Holding Up Green Energy: Counterparty Risk in the Indian Solar Power Market*

Nicholas Ryan†

August 19, 2022

Abstract

This paper studies how the risk of hold-up affects procurement. I use data on the universe of solar power auctions in India. The Indian context allows clean estimates of counterparty risk, because solar plants set up in the same states, by the same firms, are procured in auctions intermediated by either risky states themselves or the trusted central government. I find that the counterparty risk of an average state increases solar prices by 10%. This risk premium sharply reduces investment, because demand for green energy is elastic. Contract intermediation by the central government eliminates the counterparty risk premium.

*Thank you to Rahul Banerjee, Sushanta Chatterjee, Jose Miguel Abito, Natalia Fabra, Phil Haile, Bård Harstad, Jonas Hjort, Paul Joskow, Michael Kremer, Benjamin Olken, Katja Seim, Joseph Shapiro and Christopher Woodruff for helpful comments and discussions. Thank you to seminar and conference participants at Berkeley/Harvard/Yale EEE, Carnegie Mellon, Colorado, Columbia, Chicago, Duke, HKUST, IIM Bangalore, Indiana, Michigan, UCLA, ASSA, NBER DEV, NBER IO, 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.

†Department of Economics, Yale University, Box 208269, New Haven, CT 06520-8269 (e-mail: nicholas.ryan@yale.edu.)

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 likely scale and pace of this green energy revolution are unfathomable. 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. As countries grow, green energy serves both to head off increases in emissions and to meet rapid growth in energy demand (Wolfram, Shelef and Gertler, 2012; EIA, 2019). 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 is still growing, to meet rising demand (Panel B).

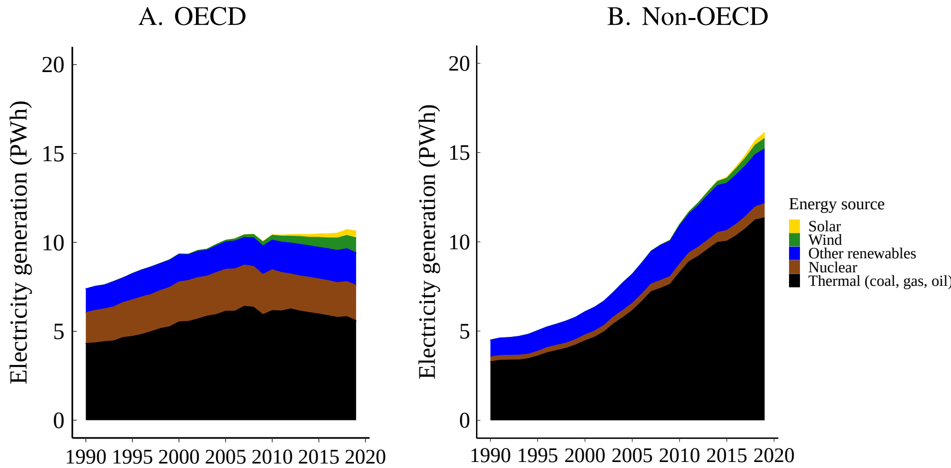
I conjecture that hold-up—foregone investment due to contractual risk—might hinder the green energy revolution. Weak contract enforcement leads developing countries to produce less in industries that use relationship-specific assets (Nunn, 2007). Investments in power generation are highly relationship-specific (Joskow, 1987). Once a power plant is built, it loses bargaining power in input and output markets. The grid may host few buyers, or only one: a state-run utility. Together, weak contract enforcement and this asset specificity create hold-up risk (Williamson, 1975; Klein, Crawford and Alchian, 1978). Rapid technological progress in renewable energy may exacerbate the hold-up problem by pulling down costs over time. Buyers of green energy can always buy it more cheaply from new projects than by honoring 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. This risk has caused major renewable energy auctions around the world to be cancelled and contracts to be thrown out.[1] When counterparty 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 solar power 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

[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).

Figure 1: Growth in electricity generation by energy source



This figure shows electricity generation by energy source over time. The series are constructed from the "Our World in Data" series on electricity. 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 in the bottom (black) segment emits greenhouse gases.

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 (see Section 2). 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 firms from signing 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 solar firms from state 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. Appendix Figure B2 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 (Section 4). 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 two 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 as large as the mean mark-up of bid prices over cost among all bidders (11%) and two-thirds as large as the mean mark-up among winning bidders (16%). Alternatively, we can benchmark the risk premium against the effect of varying solar energy 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 downwards by a massive 2.4 standard deviations in the distribution of solar irradiance across bids. By either benchmark, risk is a major determinant of prices.

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.

A range of additional analysis supports the interpretation that counterparty risk causes higher solar prices. I use a second data set, on solar contracts, rather than auction bids, to replicate closely and to extend the first two main findings on counterparty risk. The contract data allow especially rich specifications with district and firm fixed effects, to control for unobserved determinants of solar production costs, and yield estimates of the counterparty risk premium similar to those from auction bids. Firms may face high risk from states with shaky finances, even if those states do not *deliberately* hold them up. I test for the importance of strategic default, as opposed to exogenous

[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).

risk, using differences in bargaining power across firms. 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 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.

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, price caps on the bids at solar power auctions, to try to hold prices down. During the same period, the capacity awarded at auction fell far short of what buyers sought, and the solar boom markedly slowed (Figure 4).

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 (Section 5). The model describes optimal bidding in a multi-unit procurement auction using the share auction framework (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 counterparty risk they face in a given state. The distributions of costs and counterparty risks are separately identified in the model under the plausible assumption that central auctions pose no counterparty risk. I estimate the primitive distribution of bidder costs by inferring costs from the bid data and modeled optimal mark-ups (Kang and Puller, 2008; Hortaçsu and McAdams, 2010) (Section 6).

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 solving for the equilibrium prices and quantities that result. A ceiling price reduces participation from potential solar bidders with costs too high to 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 supply curve faced by a procuring state shifts inwards sharply the higher is that state's risk (Figure 7, panel B). The all-India solar supply curve would shift inwards by 20% (37%) if the whole country moved from the level of risk of the central government to that of an average-risk (high-risk) state. These large differences in supply arise due to risk alone, as the model counterfactuals hold constant factors like the costs of solar generation and market structure.

I apply the model to study the foregone solar investment caused by the widespread adoption of ceiling prices from 2018 to 2020 (Figure 4) (Section 7). 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 and the remaining bidders in an auction respond by raising their mark-ups, 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 are at a disadvantage in public procurement. The prospect of a state default creates counterparty risk. Counterparty risk raises bid prices. When state demand is elastic, this risk feeds back to reduce investment. While I find that central intermediation mutes the risk premium in the Indian solar market, countries with less sophisticated institutions or still higher risk may not be able to follow this example. Power demand is growing fastest in developing countries with poor credit.[3] Section 8 discusses whether contract intermediation like that in India could be replicated elsewhere.

The main contribution of this paper is to show the importance of hold-up risk in a vital emerging market. It has proven hard empirically to separate hold-up risk from other, unobservable factors that affect firm costs.[4] In my context, contract intermediation provides policy variation in counterparty risk for firms producing the same good in the same places. This institution therefore allows for the estimation of counterparty risk conditional on the costs of production. The approach of studying contracting in a fairly homogenous industry follows in the tradition of Joskow's canonical validation of transactions cost theory.[5]

This main contribution connects the paper to work in development economics, energy economics and industrial organization. I contribute to the literature in development economics on

[3]The countries in the bottom quartile of the growth rate of electricity consumption have an average sovereign credit rating of A3, "Upper medium grade" (per Moody's). The countries in the top quartile have an average rating in the range of B2, "Highly speculative." Of 21 countries in sub-Saharan Africa rated by Moody's, 19 have sovereign credit ratings below that of India.

[4]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 or the skill of the labor force, do not covary with contract enforcement.

[5]Joskow (1987) finds that greater asset specificity for coal power plants 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 contracting is costly or contracts are not strictly enforced (Ryan, 2020).

contract enforcement. A main theme of the literature has been how relational contracts between firms may substitute for formal contracts (McMillan and Woodruff, 1999*b*,*a*; Banerjee and Duflo, 2000; Macchiavello and Morjaria, 2015, 2021). The present analysis is most closely related to work on formal contracting that measures the economic costs of weak contract enforcement, renegotiation or default (Laeven and Woodruff, 2007; van Benthem and Stroebel, 2013; Blouin and Machiavello, 2019; Ryan, 2020). I offer an unusually direct, revealed preference estimate of the importance of hold-up risk.

The paper also contributes to a fast-growing literature on the green energy revolution. Most research on investment in renewable energy has focused on developed economies and particularly on household solar adoption (van Benthem, Gillingham and Sweeney, 2008; Borenstein, 2012; Bollinger and Gillingham, 2012; Borenstein, 2017; van Benthem and Pless, 2019). A second major line of research concerns how wholesale power markets adapt to intermittent renewable generation (Joskow, 2011; Cullen, 2013; Novan, 2015; Gowrisankaran, Reynolds and Samano, 2016; Ito and Reguant, 2016; Bushnell and Novan, 2021; Butters, Dorsey and Gowrisankaran, 2021; Gonzales, Ito and Reguant, 2022). Fabra and Montero (forthcoming) study the optimal design of renewable procurement auctions when there are multiple, competing green energy technologies of uncertain cost. There is relatively little research on renewable energy in developing countries, despite a global surge in renewable investment.[6] One branch of research, parallel to the US literature on household solar adoption, studies household investment in solar micro-grids as a substitute for grid power (Fowlie et al., 2019; Burgess et al., 2020). This paper adds to the literature by linking green energy supply to contracting institutions. The results show that counterparty risk should be taken as a fundamental determinant of green energy prices in developing countries.

Finally, this paper relates to the industrial organization literature on procurement. Tadelis (2012) studies mechanism choice in procurement and calls explicitly for more research on procurement under incomplete contracts. The present paper is closest to a 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 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. A state's public procurement costs will depend not only on supply side factors, like market structure and firm performance, but also on its own ability to commit.

[6] The surge has been driven mainly by huge falls in capital costs (IRENA, 2019*a*). Policy changes like a move from feed-in tariffs to procurement auctions may also have contributed to falling prices (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 prices.

2 Institutional context

2.1 Renewable energy policy in India

India has set ambitious goals for growth in renewable energy. In 2010, the Government of India launched the Jawaharlal Nehru National Solar Mission (JNNSM) "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. That year, under the Paris Climate Accord, India set an intended nationally-determined contribution of 100 GW of installed solar capacity and 60 GW of wind by 2022 (Ministry of Environment, Forest and Climate Change, 2015). At the time these targets were set, the utility-scale solar capacity in the US was 11 GW and in India merely 5 GW.

