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

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Abstract

This study examines the consequences of U.S. tariffs on imported solar panels. We first show that tariff-exposed firms shifted production to non-tariffed locations and that domestic prices increased relative to other markets. We then develop a structural model to assess welfare effects. Our results indicate that the tariffs generated modest gains for domestic manufacturers and for government revenues, but larger losses in domestic consumer surplus and environmental benefits, thereby reducing domestic welfare. Furthermore, the tariffs *reduced* employment and wages in the domestic solar industry. In contrast, subsidizing solar panel manufacturing could increase domestic production, employment, and overall welfare.

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1 Introduction

Trade and industrial policies have experienced a global resurgence in recent years. Economic theory offers several potential justifications for trade policy interventions under specific circumstances. A large country might leverage its monopsony power in international markets by influencing the terms of trade. This incentive is particularly strong when foreign exporters possess significant market power (Brander and Spencer, 1984; Venables, 1985). In such cases, imposing tariffs on imports could enhance domestic welfare if the resulting tariff revenue and increase in domestic firm profits outweighs the negative impact on domestic consumers. Many traditional arguments for infant industry protection, such as Marshallian externalities and external scale economies, can further add to the above rationales (Harrison and Rodríguez-Clare, 2010).

A prime real-world example reflecting this line of thinking is the series of tariffs imposed on solar photovoltaic products imported into the U.S. At first glance, this industry exhibits many of the key elements highlighted in the theoretical trade policy literature: it is a relatively young, rapidly growing sector dominated by a handful of large foreign competitors that produce homogeneous, commodity-like products. U.S. policy has focused on large Chinese solar panel manufacturers, who faced antidumping and countervailing duties starting in 2012, followed by additional measures in 2014 and 2018. In 2018, the U.S. also introduced broader "safeguard" tariffs aimed at protecting domestic industry from all foreign competition.

This paper examines the effectiveness and welfare implications of the U.S. solar tariffs. We identify three critical factors that must be considered in evaluating these policies. First, large solar manufacturers are multinational firms capable of relocating production to jurisdictions that are not subject to tariffs. Second, manufacturer production choices may influence, and be influenced by, external economies of scale within each jurisdiction. Third, demand for solar panels has been actively subsidized in the U.S. because they provide benefits by reducing environmental externalities. These factors affect the trade-offs between U.S. consumer welfare, government revenue, and domestic producer surplus in response to trade policy shocks.

We begin by presenting evidence on the production relocation strategies employed by Chinese manufacturers in response to multiple rounds of U.S. tariffs. Next, we show that, despite these strategic adjustments, the overall price of solar products in the U.S. market ultimately surpassed the price in other major global markets. To understand the equilibrium implications of these tariffs, we develop a structural model of oligopolistic competition in the solar panel market, where manufacturers can source their U.S. shipments from multiple production locations. By combining our estimates of solar demand with detailed data on solar panel manufacturing activity and tariffs, we uncover country- and firm-specific capabilities in solar production. We find that the multiple rounds of U.S. solar tariffs led to modest gains for solar panel producers with domestic manufacturing facilities, but major losses in domestic consumer surplus and reduced environmental benefits. If manufacturers had not been able to relocate production in response to tariffs, the negative welfare effects would have been roughly one-quarter larger in magnitude. We do not find evidence that external economies of scale could justify the tariffs. By contrast, an industrial policy consisting of a modest subsidy for domestic solar panel manufacturing could increase welfare from both domestic and global perspectives given the presence of environmental externalities.

We develop our empirical findings in three steps. First, we compile unique data on solar shipments and production at the individual firm level over the past decade. These data reveal that Chinese manufacturers, in aggregate, quadrupled their offshore manufacturing as a share of total production, rising from just 5 percent in 2012 to 20 percent by 2019. This offshoring was primarily concentrated in Southeast Asia. We conduct an event study comparing Chinese firms exposed to U.S. tariffs to those who were not and provide clear evidence on how tariffs impact the offshoring response by Chinese firms. We also use the event study framework to compare prices for solar panels in the U.S. market to other markets around the world, and find that prices in the U.S. increased relative to other markets after tariffs went into effect.

In the second step, we model the U.S. market for solar panels by treating the electricity generation capacity of solar panels as a homogeneous product.[1] Aggregate demand for solar panels depends on the price of solar panels, government subsidies, and a set of fixed effects capturing unobserved time-varying demand shifters. We instrument for price using supply shifters, including the prices of inputs and the foreign (non-U.S.) price of solar panels, which is a 'Hausman instrument' serving as an indirect cost shifter. We find robust own-price elasticities of demand between -1.3 and -1.5, consistent with prior work (Gerarden, 2023).[2]

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 U.S. to compete in the wholesale market. We model manufacturers engaging in static Cournot competition.[3] Static Cournot competition implies a first-order condition for manufacturers' optimal quantity choices, which we use to recover estimates of post-tariff costs for manufacturers over time. We micro-found those costs by developing a model of manufacturer production sourcing using results from

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

[2]In a robustness analysis, we use additional microdata to estimate separate demand models for solar installations in the utility and non-utility sectors, and we find that the aggregate derived elasticity of demand for solar panels from these micro-founded models is very similar to estimates from our primary model.

[3]This is supported by the commoditized nature of solar panels. In the data, there is very little price dispersion across manufacturers, which we summarize in Figure B.1.

Eaton and Kortum (2002). Our model allows for the possibility of external economies of scale within each production location, building on recent work by Kucheryavyy et al. (2023).

We estimate the determinants of firms' production costs in stages. We start by using within-firm variation in production shares to identify and flexibly recover estimates of how cost efficiency varies across manufacturing locations and over time relative to the U.S. To test for external economies of scale, we project those cost efficiency estimates on measures of industry scale and fixed effects to capture the effect of external economies of scale at the location level. We then embed our preferred predictions from this analysis in the model of Cournot competition to recover the separate influences of exogenous industry-wide technological change and firm-specific productivity.

The cost efficiency and production cost estimates are intuitive and consistent with our model-free evidence. Absent tariffs, the cost of manufacturing solar panels in China over the period 2010 through 2020 is predicted to be about two-thirds the cost of manufacturing in the U.S. (all else equal). The cost of manufacturing in other solar-producing countries lies between the costs of manufacturing in China and the U.S. After accounting for the U.S. tariffs that targeted products from China beginning in 2014, manufacturing costs in China are on par with those of other solar-producing countries. After the additional, more broad-based, tariffs that went into effect in 2018, the U.S. becomes cost-competitive with other manufacturing locations. Finally, we find limited evidence of external economies of scale, with the most credible estimates pointing to scale elasticities that are not statistically distinguishable from zero.

In our third and final step, we conduct a set of counterfactual analyses to quantify the impacts of import tariffs, with and without strategic tariff avoidance via production relocation. Notwithstanding the ability of multinationals to relocate their production, the model predicts that the tariffs raised the price and lowered the quantity of solar panels. As a result, domestic consumer surplus was reduced. On the other hand, domestic producer surplus and government revenues increased. Prior to accounting for environmental considerations, the net effects of the tariffs were to harm both domestic and global welfare, even when accounting for external economies of scale. The net decrease in surplus would have been 30% larger in the absence of production relocation. Once we account for the presence of environmental externalities, the impact of the tariffs is even more negative. Consistent with observed production patterns, the domestic production share predicted by the model is small 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 the tariffs was to shift manufacturing from China to Southeast Asia, resulting in higher costs with little benefit in terms of either domestic producer surplus or national security.

We also conduct a back-of-the-envelope analysis of the domestic employment impacts of the tariffs. Imposing tariffs increased domestic manufacturing employment. However, the tariffs decreased downstream solar installation employment by more than they increased domestic manufacturing employment. This is because manufacturing labor demand depends on the number of solar panels that are produced domestically, whereas installation labor demand depends on the total number of solar panels consumed domestically, regardless of origin. On net, we find that import tariffs *decreased* domestic employment and wages in the solar industry.[4]

We conduct a second set of counterfactuals to quantify the potential effects of industrial policy as an alternative to trade policy. The Inflation Reduction Act (IRA) and the European Green New Deal have introduced policy mechanisms to mitigate climate change and hasten the energy transition. For example, the IRA established a manufacturing production tax credit for clean energy technologies produced in the U.S. We analyze a counterfactual modeled after this provision of the IRA.

Our model predicts that the domestic manufacturing subsidy would improve welfare relative to a scenario with no trade or industrial policy. This is primarily because it would, in a second-best manner, reduce the distortion created by underpriced environmental externalities.[5] We compare these impacts to a cost-equivalent subsidy that does not discriminate on the basis of solar panels' origins. That policy is more cost-effective, because it does not distort production, yielding larger benefits for both domestic and global welfare than a domestic manufacturing subsidy. Finally, manufacturing subsidies would increase employment in both solar manufacturing and solar installation, eliminate the conflicting employment impacts of imposing an import tariff on intermediate inputs like solar panels.

This work builds on the literature on the effects and incidence of U.S. trade policy. Flaaen et al. (2020) use import data and retail price data to examine how U.S. import restrictions on washing machines affect trade flows and prices.[6] By contrast, we focus on the market for solar panels, where interactions with environmental externalities are important determinants of welfare. We use rich production and sales data to provide detailed evidence of production offshoring in response to China-specific tariffs and to quantify its welfare implications. Despite these differences in approach, our descriptive results echo Flaaen et al.'s (2020) findings on the effects of antidumping duties, and our quantitative model underscores how production

[4]These solar industry estimates represent partial equilibrium results, as they do not account for offsetting impacts in other industries.

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

[6]Fajgelbaum et al. (2024) study how the U.S.-China trade war of 2018 affected the allocation and aggregate level of trade across sectors as well as countries.

relocation plays an important role in the welfare implications of tariffs. Our work also relates closely to Fajgelbaum et al. (2020), who estimate pass-through and the short-run impacts of tariffs across the U.S. economy. In our empirical context, the tariffs lead to significant firm-level adjustments in output and result in incomplete pass-through of tariffs to wholesale solar panel prices, driven by relocation and oligopolistic Cournot competition.

A related literature studies how targeted import tariffs affect multinational firms' decisions to offshore or relocate 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 understand firm responses and the implications of tariffs for the global cost structure of solar manufacturing, a policy-relevant empirical setting in which we observe the use of both targeted and broad-based tariffs. Our theoretical framework of multi-location production follows closely that of Ramondo and Rodríguez-Clare (2013) and Tintelnot (2017).

More recently, there has been a resurgence of empirical literature examining the role of trade and industrial policy in the presence of domestic distortions or external returns to scale.[7] Following Barwick et al. (2019), we focus on a case study of a single industry to provide clearer insights into the technology, market structure, and potential sources of scale economies. In ongoing work, Head et al. (2025) study the impact of industrial policy throughout the electric vehicle supply chain. Together with our analysis of the solar industry, this line of research traces out the effects of government intervention on strategic industries critical to decarbonization. Our analysis of U.S. tariff and subsidy policies also complements the broader cross-country quantification by Bartelme et al. (2019), who examine the role of industrial and trade policy across sectors and countries. Their findings indicate significant economies of scale in manufacturing, though the quantitative impact of industrial policy is relatively modest (a few percent of GDP). We use panel variation, rather than cross-sectional variation, to test for external economies of scale within an industry that has seen large shifts in scale across countries over time.

Finally, we contribute to a recent literature on the economics of solar power (e.g., Gowrisankaran et al., 2016; De Groote and Verboven, 2019; Bollinger and Gillingham,

[7]For a review of earlier work, see Harrison and Rodríguez-Clare (2010)). One notable example is Head (1994), who finds that U.S. tariffs on imported steel rails hastened the domestic industry's rise to become globally competitive. By contrast, our estimates do not reveal that the domestic solar industry has developed lasting comparative advantage. Despite this difference in industry outcomes, both papers conclude that alternative policy interventions could outperform tariffs.

2019; Langer and Lemoine, 2022; Gerarden, 2023; Bollinger et al., 2025).[8] Many of these papers focus on estimating demand for solar systems. We extend this literature by studying the upstream supply of solar panels.[9] In a closely related paper, Houde and Wang (2023) 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 as domestic manufacturing subsidies.

2 Industry Background and Data

2.1 The Solar Industry

In this study, we focus primarily on the most common solar panel technology, crystalline silicon ('c-Si'), which has come to dominate the solar panel market over the past two decades.[10] Most c-Si solar panels are produced by vertically integrated manufacturers. These firms use polysilicon as an input to manufacture wafers, then process wafers into solar cells that generate electricity through the photovoltaic effect, and finally combine solar cells into solar panels (also known as 'modules'). The price of solar panels fell by an order of magnitude between 2010 and 2020 (Figure A.1). Nonetheless, this technology is highly commoditized, with limited variation in prices across firms at a given point in time (Figure B.1).

These secular reductions in price throughout the industry contributed to rapid growth in solar technology adoption in the U.S. over the 2010s (Figure A.2). During that time

[8] Gerarden et al. (2025) review related literature in an overview of industrial policy in renewable energy.

[9] 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. Banares-Sanchez et al. (2023) analyze the impact of local production subsidies on the growth and innovation of the Chinese solar manufacturing industry. Garg and Saxena (2023) consider how tariffs and production subsidies could be combined to meet domestic production targets in the Indian solar market. In contrast to this paper, Garg and Saxena focus on the role of market power without accounting for environmental externalities, which we find to be quantitatively important in the U.S. context.

[10] Our descriptive analysis of the effects of import tariffs in section 3 focuses on c-Si manufacturers, since import tariffs only applied to c-Si technology. The model we develop and analyze in sections 4 through 7 also includes thin-film manufacturers, who use a different production process and were exempt from import tariffs, but who compete in the same end market.

period, about 65% of solar panels were used in utility-scale systems, while the remainder were used in small-scale residential and commercial systems. The primary government subsidy to encourage adoption of solar in the U.S. is the Investment Tax Credit (ITC), which offset 30% of upfront solar system costs during the study period.[11] Solar energy investors can also benefit from the tax advantage of accelerated depreciation as well as state and local subsidies.[12]

2.2 U.S. Trade and Industrial Policy

We study the impacts of four rounds of tariffs applied to U.S. imports of c-Si solar products. The first round was a set of antidumping and countervailing duties implemented in 2012 (the "2012 tariffs").[13] These duties applied to solar cells manufactured in China, regardless of whether they were imported as solar cells or after assembly into solar panels.[14] 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 c-Si products from all major exporters of solar products to the U.S.[15] The tariff declined by 5% each year until 2022, when it was

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

[12] 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.

[13] 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.

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

[15] 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

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 countervailing duties from 2012 and 2014.

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

2.3 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 an unbalanced panel of major manufacturers.[16] 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). Although the IHS data cover a subset rather than the universe of manufacturers, we show in Appendix C that they cover the significant majority of imports by value, and they exhibit similar temporal

panels were exempt from June 2019 through the end of our study period (September 2020).

[16]The unbalanced panel contains 32 manufacturers over 2010-2020 with at most 20 manufacturers in a given time period. "Shipments" data include both domestic shipments in addition to imports.

patterns to official government data on total imports.[17]

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 for the 2012 and 2014 tariffs from the U.S. Customs and Border Protection (CBP) via a Freedom of Information Act (FOIA) request.

Table 1: Summary Statistics for Main Model Sample

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

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

We use several other data sources in estimation and for ancillary analysis. Trade flows data come from the United Nations (UN) Comtrade database and the U.S. International Trade Commission (USITC) DataWeb. Data on adoption of large- and small-scale solar systems come from the U.S. Energy Information Administration (EIA) Form EIA-860, the Solar Energy Industries Association (SEIA), and the Lawrence Berkeley National Laboratory's

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

(LBNL) Tracking the Sun data set. Data on the prices of silver and aluminum come from the London Afternoon Fixing (2024) and the London Metal Exchange (2024). We convert prices from nominal to real terms using the GDP implicit price deflator from the U.S. Bureau of Economic Analysis (2024).

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

3 Descriptive Evidence of Tariff Impacts

This section presents data and reduced-form evidence regarding how Chinese manufacturers adjusted their operations to avoid tariffs, and how tariffs affected prices in the U.S. relative to other markets.

3.1 Manufacturers Offshored Production to Tariff-Free Countries

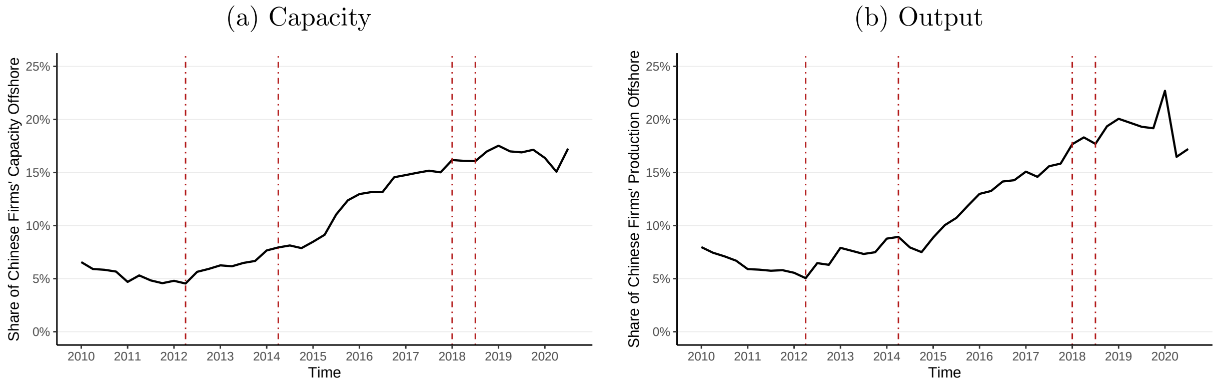
To understand how foreign manufacturers responded to the geographically targeted tariffs imposed in 2012 and 2014, we summarize how the geography of affected manufacturers' production capacity evolved over time. Figure 1 plots the share of panel capacity and production outside China for manufacturers that ever produce panels in China.[18] The vertical dashed lines represent the implementation of the four rounds of tariffs.

