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

Preliminary—Comments Welcome

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Abstract

This paper investigates the distributional welfare effects of the recent trade war in the solar sector where the U.S. government initiated trade tariffs against Chinese solar manufacturers. We estimate a structural econometric model that incorporates the vertical structure between upstream solar manufacturers and downstream solar installers. Our counterfactual simulations show that the tariffs had a large negative impact on U.S. consumers. We estimate the pass-through rate and find evidence of over-shifting; imposing a \$1 tariff increases the final price of a U.S. solar system by \$1.34. On the firm side, U.S. manufacturers gained little from the anti-dumping policies whereas U.S. installers were largely negatively affected, as well as Chinese manufacturers. Overall, our results suggest that the solar trade war led to large welfare losses in both countries and substantially slowed the adoption of solar PV.

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

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1 Introduction

After decades of trade liberalization, protectionism has reemerged in recent years, characterized by the U.S.-China trade war, the Japan-South Korea trade dispute, and the Brexit negotiation. It may even gain momentum in the post-pandemic world as a consequence of national stimulus efforts (Evenett, 2020). Protectionism measures are often initiated in fast-growing and high-value sectors, such as semiconductor, solar photovoltaic (PV), automobile, and telecommunication industries. Trade wars arise when cycles of subsidies and retaliating tariffs are enacted to protect domestic companies. The market for solar PV is a case in point on how trade wars can quickly escalate.

The goal of this paper is to quantify the welfare effects of the anti-dumping and countervailing duties initiated by the U.S. government against Chinese solar manufacturers. Using a structural econometric oligopoly model that accounts for the vertical structure of the market, we measure the incidence of these tariffs on four actors: U.S. solar manufacturers, Chinese solar manufacturers, U.S. solar installers, and U.S. consumers. In addition, we also quantify the carbon and local air pollution externalities associated with the adoption of solar PV systems that would have displaced electricity generation from fossil fuels in the absence of these tariffs.

In the past fifteen years, we have witnessed a rapid growth of the solar PV industry. The installed capacity of PV systems has soared almost 100-fold worldwide, from 6.7 GW in 2006 to 629 GW in 2019. While the solar manufacturing sector has been historically dominated by companies located in the U.S., Japan and Germany, Chinese firms have gradually gained market share since 2010.[1] The rapid growth of the Chinese solar sector was spurred by various government subsidy schemes that allowed to reduce the manufacturing costs of solar panels. Chinese manufacturers' competitors, however, suspected that these schemes provided an unfair competitive advantage. In May 2012, the U.S. Department of Commerce thus announced various duties ranging from 31% to

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

250% on Chinese solar panels. In retaliation, China also imposed tariffs on exports of polysilicon products from the U.S. Although this trade war affected companies in both countries, Chinese solar manufacturers appeared to be particularly negatively impacted. For example, Suntech Power, a Chinese firm that was 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 that these tariffs had on U.S. consumers and other domestic firms in the solar supply chain, such as installers. 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.

Though trade wars have been widely discussed, the full welfare impacts of the trade tariffs in the context of the recent U.S.-China trade war have remained underexplored, especially considering the market structure of certain industries.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 does not account for the role of market structure and, more importantly, abstracts from imperfect competition. This is a key focus of our study. 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 that aims to protect domestic upstream firms may deteriorate the profits of downstream firms by rising costs, final purchase prices and reducing overall demand. As a result, protectionist measures could lead to a contraction in market capacity and an overall welfare loss in the domestic market.

In order to measure the distribution of benefits and costs among upstream and downstream market participants, we develop a structural equilibrium model where we model the vertical structure of the industry and explicitly account for the strategic behaviors of domestic (i.e., U.S.-based) and foreign manufacturers, as well as 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 price and other product characteristics of solar PV systems.

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 that there is substantial inertia in the relationship between a given solar installer and the manufacturer(s) that provide(s) her with solar PV systems. 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 (Kellogg, 2011), among other reasons. We show that this inertia varies with past installation capacity. In our estimation, we thus explicitly take into account this inertia by modeling installer-manufacturer preferences, which capture various types of transaction costs. We found that this effect tends to increase firms' marginal costs, which suggests that inertia in the contractual vertical relationship ultimately induces cost inefficiencies. In our counterfactual simulations, we show that this inertia has a large impact on the welfare effects.

Our main data come from the Lawrence Berkeley National Laboratory (LBNL)'s *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 2012-2018. We observe when and where a household installed its solar system, the size, the price, the brand of the solar PV system,[2] 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 for the democratic party tend to install

[2]The brand of the solar PV system refers to the brand of the solar panels (modules), which is the main component of the solar PV systems.

relatively more solar PV systems. On the supply-side, we find that 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 that the statutory rates of the tariffs correspond to their effective rates.[3] Under this assumption, the results show that without the anti-dumping and countervailing duties imposed during the 2012-2018 period, the U.S. demand for solar PV systems would have been 17.2% higher. Furthermore, Chinese manufacturers incur large losses in profits due to the anti-dumping policies, and U.S. manufacturers gain little. U.S. installers suffer large losses from these trade barriers. The solar trade war had also large negative impacts on environmental externalities. In the absence of anti-dumping policies, the increase in the adoption of solar PV systems would have reduced the electricity generated from fossil fuels. We estimate that the environmental benefits arising from CO2 emissions avoided would have been 1.11 billion dollars.

Our model can also be used to estimate the pass-through rate of the tariffs. In our main simulations, we find that a \$1 tariff imposed on manufacturers leads to a \$1.34 increase in the final prices of installed PV systems. Manufacturers and installers thus over-shift the burden of the trade tariffs on U.S. consumers.

Finally, our counterfactual scenarios also show that the nature of the contractual relationship and in particular the inertia between installers and manufacturers have an important effect. If we remove the inertia in the manufacturer-installer relationships, the estimated overall welfare effect is more than 20% 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

[3] As we further discuss below, there were loopholes in the U.S. anti-dumping policies, especially in the fist wave in 2012, which 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.

impact of trade wars. The theory of strategic trade policy argues that, 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). Most empirical studies of strategic trade policy have been simulation models in which theoretical models are parameterized to simulate policy experiments (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 representation of the market structure of our focal market. In addition, this paper contributes to the literature on the incidence of trade tariffs.[4] 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 over-shifting (i.e, pass-trough rate higher than 100 percent). Most notably, Flaaen et al. (2020)'s analysis of the 2018 U.S. tariff on clothes washers implies a pass-through exceeding 100 percent. The fact that we find tariff over-shifting in the U.S. solar market is also consistent with Pless and Van Benthem (2019)'s findings, who found pass-through rates exceeding 100 percent for solar subsidies. These results for the U.S. clothes washer market and solar PV market can be attributed to the presence of market power,[5] 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 relationships. Long-term procurement contracts and organizational preferences are important drivers of the stickiness of vertical relationship 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).

[4] 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 a literature on the incidence of tariffs.

[5] Bulow and Pfleiderer (1983) and Seade (1985) provided the first theoretical evidence of tax over-shifting 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.

