The Incidence of the US-China Solar Trade War

Wenjun Wang, Sébastien Houde

Abstract: This study investigates the distributional welfare effects of the trade tariffs initiated by the US government against Chinese solar manufacturers between 2012 and 2018. We estimate a structural econometric model that incorporates the vertical structure between upstream solar manufacturers and downstream solar installers. Counterfactual simulations show that the tariffs had a small positive impact on US manufacturers but a large negative impact on US installers. Chinese manufacturers were also negatively affected economically. Moreover, we estimate the tariff pass-through rate, which we find to exceed one due to the imperfectly competitive nature of the industry. Ultimately, the burden of the solar trade war thus fell disproportionately on US consumers.

JEL Codes: F14, L10, Q50

Keywords: trade war, solar industry, structural econometric model, pass-through

AFTER DECADES OF TRADE LIBERALIZATION, protectionism has reemerged in recent years, characterized by the US-China trade war, the Japan–South Korea trade dispute, and Brexit. Protectionism measures are often initiated to target high-value

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and fast-growing technologies, such as semiconductors, solar photovoltaic (PV) power systems, automobiles, and telecommunications. Trade wars arise when cycles of subsidies and retaliatory tariffs are enacted to protect domestic firms. The market for solar PV is a case in point of how trade wars can quickly escalate.

In recent decades, the solar PV industry has grown exponentially. The cumulative installed capacity of PV systems has soared almost 180-fold worldwide, from 6.7 gigawatts (GW) in 2006 to 1,177 GW in 2022.[1] Although the solar manufacturing sector has historically been dominated by firms in the United States, Japan, and Germany, Chinese firms have gradually gained market share since 2010.[2] Various government subsidy schemes spurred the Chinese solar sector's rapid growth. Chinese manufacturers' competitors, however, suspected that these schemes provided an unfair competitive advantage, which, in May 2012, led the US Department of Commerce to announce various duties ranging from 31% to 250% on Chinese solar panels. In retaliation, China imposed tariffs on imports of polysilicon products from the United States. This trade war affected firms in both countries, but Chinese solar manufacturers appeared to be particularly negatively affected.[3] Perhaps less salient, but nonetheless equally important, are the negative impacts these tariffs had on US consumers and other domestic firms, such as installers, in the US solar supply chain. Whether this trade war generated gains for US solar manufacturers larger than the casualties to other domestic actors is an important but unanswered question. This study aims to contribute to this debate.

Our goal is to quantify the distributional welfare effects of the antidumping and countervailing duties the US government initiated against Chinese solar PV manufacturers with a focus on the US downstream residential market. Using a structural econometric oligopoly model that accounts for the vertical structure of the market and endogenizes markups, we estimate the incidence of these tariffs on five actors: US solar manufacturers, Chinese solar manufacturers, other non-US-based solar manufacturers (i.e., South Korean and others), US solar installers, and US consumers. In addition, we also quantify the carbon externality associated with solar PV systems' adoption in the United States that would have displaced electricity generated from fossil fuels in the absence of these tariffs.

Our structural equilibrium model explicitly accounts for the strategic behaviors of domestic (i.e., US-based) manufacturers, foreign manufacturers, and domestic installers. Specifically, our supply side follows Villas-Boas's (2007) three-stage oligopoly model that captures the contractual relationship between installers and manufacturers.

1. See https://www.statista.com/statistics/280220/global-cumulative-installed-solar-pv-capacity/.

2. For the period from 2010 to 2018, four Chinese manufacturers were among the top 10 solar manufacturers.

3. For example, Suntech Power, a Chinese firm once the largest solar manufacturer in the world, became insolvent a few years after the US antidumping policy came into effect.

On the demand side, we use a static discrete choice model where consumers have heterogeneous tastes for solar PV systems' prices and other product characteristics.

Our main data come from the Lawrence Berkeley National Laboratory's (LBNL) Tracking the Sun report series. This dataset provides rich household-level information on almost all installations in the US residential solar market for the period between 2012 and 2018. Using these data, we estimate our model of demand and supply for solar PV systems. The estimation results are intuitive and show interesting heterogeneity patterns. On the demand side, the price coefficient is negative and households prefer high-energy conversion efficiency. Areas with higher household incomes and higher electricity prices tend to install relatively more solar PV systems. On the supply side, we find that the marginal cost increases with energy conversion efficiency and installation labor costs.

We simulate the estimated equilibrium model under different counterfactual scenarios to evaluate the distributional welfare effects of the US-China solar trade war. In our main baseline scenario, we assume that the statutory rates of the tariffs correspond to their effective rates.[4] Under this assumption, the results show that without the antidumping duties, countervailing duties, and safeguard tariffs imposed on Chinese manufacturers during the 2012–18 period, the demand from the United States for residential solar PV systems would have been 22.5% higher. Furthermore, Chinese manufacturers incurred large losses in profits due to the trade policies, but US manufacturers, as well as South Korean manufacturers, gained little. In the US domestic market, installers and consumers suffered significant losses from these trade barriers.

The solar trade war also had large negative impacts on environmental externalities. In the absence of trade policies, the increased adoption of solar PV systems would have reduced the electricity generated from fossil fuels. We estimate that the environmental benefits of avoiding CO_2 emissions would have been \$6.11 billion.

Finally, our model can be used to estimate the pass-through rate of the tariffs. In our main simulations, we find that a \$1 tariff imposed on manufacturers leads to a \$1.17 increase in the final prices of installed PV systems. Manufacturers and installers thus overshift the burden of the trade tariffs onto US consumers. Overall, our analysis suggests that during this period, the solar trade war was detrimental to the solar industry, US-based consumers, and the environment.

Our analysis is at the nexus of the literature on trade and the environment and empirical industrial organization. First, this study improves our understanding of the impact of trade wars in sectors crucial to the deep decarbonization of the economy. The

4. As we later discuss, there were loopholes in the US antidumping policies, especially in the first wave in 2012; these allowed Chinese manufacturers to avoid part of these tariffs. Our main policy analysis focuses on the case in which Chinese manufacturers cannot circumvent the tariffs. However, we discuss strategic avoidance of the tariffs in our sensitivity tests and show that it does not impact our main conclusion regarding the pass-through rates. Ultimately, US consumers paid for the tariffs and costs of reallocating solar panel production outside China.

theory of strategic trade policy argues that governments can use import tariffs to increase domestic welfare by shifting profits from foreign to domestic firms (e.g., Spencer and Brander 1983; Dixit 1984; Brander and Spencer 1985; Krugman 1987; Miller and Pazgal 2005; Creane and Miyagiwa 2008). Trade tariffs could then serve as a proxy for a domestic industrial policy to favor sectors of strategic importance for a successful energy transition. However, these objectives might conflict with the imperative to reduce the cost of low-carbon technologies and accelerate the adoption of these particular technologies in the domestic market. Our analysis shows that trade tariffs in the solar sector were, in fact, unlikely to have helped the domestic (i.e., US) solar sector while slowing down the decarbonization of the US power sector.

Second, this study contributes to the literature on the incidence of trade tariffs and, in particular, the estimation of tariff pass-through rates accounting for the role of imperfect competition.[5] While several studies investigating recent trade wars found tariff pass-through rates between 0% and 100% (e.g., Amiti et al. 2019; Fajgelbaum et al. 2020; Cavallo et al. 2021; Fajgelbaum and Khandelwal 2022), some studies also found evidence of overshifting (i.e., pass-through rates higher than 100%). Most notably, Flaaen et al.'s (2020) analysis of the 2018 US tariff on washing machines implies a pass-through exceeding 100%. The fact that we find tariff overshifting in the US solar market is also consistent with Pless and Van Benthem's (2019) findings of pass-through rates exceeding 100% for US solar subsidies.

These results for the US washing machine market and the solar PV market can be attributed to the presence of market power and highlight the importance of having a rich representation of the market structure to measure the incidence of trade policies. Bulow and Pfleiderer (1983) and Seade (1985) provided the first theoretical evidence of tax overshifting due to market power. Anderson et al. (2001) generalized these findings to the case of an oligopoly model with multiple differentiated goods, as in our setting. Weyl and Fabinger (2013) show conditions under which overshifting can arise under perfect competition. However, accounting for imperfect competition in the incidence analysis does not always imply higher pass-through (e.g., Ganapati et al. 2020). Ultimately, this is an empirical question determined by the nature of the demand function and the degree of competition. As we show, there is a large degree of heterogeneity across local markets in the US solar context—most but not all regions experienced overshifting of the trade tariffs, and the magnitude differs greatly across regions. Overshifting is more pronounced in regions where high-income households drive higher demand for solar PV, which is consistent with theoretical predictions.

5. For instance, see Huber (1971), Feenstra (1989), Winkelmann and Winkelmann (1998), Bernhofen and Brown (2004), Trefler (2004), Broda et al. (2008), Marchand (2012), Ossa (2014), Han et al. (2016), Ludema and Yu (2016), Bai and Stumpner (2019), Irwin (2019), and Jaravel and Sager (2019) for literature on the incidence of tariffs.

Our study also contributes to the growing literature in environmental economics on the solar power sector; the diffusion of residential solar PV systems is key to addressing the negative externalities associated with electricity generation. One stream of this literature has focused on evaluating the factors that lead to the adoption of solar energy by households. These studies show that financial incentives, electricity tariffs, mandates, peer effects, and social interactions are all important drivers of adoption (Bollinger and Gillingham 2012; Burr 2016; De Groote and Verboven 2019; Gillingham and Tsvetanov 2019; Gillingham and Bollinger 2021; Dorsey, forthcoming). The timing of government subsidies can also affect households and the adoption of solar PV (Bauner and Crago 2015; Langer and Lemoine 2022). A second stream of literature has investigated the reasons for the rapid and large reduction in the costs of solar systems (Reichelstein and Sahoo 2015). For example, Bollinger and Gillingham (2019) find that when installers learn by doing, this lowers solar prices, primarily related to the non-hardware costs of the solar PV installations. Gerarden (2023) finds that consumer subsidies can encourage firms to innovate to reduce their costs over time. Our work contributes to this literature by investigating the role of trade policies, which, as we show, can be an important determinant in determining the growth of the solar PV market.