Figure 1 shows that Chinese manufacturers increased their share of panel capacity and production outside China after the 2014 tariffs took effect. This pattern is consistent with production relocation as a means to avoid paying U.S. import tariffs.[19] However, this offshoring behavior could also be explained by cost drivers that are unrelated to but correlated with tariffs in the time series.

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

[19]Appendix D.1 presents additional measures of production relocation by manufacturers that produced solar products in China, all of which are consistent with the idea that tariff-exposed manufacturers relocated production activities to avoid tariffs.

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



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

3.2 Firm Offshoring Increased with Import Tariffs

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

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

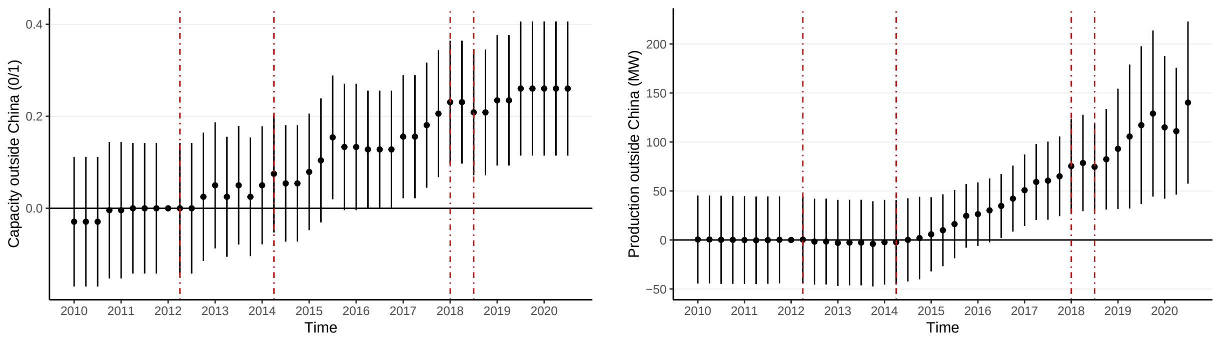
$$Y_{ft} = \sum_{t' \neq 0} \alpha^{t'} \text{Treated Manufacturer}_{ft}^{t'} + \iota_f + \kappa_t + \varepsilon_{ft}, \tag{1}$$

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

Figure 2 presents point estimates and confidence intervals for the $\alpha^{t'}$'s. The left panel plots coefficients from a linear probability model of the extensive margin decision to offshore production activity. The right panel plots coefficients from a linear regression of intensive margin offshore production levels. In both cases, treated firms increase offshore manufacturing activity over time relative to control firms.[20]

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

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



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

One potential shortcoming of this event study analysis is that the firms who are exposed to U.S. import tariffs may differ from firms who are not exposed to the tariffs at baseline. For example, treated firms may be larger given that they export to the U.S. market. While the parallel pre-trends in Figure 2 are consistent with the identifying assumption of parallel trends in the absence of treatment, the assumption is not testable. To ameliorate concerns about potential failures of the parallel trends assumption, Appendix D.2 contains estimates from two additional specifications. In the first, we focus on the subsample of firms that lie within the common support of the pre-treatment firm size distribution. The extensive margin estimates are quantitatively similar. The intensive margin estimates are attenuated somewhat but remain statistically significant and lead to the same qualitative conclusions. In the second, we compare treated Chinese firms to foreign firms that are not exposed to tariffs until 2018, and we draw the same qualitative conclusions. Thus, common cost shifters that vary over time are not able to explain observed production patterns in the raw data.

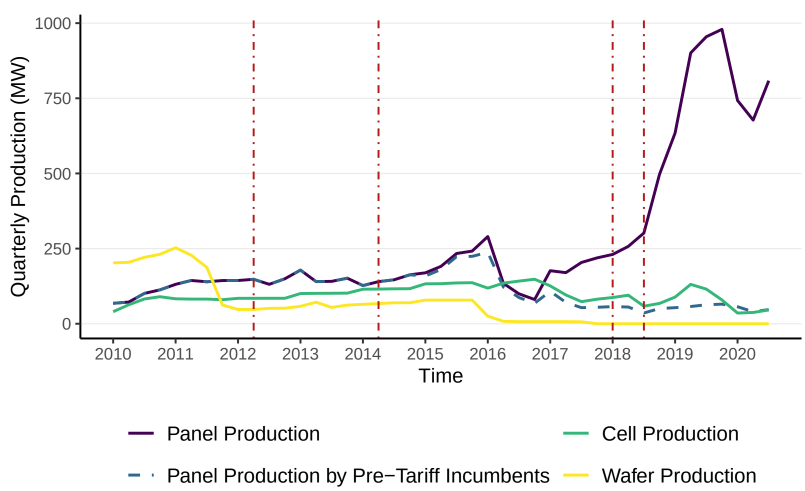
[20] Our focus is on directional rather than precise quantitative conclusions from the event study. In principle, the exact level of event study coefficients could be confounded by a failure of the stable unit treatment value assumption that stems from product market competition among these firms. However, the event studies provide clear evidence that tariffs provide incentives for offshoring, and this motivates our approach to modeling the market in order to derive quantitative conclusions.

We conclude that the antidumping and countervailing duties, particularly the 2014 tariffs, led treated Chinese firms to offshore their manufacturing activity relative to untreated firms.

3.3 Domestic Solar Panel Assembly Increased

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

Figure 3: U.S. Manufacturing Activity over Time



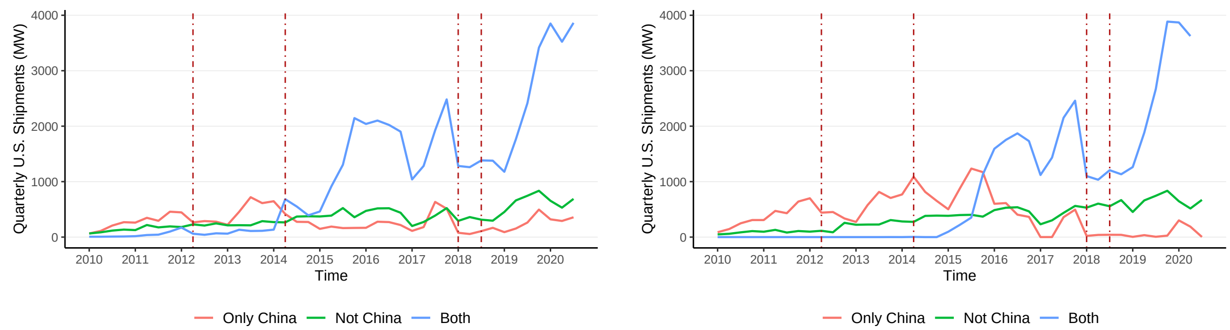
Note: This figure plots c-Si solar component output in the U.S. over time based on quarterly data from IHS Markit. Solid lines represent total output of each product from all firms. The dashed line represents output of solar panels from the subset of firms that produced solar panels in the U.S. prior to tariffs. This figure omits thin-film manufacturers, as they have a different production process that cannot be separated out into the same categories of wafers, cells, and panels, and they were not subject to tariffs. Figure D.5 replicates the time series for c-Si solar panels alongside an analogous time series for thin-film panel production. Vertical lines denote the timing of each round of tariffs.

3.4 The Market Share of Chinese Multinationals Expanded

Figure 4 shows a breakdown of major manufacturers' shipments to the U.S. based on the countries in which those manufacturers produce panels and cells, in that quarter.[21]

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

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



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

Figure 4a breaks down the time series of panel shipments into subgroups based on contemporaneous panel manufacturing locations. There are three groups: firms that manufacture only in China, firms that do not manufacture in China, and firms that manufacture both inside and outside of China. In the first part of the sample period, major Chinese manufacturers produced solar panels exclusively in China, and no manufacturers produced panels both inside and outside of China. After the 2012 tariffs took effect, most shipments were from Chinese manufacturers that continued to focus their operations in China. This is likely because the first round of duties did not preclude Chinese-based manufacturers from using cells produced in Taiwan to continue supplying the U.S. market with solar panels without paying duties.[22]

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

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

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

Figure 4b breaks the same shipments data into groups based on contemporaneous *cell* manufacturing locations. As detailed in section 2.2, the 2012 and 2014 tariffs depended on the origin of cells, not just the assembled panels. The patterns in Figure 4b are similar to Figure 4a. In the early part of the sample none of the major manufacturers were manufacturing cells both inside and outside of China. This changed in 2015 when some manufacturers expanded to manufacture cells both inside and outside of China.

3.5 Government Data Confirms that Importers Avoided Tariffs

As another piece of evidence of tariff avoidance, we submitted a FOIA request to obtain data on actual duties collected by the U.S. CBP. Table 2 presents these data. Each row contains money collected from a specific set of antidumping and countervailing duties. Each column corresponds to a fiscal year. The first few columns show that very little money was collected from the 2012 antidumping and countervailing duties during FY2012 and FY2013. This is likely due to avoidance behavior by manufacturers.[23] In later years, after the scope of duties was expanded and opportunities for tariff avoidance were curtailed, the amount of duties collected increased substantially. Based on the negligible effects of the 2012 tariffs on government revenues, and the limited change in offshoring activity until after the 2014 tariffs went into effect, the remainder of the paper focuses on the impacts of tariffs between 2014 and 2020.

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.

[23]Appendix E discusses whether firms might have avoided tariffs by transshipping rather than actual production shifting and presents additional data to assess this possibility. The data are consistent with Chinese firms offshoring the last two stages of solar panel production to avoid tariffs, and not simply transshipping completed products through third countries to evade tariffs.

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

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

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

3.6 U.S. Prices Rose Relative to Other Markets

As a final piece of descriptive evidence, we use data on solar panel prices in ten regional markets to estimate event study models of the relationship between equilibrium prices and tariffs:[24]

$$\log(p_{fmt}) = \sum_{t' \neq 0} \beta^{t'} \text{Treated Market}_{mt}^{t'} + \lambda_f + \nu_m + \rho_t + \varepsilon_{fmt}, \tag{2}$$

where p_{fmt} is the price of manufacturer f's solar panels in market m and quarter t, and Treated $\text{Market}_{mt}^{t'}$ is an indicator for the U.S. market t' quarters relative to the quarter before the 2012 tariffs went into effect. We include fixed effects for manufacturers (λ_f), markets (ν_m), and time periods (ρ_t). In a parallel specification, we compute the weighted average price of solar panels at the market-time level and then estimate the model at that level (without firm fixed effects). Standard errors are clustered by market in both cases.[25]

Figure 5 presents point estimates and confidence intervals for the $\beta^{t'}$'s. The left panel plots coefficients from the firm-level model. The immediate price effects of the 2012 tariffs are small and not significant. After the 2014 tariffs go into effect, the coefficients indicate that U.S. prices increased roughly 10% relative to prices in other markets, before falling somewhat in relative terms, possibly due to the production adjustments by firms we document above. Finally, after the additional 2018 tariffs went into effect, U.S. prices increased roughly 20% relative to other markets.

The right panel plots coefficients from the market-level model. While the sample is small,

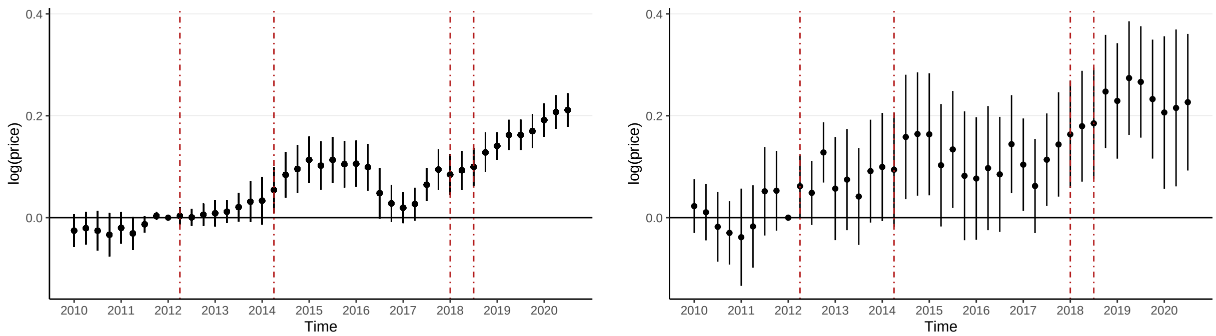
[24] The ten regional markets are: Australia, Canada, China, Europe, India, Japan, Latin America, the Middle East and Africa, the Rest of Asia-Pacific and Central Asia, and the U.S.

[25] We cluster by market because that is the level at which treatment is assigned. However, there is only one treated cluster and nine control clusters, and standard inference procedures are known to fail with too few clusters (Cameron and Miller, 2015). Despite recent developments regarding inference with few clusters (e.g., MacKinnon and Webb, 2018), we are not aware of any method that is valid in this setting. We also estimated effects using the synthetic control method and synthetic difference-in-differences, and found very similar point estimates, but inference for those methods is also subject to limitations with so few clusters. Thus we view the confidence intervals as suggestive rather than definitive. Table 3 contains coefficient estimates for each tariff period, with p-values constructed via wild bootstrap.

Figure 5: Event Study of the Effect of U.S. Import Tariffs on U.S. Solar Panel Prices

(a) Firm-level event study

(b) Market-level event study



Note: Points represent event study coefficients from estimating equation (2) via ordinary least squares, using quarterly data from IHS Markit. The left panel is from estimating a firm-level model that includes firm, market, and time fixed effects. The right panel is from estimating a market-level model that includes market and time fixed effects. For the market-level model, we first compute the weighted average price across firms. Confidence intervals are clustered by market. Vertical lines denote the timing of each round of tariffs. All event study coefficients are relative to the first quarter of 2012.

and thus the analysis is more suggestive, the broad patterns are similar: U.S. prices increased relative to other markets over time as successive tariff rounds went into effect. The point estimates are somewhat larger but are qualitatively consistent with the firm-level analysis.

Table 3 presents estimates of average effects for each tariff round. Each treatment indicator is mutually exclusive, so the coefficients can be directly interpreted as the change in prices (in log points) for the U.S. relative to other countries during each tariff round. As in the event study specifications, these estimates suggest that the initial round of tariffs had a modest impact on market prices, while the 2014 and 2018 rounds caused solar panel prices in the U.S. to increase roughly 10 and 20 percent relative to other markets.

Table 3: Tariffs Increased U.S. Prices Relative to Other Markets

	log(price)	
	(1)	(2)
$1\{2012 \text{ Tariffs}\}_{mt}$	0.03	0.07
	(0.05)	(0.01)
	[0.38]	[0.15]
$1\{2012 + 2014 \text{ Tariffs}\}_{mt}$	0.10	0.11
	(0.00)	(0.00)
	[0.12]	[0.27]
$1\{2012 + 2014 + 2018 \text{ Tariffs}\}_{mt}$	0.16	0.22
	(0.00)	(0.00)
	[0.01]	[0.20]
Firm Fixed Effects (#)	32	
Market Fixed Effects (#)	10	10
Time Fixed Effects (#)	43	43
Observations	7,504	430
R^2	0.98	0.99
Within R^2	0.04	0.15

Note: This table presents estimates of the average treatment effect of each round of U.S. import tariffs. The coefficients come from estimating a restricted version of equation (2) via ordinary least squares (where the event time treatment indicators from equation (2) are replaced with three mutually exclusive tariff round treatment indicators). Each column presents results for a different outcome variable based on quarterly data from IHS Markit. The first column presents results from estimating a firm-level model that includes firm, market, and time fixed effects. The second column presents results from estimating a market-level model that includes market and time fixed effects. For the market-level model, we first compute the weighted average price across firms. Parentheses contain p-values clustered by market. Brackets contain p-values constructed via wild bootstrap with 10,000 bootstrap samples.

4 Model

To understand the economic effects of U.S. import tariffs and alternative policies, we formulate and estimate a model of the wholesale market for solar panels. Demand in the wholesale market is derived from 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. On the supply side, solar panel manufacturers around the world ship to their U.S. subsidiaries, who compete in the wholesale market.

4.1 Demand for Solar Panels

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

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

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

In our baseline model, we use market-level data to estimate aggregate demand, as detailed later in section 5. In a robustness analysis contained in Appendix F, we also develop and estimate a micro-founded model of demand for solar panels that is derived from downstream demand for solar installations from the utility and non-utility markets.

4.2 Supply of Solar Panels

Each manufacturer, denoted as f, is characterized by its operational locations $Z \subseteq \mathbb{Z}$, cost efficiency ω, and ad valorem tariffs τ_t imposed by the U.S. on its production locations[26]. Every firm maintains a wholesale subsidiary in the U.S., which imports solar panels from the manufacturer's production sites $l \in Z$. These shipments introduce randomness regarding the *realized* cost of each panel sold.

[26]Both the operational locations and the statutory tariff can be firm-specific. For abbreviation, we denote the it as Z and τ_t without f subscript.

