Strategic Avoidance and the Welfare Impacts of U.S. Solar Panel Tariffs*

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Abstract

This study examines the effects of tariffs imposed by the United States on imported solar panels. We first provide definitive evidence that tariff-exposed firms shifted production to locations that did not face tariffs. We then develop a structural model to analyze welfare and employment effects. We find that the tariffs led to modest gains for manufacturers with domestic operations, but larger losses in domestic consumer surplus and environmental benefits. Furthermore, the tariffs *reduced* domestic solar industry employment and wages on net. By contrast, using industrial policy to subsidize solar panel manufacturing could increase domestic production, employment, and welfare.

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1 Introduction

Tariffs and industrial policy have seen a resurgence around the world in recent years. Economic theory provides a potential justification for such trade policy interventions in certain cases: if foreign exporters have market power, tariffs on imports could increase domestic welfare if they raise revenues or increase domestic firm profits more than they harm domestic consumers (Brandon and Spencer 1984). However, the effectiveness of such tariffs must account for multinational firms relocating their production activities to jurisdictions that are not subject to tariffs. Further, traditional analysis of such policies does not take into account externalities related to the goods of interest.

This study examines the effects of a series of tariffs on solar photovoltaic products imported into the United States. Much of the U.S. policy focus has been on Chinese solar panel manufacturers, who were subject to antidumping and countervailing duties first in 2012 and then again in 2014. Raw data on manufacturing activity reveal that, in aggregate, Chinese manufacturers tripled their offshore manufacturing as a share of their total manufacturing, increasing from only 5 percent in 2012 to over 15 percent by 2018. This offshoring was concentrated in Southeast Asia. Using an event study analysis that compares Chinese firms that were exposed to tariffs to others that were not, we find that this offshoring response is causal rather than simply correlational.

In 2018, the United States imposed more broad-based "safeguard" tariffs designed to protect domestic industry from foreign competition. Shortly thereafter, U.S. solar panel manufacturing increased significant relative to prior levels, but it was driven almost exclusively by additional offshoring activity by foreign firms investing in U.S. manufacturing, rather than the revitalization of domestic incumbents. As a final piece of descriptive evidence, we estimate two-way fixed effects regressions of how firms' sales, prices, and quantities correlate with firm-specific tariffs. We find that firms subject to higher tariffs sell a lower value of solar panels, and that this effect is manifested through changes in firm-specific quantities rather than firm-specific prices.

To understand the quantitative implications of the tariffs, we develop a structural model of supply and demand in the solar panel market and estimate it with data on solar manufacturer production and sales. Using our model, we quantify the welfare impacts of tariffs on solar panels, accounting for offshoring behavior by firms. We find that the recent rounds of tariffs led to modest gains for solar panel producers with domestic manufacturing facilities, but major losses in domestic consumer surplus and reduced environmental benefits. Further, the tariffs reduced total domestic employment in the solar industry by reducing solar installation jobs more than it increased solar manufacturing jobs. By contrast, a modest subsidy to domestic solar panel manufacturing – an industrial policy – could lead to on-shoring of solar panel production, increased domestic employment in the solar industry, and higher welfare from both domestic and global perspectives.

Our structural model integrates the firm's offshoring decision explicitly into a model of imperfect competition between domestic and foreign firms. This extension enriches the setting in the traditional strategic trade literature and generates different quantitative predictions on consumer welfare, domestic firm surplus, and tariff revenues compared with a model with no offshoring. This echoes the general argument that one needs to take into account offshoring while investigating the implications of trade policies (e.g., Antràs and Staiger, 2012).

An especially interesting aspect of our empirical setting is that solar panel manufacturing is not only a dominated by a relatively small number of Chinese firms, but solar panels are a product associated with environmental benefits from the production of clean electricity that offsets fossil-fuel powered electricity. With only partly internalized externalities from greenhouse gas and air pollutant emissions, the adoption of the technology is less than is socially optimal, even in the absence of tariffs. Further, solar panels are the key input into the relatively sizable solar panel installation industry, which is greatly affected by tariffs and benefits from price decreases. These aspects of the industry allow provide a more nuanced understanding of the potential rationales for, and impacts of, government intervention than in the traditional strategic trade literature, which primarily focuses on profit-shifting and terms of trade.

We model the market for solar panels by treating the electricity generation capacity of solar panels as a homogeneous product.[1] Aggregate demand for solar panels depends on the price of solar panels and government subsidies for solar technology adoption. In some specifications, we allow for unobserved time-varying demand shifters captured by fixed effects. We estimate the model using ordinary least squares and two-stage least squares. For two-stage least squares estimation, we use two sets of instruments. In the first, we use the prices of silver and aluminum, which are important input costs for solar manufacturers. The second instrument we use is the foreign price of solar panels. This "Hausman instrument" serves as an indirect measure of cost shifters, since the global integration of solar panel manufacturing creates correlations in marginal costs across end markets.

We find demand elasticities on the order of -1.5 across all three estimation strategies, consistent with prior work (Gerarden, 2023). As a robustness analysis, we also develop a model of solar panel demand derived from the downstream demand for solar installations from the utility and non-utility markets. We estimate that model using additional microdata

[1] In the industry and in this paper, solar panel quantities are denominated in watts (W) and prices are in dollars per watt ($/W). Viewed in these terms, solar panels are highly commoditized.

on residential solar installations and find similar elasticity estimates to the more parsimonious aggregate demand model.

To model the supply of solar panels by manufacturers, we combine techniques from industrial organization and trade. Manufacturers from around the world source solar panels from their production locations and ship them to the United States to compete in the wholesale market. We model manufacturers engaging in static Cournot competition.[2] Static Cournot competition implies a first-order condition for manufacturers' optimal quantity choices, which we use to recover estimates of post-tariff costs for manufacturers over time. We micro-found those costs by developing a model of manufacturer production sourcing using results from Eaton and Kortum (2002). This allows us estimate the unobserved determinants of production costs and to predict how counterfactual changes in tariffs would affect the source of solar panels, both due to shifts across manufacturers as well as shifts within manufacturer across production locations.

Estimated production costs are intuitive and consistent with our model-free evidence. Absent tariffs, the cost of manufacturing solar panels in China over the period 2014 through 2020 is predicted to range from one-half to two-thirds the cost of manufacturing in the U.S. (all else equal). Manufacturing in third countries is slightly more expensive than China. After accounting for antidumping and countervailing duties, the model predicts that third countries become the least expensive production location for most firms. Finally, the U.S. becomes cost-competitive for many firms after the additional, more broad-based tariffs went into effect in 2018.

Based on our model estimates, we conduct a set of counterfactual analyses to quantify the impact of import tariffs on the market for solar panels. Prices would have been lower and quantities would have been higher in the absence of tariffs. As a result, domestic consumer surplus and the environmental benefits from solar adoption would have been much higher. These benefits are estimated to be an order of magnitude larger than the harm to domestic producers from removing tariffs. This is because the cost disadvantage faced by domestic manufacturers was so large that tariff avoidance by offshoring production from China to other countries was more profitable than onshoring production to the U.S. during most of the sample period. The domestic production share predicted by the model is trivial prior to 2018, and even after the more broad-based 2018 tariffs domestic production is less than a quarter of domestic demand. The primary effect of removing tariffs would have been to shift manufacturing from Southeast Asia back to China, resulting in lower costs with little

[2] This is supported by the commoditized nature of solar panels as well as descriptive regressions of the impact of tariffs, which reveal that manufacturer-specific tariffs lead to reductions in a given manufacturer's market share, but not price, relative to other manufacturers.

foregone benefits in terms of either domestic producer surplus or national security benefits.

We also conduct a back-of-the-envelope analysis of the domestic employment impacts of removing tariffs. Unsurprisingly, we find that removing tariffs would have reduced domestic manufacturing employment. However, solar installation employment would have increased by a factor of five times the reduction in domestic employment. This is because manufacturing labor demand only depends on the number of solar panels that are produced domestically, whereas installation labor demand depends on the total number of solar panels demanded, both domestically and from abroad. In total, we find that removing import tariffs would have *increased*, not decreased, domestic employment and wages.

We conduct a second set of counterfactuals to quantify the potential effects of industrial policy as a substitute for trade policy. The Inflation Reduction Act (IRA) and the European Green New Deal have introduced policy mechanisms to mitigate climate change and hasten the energy transition. For example, the U.S. recently established a manufacturing production tax credit for clean energy technologies. To understand the prospective effects of these policy developments, we analyze a counterfactual where the U.S. government provides a 30 percent subsidy to domestic solar panel production.

In contrast to both the status quo and the counterfactual scenario with no tariffs, our model predicts that a domestic production subsidy would have increased the domestic production share to over 25 percent, and in some periods closer to 50 percent. This increase in U.S. production comes at the expense of production in China, with limited effect on production in other locations. Furthermore, domestic subsidies would have increased employment in both manufacturing and installation. This would eliminate the conflicting employment impacts of imposing an import tariff on intermediate inputs like solar panels.

Finally, and perhaps most surprisingly, we find that a domestic manufacturing subsidy would improve welfare relative to a scenario with no trade or industrial policy. This is primarily because it would reduce the distortion created by underpriced environmental externalities.[3] These results highlight that production subsidies could succeed where import tariffs have failed to engender a domestic solar manufacturing industry. However, the benefits and costs of these policies need to be weighed against the potential net benefits of introducing alternative policies that would fully correct negative externalities without introducing supply-side distortions in manufacturing activity.

This work builds on the literature on the effects and incidence of U.S. trade policy. Flaaen et al. (2020) use import data and retail price data to examine how U.S. import restrictions on washing machines affect trade flows and prices. By contrast, we focus on the market for

[3]The model accounts for existing subsidies to consumers to adopt solar, holding their level (but not their fiscal cost) fixed across the three counterfactuals.

solar panels, where interactions with environmental externalities are important determinants of welfare. We use rich production and sales data to provide detailed evidence of production offshoring in response to China-specific tariffs and to quantify its welfare implications. Despite these differences in approach, our descriptive results echo Flaaen et al.'s (2020) findings on the effects of antidumping duties, and our quantitative model underscores how production relocation plays an important role in the welfare implications of tariffs. Our work also relates closely to Fajgelbaum et al. (2020), who estimate pass-through and the short-run impacts of tariffs across the U.S. economy, and earlier work by Irwin (2019) on the pass-through of sugar tariffs. There is also a literature estimating the response of import prices to tariff changes (Feenstra 1989, Winkelmann & Winkelmann 1998, Trefler 2004, Broda et al. 2008, Sperot 2012, Fitzgerald & Haller 2018) and related work on the consumer gains from imports from China (e.g., Bai and Stumpner, 2019). Broadly, this literature tends to find near-complete pass-through of tariffs to consumers.

There is also some work on multinational firms' responding to tariffs by offshoring or relocating production to low-tariff countries. Flaaen et al. (2020) showed some evidence of relocation of washing machine production, and several other papers have discussed or showed some evidence of this possibility (Brainard 1997; Horstmann and Markusen, 1992; Blonigen, 2002). One challenge to studying these firm responses is that they are not directly observable in data on trade flows. By contrast, we leverage detailed manufacturing data that allow us to better understand firm responses and the implications of tariffs for the global cost structure of solar manufacturing, a particularly policy-relevant empirical setting.

Finally, we contribute to a recent literature on the economics of solar power (e.g., Gowrisankaran et al., 2016; De Groote and Verboven, 2019; Bollinger and Gillingham, 2019; Langer and Lemoine, 2022; Gerarden, 2023). Many of these papers focus on estimating demand for solar systems. We extend this literature by studying the upstream supply of solar panels.[4] The most closely related paper is Houde and Wang (2023), who also study the impact of import tariffs in the U.S. solar market. In contrast to Houde and Wang (2023), our study is more comprehensive and more focused on the supply side. Our analysis covers the whole U.S. solar market, going beyond the focus of prior work on small-scale solar systems that constitute less than half of solar electricity generation capacity additions. The data we use for descriptive evidence provide unique insight into manufacturers' activities. Our

[4]Gerarden (2023) also studies the supply of solar panels, but focuses on technological innovation by solar panel manufacturers over time rather than the distribution of their production activity over space. Garg and Saxena (2023) consider how tariffs and production subsidies could be combined to meet domestic production targets in the Indian solar market. In contrast to this paper, Garg and Saxena focus more narrowly on the role of market power without accounting for environmental externalities, which we find to be quantitatively important in the U.S. context.

modeling approach allows us to better characterize manufacturer responses, quantify how the geographic footprint of manufacturing affects the cost of solar panel production, and analyze the effects of alternative policy mechanisms such as domestic manufacturing subsidies.

2 Industry Background and Data

2.1 U.S. Trade and Industrial Policy

We study the impacts of four rounds of tariffs affecting U.S. solar imports. The first round was a set of antidumping and countervailing duties implemented in 2012 (the "2012 tariffs").[5] These duties applied to solar cells manufactured in China, regardless of whether they were imported as solar cells or after assembly into solar panels.[6] The duties varied by manufacturer to account for differences in manufacturers' pricing and the subsidies they received from the Chinese government.

The second round of tariffs, justified on the same grounds, began in June 2014 (the "2014 tariffs"). It was designed to close loopholes in the 2012 tariffs, in particular, the ability of Chinese solar cell producers to avoid tariffs by buying solar cells from Taiwanese producers or offshoring part of their cell production to Taiwan. As a result, the 2014 tariffs applied to solar panels assembled in any country using solar cells that were manufactured in either China or Taiwan. In addition, the 2014 tariffs applied to solar panels assembled in China irrespective of where the solar cells were manufactured. In other words, the 2014 tariffs covered a broader range of cell manufacturing and panel assembly locations, making it more difficult for Chinese solar manufacturers to avoid tariffs without making significant, costly changes to their operations.

The third round of tariffs affected many more countries. Under authority from Section 201 of the Trade Act of 1974, President Trump imposed a 30% tariff on cell and panel imports in February 2018. These "Section 201 tariffs" applied to crystalline silicon products from all major exporters of solar products to the U.S.[7] The tariff declined by 5% each year until 2022, when it was set to expire. Instead, President Biden extended the tariffs through 2026, with modifications.

[5] The U.S. International Trade Commission made a preliminary determination of injury in March 2012 and began collecting duties. The commission did not reach a final determination of injuries, finalizing the tariffs, until November 2012.

[6] As in the other tariff rounds, only crystalline silicon products were subject to tariffs. Alternative solar panel technologies such as thin-film products were excluded.

[7] The first 2.5 gigawatts of cell imports each year were exempt. Some developing countries, like India, South Africa, and Brazil, were exempt. None of these countries is a significant exporter to the U.S. Bifacial panels were exempt from June 2019 through the end of our study period (September 2020).

The fourth and final round of tariffs did not specifically target solar panels. Using Section 301 of the Trade Act of 1974, the U.S. Trade Representative imposed tariffs of up to 25% on imports from China. These "Section 301 tariffs" included solar cells and panels. Both the Section 201 and Section 301 tariffs apply in addition to the pre-existing antidumping and countervailing duties from 2012 and 2014.

More recently, two federal subsidies for domestic solar component manufacturing were created and expanded as part of the IRA. The Advanced Manufacturing Production Tax Credit (45X MPTC), which was established by the IRA, provides subsidies based on the production and sale of specific clean energy components. Eligible solar photovoltaic components include polysilicon, wafers, cells, and panels. The 45X MPTC is projected to cost roughly $70 billion over five years, similar in magnitude to projected spending on the ITC for solar system installations, which has historically been the largest federal subsidy to the solar market (Congressional Research Service, 2024). The Advanced Energy Project Investment Tax Credit (48C ITC), which was allocated $10 billion by the IRA, provides an upfront tax credit of 30% of capital investments in clean energy manufacturing facilities that meet prevailing wage and apprenticeship requirements. These policies motivate our counterfactual analysis that examines the effects of a United States production subsidy. The labor requirements of the 48C ITC also highlight the importance of labor market outcomes as a policy objective.

2.2 Data

The primary data source for our analysis is IHS Markit data on the global solar supply chain. The data include quarterly records of manufacturers' total production by country, which lets us track changes in production locations. It also includes quarterly records of those manufacturers' total shipments to the U.S. for the 20 largest manufacturers.[8] It does not include imports to the U.S. by country of production, so we do not directly observe the share of shipments originating in a particular country. Production and shipment quantities are in Watts (W), while prices are in dollars per Watt ($/W). Appendix A shows the aggregate trends in prices, shipments, and installations for the United States. Although the IHS data cover a subset rather than the universe of manufacturers, we show in Appendix B that they cover the significant majority of imports by value, and they exhibit similar temporal patterns to official government data on total imports.[9]

Data on the four tariff rounds comes from the Federal Register, which contains official announcements from U.S. government agencies. For the 2012 and 2014 tariffs, the Federal

[8] "Shipments" data include both domestic shipments in addition to imports.

[9] We account for the presence of a competitive fringe in the model and estimation.

Register details the antidumping and countervailing subsidy duties imposed on each manufacturer as well as each revision of the duties. We create a time series of duties for each manufacturer. The Section 201 and Section 301 tariffs are also described in the Federal Register.

We also collected government records on duties collected *ex-post*. Duties collected for the Section 201 tariffs come from the U.S. Department of Commerce. Duties collected for the 2012 and 2014 tariffs were from the U.S. Customs and Border Protection via a Freedom of Information Act (FOIA) request.

We use several other data sources in estimation and for ancillary analysis. Trade flows data come from the United Nations (UN) Comtrade database and the U.S. International Trade Commission (USITC) DataWeb. Wage data come from the International Labour Organization (2023). Data on adoption of large- and small-scale solar systems come from the U.S. Energy Information Administration (EIA) Form EIA-860, the Solar Energy Industries Association (SEIA), and the Lawrence Berkeley National Laboratory's (LBNL) Tracking the Sun data set. Data on the prices of silver and aluminum come from the London Afternoon Fixing (2024) and the London Metal Exchange (2024). We convert prices from nominal to real terms using the GDP implicit price deflator from the U.S. Bureau of Economic Analysis (2024).

Table 1 presents summary statistics for the main data sample used in estimating the model and conducting counterfactual analysis in sections 4 through 7 of the paper. The manufacturing data used throughout section 3 includes a broader set of firms for which shipments to the U.S. are unobserved.

Table 1: Summary Statistics for Main Model Sample

	Mean	Median	Min	Max	Percentiles 10th	Percentiles 90th
Market-level variables						
Price ($/W)	0.93	0.79	0.31	2.43	0.37	2.12
Quantity (GW)	2.9	2.0	0.2	10.1	0.5	5.6
Number of firms	16.8	17	12	20	13	19
Firm-level variables (%)						
Market share (raw)	6.0	3.9	0.0	37.4	0.2	15.2
Market share (adjusted)	4.7	3.1	0.0	28.6	0.2	12.1
Chinese tariff	28.7	15.2	0.0	227.3	0.0	73.7
Chinese tariff | tariff > 0	47.2	29.2	5.9	227.3	15.2	100.9
Others tariff	6.2	0.0	0.0	30.0	0.0	25.0
Others tariff | tariff > 0	23.7	25.0	11.1	30.0	11.1	30.0

Note: This table presents summary statistics for the main data sample used in sections 4 through 7 of the paper. The sample is restricted to firm-quarters with observed shipments to the U.S. This table summarizes the distributions of key variables across quarters (for market-level variables) and firm-quarters (for firm-level variables). Market shares are presented based on the data sample alone (raw) and after adjusting for the size of the competitive fringe (adjusted). All tariff rates for imports from China and Other countries are conditional on a firm actually producing in that location. Tariff rates for China include the applicable tariff(s) from all four tariff rounds.