The remainder of the paper is organized as follows. Section 1 introduces the background of the US-China solar trade war. Section 2 provides stylized facts about the manufacturer-installer relationships and the market structure. Section 3 specifies the demand and supply components of the equilibrium model. Section 4 describes the data, identification, and estimation details, and section 5 presents the estimation results. Section 6 uses the estimated model to perform policy simulations. Section 7 offers our conclusions.

1. BACKGROUND: THE US-CHINA SOLAR TRADE WAR

In this section, we provide background information on the events that led to the US-China trade war in the solar market. We first provide an overview of the US solar market, then discuss the United States' and China's solar subsidies, and, finally, consider the antidumping duties the US government imposed upon Chinese manufacturers.

1.1. The US Solar Market

The United States has one of the largest installed capacity of solar power in the world. In 2016, solar power overtook wind, hydro, and natural gas to become the largest source of new electricity capacity, as documented by the US Energy Information Administration. In 2019, the cumulative operating PV capacity exceeded 76 GW, up from just 1 GW at the end of 2009.[6] The importance of the solar industry for the United States is also reflected in its contribution to job creation. US solar employment grew by 167%

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6. See the US Solar Market Insight 2019 Year-in-Review report, released by the Solar Energy Industries Association (SEIA) and Wood Mackenzie.

from 2010 to 2019, adding more than 156,000 jobs, according to the National Solar Jobs Census.[7]

A confluence of factors spurred the rapid development of the US solar sector. On the one hand, government policies may have played a role. For example, several states have adopted renewable portfolio standards mandating that a certain share of their electricity generation come from renewable sources. At the same time, federal and state governments have also offered generous subsidies that target consumers.[8] Technology itself has improved. The manufacturing costs of solar PV systems have decreased drastically, and the efficiency of solar panels has increased. Even in the absence of subsidies, this technology has become increasingly attractive (Borenstein 2017).

In addition, the supply chain for residential solar PV has also developed rapidly. The upstream market of the solar industry consists of the manufacturing segment that produces solar PV systems (solar panels); the downstream firms consist of the installation segment that acts as distributors and providers of installation services for customers. Due to the large decrease in PV hardware costs in the past two decades, installation costs, referred to as soft costs, now constitute a larger share of the final price of solar PV (Barbose and Darghouth 2016; Fu et al. 2017).

1.2. China's Solar Subsidies

At the international level, several jurisdictions have competed to develop a strong domestic solar sector. For example, in Europe, Germany has been an early mover. Starting in the mid-2000s, the Chinese government also oriented its industrial policy to develop its domestic solar sector. As a result, in 2008, China became one of the world's largest solar panel manufacturers and then the largest producer in 2015. The extremely rapid development of its solar industry coincided with generous government subsidies and support. China's initial solar subsidies focused on the manufacturing side, and the Chinese government offered four types of subsidies to its domestic solar manufacturers

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7. See the National Solar Jobs Census 2019, released by the Solar Foundation.

8. The federal Energy Policy Act of 2005 created a 30% investment tax credit (ITC) for solar PV installations, with a $2,000 limit for residential installations. Subsequently, the Energy Improvement and Extension Act of 2008 removed the $2,000 limit, and the American Recovery and Reinvestment Act of 2009 temporarily converted the 30% tax to a cash grant (Bollinger and Gillingham 2019). The federal subsidy is believed to be an important factor in the recent growth of the solar sector. The financial subsidies for residential solar PV installations at the state level vary considerably from state to state. The incentive generally falls into four categories: (1) cash rebate, a one-time rebate provided on a $/kW basis at the time the system is installed; (2) state tax credit, additional tax credits offered by some states; (3) solar renewable energy certificates (SREC), credits the homeowner can obtain by selling solar electricity to the grid; and (4) performance-based incentives (PBI), per-kilowatt-hour credits based on the actual total energy produced by the solar PV system during a certain period of time.

(Ball et al. 2017). First, tax breaks were offered, consisting of a credit of 50% of the value-added tax. These tax breaks were first implemented in 2013 for two years; then they were extended to 2018. Second, local governments offered subsidized land (free or discounted) available to some Chinese solar manufacturers. Third, municipal and provincial governments offered cash grants. Fourth, preferential lending programs that provided advantageous loans were instituted by government-affiliated banks. In particular, the China Development Bank (CDB), a financial institution controlled by the Chinese government, has become the primary lender for Chinese solar manufacturers.

1.3. US Trade Policies

In October 2011, German-owned SolarWorld, which was then the United States' largest provider of solar panels, filed an antidumping petition against Chinese solar firms. They alleged that the Chinese government was unfairly subsidizing PV solar cells and modules by providing tax breaks, subsidized land, cash grants, preferential loans, and other benefits designed to artificially suppress Chinese export prices and drive other competitors out of the US market.

Following SolarWorld's petition, the US Department of Commerce began an investigation culminating with an announcement in October 2012 that antidumping duty rates ranging from 18.32% to 249.96% and countervailing duty rates ranging from 14.78% to 15.97% would be imposed on Chinese manufacturers. This was the first wave of US tariffs against Chinese solar manufacturers (see app. A [apps. A–E are available online] for more details about the first and second waves of tariffs).

However, this ruling applied only to solar panels made from Chinese solar cells; this created an important loophole. Some mainland Chinese companies could circumvent tariffs when exporting to the United States by outsourcing one part of the manufacturing process to Taiwan. In January 2014, SolarWorld filed another antidumping petition with the US Department of Commerce to close this loophole. In December 2014, the US Department of Commerce announced deeper firm-specific tariffs on imports of crystalline silicon photovoltaic products from both mainland China and Taiwan. The antidumping duty rates then ranged from 26.71% to 165.04%, and the countervailing duty rates then ranged from 27.64% to 49.79%. This marked the second wave of tariffs. The tariffs were imposed based on whether the products were manufactured in China. We, therefore, classify firms based on the countries where manufacturing occurred and use the labels "Chinese," "Korean," or "Other manufacturers" to designate the country of origin.[9]

9. For subsidiaries, we use the location of manufacturing to assign tariffs. For example, in the 2014 antidumping fact sheet, there are two subsidiary firms of Hanwha, a South Korean firm, that have been subject to an antidumping duty rate of 52.13% and a countervailing duty rate of 38.72%. These two subsidiaries are Hanwha SolarOne (Qidong) Co. Ltd and Hanwha SolarOne Hong Kong Limited. Although Hanwha has some ownership in these two firms,

The third wave started in February 2018, when the US government levied a 30% Section 201 tariff on all imported solar modules and cells (China, South Korea, and other countries were all subject to these safeguard tariffs). The tariff was designed to decline in annual increments of 5% over four years. Finally, the last episode of the solar trade war culminated in July 2018 when the US government levied a 25% Section 301 tariff on Chinese solar products as part of the broader US-China trade war on $50 billion of goods of all kinds (Amiti et al. 2019; Fajgelbaum et al. 2020).

2. MARKET STRUCTURE

Before proceeding to the presentation of the structural econometric model, we first investigate the market structure of the US solar industry. We show that the upstream manufacturing and downstream local markets exhibit a high degree of concentration, which motivates our vertical structure with imperfect competition.

2.1. Vertical Contracting in Manufacturer-Installer Relationship

A salient feature of the US solar industry is the vertical relationship between manufacturers and installers. Upstream companies manufacture solar panels and modules and distribute them to downstream installers. Installers sell solar products to customers and provide installation services. Typically, homeowners hire a solar installer and purchase panels and modules through it, rather than buying them directly from manufacturers. Installers play several roles. They buy solar products in bulk from manufacturers, provide expertise in designing a solar PV system, such as site selection and layout, and perform complex work to assemble solar panels together with other equipment (inverter, battery, mounting system, wiring, and solar charge controller).

In the United States, most of the PV market is not vertically integrated. However, this trend might be reversing as some solar manufacturers are starting to integrate their entire supply chain. For example, SunPower and REC Solar transformed into vertically integrated companies by offering solar installations rather than just manufacturing modules.

2.2. Market Power

To further gain insight into the market structure of the US solar industry, we take advantage of our micro dataset. We work with solar installation data from the LBNL's Tracking the Sun report series, which contains information on prices and quantities of almost all US solar PV installations. We exclude the commercial and utility-scale

we label these two subsidiaries as having production in China and assign the tariffs imposed in 2014 on those firms. In 2018, Hanwha is treated as a South Korean manufacturer affected by the 2018 tariffs, while Hanwha SolarOne (Qidong) and Hanwha SolarOne Hong Kong are treated as other Chinese manufacturers.

solar sectors and focus solely on residential solar installations.[10] At the end of 2018, there were more than a million residential solar PV installations in the United States. For each observation, we observe the installation date, location, system size, total installed price, rebate, installer name, and detailed information about solar panels used in each PV system, namely, manufacturer name, model number, technology type, and efficiency. For our analysis in this subsection, the sample period begins in 2011, the year before the first episode of the US-China solar trade war that began on March 2012, and ends in 2018 at the time of the third episode.

