Strategic Avoidance and the Welfare Impacts of Solar Panel Tariffs*

Bryan Bollinger
NYU

Todd Gerarden
Cornell

Kenneth Gillingham
Yale

Drew Vollmer
DOJ

Daniel Yi Xu
Duke

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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 large 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.

*Corresponding author: Todd Gerarden, Charles H. Dyson School of Applied Economics and Management, Cornell University, Warren Hall, Ithaca, NY 14853. Email: gerarden@cornell.edu. Website: toddgerarden.com.

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, this traditional analysis does not take into account the implications of multinational firms relocating their production activities to jurisdictions that are not subject to tariffs. Further, it assumes away any externalities related to the goods of interest.

This study examines the effects of tariffs on solar photovoltaic products imported into the United States. We develop a structural model of supply and demand in the solar panel market and estimate it with rich location-specific production and shipment data on solar manufacturers, as well as detailed data on actual installations. A focus is on the largest Chinese solar firms, which supply much of the world's solar panels. We provide evidence of notable offshoring of solar panel production from China to neighboring nations in response to China-specific tariffs, echoing recent findings by Flaaen et al. (2020) on the effects of the anti-dumping duties on clothes washers from South Korea and China. 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 an imperfectly competitive model by both foreign and U.S. 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 solar panels as homogeneous product, for they are a commodity. Aggregate demand for solar panels depends on the price of solar panels and government subsidies for solar technology adoption. Our approach allows for flexibility in the price elasticity of demand over time, and we find elasticities in the range of -1 to -2, consistent with prior work (e.g., Gerarden, 2023). We also estimate a dynamic model of the demand for solar panels derived from downstream demand for solar installations from the utility and non-utility markets as a robustness analysis, and find very similar elasticity estimates. These elasticities characterize demand in the market.

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.[1] Static Cournot competition implies a first-order condition for manufacturers' 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 to circumvent data limitations in estimation 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.

Based on our model estimates, we run a set of counterfactuals 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

[1] 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.

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 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 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.[2] 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

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

that would fully correct negative externalities without introducing supply-side distortions in manufacturing activity.

This work contributes to several literatures. Most directly, we build on the literature on the effects and incidence of U.S. trade policy. As mentioned above, Flaaen et al. (2020) examines the price effects of U.S. import restrictions on washing machines. We focus on the market for solar panels, a highly policy-relevant market associated with environmental benefits, and use our rich data to provide detailed evidence of production offshoring in response to China-specific tariffs. Our work also relates closely to Fajgelbaum et al. (2020), which estimates passthrough and the short-run impacts of tariffs across the U.S. economy, and earlier work by Irwin (2019) on the passthrough 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 passthrough 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.[3] 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 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

[3] Gowrisankaran et al. (2016); De Groote and Verboven (2019); Bollinger and Gillingham (2019); Langer and Lemoine (2022); Gerarden (2023); Houde and Wang (2023).

[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.

as domestic manufacturing subsidies.

2 Industry Background

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.

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

[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).

countervailing duties from 2012 and 2014.

3 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). While the IHS data cover a subset rather than the universe of manufacturers, we show in Appendix B that they cover the significant majority of shipments by quantity and value, and they exhibit similar temporal patterns to official government data on tottal imports and shipments.

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 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 UN Comtrade and USITC DataWeb. Wage data come from ILOSTAT. Data on adoption of large- and small-scale solar systems come from the U.S. Energy Information Administration (EIA) Form EIA-860 and the Lawrence Berkeley National Laboratory's (LBNL) Tracking the Sun data set.

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

4 Descriptive Evidence of Tariff Avoidance

4.1 After Tariffs were Imposed on Chinese Products, Most Shipments Came from Manufacturers that Operated Both Inside and Outside of China

This section presents data on production patterns that suggest Chinese manufacturers adjusted their operations to avoid tariffs. Figure 1 shows a breakdown of major manufacturers' shipments to the U.S. based on the countries in which those manufacturers produce panels and cells.[9]

Figure 1: 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

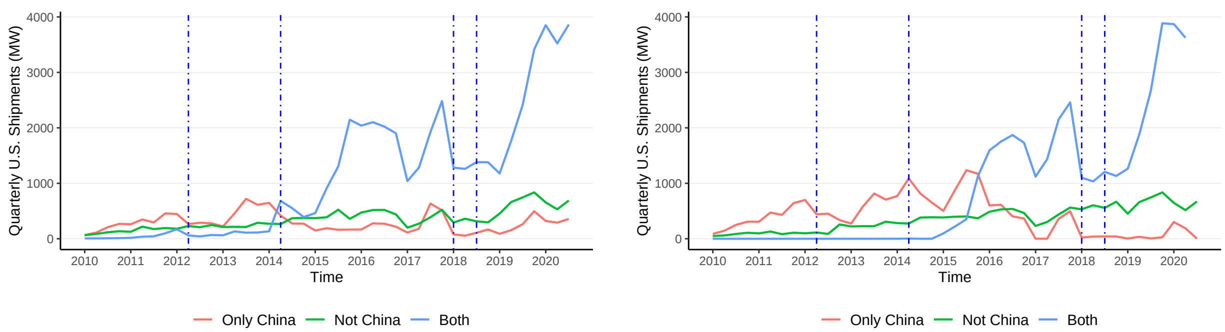


Figure 1a breaks down the time series of panel shipments into subgroups based on contemporaneous panel manufacturing locations. There are three groups: firms that manufacture only in China, firms that do not manufacture in China, and firms that manufacture both inside and outside of China. In the first 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.[10]

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

[10]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]." In Appendix C.1, we use our data to characterize 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 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.

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 1b breaks the same shipments data into groups based on contemporaneous *cell* manufacturing locations. As detailed in section 2, the 2012 and 2014 tariffs depended on the origin of cells, not just the assembled panels. The patterns in Figure 1b are similar to Figure 1a. 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.

4.2 Manufacturers Subject to Tariffs Increased Production in Tariff-Free Countries

To better understand how foreign manufacturers responded to the geographically targeted tariffs imposed in 2012 and 2014, we summarize how the geography of affected manufacturers' production evolved over time. Figure 2 plots the share of panel production outside China for manufacturers that produced panels in China prior to 2014.[11]

Figure 2: Chinese manufacturers' production shares outside China over time

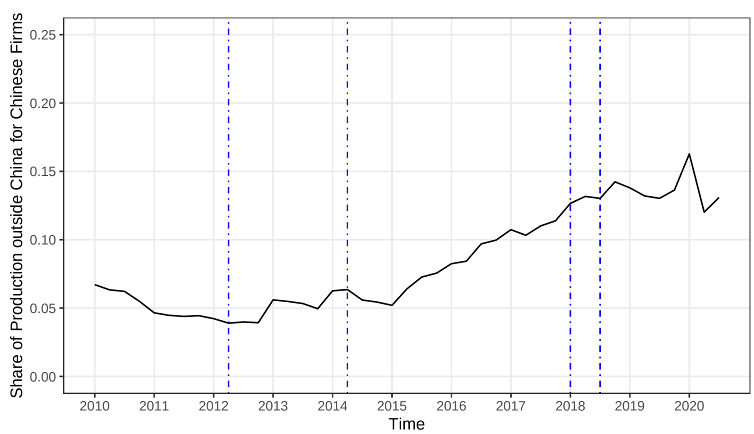


Figure 2 shows that Chinese manufacturers increased their share of panel production outside China after the 2014 tariffs took effect. This coincides with the growth of multinational

[11]We use 2014 rather than 2012 due to anecdotes about the ease of avoidance of the 2012 tariffs.

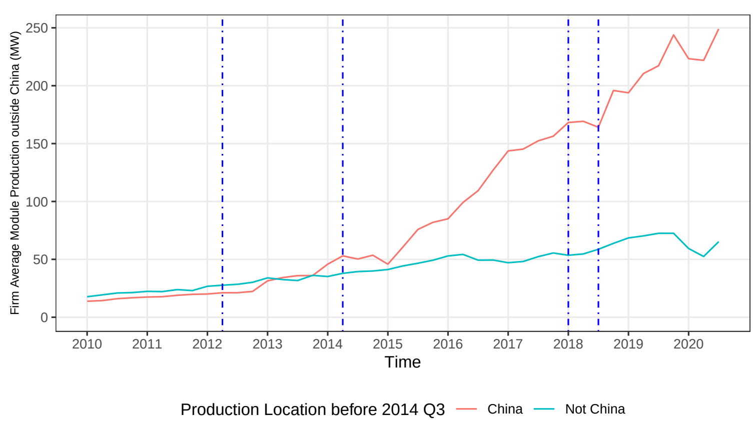
firms who manufacture both inside and outside of China in Figure 1. Both of these patterns are consistent with production relocation as a means to partially or completely avoid paying U.S. import tariffs.

