Tariff and Quality Upgrading in the Solar Panel Market

Garson Jonathan

Under the Supervision of Prof. Isabelle Méjean
and Prof. Thierry Mayer
SciencesPo Department of Economics

Abstract

Does quality matter for tariff transmission and the composition of imports? This paper investigates the role of product quality in shaping the effects of tariffs on prices and import composition, focusing on the U.S. solar panel market—a market characterized by strong product differentiation along quality dimensions. Using variation from both anti-dumping duties and the 2018 Trade War tariffs, we show that lower-quality solar panels exhibit significantly higher price elasticity in response to tariffs. Moreover, we document a shift in the composition of imports, with panels at the lower end of the quality distribution upgrading toward higher efficiency. These findings highlight that tariffs do more than raise prices—they reshape the market by altering the quality of imported goods. Considering product quality is crucial for a comprehensive assessment of trade policy, especially when evaluating the incidence of tariff measures.

Keywords: Trade, Quality, Tariffs, Heterogeneous Firms, Endogeneous Markups, Endogeneous Quality.

Acknowledgements

I would like to thank Professor Isabelle Méjean for her decisive and consistent support throughout the semester. I am also thankful to Professor Mayer for his advice during the semester and for agreeing to be part of the jury.

I am deeply grateful to my family—Pierre, Florence, and Natasha—for their unconditional support during this final year of study. It has been filled with challenges, and this success would not have been possible without you. I also think deeply about the rest of my family, and especially my grandmother. She cannot be with us to share this moment, but she will be present in my thoughts.

To Clara, thank you for your love and kindness, and for being present in all the important moments of my life—especially this one.

I am fortunate to be surrounded by such wonderful friends. I would like to thank Mathilde for her positivity, Ali for being an outstanding study buddy and such a funny person, Andrea for keeping us grounded when stress was high, Justine for her moral and intellectual support, and Lewin for his reassuring presence and steady encouragement. A heartfelt thanks also to Wiktor, Rhea, Leila, Bo, Nacho, and Hui Yen for the intense and rewarding two years we shared in this master's program.

To my friends on the banks of the Marne, thank you: Adrien, for always answering my questions and being a constant source of support; Montegut, for our walks in the woods between intense study sessions; Rayon, Gnoute, and Da, for being excellent friends who politely listened to my economic ramblings. To Théo, thank you for being my insider in the solar industry—and above all, for your support.

I extend my sincere thanks to everyone I've spent time with during this master's program who are not mentioned here by name. A special note of appreciation to my friends from Poitiers—Lola, Inés, Mayte, Juliette, Justine, Ana, Corentin, Aimée, Jule, and Salomé—and to all my classmates.

I would also like to thank my first-year economics class, taught by Stéphane Mottet and Noël Duport, who played a decisive role in shaping my interest in economics. Without your support and your talent for conveying your passion for the discipline, none of this would have been possible. More generally, I would like to thank all the professors of the Master's program for their commitment to teaching us the state of the art in economics.

I am also grateful to the administrative staff and all those working at Sciences Po—especially the CROUS and cleaning staff—for their essential contributions. For five years, they enabled us to study in outstanding conditions, and for that, I sincerely thank you.

Last but not least, I want to acknowledge everything in my life that led to this moment. Regardless of the outcomes or the limitations of this work—of which there are many—I am proud of what I have achieved. I am deeply grateful to have had the rare opportunity to work independently on a subject I care about. This has been an intense journey. It may not be the last of my career, but no matter what comes next, I am thankful to have lived it.

Contents

1 Introduction

"I will go anywhere in the world to open new markets for American products. And I will not stand by when our competitors don't play by the rules. We've brought trade cases against China at nearly twice the rate as the last administration – and it's made a difference. Over a thousand Americans are working today because we stopped a surge in Chinese tires. But we need to do more. It's not right when another country lets our movies, music, and software be pirated. It's not fair when foreign manufacturers have a leg up on ours only because they're heavily subsidized."

