panel A). However, these are differences in degree and not kind. For central (state) auctions, the 25th, 50th and 75th percentiles, respectively, of the number of bidders are 2 (2), 4

(6) and 9 (13) and of the capacity sought are 50 (52), 250 (200) and 750 (500) (all in MW). Since auctions are for multiple units of capacity, the number of bidders is a misleading measure of competition. We also report the Hirschman-Herfindahl Index (HHI) for the concentration of offered capacity across bidders at auctions, which is similar for central (0.34) and state (0.30) auctions. Despite being marginally less competitive, central auctions have lower prices on average than state auctions (INR 3.70 per kWh versus INR 4.69 per kWh), though again, there is substantial overlap in the bid price distributions.

Table 1, Panel B reports summary statistics at the bid level. The average bid offers 118.6 MW of capacity. A project of this size would require solar panels with a surface area of 500 acres. Slightly less than half of bids win. Offered bids are allocated 52.5 MW of capacity on average.

Table 1, Panel C reports summary statistics on solar power projects. Procurement in the market has shifted over time from state bilateral contracts to auctions. The projects database therefore includes many earlier plants with different characteristcs than those bought at auction. The average project is smaller (25 MW) and has a much higher tariff than the average bid at auction.

3.3 Two revolutions in the Indian solar market

Figure 4 shows the two revolutions in the Indian solar market in the last decade. The dashed line represents the capital costs of solar panels per kWh of energy produced (IRENA, 2019*b*). The solid line represents the capacity-weighted average annual price of solar electricity at auction. The scattered data points represent the capacity-weighted average prices of each auction contributing to the annual average, plotted against the date of each auction. The cross (red $\times$) markers show auctions run by states and the circle (black $\circ$) markers show auctions run by central government agencies.

The first revolution is in price, as bid prices chase after rapidly falling capital costs. From 2010 to 2019, the capital cost of a solar panel, shown by the dashed line, fell by a staggering 82%, an annual geometric mean decline of 17%. The plummeting costs of solar panels are responsible for growing solar generation investment around the world (IRENA, 2017, 2019*a*). The fall in solar energy prices in India lags the fall in costs but is ultimately about as large.

The second revolution is in the means of procurement. The nature of the market has shifted, from one in which states buy their own power to one in which the central government often buys it on their behalf. In the period from 2012 to 2015, most auctions were run by the states ($\times$ symbol). In the period from 2015 onwards, states still run many auctions, but central agencies begin to run a large number of auctions themselves (○ symbol). The shift from mainly state to a mix of state and central auctions, in 2015 and after, coincides with the steepest period of decline in realized auction prices, which lags by several years the corresponding decline in solar capital costs. Within any given year, the lowest prices are nearly all in central auctions, while state auctions yield middling or high prices. This gap is apparent continually from 2015 through the end of the sample.

3.4 Growth of the solar market and the ceiling price policy

The revolutions of Figure 4 led an historic solar boom. Figure 5 shows the capacity sought at auction and the capacity awarded at auction by year. The total height of the bar is the capacity sought at auction. The black segment of the bar is the capacity awarded at auction. The market saw enormous growth in capacity sought and awarded from 2013 to 2018, with capacity addition increasing from a few GW per year to nearly 20 GW in 2018 alone, before falling back slightly. As a point of comparison, the total utility-scale solar generation capacity in the United States in 2019 was 37 GW. India, therefore, awarded as much utility-scale capacity at auction in the years 2017 to 2019 alone as the total then installed in the United States.

The imposition of ceiling prices, maximal prices allowed for bids at auction, may be responsible for the market slowdown after 2018. After seeing newly low prices, but high price dispersion, for auctions in 2017 and 2018 (Figure 4), states and the central government were eager to limit the admissible prices for energy from solar projects. The solid red line in Figure 5, against the right-hand axis, shows the fraction of capacity sought in auctions with ceiling prices each year. Ceiling prices were not used prior to 2018, but were applied in the majority of auctions in 2019 and the first quarter of 2020. Ceiling prices may reduce capacity procured by precluding some potential higher-cost bids from submission. After 2018, the capacity awarded (bottom bar segment) makes up a smaller share of the capacity sought at auction (total bar height). The counterfactual analysis will consider the impact of this rapid policy change on the solar market.

4 Solar prices and the counterparty risk premium

This section tests the hypothesis that the price of solar power depends on the degree of counterparty risk a buyer poses.

4.1 Counterparty risk and solar bids at auction

We start by studying the prices bid in different kinds of auctions. Bid price regressions are widely used in the empirical description of auctions (see, e.g. Porter and Zona, 1993). In addition, a similar regression will be used for the homogenization of bids on observable characteristics in the estimation of the model (Section 5).

A first specification for bidder i's bid in auction t in state s and year y is

$$b_{it} = Central_t \beta_1 + Irradiance_s \beta_2 + \delta_y + \gamma_i + f(q_t) + \varepsilon_{it}. \tag{2}$$

The data are at the bid level. The main explanatory variable of interest is $Central_t$, an indicator for whether an auction was intermediated by a central tendering authority, namely SECI or NTPC (see Section 2), as opposed to a state distribution company. I control for determinants of solar production costs: solar $Irradiance_s$ in the state or group of states where an auction is run, year fixed effects δ_y, to pick up falling capital costs, and deciles of the capacity q_t sought at auction. Some specifications also include bidder fixed effects γ_i. Standard errors are clustered at the auction level. Table 2, column 1 estimates this regression.

The first finding in Table 2 is that centrally-intermediated auctions have lower prices than comparable state auctions, as suggested by Figure 4. The coefficient on the central auction dummy in the column 1 specification is -0.060 log points (standard error 0.022), meaning prices are 6% lower in an intermediated auction. As expected, solar irradiance has a large, negative and highly significant effect on bid prices. The standard deviation of irradiance across bids is 0.21 $kWh/m^2 - day$. A one standard deviation increase in irradiance therefore decreases bid prices by 6% ($= 0.21 \times -0.29 \times 100$). Solar bid prices are predictable: the R^2 of even this simple model is 0.92.

Lower prices in central auctions are consistent with intermediation mitigating risk, but this estimate is not dispositive, since it is possible that central auctions have some other advantage in cost or competitiveness, not having to do with risk. To test the hypothesized mechanism, that central intermediation lowers prices by mitigating counterparty risk, I modify the specification to include counterparty risk explicitly:

$$\begin{aligned} b_{it} \quad = \quad & Central_t \beta_1 + Irradiance_s \beta_2 + CounterpartyRisk_s \beta_3 + \\ & State_t \times CounterpartyRisk_s \beta_4 + \delta_y + \gamma_i + f(q_t) + \varepsilon_{it}. \end{aligned} \tag{3}$$

This specification resembles (2), but adds the risk measure $CounterpartyRisk_s$ (equation 1) and the interaction of counterparty risk with an indicator $State_t = 1 - Central_t$ for whether an auction is state-run (i.e., not intermediated). The coefficient β_3 therefore measures the baseline effect of state risk, in centrally-intermediated auctions, and the coefficient β_4 the effect of state risk in state-run auctions, relative to centrally-intermediated auctions. Table 2, columns 2 through 4 estimate variants of equation (3).

The second finding in Table 2 is that counterparty risk increases bid prices, but only in auctions that are not intermediated. In the column 2 specification, which does not differentiate by intermediation, the effect of counterparty risk on bids is estimated to be small and not statistically different than zero. The column 3 specification includes both a main effect of risk and an interaction of risk with whether an auction is state-run (not intermediated). The coefficient on counterparty risk in a *state*-run auction, relative to a central auction, is 0.15 log points (standard error 0.042), which is large, positive, and significantly different from zero. The total risk effect in state auctions (the sum of the main effect of counterparty risk and the interaction) is 0.10 log points, which is statistically different than zero (p-value $= 0.001$ for a test of the hypothesis that there is no effect of counterparty risk on prices in state auctions). The estimated main effect of risk in central auctions is to *decrease* prices. However, I discount this estimate, and interpret that there is no marked effect of risk on prices in central auctions, since a range of alternative specifications yield null results.[13]

Risk effects operate through changes in bids rather than the selection of what firms are willing to bid in an auction. The column 4 specification adds firm fixed effects for each of the 441 firms that bid in any auction. The estimated coefficient on counterparty risk in state run auctions is slightly smaller (0.11 log points) but remains highly significant. Most of the estimated effect of risk on bid prices is therefore present within-firm. The column 3 and 4 specifications have $R^2 = 0.93$ and 0.96, respectively. The small residual variation in solar bid prices underscores the relatively homogenous nature of utility-scale solar projects.

The counterparty risk premium is economically large. Recall, the units of the counterparty risk measure are scaled so that increasing risk from zero to one means moving from a no-risk state (grade: A+) to an average-risk state (grade: B+). By the Table 2, column 3 estimates increasing counterparty risk from zero to the state average, in a state auction, increases bid prices by 10% of the average bid price. Section 6.2 estimates that the mean mark-up of bid over cost is 16% for winning bids and 11% for all bids. The average markup for all bids is thus very similar to the counterparty risk premium in an average state. Alternately, we can benchmark the risk effect against the estimated effect of solar irradiance on bid prices. The increase in prices due to moving an auction from an Indian state with no risk to a state of average risk is the same as

[13]For example, the main effect of counterparty risk in central auctions is not statistically different from zero in regressions: in logs with firm fixed effects (Table 2, column 4); in levels instead of logs (Appendix Table B3, columns 3 and 4); and in the contract, as opposed to the auction data (Table 3, columns 3 and 4).

moving a solar plant from the solar irradiation of Louisiana to that of Kentucky, or from Kentucky to New Hampshire.[14]

The third finding in Table 2 is that central intermediation does not predict lower prices conditional on explicit controls for risk. In columns 3 and 4, after conditioning on risk and its interaction with intermediation, the main effect of the central auction dummy, in the first row, is diminished and no longer statistically different from zero. The estimated risk premium for an average state, at 10% of mean bid prices, is larger than the estimated effect of intermediation, at 6%, because the average non-intermediated auction is in a state of lower-than-average risk (such as Gujarat or Rajasthan, which have high solar potential).

The pattern of results in Table 2 supports the idea that counterparty risk is a major driver of bid prices. Prices bid at central auctions are lower than those bid in state auctions. State counterparty risk is associated with higher prices, but only when an auction is run by the state, not when an auction is centrally intermediated. This result speaks against the estimated counterparty risk premium being due to a generally high cost of investment in high-risk states, for example due to poor infrastructure; if that were so, we would expect to see risk associated with higher prices even in intermediated auctions. Moreover, lower bid prices are not due only to the selection of participants, but are observed within-bidder, across bids offered by the same firms in auctions run by different counterparties. This result argues against explanations for the risk premium based on differences in costs at the firm level.

4.2 The counterparty risk premium across modes of procurement

This part extends the analysis of solar prices with data on solar contract prices, from the projects database. The contract prices in the projects data include both contracts awarded at auction (whether state or central) and contracts set in bilateral negotiations. Table 3 presents the results. The format of the table is the same as for Table 2 and the specifications are very similar. Because the sample includes state bilateral contracts, all specifications include a main effect for bilateral contracts. The omitted category of contract in all specifications is contracts procured at state auctions, as in Table 2.

There are two findings from the contract data. First, the pattern of risk and intermediation effects estimated in contract prices closely replicates that in auction bids. In particular, I find that: (i) contracts procured in central auctions have lower prices than state contracts (column 1); (ii) contracts procured by the state have

[14] The ratio of the counterparty risk effect in an average state to the coefficient on irradiance is 0.53. Therefore a 0.53 $kWh/m^2 - day$ decrease in Global Horizontal Irradiance (GHI) causes the same increase in unit prices as moving from a state of zero risk to a state of average risk. This change in irradiance is similar to the difference in irradiance between Louisiana (GHI 4.76) and Kentucky (GHI 4.20) or between Kentucky (GHI 4.20) and New Hampshire (GHI 3.74).

higher prices in states with higher counterparty risk (column 2); (iii) conditional on explicit controls for risk, including interactions with intermediation, there is no direct effect of central auctions on prices (column 3); (iv) the estimated risk premium is similar with firm fixed effects (column 4).

The magnitudes of the coefficients on risk and intermediation initially appear larger in the contract data than in the auction data; for example, the interaction of a state-run contract with counterparty risk is 0.23 log points (standard error 0.060) (Table 3, column 3) instead of 0.15 log points (standard error 0.042) (Table 2, column 3). However, state-run projects include contracts procured through both state auctions and bilateral negotiations. To investigate differences between these procurement modes, the column 5 and 6 specifications allow for separate interactions of counterparty risk with whether a project was procured through a state auction or a state bilateral contract, relative to a central auction.

The second finding from the contract data is that the estimated risk premium is larger in contracts awarded through bilateral negotiations than through state auctions. The estimated state risk premium is 0.13 log points (standard error 0.073) in state auctions and a striking 0.33 log points (standard error 0.062) in bilateral contracts (column 5). The risk coefficient in contracts awarded for state auctions is therefore very similar to the risk coefficient for state auction bids in the auction data (Table 2) (0.13 versus 0.15). What differs is the level of risk across procurement modes: bilateral contracts have a larger risk premium than contracts procured at auction. In the column 5 specification, I reject the hypothesis that counterparty risk is equal across state auctions and state bilateral contracts (p-value $= 0.014$). The results are again similar with firm fixed effects (column 6).

The large risk premium for bilateral contracts suggests that procurement via a state auction may itself reduce the counterparty risk premium, though not entirely, as does central intermediation. There are at least two reasons for why the risk premium in bilateral state contracts is greater than in state-run auctions. It may be attributable to the increased competitiveness of auctions lowering prices, especially so in risky states. This benefit of auctions over negotiations may be expected in the procurement of a relatively homogenous good (Bajari, McMillan and Tadelis, 2009). It may also be due in part to the nature of an auction, which is transparent and public in the award of a contract, and may therefore induce a stronger commitment to pay on the part of the procurer.

4.3 Is counterparty risk due to hold up?

Solar prices are higher when bidders are exposed to risk. This finding does not necessarily imply that risk arises due to strategic default (Blouin and Machiavello, 2019). Strategic default is a widespread concern among investors and some cases of strategic default by Indian discoms are well-documented (see Section 2). However, it may be that certain states are risky for exogenous reasons, such as an unpredictable supply chain for infrastructure, but do not *deliberately* hold up green energy producers.

To investigate whether counterparty risk is strategic, I consider heterogeneity in the risk premium across firms that may be differentially exposed to risk. One of the main reasons a renewable energy project is exposed to risk is that renewable energy has high fixed costs but low variable costs. Therefore ex post a threat to withhold energy is not credible, since projects will have a positive continuation value, after investments are sunk, even at a much lower, renegotiated price. By this logic, I hypothesize that renewable energy projects owned by companies that also generate electricity from thermal power plants may be less exposed to risk. A company integrated in this way may be protected against hold-up, because it can threaten to withhold thermal power if a state attempts to renegotiate renewable power prices.

To test this idea, I link the solar auction bidding data to the thermal generation capacity owned by each bidding firm, both overall across India and in the specific state holding the solar auction. I then estimate versions of (3) allowing the counterparty risk premium to differ by whether a firm holds thermal power generation capacity in a state or not. Table 4 shows the estimates in a format mimicking Table 2.

The main result of the table is that firms with thermal capacity in the state where an auction is held are less exposed to counterparty risk. In a state of average risk, the bid prices of firms with thermal capacity rise 0.10 log points less than the 0.14 log point increase in bid prices for firms without thermal capacity (column 2). Columns 3 and 4 differentiate between the effect of having thermal capacity in a risky state in auctions that are or are not intermediated. The risk effect for different types of firms can be calculated as the appropriate sum of coefficients in column 3. For firms without thermal capacity, the estimated effect of increasing risk from zero to average risk is 0.11 log points (standard error 0.034, p-value 0.0026). For firms with thermal capacity, the same counterparty risk premium is 0.040 log points (standard error 0.032, p-value 0.21). These estimates are marginally statistically different from each other ($p < 0.10$). The same result holds with firm fixed effects in column 4.

The result suggests that thermal capacity insulates firms against counterparty risk. I interpret this result as evidence that thermal capacity may change a firm's bargaining position. If risk were purely an exogenous shock that differed across states, then we would not expect to observe differential risk effects for firms with and without thermal capacity, since all would be subject to the same shock. The specifications are subtle, since they include main effects for having thermal capacity in a state and even firm fixed effects. It is not that firms with thermal capacity have lower bids (in fact, they are somewhat higher), but that their bids rise less in risky states in state auctions relative to central auctions, as compared to the bids of firms without thermal plants.

4.4 Alternative specifications

The results across Tables 2 through 4 argue that counterparty risk causes higher solar prices. The counterparty risk premium is estimated from the interaction of higher state risk and the absence of intermediation. It is similar in magnitude in both auction and contract data and with or without firm fixed effects. Appendix B presents some alternate specifications to test the robustness of these results. Appendix Table B3 shows that the risk premium is also similar, in percentage terms, when estimated in levels instead of logarithms.

In order to bias the estimates of risk, an omitted variable affecting solar costs would have to be correlated at the auction level with the interaction of a state auction dummy and higher state counterparty risk. A candidate factor would be, for example, preferential access to infrastructure or favored sites for central auctions within risky states. There is no *a priori* evidence of such differential treatment; rather, state and central auctions appear to have similar siting options and infrastructure (as in Figure 2).

In the project data, it is possible to test more finely for unobserved cost heterogeneity, because the location of each plant is observed down to the district level. Appendix Table B4 shows bid price regression estimates from specifications using state and district fixed effects in place of state-level controls. This specification matches the granularity of Figure 2 by comparing contract prices for plants within the same district. There are 223 districts and 441 firm effects in the data. I find, again, a large and highly significant counterparty risk premium in state-run auctions and bilateral contracts, relative to central auctions, similar in magnitude to that in the main estimates.

4.5 Implications of counterparty risk for efficiency

Does even a large counterparty risk premium bear on economic efficiency? Or should it be viewed only as an advance transfer from states to firms, to compensate for the risk of non-payment?

A key consideration is whether the risk of hold-up reduces investment (Williamson, 1975; Klein, Crawford and Alchian, 1978; Tirole, 1986). In the solar procurement setting, a counterparty risk premium will reduce investment to the extent that state demand is elastic. When counterparty risk raises prices, this may reduce the quantities that states wish to procure. In other words, state demand may be elastic to increases in price induced by the state's own inability to commit.