4.2.1 Solar Panel Market Competition

We model each manufacturer f, with state variables (ω, Z, τ_t), as having an *ex-ante* expected unit cost denoted by $c_{ft} \equiv c_t(\omega, Z, \tau_t)$. These manufacturers' wholesale subsidiaries compete in the U.S. market by determining the quantity of solar panels they supply, Q^S_{ft} (measured in watts). Given the limited horizontal differentiation among solar panels, the model adopts a Cournot competition framework where the total market supply in period t, Q^S_t, is the sum of supplies from all manufacturers: $Q^S_t = \sum_f Q^S_{ft}$.[27]

Each manufacturer faces the following optimization problem:

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

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

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

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

which simplifies to:

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

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

4.2.2 Manufacturer Sourcing Decision

Each manufacturer, especially those with multiple production sites, must decide how to source solar panels to meet market demand. This decision is influenced by factors such as cost structures at various locations and ad valorem tariffs on imports from these regions, particularly relevant given the concentration of manufacturing in areas like China and the fluctuations in associated firm tariffs.

[27] Solar panels are highly commoditized, as discussed in the introduction and section 2.1. Consistent with this, there is very little price dispersion across manufacturers, which we summarize in Figure B.1. Indeed, 87 percent of solar panel capacity sold at a price within 25% of the weighted average market price.

We assume that each manufacturer, having committed to a quantity Q^*_{ft} to their wholesale counterpart *ex-ante*, must coordinate a continuum of shipments from its various production facilities to meet this committed supply volume in the U.S. market. For each shipment, the manufacturer chooses its lowest cost location $l \in Z$. The potential *post-tariff* unit production cost at each location l for the shipment depends on manufacturer- and location-specific tariff rates τ^l_t. Furthermore, unit production costs depend on productivity, $\omega\varepsilon^l_t$, where ω represents manufacturer productivity, ε^l_t is a stochastic cost shifter:

$$c^l_{ft} = \frac{\tau^l_t}{\omega\varepsilon^l_t}. \tag{4}$$

ε^l_t is independent and identically distributed across locations and orders, and is distributed Fréchet with mean T^l_t and shape parameter θ. The randomness captures any idiosyncratic reason that a specific shipment deviates from the average productivity in a location.

The term T^l_t captures the fundamental cost competitiveness of the location l due to technical efficiency and labor abundance. Throughout the text, we refer to this as "cost efficiency," or "efficiency" in short. Additionally, it might also reflect the possibility of external economies of scale within the location's region. Each individual firm's sales to the U.S. are small relative to the scale of manufacturing at the regional level, which includes the firm's production for other end markets as well as the production of all other firms for all destination markets. Thus, we assume that manufacturers treat each location's aggregate output as given, however, it is in equilibrium consistent with the firm's optimization problem encapsulated in equation (3). This model nests the case of exogenous T^l_t at the location level as a special case. This approach builds on Kucheryavyy et al. (2023), who extend workhorse trade models to allow for industry-level economies of scale and characterize their theoretical properties.

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

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

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

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

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

4.2.3 Choice of Production Locations

Chinese firms always keep their original base of operations in China. But if they want to expand and open an additional plant elsewhere—say in Southeast Asia or the U.S.—they face a one-time, location-specific startup cost. This cost is uncertain and varies across firms. In line with what we see in the data, we assume that firms can only add one new location at a time. If no new location is chosen, the cost is zero.

When deciding whether to add a location, firms weigh the immediate gains in profit from producing in that new place against the startup cost. The profitability depends not just on their own production costs, but also on the average costs $\bar{c}_t$ by other firms in the industry and on overall demand conditions D_t at the time. This means the decision to expand depends on the comparison between the expected value of operating with and without the new location, i.e., the relative difference between $\Phi_t(\omega, Z \cup l, \tau_t)$ and $\Phi_t(\omega, Z, \tau_t)$.

In principle, we could fully specify these tradeoffs and use them to define a conditional choice probability policy function $P_t^l(\omega, Z, \tau_t)$, treating it as each firm's optimal policy rule. In practice, however, the other components of our model can already be estimated conditional on a firm's observed historical location configuration. For this reason, we avoid imposing additional structure on location decisions in our estimation. Instead, as discussed in Section 5.2.3, we bound firms' location choices in the counterfactual analysis to ensure robustness.

4.3 Equilibrium

The model is characterized by a stochastic sequence of exogenous demand and tariff shocks (D_t, τ_t), as well as firms' perceived transitions of $(\bar{c}_t, T_t^l)$. A Perfect Bayesian Equilibrium consists of a sequence of firm strategies—comprising quantity (equation 3), sourcing (equation 5), and location decisions such that: (i) given their beliefs, firms' strategies are optimal; and (ii) firms' beliefs about the evolution of $(\bar{c}_t, T_t^l)$ are consistent with the realized sequence of outcomes.

5 Estimation

We outline the model estimation procedure in this section. We begin by estimating U.S. wholesale market demand for solar panels. We then describe how we estimate manufacturing costs in two stages. First, we use data on within-firm production shares across manufacturing locations to estimate the relative cost efficiency of those locations. This estimation procedure relies on our model of manufacturer sourcing decisions (based on Eaton and Kortum, 2002) but does not impose any assumptions on firm conduct. Second, we integrate the demand and cost efficiency estimates into the first order condition of the Cournot game to recover estimates of exogenous industry-wide technological change and firm-specific productivity.

5.1 Demand Estimation

We estimate a series of constant elasticity demand models:

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

where Q_t is total shipments of solar panels to the U.S. in quarter t, p_t is the wholesale price of solar panels in quarter t, and ϵ^D is the elasticity of solar panel demand with respect to price. We use $s_t = 0.4$ to capture the Investment Tax Credit and other government policies summarized in section 2.1 in a tractable manner.[28] In some specifications of equation (6), we include quarter or year fixed effects to allow for time-varying demand intercepts, α_t.

We estimate equation (6) using ordinary least squares (OLS) and two-stage least squares (2SLS). For the two-stage least squares specifications, we use two different sets of instruments. First, we use the global prices of silver and aluminum to instrument for the price of solar panels.[29] These observable cost shifters are valid instruments as long as they only affect the equilibrium quantity of solar panels through their effect on solar panel prices. The most likely threat to identification is that solar panel demand shocks affect input prices (reverse causality). This is unlikely given that solar panels destined for the U.S. market are a small share of global consumption of silver and aluminum.[30]

[28]Our use of aggregate national solar panel sales data from the wholesale market prevents us from modeling the impact of all state and local subsidies individually in this specification. However, our robustness analysis in Appendix F employs additional microdata that account for these policies, and delivers comparable demand elasticity estimates.

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

[30]In 2020, the final year of our sample, the solar industry constituted 9% of global demand for silver (Metals Focus, 2024). The U.S. constituted about 15% of global solar demand in 2020 (International Energy Agency,

Second, we use the average price of solar panels in foreign markets as an instrument for prices in the U.S. market. This instrument rests on the same economic rationale as using observable cost shifters. Since the solar industry is globally integrated, prices in other markets should reflect common cost shifters. This instrument is valid as long as demand shocks are not correlated across markets over time (Hausman, 1996; Nevo, 2001). Figure G.1 presents plots of the post-subsidy price of solar panels in the U.S. and all three prices used as instruments.

In a robustness analysis contained in Appendix F, we estimate separate models of solar installation demand for the utility and non-utility markets. For the utility market, we use a discrete choice model of the choice to invest in solar electricity generation capacity 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, building on prior work by De Groote and Verboven (2019). Finally, we aggregate these utility and non-utility demands to recover a market-level price elasticity of demand for solar panels, and compare to estimates from the aggregate demand model. See Appendix F for more details.

5.2 Supply Estimation

5.2.1 Solar Panel Market Competition

Given demand estimates, wholesale panel prices, and market shares, we can compute manufacturers' implied costs from their first order condition, $\widehat{c}_{ft}$, using equation (3). These costs correspond to expected marginal costs in the production sourcing model, which are given by equation (5). We take the log of equation (5) to derive an estimating equation for firm-level costs:

$$\log\left(\widehat{c}_{ft}\right) = -\frac{1}{\theta}\log\left(\sum_{l\in Z_{ft}}\left(\frac{\tau^l_{ft}}{T^l_t}\right)^{-\theta}\right) + \omega_{f(t)} + \xi_t + \varepsilon^S_{ft}\ . \tag{7}$$

The first term on the right-hand side of equation (7) captures the effect of each location's fundamentals on firm costs, which depends on tariffs (τ^l_{ft}), location-specific cost efficiencies (T^l_t), and the trade elasticity (θ).

To estimate the parameters of equation (7), we aggregate observed production activity into three production locations: China, the U.S., and Other (mostly Asian) Countries. This

2021). Thus, silver demand stemming from the U.S. solar market was on the order of 1% of global silver demand. For aluminum, U.S. solar's share of consumption is even smaller.

aggregation facilitates estimation of the location-specific cost efficiency terms while still capturing the key margins of response to the import tariffs we study. The location-specific terms are not separately identified in levels in this empirical model, so we normalize tariffs and location-specific cost efficiencies relative to the U.S.

We proceed to estimate the parameters of equation (7) in two steps. First, we fix the within-firm trade elasticity (θ) based on prior literature and use data on firms' production activity across locations to identify and estimate location-specific cost efficiencies in a fully flexible manner.[31] In some specifications, we parameterize the relationship between the estimated cost efficiency terms and total manufacturing output to capture possible external economies of scale. Section 5.2.2 describes this step in more detail.

Second, we substitute the resulting cost efficiency predictions into equation (7) and estimate the remaining parameters via ordinary least squares. We use manufacturer fixed effects, $\omega_{f(t)}$, to absorb variation in productivity across manufacturers. In our baseline specification, we allow these manufacturer fixed effects to evolve over time by interacting them with indicator variables for each year. Time fixed effects, ξ_t, capture exogenous industry-wide technological change and other cost shifters that vary over each quarter of the sample but not across manufacturers or locations.

5.2.2 Manufacturer Sourcing Decision

We use within-firm variation in production across locations in a given time period to identify and estimate location-specific cost efficiencies. The stochastic model of production sourcing predicts the share of production that each firm will source from each of its manufacturing locations. Using within-firm variation allows us to isolate the effect of the cost efficiencies of different locations from the productivity $\omega_{f(t)}$ of the firm. For a firm sourcing from location l to sell to product market m, that share is:[32]

$$s^l_{fmt} = \frac{(\tau^l_{fmt}/T^l_{ft})^{-\theta}}{\sum_{k \in Z_{ft}} (\tau^k_{fmt}/T^k_{ft})^{-\theta}}$$

Defining $\Phi^m(Z_{ft}, \vec{T}_{ft}, \vec{\tau}_{fmt}) = \sum_{k \in Z_{ft}} (\tau^k_{fmt}/T^k_{ft})^{-\theta}$, $\forall\, m$, we can then write the total output at each location l as a summation across destination markets:

$$y^l_{ft} = \sum_m s^l_{fmt} q_{fmt} \quad \rightarrow \quad s^l_{ft} = (T^l_{ft})^{\theta} \sum_m \frac{(\tau^l_{fmt})^{-\theta}}{\Phi^m(Z_{ft}, \vec{T}_{ft}, \vec{\tau}_{fmt})} s^q_{fmt}$$

[31] We follow Tintelnot (2017) and Head and Mayer (2019) to set $\theta = 7.5$ for our analysis in the main text, and analyze whether our results are sensitive to values ranging from 6 to 9 in Appendix J.

[32] The firm-specific productivity term $\omega_{f(t)}$ drops out since it is common across locations.

where s_{ft}^l and s_{fmt}^q are location l production share and market m sales share within each firm f at period t.

Since the U.S. ($m = US$) is the only country that imposes a substantial statutory firm- and location-specific tariff, we can consider $\Phi^{m'}(Z_{ft}, \vec{T}_{ft}, \tau_{fm't}) = \Phi(Z_{ft}, \vec{T}_{ft}, 1)$, $\forall\, m' \neq US$.[33] We can then simplify the production share equation to

$$s_{ft}^l = (T_{ft}^l)^\theta \left[\frac{(1 - s_{fUSt}^q)}{\Phi(Z_{ft}, \vec{T}_{ft}, 1)} + \frac{s_{fUSt}^q (\tau_{fUSt}^l)^{-\theta}}{\Phi^{US}(Z_{ft}, \vec{T}_{ft}, \vec{\tau}_{ft})} \right] \quad .$$

Solving the system of equations Since sourcing shares s_{ft}^l sum to one within a firm, we cannot separately identify the level of cost efficiency of each location. Instead, we use fixed point iteration to solve for the "relative efficiency" $(T_{ft}^l / T_{ft}^k)^\theta$ for the exact observed set of sourcing shares s_{ft}^l, given the parameter θ and the observed sales share s_{fUSt}^q. For each firm at each point in time, we can pick any $k \in Z_{ft}$ to calculate these objects for $l \in Z_{ft}$, $l \neq k$.

Recovering location-specific cost efficiencies We regress the log of firms' implied relative efficiencies on location-by-time dummy variables to flexibly estimate how location-specific efficiency evolves over time:

$$\left[\log(T_{ft}^l) - \log(T_{ft}^k)\right] = \underbrace{\left[\log(T_t^l) - \log(T_t^k)\right]}_{\text{location-specific dummies}} + u_{ft}^{lk}, \tag{8}$$

where T_t^k is normalized to one for $k = \text{US}$ (without loss of generality). We then substitute estimates of T_t^l into equation (7) and estimate the remaining parameters $\omega_{f(t)}$ and ξ_t via ordinary least squares.

Alternative specification: estimation of external scale economies One of the textbook economic rationales for trade barriers and industrial policy is the possibility of external economies of scale within a location. We use our estimates of the comparative advantage of each location relative to the U.S. to test for such external scale economies.[34] To do this, we

[33] In the first few years of the sample, there are no tariffs in the U.S., either. As described in sections 2 and 3, the 2012 tariffs were viewed as ineffective, and generated a negligible amount of tariff revenue, due to alleged loopholes that are not observable in our data (and which the 2014 tariffs were designed to close). For that reason, we omit the 2012 tariffs in estimation and focus our counterfactual analysis on the period 2014 through 2020. This modeling choice has no impact on our main results since the parameters of the sourcing decision are estimated flexibly by period.

[34] We focus on location-specific external scale economies because they provide the strongest rationale for protection of infant industries by national governments. If there were common technological improvements for all locations, it would not be reflected in the location-specific cost efficiency estimates, since within-firm production shares across locations are only informative about the comparative advantage of each location.

regress the location-specific cost efficiency estimates on measures of industry scale in each location over time:

$$\left[\log(T_t^l) - \log(T_t^{US})\right] = \log(T^l) + \log(T_t) + \underbrace{\gamma \left[\log(K_t^l) - \log(K_t^{US})\right]}_{\text{scale effect}} + u_t^l \tag{9}$$

We focus on static scale economies and assume that the elasticity is common across locations within the sector, in line with recent literature (e.g., Bartelme et al., 2019). γ denotes the elasticity of cost efficiency with respect to industry scale. We measure industry scale using total production in each location, denoted K_t^l. We estimate equation (9) via ordinary least squares, in some cases using lagged values of industry scale.

5.2.3 Choice of Production Locations

We use a bounding approach to account for firms' choices to add production locations. Section 3 provides descriptive evidence that Chinese firms invested in new production locations outside China in response to tariffs. In the absence of tariffs, firms may not have added offshore locations. To account for this, we take two approaches to analyze the effects of tariffs. In the first, we hold the observed set of locations fixed. This allows for firms to reallocate production across locations. In the second, we impose an extreme case where firms did not add any offshore locations after the 2014 tariffs, effectively preventing cross-country reallocation and corresponding to a hypothetical upper bound on location startup costs. Comparing the two approaches provides a sense of how production relocation moderated the effects of the tariffs.

6 Estimation Results

6.1 Demand Estimates

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

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

Table 4: Estimated Demand Elasticities

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

Note: This table presents estimated price elasticities of demand (i.e., $\widehat{\epsilon}^D$ from equation (6)). Post-subsidy price is the quantity-weighted average price of solar panels consumers face after accounting for adoption subsidies (in \$/W). Each column represents a different specification of the demand intercept through the inclusion of fixed effects. Panel A presents OLS estimates. Panel B presents IV estimates using silver and aluminum prices as instruments for solar panel prices. Panel C presents IV estimates using the foreign solar panel price as an instrument for the domestic solar panel price. All models are estimated using a quarterly time series from Q1 2010 through Q3 2020. First-stage F-statistics are from tests of the hypothesis that the excluded instrument(s) are jointly irrelevant. First-stage coefficient estimates are presented in Tables G.1 and G.2. Heteroskedasticity-robust standard errors are in parentheses.

Panel B presents 2SLS estimates in which the prices of silver and aluminum instrument for the price of solar panels. The first two columns produce estimates that are very similar to the results in Panel A. In both cases, the first-stage F-statistic is above 30.[35] In the third column, the point estimate is larger in magnitude, but the standard errors are an order of magnitude larger and the instrument is weak.

Panel C presents 2SLS estimates in which the average price of solar panels in other markets instruments for the price of solar panels in the U.S. This instrument remains well above conventional F-statistic thresholds in all three columns. The estimates in the first two

[35]Estimates of the first stage regression are presented in Appendix G.

columns are nearly identical to the OLS estimates. In the final column, the point estimate is fairly similar to the first two columns, and is smaller in magnitude than its counterparts in Panels A and B.

These results are consistent with prior estimates from Gerarden (2023), who uses earlier data to estimate similar models. As a robustness analysis, we also estimate the aggregate elasticity of demand by separately estimating downstream demand for solar systems from the utility and non-utility markets, and then combining them to recover the derived elasticity of demand with respect to price for solar panels. This procedure yields point estimates in the range of -1.45 to -1.04, consistent with the estimates in Table 4.[36] We use the specification in the first column of Panel B, with a point estimate of -1.44, as our preferred estimate for supply estimation and counterfactual analysis.

