Nurturing National Champions? Local Content in Solar Auctions and Firm Innovation

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Abstract

We study whether local content nurtures a globally competitive industry. Despite little robust evidence, local content is frequently applied in contemporary renewable energy auctions to support domestic producers if imports are cheaper. To assess the effect of local content, we explore a natural experiment in India. Starting in 2013, the Indian government simultaneously held solar auctions with and without local content, providing a previously unobserved counterfactual. We digitize the results from these 41 auctions of contracts worth 8.65 billion $ in solar module demand and collect annual revenue and solar patents of the 113 participating firms between 2004-2020. For causal identification, we compare local content participants with similar open auction participants in a dynamic difference-in-difference estimation. We find participating in or winning local content auctions has no significant effect on firms' solar patents and revenue. We identify three reasons why the policy failed. First, we show local content did not create sufficient production to enable learning by doing. Second, local content did not generate enough revenue for re-investment into R&D. Third, local content significantly reduced competition in auctions, while no alternative performance requirements were defined. The analysis illustrates the need for better-designed local content or alternative industrial policies.

JEL classification: O14, O31, O53, Q48, D22, H57, L52, L94

Keywords: Innovation, Local Content, Solar Energy, Auctions, Green Industrial Policy, Difference-in-Difference

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1 Introduction

There is a long-standing, heated debate in economics about industrial policy, in particular, infant industry or import substitution policies, such as local content requirements (LCR) (Altenburg and Rodrik, 2017; Chang, 2003; Grossman, 1981; Irwin, 2021; Krueger, 1997; Lane, 2020; Panagariya, 2011; Rodrik, 2008). LCR aim to incentivize local production if foreign product prices are cheaper than domestic ones (Irwin, 2021; OECD, 2015). This historical economic issue is reflected in contemporary renewable energy auctions. In these auctions, governments offer contracts, so-called power purchasing agreements, to the private bidder committing to build a renewable energy plan at the lowest price (Bayer, 2018; Del Río and Kiefer, 2022; Dobrotkova, Surana and Audinet, 2018). While auctions have been credited with strong price reductions as they open electricity generation to competition, private investment, and multinational companies (Dobrotkova et al., 2018; Winkler, Magosch and Ragwitz, 2018), auctions also incentivize bidders in countries without existing solar industries to import cheaper foreign components. The global solar photovoltaic industry is highly concentrated as 87% of component manufacturing, and 85% of patents are produced in just six countries (IEA, 2021, 2022; Luan, Sun and Wang, 2021). Governments outside these countries, especially in solar radiation-rich and resource-poor countries, apply LCR to counteract the price incentive to import. LCR have been applied in 145 instances since 2008, among which 28 times in renewable energy and most recently in the Inflation Reduction Act (OECD, 2015; PIIE, 2021). Proponents of LCR argue that they are temporarily necessary to protect and nurture a local, globally competitive industry (Chang, 2003; Wade, 2018), while opponents argue they induce rent-seeking, perpetuate inefficiencies, and more often than not become permanent protection schemes (Hufbauer, Schott and Cimino-Isaacs, 2013; Krueger, 1990; Panagariya, 2011).

In this paper, we empirically examine the following research question. Can local content in solar auctions incentivize local production and create a local, globally competitive solar PV industry? Innovation is arguably the crucial outcome to guarantee LCR are of temporary and not permanent nature. Without innovation, protection remains permanently necessary to maintain local products competitive with cheaper imports. We study this question with the example of the LCR introduced in India's National Solar Mission (NSM). This national flagship policy turned India from a country with barely any solar energy generation in 2010 into the fifth-largest solar market in 2022. The LCR in India targeted cells and modules, the most complex components of solar PV plans, and were designed to create manufacturing jobs and develop strategic technological autonomy and global technology leadership (Hufbauer et al., 2013; Johnson, 2016; Shrimali, Konda and Farooquee, 2016; Shrimali and Sahoo, 2014;

Shrimali, Srinivasan, Goel and Nelson, 2017; Singh and Pandey, 2021).

This paper makes three contributions. First, we create a unique panel data set of the 113 firms that participated in the solar auctions, leading to an unbalanced panel data set with 1870 observations between 2004 and 2020. This enables us to expand on previous studies, which were unable to attribute a direct effect of LCR to firms' performance as they were limited to industry-level data (Hansen, Nygaard, Morris and Robbins, 2020; Lewis and Wiser, 2007) and focused on auction-level (e.g. bidding price (Probst, Touboul, Glachant and Dechezleprêtre, 2021), realization rates (Matthäus, Schwenen and Wozabal, 2021) rather than firm-level outcomes (Del Río and Kiefer, 2022). To assess firms' innovation performance, we web-scrap each patent a firm ever filed at the Indian patent office, yielding 8,845 patents, the first filed in 1982 and the last in 2020. Based on the international patent classification codes (Shubbak, 2019), we identify that the firms filed 100 solar patents over the whole period. We complement this firm-year panel with firms' characteristics, such as annual revenue, the number of employees, the main sector of the mother company etc., from annual reports and commercial databases. To link firms' innovation performance with LCR, we digitize all the nationwide auctions conducted by the Solar Energy Corporation India until 2020, including auction characteristics such as bidding price, auction volume, eligibility, and local content requirements, and match firms' performance in auctions to the firm-year panel data (Münch and Marian, 2022). Thanks to this detailed, two-decades-long data set, we can analyze the evolution of the firms in the nascent Indian solar industry in unprecedented detail.

Second, we advance the discussion regarding the rigorous evaluation of industrial policies, such as local content, by proposing the first counterfactual-based causally identified evaluation of an LCR policy (Hansen et al., 2020). Usually, local content policies are implemented on the national level. Therefore, one either observed firms in countries exposed to local content or not. This has made it difficult to estimate a counterfactual. To estimate a counterfactual, we adopt a similar strategy as Probst, Anatolitis, Kontoleon and Anadón (2020), exploring that the Indian government ran simultaneous auctions with and without LCR from 2013 to 2017. In an ideal world, the government would have randomly made firms subject to local content or not. However, firms' decision to participate in auctions with or without local content is endogenous, raising selection bias concerns. To overcome these concerns, we apply two methods. First, we conduct a dynamic difference-in-difference estimation comparing annual solar patenting and revenue of firms that participated or won at least one LCR auction (treatment group) with firms that only participated in or won open auctions (control group). We show firms that participated in auctions with local content ("treated") have statistically equal pre-trends as firms in that participated exclusively in open auctions ("control"), fulfilling the key causal identification assumption of equal pre-trends. Second, we improve the robustness of the dynamic difference-in-difference estimation by restricting the comparison to similar firms in the LCR ("treated") and open auctions group ("control") based on weights from caliper propensity score matching. In summary, in the most robust specification, we control for time-invariant firm characteristics and pre-policy differences in solar patents and balance any characteristics between the firms in the LCR and the open auction group that predicted participation in LCR auctions. The remaining causal identification assumption is that there are no potential unobserved variables that determine LCR participation and filing of solar patents.

Third, while we find the local content policy did not significantly affect firms' solar patents and revenue, we also analyze why this was the case. For this purpose, we develop a theoretical framework of how LCR may create production and innovation. We then conduct a falsification exercise to determine which mechanisms caused the policy to be ineffective. While there is a large body of literature on industrial policy, infant industry, and import substitution policies, such as LCR, existing studies focus on the country or industry level. As a result, there is no clear microeconomic framework that lays out how these policies affect firms. We identify two mechanisms by which LCR could have created local production and innovation. The first mechanism is learning-by-doing (Andreoni and Chang, 2016; Atkin, Khandelwal and Osman, 2017; Chang and Andreoni, 2020; Lucas, 1993). Local content is supposed to provide domestic firms with demand, or in other words, orders to produce specific goods. Producing rather than importing goods, such as solar PV modules and cells, may be necessary for firms to develop their capabilities and encounter the problems that lead to innovations. The second mechanism are R&D re-investments (Aghion, Bloom, Blundell, Griffith and Howitt, 2005; Hall and Lerner, 2010; Schumpeter, 1942). The orders local content creates generate revenue for domestic firms, which can, in principle, be reinvested into R&D, e.g. to solve problems in the production process or products' performance. Second, LCR did not generate sufficient revenue for re-investment into R&D. Third, LCR significantly reduced competition in auctions, while no alternative performance requirements were defined. At the same time, we show that the total costs of the LCR policy to the government were quite low, and firms participating exclusively in open auctions, which were much larger, did not innovate significantly more. This illustrates the need for better-designed local content or alternative policies.

We contribute to the following strands of literature. First, this paper contributes to long-standing economic arguments about the impact of industrial policy (Altenburg and Rodrik, 2017; Chang, 2003; Irwin, 2021; Krueger, 1997; Panagariya, 2011; Rodrik, 2008). We follow a series of recent papers that employ the credibility revolution's empirical, reduced-form causal inference methods to re-assess and provide new evidence about industrial policy (Lane, 2020). The starting point of this literature is that "past empirical evidence [on industrial policy] is not mixed. It is often vacuous." (Lane, 2020). The same holds true for LCR. Hansen et al. (2020) review the existing literature on LCR and come to the same conclusion as Veloso (2001) twenty and Kuntze and Moerenhout (2012) ten years ago: existing studies are based on qualitative, aggregated, industry-level evidence, while quantitative, counterfactual-based evidence is rare. One exception is Probst et al. (2020) who use a Heckman selection model to investigate the impact of LCRs on bidding price in the Indian solar auctions. However, the study only looks at country-wide solar patents but cannot identify the causal impact of LCR on firms' performance indicators, such as patents or sales.

Second, this paper relates to the literature about auctions and (renewable) energy economics (Bayer, 2018; Del Río and Linares, 2014; Hochberg and Poudineh, 2018; Kruger and Eberhard, 2018; Winkler et al., 2018). Although governments worldwide adopt renewable energy auctions (IRENA, 2019), robust empirical evidence for their impact on domestic energy industries is rare. Del Río and Kiefer (2022) review the literature on the impact of auctions on innovation and find only four empirical papers out of 33 total studies considered thematically fitting, including only two quantitative studies. While both of these studies find that auctions do not encourage innovation to the same extent as feed-in-tariffs, none look at the impact of specific auction design elements. Even though there is evidence that the effectiveness of auctions depends on their design (Del Río and Linares (2014); Hochberg and Poudineh (2018)), only a few studies investigate the effect of auctions and their design elements on industrial development outcomes, such as innovation (Del Río and Kiefer, 2022). Exceptions focus exclusively on direct objectives of auctions, such as project realization rates (Matthäus et al., 2021) and bidding price (Probst et al., 2020).

Third, this paper resonates with the literature on public procurement and demand-side innovation policies in innovation economics and development economics (Atkin et al., 2017; Edler and Uyarra, 2013; Edler and Yeow, 2016; Mazzucato, 2018).

Paper structure Section 2 sketches out a verbal theoretical framework. Section 3 provides contextual information. Section 4 presents the causal identification strategy and the data. Section 5 presents the results. Section 7 concludes with policy implications and recommendations for further research.

2 Verbal Theoretical Framework: Local Content and Firm Innovation

Section 2 theorizes how LCR in public power auctions may promote domestic innovation and production. We keep the framework general so that it could apply to other latecomers countries.

The starting point of the framework is the organization of public auctions. In these auctions, bidders offering to build and operate a solar power plant at the lowest price will win a power purchasing agreement (PPA). The PPA guarantees to the bidder that the government, as in the state utility, will buy the electricity from the bidder at tariffs and duration specified in the auction for the next 25 years. The public auctions effectively create a domestic market for solar energy and generate predictable demand for the components necessary to build these plants.

Bidders must decide whether to import the components necessary to build the solar power plants or buy them from local manufacturers. Given foreign components, especially solar cells, and modules, are cheaper at the outset as domestic manufacturers have less experience and don't benefit from economies of scale yet, there is a strong price incentive for bidders to import these models. Otherwise, bidders would either have to increase their bidding price, which would reduce their chances to win, or reduce their profit margins. To counteract this price incentive, the government introduces LCR, which specifically target the components in which the government aims to develop local industry, e.g. solar cells and modules.