Appendix C.2 presents additional measures of production relocation by manufacturers that produced solar products in China and Taiwan prior to the 2014 tariffs. These other measures are consistent with the idea that tariff-exposed manufacturers relocated production activities to avoid tariffs.

4.3 Import Tariffs Appear to Have Caused Manufacturers to Offshore Production

To formalize the descriptive evidence of production offshoring in the previous sections, we use an event study to provide evidence that offshoring was a response to the tariffs rather than a coincidence. Figure 3 plots the average of manufacturers' production outside China for two groups: firms that manufactured in China prior to the 2014 tariffs and firms that did not manufacture in China prior to the 2014 tariffs. For comparability, we restrict attention to geographically diversified manufacturers.[12] As is evident from the raw data series, these two groups of manufacturers produce similar quantities of solar panels outside China in the first several years of the sample period. After the 2014 tariffs took effect, however, production outside China by Chinese manufacturers grew at a much faster rate than did production by manufacturers that did not operate in China prior to 2014.

Figure 3: Production outside China over time for Chinese vs non-Chinese manufacturers



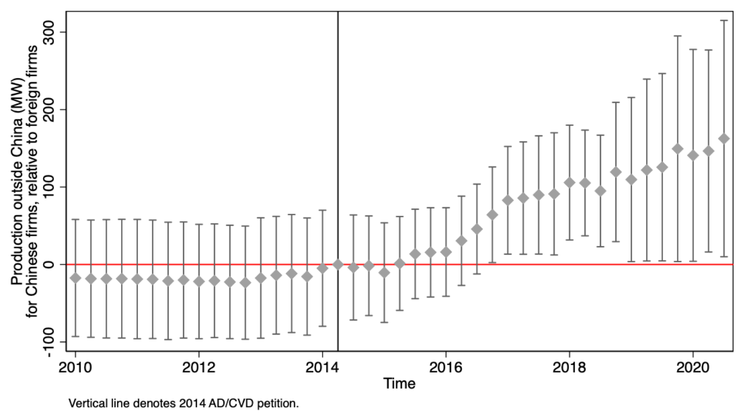
[12]There are a large number of manufacturers that only operate in China throughout the entire sample period, and whom we never observe shipping solar panels to the U.S. market. We exclude these manufacturers under the assumption that they specialize in producing products destined for markets other than the U.S. such as the Chinese market itself, and therefore they are not treated by the U.S. import tariffs.

We estimate a two-way fixed effects model to formalize the event study in Figure 3:

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

where Y_{ft} is the production 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 the 2014 tariffs went into effect, γ_f is a manufacturer fixed effect, and δ_t is a time fixed effect. Figure 4 presents point estimates and confidence intervals for the $\beta^{t'}$'s. The point estimates are similar to the difference between the treated and control groups in Figure 3. While the confidence intervals for individual coefficients are large, the post-treatment coefficients are jointly statistically significant.

Figure 4: Event study of the effect of tariffs on production offshoring by Chinese manufacturers

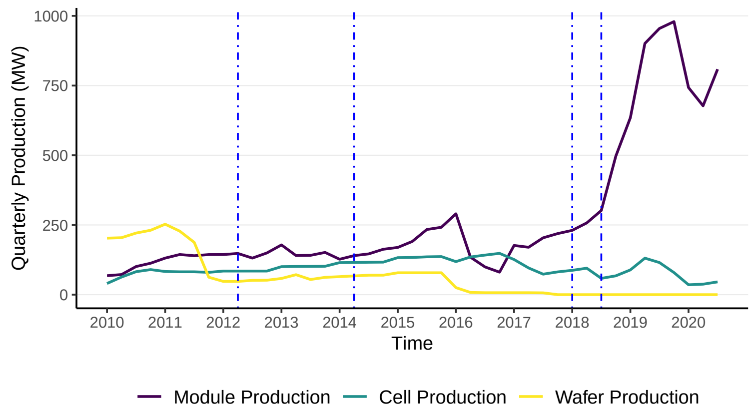


Note: Points represent event study coefficients. Confidence intervals are computed using clustering by manufacturer.

4.4 Domestic Production Increased after the 2018 Tariffs Took Effect

Figure 5 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 (module) 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. 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. All in all, the patterns in Figure 5 imply that the tariffs did not significantly increase energy independence.

Figure 5: U.S. manufacturing activity over time



4.5 Government Data Confirms that Importers Partially Avoided Tariffs

As another piece of evidence of tariff avoidance, we collected data on actual duties collected by the Census and Border Patrol through a Freedom of Information Act request. Table 1 presents these data on duties collected. 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 1: Duties collected by U.S. Customs and Border Protection

Description	Case No.	FY 2012	FY 2013	FY 2014	FY 2015	FY 2016	FY 2017	FY 2018
AD China 2012	A-570-979	2.02	2.84	34.54	147.91	183.01	16.70	33.72
AD China 2014	A-570-010			.02	1.39	2.74	.60	1.07
AD Taiwan 2014	A-583-853			10.10	51.76	42.75	3.04	1.15
CVS China 2012	C-570-980	0.79	3.89	43.19	226.51	382.55	36.84	72.74
CVS China 2014	C-570-011			26.95	0.35	0.58	0.33	0.62

Note: Duties are in millions of dollars, in nominal terms.

Appendix E presents the results of 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.[13] The results corroborate other descriptive evidence that manufacturers were able to avoid tariffs, and we find that that duty payments calculated using the constructed

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

strategic tariff rates match actual duty payments far better than the equivalent figures based on the statutory tariffs do.

4.6 Descriptive Regressions of Tariff Impacts on Prices and Quantities

We next 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:

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

where y_{ft} is a manufacturer-time-specific outcome for manufacturer f and quarter t and $\tau^S_{ft} \equiv 1 + \text{Strategic Tariff}_{ft}$.[14] 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 2 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 2: Tariffs affect quantities but not prices

	(1) ln(Value)	(2) ln(Price)	(3) ln(Quantity)
ln(1 + Strategic Tariff)	-3.37**	-0.097	-3.27**
	(1.14)	(0.066)	(1.10)
Time FE	Y	Y	Y
Manufacturer FE	Y	Y	Y
N	751	751	751

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

5 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, 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.

5.1 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 robustness analysis contained in Appendix I, we develop and estimate a microfounded model of demand for solar panels that is derived from downstream demand for solar installations from the utility and non-utility markets. 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.

5.2 Supply of Solar Panels

Each manufacturer f owns a wholesale subsidiary in the U.S. The wholesale subsidiary imports solar panels exclusively by manufacturer f, but can source shipments from all production facility locations $l \in Z_f$ operated by the manufacturer f. These shipments generate some uncertainty in terms of the *realized* cost of each panel sold by manufacturer f. We assume that the wholesale subsidiaries of each manufacturer f have *ex-ante* expected unit cost c_{ft} and compete in the U.S. market by choosing the quantity they supply, Q^S_{ft} (in Watts). Since solar panels have limited horizontal differentiation, we simplify the model with a Cournot equilibrium such that we have $Q_t = \sum_f Q^S_{ft}$.

Each manufacturer's problem is

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

with the first order condition

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

which can be rewritten as

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

where ϵ^D_t is the elasticity of solar panel demand with respect to price.

Given a chosen quantity, each manufacturer with multiple production locations needs to decide how to source its solar panels from those locations. This sourcing decision is influenced by both location fundamentals and location-specific tariffs. This is especially important for the solar panel industry given its large concentration of manufacturing activities in China and the China-specific tariff shocks. We assume that, given the *ex-ante* committed quantity Q^*_{ft}, manufacturer f needs a continuum of shipments k to fulfill Q^*_{ft}.

For each shipment k, it chooses its lowest cost location $l \in Z_f$. The potential *post-tariff* unit production cost at each location l for the shipment k depends on manufacturer productivity z^l_f, location-specific factor price w^l_t, and the manufacturer- and location-specific tariff rate τ^l_{ft}. There is also a random shock to shipment k for each l denoted as ε^l_k:

$$c^l_{fkt} = (z^l_f \varepsilon^l_k)^{-1} w^l_t \tau^l_{ft} \; .$$

ε^l_k is IID across all locations and orders and distributed Fréchet with mean T^l and shape parameter θ. The randomness captures any idiosyncratic reason that a specific shipment deviates from the average productivity in a location. Using results from the seminal work of

Eaton and Kortum (2002), the resulting minimal cost distribution is

$$F_{Z^f}(c) = 1 - exp\left(-\Phi_{ft} c^{\theta}\right), \quad \text{where } \Phi_{ft} = \sum_{l \in Z_f} T^l (z_f^l)^{\theta} (w_t^l \tau_{ft}^l)^{-\theta} .$$

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

$$c_{ft} = (\Phi_{ft})^{-1/\theta} \Gamma \left[\frac{\theta + 1}{\theta}\right] . \tag{2}$$

Intuitively, the cost to a manufacturer's subsidiary (c_{ft}) depends on the combined post-tariff cost of all its production locations (Φ_{ft}). 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.