Quantifying the elasticity of demand for state procurers is in general difficult. We do not observe the extensive margin of auctions that might have been run but were not due to high expected prices. However, there is a subsample of the data for which the elasticity of demand does not need to be estimated, because it is directly observed. Figure 5 shows how auction cancellations increased coincident with the imposition of ceiling tariffs beginning in 2018. When a state sets a ceiling tariff, a maximum price at which it is willing to buy, it is explicitly declaring demand to be elastic (at the ceiling price).

The second part of the empirical analysis, beginning in the next section, will introduce and estimate a model to quantify the effect of counterparty risk on investment when demand is elastic. This analysis can be thought of as combining the risk premium estimated in this section with declared state demand to measure the quantity of hold-up and its sensitivity to risk.

5 A model of solar power procurement

The model is a multi-unit auction model in the share auction framework of Wilson (1979). Firms offer quantities of solar capacity at different bid prices. The lowest-price bidders that together offer enough quantity to meet the demand of the procurer win contracts, at the prices they bid. The main distinguishing feature of the model is that bidders care about the counterparty risk of the party running the auction.

5.1 Set-up

A number N of firms i bid in auction t to supply solar power. Firms draw a type $\theta_{it} = (c_{it}, q_{it}) \sim \mathscr{F}$ for each auction. Types are assumed to be private information and independently and identically distributed across bidders and auctions. The first component represents a firm's idiosyncratic cost of developing a solar project, expressed as the unit cost of energy produced in INR per kWh. Idiosyncratic costs include factors like the cost of planning and financing a project, acquiring land on which to build, and connecting the plant to the transmission network. The second component of the type is the project capacity in MW.

The profit a bidder earns for winning depends on the procuring counterparty. A bid consists of two components $\sigma_{it} = (b_{it}, q_{it})$ for price and quantity. I assume that all firms bid in their full exogenous quantity type.[15] The auctions are discriminatory, in the model as in the data; the lowest bidders are awarded a power purchase contract at the price they bid. However, each procuring state s has some counterparty risk factor $\delta_s \geq 0$. A bidder awarded q_{it} at a bid price of b_{it} values this payment at $(1-\delta_s)b_{it}$ and earns profit

$$\Pi_{it}(b_{it}, q_{it}) = q_{it}((1-\delta_s)b_{it} - c_{it}).$$

States with high counterparty risk have greater risk factors δ_s. The risk factor is assumed to be common across all bidders in an auction.[16] A literal interpretation of this parameter is that firms expect delays in payment and outright non-payment to decrease the present value of the payment stream from a project by a share δ_s. More broadly, δ_s may also encompass other, hard-to-measure factors, such as the costs of carrying a buffer of liquidity to make interest payments or of legal action against counterparties.

Each bidder faces a residual demand curve. The state seeks to procure quantity QD_t in the auction. The residual demand curve in auction t is therefore

$$RD_t(p|\sigma_{-it}) \quad = \quad QD_t - \sum_{j \neq i} q_{jt} \mathbf{1}\left\{p \geq b_{jt}\right\}.$$

The residual demand curve is a step function that discretely decreases as the price crosses each price bid b_{jt} at which a quantity was offered. The quantity awarded for a bid depends on residual demand

$$Q_t(p,q|\sigma_{-it}) = \begin{cases} 0 & \text{if } RD_t(p|\sigma_{-it}) \leq 0 \\ RD_t(p|\sigma_{-it}) & \text{if } 0 < RD_t(p|\sigma_{-it}) \leq q \\ q & \text{if } q < RD_t(p|\sigma_{-it}). \end{cases} \tag{4}$$

This three-step formulation of quantity is needed because when i offers the marginal step in an auction the quantity awarded will be rationed based on the residual demand of the procurer not met at lower bid prices (as in the treasury auctions studied by Cassola, Hortaçsu and Kastl (2013)).

We define a function to return the expected quantity won with a given bid

$$H_t(p,q) = \mathbb{E}_{\sigma_{-it}}\left[Q_t(p,q|\sigma_{-it})\right]$$

[15] This assumption is not very restrictive here. The data consist of single "steps" for each bidder at a fixed price. Withholding can be achieved in expectation by raising the bid price.

[16] This assumption allows the major simplification that bidders can be of a single type ex ante. The cost is some tension with the results of Table 4, which show heterogeneity in the sensitivity to risk across firms with and without thermal plants. I find the simplification justified because only 4% of solar bids are from firms with thermal plants. The model estimates will be found to match patterns of bidding out-of-sample very well (see Section 7).

There is uncertainty about the quantity awarded for a given bid because i does not know the bids of other firms. We assume that $H_t(p,q)$ is continuous and differentiable in p, and in the empirical part approximate $H_t(\cdot,\cdot)$ as a smooth function to guarantee that this is the case.

5.2 Equilibrium bids

Consider the firm's choice of the bid price. A necessary condition for the optimality of a bid is that the choice of b_{it} maximizes expected firm profits

$$\max_b ((1-\delta_s)b - c_{it})H_t(b,q_{it}).$$

The first-order condition for this problem yields

$$b_{it} = \frac{c_{it}}{1-\delta_s} - \frac{H_t(b_{it},q_{it})}{\partial H_t(b_{it},q_{it})/\partial p}. \tag{5}$$

The condition for an optimal price bid contains two terms. The first term is the cost of supply, inflated by a factor of $1/(1-\delta_s)$; firms bid as if they have higher costs, to account for counterparty risk. The second term is the mark-up term: the firm's expected quantity won divided by the derivative of the expected quantity with respect to price. The mark-up is positive because this derivative is negative. If the firm has a high expected quantity and demand is inelastic, then the optimal mark-up will be high.

5.3 Identification

The non-parametric identification of costs follows from the first-order condition (5) for an optimal price bid. The basic identification argument, originally due to Guerre, Perrigne and Vuong (2000) for first-price auctions of a single object, has been extended to multi-unit auctions by Hortaçsu and McAdams (2010). The data contain (b_{it},q_{it}) for every bid and the quantities awarded. The function $H_t(p,q)$ giving quantity cleared as a function of the bid offered is therefore observable. The unknown pseudo-cost $\tilde{c}_{it} = c_{it}/(1-\delta_s)$ can be solved using the first-order condition (5) for optimal bidding.

This argument identifies the distribution of $\tilde{c}_{it}$ point-by-point for every bid. To decompose $\tilde{c}_{it}$ into direct costs and counterparty risk, additional assumptions are required.

Assumption 1. *For centrally intermediated auctions, counterparty risk $\delta_s = 0$.*

Assumption 1 is justified by our discussion of the institutional context in Section 2. Market participants perceive the counterparty risk in centrally-run auctions to be essentially nil, as central intermediation isolates bidders from the counterparty risk of the state distribution companies actually buying power (footnote 10).

Assumption 2. *The distribution of idiosyncratic costs c_{it} is the same in state and central auctions.*

Assumption 2 will empirically be interpreted conditional on auction-level observables. The assumption is justified by the fact that solar plants procured in centrally-run auctions are nonetheless built in the same states, with the same technology, by the same project developers as plants procured in state-run auctions, and would therefore be expected to have the same cost structures. Section 4 provides empirical support for this assumption, by showing that counterparty risk wholly accounts for the mean differences in bids between central and state-run auctions.

Under assumptions 1 and 2, the distribution of costs c_{it} is identified. Since in centrally-run auctions $\delta_s = 0$ the costs in those auctions are identified by $\tilde{c}_{it} = c_{it}$. By assumption 2, the distribution of $\tilde{c}_{it}$ in auctions for each state is the same as the distribution of cost in central auctions, up to the scaling factor $1/(1-\delta_s)$. I can therefore estimate δ_s consistently as the scaling factor such that the distributions of c_{it} in central and state auctions have the same mean.

6 Estimation of the model

This section discusses the methods used in estimation. The method for the homogenization of bids in a multi-unit auction is novel. I then present the estimates of solar production costs from the model.

6.1 Estimation methods

The main structural estimand of interest is the joint distribution of idiosyncratic costs and project capacities. To recover this distribution, there are two points that need to be addressed in the empirical application of the model. First, I have to estimate the function that relates the expected quantity awarded to a firm's bid. Second, to account for heterogeneity in observable characteristics across auctions.

Expected quantity awarded function.— On the first point, I have assumed the function $H_t(p,q)$, which gives the expected quantity awarded for a given bid, is known, continuous and differentiable. The data give every bid and the quantity awarded to that bid, so in principle this function can be estimated. In practice, however (a) the expected quantity awarded depends on bidder expectations over the bids of other bidders (b) bids are step functions and so each realization of residual demand is not continuous.

I therefore approximate $H_t(p,q)$ using a resampling procedure (Hortaçsu and McAdams, 2010). Bids are resampled from the auction being simulated and other sample auctions with weights based on auction-level observables, namely the quantity sought at auction, the year-month of the auction and the number of bidders in the auction. This resampling is necessary to accurately represent the rival quantities a bidder might have faced in a given auction. For each simulation draw, I smooth the realization of residual demand to guarantee that the derivative H_p exists (Kang and Puller, 2008). See Appendix C for details of this approximation.

Accounting for auction observables.—The second point to address in estimation is to account for observable differences across auctions. Auctions differ on dimensions like timing and scale that affect costs, for example due to the massive decline in solar capital costs over the sample (Figure 4). I wish to control for observable factors that change bid prices across auctions with a parametric method, to allow for higher-dimensional controls than would be possible through the resampling procedure alone.

Let Z_t be a set of observable characteristics for auction t. We assume that firm costs in a given auction can be represented as

$$c_{it}(Z_t) = c_{i0}\Gamma(Z_t) = c_{i0}\exp(\gamma Z_t) \tag{6}$$

where c_{i0} is the cost a firm would have drawn if the auction in question was a baseline auction and Z_t are factors that shift costs for auction t. The baseline auction has characteristics Z_0 such that $\Gamma(Z_0) = 1$.

In auctions for a single object, this multiplicatively separable cost structure passes through to multiplicatively separable equilibrium bids (Haile, Hong and Shum, 2003; Athey and Haile, 2007; Bajari, Houghton and Tadelis, 2014). Intuitively, scaling all costs in an auction up or down by a common factor, like changing the currency in which costs are measured, scales the equilibrium bids by the same factor. I obtain an analogous result for the multi-unit auction framework.

Proposition 1 (Homogenization in multi-unit auctions)**.** *Let $\beta_i(c_{i0}|Z_0, q_{it})$ be the equilibrium bid function in an auction with baseline characteristics Z_0. Suppose that costs c_{it} are independent of auction covariates and that costs have the multiplicatively separable structure* (6)*. Then the equilibrium bid function in an auction with covariates Z_t can be written $\beta_i(c_{it}|Z_t, q_{it}) = \Gamma(Z_t)\beta_i(c_{i0}|Z_0, q_{it})$.*

Appendix C has the proof. This homogenization applies to the price dimension of bids only, holding fixed the quantity dimension. The result allows a log-linear specification of how counterparty risk affects bid prices, analogous to the bid price regressions (3). In this way, the state risk premia in the structural bidding model are estimated using the same variation in state risk and intermediation underlying Tables 2 and 3.

6.2 Structural estimates

The estimation of solar production costs proceeds in three steps: homogenization, residual demand simulation and inversion of the first-order condition (5) for optimal bidding. I estimate the model on a sample of auctions without ceiling prices to recover the full distribution of costs absent selective entry.

Figure 6 shows the distribution of homogenized bids. (The regression specification for bid homogenization is presented in Appendix C, Table C6.) The solid line is the distribution of prices as bid. The dashed line is the distribution of homogenized bids. Homogenized bids represent the bids that would have been offered in an auction with the baseline values of observable characteristics: (i) bidding in the year 2019 (ii) in a central auction (iii) for a standard contract (iv) without a domestic content requirement (v) with the median level of capacity sought. While the dispersion of raw bid prices is enormous, given the span of the data and variety of projects, the homogenization regression has an $R^2 = 0.94$, so the distribution of homogenized bids is much tighter. The homogenized bid distribution has a mean of INR 3.06 per kWh and a standard deviation of INR 0.30 per kWh.

With homogenized bids in hand, I simulate the possible residual demand curves in each auction for each bidder. Appendix C describes the simulation procedure and gives examples for some auctions. The simulation of bid prices is unbiased with respect to actual bid prices and produces a plausible range of simulated residual demand curves for each bidder and auction. With the residual demand curves, I calculate the expected quantity awarded function and recover costs by inverting equation 5.

Figure 7 shows the relationship between observed bids and the resulting estimates of production cost. Each point represents the pair $(\hat{c}_{it}, b_{it})$ for a single bid. The black dashed line is the forty-five degree line. The vertical gap between the bid and the forty-five degree line is therefore the bid's mark-up. The red solid line is a locally-smoothed estimate of the mean bid price at each level of estimated cost. The auction simulations are unbiased with respect to bid prices and represent most auctions well (Figure C4).[17]

There are two main observations from the figure. First, the competitiveness of many auctions generates small to moderate markups *on average*. The mean mark-up is 11%. The mean estimated cost is INR 2.83 per kWh with a standard deviation of INR 0.42 per kWh. Second, despite that auctions are competitive,

[17]Outlying bids, particularly in less competitive auctions, sometimes face highly inelastic residual demand, which generates large estimated markups and therefore implausibly low costs. Kang and Puller (2008) similarly note that their valuation estimates diverge for extreme bids, which are likely to always be cleared or never be cleared, and impose additional restrictions on the primitive valuation functions to adjust the estimates at these extremes. I therefore impose a bound on estimated costs to limit mark-ups to a maximum of 30%, which produces the pattern of estimates at the lower left in the figure, running diagonally upwards from left to right.

estimated markups increase appreciably for low-cost bidders. Among winners, the mean estimated cost is INR 2.60 per kWh and the mean mark-up rises to 16%. The reason is that low bids are likely to be cleared unless an auction is far oversubscribed (capacity offered far exceeds capacity demanded). Bidders with low costs therefore increase their mark-ups until their bid price falls in a price band more likely to face elastic residual demand. By the same logic, markups converge to zero for bidders with relatively high costs.

The cost estimates from the model are squarely in the range of contemporary engineering benchmarks (see Appendix B, Table B5). The Central Electricity Regulatory Commission produces estimates of solar PV production costs in India and the International Renewable Energy Agency (IRENA) includes India in its international renewable energy cost comparisons. During the period from 2015 to 2018, my model estimates imply a mean generation cost of INR 3.99 per kWh (not homogenized). As a basis of comparison, the alternate sources report generation costs of INR 4.23 per kWh for 2015 (CERC, 2015), INR 3.71 per kWh for 2016 (CERC, 2016) and INR 3.79 per kWh for 2018 (IRENA, 2019*b*).

7 Counterfactual simulations: Counterparty risk and solar procurement

This section uses the model to study the effects of counterparty risk and the ceiling tariff policy on solar power procurement. The direct effects of risk on prices were explored in Section 4. The counterfactual analysis is necessary to study how risk interacts with the policy environment. Figure 5 suggests that the adoption of ceiling prices may have reduced solar investment. I am interested in whether ceiling prices are responsible for this slowdown and, in particular, in whether ceilings reduce investment in risky states.

7.1 Counterfactual scenarios

The counterfactual scenarios considered vary in two dimensions: risk and the use of ceiling prices.

Counterfactual risk.— Changing the level of risk in counterfactuals is straightforward given the structure of the model. Because risk is an auction-level observable characteristic, the bid prices that would have been bid in auctions with counterfactual levels of risk can be calculated using the homogenization regression model (12). A level of counterfactual risk is represented by a vector of observables Z_t' that describe auction risk and other observables. To simulate auction outcomes, I resample bids from auctions, in the same manner as for the simulation of residual demand, and clear the auction on each iteration.

I consider a range of scenarios with an increasing level of counterfactual risk: (1) *Central risk (full* *intermediation).* Auctions are all assumed to have the central level of risk, that is zero, as under full intermediation. (2) *Actual risk (observed intermediation).* Auctions have the level of risk estimated in the sample, given both the state where they were run and whether they were intermediated. (3) *State risk (no intermediation).* Auctions have the level of risk estimated in the sample, given the state in which they were conducted, counterfactually assuming no intermediation. (4) *State risk p75 (no intermediation).* Auctions have the level of risk of a state at the 75th percentile of the estimated risk distribution. Again, it is assumed that no auction is intermediated. All of the counterfactuals thus apply within-sample levels of risk.

Counterfactual ceiling prices.—The counterfactuals also vary the existence and the level of ceiling prices in solar auctions. Ceiling prices applied for 30 auctions for which we have complete bidding data, mainly in 2019 and 2020 (Figure 5). I run counterfactuals that either (a) remove the ceiling prices from these auctions that originally had ceilings or (b) impose or alter ceiling prices in all sample auctions, regardless of whether they had ceiling prices as originally bid.

Counterfactuals that remove ceiling prices are simple to implement. Because I observe many auctions without ceiling prices, I can resample from the distribution of equilibrium bids in such auctions to simulate what would have happened in a given auction if it did not have a ceiling price. This resampling is weighted to draw both the number of bidders and bids from similar auctions on the dimensions of auction date and capacity sought (see Appendix C for a description of the resampling). The homogenized bid prices for each sampled bid are adjusted (i.e., dehomogenized) for the observable characteristics of the auction for which they are drawn, including state risk. I call this approach simulation *As bid*, because it is a resampling procedure and does not require solving for counterfactual strategies. It is possible because my data contain auctions with different observable characteristics and both with and without ceiling prices.

Running the second kind of counterfactual, which imposes or alters a ceiling price in an auction that was originally bid without one, is more complex. Imposing or altering a ceiling price will change the equilibrium strategies of bidders in the auction game. Changing the ceiling price will alter participation in the auction, since high-cost bidders may no longer offer bids. Lower-cost bidders that still do participate will alter their bids in response to the change in competition and therefore residual demand. For example, if few bids can meet a low ceiling price, then residual demand in the auction will be inelastic and the remaining bidders may increase mark-ups. The next part describes how I solve for these equilibrium responses to ceiling prices.

7.2 Counterfactual strategies

The counterfactual approach to auctions with ceiling prices is to simplify the strategy space in order to make it feasible to solve for an equilibrium in the multi-unit auction game.

A strategy in the multi-unit auction, holding bid quantity fixed, is a function from the bidder's type (c_{it}, q_{it}) to a bid price. The estimation of costs imposed no parametric structure on either the form of this bid function or the type distribution. Finding a fixed point in the space of bid functions is generally infeasible. For this reason, leading empirical work on multi-unit auctions estimates and analyzes auction primitives (costs or valuations), but undertakes a limited range of policy counterfactuals (Cassola, Hortaçsu and Kastl, 2013; Hortaçsu and McAdams, 2010; Kang and Puller, 2008).