LCR affect domestic and international firms' decisions in the following way. Bidders that don't manufacture modules are forced to source from domestic manufacturers or set up their own manufacturing facility. Domestic manufacturers either participate directly in the auctions or may receive orders from local or international project developers. International firms, in contrast, are forced to order from local manufacturers or establish their own domestic production facilities.

LCR should expose local manufacturers to additional demand at the margin, which would not have occurred without LCR, resulting in the following two key impact mechanisms. First, additional demand should translate into additional production and opportunities for learning-by-doing (Andreoni and Chang, 2016; Arrow, 1962; Lucas, 1993). Learning-by-doing, or learning by experience, can take shape of efficiency improvements leading to productivity increases (Arrow, 1962; Lucas, 1993), learning from client requirements (Atkin et al., 2017) or development of productive capabilities, e.g. through innovation to solve problems encountered in the production process (Andreoni and Chang, 2016; Arrow, 1962; Chang and Andreoni, 2020). In contrast, in open auctions, components are imported, and thus no domestic production would occur. In summary, there are positive knowledge externalities associated with production.

A second related hypothetical impact mechanism is the additional revenue and profit generated through orders from LCR auctions. The additional revenue and profit could help firms finance investments into R&D as many firms rely on internal resources to finance R&D (Aghion et al., 2005; Hall and Lerner, 2010; Schumpeter, 1942). The orders local content creates generate revenue and profit for domestic firms, which can, in principle, be reinvested into R&D, e.g. to solve problems occurring in the production process, to test cheaper processes or materials, and improve quality, e.g. module performance or longevity. Given firms compete for market shares in the new market organized through public auctions, they have an incentive to patent particularly innovative solutions identified in the production process to avoid competitors imitating them.

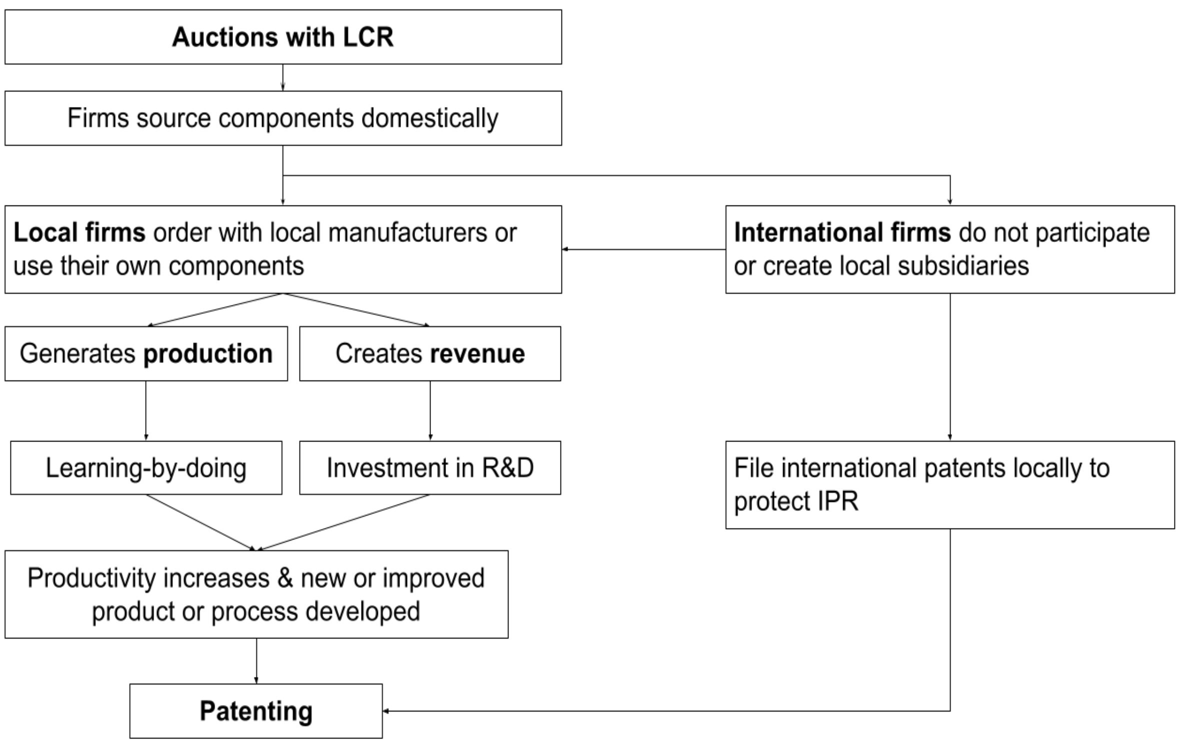

Figure 1: Verbal theoretical framework: Hypothetical impact mechanism for local content in auctions and innovation in patenting.

There are several assumptions that underline this theoretical framework. Firstly, we assume there is still a sufficient level of competition in LCR auctions. Absent sufficient competition, there is no incentive, or "stick", to propel firms to invest in R&D and learning-by-doing as they are certain to win anyways (Aghion et al., 2005; Hufbauer et al., 2013; Krueger, 1997; Panagariya, 2011; Rodrik, 2008; Wade, 2018). Secondly, we assume that the demand from LCR is sufficiently large to enable learning-by-doing and re-investment into R&D. Thirdly, LCR supporters have often been quick to assume LCR create "additional demand" for local firms. It is unclear whether demand from LCR creates additional production or simply leads firms to substitute production capacity or even reduce production to maximize profits (Grossman, 1981; Hufbauer et al., 2013). Production substitution could occur if a local company has limited production capacity and decides to sell to the government rather than to other clients. If the government pays above world market prices, which is the purpose of LCR, firms also have the incentive to produce less if that maximizes profits or stop exporting as local governments may require lower quality and pay higher prices than foreign clients.

In section 5, we empirically assess whether the two central mechanisms and the underlying assumptions have been fulfilled in the case of the LCR introduced in India's National Solar Mission, which we present next.

3 Context of the Empirical Case Study

3.1 The Jawaharlal Nehru National Solar Mission

In January 2010, the Indian government inaugurated the Jawaharlal Nehru National Solar Mission (NSM) with the aim of establishing India as a global leader in solar energy (MnRE, 2009). The NSM aimed to deploy solar energy and promote the manufacturing of solar energy components in India. The key policy tool to achieve the latter objective was the incorporation of LCR as mandatory requirement in public solar auctions. The LCR mandated that the solar PV modules and, later also, solar PV cells used by the bidders had to be manufactured in India.

The NSM was designed in three phases depicted in Figure 4 in section 4. Phase I auctions included LCR for polysilicon PV but as India did not have strong manufacturing based in thin-film technologies, thin-film was exempted from the LCR. As an unintended result, 70% of the auctioned capacity in Phase I was based on mostly imported thin-film modules (Sahoo and Shrimali, 2013).

The Indian government updated its LCR policy for phase II of the NSM. LCR were amended to encompass both PV cells and modules of both polysilicon and thin-film technologies. However, open auctions without LCR were now held in parallel. Having parallel auctions with and without LCR during Phase II provides the quasi-experimental setting that we exploit to study the impact of LCR on innovation. This phase of parallel auctions remained in place until 2017 when India stopped the inclusion of LCR in their auctions

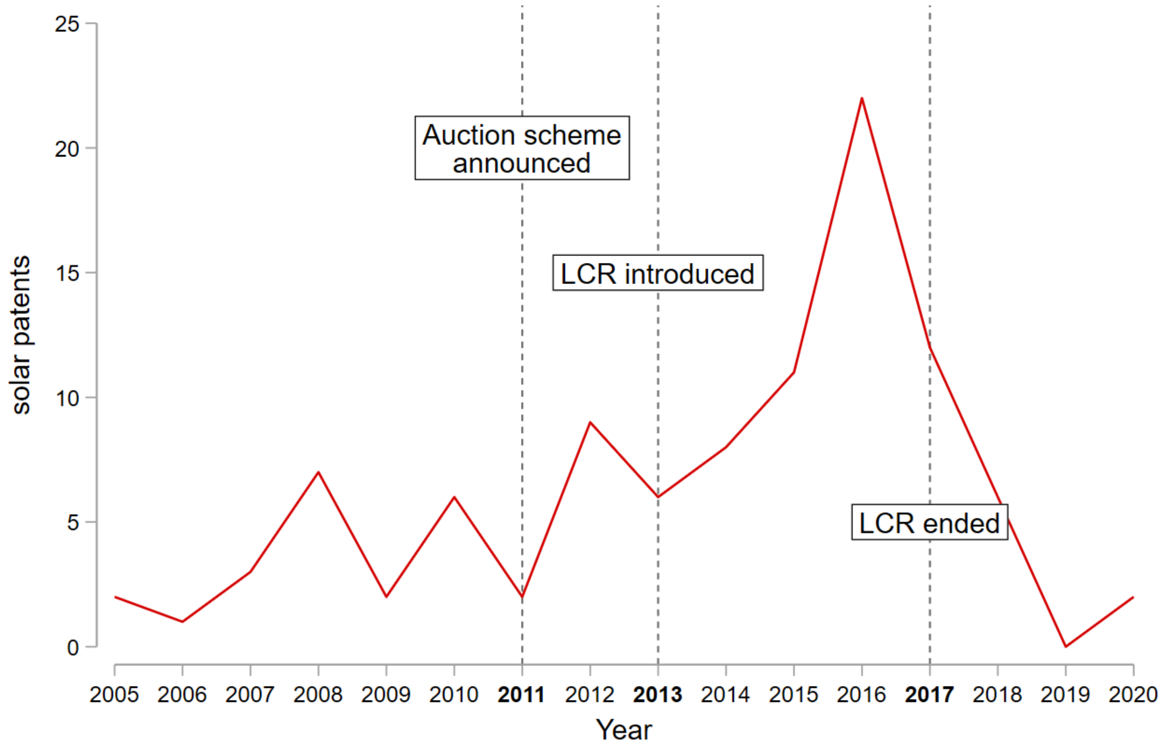

Figure 2: Evolution of solar patents filed by the 113 companies participating in solar auctions in India

after the United States had filed a complaint at the World Trade Organisation(World Trade Organization, 2018).

Therefore, Phase III of the NSM no longer includes LCR auctions. The Indian Government revised the targets for Phase III from 20 GW to 100 GW. The Indian solar sector first underwent expansion, and then consolidation as the size of auctions and solar power plants increased substantially. Consequently, the number of auction participants and the bidding price decreased (see Figure 10 in the Appendix). As of January 2022, India has installed 49.3 GW of solar power, which puts it in fifth place after China, USA, Japan, and Germany (IEA, 2021). The NSM is regarded as successful thanks to the large-scale deployment of solar energy and its long time horizon (Sahoo and Shrimali, 2013; Singh and Pandey, 2021). It can be argued that India's NSM, in which the LCR was embedded, meets the criterion of sufficient market size and demand predictability, presented as one of four key success factors of LCR by Hansen et al. (2020).

3.2 The design of Auctions and Local Content Requirements

India's LCR auction policy was rather strict as it required the manufacturing of modules and later also of PV cells to fully take place in India, contrary to other countries like South Africa or China, which mandated minimum shares of local content in their auctions. Figure 3 illustrates the steps in the manufacturing process of solar PV modules that the Indian LCR targeted (black frame).

