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

Sebastien Houde*

Wenjun Wang†

April 19, 2022

Abstract

This paper investigates the distributional welfare effects of the recent trade war in the solar manufacturing sector resulting from the U.S. government-initiated trade tariffs against Chinese solar manufacturers. Our structural econometric model incorporates 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. consumers and installers. Chinese manufacturers were also negatively economically affected. Overall, our results suggest the solar trade war led to large welfare losses in both countries and substantially slowed the adoption of solar photovoltaic technology.

JEL: F14; L10; Q50

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

*Grenoble Ecole de Management, 38000 Grenoble, France, e-mail: sebastien.houde@grenoble-em.com. Research affiliate at CEPE, ETH Zurich and Research Fellow at E4S.

†Agricultural Bank of China, e-mail: wenjunwang00@gmail.com. This paper is a revised version of Wang's PhD dissertation chapter. We would like to thank Maureen Crooper, Anna Alberini, Joshua Linn, and Kenneth Gillingham, in addition of several seminar participants at the University of Maryland, University of California Berkeley, Yale, Harvard, the U.S. Department of Energy, and the University of St-Gallen for helpful comments and suggestions.

1 Introduction

After decades of trade liberalization, protectionism has reemerged in recent years, characterized by the U.S.-China trade war, Japan-South Korea trade dispute, and Brexit negotiations. 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.

The goal of this paper is to quantify the welfare effects of the anti-dumping and countervailing duties the U.S. government initiated against Chinese solar PV manufacturers. Using a structural econometric oligopoly model that accounts for the vertical structure of the market, we measure 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 quantify the carbon externality associated with solar PV systems' adoption that would have displaced electricity generated from fossil fuels in the absence of these tariffs.

Over the past 15 years, the solar PV industry has rapidly grown. The installed capacity of PV systems has soared almost 100-fold worldwide, from 6.7 GW in 2006 to 629 GW in 2019. Although the solar manufacturing sector has been historically dominated by firms located in the United States, Japan, and Germany, Chinese firms have gradually gained market share since 2010.[1] The Chinese solar sector's rapid growth was spurred by various government subsidy schemes. 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

[1] For the period from 2010 to 2018, four Chinese manufacturers were among the top ten solar manufacturers.

countries but Chinese solar manufacturers appeared to be particularly negatively impacted. 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. 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 induced to other domestic actors is an important but unanswered question.

The welfare impacts of the recent U.S.-China trade war considering the role of market structure have remained largely underexplored.[2] In particular, the vertical relationship between domestic upstream and downstream firms is a key element to evaluate the incidence of trade policies (Ornelas and Turner, 2008; Alfaro et al., 2016)—a policy aiming to protect domestic upstream firms may deteriorate downstream firms' profits by raising costs and final purchase prices and reducing overall demand. As a result, protectionist measures could lead to a contraction in the domestic market and an overall welfare loss.

In order to measure the distribution of benefits and costs among upstream and downstream market participants, we develop a structural equilibrium model with which we model the vertical structure of the industry and explicitly account 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.

In our context, a key empirical challenge is that we do not observe the vertical contracts between downstream and upstream firms in the solar market. We find evidence there is substantial inertia in the relationship between a given solar installer and the manufacturer(s) providing the

[2] Like us, Fajgelbaum et al. (2020) estimate a demand and supply system to investigate the incidence of the recent trade tariffs. They apply their model to a large variety of products, but their analysis abstracts from the role of imperfect competition. Accounting for the vertical market structure of the solar PV market and imperfect competition is a key focus of our study.

solar PV system. This inertia could be due to switching costs induced by long-term procurement contracts (Joskow, 1985; Cicala, 2015; Di Maria et al., 2018), organizational preferences (Dyer and Chu, 2003; Li et al., 2008; Argyres et al., 2020), and/or installer-manufacturer specific learning-by-doing phenomenon (Kellogg, 2011), among other reasons. In our estimation, we take into account these various phenomena by explicitly modeling inertia that impacts firms' cost structure in the vertical contractual relationship. Ultimately, we found that this induces cost inefficiencies and greatly affects the magnitude of the welfare effects.

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. We observe when and where a household installed its solar system; the size, price, and brand of the solar PV system;[3] and the name of the installer, among other things. In addition, we observe key characteristics of each solar panel, such as energy conversion efficiency and technology type.

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 income and more supporters of the Democratic Party tend to install relatively more solar PV systems. On the supply side, we find the marginal cost increases with energy conversion efficiency, installation labor costs, and the inertia in the manufacturer-installer relationship.

We simulate the estimated equilibrium model under different counterfactual scenarios to evaluate the 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

[3]The brand of the solar PV system refers to the brand of the solar panels, which is the main component of the solar PV systems.

[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 the Chinese manufacturers cannot circumvent the tariffs. We discuss strategic avoidance of the tariffs in our sensitivity tests.

results show without the anti-dumping and countervailing duties imposed during the 2012 to 2018 period, the United States demand for solar PV systems would have been 17.2% 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 the environmental benefits arising from avoidance of CO_2 emissions would have been \$1.2 *billion*.

Our model can also 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 \$1.35 increase in the final prices of installed PV systems. Manufacturers and installers thus overshift the burden of the trade tariffs onto U.S. consumers.

Finally, our counterfactual scenarios also demonstrate that the inertia between installers and manufacturers have an important effect. If we remove the inertia from the manufacturer-installer relationships, the estimated overall welfare effect is more than 45% larger.

Our analysis is at the nexus of the literature on trade, empirical industrial organization, and environmental economics. First and foremost, this paper improves our understanding of the impact of trade wars. 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). The bulk of the empirical evidence investigating this hypothesis comes, however, from calibrated models (Baldwin and Krugman, 1986; Krugman and Smith, 2007; Etro, 2011). We add to this literature by using an estimated structural econometric model with a rich market structure representation of our focal market.

In addition, this paper contributes to the literature on the incidence of trade tariffs and, in particular, estimation of tariff pass-through rates.[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), 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 solar subsidies. These results for the U.S. washing machine market and solar PV market can be attributed to the presence of market power,[6] and highlight the importance of having a rich representation of the market structure to measure the incidence of trade policies.

Second, our paper is related to the literature in empirical industrial organization investigating frictions in the supplier-buyer vertical relationship. Long-term procurement contracts and organizational preferences are important drivers of the stickiness of vertical relationships between upstream and downstream firms (Joskow, 1985; Dyer and Chu, 2003; Li et al., 2008; Cicala, 2015; Di Maria et al., 2018; Argyres et al., 2020). Switching suppliers can also be hard for buyers if they are unwilling to bear the cost and uncertainty involved in such a change (Monarch, 2018). Kellogg (2011) showed the productivity of an upstream firm (a large oil production company) and a downstream firm (a drilling contractor) can increase with their joint experience, providing evidence of the learning-by-experience phenomenon. Our work fits in with this literature by showing the relationship between solar manufacturers and installers tends to be persistent. In our context, policies that reduce matching frictions could lead to a significant reduction in total installation prices.

Third, our paper contributes to the growing literature in environmental economics about the

[5] For instance, see Huber (1971), Feenstra (1989), Winkelmann and Winkelmann (1998), Bernhofen and Brown (2004), Trefler (2004), Broda et al. (2008), Marchand (2012), 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.

[6] Bulow and Pfleiderer (1983) and Seade (1985) provided the first theoretical evidence of tax overshifting due to market power. Anderson et al. (2001) generalised these findings to the case of an oligopoly model with multiple differentiated goods, as in our setting.

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; De Groote and Verboven, 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, 2018). 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 (2017) 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 empirical evidences on the manufacturer-installer relationships. 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 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.[7] 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.[8]

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.[9] On the other hand, the technology itself has improved. The 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

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

[8]Source: National Solar Jobs Census 2019, released by the Solar Foundation.

[9]At the federal level, the 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, and 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.

of the solar industry consists of the manufacturing segment that produces solar PV systems (solar panels); the downstream consists 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 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 to Chinese solar manufacturers.

2.3 U.S. Anti-dumping Policies

In October 2011, German-owned SolarWorld, which was then 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 and 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.[10] This was the first wave of U.S. tariffs against Chinese solar manufacturers.

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

[10]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 was in March and May 2012, respectively. The anti-dumping duties 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 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

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

The third wave started in January 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 Manufacturer-Installer Relationship

Before proceeding to the presentation of the structural econometric model, we first investigate the manufacturer-installer relationship in the U.S. solar industry. Specifically, we show there is inertia among installers to switch suppliers (manufacturers). Friction in the vertical contractual relationship thus discourages installers substituting high-cost manufacturers for low-cost manufacturers.

