Industrial Policy Under Imperfect Competition: Evidence from Utility-Scale Solar in India*

Shresth Garg† Sagar Saxena‡

Harvard University *Yale University*

August 31, 2023

Click here for the latest version.

Abstract

How do import tariffs and production subsidies, aimed at supporting a domestic industry, perform in settings with oligopolistic markets? We study this question in the context of India's utility-scale solar sector, which comprises two connected industries: an upstream industry that produces solar panels and a downstream industry that develops solar power plants. In recent years, the Indian government has relied on both import tariffs and production subsidies to support domestic producers in the upstream solar panel industry. To empirically examine the effects of these policies, we develop a structural model of the solar sector and estimate it using data from these two industries. We derive optimal policies for three scenarios – only tariffs, only subsidies, or a mix of the two – which expand upstream domestic output to a given target level. Depending on the intended magnitude of expansion, both tariffs and subsidies can improve welfare relative to no intervention. But neither dominates the other at all levels of the target, and for a range of expansion goals, a mix of both policies yields the greatest welfare gains for the sector.

*We are grateful to Pol Antras, Myrto Kalouptsidi, Robin Lee, Marc Melitz, and Ariel Pakes for their comments. We would also like to thank participants of the Harvard IO and trade workshops for their helpful feedback. We gratefully acknowledge financial support from the Lab for Economic Applications and Policy (LEAP) and the Harvard Global Institute (HGI). All errors are our own.

†Email: garg@g.harvard.edu

‡Email: sagar.saxena@yale.edu

1 Introduction

Industrial policy interventions are often targeted at expanding a given domestic industry's total production. This goal can arise from various considerations: protecting an infant industry, enhancing supply-chain resilience, correcting distortions and externalities, or pursuing political and strategic objectives. To this end, two popular industrial policy interventions are import tariffs and production subsidies. Textbook models with perfect competition suggest that while both reduce total welfare, subsidies are less costly than tariffs for achieving a given target level of domestic production (as Figure 1 illustrates).

However, in oligopolistic markets, both tariffs and subsidies can be welfare-enhancing. If foreign producers have large markups, potentially due to a cost advantage, then for a range of tariff values, tariffs can increase domestic welfare by recovering part of these markups in the form of tariff revenues. Similarly, for a range of subsidy values, subsidies can increase domestic welfare by reducing the cost disadvantage faced by domestic producers. In particular, depending on the desired level of domestic production, it may be optimal to use both tariffs and subsidies.

In this paper, we empirically examine these forces in the context of the utility-scale solar sector in India. The sector encompasses an upstream industry that produces solar panels (or modules) and a downstream industry that develops solar power plants which generate electricity for end-use. Since 2010, the downstream industry has undergone a rapid expansion in its size.[1] However, this expansion has primarily been fueled by cheap imported solar modules. As such, the share of domestic producers in the upstream industry has remained at very low levels.

To support domestic producers of solar panels, in recent years, the Indian government has introduced two major policy interventions. First, starting in August 2018, the government implemented a safeguard duty of 25% on solar cells and modules imported from China and Malaysia. From April 2022 onwards, this was converted into a basic customs duty of 40% on all imports of solar cells and modules. Second, in November 2020, the government rolled out a production-linked incentive (PLI) scheme, effectively offering a per-unit subsidy on the production of solar modules.[2]

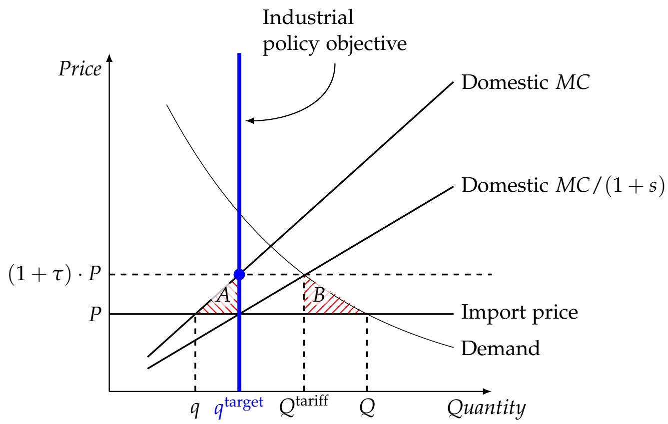
Our goal is to compute and compare the welfare impact of these upstream interventions on the entire utility-scale solar sector. To that end, we develop a structural model of the upstream and downstream industries, and estimate key supply and demand parameters using data from the two industries. We then conduct a counterfactual exercise where we increase domestic production of solar panels to a target level (say 20% more than the baseline) using tariffs, subsidies, or a mix of the two. All interventions hold this target constant, but all other equilibrium outcomes in the two industries are allowed to vary. Finally, we compute the welfare impact of each intervention by comparing the counterfactual outcomes to the baseline.

The structure of the utility-scale solar sector in India makes it an attractive setting to study the welfare effects of tariffs and subsidies. Solar panels produced by the upstream industry are

[1] Installed capacity at the end of 2020 was 35 gigawatts compared to under 200 megawatts in 2010, which corresponds to a compound annual growth rate of approximately 70%.

[2] The subsidy to the solar sector under the PLI scheme is part of a broader push to provide production-linked subsidies to a wide variety of manufacturing industries. As of 2022, subsidies totaling over $26 billion have been announced.

Figure 1: *Comparing tariffs and subsidies in a model with perfect competition*



Notes: This figure considers the welfare effects of tariffs and subsidies set to achieve a given target for domestic production. Under no tariff or subsidy, domestic production is at q. With a tariff of τ, production is reallocated to domestic producers until domestic output reaches q^{target}. This shrinks the total size of the market to Q^{tariff}, and lowers consumer surplus, part of which is captured as government revenues from tariffs. Thus, the net welfare loss is the sum of the areas labeled A and B. With a subsidy of s, marginal cost of domestic production is lower so the domestic supply curve turns outwards allowing domestic output to reach q^{target}. There is no loss in consumer surplus but the government incurs a cost equal to the subsidy amount. Since in this simple example with a linear marginal cost curve $\tau = s$, part of the subsidy expenditures are captured by domestic producers, so the net welfare cost is just the area labeled A. Thus, in this stylized model, subsidies are less costly than tariffs for achieving a given target level of domestic production.

primarily consumed in utility-scale solar projects.[3] Furthermore, the output of the downstream industry, solar power, is purchased mainly by government-run power distribution companies. Thus, in our setting, we have a simple vertical structure, which makes it straightforward to calculate all downstream welfare effects associated with policies affecting the upstream industry of solar panels. This is in contrast with other empirical settings where one might have to trace through a network of downstream industries to estimate the overall impact.

We model the upstream industry as a Cournot oligopoly, treating solar panels as homogeneous goods. Using data on quarterly market shares constructed from a novel dataset on the names of solar panel suppliers for solar power plants in India, we estimate parameters governing the cost structure of domestic and foreign producers. In contrast, the downstream industry is organized as an English auction. These are procurement auctions run by government agencies to award long-run power purchase agreements to solar plant developers who build and operate solar plants. We use auction-level bid data to estimate the private costs of developing these solar plants. Importantly, this downstream model allows us to estimate the impact of the price of solar panels on the winning bids in these auctions and the realized profits of the winning bidders.

Using this estimated model, we run counterfactuals with different policy interventions that increase domestic production by 20% over the baseline level, i.e., without tariffs or subsidies. We consider three sets of policy instruments: import tariffs, production subsidies, and a welfare-maximizing mix of import and production subsidies. Given our parameters, the optimal tariff

[3]Given the small size of the rooftop solar industry in India, we ignore any welfare effects experienced by rooftop solar projects. Instead, we treat utility-scale solar as the sole downstream consumer of solar panels in India.

that achieves the targeted production level using only tariffs is 84%; the optimal subsidy using only subsidies is 24.4%; and the optimal mix of tariffs and subsidies is a 19% tariff and a 21% subsidy.

All interventions achieve the targeted level of domestic production in the upstream industry. The tariff-only policy and the tariff-subsidy mix policy increase production by shrinking the size of the market and reallocating production from foreign producers to domestic producers. The subsidy-only policy increases production by expanding the size of the market. As such, downstream developers and consumers are better off under the subsidy-only policy but worse off under the tariff-only policy and the tariff-subsidy mix policy. However, the downstream impact is smaller under the mixed policy since it also involves a subsidy, which offsets some of the costs associated with tariffs.

Adding all up, the change in total domestic welfare, relative to baseline, is most favorable for the policy that mixes tariffs and subsidies. For this mixed policy and the subsidies-only policy, total welfare is greater than the baseline. This is despite our assumption that the total cost of production subsidies is 1.5 times the subsidy amount, i.e., the unit cost of public funds is 1.5.