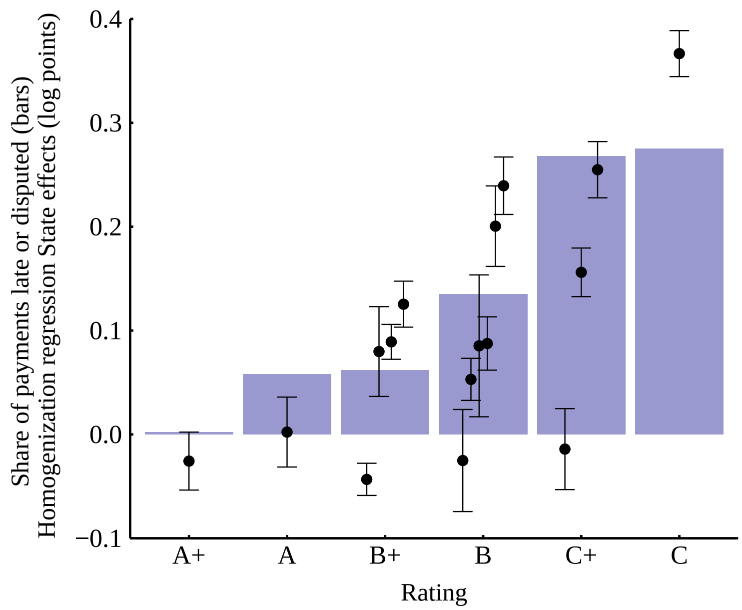
Investment in green energy raises an institutional tension between the central government and the various states. The central government has national and international goals in developing a renewable energy industry and reducing greenhouse gas emissions intensity, yet the central government does not 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 energy, 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.[7] 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.

2.2 Counterparty risk in the sale of power to state buyers

Renewable energy in India is sold only through long-term contracts, which bear 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). States have an incentive to default, because accumulating debt precipitates central gov-

[7] 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.

Figure 2: 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 bars show, 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 (Appendix A). The scattered points show the estimates of risk from the structural model of Section 5. Each point is the estimated state $\times$ state-run auction effects from the bid homogenization regression of log bids on auction characteristics, with a corresponding 95% confidence interval. The estimates therefore represent the estimated log difference in bid prices between a state run auction in a state of a given risk and a central auction. When there are multiple states of the same risk, I have added some horizontal spacing so that each state effect is visible. These model estimates are derived from bid prices without reference to the non-payment data, shown by the bars, that are used to validate the rating letter grades.

ernment bailouts, including, most recently, in 2020, 2015, 2012 and 2002. The cycle of debt accumulation and bailouts has continued in spite of structural and regulatory reforms (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 2 plots the mean share of payments from state distribution companies to generators that are late or in dispute, shown by the bars, against the state distribution company rating (the overlaid point estimates, from the model, will be discussed in Section 7). 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.

2.3 Specificity of solar investments

Firms selling to these risky state counterparties face hold-up risk because the value of their solar plant is specific to the power purchase contract signed when their plant was set up. There is no secondary market for long-term solar contracts that would allow a firm to change the buyer of their power if trade with the original procurer breaks down after a plant is built.

I attribute the absence of this market to three factors. The first factor is common between solar and other sources of power on long-term contracts: regulatory barriers to trade make India's power market less-than-perfectly integrated.[8] The other two factors are specific to renewable energy. The second factor is 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. Third, solar plants have only fixed costs, which may make them especially vulnerable to hold-up. Once a project is built, the variable cost of supplying power is zero, which creates on ongoing variable surplus for the solar firm and an incentive for the buyer to renegotiate.[9] Only about half of the fixed costs are in the panels themselves (Appendix B, Table B5). Because the "balance of systems" costs (acquiring land, setting up the panels and connecting to the grid) are wholly site-specific, it is uneconomic to move a plant once built.

These factors give rise to the counterparty risk 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).[10] More common than outright *de jure* renegotiation are disputed or delayed payments for electricity (as in Appendix Figure 2). When state distribution companies do not pay, or delay payment, this reduces the present value of the contract's stream of payments for energy supply. Lenders that anticipate payment trouble may charge solar firms a higher interest rate, raising the cost of capital *ex ante*. Firms selling to a risky counterparty have to invest more equity or carry a cash buffer to make loan

[8]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. 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).

[9]Low variable costs are a distinguishing feature of renewable energy production. Solar and wind have zero variable costs, whereas thermal (coal and gas) plants have variable costs ranging from 20 to 50% of the total cost of generation (Lazard, 2019; EIA, 2021). This range will vary with the type of generation, interest rates and the price of fuel.

[10]Bihar provides a well-documented example. 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.

payments when their receivable energy payments are delayed (India Ratings & Research, 2019). Counterparty risk may thus reduce the expected return on solar investments.

2.4 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 selling firms 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").[11] Both state and central auctions use a multi-unit discriminatory auction format. 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 central government's role in central auctions is purely *intermediation*. 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, with plants in many of the same places, as for state auctions. Appendix Figure B2 shows an example of two solar plants in the same district of Andhra Pradesh. The plants are nearby and have a similar scale and physical layout, but one plant was procured via a state auction and the other via a central auction.

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. The central obligation to pay has been tested, and upheld, on regulatory review.[12] Market observers attribute low solar prices to this guarantee: "It is understood that this

[11] 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 a 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.

[12] The guarantee was briefly, at the start of intermediation, implicit: firms expected SECI would pay because it is owned by the central government and exists to implement a high-priority policy (Rustagi and Chadha, 2020). 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 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

fall in solar tariffs is the result of [a] 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 center and the states run auctions in parallel and do not coordinate auctions with each other, or even plan their own schedules much in advance (Rustagi and Chadha, 2020). The central government does not choose to intermediate certain auctions out of some pre-determined schedule. The main motive of the center is to run enough auctions to make progress towards national capacity targets (Prateek, 2018). The "completely haphazard" and overlapping nature of auction schedules from different procurers has led to complaints from project developers (Saurabh, 2018). Notwithstanding this lack of coordination, because states can choose whether to run their own auctions, there could be auction selection: risky states may run fewer of their own auctions, to procure power through intermediated auctions instead. Consistent with some degree of selection into who runs auctions, I show that risky states have tended to intermediate more of their procurement in recent years (see Section 7 and Appendix B). Section 4.3 explains why such selection does not bias my estimates of counterparty risk.

3 Data and summary statistics

This section introduces the data 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.[13] Utility-scale solar is the dominant form of renewable energy investment in India and comprises 93% of solar capacity installed (circa 2019) (MNRE, 2020). 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

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*).

[13] 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.

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.[14]

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 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 either auctions or negotiated contracts (Section 2). 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). 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+. The grade is assigned on the basis of an index of the distribution companies' financial health, in order to "facilitate realistic assessment by Banks/FIs [financial institutions] of the risks associated with lending exposures to various state distribution utilities" (Ministry of Power, 2013, see Appendix A.3 for details). 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 distribution companies' mean letter grade from the Ministry of Power in 2012, at the start of the auction sample.[15] I define counterparty risk as:

$$CounterpartyRisk_s = \frac{4.3 - GPA_s}{4.3 - \overline{GPA_s}}. \quad (1)$$

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 2, discussed above, validates this risk measure by showing that higher risk (a lower letter grade) is associated with more late or disputed payments.

[14] 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).

[15] When states have multiple distribution companies, I use the average rating across discoms within a state to represent that state. It is appropriate to think of risk as varying at the state level because states own all the public distribution companies and indirectly determine, through common state holding companies and appointments to regulatory commissions, what contracts they will honor.

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.

There are two main findings with respect to the auction data. First, there are no significant differences in participation and competitiveness between state and central auctions. Central auctions have fewer bidders on average than state auctions and seek to procure somewhat more capacity (panel A). This apparently higher participation in state auctions turns out to be an artifact of more state auctions being run earlier in the sample, when auctions had more bidders. After controlling for the year of an auction, there are no significant differences in the number of bidders, whether an auction is over-subscribed, or competitiveness (HHI of offered bids) between state and central auctions (see Appendix B, Table B4). Since auctions are for multiple units of capacity, the number of bidders is a misleading measure of competition; an auction with many bidders may not be very competitive, if only one or two of them offer most of the capacity. I therefore measure competitiveness with the Hirschman-Herfindahl Index (HHI) for the concentration of offered capacity across bidders at auction, which is similar for central (0.34) and state (0.30) auctions. Second, while the auction types differ in scale, on average, the distributions of auction size heavily overlap (Appendix B). 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). 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).

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 that differ from 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 3 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

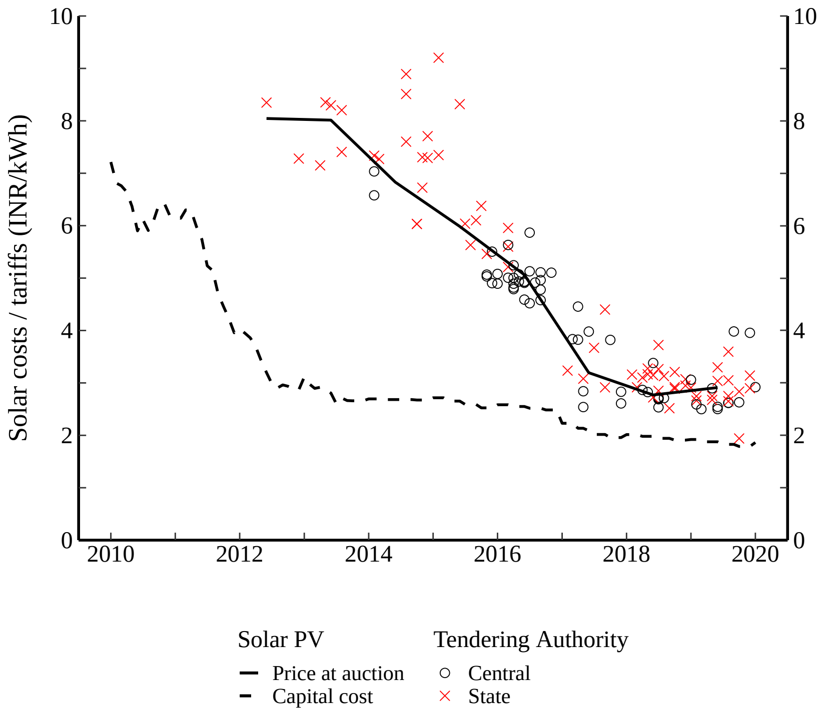
Table 1: Summary statistics on solar auctions and solar power projects

	Mean (1)	Std. dev (2)	p25 (3)	Median (4)	p75 (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-subscribed (=1)	0.91	0.29	1	1	1	309
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-subscribed (=1)	0.92	0.27	1	1	1	149
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-subscribed (=1)	0.89	0.31	1	1	1	160
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 solar power auctions and projects in India. Panel A reports summary statistics at the auction level. Panel B reports data at the bid-level. Panel C summarizes the data on solar projects, which may have been allocated either at auction or through bilateral negotiations.

solid line represents the capacity-weighted average annual price of solar electricity at auction. The scattered points represent the capacity-weighted average prices of each auction contributing to the annual average. The cross (red $\times$) markers show auctions run by states and the circle (black $\circ$) markers show auctions run by central government agencies.