3 Descriptive Evidence of Tariff Avoidance

This section presents data on production patterns that suggest Chinese manufacturers adjusted their operations to avoid tariffs.

3.1 Manufacturers Offshored Production to Tariff-Free Countries

To understand how foreign manufacturers responded to the geographically targeted tariffs imposed in 2012 and 2014, we summarize how the geography of affected manufacturers' production capacity evolved over time. Figure 1 plots the share of panel capacity and production outside China for manufacturers that ever produce panels in China.[10] The vertical dashed lines represent the implementation of the four rounds of tariffs.

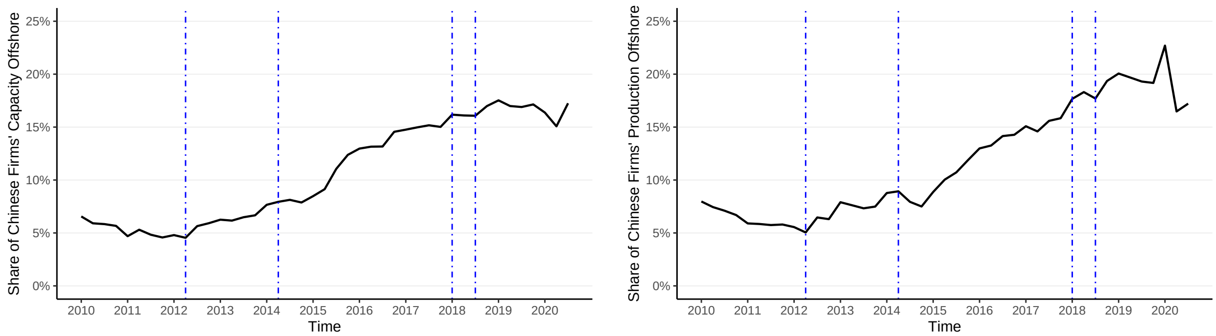
Figure 1 shows that Chinese manufacturers increased their share of panel capacity and production outside China after the 2014 tariffs took effect. This pattern is consistent with production relocation as a means to avoid paying U.S. import tariffs.[11] However, this

[10] We use the entire sample to characterize overall production activity for descriptive purposes. The patterns are similar for the subsample of firms that produced in China before the tariffs came into effect.

[11] Appendix C.1 presents additional measures of production relocation by manufacturers that produced

Figure 1: Chinese Manufacturers' Share of Panel Manufacturing outside China over Time

(a) Capacity (b) Output



Note: This figure plots aggregate offshoring of solar panel manufacturing capacity and output over time based on quarterly data on quantities from IHS Markit. In Panel (a), the sample of firms is restricted to those that have non-zero solar panel manufacturing capacity in China prior to the imposition of tariffs. Similarly, the sample in Panel (b) is defined based on non-zero solar panel output. The share offshore is computed by first aggregating outcomes inside and outside of China across firms, and then computing and plotting the share outside China. Vertical lines denote the timing of each round of tariffs.

offshoring behavior could also be explained by cost drivers that are unrelated to but correlated with tariffs in the time series.

3.2 Import Tariffs Caused Manufacturers to Offshore Production

To formalize the descriptive evidence of production offshoring in the previous section, we use an event study to provide evidence that offshoring was a response to the tariffs rather than a coincidence. In our primary specifications, we compare treated Chinese manufacturers that are assigned firm-specific rates in the Federal Register to control Chinese manufacturers that are not named and are subject to higher PRC-wide tariff rates. The primary reason that firms are not treated is that they focus on selling their products in other countries, and therefore it is not worthwhile to engage in the process to receive a firm-specific rate. This research design compares firms who are differentially exposed to U.S. import tariffs but who otherwise face common cost drivers that may or may not justify the offshoring of production activity.

We operationalize this event study by estimating a two-way fixed effects model:

$$Y_{ft} = \sum_{t' \neq 0} \beta^{t'} \text{Treated Manufacturer}^{t'}_{ft} + \gamma_f + \delta_t + \varepsilon_{ft}, \tag{1}$$

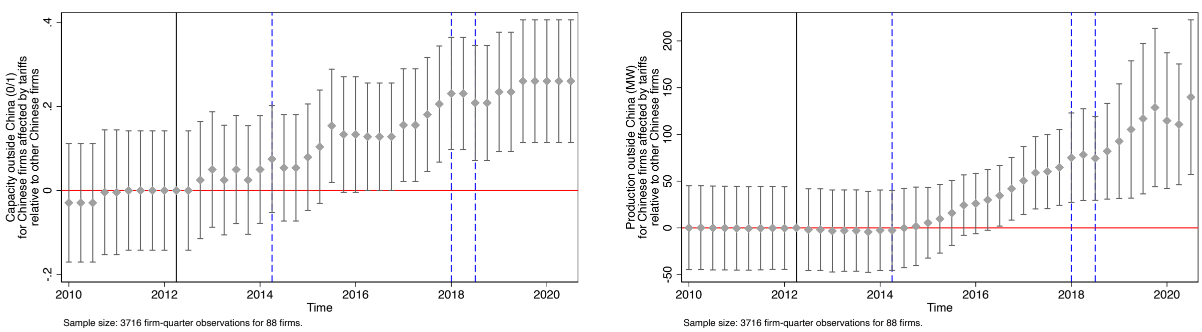
solar products in China, all of which are consistent with the idea that tariff-exposed manufacturers relocated production activities to avoid tariffs.

where Y_{ft} is capacity (binary) or production (continuous) outside China for manufacturer f in time period t, Treated Manufacturer$_{ft}^{t'}$ is a treatment indicator for being t' quarters relative to the period before or after the 2012 tariffs went into effect, γ_f is a manufacturer fixed effect, and δ_t is a time fixed effect.

Figure 2 presents point estimates and confidence intervals for the $\beta^{t'}$'s. The left panel plots coefficients from a linear probability model of the extensive margin decision to offshore production activity. The right panel plots coefficients from a linear regression of intensive margin offshore production levels. In both cases, treated firms increase offshore manufacturing activity over time relative to control firms.[12]

Figure 2: Event Study of the Effect of Tariffs on Production Offshoring by Chinese Firms

(a) Capacity (0/1) (b) Production (MW)



Note: Points represent event study coefficients from estimating equation 1 via ordinary least squares. Confidence intervals are robust to heteroskedasticity. The left panel is from estimating a linear probability model where the outcomes are binary indicators of whether a firm has any production capacity outside China. The right panel is from estimating a linear model where the outcomes are continuous measures of production output outside China in megawatts (MW). Vertical lines denote the timing of each round of tariffs. All event study coefficients are relative to the second quarter of 2012.

One potential shortcoming of this event study analysis is that the firms who are exposed to U.S. import tariffs may differ from firms who are not exposed to the tariffs at baseline. For example, treated firms may be larger given that they export to the U.S. market. While the parallel pre-trends in Figure 2 are consistent with the identifying assumption of parallel trends in the absence of treatment, the assumption is not testable. To ameliorate concerns about potential failures of the parallel trends assumption, Appendix C.2 contains estimates from two additional specifications. In the first, we focus on the subsample of firms that lie within the common support of the pre-treatment firm size distribution. The extensive

[12] Our focus is on qualitative rather than quantitative conclusions here. In principle, the precise level of event study coefficients may be confounded by a failure of the stable unit treatment value assumption that stems from product market competition among these firms. However, the event studies provide clear evidence on the *qualitative* effects of tariffs on offshoring incentives that motivate our approach to modeling the market in order to derive quantitative conclusions.

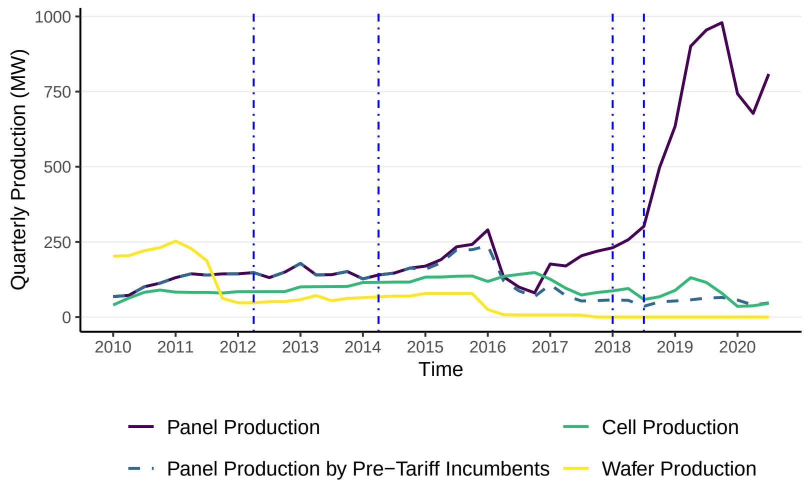
margin estimates are quantitatively similar. The intensive margin estimates are attenuated somewhat but remain statistically significant and lead to the same qualitative conclusions. In the second, we compare treated Chinese firms to foreign firms that are not exposed to tariffs until 2018, and draw the same qualitative conclusions. Thus, common cost shifters that vary over time are not able to explain observed production patterns in the raw data. We conclude that the antidumping and countervailing duties, particularly the 2014 tariffs, caused treated Chinese firms to offshore their manufacturing activity.

3.3 Domestic Solar Panel Assembly Increased

Figure 3 summarizes total production of solar panels, cells, and wafers in the U.S. over time. Prior to 2018, there was relatively little variation in the production of solar cells and panels despite significant growth in the size of the global solar market. After the Section 201 tariffs were imposed in early 2018, there was a significant increase in domestic solar panel assembly. This increase was driven by the entry of foreign manufacturers, which were able to import solar cells produced abroad without paying tariffs under the 2.5 GW solar cell import exemption.[13] By and large, manufacturing by domestic incumbents continued to decline. This is evident in the domestic production of cells and wafers, neither of which increased in the aftermath of the Section 201 tariffs. In all, the patterns in Figure 3 imply that the tariffs did not significantly increase energy independence.

[13] Appendix C.3 decomposes these aggregate trends by cohorts of entry into U.S. manufacturing.

Figure 3: U.S. Manufacturing Activity over Time



Note: This figure plots crystalline silicon solar component output in the U.S. over time based on quarterly data from IHS Markit. Solid lines represent total output of each product from all firms. The dashed line represents output of solar panels from the subset of firms that produced solar panels in the U.S. prior to tariffs. This figure omits thin-film manufacturers, as they have a different production process that cannot be separated out into the same categories of wafers, cells, and panels. Figure C.6 replicates the time series for crystalline silicon solar panels alongside an analogous time series for thin-film panel production. Vertical lines denote the timing of each round of tariffs.

3.4 The Market Share of Chinese Multinationals Expanded

Figure 4 shows a breakdown of major manufacturers' shipments to the U.S. based on the countries in which those manufacturers produce panels and cells, in that quarter.[14]

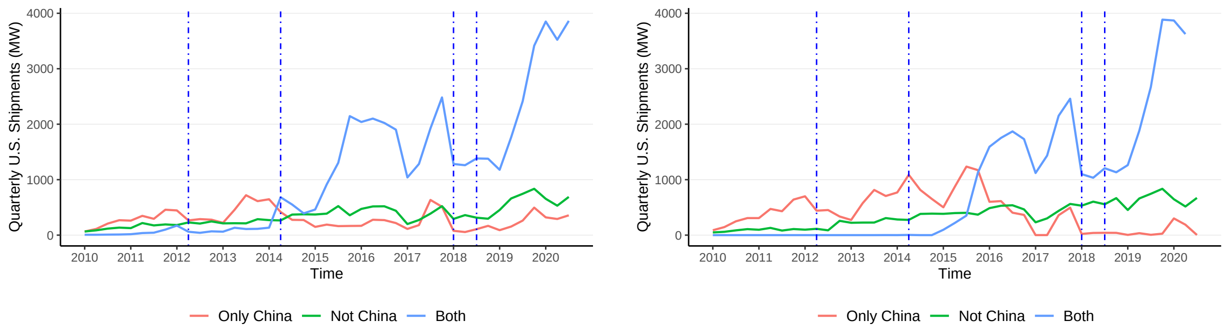
Figure 4a breaks down the time series of panel shipments into subgroups based on contemporaneous panel manufacturing locations. There are three groups: firms that manufacture only in China, firms that do not manufacture in China, and firms that manufacture both inside and outside of China. In the first part of the sample period, major Chinese manufacturers produced solar panels exclusively in China, and no manufacturers produced panels both inside and outside of China. After the 2012 tariffs took effect, most shipments were from Chinese manufacturers that continued to focus their operations in China. This is likely because the first round of duties did not preclude Chinese-based manufacturers from using cells produced in Taiwan to continue supplying the U.S. market with solar panels without paying duties.[15]

[14]The sample is restricted to include only crystalline-silicon solar manufacturers and exclude thin-film manufacturers that are not subject to tariffs.

[15]U.S. International Trade Commission (2015, p. 4) states that "SolarWorld alleged that [panel] assemblers in China either bought cells from producers in Taiwan or shipped wafers to Taiwan to be processed into cells and returned to China for assembly into [panels]." Appendix C.4 summarizes the geography of solar component production over time. The global production shares of panels and cells in China and Taiwan around the time of the 2012 tariffs are consistent with these anecdotes. China's share of global panel production was essentially flat from 2014 to 2014. Meanwhile, China's share of global cell production decreased during

Figure 4: Shipments to the U.S. by Major Manufacturers of c-Si Solar Panels

(a) Shipments by Panel Manufacturing Location (b) Shipments by Cell Manufacturing Location



Note: This figure plots shipments to the U.S. based on quarterly data from IHS Markit. Shipments are plotted separately based on the locations where solar manufacturers have active production facilities, since shipments are only observed at the firm level, not the firm and origin of shipments. Red lines represent shipments from firms that only manufacture in China. Green lines represent shipments from firms that only manufacture outside of China. Blue lines represent shipments from firms that manufacture both in and outside of China. Firms' assignments to each group are based on contemporaneous manufacturing activity, so that the firms comprising each line change over time. For each line, total shipments are computed by aggregating across all firms in that group in that time period. Figure 4a defines groups based on panel manufacturing locations, whereas 4b is based on cell manufacturing locations. Vertical lines denote the timing of each round of tariffs.

Later, after the 2014 tariffs took effect, there was a pronounced shift of Chinese manufacturers away from producing panels exclusively in China toward producing in multiple countries. This is evident in the increase in the shipments from the category "Both" and the decrease from "Only China." These changes capture both shifts in production across manufacturers conditional on their locations as well as shifts in production across locations within manufacturers. These geographically diversified manufacturers came to dominate shipments to the U.S. market. In comparison, manufacturers that did not manufacture in China exhibit less variation in response to tariffs, so that the growth of shipments from manufacturers in the "Both" category do not reflect a broader trend of geographical diversification.

Figure 4b breaks the same shipments data into groups based on contemporaneous *cell* manufacturing locations. As detailed in section 2.1, the 2012 and 2014 tariffs depended on the origin of cells, not just the assembled panels. The patterns in Figure 4b are similar to Figure 4a. In the early part of the sample none of the major manufacturers were manufacturing cells both inside and outside of China. This changed in 2015 when some manufacturers expanded to manufacture cells both inside and outside of China.

that period, while Taiwan's share increased during that period. In the aftermath of the 2014 tariffs, both remained somewhat lower as the share of cells produced in Southeast Asia increased.

3.5 Government Data Confirms that Importers Avoided Tariffs

As another piece of evidence of tariff avoidance, we submitted a FOIA request to obtain data on actual duties collected by the U.S. Customs and Border Protection. Table 2 presents these data. Each row contains money collected from a specific set of antidumping and countervailing duties. Each column corresponds to a fiscal year. The first few columns show that very little money was collected from the 2012 antidumping and countervailing duties during FY2012 and FY2013. This is likely due to avoidance behavior by manufacturers. In later years, after the scope of duties was expanded, the amount of duties collected increased substantially.

Table 2: Duties Collected by U.S. Customs and Border Protection

Description	Case No.	FY2012	FY2013	FY2014	FY2015	FY2016	FY2017	FY2018	FY2019	FY2020
AD China 2012	A-570-979	2.02	2.84	34.54	147.91	183.01	16.70	33.72	1.58	26.25
AD China 2014	A-570-010			0.02	1.39	2.74	0.60	1.07	4.10	15.28
AD Taiwan 2014	A-583-853			10.10	51.76	42.75	3.04	1.15	5.03	2.57
CVD China 2012	C-570-980	0.79	3.89	43.19	226.51	382.55	36.84	72.74	1.12	48.00
CVD China 2014	C-570-011			26.95	0.35	0.58	0.33	0.62	1.15	4.01

Note: Summary of duties collected by case and fiscal year, obtained via FOIA request to the U.S. Customs and Border Protection. Duties are in millions of dollars, in nominal terms.

We perform an imputation exercise that compares predicted duty payments based on the statutory tariff rates to actual duties collected. We also compare to predicted duty payments accounting for tariff avoidance using a "strategic" tariff rate that we construct based on the extreme assumption that manufacturers source solar panels to minimize tariff payments.[16] The results shown in Appendix E corroborate the other descriptive evidence that manufacturers were able to avoid tariffs, and we find that that duty payments calculated using the constructed strategic tariff rates match actual duty payments far better than the equivalent figures based on the statutory tariffs do.[17]

3.6 Descriptive Regressions of Tariff Impacts

As a final piece of descriptive evidence, we use the ad valorem strategic tariffs described above to estimate the following panel data model of the relationship between equilibrium outcomes and tariff rates at the manufacturer level:

$$\log(y_{ft}) = \alpha \log(\tau^S_{ft}) + \gamma_f + \nu_t + \varepsilon_{ft}, \tag{2}$$

[16] Appendix D details the construction of the strategic tariff rates.

[17] Appendix F discusses whether firms might have avoided tariffs by transshipping rather than actual production shifting. We provide descriptives to show that the data are consistent with Chinese firms offshoring the last two stages of solar panel production to avoid tariffs, and not simply transshipping completed products through third countries to evade tariffs.

where y_{ft} is a manufacturer-time-specific outcome for manufacturer f and quarter t and $\tau^S_{ft} \equiv 1 + \text{Strategic Tariff}_{ft}$.[18] We include fixed effects for manufacturers (γ_f) and time (ν_t). This estimation provides insights into the impacts of tariffs on equilibrium prices and quantities, which can be used to motivate key assumptions in our structural model.

Table 3 presents estimates of α for three different outcomes. In column 1, we regress the value of a manufacturer's shipments on its strategic tariff. Manufacturers that experience higher strategic tariffs in a given period tend to ship a lower value of solar panels to the U.S. in that period. In columns 2 and 3, we decompose the effect on value into separate effects on prices and quantities. The relationship between strategic tariff rates and manufacturer-specific prices is small and indistinguishable from zero. In contrast, the relationship between strategic tariff rates and quantities is large and statistically significant. These estimates are consistent with a model of Cournot competition in which manufacturers respond to cost shocks by adjusting quantities, and those quantity adjustments affect the market price but do not produce manufacturer-specific differences in price.