The US solar market for upstream manufacturers and downstream installers is relatively concentrated, although entry is not restricted. There were more than 250 different solar manufacturers operating in the US market from 2011 to 2018, but the 10 largest manufacturers accounted for approximately 80% of the solar PV sales. Manufacturers from the United States, China, South Korea, Germany, and Japan dominated the market. The US downstream market is more fragmented due to its local nature. There have been 4,895 different firms that have installed at least one residential PV system in the United States during the sample period. However, about 50% of these installers installed no more than five systems, and several firms with a small number of installations are, in fact, contractors for other types of services in the building and construction sector, for example, electricians (OShaughnessy 2018).

However, over time, the local market for PV installations has remained highly concentrated. As shown in panel B of table B1 (tables B1–B8, C1, D1–D5, E1–E4 are available online), on average, although the number of different active installers for each state has increased from 89 in 2011 to 247 in 2018, the market share for the largest installer in each state has only decreased from 32.53% in 2011 to 26.48% in 2018. The 15 largest installers represented approximately 50% of all US solar PV installations during the 2011–18 period.

On average, each installer worked with approximately four different manufacturers between 2011 and 2018 (see panel A of table B1). However, there is substantial heterogeneity between installers with activities in the United States and those who are only active in a few regional markets. For example, Tesla Energy, the largest solar installer in the United States, purchased solar panels from 52 different solar manufacturers. In contrast, the whole sample of installers works with a median of two different manufacturers.

2.3. Variation in Market Share During the Trade War

Figure 1 shows the time trend of market share for Chinese, US, and South Korean manufacturers.[11] In 2011-Q1, 20.3% of the installations done by US installers used

10. The residential solar sector accounts for the majority of the US solar market in terms of number of installations.

11. To create fig. 1, we extended the sample period to 2010–19 to better show the pre- and post-trends.

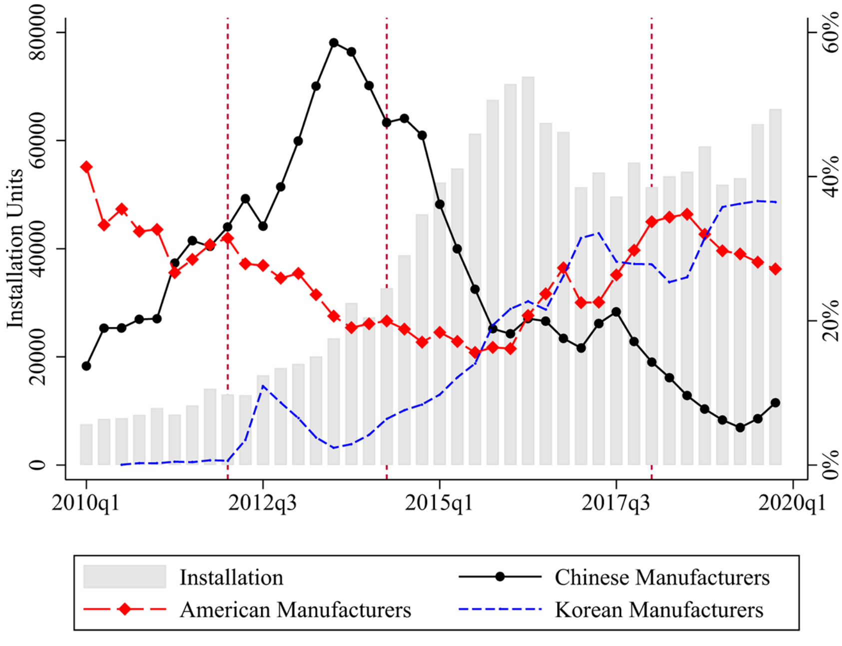

Figure 1. Market share for manufacturers through years. This figure shows the market share of manufacturers and the number of installation units across different quarters from 2010 to 2019. The bars (*left axis*) represent the number of total installation units. The solid line, line with squares, and dashed line represent the time trend of the market share for Chinese, US, and South Korean manufacturers, respectively. The three vertical lines represent the beginning of the three waves of antidumping policies (2012-Q1, 2014-Q2, and 2018-Q1).

solar panels produced by Chinese manufacturers. After the first wave of antidumping policies that began in March 2012, we saw a continued increase in the market share of Chinese manufacturers, culminating in 2013-Q4. This increase could be due to the fact that mainland Chinese firms accelerated their exports by evading duties by assembling panels from cells produced in Taiwan, a loophole that we discussed in section 1.3. However, this export-snatching effect gradually diminished when the Chinese manufacturers noticed that the US government was taking possible actions to close this loophole. After the second wave of trade policies starting in 2014, the market share of Chinese manufacturers decreased to approximately 20%; it further decreased to 8.6%, which is approximately 12% points below the level before the trade war, after the third wave of trade policies starting in 2018. The market share of US manufacturers is strongly negatively correlated with the market share of Chinese manufacturers and thus shows the exact opposite pattern.[12]

12. Figure B1 (figs. B1, B2 are available online) shows the proportion of Chinese manufacturers with which each installer was working. We observe a similar trend as in fig. 1.

Furthermore, South Korean manufacturers have become increasingly important players in the US market. They seemed to have benefited from the US-China solar trade war. Their aggregated market share rose from nearly zero in 2011 and steadily increased to about 35% in 2019.

3. STRUCTURAL ECONOMETRIC MODEL

We now outline a structural econometric model of the US solar industry where demand and supply are represented. The demand side is modeled with a discrete choice framework with rich heterogeneity in preferences. The supply side captures the vertical structure in which the upstream manufacturers determine the wholesale price of solar PV systems and the downstream installers determine the retail price while providing installation service to consumers. We focus on modeling preferences for residential consumers and, in particular, owners of a single-family home. Our sample period covers the early stages of the adoption of solar PV in the United States, and those households represent the primary market during this period. Nonresidential consumers represent only 3.4% of the installations made during that period.

3.1. Consumer Demand for Solar PV

The purpose of the demand model is to capture the preferences for the price and the main characteristics of solar PV systems. A consumer can choose the solar installer and the model of the solar PV system to install.[13] Because our data are aggregated to the PV model/installer/year level, we assume that the consumer's choice is a combination of model and installer, indexed by j. That is, consumers have preferences for both the manufacturer that produces a given PV system and the installer who performs the installation of the said PV system. We use a static random coefficient discrete choice model to analyze consumer purchase decisions. The conditional indirect utility function of consumer i in region w, where a region denotes a metropolitan statistical area (MSA), from purchasing and installing j good during year t is given by

$$U_{ijwt} = \beta_i X_j + \alpha_i p_{jwt} + \gamma D_w + \kappa E_w + \lambda_m + \eta_{rt} + \zeta_{jt} + \epsilon_{ijwt}. \tag{1}$$

In equation (1), X_j is a vector of observed product characteristics such as energy conversion efficiency and technology type. The term β_i is a vector of consumer preference-specific marginal utilities (assumed to be random) associated with the product characteristics in X_j; p_{jwt} is the average consumer purchase price for j in MSA w during year t, net of government subsidies and divided by the size of the solar PV system installed; and α_i represent the marginal disutility of price (also assumed to be random). The term D_w is a vector of demographic variables (including income, education, urbanization, race, and

13. The model of the solar PV system refers to the model of the solar panels used in the PV systems.

political orientation) for each MSA w and captures household-specific preferences.[14] The term E_w is the average electricity price in the state that MSA w belongs to. We also control for solar manufacturer fixed effect λ_m, where m represents the solar manufacturer, as well as installer-year fixed effect η_{rt}, where r represents the solar installer. Solar manufacturer fixed effect λ_m captures customer preference for a solar brand, and installer-year fixed effect η_{rt} captures the installer's service and advertising strategies at different points in time.[15] Finally, ζ_{jt} are the product characteristics unobserved by the econometrician but observed by the consumers and firms; and ϵ_{ijwt} is an independent and identically distributed (i.i.d.) error term and follows the type I extreme value distribution.

The heterogeneous taste parameters for product characteristics are modeled as

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Sigma \nu_i, \tag{2}$$

where ν_i is a random draw from a multivariate standard normal distribution (i.e., $\nu_i \sim N(0, \mathbf{1})$), Σ is a diagonal scaling matrix. This specification allows the taste parameters for the solar PV price and nonprice characteristics to vary across consumers.

The predicted market share of product j is given by

$$s_{jwt}(X_j, p_{jwt}, D_w, E_w; \alpha, \beta, \gamma, \kappa, \Sigma) = \int \frac{\exp(\delta_{jwt} + \mu_{ijwt})}{1 + \sum_{j=1}^{J} \exp(\delta_{jwt} + \mu_{ijwt})} dF(\nu), \tag{3}$$

where $\delta_{jwt} = X_j\beta + \alpha p_{jwt} + \gamma D_w + \kappa E_w + \lambda_m + \eta_{rt} + \zeta_{jt}$ is the mean utility across consumers obtained from purchasing and installing product j; μ_{ilwt} is a consumer-specific deviation from the mean utility level associated with the consumer tastes for different product characteristics; and $F(\cdot)$ is the standard normal distribution function.

The market share for the outside goods is usually defined as one minus the shares of the inside goods. To include the no-purchase option into the choice set of the outside goods, we define the market size on each MSA-year level as $M_w \times A \times V \times L$, where M_w is the number of single-unit houses in MSA w; A is the proportion of single-unit houses with a value greater than \$100,000;[16] V is the percentage of solar-viable buildings in that MSA level; L is the maximum proportion of potential adopters that would

14. In app. D, we discuss why we choose to include MSA-level demographic variables instead of MSA-level fixed effects in the demand side.

15. In this context, installers do the advertising and offer different types of contracts, which could be correlated with pricing strategies. The installer-year fixed effect η_{rt} aims to capture these potential confounders.

16. We choose a house value of \$100,000 or greater as a cut-off to define potential adopters. The estimation results do not change significantly with other cut-off values.

install solar PV systems and we assume it to be 15%.[17] The observed market share of product j is then given by $s_{jwt} = q_{jwt}/(M_w \times A \times V \times L)$, where q_{jwt} is the actual demand of product j in MSA w during year t.

