The Incidence of the U.S.-China Solar Trade War

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Abstract

This paper investigates the distributional welfare effects of the trade tariffs initiated by the U.S. government against Chinese solar manufacturers between 2012 and 2018. We estimate a structural econometric model incorporating the vertical structure between upstream solar manufacturers and downstream solar installers. Counterfactual simulations show the tariffs had a small positive impact on U.S. manufacturers but a large negative impact on U.S. installers. Chinese manufacturers were also negatively economically affected. 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 felt disproportionately on U.S. consumers.

JEL: F14; L10; Q50

Key Words: Trade War; Solar Industry; Structural Econometric Model; Pass-Through

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1 Introduction

After decades of trade liberalization, protectionism has reemerged in recent years, characterized by the U.S.-China trade war, the Japan-South Korea trade dispute, and Brexit. Protectionism measures are often initiated to target fast-growing and high-value technologies, such as semiconductors, solar photovoltaic (PV) power systems, automobiles, and telecommunications. Trade wars arise when cycles of subsidies are provided, and retaliating tariffs are enacted to protect domestic firms. The market for solar PV is a case in point of how trade wars can quickly escalate.

Over the past decades, the solar PV industry has grown exponentially. The cumulative installed capacity of PV systems has soared almost 180-fold worldwide, from 6.7 GW in 2006 to 1,177 GW in 2022.[1] Although the solar manufacturing sector has been historically 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 these schemes provided an unfair competitive advantage, which, in May 2012, led the U.S. 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 impacted.[3] Perhaps less salient, but nonetheless equally important, are the negative impacts these tariffs had on U.S. consumers and other domestic firms, such as installers, in the U.S. solar supply chain. Whether this trade war generated gains for U.S. solar manufacturers larger than the casualties to other domestic actors is an important but unanswered question. This paper aims to contribute to this debate.

[1]Source: 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 ten 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 U.S. anti-dumping policy came into effect.

Our goal is to quantify the distributional welfare effects of the anti-dumping and countervailing duties the U.S. government initiated against Chinese solar PV manufacturers with a focus on the U.S. 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: U.S. solar manufacturers, Chinese solar manufacturers, other non-U.S.-based solar manufacturers (i.e., South Korean and others), U.S. solar installers, and U.S. 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., U.S.-based), foreign manufacturers, and domestic installers. Specifically, our supply side follows Berto Villas-Boas (2007)'s three-stage oligopoly model that captures the contractual relationship between installers and manufacturers. 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 U.S. 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 coefficient on price 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 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 U.S.-China solar trade war. In our main baseline scenario, we assume the statutory rates of the tariffs correspond to their effective rates.[4] Under this assumption, the results show without the anti-dumping and countervailing duties imposed on Chinese manufacturers during the 2012 to 2018 period, the United States demand for residential solar PV systems would have been 24.7% higher. Furthermore, Chinese manufacturers incurred large losses in profits due to the anti-dumping policies, but U.S. manufacturers, as well as South Korean manufacturers, gained little. In the U.S. domestic market, installers and consumers suffered large losses from these trade barriers.

The solar trade war also had large negative impacts on environmental externalities. In the absence of anti-dumping 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 \$6.80 billion.

Finally, our model can be used to estimate the pass-through rate of the tariffs. In our main simulations, we find a \$1 tariff imposed on manufacturers leads to a \$1.16 increase in the final prices of installed PV systems. Manufacturers and installers thus overshift the burden of the trade tariffs onto U.S. consumers. Overall, our analysis suggests that during this period the solar trade war was detrimental to the solar industry, U.S.-based consumers, and the environment.

Our analysis is at the nexus of the literature on trade and the environment, and empirical industrial organization. First and foremost, this paper improves our understanding of the impact of trade wars in sectors crucial for the deep decarbonization of the economy. The theory of strategic trade policy argues governments can use import tariffs to raise 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

[4] As we later discuss, there were loopholes in the U.S. anti-dumping policies, especially in the first wave in 2012; these allowed Chinese manufacturers to avoid part of these tariffs. Our main policy analysis focuses on a case where Chinese manufacturers cannot circumvent the tariffs. We, however, 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, U.S. consumers paid for the tariffs and the costs of reallocating solar panels production outside China.

for a successful energy transition. However, these objectives might conflict with the imperative of lowering the cost of low-carbon technologies and accelerating 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., U.S.) solar sector, while slowing down the decarbonization of the U.S. power sector.

In addition, this paper 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] Whereas most papers investigating recent trade wars found tariff pass-through rates between 0 and 100 percent (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 percent). Most notably, Flaaen et al. (2020)'s analysis of the 2018 U.S. tariff on washing machines implies a pass-through exceeding 100 percent. The fact we find tariff overshifting in the U.S. solar market is also consistent with Pless and Van Benthem (2019)'s findings of pass-through rates exceeding 100 percent for U.S. solar subsidies.

These results for the U.S. washing machine market and 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. Accounting for imperfect competition in incidence analysis does not always imply higher pass-through, however (e.g., Ganapati et al., 2020). Ultimately this is an empirical question determined by the nature of the demand function and degree of competition. As we show, there is a large degree of heterogeneity across local markets in the U.S. solar context—

[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), Jaravel and Sager (2019) for literature on the incidence of tariffs.

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 stronger demand for solar PV, which is consistent with theoretical predictions.

Our paper also contributes to the growing literature in environmental economics about the solar power sector; the diffusion of residential solar PV systems is key for addressing the negative externalities associated with electricity generation. One stream of this literature has focused on evaluating the factors leading to solar adoption by households. These studies show 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; Dorsey, 2020; Gillingham and Bollinger, 2021). 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 literature stream has investigated the reasons for the large and rapid reduction in the costs of solar systems (Reichelstein and Sahoo, 2015). For instance, Bollinger and Gillingham (2019) find when installers learn by doing, this lowers solar prices, primarily related to the non-hardware costs of the solar PV installations. Gerarden (2023) finds 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 rest of the paper is organized as follows. Section 2 introduces the background of the U.S.-China solar trade war. Section 3 provides stylized facts regarding the manufacturer-installer relationships and market structure. Section 4 specifies the demand and supply components of the equilibrium model. Section 5 describes the data, identification, and estimation details, and Section 6 presents the estimation results. Section 7 uses the estimated model to perform policy simulations. Section 8 offers our conclusions.

2 Background: The U.S.-China Solar Trade War

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

2.1 The U.S. Solar Market

The United States has one of the world's largest installed capacity of solar power. In 2016, solar power overtook wind, hydro, and natural gas to become the largest source of new electricity capacity (EIA, 2018). 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 by its contribution to job creation. U.S. solar employment grew by 167% from 2010 to 2019, adding more than 156,000 jobs, according to the National Solar Jobs Census.[7]

The rapid development of the U.S. solar sector was spurred by a confluence of factors. On one hand, government policies may have played a role. For instance, several states have adopted renewable portfolio standards mandating a certain share of their electricity generation comes from renewable sources. At the same time, federal and state governments have also offered generous subsidies that target consumers.[8] On the other hand, the technology itself has improved. The

[6]Source: U.S. Solar Market Insight 2019 Year-in-Review report, released by the Solar Energy Industries Association (SEIA) and Wood Mackenzie.

[7]Source: 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 subsidy for residential solar PV installations at the state level varies 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.

manufacturing costs of solar PV systems have drastically decreased, and the efficiency of solar panels has increased. Even absent subsidies, this technology has become increasingly attractive (Borenstein, 2017).

Moreover, the supply chain for residential solar PV has also quickly developed. 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 over the past two decades, the installation costs, referred to as soft costs, now constitute a larger and major share of the final solar PV price (Barbose and Darghouth, 2016; Fu et al., 2017).

2.2 China's Solar Subsidies

At the international level, several jurisdictions have been competing 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 manufacturers of solar panels 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 with the Chinese government offering four types of subsidies to its domestic solar manufacturers (Ball et al., 2017). First, tax breaks, which consisted of a credit of 50% of the value-added tax, were offered. These tax breaks were first implemented in 2013 for two years; then they were extended through 2018. Second, local governments made subsidized (free or discounted) land 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.

2.3 U.S. Anti-dumping Policies

In October 2011, German-owned SolarWorld, which was then the United States' largest provider of solar panels, filed an anti-dumping petition against Chinese solar firms. They alleged 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 U.S. market.

Following SolarWorld's petition, the U.S. Department of Commerce began an investigation culminating with an announcement on October 2012 that anti-dumping 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.[9] This was the first wave of U.S. tariffs against Chinese solar manufacturers.[10]

However, this ruling applied only to solar panels made from Chinese solar cells; this created an important loophole. Some mainland Chinese firms could circumvent the tariffs when exporting to the United States by outsourcing one piece of the manufacturing process to Taiwan. In January 2014, SolarWorld thus filed another anti-dumping petition with the U.S. Department of Commerce to close this loophole. In December 2014, the U.S. Department of Commerce announced deeper firm-specific tariffs on imports of crystalline silicon photovoltaic products from both mainland China and Taiwan. The anti-dumping duty rates then ranged from 26.71% to 165.04%, and the

[9]The provisional anti-dumping duty deposits and countervailing duty deposits were collected as of the date of publication of the Commerce Department's preliminary determinations, which were in March and May 2012, respectively. The anti-dumping duties (AD) fell into four categories: 1) 31.73% for Suntech Power; 2) 18.32% for Trina Solar; 3) 25.96% for 59 other listed manufacturers; and 4) 249.96% for all other remaining Chinese manufacturers. The countervailing duties (CVD) fell into three categories: 1) 14.78% for Suntech Power; 2) 15.97% for Trina Solar; and 3) 15.24% for all other Chinese manufacturers. For details, see `https://enforcement.trade.gov/download/factsheets/factsheet_prc-solar-cells-ad-cvd-finals-20121010.pdf`

[10]In the first wave, the U.S. Department of Commerce issued its preliminary determinations on anti-dumping and countervailing duties (AD/CVD) in March and May 2012, respectively, and issued its final determinations in Oct 2012. The provisional AD deposits and CVD deposits were collected as of the date of publication of the U.S. Commerce Department's preliminary determinations, which were also in March and May 2012, respectively. The first wave of AD/CVD investigation thus began in March 2012 (2012-Q1).

countervailing duty rates then ranged from 27.64% to 49.79%.[11] This marked the second wave of tariffs.[12]

The third wave started in February 2018, when the U.S. government put an additional 30% 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 step down in 5% annual increments over four years. Finally, the last episode of the solar trade war culminated in July 2018 when the U.S. government put another 25% tariff on Chinese solar products as a part of the broader U.S.-China trade war on $50 billion of goods of all kinds (Amiti et al., 2019; Fajgelbaum et al., 2020).

3 Market Structure

Before proceeding to the presentation of the structural econometric model, we first investigate the market structure of the U.S. 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.

[11] The provisional anti-dumping duty deposits and countervailing duty deposits were collected as of the date of publication of the U.S. Commerce Department's preliminary determinations, which were in June and July 2014, respectively. The anti-dumping duties fall into four categories: 1) 26.71% for Trina Solar; 2) 78.42% for Renesola/Jinko; 3) 52.13% for 43 other listed Chinese manufacturers; 4) 165.04% for all remaining Chinese manufacturers. The countervailing duties fall into three categories: 1) 49.79% for Trina Solar; 2) 27.64% for Suntech Power; 3) 38.72% for all other Chinese manufacturers. For details, see `https://enforcement.trade.gov/download/factsheets/factsheet-multiple-certain-crystalline-silicon-photovoltaic-products-ad-cvd-final-121614.pdf`

[12] In the second wave, the U.S. Department of Commerce issued its preliminary determinations on AD and CVD in June and July 2014, respectively, and issued its final determinations in Dec 2014. The provisional AD deposits and CVD deposits were collected as of the date of publication of the U.S. Commerce Department's preliminary determinations, which were in June and July 2014, respectively. Therefore, the second wave of AD/CVD investigation began in June and July 2014 (2014-Q2).

3.1 Vertical Contracting in Manufacturer-Installer Relationship

A salient feature of the U.S. solar industry is the vertical relationship between manufacturers and installers. The upstream companies manufacture solar panels and modules and distribute them to the downstream installers. The installers resell the solar products to the 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 execute complex work to assemble solar panels together with other equipment (inverter, battery, mounting system, wiring, and solar charge controller).

In the U.S., most of the PV market is not vertically integrated. This trend, however, might be reverting as some solar manufacturers are starting to integrate their whole supply chain. For example, SunPower and REC Solar transformed into vertically integrated companies by offering solar installations rather than just manufacturing modules.

3.2 Market Power

To further gain insights into the market structure of the U.S. solar industry, we exploit 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 U.S. solar PV installations. We exclude the commercial and utility-scale solar sectors and focus solely on residential solar installations.[13] As of the end of 2018, there were over one million residential solar PV installations in the U.S. Our final sample has a rich set of observables and covers 23.8% of the whole sample (21.6% of installed capacity). For each observation, we observe the installation date, location,

[13]During 2012-2018, the residential solar sector accounts for 96.6%) of the U.S. solar market in terms of number of installations. For the estimation, we use a subsample of the whole universe of residential installations. The subsample's construction is described in Appendix B.

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, the sample period begins in 2011, the year before the first episode of the U.S.-China solar trade war that began on October 2012, and ends in 2018 at the time of the third episode.

The U.S. solar market for upstream manufacturers and downstream installers is relatively concentrated, although entry is not restricted. There were around 250 different solar manufacturers operating in the U.S. 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, German, and Japan dominated the market. The U.S. 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, e.g., electricians (OShaughnessy, 2018).

Over time, the local market for PV installations has remained highly concentrated, however. As shown in Panel B of Table 1, 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 highest-volume installers accounted for approximately 50% of all U.S. solar PV installations during the 2011-2018 period.

On average, each installer worked with approximately four different manufacturers between 2011 and 2018 (see Panel A of Table 1). However, there is substantial heterogeneity between installers with activities across the United States and those only active in a few regional markets. For example, Tesla Energy, the largest solar installer in the United States, procured solar panels from 50 different solar manufacturers. In contrast, the whole sample of installers works with a median of 2 different manufacturers.