6 Estimation

We outline model estimation 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.

6.1 Demand for Solar Panels

We estimate a series of constant elasticity demand models:

$$\log(Q_t) = \alpha_{0(t)} + \epsilon^D_{(t)} \log\left((1 - s_t) p_t\right) + \varepsilon^a_t \tag{3}$$

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.[15] Solar energy investors can also benefit from the tax advantage of accelerated depreciation as well as state and local subsidies.[16] We use $s_t = 0.4$ to capture these policies in a tractable manner.[17]

We allow for time-varying demand intercepts in some specifications via the inclusion of year fixed effects, $\alpha_{0(t)}$. Similarly, we allow for variation in the demand elasticity over time in some specifications through interaction terms and sample restrictions. We estimate equation 3 using ordinary least squares.

6.2 Supply Estimation

Given demand estimates, wholesale panel prices, and market shares, we can compute manufacturers' implied costs from their first order condition using equation (1). In a parsimonious version of the model, we use a constant demand elasticity, $\epsilon_t^D = \epsilon^D$. Alternatively, we can use a time-varying elasticity from aggregating demand from the residential and utility-scale solar markets.[18] Both approaches yield estimates of manufacturers' costs, $\widehat{c}_{ft}$.

In the production sourcing model, expected marginal costs are given by equation (2). Under the assumption that the manufacturer-specific productivity component z_f^l is common across locations within each manufacturer, we can take the log of equation (2) to derive our estimating equation:

$$\log\left(\widehat{c}_{ft}\right) = -\frac{1}{\theta}\log\left(\sum_{l\in Z_f}\left(\frac{w_t^l \tau_{ft}^l}{T^l}\right)^{-\theta}\right) + \alpha_f + \beta_t + \varepsilon_{ft} \; . \tag{4}$$

We use manufacturer fixed effects, α_f, to absorb manufacturer-specific productivities. Time fixed effects, β_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 (4), 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

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

[16] 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.

[17] 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 I employs additional microdata that account for these policies.

[18] See Appendix I for details.

model, so we normalize wages, tariffs, and location-specific productivity terms relative to the U.S.

We use non-linear least squares to estimate T^l, α_f, and β_t for different values of θ based on a range of values from the prior literature.

7 Estimation Results

7.1 Demand Estimates

Aggregate demand estimates from the constant elasticity specification are shown in Table 3. The estimates are directly interpretable as elasticities of total solar panel demand with respect to the price of solar panels. The estimated elasticities range from -1 to -2 across all specifications. These are consistent with both OLS and IV estimates from Gerarden (2023), who uses earlier data to estimate similar models. Furthermore, they are quite similar to aggregate elasticity estimates obtained by separately estimating downstream demand for solar installations from the utility and non-utility market (see Appendix Figure I.2). For supply estimation and counterfactual analysis, we use the simplest specification in the first column, which is the median elasticity across the estimates.

Table 3: Estimated Demand Elasticities

	log(Quantity)			
	(1)	(2)	(3)	(4)
log(Wholesale price)	-1.46***	-1.45***	-1.97**	
	(0.11)	(0.11)	(0.81)	
log(Wholesale price) × pre-tariffs				-1.60***
				(0.21)
log(Wholesale price) × post-tariffs				-1.28***
				(0.24)
Quarter Fixed Effects		Y		
Year Fixed Effects			Y	
Observations	43	43	43	43
R^2	0.80	0.81	0.91	0.81
Within R^2		0.81	0.18	

Notes: This table presents estimated price elasticities of demand (i.e., $\widehat{\epsilon}^D_{(t)}$ from equation 3). All columns are estimated via ordinary least squares. The final column presents results from a fully interacted model that allows for a different demand intercept and different elasticity of demand for earlier and later time periods. The pre-tariff period is 2010 through the first quarter of 2014. The post-tariff period is the second quarter of 2014 through the third quarter of 2020. Heteroskedasticity-consistent standard errors are in parentheses.

7.2 Supply Estimates

Table 4 presents estimates of the location-specific productivity terms in equation (4) 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.

Table 4: Location-Specific Productivity Estimates

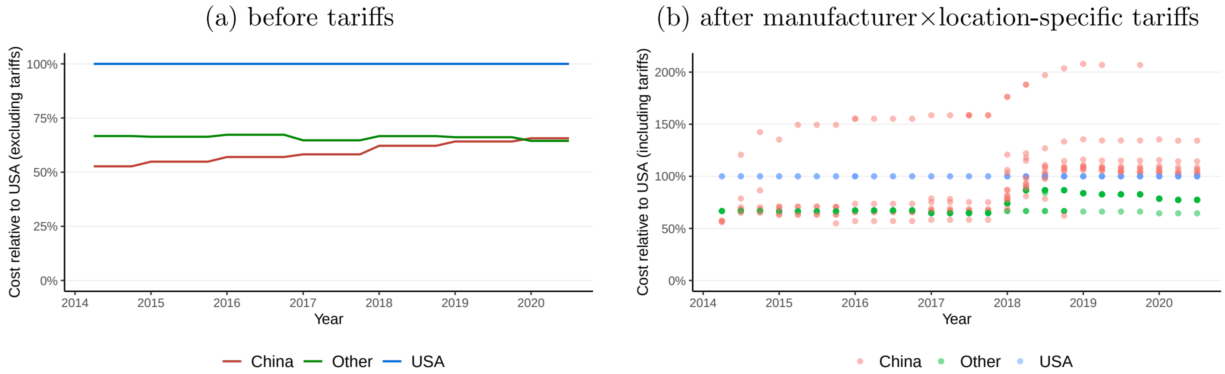
	(1)	(2)	(3)
Other's relative state of technology ($\widetilde{T}_{other}$)	0.71***	0.67***	0.65***
	(0.07)	(0.04)	(0.03)
China's relative state of technology ($\widetilde{T}_{china}$)	0.34***	0.32***	0.31***
	(0.04)	(0.02)	(0.02)
Num.Obs.	751	751	751
θ	5.00	7.50	10.00

Figure 6a 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.[19] The model predicts that manufacturing 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 6b 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 4. In the period before tariffs were imposed, China was the least costly production location. After the 2014 antidumping and countervailing duties were

[19]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 4 separately for each location, using predicted values for T^l and with no tariffs (i.e., $\tau^l_{ft} = 0$). This corresponds to the relative production costs of each location for a thought experiment in which a given firm manufactured in one location 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.

Figure 6: Location-Specific Cost Predictions



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.

8 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.1 presents analogous results holding the set of production locations each manufacturer has fixed.

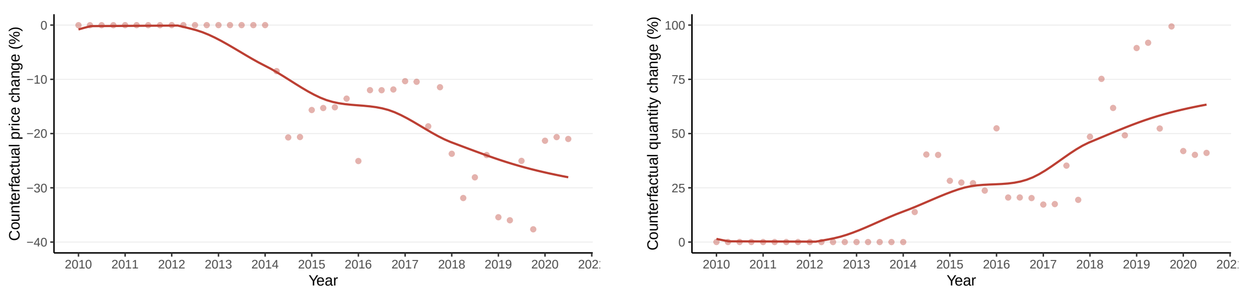
8.1 Tariff Removal

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 4, 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 7. The first column of numbers in Table 5 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 much lower with tariffs than without.[20] The tariffs made domestic and tariff-exempted producers better off, though the benefits to producers are small relative to the harms to consumers and third parties. Foreign producer surplus would have been lower with tariffs, enough so that aggregate producer surplus would have been lower on net. Finally, government revenue was higher due to an increase in tariff revenue and a decrease in tax expenditures to subsidize solar adoption.