Table 3: Tariffs Affect Quantities but Not Prices

	(1) log(Value)	(2) log(Price)	(3) log(Quantity)
log(1 + Strategic Tariff)	-3.37**	-0.097	-3.27**
	(1.14)	(0.066)	(1.10)
Firm Fixed Effects	Y	Y	Y
Time Fixed Effects	Y	Y	Y
N	751	751	751

Note: This table presents estimates of α from estimating equation 2 via ordinary least squares. Each column presents results for a different outcome variable based on quarterly data from IHS Markit. Strategic tariffs are constructed as described in Appendix D. All columns include firm and time fixed effects. Heteroskedasticity-consistent standard errors are in parentheses.

4 Model

To understand the real economic effects of U.S. import tariffs, we formulate and estimate a model of the market for solar panels. The U.S. solar panel market involves several players. First, we need to consider the final downstream demand for solar installations. This demand comes from residential and commercial customers in local markets, as well as large utility-scale projects at the national level. Each local market is served by a finite set of installers. Second,

[18] The tariffs are ad valorem, so a 30% tariff would correspond to $\tau^S_{ft} = 1.3$. This functional form is standard in the literature (e.g., Fajgelbaum et al., 2020).

both national utility-scale projects and local installers source solar panel inputs from the wholesale market. Solar panel manufacturers around the world ship to their U.S. subsidiaries to participate in the wholesale market.

4.1 Demand for Solar Panels

Aggregate demand for solar panels in the U.S. depends on the price of solar panels as well as observed and unobserved demand shifters:

$$Q_t^D = Q_t^D(p_t, s_t),$$

where Q_t^D is the quantity of solar panels (in Watts) demanded in time period t. The quantity of solar panels demanded depends on the wholesale price of solar panels, p_t, and on government subsidies to encourage adoption of solar technology, s_t. Other, potentially unobserved, demand shifters are subsumed into the dependence of the demand function on t.

In a robustness analysis contained in Appendix G, we develop and estimate a micro-founded model of demand for solar panels that is derived from downstream demand for solar installations from the utility and non-utility markets, while also allowing installers to increase their panel inventory in periods of lower price. For the utility market, we use a parsimonious discrete choice model of the choice to invest in solar versus other electricity generating technologies. For the residential and small commercial market, we develop a dynamic nested logit model to characterize the behavior of forward-looking consumers deciding whether to adopt a solar system that builds on De Groote and Verboven (2019) and Bollinger and Gillingham (2019). We also model solar system installers competing on price in local geographic markets. Finally, we aggregate these utility and non-utility demands to recover a market-level price elasticity of demand for solar panels.

4.2 Supply of Solar Panels

Each manufacturer, denoted as f, is characterized by its operational locations $Z \subseteq \mathbb{Z}$, cost efficiency ω, and ad valorem tariffs τ_t imposed by the U.S. on its production locations. Every firm maintains a wholesale subsidiary in the U.S., which imports solar panel shipments from the manufacturer's production sites $l \in Z$. These shipments introduce uncertainty regarding the *realized* cost of each panel sold.

We model each manufacturer f, with state variables (ω, Z, τ_t), as having an *ex-ante* expected unit cost denoted by $c_{ft} \equiv c_t(\omega, Z, \tau_t)$. These manufacturers compete in the U.S. market primarily by determining the quantity of solar panels that they supply, Q_{ft}^S (measured in Watts). Given the limited horizontal differentiation among solar panels, the model adopts a Cournot competition framework where the total market supply in period t, Q_t, is the sum of supplies from all manufacturers: $Q_t = \sum_f Q^S_{ft}$.

Each manufacturer faces the following optimization problem:

$$\max_{Q^S_{ft}} \quad (p_t - c_{ft})Q^S_{ft},$$

where p_t represents the market price of solar panels at time t, and c_{ft} denotes the expected unit cost for manufacturer f at time t. The objective function represents the variable profit from selling solar panels.

The first order condition for this optimization problem is given by:

$$\frac{Q^S_{ft}}{Q_t}\left[\frac{d\log Q_t}{dp_t}\right]^{-1} + p_t - c_{ft} = 0,$$

which simplifies to:

$$c_{ft} = p_t\left(1 + \frac{1}{\epsilon^D_t}\frac{Q^S_{ft}}{Q_t}\right), \tag{3}$$

where ϵ^D_t denotes the price elasticity of demand for solar panels at time t. This expression adjusts the cost c_{ft} to reflect the competitive interaction among manufacturers through the term involving the market share $\frac{Q^S_{ft}}{Q_t}$ and the demand elasticity.

Additionally, each manufacturer, particularly those with multiple production sites, must decide how to source solar panels to fulfill market demand. This decision is influenced by factors such as the cost structures at different locations and ad valorem tariffs imposed on imports from these locations, which are particularly relevant due to significant manufacturing concentration in regions like China and associated tariff fluctuations.

We assume that each manufacturer, having committed to a quantity Q^*_{ft} *ex-ante*, must coordinate a continuum of shipments from its various production facilities to meet this committed supply volume in the market.

For each shipment, the manufacturer chooses its lowest cost location $l \in Z$. The potential *post-tariff* unit production cost at each location l for the shipment depends on location-specific factor prices w^l_t and manufacturer- and location-specific tariff rates τ^l_t. Furthermore, unit production costs depend on productivity, $\omega\varepsilon^l E(K^l_t)$, where ω represents manufacturer productivity, ε^l is a stochastic cost shifter, and K_t^l is a measure of industry size:

$$c_t^l = \frac{w_t^l \tau_t^l}{\omega \varepsilon_t^l E(K_t^l)}. \tag{4}$$

ε_t^l is IID across all locations and orders and distributed Fréchet with mean T_t^l and shape parameter θ. The randomness captures any idiosyncratic reason that a specific shipment deviates from the average productivity in a location.

The term $E(K_t^l)$ captures the possibility of external economies of scale within a location (e.g., country or larger region). Each individual firm's sales to the U.S. are small relative to the scale of manufacturing at the location level, which includes the firm's production for other end markets as well as the production of all other firms for all end markets. Thus, we treat K_t^l as exogenous to the firm and therefore consistent with the firm's optimization problem encapsulated in equation 3. The curvature of productivity with respect to industry size determines the presence and strength of scale effects. This model nests the case of constant returns to scale at the location level as a special case. This approach builds on Kucheryavyy et al. (2023), who extend workhouse trade models to allow for industry-level economies of scale and characterize their theoretical properties.

Using results from the seminal work of Eaton and Kortum (2002), the resulting minimal cost distribution is

$$F_t(c; \omega, Z, \tau_t) = 1 - exp\left(-\Phi_t(\omega, Z, \tau_t)c^\theta\right), \quad \text{where} \;\; \Phi_t(\omega, Z, \tau_t) = \sum_{l \in Z} (\omega T_t^l E(K_t^l))^\theta (w_t^l \tau_t^l)^{-\theta}.$$

Given this stochastic structure and the fact that there is close to a continuum (i.e., a large number) of solar panel shipments, manufacturers' *ex-ante* expected unit costs are given by

$$c_t = (\Phi_t(\omega, Z, \tau_t))^{-1/\theta} \, \Gamma \left[\frac{\theta + 1}{\theta}\right]. \tag{5}$$

Intuitively, the cost to a manufacturer's subsidiary (c_t) depends on the combined post-tariff cost of all its production locations. If one of the locations, say China, has an abrupt tariff increase, the manufacturer will respond by reallocating its shipments to other potential sourcing locations. The degree to which that response allows them to avoid the tariffs depends on the set of locations where they have production facilities and the cost structure in those other locations. As θ gets larger, the manufacturer is more likely to allocate each unit of production to the location with the largest value of $T_t^l E(K_t^l)/(w_t^l \tau_t^l)$, i.e. the location with the best post-tariff unit cost.

4.3 Choice of Production Location

Firms always operate in their home locations, which, in our case, is predominantly China. However, to add one more production location in Southeast Asia and/or the U.S., they need to incur a random sunk cost F_s^l. We assume only one location can be added each time period and $F_s^l = 0$ if $l \in \emptyset$ (no location added).

Under Cournot competition, each firm's static profit is defined by its expected cost $c_t(\omega, Z, \tau_t)$, the industry average $\bar{c}_t$, and any time-varying demand shifter D_t. The firm's value of adding one location is then:

$$\begin{aligned} V(\Phi_t(\omega, Z, \tau_t), F_s; \bar{c}_t, D_t) = max_{l \in \{\emptyset, Z^C\}} \quad & \pi(\Phi_t(\omega, Z \cup l, \tau_t); \bar{c}_t, D_t) - F_s^l \\ & + \beta E_{\tau_{t'}, \bar{c}_{t'}, D_{t'}} [V(\Phi_{t'}(\omega, Z \cup l, \tau_{t'}), \bar{c}_{t'}, D_{t'}) | \tau_t, \bar{c}_t, D_t] \end{aligned}$$

where $V(\Phi_{t'}(\omega, Z \cup l, \tau_{t'}); \bar{c}_{t'}, D_{t'})$ represents the integrated value function and Z^C denotes the set of locations not yet operated by the firm. This scenario provides the basis for a conditional choice probability equation $P_t^l(\omega, Z, \tau_t)$ which we can estimate using a flexible probalistic regression. The key explanatory variable is the relative difference between $\Phi_t(\omega, Z \cup l, \tau_t)$ and $\Phi_t(\omega, Z, \tau_t)$.

5 Estimation

We outline estimation of the model in this section. We first describe how we estimate demand for the entire market with a parsimonious constant elasticity specification. We then describe how we estimate separate downstream models of demand from residential/commercial consumers and utility-scale consumers. We then proceed to describe how we integrate these estimates into estimation of manufacturing costs from the wholesale market Cournot equilibrium.

5.1 Demand Estimation

We estimate a series of constant elasticity demand models:

$$\log(Q_t) = \alpha_{0(t)} + \epsilon^D \log((1 - s_t)p_t) + \varepsilon_t^D \tag{6}$$

where Q_t is total shipments of solar panels to the U.S. in quarter t, p_t is the wholesale price of solar panels in quarter t, and ϵ^D is the elasticity of solar panel demand with respect to price. The primary government subsidy to encourage adoption of solar technology in the U.S. is the Investment Tax Credit (ITC), which offset 30 percent of upfront solar system costs during the study period.[19] Solar energy investors can also benefit from the tax advantage of accelerated depreciation as well as state and local subsidies. We use $s_t = 0.4$ to capture these policies in a tractable manner.[20] In some specifications of equation 6, we include quarter or year fixed effects to allow for time-varying demand intercepts, $\alpha_{0(t)}$.

We estimate equation 6 using ordinary least squares (OLS) and two-stage least squares (2SLS). For the two-stage least squares specifications, we use two different sets of instruments. First, we use the global prices of silver and aluminum to instrument for the price of solar panels.[21] These observable cost shifters are valid instruments as long as they only affect the equilibrium quantity of solar panels through their effect on solar panel prices. The most likely threat to identification is that solar panel demand shocks affect input prices (reverse causality). This is unlikely given that solar panels destined for the U.S. market are a small share of global consumption of silver and aluminum.[22]

Second, we use the average price of solar panels in foreign markets as an instrument for prices in the U.S. market. This instrument rests on the same economic rationale as using observable cost shifters. Since the solar industry is globally integrated, prices in other markets should reflect common cost shifters. This instrument is valid as long as demand shocks are not correlated across markets over time (Hausman, 1996; Nevo, 2001).

5.2 Supply Estimation

Given demand estimates, wholesale panel prices, and market shares, we can compute manufacturers' implied costs from their first order condition, $\widehat{c}_{ft}$, using equation (3). These costs correspond to expected marginal costs in the production sourcing model, which are given by

[19] The ITC was 30% from 2010 through 2019, reduced to 26% in 2020, and increased back to 30% in 2022.

[20] According to estimates from Borenstein (2017), accelerated depreciation can reduce the cost of a solar system 12.6% to 15.2% after state incentives and the ITC. Our use of aggregate national solar panel sales data makes it difficult to model the impact of all state and local subsidies individually. However, our robustness analysis in Appendix G employs additional microdata that account for these policies.

[21] Silver is used to construct electrical contacts on solar cells to create a complete circuit for harnessing electricity. Aluminum is used for back surface coatings and mounting frames.

[22] In 2020, the final year of our sample, the solar industry constituted 9% of global demand for silver (Metals Focus, 2024). The U.S. constituted about 15% of global solar demand in 2020 (International Energy Agency, 2021). Thus, silver demand stemming from the U.S. solar market was on the order of 1% of global silver demand. For aluminum, solar share of consumption is even smaller.

equation (5). We take the log of equation (5) to derive our estimating equation:

$$\log\left(\widehat{c}_{ft}\right) = -\frac{1}{\theta}\log\left(\sum_{l\in Z_f}\left(\frac{w_t^l\tau_{ft}^l}{T_t^l K_t^{l\gamma}}\right)^{-\theta}\right) + \omega_f + \xi_t + \varepsilon_{ft}^S\,. \tag{7}$$

The first term on the right-hand side of equation (7) captures the effect of each location's fundamentals on firm costs. We assume that external economies of scale take a constant elasticity form, i.e., $E(K_t^l) = K_t^{l\gamma}$, where γ denotes the elasticity of productivity with respect to industry size. We use manufacturer fixed effects, ω_f, to absorb variation in productivity across manufacturers. Time fixed effects, ξ_t, capture cost shifters that vary over time but not across manufacturers or locations. Wages (w_t^l) and tariffs (τ_{ft}^l) are observed.

To estimate equation (7), we aggregate observed production activity into three production locations: China, the U.S., and Other. This aggregation facilitates estimation of the location-specific productivity terms while still capturing the key margins of response to the import tariffs we study. The location-specific terms are not separately identified in this empirical model, so we normalize wages, tariffs, industry scale, and location-specific productivity terms relative to the U.S.

We use non-linear least squares to estimate T_t^l, γ, ω_f, and ξ_t for different values of θ based on a range of values from the prior literature.

5.3 Production Location Estimation

The time-varying demand shifter

$$\widehat{D}_t \equiv \widehat{\alpha}_{0(t)} + \widehat{\epsilon}^D \log\left(1 - s_t\right) + \widehat{\varepsilon}_t^D$$

is uncovered from aggregate demand estimation. Similarly, the firm-specific cost shifter $\widehat{\omega}_f$ and location-year specific cost $\widehat{T}_t^l$ are uncovered from the static first order condition.

If we assume perfect foresight of $\widehat{D}_t$, and the relevant market competition can be summarized by payoff relevant aggregate state variable

$$\widehat{\overline{c}}_t \equiv \frac{1}{F}\sum_f \widehat{c}_{ft} = \frac{1}{F}\sum_f [\Phi_t(\widehat{\omega}_f, Z_{ft}, \tau_{ft}^l; \widehat{T}_t^l, \widehat{\gamma})]^{-\frac{1}{\theta}}.$$

As a first-cut of the empirical pattern, we run a logit/probit regression of offshoring to Southeast Asia and the United States that includes the explanatory variables $\widehat{\omega}_f, \widehat{D}_t, \widehat{\overline{c}}_t, \tau_{ft}^l$.

6 Estimation Results

6.1 Demand Estimates

Aggregate demand estimates from the constant elasticity specification in equation 6 are shown in Table 4. The estimates are directly interpretable as elasticities of total U.S. solar panel demand with respect to the price of solar panels.

Table 4: Estimated Demand Elasticities

	log(Quantity)		
	(1)	(2)	(3)
Panel A: OLS			
log(Net price)	-1.34***	-1.34***	-1.95**
	(0.10)	(0.10)	(0.79)
R^2	0.80	0.81	0.91
Within R^2		0.81	0.19
Panel B: 2SLS using input prices			
log(Net price)	-1.44***	-1.43***	-3.28**
	(0.13)	(0.14)	(1.48)
First-stage F-statistic	33.6	31.1	6.2
Panel C: 2SLS using Hausman instruments			
log(Net price)	-1.34***	-1.33***	-1.55
	(0.10)	(0.10)	(1.00)
First-stage F-statistic	9,967.3	10,195.9	163.7
Quarter Fixed Effects		Y	
Year Fixed Effects			Y
Observations	43	43	43

Note: This table presents estimated price elasticities of demand (i.e., $\hat{\epsilon}^D$ from equation 6). Net price is the quantity-weighted average price of solar panels consumers face after accounting for adoption subsidies (in \$/W). Each column represents a different specification of the demand intercept through the inclusion of fixed effects. Panel A presents OLS estimates. Panel B presents IV estimates using silver and aluminum prices as instruments for solar panel prices. Panel C presents IV estimates using the foreign solar panel price as an instrument for the domestic solar panel price. All models are estimated using a quarterly time series from Q1 2010 through Q3 2020. First-stage F-statistics are from tests of the hypothesis that the excluded instrument(s) are jointly irrelevant. Heteroskedasticity-consistent standard errors are in parentheses.

Panel A presents OLS estimates from three specifications with increasingly flexible demand intercepts. In the first two columns, with a fixed demand intercept and a seasonally-varying demand intercept, the estimated elasticities are roughly -1.3. The third column includes year fixed effects, which allow for gradual shifts in the demand intercept over time. That specification yields a slightly larger demand elasticity of -2, though its confidence intervals include -1.3.

Panel B presents 2SLS estimates in which the prices of silver and aluminum instrument for the price of solar panels. The first two columns produce estimates that are very similar to the results in Panel A. In both cases, the first-stage F-statistic is above the conventional threshold of 10 for instrument strength. In the third column, the point estimate is larger in magnitude, but the standard errors are an order of magnitude larger and the instrument is weak.

Panel C presents 2SLS estimates in which the average price of solar panels in other markets instruments for the price of solar panels in the U.S. This instrument remains well above conventional F-statistic thresholds in all three columns. The estimates in the first two columns are essentially identical to the OLS estimates. In the final column, the point estimate is fairly similar to the first two columns, and is smaller in magnitude than its counterparts in Panels A and B.

These results are consistent with prior estimates from Gerarden (2023), who uses earlier data to estimate similar models. Furthermore, they are broadly in line with aggregate elasticity estimates obtained by separately estimating downstream demand for solar installations from the utility and non-utility markets (see Appendix Figure G.2). Given how similar the estimates are across specifications, we use the simplest specification in the first column of Panel A for supply estimation and counterfactual analysis.

6.2 Supply Estimates

Table 5 presents estimates of the location-specific productivity terms in equation (7) for different values of θ. The estimates are transformed so they are interpretable as productivity relative to the U.S. The estimates are stable across typical values in the literature. We use $\theta = 5$ as our baseline model specification for solving the model and conducting counterfactual analysis.

Figure 5a plots the estimated pre-tariff cost of manufacturing in China or Other, relative to the U.S. The predicted costs can be interpreted as the effect of differences in wages and productivity for each location on a firm's production cost if they were to hypothetically choose to manufacture exclusively in a given location.[23] The model predicts that manufacturing

[23] These predictions hold constant other, multiplicative cost shifters captured by firm and time fixed effects. The predictions are generated by exponentiating the first term on the right hand side of equation 7 separately for each location, using estimates of T_t^l and with no tariffs (i.e., $\tau_{ft}^l = 0$). This corresponds to the relative production costs of each location for a thought experiment in which a given firm manufactured in one location

Table 5: Location-Specific Productivity Estimates

	(1)	(2)	(3)
Other's relative state of technology ($\widetilde{T}_{other}$)	0.71***	0.63***	0.60***
	(0.02)	(0.01)	(0.01)
China's relative state of technology ($\widetilde{T}_{china}$)	0.31***	0.28***	0.26***
	(0.01)	(0.01)	(0.01)
Num.Obs.	711	711	711
θ	5.00	7.50	10.00

Note: This table presents estimates of mean productivity by location, normalized relative to the U.S. These preliminary estimates impose constant returns to scale ($\gamma = 0$). Standard errors clustered by time are in parentheses.

in China is least costly, with costs initially half of U.S. costs. Manufacturing in Other is predicted to be somewhat more expensive than China, initially roughly two-thirds the cost of manufacturing in the U.S. The cost predictions evolve over time due to changes in relative wages. By the end of the sample period, the cost of producing in China and Other is essentially the same, because manufacturing wages in China increased more rapidly than in Other. By contrast, the cost of manufacturing in the U.S. remains much higher.