Figure 3: Solar auction clearing prices by intermediation

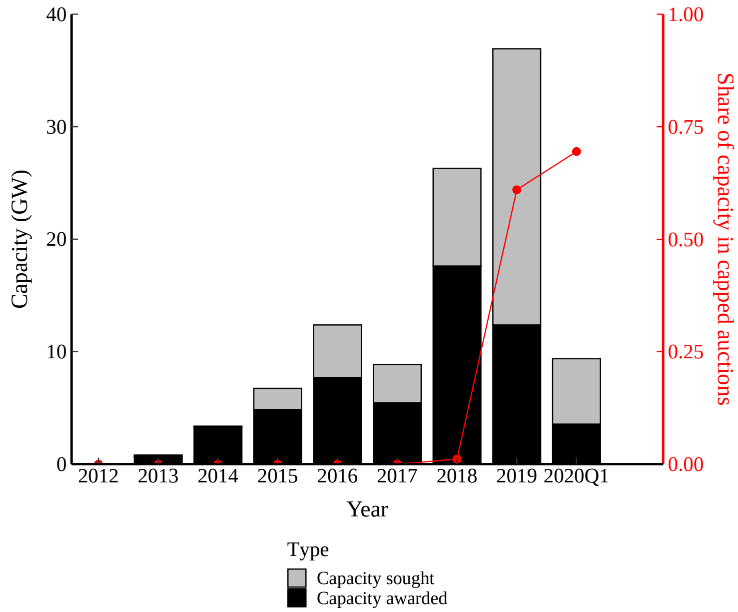


This figure shows global solar capital costs and solar prices for large scale projects in India over time. The dashed line represents the capital costs of solar panels per kWh of energy produced (IRENA, 2019*b*). The capital costs per unit of capacity (USD per Watt) have been converted to capital costs 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. The $\times$ (red) markers show auctions run by states and the $\circ$ (black) 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 ($\circ$ 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. Within any given year, the lowest prices are nearly all in central auctions, while state auctions yield middling or high prices.

Figure 4: Quantity sought and quantity awarded over time



The figure shows the capacity sought (total bar height) and capacity awarded (black bar segment) at auction by year, measured 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.

3.4 Growth of the solar market and the ceiling price policy

The revolutions of Figure 3 led an historic solar boom. Figure 4 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 3), states and the central government sought to limit the admissible prices for energy from solar projects. The solid red line in Figure 4, 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 whether the price of solar power depends on the counterparty risk of the buyer.

4.1 Counterparty risk and solar bids at auction

We start by studying the prices bid in different kinds of auctions. A first specification for bidder i's log bid in auction t in state s and year y is

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

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 3. The coefficient on the central auction dummy in column 1 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 0.22 $kWh/m^2 - day$. A one standard deviation increase in irradiance decreases bid prices by 6% ($= 0.22 \times -0.29 \times 100$). 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:

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

This specification resembles (2), but adds $CounterpartyRisk_s$ (1) and the interaction of counterparty risk with an indicator $State_t = 1 - Central_t$ for whether an auction is state-run (not intermediated). The coefficient β_3 therefore measures the baseline effect of state risk, in centrally-

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 (kWh/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 × Counterparty risk			0.15^{***}	0.11^{***}
			(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 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 ($kWh/m^2 - day$). The counterparty risk variable is a normalized version of the Ministry of Power rating for discoms in equation (1). 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 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 show 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.[16]

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. This result and the fact that participation is the same in comparable state and central auctions (Appendix Table B4) suggest that the risk premium does not arise from differences in competitiveness or firm selection in intermediated auctions. 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. 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 mark-up for all bids is thus very similar to the counterparty risk premium in an average state; the effect of counterparty risk on bids is roughly the same as the effect of imperfect competition. Alternately, we can benchmark the risk effect against the estimated effect of solar irradiance on bid prices. The increase in prices due to the risk of an average state is the same as that from moving a solar plant downwards by a massive 2.4 standard deviations in the distribution of solar irradiance across bids.[17]

The third finding in Table 2 is that central intermediation has no effect on prices in low-risk states. 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).

[16]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 B2, columns 3 and 4); and in the contract, as opposed to the auction data (Table 3, columns 3 and 4).

[17]The irradiance coefficient in Table 2, column 3 is $\hat{\beta}_{Irr} = -0.19$ log points per $kWh/m^2 - day$ and the standard deviation of irradiance across bids is 0.22 $kWh/m^2 - day$. Therefore the counterparty risk coefficient equals $0.102/(0.19 \times 0.22) = 2.4$ standard deviations of irradiance. Solar bids and projects are selected for sunnier locations. The counterparty risk effect equals 1.3 standard deviations in terms of the variation in irradiance across all Indian districts (0.40 $kWh/m^2 - day$).

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 or participation 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. This extension may be valuable for two reasons. First, it provides a chance to validate the auction bidding results, in a separate data set on the prices of contracts signed after an auction. Second, the projects data include both contracts awarded at auction and contracts set in bilateral negotiations. It therefore allows to test for a counterparty risk premium in bilateral contract prices. I expect bilateral contracts should have such a risk premium, since they are not intermediated, but signed directly with the states.

Table 3 presents the results in a similar format to that in Table 2. Because the sample includes state bilateral contracts, all specifications now 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. Columns 1 to 5 include controls for state heterogeneity directly and columns 6 to 10 omit these controls in favor of state fixed effects.

There are two findings from the contract data. First, the complete pattern of risk and intermediation effects estimated in contract prices closely replicates that in auction bids. I find that: (i) contracts procured in central auctions have lower prices than state contracts (column 1); (ii) contracts procured by the state have higher prices in states with higher counterparty risk (column 3); (iii) conditional on explicit controls for risk, including interactions with intermediation, there is no direct effect of central auctions on prices in a state of zero risk (column 4); (iv) the estimated risk premium is similar with firm fixed effects (column 5).

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

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)	(7)	(8)	(9)	(10)
Central auction (=1)	-0.15^{***}	-0.15^{***}	0.058	-0.041	-0.0078	0.100^{*}	0.10	0.068	0.083	0.14
	(0.038)	(0.037)	(0.069)	(0.081)	(0.089)	(0.051)	(0.074)	(0.054)	(0.080)	(0.098)
State bilateral (=1)	0.093^{*}	0.13^{***}	0.14^{***}	-0.034	-0.054	0.19^{***}	0.18^{***}	0.13^{**}	0.14^{*}	0.055
	(0.048)	(0.038)	(0.038)	(0.081)	(0.082)	(0.040)	(0.043)	(0.058)	(0.078)	(0.099)
Solar irradiance (kWh/m^2)	-0.28^{***}	-0.23^{***}	-0.20^{**}	-0.20^{***}	-0.23^{***}					
	(0.081)	(0.075)	(0.075)	(0.068)	(0.082)					
Counterparty risk		0.12^{***}	-0.055	-0.054	-0.060					
		(0.042)	(0.047)	(0.046)	(0.043)					
State run			0.23^{***}			0.24^{***}	0.23^{***}			
× Counterparty risk			(0.060)			(0.046)	(0.067)			
State auction				0.13^{*}	0.14^{*}			0.20^{***}	0.21^{***}	0.22^{**}
× Counterparty risk				(0.073)	(0.077)			(0.053)	(0.078)	(0.10)
State bilateral				0.33^{***}	0.30^{***}			0.27^{***}	0.25^{***}	0.30^{***}
× Counterparty risk				(0.062)	(0.052)			(0.044)	(0.069)	(0.073)
Year effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Capacity deciles	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
State effects						*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
District effects							*Yes*		*Yes*	*Yes*
Firm effects					*Yes*					*Yes*
Mean dep. var	1.91	1.91	1.91	1.91	1.91	1.91	1.91	1.91	1.91	1.91
R^2	0.87	0.88	0.89	0.90	0.96	0.92	0.95	0.92	0.95	0.98
p-val H_0: no state risk			0.0045	0.087	0.066					
p-val H_0: mode risk equal				0.014	0.035			0.11	0.53	0.39
Projects	1028	1028	1028	1028	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 data include all contract prices for solar power procured through centrally-intermediated auctions (Central auction (= 1)), state auctions (the omitted category) and state bilateral contracts (State bilateral (= 1)). 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 as specified in equation (1): a value of zero represents no risk and a value of one the average level of state risk. 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. All standard errors are clustered at the auction level and statistical significance at certain thresholds is indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

these procurement modes, the column 4 and 5 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 4). The risk coefficient in contracts awarded for state auctions is 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 4 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 5).

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 that the increased competitiveness of auctions lowers prices, especially in risky states. This benefit of auctions over negotiations is expected in the procurement of a 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 Interpretation of the estimated counterparty risk premium

The results in Tables 2 and 3 argue that bidders increase their offered prices when exposed to state counterparty risk. Here I consider alternative interpretations of these results. I do not find the results consistent with alternatives like selection into intermediation or unobserved differences between central and state auctions in project costs or in exposure to corruption.

Selection into intermediation.—The empirical strategy is based on a difference in differences across central and state-run auctions in more versus less risky states. Selection by risky states into running intermediated auctions would not bias my estimates, because of the added contrast between state-run and central auctions, conditional on risk. Selection could reduce the power of my empirical strategy. If few risky states chose to run their own auctions, prices in the remaining auctions, in low-risk states, may not much differ between central and state auctions, falsely suggesting that risk is not important because of a lack of variation in risk. This concern does not appear borne out since states of many risk levels run state auctions (Appendix B). My estimates of the counterparty risk premium are therefore reasonably precise (Table 2).

Omitted determinants of cost.—The counterparty risk premium is estimated from the interaction of higher state risk and the absence of intermediation. 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, if bidders in central auctions had better access to infrastructure, not on average, but specifically within risky states. There is no *a priori* evidence of such differential treatment; rather, firms bidding in state and central auctions have similar siting options and infrastructure (as in Appendix Figure B2). In the project data, the location of each plant is observed down to the district level, making it possible systematically to test this alternative hypothesis that the estimated risk premium is due to unobserved cost heterogeneity.

Table 3, columns 6 to 10 use the project location data to replace state-level controls with state- and district-level fixed effects. Because counterparty risk is measured at the state level, the specifications drop the main effect of counterparty risk and state-level controls. I find a pattern of results *within* state, district and firm that closely replicates that in columns 1 to 5: (i) central auctions have lower prices than state auctions (not reported); (ii) bilateral contracts have higher prices than state auctions (column 6); (iii) conditional on controls for risk, the prices in central auctions are not statistically different from the prices in state auctions (columns 8 and 9); (iv) the prices in state auctions increase relative to the prices of central auctions in states of higher risk (columns 8 and 9); (v) the prices in state bilateral contracts increase relative to the prices of central auctions in states of higher risk (columns 8 and 9). The estimated counterparty risk premium is practically invariant to whether I control for state fixed effects, district fixed effects, or district and firm fixed effects (compare across columns from columns 6 to 7 or 8 to 9 and 10, where 7 and 9 both include 223 district effects and 10 adds 441 firm effects.). The magnitude of the counterparty risk premium is similar to, or perhaps slightly larger than, that estimated with state-level controls.[18]

This additional evidence argues strongly against attributing the estimated counterparty risk premium to unobserved heterogeneity in cost. The specifications with state and district effects compare contract prices for solar power plants within the same district and the same firm. The location of a solar plant dictates solar irradiance and many of its input costs, such as the price of land and access to transmission. If it were the case that bidders in central auctions had access to unobservably lower-cost sites, specifically in risky states, we would expect the inclusion of district fixed effects for the location of each solar plant to attenuate the estimated risk premium. Observable factors are powerful predictors of solar prices: the R^2 of the regression with both district and firm fixed effects reaches 0.98 (Table 3, column 10). Yet I find no evidence of selection

[18]For example, in the column 9 estimates, the counterparty risk premium in a state auction is 0.21 (0.078) log points for a state of average risk, as compared to 0.13 log points in column 4, and 0.25 (0.069) log points in a bilateral contract, as compared to 0.33 log points in column 4.

into intermediation at the plant level on observables, such as district or firm fixed effects, that determine the prices of solar contracts.