6.2 Supply Estimates

Figure 6 presents estimates of location-specific efficiencies recovered from estimating equation (8) using the trade elasticity (θ) of 7.5 from the literature (Tintelnot, 2017; Head and Mayer, 2019). When estimating equation (8), we pool firms' relative efficiencies across quarters within each year to avoid overfitting.[37] These estimates capture the net effect of all unobserved cost shifters (after accounting for the effect of tariffs, which are observed). As detailed above, our model and estimation approach recover relative cost efficiencies, where the efficiency of manufacturing in the U.S. is normalized to one. The estimates in Figure 6 reveal that China and other countries are more efficient at manufacturing solar panels, and thus lower in cost, than the U.S. The point estimates for Chinese cost efficiency vary more over time than for other countries, starting out around the same level as the U.S. and then increasing rapidly to levels higher than other countries.

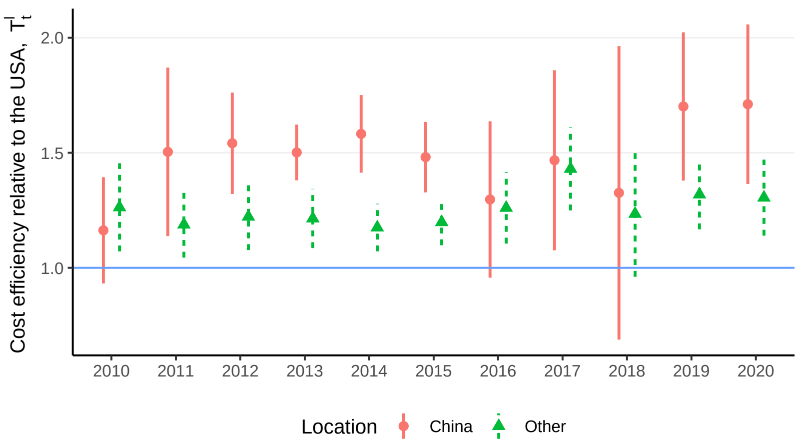
To provide a sense of how these cost efficiency estimates translate into cost level estimates, Figure 7 plots cost predictions for manufacturing locations over time, relative to the U.S. Figure 7a plots the estimated pre-tariff cost of manufacturing.[38] The model predicts that manufacturing in China is least costly, with costs around two-thirds of U.S. costs. Manufac-

[36]The estimate -1.45 is an unweighted average of the aggregate elasticities over the sample period. The estimate -1.04 is a weighted average, weighted by the size of the market over time. See Appendix F for details.

[37]While location-specific efficiency terms can be estimated period-by-period, pooling data across quarters within each year produces higher adjusted R-squared values than quarterly, biannual, or biennial regressions.

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



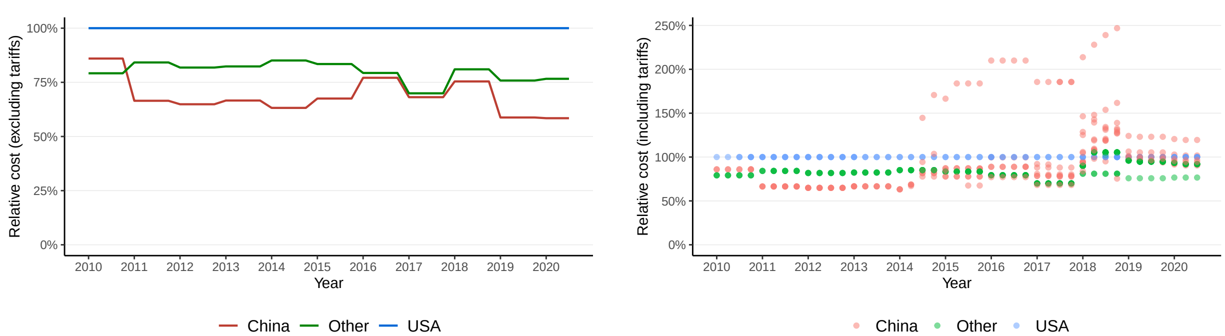
Note: This figure presents estimates of location-specific cost efficiencies over time, T_t^l, relative to the U.S. These estimates are obtained by estimating equation (8) using $\theta = 7.5$. Values above one indicate that efficiency is higher than the U.S. Standard errors are clustered by firm.

turing in other countries is predicted to be somewhat more expensive than China, roughly three-quarters the cost of manufacturing in the U.S.

Figure 7: Location-Specific Cost Predictions

(a) before tariffs

(b) after manufacturer×location-specific tariffs



Note: The lines in panel (a) are cost predictions computed based on the cost efficiency point estimates in Figure 6, with no tariffs. Predictions are made separately for each location and hold constant other cost shifters that vary across firms or over time but not across locations. The points in panel (b) represent post-tariff costs for each firm-location combination observed in the data, accounting for technology-specific tariff exemptions that affect a small number of firms.

Figure 7b plots the estimated post-tariff production cost for individual manufacturers based on the locations where they manufacture and the tariffs they are exposed to, again relative to the U.S. The estimates are consistent with the descriptive evidence on avoidance behavior presented in section 3. For most of the period before the 2014 tariffs were imposed, China was the least costly production location.[39] After the 2014 antidumping and countervailing duties were imposed, the model predicts comparable costs for manufacturing in China and other countries for most manufacturers, both of which remain well below the cost of manufacturing in the U.S. After the 2018 tariffs, the U.S. became cost-competitive with manufacturing in China and other countries.

Model Fit The model replicates several data patterns that were not targeted in estimation. The first is antidumping and countervailing duty collections, which we assess by comparing model predictions to the administrative data from CBP in Table 2. Our estimates imply that duties collected over the period 2014 through 2020 would total \$1.40 billion. Over this time period, CBP reported collecting \$1.43 billion.

Appendix H provides additional evidence of model fit by comparing model predictions to data on the share of Chinese solar panels sold in the U.S. market and on the level of solar panel production in the U.S.

Alternative specification: estimates of external scale economies Table 5 presents estimates of the elasticity of location-specific cost efficiency with respect to industry scale from estimating equation (9) via ordinary least squares. Columns 1 and 2 use contemporaneous measures of industry scale. The scale elasticity in column 2 is in the range of recent estimates from Bartelme et al. (2019). However, these specifications are likely to suffer from simultaneity, because both the dependent and independent variables depend on output in period t, which itself is influenced by transitory cost shocks. To mitigate endogeneity concerns, columns 3 and 4 regress contemporaneous efficiency on values of industry scale lagged by two quarters and one year.

When using lagged values of industry scale, the scale elasticity estimates attenuate such that they are not statistically distinguishable from zero. As a result, we use the more flexible cost efficiency parameterization without external scale economies for our main counterfactual analysis. We evaluate the implications of non-zero scale elasticities in robustness analysis in Appendix I, using the scale elasticity from column 2 to be conservative. Figure I.1 presents location-specific cost estimates when allowing for external economies of scale. While changes in scale over time affect the relative cost of manufacturing of different locations, the relative cost levels are consistent with the patterns observed in Figure 7.

[39] As discussed earlier, we omit the 2012 tariffs from the model due to their limited effects. The counterfactual analysis in section 7 focuses on the period 2014 through 2020, when tariffs were binding.

Table 5: Scale Elasticity Estimates

	$\log(T_t^l) - \log(T_t^{US})$			
	(1)	(2)	(3)	(4)
$\log(K_t^l) - \log(K_t^{US})$	0.03	0.12^{**}		
	(0.02)	(0.05)		
$\log(K_{t-2}^l) - \log(K_{t-2}^{US})$			0.04	
			(0.04)	
$\log(K_{t-4}^l) - \log(K_{t-4}^{US})$				-0.01
				(0.04)
Location Fixed Effects	Y	Y	Y	Y
Year Fixed Effects		Y	Y	Y
Observations	86	86	82	78
R^2	0.37	0.66	0.72	0.74
Within R^2	0.04	0.09	0.02	0.001

Note: This table presents estimates of the elasticity of cost efficiency with respect to industry scale, capturing static external economies of scale across firms within a given location. The dependent variable contains quarterly estimates of the efficiency manufacturing in location l, relative to the US, estimated using equation (8). The dependent variable is the total output of all firms in location l relative to the US. Heteroskedasticity-robust standard errors are in parentheses.

7 Counterfactual Analysis

We solve the model to simulate counterfactuals that compare the effects of tariffs to scenarios without tariffs, both with and without production relocation. We start by decomposing the tariff's effects absent any environmental considerations and absent the ITC and other consumer subsidies that exist in the data.[40] This isolates the conventional trade policy impacts of tariffs from their interaction with environmental policy. We then account for subsidies for solar adoption and unpriced environmental externalities. Finally, we analyze the potential effects of the IRA's domestic manufacturing subsidies, as well as a non-discriminatory subsidy that has the same budgetary impact as the IRA.

Appendix I presents analogous results that incorporate static external economies of scale within each location. Appendix J presents analogous results using trade elasticity values that range from 6 to 9. All qualitative findings about the welfare effects of the tariffs are robust to the inclusion of scale economies and alternative values of the trade elasticity.

[40] In other words, we modify equation (6) by setting s_t to zero.

7.1 Welfare Impacts Absent Environmental Considerations

Table 6 summarizes the welfare impacts of the tariffs relative to a counterfactual scenario of no intervention, for a thought experiment in which there are no subsidies for solar technology adoption (i.e., no ITC) and no environmental externalities. This helps to isolate the traditional forces at work in trade policy from the additional considerations of environmental policy.

Table 6: Welfare Impacts of Tariffs Absent Environmental Considerations

	Impacts over 2014-2020 ($, billions):	
	With Relocation	Without Relocation
Δ in Consumer Surplus	-5.5	-6.6
Δ in Producer Surplus	-0.1	-0.4
Δ in Producer Surplus (USA)	0.8	1.0
Δ in Producer Surplus (China)	-0.9	-1.6
Δ in Producer Surplus (Other)	0.0	0.2
Δ in Government Revenue (Revenues - Outlays)	2.0	2.3
Δ in Tariff Revenues	2.0	2.3
Δ in Domestic Welfare	-2.7	-3.3
Δ in Total Welfare	-3.6	-4.7

Note: This table summarizes welfare impacts of tariffs relative to a counterfactual scenario of no intervention, in a hypothetical with no subsidies for solar technology adoption and no environmental externalities. The column "With Relocation" presents results from computing equilibria given the observed set of production locations. The column "Without Relocation" presents results from computing equilibria given a counterfactual set of production locations in which offshore production locations established after tariffs are replaced by production locations in the firm's home country. The change in domestic welfare excludes changes in producer surplus for foreign manufacturers.

We present two alternative sets of results. The first column presents results from computing equilibria given the observed set of production locations, which allows firms to reallocate production in response to tariffs. The second column is based on a counterfactual set of production locations in which all offshore production locations established after tariffs are replaced by the predominant manufacturing location of the firm prior to tariffs. This modeling choice is motivated by the descriptive evidence in section 3, which suggests that many of these production locations outside China were established in response to the tariffs. This second set of numbers can be considered as the upper bounds of the tariff impacts since some offshoring production in the data may not have been in response to the tariffs.

The model predicts that, in aggregate, the tariffs would have reduced U.S. welfare absent environmental considerations, both with and without production relocation. This is despite the fact that import tariffs in this setting could theoretically improve welfare by a combination of increasing government revenues, improving terms of trade, and shifting profits from foreign manufacturers to domestic manufacturers. The loss in consumer surplus would be between \$5.5 and \$6.6 billion, which is between 6.6 and 6.9 times the increase in producer surplus in the U.S. The increase in government revenue would be between \$2 and \$2.3 billion.

Our results are not sensitive to the omission of external economies of scale. Table I.1 contains results that include external scale economies and endogenize each location's scale in each scenario. Across both scenarios, the tariffs reduce domestic welfare.

In the scenario in which we restrict production location, which could be similarly achieved by basing tariff rates on the country of ownership rather than the country of production, we find that consumer surplus would have declined by 20% more as a result of the tariffs, and the net loss in total producer surplus would have been four times as large. The lost surplus for Chinese firms would have been 80% higher, and the surplus gain for US manufacturers would have been 25% higher. Production relocation also undermined tariff revenue, since the government would have collected 15% more from importers if they could not relocate production. Without relocation, the decline in domestic welfare would have been 22% larger and the decline in total welfare would have been 30% larger. These results corroborate the reduced-form evidence of producer responses in section 3, and underscore the quantitative importance of production relocation in response to tariffs.

The key finding of these results is that even without solar subsidies and uninternalized environmental externalities, the tariffs lead to a net surplus loss. We next discuss these results for the policy scenarios that include domestic subsidies and account for environmental considerations.

7.2 Welfare Impacts of the Tariffs

In this set of counterfactual analyses, we quantify solar market outcomes if tariffs had not been imposed with all other factors fixed as they are in estimation, including the ITC. The figures and tables that follow present results that compare model predictions for the scenario with tariffs to a baseline scenario without tariffs.

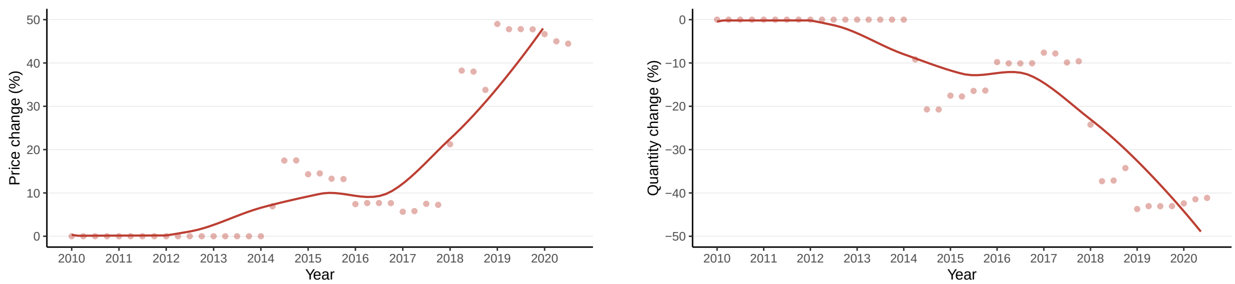
Figure 8 visualizes model predictions of the impact of the tariffs on prices and quantities, allowing for production relocation to the set of observed manufacturing locations. As expected, tariffs increased prices in the U.S. market relative to what they would have been otherwise. The model estimates are qualitatively similar but larger in magnitude than the reduced-form estimates in Figure 5.[41] By raising prices, the tariffs reduced the quantity of solar panels

[41]The model restricts the tariff's effects to be zero prior to 2014 due to data limitations with respect to low-cost avoidance of the 2012 tariffs, as described in section 3. Thus, the model and reduced-form estimates are only comparable starting in 2014.

purchased in the U.S.

Figure 8: Impacts of Tariffs on Prices and Quantities

(a) Percentage Change in Wholesale Price (b) Percentage Change in Quantity



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

We use our model-predicted price changes to compute the elasticity of solar panel prices with respect to tariffs, i.e., the tariff pass-through rate. To do so, we divide the predicted percentage change in the price of solar panels by the weighted-average percentage change in the tariff rate.[42] The estimated pass-through rate for the 2014 tariffs targeting Chinese production averaged 0.44 over the period 2014 through 2017. For the more broad-based 2018 tariffs, the pass-through rate was higher, averaging 0.67. This is to be expected, since the response of equilibrium prices depends on the extent to which all firms are exposed to tariffs.

The first column of numbers in Table 7 summarizes the resulting welfare impacts of the tariffs (still allowing for production relocation) relative to the counterfactual scenario with no tariffs. As with the scenario without the ITC, domestic consumer surplus is predicted to be much lower with tariffs than without. This measure captures reductions in consumer surplus from foregone transactions as well as transfers from consumers to the government in the form of tariff revenues and adoption subsidy outlays. The model predicts that, in aggregate, tariffs made domestic producers better off at the expense of foreign producers, though the benefits to producers are small relative to the harms to consumers. Government revenue is predicted to be higher due to an increase in tariff revenue and a decrease in tax

[42] The weighted-average tariff rate is computed by taking a weighted average across locations within each firm, and then across firms: $\widehat{\Delta\tau_t} = \sum_f \widehat{s}_{ft}(\tau = 0) \sum_l \widehat{s}^{l,US}_{ft}(\tau = 0)\Delta\tau^l_{ft}$, where $\widehat{s}^{l,US}_{ft}(\tau = 0)$ denotes the share of production firm f sources from location l for the U.S. market, and $\widehat{s}_{ft}(\tau = 0)$ denotes each firm's market share in equilibrium, both in the absence of tariffs. This is similar to the tariff pass-through calculation in Flaaen et al. (2020), though we use firm-level data along with the production sourcing model to account for the fact that firms face different tariffs depending on their production location, and production locations face different tariffs depending on the firm.

expenditures to subsidize solar adoption under the federal ITC.[43]

Table 7: Welfare Impacts of Tariffs

	Impacts over 2014-2020 ($, billions):	
	With Relocation	Without Relocation
Δ in Consumer Surplus	-6.9	-8.3
Δ in Producer Surplus	-0.3	-0.9
Δ in Producer Surplus (USA)	1.6	2.0
Δ in Producer Surplus (China)	-2.0	-3.3
Δ in Producer Surplus (Other)	0.1	0.4
Δ in Government Revenue (Revenues - Outlays)	14.3	17.1
Δ in Tariff Revenues	4.2	4.9
Δ in Adoption Subsidy Outlays	-10.1	-12.2
Δ in Environmental Benefits	-148.4	-184.5
Δ in Local Pollution Benefits	-27.8	-34.6
Δ in Global Pollution Benefits	-120.5	-149.8
Δ in Domestic Welfare	-18.8	-23.8
Δ in Total Welfare	-141.2	-176.6

Note: This table summarizes welfare impacts of tariffs relative to a counterfactual scenario of no intervention. The column "With Relocation" presents results from computing equilibria given the observed set of production locations. The column "Without Relocation" presents results from computing equilibria given a counterfactual set of production locations in which offshore production locations established after tariffs are replaced by production locations in the firm's home country. The change in domestic welfare excludes changes in producer surplus for foreign manufacturers and all changes in global pollution benefits (some of which spill over to other countries due to the nature of global pollutants).