To simplify the counterfactual problem I constrain the space of bidding strategies. A *constrained strategy equilibrium* (CSE) is an approximation to Nash equilibrium in a constrained, parametric space of strategy functions (Armantier, Florens and Richard, 2008). Finding a Nash equilibrium in this constrained space may be far simpler than finding a nonparametric best response function. In the auction game, moreover, there is a great deal of economic structure to discipline the form of bid strategy functions. I specify the bid function in an auction t with reserve price r as

$$b(c_{it}, q_{it}|\alpha_i, r) = \begin{cases} \varnothing & \text{if } c_{it} > r \\ c_{it} + \alpha_i(r - c_{it}) & \text{otherwise.} \end{cases} \tag{7}$$

for some parameter $\alpha_i \in [0,1]$ governing markups. This form has several appealing features. It assumes that bidders participate in an auction if and only if their cost is below the ceiling price. Bids are increasing in costs (unless $\alpha_i = 1$). Bids are shaded towards the ceiling; the parameter α_i gives the markup of bids over costs as a fraction of the distance from cost to the ceiling price. At the boundary of participation, bidders with a cost equal to the ceiling price will bid the ceiling and earn no markup.

A constrained strategy equilibrium consists of mutual best responses in the parameter α for all bidders. Consider the problem of a bidder setting a bid strategy function before knowing their type. From this *ex ante* view, the payoff from choosing α_i is given by

$$V(\alpha_i) = \mathbb{E}_{\theta_i}\left[((1-\delta_s)b(c_{it}, q_{it}|\alpha_i, r) - c_{it})H_t(b(c_{it}, q_{it}|\alpha_i, r), q_{it} \mid \alpha_{-i})\right]. \tag{8}$$

where the bid function takes as arguments the two components of the type. The expected quantity awarded depends on α_i directly, as it sets i's bid, but also on the parameters $\alpha_{-i} = \{\alpha_j : j \neq i\}$ of rivals' bid functions.

The bidding firm maximizes this payoff over α_i. The first-order condition for this maximization is

$$\mathbb{E}_{\theta_i}\left[(r-c_{it})\left(b(c_{it},q_{it}|\alpha_i,r)-\frac{c_{it}}{(1-\delta_s)}+\frac{H_t(b(c_{it},q_{it}|\alpha_i,r),q_{it}\mid\alpha_{-i})}{\frac{\partial H_t(b(c_{it},q_{it}|\alpha_i,r),q_{it}|\alpha_{-i})}{\partial b(c_{it},q_{it}|\alpha_i,r)}}\right)\right] = 0. \qquad (9)$$

This expression is analogous to the first-order condition (5). Equation (5) applies pointwise for a realization of the bid type. Equation (9), above, is the *ex ante* analog of the pointwise first-order condition when the type is unknown. The outer expectation is over a bidder's own type. The choice of α_i sets the expectation of the first-order condition, weighted by how far the ceiling price exceeds costs, since a change in the parameter α_i has a larger effect on profits when this ceiling "headroom" is larger.

A constrained strategy equilibrium consists of a profile $\alpha^* = (\alpha_i^*\ \alpha_{-i}^*)$ such that equation (9) is satisfied for all bidders. In the *ex ante* symmetric case, the equilibrium can be described by a scalar bidding parameter α^* satisfying the single equation (9) with $\alpha_i = \alpha^*$ and $\alpha_j = \alpha^*$ for all $j \neq i$. The first-order condition for an optimal α may not have an internal solution $\alpha^* \in (0,1)$. For example, if an auction is not expected to be very competitive, bidders may expect to be cleared even if they bid near the ceiling. In this case the first-order condition will be negative even as $\alpha \to 1$, so that in equilibrium bidders will all set $\alpha^* = 1$ and have their markups constrained by the ceiling price.

Different auctions have different equilibria depending on the level of the ceiling price, risk, expected participation, and the quantities bidders may be expected to offer. I solve for a separate α_t^* for each auction and each risk and ceiling price scenario. Appendix C describes the algorithm used to solve equation 9.

7.3 Counterfactual results

Validation of counterfactual strategies.—This part validates the counterfactual strategies by comparing auction outcomes using these strategies to the outcomes observed in the data. The validation covers both auctions in the estimation sample and, separately, an out-of-sample comparison to the data for auctions originally bid with ceiling prices.

Figure 8 compares the distributions of bids to simulated counterfactual distributions of bids. The left column shows distributions in the full sample used for estimation of bidder costs, which is deliberately restricted to exclude auctions with ceilings. The bid prices are homogenized. The right column shows distributions in the ceiling sample of auctions in which ceiling prices applied in the data. In the ceiling price sample, the horizontal axis has been normalized to show bid prices as a fraction of the ceiling price in each auction, rather than in their original units (INR per kWh). The top row shows the distribution of bids in the data. The middle row shows the simulated distribution of bids using an *As bid* strategy, a weighted resampling of the equilibrium bids from auctions similar to each auction in the sample. The last row shows counterfactual simulations of bids using the constrained strategy equilibrium (CSE).

There are three main findings on the accuracy of the simulations with respect to bid prices. First, in the estimation sample, without ceiling prices, the weighted resampling of bids *As bid* matches the data very well. The simulated distributions of winning and losing bids (Figure 8, panel C) mirror those in the data (panel A). Second, in the sample of auctions with ceiling prices, a naïve *As bid* simulation does not match the distribution of bids in the data. In the data, most bids in auctions with ceiling prices are offered very close to the ceiling (panel B). The *As bid* resampling—assuming bidders did not alter their strategies in auctions with ceiling prices—predicts that a longer tail of bids should be offered at prices well below the ceiling price (panel D). Third, the constrained strategy equilibrium matches the distribution of prices in the ceiling sample much better than the naïve simulations. The distribution of bid prices under the constrained strategy equilibrium, in panel F, is stacked up against the ceiling price, to a somewhat greater degree even than is observed in the data (panel B).

The difference in the bid price distributions between the *As bid* simulations (panel D) and the constrained strategy equilibrium (panel F) is consistent with ceiling prices causing a change in equilibrium bidding strategies. Inframarginal bidders, anticipating lower participation when a ceiling price is set, increase their markups in response. For this reason ceiling prices may achieve smaller reductions in average solar prices than expected based upon the naïve assumption that bidders would not alter their strategies.[18]

Figure 8 can be read together with Table 5, which compares the fit of the simulations to the data for a wider range of auction outcomes including participation and quantity. In Table 5 columns 1 and 2 compare outcomes in the estimation sample and columns 3 through 5 in the ceiling price sample. Each column contains auction outcomes under a different strategy: the data (columns 1 and 3), the *As bid* simulation (columns 2 and 4), or the constrained strategy equilibrium (column 5).

Table 5 reinforces and extends the findings of Figure 8: *As bid* simulation matches auction outcomes well in the estimation sample, but the constrained strategy equilibrium has a much stronger fit in the ceiling price sample. Within the estimation sample, the *As bid* resampling predicts quantity awarded accurately

[18] *A priori* it is plausible that the pattern of bidding in Figure 8, panel B could represent collusion. Knittel and Stango (2003) find tacit collusion near the ceiling price (interest rate cap) in the market for credit cards. The constrained strategy equilibrium price distribution in panel F shows unilateral best responses for each bidder. Therefore collusion is not necessary to rationalize the large number of bids near the ceiling price in auctions with ceilings.

(359 MW versus 366 MW in the data) as well as price (mean winning bid INR 2.92 per kWh versus INR 2.96 per kWh in the data) (comparing column 2 to column 1). In the ceiling sample, however, the *As bid* strategy underpredicts quantity awarded as well as price. This naïve simulation predicts that there will be lower participation, but also markedly lower prices, than is actually the case for auctions with ceiling prices (comparing column 4 to column 3). By contrast, the constrained strategy equilibrium is accurate in predicting: (i) the level of participation in ceiling price auctions (2.93 bids per auction versus 2.67 in the data), (ii) the quantity awarded (499 MW versus 451 MW in the data), and (iii) the mean bid price (INR 2.98 per kWh in both the data and the model) (comparing column 5 to column 3).

These findings together suggest that the constrained strategy equilibrium approximates bidding and participation well in the sample of auctions with ceiling prices. These fit comparisons provide an out-of-sample test of the model, as the auctions with ceiling prices were not used in the estimation of costs. The fit of the model to participation and quantity outcomes shows that the assumption that a bidder bids if they have cost beneath the ceiling is a good approximation to participation behavior. Moreover, the validation shows that the equilibrium behavior in auctions with ceiling prices differs markedly from equilibrium behavior in auctions without ceilings. When a ceiling price is set, bidders do not just draw from a truncated version of the distribution of equilibrium bids in auctions without ceiling prices. Rather, bidders mark up their bids to a greater extent *in response to* ceiling prices that reduce participation.

Counterfactual auction outcomes under varying risk.—This part projects auction outcomes under varying levels of ceiling prices and counterparty risk. Figure 9 shows counterfactual auction outcomes. Each point shows the market outcome in one simulation, plotting the capacity-weighted winning bid price at auction against the fraction of quantity sought at auction that is successfully awarded. The sample covers all auctions in the data, not only those that originally had ceiling prices. The labels on each point give the level of the uniform ceiling price counterfactually imposed. For example, at a ceiling price of INR 3.5 per kWh, the mean price at which solar power is bought is about INR 3.2 per kWh (panel A, solid, black line). Each curve, traced out by changing the ceiling price policy, represents the aggregate supply curve for solar power in India that would obtain at different levels of procurer counterparty risk.

Panel A illustrates the importance of using the constrained strategy equilibrium (CSE) to predict counterfactual outcomes. The panel compares market outcomes under the CSE (solid, black line) and under a naïve *As bid* strategy (dotted, red line). At each level of the ceiling price the equilibrium quantity is higher under the CSE, because under the CSE participation is based on cost. Therefore some firms that would bid above the ceiling price, in the absence of a ceiling, lower their bids beneath the ceiling to participate in the auction. While participation is higher under the CSE, market prices are also higher. The reason is that inframarginal bidders tend to increase their bids in response to the imposition of a ceiling (recall the comparison of panels B and F in Figure 8).

In Figure 9, panel B, all counterfactuals use the preferred CSE. The three curves show market outcomes for different levels of procurer risk: central risk (blue), state risk (black) and high state risk (the 75th percentile of state risk, in red). The main result of panel B is that higher-risk counterparties face sharply lower supply curves than lower-risk counterparties. Consider a ceiling tariff of INR 3 per kWh, which is around the modal ceiling price in the data. The imposition of ceiling tariffs at this level in all auctions would result in procurement of 76% of the quantity sought, if those auctions were centrally intermediated, 61%, if all auctions had their state level of risk, and 48%, if all auctions were run by a high-risk state. Moving from the central level of risk to a high level of risk therefore sacrifices 28 pp (37%) of the quantity sought. At the same time, the average winning price for bids that do meet the ceiling remains somewhat higher in the high-risk scenario. At lower ceiling prices, comparable to the equilibrium outcomes in the largest central auctions without ceilings (INR 2.5 per kWh), participation in high-risk states declines steeply, so that hardly any quantity is procured (solid red line).

Counterfactual auction outcomes without ceiling prices.—With the model, I can study procurement under any given level of risk and ceiling price policy, including under the actual levels of risk and ceiling prices in the data. Table 6 shows counterfactual auction outcomes in the sample of auctions that originally had ceiling prices. Simulations without a ceiling price use the *As bid* strategy (panel A); simulations with a ceiling price use the constrained strategy equilibrium (panel B). The columns of the table vary counterparty risk, with the level of risk increasing across the columns from left to right. The rows of the table show the mean values of each variable across auctions and simulations. Price-like variables are weighted by bid quantity to measure the mean price or cost of a unit of power.

Panel A validates the model's representation of risk. The simulated effect of risk on prices in the ceiling sample is very similar to the effect of counterparty risk previously estimated in the regression analysis of Section 4. In panel A, without ceiling prices, the mean price of all bids, relative to a central auction without risk (column 1), is 5% higher at the actual level of risk (which includes intermediation in some auctions) (column 2), 12% higher at the mean level of state risk (column 3) and 19% higher at the 75th percentile of state risk (column 4). The close agreement between the effect of risk in the prior bidding regressions and the model estimates is expected because the model adjusts for risk using a homogenization regression for log bid prices (11).

There are three main results from the counterfactual analysis. First, the ceiling prices imposed in the data from 2018 to 2020 markedly reduced quantity procured. Consider Table 6, column 2, representing auction outcomes at the actual level of risk. Comparing panel B, with ceiling prices, to panel A, without ceiling prices, we see that the ceiling binds 31% of the time (panel B, row 8), which increases the share of auctions undersubscribed by 15 pp (31%) and reduces mean quantity procured per auction by 16% (471 MW, in panel B, against 563 MW, in panel A).

Second, the foregone capacity for the same set of ceiling prices is steeply increasing in the degree of counterparty risk faced by bidders. When demand is inelastic, without ceiling prices, risk increases prices but has no effect on the quantity awarded (panel A, across columns). With ceiling prices, risk decreases quantity because fewer bidders are willing to meet a given ceiling after accounting for the risk premium added to their bids. If the same ceiling prices imposed in the sample were kept, but all auctions were centrally intermediated, then ceiling prices would reduce capacity awarded by only 11% (column 1, panel B versus panel A). If all auctions had the average level of state risk, ceiling tariffs would reduce capacity awarded by 23% (column 3). Finally, if all auctions had a high (75th percentile) level of risk, ceiling tariffs would reduce capacity awarded by 31% (column 4). High risk therefore doubles the quantity of solar power held up relative to the 16% loss of quantity in the baseline case. In this scenario, when risky states nonetheless impose ceiling tariffs, the ceiling binds 58% of the time and fully 76% of auctions award less than the quantity they sought (panel B, column 4).

Third, despite these large effects on quantity, imposing ceiling prices has a negligible effect on the actual prices paid for solar energy. Under the actual level of risk in the sample, ceiling prices, which cut quantity awarded by 16%, reduced winning bid prices by a mere 1% (column 2, panel B versus panel A). At higher levels of risk, ceiling prices would reduce prices paid by from 6% (column 3, mean state risk) up to 14% (column 4, high level of state risk). The muted effects of ceiling prices on actual prices paid are due to the ceiling price acting in two opposing ways: a ceiling may force bidders to lower markups to participate in an auction, but also increase markups, conditional on participation, for those bidders who would have met the ceiling in any case (Figure 8).

Discussion.— Procuring states of higher risk face a sharp policy trade-off between holding down prices and reducing investment. At the time ceiling prices were introduced by the central government, market observers worried that this policy change would stifle the solar boom. Raj Prabhu, the CEO of Mercom Capital Group, specifically warned that the prices obtained by the central government might not be realistic for other parties: "The downside is that all other state and government agencies will want to set similar tariff levels [i.e., ceilings] no matter what the project economics are in that state and this has happened over and over in the past. The tender and auction activity typically comes to a halt after something like this is announced" (Kabeer, 2018).

The counterfactual analysis quantifies this effect and shows that not only do states reduce investment by setting ceiling prices, but they do so for very little gain in terms of lower energy prices. It may seem that there is an obvious policy change to solve this problem: do not set ceiling prices. India moved towards this with the central government lifting ceilings in their own auctions at the end of my sample period. However, the recommendation might miss the point: ceiling prices are imposed because states trade-off different power sources and therefore have elastic demand for green energy. The state regulator in Bihar, for example, stated explicitly that they would not allow the state to buy solar power at high prices.[19] If this is the case in general, then removing ceiling prices will not change states' underlying demand but may lead instead to high-risk states running fewer auctions. Appendix B presents some evidence that solar procurement in state-run, non-intermediated auctions has indeed been shifting towards lower-risk states over time (Figure B3).

8 Conclusion

This paper studies the effects of counterparty risk and procurement policy on the market for new solar power plants in India. The institutions of the Indian solar market allow a clean view of counterparty risk, since solar plants set up with the same technology, by the same firms, in the same places, are procured in auctions with varying levels of risk and intermediation. I find that the threat of hold-up increases the price of green energy by 10% in an average state. The intermediation of the central government eliminates this risk premium.

[19] Bihar has above-average state risk (2012 rating of "B"). The state regulator in 2019 rejected the result of a solar procurement auction that yielded higher prices than in other auctions in India and in neighboring states. The ruling states: "Comparing the rates of these states with that of Bihar, the difference is too large to be accepted and adopted. The Commission views that buying solar energy which is at this rate which is obviously much higher than the prevailing market rates, will be injustice to the end electricity consumers as they have to bear the brunt of higher cost of power" (Bihar Electricity Regulatory Commission, 2019). This rejection resulted in a state-ordered downward renegotiation of the solar price that had been revealed at auction.

Developing countries are sensitive to the price of energy for their citizens. When demand is elastic, the counterparty risk premium—induced by a procurer's own lack of commitment—feeds back to reduce the quantity of green energy procured. In India during my study period, procurers try to counteract the risk premium by setting ceiling prices to limit bids at auction. I use a model to quantify the effect of this policy and trace out the solar supply curves that all India would face under alternate levels of its own counterparty risk. I find that ceiling prices reduced new solar power capacity addition by 16%, but hardly lowered procurement costs, because bidders respond to the lower participation in auctions with ceilings by raising their bids. The higher the risk in a state, the sharper the trade-off between trying to suppress the risk premium and reducing investment.

The results provide a novel justification for intervention to enforce contracts in green energy markets. In the Indian context, I find that intermediation by the central government fully mitigates counterparty risk. Intermediation is an imperfect solution to hold-up, since a commitment by a third party to back a power contract may worsen moral hazard and cause strategic default. The Indian central government is a powerful intermediary, because it has both the credibility to pay and the power to force, or at least urge, states to honor their contracts. In many countries such an ideal intermediary may not exist. Most countries in sub-Saharan Africa have sovereign credit ratings well below that of India's central government. Sovereign ratings likely overstate how much countries are inclined to honor domestic obligations to private firms. One could imagine international lenders, or regional power pools, taking an intermediary role. The World Bank has started a guarantee program, "Scaling Solar," to back the power purchase contracts that emerge from renewable energy auctions in high-risk countries (Braud, 2018). This program has the right idea, but it is far too small: to date it has supported auctions in Zambia and Senegal totaling 136 MW of solar capacity procured, 0.2% of the capacity allocated at auction in India over my sample period.