— Barack Obama, *State of the Union*, January 2012

These claims of unfair trade practices from Chinese companies are now more than a decade old. The consequences of China's integration into the world economy have been widely discussed both inside and outside academia (Autor et al., 2013, 2021). The United States has been particularly proactive against China's alleged unfair trade practices. Over the past decade, this rivalry has grown, exemplified by the rising number of anti-dumping inquiries against Chinese firms and the Trade War initiated by President Trump in 2018, which also affected undirectly other trade partners such as South Korea (Fajgelbaum et al., 2020, 2024).

A long-standing argument against Chinese firms is that they engage in "dumping" on American firms—not only by being cheaper through subsidies but also by offering lower-quality products. By providing lower-quality goods, Chinese firms exert downward pressure on prices, gradually eroding the market share of domestic producers until local production becomes unsustainable.

In our analysis, we focus on the claim that Chinese solar panels are of lower quality and investigate how tariffs influence the quality composition of imported solar panels and how quality affects tariff transmission to prices. These considerations raise the broader question of whether tariffs can level the playing field not only on prices but also on product quality.

Solar panels offer an instructive case. First, successive U.S. administrations since Obama have deemed them both a "strategic" good—given their current and future role in decarbonizing the economy—and a product subject to significant Chinese subsidies. Second, this industry has experienced several waves of tariffs imposed on both Chinese and non-Chinese manufacturers between 2010 and 2018. In 2012 and 2014, following anti-dumping inquiries, substantial tariffs were imposed on all Chinese firms. Tariff rates were set based on the estimated "dumping margins" and the firms' willingness to cooperate. Although the selection into tariff imposition is not exogenous, we complement our analysis with a study of the 2018 trade wars. Following Fajgelbaum et al. (2020), we assume there was little anticipation, making this a useful complementary test to our results. Our analysis is restricted to California cases, but we are confident that these results are generalizable to the United States, as California represents two-thirds of the U.S. market for solar panels.

To answer these questions, we frame our empirical work within the theoretical context of a Melitz and Ottaviano (2008) heterogeneous firms model, extended by Antoniades (2015) and Ludema and Yu (2016) to incorporate endogenous quality choice across markets. We derive theoretical results under the imposition of a tariff in the Home country on imports from a Foreign country, and we empirically assess the heterogeneous impact of tariffs on price variations along quality dimensions. We find that lower-quality solar panels experience relatively larger price increases than their higher-quality counterparts. We also document a significant shift in the quality composition of imports: lower-quality panels improve considerably, likely by exiting the market for higher-quality models and repositioning at the lower end of the distribution.[1] We interpret this as limited evidence of an Alchian–Allen effect. Finally, we show limited evidence that the elasticity of demand is convex, supporting our hypothesis that higher-quality solar panels face lower demand elasticities.

Taking the quality channel into account is important for pass-through analysis, as a shift in the composition of imports toward higher-quality goods can lead to an overestimation of tariff pass-through. Moreover, changes in quality composition induced by tariffs are also relevant when comparing the effects of tariffs to other trade restrictions such as quotas. This issue has received, to the best of our knowledge, relatively little direct academic attention — and here lies our core contribution.

Finally, we indirectly contribute to the broader debate on the tension between trade policy and decarbonization objectives. By raising prices, tariffs can limit the adoption of goods with positive environmental externalities—particularly when domestic alternatives are scarce or non-existent. While we do not adopt a normative position, this trade-off is inherent to policies targeting climate-related goods.

[1] More cautiously, we document a change in the quality distribution at the top, which appears negatively affected by the tariff. This result is preliminary and discussed with caution in the appendix.

2 Literature Review

Our work lies at the intersection of several literatures. The first and most direct is the literature on tariff pass-through. Although we cannot directly estimate pass-through due to the absence of panel cost data, our analysis is closely related to this body of work.