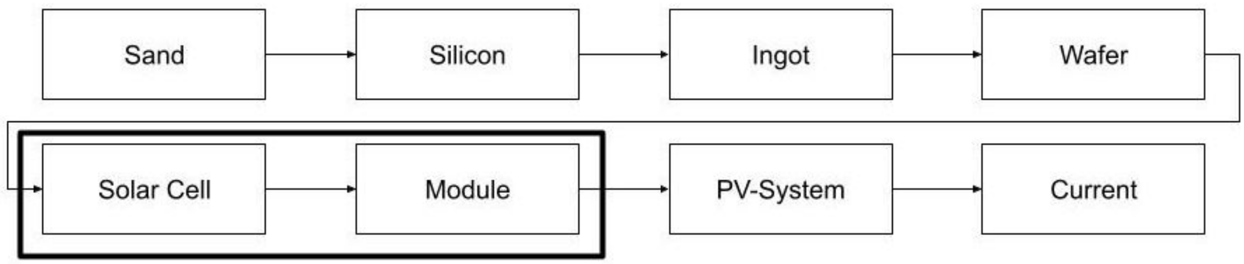

Figure 3: Steps in the manufacturing process of solar PV modules. Black frame refers to components targeted by LCR. Own depiction based on Mustafa Ergin Şahin and Halil İbrahim Okumuş (2016)

Regarding the success factors stated by Hansen et al. (2020), it can be argued that, after fixing initial policy loopholes, there was policy coherence, as the LCR was clear and accompanied by other support in the NSM. However, the LCR were also restrictive, which may jeopardize the economic efficiency as documented, for example, for the bidding price by (Probst et al., 2020). Hansen et al. (2020)'s final criterion, an industrial base, is arguably in place, as India already had a small, export-oriented PV module manufacturing industry before the NSM (Johnson, 2016) and features several large conglomerates, such as Tata, Adani or Mahindra. Hence, ex-ante, it appears that the Indian solar LCR fulfilled most of the policy-level success factors defined in the literature, which we further assess in the empirical analysis.

Table 1 provides an overview of the characteristics and differences between LCR and open auctions. LCR auctions are less competitive as only 4.82 bidders, on average, are participating compared to 8.9 bidders in open auctions. LCR auctions are much smaller in auctioned capacity, with an average of 50 MW per auction compared to 750 MW in the open auctions. The size difference is also reflected in the higher share of solar park projects and the average plant size, which is more than tenfold in open auctions (255 MW) compared to LCR auctions (20 MW). A fourth difference is the higher average bid price in the LCR auctions, which re-confirms the findings by Probst et al. (2020). We explore in section 5.3 and section 5.4 how the different auction characteristics may have affected the impact of

Table 1: Balance table: Characteristics of auctions with and without local content

Variable	(1) auction w/o LCR Mean (SD)	(2) LCR auction Mean (SD)	T-test P-value (1)-(2)
number of bidders	8.90	4.82	0.06*
	(7.15)	(5.76)	
BOO+PPA vs. EPC+O&M	1.10	1.36	0.11
	(0.31)	(0.50)	
total MW auctioned	750.43	49.73	0.00***
	(1,184.14)	(109.31)	
international bidders invited	1.33	1.09	0.06 *
	(0.48)	(0.30)	
projects in solar park	0.30	0.09	0.10*
	(0.47)	(0.30)	
climate zone of plant location	2.23	1.91	0.27
	(0.82)	(0.83)	
technology neutral	1.90	1.64	0.11
	(0.31)	(0.50)	
max. plant size	255.10	20.18	0.00***
	(347.81)	(20.18)	
final bid price, INR/kwh	1.41	3.18	0.04 **
	(2.00)	(2.56)	
length of contract	23.40	18.64	0.10 *
	(4.90)	(8.97)	
international quality standards	12.77	14.82	0.18
	(2.60)	(4.87)	
viability-gap-funding, INR	23080464.16	55392127.27	0.41
	(53525686.01)	(127339657.93)	
N	30	11	

Notes: The value displayed for t-tests are p-values. Standard deviations are robust.
All missing values in balance variables are treated as zero.
***, **, and * indicate significance at the 1, 5, and 10 percent critical level.
Abbreviations for two types of legal contracts:
BOO = Build, Own, Operate. PPA = Power Purchasing Agreement.
EPC = Engineering, Procurement, Construction. O&M = Operation & Maintenance.

LCR and open auctions.

4 Data and Methods

4.1 Causal Identification Strategy

Our central identification strategy explores that the Indian government ran simultaneous auctions with and without LCR between 2013 and 2017, as in (Probst et al., 2021). In contrast to Probst et al. (2021), we focus on the firm rather than the bid level to identify whether participation in LCR auctions has had an impact on firms patenting activities and sales. The LCR or treatment group consists of 33 firms that either exclusively participated in LCR auctions or participated in both auction types. The non-LCR group or control group comprises 80 firms that only participated in open auctions.

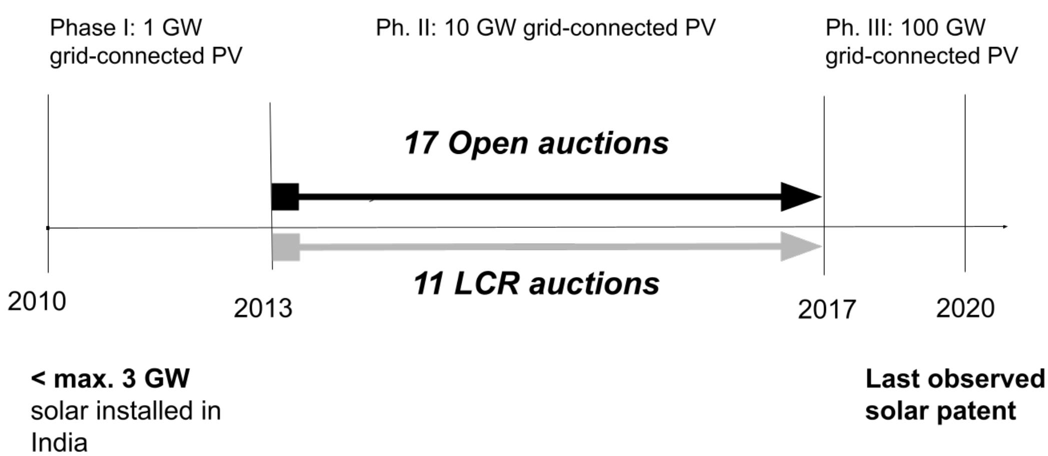

Figure 4: Nurturing a domestic solar sector from scratch to 50 GW solar energy: India's Jawaharlal Nehru National Solar Mission. Sources: Own elaboration based on Johnson (2016); MnRE (2009), SECI online archives & data from Indian patent office. Note: The capacity objective for Phase III was revised from originally 20 GW to 100 GW. Objectives may not necessarily match with the allocated capacity ex-post.

Since we dispose of annual sales and patent data, we can compare post and pre-treatment outcomes of the firms in the LCR ("treatment") and non-LCR group ("control"). The causal identification assumption is that the pre-treatment trend in solar patenting activity among matched non-LCR (control) group firms is not statistically different from matched LCR (treatment) group firms and is assumed would have developed similarly in absence of the treatment (LCR). We examine this assumption through an event study design in figure 6.

There was no significant difference in the outcome variable before LCR introduction in 2013 in both the matched and unmatched samples.

Despite equal pre-trends, firms could select in which auction type to participate since 2013. Treated and untreated firms differ both in their pre-treatment levels of the outcome variable and some of their characteristics. Hence, LCR participation may be correlated with (un-) observable differences in firm characteristics that may also affect patenting and sales. For these reasons, we combine the difference-in-difference estimation with propensity score matching (PSM). The intuition of PSM is to identify a single or a weighted combination of several firms in the control group that constitute a control unit as similar as possible to a firm or several firms in the treatment group. Table 2 provides results from a balance test on the firm characteristics that predict participation in LCR auctions (see section 5.1) before (columns 1 and 2) and after matching (columns 3 and 4). The PSM procedure eliminates statistically significant differences between LCR and open auction participants in the variables that predict LCR participation. This implies that conditional on matching, LCR participation should not be correlated with any other firm characteristics that predict participation in LCR auctions anymore.

Table 2: Balance table: Firm characteristics predicting participation in auctions with & without local content before & after matching

	Unmatched			Matched		
Variable	no LCR participation Mean (SD)	LCR participation Mean (SD)	T-Test (1)-(2) P-Value	no LCR participation Mean (SD)	LCR participation Mean (SD)	T-test (3)-(4) P-Value
log_total_employees	4.77	4.75	0.95	4.93	4.61	0.51
	(1.95)	(2.18)		(2.87)	(2.00)	
ihs transf. pre-LCR sales	15.38	18.35	0.06*	18.28	17.93	0.82
	(8.47)	(7.27)		(7.87)	(7.27)	
solar patents 2001-2010	0.03	0.58	0.26	0.11	0.06	0.67
	(0.16)	(2.80)		(0.74)	(0.36)	
indian company	0.71	0.91	0.01***	0.86	0.90	0.56
	(0.46)	(0.29)		(0.40)	(0.30)	
manufacturing company	0.07	0.33	0.00***	0.18	0.29	0.34
	(0.27)	(0.48)		(0.76)	(0.46)	
part 1 NSM	0.03	0.09	0.22	0.12	0.10	0.81
	(0.16)	(0.29)		(0.72)	(0.30)	
N	80	33		79	31	

Notes: The value displayed for t-tests are p-values. Standard deviations are robust
All missing values in balance variables are treated as zero.***, **, and *, indicate significance at the 1, 5, and 10 percent critical level.
Balance is evaluated for all variables that predicted participation in LCR.
Sample size is reduced after matching given firms outside the caliper are excluded.

One potential concern is that our definition of the treatment variable may not correctly assign treatment status. Given that we declare a firm as treated once it has participated in at least one LCR auction, we may misallocate firms to treatment (LCR status) that may have only once participated once in an LCR auction. To assess that, we calculate the share of LCR auction participation for all firms that had at least once participated in LCR auctions between 2013 and 2017. Figure 12 in the appendix illustrates that for 25 out of the 33 firms, LCR auctions made up 50% or more of all the auctions they participated in between 2013 and 2017. Accordingly, participating in an LCR auction was important for these firms' business strategies.

4.2 Matching Procedure

We follow the steps outlined in Caliendo and Kopeinig (2008) for the PSM analysis. We opt for a logit model over a probit model to estimate a propensity score (PS) as the former has more density mass in the bounds, which fits better to our data (for details, see 5.1).

We only select variables that are either static over time or have been measured before the start of the treatment in 2013, seem important from economic logic, and use the significance method to decide which variables to drop (Caliendo and Kopeinig, 2008). The final logit estimation is shown in equation 1:

$$\begin{aligned} P(Y_i = 1) = &\beta_0 + \beta_1\, solarpatents_i + \beta_2\, empl_i + \beta_3\, indian_i + \beta_4\, manuf_i + \\ &\beta_5\, nsm_i \, + \, \beta_6\, sales_i \, + \varepsilon_i \end{aligned} \tag{1}$$

where $P(Y_i{=}1)$ is a dummy variable that equals 1 if a firm participated in at least one auction with local content, *solarpatents* is the number of solar patents filed before the initiation of the NSM in 2011, *empl* is the log-transformed number of employees before the LCR in 2013, *indian* is a dummy whether a company is considered Indian, *manuf* is a dummy whether the company is a manufacturer, *nsm* is a dummy whether the company has already participated in the first phase of the NSM auctions, and *sales* is the inverse hyperbolic sine transformation of the average sales of the company in the years before LCR in 2013 or the first year of available data if the company was founded after 2013. The results of the PS estimation are discussed in Section 5.1.

We employ a caliper radius matching (Dehejia and Wahba, 2002) but also provide results from nearest neighbor matching with replacement as a robustness check. Caliper radius matching reduces bias by limiting matches to control observations within a radius of the propensity score, called the "caliper", of the treated observation (Cochran and Rubin, 1973; Lunt, 2014). We adopt a conventional, a rather strict caliper radius of 0.2 standard deviations of the propensity score (0.05 and 0.1 PS units) that should eliminate 93 to 98% of the remaining bias (Austin, 2011; Cochran and Rubin, 1973). We use caliper matching with equal weights rather than distance-weighted radius matching as we have several observations with identical PS (Huber, Lechner and Wunsch, 2013).

Observations outside the caliper are dropped, which is how common support is imposed.