For the tariff-only policy, total welfare is lower than the baseline. However, this may only be the case for some policy targets. In the appendix, we consider a case where the policymaker wishes to expand domestic production of solar panels by 5%. Here, the tariff-only policy is welfare-improving, and the increase in welfare relative to the baseline is greater than the subsidy-only policy. This is because the tariff level required to achieve this target is much lower, about 30%. At this tariff level, the gains in government revenues are large enough to offset downstream costs. These results indicate that neither instrument dominates the other at all target levels, and for a range of policy targets, it might be optimal to employ both.

It is important to highlight that the analysis in this paper has several important limitations. First, even for temporary interventions, the associated costs and benefits might take years, if not decades, to be realized. One needs long-run data which capture the full trajectory of all relevant sectors to calculate total costs and benefits (Hansen, Jensen, and Madsen 2003; Harris, Keay, and Lewis 2015; Head 1994; Irwin 2000b). While we capture the short-run components of welfare we abstract away from long-run or dynamic considerations such as learning by doing, declining barriers to entry, or reputation (Schmalensee 1982) which provide additional incentives for offering industrial protection. Second, it is difficult to fully capture the spillover effects. Subsidies benefit not only the targeted industry but also the full network of upstream and downstream industries. Similarly, tariffs may benefit input suppliers of the protected domestic industry and at the same time, hurt the downstream buyers. In addition, an expansion in the targeted sector might impose costs on other sectors a la Dixit and Grossman (1986). We capture the effect on downstream firms and consumers, but do not incorporate effects upstream or in adjacent industries. Third, there is no easy way to compute the value of strategic benefits gained from reducing reliance on foreign producers. Industrial protection measures which might appear to be very costly in a myopic sense might help improve the international bargaining power of a country resulting in long-run political and economic benefits. Finally, despite our focus on solar energy, we do not consider environmental costs or benefits associated with changes in the size of this sector.

Related literature. Our work adds to the large literature evaluating the impact of industrial policy interventions. The set of papers closest to our work focus on individual sectors and use structural modeling techniques to estimate the costs and benefits of tariffs and subsidies (see Baldwin and Krugman (1988a,b), Barwick, Kalouptsidi, and Zahur (2021), Head (1994), Irwin (2000a,b), and Kalouptsidi (2018)). Similar to Barwick, Kalouptsidi, and Zahur (2021) we compare alternative policy instruments, although we focus on a different set of instruments in a different setting. A second set of papers evaluates the effects of industrial policy by exploiting natural experiments for identification (see Juhász (2018) and Lane (2021)). A few recent papers (Bartelme et al. (2019) and Lashkaripour and Lugovskyy (2019)) have used quantitative trade models to evaluate the potential of industrial policy at the economy wide level. Finally, recent theoretical work by Itskhoki and Moll (2019) and Liu (2019) consider the role of industrial policy in correcting market distortions.

We also contribute to the literature measuring the welfare impact of protectionism. Following the US-China trade war of 2018, there has been a renewed interest in measuring costs of trade policy (see Amiti, Redding, and Weinstein (2019), Cavallo et al. (2021), Fajgelbaum et al. (2020), and Flaaen, Hortaçsu, and Tintelnot (2020)). Recent work on the impact of trade policy in different settings include Amiti and A. K. Khandelwal (2013), Amiti and Konings (2007), Edmond, Midrigan, and Xu (2015), Goldberg et al. (2010), Irwin (2019), and Topalova and A. Khandelwal (2011). We contribute to this literature by zooming in on a single industry and comparing the welfare impact of alternative policies intended to support domestic production. By focusing on a single industry we can capture both the direct impact of these policies on the targeted sector and the indirect impact on downstream sector.

2 Setting & Data

In this section, we describe our empirical setting – the utility-scale solar sector in India. We begin by highlighting the key features of the upstream and downstream industries within this sector, and outline the various industrial policy interventions that have been deployed to support the domestic production of solar panels. We conclude this section by providing details about the data we use to estimate our model.

2.1 The Downstream Industry: Solar Power Plants

The downstream industry comprises utility-scale solar power plants, which generate electricity from solar energy. The term *utility-scale* is used to indicate the power generation capacity of each solar plant, typically greater than 1 megawatts (MW), and the intended end-use — solar power generated through these plants is fed into the electricity transmission grid operated by various state-run power distribution companies (DISCOMs). These DISCOMs then distribute this electricity to agricultural, industrial, and residential consumers.

To incentivize large upfront investments in the construction of these plants, DISCOMs sign long-term power purchase agreements (PPA), usually 25 years, which guarantee long-run revenues for the developers of these solar plants. These power purchase agreements can be bilaterally negotiated or, in most cases, awarded through an auction process. In these auctions, participants bid on the rate at which they would sell electricity for the duration of the PPA. The PPAs are then awarded to developers with the lowest bids.

Since 2010, state agencies in India have experimented with multiple auction formats to award these power purchase agreements. In the early years, they relied on sealed bid auctions. They have also experimented with auctions where the price of electricity is nominally fixed, and firms instead bid on capital subsidy they require from the government to build these solar plants. However, in recent years, the most frequently used auction format has been a multi-unit English auction. We describe this auction game in detail below.

Suppose the auctioneer wants to incentivize development of a solar plant of total capacity Q (say, 1 GW). As such, it will broadcast a call for applications, formally known as a Request for Selection (RFS). Interested developers submit an initial bid containing a quantity bid (say, 200 MW) and a price bid (say, INR 4/kWh). In this example, the bidder is proposing to erect a solar plant of capacity 200 MW and sell the electricity generated by it at a rate of INR 4 per kilowatt-hour. Based on some basic financial and techno-commercial criteria[4], as well as the initial bids, a subset of respondents are invited to participate in an English auction.[5]

This English auction is conducted online. Starting at the initial sealed bid, bidders are allowed to adjust their price bids downwards while holding quantity bids fixed. At all times, the bids (but not the identities) of all other participants are visible to everyone. The auction ends when no player adjusts their bids for a pre-specified duration of time (say, 8 minutes). Capacity allocations are made in the order of increasing price bids, starting with the lowest bid, until the initial target Q is met. All winners sign a PPA with the auctioneer at their final price bid in the auction.

In Figure 2a, we plot the cumulative installed capacity of solar power plants in India over the past decade or so. In 2010, the total installed solar photovoltaic (PV) capacity in India was under 200 megawatts (MW). By 2021, the total installed capacity was over 35 gigawatts (GW) with another 52 GW in pipeline.

2.2 The Upstream Industry: Solar Panels

The upstream industry produces solar panels. A solar panel, also known as a module, is a collection of solar photovoltaic (PV) cells that convert sunlight to electricity. These panels are marketed in terms of watts (W) per piece and serve as the primary input for the downstream solar power plants. For instance, a 100 MW solar plant would require 400,000 pieces of 250 W solar modules. At a conservative price of $100 a piece, that equals an investment of over $40 million in solar modules alone.

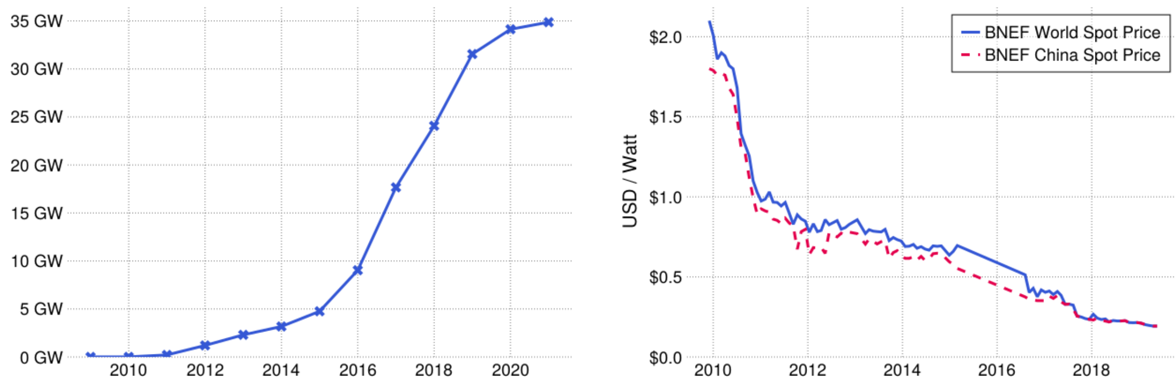
Despite the large demand generated for these modules by the downstream industry, domestic solar module manufacturing has failed to take off. Globally and in India, solar modules from China dominate this industry. In the first half of the past decade, the market share of Chinese solar modules in the utility-scale solar sector in India was approximately 100%. While there has

[4] This is to ensure that the bidder would be able to build and operate a plant of the proposed size.

[5] In our data, we do not observe the initial price bid nor do we see the full set of initial respondents. For each auction, we only observe the set of participants invited to the second-stage of the auction process and their final price and quantity bids. As such, in our model and estimation, we disregard the first-stage selection process.