3.3 Variation in Market Share During the Trade War

Figure 1 shows the time trend of market share for Chinese, U.S., and South Korean manufacturers.[14] In 2011-Q1, 20.3% of the installations done by U.S. installers used solar panels produced by Chinese manufacturers. After the first wave of anti-dumping policies starting in October 2012, we witnessed 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 the duties by assembling panels from cells produced in Taiwan, a loophole that we discussed in Section 2.3. However, this export-snatching effect gradually diminished when the Chinese manufacturers noticed the U.S. government was taking possible actions to close this loophole. After the second wave of anti-dumping policies starting in 2014, the market share of Chinese manufacturers decreased to approximately 20%; it further decreased to 8.6%, which is about 12% points below the level before the trade war, after the third wave of anti-dumping policies starting in 2018. U.S. manufacturers' market share is strongly negatively correlated with Chinese manufacturers' market share and thus displays the exact opposite pattern.[15] Moreover, South Korean manufacturers have become increasingly important players in the U.S. market. They seemed to have benefited from the U.S.-China solar trade war. Their aggregated market share soared from nearly zero in 2011 and steadily increased to reach about 35% in 2019.

4 Structural Econometric Model

We now outline a structural econometric model of the U.S. solar industry where demand and supply are represented. The demand side is modeled with a discrete choice framework with rich

[14] To create Figure 1, we extended the sample period from 2010 to 2019 to better show the pre- and post-trends.

[15] Figure A1 shows the proportion of Chinese manufacturers each installer was working with. We observe a similar trend as in Figure 1.

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 for the consumers. We focus on modeling preferences for residential consumers, and in particular owners of a single-family house. Our sample period covers the early stages of the adoption of solar PV in the U.S., and those households represent the primary market during this period. Non-residential consumers represent only 3.4% of the installations made during that period (see Appendix B for further details).

4.1 Consumer Demand for Solar PV

The purpose of the demand model is to capture the preferences for price and solar PV systems' main characteristics. A consumer can choose the solar installer and the model of the solar PV system to install.[16] Because our data are aggregated to the PV model/installer/year level, we assume a consumer's choice is a model-installer combination, indexed by j. That is, consumers have preferences for both the manufacturer producing a given PV system and the installer performing 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 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

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

In equation (1), X_j is a vector of observed product characteristics such as energy conversion efficiency and technology type. 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

[16]The model of the solar PV system refers to the model of the solar panels used in the PV systems.

by the size of the solar PV system installed; and α_i represent the marginal disutility of price (also assumed to be random). D_w is a vector of demographic variables (including income, education, urbanization, race, and political orientation) for each MSA w and captures household-specific preferences.[17] 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 times.[18] Finally, ζ_{jt} are the product characteristics unobserved by the econometrician but observed by the consumers and firms; and ϵ_{ijwt} is an i.i.d error term and follows the type I extreme value distribution.

The heterogeneous taste parameters for product characteristics are modeled as

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

where v_i is a random draw from a multivariate standard normal distribution (i.e., $v_i \sim N(0, \mathbf{1})$), Σ is a diagonal scaling matrix. This specification allows the taste parameters for the solar PV price and non-price 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. $F(\cdot)$

[17] In Appendix C, we discuss why we choose to include MSA-level demographic variables instead of MSA-level fixed effects in the demand side.

[18] 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.

is the standard normal distribution function.

The market share for the outside goods is usually defined as one minus the shares of 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 [19]; V is the percentage of solar-viable buildings in that MSA level; L is the maximum proportion of potential adopters that would install solar PV systems and we assume it to be 15% [20]. 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 (1994)'s 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 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 dynamics have a first-order effect on the demand estimates in this context.

[19] 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.

[20] Our results are robust to other assigned values of L. In Table C5, we report estimation results for the demand and supply side using $L = 20\%$ and $L = 10\%$, respectively.

4.2 Supply Side

In this section, we derive an estimating equation to recover the key primitives in the vertical structure of the U.S. solar market. Specifically, the equation approximates the solar manufacturers' and installers' optimizing behavior 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 Berto 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 that represents the pricing equilibrium, thus, shorter outcomes in the solar market. In the first stage, the solar manufacturers choose their products. In the second stage, they choose the wholesale prices charged to the solar installers, given the realized demand and marginal cost shocks. In the third stage, the 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 tariff-inclusive retail price p^e_{jt} after observing the set of solar PV models available (denoted by J_{rt}), tariff-exclusive wholesale prices (p^m_{jt}), the tariff rate imposed on the solar panels (τ_{jt}), and the given 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 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 $p^e_{jt} - p^m_{jt} - c^r_{jt}$.

Each installer r's profit function in period t is given by

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

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

$$p_t^e - p_t^m \cdot (1+\tau_t) - c_t^r = -(T_{rt} * \Delta_{rt})^{-1} s_t(p^e) \tag{6}$$

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 $(k,j) = \frac{\partial s_{jt}}{\partial p_{kt}}$.

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

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

where c_{jt}^m is the marginal cost for solar manufacturers that produce j. The first order condition is given by[21]

$$p_t^m - c_t^m = -(T_{mt} * \Delta_{mt})^{-1} s_t(p^e)/(1+\tau_t) \tag{8}$$

where T_{mt} is the ownership matrix for solar manufacturer m, analogously defined as the matrix T_{rt} above. Δ_{mt} is the solar manufacturer's response matrix with element $(k,j) = \frac{\partial s_{jt}}{\partial p_{kt}^m}$, 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,

$$mc_t = (1+\tau_t) c_t^m + c_t^r = p_t^e + (T_r * \Delta_{rt})^{-1} s_t(p^e) + (T_m * \Delta_{mt})^{-1} s_t(p^e) \tag{9}$$

[21] Differentiating equation (7) with respect to p^m yields to $s_j(p^e) + (1+\tau_j) \sum_{j \in J_{rt}} (p_k^m - c_k^m) \frac{\partial s_k}{\partial p_j^m} = 0$.

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

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

where Y_t includes the solar panel's energy conversion efficiency (eff) and the wage rate in roofing ($wage$). We allow for a non-linear 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, $eff \times \tau$, $eff \times \tau^2$, $eff^2 \times \tau$, and $eff^2 \times \tau^2$). The possible non-relationship between tariffs and costs may arise from non-linearities, i.e., 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.[22]

Combining equations (9) and (10) yields

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

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 non-linear (two-part tariff) pricing models proposed by Berto Villas-Boas (2007). The models with non-linear 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

[22] In Appendix C, we experiment with manufacturer-fixed effects in the supply-side estimation. Table C4 shows our model is robust by adding a manufacturer-fixed effect on the cost side.

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

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

For the other alternative model (denoted *Model* 3), we assume the opposite: 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

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

Equation (13) and (12) both correspond to different types of non-linear vertical contracts and can be readily estimated by simply substituting the appropriate ownership matrix. In Section 6, 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.

5 Implementation

5.1 Data

In our estimation of the structural model and subsequent simulations, we restrict our sample to the period 2012-2018 to obtain parameter estimates corresponding to the period of the main episodes of the U.S.-China solar trade war. As before, the main dataset comes from the LBNL's *Tracking the Sun* report series, as described in Section 3, and we focus only on residential solar PV installations, which account for the majority of the U.S. solar market between 2012 and

2018.[23] We combine the dataset with four other data sources: (1) demographic data from the U.S. Census Bureau, which provide county-level demographic variables on income, education, urbanization, race, and political orientation across the United States;[24] (2) electricity price data from the U.S. Energy Information Administration; (3) labor market data from the U.S. Bureau of Labor Statistics, which provide 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 U.S. county. After merging the data and selecting observations with the information required for the estimation procedure, our final sample accounts for 21.6% of all U.S. residential solar PV installed capacity during the 2012-2018 period. Appendix B describes how we constructed our sample and compares it with the full universe of installations, and shows that our estimation sample represents well the U.S. residential solar market.

Conducting the analysis at the MSA level, we thus use county-level identifiers in the dataset to construct MSA-level variables, which are averages across all counties in each MSA.[25] To define the inside goods for the analysis, we distinguish solar PV models that have significant sales (more than 3,000 units) in the United States and define a generic inside good with all other models.[26] The sample consists of 58 models produced by 10 solar manufacturers, and these solar manufacturers include three Chinese companies (Canadian Solar, Trina Solar, and Yingli Energy), one U.S. 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 A1 in Appendix A, we report an exhaustive list of solar system models found in the sample.

[23]During 2012-2018, the residential solar sector accounted for more than 95% of the U.S. solar market in terms of the number of installations and represents 54% of the market in terms of installed capacity.

[24]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.

[25]In the original dataset, the U.S. 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.

[26]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 1 generic group of installers.[27] We consider the 20 largest installers who have a significant market share across the United States (see Table A2 in the appendix), 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 they used in this given market (MSA-year). This means the same installer located in different markets (in space or time) may have a different consideration set when it comes to choosing a solar system. For manufacturers, the ownership matrix is defined at the national and yearly levels.

Table 2 reports summary statistics for the key variables we used in the estimation. Panel A lists the product characteristics of the solar PV systems. Over the sample period, the average total installed price (gross of subsidy) for a solar PV system was \$4.24/W with a standard deviation of \$0.87/W. The average final price a U.S. consumer paid for a solar PV system is \$4.07/W, which implies the average government subsidy consumers received represents 4% of the total installed price.[28] In those calculations, the Federal Investment Tax Credit for solar, which households could use to reduce their tax liabilities, is not included. The average energy conversion efficiency for solar PV systems is 0.18 with a standard deviation of 0.02. Energy conversion efficiency quantifies a solar PV's ability to convert sunlight into electricity. Higher efficiency indicates a panel can convert solar energy at a lower cost. Technology is a dummy variable that equals to one if the

[27] 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 Appendix C, as a robustness check, we group the installers into 10 + 1 generic and re-estimate the model for our linear-pricing model (i.e., double marginalization by manufacturers and installers). As shown in Table C1, the estimation results are similar to those in our main results. It implies that our model is robust to different classifications of installer groups.

[28] The government subsidy consumers received as a share of the total installed price has been declining over time. In 2012, the subsidies accounted for approximately 10% of the installed price. This ratio decreased to only approximately 2% in 2018.

solar PV system is made of polycrystalline panels and zero if it is made of monocrystalline panels. About 40% of the solar PV systems are made of polycrystalline panels.[29] Panel B lists demographic information at the MSA level. The average median housing price (our proxy for household income) is $451,000, and the average population density is 990 persons per square mile. On average, 27% of the observations are from regions where people have a bachelor's degree or higher, 50% people are white, and 55% of people voted for candidates in the Democratic Party in 2008. Panel C lists the summary statistics for other variables. The average number of single-unit houses at the MSA level is 538,947; 92% of the houses have values greater than $100,000. The average wage rate for PV installation across different MSAs is $24.83/hour. Finally, the average electricity price on the state level has a mean value of 17.15 cents/kWh with a standard deviation of 1.56 cents/kWh.

5.2 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) (thereafter referred 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 deter-

[29] Monocrystalline solar panels are generally considered a premium solar product, and their main advantages are higher efficiencies and sleeker aesthetics compared to polycrystalline solar panels.

mined 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 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.

In order to investigate our instrumental variables, we first use a simple two-stage least square (2SLS) regression to estimate equation (4). Table A3 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.[30] The F-tests of the joint significance of the instruments in all three models yield values greater than 10. The results suggest 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 A4 show that the instrumental variables lead to a significant and negative price coefficient. Overall, the sets of BLP instruments where we approximate the equilibrium pricing equation with a richer set of variables (Columns 2 and 3 in Tables A3 and A4) perform well in our setting and led to a stable coefficient on price. For our main structural estimation with random coefficients, we use the same instruments as in column 3 described above.

5.3 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

[30] In column 3, the instrumental variables thus consist of five variables, that is, BLP_eff, BLP_tech, $(BLP\_eff)^2$, $(BLP\_tech)^2$, $BLP\_eff \times BLP\_tech$.

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.

6 Estimation Results

Table 3 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). The upper panel 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 non-price characteristics (the matrix Σ). The price coefficient is negative and statistically significant at conventional levels of significance. In *Model 1* (linear vertical contracts), the coefficient on panel efficiency is positive and statistically significant at the 1% level, suggesting 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 1*), suggesting areas with higher income tend to adopt more solar PV systems. The coefficient on urbanization is negative and significant at the 1% level, implying 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 and significant at the 1% level, 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 people living in areas with lower education levels have a higher demand for solar PV systems. This might be due to the fact that areas with residents with high levels of education across the United States are also located in areas less suitable for installing solar PV systems, which is not captured by our set of controls, notably the coarse categorical variable for urban/rural.[31] In *Model 2* (non-linear contract with bargaining power to the downstream firms) and *Model 3* (non-linear contract with bargaining power to the upstream firms), the taste variation parameter on price is statistically significant at conventional levels, showing consumers are heterogeneous with respect to their tastes for solar PV prices.

The demand parameter in Table 3 yields a mean own-price elasticity of demand of -4.26, -4.58, and -4.26 across *Models* 1, 2, and 3, respectively. Our estimates fall within the wide 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) infers 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 $[0.003; 0.101]$, as shown in Table A5. 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).

Summary statistics on price-cost margins and recovered marginal costs for installed solar PV systems are reported in the first column of Table A6 in the appendix. These statistics are broken down by upstream manufacturers/downstream installers of solar PV systems. Under the linear vertical contract specification (*Model* 1), the mean margins for upstream manufacturers and

[31] 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 not suitable 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.

downstream installers are \$0.898/W and \$0.987/W, respectively, yielding a mean total margin (upstream and downstream) of \$1.885/W. On average, the ratio of margin to total installed price, the Lerner Index, is 0.46. If we consider, non-linear vertical contracts, the overall magnitude of the margins is smaller. If installers entirely determine the price-cost margins (*Model* 2), the mean margin is \$0.911/W; and when only manufacturers determine the price-cost margins (*Model* 3), the mean margin is \$0.897/W.

Table 3 also reports additional estimation results on the supply side in our main specification. The significant and positive coefficient on energy conversion efficiency suggests marginal costs increase with efficiency rate, as expected. The positive and statistically significant coefficient on wage rate also suggests marginal costs increase with labor costs.