We use Berry's (1994) transformation to explore our instrumental strategy where the dependent variable is the natural log of the market share of product j in MSA w during year t:

$$\ln s_{jwt} - \ln s_{0wt} = X_j\beta + \alpha p_{jwt} + \gamma D_w + \kappa E_w + \lambda_m + \eta_{rt} + \zeta_{jt}, \tag{4}$$

where s_{0wt} is the market share of the outside good.

Note that we assume that the model is static; consumers are thus not forward looking. In theory, forward-looking consumers may have anticipated the decrease in the price of solar PV systems and delayed their purchase decisions. In such a case, a static demand specification may underestimate the true price elasticity (Aguirregabiria and Nevo 2013). However, as argued by Gerarden (2023), consumers appear to be myopic in this context. In fact, even governments, industry practitioners, and academic experts did not anticipate the recent sharp decline in solar prices. Therefore, it is unlikely that the dynamics have a first-order effect on the demand estimates in this context.

3.2. Supply Side

In this section, we derive an estimating equation to recover key primitives in the vertical structure of the US solar market. Specifically, the equation approximates the optimizing behavior of solar manufacturers and installers in their vertical contracting relationship. The structural econometric model is inspired by Gayle (2013) and Fan and Yang (2020), and the price-cost margins are derived in the spirit of Villas-Boas (2007). Our approach to account for tariffs in the cost function follows Konishi and Zhao (2017).

The supply side consists of a three-stage game representing the pricing equilibrium and, thus, shorter outcomes in the solar market. In the first stage, solar manufacturers choose their products. In the second stage, given the realized demand and the marginal cost shocks, they choose the wholesale prices charged to the solar installers. In the third stage, solar installers choose the subsidized retail prices.

We explain the solution of this game in the context of one particular geographical market. With a slight abuse of notation, we thus omit the subscript w, which denotes the MSA. The standard way to solve this game is to use backward induction and to solve for the subgame perfect Nash equilibrium. In our context, this works as follows. In the final stage of the model, the solar installer r chooses a retail price inclusive of tariffs p^e_{jt} after observing the set of available solar PV models (denoted by J_{rt}), wholesale prices exclusive of tariffs (p^m_{jt}), the tariff rate imposed on solar panels (τ_{jt}), and the given

17. Our results are robust to other assigned values of L. In table D5, we report the estimation results for the demand and supply side using $L = 20\,\%$ and $L = 10\,\%$, respectively.

demand shock. The tariff-inclusive retail price p^e_{jt} is a package price charged to the consumer; it includes the after-tariff solar PV system price $p^m_{jt} \cdot (1 + \tau_{jt})$ and the installation price. If we suppose that the marginal cost for the solar installer to complete an installation j is c^r_{jt} per consumer, then the installer r's profit is $p^e_{jt} - p^m_{jt} \cdot (1 + \tau_{jt}) - c^r_{jt}$.

The profit function of each installer r in period t is given by

$$\max \ \pi_{rt} = \sum_{j \in J_{rt}} \left[p^e_{jt} - p^m_{jt} \cdot (1 + \tau_{jt}) - c^r_{jt} \right] s_{jt}(p^e), \tag{5}$$

where M is the market size. Then the first-order condition of the pricing problem is given by

$$p^e_t - p^m_t \cdot (1 + \tau_t) - c^r_t = -(T_{rt} \cdot \Delta_{rt})^{-1} s_t(p^e), \tag{6}$$

where T_{rt} is the installer's ownership matrix with the general element $T_{rt}(k, j)$ equal to one when both products k and j are sold by the same installer and zero otherwise; Δ_{rt} is the installer's response matrix, with element $(k, j) = \partial s_{jt} / \partial p_{kt}$.

In the second stage, solar manufacturers choose wholesale prices charged to installers after observing demand and marginal cost shocks. Solar manufacturer m's profit-maximizing problem for a set of products J_{mt} is therefore

$$\max \ \pi_{mt} = \sum_{j \in J_{mt}} \left[p^m_{jt} - c^m_{jt} \right] M s_{jt}(p^e), \tag{7}$$

where c^m_{jt} is the marginal cost for solar manufacturers that produce j. The first-order condition is given by[18]

$$p^m_t - c^m_t = -(T_{mt} \cdot \Delta_{mt})^{-1} s_t(p^e) / (1 + \tau_t), \tag{8}$$

where T_{mt} is the ownership matrix for solar manufacturer m, analogously defined as the matrix T_{rt} above. The term Δ_{mt} is the solar manufacturer response matrix with element $(k, j) = \partial s_{jt} / \partial p^m_{kt}$, which represents the first derivative of the market share of all solar PV systems with respect to all wholesale prices.

Combining equations (6) and (8) yields the solar manufacturer's and installer's joint tariff-inclusive marginal cost mc_t,

$$mc_t = (1 + \tau_t) c^m_t + c^r_t = p^e_t + (T_r \cdot \Delta_{rt})^{-1} s_t(p^e) + (T_m \cdot \Delta_{mt})^{-1} s_t(p^e). \tag{9}$$

Next, we assume that the joint marginal cost depends on a vector of nontariff-related cost shifters Y_t and tariff-related cost shifters Z_t. The joint marginal cost is

$$mc_t = \Phi Y_t + \Psi Z_t + \eta_{rt} + \varepsilon_t \tag{10}$$

18. Differentiating eq. (7) with respect to pm yields $s_j(p^e) + (1 + \tau_j) \Sigma_{j \in J_{rt}} (p^m_k - c^m_k)(\partial s_k / \partial p^m_j) = 0$.

where Y_t includes the solar panel's energy conversion efficiency (Eff) and the wage rate in roofing (Wage). We allow for a nonlinear relationship between tariffs and manufacturing costs to flexibly capture the different margins by which tariffs could impact manufacturers. In particular, the vector Z_t consists of tariff rate, the square of tariff rate, and their interaction terms with energy conversion efficiency (i.e., τ, τ^2, Eff $\times$ τ, Eff $\times$ τ^2, Eff^2 $\times$ τ, and Eff^2 $\times$ τ^2). The possible nonrelationship between tariffs and costs may arise from nonlinearities, that is, lumpy adjustments in the production process and the reorganization of manufacturers' production along their global supply chain, for instance. Finally, η_{rt} is an installer-year fixed effect, which captures installer heterogeneity across years.[19]

Combining equations (9) and (10) yields

$$p_t^e + (T_{rt} \cdot \Delta_{rt})^{-1} s_t(p^e) + (T_{mt} \cdot \Delta_{mt})^{-1} s_t(p^e) = \Phi Y_t + \Psi Z_t + \eta_{rt} + \varepsilon_t, \qquad (11)$$

which we bring to the data for estimation.

Equation (11) corresponds to the linear pricing model (we denote it model 1) with double marginalization. We also consider two alternative specifications of the vertical contracts that correspond to nonlinear (two-part tariff) pricing models proposed by Villas-Boas (2007). The models with nonlinear contracts allow us to provide upper bounds on the extent of market power and, thus, manufacturers' or installers' ability to determine high margins in this market.

First, we assume that the solar manufacturer chooses to set the wholesale price equal to its marginal cost, and the installer entirely determines the markup. We will refer to this as model 2, where the equation for the implied price-cost margin is given by

$$p_t^e + (T_{rt} \cdot \Delta_{rt})^{-1} s_t(p^e) = \Phi Y_t + \Psi Z_t + \eta_{rt} + \varepsilon_t. \qquad (12)$$

We assume the opposite for the other alternative model (denoted model 3): the installer's margin is zero, and the solar manufacturer's pricing decision determines the markup. In this case, the implied price-cost margin is given by

$$p_t^e + (T_{mt} \cdot \Delta_{rt})^{-1} s_t(p^e) = \Phi Y_t + \Psi Z_t + \eta_{rt} + \varepsilon_t. \qquad (13)$$

Equations (13) and (12) correspond to different types of nonlinear vertical contracts and can be readily estimated by simply substituting the appropriate ownership matrix. In section 5, we thus jointly estimate demand- and supply-side parameters under each alternative specification of the vertical contractual relationship and use non-nested statistical tests based on Rivers and Vuong (2002) to select the model specification that best fits the data.

19. In app. D, we experiment with manufacturer-fixed effects in the supply-side estimation. Table D4 shows that our model is robust by adding a manufacturer-fixed effect on the supply side.

4. IMPLEMENTATION

4.1. Data

In our estimation of the structural model and subsequent simulations, we restrict our sample to the period 2012–18 to obtain parameter estimates corresponding to the period of the main episodes of the US-China solar trade war. As before, the primary dataset comes from the LBNL's Tracking the Sun report series, as described in section 2, and we focus only on residential solar PV installations, which account for most of the US solar market between 2012 and 2018.[20] We combine the dataset with four other data sources: (1) demographic data from the US Census Bureau, which provides county-level demographic variables on income, education, urbanization, race, and political orientation across the United States;[21] (2) electricity price data from the US Energy Information Administration; (3) labor market data from the US Bureau of Labor Statistics, which provides the hourly wage rate for roofing installers across different states; and (4) solar potential data from the Google Project Sunroof, which we use to estimate the technical solar potential of all solar-viable buildings in each US county. After merging the data and selecting observations with the information required for the estimation procedure, our final sample represents 21.6% of all solar PV installed in the United States during the 2012–18 period. Appendix C.1 describes how we construct our sample and compare it with the entire universe of installations. It shows that our estimation sample represents the US residential solar market well.