Figure 7: 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. 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 6 presents a back-of-the-envelope calculation of the domestic employment impacts of the tariffs. We do so by multiplying the models' predictions for changes in domestic manufacturing and solar adoption by the average labor intensity of each activity derived from ancillary data. 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

[20]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 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).

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 7 presents an analogous calculation that incorporates wage data for solar manufacturing and installation jobs to put the employment numbers in context. Installation jobs have lower wages, so this reduces the relative contribution of installation wages, but they are still four times larger than the change in manufacturing wages.

Table 5: Welfare Impacts

	Impacts over 2010-2020 ($, billions):	
	Actual Tariffs	Counterfactual Subsidy
Δ in Consumer Surplus	-7.4	1.3
Δ in Producer Surplus	-5.3	-0.4
Δ for Non-tariff-exposed	2.2	0.0
Δ for Tariff-exposed	-7.4	-0.5
Δ in Government Revenue	14.3	-7.2
Δ in Tariff Revenue	2.8	0.0
Δ in Adoption Subsidy Expenditure	-11.4	2.0
Δ in Manufacturing Subsidy Expenditure	0.0	5.2
Δ in Environmental Benefits	-97.3	22.1
Δ in Local Pollution Benefits	-65.5	14.9
Δ in Global Pollution Benefits	-31.8	7.2
Δ in Domestic Welfare	-56.6	8.9
Δ in Total Welfare	-95.8	15.7

Note: The change in domestic surplus excludes changes in producer surplus for tariff-exposed manufacturers as well as changes in global pollution benefits (some of which are domestic and some of which spill over to other countries due to the nature of global pollutants).

Table 6: Domestic Employment Impacts (job-years)

	Impacts over 2010-2020 (job-years, thousands):	
	Actual Tariffs	Counterfactual Subsidy
Δ in Manufacturing job-years	89.8	864.6
Δ in Installation job-years	-460.0	95.4
Δ in Total job-years	-370.1	960.0

Table 7: Domestic Employment Impacts (wages)

	Impacts over 2010-2020 (wages, billions):	
	Actual Tariffs	Counterfactual Subsidy
Δ in Manufacturing wages	5.5	52.5
Δ in Installation wages	-21.3	4.4
Δ in Total wages	-15.8	56.9

8.2 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 Inflation Reduction Act 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.

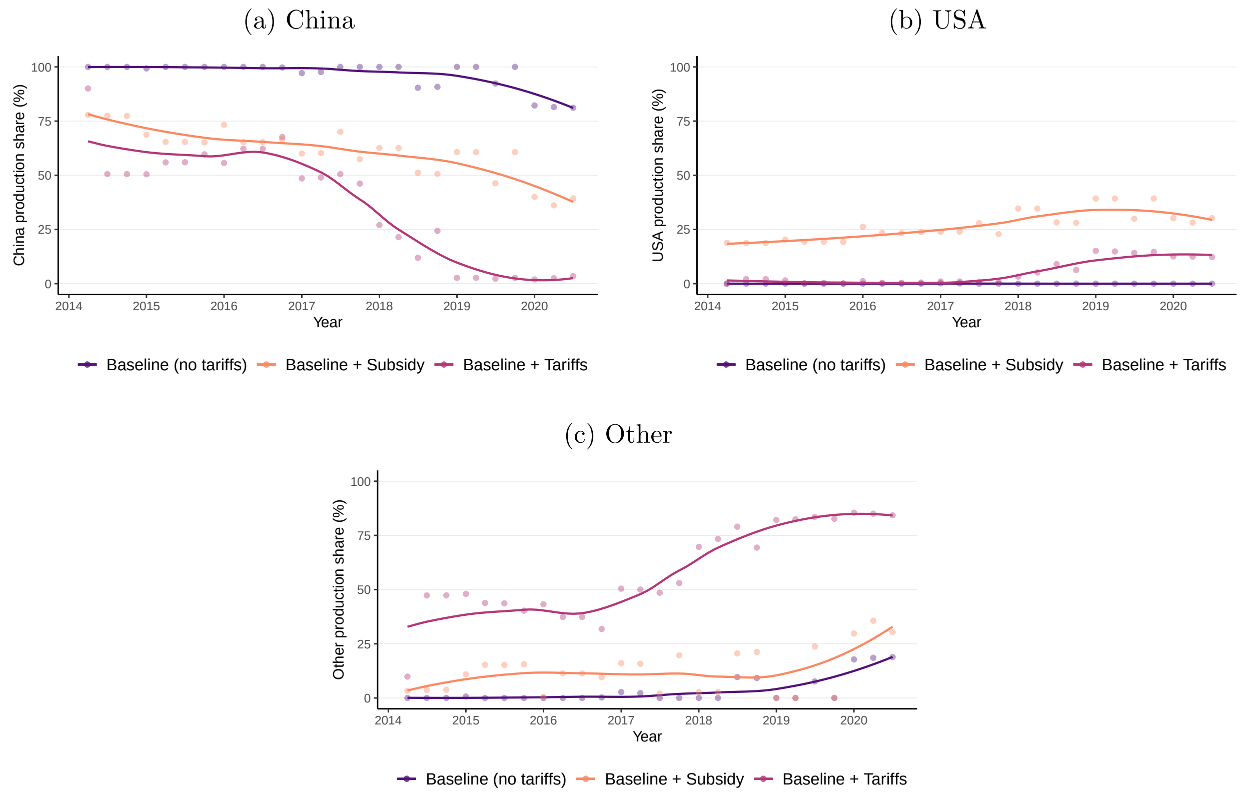
The production subsidy leads to lower prices and higher quantities in equilibrium, relative to the scenario with no tariffs and no production subsidy. In contrast to *both* the status quo ("Baseline + Tariffs") and the scenario with no tariffs ("Baseline (no tariffs)"), the domestic production subsidy yields a large increase in the share of solar panels produced domestically (Figure 8).[21] 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 manufacturing impacts need to be weighed against their fiscal cost as well as their broader impacts.

The final column of Table 5 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.[22]

[21]To assess model fit, Appendix Figure G.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.

[22]This result is primarily driven by the presence of an underpriced environmental externality. In principle,

Figure 8: Counterfactual Production Shares



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 H.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.

Tables 6 and 7 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.

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.

9 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*.

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 Inflation Reduction Act 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 address environmental externalities, avoid creating misallocation in manufacturing activity, and thereby yield larger welfare gains.

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Appendix

A Aggregate Trends

Figure A.1: Solar panel prices over time

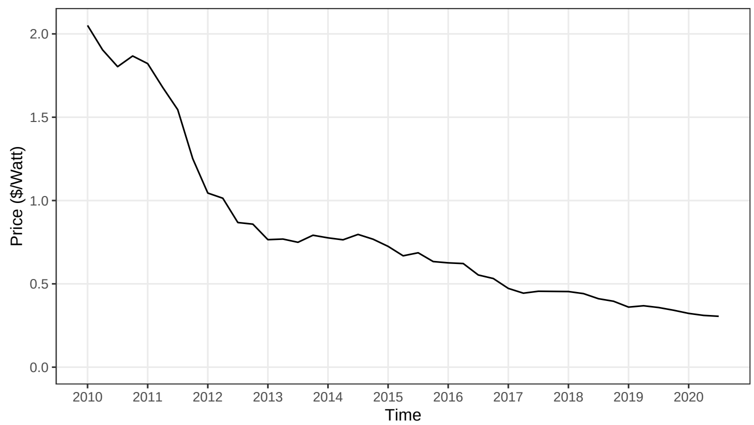
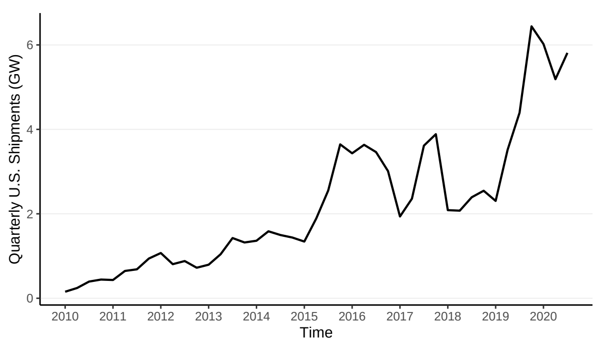
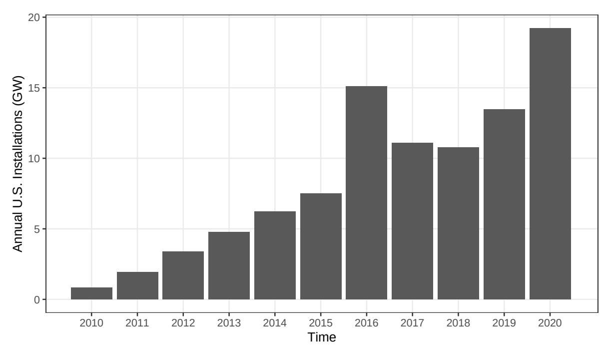