The coefficients on tariff-related terms (i.e., τ, τ^2, $eff \times \tau$, $eff \times \tau^2$, $eff^2 \times \tau$, and $eff^2 \times \tau^2$) are all significant at the 1% level. In *Model* 1, given the mean value of energy conversion efficiency is 0.18, we can replace this value into the cost function and find that the tariff-related part collapses into -0.252τ + 0.203τ^2, which indicates that the joint marginal cost increases with the tariff rate when the tariff rate is greater than 62% (0.252/(0.203*2)). As the median value of non-zero 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; Gayle, 2013; Bonnet et al., 2013; Haucap et al., 2021), and use the non-nested tested proposed by Rivers and Vuong (2002). In Table A7, we report the test statistic for each pairwise comparison between the three specifications. The test statistics are all very close to zero, suggesting that these three models are statistically indistinguishable. We will thus focus on *Model* 1 with linear contracts but will, nonetheless, report the policy results for all three different types of models.

7 Policy Analysis of Trade Tariffs

We now investigate the incidence of the U.S.-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), U.S. installers, and U.S. consumers.[32]

We simulate three sets of scenarios. First, we remove the U.S. anti-dumping and countervailing duties imposed on Chinese solar manufacturers during the three waves of tariffs spanning the 2012 to 2018 period. We 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 U.S.-China trade war.

Second, conditional on the first scenario, we additionally remove the U.S. anti-dumping duties 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 U.S. Department of Commerce. The rationale for this scenario is the fact that Chinese solar manufacturers exploited various loopholes to avoid the brunt of the tariffs. One notable example of such behavior, which has been well-documented and we previously discussed, occurred in the first wave of tariffs when mainland Chinese manufacturers relocated their panel assembly lines to Taiwan. As a result, it is believed this wave of tariffs was largely ineffective. Of course, the reallocation of the assembly lines might have increased the panels' manufacturing costs, but these were presumably less than the statutory

[32]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

$$\Delta CS = -\frac{1}{\alpha}\left[\ln\left(\sum_{j=1}^{J}\exp(W_j^1)\right) - \ln\left(\sum_{j=1}^{J}\exp(W_j^0)\right)\right] \tag{14}$$

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.

rates imposed. In our data, we cannot measure to what extent Chinese manufacturers could have evaded the tariffs through production reallocation and the final impact it may have had on their costs. We can, however, vary exogenously 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 U.S. solar market.

The solar PV industry has a long value chain. The solar PV modules manufactured in the United States may use polysilicon, ingots/wafers, and cells imported from China. We do not observe those elements of the supply chain. Therefore, we cannot precisely account for them in the estimation. However, it may have implications for who is ultimately exposed to the tariffs in the supply chain. To capture the overall downstream impact of the tariffs, we consider another counterfactual scenario in which we assume U.S. manufacturers are partly affected by the tariffs imposed on the Chinese manufacturers due to the fact that they could procure some parts of their solar systems from China upstream in the supply chain. In this scenario, we assume that U.S. manufacturers (only in our model) face 10% of the statutory tariffs imposed on Chinese manufacturers. This percentage is chosen for illustration purposes and could easily be scaled down/up to reflect alternative scenarios. The results for this scenario are in Appendix D.

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 U.S. residential sector, such as local rebates and subsidies, investment tax credits, and electricity tariffs (Borenstein, 2017).

7.1 Important Parameters

Before proceeding further, we discuss three important parameters required to perform the simulations. First, we present the exact anti-dumping and countervailing duties imposed on Chinese manufacturers in Table A8. Panel A lists the anti-dumping and countervailing duty rates imposed on Chinese and foreign solar manufacturers represented in our model during the three waves of tariffs. In the first wave starting in 2012, Trina Solar received anti-dumping duty rates of 18.32% and countervailing duty rates of 15.97%, whereas Canadian Solar and Yingli Energy both received anti-dumping duty rates of 25.96% and countervailing duty rates of 15.24%. These tariffs were then increased in the second (2014) and third (2018) waves. All foreign solar manufacturers were subject to 30% anti-dumping duty rates in the third wave of tariffs for the year 2018.

Second, to simulate these tariffs, we must know the proportion of panel cost versus non-panel cost in a typical residential solar PV installation. This is because the anti-dumping and countervailing duties were only imposed on the solar panel prices (or system module prices), not on the final prices of installed systems. The challenge is that we have no data on import prices and the solar panel prices charged by the installers are also not observable in our dataset; we can only observe the total installed price consumers pay, which includes the panel price and non-panel cost (e.g, labor, overhead, and marketing costs associated with solar PV installations (Bollinger and Gillingham, 2019)). To calculate the tariffs imposed on panels, we must recover the solar panel prices from the consumer purchase prices by interpolating the fraction of the total price that could be attributed to the panels versus the labor-related costs (also referred to as the so-called soft costs). To do so, we compute the model-implied solar panel price, which is the tariff-exclusive consumer purchase price, we estimate, multiplied by the ratio of panel cost in a typical residential solar PV installation reported by LBNL. The tariff-exclusive consumer purchase price is, thus, calculated as the summation of tariff-exclusive joint marginal cost, manufacturer markup, and installer markup, where the tariff-exclusive joint marginal cost is obtained by subtracting the tariff terms from the estimated tariff-inclusive joint marginal cost.

Panel B in Table A8 reports the actual and model-implied solar panel prices. Column 1-2 show the actual solar panel prices and their ratios in total installed prices from 2012 to 2018, reported by LBNL. In 2012, the panel prices accounted for 17.91% of the total installed price, but it decreased to 15.48% in 2018. Our model-implied panel prices shown in column 3 match well the actual prices. Finally, we compute the dollar value of the tariffs imposed on panels, based on model-implied panel prices and the anti-dumping and countervailing duties

Lastly, we consider the parameters required to quantify the environmental benefits that arise from residential solar PV adoption. By displacing natural gas- or coal-fired power generation, residential solar PV systems reduce greenhouse gas emissions and other pollutants. We focus on quantifying the CO_2 externality. We set 25 years as the time limit for estimating environmental benefit because most manufacturers provide a 25-year warranty on their solar products (Gillingham and Tsvetanov, 2019). During our sample period, Zivin et al. (2014) estimated the average carbon dioxide emission rate across all U.S. regions was 0.000605 tons of CO_2 per kWh. If we assume the average number of full sunlight hours is four hours per day, the amount of greenhouse gas emissions (in tons) avoided both now and for the next 25 years is $\textit{Installed Solar Capacity} \times 4 \times 365 \times 25 \times 0.000605$. For the social cost of carbon, we apply the result in Rennert et al. (2022), in which he estimated the social cost of carbon (SCC) is \$185 per ton of CO_2 in 2020 U.S. dollars.[33]

7.2 Simulations

In this subsection, 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 conduct the policy analysis using *Models* 2 and 3 to assess the robustness of our results with respect to the nature of the vertical contracts. These results are also reported in the main tables.

7.2.1 Removing Tariffs on Chinese Manufacturers

To determine the effects of removing anti-dumping policies, we first remove the U.S. tariffs against Chinese solar manufacturers and examine the equilibrium response, welfare change, and related environmental benefits/losses. Table 4 presents the results. Panel A shows the total

[33]We convert the social cost of carbon in Rennert et al. (2022) to the value in 2015 U.S. dollars

market capacity of the U.S. solar market would have been 24.7% larger if the anti-dumping and countervailing duties 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, the sales of solar panels by Yingli Energy would have been 92.8% 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, i.e., the number of adopters.

Panel B shows the welfare changes among the different market participants. Removing the anti-dumping policies provides welfare gains of $412.6, $356.4, and $342.4 million for U.S. consumers, Chinese manufacturers, and U.S. installers, respectively. The losses for U.S. manufacturers are only $8.6 million, whereas the decrease in U.S. tariff revenues is $507.8 million. This suggests that U.S. 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 U.S. and China. South Korean and other non-U.S.-based manufacturers benefited slightly from the U.S. tariffs.

Panel C reports the related environmental benefit/loss. It shows the emission of carbon dioxide would have been lower by 8.6 million tons in the absence of tariffs, which translates into an externality cost of $1.47 billion. Since the data in our final sample accounts for 21.6% of U.S. residential solar PV installation capacity, the overall benefits associated with reducing the CO_2 externality for the whole United States would amount to $6.80 billion.[34]

We next investigate how the anti-dumping policy impacted 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.

[34]We only consider the environmental benefits brought by the installations of residential solar PV systems. The externality related to commercial and utility-scale solar PV systems are not included in our analysis.

This also corresponds to an increase in the final price if we were to assume no demand-and-supply responses. In Table 7, we thus report the average change in final prices for affected PV systems without and with an equilibrium response.[35] 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 116%. It implies that a $1 dollar increase in tariff leads to a $1.16 increase in the final price of an installed solar PV system in the United States. We thus find evidence of tariff overshifting in the U.S. solar market. Our results are consistent with the recent evidence of Pless and Van Benthem (2019), who also find pass-through rates exceeding 100 percent while investigating solar subsidies.

A pass-through rate higher than unity can be attributed to the presence of market power. At first, the U.S. solar market, especially the installation market, could appear to be 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 tariff pass-through rate. We thus 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.[36] For each average demand elasticity, we put a universal cost shock (a tariff rate of 100%) on the solar manufacturers and calculate the average tariff pass-through rate for all PV systems. Table 8 reports the results: the pass-through rate increases with the elasticity of the demand. In a pure monopoly setting, this result would be

[35] 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-U.S. panels).

[36] We scale the parameter α by a constant such that the average demand elasticity ranges from -1 to -4.26. Bonnet et al. (2013) proposed a similar approach.

counterintuitive, 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 and face higher electricity prices, 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 are able to shift more tariffs to consumers. For other demographic characteristics, the patterns are less striking, as presented by Figure A2.

7.2.2 Removing All Tariffs

In the third set of counterfactual scenarios, we simulate the impact of tariffs by removing the anti-dumping and countervailing duties imposed on Chinese and all other foreign manufacturers. Table 5 reports the results. Panel A shows the total market capacity of the U.S. solar market would have expanded by 26.9% 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 (except for Hanwha). For instance, the sales of solar panels made by LG would increase by 5.8% in these scenarios, whereas it was only a 1.4% decrease in the previous scenario.

Conditional on the first scenario, additionally removing the anti-dumping duties imposed on on all other foreign manufacturers (in 2018) make the market further expand. This can be readily seen in Panel B, which reports the welfare changes in dollars. Now, in the absence of tariffs, the welfare gains for U.S. consumers, Chinese manufacturers, and U.S. installers would have been \$436.2, \$356.0, and \$365.0 *million*, respectively. Whereas, the losses for U.S. manufacturers and U.S. tariff revenue would have been \$9.4 and \$532.9 *million*, respectively. In Panel C, the change in the environmental externality is also larger. Overall, the changes in the different welfare metrics are more than 7% larger relative to the first set of scenarios.

7.2.3 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 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 the different waves of tariffs had different loopholes. As a result, the degree of strategic avoidance is likely to have varied over the duration of 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 6, 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 U.S. market, is rather linear.[37]

Second, as shown in Table 7, the tariff pass-through rate remains virtually unaffected: it is 116%. 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 thus robust to the presence of strategic avoidance. Ultimately, it means that U.S. consumers are the ones bearing the burden of the tariffs, whether this is due to the trade tariffs themselves or the higher production costs due to the reallocation of production along the global supply chain.

Altogether, these results show an important advantage of our structural model. We can easily mimic different policies impacting the cost structure of the whole industry, whether they are trade tariffs, mergers, or climate policies, as well as cost shocks due to supply-chain constraints, and quantify their welfare effects.

[37] We do not have information about the supply-chain effects for solar panels outside the United States. We should, however, expect non-linear 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.

8 Conclusion

In this paper, we provide one important piece of the puzzle to study the incidence of the recent U.S.-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 U.S. market. To that end, we propose a structural econometric model that models both the demand—and supply-side effects. Using the estimated model, we simulate the equilibrium response to the trade tariffs under various scenarios.

In our main set of scenarios, we show the installed capacity in the U.S. solar market would have increased by 24.7% more in the absence of trade tariffs. Although, the tariffs protected U.S. manufacturers, neither installers nor consumers in the United States were largely negatively affected. The increase in government revenues from these tariffs is large, but they are not enough to offset the negative impacts on the domestic market. We also find 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 $1.16 for PV systems using panels subject to such a tariff. Overshifting is surprising but not uncommon in imperfectly competitive markets. In the U.S. solar market, market power appears to be important in both the upstream and downstream markets: a few manufacturers have large market shares, and installers hold significant market power in local regional markets.

We conclude by highlighting a few caveats to our paper and directions for future research. First, in the absence of dynamic on the supply-side, we cannot quantify the impact of market expansion/contraction on the cost structure of the industry. In particular, the market contraction induced by trade tariffs could have reduced economies of scale, which would have increased manufacturing costs in the domestic and foreign markets. Second, we restrict our analysis to the residential solar sector, without taking into account the commercial and utility-scale solar PV systems, which may underestimate the impact of the trade war on the U.S. solar market. Third, our quantification of the environmental externality focuses only on CO_2 and does not consider the marginal power producer in each region and year. There is substantial temporal and spatial heterogeneity associated with power generation displacement due to added capacity in renewable energy (Novan, 2015; Callaway et al., 2018; Sexton et al., 2018). A more granular and spatially disaggregated model would be required to quantify such effects.

References

Aguirregabiria, Victor, and Aviv Nevo. 2013. Recent developments in empirical io: Dynamic demand and dynamic games. *Advances in Economics and Econometrics* 3: 53–122.

Alfaro, Laura, Paola Conconi, Harald Fadinger, and Andrew F Newman. 2016. Do prices determine vertical integration? *The Review of Economic Studies* 83 (3): 855–888.

Altonji, Joseph G, Todd E Elder, and Christopher R Taber. 2005. Selection on observed and unobserved variables: Assessing the effectiveness of catholic schools. *Journal of political economy* 113 (1): 151–184.

Amiti, Mary, Stephen J Redding, and David E Weinstein. 2019. The impact of the 2018 tariffs on prices and welfare. *Journal of Economic Perspectives* 33 (4): 187–210.

Anderson, Simon P, Andre De Palma, and Brent Kreider. 2001. Tax incidence in differentiated product oligopoly. *Journal of Public Economics* 81 (2): 173–192.