3.1 Data Preparation

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 residential U.S. solar PV installations. As of the end of 2018, the dataset included over one million residential solar PV installations with

[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`

a rich set of observables. For each observation, we observe installation date, location, system size, total installed price, rebate, installer name, and detailed information about solar panels used in each PV system, namely manufacturer name, model number, technology type, and efficiency. In this analysis, our unit of observation is a manufacturer-installer working relationship event, which consists of an installer who installs the manufacturer's PV systems. Our sample period begins in 2011, the year prior to 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.

3.2 Vertical Market Structure

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 market for PV installations has remained highly concentrated. 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). There is, however, substantial heterogeneity between installers with activities across the whole United States and the ones 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, whereas the whole sample of installers work with a median of 2 different manufacturers.

Figure 1 shows the time trend of market share for Chinese, U.S. and South Korean manufacturers and provides the first evidence of inertia in the installer and manufacturer relationship.[12] 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 through 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' market share and thus displays the exact opposite pattern.[13] Moreover, South Korean manufacturers have become an increasingly important player 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.

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

[13]Figure A1 shows the proportion of Chinese manufacturer each installer was working with from an installer's perspective; we see a similar trend as in Figure 1.

3.3 Switching Behavior in Manufacturer-Installer Relationships

We now examine switching behavior between manufacturers and installers. Specifically, we use a regression model to quantify the likelihood an installer would switch between different manufacturers across years. We follow closely the approach proposed by Monarch (2018). Our unit of analysis is a manufacturer-installer trading relationship event.[14] We define our outcome variable with the dummy variable $Stay_{rmt}$ as the baseline definition of no-switching behavior. The dummy takes a value of one if the installer r acquiring solar panels in year t from a manufacturer m also purchased solar panels from that manufacturer in the following year $t+1$, and zero otherwise. We generate this variable for the whole universe of U.S. residential solar PV installations from 2011 through 2018.

In Panel B of Table 1, we show summary statistics related to the dependent variable. Overall, they show a sizable share of U.S. installers remained with the same manufacturer over time. From 2011 to 2018, the average proportion of installers who chose to stay with their current suppliers in the next year is around 60%. As suggested by Monarch (2018), we can compare this share to what would happen if buyers were to randomly select panels from suppliers, which is the benchmark if there were no switching costs. In our sample, there are approximately 130 large manufacturers able to supply solar panels to U.S. installers.[15] If each supplier had an equal chance to be chosen, the probability an installer stays with the same manufacturer would be 1/130, or only 0.8%. This suggests that path dependence is thus very high in our sample.

There are several potential explanations for the persistence in the installer-manufacturer relationship. The learning-by-experience phenomenon, as suggested by Kellogg (2011), could be one explanation. As suggested by Monarch (2018), switching costs, which are due to the

[14] Although one manufacturer produces multiple types of solar panels, we regard these different panels as one product. Quality differences across different panels made by the same manufacturer are likely to be small and to remain unaffected by the anti-dumping policies.

[15] To derive this statistic, we consider only installers who have no less than 10 solar PV installations and manufacturers whose panels have been used in no less than 10 solar PV systems in the United States in our sample.

monetary and non-monetary costs of renegotiating contracts or simply organizational inertia, could be another one. These different explanations will, however, have different implications on the cost structure of the industry. Learning-by-experience induces cost efficiency over time, which we refer as a positive selection effect for a given installer-manufacturer pair. Switching costs, on the other hand, should have the opposite effect and lead to cost inefficiency. In the presence of large switching costs, manufacturers could anticipate this and charge higher prices. In this case, we would have a negative selection effect. In practice, both effects could be present. Which one dominates is an empirical question.

The implication of these selection effects on costs should also be a function of past experience. The more experience an installer-manufacturer pair has together not only the more learning opportunities there are but also the more cost inefficiencies might subsist. We thus investigate how the total installed PV capacity for a manufacturer-installer pair in the previous years, which we denote F, correlate with switching behaviors. To do so, we estimate the following model to examine the determinants of longevity in the manufacturers-installer relationship.

$$Stay_{rmt} = \alpha + \theta F_{rmt} + \beta p_{rmt} + \rho X_{mt} + \lambda_{rm} + \eta_t + \nu_{rmt} \tag{1}$$

where F_{rmt} is the $Ln(1 + Capacity)$, in which $Capacity$ is the total solar PV capacity that installer r has installed using the solar panels made by manufacturer m until year t. Our coefficient of interest is thus θ. We add the average installed price (unit value) for the manufacturer-installer pair in year t, denoted p_{rmt}, and a set of variables for observed product quality (including average energy conversion efficiency and average technology type for solar panels produced) for manufacturer m in year t, denoted X_{mt}, as control variables given that within an installer-manufacturer pair these characteristics evolve over time and could determine the decision to switch suppliers. Finally, λ_{rm} is a manufacturer-installer fixed effect, η_t is a year fixed effect, and ν_{rmt} is the error term.

One concern is that the price variable is correlated with past experiences and other unobservables; thus it is possibly endogenous. We perform two robustness tests to assess whether it affects the coefficient θ. First, we simply omit the price and quality variables from the regression. Second, we use an instrumental variable strategy. Specifically, we choose two variables as instruments for the installed price. The first instrument is a dummy variable that equals to one if the tariffs are put in place and zero otherwise. The second instrument is the dollar amount for the tariffs, by multiplying the average installed price in 2011 (i.e., before the tariffs were put in place) by the tariff rates. They are effectively cost-shifters that impact the manufacturers' price and are uncorrelated with past experience between a given manufacturer-installer pair.

For this estimation, the sample period is from 2011 to 2018. Because the installer's market is too fragmented, we drop observations for installers who have installed no more than 10 systems. These small installers may actually represent firms from electrical contracting industries where PV installation is not their primary business. We also drop observations for solar manufacturers whose panels are used in no more than 10 solar PV systems. To control for extreme values, the installed price are winsorized at 1% and 99% levels. Finally, the data are aggregated on the manufacturer-installer year level. The standard errors are clustered at the manufacturer-installer pair level.

Table 2 reports the estimation results for different specifications that use OLS and the 2SLS regressions. Columns (1) to (3) show the results from simplest to saturated models that use OLS regressions. It indicates that past experience in manufacturer-installer relationships is strongly correlated with a higher probability of an installer staying with its upstream manufacturer. It implies an installer will be reluctant to switch to a different manufacturer if the installer has substantial prior experience working with a given manufacturer. Columns (4) to (5) show that results from using the 2SLS regression—the impact of manufacturer-installer cumulative experience is of similar magnitude than for the OLS regressions. The results in Table A1 also show that the two instruments have a positive and significant correlation with installed prices.[16] The magnitude of these estimates imply that if the cumulative installation capacity in an installer-manufacturer pair were to double, i.e., an increases of 100%, it will increase the probability they work together subsequently by approximately 3 to 6 percentage points.

To summarize, we showed that manufacturer-installer specific experience is positively correlated with a higher probability of an installer not switching among its upstream manufacturers. We use these results to guide our modeling of the vertical structure of the supply side that follows.

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 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.

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.[17] 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 decision. The conditional indirect utility of consumer i in region w,

[16] The F-tests for the first-stage regressions all yield values greater than 10.

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

where a region denotes a Marketing Strategic Area (MSA), from purchasing and installing j good during year t is given by

$$U_{ijwt} = \beta_i X_j + \alpha_i p_{jwt} + \gamma D_w + \lambda_{j(mr)} + \eta_t + \zeta_{jt} + \epsilon_{ijwt} \tag{2}$$

In equation (2), X_j is a vector of observed product characteristics such as energy conversion efficiency and technology type. For each product j, we also have an additional product characteristic that consists of a solar manufacturer-installer pair fixed effect, denoted by $\lambda_{j(mr)}$, where m represents the solar manufacturer and r represents the solar installer. This fixed effect is crucial in capturing preferences for manufacturer-installer pair. This implies the same PV model installed by a different installer can be valued differently by consumers. β_i is a vector of consumer preference—specific marginal utilities (assumed to be random) associated with the product characteristics in X_j; p_{jwt} is the average consumer purchase price for j in MSA w during year t, net of government subsidies and divided by the size of the solar PV system installed; and α_i represent the marginal disutility of price (also assumed to be random). 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. Finally, η_t is a year fixed effect; ζ_{jt} is the product characteristics unobserved by the econometrician but observed by the consumers and firms; and ϵ_{ijwt} is the i.i.d error term and follows the type I extreme value distribution.