Figure A.2: Solar panel quantities over time

(a) Shipments (IHS Markit)

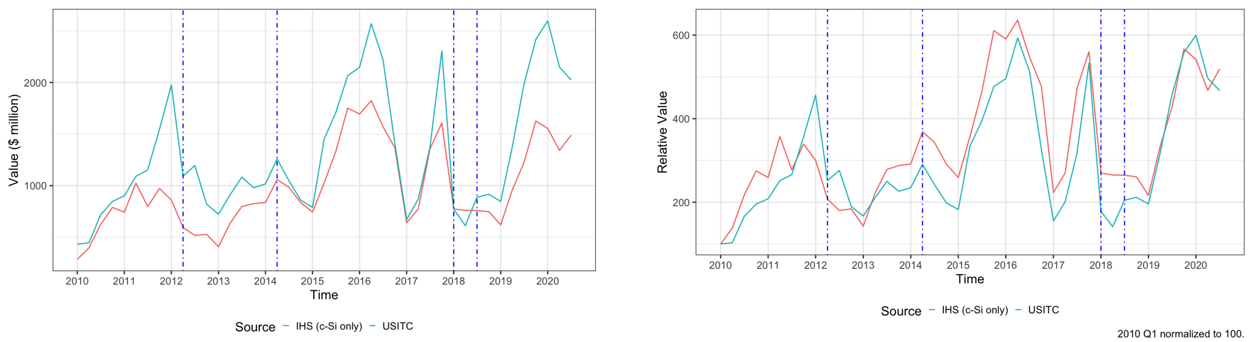


(b) Installations (SEIA)



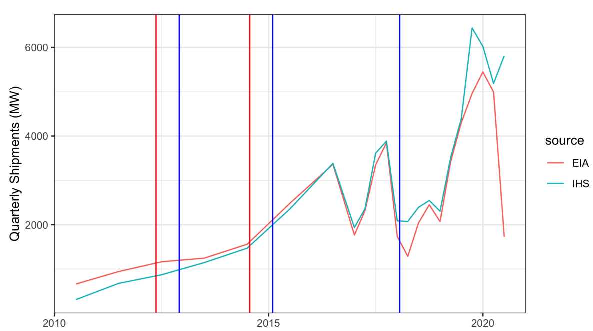
B Comparison of IHS Markit and Government Data

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.

Figure B.2: Comparison of IHS shipments to EIA shipment records



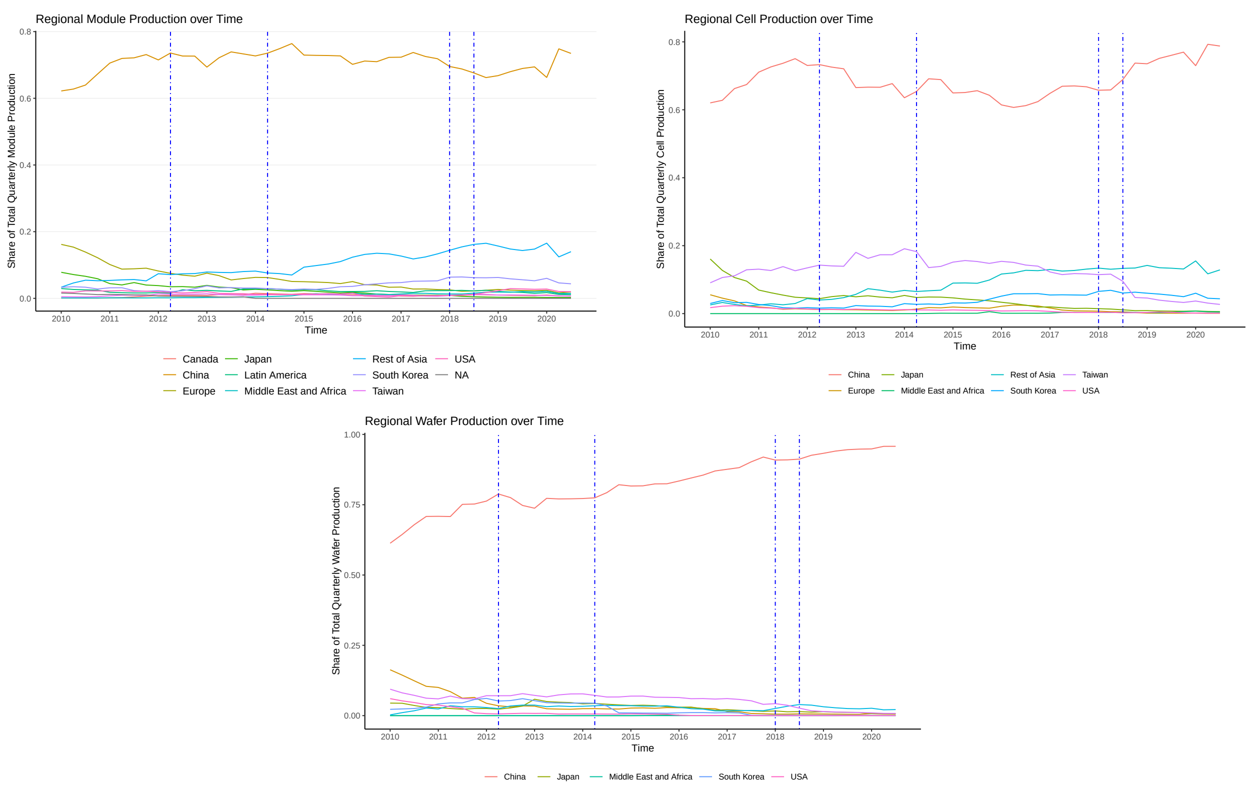
Note: This figure plots a comparison of shipment quantities (MW) between IHS and the U.S. Energy Information Administration (EIA). The EIA data are reported annually until 2016, so we compute the annual equivalent from IHS Markit from 2010 through 2016, after which we compare shipments on a quarterly basis.

C Geographic Distribution of Production

C.1 Global Production Shares by Region

Figure C.1 plots production activity by region over time. The cell production time series 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. 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.1: Global Production Shares by Region



C.2 Production Offshoring by Chinese and Taiwanese Manufacturers

This appendix summarizes changes in the geographic distribution of manufacturers' production over time, both for manufacturers that produced in China or Taiwan prior to the 2014 tariffs and for their competitors who were not subject to tariffs. We classify manufacturers based on their production locations prior to the 2014 tariffs and focus on impacts in the latter half of the sample period due to anecdotes of easy avoidance of the 2012 tariffs first round of AD/CVD.

Figure C.2 focuses in on manufacturers that operated in China or Taiwan prior to the 2014 tariffs, plotting the share of these manufacturers' production in China and Taiwan over time. The first panel is the mirror image of Figure 2 in the main text, and it shows that the share of panels produced in China by manufacturers that produced panels in China prior to the 2014 tariffs gradually fell after the 2014 tariffs took effect. A similar pattern is evident when considering both Chinese and Taiwanese panel manufacturers together.

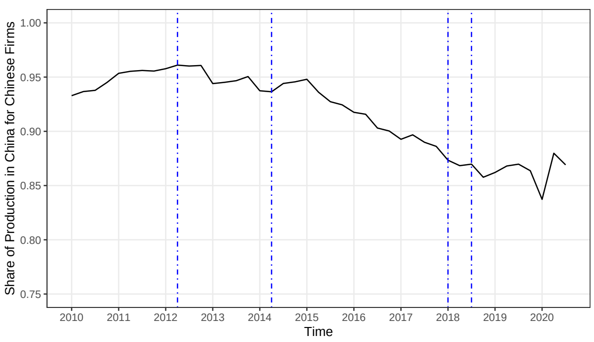
The geographic distribution of solar cell production is even more stark. At the beginning of the sample period, the manufacturers that operated in China and Taiwan operated in those countries exclusively. After the 2014 tariffs took effect, those manufacturers expanded their overseas operations to produce approximately 10 percent of their solar cells outside China and Taiwan from 2017 through 2020.