Kellogg (2011) showed that the productivity of an upstream firm (a large oil production company) and a downstream firm (a drilling contractor) can increases with their joint experience, providing evidence of learning-by-experience. Our work fits in with this literature by showing that the relationship between solar manufacturers and installers tend to be persistent. Policies that reduce matching frictions could lead to a significant reduction in total installed prices.

Third, our paper contributes to the growing literature in environmental economics on the solar power sector, which is key in addressing the negative externalities associated with electricity generation. One stream of this literature has focused on evaluating the factors leading to the adoption of residential solar power. These studies show that financial incentives, mandates, peer effects and social interactions are all important drivers of solar adoption in the U.S. (Bollinger and Gillingham, 2012; Burr, 2016; Gillingham and Tsvetanov, 2019; De Groote and Verboven, 2019; Dorsey, 2020; Gillingham and Bollinger, 2021). The timing of government subsidy can also affect households and the adoption of solar PV (Bauner and Crago, 2015; Langer and Lemoine, 2018). A second stream of the literature has investigated the reasons that explain the large and rapid reduction in the costs of solar systems (Reichelstein and Sahoo, 2015). For instance, Bollinger and Gillingham (2019) find that learning-by-doing among installers lowers the solar prices, primarily the non-hardware costs of the solar PV installations. Gerarden (2017) finds that consumer subsidies can encourage firms to innovate to reduce their costs over time. Our work contributes to this literature by investigating the role of trade policies, which, as we show, can be an important determinant in determining the growth of the solar PV market.

The 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 concludes.

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

In this section, we provide background information to understand 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. and China's solar subsidies, and finally the anti-dumping duties initiated by the U.S. government against Chinese manufacturers.

2.1 The U.S. Solar Market

The U.S. has one of the world's largest installed capacity of solar power. In 2016, solar power overtook wind, hydro and natural gas to become the largest source of new electricity capacity (EIA, 2018). In 2019, the cumulative operating PV capacity exceeded 76 GW, up from just 1 GW at the end of 2009.[6] The importance of the solar industry for the U.S. is also reflected by its contribution to job creation. Solar employment in the U.S. grew by 167% from 2010 to 2019, adding more than 156,000 jobs, according to the National Solar Jobs Census.[7]

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

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

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

subsidies targeting consumers.[8] On the other hand, the technology itself has improved. The manufacturing costs of solar PV systems have drastically decreased whereas 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 of the solar industry consists of the manufacturing segment that produces solar PV systems (solar panels), whereas the downstream consists of the installation segment that acts as distributors and provider of installation service for the customers. Though the installation may seem straightforward, there are numerous activities and costs associated with it, such as permitting, inspections, balance of systems components, other installation-related tasks that are labor intensive, as well as long-term maintenance and repair. Due to the large decrease in PV hardware costs over the past two decades, the installation costs, which are referred as the 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. In Europe, Germany has been an early mover. Starting in the mid-2000s, the Chinese government has oriented its industrial policy to develop the solar sector. As a result, in 2008, China became one of the world's largest manufacturers of solar panels and the largest producer in 2015. The extremely rapid development of its solar industry coincided with generous

[8] 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 leading to the recent growth of the solar sector. The financial subsidy for residential solar PV installations at the state level varies considerably from place to place 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, an additional tax credits offered by some states; 3) Solar Renewable Energy Certificates (SREC), credits that the homeowner can obtain by selling the solar electricity to the grid; 4) Performance-based Incentives (PBI), per kilowatt-hour credits that are paid based on the actual total energy produced by the solar system during a certain period of time.

government subsidies and support. China's solar subsidies initially focused on the manufacturing side. There have been four types of subsidies provided by the Chinese government to its domestic solar manufacturers (Ball et al., 2017). First, there have been tax breaks, which consisted of a credit of 50% of the value-added tax. These tax breaks were first implemented in 2013 for two years, and then extended through 2018. Second, there have been subsidized land, where some Chinese solar manufacturers received free or discounted land from local governments. Third, there have been cash grants offered by municipal and provincial governments. Fourth, there have been preferential lending programs where government-affiliated banks have provided advantageous loans. In particular, the China Development Bank (CDB), an organization controlled by the Chinese government, has been the primary lender to Chinese solar manufacturers.

2.3 U.S. Anti-dumping Policies

In October 2011, German-owned SolarWorld, which was then America's largest solar panel manufacturer, filed an anti-dumping petition against Chinese solar companies. They alleged that the Chinese government was unfairly subsidizes crystalline silicon photovoltaic 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% and 15.9% would be imposed on Chinese manufacturers.[9] This was the first wave of U.S. tariffs against Chinese solar

[9]The provisional anti-dumping duty deposits and countervailing duty deposits were collected as of the date of publication of Commerce'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 fifty-nine 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`

manufacturers.

However, this ruling applied only to solar panels made from Chinese solar cells, which created an important loophole. Some Chinese companies could circumvent the tariffs when exporting to the U.S. 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 China and Taiwan. The anti-dumping duty rates then ranged from 26.71% to 165.04% and the countervailing duty rates then ranged from 27.64% to 49.79%.[10] This marked the second wave of tariffs.

The third wave started on January 2018, when the U.S. government put additional 30% tariffs on all imported solar modules and cells (China, Korea and other countries were all subject to this safeguard tariffs) given the existing tariffs on Chinese solar products. The tariff was designed to step down in 5% annual increments over four years. Finally, the last episode of the solar trade war culminated on July 2018 when the U.S. government put another 25% tariffs on Chinese solar products as a part of the broader U.S.-China trade war on $50 billion dollars 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 that there is inertia among installers to switch suppliers (manufacturers). Frictions in the vertical contractual

[10] The provisional anti-dumping duty deposits and countervailing duty deposits were collected as of the date of publication of Commerce's preliminary determinations, which was 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 forty-three 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`

relationship thus discourage installers to substitute from high-cost to low-cost manufacturers.

3.1 Data Preparation

We work with solar installation data from the Lawrence Berkeley National Laboratory (LBNL)'s *Tracking the Sun* report series, which contains information on prices and quantities of all residential U.S. solar PV installations. The original sources of the data come from state agencies and utility companies that manage solar PV incentive programs and solar energy credits. As of the end of 2018, the dataset included over one million solar PV installations with 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 each module 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 that install the manufacturer's PV modules. Our sample period begins in 2012, just prior 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. While there were around 270 different solar manufacturers operating in the U.S. market from 2012 to 2018, the ten largest manufacturers accounted for approximately 80% of the solar module sales. Manufacturers from the U.S., China, South Korea, German and Japan dominated the market. The downstream market is more fragmented due to its local nature. There have been 4,990 different firms that have installed at least one residential PV system in the U.S. during the sample period. However, about 50% of these installers installed no more than five systems and many may represent firms from related industries (such as electrical contracting) where PV installation is not their primary activity (OShaughnessy, 2018).