The heterogeneous taste parameters for product characteristics are modeled as

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Sigma v_i \tag{3}$$

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

$$s_{jwt}(X_j, p_{jwt}; \alpha, \beta, \Sigma, \eta, \zeta) = \int \frac{exp(\delta_{jwt} + \mu_{ijwt})}{1 + \sum_{l=1}^{J} exp(\delta_{lwt} + \mu_{ilwt})} dF(\nu) \tag{4}$$

where $\delta_{jwt} = X_j\beta + \alpha p_{jwt} + Z_w\theta + \lambda_{mr} + \eta_t + \zeta_{jt}$ 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. $F(\cdot)$ 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 $M_w \times A \times V$, where M_w is the number of single-unit houses in MSA w; A is the proportion of single-unit houses with value greater than \$100,000;[18] and V is the percentage of solar-viable buildings in that MSA level. The observed market share of product j is then given by $s_{jwt} = q_{jwt}/(M_w \times A \times V)$, where q_{jwt} is the actual demand of product j in MSA w during year t.

For estimating a simple multinomial logit model, we can use Berry (1994)'s transformation and express the trans-log version of the predicted market share of product j in MSA w during year t as

$$\ln s_{jwt} - \ln s_{0wt} = X_j\beta + \alpha p_{jwt} + Z_w\theta + \lambda_{mr} + \eta_t + \zeta_{jt} \tag{5}$$

where s_{0wt} is the market share of the outside good. Below, we use these trans-log market shares to investigate our instrumental variables.

Note, we assume the model is static; consumers are thus not forward looking. In theory, forward-looking consumers may have anticipated the drastic decrease in the price of solar PV systems and delayed their purchase decisions. In such a case, a static demand specification may

[18] 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.

underestimate the true price elasticity (Aguirregabiria and Nevo, 2013). However, as argued by Gerarden (2017) and demonstrated by De Groote and Verboven (2019), consumers might be quite myopic in this context. In fact, even government and industry practitioners did not anticipate the recent sharp decline in prices. Therefore, it is unlikely dynamics have a first-order effect on the demand estimates in this context.

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).

The supply side consists of a three-stage game. 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 a context of one particular geographical market. With a slight abuse of notation, we thus omit the subscript w, which denotes the MSA. The standard way to solve this game is to use backward induction and to solve for the subgame perfect Nash equilibrium. In our context, this works as follows. In the final stage of the model, the solar installer r chooses a retail price p_{jt} after observing the set of solar PV models available (denoted by J_{rt}), wholesale prices (p^m_{jt}), and the given demand shock. The retail price p_{jt} is a package price charged to the consumer; it includes the solar PV system price 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 $p_{jt} - p^m_{jt} - c^r_{jt}$.

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

$$\max \pi_{rt} = \sum_{j \in J_{rt}} \left[p_{jt} - p_{jt}^m - c_{jt}^r \right] M s_{jt}(p) \tag{6}$$

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

$$p_t - p_t^m - c_t^r = -(T_{rt} * \Delta_{rt})^{-1} s_t(p) \tag{7}$$

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

$$\max \pi_{mt} = \sum_{j \in J_{mt}} \left[p_{jt}^m - c_{jt}^m \right] M s_{jt}(p) \tag{8}$$

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

$$p_t^m - c_t^m = -(T_{mt} * \Delta_{mt})^{-1} s_t(p) \tag{9}$$

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 (7) and (9) yields the solar manufacturer' and installer's joint marginal cost mc_t,

$$mc_t = c_t^m + c_t^r = p_t + (T_r * \Delta_{rt})^{-1} s_t(p) + (T_m * \Delta_{mt})^{-1} s_t(p) \tag{10}$$

Next, we assume the joint marginal cost depends on a vector of cost-shifters Y_t. Moreover, we add a friction term, denoted F_t, which we discuss in more detail below. The joint marginal cost is

$$mc_t = \gamma Y_t + \pi F_t + \kappa + \varphi + \varepsilon_t \tag{11}$$

where Y_t includes solar panel's energy conversion efficiency and the wage rate in roofing; κ is an installer fixed effect; and φ is year fixed effect. These fixed effects capture installer heterogeneity and yearly cost shock to the whole industry, respectively.

The friction term F_t is defined as $Ln(1 + Capacity)$, in which $Capacity$ is the cumulative installed capacity for a manufacturer-installer pair until year t. As discussed in Section 3, it captures various phenomena that could induce either cost efficiencies or inefficiencies in a manufacturer-installer contracting relationship. A priori, we do not know which phenomena dominate in our setting. We do know, however, it varies with the amount of experience within each manufacturer-installer pair.

Combining equations (10) and (11) yields

$$p_t + (T_{rt} * \Delta_{rt})^{-1} s_t(p) + (T_{mt} * \Delta_{mt})^{-1} s_t(p) = \gamma Y_t + \pi F_t + \kappa + \varphi + \varepsilon_t \tag{12}$$

which we bring to the data for estimation.

Equation (12) 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 two non-linear contracts we consider allow us to provide upper bounds on the extent of market power, and thus ability to determine margins, that manufacturers or installers might derive in this market.

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

$$p_t + (T_{rt} * \Delta_{rt})^{-1} s_t(p) = \gamma Y_t + \pi F_t + \kappa + \varphi + \varepsilon_t \tag{13}$$

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

$$p_t + (T_{mt} * \Delta_{rt})^{-1} s_t(p) = \gamma Y_t + \pi F_t + \kappa + \varphi + \varepsilon_t \tag{14}$$

Equation (14) and (13) both corresponds to different type of non-linear vertical contracts and can be readily estimated by simply substituting the right 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, which we combine with three other data sources: (1) demographic data from the U.S. Census Bureau, which provide county-level demographic variables on income, education, population density, race, and political orientation across the United States;[19] (2) labor market data from the U.S. Bureau of Labor Statistics, which provide the hourly wage rate for roofing installers across different states; and (3) solar potential data from the Google Project Sunroof, which we use to estimate the technical solar potential of all solar-viable buildings in that county.

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. To define the inside goods for the analysis, we focus on solar PV models that have significant sales (more than 3,000 units) in the United States. The sample consist 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). The data in our final sample accounts for 21.6% of all U.S. solar PV installations. In Table A2 in the appendix, we report an exhaustive list of solar system models found in the sample.

For the downstream market, because there is a large number of installers in the sample, we classify the installers into 11 groups. The first 10 groups represent the installers who have significant market share across the United States (Table A3 in the appendix), and the eleventh group represents the rest of the installers.

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 level.

Table 3 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

[19]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.

total installed gross subsidy price for a solar PV system is \$4.23/W with a standard deviation of \$0.87/W. The average final price the consumer paid for a solar PV system is \$4.06/W, which implies the average government subsidy consumers received represents 4% of the total installed price.[20] 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 solar PV system is made of polycrystalline panels and zero if it is made of monocrystalline panels. About 43% of the solar PV systems are made of polycrystalline panels.[21] Panel B lists demographic information at the MSA level. The average median housing price (our proxy for household income) is \$442,000, and the average population density is 970 persons per square mile. On average, 27% of the observations are from regions where people have a bachelor's degree or higher, 51% 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 499,755; 91% of the houses have values greater than \$100,000. The average wage rate for PV installation across different MSAs is \$24.79/hour. Finally, the inertia term we constructed has a mean value of 10.46 with a standard deviation of 1.85.

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 (2), leading to an endogeneity problem. We use the instrumental variable strategy proposed by Berry et al. (1995): we identify the coefficient on the price using a variation from other product characteristics, (i.e., the varia-

[20]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.

[21]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.

tion in prices induced by product differentiation). In particular, we use instruments based on a first-order approximation of the equilibrium pricing function (Gandhi and Houde, 2019). The instruments 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. The exclusion restriction holds to the extent that short-run demand shocks are not correlated with product characteristics determined by a long-run development process (Li, 2017). We thus construct Berry et al. (1995)'s instruments (thereafter refereed as BLP) 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.

In order to investigate our instrumental variables, we first use a simple two-stage least square (2SLS) regression to estimate equation (5). Table A4 reports the results for the first-stage regression in which price is regressed on the different instruments. Model 1 uses only BLP_eff and BLP_tech. Model 2 adds the square term of BLP_eff and square term of BLP_tech. Model 3 additionally adds the interaction term of BLP_eff and BLP_tech to construct the instrumental variables.[22] 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 A5 show that BLP instruments lead to a significant and negative price coefficient. Overall, the BLP instrumental variable set performs well in our setting.

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

[22] In Model 3, the instrumental variable set thus includes five variables, that is, BLP_eff, BLP_tech, $(BLP\_eff)^2$, $(BLP\_tech)^2$, and $BLP\_eff \times BLP\_tech$.