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

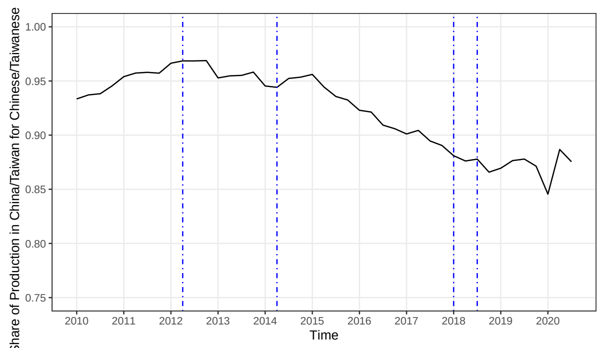
Figure C.2: Share of Production in China/Taiwan for Chinese/Taiwanese Manufacturers

sample restricted to manufacturers that produced in China/Taiwan before 2014 AD/CVD

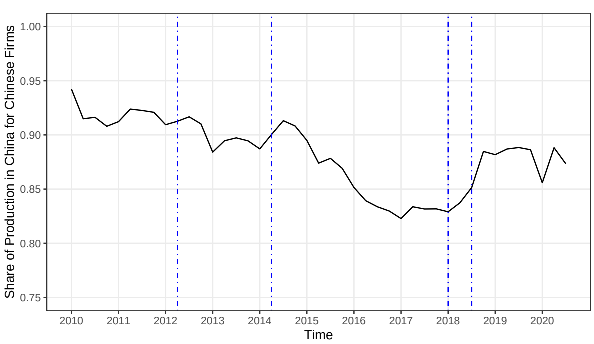
(a) Panels - China



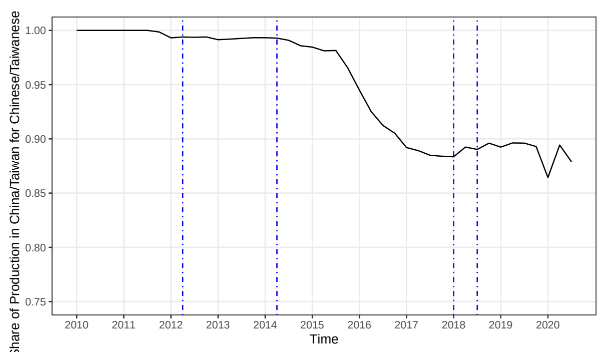
(b) Panels - China and Taiwan



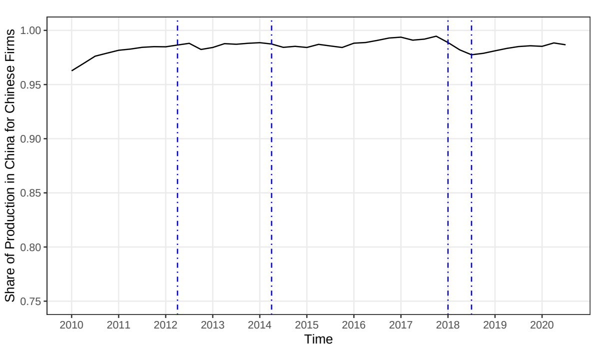
(c) Cells - China



(d) Cells - China and Taiwan



(e) Wafers - China



(f) Wafers - China and Taiwan

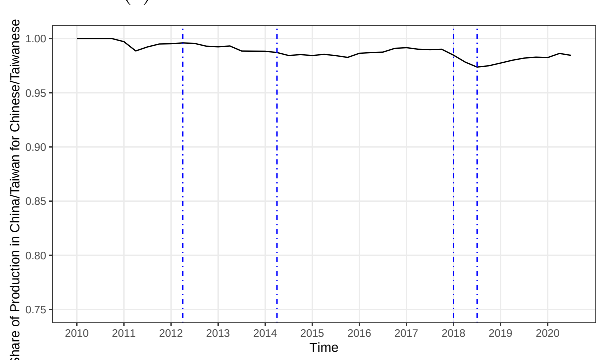
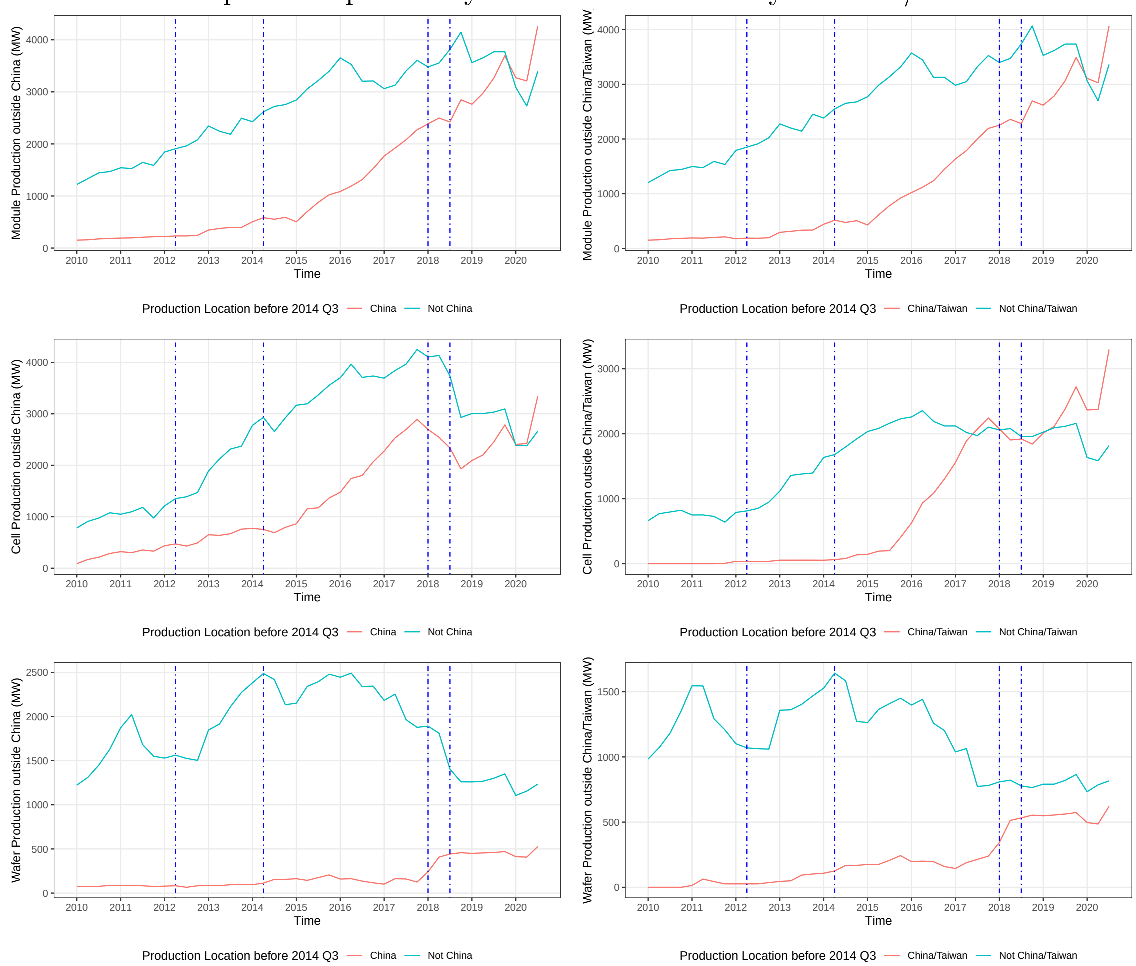


Figure C.3 plots total production activity *outside* China and Taiwan over time, comparing manufacturers that operate in China and Taiwan to manufacturers that do not. As before, the classification of manufacturers into Chinese/Taiwanese and not Chinese/Taiwanese is based on production locations prior to the 2014 tariffs. The manufacturers that do not manufacture in China and Taiwan prior to the 2014 tariffs provide an informal control group.

Figure C.3: Production Outside China/Taiwan by Tariff Exposure Groups

tariff exposure is proxied by manufacturers' activity in China/Taiwan



The patterns in Figure C.3 provide additional evidence 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 and Taiwanese manufacturers increased their panel and cell production in countries other than China and Taiwan faster than the rate at which unaffected manufacturers increased their production in the same countries. The effect is most pronounced when looking at cell manufacturers with a manufacturing presence in China and/or Taiwan (middle right panel). Wafers provide an informal placebo test, as they are not covered by the duties.