Through time, the market for PV installations has become increasingly concentrated. As shown in Panel B of Table 1, on average, the number of different active installers for each state has increased from 90 in 2012 to 215 in 2018, while the market share for the largest installer in each state has increased from 32.51% in 2012 to 46.15% in 2018. The 15 highest-volume installers accounted for approximately 50% of U.S. solar PV installations during the 2012-2018 period.

On average, each installer worked with approximately four different manufacturers between 2012 and 2018 (see Panel A of Table 1). Installers with a national footprint worked with more manufacturers compared to installers that operated only in a few local geographical markets. For example, Tesla Energy, the largest solar installer in the U.S. procured solar panels from 50 different solar manufacturers, while Solergy, a local installer operating mainly in Texas, worked with only one manufacturer.

Figure 1 shows the time trend of market share for Chinese manufacturers and U.S. manufacturers, which provides the first evidence of inertia in the installer and manufacturer relationship. In 2011-Q1, 23.16% of the installations done by U.S. installers used solar modules 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-Q3. This increase could be due to the fact that Chinese companies 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 companies noticed the U.S. government were 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%. After the third wave of anti-dumping policies starting in 2018, the market share of Chinese manufacturer decreased to 15.58%, which is about 8% points below the pre-trade war level. Compared with Chinese manufacturers, the market share of U.S. manufacturers was relatively stable.[11]

3.3 Switching Behavior in Manufacturer-Installer Relationships

We now examine switching behavior between manufacturers and installers. Specifically, we use a regression model to quantity the likelihood that an installer switches 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.[12] We define our outcome variable with a dummy variable $Stay_{rmt}$ as the baseline definition of no-switching behavior. The dummy takes a value of one if installer r acquiring solar modules in year t from a manufacturer m also purchased solar modules from that manufacturer in the following year $t+1$, and zero otherwise. In another specification, we also use the dependent variable: $StayVol_{rmt}$, which is defined as the logarithm of one plus the solar PV capacity that installer r has installed using the solar modules made by manufacturer m in year $t+1$. We generate these two variables for the whole universe of U.S. residential solar PV installations from 2012 through 2018.

In Panel B of Table 1, we show summary statistics related to the dependent variable. Overall, they show that a sizable share of U.S. installers maintained the same manufacturer over time. From 2012 to 2018, the average proportion of installers that chose to stay with their current suppliers in the next year increased from 48.10 % to 58.80%, and the overall average is 55%. As suggested by Monarch (2018), we can compare this share to what would happen if buyers were to randomly select modules from suppliers, which is the benchmark if their were no switching costs. In our sample, there are approximately 149 large manufacturers that can supply PV modules to U.S.

[11]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.

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

installers.[13] If each supplier had equal chance to be chosen, the probability that an installer stay with the same manufacturer would be 1/149, or only 0.7%. Path dependence is thus very high in our sample.

There are several potential explanations for the persistence in the installer-manufacturer relationship. Learning-by-experience, as suggested by Kellogg (2011), could be one explanation. Switching costs, as suggested by Monarch (2018), which are due to the 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. For a given installer-manufacturer pair observed at a point in time, learning-by-experience would then be at the source of what we refer as a positive selection effect. 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 function of past experience. The more experience an installer-manufacturer pair has together the more learning opportunities there is 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 $Log(1 + Capacity)$, 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

[13] Given that some small installers and small manufacturers have few observations in the dataset and may bias our estimation, we delete those installers that have less than 10 installations and those manufacturers that have less than 10 sales in the United States from our sample.

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 endogeneous. We perform two robustness tests to assess whether it impacts the coefficient θ. First, we simply omit the price and quality variables from the regression. Second, we use an instrumental variable strategy. Specifically, we use the tariffs imposed on Chinese solar manufacturers as instruments for the installed price.[14]. They are effectively cost-shifters that impact the manufacturers' price and that are uncorrelated with past experience between a given manufacturer-installer pair.

For this estimation, the sample period is from 2012 to 2018. Since 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 installations is not their primary business. We also drop observations for solar manufacturers whose panels are used in no more than 10 installed 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

[14]The value of the instrumental variable for the installed price of solar PVs using panels produced by non-Chinese manufacturers from 2012 to 2017 is zero. However, in the third wave (2018) of antidumping duties, the U.S. government put additional 30% tariffs on all imported solar modules and cells. Therefore, the value of instrumental variable for the installed price of solar PVs using panels produced by other manufacturers (non-American and non-Chinese) is 30% in 2018.

regressions. Columns (1) - (3) show that past experience in manufacturer-installer relationships is strongly correlated with a higher probability of an installer staying with its upstream manufacturer. It implies that an installer is reluctant to switch to a different manufacturers if she has substantial prior experience working with a given manufacturer. Columns (4) shows that results hold using the level of installations as a dependent variable, denoted $StayVol$, instead of the dummy variable $Stay$.

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

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 the main characteristics of solar PV systems. A consumer can choose the solar installer as well as different models of solar PV systems to install. Since our data are aggregated to the module model/installer/year level, we assume that a consumer's choice is a module-installer combination, indexed by j. That is, consumers have preferences for both the manufacturer producing a given PV module and the installer performing the installation of the say module. We use a static random coefficient discrete choice model to analyze consumer purchase decision. The conditional indirect utility of consumer

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

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

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 that the same PV module 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_{ijt} 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 house in MSA w; A is the proportion of single-unit houses with value greater than 100,000 US dollars;[15] and V is the percentage of buildings which are solar-viable in that MSA level. The observed market share of product j is then given by $s_{jwt} = q_{jwt}/(M_w \times A \times V)$.

For a simple mulitnomial 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 that the model is static and, thus, consumers are not forward looking. In theory, forward-looking consumers may have anticipated the drastic decrease in the price of solar PV systems and delay their purchase decision. In such a case, a static demand specification may underestimate the true price elasticity (Aguirregabiria and Nevo, 2013). However, as argued by

[15] We choose a house value of 100,000 US dollars or greater as a cut-off to define potential adopters. The estimation results do not change significantly with this cut-off value.

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 that 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. To solve for this game, it is standard 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 retail price p_{jt} after observing the set of solar PV 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, which includes the price of the solar PV system and the price on the installation. 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 price that they charge installers after observing demand and marginal cost shocks. Solar manufacturer m's profit-maximizing problem for is 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 that 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 details below. The joint marginal cost is

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

where Y_t includes modules' 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 the total installed capacity for a manufacturer-installer pair in the previous one year. As discussed in Section 3, it captures various phenomena that could induce 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, that 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.

5 Implementation

5.1 Data

For estimating the model, the main dataset comes from the Lawrence Berkeley National Laboratory (LBNL)'s *Tracking the Sun* report series, as described in Section 3, which we combine with 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 U.S.;[16] (2) labor market data from the U.S. Bureau of Labor Statistics, which provide hourly wage rate for roofing across different states; and (3) solar potential data from the Google Project Sunroof, which we use to estimate the technical solar potential of all buildings in each U.S. county and to determine the percentage of buildings that are solar-viable in that county.