Figure 5: Location-Specific Cost Predictions

(a) before tariffs (b) after manufacturer×location-specific tariffs

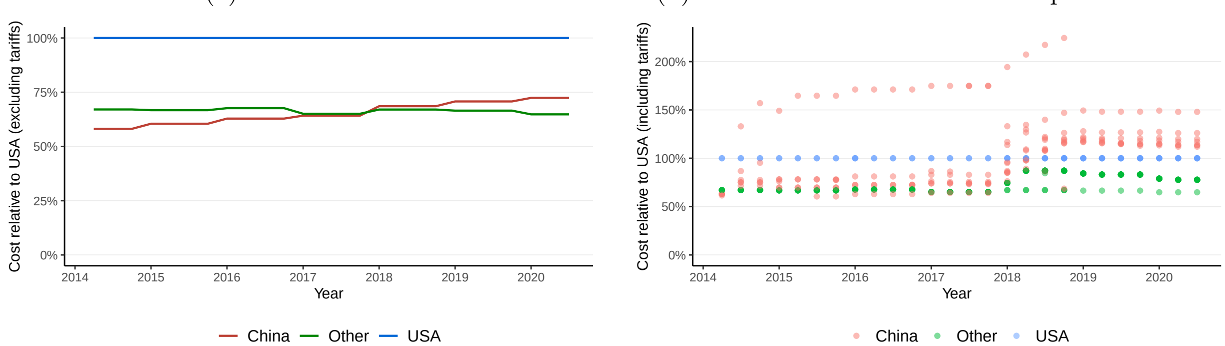


Figure 5b plots the estimated post-tariff production cost for individual manufacturers based on the locations where they manufacture and the tariffs they are exposed to, again relative to the U.S. The estimates are consistent with the descriptive evidence on avoidance behavior presented in section 3. In the period before tariffs were imposed, China was the least costly production location. After the 2014 antidumping and countervailing duties were

or another (but not multiple). It does not account for the combined effects of producing in multiple locations, and it does not account for any fixed costs of producing in a given location.

imposed, the model predicts higher costs for manufacturing in China than Other for most manufacturers. After the 2018 tariffs, the cost of manufacturing in China was higher than the U.S. for all manufacturers.

7 Counterfactual Analysis

The constant elasticity aggregate demand model can be solved analytically given the demand estimates and a set of counterfactual cost predictions that result from changes in tariff rates, factor prices, or the set of production locations each manufacturer has. In this section, we outline results for a series of counterfactuals: the status quo, removing all observed import tariffs, and implementing a domestic manufacturing subsidy in lieu of import tariffs.

The results in this section allow for endogeneity in the set of production locations each manufacturer has. Appendix H provides evidence of model fit and Appendix I.1 presents analogous results holding the set of production locations each manufacturer has fixed.

7.1 Tariff Removal

In this set of counterfactual analyses, we quantify solar market outcomes if tariffs had not been imposed. The figures and tables that follow present results that compare the model predictions for the scenario with tariffs to a baseline scenario without tariffs. The scenario with tariffs is the market equilibrium holding manufacturer production locations and all other factors fixed as they are in estimation. The scenario without tariffs is based on the market equilibrium with no tariffs, and based on a counterfactual set of production locations in which we replace any offshore production locations that were established after the tariffs went into effect with domestic production locations in their predominant manufacturing location prior to tariffs. This modeling choice is motivated by the descriptive evidence in section 3, which suggests that many of these production locations outside China were established in response to the tariffs.

Without tariffs, prices would have been lower and quantities would have been higher, as visualized in Figure 6. The first column of numbers in Table 6 summarizes the welfare impacts of the tariffs relative to the counterfactual scenario with no tariffs. Domestic consumer surplus and the environmental benefits from solar adoption are predicted to be much lower with tariffs than without.[24] Over the period 2014 through 2020, the tariffs made domestic producers

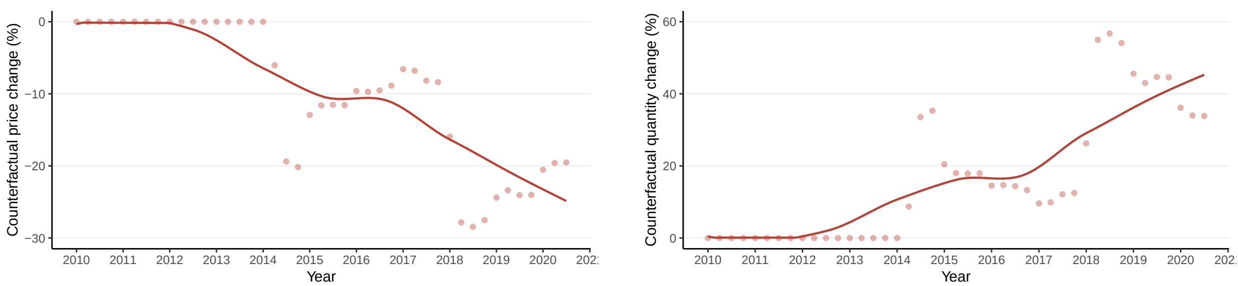
[24] We compute environmental benefits using results from Sexton et al. (2021), which provides econometric estimates of the avoided pollution damages from U.S. solar systems. For local damages from criteria air pollutants, we use estimates of the national average avoided pollution damages from nitrous oxides, fine particulate matter, and sulfur dioxide. For global damages from carbon dioxide emissions, we take a similar

better off at the expense of foreign producers, though the benefits to producers are small relative to the harms to consumers and third parties. Foreign producer surplus is predicted to be lower with tariffs, enough so that aggregate producer surplus is lower on net than it would have been without tariffs. Finally, government revenue is predicted to be higher due to an increase in tariff revenue and a decrease in tax expenditures to subsidize solar adoption under the federal ITC.

Figure 6: Impacts of Removing Tariffs on Prices and Quantities

(a) Percentage Change in Wholesale Price

(b) Percentage Change in Quantity



Note: This figure plots changes in model predictions for a scenario with no tariffs, relative to a model predictions for the status quo. In the counterfactual scenario with no tariffs, any offshore production locations that were established after tariffs went into effect are replaced with production locations in a given firm's home country. Points denote model predictions for each quarter under the baseline model estimates. Lines are smoothed conditional means, predicted using local linear regression.

Table 7 presents a back-of-the-envelope calculation of the domestic employment impacts of the tariffs. We compute these impacts by multiplying model predictions of changes in domestic manufacturing and solar adoption by the average labor intensity of each activity.[25] This approach predicts that tariffs increased domestic manufacturing employment, but that solar installation employment decreased by a factor of five times the reduction in domestic employment. This is because manufacturing labor demand only depends on the number of solar panels that are produced domestically, whereas installation labor demand depends on the total number of solar panels demanded, both domestically and from abroad. Table 8 presents an analogous calculation that incorporates wage data for solar manufacturing and installation jobs to put the employment numbers in context.[26] Installation jobs have lower

approach, but we update them by using the U.S. Government's current estimate of the social cost of carbon ($51 per metric ton CO_2).

[25]We compute the labor intensities of manufacturing and installation (including sales and distribution) by dividing the number of domestic jobs in each sector of the industry (from Solar Energy Industries Association, 2021) by the amount of capacity manufactured and shipped (from IHS Markit). We use annual data to compute labor intensities to account for improvements in labor productivity over time. Finally, we estimate overall employment impacts by multiplying these estimates of job-years per unit capacity by model predictions of changes in the capacity of solar panels manufactured and installed between any two counterfactuals.

[26]For manufacturing wages, we use annual average U.S. manufacturing wages from the International Labour

Table 6: Welfare Impacts

	Impacts over 2014-2020 ($, billions):	
	Actual Tariffs	Counterfactual Subsidy
Δ in Consumer Surplus	-5.6	2.4
Δ in Producer Surplus	-1.1	0.2
Δ in Producer Surplus (USA)	1.5	0.2
Δ in Producer Surplus (China)	-2.4	0.2
Δ in Producer Surplus (Other)	-0.2	-0.1
Δ in Government Revenue	10.3	-9.6
Δ in Tariff Revenue	4.0	0.0
Δ in Adoption Subsidy Expenditure	-6.3	2.7
Δ in Manufacturing Subsidy Expenditure	0.0	6.9
Δ in Environmental Benefits	-60.1	27.8
Δ in Local Pollution Benefits	-40.4	18.7
Δ in Global Pollution Benefits	-19.6	9.1
Δ in Domestic Welfare	-34.3	11.6
Δ in Total Welfare	-56.4	20.7

Note: This table summarizes welfare impacts of alternative government interventions relative to a counterfactual scenario of no intervention. The column "Actual Tariffs" corresponds to the status quo. The column "Counterfactual Subsidy" corresponds to a scenario in which the U.S. provides a 30 percent subsidy to U.S. manufacturing (by any manufacturer, regardless of their home country). The change in domestic welfare excludes changes in producer surplus for tariff-exposed manufacturers and all changes in global pollution benefits (since some of which spill over to other countries due to the nature of global pollutants).

wages, so this reduces the relative contribution of installation wages, but they are still about four times larger than the change in manufacturing wages.

Organization (2023) due to a lack of available data on solar manufacturing wages. For installation wages, we use annual average solar photovoltaic installer compensation reported by the Solar Energy Industries Association (2021). This is conservative, as other occupations within the downstream solar industry receive higher compensation than solar installers. In both cases, we use a time-invariant measure of wages from 2020 since we do not observe solar installer wages over time. Finally, we compute wage impacts by multiplying the employment impact estimates described above by the relevant wage.

Table 7: Domestic Solar Industry Employment Impacts

	Impacts over 2014-2020 (job-years, thousands):	
	Actual Tariffs	Counterfactual Subsidy
Δ in Manufacturing job-years	78.5	885.3
Δ in Installation job-years	-329.0	153.3
Δ in Total job-years	-250.5	1038.6

Note: This table summarizes employment impacts estimated by multiplying model-predicted changes in domestic solar manufacturing and installation quantities by time-varying sector-specific labor intensities derived from Solar Energy Industries Association (2021).

Table 8: Domestic Solar Industry Wage Impacts

	Impacts over 2014-2020 (wages, billions):	
	Actual Tariffs	Counterfactual Subsidy
Δ in Manufacturing wages	4.8	53.7
Δ in Installation wages	-15.2	7.1
Δ in Total wages	-10.5	60.8

Note: This table summarizes wage impacts estimated by multiplying predicted changes in domestic solar manufacturing and installation employment by sector-specific wages derived from Solar Energy Industries Association (2021) and International Labour Organization (2023).

7.2 Domestic Manufacturing Subsidies

In a second counterfactual analysis, we quantify the potential effects of removing tariffs and replacing them with a subsidy for manufacturing solar panels in the U.S. This counterfactual is motivated by provisions of the IRA of 2022 that established a manufacturing production tax credit. We solve the model with a 30 percent subsidy to U.S. manufacturing beginning at the time the 2014 tariffs were imposed.

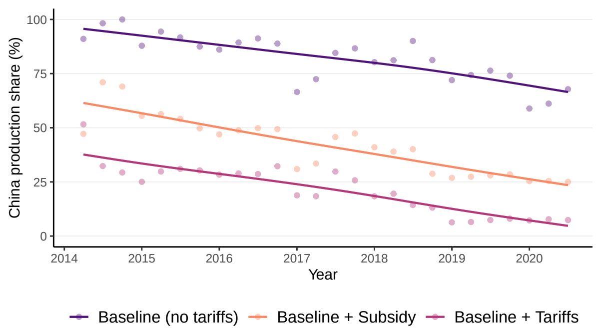
The production subsidy leads to lower prices and higher quantities in equilibrium, relative to the scenario with no tariffs and no production subsidy. In contrast to *both* the status quo ("Baseline + Tariffs") and the scenario with no tariffs ("Baseline (no tariffs)"), the domestic production subsidy yields a large increase in the share of solar panels produced domestically (Figure 7).[27] This increase in U.S. production comes at the expense of production in China, with a limited effect on production in Other locations (relative to the scenario with no tariffs). These results highlight that production subsidies could succeed where import tariffs have failed to engender a domestic solar manufacturing industry. That said, these domestic

[27]To assess model fit, Appendix Figure H.1 compares model-predicted production shares under the status quo to data on import shares from the USITC. The import data corroborates the stark decline in solar panels from China predicted by the model.

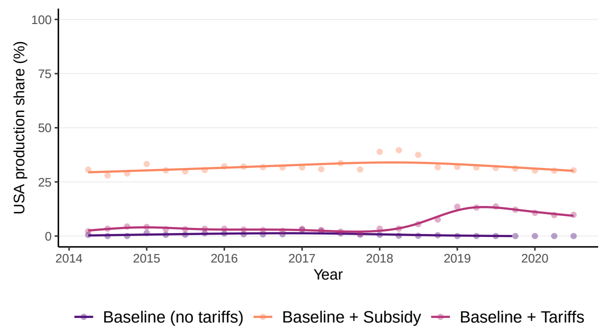
manufacturing impacts need to be weighed against their fiscal cost as well as their broader impacts.

Figure 7: Counterfactual Production Shares

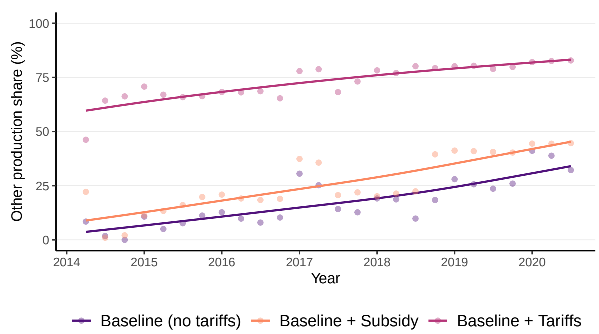
(a) China



(b) USA



(c) Other



Note: Plots present model predictions for each scenario. "Baseline + Tariffs" corresponds to the status quo. "Baseline (no tariffs)" corresponds to a counterfactual with no tariffs. "Baseline + Subsidy" corresponds to a counterfactual with a domestic manufacturing subsidy (and no tariffs). In "Baseline (no tariffs)", any offshore production locations that were established after tariffs went into effect are replaced with production locations in a given firm's home country. In "Baseline + Subsidy", all firms are exogenously given a U.S. manufacturing location if they do not already have one in the status quo. Appendix Figure I.2 presents analogous model predictions under the scenario where each firm's set of production locations is unchanged from the status quo. Points denote model predictions for each quarter under the baseline model estimates. Lines are smoothed conditional means, predicted using local linear regression.

The final column of Table 6 summarizes the prospective welfare impacts of a domestic manufacturing subsidy, relative to a scenario with no tariffs. Unsurprisingly, the lower prices and higher quantities would yield increases in consumer surplus and external environmental benefits. On the other hand, the subsidy would impose a fiscal cost, both directly through subsidies to manufacturers and indirectly through increased subsidies to adoption because of the increase in quantities. On net, the private and external benefits of the manufacturing subsidy would outweigh these public costs, leading to an increase in welfare. The primary driver of this result is the magnitude of environmental benefits.[28]

Tables 7 and 8 present estimates of the prospective domestic employment impacts of subsidizing domestic production, relative to a scenario with no tariffs. In contrast to the use of trade policy, which reduced domestic employment and wages on net, incorporating a domestic production subsidy yields increases in both manufacturing and installation. This approach eliminates the countervailing employment impacts of imposing import tariffs on intermediate inputs, leading to increases in net employment and wages.

8 Conclusion

We draw three sets of conclusions from studying trade and industrial policy in the market for solar panels. First, we provide model-free evidence that U.S. import tariffs on solar panels led Chinese solar panel manufacturers to relocate production to third countries to avoid paying tariffs. As a result, the tariffs had limited success in raising tariff revenue and on-shoring manufacturing activity to the U.S.

We then develop a model to quantify the welfare consequences of the tariffs, taking into account strategic responses by solar panel manufacturers. We find that tariffs on solar panels decreased welfare, both from a domestic and from a global perspective. Third-party effects due to environmental externalities, which are a unique feature of this market, are a quantitatively important driver of this result. Furthermore, we find that the import tariffs *decreased* domestic solar sector employment and wages on net, because they reduced solar installation employment several times more than they increased solar manufacturing employment.

Third and finally, we analyze the effects of replacing trade policy with industrial policy. We find that a modest subsidy for domestic solar panel manufacturing could significantly increase the domestic production share, eliminate the conflicting employment impacts of import tariffs on an intermediate input, and raise both domestic and global welfare.

One important limitation of this study is that we do not model dynamic effects of government intervention, such as learning-by-doing. In theory, temporary trade policy could be justified if it allows domestic firms in an infant industry to establish strong competitive positions that persist over time. In practice, this infant industry argument seems insufficient to justify the particular import tariffs we study, since they largely failed to engender a domestic solar manufacturing industry *ex-post*. In particular, there was a decided lack of wafer and cell

[28]This result is primarily driven by the presence of an underpriced environmental externality. In principle, if the solar adoption subsidy was set at a level that aligned with the external marginal benefits of solar adoption, the domestic manufacturing subsidy may reduce rather than raise welfare.

production in the aftermath of the tariffs, even as panel assembly increased modestly due to domestic investment by foreign firms. Going forward, federal subsidies for clean energy manufacturing under the IRA are likely to lead to increased domestic manufacturing given our empirical results and the fact that the tax credits were designed to provide incentives for domestic production throughout the supply chain.

Taken together, our results provide novel evidence on the impact of trade policy on the global cost structure of solar panel manufacturing, and on the potential impacts of industrial policies such as the IRA and the European Green New Deal. However, these results do not imply that protectionism is justified, even if replacing trade policy with industrial policy could increase welfare relative to no intervention. Alternative policies such as Pigouvian taxes or import subsidies could yield larger welfare gains by addressing environmental externalities without creating misallocation in manufacturing activity.