Figure 2: *Indian solar capacity and global solar module prices*

(a) *Cumulative installed solar capacity* **(b)** *Solar module price per watt*



Notes. In the left panel, we plot the sum total of the capacities of all commissioned solar plants upto a given year as recorded in the projects database of our data provider, Bridge to India. In the right panel, we show the monthly average spot prices of multi crystalline silicon modules, expressed in price per watt. These values are obtained from the Bloomberg New Energy Finance (BNEF) Solar Spot Price Index.

been an uptick in domestic manufacturing in recent years, Chinese solar modules still command a majority share of the market. Industry experts point to several reasons behind China's relative dominance in the industry, including the availability of cheap credit, free land, manufacturing subsidies by the Chinese government, and the presence of an "ecosystem" that makes it easier to procure raw materials such as cells, wafers, and polysilicon.

In recent years, the Indian government has introduced two major policy interventions to support the domestic production of solar modules.[6] There are: (1) tariffs on imported solar modules, and (2) production subsidies for domestic producers of solar panels.

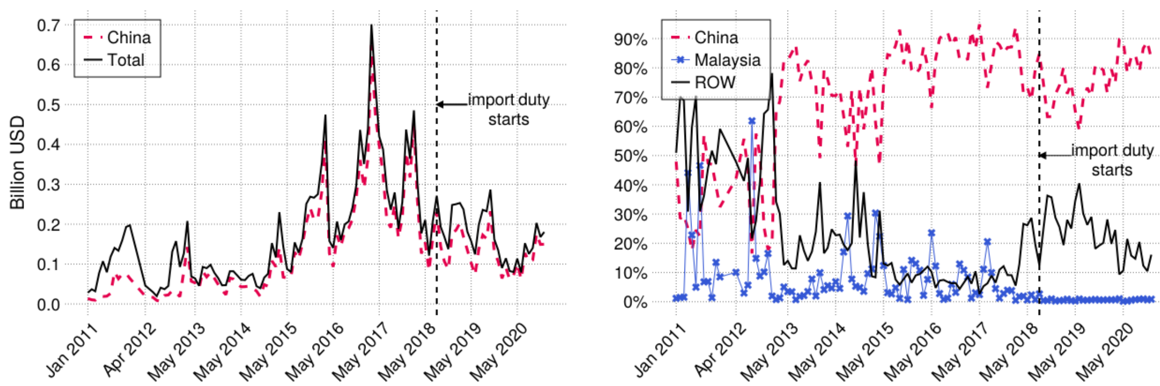
The Indian government first introduced safeguard tariffs against Chinese and Malaysian modules in August 2018. The initial import duty was set at 25% for one year, and then reduced by 5 percentage points every six months until July 2020. These safeguard tariffs remained at 15% until April 2022, when the government imposed a basic customs duty against all imports of solar cells and modules. This basic customs duty is set at 40% for solar modules and 25% for solar cells. We show the impact of the initial safeguard tariffs in Figure 3. Tariffs affected the composition of imports into the country. The value of imports from Malaysia essentially dropped to zero and there was a small dip in the imports from China; while imports from the rest of the world picked up. However, imports from China continued to make up a large share of total imports into India.

In 2020, the Indian government also announced plans to subsidize manufacturing in the domestic solar module industry. As part of a broader push to boost manufacturing in 13 key sectors,

[6] In the past, the Indian government has also tried to support the domestic module manufacturing industry through two other channels — Domestic Content Requirement (DCR) auctions and Modified Special Incentive Package (MSIP) Scheme. The former is a class of auctions where the winners must procure their solar modules from domestic manufacturers, while the latter is a set of investment incentives to support manufacturing industries. The impact of these policies on domestic solar module production is unclear and not investigated in this paper. Conversations with industry experts suggest that take-up of the MSIP scheme, announced in 2012, has been very low.

Figure 3: *Impact of safeguard duties against China and Malaysia*

(a) *Import value (billion USD)* **(b)** *Share of total imports*



Notes. This figure plots monthly imports of products categorized under HS code 854140 into India as recorded under UN Comtrade Database. In the right panel, share of imports are calculated using value of imports recorded in US dollars; ROW refers to value of all imports excluding China and Malaysia.

the government has pledged $25 billion under Production Linked Incentive (PLI) Schemes. Of this, approximately $600 million has been earmarked to incentivize production in the solar PV module industry. The PLI scheme is quantity-based i.e. firms will receive subsidy per unit of module produced. The subsidy would be offered to pre-approved plants for a period of five years, and depending on module efficiency and temperature, can range from INR 2.25 to INR 3.75 per watt. Using the Bloomberg New Energy Finance (BNEF) Solar Spot Price Index in early 2020 as a benchmark (see Figure 2b), this corresponds to a subsidy rate of 15-25%.

2.3 Data

We rely on three primary sources of data for our estimation. These include data on (1) government-run auctions, (2) solar plants/projects, and (3) imports of solar modules.

The *auctions* dataset contains auction-level data on the universe of solar auctions held in India. We obtained this dataset from a market research firm, Bridge to India, which aggregates these data from various official and private sources. In these data, we observe each auction's characteristics, particularly the total capacity being auctioned and the various dates associated with the auction, such as announcement date, bid submission date, and results date. Each auction is also linked to detailed bid-level data, including the price and quantity bids of all bidders and the associated outcome of their bid. We restrict the auctions dataset to those that were held as multi-unit English auctions[7]. This left us with 52 auctions with 312 total bids, of which 48% were successful in winning a power purchase agreement. Overall, these auctions resulted in the

[7]Some auctions involved simultaneous bids on multiple tenders which were not disaggregated by our data provider. As such, we observe the same bidder submitting multiple bids for the same RFS. We exclude these auctions too.

Table 1: *Effect of module prices on auction bids*

	(log) Bid	(log) Maximum winning bid	(log) Weighted winning bid
	(1)	(2)	(3)
(log) Price of solar panels	0.83***	0.76***	0.76***
	(0.15)	(0.10)	(0.10)
N	312	52	52
R^2	0.59	0.52	0.52

Notes. This table contains the results from regressing auction bids on solar panel prices, inclusive of import tariffs. For column (1), standard errors are clustered at the auction-level and given in parentheses. For columns (2) and (3), regressions are at auction-level and standard errors are reported in parentheses.

allocation of 24.6 GW of solar capacity.[8] In Table 1, we provide preliminary evidence on the impact of the price of solar panels on price bids placed by developers in solar auctions. We find that a 1% increase in the price of solar panels is associated with a 0.8% increase in the price bid. Importantly, a large share of the total variation in bids is explained by only the price of solar panels.

The *projects* database is also compiled and provided to us by Bridge to India. It includes solar project-level data on the status of all solar projects in India. The key variables of interest for us are the (1) commissioning date of a project and (2) the identity of the solar panel supplier. Using data on 1,970 projects totaling 45 GW in solar capacity for which the identity of the solar module supplier is available, we construct supplier-level market shares in the upstream industry.

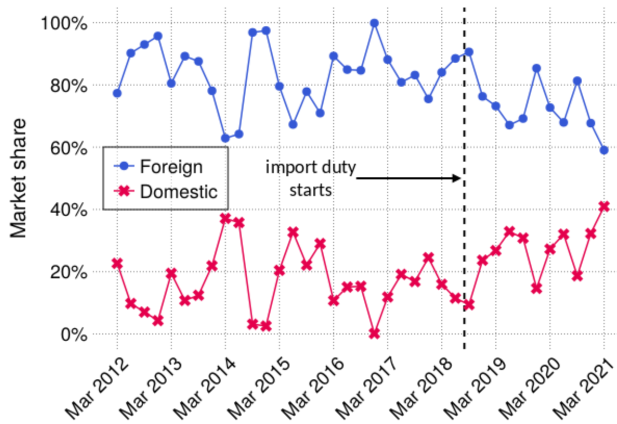
It takes about 12-18 months to build a solar plant, and our conversations with industry experts suggest that solar modules are one of the last items to be deployed in a solar plant. We use this feature of the industry to construct a smooth time series for firm-level market shares. For each project, we divide the total project capacity equally over the three months prior to its commissioning. Aggregating over all projects supplied by a given supplier yields a smooth monthly series on sales by each module manufacturer. We aggregate these monthly series by quarter, and present the market shares of foreign and domestic firms in Figure 4. Domestic market share is stable at around 10% before the import duty starts, and gradually increases after the duty starts.

Finally, the *imports* database records transaction-level data between 2014 and 2020 on imports of products categorized under HS code 8541[9]. We manually clean text fields describing the product being imported to construct a monthly price per watt series for imported modules. This involved identifying the peak-wattage of each product being imported (e.g. 250 W) and the number of panels being imported, and then dividing total value of the shipment by the total imported watts. As a robustness check, in Figure B.1, we plot our constructed measure of imported module prices against the spot prices recorded in the Bloomberg New Energy Finance

[8]Our initial set of filters yielded 60 auctions with 375 total bids, but the price data for solar panels further restricted this sample to 52 auctions.