We conduct 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 modules that have significant sales (more than 3,000 units) in the U.S. The sample consist of 58 models produced by ten solar manufacturers, and these solar manufacturers include three Chinese companies (Canadian Solar, Trina Solar and Yingli Energy), two US companies (SunPower and REC Solar), two South Korean companies (Hanwha, Hyundai and LG), one Japanese companies (Kyocera Solar), and one German companies (Solar World). In Table A2 in the appendix, we report an exhaustive list of solar module models found in the sample.

For the downstream market, given there is a large number of installers in the sample, we classified the installers into eleven groups. The first ten groups represent the installers who have significant market share across the U.S. (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 module they used in this given market (MSA-year). This means that the same installer located in different markets (space or time) may have a different consideration set when it comes to choose solar module. 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

[16] 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 price gross of subsidy for a solar PV system is \$4.23/W, with a standard deviation of \$0.87/W. The average final price paid by the consumer for a solar PV system is \$4.06/W, which implies that the average government subsidy received by the consumers represents 4% of the total installed price.[17] The average energy conversion efficiency for solar panels 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 that a panel can convert solar energy at a lower cost. Technology is a dummy variable which equals to one if the solar module is made of polycrystalline panels and zero if it is made of monocrystalline panels. About 43% of the solar modules are made of polycrystalline cells.[18] Panel B lists demographic information at the MSA level. The average median housing price (our proxy for household income) is 442k dollars 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 whites, and 55% people voted for 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, and 91% of the houses have values greater than 100,000 US dollars. The average wage rate for PV installation across different MSAs is \$24.79/hour. Finally, the inertia term we constructed, defined as the logarithm of installed capacity for manufacturer-installer pair, has a mean value of 9.94 with a standard deviation of 2.12.

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 (1994) where we identify the

[17] The government subsidy received by consumers 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.

[18] Monocrystalline solar panels are generally thought of as a premium solar product and their main advantages are higher efficiencies and sleeker aesthetics compared to polycrystalline solar panels.

coefficient on the price using variation from other product characteristics, i.e., the variation 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 hold 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 BLP instruments using product characteristics that are determined early in the manufacturing process and that 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.[19] The F-tests of the joint significance of the instruments in all three models yield values greater than 10. The results suggest that the instruments do have explanatory power. Moving to the second-stage estimates, Berry-style market shares (i.e., $\ln s_{jwt} - \ln s_{0wt}$) are regressed on the instrumented prices. The results in Table A5 show that BLP instruments lead to a significant and negative price coefficient. Overall, the BLP instrumental variable set performs well in our setting.

6 Estimation Results

We jointly estimate the demand-side and supply-side using the Generalized Method of Moments (GMM). As recommended by Dubé et al. (2012) and Grigolon et al. (2018), we pay close

[19]In Model 3, the instrumental variable set thus includes five variables, i.e., BLP_eff, BLP_tech, $(BLP\_eff)^2$, $(BLP\_tech)^2$, $BLP\_eff \times BLP\_tech$.

attention to a variety of computational issues. First, we approximate the integral for the market shares using 200 draws of a quasi-random number sequence for each market. Second, we use a tight convergence level of 1e12 for the contraction mapping of the inner loop within the GMM objective function. Third, we use the advanced optimization algorithms in Knitro to minimize the GMM objective function and set a strict tolerance level at 1e-6. Fourth, we use a set of 20 starting values to search for a global minimum, and verify the solution by checking the first-order and second-order conditions. Finally, we use optimal instruments, which greatly improves the efficiency of the estimator.

Table 4 reports the estimation results in our main specification. The upper panel reports the mean marginal utility for each product characteristics (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 module efficiency is positive and statistically significant at the 1% level, suggesting that consumers favor solar PV with higher energy conversion efficiency. The coefficient on technology is positive although statistically insignificant.

The coefficients on income and political orientation are all positive and statistically significant at conventional levels, suggesting that areas with higher income and more supporters for the democratic party tend to adopt more solar PV systems. The coefficient on urbanization is negative and significant at the 1% level, implying that people in urban areas are less likely to install solar PV systems. The above results are intuitive and in line with previous findings (Kwan, 2012; Chernyakhovskiy, 2015). The coefficient on education is negative and significant at 1% level, suggesting that people living in areas with lower education levels have higher demand for solar PV system. This might seem counterintuitive, but it may be due to the fact that areas with high levels of education across the U.S. are located in areas less suitable for installing solar PV systems.[20] The taste variation parameter on price is statistically significant at 5% level, showing that consumers are heterogeneous with respect to their tastes for solar module prices.

The demand parameter in Table 4 yields a mean own-price elasticity of demand of -3.64. 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 A7 in the appendix. These statistics are broken down by upstream manufacturers/downstream installers of the solar PV systems. The mean margins for upstream manufacturers and downstream installers are \$0.807/W and \$1.162/W, respectively, yielding a mean total margin (upstream and downstream) of \$1.969/W. On average, the ratio of margin to total installed price, the Lerner Index, is 0.485.

Table 4 also reports additional estimation result on the supply side in our main specification. The significant and positive coefficient on energy conversion efficiency suggests that marginal costs are increasing with efficiency rate, as expected. The positive and statistically significant coefficient on wage rate also suggests that marginal costs are increasing with labor costs.

The estimated coefficient on the friction term is positive and significant at the 1% level. It implies that 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 that our modeling of selection effects is

[20]With respect to education, our findings are consistent with Sommerfeld (2016) who found that areas with the highest numbers of university educated persons have very low rates of installation of solar PV systems based on the setting of the Australian market. He argues that areas with the highest number of university educated persons tend also to be areas with a high concentration of units and apartments, which are not suitable for installing solar PV.

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 that switching costs are large enough to ultimately induce a negative selection at the installer-manufacturer level. Below, we also show that it has important implications for estimating the effect of trade tariffs in this market.

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 that trade tariffs had on manufacturers (U.S., China, and others), U.S. installers, and U.S. consumers.[21]

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 2012-2018 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 that the effective rates of the trade tariffs could have differed from the statutory rates announced by the U.S. Department of Commerce. The rationale for this scenario is the fact that Chinese solar manufacturers exploited various

[21] 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

$$\Delta CS = -\frac{1}{\alpha}\left[\ln\left(\sum_{j=1}^{J}\exp(W_j^1)\right) - \ln\left(\sum_{j=1}^{J}\exp(W_j^0)\right)\right] \tag{13}$$

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

loopholes to avoid the brunt of the tariffs. One notable example of such behavior, which has been well-documented and we discussed before, occurred in the first wave of tariffs when Chinese manufacturers relocated their panels assembly lines to Taiwan. As a result, it is believe that this wave of tariffs was largely ineffective. Of course, the reallocation of the assembly lines might have increased the manufacturing costs of the panels but presumably less than the statutory rates imposed. In our data, we cannot measure the which 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, the exact anti-dumping and countervailing duties imposed on Chinese manufacturers. Panel A of Table A6 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 need to know the proportion of module price versus non-module cost in a typical residential solar PV installation. This is because the anti-dumping and countervailing duties were only imposed on the solar module prices produced by the Chinese manufacturers and not on the final prices of installed systems. The challenge is that solar module prices are not observable in our dataset. We can only observe the total installed price faced by a consumer, which includes the module price and non-module cost, with the latter involving labor, overhead and marketing costs associated with solar PV installations (Bollinger and Gillingham, 2019). To calculate the tariffs imposed on each Chinese module, we recover the solar module price from the total installed prices by interpolating the fraction of the total price that could be attributed to the module. Panel B in Table A6 reports the breakdown of the total installed price in different cost components from 2012 to 2018, as reported by LBNL. In 2012, the module price accounted for 17.91% of the total installed price, while it decreased to 15.48% in 2018. Based on these data, we approximate the module prices and compute the dollar value of the tariffs imposed on each Chinese module.