Bai, Liang, and Sebastian Stumpner. 2019. Estimating us consumer gains from chinese imports. *American Economic Review: Insights* 1 (2): 209–24.

Ball, Jeffrey, Dan Reicher, Xiaojing Sun, and Caitlin Pollock. 2017. The new solar system: China's evolving solar industry and its implications for competitive solar power in the united states and the world. Technical report, Stanford University, CA (United States).

Barbose, Galen L, and Naïm R Darghouth. 2016. Tracking the sun : The installed price of residential and non-residential photovoltaic systems in the united states (washington: Us department of energy, 2016). *available at emp.lbl. gov/publications/tracking* .

Bauner, Christoph, and Christine L Crago. 2015. Adoption of residential solar power under uncertainty: Implications for renewable energy incentives. *Energy Policy* 86: 27–35.

Bernhofen, Daniel M, and John C Brown. 2004. A direct test of the theory of comparative advantage: the case of japan. *Journal of Political Economy* 112 (1): 48–67.

Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. Automobile prices in market equilibrium. *Econometrica: Journal of the Econometric Society* : 841–890.

Berry, Steven T. 1994. Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics* : 242–262.

Berto Villas-Boas, Sofia. 2007. Vertical relationships between manufacturers and retailers: Inference with limited data. *The Review of Economic Studies* 74 (2): 625–652.

Bollinger, Bryan, Todd Gerarden, Kenneth Gillingham, Drew Vollmer, and Daniel Yi Xu. 2024. Strategic avoidance and the welfare impacts of solar panel tariffs .

Bollinger, Bryan, and Kenneth Gillingham. 2012. Peer effects in the diffusion of solar photovoltaic panels. *Marketing Science* 31 (6): 900–912.

———. 2019. Learning-by-doing in solar photovoltaic installations. *Available at SSRN 2342406* .

Bonnet, Céline, and Pierre Dubois. 2010. Inference on vertical contracts between manufacturers and retailers allowing for nonlinear pricing and resale price maintenance. *The RAND Journal of Economics* 41 (1): 139–164.

Bonnet, Celine, Pierre Dubois, Sofia B Villas Boas, and Daniel Klapper. 2013. Empirical evidence on the role of nonlinear wholesale pricing and vertical restraints on cost pass-through. *Review of Economics and Statistics* 95 (2): 500–515.

Borenstein, Severin. 2017. Private net benefits of residential solar pv: The role of electricity tariffs, tax incentives, and rebates. *Journal of the Association of Environmental and Resource Economists* 4 (S1): S85–S122.

Brander, James A, and Barbara J Spencer. 1985. Export subsidies and international market share rivalry. *Journal of International Economics* 18 (1-2): 83–100.

Broda, Christian, Nuno Limao, and David E Weinstein. 2008. Optimal tariffs and market power: the evidence. *American Economic Review* 98 (5): 2032–65.

Bulow, Jeremy I, and Paul Pfleiderer. 1983. A note on the effect of cost changes on prices. *Journal of political Economy* 91 (1): 182–185.

Burr, Chrystie. 2016. Subsidies and investments in the solar power market. *University of Colorado at Boulder Working Paper* .

Callaway, Duncan S, Meredith Fowlie, and Gavin McCormick. 2018. Location, location, location: The variable value of renewable energy and demand-side efficiency resources. *Journal of the Association of Environmental and Resource Economists* 5 (1): 39–75.

Cavallo, Alberto, Gita Gopinath, Brent Neiman, and Jenny Tang. 2021. Tariff pass-through at the border and at the store: Evidence from us trade policy. *American Economic Review: Insights* 3 (1): 19–34.

Chernyakhovskiy, Ilya. 2015. Solar pv adoption in the united states: An empirical investigation of state policy effectiveness .

Crago, Christine Lasco, and Ilya Chernyakhovskiy. 2017. Are policy incentives for solar power effective? evidence from residential installations in the northeast. *Journal of Environmental Economics and Management* 81: 132–151.

Creane, Anthony, and Kaz Miyagiwa. 2008. Information and disclosure in strategic trade policy. *Journal of International Economics* 75 (1): 229–244.

De Groote, Olivier, and Frank Verboven. 2019. Subsidies and time discounting in new technology adoption: Evidence from solar photovoltaic systems. *American Economic Review* 109 (6): 2137–72.

Dixit, Avinash. 1984. International trade policy for oligopolistic industries. *The Economic Journal* 94: 1–16.

Dorsey, Jackson. 2020. Access to alternatives: Increasing rooftop solar adoption with online platforms. *Kelley School of Business Research Paper* (19-11).

Dubé, Jean-Pierre, Jeremy T Fox, and Che-Lin Su. 2012. Improving the numerical performance of static and dynamic aggregate discrete choice random coefficients demand estimation. *Econometrica* 80 (5): 2231–2267.

Fajgelbaum, Pablo D, Pinelopi K Goldberg, Patrick J Kennedy, and Amit K Khandelwal. 2020. The return to protectionism. *The Quarterly Journal of Economics* 135 (1): 1–55.

Fajgelbaum, Pablo D, and Amit K Khandelwal. 2022. The economic impacts of the us–china trade war. *Annual Review of Economics* 14: 205–228.

Fan, Ying, and Chenyu Yang. 2020. Competition, product proliferation, and welfare: A study of the us smartphone market. *American Economic Journal: Microeconomics* 12 (2): 99–134.

Feenstra, Robert C. 1989. Symmetric pass-through of tariffs and exchange rates under imperfect competition: An empirical test. *Journal of International Economics* 27 (1-2): 25–45.

Flaaen, Aaron, Ali Hortaçsu, and Felix Tintelnot. 2020. The production relocation and price effects of us trade policy: the case of washing machines. *American Economic Review* 110 (7): 2103–27.

Fu, Ran, David Feldman, Robert Margolis, Mike Woodhouse, and Kristen Ardani. 2017. Us solar photovoltaic system cost benchmark: Q1 2017. Technical report, EERE Publication and Product Library.

Ganapati, Sharat, Joseph S Shapiro, and Reed Walker. 2020. Energy cost pass-through in us manufacturing: Estimates and implications for carbon taxes. *American Economic Journal: Applied Economics* 12 (2): 303–42.

Gandhi, Amit, and Jean-François Houde. 2019. Measuring substitution patterns in differentiated products industries. Technical report, National Bureau of Economic Research.

Gayle, Philip G. 2013. On the efficiency of codeshare contracts between airlines: is double marginalization eliminated? *American Economic Journal: Microeconomics* 5 (4): 244–273.

Gerarden, Todd D. 2023. Demanding innovation: The impact of consumer subsidies on solar panel production costs. *Management Science* .

Gillingham, Kenneth, Hao Deng, Ryan Wiser, Naim Darghouth, Gregory Nemet, Galen Barbose, Varun Rai, et al. 2016. Deconstructing solar photovoltaic pricing. *The Energy Journal* 37 (3).

Gillingham, Kenneth, and Tsvetan Tsvetanov. 2019. Hurdles and steps: Estimating demand for solar photovoltaics. *Quantitative Economics* 10 (1): 275–310.

Gillingham, Kenneth T, and Bryan Bollinger. 2021. Social learning and solar photovoltaic adoption. *Management Science* .

Grigolon, Laura, Mathias Reynaert, and Frank Verboven. 2018. Consumer valuation of fuel costs and tax policy: Evidence from the european car market. *American Economic Journal: Economic Policy* 10 (3): 193–225.

Han, Jun, Runjuan Liu, Beyza Ural Marchand, and Junsen Zhang. 2016. Market structure, imperfect tariff pass-through, and household welfare in urban china. *Journal of International Economics* 100: 220–232.

Haucap, Justus, Ulrich Heimeshoff, Gordon J Klein, Dennis Rickert, and Christian Wey. 2021. Vertical relations, pass-through, and market definition: Evidence from grocery retailing. *International Journal of Industrial Organization* 74: 102693.

Huber, J Richard. 1971. Effect on prices of japan's entry into world commerce after 1858. *Journal of Political Economy* 79 (3): 614–628.

Irwin, Douglas A. 2019. Tariff incidence: evidence from us sugar duties, 1890–1914. *National Tax Journal* 72 (3): 599–616.

Jaravel, Xavier, and Erick Sager. 2019. What are the price effects of trade? evidence from the us and implications for quantitative trade models .

Konishi, Yoshifumi, and Meng Zhao. 2017. Can green car taxes restore efficiency? evidence from the japanese new car market. *Journal of the Association of Environmental and Resource Economists* 4 (1): 51–87.

Krugman, Paul R. 1987. Is free trade passé? *Journal of Economic Perspectives* 1 (2): 131–144.

Kwan, Calvin Lee. 2012. Influence of local environmental, social, economic and political variables on the spatial distribution of residential solar pv arrays across the united states. *Energy Policy* 47: 332–344.

Langer, Ashley, and Derek Lemoine. 2022. Designing dynamic subsidies to spur adoption of new technologies. *Journal of the Association of Environmental and Resource Economists* 9 (6): 1197–1234.

Li, Jing. 2017. Compatibility and investment in the us electric vehicle market. *Job Market Paper* 23.

Li, Yanan, Jia Liu, and Wenjun Wang. 2024. Whack-a-mole effect: Social insurance policy and tax avoidance. *Available at SSRN 4879080* .

Ludema, Rodney D, and Zhi Yu. 2016. Tariff pass-through, firm heterogeneity and product quality. *Journal of International Economics* 103: 234–249.

Marchand, Beyza Ural. 2012. Tariff pass-through and the distributional effects of trade liberalization. *Journal of Development Economics* 99 (2): 265–281.

Miller, Nolan H, and Amit Pazgal. 2005. Strategic trade and delegated competition. *Journal of International Economics* 66 (1): 215–231.

Muller, Nicholas Z, Robert Mendelsohn, and William Nordhaus. 2011. Environmental accounting for pollution in the united states economy. *American Economic Review* 101 (5): 1649–75.

Novan, Kevin. 2015. Valuing the wind: renewable energy policies and air pollution avoided. *American Economic Journal: Economic Policy* 7 (3): 291–326.

OShaughnessy, Eric J. 2018. The evolving market structure of the us residential solar pv installation industry, 2000-2016. Technical report, National Renewable Energy Lab.(NREL), Golden, CO (United States).

Ossa, Ralph. 2014. Trade wars and trade talks with data. *American Economic Review* 104 (12): 4104–4146.

Pless, Jacquelyn, and Arthur A Van Benthem. 2019. Pass-through as a test for market power: An application to solar subsidies. *American Economic Journal: Applied Economics* 11 (4): 367–401.

Reichelstein, Stefan J, and Anshuman Sahoo. 2015. Cost and price dynamics of solar pv modules .

Rennert, Kevin, Frank Errickson, Brian C Prest, Lisa Rennels, Richard G Newell, William Pizer, Cora Kingdon, et al. 2022. Comprehensive evidence implies a higher social cost of co2. *Nature* 610 (7933): 687–692.

Rivers, Douglas, and Quang Vuong. 2002. Model selection tests for nonlinear dynamic models. *The Econometrics Journal* 5 (1): 1–39.

Seade, Jesus. 1985. Profitable cost increases and the shifting of taxation: equilibrium responses of markets in oligopoly. Technical report.

Sexton, Steven E, A Justin Kirkpatrick, Robert Harris, and Nicholas Z Muller. 2018. Heterogeneous environmental and grid benefits from rooftop solar and the costs of inefficient siting decisions. Technical report, National Bureau of Economic Research.

Small, Kenneth A, and Harvey S Rosen. 1981. Applied welfare economics with discrete choice models. *Econometrica: Journal of the Econometric Society* : 105–130.

Sommerfeld, Jeffrey. 2016. Residential customers and adoption of solar pv. Ph.D. thesis, Queensland University of Technology.

Sorrenti, Giuseppe, Ulf Zölitz, Denis Ribeaud, and Manuel Eisner. 2024. The causal impact of socio-emotional skills training on educational success. *Review of Economic Studies* : rdae018.

Spencer, Barbara J, and James A Brander. 1983. International r & d rivalry and industrial strategy. *The Review of Economic Studies* 50 (4): 707–722.

Trefler, Daniel. 2004. The long and short of the canada-us free trade agreement. *American Economic Review* 94 (4): 870–895.

Wang, Wenjun. 2024. You scratch my back and i scratch yours: evidence from relationship-based bidding in ipo auctions. *Review of Quantitative Finance and Accounting* : 1–21.

Weyl, E Glen, and Michal Fabinger. 2013. Pass-through as an economic tool: Principles of incidence under imperfect competition. *Journal of Political Economy* 121 (3): 528–583.

Whitefoot, Kate S, Meredith L Fowlie, and Steven J Skerlos. 2017. Compliance by design: Influence of acceleration trade-offs on co2 emissions and costs of fuel economy and greenhouse gas regulations. *Environmental science & technology* 51 (18): 10307–10315.

Winkelmann, Liliana, and Rainer Winkelmann. 1998. Tariffs, quotas and terms-of-trade: The case of new zealand. *Journal of International Economics* 46 (2): 313–332.

Zivin, Joshua S Graff, Matthew J Kotchen, and Erin T Mansur. 2014. Spatial and temporal heterogeneity of marginal emissions: Implications for electric cars and other electricity-shifting policies. *Journal of Economic Behavior & Organization* 107: 248–268.