Corruption.—Large infrastructure projects like solar plants may have to offer kickbacks or bribes to move a project along (though I have found no specific reports to this effect in the context of the Indian solar industry). Such side-payments would increase project costs and therefore bids. The analysis suggests that corruption varying across states is unlikely to account for my results. Land acquisition is, by far, the greatest obstacle to getting solar plants built (Kumar and Thapar, 2017). The side payments that would be envisioned in response—such as in land deals, or in securing environmental clearance—are based on where a project is built. This kind of payment would, like other cost-based factors, be common across central and state auctions in the same place, and would not generate a pattern of higher bids for projects in risky states only when procured via state auctions. Differential corruption in state auctions in the procurement process itself is also unlikely, for procurement via auctions, because there is no discretion in the contract award; bids are opened publicly and the contract awarded to the lowest bidders that meet the capacity sought.

Strategic versus exogenous default.—Solar prices are higher when bidders are exposed to risk. This finding does not necessarily imply that risk arises due to strategic default. 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 protect itself against hold-up by threatening to withhold thermal power if a state attempts to renegotiate renewable power prices.

The main result of Appendix Table B3 is that firms with thermal capacity in the state where a given auction is held do not bid a risk premium in that auction. I interpret this result as evidence that thermal capacity changes a firm's bargaining position. If risk were purely an exogenous shock that differed across states, then we would not expect differential risk effects for firms with and without thermal capacity, since all would be subject to the same shock.

4.4 Implications of counterparty risk for efficiency

Does the counterparty risk premium bear on economic efficiency? Wholesale power demand is often thought of as inelastic in aggregate. If demand for green energy were inelastic, the risk premium could be viewed only as an advance transfer from states to firms, to compensate for later default.

In the Indian solar market, demand for green energy is best thought of as elastic to some extent. States trade-off green energy against other sources of power. States explicitly declared their demand to be elastic by setting ceiling prices, maximum allowable bid prices, for some solar auctions during my sample period. When ceiling prices were introduced, market observers worried that this policy would stifle solar investment in states with higher costs.[19] Figure 4 shows how auctions awarded a lesser share of the capacity they sought after the imposition of ceiling tariffs.

The policy of setting ceiling prices creates a trade-off such that counterparty risk can have real effects on investment. The severity of this trade-off depends on the composition of bids. If bids have high mark-ups, then a ceiling price could lower bid prices, and procurement costs, without scaring off higher-cost bidders. If bids are instead driven mainly by bidder costs and risk, then a ceiling price will deter auction participation and reduce investment, particularly in risky states. A given state cannot precisely forecast the effects of imposing a ceiling price without knowing what determines bid prices.

The second part of the empirical analysis, beginning in the next section, will introduce and estimate a model to separate observed bids into costs, risk and mark-ups. The model estimates are then used 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 (Wilson, 1979). The main distinguishing feature of the model is that bidders care about the counterparty risk of the procurer.

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 identi-

[19] Raj Prabhu, the CEO of Mercom Capital Group, 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).

cally 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 (INR per kWh). Idiosyncratic costs include factors like the cost of planning and financing a project, acquiring land, and connecting the plant to the transmission network. The second component of the type is the project capacity in MW. Bidders are envisioned as having potential project sites of different sizes.

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.[20] 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

$$\Pi_{it}(b_{it}, q_{it}) = q_{it}((1-\delta_s)b_{it} - c_{it}). \tag{4}$$

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.[21] A literal interpretation of this parameter is that firms expect delays in payment and outright default to decrease the present value of the revenue from a project by a share δ_s. More broadly, δ_s may also encompass other, hard-to-measure factors, such as higher financing costs in risky states or the costs 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

$$RD_t(p|\sigma_{-it}) \;=\; QD_t - \sum_{j \neq i} q_{jt} \mathbf{1}\left\{p \geq b_{jt}\right\}. \tag{5}$$

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

$$Q_t(p,q|\sigma_{-it}) = \begin{cases} 0 & \text{if } RD_t(p|\sigma_{-it}) \leq 0 \\ RD_t(p|\sigma_{-it}) & \text{if } 0 < RD_t(p|\sigma_{-it}) \leq q \\ q & \text{if } q < RD_t(p|\sigma_{-it}). \end{cases} \tag{6}$$

When i offers the marginal step in an auction, the quantity awarded will be rationed based on

[20] 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. Fabra and Llobet (forthcoming) show that this logic implies that bidders with capacity less than the total auction demand will not wish to withhold in the multi-unit auction. Bidders cannot increase their quantity with q_{it} fixed. Other work on multi-unit auctions makes an analogous assumption that valuations for quantities beyond those demanded are zero, such that bidder demand can be at most the quantity demanded in the data (Kang and Puller, 2008; Hortaçsu and McAdams, 2010).

[21] 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 B3, 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).

residual demand. We define a function for the expected quantity won with a given bid

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

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

$$b_{it} = \frac{c_{it}}{1-\delta_s} - \frac{H_t(b_{it},q_{it})}{\partial H_t(b_{it},q_{it})/\partial p}. \tag{7}$$

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 (7) for an optimal bid. The basic identification argument, 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 (7) 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 12).

Assumption 2. *The distribution of idiosyncratic costs c_{it}, conditional on auction-level observable characteristics, is the same in state and central auctions.*

The assumption is justified by the fact that solar plants procured in centrally-run auctions are nonetheless built in the same places, with the same technology, by the same project developers as plants procured in state-run auctions. 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. 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 to address in the empirical application of the model. First, I estimate the function that relates the expected quantity awarded to a firm's bid. Second, I control 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 so that its derivative H_p exists (Hortaçsu and Puller, 2008; Kang and Puller, 2008). See Appendix C for details.

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 3). 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. I assume that firm costs can be represented as

$$c_{it}(Z_t) = c_{i0}\Gamma(Z_t) = c_{i0}\exp(\gamma Z_t) \tag{8}$$

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

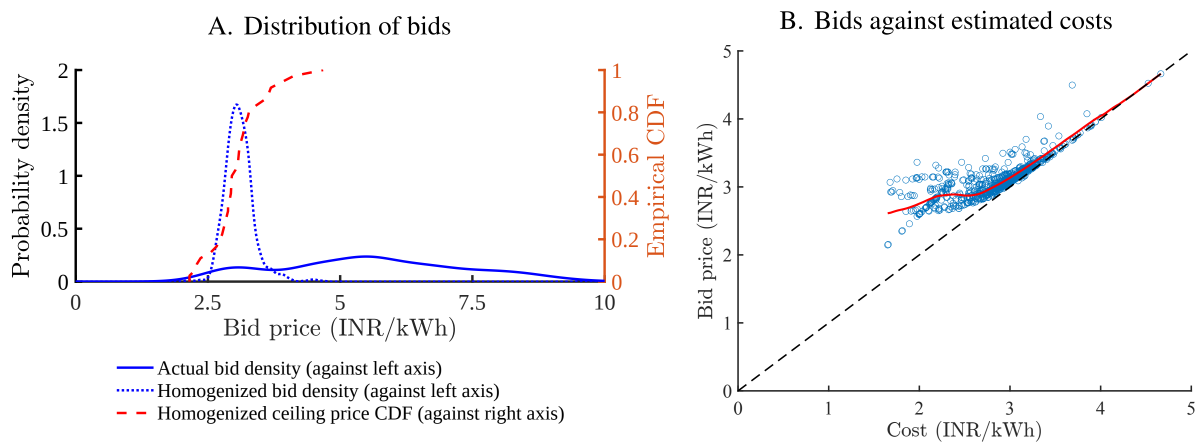
I prove that this multiplicatively separable cost structure passes through to multiplicatively separable equilibrium bids in the multi-unit auction (see Appendix C). Similar results are widely used in the literature on auctions for a single object (Haile, Hong and Shum, 2003; Athey and Haile, 2007; Bajari, Houghton and Tadelis, 2014). This homogenization 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 model are estimated using the same variation in state risk and intermediation underlying Tables 2 and 3.

6.2 Structural estimates of counterparty risk and costs

The estimation of solar costs proceeds in three steps: homogenization, residual demand simulation and inversion of the optimal bidding condition (7). I estimate the model on a sample of auctions without ceiling prices to recover the full distribution of costs absent selective entry.

Figure 5, panel A shows the distribution of homogenized bids. (Appendix C, Table C6 presents estimates of the regression for bid homogenization.) The solid line is the distribution of prices as bid. The dotted 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. To get a sense of whether ceiling prices are likely to bind, I overlay, on the homogenized bid distribution, the CDF of ceiling prices set by procurers in auctions with ceiling prices (dashed line

Figure 5: Model estimates of homogenized bids and costs



The figure shows the distributions of bids and estimated costs. Panel A compares the raw distribution of prices as bid (solid line) to the distribution of homogenized bids (dotted line) (both against the left axis). 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 year, scale and state fixed effects. The dashed line is the cumulative distribution function (CDF) for the distribution of homogenized ceiling prices at auction (against the right axis). Panel B plots homogenized bids against estimated productions costs. Each point represents the pair $(b_{ai}, \hat{c}_{ai})$ for a single bid. The vertical gap between the bid and the forty-five degree line is 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.

against right axis). Ceiling prices are extremely aggressive; more than half of ceiling prices are set below the mode of the homogenized bid distribution.

The homogenization regression yields estimates of state-specific risk. State risk is recovered from the coefficients on the interaction of state fixed effects with whether an auction is run by the state (and not intermediated). Figure 2, introduced above, compares the risk estimates from the model (as points) against state ratings (on the horizontal axis) and non-payment data (shown by the bars). The estimated risk effects, in log points, are steeply increasing as state risk increases from left to right, following the bars. Neither the state ratings nor the non-payment data are used in the estimation of the model. The model nonetheless recovers a counterparty risk profile that has a similar form, level and slope as the data on late and disputed payments.

With homogenized bids in hand, I simulate the possible residual demand curves in each auction for each bidder. The simulation of bid prices is unbiased with respect to actual bids and produces a plausible range of simulated residual demand curves for each bidder and auction (Appendix C). With the residual demand curves, I calculate the expected quantity awarded function and recover costs by inverting equation (7).

Figure 5, panel B 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.[22] The red solid line is a locally-smoothed estimate of the mean bid price at each level of estimated cost.

There are two main observations from the figure. First, the competitiveness of many auctions generates 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, 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).[23]

7 Counterfactuals: 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 4 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 vary in two dimensions: risk and the use of ceiling prices.

Counterfactual risk.—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

[22]Outlying bids, mainly 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 impose a bound on estimated costs to limit mark-ups to a maximum of 30%, which produces the pattern at the lower left in the figure, running diagonally upwards from left to right.

[23]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*).

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.

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 4). 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 my data contain auctions both with and without ceiling prices. Using the many auctions without ceiling prices, I resample from the distribution of equilibrium bids 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.