D Construction of Strategic Tariff Rates

Section 4 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 4.6 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 $\text{Tariff}_{flt,X}$ denote the statutory tariff rates applying to manufacturer f's production in location l at time t under tariff round X.[23] 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

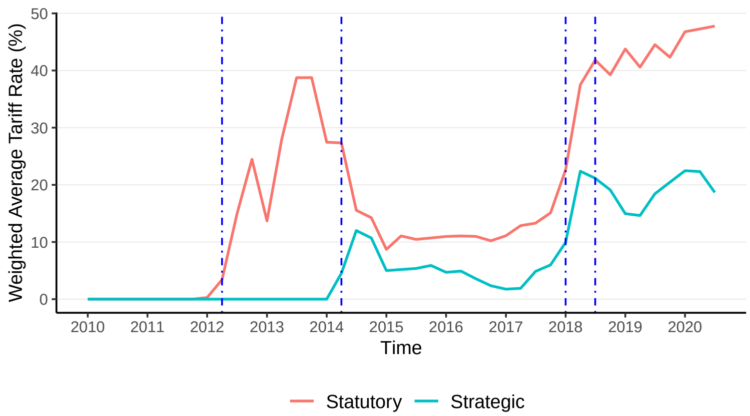
$$\begin{aligned}
\text{Strategic Tariff}_{ft} = \min_{\mathbf{q}_{ft}} \sum_{l} \Big(& \min\{\text{Statutory Tariff}_{flt,2012},\ \text{Statutory Tariff}_{flt,2014}\} + \\
& \text{Statutory Tariff}_{flt,S201} + \text{Statutory Tariff}_{flt,S301}\Big) \frac{q_{flt}}{Q_{ft}} \\
& \text{subject to} \sum_{l}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

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.[24]

[23] 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.

[24] 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



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

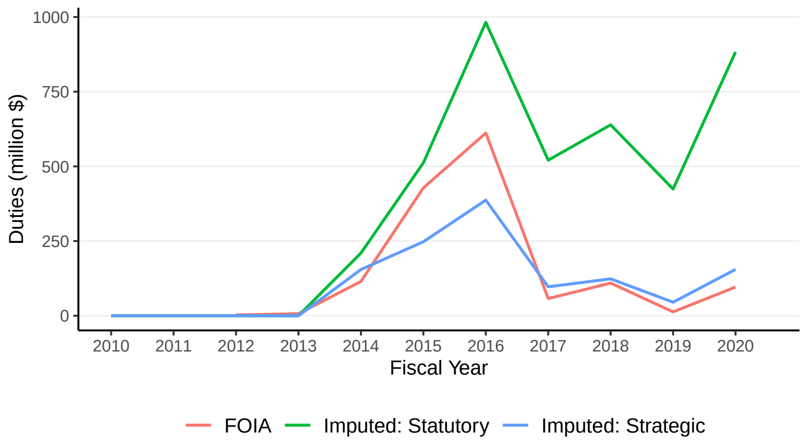


Table E.1: Section 201 Tariffs

	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

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: The Solar System Production Steps

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. Polysilicon and wafers, both exempt from tariffs, are reported separately. 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.[25] To facilitate comparisons, we converted all three time series from trade values to gigawatts of electricity capacity using price indices for each product category.

[25] 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 the USITC 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 Southeast Asia (annual)

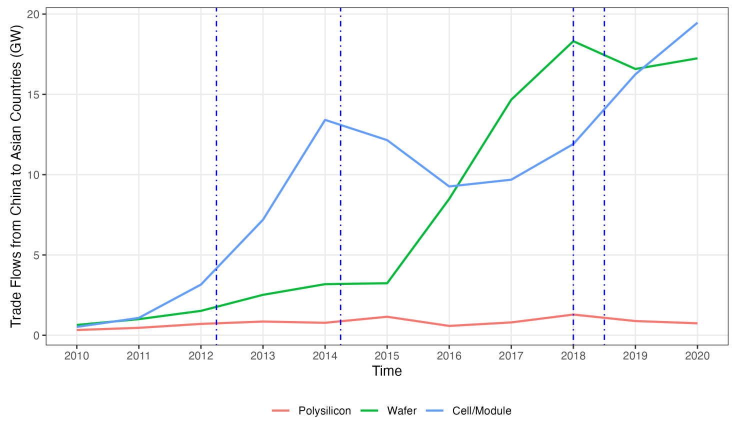


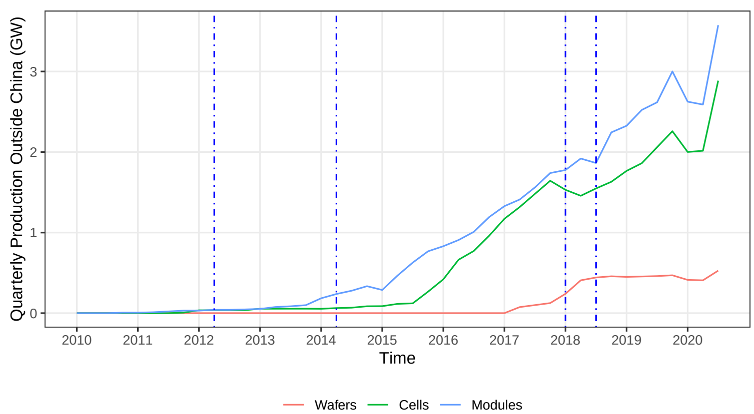
Figure F.2 shows that Chinese exports of polysilicon to other parts of Southeast Asia are flat and low in comparison to other solar products. By contrast, Chinese exports of wafers increase significantly after the 2014 tariffs go into effect. Wafers are the last stage of intermediate goods production 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 simply evading tariffs, there would be no reason to export wafers. Finally, Chinese exports of cells and panels to Southeast Asia also increase over time. However, this trend precedes 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 Southeast Asia than by tariff evasion.

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.

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 operated in China prior to tariffs. The figure was made using reported production levels from IHS. The increase in cell and panel production outside China after 2014 is consistent with manufacturers offshoring production of cells and panels to avoid U.S. antidumping and countervailing duties. By contrast, the figure shows no concomitant offshoring of wafer production, which is intuitive since wafers produced in China were not subject to duties.

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



G Model Fit

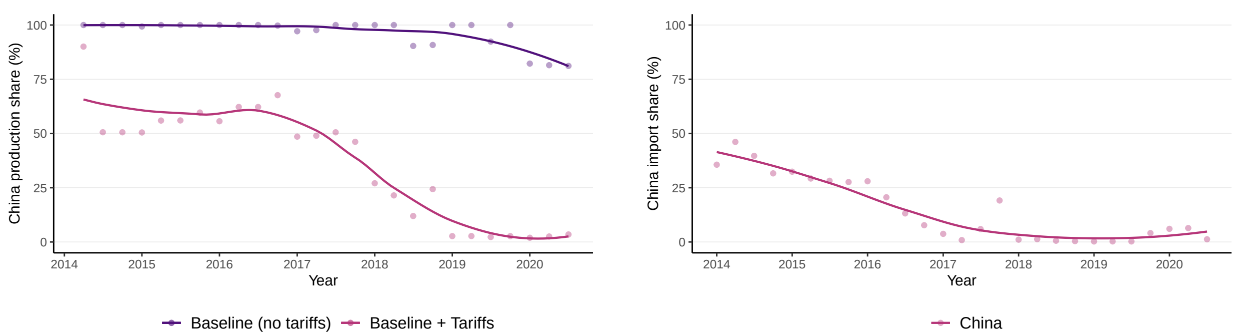
G.1 Model-Predicted Production Shares vs Observed Import Shares

The counterfactual analysis summarized in Figure 8 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 G.1 compares production shares predicted by the model to import shares recorded by the USITC.

Figure G.1: China's Share over Time

(a) Model Predictions (b) USITC Import Data



H Additional Counterfactual Results

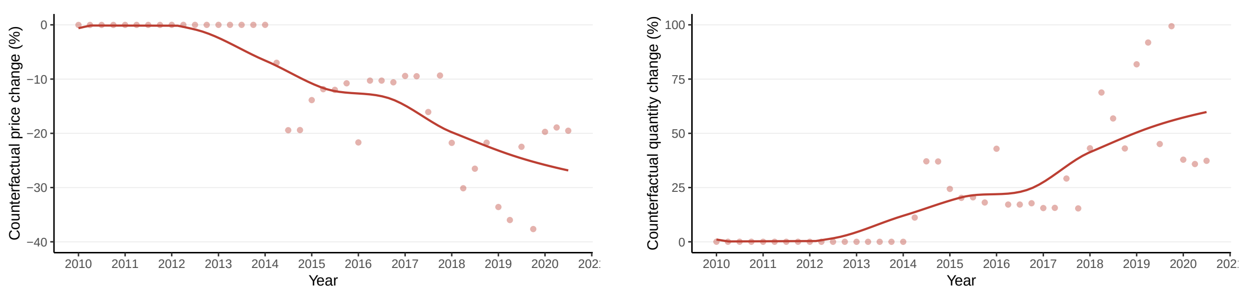
H.1 Model Predictions Holding Manufacturing Capacity Fixed

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 4, 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 H.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. In the counterfactual scenario with no tariffs, each firm's set of production locations is unchanged from the status quo (though the production shares are allowed to respond endogenously). Points denote model predictions for each quarter under the baseline model estimates. Lines are smoothed conditional means, predicted using local linear regression.