Dubé et al. (2012) and Grigolon et al. (2018).

1. We perform the numerical integration of the market shares using 200 draws of a quasi-random number sequence and we do so for each market.

2. We set the convergence level for the contraction mapping of the inner loop within the GMM objective function at $1e^{-12}$.

3. We set a strict tolerance level at $1e^{-6}$ and optimize the objective function using the advanced optimization algorithms in Knitro.

4. 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 4 reports both demand and supply side estimates under each of the alternate supply specifications (*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 (θ), and finally, the variation in taste for price and non-price characteristics (the matrix Σ). The price coefficient is negative and statistically significant at the 1% level. 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 and the dummy for Democrats are all positive and most of them are statistically significant at conventional levels, suggesting areas with higher income and more Democratic Party supporters 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 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 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 on controls, notably the coarse categorical variable for urban/rural.[23] The taste variation parameter on price is statistically significant at the 5% level in *Model 1*, showing consumers are heterogeneous with respect to their tastes for solar PV prices.

The demand parameter in Table 4 yields a mean own-price elasticity of demand of -3.65, -4.30 and -4.31 across *Model* 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.

Summary statistics on price-cost margins and recovered marginal costs for installed solar PV systems are reported in the first column of Table A8 in the appendix. These statistics are broken down by upstream manufacturers/downstream installers of the solar PV systems. Under the linear vertical contract specification (*Model* 1), the mean margins for upstream manufacturers and downstream installers are \$0.840/W and \$1.162/W, respectively, yielding a mean total margin (upstream and downstream) of \$2.002/W. On average, the ratio of margin to total installed price, the Lerner Index, is 0.49. 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 \$0.955/W; and when only manufacturers determine the price-cost margins (*Model* 3), the mean margin is \$0.941/W.

[23] 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 bachelor's degree tend to be the areas with 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 education attainment on solar PV adoption is negative but not statistically significant.

Table 4 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 estimated coefficient on the friction term is positive and significant at the 1% level. It implies installer-manufacturer pairs who work together and have frequent interactions exhibit higher joint marginal costs. On the net, any phenomena that lead to a negative selection effect thus dominate—as an installer-manufacturer pair contracts more together, additional cost-inefficiencies creep in, and this leads to higher marginal costs. Note our modeling of selection effects is reduced-form in nature and cannot distinguish between various underlying phenomena. Moreover, we do not know if the impact is on the manufacturers' costs, installers' costs, or both. Nonetheless, our estimate implies switching costs are large enough to ultimately induce a negative selection at the installer-manufacturer level. In the next section, we also show it has important implications for estimating the effect of trade tariffs in this market.

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 A6, we report the test statistic for each pairwise comparison between the three specifications. Focusing on the specifications with non-linear contracts, we find that *Model* 2, where installers entirely determine the price-cost margins, fits the data slightly better compared to *Model* 3, where, at the opposite, manufacturers entirely determine the price-cost margins (T=0.54). However, the specification with linear vertical contracts (*Model* 1) offers the best fit overall. Compared to *Model* 2, the test statistic is T=1.09, which suggests that *Model* 1 dominates *Model* 2, but the difference is also not statistically significant at the 5% level. We will thus report the policy results for all three different types of models.

7 Policy Analysis of Trade Tariffs

We now use the estimated structural model to investigate the incidence of the U.S.-China solar trade war. We 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.[24]

We simulate three sets of scenarios. First, we remove all 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 trade war.

Second, we perform a similar exercise, but we remove (both in the baseline and counterfactual scenarios) the inertia term in the manufacturer-installer relationship. These scenarios illustrate how frictions in the vertical contractual relationship interact with the effects of tariffs.

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 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 rates imposed.

[24] 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

$$\Delta CS = -\frac{1}{\alpha}\left[\ln\left(\sum_{j=1}^{J}\exp(W_j^1)\right) - \ln\left(\sum_{j=1}^{J}\exp(W_j^0)\right)\right] \tag{15}$$

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.

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.

7.1 Important Parameters

Before proceeding further, we discuss three important parameters required to perform the simulations. First, we address the exact anti-dumping and countervailing duties imposed on Chinese manufacturers. Panel A of Table A7 lists the anti-dumping and countervailing duty rates imposed on the three Chinese 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 receive 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.

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) related to the Chinese manufacturers, not on the final prices of installed systems. The challenge is solar panel prices are 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 Chinese panels, we recover the solar panel prices from the total installed prices by interpolating the fraction of the total price that could be attributed to the panels. Panel B in Table A7 reports the breakdown of the total installed price in different cost components from 2012 to 2018, as 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. Based on these data, we approximate the panel prices and compute the dollar value of the tariffs imposed on Chinese panels.

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 Nordhaus (2017), in which he estimated the SSC is \$36 per ton of CO_2 in 2015 U.S. dollars.

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 Anti-dumping Policies

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 benefit/loss. Table 5 presents the results. Panel A shows the total market capacity of the U.S. solar market would have been 17.2% 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 80.2% 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 changed little. There is little substitution from Chinese to non-Chinese manufacturers. The impact of the trade tariffs is thus primarily on the extensive margin.

Panel B shows the welfare changes among the different market participants. Removing the anti-dumping policies provides welfare gains of $369.6, $271.4, and $291.8 *million* for U.S. consumers, Chinese manufacturers, and U.S. installers, respectively. The losses for U.S. manufacturers is only $4.6 *million*, whereas the decrease in U.S. tariff revenues is $366.0 *million*. This suggests the 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 7.0 *million* tons in the absence of tariffs, which translates into an externality cost of $253.3 *million*. Since the data in our final sample accounts for 21.6% of U.S. solar PV installations, the overall benefits associated with reducing the CO_2 externality for the whole United States would amount to $1.2 *billion*.

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.

This also corresponds to an increase in final price if we were to assume no demand-and-supply responses. In Table 8, we thus report the average change in final prices for affected PV systems (i.e., the ones using Chinese panels) without and with an equilibrium response. The ratio of these two prices corresponds to our pass-through rates. We find the average tariff pass-through rate is 135%. It implies that a $1 dollar increase in tariff leads to a $1.35 increase in the final price of an installed solar PV system in the United States. We thus find 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 about the role of local market power, we investigate the relationship between installer's markup and the Herfindahl-Hirschman Index (HHI) for each market (MSA-year). Figure 2 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 (3), keeping all other parameters constant.[25] 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 9 reports the results: the pass-through rate increases with the elasticity of the demand. In a pure monopoly setting, this result would be 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

[25] We scale the parameter α by a constant such that the average demand elasticity ranges from -1 to -3.65. Bonnet et al. (2013) proposed a similar approach.

market and thus a higher pass-through rate.

7.2.2 Removing Inertia in Vertical Contracting

In the second set of counterfactual scenarios, we simulate the impact of anti-dumping policies in the absence of inertia in the manufacturer-installer contractual relationship. Table 6 reports the results. Panel A shows the total market capacity of the U.S. solar market would have expanded by 13.2% in the absence of tariffs—the distribution and magnitude of the change in demand across manufacturers is similar but smaller in percentage terms than in the first set of scenarios. For instance, the sales of solar panels made by Canadian Solar would increase by 60.6% in these scenarios, whereas it was 72.8% before.

This smaller percentage change arises because removing the inertia term increases the market size in both the baseline and counterfactual scenarios. In our setting, the inertia is at the source of cost inefficiencies, and thus removing it makes firms, manufacturers, and installers more cost-efficient; thus, overall, the market expands. Removing the inertia is thus akin to creating a positive cost shock that impacts the whole supply-side sector. This creates a market expansion. In the absence of such inertia, the impacts of trade tariffs are smaller in relative terms simply because the overall solar market is larger in the baseline scenario. In level, the impacts are, however, larger.

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 \$524.1, \$407.1, and \$426.6 *million*, respectively. Whereas, the losses for U.S. manufacturers and U.S. tariff revenue would have been \$8.7 and \$534.9 *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 45% larger relative to the first set of scenarios.

7.2.3 Statutory versus Effective Rates

In this third set of scenarios, 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 chose this percentage to illustrate the role of strategic tariff avoidance as documented by Bollinger et al. (2021). We recognize the different waves of tariffs had different loopholes. As a result, the degree of strategic avoidance is likely to have varied significantly 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 7, the magnitude of the changes for the different metrics reported are about 50%. Qualitatively, the results remain the same. The impact of strategic avoidance, at least on the U.S. market, is rather linear.[26]

Second, as shown in Table 8, the tariff pass-through rate remains virtually unaffected: it is 137%. The incidence of the effective tariff rate on consumers is thus similar to that of the statutory rate.