The scale of green energy investment that is needed to slow global climate change while meeting growth in global energy demand is beyond comprehension. A large and increasing share of renewable energy investment is expected to come in developing countries, which are both less able to reliably enforce contracts and more sensitive to energy prices. The problem of holding up green energy described here may therefore hinder much of the new investment in renewable energy production around the world.

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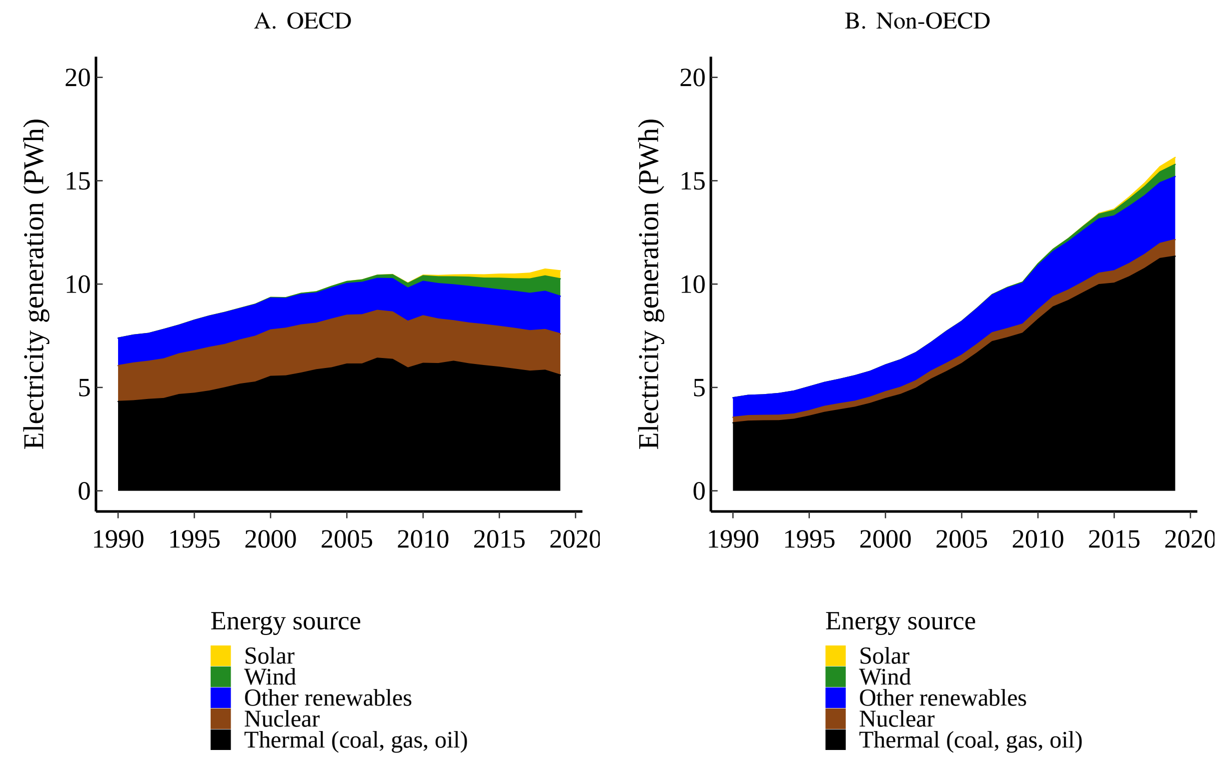
9 Figures

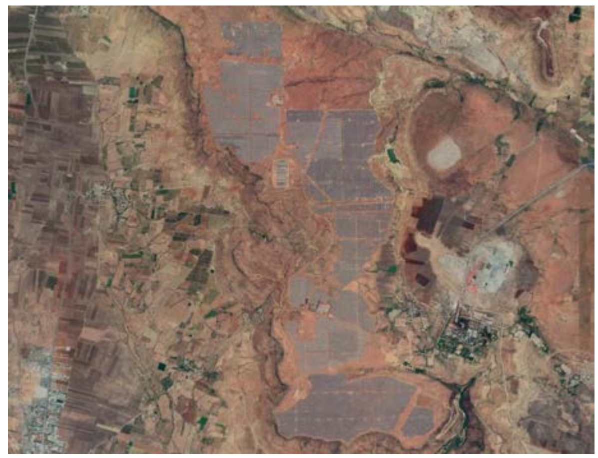
Figure 1: Growth in electricity generation by energy source



This figure shows electricity generation by energy source over time. The series are constructed from electricity mix data in the “Our World in Data" series on energy. Panel A shows the growth of electricity production in the 37 OECD countries and Panel B in the 144 other countries in the data. Generation with the energy sources in the bottom (black) segment emits greenhouse gases.

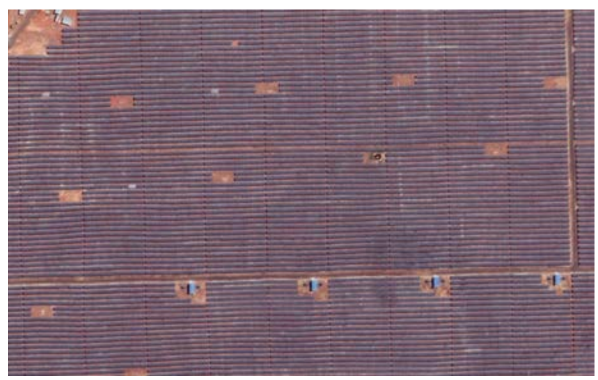
Figure 2: Power plants allocated by state and centrally intermediated auctions

A. Andhra Pradesh, central auction



B. Andhra Pradesh, state auction

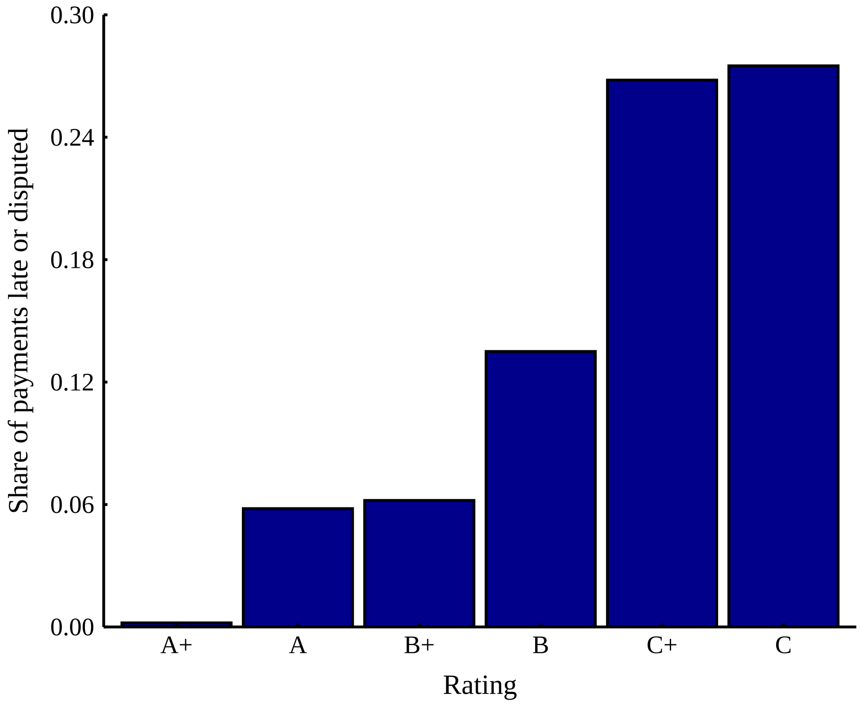
C. Andhra Pradesh, central auction (zoomed in)



D. Andhra Pradesh, state auction (zoomed in)

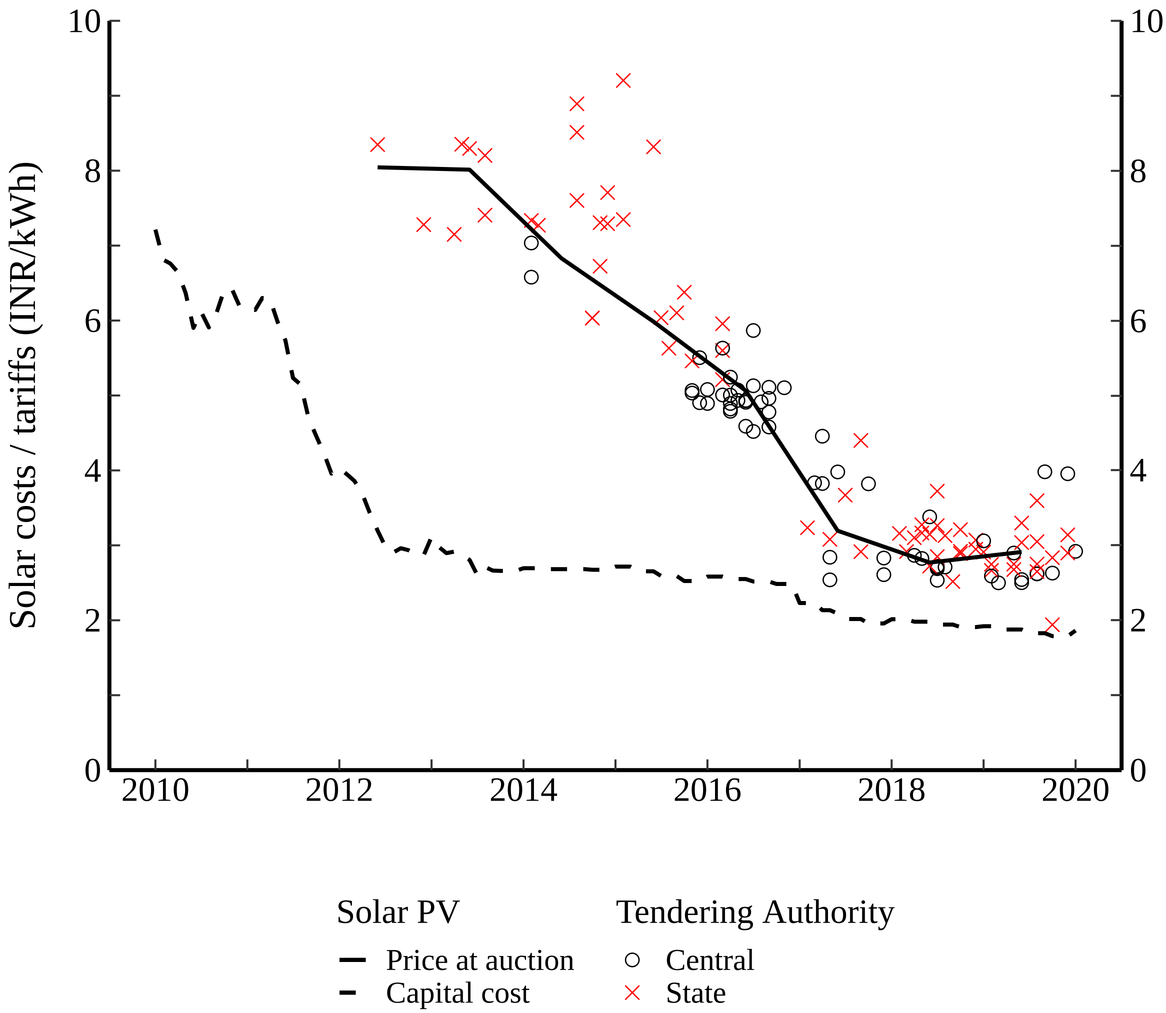
This figure shows satellite images of two typical solar power projects allocated through centrally intermediated and state auctions, built in the state of Andhra Pradesh. Panel A and Panel C show photos of the NP Kunta Ultra Mega Solar Power Project (900 MW), a project that was allocated via a centrally intermediated auction, and is located in the Anantpur district of Andhra Pradesh. Panels B and D show photos of the Ananthapuramu - II Mega Solar Park (400 MW), a project that was allocated without central intermediation, and is also located in the Anantpur district of Andhra Pradesh.

Figure 3: Counterparty risk by state distribution company rating



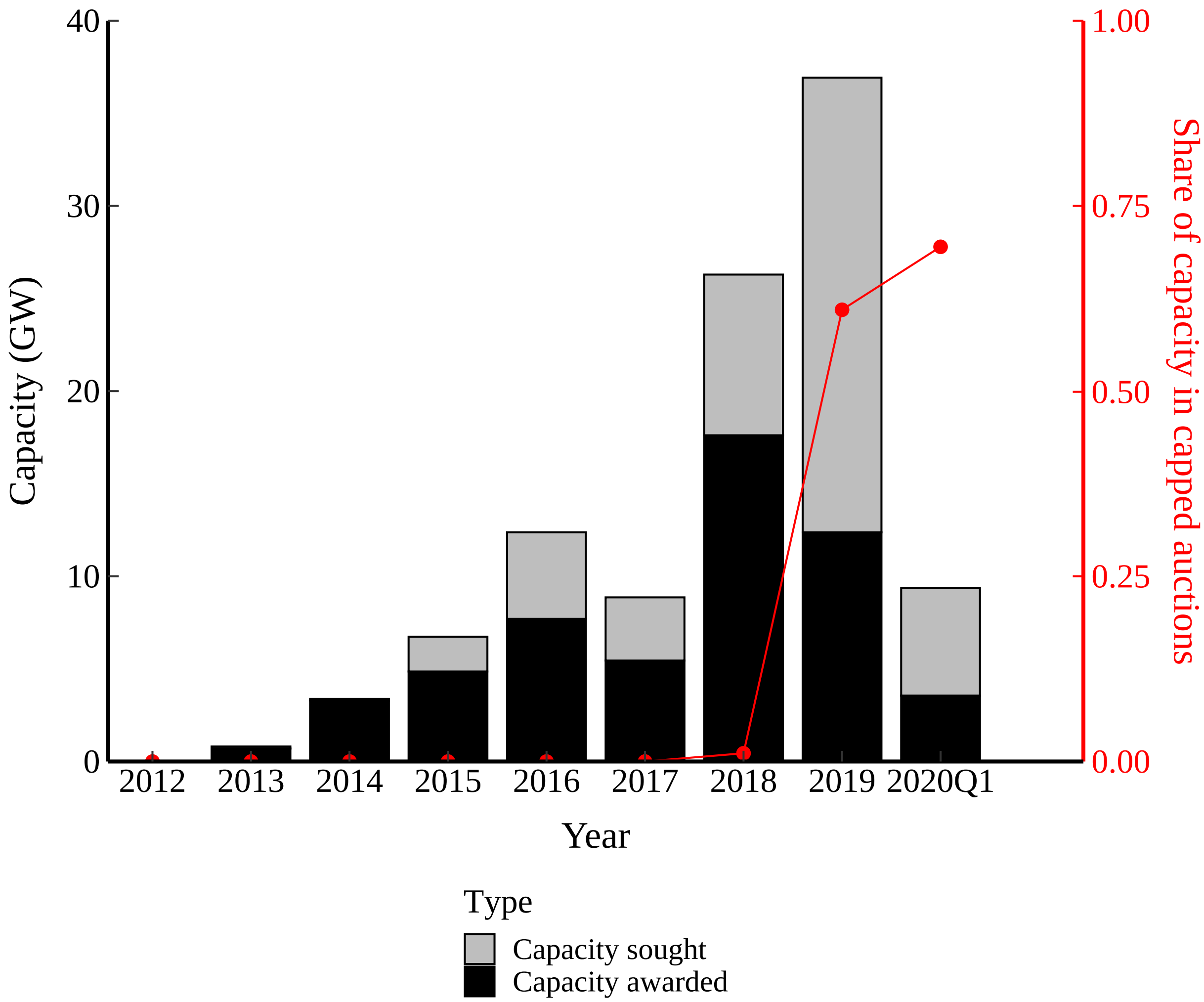
This figure shows how payment risk varies depending on the rating of state distribution companies. The horizontal axis shows the letter grade assigned by the Ministry of Power, Government of India to a state distribution company. The vertical axis shows, for the group of state distribution companies within each letter grade bin, the mean share of payments from those companies to power generators that are late or disputed. The payment data come from a database called Praapti that the Ministry of Power launched in 2017 explicitly to track how much distribution companies were failing to pay to power generating companies. See Appendix A for a full data description.

Figure 4: Solar auction clearing prices by intermediation



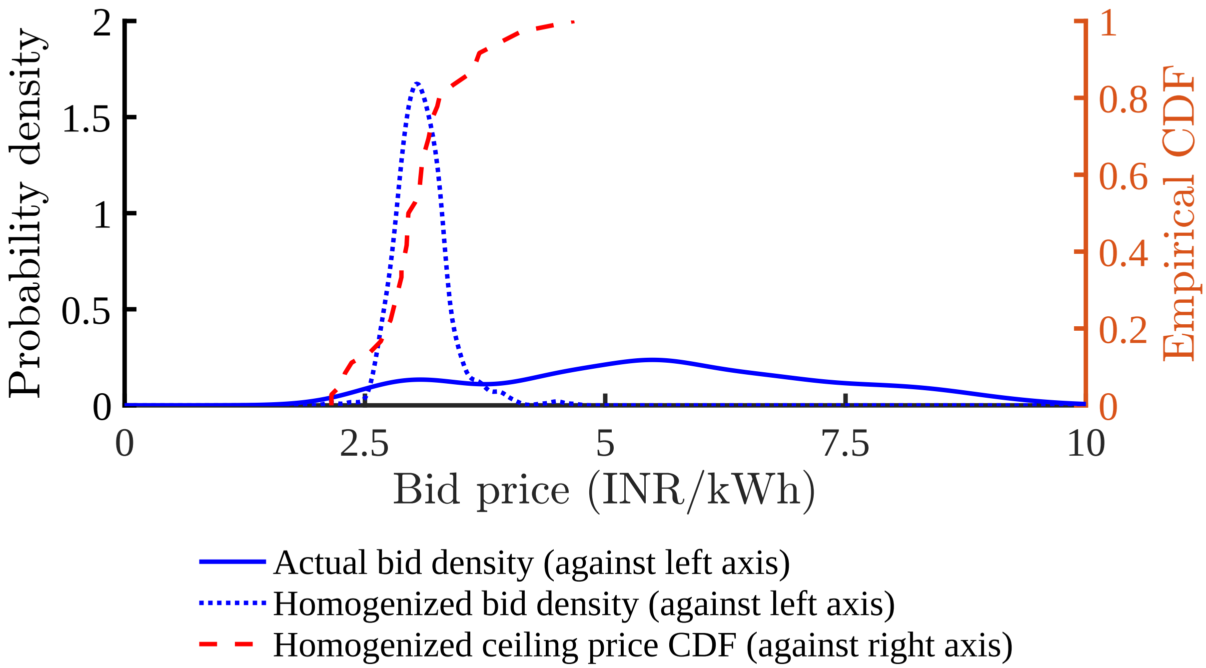
This figure shows solar costs and prices for large scale solar projects in India over time. The dashed line represents the capital costs of solar panels per kWh of energy produced (IRENA, 2019*b*). The capital costs per unit of capacity (USD per Watt) have been converted to capital costs per unit energy using a discount rate of 10% over a 25-year life and an assumed capacity factor of 18%. The solid line represents the capacity-weighted annual average price of solar electricity at auction, constructed by the author. The scattered data points represent the capacity-weighted average prices of each auction contributing to the annual average, plotted against the date of each auction. The × (red) markers show auctions run by states and the hollow circle (black) markers show auctions run by central government agencies.