Lastly, 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 CO2 externality. We set 25 years as the time limit for estimating environmental benefit, as most manufacturers provide a 25-year warranty on their solar products Gillingham and Tsvetanov (2019). During our sample period, Zivin et al. (2014) estimated that the average carbon dioxide emission rate across all U.S. regions was 0.000605 tons of CO2 per kWh. If we assume that the average number of full sunlight hours is 4 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 CO2 in 2015 US\$.

7.1.1 Removing Anti-dumping Policies

We first remove the U.S. tariffs against Chinese solar manufacturers and examine the equilibrium response, welfare change, and the related environmental benefit/loss. In Table 5, we present the results for the three waves of anti-dumping policies separately, and then the overall effect across the three waves (last column). Panel A shows that 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 (REC Solar, SunPower, Hanwha, Hyundai, LG, Kyocera and Solar World) 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. Among the three waves of anti-dumping policies, the second wave had the largest effect. We find that 79.7% (13.7/17.2) of the added solar capacity in the counterfactual scenario happened during the second wave, which also lasted the longest (2013-2017).

Panel B shows the welfare changes among the different market participants. Removing the anti-dumping policies provides welfare gains of 375.5, 271.4 and 291.8 million dollars for U.S. consumers, Chinese manufacturers, and U.S. installers, respectively. The losses for U.S. manufacturers is only 6.6 million dollars, whereas the decrease in U.S. tariff revenues is 365.6 million dollars. This suggests that the U.S. manufacturers gained little from the trade war. At the same time, the government revenues collected from the tariffs would have not have been enough to compensate consumers and installers. Overall, the domestic market does not benefit from the tariffs.

Panel C reports the related environmental benefit/loss. It shows that the emission of carbon dioxide would have been lower by 7.0 million tons in the absence of tariffs, which translates in an externality cost of 252.9 million dollars (in 2015$). Since the data in our final sample accounts for 21.6% of U.S. solar PV installations, the overall benefits associated with reducing the CO2 externality for the whole U.S. would amount to 1.2 billion dollars.

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 modules as predicted by the equilibrium model with the specific tariff that applies to this module, which also corresponds to an increase in final price if 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 modules) without and with an equilibrium response. The ratio of these two prices corresponds to our pass-through rates. We find that the average tariff pass-through rate is 134%. It implies that a $1 dollar increase in tariff leads to a $1.34 increase in the final price of an installed solar PV system in the U.S. The fact that we find tariff over-shifting in the U.S. solar market is surprising but consistent with the recent evidence of Pless and Van Benthem (2019). They 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 market for installation, could appear to be competitive given 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.[22] For each average demand elasticity, we put a universal cost shock (a tariff rate of 100%) on the solar manufacturers and calculate the average (capacity-weighted) 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 counter-intuitive but this is consistent with other evidence in settings with multi-product oligopoly. For instance, Bonnet et al. (2013) find similar results using a structural

[22]We scale the parameter α by a constant such that the average demand elasticity ranges from -1 to -4. Bonnet et al. (2013) proposed a similar approach.

oligopoly model of the German coffee market. An increase in demand elasticity implies a more competitive market and thus a higher pass-through rate.

7.1.2 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 that the total market capacity of U.S. solar market would have expanded by 14.1% in the absence of tariffs—the distribution and magnitude of the change in demand across manufacturers is similar but smaller in percentage term than in the first set of scenarios. For instance, the sales of solar panels made by Canadian Solar would increase by 64.3% in these scenarios, whereas it was 72.7% before.

The reason for this smaller percentage change is that removing the inertia term increases both the market size in the baseline and counterfactual scenarios. In our setting, the inertia is at the source of cost inefficiencies and removing it makes firms, manufacturers and installers, more cost-efficient, thus, overall, the market expands. Removing the inertia is thus akin to create a positive cost shock that impacts the whole supply-side. This creates a market expansion. In the absence of such inertia, the impacts of trade tariffs are smaller in relative term 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 442.3, 348.1 and 368.6 million dollars, respectively. Whereas, the losses for U.S. manufacturers and U.S. tariff revenue would have been 11 and 465.1 million dollars, respectively. In Panel C, the change in the environmental externality is also larger. Overall, the changes in the different welfare metrics are about 20% larger relative to the first set of scenarios.

7.1.3 Statutory versus Effective Rates

In this third set of scenarios, we reduce the statutory rates in all three waves to mimic the production re-allocation behaviors of Chinese manufacturers to avoid part of the tariffs. Specifically, we assume that the effective rates are 50% of the statutory rates that were announced. We chose this percentage to illustrate the role of strategic tariff avoidance as documented by Bollinger et al. (2021). We recognize that 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.[23]

Second, as shown in Table 8, the tariff pass-through rate remains virtually unaffected. It is 135%. The incidence of the effective tariff rate on consumers is thus similar to the one 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. Using the estimated model, we simulate equilibrium response to the trade tariffs under various scenarios.

In our main set of scenarios, we show that 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

[23]We do not have information about the supply-chain for solar PV modules outside the U.S. We should, however, expect non-linear impacts in the manufacturing supply-chain due to capacity constraints and economies of scale, especially when large fraction of the production is re-allocated to different countries.

U.S. manufacturers, installers and consumers in the U.S. were largely negatively affected. The increase in government revenues from these tariffs is large, but not enough to offset the negative impacts on the domestic market. We also find that the CO2 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 over-shifting: a $1 tariff on Chinese manufacturers increases the final price by $1.34 for PV systems using panels subject to such tariff. Over-shifting 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 appear to 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 in our structural estimation, we find that installers then to 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 impact the overall level of our welfare changes, but not the distribution across market participants nor the pass-through rate of the tariffs.

We conclude by highlighting a few caveats of our paper. First, we did not endogenize the choice of suppliers (i.e., manufacturers providing modules) made by installers. To properly account for the role of switching costs and past experience in the vertical structure, a dynamic supply model would be required. Second, our quantification of the environmental externality focuses only on CO2 and does not consider the marginal power producer in each region and year. There is substantial temporal and spatial heterogeneity associated with the displacement of power generation 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 effect.