Given that we conduct the analysis at the MSA level, we therefore use county-level identifiers in the dataset to construct MSA-level variables, which are averages across all counties in each MSA.[22] To define the inside goods for the analysis, we distinguish solar PV models that have significant sales (3,000 units or more) in the United States and represent a generic inside good with all other models.[23] The sample consists of 58 models produced by 10 solar manufacturers. These solar manufacturers include three Chinese companies (Canadian Solar, Trina Solar, and Yingli Energy), one US company (SunPower), three South Korean companies (Hanwha, Hyundai, and LG), one Japanese company (Kyocera Solar), one German company (SolarWorld), and one Norwegian company (REC Solar). In table B2, we report an exhaustive list of solar system models in the sample.

20. During 2012–18, the residential solar sector accounted for more than 95% of the US solar market in terms of the number of installations and represents 54% of the market in terms of installed capacity.

21. Following Chernyakhovskiy (2015) and Kwan (2012), we take median housing price as a proxy for household income and use population density to measure urbanization effect.

22. In the original dataset, the US residential solar installations were spread across 182 MSAs, with each MSA having around three adjacent counties on average. In our final sample for estimation, we have 60 MSAs.

23. We focus on popular solar PV models, rather than all models, as the latter will make the pool of inside goods too large and increase our computation burden significantly.

For the downstream market, because there is a large number of installers in the sample, we distinguish 20 installers and consider one generic group of installers.[24] We consider the 20 largest installers who have a significant market share across the United States (see table B3), and the generic group represents the rest of the installers. Among the 21 groups of installers, SunPower and REC Solar also operate as solar manufacturers, indicating that they are vertically integrated players in the solar market.

For installers, the ownership matrix is defined at the MSA and yearly level and corresponds to the universe of solar system models used in this market (MSA-year). This means that the same installer located in different markets (in space or time) may have a different consideration set when choosing a solar system. For manufacturers, the ownership matrix is defined at the national and yearly levels. Table 1 reports summary statistics for the key variables we used in the estimation. A detailed description can be found in appendix C.2.

4.2. Identification

For the demand-side estimation, the purchase price p_{jwt} is expected to be correlated with unobserved product characteristics, the term ζ_{jt} in equation (1), leading to an endogeneity problem. Our identification strategy uses instrumental variables to mitigate endogeneity concerns.

Our instrumental variables utilize the strategy first proposed by Berry et al. (1995) (hereafter referred to as BLP) and focus on exploiting supply-side variation in prices. In particular, we identify the coefficient on price using variations induced by product differentiation and location in the product space of product characteristics. As suggested by Gandhi and Houde (2019), the instruments are based on a first-order approximation of the equilibrium pricing function—they are constructed by adding up the values of characteristics of other products made by the same manufacturer and the characteristics of products made by other manufacturers in each local market. The exclusion restriction holds to the extent that short-run demand shocks or policies, such as rebates for solar or the investment tax credit, are not correlated with product characteristics determined by the long-run development process of solar technology (Li 2017). We thus construct our BLP's instruments using product characteristics that are determined early in the manufacturing process and could not be influenced by pricing strategies, namely, energy conversion efficiency and the technology type, which we denote by BLP_Eff and

24. We define a product as a model-installer combination; therefore it is not feasible to include all installers, as adding one more installation company will make the size of our inside goods grow exponentially and increase the computation time substantially. In app. D, as a robustness check, we group the installers into 10 + 1 generic and reestimate the model for our linear-pricing model (i.e., double marginalization by manufacturers and installers). As shown in table D1, the estimation results are similar to those in our main results. This implies that our model is robust in different classifications of installer groups.

Table 1. Summary Statistics for Key Variables

Variable	Description	Max	Min	Mean	SD
A. Characteristics:					
InstalledPrice	Total installed price ($/watt)	8.39	1.74	4.24	.87
Subsidy	Government subsidies ($/watt)	5.64	0	.17	.41
Price	Consumer purchase price ($/watt)	7.73	1.73	4.07	.89
Efficiency	Energy conversion efficiency	.22	.15	.18	.02
Technology	=1, if poly; =0 if mono	1	0	.40	.49
B. Demographics:					
Income	Median housing price ($100K)	7.94	1.05	4.51	1.88
Education	Fraction of bachelor degree	.49	.12	.27	.09
Urbanization	Population (1,000) per square mile	6.32	.01	1.01	1.57
Race	Fraction of white people	.94	.14	.50	.16
Democrats	Fraction of voting for Democrats	.77	.36	.55	.10
C. Other variables:					
NHouse	Number of single-unit houses	2,467,089	19,764	542,764	689,965
SolarPotential	Fraction of solar-viable houses	.96	.58	.88	.07
HouseAbove	Fraction of house greater than $100K	.98	.46	.92	.07
InstallWage	Wage rate ($/hour) in installation	25.79	20.90	24.87	.85
Tariff	Tariff rate (%)	145.85	0	26.45	39.49
EPrice	Electricity price (cent/kWh)	20.94	10.57	17.07	1.60

Note. The prices are in 2015 US dollars; kWh = kilowatt-hour.

BLP_Tech, respectively. As in Whitefoot et al. (2017), our validity of the supply-side cost shifters is based on the timing of the production decisions and the fact the technology development occurs well before final prices are determined.

To investigate our instrumental variables, we first use a simple two-stage least square (2SLS) regression to estimate equation (4). Table B4 reports the results for the first-stage regression in which price is regressed on the different instruments. Column 1 uses only BLP_Eff and BLP_Tech. Column 2 adds the square term of BLP_Eff and the square term of BLP_Tech. Column 3 additionally adds the interaction term of BLP_Eff and BLP_Tech.[25] The *F*-tests of the joint significance of the instruments in all three models yield values greater than 10. The results suggest that the instruments do have explanatory power. Moving to the second-stage estimates, Berry-style market shares (i.e., $\ln s_{jwt} - \ln s_{0wt}$) are regressed on the instrumented prices. The results in table B5 show that the instrumental variables lead to a significant and negative price coefficient.

25. In col. 3, the instrumental variables thus consist of five variables, that is, BLP_Eff, BLP_Tech, $(\text{BLP\_Eff})^2$, $(\text{BLP\_Tech})^2$, BLP_Eff × BLP_Tech.

Overall, the sets of BLP instruments where we approximate the equilibrium-pricing equation with a richer set of variables (cols. 2 and 3 in tables B4 and B5) perform well in our setting and lead to a stable coefficient on price. We use the same instruments as in column 3 described above for our main structural estimation with random coefficients.

4.3. Computations

We jointly estimate the demand-side and supply-side results using the generalized method of moments (GMM). For the computations, we follow closely the following recommendations of Dubé et al. (2012) and Grigolon et al. (2018). In particular, we perform the numerical integration of the market shares using 200 draws of a quasi-random number sequence, and we do so for each market. We set the convergence level for the contraction mapping of the inner loop within the GMM objective function at $1e^{-12}$. We set a strict tolerance level at $1e^{-6}$ and optimize the objective function using the advanced optimization algorithms in Knitro. Finally, we search for a global minimum and verify the solution by checking the first-order and second-order conditions using 20 different starting values for our optimization problem.

5. ESTIMATION RESULTS

Table 2 reports both demand- and supply-side estimates under each of the alternate supply specifications of the vertical contracts (model 1, model 2, and model 3). Panel A reports the mean marginal utility for each product characteristic (α and β), the coefficients for the demographics (γ), the coefficient for electricity price (κ), and finally, the variation in taste for price and nonprice characteristics (the matrix Σ). The price coefficient is negative and statistically significant at conventional levels of significance. The coefficient on panel efficiency is positive and statistically significant at the 1% level, suggesting that consumers favor solar PV with higher energy conversion efficiency. The coefficient on technology is negative, although statistically insignificant.

The coefficients on income are positive and statistically significant at conventional levels (except for model 2), suggesting that areas with higher income tend to adopt more solar PV systems. The coefficient on urbanization is negative and significant at the 1% level, implying that people in urban areas are less likely to install solar PV systems. The coefficients on Democrats are positive and statistically significant at conventional levels of significance, indicating that areas with more Democratic Party supporters install more solar PV systems. In model 1, the coefficient on electricity price is positive with a p-value of 0.13, suggesting that higher energy prices encourage residents to adopt solar power technology. The above results are intuitive and in line with previous findings (Kwan 2012; Chernyakhovskiy 2015). The coefficient on education is negative and significant at the 1% level, suggesting that people living in areas with lower education levels have a higher demand for solar PV systems. This might be because areas with residents with high levels of education across the United States are also located in areas less suitable for

Table 2. Estimation Result for Main Specification

	Model 1		Model 2		Model 3	
	Estimates	SE	Estimates	SE	Estimates	SE
	A. Demand Side					
Means, (α, β):						
Constant	−16.323***	(.988)	−16.300***	(.961)	−16.322***	(.988)
Price	−1.289***	(.418)	−1.302**	(.610)	−1.289***	(.429)
Efficiency	42.237***	(10.105)	42.564***	(5.877)	42.268***	(9.182)
Technology	−1.295	(3.571)	−1.366	(4.366)	−1.309	(3.464)
Demographics (γ):						
Income	.243**	(.113)	.251	(.166)	.243**	(.117)
Education	−6.936***	(1.923)	−7.088***	(2.671)	−6.941***	(1.970)
Urbanization	−.273***	(.043)	−.271***	(.069)	−.273***	(.046)
Race	.691	(.555)	.734	(.843)	.692	(.578)
Democrats	1.150**	(.546)	1.192**	(.530)	1.152**	(.537)
Electricity price (κ):						
Eprice	.079	(.052)	.079	(.085)	.079	(.056)
Taste variation (Σ):						
Price	.302	(.285)	.280	(.419)	.301	(.292)
Efficiency	1.007	(33.297)	.578	(48.307)	.914	(34.712)
Technology	−1.185	(3.535)	−1.251	(4.349)	−1.199	(3.602)
Fixed effects:						
Manu FE	Yes		Yes		Yes	
Inst-year FE	Yes		Yes		Yes	
	B. Cost Side					
Constant	−3.862***	(.024)	−2.377***	(.008)	−3.178***	(.024)
Efficiency	4.380***	(.020)	4.802***	(.006)	4.911***	(.020)
Wage Rate	.199***	(.0003)	.177***	(.0001)	.207***	(.0003)
Tariff	−8.071***	(.246)	−20.530***	(.081)	−11.835***	(.251)
Tariff^2	11.320***	(.330)	23.894***	(.108)	14.876***	(.338)
Efficiency × tariff	101.986***	(2.786)	238.208***	(.916)	144.281***	(2.849)
Efficiency × tariff^2	−137.366***	(3.855)	−277.319***	(1.267)	−178.165***	(3.941)
Efficiency^2 × tariff	−322.671***	(7.859)	−692.793***	(2.583)	−441.942***	(8.036)