[9]HS Code 8541 is defined as "Diodes, transistors and similar semiconductor devices; photosensitive semiconductor devices, incl. photovoltaic cells whether or not assembled in modules or made up into panels (excluding photovoltaic generators); light emitting diodes; mounted piezoelectric crystals; parts thereof".

Figure 4: *(Smoothed) Quarterly Market Shares in the Upstream Market*



Notes. This figure uses data on project-level module suppliers to plot market shares of foreign and domestic module manufacturers. For each project, the total project capacity is evenly split over the three months prior to its commissioning and assigned to its supplier. Aggregating over all projects yields a smooth monthly series on sales by each module manufacturer. The above figure plots quarterly market shares derived from this smooth monthly series.

(BNEF) Solar Spot Price Index. We find that our constructed measure tracks the BNEF index quite closely, with a correlation coefficient of 0.96.

3 Model

In this section, we present a model of the utility-scale solar sector which consists of two industries: the upstream industry which produces solar panels, and the downstream industry which produces solar power. We detail how each industry is organized, and describe how these industries interact with each other.

The objective of this model is to allow us to evaluate how different industrial policy interventions in the upstream industry affect equilibrium outcomes in the entire utility-scale sector. In particular, the model allows us to trace out the impact of tariffs and subsidies for solar panels on the profits of domestic firms and the welfare of the ultimate buyer of solar power.

3.1 Upstream supply of solar panels

In the upstream industry, firms produce solar panels (or modules). There are two types of firms in this industry: domestic firms and foreign firms. Each firm is index by j, and $\mathcal{J}_t = \bigcup_h \mathcal{J}_{ht}$ denotes the set of all active firms in period t, where $h \in \{domestic, foreign\}$ is the type of firm j. Depending on its type, each firm is subject to an ad valorem tax τ_{ht}; when positive, this is a *tariff*, and when negative, this serves as a *subsidy*.

Solar panels are homogeneous goods that are sold at a single price in each period t. This market price of solar panels, p_t, is determined by the inverse demand function for solar panels,

$D^{-1}(Q_t^{supply})$, where $Q_t^{supply} = \sum_{j \in \mathcal{J}_t} q_{jt}$ is the total quantity of solar panels supplied in the market.

Firms differ in their costs of production as well as their eligibility for a tax or a subsidy; both affect firm production decisions. Let $C_{jt}(q)$ be the total cost of production of firm j in period t when it produces q units of solar panels. Firm $j \in \mathcal{J}_t$ chooses quantity q to maximize variable profits

$$\max_{q} \ \pi_{jt}^{u}(q) = (1 - \tau_{ht}) \cdot p_t \cdot q - C_{jt}(q) \tag{1}$$

which gives rise to the optimal quantity q_{jt}^{*} and profits $\pi_{jt}^{u}(q_{jt}^{*})$.

Finally, all active firms also pay a fixed cost of accessing the domestic market, denoted by λ_{jt}. Therefore, the *net payoff* of an upstream firm j is

$$V_{jt}(q_{jt}^{*}) = \pi_{jt}^{u}(q_{jt}^{*}) - \lambda_{jt} \tag{2}$$

In equilibrium, only firms with positive net payoff, $V_{jt}(q_{jt}^{*}) \geq 0$, are active in period t in the upstream industry.

3.2 Downstream supply of solar power plants

In the downstream industry, firms build solar power plants. These power plants generate electricity which is sold to power distribution companies. The cost of solar panels makes up a large share of the total cost of building a solar power plant; as such, the price of solar panels is a potentially important determinant of the price of solar power. Since we expect policy interventions in the upstream industry to change the equilibrium price of solar panels, the purpose of this part of the model is to understand how changes in the price of solar panels translate into changes in the price of solar power. One could estimate this elasticity by modeling the reduced-form relationship between the price of solar power and the price of solar panels, as we did in Section 2.3. However, this approach precludes us from computing the impact of policy interventions on firm profits in the downstream industry. Here, we introduce a simple model that allows us to recover the cost function of solar plant developers, and also structurally estimate the elasticity of the price of solar power with respect to the price of solar panels.

The output of the downstream industry is measured in terms of *solar power generation capacity*, which is developed through auctions. We denote a specific auction by k. In auction k, the auctioneer auctions off total capacity A_k. The participants in these auctions are solar plant developers, indexed by $i \in \mathcal{N}_k$, where $\mathcal{N}_k$ is the set of all participants in auction k. Participant i enters the auction with a pre-committed capacity bid $a_{ik} \leq A_k$; this is the capacity of the solar plant that would be developed by the participant if it wins.[10] Depending on the relative magnitudes of the capacity bids and the total capacity being auctioned, there may be multiple winners in a given auction. Therefore, these auctions are multi-unit auctions.

[10]We do not model how participants choose their capacity bid, or how they decide whether to enter a given auction. For the purposes of this model, these are exogenous. However, when we compute counterfactuals, we describe how we pick these quantities.

The winners in auction k, denoted by $\mathcal{N}_k^W \subseteq \mathcal{N}_k$, sign a contract with the auctioneer for L years. This contract is a power purchase agreement which specifies the price per unit of power, usually expressed in kilowatt-hour (kWh), that each winning developer would receive from the offtaker for its bid capacity a_{ik} for the next L years. If this price is b, the net present value of the stream of revenues per unit capacity is $r(b)$. We compute this net present value as follows

$$r(b) = \sum_{l=0}^{L-1} \beta^l \times b \times c.u.f. \times 24 \times 365$$

where β is the discount factor and $c.u.f.$ is the capacity utilization factor, which adjusts for the fact that a solar plant does not generate electricity at all hours of a day.

For developer i, the constant marginal cost of developing solar power plant capacity is $e_{ik}(p)$, where p is the price of solar panels at the time of the auction. Let $\pi_{ik}^d(b, p)$ be the *profits per unit capacity*, conditional on winning, at purchase price b and module price p, where

$$\pi_{ik}^d(b, p) = r(b) - e_{ik}(p) \tag{3}$$

Thus, all else equal, a higher price of solar panels reduces the profits of solar plant developers.

Next, we describe how winners and winning solar power prices are determined. In modeling the auction format, we make one simplification: we assume that the auction is organized as a descending-bid ("button press") auction. This abstracts away from the dynamic structure of an English auction which is difficult to capture in a model.

In this auction, the auctioneer starts off at a sufficiently high bid such that $\pi_{ik}^d(\hat{b}, p) > 0$ for all participants, and keeps lowering it. At each bid $\hat{b}$, all auction participants with $\pi_{ik}^d(\hat{b}, p) = 0$ drop out. The auctioneer stops at bid b^* when the total capacity bid by all remaining participants equals A_k.[11] The price b^* is the *uniform price* of the auction, and all winners receive this price.[12]

Since these solar plant developers are domestic firms, their profits factor into our estimates of total welfare under alternative industrial policy interventions. These profits are given by

$$\pi_k^d(b^*, p) = \sum_{i \in \mathcal{N}_k^W} \pi_{ik}^d(b^*, p) \cdot a_{ik} \tag{4}$$

3.3 Downstream demand for solar power

The power generated by solar power plants is sold to power distribution companies. Depending on the price of solar power, these power distribution companies may demand more or less solar power. This price of solar power b, determined by the auction process described above, is in itself

[11] In certain cases, the remaining quantity might be greater than A_k but lowering the bid further would result in another participant dropping out so that the remaining total capacity bid is less than A_k. Here, the auctioneer awards only part of the capacity bid by the remaining participant with the highest marginal cost such that the total capacity awarded equals A_k.

[12] This is a consequence of the assumption of descending-bid auction. In the solar auctions conducted in India, participants receive the price they bid in the online English auction. However, due to our simplication of the auction format, we do not generate variation in the prices received by winners.

a function of the price of solar panels p. Thus, we can write the demand for solar power as

$$\begin{aligned} Q_t^{demand} &= \widetilde{D}(b(p)) \\ &= D(p) \end{aligned} \tag{5}$$

where quantity Q_t^{demand} is expressed in the same units as plant capacity and the quantity of solar panels. In the above equation, $\widetilde{D}(b)$ is the demand function which gives rise to the procurement auctions in the downstream industry, while $D(p)$ is the reduced-form demand function which generates demand for solar modules.

3.4 Equilibrium

This is a full-information, simultaneous-move static game. Each period t is an independent market, and the equilibrium of each market is a price p^* of solar modules such that the quantity of solar panels supplied in the upstream industry equals the quantity of solar panels demanded in the downstream industry, which in turn equals the quantity of solar power supplied in the downstream industry. At this equilibrium price, the auctioneer conducts one auction with total capacity $A = \widetilde{D}(b(p^*))$, which yields $b(p^*)$ as the equilibrium price of solar power. Finally, at this price, firms in the upstream industry are in a static Cournot-Nash equilibrium with respect to their production decisions.