Figure 15 illustrates substantial common support at the lower levels of the PS, while common support is weaker at higher levels of the PS. There are fewer firms that share the characteristics predicting LCR participation that did not participate in LCR auctions. We lose two firms (Bharat and Photon) in the LCR group with the highest PS when imposing a narrow caliper of 0.05 PS units. Firms in the control group with a high propensity score, such as Acme and Mahindra, play an important role, given they serve as counterfactuals for more than one similar firm in the treatment group. Overall, as we lose at most 2 companies in the strictest caliper matching, common support holds reasonably.

4.3 Model specification

We estimate two main difference-in-difference specifications. The first specification is a dynamic difference-in-difference equation similar to Miller, Johnson and Wherry (2021). In addition, we add weights from propensity score matching as in Munch and Schaur (2018). This leads to the following specification:

$$Y_{i,t} = \sum_{\tau=-8}^{-1} \gamma_\tau (w_c * LCR_{i,\tau}) + \sum_{\tau=0}^{7} \delta_\tau (w_c * LCR_{i,\tau}) + \varepsilon_{i,t} \tag{2}$$

where i is an index for each firm, t for each year and τ for each pre- and post-treatment year. $Y_{i,t}$ is the number of annual solar patents or revenue. LCR is a treatment dummy equal to one in year 0 (= 2013) for all firms participating in an LCR auction. Note that each firm is multiplied with a caliper weight w_c based on the PSM outlined in equation 1. We estimate equation 2 with a linear model and report heteroskedasticity-robust standard errors clustered at the firm level to account for serial correlation.

The second difference-in-difference specification is equivalent to what (Goodman-Bacon, 2021) calls a canonical 2x2 design. In this case, we simply aggregate all solar patents filed by the firms in the LCR and in the open auction group before and after the policy. The advantage of this approach is that sum several small changes into one aggregated effect, given annual patenting occurs erratically. Combining the PSM with the 2x2 difference-in-difference approach, as in Munch and Schaur (2018), leads to the following two main specifications for the estimation of the treatment effect on the treated:

$$\delta_{ATT} = \frac{1}{N} + \Sigma_{i=1}^{N} (\Delta y_i^T - w_c * \Delta y_i^C) \tag{3}$$

where ΔY represents the difference in solar patents or revenue for firm i in the treatment group T or control group C summed over the pre-treatment period 2005-2012 and post-treatment period 2013-2020. W refers to the weight that each of the control observations receives. Note that w does not vary across firms i but only across calipers c, as it is the same for all firms within the same caliper c.

We also run several other specifications to examine the robustness of the results. Given the LCR policy focused on cells and modules, we also run the main specification but count only cell and module solar patents. Given solar patent count may be sensitive to outliers, we run a specification excluding firms (Sunedison & Bosch) with high patent count and low auction participation. As winning rather than participating in an auction may incentivize innovation and sales, we also run a specification where treated and control group firms are limited to firms having either won at least one LCR or one open auction. Similarly, we examine whether the number of won LCR auctions rather than a simple LCR dummy changes the results. Finally, as mentioned, we explore the robustness of the results to the choice of the matching algorithm by looking at both caliper and nearest neighbor matching.

4.4 Variables and Data Collection

Table 3 provides an overview of the dependent treatment variable as well as other firm-level variables that were used in the PSM. The main outcome variable is the number of solar patent applications per company filed at the Indian patent office, either annually or cumulative, before and after the introduction of the LCR policy in the second phase of the NSM. We also examine the number of cells and module-related patents. We follow an established approach in the literature by using patents as an indicator of innovation output (Griliches, 1990). While companies may use informal methods of intellectual property protection, such as trade secrecy, patents present a quantifiable measure of inventive innovation and have been increasingly filed in emerging markets in the solar industry (Luan et al., 2021).

We use firms' revenue as a secondary outcome variable to approximate their production. Revenues are a more immediate outcome than patents and may directly capture a potential demand effect from LCR auctions. We use the revenue from the latest year available in the data to allow for the longest possible time span between auction participation and outcome.

The main explanatory or treatment variable is a dummy variable equal to one (the firm is treated) if a company ever participated in an LCR auction during the second phase of the NSM or zero otherwise (the firm is in the control group). Given LCR participation may have been infrequent or unsuccessful, we create a continuous treatment variable that refers to the number of times a company participated and a dummy of whether a firm has ever won an LCR auction. Control variables used in the PSM are listed in **??**.

The data flowchart in figure 9 in the appendix illustrates how different data sources have been combined. Firstly, data about auctions, technical and financial eligibility criteria, and

Table 3: Descriptive Statistics

Variable	Mean	SD	Min	Max
solar patents 2011-2020	0.696	2.850	0	18
solar patents 2001-2010	0.188	1.528	0	16
participated (or not) in LCR auction	0.295	0.458	0	1
indian company	0.768	0.424	0	1
manufacturing company	0.152	0.360	0	1
ihs transf. pre-LCR sales	16.40	8.106	0	27.71
ihs transf. post-LCR sales	21.35	3.085	10.17	28.36
log_total_employees	4.763	2.020	0	10.65
part 1 NSM	0.0446	0.207	0	1
Observations	112			

Note: There are 112 observations as employees is missing for one company.

the firms bidding have been collected from the Solar Energy Corporation India (SECI) online archives as outlined in Münch and Marian (2022). [1]

Secondly, we searched the Indian Patent Office's online portal using the bidding firms' name as the applicant name.[2] After refinement of the firm name, leaving out common words and terms relating to the legal form of the company, we could identify and semi-automatically web-scrape 8,845 patents filed by these firms at the Indian patent office. We used the list of international patent classification (IPC) codes relating to solar PV components by Shubbak (2019) to identify all solar-related patents among the 8,845 patents.

Thirdly, we collected data about the firm characteristics such as origin and number of employees in Mergent Intellect's database as in (Probst et al., 2021). Revenue data was obtained through the Indian data provider Tofler, which digitally compiles the financial data that firms file to the Indian Ministry of Corporate Affairs. To avoid the inclusion of revenues that may have been unaffected by the auctions, we only used revenue data from the legal entity mentioned in the auction documents rather than its Indian or foreign mother company.

5 Results

5.1 What Predicts Participation in Auctions with Local Content?

In the following, we present what is, according to our knowledge, the first analysis of the characteristics of firms that participate in solar auctions, and in particular, solar auctions

[1]Link to SECI's online archives: https://www.seci.co.in/archives/data_archives, last accessed May 15th 2022.

[2]Link to Indian Patents Office's online search portal: https://ipindiaservices.gov.in/publicsearch, last accessed May 15th 2022.

with local content. Importantly, the predictive characteristics of companies participating in LCR auctions are in line with the theoretical framework presented in section 2 as manufacturers disproportionally participate in LCR auctions, while engineering, procurement, and construction (EPC) companies, who import components, predominantly select into open auctions. Table 6 in the appendix illustrates that being an Indian (solar) manufacturer, an electronics component manufacturer, and the number of solar patents filed between 2001 and 2010, and average sales before LCR positively predict a firm's participation in LCR auctions. Figure 11 in the appendix illustrates that most companies that participated in solar auctions (with or without local content), in general, had electrical services or EPC of infrastructure projects as their core business.

Table 5 in the appendix illustrates how firms in open and local content auctions differ. Firstly, LCR auction participants were almost exclusively of Indian ownership. Only 3 out of 33 or 9% of the firms in LCR auctions were international, while 23 of 80 or 28.75% of open auction participants were international. Secondly, 11 of the 17 manufacturing companies participated in the LCR auctions. Finally, even after controlling for outliers, firms in LCR auctions were, on average, still 5 years older than firms in open auctions. This suggests that LCR auctions primarily attracted the intended target group: local, incumbent manufacturers of solar modules or related products.

5.2 What is the Impact of Local Content on Firm Innovation?

We first examine visually the evolution of solar patents filed by the firms that participated in the Indian solar auctions (Figure 5). While the absolute amount of solar patents filed by the 113 participating firms is rather low (100 since 1982, thereof 99 since 2001), the dynamic has increased since the beginning of the NSM as the firms filed in the last decade twice as many solar patents as in the previous three decades from 1982 to 2010.

A naive comparison of LCR participants with non-participants after the LCR policy suggests that LCR participants accumulated 14 additional patents compared to non-participants (figure 5). Such a comparison, however, necessitates the unlikely assumption that non-participants constitute a good counterfactual for participants and that there were no differences before the policy introduction, which we show is not the case (see table 5). A more credible but still simple pre-post comparison of means suggests that LCR had a negative effect and reduced patenting activity in the LCR group by 3 patents compared to the firms in the open auction scheme.[3] The negative effect is driven by the higher relative increase in patents among open auction participants (+1500%) vs. LCR participants (+142%).

[3] (46-19)-(32-2)= 27 - 30 = -3

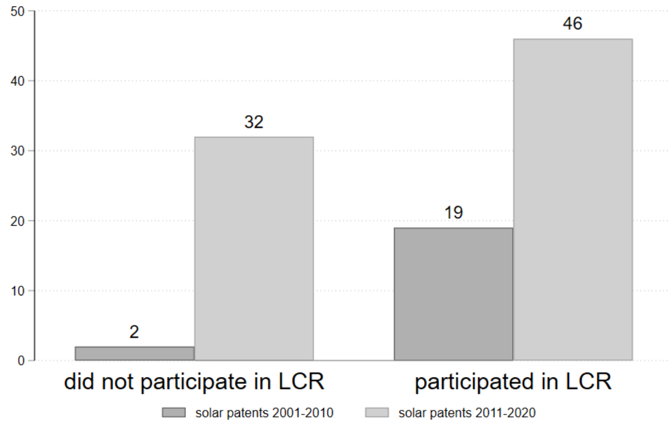

Figure 5: Solar patents filed by firms participating in solar auctions before and after the use of LCR

Figure 6 illustrates the estimates of the yearly effect of LCR on a firm's solar patenting activity. The results from the unmatched sample suggest that LCR had a small negative effect, which is only statistically significant at the 10 percent level, and which only manifests once LCR ceased in 2017. The matched estimates, which weigh non-LCR participants such that they are similar to LCR participants, illustrate that LCR had no statistically significant effect on a firm's patenting activity at any conventional level of statistical significance.

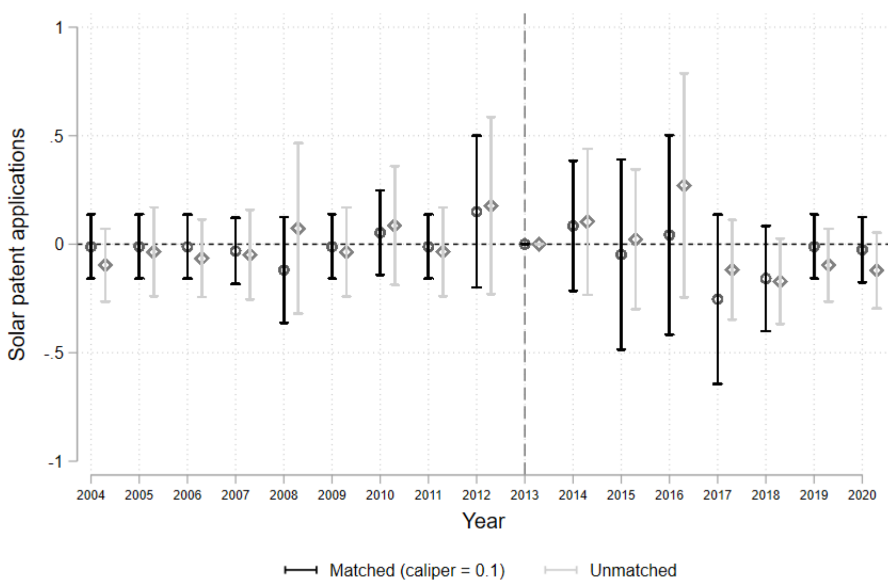

Figure 6: The impact of LCR on firm's solar patenting activity. Black points are point estimates of the number of filed solar patents from a propensity score weighted, and grey points refer to unweighted (left panel) firm-year panel DiD specification. Bars show 95% confidence intervals, and the vertical dotted line shows the year of LCR (treatment) introduction.