Table H.1: Welfare Impacts

	Impacts over 2010-2020 ($, billions):	
	Actual Tariffs	Counterfactual Subsidy
Δ in Consumer Surplus	-6.7	0.3
Δ in Producer Surplus	-4.4	0.0
Δ for Non-tariff-exposed	2.2	0.1
Δ for Tariff-exposed	-6.6	-0.2
Δ in Government Revenue	13.1	-1.6
Δ in Tariff Revenue	2.8	0.0
Δ in Adoption Subsidy Expenditure	-10.3	0.4
Δ in Manufacturing Subsidy Expenditure	0.0	1.2
Δ in Environmental Benefits	-88.4	4.1
Δ in Local Pollution Benefits	-59.5	2.8
Δ in Global Pollution Benefits	-28.9	1.3
Δ in Domestic Welfare	-51.0	1.5
Δ in Total Welfare	-86.4	2.7

Note: The change in domestic surplus excludes changes in producer surplus for tariff-exposed manufacturers as well as changes in global pollution benefits (some of which are domestic and some of which spill over to other countries due to the nature of global pollutants).

Table H.2: Domestic Employment Impacts (job-years, aggregate demand model)

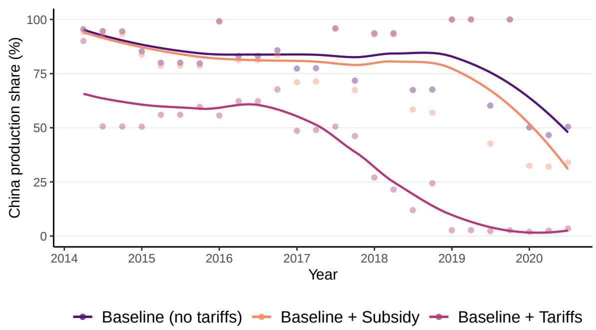
	Impacts over 2010-2020 (job-years, thousands):	
	Actual Tariffs	Counterfactual Subsidy
Δ in Manufacturing job-years	78.8	130.8
Δ in Installation job-years	-412.2	17.0
Δ in Total job-years	-333.3	147.8

Table H.3: Domestic Employment Impacts (wages, aggregate demand model)

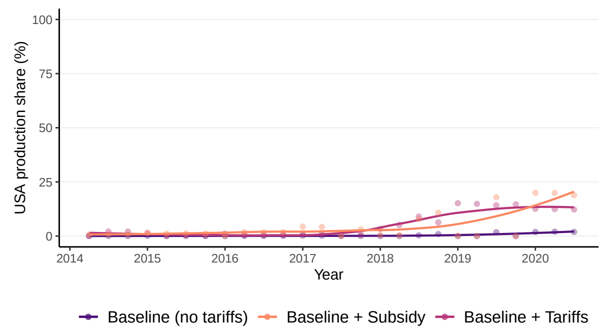
	Impacts over 2010-2020 (wages, billions):	
	Actual Tariffs	Counterfactual Subsidy
Δ in Manufacturing wages	4.8	7.9
Δ in Installation wages	-19.1	0.8
Δ in Total wages	-14.3	8.7

Figure H.2: Counterfactual Production Shares

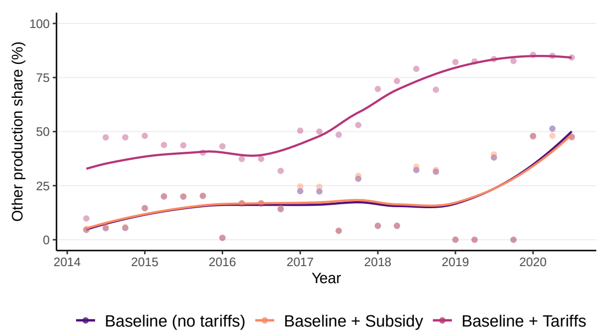
(a) China



(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 all three cases, 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.

I Robustness Analysis: Detailed Demand Model

I.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.

I.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.

I.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

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

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

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

where m_t^u is the potential market size.

I.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.[26] 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:

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

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

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

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

[26] 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:

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

where the inclusive value of installation is defined as

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

Given a Markovian perceived transition of $(\xi_{t+1}, \mathbf{x}_{t+1})$ and the mean utility function $\delta(\cdot)$, equations I.3, I.4, and I.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 $\epsilon_{jt}^c \equiv \frac{\partial \ln s_{jt}}{\partial \ln p_{jt}^s}$. 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).

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

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

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

I.3 Estimation

I.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:

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

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.

I.3.2 Residential and Commercial Market Demand Estimation

As we laid out in the model section I.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 I.3 and I.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 $\bar{V}(\mathbf{x}_{t+1}) \equiv \gamma_{euler} + \ln\left[exp(\delta_0(\mathbf{x}_{t+1})) + D_I(\mathbf{x}_{t+1})^{1-\sigma}\right]$ 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

$$\delta_0(\mathbf{x}_t) \equiv \beta E_t\left[\bar{V}(\mathbf{x}_{t+1})|\mathbf{x}_t\right] = \beta E_t\left[\delta_{1t+1} - \sigma \log P^I(\mathbf{x}_{t+1}) - (1-\sigma)\log P_1(\mathbf{x}_{t+1})\Big|\, \mathbf{x}_t\right] \quad \text{(I.6)}$$

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 I.6, we have

$$\log s_{jt} - \log s_{0t} = \delta_{jt} + \sigma \log s_{j|It} - \beta E_t\left[\delta_{1t+1} - \sigma \log P^I(\mathbf{x}_{t+1}) - (1-\sigma)\log P_1(\mathbf{x}_{t+1})|\mathbf{x}_t\right] \quad \text{(I.7)}$$

The above equation I.7 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 (I.7) 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.[27] 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).

I.4 Estimation Results

I.4.1 Utility-Scale Market Demand Estimates

Utility-scale demand estimates are shown in Table I.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:

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

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

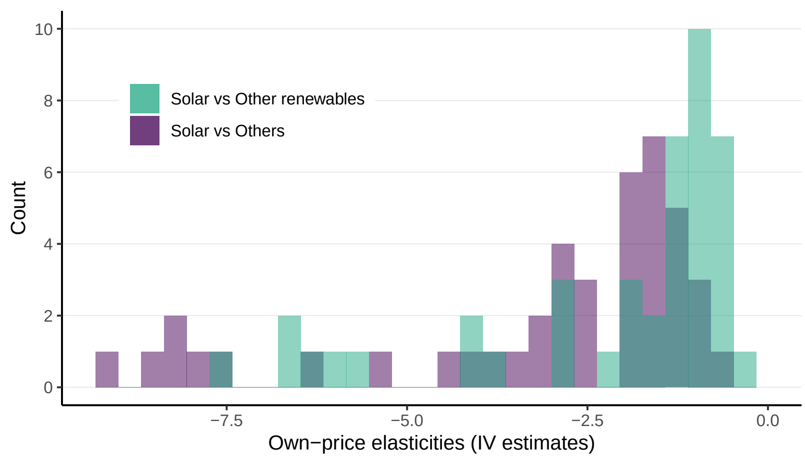
Figure I.1 presents the distribution of these elasticities across time periods.

Table I.1: Utility-Scale Demand Estimates

	$log(s_{solar}) - log(s_{allother})$			$log(s_{solar}) - log(s_{renewables})$		
	(1)	(2)	(3)	(4)	(5)	(6)
Solar panel price (after subsidy)	-2.49***	-2.48***	-4.47***	-2.14***	-2.12***	-3.66**
	(0.33)	(0.32)	(1.12)	(0.34)	(0.33)	(1.78)
Year Fixed Effects			X			X
Estimator	OLS	IV	IV	OLS	IV	IV
Observations	43	43	43	43	43	43
R^2	0.66	0.66	0.78	0.57	0.57	0.81

Notes: The table presents four regressions of the specification $\delta_t^u = \alpha_0^u + \alpha^u w_t + \epsilon_t^u$. In columns 1-3 the market is defined as solar vs all other electricity capacity additions (no additional outside good). In columns 4-6 the market is defined as solar vs all other renewable capacity additions (no additional outside good). The instrumental variable in columns 2, 3, 5, and 6 is the solar price outside the USA. Heteroskedastic robust standard errors are in parentheses. Significance levels are denoted as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure I.1: Utility-Scale Demand Elasticity Estimates



I.4.2 Residential and Commercial Market Demand Estimates

Residential and commercial demand estimates are shown in Table I.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).

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

Table I.2: Residential and Commercial Demand Estimates

	OLS	IV		
Variable		1st Stage, price	1st stage, nest	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%.

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.

I.4.3 Aggregate Elasticity Estimates

Figure I.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 baseline constant elasticity specification 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 I.2: Combined Elasticity Estimates