8 Conclusion

In this paper, we examine the incidence of the recent U.S.-China trade war in the solar PV market. We pay close attention to the vertical structure of the industry and the impact on consumers in the U.S. market. To that end, we propose a structural econometric model where we model both the demand- and supply-side effects. Using the estimated model, we simulate 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 17.2% more in the absence of trade tariffs. Although, the tariffs protected

[26] 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.

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 \$1.35 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 also investigate the role of inertia in the vertical contractual relationship between installers and manufacturers. Using reduced-form evidence and our structural estimation, we find installers stay with the same suppliers. We do not distinguish the precise phenomena leading to such inertia, but switching costs that induce cost-inefficiencies in a manufacturer-installer working pair appear to dominate. Accounting for this inertia in our policy analysis impacts the overall level of our welfare changes, but it does not affect either the distribution across market participants or the pass-through rate of the tariffs.

We conclude by highlighting a few caveats to our paper. First, we did not endogenize the installers' search process to find new manufacturers. To fully distinguish for the role of switching costs and past experience in the vertical structure, a dynamic supply model of search would be required. Second, 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. 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). A more granular and spatially disaggregated model would be required to quantify such effects.

References

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

Alfaro, L., P. Conconi, H. Fadinger, and A. F. Newman (2016). Do prices determine vertical integration? *The Review of Economic Studies 83*(3), 855–888.

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

Anderson, S. P., A. De Palma, and B. Kreider (2001). Tax incidence in differentiated product oligopoly. *Journal of Public Economics 81*(2), 173–192.

Argyres, N., J. Bercovitz, and G. Zanarone (2020). The role of relationship scope in sustaining relational contracts in interfirm networks. *Strategic Management Journal 41*(2), 222–245.

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

Baldwin, R. and P. R. Krugman (1986). Market access and international competition: a simulation study of 16k random access memories.

Ball, J., D. Reicher, X. Sun, and C. 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, G. L. and N. 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, C. and C. L. Crago (2015). Adoption of residential solar power under uncertainty: Implications for renewable energy incentives. *Energy Policy 86*, 27–35.

Bernhofen, D. M. and J. 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, S., J. Levinsohn, and A. Pakes (1995). Automobile prices in market equilibrium. *Econometrica: Journal of the Econometric Society*, 841–890.

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

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

Bettendorf, L. and F. Verboven (2000). Incomplete transmission of coffee bean prices: evidence from the netherlands. *European Review of Agricultural Economics 27*(1), 1–16.

Bollinger, B., T. Gerarden, K. Gillingham, D. Vollmer, and D. Yi Xu (2021). Stockpiling and avoidance of united states solar panel tariffs. Technical report, Yale University.

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

Bollinger, B. and K. Gillingham (2019). Learning-by-doing in solar photovoltaic installations. *Available at SSRN 2342406*.

Bonnet, C. and P. 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, C., P. Dubois, S. B. Villas Boas, and D. 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, S. (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, J. A. and B. J. Spencer (1985). Export subsidies and international market share rivalry. *Journal of International Economics 18*(1-2), 83–100.

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

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

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

Callaway, D. S., M. Fowlie, and G. 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, A., G. Gopinath, B. Neiman, and J. 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, I. (2015). Solar pv adoption in the united states: An empirical investigation of state policy effectiveness.

Cicala, S. (2015). When does regulation distort costs? lessons from fuel procurement in us electricity generation. *American Economic Review 105*(1), 411–44.

Crago, C. L. and I. 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, A. and K. Miyagiwa (2008). Information and disclosure in strategic trade policy. *Journal of International Economics 75*(1), 229–244.

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

Di Maria, C., I. Lange, and E. Lazarova (2018). A look upstream: Market restructuring, risk, procurement contracts and efficiency. *International Journal of Industrial Organization 57*, 35–83.

Dixit, A. (1984). International trade policy for oligopolistic industries. *The Economic Journal 94*, 1–16.

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

Dubé, J.-P., J. T. Fox, and C.-L. Su (2012). Improving the numerical performance of static and dynamic aggregate discrete choice random coefficients demand estimation. *Econometrica 80*(5), 2231–2267.

Dyer, J. H. and W. Chu (2003). The role of trustworthiness in reducing transaction costs and improving performance: Empirical evidence from the united states, japan, and korea. *Organization Science 14*(1), 57–68.

Etro, F. (2011). Endogenous market structures and strategic trade policy. *International Economic Review 52*(1), 63–84.

Evenett, S. J. (2020). *COVID-19 and trade policy: Why turning inward won't work*. CEPR Press.

Fajgelbaum, P. D., P. K. Goldberg, P. J. Kennedy, and A. K. Khandelwal (2020). The return to protectionism. *The Quarterly Journal of Economics 135*(1), 1–55.

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

Feenstra, R. 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, A., A. Hortaçsu, and F. 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, R., D. Feldman, R. Margolis, M. Woodhouse, and K. Ardani (2017). Us solar photovoltaic system cost benchmark: Q1 2017. Technical report, EERE Publication and Product Library.

Gandhi, A. and J.-F. Houde (2019). Measuring substitution patterns in differentiated products industries. Technical report, National Bureau of Economic Research.

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

Gerarden, T. (2017). Demanding innovation: The impact of consumer subsidies on solar panel production costs. Technical report, Working paper, Harvard University.

Gillingham, K., H. Deng, R. Wiser, N. Darghouth, G. Nemet, G. Barbose, V. Rai, and C. Dong (2016). Deconstructing solar photovoltaic pricing. *The Energy Journal 37*(3).

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

Gillingham, K. T. and B. Bollinger (2021). Social learning and solar photovoltaic adoption. *Management Science*.

Grigolon, L., M. Reynaert, and F. 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, J., R. Liu, B. U. Marchand, and J. Zhang (2016). Market structure, imperfect tariff pass-through, and household welfare in urban china. *Journal of International Economics 100*, 220–232.

Haucap, J., U. Heimeshoff, G. J. Klein, D. Rickert, and C. Wey (2021). Vertical relations, pass-through, and market definition: Evidence from grocery retailing. *International Journal of Industrial Organization 74*, 102693.

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

Hughes, J. E. and M. Podolefsky (2015). Getting green with solar subsidies: evidence from the california solar initiative. *Journal of the Association of Environmental and Resource Economists 2*(2), 235–275.

IAWG (2013). *Technical Support Document: Technical Update of the Social Cost of Carbon for Regulatory Impact Analysis-Under Executive Order 12866*. Ph. D. thesis, Citeseer.

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

Jaravel, X. and E. Sager (2019). What are the price effects of trade? evidence from the us and implications for quantitative trade models.

Joskow, P. L. (1985). Vertical integration and long-term contracts: The case of coal-burning electric generating plants. *Journal of Law, Economics, & Organization 1*(1), 33–80.

Kellogg, R. (2011). Learning by drilling: Interfirm learning and relationship persistence in the texas oilpatch. *The Quarterly Journal of Economics 126*(4), 1961–2004.

Krugman, P. and A. Smith (2007). *Empirical studies of strategic trade policy.* University of Chicago Press.

Krugman, P. R. (1986). *Strategic trade policy and the new international economics.* MIT Press.

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

Kwan, C. L. (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, A. and D. Lemoine (2018). Designing dynamic subsidies to spur adoption of new technologies. Technical report, National Bureau of Economic Research.

Li, D., L. Eden, M. A. Hitt, and R. D. Ireland (2008). Friends, acquaintances, or strangers? partner selection in r&d alliances. *Academy of Management Journal 51*(2), 315–334.

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

Ludema, R. D. and Z. Yu (2016). Tariff pass-through, firm heterogeneity and product quality. *Journal of International Economics 103*, 234–249.

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

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

Monarch, R. (2018). "it's not you, it's me": Prices, quality, and switching in us-china trade relationships. *The Review of Economics and Statistics*, 1–49.

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

Nordhaus, W. D. (2017). Revisiting the social cost of carbon. *Proceedings of the National Academy of Sciences 114*(7), 1518–1523.

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

Ornelas, E. and J. L. Turner (2008). Trade liberalization, outsourcing, and the hold-up problem. *Journal of International Economics 74*(1), 225–241.

OShaughnessy, E. 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).

Pless, J. and A. 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, S. J. and A. Sahoo (2015). Cost and price dynamics of solar pv modules.

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

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

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

Sommerfeld, J. (2016). *Residential customers and adoption of solar PV*. Ph. D. thesis, Queensland University of Technology.

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

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

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

Zivin, J. S. G., M. J. Kotchen, and E. 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.