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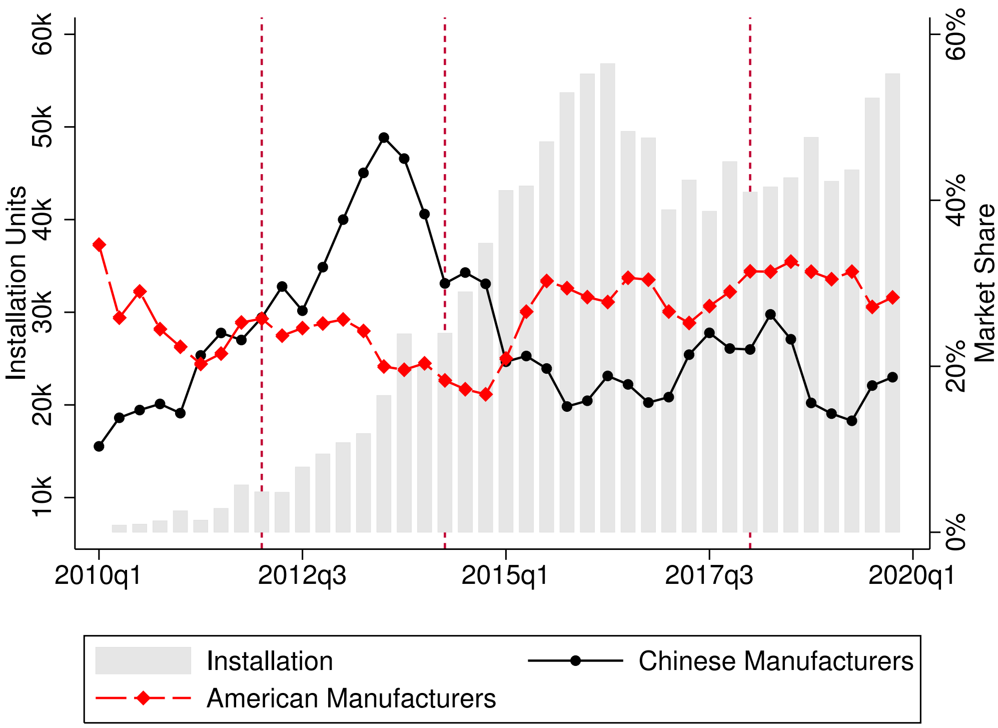

Figure 1: Market Share for Manufacturers through Years

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 (right axis) represents the time trend of the market share of Chinese manufacturers. The red dash line (right axis) represents the time trend of the market share of American manufacturers. The three vertical lines represents the beginning of the three waves of anti-dumping policies (2012Q1, 2014Q2 and 2018Q1).

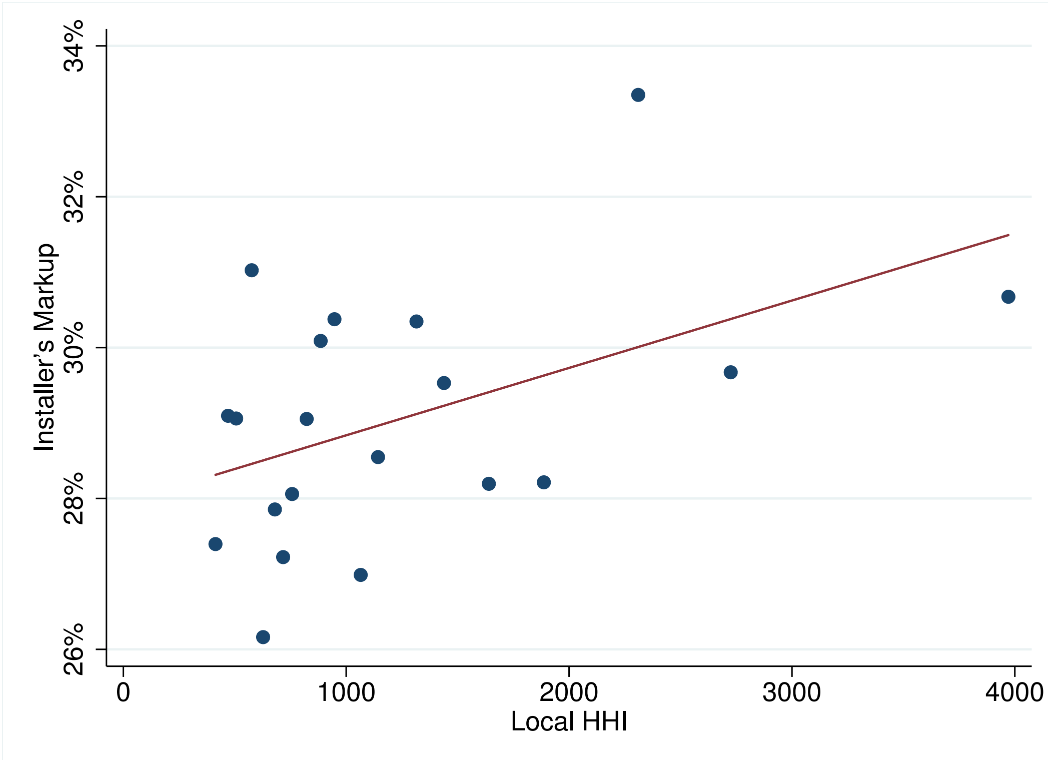

Figure 2: Relationship between Installer's Markup and Local HHI

Notes: This figure provides a non-parametric way of visualizing the relationship between installer's markup and HHI. The vertical axis is the installer's markup as a percentage of total installed price, and the horizontal axis is the Herfindahl-Hirschman Index (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, then creates a scatterplot 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	3.84	4.11	1	1	2	5	9	50

Panel B: Distribution of Installers across Years			
Year	No. installers per state	CR1 (%)	Staying with Manufacturers (%)
2012	90	32.51	48.10
2013	93	53.95	36.88
2014	103	34.65	50.05
2015	145	34.25	67.18
2016	196	30.70	56.26
2017	198	31.97	55.01
2018	215	46.15	58.80

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 that each installer works with from 2012 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; the third column is the average proportion of installers that stay with their current manufacturers in the next year.