The literature on tariff pass-through is an old question that has expanded significantly in recent years, particularly following the presidency of Donald Trump and the resurgence of protectionist policies. In their seminal study, Fajgelbaum et al. (2020) analyzed the broad effects of the 2018 trade war and found that most of the tariffs were fully passed through to American consumers, resulting in an estimated $7.2 billion in additional costs.

Closer to our specific setting, Flaaen et al. (2020) studied the case of washing machines, an industry that—like solar panels—was subject to successive waves of anti-dumping tariffs. While Korea, not China, was the primary target, the dynamics were strikingly similar. Korean firms initially mitigated tariff impacts by relocating production outside affected areas, but prices increased substantially in response to the second tariff wave in 2016 and again during the 2018 trade war. We observe a similar pattern in our data: the first trade tariff had a limited price effect at the installation level, whereas subsequent tariff increases led to more pronounced price changes.

Our work is also indebted to Ludema and Yu (2016), and more indirectly to Antoniades (2015), who developed models with endogenous quality choice and variable markups. Ludema and Yu (2016) focused on how endogenous quality responses shape pass-through under trade liberalization. They showed that firms often respond to tariff reductions by upgrading quality and increasing prices, leading to incomplete pass-through. Importantly, they found that this response varies across industries depending on the scope for quality differentiation. In industries with greater quality scope, higher-productivity firms were more likely to increase both quality and prices.

Our contribution builds on this framework but shifts focus: we estimate price elasticity to tariff, but we focus on how tariffs induce changes in the quality composition of imports—an aspect of trade response that has received far less attention in the literature.

Trade and quality have received considerable attention in the literature, particularly in relation to trade patterns. Hallak (2006) is one of the seminal studies in this area, examining how product quality influences bilateral trade flows between countries. Within a classical trade model with CES demand, he introduces a quality shifter at the product level and shows that this improves predictions: developed countries tend to trade more among themselves and exchange higher-quality goods.

Building on this, Baldwin and Harrigan (2011) incorporated quality into the Melitz (2003) framework, creating a theoretical foundation that proved fertile for further empirical work. Notably, Crozet et al. (2012) provided one of the first direct measures of quality and its relationship to both pricing and market access. Studying Champagne exports, they showed that higher-quality products command higher prices and reach more distant or less accessible markets.

This study marked a shift away from earlier work relying on indirect proxies for quality (Khandelwal, 2010)[2]. In line with these findings, we show that only higher-quality goods are able to access more complex markets in response to tariff increases.

Following this theoretical framework, Chen and Juvenal (2016) provides empirical evidence from the Argentine wine industry that exchange rate movements generate heterogeneous responses along the quality dimension. They show that firms' perceived demand elasticity declines with product quality. As a result, higher-quality firms adjust prices more than quantities in response to exchange rate changes and exhibit lower exchange rate pass-through. These findings are consistent with the view that quality shapes how firms respond to international price shocks[3].

Beyond classical trade pattern models, we also draw intuition on the effect of tariffs on the quality composition of imports from a related subfield that focuses on additive trade costs and Alchian–Allen effects. Among contributions, the work of Hummels and Skiba (2004) is perhaps the most influential. They show that exporters charge destination-specific prices that covary positively with shipping costs and negatively with tariffs.[4]

We argue, however, that when examining within-industry price variation

[2]It is important to note that estimating product quality in traded goods remains challenging. Indirect approaches—such as using unit values as proxies for quality (Feenstra and Romalis, 2014), or exploiting exchange rate fluctuations on the import side (Piveteau and Smagghue, 2019)—have been developed, but each comes with its own set of limitations and assumptions.