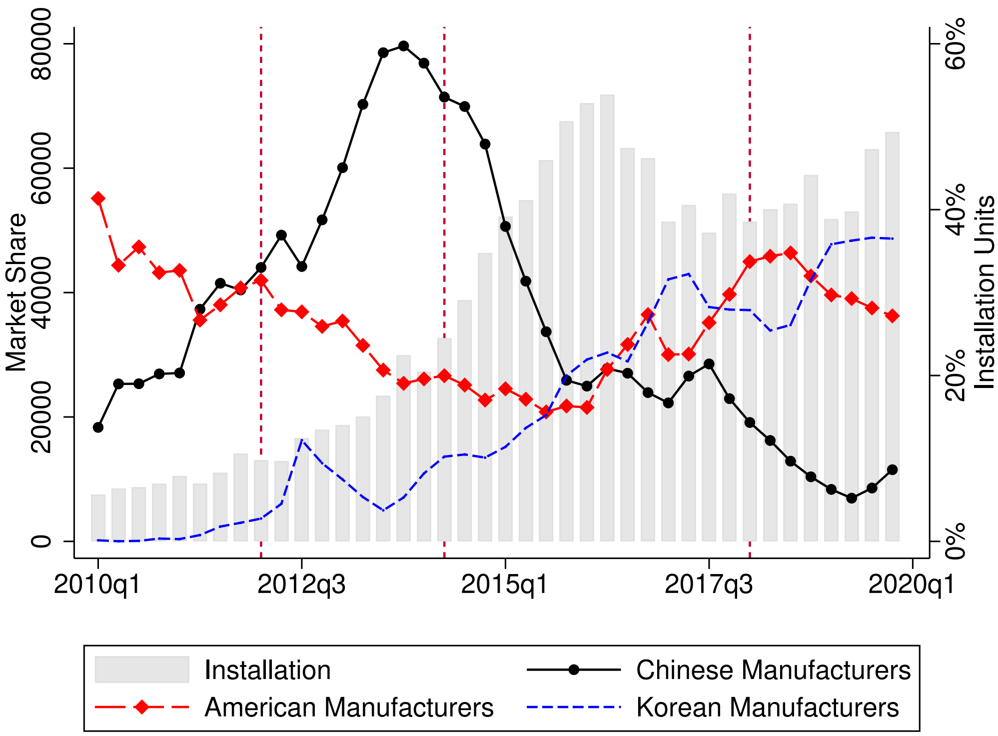

Figure 1: Market Share for Manufacturers through Years

Notes: This figure shows the market share of manufacturers and installation units across different quarters from 2010Q1 to 2019Q4. The grey bar (left axis) represents the number of total installation units through different quarters. 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 (2012Q1, 2014Q2, and 2018Q1).

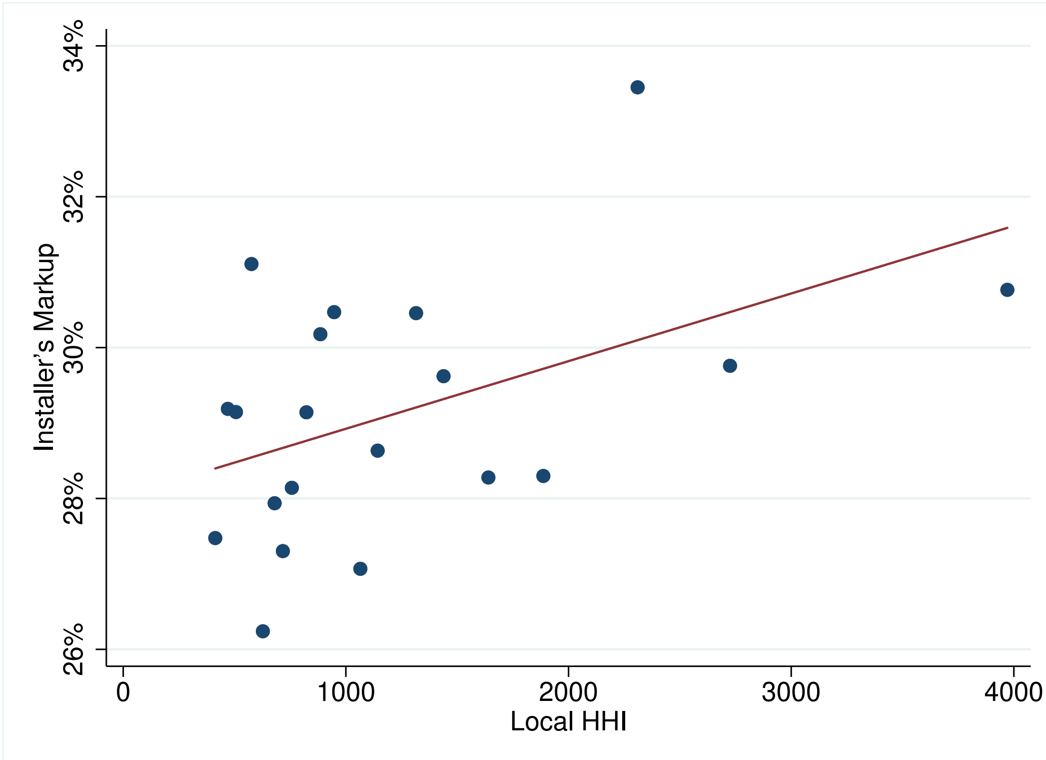

Figure 2: Relationship between Installer's Markup and Local HHI

Notes: This figure provides a non-parametric way of visualizing the relationship between installer's markup and 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.

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	No. installers per state	CR1 (%)	Staying with Manufacturers (%)
2011	89	32.53	57.75
2012	99	29.33	57.14
2013	110	28.06	55.71
2014	119	30.39	62.62
2015	165	31.09	75.94
2016	229	23.96	64.42
2017	234	24.40	61.36
2018	247	26.48	54.74

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; and the third column is the average proportion of installers staying with their current manufacturers in the next year.

Table 2: Past Experience and Installers' Switching Behavior

	OLS	OLS	OLS	2SLS	2SLS
	Stay	Stay	Stay	Stay	Stay
Variables	(1)	(2)	(3)	(4)	(5)
Ln(1+Capacity)	0.078***	0.049***	0.041***	0.033***	0.061***
	(0.001)	(0.004)	(0.004)	(0.008)	(0.010)
Installed Price			-0.010*	0.286	-0.302
			(0.005)	(0.192)	(0.250)
Efficiency			12.042***	11.647***	11.513***
			(0.616)	(0.792)	(1.077)
Technology			0.003	0.008	-0.001
			(0.016)	(0.018)	(0.022)
Constant	0.312***				
	(0.007)				
Year F.E.	No	Yes	Yes	Yes	Yes
Manufacturer-Installer F.E.	No	Yes	Yes	Yes	Yes
Observations	27,423	20,379	20,379	20,379	16,749
R-squared	0.075	0.008	0.040	-	-

Note: This table reports the regression results on solar installers' switching behavior. Columns (1) - (3) show the results using OLS method, and columns (4) - (5) show the results using 2SLS method. In column (4), the instrument variable for the installed price is $Tariff$, which equals to one if the tariff is put in place and zero otherwise. In column (5), the instrument variable for the installed price is $Tariff\_dollar$, which translates the tariff into dollar amount by using the average installed price in 2011 multiplied by the tariff rates. Manufacturers with less than 10 solar PV systems are excluded from our sample. Installers with fewer than 10 solar PV system installations are also excluded from our sample. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Summary Statistics for Key Variables

Variable	Description	Max	Min	Mean	SD
A. Characteristics					
InstalledPrice	Total installed price ($/Watt)	8.39	1.74	4.23	0.87
Subsidy	Government subsidies ($/Watt)	5.22	0	0.17	0.37
Price	Consumer purchase price ($/Watt)	7.73	1.73	4.06	0.89
Efficiency	Energy conversion efficiency	0.22	0.15	0.18	0.02
Technology	=1, if poly; =0 if mono	1	0	0.43	0.50
B. Demographics					
Income	Median housing price ($100K)	7.94	1.05	4.42	1.89
Education	% Bachelor degree	0.49	0.12	0.27	0.09
Urbanization	% Population density ($1,000)	6.32	0.01	0.97	1.56
Race	% White people	0.94	0.14	0.51	0.16
Democrats	% Voting for democratics in 2008	0.77	0.36	0.55	0.10
C. Other Variables					
NHouse	Number of single-unit houses	2,467,089	19,764	499,755	668,519
SolarPotential	% Solar-viable houses	0.96	0.58	0.87	0.07
HouseAbove	% House with value greater than 100K	0.98	0.46	0.91	0.08
InstallWage	Wage rate (2015$/hour) in installation	25.79	20.90	24.79	0.90
Friction Term	Log(1 + $Capacity$)	12.80	1.04	10.46	1.85