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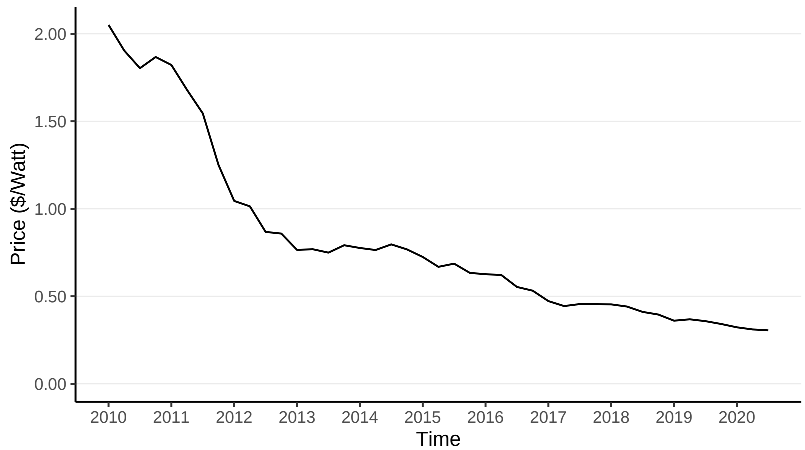
Appendix

A Aggregate Trends

Figure A.1: Solar Panel Prices over Time

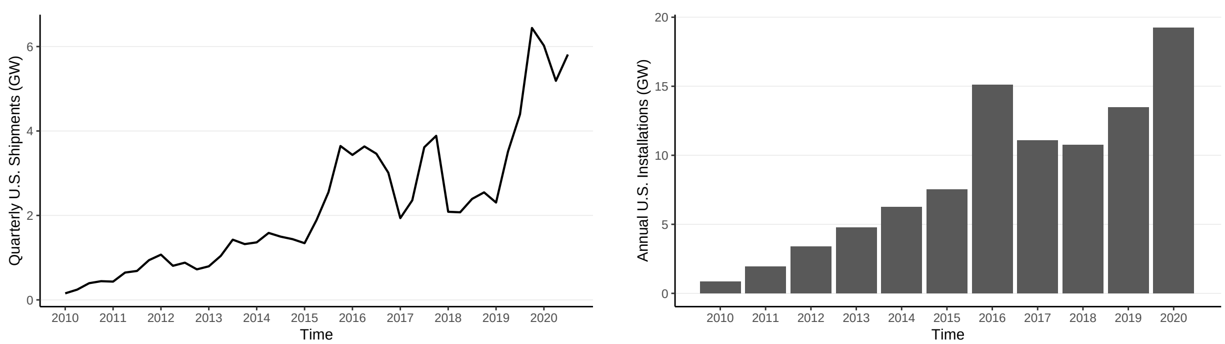


Note: This figure plots the quantity-weighted average wholesale price of solar panels in the U.S. over time based on quarterly data from IHS Markit. Prices are in nominal terms.

Figure A.2: Solar Panel Quantities over Time

(a) Shipments

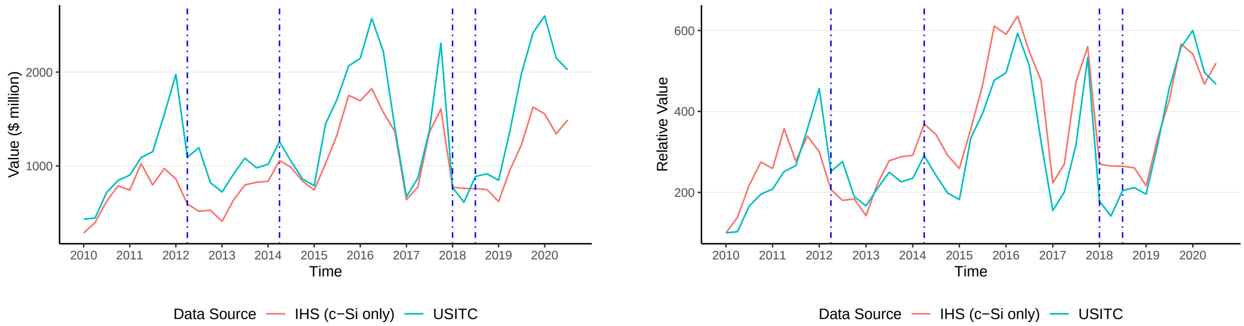
(b) Installations



Note: This figure plots the total quantity of solar panels consumed in the U.S. over time in gigawatts (GW). Figure A.2a plots quarterly shipments based on data from IHS Markit. Figure A.2b plots annual installations based on data from SEIA.

B Comparison of IHS Markit and Government Data

Figure B.1: Comparison of IHS shipments to USITC Import Records



Note: This figure plots time series comparisons of shipment value from IHS Markit to import value from USITC's DataWeb. For import value we use cost, insurance, and freight (or CIF). The left panel is in absolute terms. The right panel is in relative terms with Q1 2010 values normalized to 100. Both panels are constructed using data on crystalline silicon solar panels, omitting thin-film photovoltaic products. Vertical lines denote the timing of each round of tariffs. Values are in nominal terms.

C Additional Details on Production Activity

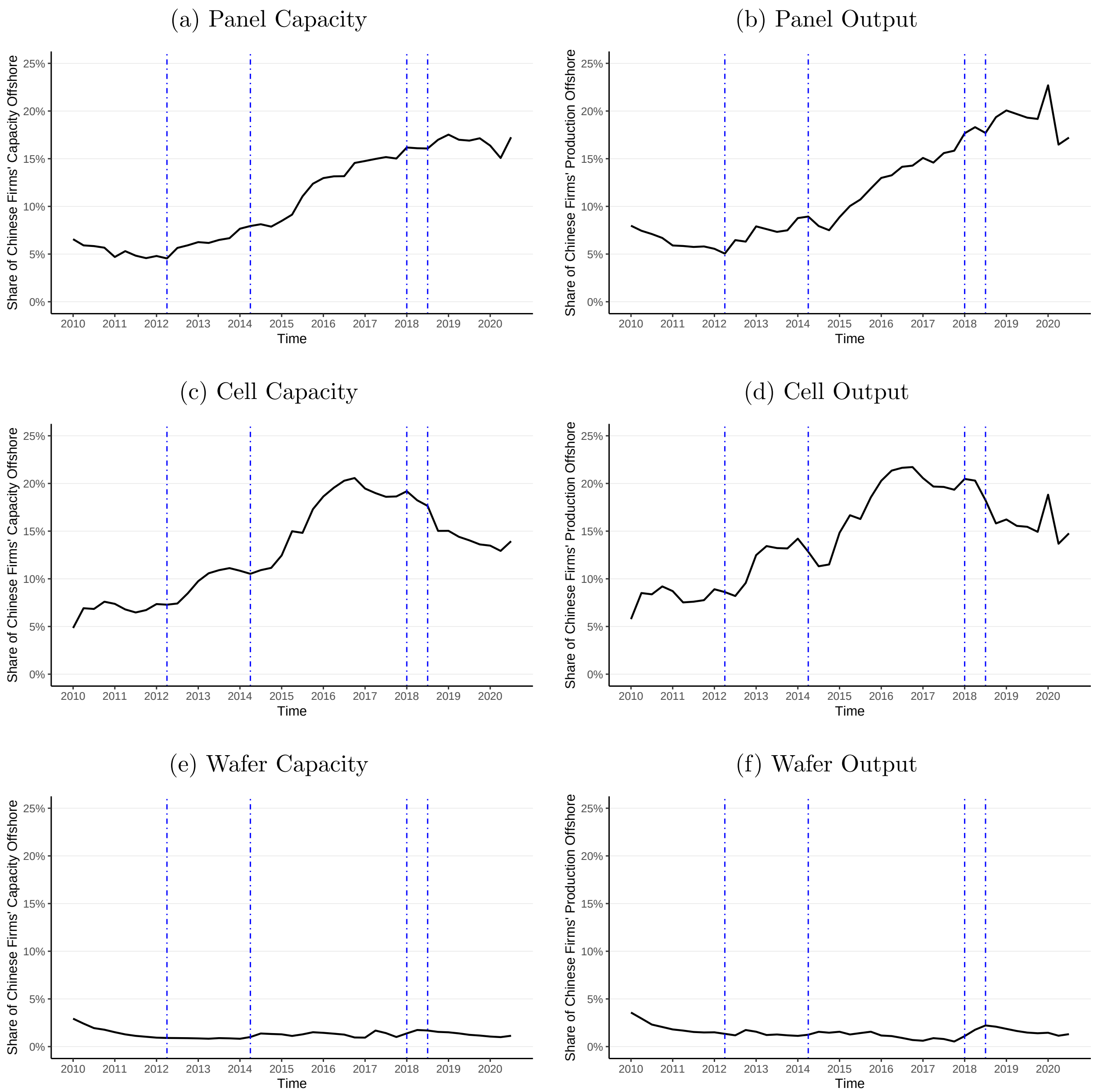
C.1 Production Offshoring by Chinese Manufacturers

This appendix summarizes changes in the geographic distribution of manufacturers' production over time, both for manufacturers that produced in China and for their competitors who were not subject to tariffs. For descriptive purposes, we classify manufacturers as Chinese if they manufacture solar components in China prior to the imposition of tariffs.

Figure C.1 summarizes trends in offshoring by plotting the share of Chinese manufacturers' capacity and production outside China over time. The first row is identical to Figure 1 in the main text, and it shows that the share of Chinese firms' panel production capacity and actual production outside China was falling in the first few years of the sample and then gradually rose after the tariffs took effect. Cell capacity and production, in the second row, exhibit similar growth in offshoring between 2012 and 2018.

By contrast, the share of Chinese firms' wafer production capacity and output did not change much over time. Unlike solar panels and cells, products containing Chinese-produced wafers were not subject to duties. Thus, the relatively low and stable offshoring shares for wafers in China support the conclusion that cell and panel production offshoring by these manufacturers was a response to location-specific import tariffs.

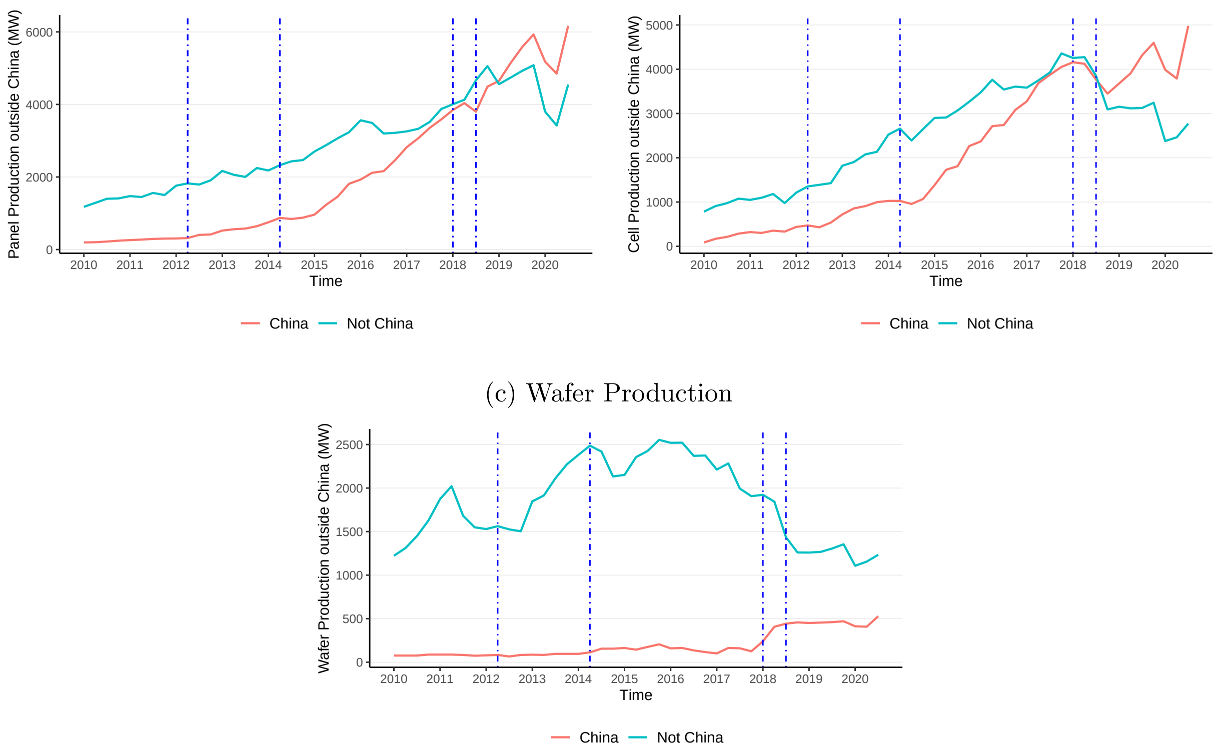
Figure C.1: Share of Offshore Manufacturing for Chinese Manufacturers



Note: This figure plots aggregate offshoring of solar manufacturing capacity and output over time based on quarterly data on quantities from IHS Markit. For each plot, the sample of firms is restricted to those that are active in China in that particular product prior to the imposition of tariffs (similarly, "active" is defined based on non-zero values of the relevant outcome in each plot). The share offshore is computed by first aggregating outcomes inside and outside of China across firms, and then computing and plotting the share outside China. Vertical lines denote the timing of each round of tariffs.

Figure C.2 plots total solar component production activity outside China over time in levels, comparing manufacturers that produced that component in China prior to tariffs to manufacturers that only produced that component outside of China prior to tariffs (and omitting any firms that only began producing after tariffs went into effect).

Figure C.2: Manufacturing Activity Outside China by Tariff Exposure Groups



(a) Panel Production

(b) Cell Production

(c) Wafer Production

Note: This figure plots the total level of solar component output outside of China for two different groups of firms over time based on quarterly data from IHS Markit. For each plot, firms are classified into the group "China" if they produce that component in China prior to tariffs. They are classified into "Not China" if they produce prior to tariffs but not in China. Total production quantities outside China are then aggregated and plotted by group. Vertical lines denote the timing of each round of tariffs.

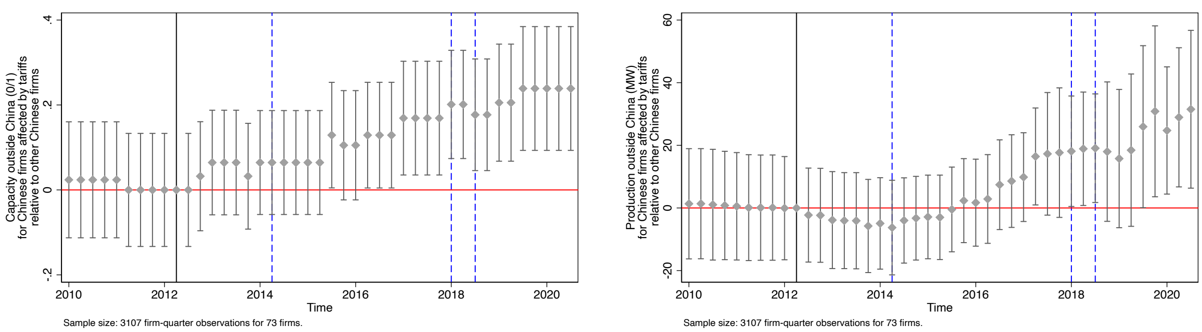
The patterns in Figure C.2 provide additional evidence consistent with the idea that production offshoring by tariff-exposed manufacturers was a response to location-specific import tariffs. The time series are suggestive of a differential response in production activity in the aftermath of the 2014 tariffs, as Chinese manufacturers increased their panel and cell production outside China at faster rates than unaffected manufacturers. Wafers provide an informal placebo test, as they are not covered by the duties. In contrast to panels and cells, Chinese manufacturers do not increase wafer production outside China until the end of the sample period, and even then the magnitude of offshore production is much smaller than for panels and cells.

C.2 Additional Event Study Estimates

Figure C.3 presents event study coefficients based on the subsample of firms that lie within the common support of the pre-treatment firm size distributions for treated and control firms.

Figure C.3: Event Study Comparing a Subsample of Chinese Manufacturers of Similar Size

(a) Capacity (0/1) (b) Production (MW)

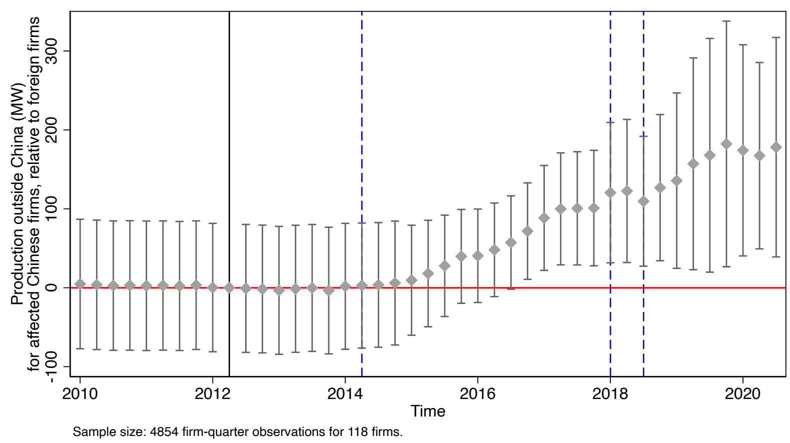


Note: Points represent event study coefficients from estimating equation 1 via ordinary least squares. Confidence intervals are robust to heteroskedasticity. Figure C.2a is from estimating a linear probability model where the outcomes are binary indicators of whether a firm has any production capacity outside China. Figure C.2b is from estimating a linear model where the outcomes are continuous measures of production output outside China in megawatts (MW). Vertical lines denote the timing of each round of tariffs. All event study coefficients are relative to the second quarter of 2012. The sample for these event studies are the firms that lie within the common support of the pre-treatment firm size distributions for treated and control firms.

Finally, we compare the same treated Chinese firms to a control group of foreign firms who are not exposed to location-specific tariffs. Foreign firms always manufacture outside of China by construction, so there is no variation available to estimate an extensive margin event study. Figure C.4 presents intensive margin event study coefficients. In this comparison, treated Chinese manufacturers appear to increase manufacturing output outside China at a higher rate than their foreign competitors do outside China. This result reinforces the conclusion that tariffs caused treated Chinese firms to offshore their manufacturing activity.

Figure C.4: Event Study Comparing Chinese and Non-Chinese Manufacturers

(a) Production (MW)



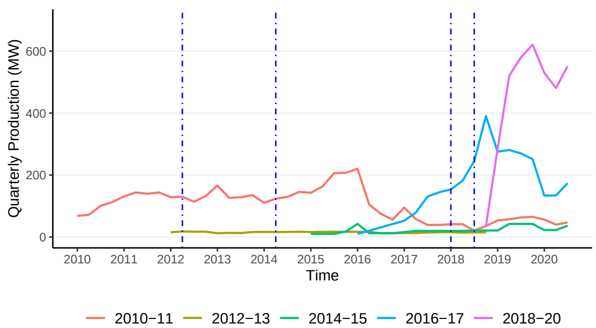
Note: Points represent event study coefficients from estimating equation 1 via ordinary least squares. Confidence intervals are robust to heteroskedasticity. The plotted coefficients are from estimating a linear model where the outcomes are continuous measures of production output outside China in megawatts (MW). Vertical lines denote the timing of each round of tariffs. All event study coefficients are relative to the second quarter of 2012. The sample for these event studies are Chinese firms assigned firm-specific tariff rates (treated) and foreign firms not subject to tariffs prior to 2018 (control).

C.3 U.S. Manufacturing by Cohort

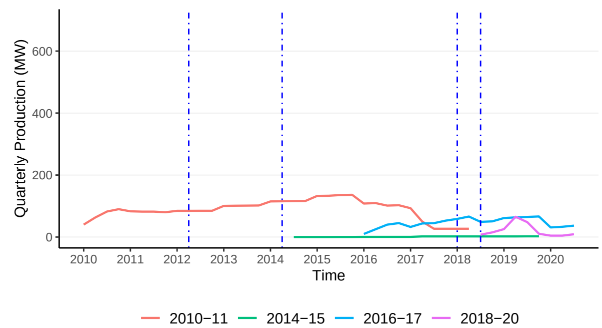
Figure C.5 plots aggregate domestic manufacturing activity by cohort based on the first period in which a firm produces each product in the U.S. Output by the 2010-2011 cohort of domestic firms who initially produced panels, cells, and wafers generally declined over time in the face of import competition. The dominant source of the growth in domestic manufacturing output toward the end of the sample period was the cohort of firms that entered panel production after the broad-based Section 201 tariffs went into effect in 2018.