To account for the external (i.e., unpriced) impacts of changes in solar panel adoption, we adapt prior estimates of the value of avoided air pollution damages. We use results from Sexton et al. (2021), who provide econometric estimates of the avoided pollution damages from U.S. solar systems, which we refer to as environmental benefits. For local pollution benefits, we use their estimates of avoided pollution damages from nitrous oxides, fine particulate matter, and sulfur dioxide. For global pollution benefits from changes in carbon dioxide emissions, we take a similar approach, but we update them by using U.S. Environmental Protection Agency (2023) estimates of the social cost of carbon of $190 per metric ton CO_2 for emissions in 2020 (in 2020 dollars). Finally, we reweight their estimates to reflect the

[43] $1.40 billion of the increase in tariff revenue comes from antidumping and countervailing duties collected from 2014 through 2020; in Table 2, we show that actual duties collected from these rounds of tariffs totaled $1.43 billion over the same period. Note that the government revenue change results from transfers, which are partially offset by changes in consumer and producer surplus. Only the change in government revenue net of these transfers factors into domestic and total welfare.

spatial distribution of solar panels installed between 2014 and 2020.[44] We then use these estimates in conjunction with our model predictions to compute the environmental benefits from import tariffs and present them in Table 7.

We interpret the environmental benefits in Table 7 as upper bounds since they impose some important assumptions. First, since we do not model demand in other countries, the global pollution benefit calculations assume that a reduction in solar panels installed in the U.S. due to tariffs is not offset by an increase in solar panels installed in other countries. Appendix Figure K.1 shows that there were not major jumps in solar panels exports from China to other major countries around the world just after the 2018 tariffs came into effect, suggesting that China did not appear to export more solar panels elsewhere in response to the U.S. tariffs. This evidence suggests that forgone benefits from greenhouse gas reductions were not simply offset by greenhouse gas reductions elsewhere.[45]

A second limitation of our calculations is that they do not include all environmental policies that may interact with the import tariffs. For example, many states have Renewable Portfolio Standard (RPS) policies that require electric utilities to meet a certain fraction of the electricity they procure with renewable energy. RPS policies complicate the welfare analysis. In the short run in a states with a binding RPS policy, higher solar costs due to tariffs would lead utilities to substitute from solar to other renewables, putting upward pressure on RPS credit prices (i.e., RECs) but not increasing emissions from electricity in that state.[46] That said, some states have revised or even not met RPS standards that had been laid out years before due to high costs or difficulties in meeting the standards. Thus, in the long run, the higher RECs prices might mean that the RPS standards would be weakened, implying that the tariffs have real emissions implications even in the RPS states. For this reason, we do not adjust our calculations for interactions with RPS policies, but we note that our estimates of the environmental effects could be an upper bound in the short run.

The potential environmental damages due to the import tariffs are substantially larger in magnitude than the their impact on conventional trade policy considerations. Forgone global pollution benefits are larger in magnitude than local impacts, but both are larger than the predicted change in government revenues. The domestic welfare impacts in Table 7 exclude changes in producer surplus for foreign manufacturers and all changes in global pollution benefits (some of which spill over to other countries due to the nature of global pollutants). The total welfare impacts incorporate all impacts, both domestic and foreign.

[44] See Appendix K for more details.

[45] One limitation is that we cannot rule out more installations of solar panels in China itself due to the tariffs. To the extent that it applies, our global environmental benefits would be an upper bound.

[46] RPS policies are implicit in our aggregate national data, so our price elasticity of demand estimates capture the average effect across states that have RPS policies and those that do not.

In total, both domestic and global welfare are reduced because the reductions in consumer surplus and environmental benefits are larger in magnitude than the increases in producer surplus and government revenue. While this accounting assumes a marginal cost of public funds of one, this qualitative conclusion is robust to substantially larger values than one. Focusing on local pollution, the tariffs reduced the ITC expenditures by $10.1 billion but correspondingly reduced the local pollution benefit by $27.8 billion, almost three times that amount. As with the first counterfactual that did not include the ITC or account for environmental impacts, restricting production relocation would have magnified the total surplus effects by about 25% (column 2 of Table 7).

7.3 Welfare Impacts of Manufacturing Subsidies

In this section we run two additional counterfactual analyses. We first quantify the potential effects of removing tariffs and replacing them with an ad valorem subsidy for manufacturing solar panels in the U.S. This counterfactual is motivated by provisions of the IRA that established a manufacturing production tax credit of seven cents per watt for domestic solar panel production. We divide the IRA subsidy by observed prices to calculate the subsidy for each period in ad valorem terms, allowing it vary over time with price. We incorporate the subsidy beginning at the time the 2014 tariffs were imposed in order to facilitate comparisons. In a second scenario, we replace the domestic manufacturing production tax credit with a non-discriminatory manufacturing subsidy that has the same total government cost. In both cases, we allow production relocation across the observed set of production locations.[47]

The first column of Table 8 shows the impact of the domestic manufacturing subsidy and the second column shows the impact of the alternative non-discriminatory subsidy. At this level of government expenditures, the welfare implications are much smaller in magnitude than those we saw in Table 7. This is driven in part by the fact that the subsidy is smaller in ad valorem terms than the tariffs. Absent the environmental benefits and adoption subsidy expenditure, the total welfare effect is negative, but when incorporating these effects, total welfare increases, in contrast to what we observed with the tariffs. The change in total welfare net of government expenditures is approximately 3.6 times larger than the government expenditures. Thus, the subsidy would increase total welfare as long as the marginal cost of public funds were below 3.6. On the other hand, the subsidy just breaks even from a domestic perspective, so it could not be justified based on domestic interests alone with a

[47] If instead firms opened additional production locations in the U.S. in response to the domestic manufacturing production tax credit, the magnitudes of total surplus calculations would be quantitatively larger but qualitatively similar, based on a bounding exercise in which all firms are endowed with a manufacturing facility in the U.S. at no cost.

Table 8: Welfare Impacts of Manufacturing Subsidies

	Subsidy impacts over 2014-2020 ($, billions):	
	45X MPTC	Non-Discriminatory
Δ in Consumer Surplus	0.1	0.2
Δ in Producer Surplus	0.0	0.0
Δ in Producer Surplus (USA)	0.1	0.0
Δ in Producer Surplus (China)	-0.1	0.0
Δ in Producer Surplus (Other)	0.0	0.0
Δ in Government Revenue (Revenues - Outlays)	-0.5	-0.5
Δ in Adoption Subsidy Outlays	0.1	0.4
Δ in Manufacturing Subsidy Outlays	0.4	0.1
Δ in Environmental Benefits	1.7	4.8
Δ in Local Pollution Benefits	0.3	0.9
Δ in Global Pollution Benefits	1.4	3.9
Δ in Domestic Welfare	0.0	0.6
Δ in Total Welfare	1.3	4.5

Note: This table summarizes welfare impacts of alternative government subsidies relative to a counterfactual scenario of no intervention. The column "45X MPTC" summarizes the effects of providing a subsidy of 7 cents per watt for solar panel manufacturing. The column "Non-Discriminatory" summarizes the effects of a subsidy that does not preference domestic manufacturing, and which has the same net government cost as the 45X MPTC subsidy (accounting for both direct and indirect fiscal impacts). In both columns, model equilibria are computed using the observed set of locations. The change in domestic welfare excludes changes in producer surplus for foreign manufacturers and all changes in global pollution benefits (some of which spill over to other countries due to the nature of global pollutants).

marginal cost of public funds above one.[48]

The positive welfare effects are greater with a non-discriminatory production tax credit, since a single dollar of government subsidy goes further when subsidizing lower-cost manufacturing than higher-cost manufacturing. The change in total welfare net of government expenditures is ten times larger than the government expenditures. Somewhat surprisingly, the total change is domestic welfare is also larger with the non-discriminatory production tax credit. Domestic manufacturer benefits are lower, as expected, and consumer benefits are higher. However, the primary reason domestic welfare increases more with the non-discriminatory production tax credit is because of the larger local pollution reduction benefits that result from the more cost-effective subsidies.

[48]Our analysis focuses on the direct economic impacts of subsidies to the solar industry, but generous subsidies may also have indirect political consequences, as De Groote et al. (2024) find in Belgium.

7.4 Employment Impacts of Tariffs and Subsidies

Panel A of Table 9 presents a back-of-the-envelope calculation of the impacts of the tariffs on domestic employment in the solar industry.[49] We compute these impacts by multiplying model predictions of changes in domestic manufacturing and solar adoption by the average labor intensity of each activity.[50] This approach predicts that tariffs increased domestic manufacturing employment, but that solar installation employment decreased by four times as much. This is because manufacturing labor demand depends on the number of solar panels that are produced domestically, whereas installation labor demand depends on the total number of solar panels consumed domestically, which includes panels produced domestically and abroad. Panel B of Table 9 presents an analogous calculation that incorporates wage data for solar manufacturing and installation jobs to put the employment numbers in context.[51] Installation jobs have lower wages, so this reduces the relative contribution of installation wages, but their change is still more than triple the change in manufacturing wages.

Table 9 also presents estimates of the prospective domestic employment and wage impacts of subsidizing domestic production, relative to a scenario with no tariffs. In contrast to the use of trade policy, which reduced domestic solar industry employment and wages on net, the domestic production subsidy would yield 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 solar industry employment and wages.

[49] These are partial equilibrium estimates of employment impacts, and do not account for general equilibrium responses in other industries. The partial equilibrium impacts are an upper bound on any full general equilibrium employment impacts.

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

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

Table 9: Domestic Solar Industry Employment and Wage Impacts

	Impacts over 2014-2020:	
	Import Tariffs	45X MPTC Subsidy
Panel A: job-years (thousands)		
Δ in Manufacturing job-years	106.2	59.4
Δ in Installation job-years	-433.8	6.1
Δ in Total job-years	-327.5	65.5
Panel B: wages (billions)		
Δ in Manufacturing wages	6.4	3.6
Δ in Installation wages	-20.1	0.3
Δ in Total wages	-13.6	3.9

Note: This table summarizes partial equilibrium employment and wage impacts of policies in the solar industry. Employment impacts are estimated by multiplying model-predicted changes in domestic solar manufacturing and installation quantities by time-varying sector-specific labor intensities derived from Solar Energy Industries Association (2021). Wage impacts are estimated by multiplying predicted changes in domestic solar manufacturing and installation employment by sector-specific wages derived from Solar Energy Industries Association (2021) and International Labour Organization (2023).

8 Conclusion

We draw three sets of conclusions from studying trade and industrial policy in the market for solar panels. First, we provide model-free evidence that U.S. import tariffs on solar panels led Chinese solar panel manufacturers to relocate production to third countries to avoid paying tariffs. This partially undermined tariff revenues and on-shoring of manufacturing activity to the U.S. Furthermore, they caused harm to consumers by raising prices in the U.S. relative to other markets.

We then develop and estimate both a demand and supply model, with the end goal of assessing the welfare consequences of the tariffs. Our supply estimates show that production efficiency is approximately 50% higher in China, relative to the U.S. With the 2014 tariffs, the implied location-specific production costs in China increase such that offshoring outside of the U.S. becomes more attractive. The 2018 tariffs help make U.S. production more competitive, but the costs generally remain higher than in other non-Chinese locations.

We use counterfactual simulations to to quantify the welfare consequences of the tariffs, with and without production location, taking into account the strategic location and quantity 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 subsidy for domestic solar panel manufacturing could increase the domestic production share, eliminate the conflicting employment impacts of import tariffs on an intermediate input, and raise both domestic and global welfare. That said, a non-discriminatory production subsidy would have larger domestic and global welfare benefits because it would generate larger reductions in both local and global air pollution.

One important limitation of this study is that we do not model dynamic effects of government intervention, such as learning-by-doing. In theory, temporary trade policy could be justified if it allows domestic firms in an infant industry to establish strong competitive positions that persist over time. In practice, this infant industry argument seems insufficient to justify the particular import tariffs we study, since they largely failed to engender a domestic solar manufacturing industry *ex-post*. In particular, there was a decided lack of wafer and cell production in the aftermath of the tariffs, even as panel assembly increased modestly due to domestic investment by foreign firms. Future federal subsidies for clean energy manufacturing like those under the IRA may lead to increased domestic manufacturing given our empirical results, especially if they are designed to provide incentives for domestic production throughout the supply chain.

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

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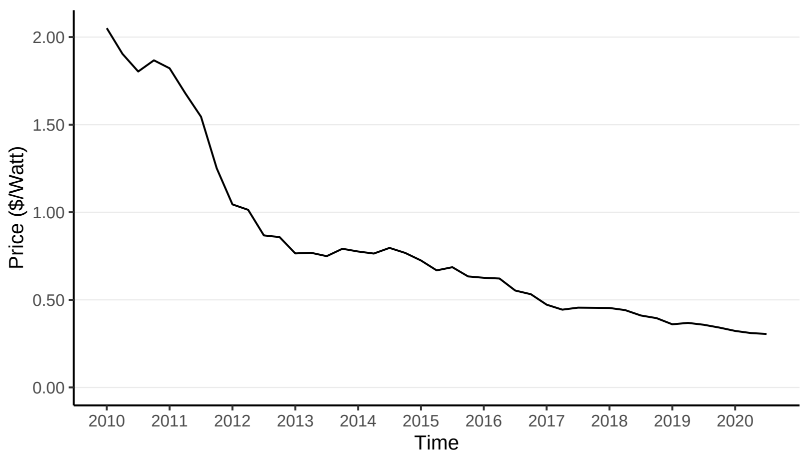
Appendix

A Aggregate Trends

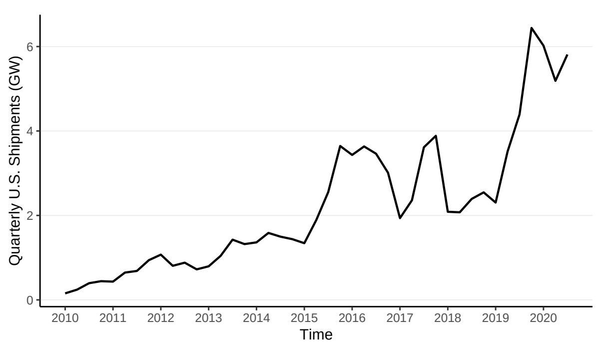
Figure A.1: Solar Panel Prices over Time



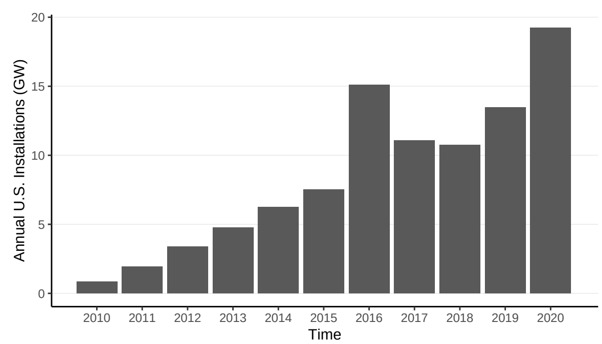
Note: This figure plots the quantity-weighted average wholesale price of solar panels in the U.S. over time based on quarterly data from IHS Markit. Prices are in nominal terms.

Figure A.2: Solar Panel Quantities over Time

(a) Shipments



(b) Installations



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

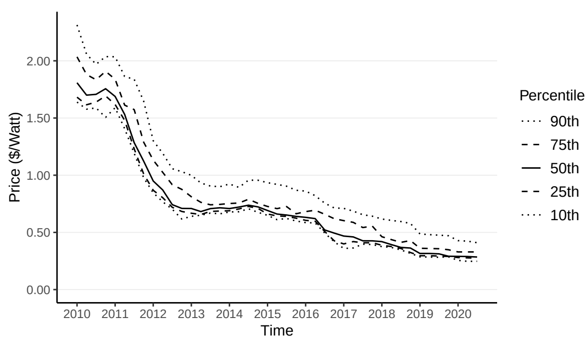
B Price Dispersion

Figure B.1 plots the distributions of absolute and relative prices in the U.S. market across manufacturers. In Figure B.1a, each line represents a different percentile of the prices observed across firms at a given point in time. The time series shows that while prices fell rapidly in this industry over the sample period, the majority of manufacturers had very similar prices at any given point in time.

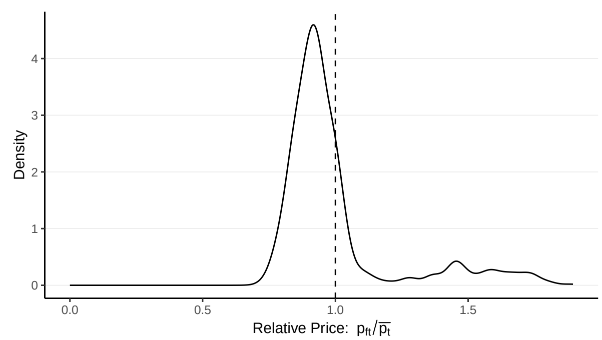
Figure B.1b eliminates the common time series variation in prices in order to summarize the degree of dispersion in relative prices across the entire sample. First, we divide each firm's price by the weighted average market price at a given point in time. We then plot the distribution of these relative prices, weighted by the quantity of each firm's shipments to the U.S. The resulting distribution is highly concentrated, with 87 percent of solar panel capacity sold within 25% of the weighted average market price.