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

Table 4: Estimation Result for Main Specification

	Model 1		Model 2		Model 3	
	Estimates	SE	Estimates	SE	Estimates	SE
Demand side						
Means, (α, β)						
Constant	-13.890***	(1.069)	-13.824***	(0.912)	-13.825***	(0.911)
Price	-1.549***	(0.504)	-1.842***	(0.441)	-1.847***	(0.436)
Efficiency	45.176***	(16.978)	52.423***	(15.649)	52.595***	(15.51)
Technology	-0.457	(0.479)	-1.123	(1.826)	-1.127	(1.858)
Demographics, (θ)						
Income	0.230**	(0.109)	0.248	(0.153)	0.248	(0.154)
Education	-7.234***	(1.676)	-7.464***	(2.110)	-7.466***	(2.125)
Urbanization	-0.226***	(0.026)	-0.239***	(0.037)	-0.239***	(0.037)
Race	0.573	(0.393)	0.509	(0.435)	0.509	(0.435)
Democrats	1.872***	(0.452)	2.002***	(0.412)	2.003***	(0.412)
Taste variation, (Σ)						
Price	0.438**	(0.224)	0.483	(0.313)	0.483	(0.315)
Efficiency	7.305	(5.833)	4.555	(7.299)	4.454	(7.360)
Technology	0.320	(1.773)	1.358	(1.672)	1.362	(1.695)
Fixed Effects						
Manu-Inst F.E.	Yes		Yes		Yes	
Year F.E.	Yes		Yes		Yes	
Cost side						
Constant	-3.417***	(0.011)	-3.156***	(0.008)	-3.267***	(0.009)
Efficiency	6.733***	(0.022)	3.963***	(0.017)	3.892***	(0.017)
Wage Rate	0.131***	(0.0004)	0.182***	(0.0003)	0.184***	(0.0003)
Friction Term	0.047***	(0.0003)	0.049***	(0.0002)	0.055***	(0.0002)
Installer F.E.	Yes		Yes		Yes	
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 $/W); Efficiency represents the energy conversion efficiency; Technology represents the type of solar photovoltaic technology, which equals to one if it is made of polycrystalline solar panels and zero otherwise; Income, Education, Urbanization, Race, and Democrats are MSA-level demographics as described in Table 3. We control for the manufacturer-installer fixed effects and year fixed effects on the demand estimation. On the supply side, Wage Rate refers to the MSA-level wage rate ($/hour) for the roofing installers, and Friction Term represents the logarithm of one plus cumulative installation capacity for a manufacturer-installer pair. We control for installer fixed effects and year fixed effects on the supply side estimation. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Simulation Results for Main Scenarios: Removing All Tariffs

Panel A: Demand Response				
Origin Country	Manufacturer	Model 1	Model 2	Model 3
China	Canadian Solar	72.8%	77.5%	79.6%
	Trina Solar	66.1%	68.4%	68.5%
	Yingli Energy	80.2%	85.9%	85.8%
USA	SunPower	-0.7%	-0.7%	-0.6%
South Korea	Hanwha	-0.6%	-1.0%	-0.8%
	Hyundai	-0.6%	-0.9%	-0.7%
	LG	-0.7%	-0.7%	-0.5%
Japan	Kyocera	-0.8%	-1.8%	-1.7%
German	Solar World	-0.8%	-0.8%	-0.7%
Norway	REC Solar	-0.5%	-1.2%	-1.0%
Total		17.2%	18.0%	18.1%
B: Welfare Distribution (in 2015$ million)				
		Model 1	Model 2	Model 3
Δ Consumer Surplus		369.6	331.7	331.0
Δ U.S. Manufacturers		-4.6	0	-3.8
Δ Chinese Manufacturers		271.4	0	279.3
Δ Korean Manufacturers		-2.9	0	-2.7
Δ Other Manufacturers		-5.8	0	-9.1
Δ Installers		291.8	266.1	0
Δ U.S. Tariff Revenue		-366.0	-382.9	-382.8
Total		553.5	214.9	211.9
Panel C: Environmental Benefit				
		Model 1	Model 2	Model 3
Δ Reduced CO2 (million tons)		7.0	7.4	7.4
Δ Reduced Cost (2015$ million)		253.3	265.6	266.2

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 6: Simulation Results: Removing All Tariffs and No Inertia

Panel A: Demand Response				
Origin Country	Manufacturer	Model 1	Model 2	Model 3
China	Canadian Solar	60.6%	66.1%	64.1%
	Trina Solar	62.3%	66.4%	65.9%
	Yingli Energy	73.7%	76.6%	75.1%
USA	SunPower	-0.9%	-0.8%	-0.7%
South Korea	Hanwha	-0.7%	-1.1%	-0.9%
	Hyundai	-0.6%	-1.1%	-0.9%
	LG	-0.9%	-0.8%	-0.7%
Japan	Kyocera	-0.6%	-1.9%	-1.9%
German	Solar World	-0.8%	-0.9%	-0.7%
Norway	REC Solar	-0.0%	-1.2%	-1.1%
Total		13.2%	14.3%	13.9%
Panel B: Welfare Distribution (in 2015$ million)				
		Model 1	Model 2	Model 3
Δ Consumer Surplus		524.1	539.9	565.0
Δ U.S. Manufacturers		-8.7	0	-10.1
Δ Chinese Manufacturers		407.1	0	501.5
Δ Korean Manufacturers		-5.1	0	-6.0
Δ Other Manufacturers		-1.7	0	-20.9
Δ Installers		426.6	446.1	0
Δ U.S. Tariff Revenue		-534.9	-639.6	-669.2
Total		807.4	346.4	360.3
Panel C: Environmental Benefit				
		Model 1	Model 2	Model 3
Δ Reduced CO2 (million tons)		11.1	13.3	14.1
Δ Reduced Cost (2015$ million)		399.2	478.8	506.0

Note: This table reports the results for demand response and welfare change if we remove all tariffs and remove inertia in vertical contracting. 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 dollars.

Table 7: Simulation Results: Effective Tariffs = 50%× Statutory Tariffs

Panel A: Demand Response				
Origin Country	Manufacturer	Model 1	Model 2	Model 3
China	Canadian Solar	33.7%	35.2%	35.0%
	Trina Solar	30.5%	31.0%	31.0%
	Yingli Energy	36.6%	38.4%	38.4%
USA	SunPower	-0.3%	-0.3%	-0.3%
South Korea	Hanwha	-0.3%	-0.5%	-0.4%
	Hyundai	-0.3%	-0.4%	-0.3%
	LG	-0.3%	-0.3%	-0.2%
Japan	Kyocera	-0.4%	-0.9%	-0.8%
German	Solar World	-0.4%	-0.4%	-0.3%
Norway	REC Solar	-0.2%	-0.5%	-0.4%
Total		7.9%	8.1%	8.1%

Panel B: Welfare Distribution (in 2015$ million)			
	Model 1	Model 2	Model 3
Δ Consumer Surplus	174.7	152.3	152.5
Δ U.S. Manufacturers	-2.2	0	-1.9
Δ Chinese Manufacturers	126.8	0	128.4
Δ Korean Manufacturers	-1.4	0	-1.3
Δ Other Manufacturers	-2.8	0	-4.3
Δ Installers	136.4	122.2	0
Δ U.S. Tariff Revenue	-149.9	-153.1	-153.1
Total	281.6	121.5	120.4

Panel C: Environmental Benefit			
	Model 1	Model 2	Model 3
Δ Reduced CO2 (million tons)	3.2	3.3	3.3
Δ Reduced Cost (2015$ million)	116.5	119.6	120.0

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 8: Tariff Pass-through

	Without Equilibrium Response		With Equilibrium Response		Pass-through
	Percent (%)	Level ($)	Percent (%)	Level ($)	
Model 1	(1)	(2)	(3)	(4)	(5)
With Inertia Term	12.69	2,911	17.05	3,765	1.35
Without Inertia Term	12.69	2,598	16.70	3,323	1.32
50% × Statutory Rates	6.34	1,549	8.60	2,063	1.37
Model 2					
With Inertia Term	12.69	2,911	14.81	3,315	1.17
Without Inertia Term	12.69	2,599	14.47	2,922	1.15
50% × Statutory Rates	6.34	1,549	7.36	1,775	1.16
Model 3					
With Inertia Term	12.69	2,911	14.68	3,292	1.16
Without Inertia Term	12.69	2,544	14.34	2,832	1.13
50% × Statutory Rates	6.34	1,549	7.41	1,778	1.17