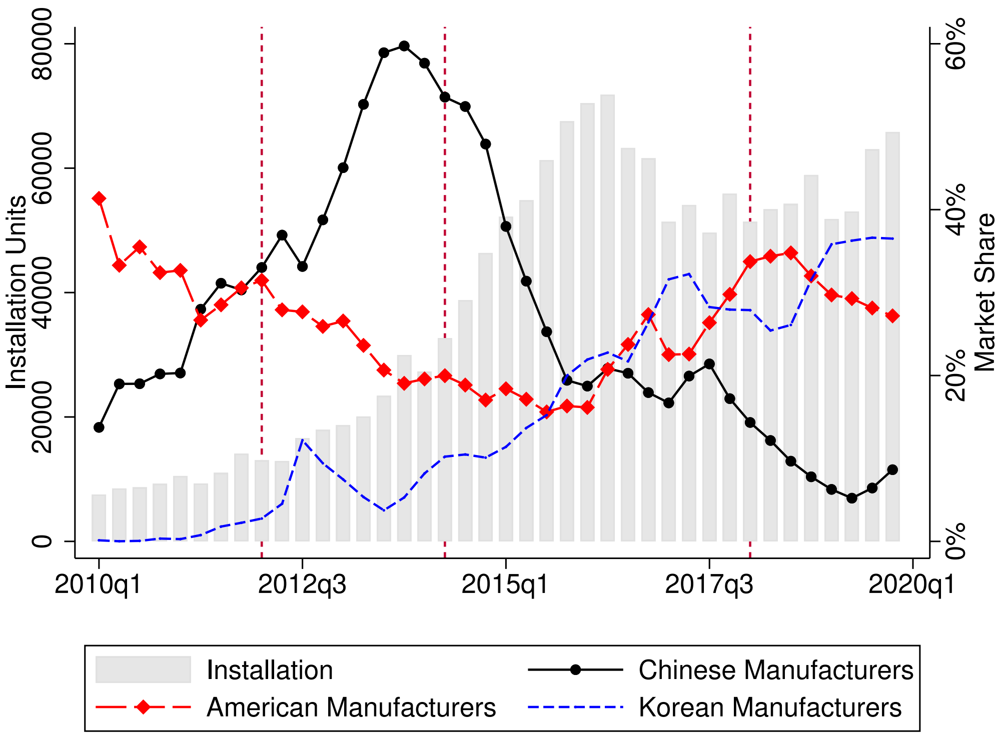

Figure 1: Market Share for Manufacturers through Years

Notes: This figure shows the market share of manufacturers and installation units across different quarters from 2010 to 2019. The grey bar (left axis) represents the number of total installation units. The black solid line, red dash line and blue line represent the time trend of the market share for Chinese, U.S. and South Korean manufacturers, respectively. The three vertical lines represents the beginning of the three waves of anti-dumping policies (2012-Q1, 2014-Q2, and 2018-Q1).

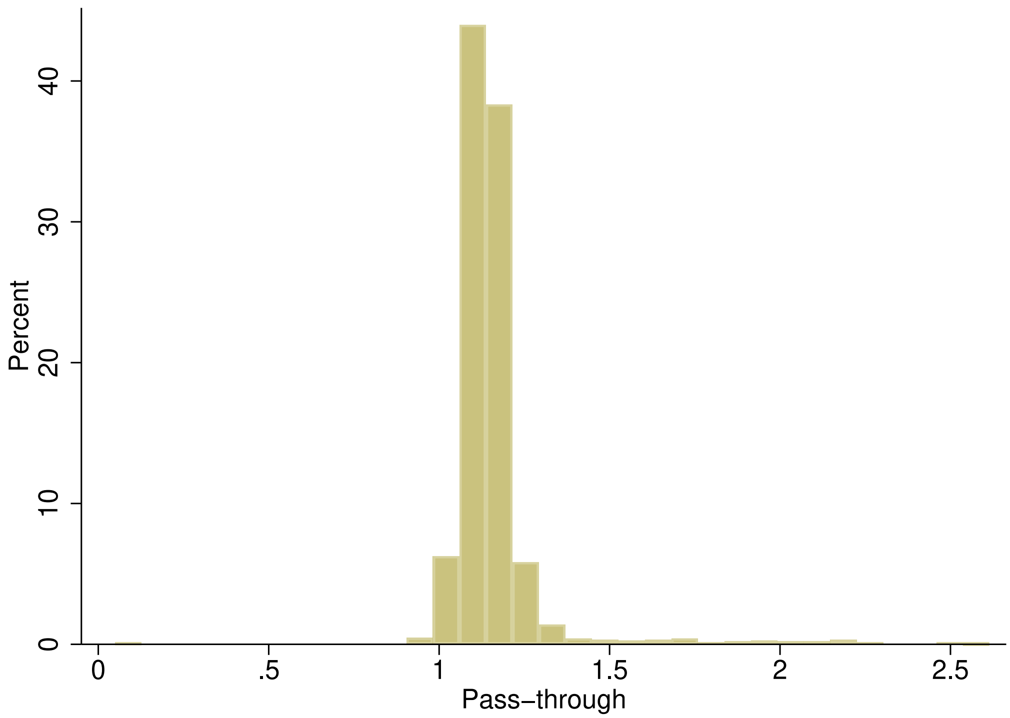

Figure 2: Distribution of Pass-through Rates

Notes: 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.

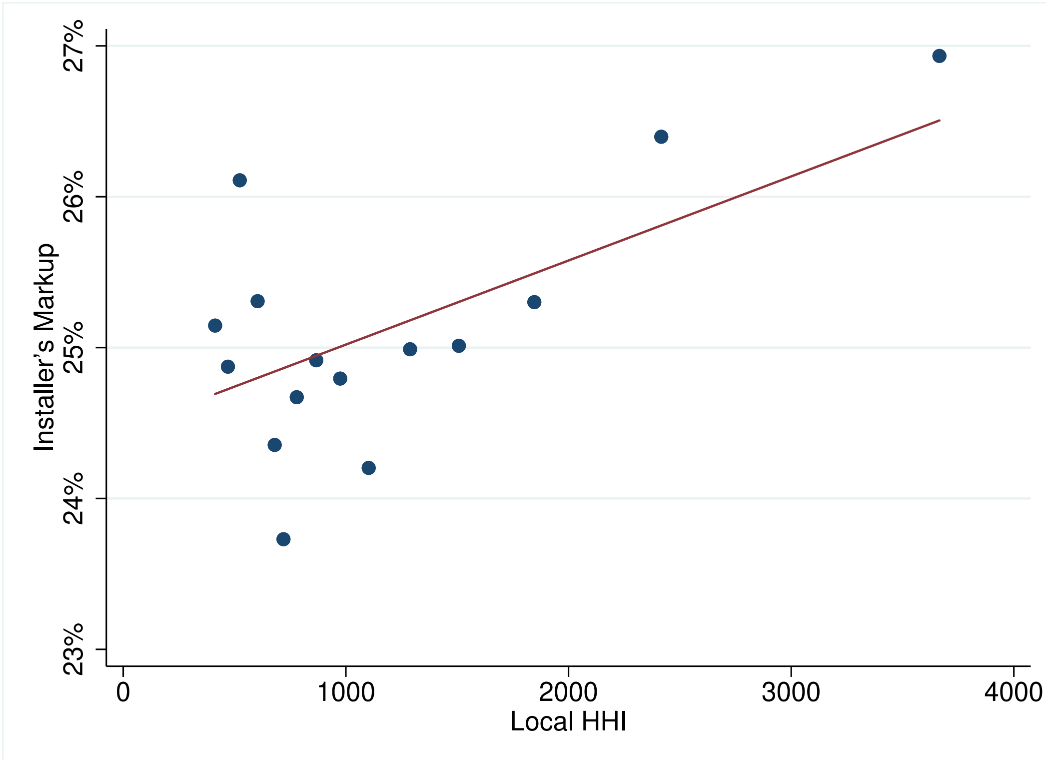

Figure 3: Relationship between Installer's Markup and Local HHI

Notes: This figure provides a non-parametric way of visualizing 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 total installed price, and the horizontal axis is the HHI for solar installers at the market level (MSA-year). We use the *binscatter* command in Stata to plot this graph. It 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 scatter plot of these data points.

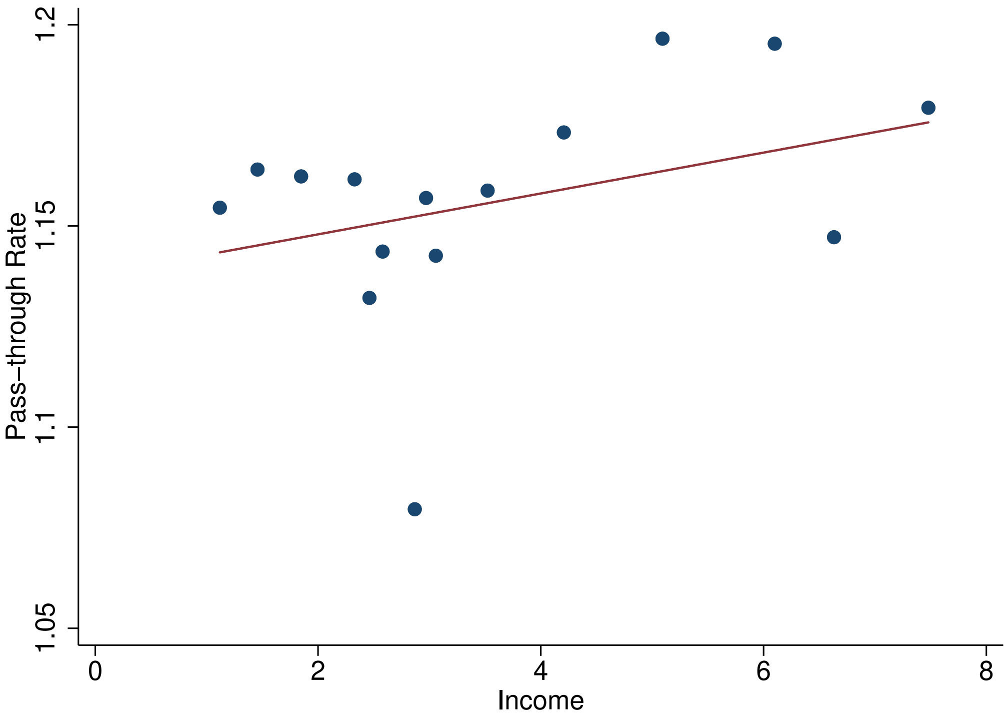

Figure 4: Pass-through Rates for Areas with Different Income

Notes: This figure shows how pass-through rates for MSAs change with income and electricity prices.

Table 1: Vertical Relationship between Installers and Manufacturers

Panel A: Number of Different Manufacturers Each Installer Works with								
	Mean	Std.Dev.	Min	25%	Median	75%	90%	Max
No. of Manufacturers	4.03	4.26	1	1	2	5	9	50

Panel B: Distribution of Installers across Years		
Year	Number of different installers per state	Market share for largest installer (%)
2011	89	32.53
2012	99	29.33
2013	110	28.06
2014	119	30.39
2015	165	31.09
2016	229	23.96
2017	234	24.40
2018	247	26.48

Note: This table provides summary statistics for the relationship between solar installers and solar manufacturers. Panel A reports the descriptive statistics for the number of different manufacturers each installer works with from 2011 to 2018. Panel B reports the distribution of statistics for the installers across years. The first column is the average number of different installers in each state; the second column is the average market share for the largest installer in each state.

Table 2: Summary Statistics for Key Variables

Variable	Description	Max	Min	Mean	SD
A. Characteristics					
InstalledPrice	Total installed price ($/Watt)	8.39	1.74	4.24	0.87
Subsidy	Government subsidies ($/Watt)	5.64	0	0.17	0.41
Price	Consumer purchase price ($/Watt)	7.73	1.73	4.07	0.89
Efficiency	Energy conversion efficiency	0.22	0.15	0.18	0.02
Technology	=1, if poly; =0 if mono	1	0	0.40	0.49
B. Demographics					
Income	Median housing price ($100K)	7.94	1.05	4.51	1.88
Education	Fraction of bachelor degree	0.49	0.12	0.27	0.09
Urbanization	Population (1,000) per square mile	6.32	0.01	0.99	1.55
Race	Fraction of white people	0.94	0.14	0.50	0.16
Democrats	Fraction of voting for democratics	0.78	0.36	0.55	0.10
C. Other Variables					
NHouse	Number of single-unit houses	2,467,089	19,764	538,947	685,149
SolarPotential	Fraction of solar-viable houses	0.96	0.58	0.88	0.07
HouseAbove	Fraction of house greater than $100K	0.98	0.46	0.92	0.07
InstallWage	Wage rate ($/hour) in installation	25.79	20.90	24.83	0.84
Tariff	Tariff rate (%)	145.85	0	26.20	39.40
EPrice	Electricity Price (cent/kWh)	20.94	10.57	17.15	1.56

Note: The prices are in 2015 U.S. dollars

Table 3: Estimation Result for Main Specification

	Model 1		Model 2		Model 3	
	Estimates	SE	Estimates	SE	Estimates	SE
Demand side						
Means, (α, β)						
Constant	-16.424***	(1.026)	-16.385***	(0.988)	-16.428***	(1.024)
Price	-1.407***	(0.459)	-1.433**	(0.629)	-1.405***	(0.462)
Efficiency	42.646***	(10.149)	43.056***	(8.025)	42.651***	(10.002)
Technology	-1.250	(3.555)	-1.300	(5.210)	-1.270	(3.641)
Demographics, (γ)						
Income	0.247**	(0.118)	0.259	(0.169)	0.247**	(0.120)
Education	-6.729***	(2.005)	-6.938***	(2.485)	-6.732***	(2.005)
Urbanization	-0.291***	(0.036)	-0.288***	(0.050)	-0.291***	(0.037)
Race	0.555	(0.534)	0.612	(0.740)	0.556	(0.540)
Democrats	1.066*	(0.586)	1.119**	(0.531)	1.067*	(0.576)
Electricity Price, (κ)						
Eprice	0.104***	(0.052)	0.106	(0.090)	0.104*	(0.055)
Taste variation, (Σ)						
Price	0.321	(0.260)	0.293	(0.411)	0.320	(0.266)
Efficiency	1.012	(33.583)	0.696	(54.931)	0.994	(34.458)
Technology	-1.142	(3.873)	-1.189	(5.427)	-1.164	(3.903)
Fixed Effects						
Manu F.E.	Yes		Yes		Yes	
Inst-Year F.E.	Yes		Yes		Yes	
Cost side						
Constant	-3.946***	(0.027)	-2.312***	(0.008)	-3.320***	(0.028)
Efficiency	4.447***	(0.023)	4.953***	(0.007)	4.969***	(0.023)
Wage Rate	0.208***	(0.0004)	0.177***	(0.0001)	0.215***	(0.0003)
Tariff	-5.244***	(0.284)	-19.671***	(0.082)	-8.614***	(0.290)
Tariff^2	9.457***	(0.381)	24.169***	(0.110)	12.747***	(0.389)
Efficiency $\times$ Tariff	70.573***	(3.219)	228.862***	(0.929)	108.493***	(3.287)
Efficiency $\times$ Tariff^2	-117.306***	(4.454)	-281.485***	(1.286)	-155.177***	(4.548)
Efficiency$^2 \times$ Tariff	-238.009***	(9.083)	-669.412***	(2.621)	-345.213***	(9.275)
Efficiency$^2 \times$ Tariff^2	366.088***	(12.997)	821.838***	(3.751)	475.590***	(13.272)
Inst-Year F.E.	Yes		Yes		Yes	