[3]Numerous other studies have explored the relationship between international pricing, quality, and trade. For instance, Manova and Zhang (2012) and Feenstra and Romalis (2014) examine pricing-to-market behavior, divergence in quality shipped across markets, and the role of endogenous quality in shaping export prices. On the demand side, Fajgelbaum et al. (2011) model how income distribution drives heterogeneous demand for quality goods and influences trade patterns. Finally, while our work does not directly address the effects of trade liberalization on quality upgrading, we acknowledge the important contributions of studies such as Verhoogen (2008), which show that exchange rate devaluation pushed more productive firms to increase their output quality, and Amiti and Khandelwal (2013) show that opening to trade can lead to significant increases in product quality.

[4]This result follows from their modeling assumption that ad valorem tariffs reduce the relative weight of per-unit transport costs.

under incomplete pass-through and along the quality dimension, it is possible to recover a form of the Alchian–Allen effect under certain assumptions. The broader literature on Alchian–Allen effects—and more generally on per-unit trade costs and import composition—was particularly active in the 1980s, when many trade restrictions took the form of quotas (Falvey, 1979; Aw and Roberts, 1986).

We contribute modestly to this literature by documenting weak empirical evidence of Alchian–Allen-type effects in the context of ad valorem tariffs and incomplete pass-through, where trade policy indirectly alters the quality composition of imports.

Finally, by focusing specifically on the solar panel industry and the impact of tariff implementation, our work relates closely to the growing literature on solar energy and the industrial organization (IO) of clean energy markets. Much of this literature has focused on estimating the effects of subsidies on the adoption of solar technology. For instance, Hughes and Podolefsky (2015) and Pless and van Benthem (2019) examine the California Solar Initiative—a major program between 2007 and 2013 that subsidized upfront installation costs. They find that subsidies were largely passed on to consumers and increased installed capacity by 53% relative to a counterfactual.

In the Belgian context, De Groote and Verboven (2019) similarly show that upfront payments strongly encouraged technology adoption and that consumers in this industry have a marked preference for immediate rebates over feed-in tariffs. Other drivers of demand, such as reductions in installer costs, have also played an important role. Gillingham et al. (2016), O'Shaughnessy et al. (2018), and Bollinger and Gillingham (2023) document that non-hardware costs declined by approximately 12% between 2002 and 2012, significantly boosting adoption.

Borenstein (2017) further highlights the role of California's tiered electricity pricing structure,[5] showing that volumetric pricing explained as much of the adoption as direct subsidies.

Despite this growing body of work,[6] the role of trade tariffs in shaping the solar industry has received comparatively little attention. This constitutes our contribution to the literature on this specific industry.

In the European context, Andres (2024) finds that EU tariff protection against Chinese competition reduced innovation for firms with existing knowledge stocks but boosted innovation for younger firms. However, she also finds

[5] Each electricity provider in California charges according to a tiered system. Households with higher income or electricity use pay a higher marginal price.

[6] We do not expand on this here, but note the rich literature on peer effects in solar adoption (Nauze, 2023) and the role of mass adoption in driving technological improvements (Gerarden, 2023).

that competition from China increased the likelihood of market exit overall.

In the U.S. context, the only known contribution is the working paper by Houde and Wang (2023), which follows a classical IO framework (i.e., BLP market share). The paper estimates the distributional impacts of the U.S.–China solar trade dispute over the 2010–2018 period, finding an average pass-through rate of 1.15[7]. However, they do not distinguish between different tariff periods or explore changes in quality composition. The authors conclude that tariff policies largely benefited Korean and U.S. manufacturers at the expense of their Chinese counterparts.

To summarize, the literature on trade and tariffs, quality, and tariff pass-through—particularly in the solar industry—is rich and extensive. We modestly contribute to this body of work by estimating the price elasticity of tariff imposition and by uncovering the dynamics of export composition changes induced by tariffs, in both targeted and global contexts.

[7]They attribute the pass-through rate greater than one to the presence of market power. However, we believe this estimate may be biased due to the use of TPO-reported prices, which are known to be inflated (Trabisch, 2013).