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

Table 9: Sensitivity Test

Average Tariff Pass-through for All PV Systems			
Demand Elasticity	Consumer's Final Price	Manufacturer's Markup	Installer's Markup
-1	1.16	0.16	0.20
-2	1.20	0.15	0.30
-3	1.26	0.44	0.50
-3.65	1.33	0.51	0.72

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 and the inertia term exists between the manufacturer-installer relationship. The sensitivity tests are based on the estimation results from Model 1. We calculate the average (capacity weighted) 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

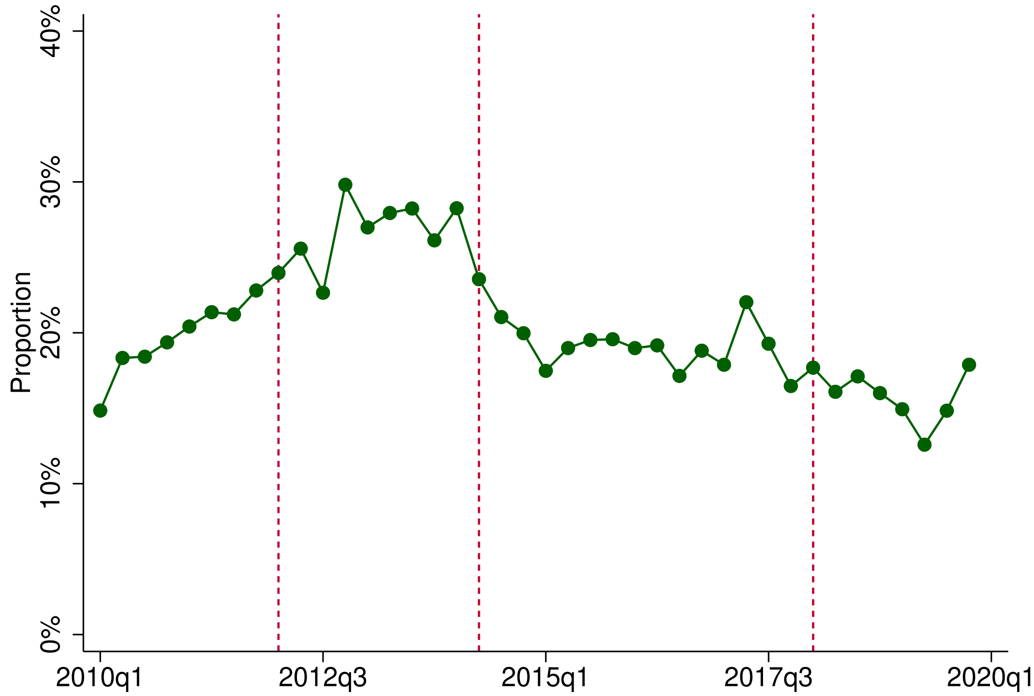

Figure A1: Proportion of Chinese Manufacturers Each Installer is Working with

Notes: This figure shows the average proportion Chinese manufacturers account for in each installer's suppliers from 2010q1 to 2019q4.

Table A1: First Stage Regression for Switching Behavior

	(1)	(2)	(3)	(4)
Variables	Price	Price	Price	Price
Tariff	0.099***	0.096***		
	(0.031)	(0.031)		
Tariff_dollar			0.424**	0.425**
			(0.182)	(0.182)
Log(1+Capacity)		0.029***	0.035***	0.033***
		(0.011)	(0.012)	(0.012)
Efficiency		1.237		2.601
		(1.535)		(1.639)
Technology		-0.017		-0.021
		(0.035)		(0.038)
Constant	3.871***	3.541***	3.621***	3.185***
	(0.010)	(0.273)	(0.056)	(0.296)
Year F.E.	Yes	Yes	Yes	Yes
Manufacturer-Installer F.E.	Yes	Yes	Yes	Yes
Observations	20,379	20,379	16,749	16,749
Cragg-Donald Wald F statistic	18.47	17.11	10.91	10.92
R-squared	0.754	0.754	0.730	0.730

Note: This table reports the first stage regression results on the switching behavior for the solar installers. Our sample period is from 2011 to 2018. $Tariff$ is a dummy variable which equals to one if the tariff is put in place and zero otherwise. $Tariff\_dollar$ translates the tariff into dollar amount by using the average installed price in 2011 multiplied by the tariff rates. Manufacturers with less than 10 solar PV systems are excluded from our sample. Installers who installed fewer than 10 solar PV systems are excluded from our sample. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A2: 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 A3: List of Solar Installers

Number	Name	Number	Name
1	Tesla Energy	7	REC Solar
2	Vivint Solar	8	Verengo
3	SunPower	9	Trinity Solar
4	Sunrun	10	Sungevity
5	PetersenDean	11	All Others
6	Titan Solar Power		

Notes: This table lists the 11 groups of solar installers in the U.S. market. The first 10 groups are the 10 biggest solar installers, as marked by numbers 1 - 10, and the 11th group is all other solar installers.

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

VARIABLES	Model 1	Model 2	Model 3
BLP_eff	0.024***	0.059***	0.045*
	(0.009)	(0.020)	(0.023)
BLP_tech	0.002	0.007	0.009
	(0.004)	(0.008)	(0.008)
$(\text{BLP\_eff})^2$		-0.002**	0.002
		(0.001)	(0.003)
$(\text{BLP\_tech})^2$		-0.0001	0.0005
		(0.0001)	(0.0004)
BLP_eff $\times BLP\_tech$			-0.003
			(0.002)
Control Variables	Yes	Yes	Yes
Manufacturer-Installer F.E.	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
Observations	6,653	6,653	6,653
Cragg-Donald Wald F statistic	30.63	21.41	18.01
R-squared	0.44	0.44	0.44

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 A5: Demand Estimation with Berry's (1994) Market Shares: Second-stage Regressions

VARIABLES	Model 1	Model 2	Model 3
Price	-2.011***	-1.263***	-1.559***
	(0.907)	(0.620)	(0.615)
Control Variables	Yes	Yes	Yes
Manufacturer-Installer F.E.	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
Observations	6,653	6,653	6,653

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 A6: Nonnested Test for Model Selection

	H2	
H1	Model 2	Model 3
Model 1	1.09	1.06
Model 2	-	0.54

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 A7: Parameters Used for Simulations

Panel A: Anti-dumping and Countervailing Duty Rate (%)

	Anti-dumping			Countervailing		
	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

Panel B: Breakdown of Total Installed Price

Year	Total Price	Panel Price	Non-Panel	% Panel Price
2012	5.71	1.02	4.7	17.91%
2013	4.91	0.98	3.9	20.04%
2014	4.51	0.85	3.7	18.92%
2015	4.42	0.76	3.7	17.16%
2016	4.23	0.56	3.7	13.33%
2017	3.99	0.48	3.5	12.09%
2018	3.78	0.59	3.2	15.48%

Note: Panel A reports the anti-dumping and countervailing duties rates imposed on the imported solar panels produced by Chinese manufacturers. It lists the anti-dumping duty rates and countervailing rates faced by different Chinese manufacturers during the three waves of anti-dumping policies (2012, 2014, and 2018) initiated by the U.S. government against China. Panel B reports the trend of solar prices from 2012 to 2018. Total Price is the total installed price ($/W), which is decomposed into panel price and non-panel price. The data is from Lawrence Berkeley National Laboratory.

Table A8: Price, Marginal Costs, and Markups

	Baseline 1	Baseline 2	Counterfactual 1	Counterfactual 2
	(1)	(2)	(3)	(4)
Model 1				
Price	4.062	3.495	3.884	3.339
Markup for manufacturer	0.840	0.837	0.824	0.833
Markup for installer	1.162	1.074	1.129	1.044
Joint marginal cost	2.126	1.636	2.126	1.636
Model 2				
Price	4.062	3.496	3.906	3.360
Markup for manufacturer	0	0	0	0
Markup for installer	0.955	0.907	0.933	0.888
Joint marginal cost	3.107	2.592	3.107	2.592
Model 3				
Price	4.062	3.423	3.907	3.290
Markup for manufacturer	0.941	0.880	0.920	0.862
Markup for installer	0	0	0	0
Joint marginal cost	3.190	2.610	3.190	2.610

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; Baseline 2 refers to the simulated scenario when the tariffs are in place and the inertia term in the manufacturer-installer relationship is removed; Counterfactual 1 refers to the simulated scenario when the tariffs are removed; Counterfactual 2 refers to the simulated scenario when the tariffs are removed and the inertia term in the manufacturer-installer relationship is also removed.