Table 2 (*Continued*)

	Model 1		Model 2		Model 3	
	Estimates	SE	Estimates	SE	Estimates	SE
$\text{Efficiency}^2 \times \text{tariff}^2$	418.109***	(11.245)	805.615***	(3.696)	535.565***	(11.497)
Inst-year FE	Yes		Yes		Yes	

Note. This table reports the demand and supply estimation results for models 1–3. The specification for each model is described in sec. 3.2. We use BLP instruments as the instrumental variable. On the demand side, Price is the average consumer purchase price (in $/W); Efficiency represents the energy conversion efficiency; Technology represents the type of solar photovoltaic technology, which equals one if it is made of polycrystalline solar panels and zero otherwise; Income, Education, Urbanization, Race, and Democrats are MSA-level demographics as described in table 1. We control for the manufacturer effects and installer-year fixed effects on the demand estimation. On the supply side, the Wage Rate refers to the MSA-level wage rate ($/hour) for the roofing installers. We control for installer-year fixed effects on the supply-side estimation. Standard errors in parentheses.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

installing solar PV systems, which is not captured by our set of controls, notably the coarse categorical variable for urban/rural.[26] None of the estimates for taste variation parameters are statistically significant, indicating that the observed heterogeneity in the coefficients is primarily accounted for by the demographic variables included in the model.

The demand parameter in table 2 yields a mean own-price elasticity of demand of −3.93, −4.15, and −3.93 across models 1, 2, and 3, respectively. Our estimates fall within the range of previous estimates on the demand for residential solar systems. Gillingham and Tsvetanov (2019) estimate a demand elasticity of −0.65 using microdata from Connecticut, while De Groote and Verboven (2019) infer an elasticity of close to −6.3 based on aggregate data from the region of Flanders in Belgium. Burr (2016) estimates price elasticities ranging from −1.6 to −4.7 across different model specifications using microdata from California. The range of the cross-price elasticities between different brands for our model 1 is [0.003; 0.091], as shown in table B6. The magnitude of our cross-price elasticities is similar to that found for other non-necessities, such as for the coffee market (Bonnet et al. 2013).

26. With respect to education, our findings are consistent with Sommerfeld (2016) and Crago and Chernyakhovskiy (2017). Based on the setting of the Australian market, Sommerfeld (2016) finds that areas with a high number of people with a bachelor's degree tend to be the areas with a large concentration of apartment units, which are unsuitable for installing solar PV systems. Crago and Chernyakhovskiy (2017) also find that the estimated effect of educational attainment on solar PV adoption is negative but not statistically significant.

Summary statistics on price-cost margins and marginal costs recovered for installed solar PV systems are reported in the first column of table B7. These statistics are broken down by upstream manufacturers/downstream installers of solar PV systems. According to the linear vertical contract specification (model 1), the mean margins for the upstream manufacturers and downstream installers are \$0.966 per watt (W) and \$1.066/W, respectively, yielding a mean total margin (upstream and downstream) of \$2.032/W. On average, the ratio of margin to consumer purchase price, the Lerner index, is 0.49. If we consider nonlinear vertical contracts, the overall magnitude of the margins is smaller. If installers entirely determine the price-cost margins (model 2), the mean margin is \$1.003/W; and when only manufacturers determine the price-cost margins (model 3), the mean margin is \$0.964/W.

Table 2 also reports additional estimation results on the supply side in our main specification. The significant and positive coefficient on energy conversion efficiency suggests that marginal costs increase with the efficiency rate, as expected. The positive and statistically significant coefficient on the wage rate also suggests that marginal costs increase with labor costs.

The coefficients on tariff-related terms (i.e., τ, τ^2, Eff $\times$ τ, Eff $\times$ τ^2, Eff^2 $\times$ τ, and Eff^2 $\times$ τ^2) are all significant at the 1% level. In model 1, given that the mean value of the energy conversion efficiency is 0.18, we can replace this value into the cost function and find that the tariff-related part collapses into $-0.168\tau + 0.141\tau^2$, which indicates that the joint marginal cost increases with the tariff rate when the tariff rate is greater than 60 %$(0.168/(0.141 \cdot 2))$. As the median value of nonzero tariff rates is 76.5%, it implies that for most of the observations, the estimated joint marginal cost increases with the tariff rate.

Before turning to the policy analysis, we compare the specifications of the vertical contracts and determine the one that best fits the data. We follow the standard procedure in the literature (e.g., Bonnet and Dubois 2010; Bonnet et al. 2013; Gayle 2013; Haucap et al. 2021) and use the non-nested test proposed by Rivers and Vuong (2002). In table B8, we report the test statistic for each pairwise comparison between the three specifications. The test statistics are close to zero, suggesting that these three models are statistically indistinguishable. Thus, we will focus on model 1 with linear contracts, but we will report the policy results for all three different types of models.

6. POLICY ANALYSIS OF TRADE TARIFFS

We now investigate the incidence of the US-China solar trade war using the estimated model. The goal is to quantify the equilibrium welfare effects trade tariffs had on manufacturers (the United States, China, South Korea, and others), US installers, and US consumers.[27]

27. To quantify consumer welfare, we follow Small and Rosen (1981) and use the compensating variation to calculate the change in consumer surplus. The expression that we use is given by

We simulate three sets of scenarios. First, we remove the US antidumping, countervailing, and safeguard tariffs imposed on Chinese solar manufacturers during the three waves of tariffs from 2012 to 2018. We then compare this counterfactual scenario with the (simulated) baseline scenario when the tariffs were in place. Comparing these two scenarios shows the overall effects of the US-China trade war.

Second, conditional on the first scenario, we remove the US safeguard tariffs imposed on all other foreign solar manufacturers during the third wave of tariffs in 2018. We compare this counterfactual scenario with the (simulated) baseline scenario.

Third, we simulate the baseline scenario, assuming the trade tariffs' effective rates could have differed from the statutory rates announced by the US Department of Commerce. The rationale for this scenario is that Chinese solar manufacturers exploited various loopholes to avoid the brunt of tariffs. One notable example of such behavior, which has been well documented and discussed previously, occurred in the first wave of tariffs when mainland Chinese manufacturers relocated their panel assembly lines to Taiwan. As a result, this wave of tariffs is believed to be largely ineffective. Of course, reallocating the assembly lines might have increased the panels' manufacturing costs, but these were presumably less than the statutory rates imposed. In our data, we cannot measure to what extent Chinese manufacturers could have evaded tariffs through production reallocation and the final impact it may have had on their costs. However, we can exogenously vary the statutory rates to mimic the final effect it would have had on manufacturer prices. In this scenario, we thus scale the tariffs by a given percentage, which illustrates the impacts of such behaviors on the final incidence of the tariffs in the US solar market.

Finally, in appendix E.2, we also consider another scenario in which we assume US manufacturers were also partly affected by the tariffs imposed on Chinese manufacturers because they could procure some parts of their solar systems from China.

For all scenarios, to isolate solely the impacts of trade tariffs in equilibrium, we hold constant other policies that could have affected the adoption of solar PV systems in the US residential sector, such as local rebates and subsidies, investment tax credits,[28] and electricity tariffs (Borenstein 2017). For our simulations, there are three particularly important sets of parameters required: the exact rates of antidumping and countervailing

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$$\Delta \mathrm{CS} = -\frac{1}{\alpha}\left[\ln\left(\sum_{j=1}^{J}\exp\left(W_j^1\right)\right) - \ln\left(\sum_{j=1}^{J}\exp\left(W_j^0\right)\right)\right],$$

where α is the consumer marginal disutility of price and W_j^0 and W_j^1 are the expected maximum utility for the consumers in the baseline and counterfactual scenario, respectively.

28. Note that given that the federal investment tax credit (ITC) for solar is an ad valorem subsidy, an increase in the final installation price of a solar system due to import tariffs will result in higher payments of the ITC. We do not model this effect, which may slightly overestimate the negative impact of tariffs on consumers in our simulations.

duties imposed on manufacturers, the proportion of panel cost versus nonpanel cost, and parameters related to quantifying environmental benefits. We discuss them in detail in appendix E.1.

Next, we discuss the simulation results for the three sets of scenarios. We focus on the results using the supply-side specification with linear vertical contracts (model 1). However, we also perform policy analysis using models 2 and 3 to assess the robustness of our results with respect to the nature of vertical contracts. These results are also reported in the main tables.