Table 4 and table A.1 in the appendix provide an overview of the results from the main, preferred specification as well as all the different robustness checks outlined in section 4. Table 4 reports the results for the pooled mean of solar patents aggregated in the ten years before and after LCRs were introduced in the NSM, and table A.1 provides the results for annual solar patent count firm panel event study difference-in-difference. Panel A in table 4 shows that the only significant estimate is a simple, unmatched post-LCR comparison of the means (Column 1), which reflects Figure 5. A simple DiD (Column 2), DiD with caliper matching (Columns 3 and 4), and restriction to LCR vs. open auction winner firms (Columns 5 and 6) as well as controlling for removing outliers (Columns 7 and 8) all suggest LCR had no significant impact on firms' solar patenting activity. Panels B and C illustrate that this result is also robust to restricting the scope of patents to module and cell solar patents (Panel B), which are the components that were targeted by the LCR policy, and the probability of filling a solar PV patent at all (Panel C).

What is more, the point estimates are small. Even if they were significant, the estimates suggest that the extensive margin of LCR participation has a close to zero effect, the magnitude of the point estimates increase to a third to almost a whole solar patent as well as a 12 to 17% reduction in the probability of filing a solar patent when narrowing the scope to cell and module patents and to winning rather than participating. Table A.1 in the appendix suggests that considering firms' intensity of LCR auction participation reduces the negative point estimate and, at times, turns it even into an insignificant positive point estimate. Table A.1 in the appendix confirms that these results are robust to the time period under investigation as all year-treatment dummies are insignificant at the 5% level across all specifications. Overall, table 4 and table A.1 suggest that LCR had no significant effect on firms' solar patenting activity.

In Panel D of 4 we report the results on post-LCR revenues. The point estimates are negative but also insignificant. Columns 1 and 2 present the results for a naive post difference and a DiD specification, columns 3 and 4 provide the estimates for 0.1 and 0.05 caliper matching DiD and similar to the patent analysis, we consider only including winning bidders (Columns 5 and 6) and excluding three outliers (NTPC, Bharat and Larsen & Toubro), which have very high revenues (Columns 7 and 8) but it does not change the result. We also estimate the treatment effect with the same 4 outcome variables of 4 using nearest neighbor matching with 1 or 2 control observations in A.1 of the appendix, which leads to the same slightly negative but insignificant estimates. Finally, we also estimate the effect using a continuous rather than a binary treatment variable. The results, which are depicted in A.1 of the appendix, are coherent with the other results.

In conclusion, the results suggest LCR did not have a significant impact on either firms'

Table 4: Results of Matching combined with Difference in Differences

			All firms		Winner firms		All w/o outliers	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Simple post difference	DiD	caliper = 0.1	caliper = 0.05	caliper = 0.1	caliper = 0.05	caliper = 0.1	caliper = 0.05
Panel A: Solar PV Patents								
participated in LCR	0.99*	0.44	-0.06	-0.03	-0.93	-0.80	-0.85	-0.78
	(0.58)	(0.57)	(0.80)	(0.80)	(1.19)	(0.69)	(0.75)	(0.63)
Constant	0.40	0.37*	0.89	0.87	1.45	0.80	1.00	0.82
	(0.31)	(0.19)	(0.57)	(0.56)	(1.14)	(0.69)	(0.74)	(0.62)
Observations	113	113	110	109	66	60	106	104
Panel B: PV Module & PV Cell Patents only								
participated in LCR	0.61	0.25	-0.33	-0.36	-0.69	-0.65	-0.47	-0.54
	(0.38)	(0.27)	(0.48)	(0.48)	(1.00)	(0.57)	(0.66)	(0.53)
Constant	0.21	0.20	0.65	0.66	1.21	0.65	0.72	0.58
	(0.21)	(0.14)	(0.44)	(0.44)	(0.95)	(0.57)	(0.63)	(0.53)
Observations	113	113	110	109	66	60	106	104
Panel C: Post-LCR solar patent (binary)								
participated in LCR	0.06	-0.00	-0.05	-0.07	-0.12	-0.17	-0.13	-0.16
	(0.06)	(0.07)	(0.10)	(0.10)	(0.20)	(0.11)	(0.14)	(0.12)
Constant	0.09**	0.06*	0.18**	0.17**	0.27	0.17	0.23*	0.20*
	(0.03)	(0.03)	(0.08)	(0.08)	(0.19)	(0.11)	(0.13)	(0.11)
Observations	113	113	110	109	66	60	106	104
Panel D: Revenues (in INR)								
participated in LCR	-2.00e+10	-2.00e+10	-1.29e+10	-1.04e+10	-3.07e+10*	-1.97e+10	-2.81e+09	-6.60e+09
	(1.33e+10)	(1.24e+10)	(8.09e+09)	(6.83e+09)	(1.73e+10)	(1.22e+10)	(4.05e+09)	(4.82e+09)
Constant	1.49e+10**	1.49e+10*	1.76e+10**	1.49e+10**	1.91e+10**	2.13e+10*	7.47e+09**	9.95e+09**
	(7.16e+09)	(7.57e+09)	(7.94e+09)	(6.66e+09)	(8.41e+09)	(1.22e+10)	(3.76e+09)	(4.56e+09)
Observations	113	113	110	109	66	60	108	104

Results in columns (1) & (2) use unmatched counterfactuals and columns (3)-(8) use matched counterfactuals based on the specified parameters.
Robust Standard errors in parentheses
** $p < 0.05$, * $p < 0.1$

solar patent innovation or their revenue. The results are robust to different matching methods, definitions of the dependent variables innovation, and sample or treatment assignment specifications. At most, the mostly negative but insignificant point estimates suggest that LCR may have had a small negative effect on firms' innovation and revenue.

5.3 Did Local Content Provide a Sufficient Carrot to Incentive Innovation?

Rodrik (2008) suggests that "carrots & sticks", providing sufficient incentives or business opportunities while simultaneously demanding efficiency and quality improvements to catch up with the global frontier, are crucial for successful industrial policy. Following this argument, we conduct a falsification exercise and assess whether LCR have created a sufficiently big incentive or demand shock.

We assess this potential explanation in three ways. First, we examine whether the firms won sufficient capacity (in MW) to result in learning-by-doing from producing the solar modules necessary to generate this capacity (see Figure 1 impact mechanism 1). Figure 14 illustrates the accumulated MW each firm won in LCR and in open auctions between 2013-2017, conditional on having at least won one LCR auction. On average, firms won only 23 MW *over the four years*, and even the best performer - Azure - received only 67 MW in total. To put this into context, large contemporary solar module manufacturing plants have an *annual* capacity of 100 MW+. No single firm won more than 67 MW or 14.4% of the total capacity allocated in LCR auctions, and the larger conglomerates won around five to eight times as much capacity in open auctions. Smaller domestic module producers, such as Vikram, Waaree, Swelect, and Surana won as much MW in LCR as in open auctions. However, the absolute MW amount they each won is less than 30 MW and thus so low that one could not expect any major learning effects or inventive activities. This is also reflected in the analysis of the patents that LCR and non-LCR firms filed. Given the LCR policy specifically targeted solar modules and cells, we analyzed, based on IPC patent codes, whether LCR participants were more likely or file more cells about the targeted components. LCR participants' patents fall more or less in the same categories as those filed by firms that never participated in LCR auctions. We conclude that the demand from local content created only little production, resulting in few opportunities for learning-by-doing over the four years.

Secondly, we assess whether LCR generated sufficient revenue for reinvestment into R&D required for patenting (see Figure 1 impact mechanism 2). Firms supported by the EU's SME R&D grant program and the US Department of Energies Small Business Innovation

Research program file on average 0.7 - 1.3 patents per million USD of R&D expenditure per company (Clancy, 2021; Howell, 2017; Santoleri, Mina, Di Minin and Martelli, 2020). This is similar to the average patent return to R&D expenditure in the US, which is around 0.5 patents per million USD R&D expenditure (Clancy, 2021). Companies that participated in LCR auctions gained on average contracts for modules worth approximately 10 million USD per firm (see Figures 7) [4]. Accordingly, firms would have had to reinvest approximately 10% of their LCR-induced revenues into R&D to generate one additional patent on average (assuming a similar patent return to private R&D in India as in the EU and the US). Indian firms reinvest on average only 0.9% of their sales and even Tata, the Indian firm with the highest R&D expenditure, only reinvested 7.1% of its sales in 2020 (Kumar, 2020). Even the firms that receive large, above-average LCR demand stimuli like Azure (42 million USD), Adani (37 million USD), Tata (34 million USD), and Waree (31 million USD), would have still only generated 1.5-2 additional patents per company assuming 5% re-investment.

Finally, we examine the costs of the policy to the government. Was the government's objective of nurturing a domestic, globally competitive solar industry aligned with the resources it invested? In total, the Indian government allocated approximately 6 GW that generated a demand for solar PV modules worth an estimated 8.65 billion USD from 2013-2017. Only around 10% of the capacity or 329 million USD worth of solar PV modules were auctioned in LCR auctions. Hence, even after assuming slightly higher module prices the overall demand that firms received from LCR auctions between 2013-2017 was small, only around 12.5-20% of the total demand. We also calculate the additional costs of the LCR policy to the Indian government compared to a scenario where the Indian government had just auctioned of the same capacity in open auctions. The results suggest the LCR policy has cost the Indian government an additional 18.5 million USD compared to a scenario where they auctioned off all the capacity in open auctions. Needless to say that these are small investment costs relative to the objective of nurturing a globally competitive and innovative solar industry and for a country of the size of India.

As a result, we conclude that the size of the demand shock from the LCR policy was too small to induce learning-by-doing from production or to generate sufficient revenue for reinvestment into R&D. Accordingly, the two main impact mechanisms identified in section 2 could not materialize.

[4] To estimate the USD amount per company, we used the allocated MW amount in auctions and multiplied it with the average international module price between 2013-2017 (source: Our World in Data global average solar (PV) module price) Given previous research Probst et al. (2020) had shown prices in Indian LCR auctions were 6% higher, we adjusted the value for LCR auctions accordingly.

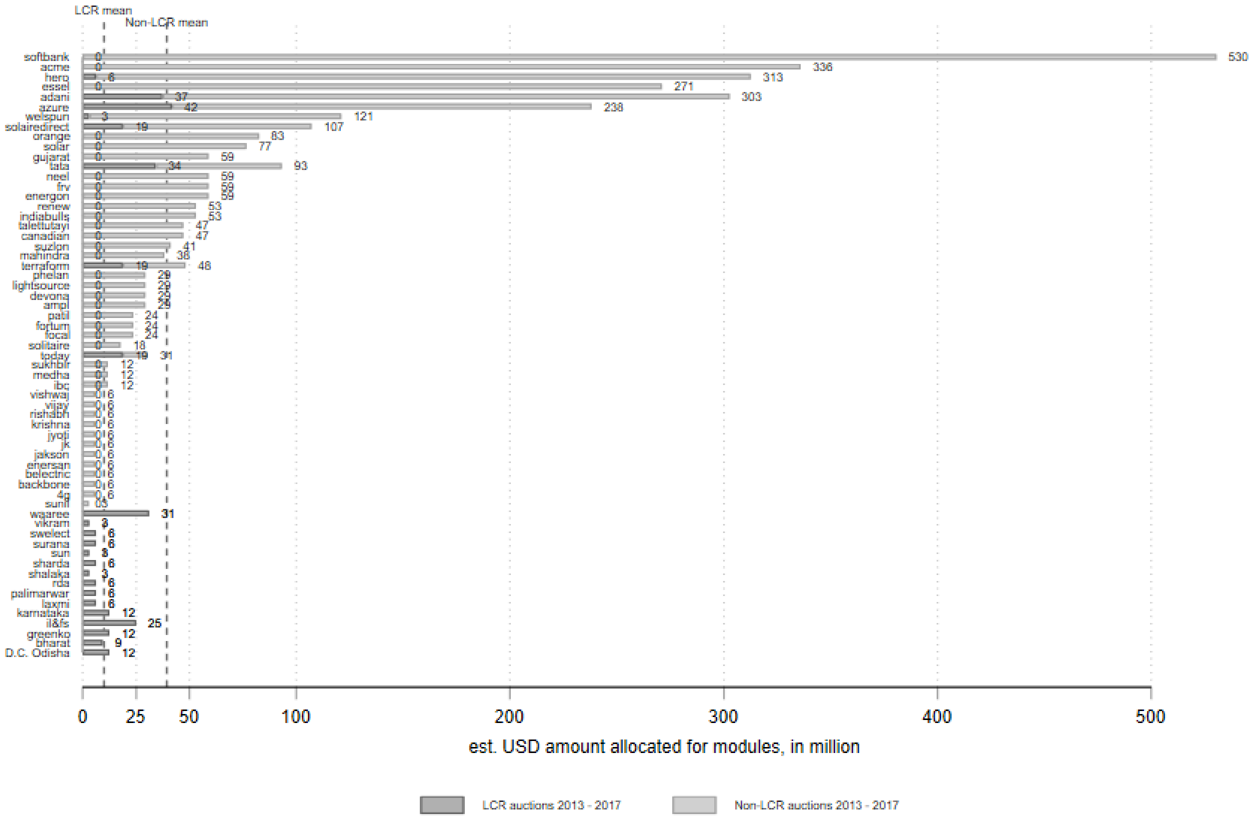

Figure 7: Est. USD value of module demand of LCR vs. open auctions (2013-2017)