Figure C.5: U.S. Manufacturing Activity over Time by Cohort of Entry

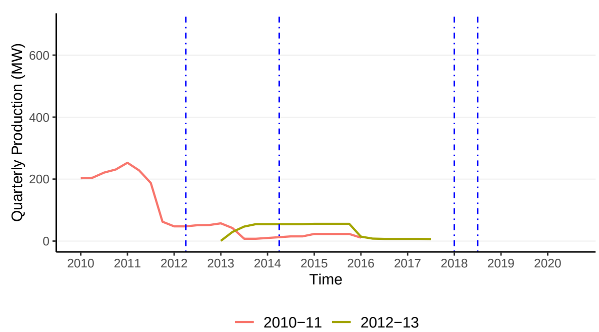
(a) Panel Production



(b) Cell Production



(c) Wafer Production



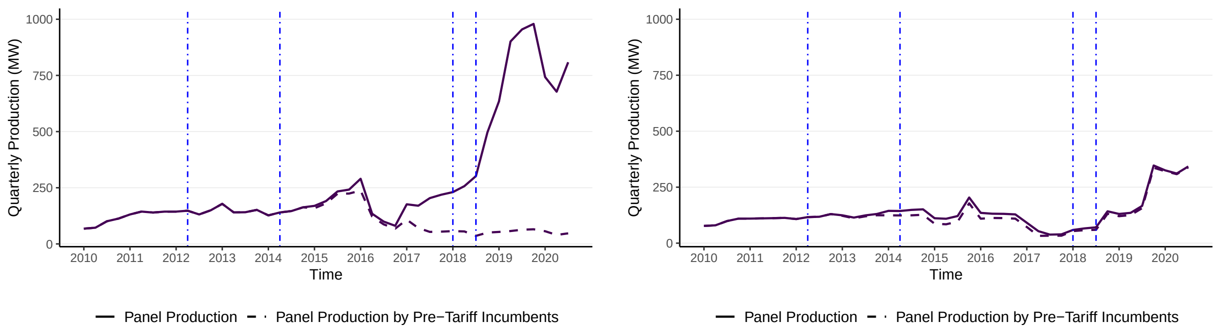
Note: This figure plots crystalline silicon solar component output in the U.S. based on quarterly data from IHS Markit. For each plot, firms are divided into cohorts based on the period during which they are first observed manufacturing in the U.S. Then, for each cohort, U.S. component output is aggregated and plotted over time. Vertical lines denote the timing of each round of tariffs.

Figure C.6 plots aggregate domestic panel production separately for crystalline silicon and thin-film technologies. The plot for crystalline silicon is a reproduction of the panel series in Figure 3 of the main text. Thin-film technologies are not subject to tariffs.

Figure C.6: U.S. Panel Manufacturing Activity over Time by Technology

(a) c-Si Technology

(b) Thin-Film Technology



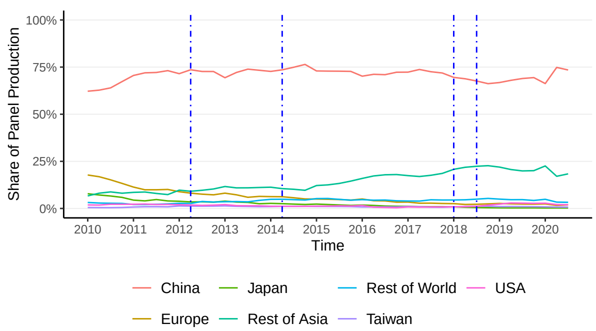
Note: This figure plots solar panel output based on quarterly data from IHS Markit. Figure C.6a plots output of crystalline silicon solar panels, while C.6b plots output of thin-film solar panels. Both panels include output from firms that produced that product in the U.S. prior to tariffs (dashed line) and output from all firms (solid line). Vertical lines denote the timing of each round of tariffs.

C.4 Global Production Shares by Region

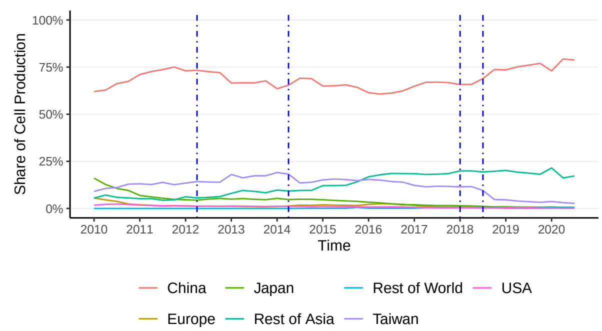
Figure C.7 plots production activity by region over time. The cell production time series in Figure C.7b provides further evidence suggestive of tariff avoidance. First, there was a small increase in cell production in Taiwan after the 2012 duties were imposed, which then decreased around the time of the investigation into extending the duties to include Taiwan. The opposite pattern is present for Chinese production, while there is no significant change in the share of panels produced in China (Figure C.7a). These changes are consistent with industry reporting that Chinese manufacturers sourced cells from Taiwan to continue exporting panels to the U.S. without having to pay duties. Over time, there was also a more gradual increase in the production share of other Asian countries, both for panels and cells. In contrast, production of wafers, which are not subject to duties directly, has gradually become more concentrated in China (Figure C.7c).

Figure C.7: Global Production Shares by Region

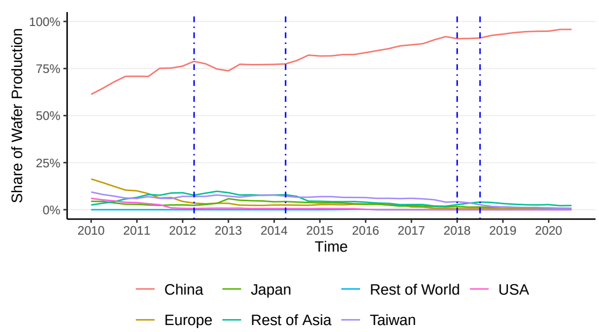
(a) Panel Production



(b) Cell Production



(c) Wafer Production



Note: This figure plots the regional composition of solar component production (by quantity) over time based on quarterly data from IHS Markit. The categories "Rest of Asia" and "Rest of World" are aggregated from country-level data. Vertical lines denote the timing of each round of tariffs.

D Construction of Strategic Tariff Rates

Section 3 provides evidence that manufacturers were able to partially avoid paying duties on their imports of solar panels by changing the locations in which they manufacture. As a result, manufacturers faced effective tariffs that were less than or equal to the statutory tariffs they ostensibly faced. Our main analysis accounts for this by developing and estimating a model of manufacturer sourcing behavior. This appendix outlines an alternative approach to account for avoidance behavior in order to present descriptive results in section 3.6 that do not require the same assumptions and model structure used in the main analysis.

To account for tariff avoidance, we compute each manufacturer's average tariff under the assumption that they source their production to minimize the tariffs they must pay. We refer to this measure as a manufacturer's "strategic" tariff rate to distinguish it from the "statutory" rates that apply before accounting for avoidance.

Let Statutory Tariff$_{flt,X}$ denote the statutory tariff rates applying to manufacturer f's production in location l at time t under tariff round X.[29] Let q_{flt} denote the quantity of panels produced in location l at time t that manufacturer f sends to the U.S., with Q_{ft} denoting the quantity of solar panels manufacturer f ships to the U.S. in period t. Finally, let $\bar{q}_{flt}$ denote manufacturer f's total production in location l at time t.

Since we do not directly observe q_{flt}, we assume that each manufacturer f at each time t selects a vector $\mathbf{q}^*_{ft}$ to minimize its tariff exposure. The resulting weighted average strategic tariff rate, which accounts for strategic choices of production locations, is given by

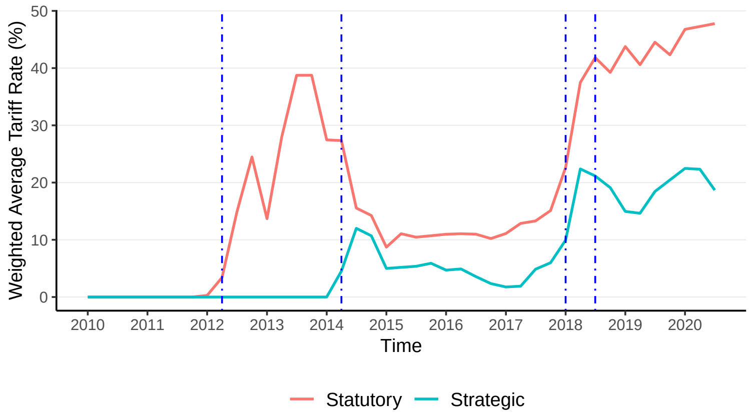
$$\begin{aligned}\text{Strategic Tariff}_{ft} = \min_{\mathbf{q}_{ft}} \sum_l \Big(& \min\{\text{Statutory Tariff}_{flt,2012},\ \text{Statutory Tariff}_{flt,2014}\} + \\ & \text{Statutory Tariff}_{flt,S201} + \text{Statutory Tariff}_{flt,S301}\Big) \frac{q_{flt}}{Q_{ft}} \\ & \text{subject to} \sum_l q_{flt} = Q_{ft},\ q_{flt} \leq \bar{q}_{flt}.\end{aligned}$$

Figure D.1 plots the weighted average of the manufacturer-specific strategic tariff rates computed by solving this optimization problem. The weighted average statutory tariff is included as a point of reference. Both are weighted by quarterly shipment volumes. As is evident from Figure D.1, the strategic tariffs are much lower than the statutory tariffs, confirming the extent to which manufacturers may have been able to avoid the tariffs.[30]

[29] We restrict attention to crystalline silicon ("c-Si") solar panels for the purposes of constructing strategic tariff rates because other technologies are exempt from tariffs.

[30] Given that the 2012 tariffs assigned to Chinese manufacturers could be relatively easily avoided by buying solar cells from Taiwanese producers or offshoring cell production to Taiwan, we assign a strategic tariff of

Figure D.1: Strategic Tariffs Are much Lower than Statutory Tariffs



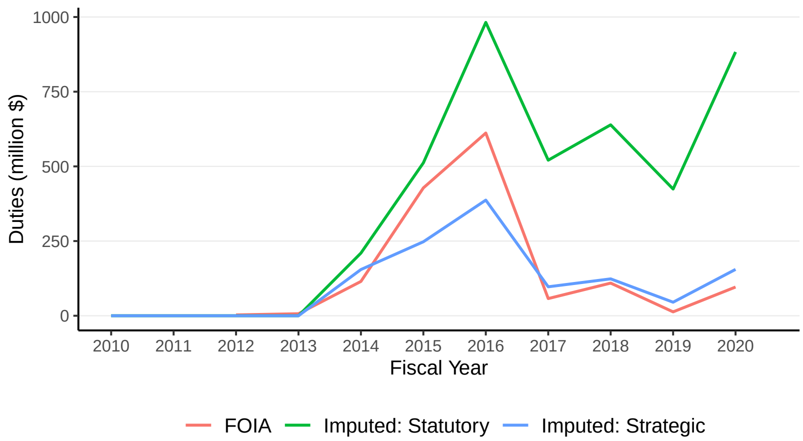
Note: Comparison of average tariff rates. Averages are weighted by quarterly shipment volumes. Strategic tariffs for China prior to the 2014 tariffs are set to zero, since Chinese firms could avoid the tariffs without having to relocate solar panel production (U.S. International Trade Commission, 2015). See section 3 for more details. Vertical lines denote the timing of each round of tariffs.

To assess whether the assumption we make to construct the strategic tariffs is reasonable, we impute duty payments based on both the statutory and strategic tariff rates and compare them to actual duties paid. We find that revenues calculated using the constructed strategic tariff rates match actual duty payments far better than the statutory tariffs do. Appendix E provides more details.

zero to all manufacturers until the 2014 tariffs take effect.

E Comparison of Imputed to Actual Duties Paid

Figure E.1: Antidumping and Countervailing Duties



Note: This figure plots observed and imputed duty payments over time. "FOIA" (in red) plots total duty payments under antidumping and countervailing duty cases for China and Taiwan, based on data obtained via FOIA request to the U.S. Customs and Border Protection (see Table 2 for more details). "Imputed: Statutory" (in green) plots imputed duty payments based on solar panel shipments reported by IHS Markit and firm-specific tariff rates from the Federal Register, before accounting for the possibility of avoidance by firms. "Imputed: Strategic" (in blue) plots imputed duty payments based on solar panel shipments data from IHS Markit and strategic tariff rates constructed by the authors as detailed in Appendix D. Duties are in nominal terms.

Table E.1: Section 201 Tariffs

	2018	2019	2020	Total
FOIA Duties Paid	449	751	576	1777
Imputed Duties: Strategic	416	613	798	1828
Imputed Duties: Statutory	487	819	946	2252

Note: This table summarizes observed and imputed Section 201 tariff payments over time. The first row is based on data obtained via FOIA request to the U.S. Customs and Border Protection. The second row summarizes imputed duty payments based on solar panel shipments data from IHS Markit and strategic tariff rates constructed by the authors as detailed in Appendix D. The third row summarizes imputed duty payments based on solar panel shipments reported by IHS Markit and firm-specific tariff rates from the Federal Register, without accounting for the possibility of avoidance by firms. Duties are in nominal terms.

F Did Firms Evade Tariffs by Transshipping?

One possible margin through which tariff-exposed manufacturers could avoid tariffs is by manufacturing solar panels in China, transshipping them through a third country in Southeast Asia, and then declaring them to be products of that country when importing them to the U.S. While we cannot directly observe this behavior, we use data on trade flows and manufacturing activity to assess whether this is a likely threat to the validity or interpretation of our analysis.

To provide context for the results in this appendix, Figure F.1 visualizes the key steps in the solar supply chain. Polysilicon production is the first step in the process, and is primarily done by upstream suppliers who are not vertically integrated and are outside the scope of our analysis. From there, vertically integrated solar manufacturers: slice polysilicon into wafers; transform the wafers into cells that produce electricity when exposed to light; and, finally, assemble the solar cells into solar panels (a.k.a. modules). Solar panels are bought by downstream firms and combined with complementary inputs to produce solar systems, which then produce electricity over time. U.S. antidumping and countervailing duties applied to solar cells and panels from China, but not to polysilicon or wafers from China.

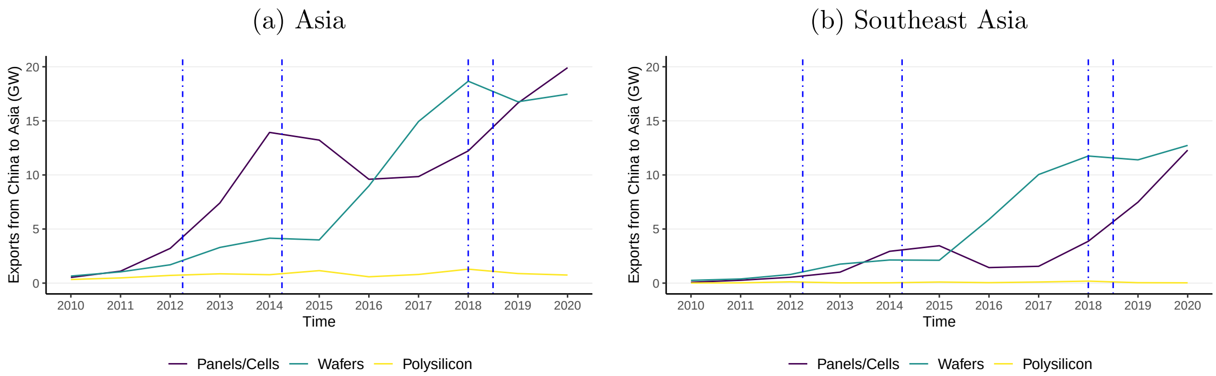
Figure F.1: Production Stages for Crystalline Silicon Solar

F.1 Solar Product Exports from China to Southeast Asia

Figure F.2 presents annual UN Comtrade data on solar product exports from China to Southeast Asian countries over time. Panels and cells, both subject to U.S. antidumping and countervailing duties if imported from China, are reported together by UN Comtrade because they fall into the same 6-digit HS code.[31] Wafers and polysilicon, both exempt from tariffs, are reported separately. To facilitate comparisons, we converted all three time series from trade values to gigawatts of electricity capacity using price indices for each product category.

[31] Solar cells and panels are classified under HS code 854140, which also includes other products unrelated to our study: "Electrical apparatus; photosensitive, including photovoltaic cells, whether or not assembled in modules or made up into panels, light-emitting diodes (LED)." It is possible that some of the growth in trade of solar cells and panels observed in Figure F.2 are due to products unaffected by the trade policies we study. While UN Comtrade does not provide a detailed breakdown of trade flows between China and Southeast Asian countries below the 6-digit level, more detailed data from USITC DataWeb shows that over one-quarter of U.S. imports of products classified under HS code 854140 during our study period were not solar products.

Figure F.2: Chinese Exports of Solar Products to Asia



Note: UN Comtrade data on annual exports of solar products from China to other Asian countries, aggregated across countries. Panel a includes countries where Chinese firms supplying the U.S. market manufacture solar cells according to the IHS data: Japan, Malaysia, the Philippines, Singapore, South Korea, Thailand, and Vietnam. Panel b excludes Japan and South Korea, which are large markets for finished solar panels. Products are identified by HS codes: panels and cells (8541.40), wafers (3818.00), and polysilicon (2804.61). Panels and cells are not separately reported by UN Comtrade. Vertical lines denote the timing of each round of tariffs.

Figure F.2 shows that Chinese exports of polysilicon to other parts of Asia are fairly flat over time. By contrast, Chinese exports of wafers increase significantly over time, particularly after the 2014 tariffs go into effect. Wafers are the last stage of intermediate goods production that could be completed in China without the final goods being subject to tariffs. Thus, the observed patterns are consistent with manufacturers avoiding tariffs by offshoring cell and panel production. If Chinese firms were to simply evade tariffs by transshipping finished solar panels, they would not need to export wafers. Finally, Chinese exports of panels and cells to other countries in Asia also increase over time. However, this trend appears to precede the U.S. antidumping and countervailing duties, and is therefore more likely to be explained by legitimate shipments of products (including non-solar products) to end consumers in other Asian countries than by tariff evasion. Consistent with this, Panel (b) shows that wafer exports quantitatively dominate panel/cell exports when removing Japan and South Korea, which are large end markets in addition to being manufacturing locations.[32]

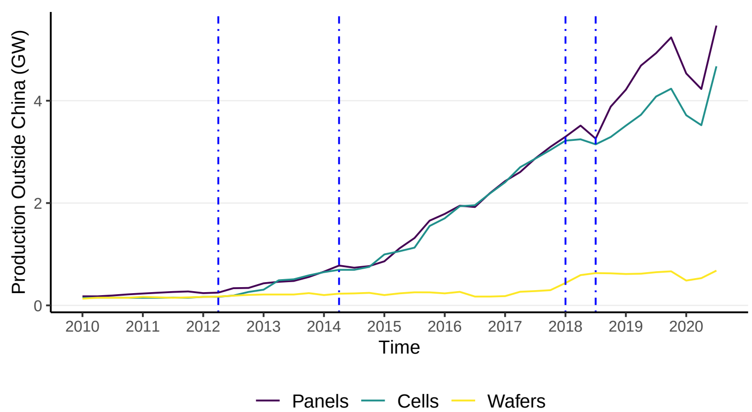
In summary, the patterns in Figure F.2 are consistent with Chinese firms offshoring the last two stages of solar panel production to avoid tariffs, and not simply transshipping completed products through third countries to evade tariffs.