Figure 5: Quantity sought and quantity awarded over time



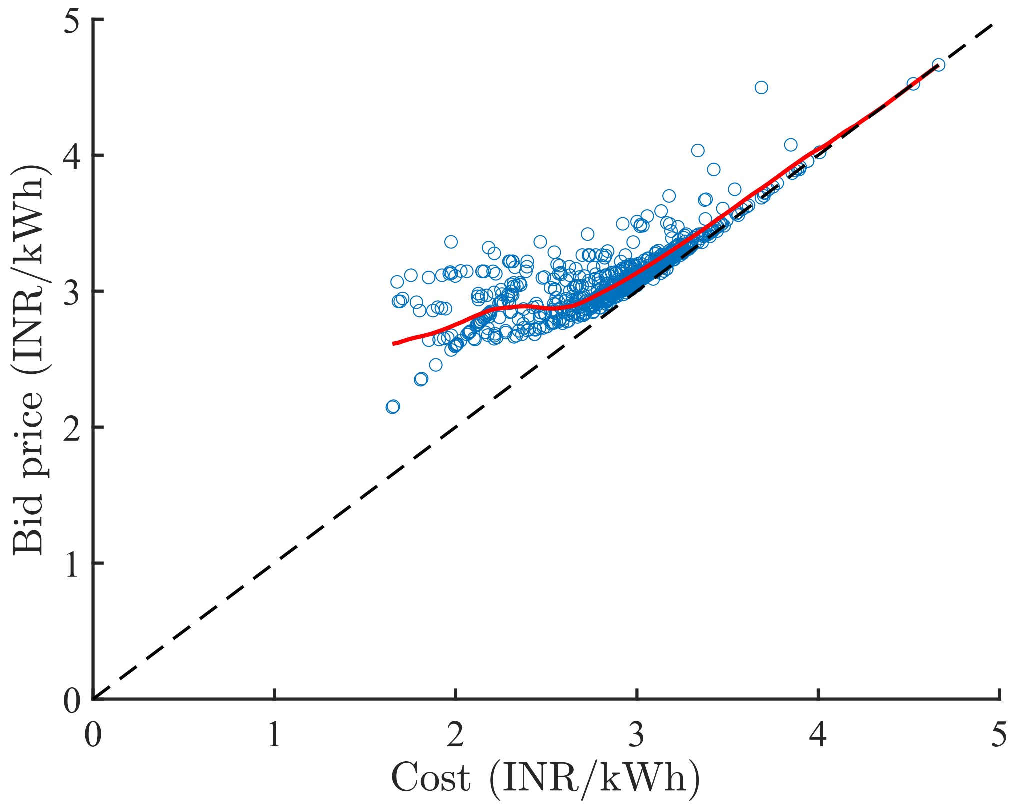
The figure shows the capacity sought at auction and the capacity awarded at auction by year. The total height of the bar is the capacity sought at auction, i.e. total demand. The black segment of the bar is the capacity awarded at auction. The capacity sought and awarded are measured in gigawatts against the left-hand axis. The capacity awarded may be less than the capacity sought due to low bidder participation or to the imposition of ceiling prices that eliminate some bids from consideration. The solid red line, against the right-hand axis, shows the fraction of capacity sought in auctions with ceiling prices each year. Ceiling prices were not used prior to 2018.

Figure 6: Distribution of homogenized bids



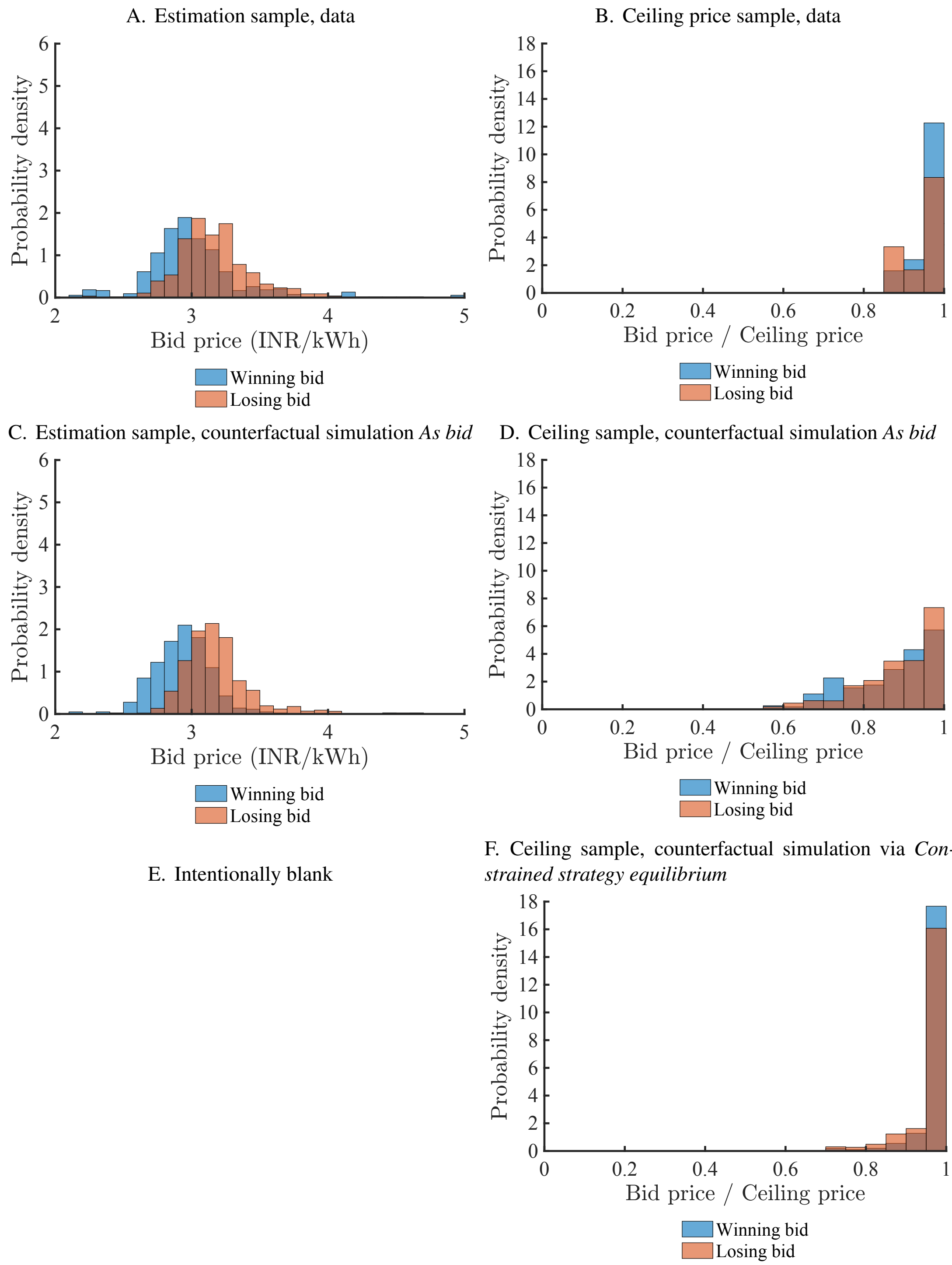
The figure shows the distribution of bids and compares them to ceiling prices. The solid line is the raw distribution of prices as bid. The dotted line is the distribution of homogenized bids. Homogenized bids are the idiosyncratic or residual components of bids after controlling for observable characteristics of auctions via a linear regression of log bid prices on auction characteristics including timing, scale and state fixed effects. Both of these distributions are measured against the density scale on the left axis. The dashed line is the cumulative distribution function (CDF) for the distribution of homogenized ceiling prices at auction. I apply the same homogenization regression estimates used to homogenize bids to homogenize ceiling prices. The CDF of the resulting ceiling price distribution is measured against the right axis.

Figure 7: Estimated costs and bidder mark-ups



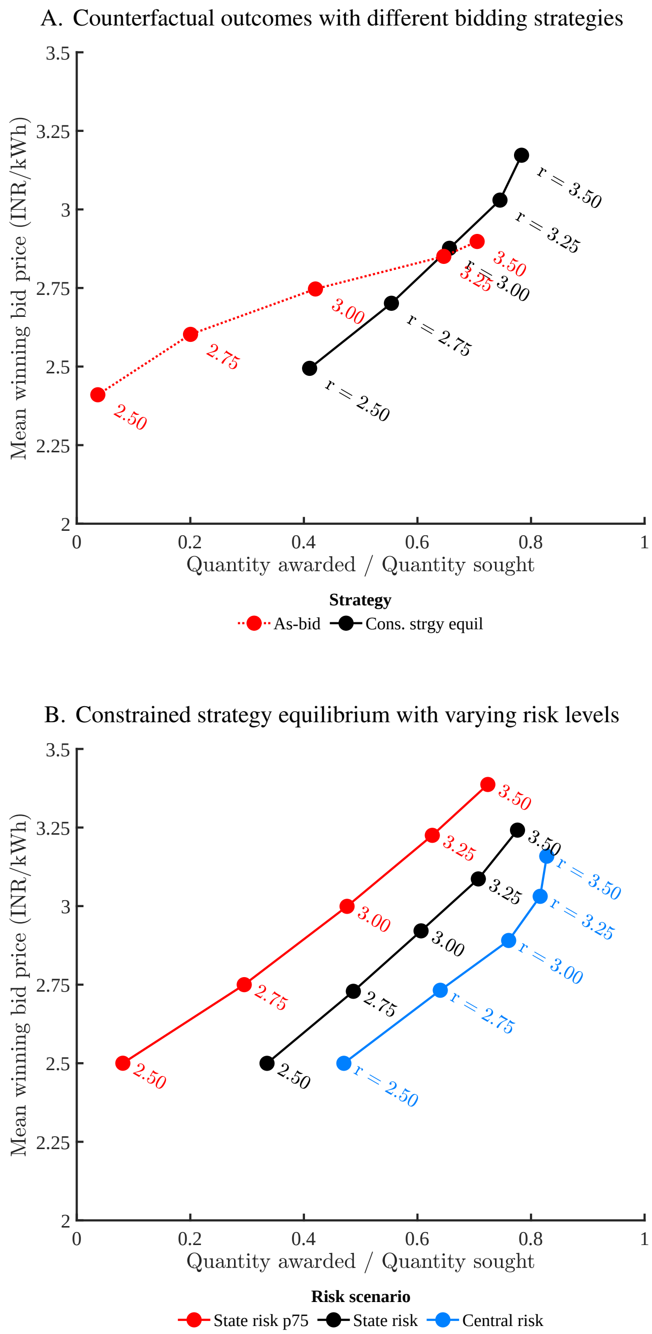
The figure shows the relationship between observed bids and estimated productions costs. Each point represents the pair $(b_{ai}, \hat{c}_{ai})$ for a single bid. The black dashed line is the forty-five degree line. The vertical gap between the bid and the forty-five degree line is therefore the bid's mark-up. The red solid line is a locally smoothed estimated of the mean bid price at each level of estimated cost. I impose a bound on estimated costs to limit mark-ups to a maximum of 30%, which produces the pattern of estimates at the lower left, running diagonally upwards from left to right.

Figure 8: Validation of counterfactual simulations



This figure validates the bid prices in counterfactual simulations of auctions against actual auction outcomes. Each panel shows a distribution of bid prices at auction. The left column of panels shows distributions in the sample of auctions used for estimation. The right column of panels shows distributions in the sample of auctions with ceiling prices, for which bid prices are normalized as a fraction of the ceiling price. The rows of panels differ in the strategies that generate bid prices. The top row shows the distribution of bid prices in the data. When ceiling prices apply (panel B), bidders only participate if their bids are beneath the ceiling price. The middle right panel (D), after resampling, bidders participate if their costs are beneath the ceiling price, and, conditional on participation, *Shade up* their bids halfway to the ceiling. These adjusted strategies are described in Section 7. The bottom row shows the distributions of bid prices in the data for each sample.

Figure 9: Counterfactual procurement by risk under uniform ceiling prices



This figure shows auction outcomes across all auctions under counterfactual levels of ceiling prices and counterparty risk. The horizontal axis shows the fraction of quantity sought at auction that is successfully awarded. The vertical axis shows the capacity-weighted winning bid price at auction. The labels on each point show the uniform ceiling price counterfactually imposed on all auctions in the data. Each curve can therefore be thought of as an aggregate supply curve for solar power traced out by changing the ceiling price policy. In panel A, the two different curves correspond to different bidding strategies used to simulate outcomes: either resampling naïvely from the bid distribution without ceiling prices (dotted, red line), or solving for the constrained strategy equilibrium in each auction (solid, black line). In panel B, all counterfactuals use the constrained strategy equilibrium. The three curves represent the equilibrium quantity awarded for each policy for different levels of counterparty risk. The rightmost curve shows central auction risk; the middle curve shows the state level of risk, and the left curve shows a high level of risk (the 75th percentile of state risk). The modal ceiling price in the data is around INR 3 per kWh (see Figure 6).

10 Tables

Table 1: Summary statistics on solar auctions and solar power projects

	Mean (1)	Std. dev (2)	25th (3)	Median (4)	75th (5)	Obs. (6)
			Panel A: Auction level variables			
All auctions						
Central auction (=1)	0.48	0.50	0	0	1	309
Bid price (INR/kWh)	4.23	2.62	2.77	3.46	5.08	155
Capacity sought (MW)	501.0	944.3	50	200	500	307
Number of bidders	8.59	11.6	2	5	10	179
Over-subscription	2.75	22.0	0.33	0.62	1	150
HHI of capacity offered	0.32	0.32	0.094	0.19	0.50	179
Central auctions						
Bid price (INR/kWh)	3.76	1.31	2.65	3.48	4.43	76
Capacity sought (MW)	655.9	1277.8	50	250	750	149
Number of bidders	6.43	6.49	2	4	9	94
Over-subscription	0.73	0.65	0.32	0.58	1	84
HHI of capacity offered	0.34	0.31	0.12	0.24	0.50	94
State auctions						
Bid price (INR/kWh)	4.67	3.38	2.89	3.35	6.19	79
Capacity sought (MW)	354.9	393.0	54	200	500	158
Number of bidders	11.0	15.1	2	6	13	85
Over-subscription	5.31	33.1	0.40	0.70	1.06	66
HHI of capacity offered	0.30	0.33	0.069	0.15	0.42	85
			Panel B: Bid level variables			
Bid price (INR/kWH)	5.23	2.15	3.18	5.46	6.59	1388
Bid selected (=1)	0.48	0.50	0	0	1	1458
Capacity bid (MW)	302.0	6778.1	10	50	200	1363
Capacity allocated (MW)	52.9	128.5	0	0	50	1497
			Panel C: Project level variables			
Auction (=1)	0.39	0.49	0	0	1	2229
Central auction (=1)	0.10	0.30	0	0	0	2229
Tariff (INR/kWh)	6.90	3.68	4.43	6.45	8.40	1221
Project capacity (MW)	25.1	61.8	1.50	5	20	2229

The table provides summary statistics on variables from the Bridge to India data on renewable power auctions and projects in India. Panel A reports summary statistics of key variables that describe the auctions run by government authorities in order to allocate renewable energy projects to producers. Panel B reports bid-level data on the auctions that are described in Panel A, where bidding steps for each bidder are aggregated into at most two bids, describing parts of the capacity bid that were selected and discarded by the auction. Finally, Panel C summarizes the data on renewable projects, which consists of both active plants and plants that are in the development pipeline. Most of these projects have not been allocated by an auction.