Table 2: Past Experience and Installers' Switching Behavior

	OLS	OLS	2SLS	2SLS
	Stay	Stay	Stay	StayVol
Variables	(1)	(2)	(3)	(4)
Log(1+Capacity)	0.095***	0.104***	0.095***	0.338***
	(0.004)	(0.004)	(0.004)	(0.020)
Installed Price	-0.012*		-0.309	-0.710
	(0.006)		(0.226)	(0.850)
Efficiency	10.711***		11.962**	51.649***
	(0.854)		(1.371)	(5.079)
Technology	0.013		0.010	0.077
	(0.021)		(0.025)	(0.088)
Year Fixed	Yes	Yes	Yes	Yes
Manufacturer-Installer Fixed	Yes	Yes	Yes	Yes
Observations	16,505	16,505	16,505	16,505
R-squared	0.088	0.069	-	-

Note: This table reports the regression results on solar installers' switching behavior. Column (1) - (2) show the results using OLS method and column (3) - (4) show the results using 2SLS method. We use the anti-dumping and countervailing duties imposed on Chinese solar manufacturers as an instrument for the installed price. Our sample period is from 2012 to 2018. Manufacturers with less than 10 solar PV systems are excluded from our sample. Installers with installations less than 10 solar PV systems 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(installation capacity for manufacturer-installer pair)	11.99	0	9.94	2.12

Notes: the prices are in 2015 US dollars

Table 4: Estimation Result for Main Specification

	Variables	Estimates	Standard Errors
Demand side parameters			
Means, (α, β)	Constant	-13.891***	(1.068)
	Price	-1.549***	(0.503)
	Efficiency	45.154***	(16.957)
	Technology	-0.458	(0.479)
Demographics, (θ)	Income	0.230**	(0.109)
	Education	-7.230***	(1.676)
	Urbanization	-0.226***	(0.026)
	Race	0.573	(0.393)
	Democrats	1.872***	(0.452)
Taste variation, (Σ)	Price	0.438**	(0.224)
	Efficiency	7.308	(5.824)
	Technology	0.320	(1.774)
Fixed Effects	Manufacturer-Installer F.E.	Yes	
	Year F.E.	Yes	
Cost side parameters			
	Constant	-2.728***	(0.010)
	Efficiency	7.507***	(0.022)
	Wage Rate	0.105***	(0.0003)
	Friction Term	0.031***	(0.0002)
	Installer F.E.	Yes	
	Year F.E.	Yes	

Note: This table reports the result for the demand and supply estimation based on random coefficient discrete choice model, We use BLP instruments as the instrumental variable. On the demand side, Price is the after-subsidy average installed price for solar module (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. On the supply side, Wage Rate refers to the MSA-level wage rate (\$/hour) for the roofing, and Friction Term represents the logarithm of solar installation capacity for manufacturer-installer pair in the past year. 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	Wave 1	Wave 2	Wave 3	Wave 1 - 3
China	Canadian Solar	0	66.1%	6.6%	72.7%
	Trina Solar	13.0%	41.5%	11.6%	66.0%
	Yingli Energy	11.7%	68.2%	0.2%	80.1%
USA	REC Solar	0	-0.4%	-0.1%	-0.5%
	SunPower	-0.1%	-0.5%	-0.1%	-0.7%
South Korea	Hanwha	0	-0.5%	-0.1%	-0.6%
	Hyundai	0	-0.6%	0	-0.6%
	LG	0	-0.6%	-0.1%	-0.7%
Japan	Kyocera	0	-0.8%	0	-0.8%
German	Solar World	0	-0.8%	-0.04%	-0.8%
Total		2.1%	13.7%	1.4%	17.2%

B: Welfare Distribution (in 2015$ million)				
	Wave 1	Wave 2	Wave 3	Wave 1 - 3
Δ Consumer Surplus	71.9	278.4	25.3	375.5
Δ U.S. Manufacturers	-0.26	-5.6	-0.7	-6.6
Δ Chinese Manufacturers	34.0	216.4	21.0	271.4
Δ Other Manufacturers	0	-5.9	-0.4	-6.3
Δ Installers	35.9	233.0	22.9	291.8
Δ U.S. Tariff Revenue	-41.0	-292.9	-31.8	-365.6
Total	100.5	423.3	36.4	560.1

Panel C: Environmental Benefit				
	Wave 1	Wave 2	Wave 3	Wave 1 - 3
Δ Reduced CO2 (million tons)	0.8	5.6	0.6	7.0
Δ Reduced Cost (2015$ million)	30.4	202.4	20.0	252.9

Note: This table reports the results for demand response and welfare change in counterfactual scenario 1. Panel A reports the demand change in percentage between counterfactual scenario 1 and baseline scenario 1. Panel B reports the welfare changes for U.S. consumers, U.S. manufacturers, U.S. installers and Chinese manufacturers if the anti-dumping policies were removed. Panel C reports the related environmental benefit. All the economic values are calculated in 2015$ dollars.

Table 6: Simulation Results: Removing All Tariffs and No Inertia

Panel A: Demand Response

Origin Country	Manufacturer	Wave 1	Wave 2	Wave 3	Wave 1 - 3
China	Canadian Solar	0	57.8%	6.5%	64.3%
	Trina Solar	5.2%	45.2%	13.3%	63.8%
	Yingli Energy	7.8%	70.2%	0.2%	78.2%
USA	REC Solar	0	-0.5%	0	-0.5%
	SunPower	-0.1%	-0.6%	-0.1%	-0.8%
South Korea	Hanwha	0	-0.6%	-0.1%	-0.6%
	Hyundai	0	-0.6%	0	-0.6%
	LG	0	-0.7%	-0.1%	-0.8%
Japan	Kyocera	0	-0.6%	0	-0.6%
German	Solar World	0	-0.8%	0	-0.8%
Total		0.9%	11.9%	1.3%	14.1%

Panel B: Welfare Distribution (in 2015$ million)

	Wave 1	Wave 2	Wave 3	Wave 1 - 3
Δ Consumer Surplus	46.0	358.6	37.7	442.3
Δ U.S. Manufacturers	-0.6	-9.1	-1.3	-11.0
Δ Chinese Manufacturers	25.0	291.1	31.8	348.1
Δ Other Manufacturers	0	-9.5	-0.7	-10.2
Δ Installers	25.3	309.2	34.0	368.6
Δ U.S. Tariff Revenue	-33.4	-385.3	-46.4	-465.1
Total	62.4	555.1	55.2	672.7

Panel C: Environmental Benefit

	Wave 1	Wave 2	Wave 3	Wave 1 - 3
Δ Reduced CO2 (million tons)	0.6	7.8	0.8	9.3
Δ Reduced Cost (2015$ million)	20.8	282.3	31.8	334.9

Note: This table reports the results for demand response and welfare change in counterfactual scenario 2. Panel A reports the demand change in percentage between counterfactual scenario 2 and baseline scenario 2. Panel B reports the welfare changes for U.S. consumers, U.S. manufacturers, U.S. installers and Chinese manufacturers between counterfactual scenario 2 and baseline scenario 2. 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	Wave 1 - 3
China	Canadian Solar	33.7%
	Trina Solar	30.5%
	Yingli Energy	36.5%
USA	REC Solar	-0.2%
	SunPower	-0.3%
South Korea	Hanwha	-0.3%
	Hyundai	-0.3%
	LG	-0.3%
Japan	Kyocera	-0.4%
German	Solar World	-0.4%
Total		7.9%
Panel B: Welfare Distribution (in 2015$ million)		
		Wave 1 - 3
Δ Consumer Surplus		177.8
Δ U.S. Manufacturers		-3.1
Δ Chinese Manufacturers		126.9
Δ Other Manufacturers		-3.0
Δ Installers		136.5
Δ U.S. Tariff Revenue		-149.9
Total		285.2
Panel C: Environmental Benefit		
		Wave 1 - 3
Δ Reduced CO2 (million tons)		3.2
Δ Reduced Cost (2015$ million)		116.2

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 U.S. consumers, U.S. manufacturers, U.S. installers and Chinese manufacturers. Panel C reports the related environmental benefit. All the economic values are calculated in 2015 $ dollars.