6.1. Removing Tariffs on Chinese Manufacturers

We first remove the US tariffs against Chinese solar manufacturers and examine the equilibrium response, welfare change, and related environmental benefits/losses to determine the effects of removing trade policies. Table 3 presents the results. Panel A shows that the total market capacity of the US solar market would have been 22.5% larger if the antidumping duties, countervailing duties, and safeguard tariffs had not been imposed on Chinese solar panels. We find a significant increase in the sales of solar panels produced by Chinese manufacturers (Canadian Solar, Trina Solar, and Yingli Energy). Specifically, Yingli Energy's sales of solar panels would have been 84.0% higher compared to the baseline scenario. In contrast, the sales of solar panels produced by non-Chinese manufacturers (SunPower, Hanwha, Hyundai, LG, Kyocera, SolarWorld, and REC Solar) would have decreased by 1%–3%. According to our estimate, the impact of the trade tariffs is thus primarily on the extensive margin, that is, the number of adopters.

Panel B shows the welfare changes among the different market participants. Removing the trade policies provides welfare gains of $400.5, $343.6, and $332.3 million for US consumers, Chinese manufacturers, and US installers, respectively. The losses for US manufacturers are only $7.6 million, whereas the decrease in US tariff revenues is $478.5 million. This suggests that US manufacturers gained little from the trade war. At the same time, the government revenues collected from the tariffs would not have been enough to compensate consumers and installers. Overall, the domestic market does not benefit from the tariffs. Panel B also shows that the trade war induced collateral effects on manufacturers based outside the United States and China. South Korean and other non-US-based manufacturers benefited slightly from the US tariffs.

Panel C reports the related environmental benefit/loss. It shows that carbon dioxide emission would have been lower by 7.7 million tons without tariffs, resulting in an externality cost of $1.32 billion. Since the data in our final sample account for 21.6% of US residential solar PV installation capacity, the overall benefits associated with reducing the CO_2 externality for the whole United States would amount to $6.11 billion.[29]

29. We only consider the environmental benefits brought by the installations of residential solar PV systems. Our analysis does not include the externalities related to commercial and utility-scale solar PV systems.

Table 3. Simulation Results: Removing Tariffs on Chinese Manufacturers

Origin Country and Manufacturer	Model 1	Model 2	Model 3
	A. Demand Response		
China:			
Canadian Solar	88.9%	116.7%	111.0%
Trina Solar	73.4%	90.8%	87.2%
Yingli Energy	84.0%	107.5%	101.7%
Unites States:			
SunPower	–1.1%	–1.5%	–1.4%
South Korea:			
Hanwha	–1.9%	–2.8%	–2.3%
Hyundai	–1.8%	–2.5%	–2.3%
LG	–1.1%	–1.6%	–1.4%
Japan:			
Kyocera	–2.2%	–3.3%	–2.9%
Germany:			
SolarWorld	–1.3%	–1.7%	–1.5%
Norway:			
REC Solar	–1.7%	–2.9%	–2.2%
Total	22.5%	28.7%	27.4%
	B. Welfare Distribution (in 2015$ million)		
Δ Consumer surplus	400.5	495.8	475.1
Δ US manufacturers	–7.6	0	–9.5
Δ Chinese manufacturers	343.6	0	417.0
Δ Korean manufacturers	–5.8	0	–6.9
Δ Other manufacturers	–15.2	0	–22.4
Δ Installers	332.3	418.9	0
Δ US tariff revenue	–478.5	–675.5	–655.0
Total	569.4	239.2	198.3
	C. Environmental Benefit		
Δ Reduced CO_2 (million tons)	7.7	10.0	9.3
Δ Reduced cost (2015$ million)	1,321.1	1,710.2	1,585.9

Note. This table reports the results for demand response and welfare change if we remove the US tariffs against Chinese solar manufacturers. Panel A reports the change in the demand percentage. Panel B reports the welfare changes for manufacturers (the United States, China, South Korea, and others), US consumers, and US installers, as well as the change in US tariff revenue. Panel C reports the related environmental benefits. All the economic values are calculated in 2015 US dollars.

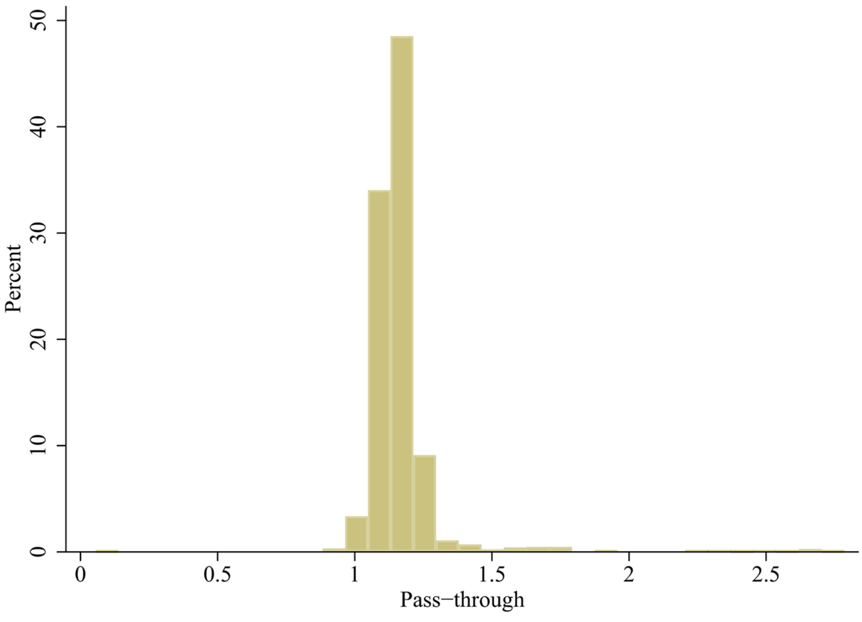

Figure 2. Distribution of pass-through rates. This figure shows the distribution of pass-through rates for solar PV systems that use Chinese-manufactured panels. Most of the pass-through rates exceed one.

Next, we investigate how trade policy affected downstream prices. We compute the pass-through rates of the tariffs by comparing the final prices of solar systems that use Chinese panels, as predicted by the equilibrium model, with the specific tariff that applies to this module. This also corresponds to an increase in the final price if we assume no demand-supply responses. In table 5, we therefore report the average change in the final prices of the affected PV systems without and with an equilibrium response.[30] The ratio of these two prices corresponds to our pass-through rates. The distribution of the pass-through rate is shown in figure 2. We find that for most systems using a Chinese-manufactured solar panel, the pass-through rate exceeds one, and the average is 117%. It implies that a \$1 dollar increase in tariff leads to a \$1.17 increase in the final price of an installed solar PV system in the United States. We thus find evidence of tariff overshifting in the US solar market. Our results are consistent with the recent evidence of Pless and Van Benthem (2019), who also find pass-through rates exceeding 100% while investigating solar subsidies.

A pass-through rate higher than unity can be attributed to the presence of market power. At first, the US solar market, especially the installation market, could appear

30. In the first and third scenarios, it refers to PV systems using Chinese panels; in the second scenario, it refers to PV systems using non-US panels.

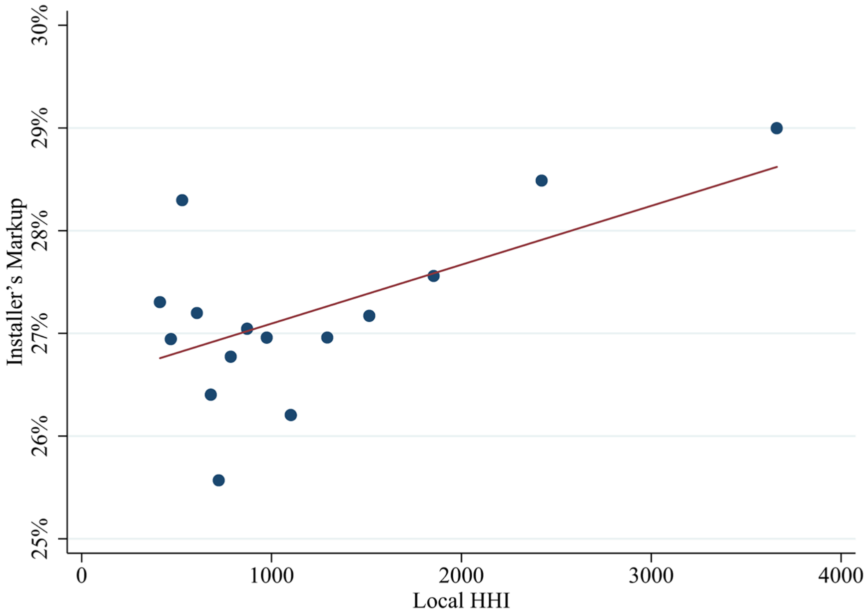

Figure 3. Relationship between installer's markup and local HHI. This figure shows the relationship between the installer's markup and the Herfindahl-Hirschman index (HHI). The vertical axis is the installer's markup as a percentage of the total installed price, and the horizontal axis is the HHI for solar installers at the market level (MSA-year). The bin-scatterplot groups the variable HHI into equal-sized bins and computes the mean of the installer's markup and HHI within each bin, respectively; it then creates a scatterplot of these data points.

competitive because of the large number of small firms. However, solar installers may hold substantial market power in local, regional markets, and this may dominate. To gain further insight into the role of local market power, we investigate the relationship between installers' markups and the Herfindahl-Hirschman index (HHI) for each market (MSA-year). Figure 3 shows a positive relationship between an installer's markup and the local HHI.

The elasticity of demand with respect to price is another factor that determines the pass-through rate of the tariff. Thus, we do sensitivity tests to explore its impact. To vary the demand elasticity, we directly change the mean of the price coefficient in the demand model, the parameter α in equation (2), keeping all other parameters constant.[31] For each average demand elasticity, we put a universal cost shock (a tariff rate of 100%) on solar manufacturers and calculate the average tariff pass-through rate for all

31. We scale the parameter α by a constant such that the average demand elasticity ranges from −1 to −3.93. Bonnet et al. (2013) proposed a similar approach.