4 Structural Estimation

4.1 Demand for solar panels

We estimate the reduced-form demand for solar panels $D(p)$, described in equation (5), using a log-linear specification as follows

$$\ln Q_t = \delta_0 + \delta_p \cdot p_t + \varepsilon_t \tag{6}$$

where Q_t is the total quantity of solar modules consumed in quarter t, and p_t is the price of solar modules in that quarter. We use data from 25 quarters, from 2014 Q1 to 2020 Q1. To address concerns about endogeneity of the price of solar panel, we instrument it using the spot price of polysilicon, which is a key raw material used in the production of solar photovoltaic cells which make up solar panels.

To measure total consumption Q_t, we rely on two approaches. First, we rely on our *imports* data to construct total quantity of solar panels (measured in megawatts) imported into India each quarter. Second, we use the *projects* data to infer the total quantity of solar panels used in utility-scale solar projects each quarter. To do so, we take the total installed capacity of each solar power plant, and assign it equally to each of the three months prior to its date of commissioning.[13] Summing up over all installed solar power plants yields quarterly consumption of solar panels.

[13]This is a reasonable assumption. Solar power plants take 12 to 18 months to construct, and solar panels are one of the last items to be installed.

Table 2: *Demand for solar panels (modules)*

	(log) price of panels	(log) quantity of panels	
		Imports	Projects
	(1)	(2)	(3)
(log) price of polysilicon	0.89		
	(0.06)		
(log) price of panels		-2.21	-1.53
		(0.56)	(0.60)
F statistic	234.79	15.72	6.45
R^2	0.72	0.55	0.42
N	25	25	25

Notes: This table presents estimated parameters of the log-linear reduced-form relationship between the price of solar panels and the demand for solar panels. The data are at the quarterly-level and span from 2014 Q1 to 2020 Q1. We instrument the price of solar panels using the price of polysilicon, which is an important raw material used in the production of solar photovoltaic cells. We present estimates from the first-stage in column (1). In columns (2) and (3), we present the estimated elasticity of demand using instrumented price of solar panels. Column (2) uses quarterly imports of solar panels into India as the dependent variable, while column (3) uses the (smooth) quarterly solar module consumption derived from the database of utility-scale solar projects in India. We report standard errors in parentheses.

We present the estimated demand parameters in Table 2. Column (1) presents results from the first-stage regression, which confirms that price of polysilicon is a strong and relevant instrument for the price of solar panels. Columns (2) and (3) present results from the second-stage regression. The estimated demand elasticity is -2.21 when we use the imports data, and -1.53 when we use the projects data. Our preferred estimate is the one derived from the projects data as it also captures demand fulfilled by domestic producers. We use this estimate in the estimation of the cost function of upstream solar panel producers, as well as in our counterfactual analysis.

4.2 Cost of production of solar panels

In this section, we estimate parameters governing the production costs of upstream solar panel producers and their fixed cost of accessing the domestic market in India. Since policy interventions will apply differently to different firms based on their *type* (i.e. domestic or foreign), we focus on estimating these parameters flexibly by firm type.

We begin by describing our functional form assumptions, and then delve into our estimation routine. We assume that the marginal cost of producing q units of solar panels in period t by firm j of type h is given by

$$\begin{aligned} mc_{jt}(q) &= c_{jt} \cdot q^{\gamma_{q,h}} \\ &= \exp\left\{\gamma_{0,h} + \gamma_{t,h} \cdot t + \nu_{jt}\right\} \cdot q^{\gamma_{q,h}} \end{aligned} \tag{7}$$

where $\nu_{jt} \sim \mathcal{N}\left(0, \sigma^2_{\gamma,h}\right)$ is a firm- and period-specific idiosyncratic shock to marginal cost. The type-specific intercept $\gamma_{0,h}$ denotes the initial stock of technological know-how of the two types of firms in this industry at $t = 0$. The parameter, $\gamma_{t,h}$, gives the rate at which marginal costs change over time. This is a period with rapid advancements in solar technology, so this parameter captures the rate of technological progress of the two types of firms. Finally, the parameter $\gamma_{q,h}$ controls how marginal costs change with quantity produced. It is informative about the type-specific returns to scale and/or type-specific latent capacity constraints.

In addition to production costs, firms are also subject to a fixed cost of accessing the domestic market, denoted by λ_{jt}, where

$$\lambda_{jt} \sim \exp\left(\frac{1}{\lambda_h}\right) \tag{8}$$

This fixed cost is crucial for matching the number of active firms in a given period.

Next, we outline our estimation routine. Let $\gamma_h = \{\gamma_{0,h}, \gamma_{t,h}, \gamma_{q,h}, \sigma_{\gamma,h}, \lambda_h\}$. As an overview, for each guess of parameters $\gamma = \{\gamma_{domestic}, \gamma_{foreign}\}$, we solve for the model-implied equilibrium in the upstream market and generate a simulated dataset with equilibrium quantities. Then, we construct moments from this simulated dataset and search for parameters that minimize the (variance-weighted) distance between these moments and their empirical counterparts.

Specifically, for each period (i.e. quarter), we take a set of *potential* firms and draw their production cost shocks and fixed cost shocks. The set of potential firms is chosen as follows: take all firms which ever show up as suppliers in the projects database between 2014 Q1 and 2020 Q1, and then drop those which were founded after the period of interest. Next, we determine the set of *active* firms i.e. the subset of potential firms which choose to operate in a given period. Here, we rely on an iterative algorithm that searches for the largest subset of potential firms which can operate with non-negative net payoff in the market. We begin with all potential firms and solve for the profit-maximizing level of output (which may be zero for some). Next, we compute the net payoff by differencing out the fixed cost of market access. If all firms have non-negative net payoff, then we stop. Else, we drop the firm with the lowest net payoff and repeat the process with the remaining firms. This procedure yields the equilibrium for one period and for one draw of cost shocks. For each period, we repeat this 30 times with a different draw of cost shocks for each potential firm.

So, given a guess $\widehat{\gamma}$, we solve the upstream equilibrium in $25 \times 30 = 750$ periods. This yields a simulated dataset with 750 quarters of data. We then compute the following moments from this simulated dataset: (1) average number of firms of each type in a period, (2) average total output by firms of each type in a period, and (3) the interquartile range of output by firms of each type in a period. We compute the first two moments separately for the pre-tariff period (2014 Q1 to 2018 Q2) and the post-tariff period (2018 Q3 to 2020 Q1). This gives us 5 moments for each type of firm, which help us identify the 5 type-specific parameters γ_h. We match these 5 moments with their empirical counterparts, as shown in Table 3.[14]

The estimated parameters are given in Table 4. Our estimates of the intercept $\gamma_{0,h}$ suggest that at $t = 0$ and $q = 0$, the marginal cost of production of domestic firms is about 83% higher than the marginal cost of production of foreign firms. The estimated rate of technological progress, $\gamma_{t,h}$,

[14]When minimizing the distance between simulated and empirical moments, we weigh each moment by the inverse of its variance. For the first two moments, we compute the variance by bootstrapping quarters 100 times. For the third moment, we take the variance across the 25 quarters in our sample.

Table 3: *Upstream Model Fit: Targeted Moments*

		Domestic		Foreign	
		Data	Model	Data	Model
		(1)	(2)	(3)	(4)
N firms	Pre-Tariff	6.7	6.6	15.6	15.7
	Post-Tariff	7.3	7.4	14.3	14.3
Total output	Pre-Tariff	230.4	270.6	1210.0	1187.7
	Post-Tariff	473.2	336.3	1447.5	1409.0
IQR output		43.0	32.2	76.3	89.9

Notes: This table presents the moments targeted in the estimation of the upstream model. We target three sets of moments: (1) number of firms, (2) total output in a quarter, and (3) interquartile range of output in a quarter. All three moments are computed separately by type of firm (domestic and foreign). For the first two sets of moment, we split the sample into pre-tariff (2014 Q1 to 2018 Q2) and post-tariff (2018 Q3 to 2020 Q1) periods. When computing data moments, we calculate these statistics at the quarter-level and then take the average across quarters. When computing simulated moments, we solve for the equilibrium in each quarter 30 times with different draws of production and entry cost shocks, and then take the average across all simulations and all quarters.

is negative for both types of firms, suggesting that marginal costs have been declining over time. However, this rate of decline is approximately 10% per year for foreign firms and 8% per year for domestic firms. Similarly, marginal costs are increasing with output for both types of firms, but the rate of increase is higher for domestic firms than for foreign firms. The estimated variance of production cost shocks is similar for both types of firms. But there are meaningful differences in the mean fixed costs of market access. We estimate that the mean fixed cost of market access for foreign firms is about 74% higher than that for foreign firms; that is, it is cheaper for domestic firms to access the domestic market than it is for foreign firms.