Table 8: Tariff Pass-through

	Without Equilibrium Reponse		With Equilibrium Response		Pass-through Percent (%)
		Level ($)	Percent (%)	Level ($)	
	(1)	(2)	(3)	(4)	(5)
With Inertia Term	12.69	2911	17.08	3,769	1.34
Without Inertia Term	12.69	2,801	16.94	3,625	1.32
50% × Statutory Rates	6.34	1,549	8.62	2,065	1.35

Note: Column (1) reports the tariff pass-through for consumer's final purchasing price for solar PVs with Chinese panels. Column (2)-(5) reports the average tariff (both in levels and in percentage) that have levied on 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	0.13	0.20
-2	1.20	0.23	0.30
-3	1.25	0.36	0.46
-3.64	1.30	0.47	0.65
-4	1.35	0.60	0.85

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 assume the inertia term exists between the manufacturer-installer relationship. We calculate the average (capacity weighted) tariff pass-through rates for consumer's final purchasing price, manufacturer's markup and installer's markup for all PV systems, respectively.

Appendices

A Additional Figures and Tables

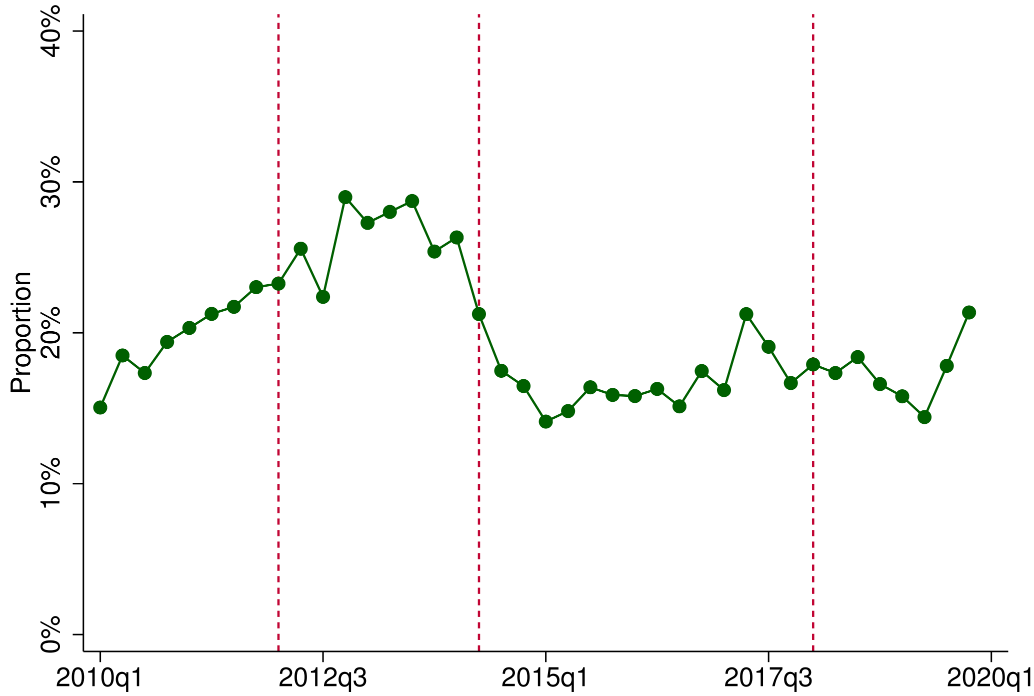

Figure A1: Proportion of Chinese Manufacturers Each Installer is Working with

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

Table A1: First Stage Regression for Switching Behavior

	(1)	(2)
VARIABLES	Installed Price	Installed Price
Tariff	0.158**	0.154**
	(0.068)	(0.067)
Log(1+Capacity)		-0.009
		(0.007)
Efficiency		4.172***
		(1.719)
Technology		-0.003
		(0.039)
Constant	3.789***	3.099***
	(0.018)	(0.302)
Year F.E.	Yes	Yes
Manufacturer-Installer F.E.	Yes	Yes
Observations	16,505	16,505
R-squared	0.741	0.742

Note: This table reports the first stage regression results on the switching behavior for the solar installers. Our sample period is from 2012 to 2018. Manufacturers with less than 10 solar PV systems are excluded from our sample. Installers with installations less 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 in the 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 eleven groups of solar installers in the US market. The first ten groups are the ten biggest solar installers as marked by number 1 - 10 and the 11th group is all other solar installers.

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

VARIABLES	Model 1	Model 2	Model 3
BLP_eff	0.024***	0.059***	0.045**
	(0.008)	(0.017)	(0.019)
BLP_tech	0.002	0.007	0.009
	0.003	(0.006)	(0.006)
$(\text{BLP\_eff})^2$		-0.002***	0.002
		(0.001)	(0.002)
$(\text{BLP\_tech})^2$		-0.0001	0.0005
		(0.0001)	(0.0003)
BLP_eff $\times BLP\_tech$			-0.003**
			(0.0015)
Control Variables	Yes	Yes	Yes
Manufacturer-Installer FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	6,653	6,653	6,653
F-statistics	30.32	21.19	17.83
R-squared	0.44	0.44	0.44

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

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

VARIABLES	Model 1	Model 2	Model 3
Price	-2.011***	-1.263***	-1.559***
	(0.394)	(0.289)	(0.298)
Efficiency	63.38***	54.87***	58.24***
	(6.480)	(5.219)	(5.453)
Technology	-0.265*	-0.398***	-0.345***
	(0.146)	(0.122)	(0.129)
Income	0.404***	0.284***	0.332***
	(0.0685)	(0.0516)	(0.0534)
Education	-9.710***	-7.788***	-8.549***
	(1.241)	(0.969)	(1.008)
Urbanization	-0.221***	-0.234***	-0.229***
	(0.0234)	(0.0200)	(0.0211)
Race	0.933***	0.858***	0.888***
	(0.259)	(0.223)	(0.235)
Democrats	2.271***	1.892***	2.043***
	(0.476)	(0.401)	(0.422)
Constant	-11.31***	-13.02***	-12.34***
	(1.205)	(0.958)	(0.999)
Observations	6,653	6,653	6,653

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

Table A6: 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	Module Price	Non-Module	% Module 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 module price and non-module cost. The data is from Lawrence Berkeley National Laboratory.

Table A7: Price, Marginal Costs, and Markups

	(1)	(2)	(3)
Variable	Baseline	Counterfactual 1	Counterfactual 2
Price ($/W)	4.062	3.884	3.568
Markup for manufacturer ($/W)	0.807	0.792	0.860
Markup for installer ($/W)	1.162	1.129	1.082
Joint marginal cost ($/W)	2.158	2.158	1.814

Note: This table reports the average price, average markups and average marginal cost for baseline and counterfactual scenarios.