PV systems. Table E4 reports the results: the pass-through rate increases with the elasticity of the demand. This result would be counterintuitive in a pure monopoly setting, but this is consistent with other evidence in settings with multiproduct oligopoly. For instance, Bonnet et al. (2013) find similar results using a structural oligopoly model of the German coffee market and argue that an increase in demand elasticity implies a more competitive market and thus a higher pass-through rate.

We also show the heterogeneity of pass-through rates with respect to the characteristics of the local markets. Figure 4 shows that regions where households have higher income have higher pass-through rates. It is intuitive. These regions have a stronger demand for solar PV systems, as evidenced by our estimation results; thus installers can shift more tariffs to consumers. The patterns are less striking for other demographic characteristics, as presented by figure B2.

6.2. Removing All Tariffs

In the second set of counterfactual scenarios, we simulate the impact of tariffs by removing the antidumping duties, countervailing duties, and safeguard tariffs imposed on

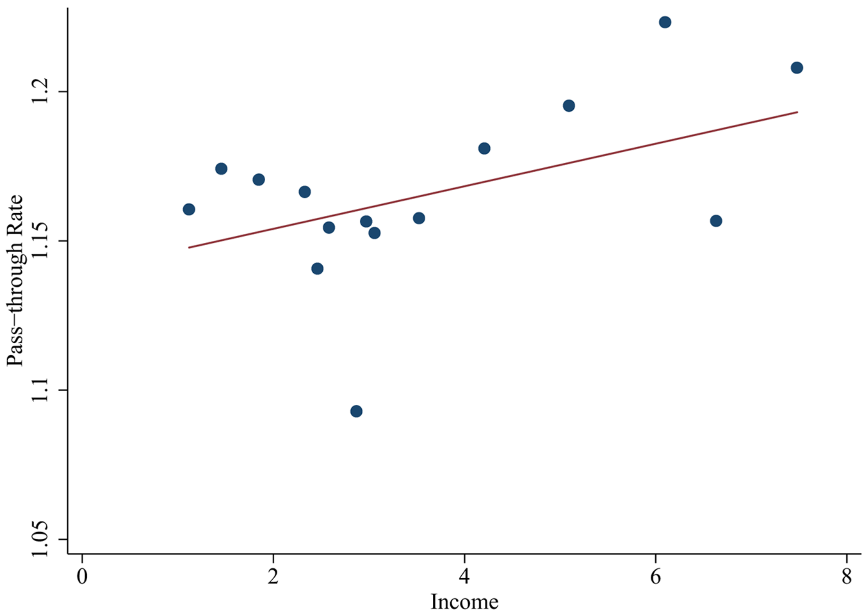

Figure 4. Pass-through rates for areas with different income. This figure shows how pass-through rates for MSAs change with income. The household income is proxied by the average median housing price (in $100K) on the MSA level. We use the binscatter command in Stata to plot this graph. It groups the household income into equal-sized bins and computes the mean of the pass-through rate and income within each bin, respectively; it then creates a scatterplot of these data points.

Chinese and all other foreign manufacturers. Table 4 reports the results. Panel A shows that the total market capacity of the US solar market would have expanded by 24.5% in the absence of tariffs. While Chinese manufacturers witnessed a demand response similar to the first set of scenarios, other foreign manufacturers experienced a reverse change. For instance, the sales of solar panels made by LG would increase by 5.5% in these scenarios, whereas it was a 1.1% decrease in the previous scenario.

Conditional on the first scenario and removing the safeguard tariffs imposed on all other foreign manufacturers (in 2018) expands the market further. This can be readily seen in panel B, which reports the welfare changes in dollars. Now, without tariffs, the welfare gains for US consumers, Chinese manufacturers, and US installers would have been \$424.1, \$343.2, and \$354.9 million, respectively, whereas the losses for US manufacturers and US tariff revenue would have been \$8.4 and \$503.2 million, respectively. In panel C, the change in the environmental externality is also larger. Overall, the changes in the different welfare metrics are about 7% larger relative to the first set of scenarios.

6.3. Statutory Versus Effective Rates

In this third scenario, we reduce the statutory rates in all three waves to mimic the Chinese manufacturers' production reallocation behaviors to avoid part of the tariffs. Specifically, we assume that the effective rates are 50% of the announced statutory rates. We choose this percentage to illustrate the role of strategic tariff avoidance as documented by Bollinger et al. (2024). We recognize that the different waves of tariffs had different loopholes. As a result, the degree of strategic avoidance is likely to have varied throughout the trade war. Ultimately, our goal is to show how our main results scale with respect to this parameter.

Two important results emerge. First, as shown in table E2, the changes for the different metrics scale proportionally with the degree of strategic avoidance—all estimates of the welfare effects are roughly 50% smaller. The impact of strategic avoidance, at least on the US market, is rather linear.[32]

Second, as shown in table 5, the tariff pass-through rate remains virtually unaffected: it is 118%. The incidence of the effective tariff rate on consumers is thus similar to that of the statutory rate. Our conclusion about overshifting of the tariff is therefore robust to the presence of strategic avoidance. Ultimately, it means that US consumers bear the burden of the tariffs, whether due to the trade tariffs themselves or the higher production costs due to the reallocation of production along the global supply chain.

32. We do not have information about the supply-chain effects for solar panels outside the United States. We should, however, expect nonlinear impacts in the manufacturing supply chain due to capacity constraints and economies of scale, especially when a large fraction of the production is reallocated to different countries.

Table 4. Simulation Results: Removing All Tariffs

Origin Country and Manufacturer	Model 1	Model 2	Model 3
	A. Demand Response		
China:			
Canadian Solar	88.6%	116.2%	110.7%
Trina Solar	73.3%	90.5%	87.0%
Yingli Energy	83.9%	107.3%	101.6%
United States:	–1.2%	–1.7%	–1.6%
SunPower			
South Korea:			
Hanwha	2.5%	2.7%	3.1%
Hyundai	1.5%	1.7%	1.9%
LG	5.5%	6.6%	6.5%
Japan:	2.3%	2.0%	2.2%
Kyocera			
Germany:	1.6%	1.8%	1.9%
SolarWorld			
Norway:			
REC Solar	2.6%	2.3%	2.9%
Total	24.5%	31.1%	29.8%
	B. Welfare Distribution (in 2015$ million)		
Δ Consumer surplus	424.1	524.0	503.6
Δ US manufacturers	–8.4	0	–10.4
Δ Chinese manufacturers	343.2	0	416.5
Δ Korean Manufacturers	10.0	0	12.0
Δ Other manufacturers	–8.8	0	–14.7
Δ Installers	354.9	446.4	0
Δ US tariff revenue	–503.2	–707.8	–687.3
Total	612.0	262.7	219.7
	C. Environmental Benefit		
Δ Reduced CO_2 (million tons)	8.3	10.7	9.9
Δ Reduced cost (2015$ million)	1,411.8	1,823.7	1,695.0

Note. This table reports the results for demand response and welfare change if we remove the tariffs on Chinese and other manufacturers. Panel A reports the change in the demand percentage. Panel B reports the welfare changes for manufacturers (the United States, China, South Korea, and others), US consumers, and US installers, as well as the change in US tariff revenue. Panel C reports the related environmental benefits. All the economic values are calculated in 2015 US dollars.

Table 5. Tariff Pass-Through

	Without Response		With Response		
	Percent (%) (1)	Level ($) (2)	Percent (%) (3)	Level ($) (4)	Pass-Through (5)
Model 1:					
Removing tariffs on China	15.12	3,330	17.69	3,953	1.17
Removing all tariffs	12.45	2,777	14.56	3,288	1.17
50% × statutory rates	6.86	1,665	8.09	1,989	1.18
Model 2:					
Removing tariffs on China	19.32	4,129	20.58	4,401	1.07
Removing all tariffs	15.88	3,444	16.91	3,667	1.06
50% × statutory rates	8.64	2,064	9.22	2,206	1.07
Model 3:					
Removing tariffs	19.75	4,209	20.91	4,487	1.05
Removing all tariffs	16.25	3,513	17.23	3,746	1.06
50% × statutory rates	8.80	2,105	9.36	2,251	1.06

Note. Columns 1–4 report the average tariff (both in percentage and levels) on solar PVs with affected panels under the scenarios of with/without equilibrium response. Column 5 reports the tariff pass-through rates for the consumer's final purchase price for solar PVs.

These results show an essential advantage of our structural model. We can easily mimic different policies impacting the cost structure of the whole industry, such as trade tariffs, mergers, climate policies, and cost shocks due to supply-chain constraints, and quantify their welfare effects.

7. CONCLUSION

This study provides an important piece of the puzzle to study the incidence of the US-China trade war in the solar PV market. We pay close attention to the industry's vertical structure and its impact on consumers in the US market with a structural econometric model that models both the demand- and supply-side effects. Using the estimated model, we simulate the equilibrium response to trade tariffs under various scenarios.

We show that the installed capacity in the US solar market would have increased by 22.5% more in the absence of trade tariffs. Although the tariffs protected US manufacturers, neither installers nor consumers in the United States were largely negatively affected. The increase in government revenues from these tariffs is significant, but it is not enough to offset the negative impacts on the domestic market. We also find that the CO_2 externality costs associated with the tariffs are large.

Our model can also be used to estimate the pass-through rate of the tariffs on the final prices of installed systems. We find evidence of tariff overshifting: a $1 tariff on

Chinese manufacturers increases the final price by $1.17 for PV systems using panels subject to such a tariff. Overshifting is surprising but not uncommon in imperfectly competitive markets. In the US solar market, market power appears to be important in upstream and downstream markets: a few manufacturers have large market shares, and installers hold significant market power in local markets.

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