5.4 Did Local Content Provide a Sufficient Stick to Incentivize Innovation?

A second potential explanation relates to the common critique that industrial policies provide too much protection and thus no incentive for beneficiaries to improve, given they are spared from competing with the globally most productive firms. If true, LCR may unintentionally and unexpectedly reduce firms' incentive to innovate.

The fact that competition in LCR auctions was considerably lower than in open auctions lends meaning to this explanation. Figure 8 illustrates that firms had, on average, a 63.5% chance that their bid would be successful in LCR auctions, which was 22 percentage points higher than in open auctions. In table 1, we have already shown that the number of bidders in LCR auctions (4.82) was only about half the number in open auctions (8.9) and that international bidders were more frequently barred from bidding in LCR auctions. Moreover, Münch and Marian (2022) showed that LCRs were not combined with any other performance requirement, such as international quality standards, which could have functioned as performance requirements in the absence of competition from international (and many national) firms. Finally, figure 13 in the appendix shows that only very few firms managed to file a single solar patent since the beginning of the LCR auctions in 2013. Most of the firms that filed solar patents are either large Indian or international conglomerates, which illustrates that the initial entry euphoria in the Indian solar auctions has been followed by a consolidation and concentration of the major share of business among a few potent players. These "infants" may not necessarily only require protection but may, in the absence of foreign competition, benefit from alternative performance requirements that push them to innovate.

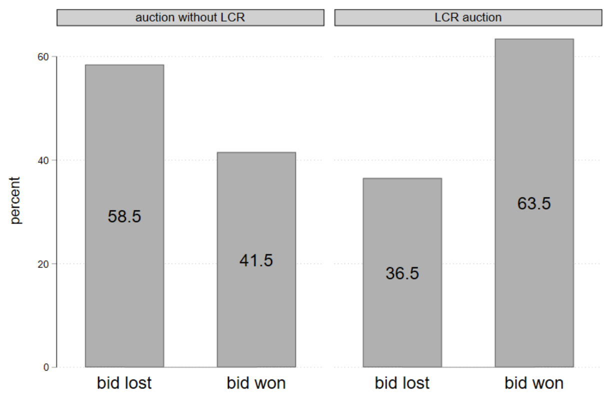

Figure 8: Probability that a firm's bid was successful in LCR vs. no-LCR auctions

5.5 Was Local Content Revenue an Additionality or a Substitute?

The results cast doubt on the idea that revenue from LCR auctions is additional. The insignificant differences in revenue with comparable, matched firms from the open auction scheme (Panel D of table 4) suggest that LCR participants would have had at least as much revenue had they participated in the open auctions. Given firms could choose to participate in LCR or open auctions or in both and given firms, especially manufacturers, are capacity constrained (e.g. through the number of manufacturing assembly lines or access to credit for EPC), LCR participants may have prioritized LCR auctions and only competed in open auctions if their present capacity was not yet saturated. In this case, revenue from LCR would have substituted revenue from open auctions rather than being additional. Given the lower competition and higher prices in LCR auctions, there was a business incentive for such strategic behavior, at least for smaller Indian module producers, but not for bigger conglomerates, as the MW volume in LCR auctions was too low for them to exclusively focus on LCR auctions.

Having said this, we want to caution against premature conclusions. As revenue is an outcome with much higher variance than patents, precise estimation ideally requires a larger sample size and, as we showed above, a more substantial treatment. For example, given the estimate standards errors in table 4, the smallest statistically significant change in revenue we could have detected was 188 million USD. As we outlined, the average demand shock was only around 10 million USD, which illustrates that we lack statistical power to measure a precise effect and therefore implies that it difficult to tell apart a null effect and type-2 error in the case of the revenue analysis.

6 Limitations

This study has limitations that should be addressed in future research. A primary concern relates to statistical power and whether we measure a true null effect or a type-II error. To assess the plausibility of the null effect, we estimate how many patents the firms in the LCR group would have needed to create to measure a statistically significant effect. We conduct ex-post power calculations to estimate the minimum statistically detectable effect size using the estimates standard errors from table 4.[5] We find that the LCR policy would have had to induce between 1.59 and 3.33 or an average of 2.1 additional patents in the LCR group relative to the open auction group to detect statistically significant effects given the sample size.

Are 2.1 patents per firm in response to an LCR policy realistic or an implausible effect? While there is no existing estimate of the specific impact of any LCR policy on firm performance, there are studies of other government support programs, which provide a good benchmark in so far as the Indian government could have opted for different policy options, such as R&D grants, to promote domestic solar component production and innovation (Clancy, 2021; Howell, 2017; Santoleri et al., 2020). Accordingly, to generate 2.1 patents per firm, LCR firms would have needed to receive an average demand shock worth 60 million USD, assuming an average 5% reinvestment of revenue into R&D and assuming every LCR dollar has the same effect as a dollar from an R&D subsidy in the EU or the US public or private sector. [6] This is six times as much as firms won on average in LCR auctions and far more than the 18.5 million the government invested into the policy. At the same time,

[5] To have an 80% chance of drawing an estimator that is 1.96 standard errors away from zero, we multiply the estimated standard errors of the LCR coefficient in table 4 with 2.8 as the inverse normal of 80% is 0.84 and $1.96 + 0.84 = 2.8$. See, for example, Ioannidis, Stanley and Doucouliagos (2017) for a more detailed explanation.

[6] $60*0.05 = 3$. $3*0.7 = 2.1$ patents. Note that we do not account for learning-by-doing in this simplified calculation. If the input-output efficiency of the LCR policy is lower (higher) than the EU or US private and public R&D, the per-company demand shock would need to be even higher (lower).

it is not an unrealistic amount. Assuming the 33 LCR participants had won 60 rather than 10 million USD, on average, the total costs would have been 1.98 billion USD or 22% of the total module demand allocated in solar auction in this period (8.65 billion).

Apart from statistical power, this study is limited to the firm-level outcomes we observe. LCR may focus on other objectives than nurturing a globally competitive local industry, such as employment creation or independence from foreign suppliers. Future studies should assess these impacts by collecting, if available, employee data to study whether LCR create jobs, even if industries may not be internationally competitive. Furthermore, LCR may promote technological capabilities that are not necessarily new to the frontier inventions, and that may not be captured well by patents or which may occur in down-or upstream companies through backward and forward linkages. Given we collect data on patents in the absence of indicators of firms' technological and innovation capabilities and focus exclusively on the firms that participate in auctions and not their suppliers, we can not capture innovation activities of this sort from these groups. Future research should further improve on this study, for example, by employing firm innovation surveys or firm administrative records to capture innovative activity that does not lead to a patent.

7 Conclusion & Policy Implications

While there has been an overall increase in patent applications in India with the onset of the National Solar Mission, we do not find evidence that LCR auctions led to more innovation or revenue among the participating firms. Overall, patenting activity of the auction participants remained quite limited, as only 14 out of 113 participants filed a solar patent in our observed period (1982-2020). However, patent applications increased significantly with the start of the LCR auction scheme in 2013. Still, the increase was even slightly more pronounced in the group participating only in the open auctions, which partially explains why the difference-in-difference estimate was insignificant. The firms that participated in LCR auctions were, on the one hand, more likely to be Indian manufacturers, which the policy aimed to promote, but on the other hand, also older, established businesses, many of whom were in economic distress even before the LCR policy started (Johnson, 2016). This creates concern the policy may have rather helped firms to survive than promote a competitive industry with global ambitions, as outlined in the government's original mission statement (MnRE, 2009).

We derive two explanations for why the LCR auction scheme did not have a significant innovation impact. The first explanation is that the demand stimulus provided by the LCR auction was insufficient. Power calculations reveal that we need to observe a minimum increase of 1.59 patents per firm to measure a statistically significant difference. Estimates from other studies from the EU and the US suggest that 1 million R&D spending results in a return between 0.5 to 1.3 patents. However, the additional demand for PV modules created by the LCR auctions only sums up to an average 10 million USD per firm, which was likely too low given firms reinvest less than 10% of their revenues in R&D. In addition, our results question the idea that revenue from LCR auctions was additional. Instead, insignificant differences with comparable, matched firms from the open auction scheme suggest that LCR participants would have received at least as much sales in open auctions. Accordingly, LCR participants may have decided to compete and generate business either from LCR or open auctions, which implies LCR revenue may have substituted revenue from open auctions rather than being additional. However, given the low intensity of the demand shock and the high variance in revenue, we can not confidently conclude whether there was a substitution in revenue and activity or whether the demand shock was simply too small to detect it in a statistically significant way in the population of firms.

A second explanation relates back to Rodrik's argument that industrial policies should not only consist of protection but also discipline firms to improve. There are two pieces of evidence that support this claim. Firstly, the competition in LCR auctions is much lower than in open ones, as the number of bidders is almost half and less international. In addition, the winning probability in LCR auctions is 63.5%, which is 22 percentage points higher than in open auctions. Finally, policy-makers did also not link LCR with alternative performance requirements, such as international quality standards (Münch and Marian, 2022).

The findings point towards the following policy implications. Firstly, governments should refrain from running LCR and open auctions in parallel in the future. The fact that the Indian government ran two different auction types in parallel created practically two different markets and bad incentives for adverse selection. On the LCR market, bidders faced low competition and high certainty to win, but auctions were so small they were unlikely to have large-scale effects. Firms faced high competition and potential gains in the open auction market. It is very likely that less competitive firms selected into the LCR market while the most competitive firms participated primarily in the open auctions. While this policy provides local manufacturers with protection, which may be necessary to survive, it does not propel them to invest in innovation and grow.

Secondly, while LCR were successful in attracting its target group, Indian module, and cell manufacturers, they significantly reduced competition. This implies it is imperative for any government using LCR in the future to combine LCR with alternative performance requirements, such as international quality standards or innovation requirements, such as improvements in cell efficiency levels that have to be gradually increased to create an impetus for improvement, as done for example in the Chinese top runner program (IEA, 2022).

Thirdly, the size of the demand shock needs to be more substantial than was the case in India and may have to last for longer than only four years. For example, the IEA (2022) documented recently that the Chinese government used several supply-side tools, such as grants, subsidies, and low-cost loans, for more than a decade before it combined them with demand-side policy tools, which it also linked to performance requirements in cell manufacturing. These lessons seem crucial for the success of new programs, such as new auctions linking component manufacturing with electricity generation as used in Turkey and India, and India's recent production-linked incentive scheme (IEA, 2022). Otherwise, government support will remain a condition for India's (and other countries) solar industry continuation.