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 (Kang and Puller, 2008; Hortaçsu and McAdams, 2010).

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). In the auction game 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

$$b(c_{it}, q_{it}|\alpha_i, r) = \begin{cases} \varnothing & \text{if } c_{it} > r \\ c_{it} + \alpha_i(r - c_{it}) & \text{otherwise.} \end{cases} \quad (9)$$

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

$$V(\alpha_i) = \mathbb{E}_{\theta_i}\left[\left((1-\delta_s)b(c_{it}, q_{it}|\alpha_i, r) - c_{it}\right)H_t(b(c_{it}, q_{it}|\alpha_i, r), q_{it} \mid \alpha_{-i})\right]. \quad (10)$$

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

$$\mathbb{E}_{\theta_i}\left[(r - c_{it})\left(b(c_{it}, q_{it}|\alpha_i, r) - \frac{c_{it}}{(1-\delta_s)} + \frac{H_t(b(c_{it}, q_{it}|\alpha_i, r), q_{it} \mid \alpha_{-i})}{\frac{\partial H_t(b(c_{it}, q_{it}|\alpha_i, r), q_{it}|\alpha_{-i})}{\partial b(c_{it}, q_{it}|\alpha_i, r)}}\right)\right] = 0. \quad (11)$$

Equation (11), above, is the *ex ante* analog of the pointwise first-order condition (7) 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 (11) 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 (11) 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 (see Appendix C for details).

7.3 Counterfactual results

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

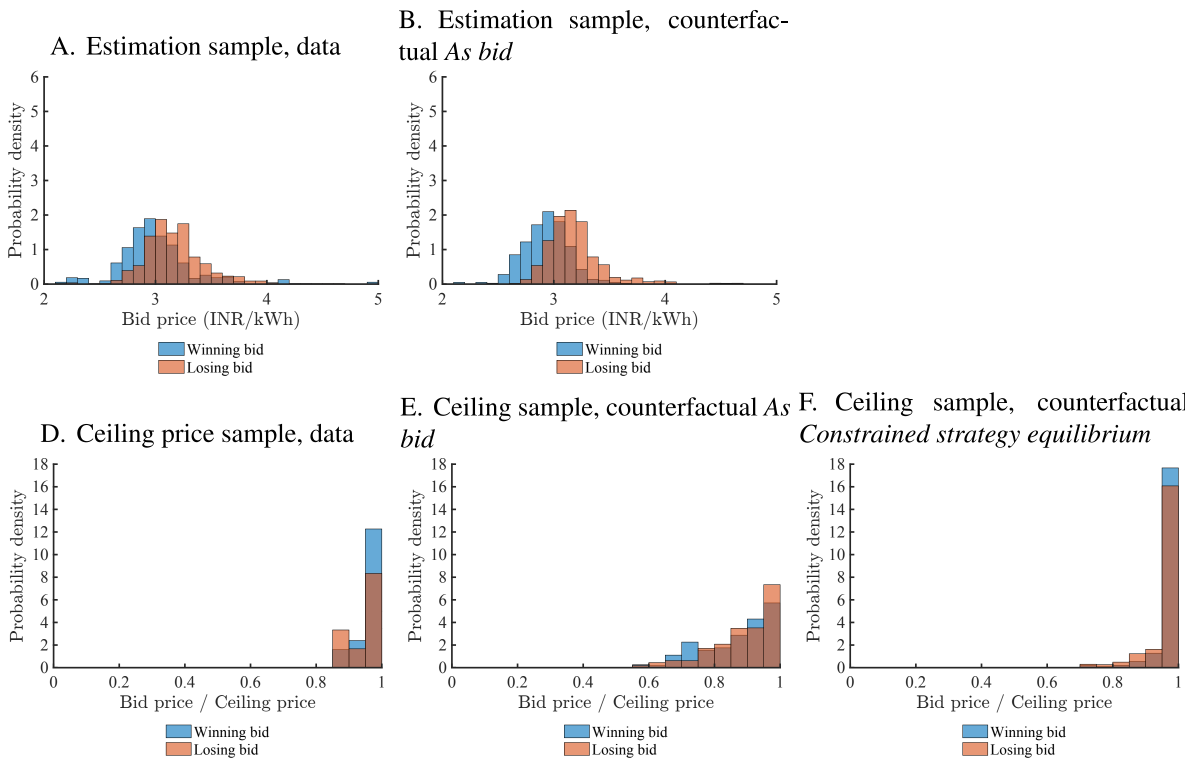
Figure 6 compares the distributions of bids to simulated counterfactual distributions of bids. The top row shows distributions in the full sample used for estimation of bidder costs, which is deliberately restricted to exclude auctions with ceilings. The bid prices are homogenized. The bottom row shows distributions in the ceiling sample of auctions that had ceiling prices applied in the data. In the ceiling 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).

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 (Figure 6, panel B as compared to 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 D). 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 E). 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 D).

Figure 6 validates the model's predictions for the distribution of bid prices. The constrained strategy equilibrium also produces a good fit to participation and quantities bid in auctions with ceiling prices (Appendix C, Table C7). 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 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. When a ceiling price is set, inframarginal 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. For this reason, ceiling prices may achieve smaller reductions in average solar prices

Figure 6: Validation of counterfactual simulations



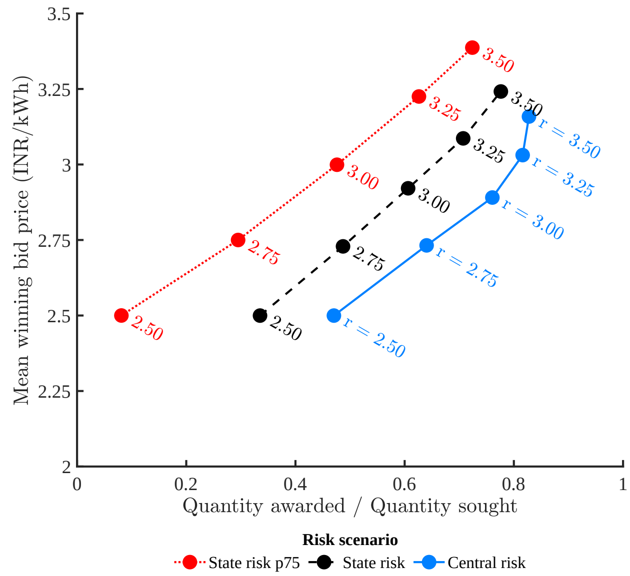
This figure validates the bid prices in counterfactual simulations of auctions against actual auction outcomes. Each panel shows a distribution of bid prices at auction. The top row shows distributions in the sample of auctions used for estimation. The bottom row of panels shows distributions in the sample of auctions with ceiling prices, for which bid prices are normalized as a fraction of the ceiling price. The column of panels differ in the strategies that generate bid prices. The strategies are described in Section 7. The left column shows the distribution of bid prices in the data. The middle column shows simulations of resampled bids *As bid*. The right column shows the distribution of bid prices in the *Constrained strategy equilibrium*.

than expected based upon the naïve assumption that bidders would not alter their strategies.

Counterfactual auction outcomes under varying risk.—This part projects auction outcomes under varying levels of ceiling prices and counterparty risk. Figure 7 shows counterfactual auction outcomes using the *Constrained strategy equilibrium*. 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. Each curve, traced out by changing the ceiling price policy, represents the aggregate supply curve for solar power in India that would face at different levels of procurer counterparty risk: central risk (solid), state risk (dashed) and high state risk (dotted).

The main result in Figure 7 is that the supply curves for higher-risk counterparties shift sharply

Figure 7: 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. All counterfactuals use the constrained strategy equilibrium. The three curves represent the equilibrium quantity awarded for each policy for different levels of counterparty risk: central (solid line at right), mean state (dashed at center) and p75 state (dotted at left). The modal ceiling price in the data is around INR 3 per kWh (see Figure 5, panel A).

inwards relative to what would be offered to the central government. 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 an average (high) level of risk therefore sacrifices 20% (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 (INR 2.5 per kWh), comparable to the equilibrium outcomes in the largest central auctions without ceilings, participation in high-risk states declines steeply, so that hardly any quantity is procured (solid red line).

These large differences in supply arise due to risk alone, as the model counterfactuals hold constant market structure, the distribution of costs and the procurement mechanism. Risk has a large effect on participation because procurers set very aggressive ceiling prices (Figure 5, panel A) and, given the level of competition in auctions, bidders with moderate or higher costs tend to offer small mark-ups (Figure 5, panel B).

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 4 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.

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).

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 4, 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

Table 4: 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
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. 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).

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 6).

Discussion.—Procuring states of higher risk face a sharp policy trade-off between holding down prices and reducing investment. 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 prices.

It may seem that there is an obvious policy change to solve this problem: do not set ceiling prices. Government intervention in energy markets through price controls can have large allocative costs.[24] India moved towards removing ceilings when 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. If this is the case, then removing ceiling prices will not change states' underlying demand but may lead instead to high-risk states running fewer auctions. I find some evidence that solar procurement in state-run auctions has indeed been shifting, slowly, towards lower-risk states over time (Appendix B, Figure B4).

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.

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 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

[24] For example, Davis and Kilian (2011) study the imposition of ceiling prices in the US residential market for natural gas, and estimate that price ceilings generated a deadweight loss of $3.6 billion per year for a 35-year period.

under alternate levels of its own counterparty risk. I find that ceiling prices reduced new solar power capacity by 16%, but hardly lowered procurement costs, because bidders respond to the lower participation in auctions with ceilings by raising their bids. Counterparty risk sharpens the trade-off between trying to hold down energy prices 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. 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 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.

It is hard to comprehend how much green energy investment is needed to slow global climate change while meeting growth in energy demand. A large share of this investment will come in developing countries, which are both less able to enforce contracts and more sensitive to energy prices. The problem of holding up green energy may therefore hinder much-needed investment in renewable energy around the world.

References

Acemoglu, Daron, Simon Johnson, and Todd Mitton. 2009. "Determinants of vertical integration: financial development and contracting costs." *The Journal of Finance*, 64(3): 1251–1290.

Aggarwal, Manu, and Arjun Dutt. 2018. "State of the Indian Renewable Energy Sector: Drivers, Risks and Opportunities." Council on Energy, Environment and Water.

Amirapu, Amrit. 2021. "Justice Delayed is Growth Denied: The Effect of Slow Courts on Relationship-Specific Industries in India." *Economic Development and Cultural Change*, 70(1).

Armantier, Olivier, Jean-Pierre Florens, and Jean-Francois Richard. 2008. "Approximation of Nash equilibria in Bayesian games." *Journal of Applied Econometrics*, 23(7): 965–981.

Athey, Susan, and Philip A Haile. 2007. "Nonparametric approaches to auctions." *Handbook of econometrics*, 6: 3847–3965.

Bajari, Patrick, and Steven Tadelis. 2001. "Incentives versus transaction costs: A theory of procurement contracts." *The Rand Journal of Economics*, 32(3): 387–407.

Bajari, Patrick, Robert McMillan, and Steven Tadelis. 2009. "Auctions versus negotiations in procurement: an empirical analysis." *The Journal of Law, Economics, & Organization*, 25(2): 372–399.