[32]Japan introduced a feed-in tariff in 2012 in the aftermath of the Fukushima Daiichi nuclear disaster. Gerarden (2023) found that this feed-in tariff increased Japenese demand for solar panels significantly during the middle of our sample period.

F.2 Solar Product Production by Chinese Manufacturers

Figure F.3 presents total solar product production outside China for manufacturers in our analysis sample that produced solar panels in China prior to tariffs. The figure was made using production levels reported by IHS Markit. The increase in cell and panel production outside China over time is consistent with manufacturers offshoring production of cells and panels to avoid U.S. antidumping and countervailing duties, rather than simply transhipping completed panels.[33] By contrast, the figure shows no concomitant rise in offshore production of wafers, which were not subject to duties.

Figure F.3: Chinese Manufacturers' Production outside China over Time



Note: Constructed using quarterly data from IHS Markit on production of solar panels, cells, and wafers outside China over time for firms in the main analysis sample that produced solar panels in China prior to tariffs. Vertical lines denote the timing of each round of tariffs.

[33]After 2018, offshore panel production grew beyond the level of offshore cell production. The primary driver of this divergence in the data is panel production in the United States, most likely to avoid the Section 201 tariffs.

G Robustness Analysis: Detailed Demand Model

G.1 Data

To estimate demand for solar solar systems in the utility market, we use data from the U.S. Energy Information Administration (EIA) Form EIA-860.

To estimate demand for solar solar systems in the U.S. residential and commercial market, we use records of small-scale solar system installations from the Lawrence Berkeley National Laboratory's (LBNL) Tracking the Sun data set. This data set includes residential and business, commercial, non-profit, and government solar installations reported to the LBNL through 2020. We trim the data to consider installations since 2010, and we exclude very large installations from the residential and commercial demand estimation (any installation over 100kW in size). To size the market, we use annual data on owner-occupied homes from the 2020 U.S. Census Bureau Population and Housing data and commercial establishments data from the U.S. Census Bureau County Business Patterns database. Construction sector wage data is from the Bureau of Labor Statistics.

G.2 Model

Solar panels are an intermediate good, and demand for them is derived from demand for residential and utility-scale solar systems. Thus, in addition to modeling aggregate demand parsimoniously, we model the demand for solar systems in both downstream markets and then combine them to recover aggregate demand for solar panels:

$$Q_t^D(p_t) = Q_t^C(p_t) + Q_t^U(p_t),$$

where Q_t^C is demand from the residential and commercial market, and Q_t^U is demand from the utility-scale market.

G.2.1 Demand from the Utility-Scale Solar Market

We model the national utility-scale consumer demand using a random utility model. Since we only observe market-level data for the utility-scale market, we use a parsimonious model of a representative consumer with the mean utility function

$$\delta_t^u = \alpha_{0(t)}^u + \alpha^u p_t + \epsilon_t^u. \tag{G.1}$$

Under the assumption that ϵ_t^u is i.i.d. type I extreme value, utility-scale demand is given by:

$$Q_t^U(p_t) = m_t^u \frac{\exp(\delta_t^u)}{1+\exp(\delta_t^u)} \tag{G.2}$$

where m_t^u is the potential market size.

G.2.2 Demand from the Residential and Commercial Solar Market

Demand for Residential and Commercial Solar Systems We assume a continuum of market (county) m at time t, each with a set of local installers J_{mt}. Throughout the rest of this section we will suppress the m subscript for notational clarity. Each local installer $j \in J_t$ differs by a time invariant characteristic x_j and the price per unit Watt of installation p_{jt}^s.[34] We define the mean utility of installation with installer j as $\delta(\xi_j, p_{jt}^s)$. Each local consumer i also has an idiosyncratic random utility shock for installation $\zeta_{It}^i + (1-\sigma)\epsilon_{jt}^i$, the classic nested Logit model in which the upper-level nest is whether to install solar or not. A consumer's installation decision is *dynamic* as in De Groote and Verboven (2019): they first decide whether to install at current period t or wait for the future. All installations constitute a terminal state.

We start by defining the mean utility of non-installation δ_{0t} for the consumer. To calculate their option value of waiting, the consumers will need to form perception of the transition of installer composition and pricing. Denote the set of installer characteristics as $\xi_t = \{\xi_j \;\; \forall j \in J_t\}$ and state variables (prices, rebates, electricity rates, etc.) as $\mathbf{x}_t = \{x_{jt} \;\; \forall j \in J_{mt}\}$. The mean utility of non-installation can be defined as:

$$\delta_{0t} \equiv \delta_0(\xi_t, \mathbf{x}_t) = u_0 + \beta E_t[\bar{V}(\xi_{t+1}, \mathbf{x}_{t+1})|\xi_t, \mathbf{x}_t] \tag{G.3}$$

where the integrated value function$\bar{V}(\xi_{t+1}, \mathbf{x}_{t+1})$ is:

$$\begin{aligned}\bar{V}(\xi_{t+1}, \mathbf{x}_{t+1}) = \int_{\zeta', \epsilon'} \max\Big\{ & \delta_0(\xi_{t+1}, \mathbf{x}_{t+1}) + \zeta_N^{'} + (1-\sigma)\epsilon_0^{'}, \\ & \max_{j \in J_{t+1}} \Big(\delta(\xi_{jt+1}, x_{jt+1}) + \zeta_I^{'} + (1-\sigma)\epsilon_j^{'}\Big)\Big\} dG(\zeta', \epsilon')\end{aligned}$$

Under the assumption that the random utility shocks are i.i.d. type I extreme value, we can

[34] The superscript s is denotes that these are *system* prices, as distinct from solar panel prices, which are denoted p_t without a superscript.

substantially simplify the above equation. We can write the integrated value function as:

$$\bar{V}_{t+1}(\xi_{t+1}, \mathbf{x}_{t+1}) = \gamma_{euler} + \log\left[\exp(\delta_0(\xi_{t+1}, \mathbf{x}_{t+1})) + D_I(\xi_{t+1}, \mathbf{x}_{t+1})^{1-\sigma}\right] \tag{G.4}$$

where the inclusive value of installation is defined as

$$D_{It+1} \equiv D_I(\xi_{t+1}, \mathbf{x}_{t+1}) = \sum_{j \in J_{t+1}} \exp(\delta(\xi_j, x_{jt+1})/(1-\sigma)). \tag{G.5}$$

Given a Markovian perceived transition of $(\xi_{t+1}, \mathbf{x}_{t+1})$ and the mean utility function $\delta(\cdot)$, equations G.3, G.4, and G.5 fully describes the consumer's problem.

We can then define the overall market share of installer $j \in J_t$ as (denote $\delta_{jt} \equiv \delta(\xi_j, x_{jt})$)

$$s_{jt} = \underbrace{\frac{\exp(\delta_{jt}/(1-\sigma))}{D_{It}}}_{s_{j|It}} \times \underbrace{\frac{D_{It}^{1-\sigma}}{\exp(\delta_{0t}) + D_{It}^{1-\sigma}}}_{\text{share of installation } s_{It}}$$

In sum, compared with a standard model of static demand with exogenous outside options, the consumers here take into account the changing composition of installers and, more importantly, the future prices. It also implies that, the effective market size becomes smaller overtime since a growing fraction of local residence and commercial users have already installed solar systems.

Installer Profit Maximization In calculating optimal installer markups, we assume that installers maximize profit *without* taking into account how their pricing affecting consumer belief and thus *the option value of waiting* δ_{0t}. Most of the local installers are relatively small and it might justify the assumption that they do not conduct sophisticated dynamic pricing. With large within-group substitution that would arise with a large nest parameter, we also believe the first order condition constitutes reasonable assumption, since with large substitution across installers, there is limited value to a installer in adjusting prices today in anticipation of being able to capture that same consumer in the next period.

Within each residential/commercial market, the installers $j \in J_t$ compete in price and maximize their profit:

$$\max_{p_{jt}^s} \left[p_{jt}^s - c_{jt}\right] s_{jt} \equiv \left[p_{jt}^s - c_{jt}\right] \frac{\exp(\delta_{jt}/(1-\sigma))}{D_{It}} \times \frac{D_{It}^{1-\sigma}}{\exp(\delta_{0t} + D_{It}^{1-\sigma})}$$

The FOCs depend on demand elasticity $\epsilon_{jt}^c \equiv \frac{\partial \log s_{jt}}{\partial \log p_{jt}^s}$. With the parametric assumption

$\delta(\xi_j, x_{jt}) = \xi_j \alpha^{\xi} + p^s_{jt}\alpha^p$ in we define p^s_{jt} as the post-rebate price the consumer pays, we have:

$$\epsilon_{jt} = -\alpha^p \frac{\partial s_{jt}}{\partial \delta_{jt}} \frac{p^s_{jt}}{s_{jt}} = \frac{-\alpha^p}{1-\sigma} p^s_{jt} \left[1 - \sigma s_{j|It} - (1-\sigma) s_{jt}\right]$$

The optimal price is $\frac{p^{s*}_{jt} - c_{jt}}{p^{s*}_{jt}} = -1/\epsilon^c_{jt}$, as a result follows the standard additive markup as shown in, for instance, Berry (1994).

$$p^s_{jt} = c_{jt} + w_t - r_t + \frac{(1-\sigma)/\alpha^p}{\left[1 - \sigma s_{j|It} - (1-\sigma) s_{jt}\right]} \equiv c_{jt} + w_t - r_t + \mu_{jt}$$

in which r_t is the consumer rebate amount and installer costs, c_{jt}, include factors such as wage rates.

Aggregating to Derive Demand for Solar Panels from the Residential Market Installer pricing depends on the costs, $\mathbf{c}_t = \{c_{jt} \ \ \forall j \in J_{mt}\}$, as well as the solar wholesale price p_t. We can define the market demand for solar panel input at each market m as

$$q^C(\xi_t, \mathbf{c}_t, m_t, p_t) = m_t \times s_I(\xi_t, \mathbf{c}_t, \delta_{0t}, p_t)$$

where m_t is the effective market size, i.e., the residential and commercial customers who have not installed solar. We then sum over the (approximately) continuum of locations to obtain the aggregate residential and commercial demand as

$$Q^C_t(p_t) = \int q^C(\xi_t, \mathbf{c}_t, \delta_{0t}, m_t, p_t) dF(\xi_t, \mathbf{c}_t, \delta_{0t}, m_t)$$

where $F(\xi_t, \mathbf{c}_t, \delta_{0t}, m_t)$ is the empirical distribution of all the relevant state variables for each market. The semi-elasticity of residential and commercial demand for solar panels with respect to price is

$$\frac{d \log Q^C(p_t)}{dp_t} = \int \frac{\partial \log q^C(\xi_t, \mathbf{c}_t, \delta_{0t}, m_t, p_t)}{dp_t} \frac{q^C_t}{Q^C_t} dF(\xi_t, \mathbf{c}_t, \delta_{0t}, m_t) \ .$$

G.3 Estimation

G.3.1 Utility-Scale Market Demand Estimation

Under the maintained assumption that ϵ_t^u is distributed type I extreme value, we can derive the following estimating equation:

$$\log(s_t^{\text{solar}}) - \log(s_t^{\text{other}}) = \alpha_{0(t)}^u + \alpha^u p_t + u_t \tag{G.6}$$

where s_t^{solar} is the share of new utility-scale electricity generation capacity in a given time period that comes from solar, and s_t^{other} is the share that comes from other sources. To compute these market shares, we use either all new electricity generation capacity or the subset of new capacity that employs renewable energy technologies. We allow for coarse time-varying demand intercepts in some specifications via the inclusion of year fixed effects. We estimate the equation using ordinary least squares and instrumental variables. For instrumental variable estimation, we use prices for solar panels outside the U.S. as an instrument for prices in the U.S. This instrument is similar in spirit to using cost shifters to instrument for price when estimating demand, as they should reflect common cost shifters (both observable and unobservable). The instrument is valid under the assumption that supply shocks are correlated across markets but demand shocks are not.

G.3.2 Residential and Commercial Market Demand Estimation

As we laid out in the model section G.2.2, for a market m with current state $\mathbf{x}_t$, the consumer's solar adoption probability is

$$P^I(\mathbf{x}_t) = \frac{D_I(\mathbf{x}_t)^{1-\sigma}}{exp(\delta_0(\mathbf{x}_t)) + D_I(\mathbf{x}_t)^{1-\sigma}}$$

in which we again drop the m subscript for clarity.

We could use equations G.3 and G.4 to evaluate the integrated value function $\bar{V}(\mathbf{x}_{t+1})$ and then compute the option value of waiting $\delta_0(\mathbf{x}_t)$. To alleviate the computational burden, we instead follow (Hotz and Miller, 1993; Arcidiacono and Miller, 2011) to express the integrated value function $\bar{V}(\mathbf{x}_{t+1})$ in terms of the choice probabilities of adoption $Pr^I(\mathbf{x}_{t+1})$ and any specific choice probability for $j = 1$:

$$P_1(\mathbf{x}_{t+1}) = \frac{exp(\delta_{1t+1}/(1-\sigma))}{D_I(\mathbf{x}_{t+1})} \times \frac{D_I(\mathbf{x}_{t+1})^{1-\sigma}}{exp(\delta_0(\mathbf{x}_{t+1})) + D_I(\mathbf{x}_{t+1})^{1-\sigma}}$$

Combine the two choice probability equations above, we can then express the integrated value function $\bar{V}(\mathbf{x}_{t+1}) \equiv \gamma_{euler} + \log\left[exp(\delta_0(\mathbf{x}_{t+1})) + D_I(\mathbf{x}_{t+1})^{1-\sigma}\right]$ in terms of $P^I(\mathbf{x}_{t+1})$ and $P_1(\mathbf{x}_{t+1})$:

$$\bar{V}(\mathbf{x}_{t+1}) = \gamma_{euler} + \delta_{1t+1} - \sigma \log P^I(\mathbf{x}_{t+1}) - (1-\sigma)P_1(\mathbf{x}_{t+1})$$

Assume without loss of generality that $u_0 = -\beta\gamma_{euler}$, we can then express $\delta_0(\mathbf{x}_t)$ also in terms of choice probabilities

$$\delta_0(\mathbf{x}_t) \equiv \beta E_t\left[\bar{V}(\mathbf{x}_{t+1})|\mathbf{x}_t\right] = \beta E_t\left[\delta_{1t+1} - \sigma \log P^I(\mathbf{x}_{t+1}) - (1-\sigma)\log P_1(\mathbf{x}_{t+1})\middle| \mathbf{x}_t\right] \quad \text{(G.7)}$$

To obtain our estimation equation, we normalize the market share of each installer j with respect to the non-installation share $s_{0t} \equiv 1 - s_{It} = \frac{exp(\delta_0(\mathbf{x}_t))}{exp(\delta_0(\mathbf{x}_t))+D_I(\mathbf{x}_t)^{1-\sigma}}$:

$$\log s_{jt} - \log s_{0t} = \frac{\delta_{jt}}{1-\sigma} - \delta_0(\mathbf{x}_t) - \sigma \log D_I(\mathbf{x}_t)$$

Using the fact that $\log D_I(\mathbf{x}_t) = (\log s_{It} - \log s_{0t} + \delta_0(\mathbf{x}_t))/(1-\sigma)$, we can simplify the market share equation to

$$\log s_{jt} - \log s_{0t} = \delta_{jt} - \delta_0(\mathbf{x}_t) + \sigma \log s_{j|It}$$

Substitute the option value of non-installation $\delta_0(\mathbf{x}_t)$ with the conditional choice probability expression in equation G.7, we have

$$\log s_{jt} - \log s_{0t} = \delta_{jt} + \sigma \log s_{j|It} - \beta E_t\left[\delta_{1t+1} - \sigma \log P^I(\mathbf{x}_{t+1}) - (1-\sigma)\log P_1(\mathbf{x}_{t+1})|\mathbf{x}_t\right] \quad \text{(G.8)}$$

The above equation G.8 constitutes our main empirical specification. Compared with standard nested logit model (i.e. Berry (1994)), the augmented δ_{1t+1} and conditional choice probability terms summarizes the option value of installing next period.

Our empirical specification accommodates several practical considerations. We define the state variables as $\mathbf{x}_t = (\xi_t, \mathbf{p}_t, r_t, \mathbf{z}_{jt}, \eta_t)$. The unit price per Watt of installation p^s_{jt} is adjusted by market-specific rebate r_t. The vector $\mathbf{z}_{jt}$ includes the average size and the the fraction of the installations that are third-party owned performed by installer j in the county in quarter t. We assume that the consumer mean utility δ_{jt} contains an IID transitory component ξ_{jt}. Finally, we allow for state X quarter and installer X county fixed effects, η_t and μ_j (still abstracting from the m notation here). Other potentially relevant state variables such as electricity rates we subsume in the η_t.

$$\delta_{jt} = \xi_j + \alpha^p p^s_{jt} + \mathbf{z}_{jt}\phi + \eta_t + \mu_j + \xi_{jt}$$

To determine the potential market, we use the number of establishments and number of owner-occupied homes. We multiply the (time-varying) number of business establishments in the county by the average non-residential installation size in the county and add this to the (time-varying) number of owner-occupied homes in the county by the average residential installation size to get a measure of the potential market. We set the starting market size to the larger of this value and twice the observed MW of installations. For each period, we adjust the non-adopting market size downwards using the MW of installations in the previous period.

In order to calculate the expected next period probabilities, we assume that consumers expect AR(1) transitions for solar prices, rebates, adoption probability and within-group adoption probability. We include installer x county and state X time fixed effects in these AR(1) regressions, which implies that consumers expect the shocks to these variables due to factors such as changes in the electricity rates, incentive policies, and tariffs.

$$\begin{aligned}\log s_{jt} - \log s_{0t} - \beta E_t[\log P_1(\mathbf{x}_{t+1})|\mathbf{x}_t] = (\xi_j - \beta\xi_1) + \alpha^p(p^s_{jt} - \beta p_{1t+1}) + (\mathbf{z}_{jt} - \beta\mathbf{z}_{1t+1})\phi \\ +(\eta_t - \beta\eta_{t+1}) + \sigma\left(\log s_{j|It} + \beta E_t[\log P^I(\mathbf{x}_{t+1}) - \log P_1(\mathbf{x}_{t+1})|\mathbf{x}_t]\right) + \xi_{jt}\end{aligned}$$

For identification, we need instruments for the price and for the within-group share parameter. We use mean wages in the construction and utility industries as cost shifters and the average per Watt rebate amount. We also use two BLP-type instruments, the mean size of installations performed by other installers within the county, and the fraction of installations performed by other installers within the county that are third-party installations.