Note: This table reports the results for the demand and supply estimation for *Models* 1-3. The specification for each model is described in Section 4.2. We use BLP instruments as the instrumental variable. On the demand side, Price is the average consumer purchase price (in $/W); Efficiency represents the energy conversion efficiency; Technology represents the type of solar photovoltaic technology, which equals to one if it is made of polycrystalline solar panels and zero otherwise; Income, Education, Urbanization, Race, and Democrats are MSA-level demographics as described in Table 2. We control for the manufacturer effects and installer-year fixed effects on the demand estimation. On the supply side, Wage Rate refers to the MSA-level wage rate ($/hour) for the roofing installers. We control for installer-year fixed effects on the supply side estimation. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Simulation Results: Removing Tariffs on Chinese Manufacturers

Panel A: Demand Response				
Origin Country	Manufacturer	Model 1	Model 2	Model 3
China	Canadian Solar	99.6%	131.7%	122.5%
	Trina Solar	81.5%	101.8%	95.8%
	Yingli Energy	92.8%	120.0%	111.1%
USA	SunPower	-1.3%	-1.8%	-1.7%
South Korea	Hanwha	-2.2%	-3.1%	-2.6%
	Hyundai	-2.1%	-2.8%	-2.5%
	LG	-1.4%	-1.9%	-1.7%
Japan	Kyocera	-2.5%	-3.7%	-3.3%
German	SolarWorld	-1.5%	-2.1%	-1.8%
Norway	REC Solar	-1.9%	-3.3%	-2.5%
Total		24.7%	31.8%	29.8%
B: Welfare Distribution (in 2015$ million)				
		Model 1	Model 2	Model 3
Δ Consumer Surplus		412.6	511.6	485.8
Δ U.S. Manufacturers		-8.6	0	-10.7
Δ Chinese Manufacturers		356.4	0	427.6
Δ Korean Manufacturers		-6.1	0	-7.3
Δ Other Manufacturers		-16.0	0	-23.4
Δ Installers		342.4	431.3	0
Δ U.S. Tariff Revenue		-507.8	-715.4	-683.3
Total		572.8	227.4	188.6
Panel C: Environmental Benefit				
		Model 1	Model 2	Model 3
Δ Reduced CO2 (million tons)		8.6	11.2	10.2
Δ Reduced Cost (2015$ million)		1,468.1	1,922.5	1,738.1

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

Table 5: Simulation Results: Removing All Tariffs

Panel A: Demand Response				
Origin Country	Manufacturer	Model 1	Model 2	Model 3
China	Canadian Solar	99.3%	131.1%	122.1%
	Trina Solar	81.3%	101.5%	95.5%
	Yingli Energy	92.7%	119.8%	111.0%
USA	SunPower	-1.4%	2.0%	-1.8%
South Korea	Hanwha	2.6%	2.7%	3.1%
	Hyundai	1.5%	1.7%	1.9%
	LG	5.8%	6.9%	6.8%
Japan	Kyocera	2.4%	2.0%	2.2%
German	SolarWorld	1.6%	1.8%	1.9%
Norway	REC Solar	2.8%	2.4%	3.0%
Total		26.9%	34.4%	32.3%

B: Welfare Distribution (in 2015$ million)			
	Model 1	Model 2	Model 3
Δ Consumer Surplus	436.2	539.5	513.9
Δ U.S. Manufacturers	-9.4	0	-11.7
Δ Chinese Manufacturers	356.0	0	427.1
Δ Korean Manufacturers	9.6	0	11.2
Δ Other Manufacturers	-9.4	0	-15.5
Δ Installers	365.0	458.6	0
Δ U.S. Tariff Revenue	-532.9	-747.8	-715.4
Total	615.1	250.3	209.5

Panel C: Environmental Benefit			
	Model 1	Model 2	Model 3
Δ Reduced CO2 (million tons)	9.2	12.0	10.8
Δ Reduced Cost (2015$ million)	1,565.9	2,045.6	1,853.8

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 demand change in percentage. Panel B reports the welfare changes for manufacturers (the United States, China, South Korea and others), U.S. consumers, and U.S. installers. Panel C reports the related environmental benefit. All the economic values are calculated in 2015 U.S. dollars.

Table 6: Simulation Results: Effective Tariffs = 50%× Statutory Tariffs

Panel A: Demand Response				
Origin Country	Manufacturer	Model 1	Model 2	Model 3
China	Canadian Solar	40.2%	50.6%	47.5%
	Trina Solar	33.7%	40.5%	38.4%
	Yingli Energy	38.1%	47.0%	44.0%
USA	SunPower	-0.6%	-0.8%	-0.7%
South Korea	Hanwha	-1.0%	-1.3%	-1.1%
	Hyundai	-0.9%	-1.2%	-1.1%
	LG	-0.6%	-0.8%	-0.7%
Japan	Kyocera	-1.0%	-1.5%	-1.4%
German	SolarWorld	-0.6%	-0.9%	-0.8%
Norway	REC Solar	-0.8%	-1.4%	-1.0%
Total		10.1%	12.4%	11.7%

Panel B: Welfare Distribution (in 2015$ million)			
	Model 1	Model 2	Model 3
Δ Consumer Surplus	174.5	207.1	198.5
Δ U.S. Manufacturers	-3.7	0	-4.6
Δ Chinese Manufacturers	148.8	0	172.3
Δ Korean Manufacturers	-2.7	0	-3.2
Δ Other Manufacturers	-6.9	0	-10.2
Δ Installers	143.5	172.8	0
Δ U.S. Tariff Revenue	-180.4	-237.5	-229.8
Total	273.1	142.4	123.1

Panel C: Environmental Benefit			
	Model 1	Model 2	Model 3
Δ Reduced CO2 (million tons)	3.6	4.5	4.1
Δ Reduced Cost (2015$ million)	611.0	766.8	696.7

Note: This table reports the simulation results for demand response and welfare change where all the statutory tariff rates are reduced by 50%. Panel A reports the demand change in percentage. Panel B reports the welfare changes for manufacturers (the United States, China, South Korea and others), U.S. consumers, and U.S. installers. Panel C reports the related environmental benefit. All the economic values are calculated in 2015 U.S. dollars.

Table 7: Tariff Pass-through

	Without Response		With Response		Pass-through
	Percent (%)	Level ($)	Percent (%)	Level ($)	
Model 1	(1)	(2)	(3)	(4)	(5)
Removing Tariffs on China	15.06	3,345	17.53	3,955	1.16
Removing All Tariffs	12.40	2,786	14.42	3,286	1.16
50% × Statutory Rates	6.84	1,673	8.02	1,989	1.17
Model 2					
Removing Tariffs on China	18.89	4,083	19.98	4,320	1.06
Removing All Tariffs	15.52	3,402	16.41	3,595	1.06
50% × Statutory Rates	8.47	2,042	8.98	2,165	1.06
Model 3					
Removing Tariffs	19.30	4,161	20.45	4,442	1.05
Removing All Tariffs	15.88	3,469	16.84	3,704	1.06
50% × Statutory Rates	8.62	2,080	9.17	2,228	1.06

Note: Columns (1) to (4) report the average tariff (both in percentage and in 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.

Table 8: Sensitivity Test

Average Tariff Pass-through for All PV Systems			
Demand Elasticity	Consumer's Final Price	Manufacturer's Markup	Installer's Markup
-1	1.017	-0.007	0.019
-2	1.056	0.017	0.038
-3	1.095	0.039	0.058
-4.26	1.150	0.066	0.088

Note: This table reports the sensitivity tests on tariff pass-through rates if we assume a tariff rate of 100% is levied on all solar manufacturers. The sensitivity tests are based on the estimation results from Model 1. We calculate the average tariff pass-through rates for the consumer's final purchasing price, manufacturer's markup, and installer's markup for all PV systems, respectively.

Appendices

A Additional Figures and Tables

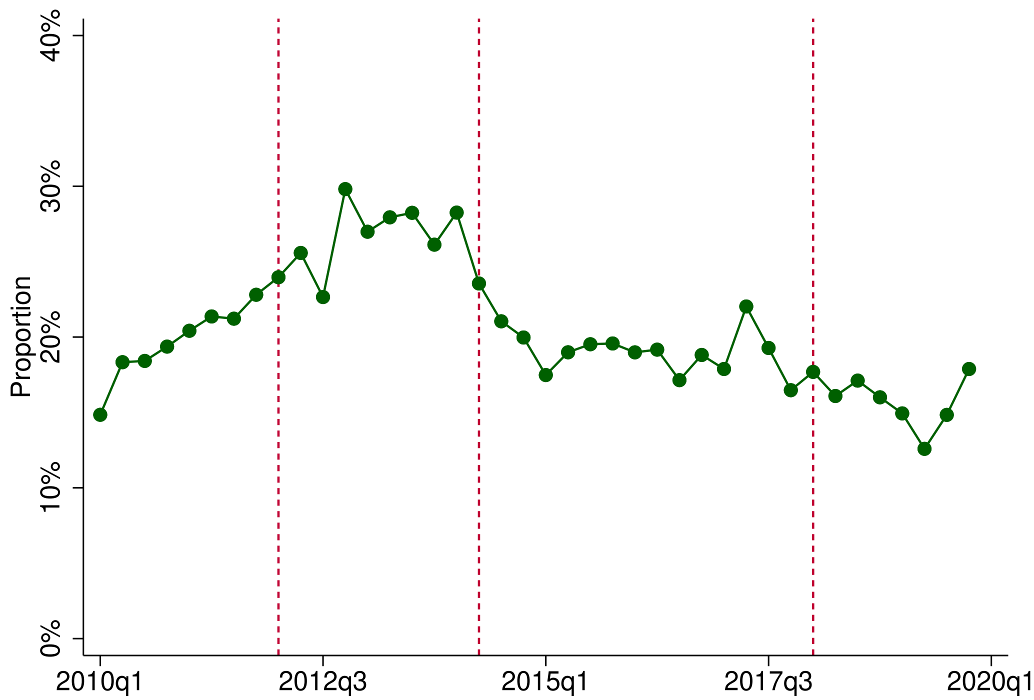

Figure A1: Share of Each Installer's Systems that Use Chinese Panels

Notes: This figure depicts the share of each installer's systems that use products from Chinese manufacturers and the share is calculated based on the number of solar PV systems.

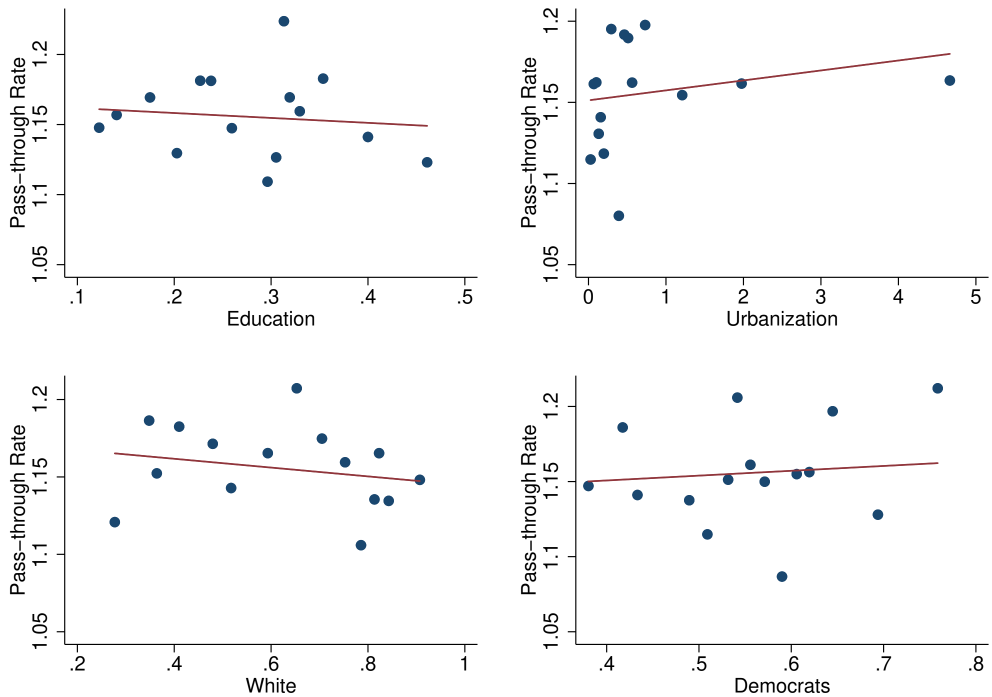

Figure A2: Heterogeneity in Pass-through for Demographics

Notes: This figure shows how the pass-through rate changes with different demographics.

Table A1: List of Models for the Solar Panels

Brand	Model	Brand	Model
Canadian Solar	CS6K-275M	SolarWorld	SW 280 Mono Black
	CS6K-280M		SW 280 mono
	CS6P-255P		SW 285 Mono
	CS6P-255PX		SW 285 Mono Black
	CS6P-260P		SW 290 mono
	CS6P-265P	SunPower	SPR-230NE-BLK-D
Hanwha	Q.PEAK BLK-G4.1 290		SPR-327NE-WHT-D
	Q.PEAK BLK-G4.1 295		SPR-E20-327
	Q.PLUS BFR G4.1 280		SPR-E20-327-C-AC
	Q.PRO BFR G4 260		SPR-X20-250-BLK
	Q.PRO BFR G4 265		SPR-X21-335-BLK-C-AC
	Q.PRO BFR-G4.1 265		SPR-X21-335-BLK-D-AC
Hyundai	HiS-M260RG		SPR-X21-345
	HiS-S265RG		SPR-X21-345-C-AC
Kyocera Solar	KU260-6XPA		SPR-X21-345-D-AC
	KU265-6ZPA		SPR-X22-360-C-AC
LG	LG300N1K-G4		SPR-X22-360-D-AC
	LG310N1C-G4	Trina Solar	TSM-240PA05
	LG315N1C-G4		TSM-245PA05.18
	LG315N1C-Z4		TSM-250PA05.18
	LG320E1K-A5		TSM-260PD05.08
	LG320N1C-G4		TSM-260PD05.18
	LG330N1C-A5		TSM-300DD05A.18(II)
	LG335N1C-A5	Yingli Energy	YL240P-29b
	LG360Q1C-A5		YL245P-29b
REC Solar	REC260PE		YL250P-29b
	REC260PE Z-LINK		YL255P-29b
	REC260PE-US		YL260P-29b
	REC275TP		
	REC290TP2 BLK		

Notes: This table lists all the models of the solar panels used for our inside goods.