Table 2: Counterparty risk premium in solar bid prices at auction

	Dependent variable: Log of bid price (INR/kWh)			
	(1)	(2)	(3)	(4)
Central auction (=1)	-0.060^{***}	-0.058^{**}	0.035	0.010
	(0.022)	(0.023)	(0.036)	(0.034)
Solar irradiance (W/m^2)	-0.29^{***}	-0.28^{***}	-0.19^{***}	-0.16^{***}
	(0.050)	(0.050)	(0.049)	(0.045)
Counterparty risk		0.014	-0.048^{**}	-0.040
		(0.021)	(0.023)	(0.024)
State auction ×			0.15^{***}	0.11^{***}
Counterparty risk			(0.042)	(0.038)
Year effects	*Yes*	*Yes*	*Yes*	*Yes*
Capacity deciles	*Yes*	*Yes*	*Yes*	*Yes*
Firm effects				*Yes*
Mean dep. var.	1.62	1.62	1.62	1.62
R^2	0.92	0.92	0.93	0.96
p-value H_0: no state risk			0.0011	0.0082
Auctions	124	124	124	124
Bids	1166	1166	1166	1166

This table reports coefficients from regressions of the log bid price in auctions on an indicator for central intermediation and measures of counterparty risk. The dependent variable in all specifications is the price per unit energy (INR per kWh) bid. The indicator for central auction denotes an auction that is intermediated by the central government. State auction is the complement of central auction: an auction that is run by a state and *not* intermediated. Solar irradiance is the 75th percentile of the Global Horizontal Irradiation (GHI) incident in the state or states where the auction is run and is measured in units of watts (W) per meter squared (m^2). The counterparty risk variable is a normalized version of the Ministry of Power rating for discoms described in Figure 3. Equation (1) shows the normalization; a value of zero represents no risk and a value of one the average level of state risk. All specifications include year effects and fixed effects for deciles of the quantity sought at auction. The column 4 specification additionally includes fixed effects for each bidding firm. The p-value in the table footer is for a test of whether the sum of the coefficients on Counterparty risk and State auction × Counterparty risk equals zero (in columns 3 and 4). All standard errors are clustered at the auction level and statistical significance at certain thresholds is indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Counterparty risk premium in solar contract prices across all modes of procurement

	Dependent variable: Log of tariff (INR/kWh)					
	(1)	(2)	(3)	(4)	(5)	(6)
Central auction (=1)	-0.15^{***}	-0.15^{***}	0.058	0.049	-0.041	-0.0078
	(0.038)	(0.037)	(0.069)	(0.074)	(0.081)	(0.089)
State bilateral (=1)	0.093^{*}	0.13^{***}	0.14^{***}	0.081^{*}	-0.034	-0.054
	(0.048)	(0.038)	(0.038)	(0.043)	(0.081)	(0.082)
Solar irradiance	-0.28^{***}	-0.23^{***}	-0.20^{**}	-0.23^{***}	-0.20^{***}	-0.23^{***}
	(0.081)	(0.075)	(0.075)	(0.083)	(0.068)	(0.082)
Counterparty risk		0.12^{***}	-0.055	-0.059	-0.054	-0.060
		(0.042)	(0.047)	(0.043)	(0.046)	(0.043)
State run × Counterparty risk			0.23^{***}	0.20^{***}		
			(0.060)	(0.062)		
State auction × Counterparty risk					0.13^{*}	0.14^{*}
					(0.073)	(0.077)
State bilateral × Counterparty risk					0.33^{***}	0.30^{***}
					(0.062)	(0.052)
Year effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Capacity deciles	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm effects				*Yes*		*Yes*
Mean dep. var	1.91	1.91	1.91	1.91	1.91	1.91
R^2	0.87	0.88	0.89	0.96	0.90	0.96
p-val H_0: no state risk			0.0045	0.0086	0.087	0.066
p-val H_0: mode risk equal					0.014	0.035
Projects	1028	1028	1028	1028	1028	1028

This table reports coefficients from regressions of the log bid price in solar power purchase contracts on an indicator for central intermediation and measures of counterparty risk. The dependent variable in all specifications is the log price per unit energy (INR per kWh). The data include all contract prices for solar power procured through central auctions, state auctions and state bilateral contracts. The indicator for central auction denotes an auction that is intermediated by the central government. State auction indicates an auction that is run by a state and *not* intermediated. State bilateral indicates a contract procured by a state through bilateral negotiations and not at auction. State run indicates a contract procured without central intermediation; that is, through either a state auction or state bilateral contract. Solar irradiance is the 75th percentile of the Global Horizontal Irradiation (GHI) incident in the state or states where the auction is run and is measured in units of watts (W) per meter squared (m^2). The counterparty risk variable is a normalized version of the Ministry of Power rating for discoms described in Figure 3. Equation (1) shows the normalization; a value of zero represents no risk and a value of one the average level of state risk. All specifications include year effects and fixed effects for deciles of the quantity sought at auction. The column 4 and 6 specifications additionally include fixed effects for each bidding firm. The first p-value in the table footer is for a test of whether the sum of the coefficients on Counterparty risk and State run × Counterparty risk equals zero (in columns 3 and 4), or of whether the sum of the coefficients on Counterparty risk and State auction × Counterparty risk equals zero (in columns 5 and 6). The second p-value in the table footer is for a test of the equality of the coefficients on State auction × Counterparty risk and State bilateral × Counterparty risk (in columns 5 and 6). All standard errors are clustered at the auction level and statistical significance at certain thresholds is indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: A test for whether counterparty risk is due to hold-up

	Dependent variable: Log bid price (INR per kWh)			
	(1)	(2)	(3)	(4)
Central auction (=1)	0.022	0.023	0.023	-0.010
	(0.035)	(0.035)	(0.035)	(0.038)
Solar irradiance (W/m^2)	-0.19^{***}	-0.19^{***}	-0.19^{***}	-0.16^{***}
	(0.050)	(0.050)	(0.050)	(0.046)
Counterparty risk	-0.036^{*}	-0.031	-0.032	-0.022
	(0.022)	(0.022)	(0.022)	(0.025)
State auction × Counterparty risk	0.14^{***}	0.14^{***}	0.14^{***}	0.099^{**}
	(0.041)	(0.040)	(0.041)	(0.038)
Thermal in state (=1) × Counterparty risk		-0.097^{***}	-0.066^{*}	-0.062
		(0.030)	(0.035)	(0.040)
Thermal in state (=1) × State auction × Risk			-0.047^{*}	-0.064^{**}
			(0.026)	(0.028)
Year effects	*Yes*	*Yes*	*Yes*	*Yes*
Capacity deciles	*Yes*	*Yes*	*Yes*	*Yes*
Thermal controls	*Yes*	*Yes*	*Yes*	*Yes*
Firm controls	*Yes*	*Yes*	*Yes*	
Firm fixed effects				*Yes*
Mean dep. var	1.62	1.62	1.62	1.62
R^2	0.93	0.93	0.93	0.96
p-val H_0: no state risk	0.0045	0.0027	0.0026	0.016
p-val H_0: no state risk if thermal capacity			0.21	0.57
Auctions	124	124	124	124
Bids	1166	1166	1166	1166

This table reports regressions of log bid prices in the auction data on variables for intermediation and risk with additional controls for the characteristics of bidding firms. Most of the variables are described in the notes to Table 2. In addition, the specifications contain firm-level variables for whether a firm bidding in a solar auction also has thermal generation capacity. Thermal in state is a dummy for whether a firm has any thermal generating capacity in the state or states holding the auction. Thermal controls consist of the thermal in state dummy and the continuous thermal capacity (GW) held by the bidding firm in that state or states. Columns 1 to 3 additionally include control variables for firm age and whether the firm has any business outside the power sector (coefficients not reported). Column 4 replaces these controls with firm fixed effects. The first p-value is for a test that the sum of the Counterparty risk and State auction × Counterparty risk coefficients is equal to zero. The second p-value is for a test that counterparty risk has a null effect on bid price for a firm with 1 GW of generating capacity within the state holding the auction. Standard errors are clustered by auction. The statistical significance of coefficients at certain thresholds is indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 5: Comparison of actual and simulated auction outcomes

Sample	Estimation		Ceiling		
Bid price strategy	Data (1)	As bid (2)	Data (3)	As bid (4)	CSE (5)
Participation					
Potential bids		11.47		4.62	4.62
Bids submitted	11.94	11.47	3.53	2.33	3.60
Bids cleared	5.96	4.43	2.67	1.99	2.93
Quantity					
Quantity sought (MW)	387.43	387.43	795.33	795.33	795.33
Quantity offered (MW)	1010.61	954.45	735.87	427.84	642.64
Quantity awarded (MW)	366.27	358.62	450.72	350.56	498.69
Undersubscribed (=1)	0.26	0.17	0.53	0.79	0.62
Ceiling binds (=1)		0.00		0.61	0.28
Prices and costs					
Mean bid, all (INR/kWh)	3.06	3.06	2.98	2.85	2.98
Mean bid, winning (INR/kWh)	2.96	2.92	2.92	2.83	2.97
Marginal bid (INR/kWh)	3.04	3.03	2.97	2.90	2.98
Mean cost (INR/kWh)	2.53	2.50		2.25	2.30
Markup (INR/kWh)	0.43	0.42		0.59	0.67
Markup (%)	0.19	0.19		0.27	0.31

The table compares auction outcomes in the data to auction outcomes from simulations. The outcomes are compared across two samples of auctions: the first consists of the estimation sample, and the second the ceiling sample. The simulations utilize different strategies for participation and bidding in auctions with ceilings and each column reports outcomes under a different strategy. Columns (1) and (3) report actual outcomes from the data. In columns (2) and (4), the auctions are counterfactually cleared without any bid-shading, with participation in auctions with ceilings governerned by whether a bidder's cost is above the reserve. In columns (5), I report outcomes in ceiling auctions where I solve for the constrained strategy equilibrium (CSE).

Table 6: Counterfactual auction outcomes, sample with ceiling price

	Central risk (1)	Actual risk (2)	State risk (3)	State risk p75 (4)
Panel A: No ceiling prices				
Participation				
Potential bids	4.62	4.62	4.62	4.62
Bids submitted	4.62	4.62	4.62	4.62
Bids cleared	3.35	3.35	3.35	3.35
Quantity				
Quantity sought (MW)	795.33	795.33	795.33	795.33
Quantity offered (MW)	823.01	823.01	823.01	823.01
Quantity awarded (MW)	563.24	563.24	563.24	563.24
Undersubscribed (=1)	0.49	0.49	0.49	0.49
Ceiling binds (=1)	0.00	0.00	0.00	0.00
Prices and costs				
Mean bid, all (INR/kWh)	3.02	3.18	3.40	3.60
Mean bid, winning (INR/kWh)	2.96	3.11	3.33	3.53
Marginal bid (INR/kWh)	3.09	3.26	3.48	3.70
Mean cost (INR/kWh)	2.41	2.54	2.71	2.88
Markup (INR/kWh)	0.55	0.58	0.62	0.66
Markup (%)	0.25	0.25	0.25	0.25
Panel B: Actual ceiling prices				
Participation				
Potential bids	4.62	4.62	4.62	4.62
Bids submitted	3.60	3.45	3.07	2.50
Bids cleared	2.93	2.77	2.52	2.19
Quantity				
Quantity sought (MW)	795.33	795.33	795.33	795.33
Quantity offered (MW)	642.64	613.89	554.02	457.83
Quantity awarded (MW)	498.69	470.65	434.85	390.19
Undersubscribed (=1)	0.62	0.64	0.69	0.76
Ceiling binds (=1)	0.28	0.31	0.42	0.58
Prices and costs				
Mean bid, all (INR/kWh)	2.98	3.08	3.14	3.03
Mean bid, winning (INR/kWh)	2.97	3.07	3.13	3.02
Marginal bid (INR/kWh)	2.98	3.08	3.14	3.02
Mean cost (INR/kWh)	2.30	2.33	2.44	2.56
Markup (INR/kWh)	0.67	0.74	0.69	0.46
Markup (%)	0.31	0.34	0.31	0.19

The table reports counterfactual auction outcomes in the sample of auctions that were originally bid with ceiling prices. The counterfactuals vary in two dimensions. Across the panels, panel A shows outcomes without ceiling prices and panel B shows outcomes with ceiling prices. Across the columns, the simulations vary in the level of counterparty risk, with risk increasing from left to right: the risk of a central auction (column 1), the actual level of risk accounting for state risk and intermediation (column 2), state risk if there had been no intermediation (column 3) and state risk set for all states at the estimated 75th percentile of the state risk distribution (column 4). The counterfactual simulations for auctions without ceiling prices use the *As bid* strategy and for auctions with ceiling prices the *Shade up* strategy. These strategies are described in Section 7 and validated against the data in Table 5.

A Appendix: Data

1.1 Auctions

Data on auctions are from Bridge to India, a consulting firm that collects data on renewable energy in India. The data are originally sourced from public documents put out by utilities and regulators. There are a total of 2095 bids across 309 auctions in the raw data, of which 124 auctions have data on all bids, 31 auctions have data on some (but not all) bids, and 154 auctions have no bid level data. Most of the auctions that do not have bid level data available were cancelled without any quantity awarded.

I clean the auction data to (i) establish a homogenous sample of auctions with all the data needed for analysis (ii) convert bid prices, where necessary, into per unit energy terms. The subsections below describe these steps.

Sample construction in auction data.—I impose several sample restrictions to create a data set of homogenous auctions and their bids. Table A1 describes the sample restrictions. For all analysis, I impose the following restrictions: auctions must be for ground-mounted solar photovoltaic power plants (as opposed to, for example, floating solar plants), the capacity sought at auction must be at least 5 MW (to exclude idiosyncratic projects linked to industrial plants), and auctions must not be in Odisha.[20] These restrictions yield 232 auctions with 1264 bids offering 124 GW of capacity. All bids with prices and covariates in this sample are used in the regression analysis.

Further sample restrictions, shown further down in the table, are imposed for particular portions of the structural analysis. I form the *estimation sample* for the estimation of bidder costs by requiring that auctions have bid prices available for all bids and do not have ceiling tariffs. These restrictions are important to estimate the complete, uncensored distribution of bids and therefore costs. If bid prices were partially available, or a ceiling price had been imposed, the estimated distribution of bids would not represent the true and complete latent distribution of bid prices.

The *counterfactual sample* does not require that bid prices be available, since bids in counterfactuals are simulated from the distribution of bidder types and bids estimated using the estimation sample.

Finally, the *ceiling sample* consists only of auctions in which ceiling prices were originally imposed.

[20]Odisha is an odd state because it has privatized its distribution companies, which makes it difficult to measure counterparty risk. We also drop auctions in the Andaman and Nicobar Islands; however, this restriction is redundant since all such projects are too small to make the sample.

This sample is used for the validation of counterfactual strategies and the counterfactual simulations of auction outcomes. The auctions in the ceiling sample are deliberately excluded from the estimation sample so as not to bias the estimation of costs.

Table A1: The effect of sample restrictions on sample size

	Auctions (1)	Bids (2)	Capacity (GW) (3)
None	309	1541	154
Keep ground-mounted projects only	241	1288	125
Keep auctions with capacity sought $\geq$ 5 MW	240	1288	125
Drop Odisha	232	1264	124
Estimation sample			
Keep auctions with all tariffs available	102	929	54
Drop auctions with ceiling tariffs	80	865	30
Counterfactual sample			
Drop manufacturing-linked auctions	229	1262	104
Ceiling sample			
Drop auctions without ceilings	44	109	48

This table reports the cumulative effect of sample restrictios on sample size. The columns report different aspects of sample size: column (1) reports the number of auctions in the sample, column (2) represents the number of bids, and column (3) shows the total capacity sought by auctions in the sample. The first four rows report the restrictions applied to create the baseline descriptive sample, which consists of 1264 bids across 232 auctions. The rows below show the additional restrictions needed to construct the estimation, counterfactual, and ceiling samples.

Converting subsidies and select bid prices to per unit energy terms.—Bid-prices in the auction data usually consist of a tariff quoted as a price per unit of energy supplied (INR per kWh). However, in 17 auctions in our sample, the government offers so-called viability gap funding (VGF), which is a capital subsidy per unit of capital (typically in INR per MW terms). Viability gap funding is a subsidy meant to make up the gap between the prices of green and brown energy projects in order to encourage green energy investment. In these auctions, firms submit bids over both the base tariff and the VGF, with the former denominated in energy terms and the latter in terms of capacity.

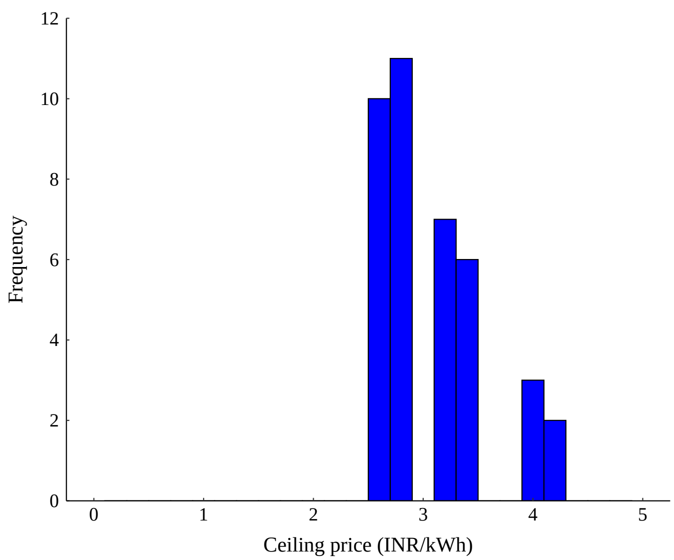
To harmonize all prices in energy terms, we adjust for these subsidies by calculating their per unit energy equivalents. I solve for the "levelized" price P that satisfies

$$C = \sum_{t=1}^{T} \frac{PE}{(1+r)^t}.$$

where C is the subsidy in capacity terms, T is the time horizon over which the present-value is calculated, and r is the interest rate used to discount future payment streams. $E = c_E \times 24$ hours $\times$ 365 days is the amount of energy (measured in kilowatt-hours) that one kilo-watt of capacity would generate in a year. The term c_E represents the capacity factor, the ratio of expected energy output to the maximum possible amount of energy that could be generated by a given plant (if the sun were shining all the time). I set $T = 25$ to match the horizon of power purchase contracts. I set $r = 0.10$. The prime corporate borrowing rate in India was around 12% during my sample periods, but large, collateralized solar plants often have lower borrowing costs. I set $c_E = 0.18$ which is a reasonable mean capacity factor for solar PV plants in India.

Ceiling prices.— 50 out of the 309 auctions in our raw data sample had ceiling prices. In these auctions, bids can only be submitted if they are beneath the ceiling price (commonly called a a "reserve" price elsewhere). The mean ceiling price is roughly INR 3.08 per kWh with a standard deviation of INR 0.43 per kWh. Figure A1 shows the distribution of ceiling tariffs in our sample.

Figure A1: Distribution of ceiling prices in the auction data



This figure shows the distribution of ceiling prices in the subset of auctions that stipulate ceiling prices. The x-axis shows the ceiling price imposed in the auction and the y-axis counts the number of auctions with a particular ceiling price.

1.2 Projects

The data on projects are also procured from Bridge to India and complement the data on auctions. The observations are comprised of information on solar power plants that have either been commissioned, meaning they have begun generating energy, or have been contracted and are currently in the development pipeline. The full sample consists of 2229 projects which are located across 27 states and union territories in India. The active projects in our sample were commissioned between the years 2009 and 2020.

1.3 Counterparty risk

The measure of counterparty risk is collected by the Ministry of Power (Ministry of Power, 2013). The raw data on ratings consist of letter grades assigned to each distribution company. The letter grades are assigned by the MoP after utilites are rated by a credit rating agency such as ICRA or CARE. The letter grade scale was chosen deliberately to differ from the typical scale for corporate credit ratings, in order to account for the unique, integrated nature of the ratings. The ratings are meant to capture both "operational and financial performance" and "the risks associated with lending exposures to various distribution utilities." In addition, the Ministry of Power wanted to use a novel scale to compare each company "with other distribution utilities only," rather than the corporate sector at large.

I aggregate the MoP data to the state level by converting the letter grades to grade point averages (GPA) as described in the text, and then calculating the mean GPA for each state-year observation. I then use the normalized grade point average for states in the fiscal year 2012-13, at the start of the sample, as the measure of counterparty risk. The resulting letter grades range from A+ to C, as shown in Figure 3.

Figure 3 validates the measure of risk using data from the "Payment Ratification And Analysis in Procurement for bringing Transparency in Invoicing of generators" (PRAAPTI) scheme, a Ministry of Power program to highlight non-payment by state utilities.[21] This data contain records of invoices from power producing firms seeking payment from state utilities. The main limitation of the PRAAPTI data is that reporting of a late or disputed invoice is voluntary. Therefore, there may be selection into reporting in different states, which plausibly could depend on counterparty risk, and the coverage of the data is also incomplete.