4.3 Cost of developing solar power plants

We estimate the per unit cost of developing solar power plants, $e_{ik}(p)$, using auction-level bid data. In this data, for each auction, we observe the full set of participants in the online auction, their final bids, as well as their status (i.e. whether they won or lost the auction).

As discussed in Section 3.2, we abstract away from the actual English auction by assuming that the auction is organized as a descending-bid auction. Under this simplification, participants drop out when the prevailing bid b is such that their profits per unit capacity $\pi^d_{ik}(b, p)$ are equal to zero. Specifically, for the set of participants who lose the auction, we have

$$\pi^d_{ik}(b_{ik}, p) = 0 \quad \forall i \in \mathcal{N}^L_k = \mathcal{N}_k \setminus \mathcal{N}^W_k \tag{9}$$

where b_{ik} is the final bid observed in the data, and p is the price of solar panels at the time of auction k.

The direct consequence of (9) is that, for losers in each auction, the cost of developing a solar

Table 4: *Upstream cost parameters*

	Domestic	Foreign
	(1)	(2)
Intercept, γ_0	4.95	4.35
	[]	[]
Time, γ_t	-0.08	-0.10
	[]	[]
Quantity, γ_q	0.77	0.71
	[]	[]
Standard deviation of cost shocks, σ_γ	2.59	2.48
	[]	[]
Mean of fixed costs, λ	12.88	22.39
	[]	[]

Notes: This table presents the estimated parameters of the upstream industry where firms supply solar modules. The parameter γ_0 gives the mean level of (log) marginal costs at $t = 0$ and $q = 0$; γ_t captures the rate at which marginal costs change over time for the two types of firms in our data; γ_0 gives the mean level of marginal costs at $t = 0$ and $q = 0$; γ_q controls how marginal costs change with output level; σ_γ is the standard deviation of the idiosyncratic cost shock for the two types of firms in our data. The parameter λ governs the fixed cost of accessing the domestic market for the two types of firms in our data. The data are at the quarterly-level and span from 2014 Q1 to 2020 Q1. We report the 95% confidence interval in parentheses, estimated via bootstrap.

power plant must equal the net present value of the stream of revenues from one unit of capacity at the final bid b_{ik}. That is,

$$e_{ik} = r(b_{ik}) \quad \forall i \in \mathcal{N}_k^L = \mathcal{N}_k \setminus \mathcal{N}_k^W \tag{10}$$

The cost of developing one unit of solar power plant capacity is given by

$$e_{ik} = \eta_0 + \eta_p \cdot p_{t(k)} + \eta_{ik} \tag{11}$$

where $p_{t(k)}$ is the price of solar panels at the time of the auction, and $\eta_{ik} \sim \mathcal{N}\left(0, \sigma_\eta^2\right)$ is a firm- and auction-specific idiosyncratic shock. Combining (10) and (11), we have

$$r(b_{ik}) = \eta_0 + \eta_p \cdot p_{t(k)} + \eta_{ik} \quad \forall i \in \mathcal{N}_k^L = \mathcal{N}_k \setminus \mathcal{N}_k^W \tag{12}$$

Standard approaches such as OLS or MLE, for estimating (12), cannot directly be applied here since the set of losers in an auction do not constitute a random sample. In particular, firms with a higher draw of the cost shock η_{ik} are more likely to end up in the set of losing firms.

We deal with this selection issue by exploiting the *relative rank* of each bid within an auction as follows. Let $\boldsymbol{\eta} = \left\{\eta_0, \eta_1, \sigma_\eta\right\}$. For a guess $\widehat{\boldsymbol{\eta}}$. We can recover $\widehat{\eta}_{ik}(\widehat{\boldsymbol{\eta}}) = r(b_{ik}) - \widehat{\eta}_0 - \widehat{\eta}_p \cdot p_{t(k)}$. If r_{ik} is the i^{th} lowest bid in auction k, then $\widehat{\eta}_{ik}(\widehat{\boldsymbol{\eta}})$ must be the i^{th} lowest draw out of $|\mathcal{N}_k|$ draws

Table 5: *Downstream cost parameters*

	Estimate
	(1)
Intercept, η_0	-16.19
	[-27.39, -8.11]
Price of solar panels, η_p	2.76
	[2.39, 3.14]
Standard deviation of cost shocks, σ_η	12.07
	[7.97, 16.55]

Notes: This table presents estimated parameters which govern the per unit cost of developing solar power plant capacity. Price of solar panels is inclusive of import tariffs, if any, in the month of the auction. We report the 95% confidence interval in square brackets, estimated via 300 bootstraps where we sample auctions with replacement.

from $\mathcal{N}\left(0, \widehat{\sigma}_\eta^2\right)$. Using the density function for the i^{th} order statistic given $\widehat{\sigma}_\eta^2$, we can compute the probability that $\widehat{\eta}_{ik}$ is the i^{th} lowest draw. Doing this across all losing bids and all auctions, we can construct a likelihood of the data, $\mathcal{L}(\widehat{\boldsymbol{\eta}})$. We estimate $\boldsymbol{\eta}$ by maximizing this likelihood, and present the estimated parameters in Table 5.

4.4 Demand for solar power plants

To compute welfare statistics under different policy interventions, we also need to estimate the demand for solar power plants $\widetilde{D}(b)$ as a function of the price of solar power b. As discussed in Section 3.3, we have

$$\widetilde{D}(b(p)) = D(p)$$

where $D(p)$ is the reduced-form relationship between the price of solar panels and the demand for solar panels, estimated in Section 4.1. Let $\widetilde{D}(p)$ be an isoelastic function with price elasticity of demand δ_b. Then, the above equation can be used to derive the following relationship between elasticities

$$\delta_p = \delta_b \cdot \delta_a \tag{13}$$

where $\delta_p = \frac{\partial \ln D(p)}{\partial \ln p}$ is the price elasticity of demand for solar panels, $\delta_b = \frac{\partial \ln \widetilde{D}(b)}{\partial \ln b}$ is the price elasticity of demand for solar power, and δ_a is the elasticity of the winning auction bid with respect to the price of solar panels. Since we already have an estimate for δ_p, if we were to estimate δ_a, we can back out δ_b using the above relationship.

We estimate δ_a by simulating auction game play 100,000 times under a baseline price and baseline auction size. This baseline price and auction size are computed by solving the upstream industry equilibrium at no tariff or subsidy. We set the number of auction participants to 5, which is the median number of participants in our dataset.[15] Each auction play yields a winning bid, and we take mean over simulations to compute the average winning bid. Then, we increase the baseline module price and simulate auction play another 100,000 times. Finally, we take the ratio of the percentage change in the average winning bid to the percentage change in the baseline module price to recover δ_a.

For this simulated auction, we determine the size of the auction and the corresponding module price by solving for the equilibrium in the upstream industry at baseline, i.e., at zero import tariffs and zero production subsidies. These values are given in Table 7. Using the procedure described above, we estimate δ_a to be 1.03; that is, a 1% increase in the price of solar panels leads to a 1.03% increase in the winning bid. We use this to back out δ_b to be -1.49.

5 Counterfactual Analysis: Comparing Policy Interventions

In this section, we use our estimated model to compare the impact of different upstream policy interventions on the entire utility-scale solar sector. When comparing different policy interventions, we hold the target level of domestic upstream production fixed – that is, each policy intervention expands domestic production of solar panels to the same target level. However, all other outcomes in the sector are allowed to vary by policy intervention.

We consider three sets of policy instruments available to policymakers: import tariffs only, production subsidies only, and both import tariffs and production subsidies. For the first two, we compute the level of tariff/subsidy that achieves the given target for domestic production. For the case where both tariffs and subsidies are available, we compute the optimal mix that maximizes total domestic welfare while achieving the given target for domestic production.

We set the policy target for domestic production to be 20% higher than the baseline level of domestic production. The optimal policies that achieve this target are given in Table 6. For the scenario with only import tariffs, the optimal tariff is 83.8%. If using only production subsidies, the optimal subsidy is 24.4%. Finally, if using a mix of the two, the optimal tariff is 19.2%, and the optimal subsidy is 20.5%. Note that the estimated levels of tariff and subsidy under the mixed policy are similar to the levels adopted in India.[16]

Before comparing welfare outcomes, we briefly describe how we solve for the equilibrium in the entire utility-scale solar sector for different values of import tariffs and production subsidies. We first solve for the equilibrium in the upstream solar panel industry, given the estimated upstream cost parameters and demand parameters, presented in Tables 2 and 4. Here, we set the time period t to be such that the market is in 2019. All firms established by 2019 are included in the set of potential firms, and we arrive at the equilibrium set of active firms using the procedure described in Section 4.2. This yields an equilibrium price and quantity of solar modules. We use these to simulate auction play 20,000 times in the downstream industry and compute solar plant developers' average profits and the average winning bid. Finally, using our estimates of the price

[15] Each participant bids the same share of total auction capacity (q_{ik}/Q_k), where the share is assumed to be the average capacity share computed using observed bids in the data.