Figure B.1: Solar Panel Manufacturers' Prices

(a) Price Levels



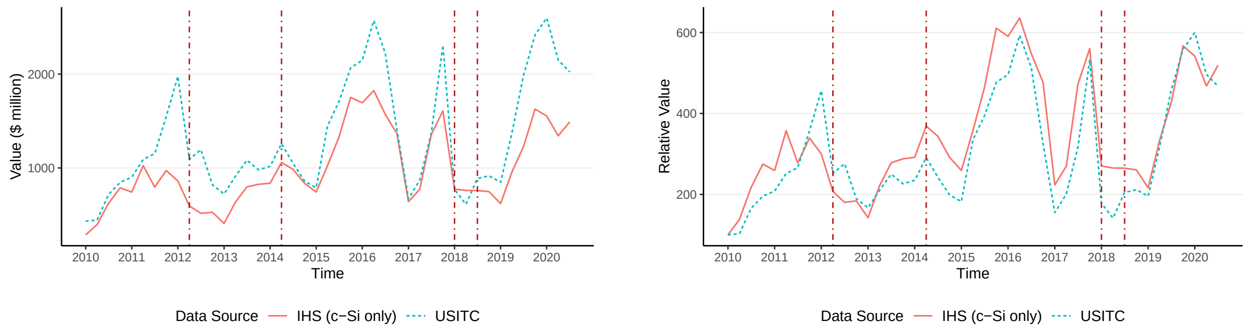
(b) Relative Prices



Note: This figure plots the distribution of prices across firms based on quarterly data from IHS Market. Prices are in nominal terms. Figure B.1a plots percentiles of the distribution of prices across firms over time. Figure B.1b presents the pooled distribution of relative prices after normalizing them within each time period.

C Comparison of IHS Markit and Government Data

Figure C.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 c-Si solar panels, omitting thin-film photovoltaic products. Vertical lines denote the timing of each round of tariffs. Values are in nominal terms.

D Additional Details on Production Activity

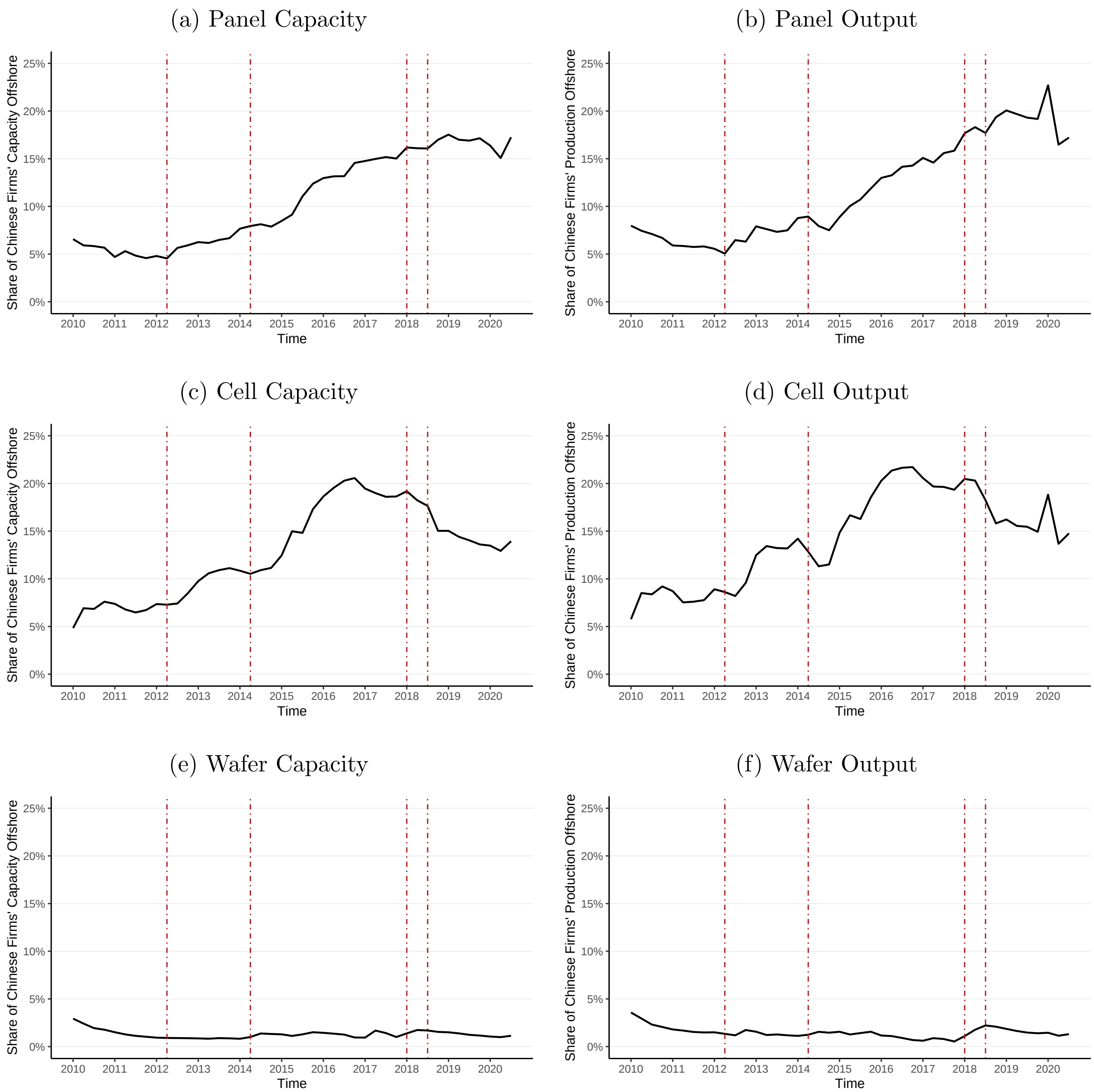
D.1 Production Offshoring by Chinese Manufacturers

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

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

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

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

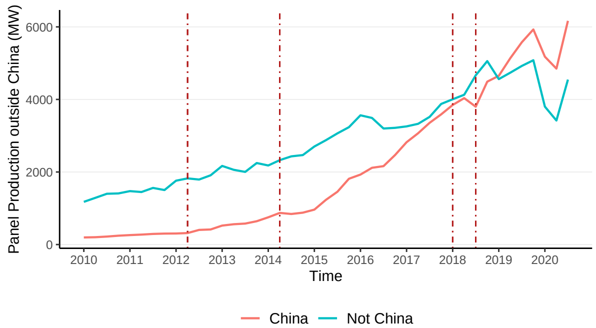


Note: This figure plots aggregate offshoring of solar manufacturing capacity and output over time based on quarterly data on quantities from IHS Markit. For each plot, the sample of firms is restricted to those that are active in China in that particular product prior to the imposition of tariffs (similarly,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

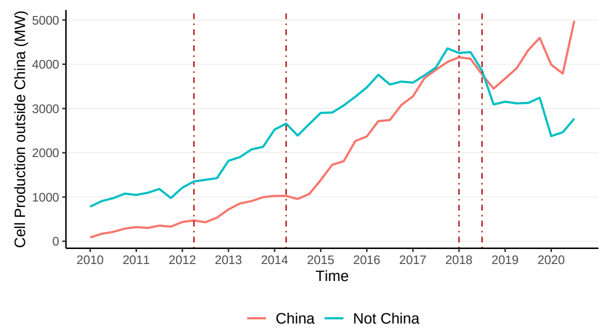
Figure D.2 plots total solar component production activity outside China over time in levels, comparing manufacturers that produced that component in China prior to tariffs to manufacturers that only produced that component outside of China prior to tariffs (and omitting any firms that only began producing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

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

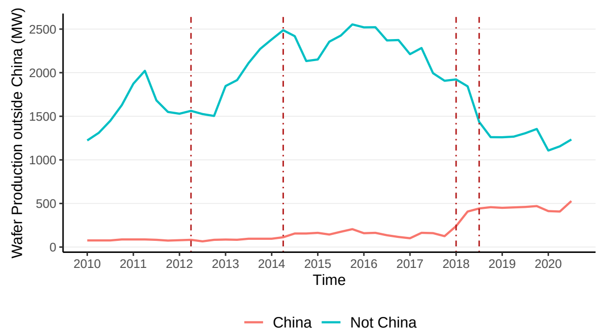
(a) Panel Production



(b) Cell Production



(c) Wafer Production



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

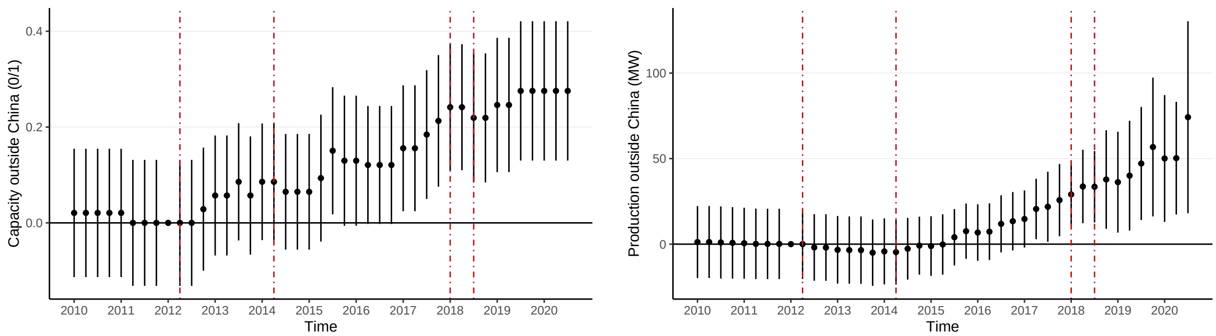
The patterns in Figure D.2 provide additional evidence consistent with the idea that production offshoring by tariff-exposed manufacturers was a response to location-specific import tariffs. The time series are suggestive of a differential response in production activity in the aftermath of the 2014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

D.2 Additional Event Study Estimates

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

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

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

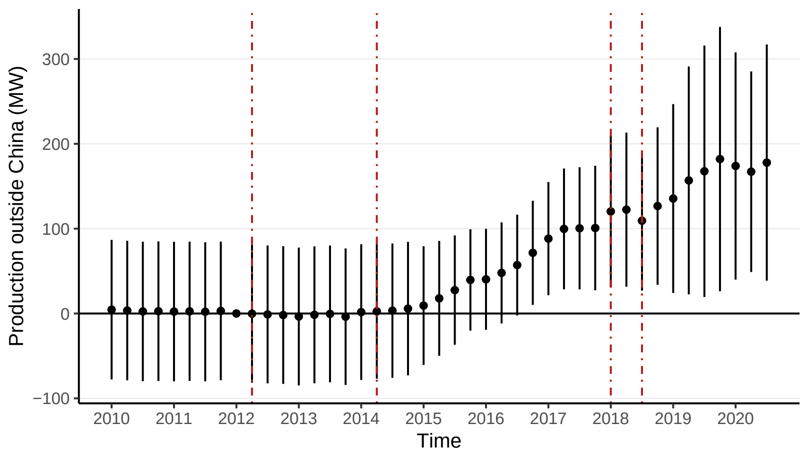


Note: Points represent event study coefficients from estimating equation (1) via ordinary least squares. Confidence intervals are robust to heteroskedasticity. Figure D.2a is from estimating a linear probability model where the outcomes are binary indicators of whether a firm has any production capacity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

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

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

(a) Production (MW)

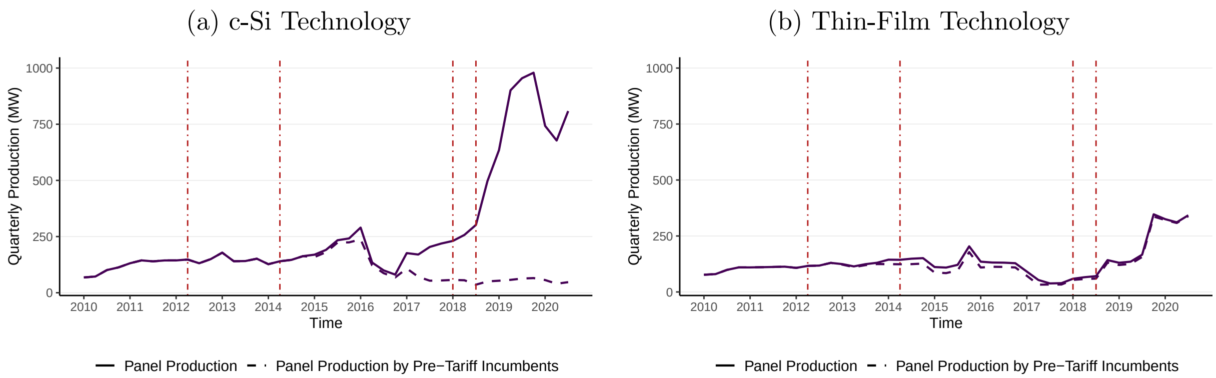


Note: Points represent event study coefficients from estimating equation (1) via ordinary least squares. Confidence intervals are robust to heteroskedasticity. The plotted coefficients are from estimating a linear model where the outcomes are continuous measures of production output outside China in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

D.3 U.S. Panel Production by Technology

Figure D.5 plots aggregate domestic panel production separately for c-Si and thin-film technologies. Figure D.5a is a reproduction of the panel series in Figure 3 of the main text. Figure D.5b plots domestic production by manufacturers of thin-film panels, which are not subject to tariffs. The dominant source of the growth in domestic manufacturing output toward the end of the sample period was the cohort of c-Si manufacturers that entered panel production after the broad-based Section 201 tariffs went into effect in 2018.

Figure D.5: U.S. Panel Manufacturing Activity over Time by Technology



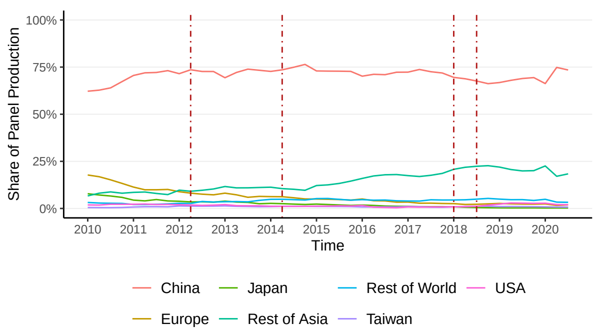
Note: This figure plots solar panel output based on quarterly data from IHS Markit. Figure D.5a plots output of c-Si solar panels, while D.5b plots output of thin-film solar panels. Both panels include output from firms that produced that product in the U.S. prior to tariffs (dashed line) and output from all firms (solid line). Vertical lines denote the timing of each round of tariffs.

D.4 Global Production Shares by Region

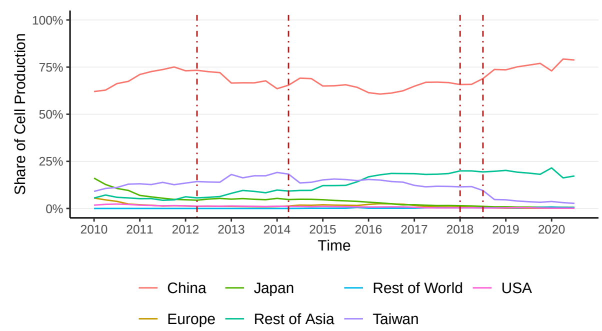
Figure D.6 plots production activity by region over time. The cell production time series in Figure D.6b provides further evidence suggestive of tariff avoidance. First, there was a small increase in cell production in Taiwan after the 2012 duties were imposed, which then decreased around the time of the investigation into extending the duties to include Taiwan. The opposite pattern is present for Chinese production, while there is no significant change in the share of panels produced in China (Figure D.6a). 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 D.6c).

Figure D.6: Global Production Shares by Region

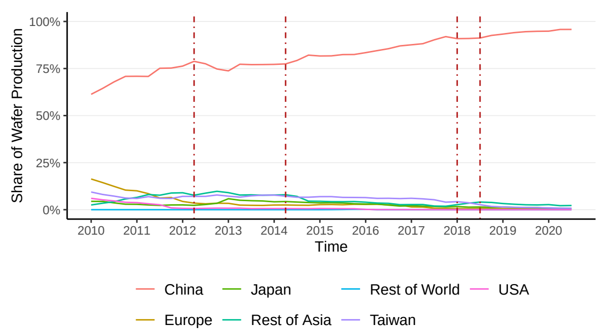
(a) Panel Production



(b) Cell Production



(c) Wafer Production



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

E 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 E.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 c-Si solar cells and panels from China, but not to polysilicon or wafers from China.

Figure E.1: Production Stages for Crystalline Silicon Solar

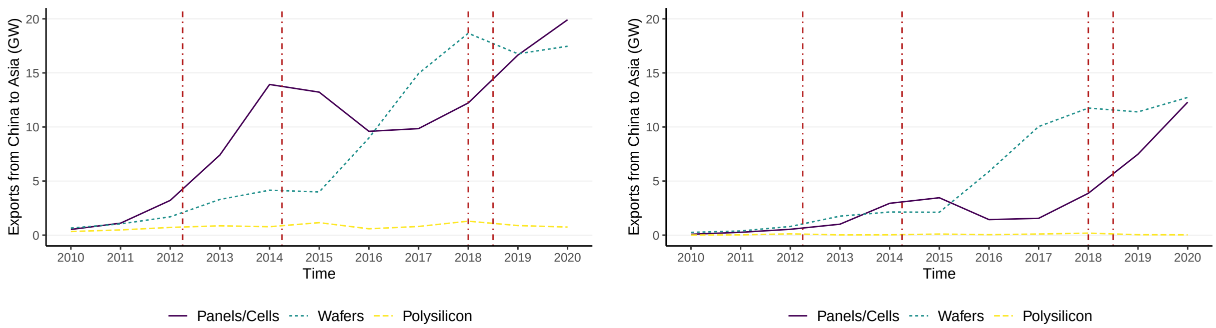
E.1 Solar Product Exports from China to Southeast Asia

Figure E.2 presents annual UN Comtrade data on solar product exports from China to Southeast Asian countries over time. Panels and cells, both subject to U.S. antidumping and countervailing duties if imported from China, are reported together by UN Comtrade because they fall into the same 6-digit HS code.[52] Wafers and polysilicon, both exempt from tariffs, are reported separately. To facilitate comparisons, we converted all three time series from trade values to gigawatts of electricity capacity using price indices for each product category.