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A Appendix

A.1 Tables

Table 5: Mean differences of key characteristics between firms that participate in LCR auctions and those who do not

Variable	(1) did not participate in LCR Mean/SD	(2) participated in LCR Mean/SD	T-test P-value (1)-(2)
(firstnm) indian	0.78	0.94	0.01**
	(0.42)	(0.25)	
filed patent before 2012	0.15	0.09	0.39
	(0.36)	(0.30)	
non-solar patents 1982-2011	10.36	71.31	0.24
	(75.47)	(292.71)	
solar patents 1982-2011	0.03	0.69	0.26
	(0.16)	(3.36)	
solar patents 2012-2021	0.40	1.38	0.21
	(1.75)	(4.30)	
non-solar patents 2012-2021	14.50	126.19	0.24
	(100.09)	(537.29)	
Indian SOE	0.03	0.09	0.21
	(0.16)	(0.30)	
age	20.88	30.84	0.09*
	(22.36)	(30.53)	
main business is energy	0.60	0.63	0.81
	(0.49)	(0.49)	
manufacturing company	0.07	0.34	0.00***
	(0.27)	(0.48)	
solar manufacturing	0.04	0.25	0.01***
	(0.19)	(0.44)	
subsidiary of mother company	1.29	1.19	0.25
	(0.46)	(0.40)	
N	80	32	

Notes: The value displayed for t-tests are p-values. Standard deviations are robust. All missing values in balance variables are treated as zero. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table 6: Selection of variables used for PSM

	(1) Indian	(2) HQ in Delhi	(3) pre-LCR patents	(4) pre-LCR solar patents	(5) pre-LCR sales	(6) pre-LCR employees	(7) Sector	(8) Electronics	(9) SOE	(10) Age	(11) Energy focus	(12) Manufacturer	(13) Subsidiary	(14) Phase 1	(15) All	(16) Final
indian	1.40**		1.39**	1.50**	1.23*	1.45**	1.35*	1.40*	1.33*	1.34*	1.39*	1.61**	1.58*	1.61*	1.72	1.78**
	(0.66)		(0.65)	(0.65)	(0.69)	(0.69)	(0.72)	(0.75)	(0.75)	(0.73)	(0.77)	(0.75)	(0.82)	(0.83)	(1.05)	(0.83)
HQ in Delhi=1		-0.08														
		(0.51)														
not solar patents, ihs transformed			0.07												-0.79	
			(0.18)												(0.54)	
solar patents 2001-2010				1.24											4.23**	1.67*
				(0.81)											(2.07)	(0.96)
ihs transf. pre-LCR sales					0.03										0.05	0.04
					(0.03)										(0.04)	(0.03)
log_total_employees						-0.05									-0.23	-0.29**
						(0.11)									(0.18)	(0.15)
industry							0.66									
							(1.25)									
construction							-0.71									
							(1.02)									
business services							-1.04									
							(1.10)									
electrical services, EPC							-0.46									
							(0.86)									
electronics, component manufacturers							1.51									
							(0.98)									
utility							0.00									
							(.)									
sector															0.19	
															(0.25)	
electronics sector=1								1.97***	1.96***	1.85***	1.99***					
								(0.61)	(0.61)	(0.64)	(0.63)					
Indian SOE=1									1.09						1.36	
									(0.95)						(1.55)	
age										0.01					0.00	
										(0.01)					(0.01)	
main business is energy=1											-0.06				0.00	
											(0.49)				(0.62)	
manufacturing company=1												1.99***			1.72**	
												(0.59)			(0.80)	
solar manufacturing=1													1.59***	1.49**		1.65**
													(0.58)	(0.61)		(0.68)
subsidiary of mother company													-0.00			
													(0.54)			
part 1 NSM=1														1.07	1.09	1.01
														(1.13)	(1.78)	(1.16)
subsidiary															-0.26	
															(0.67)	
Constant	-2.04***	-0.87***	-2.07***	-2.22***	-2.49***	-1.83***	-1.81	-2.31***	-2.31***	-2.43***	-2.27***	-2.57***	-2.42**	-2.49***	-3.26***	-2.06**
	(0.62)	(0.23)	(0.59)	(0.61)	(0.65)	(0.70)	(1.11)	(0.73)	(0.73)	(0.68)	(0.87)	(0.74)	(1.21)	(0.84)	(1.21)	(0.84)
Observations	113	113	113	113	113	112	110	113	113	113	113	113	113	113	112	112

Standard errors in parentheses

All estimtes are based on a Logit model with robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Predicting participation in LCR auctions

	(1)
	participated (or not) in LCR auction
participated (or not) in LCR auction	
log_total_employees	-0.29**
	(0.15)
ihs transf. pre-LCR sales	0.04
	(0.03)
solar patents 2001-2010	1.67*
	(0.96)
indian company	1.78**
	(0.83)
solar manufacturing	1.65**
	(0.68)
part 1 NSM	1.01
	(1.16)
Constant	-2.06**
	(0.84)
Observations	112

Standard errors in parentheses

Estimates are based on a Logit model with robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Difference-in-difference combined with PSM

	All firms		Winner firms		All w/o outliers	
	(1)	(2)	(3)	(4)	(5)	(6)
	caliper = 0.1	caliper = 0.05	caliper = 0.1	caliper = 0.05	caliper = 0.1	caliper = 0.05
participated in LCR × year=2004	-0.01	-0.02	-0.10	0.00	-0.06	0.01
	(0.08)	(0.08)	(0.10)	(0.00)	(0.07)	(0.01)
participated in LCR × year=2005	-0.01	-0.02	-0.00	0.00	0.01	0.01
	(0.08)	(0.08)	(0.14)	(0.00)	(0.10)	(0.01)
participated in LCR × year=2006	-0.01	-0.02	-0.05	0.00	-0.03	0.01
	(0.08)	(0.08)	(0.11)	(0.00)	(0.08)	(0.01)
participated in LCR × year=2007	-0.03	-0.03	-0.00	0.00	-0.00	-0.00
	(0.08)	(0.08)	(0.14)	(0.00)	(0.10)	(0.01)
participated in LCR × year=2008	-0.12	-0.12	0.17	-0.03	0.14	-0.01
	(0.12)	(0.12)	(0.30)	(0.03)	(0.23)	(0.02)
participated in LCR × year=2009	-0.01	-0.02	-0.00	0.00	0.01	0.01
	(0.08)	(0.08)	(0.14)	(0.00)	(0.10)	(0.01)
participated in LCR × year=2010	0.05	0.05	0.05	0.00	0.08	0.05
	(0.10)	(0.10)	(0.17)	(0.00)	(0.13)	(0.04)
participated in LCR × year=2011	-0.01	-0.02	-0.00	0.00	0.01	0.01
	(0.08)	(0.08)	(0.14)	(0.00)	(0.10)	(0.01)
participated in LCR × year=2012	0.15	0.15	0.10	0.00	0.08	0.01
	(0.18)	(0.18)	(0.21)	(0.00)	(0.16)	(0.01)
participated in LCR × year=2014	0.08	0.08	0.05	0.00	0.04	0.01
	(0.15)	(0.16)	(0.17)	(.)	(0.13)	(0.01)
participated in LCR × year=2015	-0.05	-0.05	-0.48	-0.25	-0.35	-0.22
	(0.22)	(0.23)	(0.40)	(0.23)	(0.26)	(0.21)
participated in LCR × year=2016	0.04	0.06	0.23	-0.15	-0.04	-0.14
	(0.23)	(0.24)	(0.42)	(0.11)	(0.26)	(0.12)
participated in LCR × year=2017	-0.25	-0.28	-0.49	-0.26	-0.26	-0.20
	(0.20)	(0.20)	(0.40)	(0.23)	(0.27)	(0.21)
participated in LCR × year=2018	-0.16	-0.15	-0.34	-0.13	-0.24*	-0.14
	(0.12)	(0.12)	(0.21)	(0.11)	(0.14)	(0.11)
participated in LCR × year=2019	-0.01	-0.02	-0.10	0.00	-0.06	0.01
	(0.08)	(0.08)	(0.10)	(0.00)	(0.07)	(0.01)
participated in LCR × year=2020	-0.03	-0.03	-0.11	-0.04	-0.08	-0.01
	(0.08)	(0.08)	(0.10)	(0.04)	(0.07)	(0.02)
Observations	1870	1853	1122	1020	1802	1768

Standard errors in parentheses

Event window before-after 2013, with 2013 as baselevel for year dummmies.

Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Robustness: Results with Neareast Neighbour Matching

	1 nearest neighbor		2 nearest neighbors			
	(1)	(2)	(3)	(4)	(5)	(6)
	All firms	Winner firms	All w/o outliers	All firms	Winner firms	All w/o outliers
			Panel A: Solar PV Patents			
participated in LCR	-1.33	-1.38	-0.97	-0.42	-0.44	-0.41
	(1.53)	(1.42)	(0.99)	(1.02)	(0.89)	(0.58)
Constant	2.15	1.88	1.31	1.24	0.94	0.75
	(1.43)	(1.39)	(0.96)	(0.87)	(0.83)	(0.53)
Observations	51	35	49	65	45	62
			Panel B: PV Module & PV Cell Patents only			
participated in LCR	-1.36	-0.96	-0.56	-0.61	-0.23	-0.09
	(1.20)	(1.22)	(0.86)	(0.74)	(0.75)	(0.51)
Constant	1.82	1.46	0.94	1.06	0.73	0.47
	(1.18)	(1.18)	(0.83)	(0.71)	(0.69)	(0.46)
Observations	51	35	49	65	45	62
			Panel C: Post-LCR solar patent (binary)			
participated in LCR	-0.12	-0.21	-0.22	-0.06	-0.02	-0.16
	(0.16)	(0.24)	(0.18)	(0.12)	(0.16)	(0.17)
Constant	0.27*	0.38	0.34*	0.21**	0.19	0.28*
	(0.14)	(0.23)	(0.17)	(0.11)	(0.14)	(0.15)
Observations	51	35	49	65	45	62
			Panel D: Revenues (in INR)			
participated in LCR	-8.92e+09	-1.78e+10	-2.19e+09	-9.50e+09	-1.42e+10	-9.57e+08
	(1.05e+10)	(1.57e+10)	(4.20e+09)	(1.04e+10)	(1.41e+10)	(3.42e+09)
Constant	3.84e+09	9.12e+09	6.66e+09*	4.43e+09	5.55e+09	5.43e+09*
	(3.37e+09)	(7.50e+09)	(3.92e+09)	(3.33e+09)	(4.00e+09)	(3.07e+09)
Observations	51	35	54	65	45	67

Robust Standard errors in parentheses

** $p < 0.05$, * $p < 0.1$

Table 10: Adjusted for Treatment Intensity: Difference-in-Differences combined with propensity score matching