Each invoice in the PRAAPTI database consists of an invoice identifier, the date on which the invoice appeared in the dataset, the debtor utility, the generator who filed the complaint, an indicator for whether the pending amount in the invoice was overdue, the total rupee amount pending to be paid to the generator, the total amount that is late and the total rupee amount in dispute between the generator and the utility company. Invoices do not uniquely identify each observation in the dataset since multiple complaints based on the same invoice show up in the database. To account for this, I collapse the data for each invoice into a single observation by retaining the first observation where an invoice was marked overdue. I then aggregate

[21]The clumsy acronym is a Sanskit term that means the ability to obtain or acquire. *Prapti*, as a *siddhi* or power of advanced yoga practioners, has a connotation of ubiquity or the ability to enter everywhere. In our context, it may refer to the ability of the central government to use this data to peer into the finances of the state discoms.

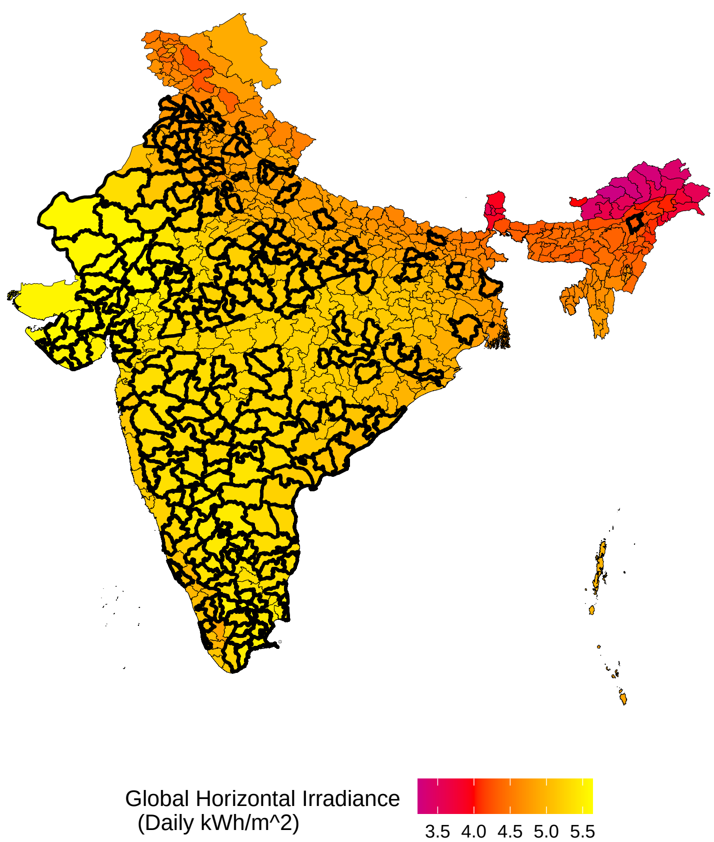
the invoice-level payment variables to the state-level and calculate the share of payments that are late or disputed in each state.

1.4 Solar irradiance

Solar irradiance is the power per unit area received from the sun as electromagnetic radiation. I use data on the yearly average of solar potential at the coordinate-grid level from the Global Solar Atlas to compute state- and district-wide averages within India. Solar potential is measured by *global horizontal irradiance* (GHI), the power received from shortwave radiation on a plane horizontal to the surface of Earth. GHI is the main measure of irradiance used to forecast output from solar photovoltaic plants, because it is a total measure, including both direct sun and indirect sun that may be scattered off of the atmosphere and arrive at varying odd angles.

Figure A2 shows solar irradiance across India at the district level. The boundaries of administrative districts are shown. Districts that contain at least one solar project appearing in the dataset have bold outlines in the map, showing the geographic extent of solar projects in the country. There are 223 districts with a solar plant covering nearly the full extent of the country, with the exception of the northeastern states and far northern districts. While India generally has high solar potential, there is nonetheless considerable variation in the solar potential of districts in which solar plants are built. Less productive districts, e.g. in Punjab, may have GHI of 4.0 kWh/m^2 per day, while the most productive districts approach 5.5 kWh/m^2 per day.

Figure A2: Solar irradiance in India



This figure shows Global Horizontal Irradiance (GHI), the industry-standard measure of solar photovaltaic generation potential, across India. The boundaries of administrative districts are shown. Districts that contain at least one solar project appearing in the dataset have bold outlines in the map, showing the geographic extent of solar projects in the country.

B Appendix: Supplementary results

2.1 Context: Bailouts of Indian distribution companies

This part describes the pattern of bailouts for state-government-owned electricity distribution companies, to establish that these companies are unreliable counterparties. These discoms are run by the state governments to distribute power. They often run financial losses, due to the provision of subsidized power to agricultural and domestic users of electricity, as well as to technical and commercial losses. Discoms accumulate liabilities by not paying both public and private generating companies for power delivered. Over time, discoms' financial position deteriorates, until they are no longer able to buy power or get credit. At that point, the state governments and central government bail them out.

Table B2 gives a recounting of the four massive bailouts since the year 2000. Each bailout has a value of between 0.5% and 2% of GDP. Bailouts involve some combination of debt forgiveness and restructuring, including the assumption or refinancing of distribution company debt by the state governments. Because distribution companies are subject to a soft budget constraint, they have an incentive to add liabilities by not paying private producers of power. The cycle of bailouts therefore helps sustain counterparty risk.

Table B2: Bailouts of State-owned Distribution Companies since 2000

Year	Creditors	Current Value	Constant Value	% GDP	Financial Details	Other Measures
2020[a]	Generators & Gov't Finance Institutions (GFIs)	900B INR	12.01B USD	0.44%	Liquidity injection divided into two tranches: the first contingent on a repayment plan to creditors and the second contingent on not having any bills overdue and having a plan to bring down technical losses.	Intended as a stopgap measure until the Electricity Act Reform is introduced.
2015 (UDAY)[bcd]	Banks	2090B INR	36.39B USD	1.52%	States shall take over 75 percent of discom debt as on 30 September 2015 over two years. 50 percent of discom debt shall be taken over in 2015-16 and 25 percent in 2016-17. States taking over and funding at least 50 percent of the future losses.	Operational attempts to reduce deficit, such as reducing losses and increasing efficiency.
2012[e]	Banks	1900B INR	45.26B USD	1.91%	States required to take on 50 percent of outstanding short-term liabilities up to March 31, 2012. They will be converted into bonds and issued to lenders, with liability falling to the states. The other 50 percent will be restructured such that there will be a 3-year moratorium on repayments.	Performance incentives issued by Central Government for meeting certain operational and financial targets.
2001 & 2002[e]	Centrally-owned generators / CPSUs	400B INR	18.23B USD	1.84%	50 percent of the interest on delayed payments was waived and the remaining amount (full principal plus remaining interest) converted into bonds by the state government.	APDRP and Electricity Act of 2003 intended to deliver increased profitability for discoms and structural reforms to the power sector, respectively.

Constant Value Calculations are in 2020 USD, converted from Indian 2020 inflation-adjusted values using July 2020 conversion rates. *CPSUs* represent Central Public Sector Undertakings, primarily in the generating sector. *GFIs* represent Government Finance Institutions such as the PFC and the REC. GDP calculations are from tradingeconomics. Sources: [a] Mercom India (2020) [b] Economic Times India (2017) [c] Hindu Business Line (2016) [d] Financial Express (2015) [e] World Bank: *Khurana, Mani; Banerjee, Sudeshna Ghosh.* (2015)

2.2 Alternate solar price regression specifications

This subsection shows alternate specifications and robustness checks for the regressions in Tables 2 and 3.

Bid price regressions with the dependent variable in levels.—Table B3 shows regressions of bid prices at auction on counterparty risk and various controls. The specifications are the same as in Table 2 in the main text, except that the dependent variable is the level of the bid price (in INR per kWh) instead of its logarithm.

Table B3: Counterparty risk premium in solar bid prices at auction

	Dependent variable: Bid price (INR/kWh)			
	(1)	(2)	(3)	(4)
Central auction (=1)	-0.27^{**}	-0.26^{**}	0.18	0.045
	(0.11)	(0.12)	(0.22)	(0.18)
Solar irradiance (W/m^2)	-1.57^{***}	-1.51^{***}	-1.09^{***}	-0.82^{***}
	(0.32)	(0.31)	(0.34)	(0.30)
Counterparty risk		0.097	−0.20	−0.16
		(0.13)	(0.12)	(0.12)
State auction ×			0.70^{**}	0.48^{*}
Counterparty risk			(0.29)	(0.24)
Year effects	*Yes*	*Yes*	*Yes*	*Yes*
Capacity deciles	*Yes*	*Yes*	*Yes*	*Yes*
Firm effects				*Yes*
Mean dep. var.	5.40	5.40	5.40	5.40
R^2	0.89	0.89	0.90	0.95
p-value H_0: no state risk			0.014	0.049
Auctions	124	124	124	124
Bids	1166	1166	1166	1166

This table reports coefficients from regressions of the bid price in auctions on an indicator for central intermediation and measures of counterparty risk. The dependent variable in all specifications is the price per unit energy (INR per kWh) bid. The indicator for central auction denotes an auction that is intermediated by the central government. State auction is the complement of central auction: an auction that is run by a state and *not* intermediated. Solar irradiance is the 75th percentile of the Global Horizontal Irradiation (GHI) incident in the state or states where the auction is run and is measured in units of watts (W) per meter squared (m^2). The counterparty risk variable is a normalized version of the Ministry of Power rating for discoms described in Figure 3. Equation (1) shows the normalization; a value of zero represents no risk and a value of one the average level of state risk. All specifications include year effects and fixed effects for deciles of the quantity sought at auction. The column 4 specification additionally includes fixed effects for each bidding firm. The p-value in the table footer is for a test of whether the sum of the coefficients on Counterparty risk and State auction × Counterparty risk equals zero (in columns 3 and 4). All standard errors are clustered at the auction level and statistical significance at certain thresholds is indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Counterparty risk premium with state and district fixed effects.— In the contract price data it is possible to use more granular controls for plant location because the state and district of each plant is observed. Table B4 shows bid price regression estimates from specifications using state and district fixed effects. The specifications in Table B4, columns 1 through 5 are the same as those in Table 3, in the main text, from column 1 and columns 3 through 6, except that state-level covariates have been replaced with state and district fixed effects. The specifications therefore do not include a main effect for counterparty risk or solar irradiance, which vary only at the state level.

2.3 Comparison of estimated solar costs to engineering estimates

Table B5 compares estimates for the cost of suppling solar power, from the bidding model results reported in Section 6.2, to independent engineering estimates of solar production costs from the same period. Column 1 shows the mean estimated cost in the model for auctions from 2015 through 2018 (without homogenization, as is appropriate for an external cost comparison). Columns 2 through 4 show independent estimates of solar production costs from regulatory and analyst reports covering the same period (CERC, 2015, 2016; IRENA, 2019*b*). The headline cost for each estimate is reported as "Total costs (INR/kWh)" and a decomposition into sub-costs is reported for the engineering estimates. When costs were originally reported per unit of capacity, they have been converted to costs per unit energy to compare to the per unit energy bid prices at auction.

2.4 Counterparty risk by intermediation over time

The risk premium in state auctions suggests that risky states should prefer to run intermediated auctions. This may lead to differences in the composition of auctions, where only less risky states choose to run their own auctions. Figure B3 tests this hypothesis by showing the mean risk rating of procurers running state auctions (solid, red line) and central auctions (dashed, black line) over time. Procurers in state and central auctions have similar risk levels in general. There is some evidence that the rating of procurers running state auctions has increased over time (i.e., less risky procurers have run state auctions) from 2016 onwards, after the central government began intermediating more auctions itself.

Table B4: Counterparty risk premium in solar contract prices across all modes of procurement, with state and district fixed effects in place of state-level controls

	Dependent variable: Log of tariff (INR/kWh)				
	(1)	(2)	(3)	(4)	(5)
Central auction (=1)	-0.12^{***}	0.10	0.17^{*}	0.083	0.14
	(0.043)	(0.074)	(0.084)	(0.080)	(0.098)
State bilateral (=1)	0.16^{***}	0.18^{***}	0.13^{**}	0.14^{*}	0.055
	(0.044)	(0.043)	(0.053)	(0.078)	(0.099)
State run × Counterparty risk		0.23^{***}	0.24^{***}		
		(0.067)	(0.084)		
State auction × Counterparty risk				0.21^{***}	0.22^{**}
				(0.078)	(0.10)
State bilateral × Counterparty risk				0.25^{***}	0.30^{***}
				(0.069)	(0.073)
Year effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Capacity deciles	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
State effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
District effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm effects			*Yes*		*Yes*
Mean dep. var	1.91	1.91	1.91	1.91	1.91
R^2	0.94	0.95	0.98	0.95	0.98
p-val H_0: mode risk equal				0.53	0.39
Projects	1028	1028	1028	1028	1028

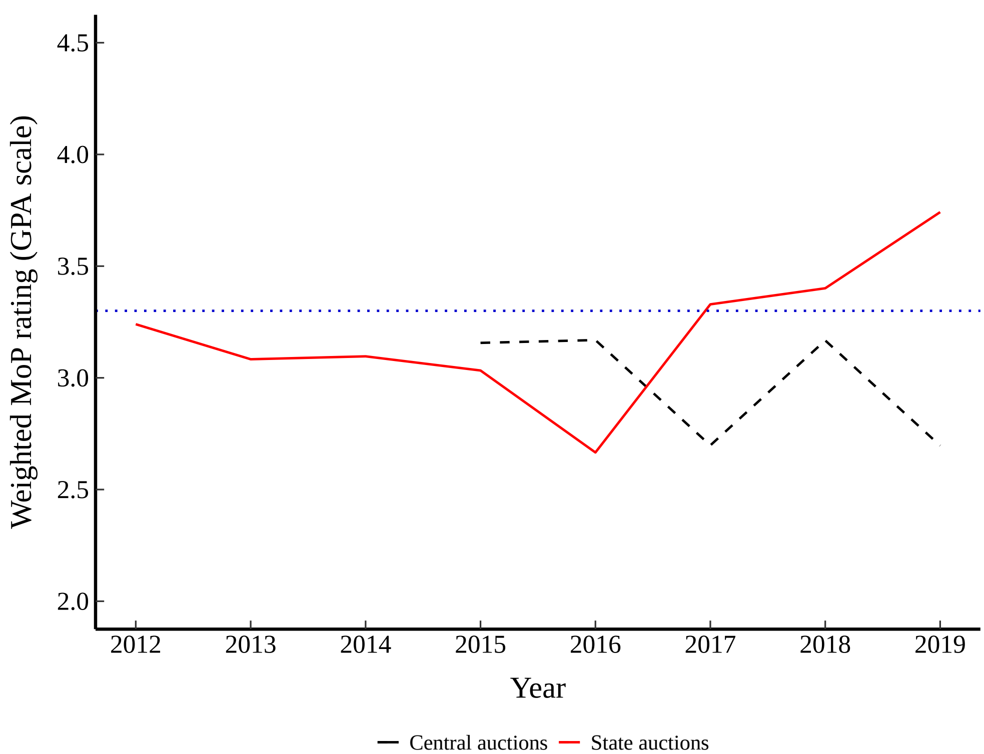
This table reports coefficients from regressions of the log bid price in solar power purchase contracts on an indicator for central intermediation and measures of counterparty risk. The data and variables are the same as in the paper Table 3. This table replaces the state-level controls in Table 3 with state and district fixed effects for the project location. The dependent variable in all specifications is the log price per unit energy (INR per kWh). The data include all contract prices for solar power procured through central auctions, state auctions and state bilateral contracts. The indicator for central auction denotes an auction that is intermediated by the central government. State auction indicates an auction that is run by a state and *not* intermediated. State bilateral indicates a contract procured by a state through bilateral negotiations and not at auction. State run indicates a contract procured without central intermediation; that is, through either a state auction or state bilateral contract. The counterparty risk variable is a normalized version of the Ministry of Power rating for discoms described in Figure 3; Equation (1) shows the normalization; a value of zero represents no risk and a value of one the average level of state risk. All specifications include year effects, fixed effects for deciles of the quantity sought at auction, state fixed effects and district fixed effects. The column 3 and 5 specifications additionally include fixed effects for each bidding firm. The p-value in the table footer is for a test of the equality of the coefficients on State auction × Counterparty risk and State bilateral × Counterparty risk (in columns 4 and 5). All standard errors are clustered at the auction level and statistical significance at certain thresholds is indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B5: Solar cost estimates

	Model (1)	CERC 2015-16 (2)	CERC 2016-17 (3)	IRENA (4)
Year	All	2015	2016	2018
Total costs (INR m / MW)		60.7	53.0	54.3
Total costs (INR/kWh)	3.99	4.23	3.71	3.79
Panel costs		2.32	2.29	1.48
Installation costs		1.4	1.04	1.42
Land costs		0.17	0.17	
Other costs		0.39	0.19	0.89
Bid price (INR/kWh)	4.50			

This table reports estimates of total solar project costs from secondary sources. Column (1) shows our mean model estimates of costs and bid prices, with the average taken across years 2015-2018. Column (2) reports costs from a 2015 report compiled by the Central Electricity Regulatory Commission (CERC). Column (3) reports estimates from the version of the report compiled in 2015. Column (4) reports cost estimates from the International Renewable Energy Agency (IRENA), compiled in 2018. Costs are originally denominated in capacity terms (as shown in row 2), which we translate into energy termsusing a present value calculation.

Figure B3: Change in counterparty risk over time for procurers



The figure shows the weighted average rating of states running procurement auctions by year. The rating is the GPA-equivalent of the letter grade given by Ministry of Power (2013) for 2012. A normalized version of this rating is used to measure counterparty risk in the empirical analysis. In each year, the series shows the weighted average rating of procurers running solar auctions either as states themselves or through intermediated auctions of the central government. The weights are the capacity of solar power sought to be procured at each auction. Because the ratings are static, the changes in the series show changes in the risk composition of which states are running auctions. The dotted horizontal line shows the average state rating ("B+").

C Appendix: Model

3.1 Proof of homogenization of bid prices in a multi-unit auction

This part contains the proof of proposition 1. The proof shows that rescaling bid prices and costs by a common factor maintains the first-order necessary conditions for equilibrium bidding.