Bajari, Patrick, Stephanie Houghton, and Steven Tadelis. 2014. "Bidding for incomplete contracts: An empirical analysis of adaptation costs." *American Economic Review*, 104(4): 1288–1319.

Banerjee, Abhijit V, and Esther Duflo. 2000. "Reputation effects and the limits of contracting: A study of the Indian software industry." *The Quarterly Journal of Economics*, 115(3): 989–1017.

Bellini, Emiliano. 2019. "Turkey scraps 1 GW solar tender." PV Magazine.

van Benthem, Arthur, and Jacquelyn Pless. 2019. "Pass-through as a test for market power: An application to solar subsidies." *American Economic Journal: Applied Economics*, 11(4): 367–401.

van Benthem, Arthur, and Johannes Stroebel. 2013. "Resource extraction contracts under threat of expropriation: Theory and evidence." *Review of Economics and Statistics*, 95(5): 1622–1639.

van Benthem, Arthur, Kenneth Gillingham, and James Sweeney. 2008. "Learning-by-doing and the optimal solar policy in California." *The Energy Journal*, 29(3).

Bhattacharya, Vivek, Andrey Ordin, and James W Roberts. 2020. "Bidding and Drilling Under Uncertainty: An Empirical Analysis of Contingent Payment Auctions." *Mimeo, Northwestern University*.

Bihar Electricity Regulatory Commission. 2019. "Case No. 21/2019." Bihar Electricity Regulatory Commission.

Blouin, Arthur, and Rocco Machiavello. 2019. "Strategic Default in the International Coffee Market." *The Quarterly Journal of Economics*, 134(2): 895–951.

Boehm, Johannes, and Ezra Oberfield. 2020. "Misallocation in the Market for Inputs: Enforcement and the Organization of Production." *The Quarterly Journal of Economics*, 135(4): 2007–2058.

Bollinger, Bryan, and Kenneth Gillingham. 2012. "Peer effects in the diffusion of solar photovoltaic panels." *Marketing Science*, 31(6): 900–912.

Borenstein, Severin. 2012. "The private and public economics of renewable electricity generation." *Journal of Economic Perspectives*, 26(1): 67–92.

Borenstein, Severin. 2017. "Private net benefits of residential solar PV: The role of electricity tariffs, tax incentives, and rebates." *Journal of the Association of Environmental and Resource Economists*, 4(S1): S85–S122.

Bose, A.S., and S. Sarkar. 2019. "India's e-reverse auctions (2017–2018) for allocating renewable energy capacity: An evaluation." *Renewable and Sustainable Energy Reviews*, 112: 762 – 774.

Braud, Arnaud. 2018. "Guarantees Light the Way for Clean Energy through Renewable Auctions." World Bank.

Burgess, Robin, Michael Greenstone, Nicholas Ryan, and Anant Sudarshan. 2020. "Demand for Electricity on the Global Electrification Frontier." *Mimeo, Yale University*.

Bushnell, James, and Kevin Novan. 2021. "Setting with the Sun: The impacts of renewable energy on conventional generation." *Journal of the Association of Environmental and Resource Economists*, 8(4): 759–796.

Butters, R Andrew, Jackson Dorsey, and Gautam Gowrisankaran. 2021. "Soaking up the sun: Battery investment, renewable energy, and market equilibrium." National Bureau of Economic Research.

CERC. 2015. "Determination of Benchmark Capital Cost Norm for Solar PV power projects and Solar Thermal power projects applicable during FY 2015-16."

CERC. 2016. "Determination of Benchmark Capital Cost Norm for Solar PV power projects and

Solar Thermal power projects applicable during FY 2016-17."

CERC. 2020*a*. "Petition No. 127/MP/2019." *Central Electricity Regulatory Commission*.

CERC. 2020*b*. "Petition No. 299/MP/2019." *Central Electricity Regulatory Commission*.

CERC. 2020*c*. "Petition No. 388/MP/2019." *Central Electricity Regulatory Commission*.

Chandrasekaran, Kaavya. 2017. "After Uttar Pradesh, Jharkhand manages to renegotiate solar tariffs." The Economic Times.

Cullen, Joseph. 2013. "Measuring the environmental benefits of wind-generated electricity." *American Economic Journal: Economic Policy*, 5(4): 107–33.

Davis, Lucas W, and Lutz Kilian. 2011. "The allocative cost of price ceilings in the US residential market for natural gas." *Journal of Political Economy*, 119(2): 212–241.

Deign, Jason. 2019. "Industry stunned as Mexico cancels clean power auction." Green Tech Media.

Deshmukh, Ranjit, Ashwin Gambhir, and Girish Sant. 2011. "India's Solar Mission: Procurement and Auctions." *Economic and Political Weekly*, 46(28): 22–26.

EIA. 2019. "International Energy Outlook 2019." Energy Information Administration.

EIA. 2021. "Annual Energy Outlook." Energy Information Administration.

Fabra, Natalia, and Gerard Llobet. forthcoming. "Auctions with Unknown Capacities: Understanding Competition among Renewables." *The Economic Journal*.

Fabra, Natalia, and Juan Pablo Montero. forthcoming. "Technology-Neutral vs. Technology-Specific Procurement." *The Economic Journal*.

Forum of Regulators. 2019. "Review of Status of Open Access in Distribution." Forum of Regulators.

Fowlie, Meredith, Yashraj Khaitan, Catherine Wolfram, and Derek Wolfson. 2019. "Solar Microgrids and Remote Energy Access: How Weak Incentives Can Undermine Smart Technology." *Economics of Energy & Environmental Policy*, 8(1): 59–84.

Gonzales, Luis E, Koichiro Ito, and Mar Reguant. 2022. "The Dynamic Impact of Market Integration: Evidence from Renewable Energy Expansion in Chile." National Bureau of Economic Research.

Gowrisankaran, Gautam, Stanley S Reynolds, and Mario Samano. 2016. "Intermittency and the value of renewable energy." *Journal of Political Economy*, 124(4): 1187–1234.

Guerre, Emmanuel, Isabelle Perrigne, and Quang Vuong. 2000. "Optimal nonparametric estimation of first-price auctions." *Econometrica*, 68(3): 525–574.

Haile, Philip A, Han Hong, and Matthew Shum. 2003. "Nonparametric tests for common values at first-price sealed-bid auctions." National Bureau of Economic Research.

Hortaçsu, Ali, and David McAdams. 2010. "Mechanism choice and strategic bidding in divisible good auctions: An empirical analysis of the turkish treasury auction market." *Journal of Political Economy*, 118(5): 833–865.

Hortaçsu, Ali, and Steven L Puller. 2008. "Understanding strategic bidding in multi-unit auctions: a case study of the Texas electricity spot market." *The RAND Journal of Economics*, 39(1): 86–114.

IEA. 2021. "Net Zero by 2050: A Roadmap for the Global Energy Sector." International Energy Agency.

India Ratings & Research. 2019. "Receivable Disruption from Counterparties More Frequent, to Impair Renewables Progress." Fitch Group.

IRENA. 2017. "Renewable Energy Auctions: Analysing 2016." International Renewable Energy

Agency.
IRENA. 2018. "Renewable Energy Auctions: Cases from sub-Saharan Africa." International Renewable Energy Agency.
IRENA. 2019*a*. "Renewable Energy Auctions: Status and Trends Beyond Price." International Renewable Energy Agency.
IRENA. 2019*b*. "Renewable Power Generation Costs in 2018."
IRENA. 2021. "World Energy Transitions Outlook." International Renewable Energy Agency.
Ito, Koichiro, and Mar Reguant. 2016. "Sequential markets, market power, and arbitrage." *American Economic Review*, 106(7): 1921–57.
Joskow, Paul L. 1987. "Contract duration and relationship-specific investments: Empirical evidence from coal markets." *The American Economic Review*, 77(1): 168–185.
Joskow, Paul L. 1988. "Asset specificity and the structure of vertical relationships: empirical evidence." *The Journal of Law, Economics, & Organization*, 4(1): 95–117.
Joskow, Paul L. 1990. "The performance of long-term contracts: further evidence from coal markets." *The Rand Journal of Economics*, 251–274.
Joskow, Paul L. 2011. "Comparing the costs of intermittent and dispatchable electricity generating technologies." *American Economic Review*, 101(3): 238–41.
Kabeer, Nitin. 2018. "Recent Cancellations of Solar Auctions Have Set a Bad Precedent." Mercom India.
Kang, Boo-sung, and Steven L Puller. 2008. "The effect of auction format on efficiency and revenue in divisible goods auctions: A test using Korean treasury auctions." *The Journal of Industrial Economics*, 56(2): 290–332.
Klein, Benjamin, Robert G Crawford, and Armen A Alchian. 1978. "Vertical integration, appropriable rents, and the competitive contracting process." *The Journal of Law and Economics*, 21(2): 297–326.
Kumar, Alok, and Sushanta Chatterjee. 2012. *Electricity sector in India: policy and regulation.* Oxford University Press.
Kumar, Amit, and Sapan Thapar. 2017. "Addressing Land Issues for Utility Scale Renewable Energy Deployment in India." TERI School of Advanced Studies.
Laeven, Luc, and Christopher Woodruff. 2007. "The quality of the legal system, firm ownership, and firm size." *The Review of Economics and Statistics*, 89(4): 601–614.
Lazard. 2019. "Lazard's levelized cost of energy analysis." Lazard 13.
Lewis, Gregory, and Patrick Bajari. 2014. "Moral hazard, incentive contracts, and risk: evidence from procurement." *Review of Economic Studies*, 81(3): 1201–1228.
Macchiavello, Rocco, and Ameet Morjaria. 2015. "The value of relationships: evidence from a supply shock to Kenyan rose exports." *American Economic Review*, 105(9): 2911–45.
Macchiavello, Rocco, and Ameet Morjaria. 2021. "Competition and relational contracts in the Rwanda coffee chain." *The Quarterly Journal of Economics*, 136(2): 1089–1143.
Market Screener. 2017. "Ministry of New and Renewable Energy: Historic low Tariff of Rs. 2.44 per unit discovered in Bhadla Phase-III Solar Park in auction by SECI." Market Screener.
Mathavan, Deeptha. 2008. "From Dabhol to Ratnagiri: The electricity act of 2003 and reform of India's power sector." *Columbia Journal of Transnational Law*, 47(2): 387–417.
McMillan, John, and Christopher Woodruff. 1999*a*. "Dispute prevention without courts in Vietnam." *Journal of law, Economics, and Organization*, 15(3): 637–658.
McMillan, John, and Christopher Woodruff. 1999*b*. "Interfirm relationships and informal credit

in Vietnam." *The Quarterly Journal of Economics*, 114(4): 1285–1320.

Ministry of Environment, Forest and Climate Change. 2015. "India's Intended Nationally Determined Contributions: Towards Climate Justice." Government of India.

Ministry of New and Renewable Energy. 2010. "Jawaharlal Nehru National Solar Mission: Towards Building Solar India." Government of India.

Ministry of Power. 2013. "State Distribution Utilities First Annual Integrated Rating." *Ministry of Power, Government of India*.

MNRE. 2020. "Physical Progress (Achievements)." Ministry of New and Renewable Energy.