[52]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 E.2 are due to products unaffected by the trade policies we study. While UN Comtrade does not provide a detailed breakdown of trade flows between China and Southeast Asian countries below the 6-digit level, more detailed data from USITC DataWeb shows that over one-quarter of U.S. imports of products classified under HS code 854140 during our study period were not solar products.

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

(a) Asia (b) Southeast Asia



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

Figure E.2 shows that Chinese exports of polysilicon to other parts of Asia are fairly flat over time. By contrast, Chinese exports of wafers increase significantly over time, particularly after the 2014 tariffs go into effect. Wafers are the last stage of intermediate goods production that could be completed in China without the final goods being subject to tariffs. Thus, the observed patterns are consistent with manufacturers avoiding tariffs by offshoring cell and panel production. If Chinese firms were to simply evade tariffs by transshipping finished solar panels, they would not need to export wafers. Finally, Chinese exports of panels and cells to other countries in Asia also increase over time. However, this trend appears to precede the U.S. antidumping and countervailing duties, and is therefore more likely to be explained by legitimate shipments of products (including non-solar products) to end consumers in other Asian countries than by tariff evasion. Consistent with this, Panel (b) shows that wafer exports quantitatively dominate panel/cell exports when removing Japan and South Korea, which are large end markets in addition to being manufacturing locations.[53]

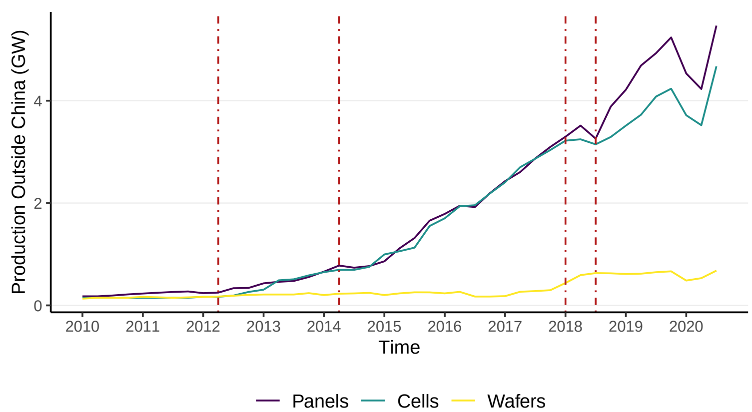
In summary, the patterns in Figure E.2 are consistent with Chinese firms offshoring the last two stages of solar panel production to avoid tariffs, and not simply transshipping completed products through third countries to evade tariffs.

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

E.2 Solar Product Production by Chinese Manufacturers

Figure E.3 presents total solar product production outside China for manufacturers in our analysis sample that produced solar panels in China prior to tariffs. The figure was made using production levels reported by IHS Markit. The increase in cell and panel production outside China over time is consistent with manufacturers offshoring production of cells and panels to avoid U.S. antidumping and countervailing duties, rather than simply transhipping completed panels.[54] By contrast, the figure shows no concomitant rise in offshore production of wafers, which were not subject to duties.

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



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

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

F Robustness Analysis: Detailed Demand Model

As an alternative to the aggregated market model in the main text, in which we estimate a constant elasticity demand system, we develop and estimate a micro-founded model of demand for solar panels that is derived from downstream demand for solar installations from the utility and non-utility markets, while also allowing installers to increase their solar panel inventory in periods of lower price.

F.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. These data include the time of installation of new grid-connected generating resources and the type.

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 LBNL 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.

F.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.

F.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

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

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

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

where m_t^u is the potential market size.

The outside option is investment in generating capacity other than solar. We do not allow for non-investment, given that utility companies need to meet baseline levels of demand. We think it is reasonable to use a static model of investment given that utility companies cite deferment of new generating resources as a net benefit (Bollinger and Hartmann, 2020).

F.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 watt of installation p_{jt}^s.[55] 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. Consumers' option value of waiting will depend on their beliefs about future installer characteristics and the transition of the relevant state variables, such as installer prices and rebates. 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

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

defined as:

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

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

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

Under the assumption that the random utility shocks are i.i.d. type I extreme value, we can substantially simplify the above equation. We can write the integrated value function as:

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

where the inclusive value of installation is defined as

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

Given a Markovian perceived transition of $(\xi_{t+1}, \mathbf{x}_{t+1})$ and the mean utility function $\delta(\cdot)$, equations (F.3), (F.4), and (F.5) fully describes the consumer's problem.[56]

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.

[56]We assume that consumers believe that installer-specific states and next period adoption probabilities evolve according to and AR(1) process with the inclusion of installer X county and quarter fixed effects; for county-level state variables, we estimate AR(1) regressions including one observation for each county and time period and include county and quarter fixed effects. These assumptions allow consumers to account for installer strength within their market and to anticipate changes in federal policies and incentives.

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

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

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

The FOCs depend on demand elasticity $\epsilon_{jt}^c \equiv \frac{\partial \log s_{jt}}{\partial \log p_{jt}^s}$. With the parametric assumption $\delta(\xi_j, x_{jt}) = \xi_j \alpha^\xi + p_{jt}^s \alpha^p$ in we define p_{jt}^s as the post-rebate price the consumer pays, we have:

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

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

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

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

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

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

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

F.3 Estimation

F.3.1 Utility-Scale Market Demand Estimation

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

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

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

F.3.2 Residential and Commercial Market Demand Estimation

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

For identification, we need instruments for the price and for the within-group share parameter. We use rebates per Watt and BLP-style instruments commonly used in the literature (Gandhi and Houde, 2019; Almagro et al., 2024), namely the difference in the average size of an installation performed in the county by that installer relative to its competitors in the market, and the share of third party installations performed in the county by that installer relative to its competitors.

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 (F.8) for using each installer in each market as the reference installer, and then average these equations at the market level. In other words, this is as if we choose a hypothetical reference installer whose log conditional choice probability is

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

and the average expected mean utility is

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

The estimation equation then becomes

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

We use aggregate data for our CCP estimation, as was done by De Groote and Verboven (2019), because this enables us to use the full dataset in estimation.[57] 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).

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

F.4 Estimation Results

F.4.1 Utility-Scale Market Demand Estimates

Utility-scale demand estimates are shown in Table F.1. In contrast to the constant elasticity demand model in the main text, these coefficients are not immediately interpretable as demand elasticities. We use the IV estimates with year fixed effects from column 3 to construct estimated utility-scale elasticities for each time period as follows:

$$\widehat{\epsilon_t^u} = \widehat{\alpha^u} p_t \left(1 - s_t^{solar}\right). \tag{F.9}$$

Table F.1: Utility-Scale Demand Estimates

	$\log(s^{\text{solar}}) - \log(s^{\text{all other}})$			$\log(s^{\text{solar}}) - \log(s^{\text{renewables}})$		
	(1)	(2)	(3)	(4)	(5)	(6)
Solar panel price (after subsidy)	-3.44***	-3.43***	-6.39***	-2.95***	-2.93***	-5.20**
	(0.44)	(0.44)	(1.59)	(0.47)	(0.45)	(2.46)
Year Fixed Effects			X			X
Estimator	OLS	IV	IV	OLS	IV	IV
Observations	43	43	43	43	43	43
R^2	0.67	0.67	0.78	0.57	0.57	0.81
First-stage Wald statistic		4,135.5	231.2		4,135.5	231.2

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

F.4.2 Residential and Commercial Market Demand Estimates

Residential and commercial demand estimates are shown in Table F.2. As expected, in the OLS regressions, the point estimates for the price coefficient are close to zero, presumably due to the endogeneity of price, especially with respect to unobserved quality (or perceived quality). For the IV regressions, we pass the over-identification test of excluded instruments at $p = .24$ (J-statistic of 1.37) with a Cragg-Donald Wald weak identification F statistic of 35.3, and a Kleibergen-Paap rk LM statistic of 28.9. rejecting weak identification at $p < 0.001$. The median demand elasticity is -1.16, and the group elasticity (the household response when all installer prices increase together) is -0.58.

Table F.2: Residential and Commercial Demand Estimates

Variable	OLS	IV 1st Stage, price	IV 1st stage, nest	IV 2nd stage
price ($/W)	-0.001			-0.152**
	(0.001)			(0.057)
size (MW)	0.002	-0.441***	-0.431***	-0.192***
	(0.005)	(0.067)	(0.075)	(0.052)
nest parameter (σ)	0.979***			0.535***
	(0.002)			(0.089)
rebate ($/W)		-0.570***	0.086	
		(0.039)	(0.072)	
mean size relative to competitor		0.023	0.144**	
		(0.026)	(0.046)	
mean third party relative to competitor		-0.032	-0.258***	
		(0.037)	(0.045)	
R-squared	0.984	0.512	0.695	0.739
N	147053	148037	147053	147053

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

F.4.3 Aggregating Segments

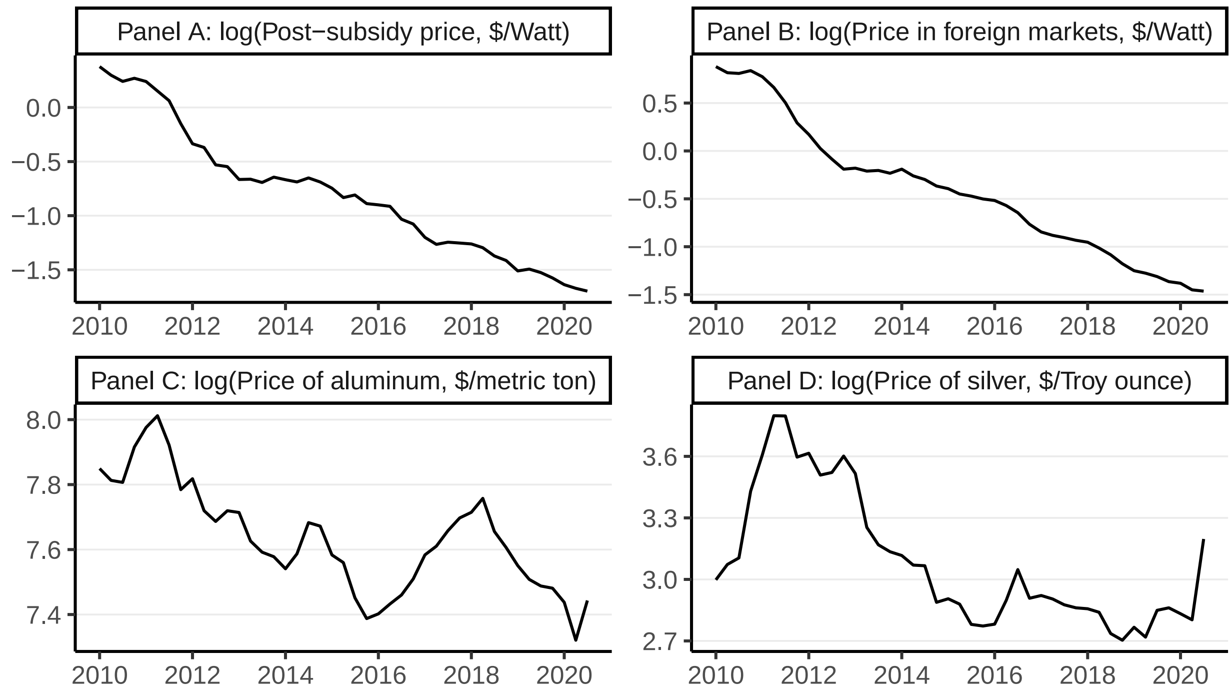
Since total demand for solar panels is derived from demand for residential and utility-scale solar systems, the aggregate demand elasticity is:

$$\epsilon_t^D = \epsilon_t^C \left(\frac{Q_t^C}{Q_t^D} \right) + \epsilon_t^U \left(\frac{Q_t^U}{Q_t^D} \right) \quad . \tag{F.10}$$

Combining the estimates from the two previous subsections, the average value of the price elasticity over time is -1.45 (-1.04 when weighted by sales volume), which is similar to the instrumental variables estimates in Table 4, which range from -1.33 to -1.55.

G Demand Instruments and First-Stage Estimates

Figure G.1: Prices of Solar Panels and Instrumental Variables



Note: This figure plots the post-subsidy price of solar panels in the U.S. market (Panel A) and three other prices used as instruments in demand estimation: the average price of solar panels in markets other than the U.S. (Panel B); the price of aluminum (Panel C); and the price of silver (Panel D). All values are in 2020 dollars (prior to taking logs).

Table G.1: First-Stage Estimates using Input Prices

	log(Post-subsidy price)		
	(1)	(2)	(3)
log(Price of silver)	0.57**	0.58*	-0.20*
	(0.28)	(0.29)	(0.10)
log(Price of aluminum)	2.00***	1.99***	0.71**
	(0.65)	(0.67)	(0.28)
Quarter Fixed Effects		Y	
Year Fixed Effects			Y
Observations	43	43	43
R^2	0.63	0.63	0.99
Within R^2		0.63	0.29
F-test (1st stage)	33.6	31.1	6.2

Note: This table presents first-stage estimates corresponding to Panel B of Table 4, for which the prices of silver and aluminum serve as instruments for the post-subsidy price of solar panels. Each column represents a different specification of the demand intercept through the inclusion of fixed effects. All models are estimated using a quarterly time series from Q1 2010 through Q3 2020. First-stage F-statistics are from tests of the hypothesis that the excluded instrument(s) are jointly irrelevant. Heteroskedasticity-robust standard errors are in parentheses.

Table G.2: First-Stage Estimates using Hausman Instruments

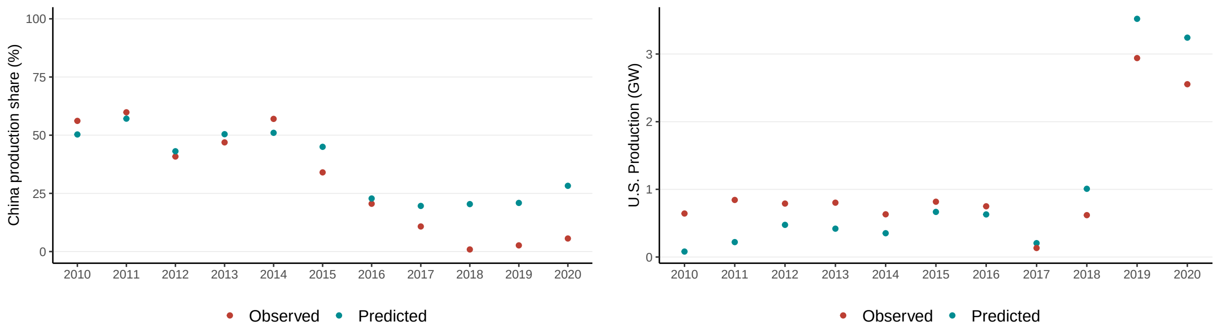
	log(Post-subsidy price)		
	(1)	(2)	(3)
log(Price in foreign markets)	0.86***	0.86***	0.72***
	(0.01)	(0.01)	(0.06)
Quarter Fixed Effects		Y	
Year Fixed Effects			Y
Observations	43	43	43
R^2	1.0	1.0	1.0
Within R^2		1.0	0.84
F-test (1st stage)	9,967.3	10,195.9	163.7

Note: This table presents first-stage estimates corresponding to Panel C of Table 4, for which the average price of solar panels in foreign (non-U.S.) markets serve as an instrument for the post-subsidy price of solar panels in the U.S. Each column represents a different specification of the demand intercept through the inclusion of fixed effects. All models are estimated using a quarterly time series from Q1 2010 through Q3 2020. First-stage F-statistics are from tests of the hypothesis that the excluded instrument(s) are jointly irrelevant. Heteroskedasticity-robust standard errors are in parentheses.

H Model Fit

Figure H.1: Model Fit: Solar Panel Production

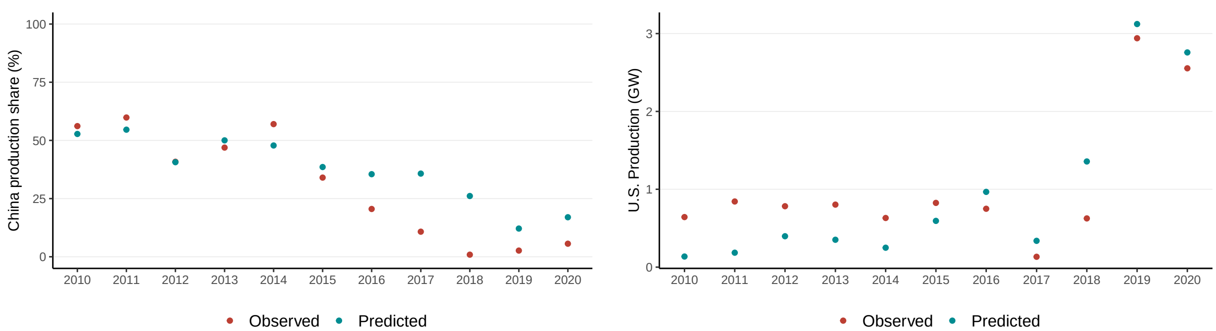
(a) Chinese Production Share (b) U.S. Production Level



Note: This figure compares model predictions and data on production of solar panels. Panel (a) compares model predictions of the share of solar panels consumed in the U.S. that are sourced from China to data on imports. “Observed” points are based on data from USITC DataWeb on the value share of solar panel imports by value that come from China and Taiwan. Panel (b) compares model predictions and data on U.S. production of solar panels. “Observed” points are based on data from IHS Markit on the quantity of solar panels produced in the U.S. In both panels, “Predicted” points are based on the model in section 4 and estimates in section 6.