			All firms		Winner firms		All w/o outliers	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Simple post difference	DiD	caliper = 0.1	caliper = 0.05	caliper = 0.1	caliper = 0.05	caliper = 0.1	caliper = 0.05
Panel A: Solar PV Patents								
No. of times participated in an LCR auction	0.51*	0.21	-0.02	-0.01	-0.17	-0.41	-0.19	-0.16
	(0.31)	(0.20)	(0.28)	(0.27)	(0.46)	(0.36)	(0.36)	(0.32)
Constant	0.45	0.41**	0.88*	0.86*	1.14	0.69	0.72	0.55
	(0.30)	(0.20)	(0.51)	(0.50)	(0.98)	(0.60)	(0.63)	(0.53)
Observations	113	113	110	109	66	60	106	104
Panel B: PV Module & PV Cell Patents only								
No. of times participated in an LCR auction	0.37*	0.18	-0.08	-0.08	-0.14	-0.33	-0.09	-0.14
	(0.20)	(0.15)	(0.20)	(0.20)	(0.37)	(0.30)	(0.28)	(0.24)
Constant	0.22	0.19	0.55	0.54	1.00	0.57	0.56	0.42
	(0.20)	(0.13)	(0.36)	(0.36)	(0.80)	(0.50)	(0.52)	(0.43)
Observations	113	113	110	109	66	60	106	104
Panel C: Post-LCR solar patent (binary)								
No. of times participated in an LCR auction	0.07*	0.04	0.02	0.02	0.02	-0.09	0.01	0.00
	(0.03)	(0.06)	(0.07)	(0.07)	(0.10)	(0.06)	(0.09)	(0.09)
Constant	0.08**	0.04	0.14*	0.12	0.18	0.15	0.16	0.12
	(0.03)	(0.03)	(0.07)	(0.07)	(0.17)	(0.10)	(0.12)	(0.10)
Observations	113	113	110	109	66	60	106	104
Panel D: Revenues (in INR)								
No. of times participated in an LCR auction	-9.88e+09	-9.88e+09	-4.38e+09	-3.32e+09	-1.08e+10	-1.00e+10	-5.28e+08	-1.55e+09
	(7.00e+09)	(7.52e+09)	(3.36e+09)	(2.84e+09)	(8.32e+09)	(6.46e+09)	(1.80e+09)	(2.11e+09)
Constant	1.36e+10**	1.36e+10*	1.46e+10**	1.23e+10**	1.35e+10*	1.86e+10*	6.48e+09**	7.91e+09**
	(6.84e+09)	(6.94e+09)	(6.37e+09)	(5.33e+09)	(7.67e+09)	(1.06e+10)	(3.01e+09)	(3.75e+09)
Observations	113	113	110	109	66	60	108	104

Results in columns (1) & (2) use unmatched counterfactuals and columns (3)-(8) use matched counterfactuals based on the specified parameters.
Robust Standard errors in parentheses
** $p < 0.05$, * $p < 0.1$

A.2 Figures

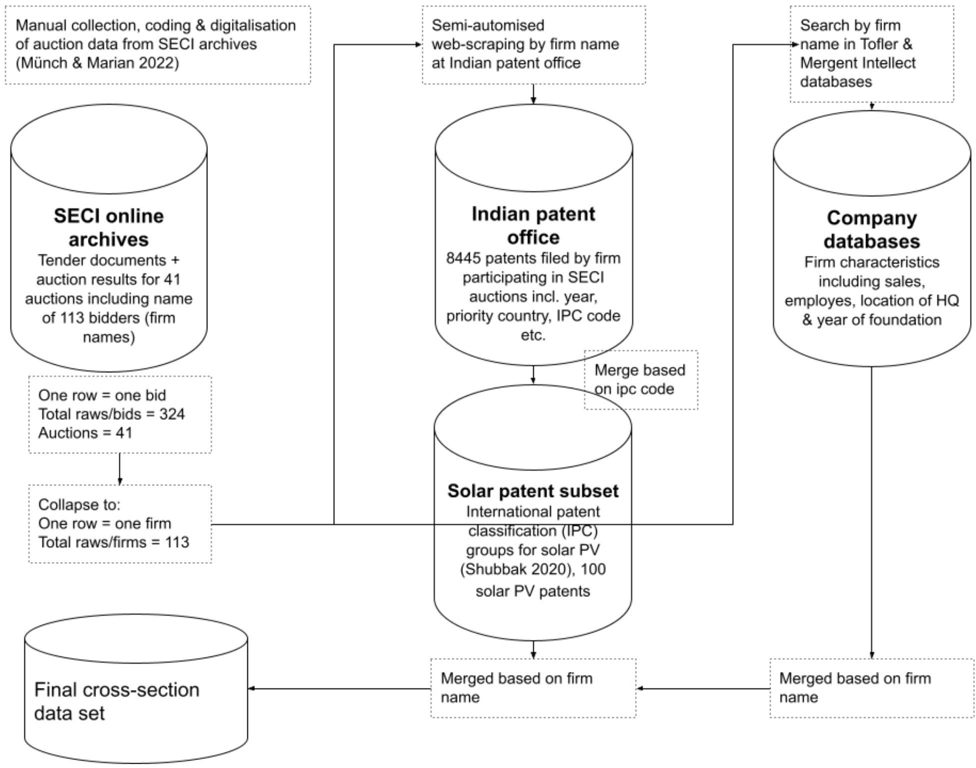

Figure 9: Data flowchart illustrating the construction and combination of the different data sources

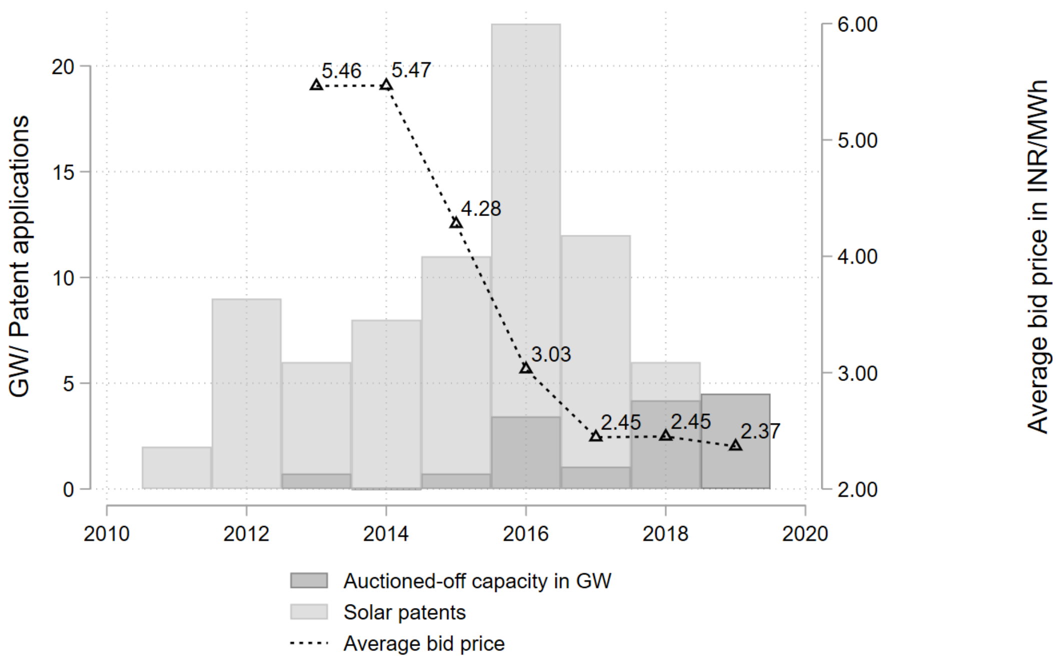

Figure 10: Auctioned capacity, patent applications and bid price development

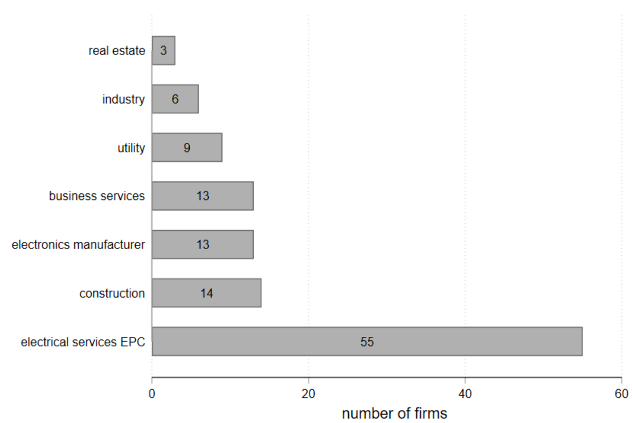

Figure 11: Auction participants by main sectors

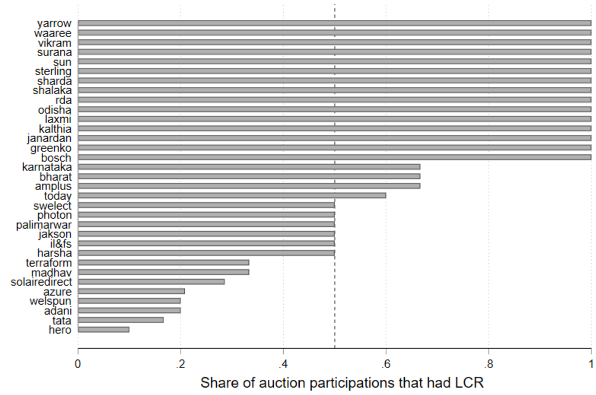

Figure 12: Share of LCR auctions among LCR participants

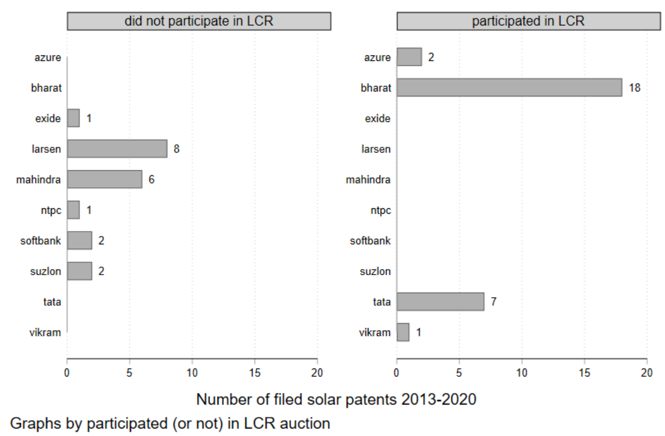

Figure 13: The firms that filed solar patents and their participation in LCR auctions

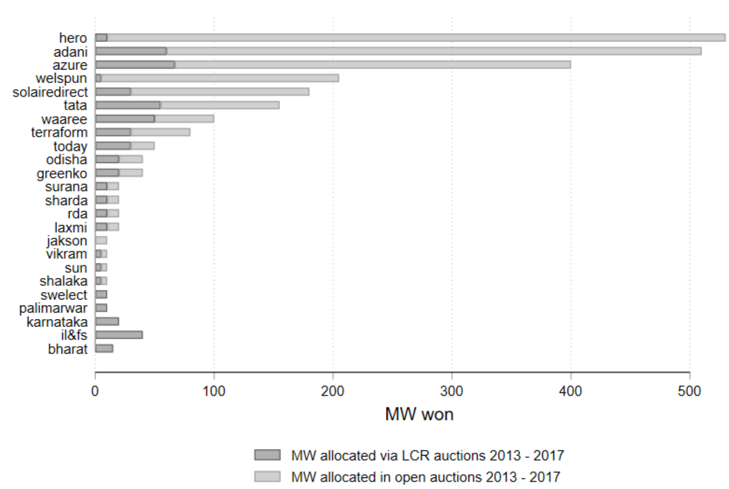

Figure 14: Demand shock LCR vs. open auctions: MW won 2013-2017

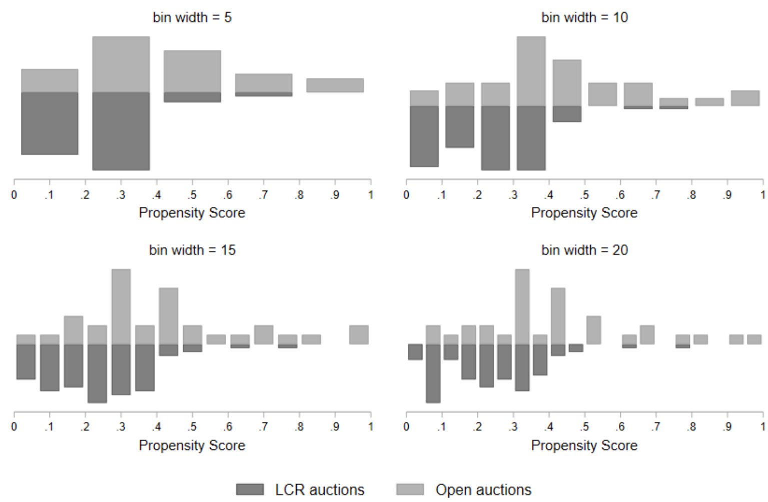

Figure 15: Common support for the whole sample. Several bin width are reported for transparency.