Novan, Kevin. 2015. "Valuing the wind: renewable energy policies and air pollution avoided." *American Economic Journal: Economic Policy*, 7(3): 291–326.

Nunn, Nathan. 2007. "Relationship-specificity, Incomplete Contracts, and the Pattern of Trade." *The Quarterly Journal of Economics*, 122(2): 569–600.

Prateek, Saumy. 2018. "MNRE Drafts Schedule for Issue of Solar Tenders to Ensure Sustained Activity." Mercom India.

Probst, Benedict, Vasilios Anatolitis, Andreas Kontoleon, and Laura Díaz Anadón. 2020. "The short-term costs of local content requirements in the Indian solar auctions." *Nature Energy*, 5(11): 842–850.

Rustagi, Vinay, and Mridul Chadha. 2020. "India Country Report: International Experiences in Designing and Implementing Renewable Energy Auctions for sub-Saharan Africa." *Energy and Economic Growth Research Programme*.

Ryan, Nicholas. 2020. "Contract Enforcement and Productive Efficiency: Evidence from the Bidding and Renegotiation of Power Contracts in India." *Econometrica*, 88(2): 383–424.

Ryan, Nicholas. 2021. "The competitive effects of transmission infrastructure in the indian electricity market." *American Economic Journal: Microeconomics*, 13(2): 202–42.

Saurabh. 2018. "India Proposes Solar Auction Schedule." Clean Technica.

Shrimali, Gireesh, Charith Konda, and Arsalan Ali Farooquee. 2016. "Designing renewable energy auctions for India: Managing risks to maximize deployment and cost-effectiveness." *Renewable Energy*, 97: 656 – 670.

Tadelis, Steven. 2012. "Public procurement design: Lessons from the private sector." *International Journal of Industrial Organization*, 30(3): 297–302.

Williamson, Oliver E. 1975. *Markets and Hierarchies: Analysis and Antitrust Implications.* New York: Free Press.

Wilson, Robert. 1979. "Auctions of shares." *The Quarterly Journal of Economics*, 93(4): 675–689.

Wolfram, Catherine, Orie Shelef, and Paul Gertler. 2012. "How will energy demand develop in the developing world?" *Journal of Economic Perspectives*, 26(1): 119–38.

Online Appendix

Holding Up Green Energy: Counterparty Risk in the Indian Solar Power Market

Nicholas Ryan

A Appendix: Data

A.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.[25] 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

[25] 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.

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. 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.

A.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.

A.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.

The rating is based on an index with three broad components: financial performance, regulatory practices (that are viewed as sustaining financial performance) and operations. The data for the components are drawn from financial accounts and regulatory reports. The most important component is the present financial health of the company at 60% of the total index weight. Financial health includes sub-components like whether power tariffs cover costs, the amount of debt the company carries and the status of receivable and payable accounts. While the rating is holistic, the intention of the index is to serve as a guide to risk. Ministry of Power (2013) states the goal of the rating as: "The integrated rating methodology would facilitate realistic assessment by Banks/FIs [financial institutions] of the risks associated with lending exposures to various state distribution utilities and enable funding with appropriate loan covenants for bringing overall improvement in operational, financial and managerial performance."

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 2.

Figure 2 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.[26] 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 the invoice-level payment variables

[26] 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.

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

A.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 A1 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.

B Appendix: Supplementary results

B.1 Auction characteristics by intermediation status

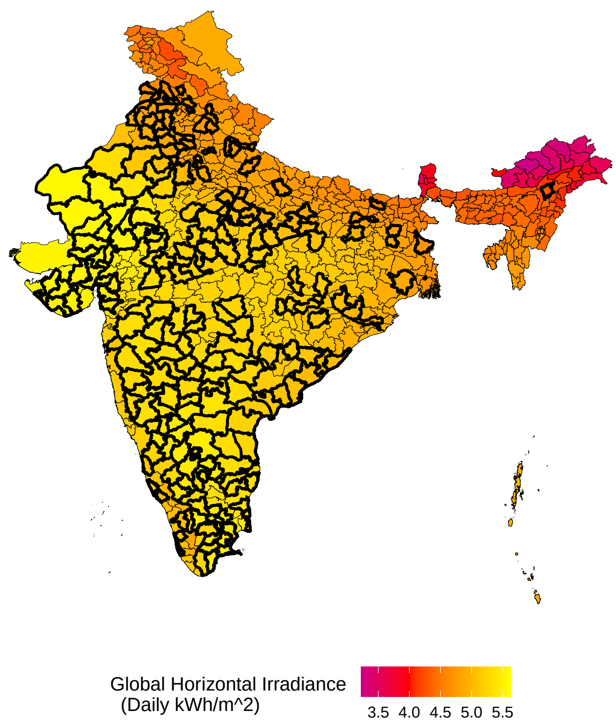
This subsection discusses the characteristics of state-run and centrally-intermediated auctions. It can be read as an extension of Section 3.2 and Table 1 in particular.

Appendix Figure B2 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.

Figure B3 shows the distributions of auction characteristics by intermediation status. The top row shows the distribution of characteristics in central auctions, and the bottom row the distribution in state auctions. The three columns show the distributions of solar irradiance, quantity sought, and counterparty risk, respectively.

The figure shows broad overlap between the characteristics of central and state auctions. The support of the distributions of all the auction characteristics is similar: there are both state and central auctions with high and low irradiance, high and low quantity and high and low risk. There

Figure A1: 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.

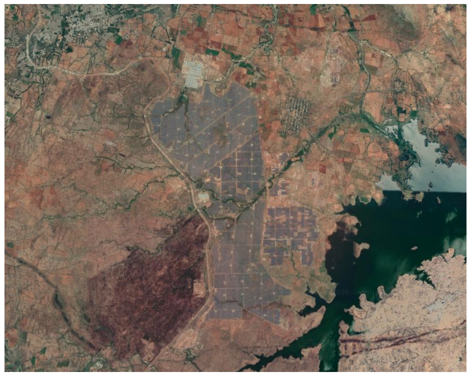
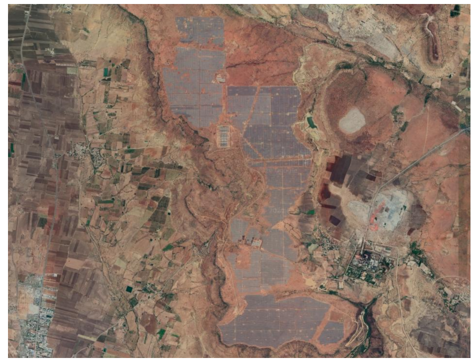
are two substantive differences between the distributions of characteristics shown. First, central auctions are less likely to be held in places with very low solar irradiance. This makes sense: the central government can intermediate auctions in many different locations and favors locations with higher solar potential. Second, there is a smaller fraction of central as compared to state auctions in very low risk (A or A+) states. This pattern suggests that states with low risk might prefer to run their own auctions, or that risky states may prefer to intermediate their auctions.

Figure B4 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 the middle part of the sample. 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.

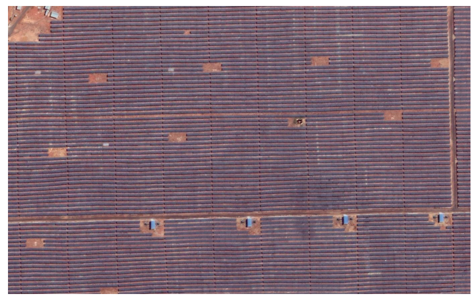
B.2 Alternate solar price regression specifications

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

Figure B2: Power plants allocated by state and centrally intermediated auctions

A. Andhra Pradesh, central auction B. Andhra Pradesh, state auction

C. Andhra Pradesh, central auction (zoom) D. Andhra Pradesh, state auction (zoom)

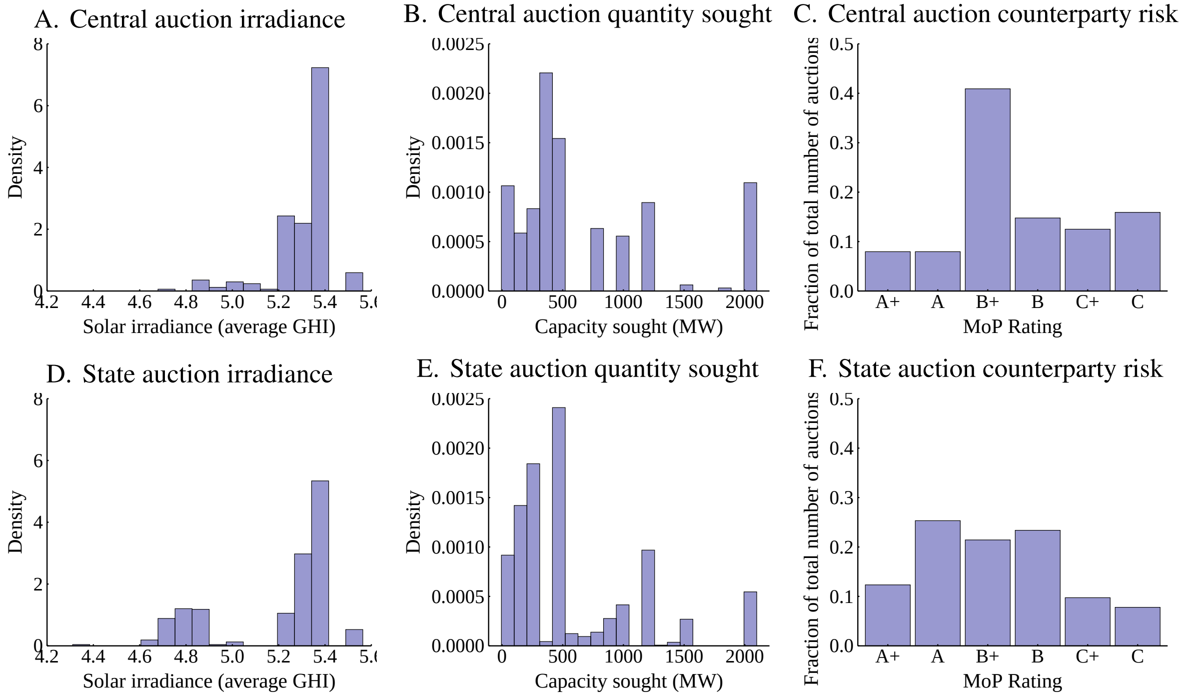
This figure shows satellite images of two typical solar power projects allocated through centrally intermediated and state auctions, built in the state of Andhra Pradesh. Panel A and Panel C show photos of the NP Kunta Ultra Mega Solar Power Project (900 MW), a project that was allocated via a centrally 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.

Bid price regressions with the dependent variable in levels.—Table B2 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).