Figure H.2: Model Fit: Solar Panel Production with External Scale Economies

(a) Chinese Production Share (b) U.S. Production Level



Note: This figure compares model predictions and data on production of solar panels. Panel (a) compares model predictions of the share of solar panels consumed in the U.S. that are sourced from China to data on imports. “Observed” points are based on data from USITC DataWeb on the value share of solar panel imports by value that come from China and Taiwan. Panel (b) compares model predictions and data on U.S. production of solar panels. “Observed” points are based on data from IHS Markit on the quantity of solar panels produced in the U.S. In both panels, “Predicted” points are based on the model in section 4 and estimates in section 6. Both panels account for static external economies of scale.

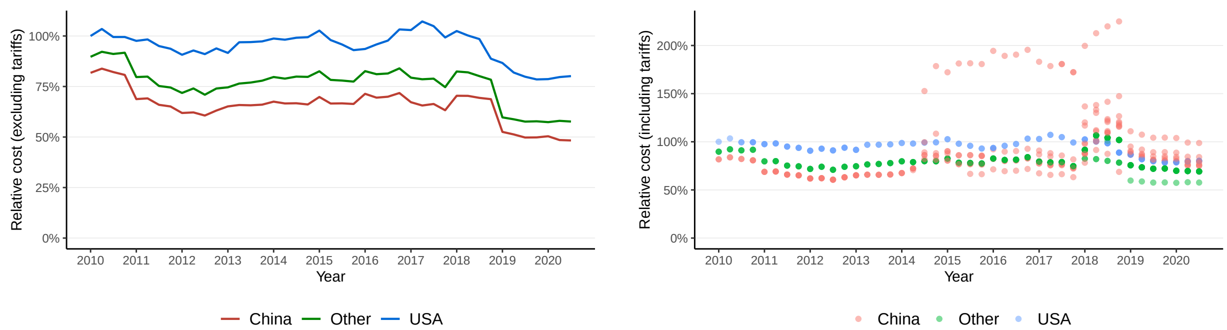
I Counterfactual Results with Static Scale Economies

I.1 Cost Predictions with External Scale Economies

Figure I.1: Location-Specific Cost Predictions

(a) before tariffs

(b) after manufacturer×location-specific tariffs



Note: The lines in panel (a) are based on the predictions of column 2 of Table 5, normalizing each location's scale over time relative to the U.S. in the initial period. The evolution of each line over time within location captures how time series variation in that location's industry scale affects its manufacturing costs. The points in panel (b) represent post-tariff costs for each firm-location combination observed in the data.

I.2 Welfare Impacts Absent Environmental Considerations

Table I.1: Welfare Impacts with External Scale Economies

	Impacts over 2014-2020 ($, billions):	
	With Relocation	Without Relocation
Δ in Consumer Surplus	-5.0	-7.3
Δ in Producer Surplus	-0.2	-0.6
Δ in Producer Surplus (USA)	0.9	0.7
Δ in Producer Surplus (China)	-1.1	-1.4
Δ in Producer Surplus (Other)	0.0	0.1
Δ in Government Revenue (Revenues - Outlays)	2.0	3.0
Δ in Tariff Revenues	2.0	3.0
Δ in Domestic Welfare	-2.1	-3.6
Δ in Total Welfare	-3.2	-5.0

Note: This table summarizes welfare impacts of tariffs relative to a counterfactual scenario of no intervention, in a hypothetical with no subsidies for solar technology adoption and no environmental externalities. The column "With Relocation" presents results from computing equilibria given the observed set of production locations. The column "Without Relocation" presents results from computing equilibria given a counterfactual set of production locations in which offshore production locations established after tariffs are replaced by production locations in the firm's home country. Both columns account for static external economies of scale. The change in domestic welfare excludes changes in producer surplus for foreign manufacturers.

I.3 Welfare Impacts of the Tariffs

Table I.2: Welfare Impacts with External Scale Economies

	Impacts over 2014-2020 ($, billions):	
	With Relocation	Without Relocation
Δ in Consumer Surplus	-7.1	-8.9
Δ in Producer Surplus	-0.5	-0.6
Δ in Producer Surplus (USA)	1.6	2.5
Δ in Producer Surplus (China)	-2.1	-4.0
Δ in Producer Surplus (Other)	0.0	1.0
Δ in Government Revenue (Revenues - Outlays)	14.5	17.3
Δ in Tariff Revenues	4.1	4.3
Δ in Adoption Subsidy Outlays	-10.4	-13.1
Δ in Environmental Benefits	-145.2	-189.1
Δ in Local Pollution Benefits	-27.3	-35.5
Δ in Global Pollution Benefits	-117.9	-153.6
Δ in Domestic Welfare	-18.2	-24.5
Δ in Total Welfare	-138.2	-181.2

Note: This table summarizes welfare impacts of tariffs relative to a counterfactual scenario of no intervention. The column "With Relocation" presents results from computing equilibria given the observed set of production locations. The column "Without Relocation" presents results from computing equilibria given a counterfactual set of production locations in which offshore production locations established after tariffs are replaced by production locations in the firm's home country. Both columns account for static external economies of scale. The change in domestic welfare excludes changes in producer surplus for foreign manufacturers and all changes in global pollution benefits (some of which spill over to other countries due to the nature of global pollutants).

I.4 Manufacturing Subsidies

Table I.3: Welfare Impacts with External Scale Economies

	Subsidy impacts over 2014-2020 ($, billions):	
	45X MPTC	Non-Discriminatory
Δ in Consumer Surplus	0.1	0.5
Δ in Producer Surplus	0.2	0.0
Δ in Producer Surplus (USA)	0.3	0.0
Δ in Producer Surplus (China)	-0.3	0.0
Δ in Producer Surplus (Other)	0.2	0.0
Δ in Government Revenue (Revenues - Outlays)	-0.8	-0.8
Δ in Adoption Subsidy Outlays	0.2	0.7
Δ in Manufacturing Subsidy Outlays	0.6	0.1
Δ in Environmental Benefits	2.5	9.5
Δ in Local Pollution Benefits	0.5	1.8
Δ in Global Pollution Benefits	2.1	7.7
Δ in Domestic Welfare	0.2	1.5
Δ in Total Welfare	2.1	9.2

Note: This table summarizes welfare impacts of alternative government subsidies relative to a counterfactual scenario of no intervention. The column "45X MPTC" summarizes the effects of providing a subsidy of 7 cents per watt for solar panel manufacturing. The column "Non-Discriminatory" summarizes the effects of a subsidy that does not preference domestic manufacturing, and which has the same net government cost as the 45X MPTC subsidy (accounting for both direct and indirect fiscal impacts). In both columns, model equilibria are computed using the observed set of locations. Both columns account for static external economies of scale. The change in domestic welfare excludes changes in producer surplus for foreign manufacturers and all changes in global pollution benefits (some of which spill over to other countries due to the nature of global pollutants).

I.5 Employment Impacts

Table I.4: Domestic Solar Industry Employment Impacts

	Impacts over 2014-2020 (job-years, thousands):	
	Import Tariffs	45X MPTC Subsidy
Δ in Manufacturing job-years	131.1	272.9
Δ in Installation job-years	-451.1	11.2
Δ in Total job-years	-319.9	284.1

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

Table I.5: Domestic Solar Industry Wage Impacts

	Impacts over 2014-2020 (wages, billions):	
	Import Tariffs	45X MPTC Subsidy
Δ in Manufacturing wages	8.0	16.6
Δ in Installation wages	-20.9	0.5
Δ in Total wages	-12.9	17.1

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

J Robustness: Alternative Trade Elasticity Values

In the main text, we fix the trade elasticity (θ) at 7.5 based on prior literature. This appendix summarizes how the counterfactual results change with the trade elasticity. To do so, we replicate the full analysis for alternative values of the trade elasticity ranging from 6 to 9. The results are robust to these alternative assumptions: varying the trade elasticity has a small impact on the quantitative estimates, and the qualitative conclusions are unaffected.

We summarize this sensitivity analysis by focusing on the most policy-relevant scenario: the impacts of tariffs when firms are allowed to relocate their production endogenously. Table J.1 summarizes the case absent environmental considerations, and Table J.2 summarizes the case with environmental considerations.

J.1 Welfare Impacts Absent Environmental Considerations

Table J.1: Welfare Impacts with Alternative Trade Elasticities

	Impacts over 2014-2020:		
	$\theta = 6$	$\theta = 7.5$	$\theta = 9$
Δ in Consumer Surplus	-5.7	-5.5	-5.3
Δ in Producer Surplus	-0.2	-0.1	-0.1
Δ in Producer Surplus (USA)	0.8	0.8	0.8
Δ in Producer Surplus (China)	-1.0	-0.9	-0.9
Δ in Producer Surplus (Other)	0.0	0.0	0.1
Δ in Government Revenue (Revenues - Outlays)	2.1	2.0	1.9
Δ in Tariff Revenues	2.1	2.0	1.9
Δ in Domestic Welfare	-2.7	-2.7	-2.7
Δ in Total Welfare	-3.7	-3.6	-3.6

Note: This table analyzes the sensitivity of the results in Table 6 to alternative values of the trade elasticity. The column $\theta = 7.5$ replicates the first column of numbers in Table 6. As in Table 6, this table summarizes welfare impacts of tariffs relative to a counterfactual scenario of no intervention, in a hypothetical with no subsidies for solar technology adoption and no environmental externalities. All three columns report results from computing equilibria given the observed set of production locations, without static external economies of scale. The change in domestic welfare excludes changes in producer surplus for foreign manufacturers.

J.2 Welfare Impacts of the Tariffs

Table J.2: Welfare Impacts with Alternative Trade Elasticities

	Impacts over 2014-2020:		
	$\theta = 6$	$\theta = 7.5$	$\theta = 9$
Δ in Consumer Surplus	-7.1	-6.9	-6.7
Δ in Producer Surplus	-0.4	-0.3	-0.2
Δ in Producer Surplus (USA)	1.7	1.6	1.6
Δ in Producer Surplus (China)	-2.0	-2.0	-2.0
Δ in Producer Surplus (Other)	-0.1	0.1	0.1
Δ in Government Revenue (Revenues - Outlays)	14.9	14.3	13.7
Δ in Tariff Revenues	4.5	4.2	3.9
Δ in Adoption Subsidy Outlays	-10.4	-10.1	-9.8
Δ in Environmental Benefits	-153.4	-148.4	-144.0
Δ in Local Pollution Benefits	-28.8	-27.8	-27.0
Δ in Global Pollution Benefits	-124.6	-120.5	-117.0
Δ in Domestic Welfare	-19.3	-18.8	-18.4
Δ in Total Welfare	-146.0	-141.2	-137.2

Note: This table analyzes the sensitivity of the results in Table 7 to alternative values of the trade elasticity. The column $\theta = 7.5$ replicates the first column of numbers in Table 7. As in Table 7, this table summarizes welfare impacts of tariffs relative to a counterfactual scenario of no intervention, in a hypothetical with no subsidies for solar technology adoption and no environmental externalities. All three columns report results from computing equilibria given the observed set of production locations, without static external economies of scale. The change in domestic welfare excludes changes in producer surplus for foreign manufacturers and all changes in global pollution benefits (some of which spill over to other countries due to the nature of global pollutants).

K Environmental Impacts Calculations

We use estimates from Sexton et al. (2021) to calculate the external environmental impacts of counterfactual changes in solar adoption. Sexton et al. (2021) use a combination of engineering simulations, econometric estimation, and integrated assessment modeling to estimate the avoided damages due to the addition of a representative solar system at the zip code level throughout the contiguous U.S.[58] The estimates include avoided damages from emissions of nitrous oxides, fine particulate matter, sulfur dioxide, and carbon dioxide. We use these zip code-level estimates to compute the weighted average avoided damages from solar systems installed over the period 2014 to 2020, since that is the period of interest for counterfactual simulations. These estimates are based on the assumption that solar adoption that is marginal to policy changes of interest has the same spatial distribution as the average of all the solar capacity installed between 2014 and 2020.

We compute avoided damages in three steps. We start with zip code-level estimates from the Sexton et al. replication package (Kirkpatrick et al., 2021), which are annual flows measured in 2014 dollars per system. We convert from 2014 to 2020 dollars using the U.S. GDP implicit price deflator from the U.S. Bureau of Economic Analysis (2024). We then divide by 4.32 kilowatts (kW) per system. This yields annual flows in 2020 dollars per kW of solar capacity. We also convert from the assumed social cost of carbon of \$41 per metric ton CO_2 to the more recent estimate of \$190 per metric ton CO_2 for emissions in 2020 (U.S. Environmental Protection Agency, 2023). We then convert these annual flows to a present discounted value using a lifetime of 20 years and discount rate of 5%, following the assumptions used by Sexton et al. (2021). This yields estimates of the present discounted value of avoided emissions from one additional kW of solar capacity in each zip code.

In the second step, we combine data from two sources to construct the share of all solar capacity installed over the period 2014 to 2020 that was installed in each zip code. The first is utility-scale solar system capacities from Form EIA-860, a survey of all electric power plants with at least one megawatt (MW) of combined nameplate capacity. The second is small-scale solar system capacities from the Lawrence Berkeley National Lab's "Tracking the Sun" data file (2024 edition). We remove all systems with DC capacity above 1 MW to form the complement of the Form EIA-860 data. For both data sources, we remove solar systems installed before 2014 or after 2020. We then combine the two and aggregate to obtain the

[58]Sexton et al. (2021) estimate marginal emissions by power plants, which they then combine with potential solar generation in each of 30,105 zip codes – simulated using the National Renewable Energy Laboratory's System Advisor Model – to predict the change in emissions due to an additional 4.32 kilowatts (kW) of solar capacity (the "typical" system size adopted by the authors) throughout the country. They monetize these impacts using the AP3 integrated assessment model. See Sexton et al. (2021) for more details

total installed capacity in each zip code.

In the third and final step, we compute the national weighted average of the present discounted value of avoided pollution damages per watt for each pollutant. Table K.1 presents the results. In counterfactual analysis, we use these numbers to compute aggregate changes in local and global externalities. Local pollution externalities consist of damages from nitrous oxides, fine particulate matter, and sulfur dioxide. Global pollution externalities consist of climate damages from emissions of CO_2 using a social cost of carbon of $190 per metric ton.

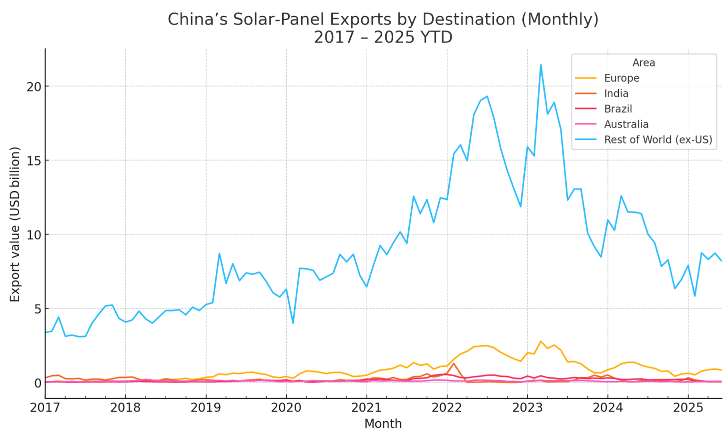
Table K.1: Estimates of the Value of Avoided Pollution Damages (PDV, $ per watt)

Pollutant	Avoided Damages ($/Watt)
CO_2 (SCC = $51/ton)	0.65
CO_2 (SCC = $190/ton)	2.43
NO_x	0.10
$PM_{2.5}$	0.06
SO_2	0.40

Note: This table presents estimates of the national weighted average present discount value of avoided damages per watt. The weights correspond to the cumulative solar photovoltaic generation capacity installed between 2014 and 2020 in each zip code. Present discounted values are computed using a lifetime of 20 years and discount rate of 5%. All numbers are in 2020 dollars.

As mentioned in the main text, we use these calculations to provide a plausible upper bound on the magnitude of the environmental impacts of import tariffs and domestic manufacturing subsidies. One reason these calculations represent an upper bound is the possibility that China may have diverted some of the solar panels that were no longer being sold to the U.S. to sell them in other geographic markets. In Figure K.1 below, we observe that there were no notable spikes of exports from China to other countries at the beginning of 2018 when the third and fourth rounds of tariffs were implemented. These data are only available starting in 2017, so we cannot look at the earlier tariffs. But this evidence suggests that it is unlikely that the solar panels no longer being sent to the U.S. due to the tariffs were sent elsewhere, and likely were just not produced. To the extent that they were produced and installed in China, our change in greenhouse gas externalities estimate is an upper bound. In the short run, RPS policies could also be a reason why our estimate is an upper bound. However, even reducing the estimate substantially would not change the qualitative conclusions of our analysis.

Figure K.1: Chinese Manufacturers' Solar Exports to Leading Countries



Note: Constructed using publicly available quarterly data from Ember (https://ember-energy.org/data/china-solar-exports-data/).