Table A2: List of Solar Installers

Number	Name	Number	Name
1	All Others	12	Semper Solarisnstruction
2	Tesla Energy	13	Baker Electric
3	Sunrun	14	Leonard Roofing
4	SunPower	15	Grid Alternatives
5	Vivint Solar Developer	16	Solcius
6	Verengo	17	Freedom Forever
7	Petersen Dean	18	Sullivan Solar Power
8	Sungevity	19	Nrg Residential Solar Solutions
9	REC Solar	20	Titan Solar Power
10	Horizon Solar Power	21	Smart Energy Solar
11	Trinity Solar		

Notes: This table lists the 21 groups of solar installers in the U.S. market. The 2-21 groups are the 20 biggest solar installers, as marked by numbers 2 - 21, and the 1st group is all other solar installers.

Table A3: Demand Estimation with Berry's (1994) Market Shares: First-stage Regressions

VARIABLES	(1)	(2)	(3)
BLP_eff	-0.002	0.046***	0.046***
	(0.004)	(0.01)	(0.011)
BLP_tech	0.007***	0.002	0.002
	(0.002)	(0.005)	(0.005)
$(\text{BLP\_eff})^2$		-0.001***	-0.001**
		(0.0003)	(0.0006)
$(\text{BLP\_tech})^2$		0.000003	0.000007
		(0.00007)	(0.0002)
BLP_eff × BLP_tech			-0.00001
			(0.0005)
Control Variables	Yes	Yes	Yes
Manufacturer F.E.	Yes	Yes	Yes
Installer-Year F.E.	Yes	Yes	Yes
Observations	7,612	7,612	7,612
Cragg-Donald Wald F statistic	17.98	20.16	16.12
Adjusted R-squared	0.48	0.48	0.48

Note: This table reports the results for the first-stage regression. The variables BLP_eff and BLP_tech are the BLP instruments based on the product characteristics. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A4: Demand Estimation with Berry's (1994) Market Shares: Second-stage Regressions

VARIABLES	(1)	(2)	(3)
Price	-4.674***	-1.577***	-1.581***
	(0.880)	(0.327)	(0.328)
Control Variables	Yes	Yes	Yes
Manufacturer F.E.	Yes	Yes	Yes
Installer-Year F.E.	Yes	Yes	Yes
Observations	7,612	7,612	7,612

Note: This table reports the results for the second-stage regression. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A5: Mean Own-Price and Cross-Price Elasticities for 10 Brands

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Canadian Solar	-4.181	0.007	0.006	0.063	0.006	0.049	0.008	0.007	0.016	0.013
(2) Hanwha	0.008	-4.078	0.008	0.069	0.005	0.050	0.008	0.006	0.011	0.013
(3) Hyundai	0.006	0.008	-3.701	0.058	0.005	0.039	0.007	0.005	0.008	0.010
(4) Kyocera Solar	0.009	0.012	0.007	-4.833	0.005	0.062	0.008	0.007	0.011	0.017
(5) LG	0.005	0.004	0.003	0.027	-3.998	0.019	0.008	0.007	0.011	0.005
(6) REC Solar	0.008	0.009	0.006	0.071	0.006	-4.330	0.009	0.007	0.014	0.016
(7) SolarWorld	0.006	0.005	0.005	0.048	0.007	0.035	-4.248	0.008	0.008	0.008
(8) SunPower	0.005	0.004	0.004	0.035	0.006	0.022	0.009	-4.345	0.012	0.006
(9) Trina	0.009	0.008	0.005	0.087	0.005	0.055	0.007	0.007	-4.438	0.015
(10) Yingli Energy	0.010	0.008	0.006	0.101	0.005	0.077	0.008	0.007	0.025	-4.523

Table A6: Price, Marginal Costs, and Markups

	Baseline 1	Counterfactual 1
	(1)	(2)
Model 1		
Price	4.124	3.946
Markup for manufacturer	0.898	0.884
Markup for installer	0.987	0.972
Joint marginal cost	2.295	2.295
Model 2		
Price	4.093	3.902
Markup for manufacturer	0	0
Markup for installer	0.911	0.900
Joint marginal cost	3.182	3.182
Model 3		
Price	4.120	3.921
Markup for manufacturer	0.897	0.883
Markup for installer	0	0
Joint marginal cost	3.279	3.279

Note: This table reports the average price, markups, and joint marginal cost for baseline and counterfactual scenarios. Baseline 1 refers to the simulated scenario when the tariffs are in place; Counterfactual 1 refers to the simulated scenario when the tariffs are removed. For solar manufacturers SunPower and REC Solar, we set the installer markup to be zero if they also operate as installers for the same solar installations.

Table A7: Nonnested Test for Model Selection

	H2	
H1	Model 2	Model 3
Model 1	0.0005	-0.0017
Model 2	-	-0.0001

Note: This table reports the results from the nonnested test for a size of $\alpha = 0.5$. Model χ is presented in the columns and model χ' in the rows. The null hypothesis that model χ is asymptotically equivalent to χ' is not rejected if the test statistics is between -1.64 and 1.64. The null is rejected in favor of the assumption that model χ is asymptotically better than model χ' if the test statistics is greater than 1.64. See Rivers and Vuong (2002) and Bonnet and Dubois (2010) for more details.

Table A8: Parameters Used for Simulations

Panel A: Anti-dumping and Countervailing Duties (%)						
	Anti-dumping Duties			Countervailing Duties		
	2012	2014	2018	2012	2014	2018
Trina Solar	18.32	26.71	81.71	15.97	49.79	49.79
Canadian Solar	25.96	52.13	107.13	15.24	38.72	38.72
Yingli Energy	25.96	52.13	107.13	15.24	38.72	38.72
Hanwha	-	-	30	-	-	-
Hyundai	-	-	30	-	-	-
LG	-	-	30	-	-	-
Kyocera	-	-	30	-	-	-
Solar World	-	-	30	-	-	-
REC Solar	-	-	30	-	-	-

Panel B: Actual and Model-implied Solar Panel Price			
Year	Panel Price	% Panel Price	Model-implied Panel Price
2012	1.02	17.91%	0.92
2013	0.98	20.04%	0.94
2014	0.85	18.92%	0.80
2015	0.76	17.16%	0.73
2016	0.56	13.33%	0.54
2017	0.48	12.09%	0.49
2018	0.59	15.48%	0.60

Note: Panel A reports the anti-dumping and countervailing duties rates imposed on the imported solar panels. It lists the anti-dumping duty rates and countervailing rates faced by Chinese and other foreign manufacturers during the three waves of anti-dumping policies (2012, 2014, and 2018) initiated by the U.S. government. Panel B reports the trend of solar panel prices from 2012 to 2018. Column 1 reports the average prices ($/W) of solar panels for U.S. residential solar PV systems and column 2 reports the averages of the ratio of solar panel price to total installed price, both provided by Lawrence Berkeley National Laboratory. Column 3 reports the averages of model-implied solar panel prices ($/W).

B Details on Sample Construction

During the 2012-2018 period, the raw LBNL data reports 1,238,518 installations of residential solar systems. We refer to these installations as the full sample. To conduct our estimation, we have constructed a subsample with the following restrictions, which we next describe in detail. Table B1 compares the full sample with our estimation sample in terms of various observables. Our estimation sample matches well the full sample during this period.

Step 1: Dropping observations with missing information about installation prices, panel efficiency, panel technology, and module model. This step resulted in dropping 38.6% of observations of the full sample.

Step 2: Dropping observations with missing manufacturer or installer information. This step resulted in dropping 1.4% of observations of the full sample.

Step 3: We focus on large manufacturers and neglect solar models made by small firms. In particular, we only focus on the top 10 manufacturers in terms of sales. This step resulted in dropping 12.5% of observations of the full sample.

Step 4: We focus on popular models produced by these manufacturers. In particular, we only focus on popular models with sales greater than or equal to 3000 during sample period. This step resulted in dropping 18.3% of observations of the full sample.

Step 5: Winsorization on prices. We winsorize on extreme values on prices. Due to the fact that consumers get subsidies for installing solar PVs, some consumers may have paid a very low price for their system. In fact, the bottom 1% of the price is very close to zero, which may make the marginal cost become negative in our estimation. To avoid this issue, we choose an asymmetric winsorization (dropping the top 1% and bottom 5%). This step resulted in dropping 1.8% of observations of the full sample.

Step 6: We drop observations with missing information on the location of the installations. This step resulted in dropping 3.5% of observations of the full sample.

After implementing steps 1- 6, our sample includes 296,431 installations, which accounts for 23.9% of the raw data. For the estimation, we aggregate the data at the MSA-year-model-installer level, and merge it with MSA's demographics. For some MSAs, we do not have their demographic information, so the merge could further drop some observations. In addition, we have to drop MSA-year observations where our instrumental variables have no variation, which occurs when a market (MSA-year) has only one model-installer pair. Our final sample for estimation thus includes 294,841 installations, which accounts for 23.8% of the full sample. The total installed capacity of our estimation sample is 1,853,780 kilowatts, which accounts for 21.6% of the full sample.

Below in Table B1, we compare, based on observables we collected, our subsample with the full sample and the subsamples obtained after implementing each of the steps described above. In particular, Table B1 is similar to Table 2 in the main text, but shows summary statistics for the different samples.

In the last column of Table B1, we also show statistics for the non-residential sample, which we do not use in this paper. Compared to the non-residential sample, we find that our sample mainly differed in terms of system size. The non-residential installations are also much bigger than the residential installations.

Table B1: Summary Statistics for Different Sample

	Step 1-6	Step 1-5	Step 1-4	Step 1-3	Step 1-2	Step 1	Residential	Non-residential
Obs	296,431	340,144	361,854	588,217	742,854	760,326	1,238,518	43,952
InstalledPrices	4.24	4.22	4.14	4.06	4.06	4.06	4.91	3.71
($/Watt)	(1.01)	(1.00)	(1.82)	(1.98)	(2.08)	(2.26)	(702.36)	(16.02)
System Size	6.29	6.42	6.44	6.56	6.58	6.75	6.98	165.54
(kW)	(3.77)	(3.76)	(3.89)	(4.95)	(5.19)	(39.39)	(44.14)	(537.85)
Efficiency	0.18	0.18	0.18	0.18	0.18	0.18	0.17	0.17
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Technology	0.48	0.47	0.47	0.46	0.45	0.45	0.47	0.53
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Income	4.92	4.91	4.90	4.83	4.79	4.78	4.58	3.86
($100K)	(1.74)	(1.74)	(1.73)	(1.76)	(1.80)	(1.80)	(1.84)	(1.87)
Education	0.29	0.29	0.28	0.28	0.28	0.28	0.29	0.30
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.08)
Urbanization	1.54	1.54	1.50	1.49	1.45	1.44	1.46	1.81
	(1.88)	(1.89)	(1.86)	(1.85)	(1.81)	(1.80)	(1.85)	(2.10)
Race	0.46	0.46	0.46	0.47	0.47	0.47	0.49	0.59
	(0.12)	(0.12)	(0.12)	(0.13)	(0.13)	(0.13)	(0.14)	(0.18)
Democrats	0.56	0.56	0.56	0.55	0.55	0.55	0.55	0.55
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)	(0.10)
EPrice	16.95	17.09	17.10	17.06	16.99	16.96	16.52	15.94
(cent/kWh)	(1.51)	(1.54)	(1.51)	(1.66)	(1.78)	(1.82)	(2.14)	(2.71)

C Robustness Check for Model Estimation

We conduct robustness checks to assess the impacts of different modeling choices.

First, we group the installers into 10+1 generic and re-estimate the results for our linear-pricing model. The top 10 installers make up around 60% of the total installations in our final sample, while the residual group of installer accounts for the rest 40%. Table C1 reports the estimation results for the demand and supply side for the 10+1 generic group and the results are consistent with that for the 20+1 generic group, as shown in Table 3. The pass-through we calculated for the 10+1 generic group is 1.18, while it is 1.16 for the 20+1 generic. With a smaller number of installers, market power increases, and this leads to more overshifting. The results are, however, very similar.

Second, we add the MSA-fixed effect to the demand side to investigate the role of region-specific unobservables, which might not be captured by the demographic variables, in the demand model. We investigate this point using a linear demand model based on Berry (1994)'s style log market shared estimated with 2SLS. The linear demand model gives us more flexibility (notably for computational reasons) to do robustness tests and sensitivity analysis.

Given that MSA-fixed effects are co-linear with demographic variables at the MSA level, we estimate a model that excluded demographics and included only MSA-fixed effects. As a comparison, we also estimate a model with no MSA-fixed effects and no demographics, and a model, which is the main specification in the paper, with demographic variables. Table C2 reports the first-stage results of the 2SLS estimation. A few patterns emerge. Comparing the model with MSA-fixed effects (Column 1) and demographic variable (Column 3), the first-stage estimates tend to be similar, except that they are much less precise with MSA-fixed effects (Column 1). This is to be expected as we have significantly more controls (we have 60 MSAs). However, with these fixed effects, the instruments are now weak and we have little gains in explaining unobserved heterogeneity in prices. Indeed, in the first stage, the adjusted R-squared is about the same between the two specifications (note that even when we exclude demographic variables (Column 2), we can explain a substantial amount of variation in prices only with our instrumental variables (R-squared = 0.44). With MSA fixed effects (Column 1), the F-statistic collapses to F=4.33. With these weak instruments, our second-stage estimate for the price coefficient is close to zero, as shown in Column 1 of Table C3. In sum, the MSA fixed effects greatly decrease the signal-to-noise ratio.