A test for whether counterparty risk is due to hold-up.—To test whether the counterparty risk premium is due to hold-up, rather than exogenous state-level risk, 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. Appendix Table B3 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

Figure B3: Auction characteristics by intermediation

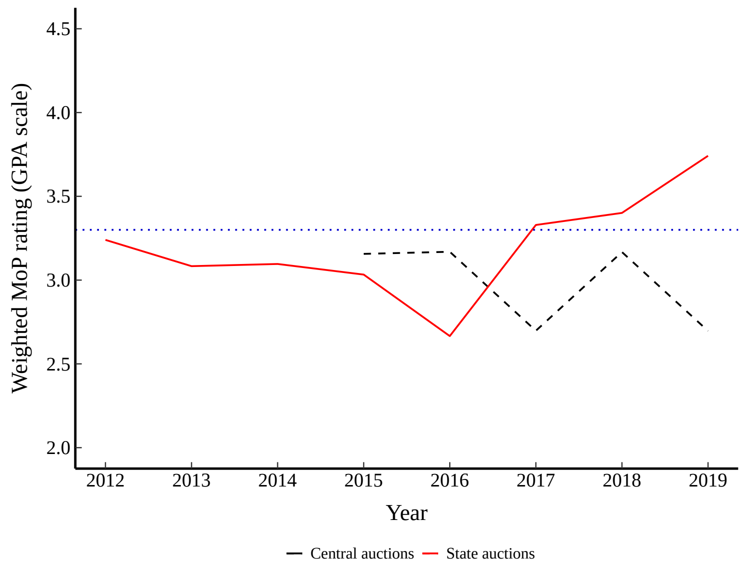


The figure compares the distributions of auction characteristics for centrally-intermediated auctions (top row) as compared to state auctions (bottom row). The first column shows the distributions of solar irradiance. This column uses the data on commissioned projects where the location of all projects is observed. Irradiance is Global Horizontal Irradiance measured in kWh per m^2. The second column shows the distributions of capacity sought in each auction in MW. The distribution is truncated at 2000 MW; two central auctions exceed this level in the data. The third column shows the distribution of MoP ratings for the underlying procurer in 2012. This column restricts the sample to auctions in only one state in order to assign a single counterparty risk rating.

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 in the procuring state, 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 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, compared to the bids of firms without thermal plants.

Figure B4: 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+").

B.3 Effect of intermediation and risk on participation in auctions

Table B4 presents regressions at the auction level of different measures of participation on whether an auction is intermediated and measures of counterparty risk. There are three different measures of participation: the number of bids in the auction (columns 1 to 3), whether an auction is over-subscribed (more capacity was offered than the procurer sought to buy) (columns 4 to 6), and the Hirschman-Herfindahl Index (HHI) of offered capacity (columns 7 to 9).

The over-arching conclusion is that risk has no significant effect on participation or competitiveness in auctions. Without any controls, centrally-intermediated auctions have significantly fewer bids (column 1), yet are more likely to be over-subscribed (column 4). However, these differences are an artifact of state auctions starting earlier in the sample, at a time when many more, smaller bids were typically offered (see Figure 3). Controlling for year fixed effects alone eliminates these apparent differences in the number of bids (column 2) and oversubscription (column 5) between central and state auctions. Similarly, there are no significant differences in participation when also adding fixed effects for auction scale (deciles of the capacity sought at auction) (columns 3 and 6). The HHI is a measure of the concentration of offered bids in an auction, scaled between 0 and 1. There is no significant difference in the concentration of offered bids in central

Table B2: 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 (kWh/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 × Counterparty risk			0.70^{**}	0.48^{*}
			(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 2. 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 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

versus state auctions (columns 7 through 9).

In addition to not finding any effect of intermediation *per se* on participation, I also find that there is no effect of counterparty risk itself on participation in state auctions (coefficients on "State auction × counterparty risk.") For example, increasing counterparty risk in a state auction from zero to the average state risk is estimated to decrease the number of bids offered by -0.31 (standard error 2.97), on a mean number of bids offered of 8.63 (column 3). Therefore it does not appear that changes in auction participation are a main mechanism through which risk affects prices bid.

Table B3: 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 (kWh/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 ×	0.14***	0.14***	0.14***	0.099**
Counterparty risk	(0.041)	(0.040)	(0.041)	(0.038)
Thermal in state (=1) ×		−0.097***	−0.066*	−0.062
Counterparty risk		(0.030)	(0.035)	(0.040)
Thermal in state (=1) ×			−0.047*	−0.064**
State auction × Risk			(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 *** $p < 0.01$.

B.4 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.

Table B4: The effect of central intermediation on auction participation

	Dependent variable:								
	Number of bids			*Oversubscribed (=1)*			*HHI*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Central auction (=1)	-5.13^{**}	-2.05	-4.52	0.20^{***}	0.028	0.0039	0.089	-0.16	-0.078
	(2.04)	(9.35)	(9.59)	(0.054)	(0.26)	(0.25)	(0.058)	(0.27)	(0.27)
Counterparty risk		1.65	1.68		-0.0095	0.039		-0.16^{*}	-0.13
		(2.96)	(3.02)		(0.081)	(0.080)		(0.085)	(0.084)
State auction × Counterparty risk		1.02	-0.31		-0.053	-0.025		-0.089	-0.050
		(2.89)	(2.97)		(0.079)	(0.079)		(0.083)	(0.082)
Year effects		*Yes*	*Yes*		*Yes*	*Yes*		*Yes*	*Yes*
Capacity deciles			*Yes*			*Yes*			*Yes*
Mean dep. var	8.63	8.63	8.63	0.88	0.88	0.88	0.32	0.32	0.32
R^2	0.046	0.31	0.39	0.095	0.31	0.42	0.018	0.27	0.40
Auctions	135	135	135	135	135	135	135	135	135

This table reports coefficients from regressions of measures of participation in solar power auctions on an indicator for central intermediation and measures of counterparty risk. The data are at the auction level. The dependent variables are: the number of bids in an auction (columns 1 to 3); an indicator for whether an auction is oversubscribed, meaning more capacity was offered than the procurer sought (columns 4 to 6); the Hirschman-Herfindahl Index (HHI) for offered capacity in an auction (columns 7 to 9). 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. The counterparty risk variable is a normalized version of the Ministry of Power rating for discoms described in Figure 2. Equation (1) shows the normalization; a value of zero represents no risk and a value of one the average level of state risk. Specifications include year effects and fixed effects for deciles of the quantity sought at auction as indicated in the footer. Statistical significance at certain thresholds is indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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.

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.

C Appendix: Model

C.1 Proof of homogenization of bid prices in a multi-unit auction

This part shows that bid homogenization preserves equilibrium strategies in a multi-unit auction, provided that bids are multiplicatively separately in observable auction characteristics (as in 8).

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* (8)*. Then the equilibrium bid function in an auction with covariates Z_t can be written $\beta_i(c_{it}|Z_t, q_{it}) = \Gamma(Z_t)\beta_i(c_{i0}|Z_0, q_{it})$.*

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. The proof shows that rescaling bid prices and costs by a common factor maintains the first-order necessary conditions for equilibrium bidding. The homogenization proof applies for auctions without a ceiling price, which comprise the estimation sample for the estimation of bidder costs.

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

$$Q_t(p,q|Z_t,\sigma_{-i}) = \begin{cases} 0 & \text{if } RD_t(p|Z_t,\sigma_{-i}) \leq 0 \\ RD_t(p|Z_t,\sigma_{-i}) & \text{if } 0 < RD_t(p|Z_t,\sigma_{-i}) \leq q \\ q & \text{if } q < RD_t(p|Z_t,\sigma_{-i}). \end{cases} \tag{12}$$

Conditional residual demand is

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

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

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

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

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

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 (8) 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. □

C.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

$$\ln b_{ait} = \ln b^0 + \alpha_t + \alpha_s + \alpha_s Central_{at} + \beta_1 Z_{at} + \tilde{b}_{ait} \tag{13}$$

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

$$\ln b^h_{ait} = \ln b^0 + \beta_1 Z^0_{at} + \tilde{b}_{ait} \tag{14}$$

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.

C.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.

Table C6: Regression estimates for bid homogenization

Dependent variable: Log of bid price (INR/kWh)		
	Coefficient	Std Error
	(1)	(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 $\times$ 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 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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

$$\widetilde{RD}_t(p|\sigma^s_{-i}) = QD_t - \sum_{j\neq i} q^s_j \Phi\left(\frac{p-b^s_j}{h_p}\right) \tag{15}$$

$$\frac{\partial \widetilde{RD}_t(p|\sigma^s_{-i})}{\partial p} = -\sum_{j\neq i} q^s_j \frac{1}{h_p}\phi\left(\frac{p-b^s_j}{h_p}\right) \tag{16}$$

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

$$\widetilde{QS}(p|\sigma_i) = q_i\Phi\left(\frac{p-b_i}{h_p}\right). \tag{17}$$

With this form, $\widetilde{QS}$ is continuous and differentiable but approximates the step function (6) as h_p becomes small.

The market-clearing condition for a simulation draw s is

$$\widetilde{QS}(p|\sigma_i) = \widetilde{RD}_t(p|\sigma^s_{-i}), \tag{18}$$

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

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

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 (17) contains b_i as its first element. For a given simulation, implicitly differentiating (18) yields

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

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

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

With these approximations to quantity awarded and its derivative, I form the mark-up term in equation 7.

C.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^s_t draws of θ.
   - Let the draws for bidder $i = 1$ represent the type of bidder i.
   - Draws for $j = 2, \ldots, N^s_t$ represent the types of rival bidders.
2. **Constrained strategy function**. Posit a bidding function $b(\theta_i|\alpha, r)$ as in (9) that yields a bid price conditional on type and parameter α.
3. **Solve for constrained equilibrium**. Form the components of (11) and solve the equation for α^*.
   - **Expected quantity awarded**. Using the simulation draws, approximate the expected quantity awarded function

$$H(p,q|\alpha_j) = \mathbb{E}_{\theta_{-i}}\left[Q_t(p,q|b(\theta_{-i}|\alpha_{-i}, r))\right]. \tag{19}$$

     - 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 (11) using the simulation draws.

$$\frac{1}{S}\sum_{s=1}^{S}\left[(r - c^s_{it})\left(b(c^s_{it}, q^s_{it}|\alpha, r) - \frac{c^s_{it}}{(1-\delta_s)} + \frac{H_t(b(c^s_{it}, q^s_{it}|\alpha, r), q^s_i|\alpha)}{\frac{\partial H_t(b(c^s_{it}, q^s_{it}|\alpha, r), q^s_i|\alpha)}{\partial b(c^s_{it}, q^s_{it}|\alpha, r)}}\right)\right] = 0.$$

     The components of this condition are calculated as

     - $(r - c^s_{it})$ using the type drawn for θ^s_i and bid function.

– $\frac{c^s_{it}}{(1-\delta_s)}$ using the type drawn for θ^s_i and risk.
– $H_t(b(c^s_{it}, q^s_{it}|\alpha, r), q^s_i|\alpha)$ and its derivative. Using they type drawn for θ^s_i, bid function, and simulation of quantity awarded over rivals' types.

C.5 Validation of counterfactual strategies

Table C7 compares the fit of the simulations to the data for a range of auction outcomes. The main findings of Table C7 are that *As bid* simulation matches auction outcomes well in the estimation sample, but that the constrained strategy equilibrium has a much stronger fit in the ceiling price sample. In the ceiling sample, the constrained strategy equilibrium is accurate for: (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), and (iii) the mean bid price (INR 2.98 per kWh in both the data and the model) (comparing column 5 to column 3). I conclude that the constrained strategy equilibrium approximates bidding and participation well in the sample of auctions with ceiling prices.

Table C7: 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).