Lemma 1. *If $\beta_j(c_{jt}|Z_t,q_{jt}) = \Gamma(Z_t)\beta_j(c_{jt}|Z_0,q_{jt})$, then the expected quantity awarded in an auction with covariates Z_t can be written as $H_t(p\Gamma(Z_t),q_{it}|Z_t) = H_t(p,q_{it}|Z_0)$.*

Proof. (Lemma 1). The function $H_t(\beta_i(c_{i0}|Z_0,q_{it}),q_{it}|Z_t)$ gives the expected quantity awarded in an auction conditional on covariates Z_t.

$$H_t(p,q_{it}|Z_t) = \mathbb{E}_{\sigma_{-i}}\left[Q_t(p,q_{it}|Z_t,\sigma_{-i})\right]$$

This conditional expected quantity awarded is defined, in turn, in terms of conditional quantity awarded and conditional residual demand. Conditional quantity awarded is

$$Q_t(p,q|Z_t,\sigma_{-i}) = \begin{cases} 0 & \text{if } RD_t(p|Z_t,\sigma_{-i}) \le 0 \\ RD_t(p|Z_t,\sigma_{-i}) & \text{if } 0 < RD_t(p|Z_t,\sigma_{-i}) \le q \\ q & \text{if } q < RD_t(p|Z_t,\sigma_{-i}). \end{cases} \tag{10}$$

Conditional residual demand is

$$RD_t(p|Z_t,\sigma_{-i}) \quad = \quad QD_t - \sum_{j\neq i} q_j \mathbf{1}\left\{p \ge \beta_j(c_{jt}|Z_t,q_{jt})\right\}.$$

Under the bidding factor conjecture $\beta_j(c_{jt}|Z_t,q_{jt}) = \Gamma(Z_t)\beta_j(c_{jt}|Z_0,q_{jt})$, the residual demand curve is

$$\begin{aligned} RD_t(p\Gamma(Z_t)|Z_t,\sigma_{-i}) &= QD_t - \sum_{j\neq i} q_j \mathbf{1}\left\{p\Gamma(Z_t) \ge \Gamma(Z_t)\beta_j(c_{jt}|Z_0,q_{jt})\right\} \\ &= QD_t - \sum_{j\neq i} q_j \mathbf{1}\left\{p \ge \beta_j(c_{jt}|Z_0,q_{jt})\right\} \\ &= RD_t(p|Z_0,\sigma_{-i}), \end{aligned}$$

equivalent to residual demand in a baseline auction as a function of a rescaled bid price. The result follows from constructing conditional expected quantity awarded and conditional quantity awarded from this conditional residual demand. □

Proof. (Homogenization). In an auction with baseline characteristics, an optimal bid satisfies

$$\beta_i(c_{i0}|Z_0, q_{it}) = c_{i0} - \frac{H_t(\beta_i(c_{i0}|Z_0, q_{it}), q_{it}|Z_0)}{\partial H_t(\beta_i(c_{i0}|Z_0, q_{it}), q_{it}|Z_0)/\partial p}.$$

By Lemma 1, we can write the optimal bid in an auction with characteristics Z_t as

$$\begin{aligned}\beta_i(c_{it}|Z_t, q_{it}) &= c_{it} - \frac{H_t(\beta_i(c_{it}|Z_t, q_{it}), q_{it}|Z_t)}{\partial H_t(\beta_i(c_{it}|Z_t, q_{it}), q_{it}|Z_t)/\partial[p\Gamma(Z_t)]} \\ &= \Gamma(Z_t)c_{i0} - \frac{H_t(\beta_i(c_{i0}|Z_0, q_{it}), q_{it}|Z_0)}{\partial H_t(\beta_i(c_{i0}|Z_0, q_{it}), q_{it}|Z_0)/\partial p}\Gamma(Z_t) \\ &= \Gamma(Z_t)\beta_i(c_{i0}|Z_0, q_{it}).\end{aligned}$$

where the second line applies (6) and takes the derivative, in the mark-up term, with respect to the rescaled bid price. Since this argument applies for any bidder i, provided that other bidders j follow the bidding factor conjecture, rescaling all equilibrium bid functions together constitutes an equilibrium strategy profile. □

3.2 Regression specification for bid homogenization

We can therefore "homogenize" bids by adjusting for auction observables as follows. First, we regress bids on auction characteristics

$$\ln b_{ait} = \ln b^0 + \alpha_t + \alpha_s + \alpha_s Central_{at} + \beta_1 Z_{at} + \tilde{b}_{ait} \tag{11}$$

where $\ln b_{ait}$ is the log of the bid actually offered, $\ln b^0$ is the intercept, α_t are fixed effects for the year of the auction, α_s are fixed effects for the state of the auction, δ_s are fixed effects for the state of the auction interacted with an indicator for central intermediation, Z_{at} are observable characteristics of the auction, and $\tilde{b}_{ait}$ is the idiosyncratic component of the bid. We specify Z_{at} to include the quantity sought and the quantity sought squared. The number of bidders in the auction is accounted for by weighting the draws of the resampling procedure. We do not directly control for solar capital cost because capital costs vary only over time and will be absorbed flexibly by the year fixed effects.

The second step is to form homogenized bids as predictions

$$\ln b^h_{ait} = \ln b^0 + \beta_1 Z^0_{at} + \tilde{b}_{ait} \tag{12}$$

where Z^0_{at} are the characteristics of a baseline auction. I omit from the regression the "state" fixed effect when the auction is centrally intermediated and the time fixed effect for the year 2019. The constant therefore represents the mean log bid that would have been offered in a central auction in that year. I use this homogenized sample of bids to estimate bidder costs.

Table C6: Regression estimates for bid homogenization

Dependent variable: Log of bid price (INR/kWh)	Coefficient (1)	Std Error (2)
Capacity sought (MW)	−0.0091	(0.067)
Capacity sought squared	−0.0814	(0.059)
Year = 2012	0.903***	(0.053)
Year = 2013	0.849***	(0.042)
Year = 2014	0.769***	(0.041)
Year = 2015	0.605***	(0.041)
Year = 2016	0.540***	(0.042)
Year = 2017	0.0454	(0.042)
Year = 2018	−0.0297	(0.042)
Domestic content required (=1)	0.0504***	(0.016)
EPC contract (=1)	−0.297***	(0.066)
Constant	1.132***	(0.046)
State effects	*Yes*	
State × central effects	*Yes*	
R^2	0.94	
Observations (bids)	864	

This table reports coefficients from a regression of the log bid price in auctions on auction characteristics. The regression estimates are used for the homogenization of bids in the auction model. The explanatory variables include: a quadratic function of capacity sought at auction, year fixed effects, a dummy for whether the auction required domestically-produced panels to be used in solar plants, a dummy for whether the auction awarded an Engineering, Procurement and Construction (EPC) contract, state fixed effects, and state fixed effects interacted with central intermediation. All standard errors are clustered at the auction level and statistical significance at certain thresholds is indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.3 Simulation of residual demand curves facing each bidder

This part describes how the expected quantity awarded function is constructed, in two steps. The first step is to resample bids to represent the distribution of residual demand curves that a bidder in a particular auction may have faced. The second step is to smooth the bids drawn in each simulation so that the residual demand curve is continuous and differentiable.

Resampling of bids.— We approximate the expected quantity awarded function $H_t(p,q)$ for each bidder by resampling from the bids offered in the bidder's original auction and other similar auctions. Resampling is a way to represent the uncertainty faced by a bidder over the bids of other firms at the time of bidding. Let N_a be the number of bids offered in auction a. The resampling approach follows these steps:

1. Fix a bidder i and their bid $\sigma_{it} = \{b_{it}, q_{it}\}$ in an auction t.

2. Draw a random sample of $N_t - 1$ bids σ_{-i}. Each bid is drawn with probability weights, described below, to favor bids from similar auctions.

3. Construct the residual demand curve facing i when the bids σ_{-i} are submitted.

4. Calculate the realized quantity awarded to i and the slope of residual demand at the realized quantity.

Bids are resampled in step (2) with weights that depend on the difference between the observable characteristics of an original auction and those of the other auctions in the sample. The weight, without normalization, for bids sampled for auction t from auction t' in the sample of N auctions is

$$W(Z_t, Z_{t'}) = \frac{1}{N_t} \frac{K\left(\frac{Z_t - Z_{t'}}{h_Z}\right)}{\sum_{t'=1}^{N} K\left(\frac{Z_t - Z_{t'}}{h_Z}\right)}.$$

In this way, bids are more likely to be drawn when they were submitted in auctions close to the original auction. I specify the kernel function $K(\cdot)$ as the product of independent normal probability density functions for each dimension of Z_t.

The prices of resampled bids are homogenized with highly predictive regression specifications. The main purpose of this non-parameteric reweighting is to additionally represent the bid quantities and the joint distribution of quantities and homogenized prices well. The vector Z_t includes the logarithm of capacity sought, the year-month an auction was held, and the number of bidders at auction. The bandwidth parameter h_Z values for these three characteristics are set to 1, 12 months and 5 bidders. With a Gaussian kernel, all bids from all auctions are sampled with positive probability, though practically, with these bandwidths, most bids are drawn from the most similar three to five auctions (including the original auction). This weighting allows the resampling to capture differences between large and small auctions and changes in the size composition of bids over time.

Smoothing of residual demand realizations.—The expected quantity function is built from simulation draws indexed by s. On each simulation draw, we form residual demand as

$$\widetilde{RD}_t(p|\sigma_{-i}^s) = QD_t - \sum_{j \neq i} q_j^s \Phi\left(\frac{p - b_j^s}{h_p}\right) \tag{13}$$

$$\frac{\partial \widetilde{RD}_t(p|\sigma_{-i}^s)}{\partial p} = -\sum_{j \neq i} q_j^s \frac{1}{h_p} \phi\left(\frac{p - b_j^s}{h_p}\right) \tag{14}$$

where Φ and ϕ are the normal CDF and PDF functions, respectively, and INR h_p per kWh is a bandwidth parameter for smoothing residual demand. This function is continuous, decreasing and differentiable in p. I set $h_p = 0.10$ INR per kWh throughout the analysis, about 1/30 of the level of a typical homogenized bid. Similarly, we define the own quantity supplied as

$$\widetilde{QS}(p|\sigma_i) = q_i \Phi\left(\frac{p - b_i}{h_p}\right). \tag{15}$$

With this form, $\widetilde{QS}$ is continuous and differentiable but approximates the step function (4) as h_p becomes small.

The market-clearing condition for a simulation draw s is

$$\widetilde{QS}(p|\sigma_i) = \widetilde{RD}_t(p|\sigma^s_{-i}), \tag{16}$$

with equilibrium price p^{s*}. The bidder i is awarded $\widetilde{QS}(p^{s*}|\sigma_i)$ on that draw. We then approximate the function H with the simulated expectation

$$\widehat{H}_t(p,q) \quad = \quad \frac{1}{S}\sum_{s=1}^{S} \widetilde{QS}(p^{s*}|\sigma_i).$$

We similarly approximate the derivative of quantity awarded with respect to price, $\partial H/\partial p$. An increase in the bid price b_i decreases quantity awarded. The bid σ_i in (15) contains b_i as its first element. For a given simulation, implicitly differentiating (16) yields

$$\frac{dQS^{s*}}{db_i} \quad = \quad -\frac{\partial \widetilde{QS}(p|\sigma_i)}{\partial b_i} \frac{\frac{\partial \widetilde{RD}_t(p|\sigma^s_{-i})}{\partial p}}{\frac{\partial \widetilde{QS}(p|\sigma_i)}{\partial p} - \frac{\partial \widetilde{RD}_t(p|\sigma^s_{-i})}{\partial p}}.$$

The derivatives on the right-hand side are known from the functions above and can be evaluated at the equilibrium price p^{s*}. This yields the slope of expected quantity awarded with respect to the bid price offered as

$$\left.\frac{\partial \widehat{H}_t(p,q)}{\partial p}\right|_{p=b_i} \quad = \quad \frac{1}{S}\sum_{s=1}^{S} \frac{dQS^{s*}}{db_i}.$$

With these approximations to quantity awarded and its derivative, I form the mark-up term in equation 5.

Examples of residual demand simulation.—Figure C4 shows the simulation of residual demand for two bidders in two different auctions. Within each panel, the red, weakly increasing step function is the bidder's own supply curve. The black, decreasing step function is the actual realization of residual demand in the auction for a certain bidder. The dashed blue curve is a kernel-smoothed version of that residual demand realization using a Gaussian kernel with bandwidth INR 0.10 per kWh. The thin solid lines are alternative realizations of residual demand that are drawn in simulations.

The simulations provide intuition for why bidders may be estimated to have higher or lower mark-ups. The auction in Panel A is fairly competitive. The bidder offers own supply equal to the full quantity of 150 MW sought in the auction. While that full quantity is very unlikely to be cleared, there are many draws of opponent bids for which *part* of the quantity offered will be cleared, and therefore the simulated residual demand slope will be fairly large (in absolute value). In Panel B, the auction is *extremely* competitive, with much more quantity offered in aggregate than is sought by the procurer. The bid highlighted is offered at a high price relative to the simulated residual demand curves shown. The expected slope of residual demand is therefore small, but the quantity awarded to this bidder in expectation will also be small. The low expected quantity and residual demand slope have opposing effects on the mark-up in this case. In practice bidders with moderate to high costs are typically estimated to have relatively small markups because they are so unlikely to be cleared (i.e., awarded much quantity).

3.4 Solving for constrained strategy equilibria

With the above definition of a constrained strategy equilibrium we can build an algorithm for finding the optimal α^*. Fix an auction a with a level of risk δ_s. We can draw from the distribution of types $\theta_i = (c_i, q_i)$.

1. **Simulate**. Draw $s = 1, \ldots, S$ auctions where each auction consists of N_t^s draws of θ.
   - Let the draws for bidder $i = 1$ represent the type of bidder i.
   - Draws for $j = 2, \ldots, N_t^s$ represent the types of rival bidders.
2. **Constrained strategy function**. Posit a bidding function $b(\theta_i|\alpha, r)$ as in (7) that yields a bid price conditional on type and parameter α.
3. **Solve for constrained equilibrium**. Form the components of (9) and solve the equation for α^*.
   - **Expected quantity awarded**. Using the simulation draws, approximate the expected quantity awarded function

$$H(p, q|\alpha_j) = \mathbb{E}_{\theta_{-i}}\left[Q_t(p, q|b(\theta_{-i}|\alpha_{-i}, r))\right]. \tag{17}$$

- For each set of type draws, calculate bids using the constrained strategy function.
- Use these constrained bids to approximate residual demand.

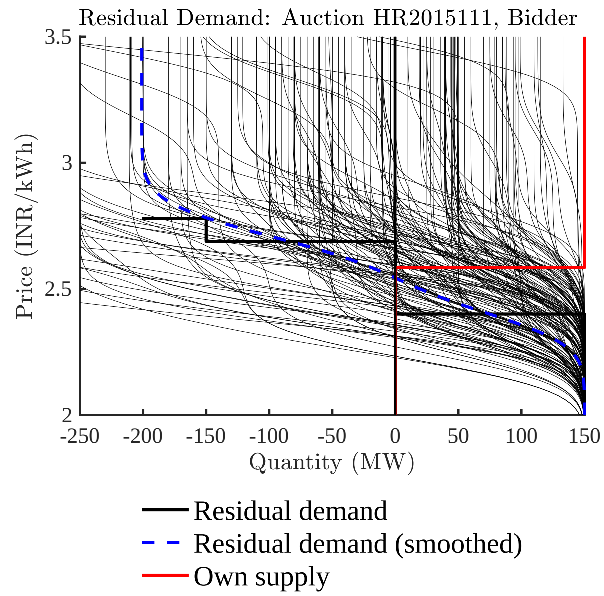
- **First-order condition**. Form the first-order condition (9) using the simulation draws.

$$\frac{1}{S}\sum_{s=1}^{S}\left[(r-c_{it}^{s})\left(b(c_{it}^{s},q_{it}^{s}|\alpha,r)-\frac{c_{it}^{s}}{(1-\delta_{s})}+\frac{H_{t}(b(c_{it}^{s},q_{it}^{s}|\alpha,r),q_{i}^{s}|\alpha)}{\frac{\partial H_{t}(b(c_{it}^{s},q_{it}^{s}|\alpha,r),q_{i}^{s}|\alpha)}{\partial b(c_{it}^{s},q_{it}^{s}|\alpha,r)}}\right)\right] \quad = \quad 0.$$

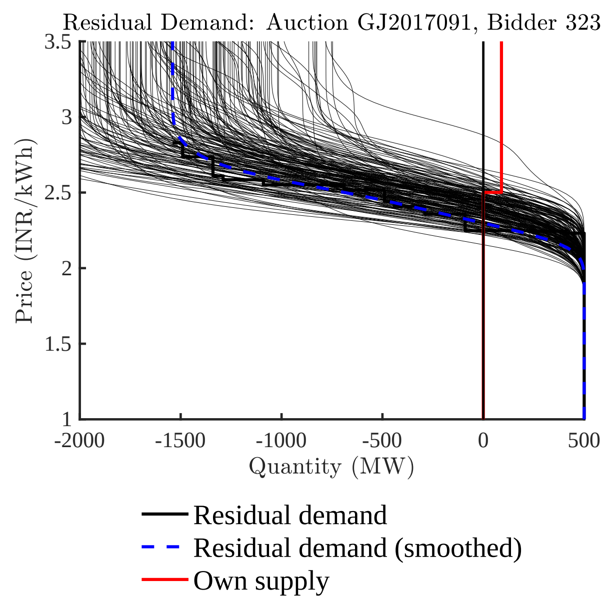
The components of this condition are calculated as

- $(r-c_{it}^{s})$ using the type drawn for θ_{i}^{s} and bid function.
- $\frac{c_{it}^{s}}{(1-\delta_{s})}$ using the type drawn for θ_{i}^{s} and risk.
- $H_{t}(b(c_{it}^{s},q_{it}^{s}|\alpha,r),q_{i}^{s}|\alpha)$ and its derivative. Using they type drawn for θ_{i}^{s}, bid function, and simulation of quantity awarded over rivals' types.

Figure C4: Simulation of residual demand



A. Haryana 2015 (150 MW)



B. Gujarat 2017 (500 MW)

The figures show the simulation of residual demand for two bidders in two different auctions. Within each panel, the red, weakly increasing step function is the bidder's own supply curve. The black, decreasing step function is the actual realization of residual demand in the auction for a certain bidder. The dashed blue curve is a kernel-smoothed version of that residual demand realization using a Gaussian kernel with bandwidth INR 0.10 per kWh. The thin solid lines are alternative realizations of residual demand that are drawn in simulations. When calculating the derivative of residual demand at the clearing price on each iteration, I smooth both the residual demand and the own-supply curve.