Which installer is used to control for future utility does not matter in theory, but the challenge we face is that there is no one installer that is well represented in all markets in all years. Thus we use a novel strategy in which we write down equation (G.8) for using each installer in each market as the reference installer, and then average these equations at the market level. In other words, this is as if we choose a hypothetical reference installer whose log conditional choice probability is

$$\overline{\log P^A(\mathbf{x}_{t+1})} = \frac{1}{|J_{t+1}|}\sum_{j\in J_{t+1}} \log P_j(\mathbf{x}_{t+1})$$

and the average expected mean utility is

$$\frac{1}{|J_{t+1}|}\sum_{j\in J_{t+1}}(\xi_j+\alpha^p p_{jt+1}+\eta_{t+1})\equiv\overline{\xi}+\alpha^p\overline{p}_{t+1}+\eta_{t+1}$$

The estimation equation then becomes

$$\begin{aligned}\log s_{jt}-\log s_{0t}-\beta E_t[\overline{\log P^A(\mathbf{x}_{t+1})}|\mathbf{x}_t]&=(\xi_j-\overline{\xi})+\alpha^p(p^s_{jt}-\beta\overline{p}_{t+1})+(\mathbf{z}_{jt}-\beta\overline{\mathbf{z}}_{t+1})\phi\\&+(\eta_t-\beta\eta_{t+1})+\sigma\left(\log s_{j|It}+\beta E_t[\log P^I(\mathbf{x}_{t+1})-\overline{\log P^A(\mathbf{x}_{t+1})}|\mathbf{x}_t]\right)+\xi_{jt}\end{aligned}$$

We use aggregate data for our CCP estimation, as was done by De Groote and Verboven (2019), because this enables us to use the full dataset in estimation.[35] Furthermore, there is little to be gained from using disaggregated data since the only household level state in our state space is whether the household has already installed solar (if they have, this precludes them from installing in the future). This approach does limit attempts to identify within-county unobserved heterogeneity, but since solar PV adoption is still early along the adoption curve in our empirical setting, the marginal consumer is likely not changing significantly. We use a quarterly discount rate of 0.966 which correspond to an annual discount rate of 0.87, consistent with that estimated by De Groote and Verboven (2019). This expression only depends on the values of the current and next period state variables and the next period adoption probabilities. These probabilities are calculated at the county-quarter level which is essential since the model includes market-level unobservables.

The purpose of this demand estimation is to allow for incomplete pass-through of the tariffs in the residential and commercial market in which previous research has documented installer market power (Bollinger and Gillingham, 2019; De Groote and Verboven, 2019).

G.4 Estimation Results

G.4.1 Utility-Scale Market Demand Estimates

Utility-scale demand estimates are shown in Table G.1. In contrast to the constant elasticity demand model, these coefficients are not immediately interpretable as demand elasticities. We use the IV estimates with year fixed effects to construct estimated utility-scale elasticities for each time period as follows:

$$\widehat{\epsilon^u_t}=\widehat{\alpha^u}p_t\left(1-s^{solar}_t\right). \tag{G.9}$$

[35] Including a separate observation for each household x month combination would make the estimation intractable.

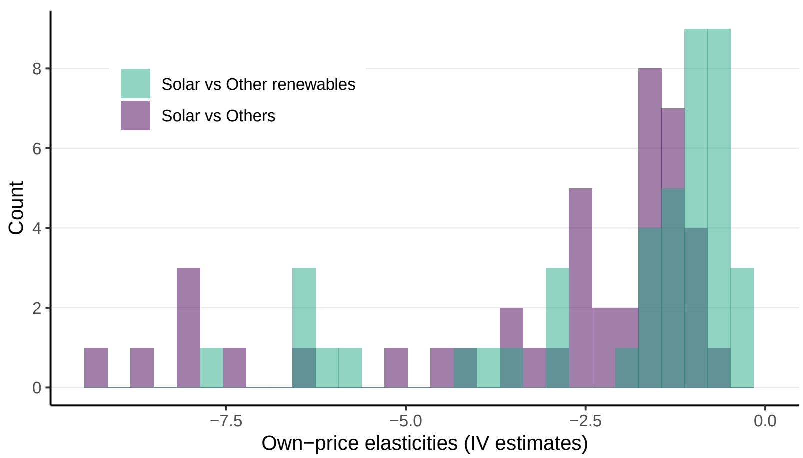
Figure G.1 presents the distribution of these elasticities across time periods.

Table G.1: Utility-Scale Demand Estimates

	$\log(s^{\text{solar}}) - \log(s^{\text{all other}})$			$\log(s^{\text{solar}}) - \log(s^{\text{renewables}})$		
	(1)	(2)	(3)	(4)	(5)	(6)
Solar panel price (after subsidy)	-3.44***	-3.43***	-6.39***	-2.95***	-2.93***	-5.20**
	(0.44)	(0.44)	(1.59)	(0.47)	(0.45)	(2.46)
Year Fixed Effects			X			X
Estimator	OLS	IV	IV	OLS	IV	IV
Observations	43	43	43	43	43	43
R^2	0.67	0.67	0.78	0.57	0.57	0.81

Note: This table presents estimates of the price coefficient α^u from equation G.6 using six different estimation procedures. In columns 1-3 the market is defined as solar with all other electricity capacity additions as the outside good. In columns 4-6 the market is defined as solar with renewable electricity capacity additions as the outside good. The instrumental variable in columns 2, 3, 5, and 6 is the price of solar panels outside the USA. Columns 3 and 6 include year fixed effects. Heteroskedasticity-robust standard errors are in parentheses. Significance levels are denoted as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure G.1: Utility-Scale Demand Elasticity Estimates



Note: This figure plots the distribution of quarterly price elasticities of demand for solar panels in the utility-scale market. Elasticities are computed following equation G.9, using the IV estimates with year fixed effects from Table G.1 (columns 3 and 6) in conjunction with data on prices and market shares.

G.4.2 Residential and Commercial Market Demand Estimates

Residential and commercial demand estimates are shown in Table G.2. In the IV regressions, we instrument for price and within-group market share using county-level wage rates for both utilities and construction, and the mean value for installation size and third party for competitor installers within the county, all interacted with regional fixed effects (Northeast, Southeast, Midwest, Southwest, and West).

Table G.2: Residential and Commercial Demand Estimates

Variable	OLS	IV 1st Stage, price	IV 1st stage, nest	IV 2nd stage
price ($/W)	0.001			-0.084***
	(0.002)			(0.024)
size (MW)	-0.004	-0.463***	-0.260***	-0.045**
	(0.010)	(0.116)	(0.063)	(0.018)
nest parameter (σ)	0.944***			0.892***
	(0.004)			(0.043)
rebate ($/W)		-0.851***	-0.096*	
		(0.047)	(0.049)	
normalized construction wage rate				
mean competitor size (MW)		-0.035	-0.168***	
		(0.031)	(0.048)	
mean competitor third-party owned		-0.024	0.148+	
		(0.081)	(0.081)	
R-squared	0.970	0.514	0.703	0.924
N	149419	151779	149406	149406

Note: Standard errors clustered by installer are in parentheses, * 5%, ** 1%, *** 0.1%.

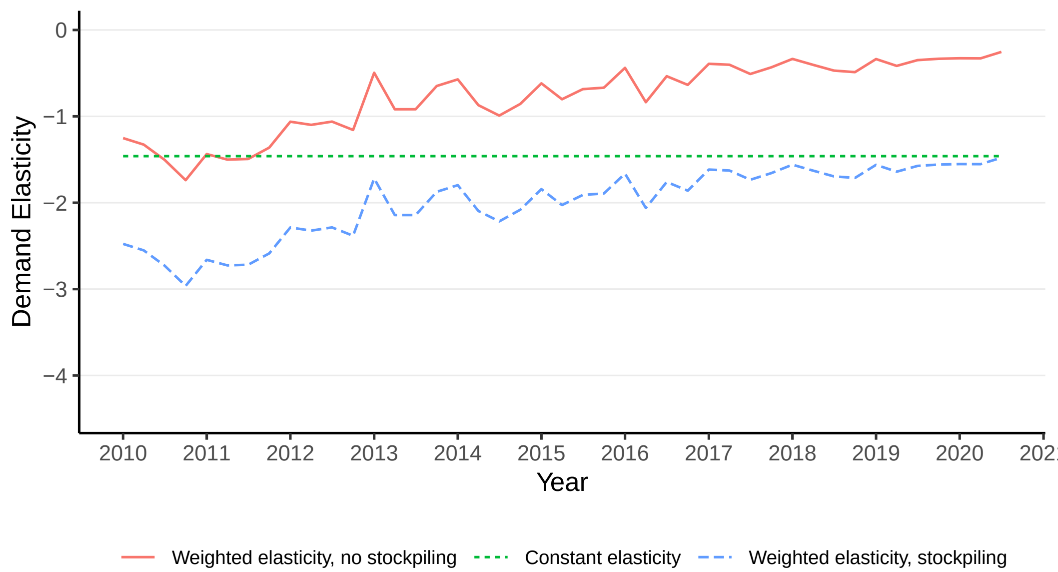
As expected, in the OLS regressions, the point estimates for the price coefficient are close to zero, presumably due to the endogeneity of price, especially with respect to unobserved quality (or perceived quality). For the IV regressions, we pass the over-identification test of excluded instruments at $p > 0.5$ (J-statistic of 1.69) with a Cragg-Donald Wald weak identification F statistic of 60.7, and a Kleibergen-Paap rk LM statistic of 33.4, rejecting weak identification at $p < 0.001$.

The demand estimates imply an average optimal markup of $0.76 per Watt. The low markup results from the large elasticities, with an average of -4.6 across observations. These large elasticities are in large part driven by substantial substitution across installers, due to the large nest parameter. The small markups imply that much of the equilibrium panel cost increases due to tariffs will be passed on to the end residential and commercial customers. Since these customers exhibit low price elasticity (at the median observation) when the prices offered by all installers increase, we can expect only a moderate demand response for this segment of the market.

G.4.3 Aggregate Elasticity Estimates

Figure G.2 plots aggregate elasticity estimates from three different specifications. The solid red line represents the aggregate demand elasticity derived directly from the downstream demand models for the utility-scale and residential and commercial markets. The dashed blue line represents an alternative estimate that allows for stockpiling behavior by installers in a reduced-form manner. The dotted green line represents the baseline constant elasticity specification, which lies in between the two specifications and is quite similar to the weighted elasticity that allows for stockpiling for the time period during which tariffs were in place.

Figure G.2: Combined Elasticity Estimates



H Model Fit

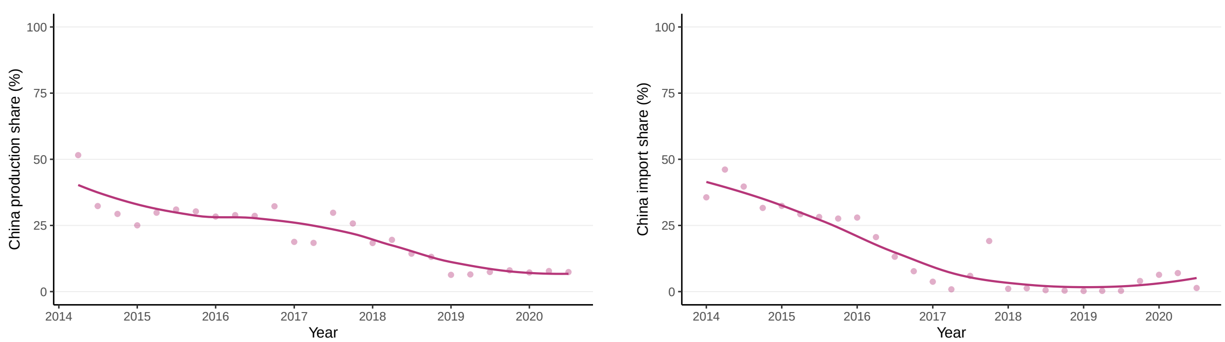
H.1 Model-Predicted Production Shares vs Observed Imports

The counterfactual analysis summarized in Figure 7 predicts that, under the status quo, the share of U.S. consumed solar panels produced in China fell from roughly half in 2014 to nearly zero in 2019 and 2020.

To assess whether this model prediction is reasonable, we use USITC data to plot import shares (by value) over time. Figure H.1 compares production shares predicted by the model to import shares reported by the USITC. The model effectively replicates the significant decline of China's import share after tariffs went into effect, despite the fact that the import share was not a target of estimation.

Figure H.1: Share of U.S. Panels from China over Time

(a) Model Predictions (b) USITC Import Data



Note: Figure H.1a plots baseline model predictions of the share of solar panels consumed in the U.S. that are sourced from China, based on the model in section 4 and estimates in section 6. Figure H.1b plots data from USITC DataWeb on the value share of solar panel imports by value that come from China.

I Additional Counterfactual Results

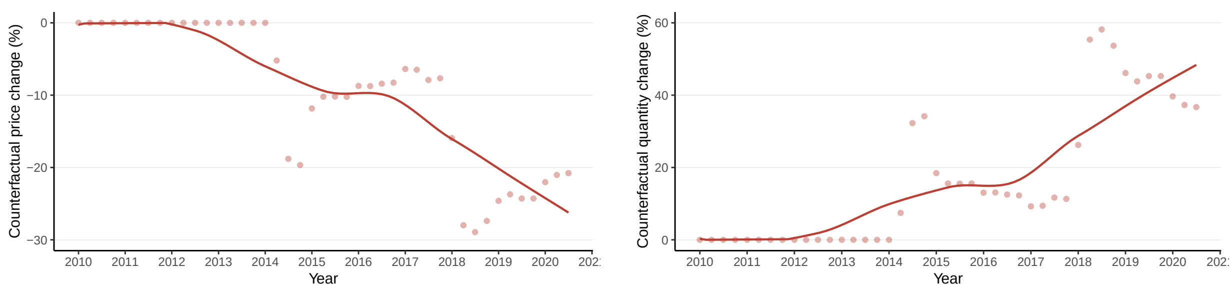
I.1 Model Predictions Holding Manufacturing Capacity Fixed

Though we do not model and endogenize manufacturing capacity, we use a bounding exercise to account for the impacts of endogenous manufacturing capacity investment on outcomes. Motivated by the descriptive results in section 3, the main text presents results in which we vary manufacturing capacity in counterfactuals. This section presents an analogous set of results in which we hold the observed set of locations in which each manufacturer produces fixed in counterfactuals. While the quantitative results are generally smaller in magnitude than the results in the main text, the qualitative conclusions are unchanged.

Figure I.1: Impacts of Removing Tariffs on Prices and Quantities

(a) Percentage Change in Wholesale Price

(b) Percentage Change in Quantity



Note: Plots present changes in model predictions for a scenario with no tariffs, relative to a model predictions for the status quo. Points denote model predictions for each quarter under the baseline model estimates. Lines are smoothed conditional means, predicted using local linear regression. In both cases, each firm's set of production locations is held fixed to match observed locations under the status quo.

Table I.1: Welfare Impacts

	Impacts over 2014-2020 ($, billions):	
	Actual Tariffs	Counterfactual Subsidy
Δ in Consumer Surplus	-5.5	0.5
Δ in Producer Surplus	-0.9	0.5
Δ in Producer Surplus (USA)	1.4	0.5
Δ in Producer Surplus (China)	-2.2	-0.4
Δ in Producer Surplus (Other)	-0.1	0.3
Δ in Government Revenue	10.2	-3.1
Δ in Tariff Revenue	4.0	0.0
Δ in Adoption Subsidy Expenditure	-6.3	0.5
Δ in Manufacturing Subsidy Expenditure	0.0	2.6
Δ in Environmental Benefits	-60.7	4.9
Δ in Local Pollution Benefits	-40.9	3.3
Δ in Global Pollution Benefits	-19.8	1.6
Δ in Domestic Welfare	-34.7	1.1
Δ in Total Welfare	-56.8	2.7

Note: This table summarizes welfare impacts of alternative government interventions relative to a counterfactual scenario of no intervention. The column "Actual Tariffs" corresponds to the status quo. The column "Counterfactual Subsidy" corresponds to a scenario in which the U.S. provides a 30 percent subsidy to U.S. manufacturing (by any manufacturer, regardless of their home country). The change in domestic welfare excludes changes in producer surplus for tariff-exposed manufacturers and all changes in global pollution benefits (since some of which spill over to other countries due to the nature of global pollutants). In all cases, each firm's set of production locations is held fixed to match observed locations under the status quo.

Table I.2: Domestic Solar Industry Employment Impacts

	Impacts over 2014-2020 (job-years, thousands):	
	Actual Tariffs	Counterfactual Subsidy
Δ in Manufacturing job-years	64.3	278.3
Δ in Installation job-years	-325.6	27.6
Δ in Total job-years	-261.3	305.9

Note: This table summarizes employment impacts estimated by multiplying model-predicted changes in domestic solar manufacturing and installation quantities by time-varying sector-specific labor intensities derived from Solar Energy Industries Association (2021). In all cases, each firm's set of production locations is held fixed to match observed locations under the status quo.

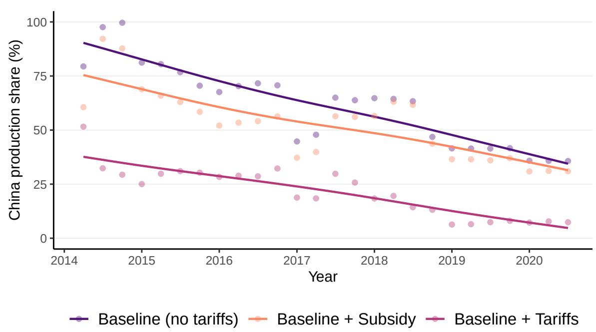
Table I.3: Domestic Solar Industry Wage Impacts

	Impacts over 2014-2020 (wages, billions):	
	Actual Tariffs	Counterfactual Subsidy
Δ in Manufacturing wages	3.9	16.9
Δ in Installation wages	-15.1	1.3
Δ in Total wages	-11.2	18.2

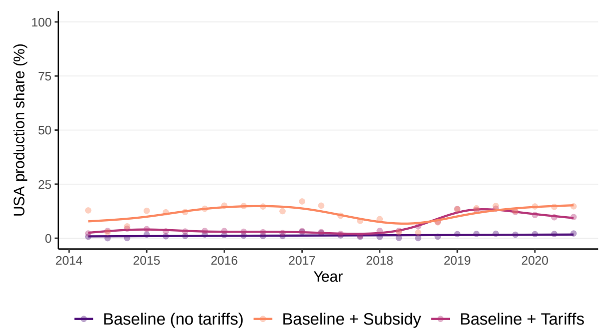
Note: This table summarizes wage impacts estimated by multiplying predicted changes in domestic solar manufacturing and installation employment by sector-specific wages derived from Solar Energy Industries Association (2021) and International Labour Organization (2023). In all cases, each firm's set of production locations is held fixed to match observed locations under the status quo.

Figure I.2: Counterfactual Production Shares

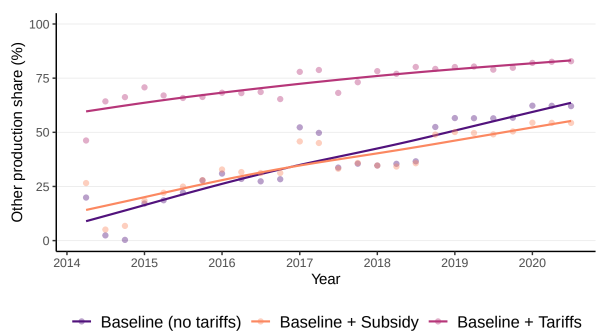
(a) China



(b) USA



(c) Other



Note: This figure plots model predictions for three factual and counterfactual scenarios. "Baseline + Tariffs" corresponds to the status quo. "Baseline (no tariffs)" corresponds to a counterfactual with no tariffs. "Baseline + Subsidy" corresponds to a counterfactual with a domestic manufacturing subsidy (and no tariffs). Points denote model predictions for each quarter under the baseline model estimates. Lines are smoothed conditional means, predicted using local linear regression. In all cases, each firm's set of production locations is held fixed to match observed locations under the status quo.