We thus investigate the role of observables in our IV using an alternative strategy. Note that when we compare Column 2, which corresponds to the model with no controls, and Column 3, we find that the first stage's demographic variables are important. Nonetheless, as reported in Table C3, the demand estimates in the second stage remain in the same range relative to a much less conservative model with no such controls. This suggests that unobservables might not be an important source of bias. We can formally investigate this using the approach proposed by Altonji et al. (2005), which is a widely adopted method in addressing issues arising from omitted variable bias (see Sorrenti et al., 2024 for a recent application, for instance). Following Altonji et al. (2005), β_L is the estimated price coefficient for a regression with little control, in our case price, efficiency, technology, electricity price and installer-year fixed effects (Column 2 of Table C3); and β_F is the estimated price coefficient for a regression that contains price and a full set of controls (including the MSA-level demographic variables), as well as the installer-year fixed effect (Column 3 of Table C3). Altonji et al. (2005)'s approach consists of comparing the coefficients using the following ratio $|\beta_F/(\beta_L - \beta_F)| = 1.581/(1.581 - 0.986) = 2.66$. A large value, in particular away from zero, suggests that the selection bias due to unobservable variables would need to be important to nullify the estimated effect. In our case, the selection bias due to unobservable variables would have to be 2.66 times stronger than that the effect due to observable variables to completely nullify the estimated effect. Given that we find a large value for the ratio, we do not have strong concerns regarding a selection bias solely caused by unobservables.

Third, we experiment with manufacturer-fixed effects in the supply-side estimation. The estimation result is displayed in Table C4. The demand-side estimates are mostly unaffected by the introduction of those fixed effects. For the cost-side estimates, the coefficients that aim to capture cost variation due to the efficiency and wage rate are consistent with our prior results. It suggests that our tariff-exclusive cost estimates are robust to adding manufacturer-fixed. For the coefficients related to tariffs, we see differences in magnitude and sign. Note that we estimate a non-linear relationship between tariffs and costs. We thus face a trade-off between capturing the variation with a little fewer controls or having a set of more conservative estimates. Ultimately, we decided to favor the former, as our goal is to provide a full set of counterfactual scenarios, and decided to conduct the main analysis without manufacturer-fixed effects. Note that such trade-offs are very common in such structural estimation endeavors. Our estimation approach follows closely Fan and Yang (2020) who do the same. Fan and Yang (2020) builds a structural model for the U.S. smartphone industry, in which they add brand fixed effect, carrier-year fixed effect on the demand side and add only carrier-year fixed effect on the cost side.

Fourth, we change our market size and re-estimate our model. In Section 4, we define the market size as $M_w \times A \times V \times L$, where we use a scaling factor L to capture barriers and other frictions that restrict the potential market size. We set L=15% in our main results, but also conduct robustness tests where L=10% or L=20%. Table C5 shows that our results are robust to different assigned values of L.

Table C1: Estimation Results for 10+1 Generic Installers

	Estimates	SE
Demand side		
Means, (α, β)		
Constant	-15.624***	(0.901)
Price	-1.477***	(0.502)
Efficiency	49.103***	(10.003)
Technology	-0.791	(1.234)
Demographics, (γ)		
Income	0.270*	(0.164)
Education	-6.854**	(2.998)
Urbanization	-0.271***	(0.056)
Race	0.365	(0.801)
Democrats	0.838	(0.798)
Electricity Price, (κ)		
Eprice	0.109***	(0.030)
Taste Variation		
Price	0.334	(0.358)
Efficiency	1.048	(11.650)
Technology	-0.629	(2.383)
Fixed Effects		
Manufacturer F.E.	Yes	
Installer-Year F.E.	Yes	
Cost side		
Constant	-3.603***	(0.011)
Efficiency	5.162***	(0.023)
Wage Rate	0.193***	(0.0004)
Tariff	-12.590***	(0.291)
Tariff^2	13.604***	(0.385)
Efficiency $\times$ Tariff	152.696***	(3.304)
Efficiency $\times$ Tariff^2	-164.834***	(4.495)
Efficiency$^2\times$ Tariff	-470.719***	(9.344)
Efficiency$^2\times$ Tariff^2	504.342***	(13.110)
Installer-Year F.E.	Yes	

Note: This table reports the robustness check for the main results by grouping the installers into 10+1 generic. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C2: First-stage: 2SLS Results with and without MSA-fixed effect

VARIABLES	(1)	(2)	(3)
BLP_eff	0.039***	0.108***	0.046***
	(0.014)	(0.010)	(0.011)
BLP_tech	-0.003	-0.003	0.002
	(0.006)	(0.005)	(0.005)
$(\text{BLP\_eff})^2$	-0.001	-0.005***	-0.001**
	(0.0007)	(0.0006)	(0.0006)
$(\text{BLP\_tech})^2$	0.0001	-0.0006***	0.00001
	(0.0002)	(0.0002)	(0.0002)
BLP_eff $\times$ BLP_tech	-0.0001	0.002***	-0.00001
	(0.0006)	(0.0005)	(0.0005)
Efficiency	5.808***	6.563***	6.220***
	(1.351)	(1.406)	(1.365)
Technology	0.052	0.034	0.043
	(0.036)	(0.037)	(0.036)
Eprice	0.015	0.054***	0.039***
	(0.021)	(0.005)	(0.005)
Income			0.140***
			(0.008)
Education			-2.533***
			(0.232)
Urbanization			0.0003
			(0.007)
White			0.371***
			(0.094)
Democrats			0.507***
			(0.145)
Constant	3.540***	3.146***	3.034***
	(0.431)	(0.254)	(0.250)
MSA-Fixed	Yes	No	No
Installer-year Fixed	Yes	Yes	Yes
Observations	7,612	7,612	7,612
Cragg-Donald Wald F Statistic	4.33	82.37	16.12
Adjusted R-squared	0.49	0.44	0.48

Note: The dependent varialbe is Berry (1994)'s market share. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table C3: Second-Stage: 2SLS Results with and without MSA-fixed effect

VARIABLES	(1)	(2)	(3)
Price	0.005	-0.986***	-1.581***
	(0.500)	(0.134)	(0.328)
Efficiency	35.067***	43.369***	44.780***
	(4.287)	(3.927)	(4.456)
Technology	-0.761***	-0.754***	-0.696***
	(0.087)	(0.103)	(0.108)
Eprice	0.134***	0.067***	0.116***
	(0.049)	(0.017)	(0.021)
Income			0.321***
			(0.056)
Education			-7.936***
			(0.981)
Urbanization			-0.271***
			(0.020)
Race			0.891***
			(0.231)
Democrats			1.371***
			(0.394)
Constant	-16.066***	-11.002***	-9.297***
	(1.793)	(0.825)	(1.298)
MSA F.E.	Yes	No	No
Installer-Year F.E.	Yes	Yes	Yes
Observations	7,612	7,612	7,612

Note: This table reports the 2SLS results with and without MSA-fixed effect for the demand side. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C4: Estimation Results by Adding Manufacturer-fixed Effect

	Estimates	SE
Demand side		
Means, (α, β)		
Constant	-16.425***	(1.025)
Price	-1.407***	(0.460)
Efficiency	42.650***	(9.895)
Technology	-1.256	(3.582)
Demographics, (γ)		
Income	0.247**	(0.119)
Education	-6.728***	(2.004)
Urbanization	-0.291***	(0.036)
Race	0.555	(0.536)
Democrats	1.066*	(0.581)
Electricity Price, (κ)		
Eprice	0.104***	(0.053)
Taste variation, (Σ)		
Price	0.321	(0.261)
Efficiency	0.991	(33.819)
Technology	-1.149	(3.881)
Fixed Effects		
Manufacturer F.E.	Yes	
Installer-Year F.E.	Yes	
Cost Side		
Constant	-4.919***	(0.031)
Efficiency	4.136***	(0.061)
Wage Rate	0.211***	(0.0004)
Tariff	34.823***	(0.327)
Tariff^2	-17.259***	(0.421)
Efficiency $\times$ Tariff	-373.334***	(3.648)
Efficiency $\times$ Tariff^2	178.764***	(4.920)
Efficiency$^2\times$ Tariff	1014.513***	(10.210)
Efficiency$^2\times$ Tariff^2	-458.055***	(14.404)
Manufacturer F.E.	Yes	
Installer-Year F.E.	Yes	

Note: This table reports the robustness check for the main results by adding manufacturer-fixed effect on the supply side. Both the demand side and the supply side include the manufacturer-fixed effect and installer-year fixed effect. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C5: Estimation Result for Using Alternative Market Size

	$L = 20\%$		$L = 10\%$	
	Estimates	SE	Estimates	SE
Demand side				
Means, (α, β)				
Constant	-16.597***	(1.050)	-16.366***	(1.115)
Price	-1.494***	(0.430)	-1.160*	(0.622)
Efficiency	42.930***	(11.522)	41.184***	(8.192)
Technology	-1.454	(3.362)	-1.076	(3.005)
Demographics, (γ)				
Income	0.255**	(0.102)	0.210	(0.143)
Education	-6.941***	(1.748)	-5.966**	(2.381)
Urbanization	-0.286***	(0.033)	-0.308***	(0.043)
Race	0.611	(0.470)	0.356	(0.622)
Democrats	1.129**	(0.525)	0.854	(0.632)
Electricity Price, (κ)				
Eprice	0.106**	(0.044)	0.098*	(0.057)
Taste variation, (Σ)				
Price	0.335	(0.241)	0.336	(0.249)
Efficiency	1.334	(28.144)	0.834	(31.952)
Technology	-1.338	(3.133)	-0.946	(4.096)
Fixed Effects				
Manufacturer F.E.	Yes		Yes	
Installer-Year F.E.	Yes		Yes	
Cost side				
Constant	-3.899***	(0.027)	-3.184***	(0.007)
Efficiency	4.497***	(0.023)	3.676***	(0.006)
Wage Rate	0.209***	(0.0004)	0.162***	(0.0001)
Tariff	-4.696***	(0.283)	-20.055***	(0.077)
Tariff^2	8.841***	(0.381)	24.814***	(0.103)
Efficiency $\times$ Tariff	64.556***	(3.211)	232.177***	(0.871)
Efficiency $\times$ Tariff^2	-110.346***	(4.444)	-286.631***	(1.205)
Efficiency$^2 \times$ Tariff	-221.599***	(9.061)	-672.944***	(2.457)
Efficiency$^2 \times$ Tariff^2	346.436***	(12.966)	828.342***	(3.516)
Installer-Year F.E.	Yes		Yes	

Note: This table reports the robustness check for the main results by defining alternative market size. We control for the manufacturer-fixed effect and installer-year fixed effect on the demand side and control for installer-year fixed effect on the supply side. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

D Additional Simulations: U.S. Manufacturers Partial Exposure to Tariffs

We do not observe all manufacturers' decisions along the global solar supply chain. Some U.S. manufacturers could procure parts of their solar panels from China and, thus, be partly exposed to trade tariffs. In our policy exercise, we might thus be too restrictive when defining which firms are impacted and conservative on the overall downstream impact of the tariffs.

To account for the partial exposure of U.S. manufacturers to tariffs, we simulate an additional scenario (counterfactual scenario 4). We assume that U.S. manufacturers (only one in our model, i.e., SunPower) face 10% of the tariffs imposed on Chinese firms. We do this for Model 1 only, i.e., the linear-pricing model. We implement this approach as follows. First, we compute the average tariff rate of all Chinese firms each year weighted by their market shares. We refer to this average tariff rate as *Avg_Tariff*. Second, we implement Scenario 1 of the main policy analysis but also impose a fraction of this average tariff rate on U.S. manufacturer SunPower. In particular, we assume that SunPower may have faced 10% of the average tariff (10%**Avg_Tariff*). In the cost function of SunPower, we use the coefficient on tariffs estimated for China to add this additional cost. Note that the percentage we use, 10%, is only for illustration purposes and represents an *exposure coefficient*, which could easily be varied.

Table D1 displays the demand response and welfare effect for this fourth counterfactual scenario. The results show that the total market capacity for the U.S. solar market would have been 26.5% larger if the anti-dumping and countervailing duties had not been imposed on Chinese solar products and the U.S. firm would not have been exposed. While Chinese manufacturers experienced a demand response similar to the counterfactual scenario 1, the sales of solar panels made by the U.S. manufacturer SunPower would increase by 5.5%, whereas it was a 1.3% decrease before. The change in total welfare gain and environmental externality are also larger.

The pass-through rate for this scenario is 1.18, which is very similar to that (1.16) in our first set of counterfactual scenarios. Our estimate of the pass-through of tariffs is, thus, also robust to the fact that tariffs could have also impacted, indirectly, local firms.

Table D1: Simulation Results: U.S. Manufacturers Partial Exposure to Tariffs

Panel A: Demand Response		
Origin Country	Manufacturer	Model 1
China	Canadian Solar	99.3%
	Trina Solar	81.3%
	Yingli Energy	92.7%
USA	SunPower	5.5%
South Korea	Hanwha	-2.4%
	Hyundai	-2.2%
	LG	-1.6%
Japan	Kyocera	-2.6%
German	SolarWorld	-1.7%
Norway	REC Solar	-2.0%
Total		26.5%
B: Welfare Distribution (in 2015$ million)		
		Model 1
Δ Consumer Surplus		446.0
Δ U.S. Manufacturers		25.4
Δ Chinese Manufacturers		355.5
Δ Korean Manufacturers		-6.8
Δ Other Manufacturers		-17.1
Δ Installers		375.0
Δ U.S. Tariff Revenue		-253.7
Total		924.2
Panel C: Environmental Benefit		
		Model 1
Δ Reduced CO2 (million tons)		9.4
Δ Reduced Cost (2015$ million)		1,606.3

Note: This table reports the results for demand response and welfare change when we implement counterfactual scenario 1 of the policy analysis but also impose a tariff rate on U.S. manufacturers (SunPower), which is 10% of the average tariffs imposed on Chinese firms. Panel A reports the demand change in percentage. Panel B reports the welfare changes for manufacturers (the United States, China, South Korea, and others), U.S. consumers, and U.S. installers. Panel C reports the related environmental benefits. All the economic values are calculated in 2015 U.S. dollars.