[16] In Appendix A, we consider a lower target of 5% increase in domestic production and find that the optimal policy mix leans more heavily towards tariffs, as shown in Table A.1.

Table 6: *Optimal policy interventions to increase upstream domestic share by 20%*

	Tariffs only	Subsidies only	Both
	(1)	(2)	(3)
Import tariff	83.8%		19.2%
Production subsidy		24.4%	20.5%

Notes: This table presents the levels of import tariffs and/or production subsidies required to expand domestic production of solar panels by 20% relative to a baseline without any tariffs or subsidies. Columns (1) and (2) consider scenarios where only tariffs and only subsidies can be used, respectively. In column (3), we consider a scenario where a mix of tariffs and subsidies can be used to achieve the target, and we report the levels which achieve this target while maximizing total domestic welfare.

elasticity of demand for solar power, δ_b, we compute the change in consumer surplus relative to the baseline under the assumption of an isoelastic demand curve.

At each equilibrium of the utility-scale solar sector, we can compute total domestic welfare as follows. The key components of total domestic welfare are (1) government revenues/expenditures, (2) total profits of domestic upstream producers, (3) total profits of downstream solar plant developers, and (4) consumer surplus associated with solar power consumption. For tariffs, government revenues are $\tau \cdot p \cdot q_j$ summed over all active foreign firms. For subsidies, government expenditures are $\eta \cdot \tau \cdot p \cdot q_j$ summed over all active domestic firms, where η is the cost of public funds. We set $\eta = 1.5$ for all results in this section, i.e., the cost of 1 rupee of production subsidy is 1.5 rupees. Total profits of domestic upstream producers are net of the fixed cost of accessing the domestic market. The profits of downstream solar plant developers are given in (4). Recall that these are net present values of power purchase agreements spread over 25 years. Finally, the change in consumer surplus relative to the baseline is given by

$$\Delta CS(\tau) = -\left(\frac{b(\tau)A(\tau) - b_0 A_0}{1 + \delta_b}\right)$$

where $b(\tau)$ and b_0 are the average winning bids under a given counterfactual and baseline, respectively, and $A(\tau)$ and A_0 are the corresponding quantities of solar capacity auctioned.

We begin by describing outcomes in the upstream industry of solar panels. These are summarized in Table 7.[17] Under the optimal tariff-only policy, the equilibrium price of solar panels is 78% higher, and the total output is 50% lower than the baseline scenario. Domestic output is 20% higher, as intended, and correspondingly, the number of domestic producers and their net profits go up by 45% and 94%, respectively. Thus, tariffs reallocate production to domestic producers, by expanding production by incumbents and allowing additional high cost domestic producers to operate in the market. But, they do so by shrinking the total size of the industry. In contrast, under the optimal subsidy-only policy, solar panels are 2% cheaper and total production is 5% higher. Domestic output still reaches the intended target, but this is achieved by expanding the total size of the industry. Lastly, under the optimal mixed policy, the equilibrium price of solar panels is 6% higher, and the total output is 6% lower than the baseline.

[17] We also consider an alternative target where we expand the level of domestic production by 5%. The corresponding outcomes in the upstream industry can be found in Table A.2.

Table 7: *Counterfactual outcomes in the upstream solar panel industry*

	Level	Relative to Baseline		
	Baseline	Tariffs only	Subsidies only	Both
	(1)	(2)	(3)	(4)
Price (INR/watt)	24.3	+78.2%	−2.3%	+6.0%
Total production (MW)	1579.8	−50.5%	+4.9%	−6.1%
Domestic production (MW)	461.3	+20.0%	+20.0%	+20.0%
Foreign production (MW)	1118.5	−79.6%	−1.3%	−16.9%
Number of domestic producers	7.4	+44.7%	+17.7%	+22.2%
Number of foreign producers	16.2	−63.9%	−1.3%	−10.2%
Net profits of domestic producers	4326.1	+92.6%	+43.8%	+49.1%
Net profits of foreign producers	12519.2	−94.3%	−3.4%	−28.8%

Notes: This table reports outcomes in the upstream industry of solar panels in the baseline scenario, as well as under counterfactual policies. Column (1) reports levels; net profits are reported in millions of INR. Columns (2), (3), and (4) report changes in given variables relative to baseline.

Finally, we turn to welfare outcomes in the utility-scale solar sector under various policy interventions that expand upstream domestic production by 20%.

First, we look at the impact of the tariff-only policy. At the optimal tariff rate of 84%, the government collects 8.3 billion INR, or approximately 130 million USD (2015 dollars). Domestic upstream producers also gain about 4 billion INR. But, this figure is small compared to the losses in the downstream industry. Total profits of solar plant developers fall by 8.2 billion INR, and consumer surplus falls by 11 billion INR. Overall, total domestic welfare under the tariff-only policy falls by 6.8 billion INR, or about $107 million (2015 dollars). Thus, targeting a 20% increase in domestic production of solar panels using only tariffs is welfare-reducing. However, tariffs are not always welfare-reducing. In Appendix A, we consider a scenario where the objective is to increase domestic production by 5%, and find that tariffs are welfare-enhancing in this case. The required tariff level for this target is 31%, and at this tariff, the gains in government revenue are large enough to offset losses in the downstream industry.

Next, we look at the impact of the subsidy-only policy. Under the assumption that 1 rupee of subsidy costs 1.5 rupees, we find that government expenditures on the program are 4 billion INR, or 62 million USD. Domestic upstream producers' net payoff goes up by 1.9 billion INR. At the same time, downstream developers and consumers also gain as solar modules are cheaper, and total production is higher. On the net, total domestic welfare is 1.2 billion INR ($19 million) higher under this policy. If the domestic production target is instead set to be 5% higher than the baseline, total welfare under a subsidy-only policy is still higher than the baseline. But, as shown in Table A.3, the gain in welfare is higher from a tariff-only policy, which suggests that for lower desired levels of domestic expansion, tariffs may be a more effective policy tool.

Table 8: *Welfare in the utility-scale solar sector under counterfactual policies*

	Tariffs only	Subsidies only	Both
	(1)	(2)	(3)
Δ Government Revenues	8.30	-4.01	0.95
Δ Net profits of domestic solar panel producers	4.00	1.90	2.12
Δ Profits of downstream solar plant developers	-8.19	0.79	-0.99
Δ Consumer welfare	-10.95	2.55	-0.29
Δ Total welfare	-6.83	1.24	1.80

Notes: This table shows the changes in all welfare-relevant statistics under counterfactual policies, relative to baseline. Cost of subsidy is assumed to be 1.5 times the amount of subsidy. All figures are reported in billions of Indian Rupees.

Lastly, we examine the impact of the mixed policy. Under the mixed policy with an import tariff of 19.2% and production subsidy of 20.5%, the net change in government revenues is positive. Net of subsidy expenditures, the government collects 0.95 billion INR. Domestic upstream producers gain 2.12 billion INR. Since the equilibrium solar panel price is higher, downstream developers and consumers lose, but this loss is modest compared to the tariff-only regime. For developers, total profits fall by 1 billion INR. For consumers, the loss in consumer surplus is 0.3 billion INR. Overall, total domestic welfare is 1.8 billion INR ($28 million) higher under the mixed policy. Thus, the mixed policy is welfare-enhancing relative to the baseline, and this increase in welfare is higher than the increase under the tariff-only and subsidy-only policies.

6 Conclusion

This paper examines the Indian government's efforts to expand the domestic solar panel industry through a mix of tariffs and subsidies. To do so, we develop and estimate a structural model of the utility-scale solar sector. This sector comprises two vertically linked industries: the upstream solar panel industry and the downstream solar power plant industry. The model allows us to trace the impact of different upstream policy interventions on the welfare of upstream domestic producers, downstream firms, and consumers. Our estimates suggest a substantial cost advantage for foreign producers in the upstream industry, which allows them to capture a large share of the market and earn large markups. In such a scenario, tariffs could be welfare-enhancing by enabling the government to extract part of the foreign producers' markups as tariff revenues. However, tariffs also increase the cost of solar panels for downstream firms, which reduces their profits and increases the cost of solar power for consumers. Our estimates show that the optimal policy is a mix of tariffs and subsidies, which maximizes government revenues while minimizing the impact on the downstream industry.

References

Amiti, Mary and Amit K. Khandelwal (May 2013). "Import Competition and Quality Upgrading". In: *Review of Economics and Statistics* 95.2, pp. 476–490.

Amiti, Mary and Jozef Konings (2007). "Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia". In: *The American Economic Review* 97.5, pp. 1611–1638.

Amiti, Mary, Stephen J. Redding, and David E. Weinstein (Nov. 2019). "The Impact of the 2018 Tariffs on Prices and Welfare". In: *Journal of Economic Perspectives* 33.4, pp. 187–210.

Baldwin, Richard and Paul Krugman (1988a). "Industrial Policy and International Competition in Wide-Bodied Jet Aircraft". In: *Trade Policy Issues and Empirical Analysis*. University of Chicago Press, pp. 45–78.

— (1988b). "Market Access and International Competition: A Simulation Study of 16K Random Access Memories". In: *Empirical Methods for International Trade*. First. Cambridge, MA: MIT Press, pp. 171–197.

Bartelme, Dominick et al. (Aug. 2019). *The Textbook Case for Industrial Policy: Theory Meets Data*. Working Paper 26193. National Bureau of Economic Research.

Barwick, Panle Jia, Myrto Kalouptsidi, and Nahim Bin Zahur (2021). "Industrial Policy Implementation: Empirical Evidence from China's Shipbuilding Industry".

Cavallo, Alberto et al. (Mar. 2021). "Tariff Pass-Through at the Border and at the Store: Evidence from US Trade Policy". In: *American Economic Review: Insights* 3.1, pp. 19–34.

Dixit, Avinash K and Gene M Grossman (1986). "Targeted Export Promotion With Several Oligopolistic Industries". In: *Journal of International Economics* 21.3–4, pp. 233–249.

Edmond, Chris, Virgiliu Midrigan, and Daniel Yi Xu (Oct. 2015). "Competition, Markups, and the Gains from International Trade". In: *American Economic Review* 105.10, pp. 3183–3221.

Fajgelbaum, Pablo D et al. (Feb. 2020). "The Return to Protectionism". In: *The Quarterly Journal of Economics* 135.1, pp. 1–55.

Flaaen, Aaron, Ali Hortaçsu, and Felix Tintelnot (July 2020). "The Production Relocation and Price Effects of US Trade Policy: The Case of Washing Machines". In: *American Economic Review* 110.7, pp. 2103–2127.

Goldberg, Pinelopi Koujianou et al. (2010). "Imported Intermediate Inputs And Domestic Product Growth: Evidence From India". In: *The Quarterly Journal of Economics* 125.4, pp. 1727–1767.

Hansen, Jørgen Drud, Camilla Jensen, and Erik Strøjer Madsen (June 2003). "The Establishment of the Danish Windmill Industry—Was It Worthwhile?" In: *Review of World Economics* 139.2, pp. 324–347.

Harris, Richard, Ian Keay, and Frank Lewis (Apr. 2015). "Protecting Infant Industries: Canadian Manufacturing and the National Policy, 1870–1913". In: *Explorations in Economic History* 56, pp. 15–31.

Head, Keith (Nov. 1994). "Infant Industry Protection in the Steel Rail Industry". In: *Journal of International Economics* 37.3-4, pp. 141–165.

Irwin, Douglas A. (Apr. 2000a). *Could the U.S. Iron Industry Have Survived Free Trade After the Civil War?* Working Paper 7640. National Bureau of Economic Research.

— (2000b). "Did Late-Nineteenth-Century U.S. Tariffs Promote Infant Industries? Evidence from the Tinplate Industry". In: *The Journal of Economic History* 60.2, pp. 335–360.

— (Sept. 2019). "Tariff Incidence: Evidence From U.S. Sugar Duties, 1890–1914". In: *National Tax Journal* 72.3, pp. 599–616.

Itskhoki, Oleg and Benjamin Moll (2019). "Optimal Development Policies With Financial Frictions". In: *Econometrica* 87.1, pp. 139–173.

Juhász, Réka (Nov. 2018). "Temporary Protection and Technology Adoption: Evidence from the Napoleonic Blockade". In: *American Economic Review* 108.11, pp. 3339–3376.

Kalouptsidi, Myrto (Apr. 2018). "Detection and Impact of Industrial Subsidies: The Case of Chinese Shipbuilding". In: *The Review of Economic Studies* 85.2, pp. 1111–1158.

Lane, Nathaniel (2021). "Manufacturing Revolutions: Industrial Policy and Industrialization in South Korea". Working Paper.

Lashkaripour, Ahmad and Volodymyr Lugovskyy (2019). "Profits, Scale Economies, and the Gains from Trade and Industrial Policy".

Liu, Ernest (Nov. 1, 2019). "Industrial Policies in Production Networks". In: *The Quarterly Journal of Economics* 134.4, pp. 1883–1948.

Schmalensee, Richard (1982). "Product Differentiation Advantages of Pioneering Brands". In: *The American Economic Review* 72.3, pp. 349–365.

Topalova, Petia and Amit Khandelwal (Aug. 2011). "Trade Liberalization and Firm Productivity: The Case of India". In: *Review of Economics and Statistics* 93.3, pp. 995–1009.

A Additional Counterfactuals

Table A.1: *Optimal policy interventions to increase upstream domestic share by 5%*

	Tariffs only	Subsidies only	Both
	(1)	(2)	(3)
Import tariff	31.1%		19.3%
Production subsidy		5.9%	2.5%

Notes: This table presents the levels of import tariffs and/or production subsidies required to expand domestic production of solar panels by 5% relative to a baseline without any tariffs or subsidies. Columns (1) and (2) consider scenarios where only tariffs and only subsidies can be used, respectively. In column (3), we consider a scenario where a mix of tariffs and subsidies can be used to achieve the target, and we report the levels which achieve this target while maximizing total domestic welfare.

Table A.2: *Domestic expansion by 5%: Counterfactual outcomes in the solar panel industry*

	Level	Relative to Baseline		
	Baseline	Tariffs only	Subsidies only	Both
	(1)	(2)	(3)	(4)
Price (INR/watt)	24.3	+14.8%	−0.6%	+8.1%
Total production (MW)	1579.8	−17.0%	+1.2%	−9.9%
Domestic production (MW)	461.3	+5.0%	+5.0%	+5.0%
Foreign production (MW)	1118.5	−26.0%	−0.3%	−16.0%
Number of domestic producers	7.4	+12.4%	+6.1%	+10.3%
Number of foreign producers	16.2	−14.8%	−0.2%	−9.1%
Net profits of domestic producers	4326.1	+17.1%	+10.1%	+14.2%
Net profits of foreign producers	12519.2	−41.6%	−0.9%	−26.8%

Notes: This table reports outcomes in the upstream industry of solar panels in the baseline scenario, as well as under counterfactual policies. Column (1) reports levels; net profits are reported in millions of INR. Columns (2), (3), and (4) report changes in given variables relative to baseline.

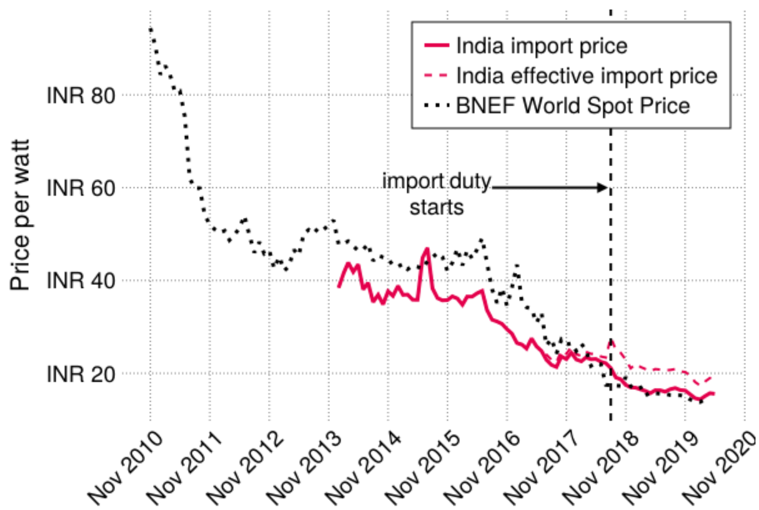
Table A.3: *Domestic expansion by 5%: Welfare under counterfactual policies*

	Tariffs only	Subsidies only	Both
	(1)	(2)	(3)
Δ Government Revenues	7.18	-0.87	4.37
Δ Net profits of domestic solar panel producers	0.74	0.44	0.61
Δ Profits of downstream solar plant developers	-2.75	0.20	-1.60
Δ Consumer welfare	-4.46	0.64	-2.42
Δ Total welfare	0.71	0.41	0.97

Notes: This table shows the changes in all welfare-relevant statistics under counterfactual policies, relative to baseline. Cost of subsidy is assumed to be 1.5 times the amount of subsidy. All figures are reported in billions of Indian Rupees.

B Additional Figures

Figure B.1: *Monthly imported module price per watt*



Notes. This figure plots monthly module prices obtained from transaction-level imports data. The solid blue line is the pre-tariff price per watt of imported solar modules, while the dashed blue line is the effective *price inclusive of duty that is faced by Indian importers. In solid black, we show the BNEF world spot price index for reference. The correlation coefficient between our manually constructed price series in solid blue and the BNEF price index is 0.96.*