3 Theory

In this section, we develop the environment in which we assume the solar market evolves in response to tariff imposition, and that guide our empirical analysis.

For this purpose, we adopt the Melitz and Ottaviano (2008) framework, prolonged by Antoniades (2015) and Ludema and Yu (2016) to integrate endogenous quality choice and disentangle the quality effect impact on pass-through. We prolonged this model by discussing further effects such as the Alchian-Allen effect.

3.1 Demand

The world is divided into two countries: Home (H) and Foreign (F). For simplicity, we assume that both countries have a representative consumer with a quasi-linear utility function. This function was developed in international trade literature by Ottaviano et al. (2002) and allows for variable markups at the firm level.

$$U = q_0^c + \int_{i\in\Omega} (\alpha + z_i) q_i^c di - \frac{1}{2}\gamma \int_{i\in\Omega} (q_i^c)^2 di - \frac{1}{2}\eta \left(\int_{i\in\Omega} q_i^c \right)^2 \tag{1}$$

We have a q_0^c the numeraire good which is homogeneous and produced by a unit of labor and is always consumed. The presence of a numeraire in our setup gives a partial equilibrium flavor to our model, since wages will not vary with trade and firms always have enough workers to deliver to all markets. In our case this partial equilibrium effect is not necessarily problematic since we only consider the specific case of tariff pass-through in solar panel trade with the U.S. We also have a differentiated good q_i^c over which consumers maximize their utility. The differentiated good is indexed by variety $i \in \Omega$ and each firm produces a unique variety of this good. α and η are strictly positive and capture the substitutability between the numeraire and the differentiated good, while γ captures the degree of horizontal differentiation between varieties. z_i is the quality scaling factor.

Using quasi-linear utility functions has the double convenience of providing a tractable framework for firms' heterogeneity while allowing for markups and quality to be determined endogenously at the firm level. The classical CES function posits constant elasticity of substitution and then constant markups which can hide strategic patterns of tariff absorption which are precious in our context.

We assume that the two markets are segmented and derive the following inverse demand function:

$$p_i^l = \alpha + z_i^l - \gamma(q_i^c)^l - \eta Q_c^l \tag{2}$$

with $l \in \{h, f\}$ and $Q_c^l = \int_{i \in \Omega} (q_i^c)^l di$

From here we can derive the linear demand for any variety in a country l by just inverting the function :

$$q^l \equiv L^l q_i^c = \frac{L^l \alpha}{\gamma + \eta N^l} + \frac{L^l}{\gamma} z_i^l - \frac{L^l}{\gamma} p_i^l - \frac{L^l N^l \eta}{\gamma + \eta N^l} \bar{z}^l + \frac{L^l N^l \eta}{\gamma + \eta N^l} \bar{p}^l \tag{3}$$

with N^l reflecting the consumption of varieties in the country l, and p^l, z^l the variety price and quality for country l. $\bar{z}^l$ and $\bar{p}^l$ represent the average quality and price of foreign and home firms selling in a market l, such that $\bar{z}^l = \frac{1}{N} \int_{i \in \Omega^*} z_i^l di$ and $\bar{p}^l = \frac{1}{N} \int_{i \in \Omega^*} p_i^l di$ with $\Omega^* \subset \Omega$ the subset of consumed variety in a country l. L^l is the population level in a country l and naturally drives up the demand for a variety. Demand for a variety is positively related to the variety's own quality and the average price, and negatively with its own price and average quality. Importantly, each firm sets independently the price, quality, and quantity exported to each market.

3.2 Firms

We assume that there is a continuum of firms N^l, each producing a unique variety, operating in each country, and that those firms are in monopolistic competition. Then, they endogenously set markups and quality, and make decisions independently of their competitors and differentiated by partner country.

Production happens only in the respective home market of each firm, they cannot move production abroad and neither implement FDI in the partner country as in Helpman et al. (2004). Additionally, all firms face an entry cost determined by f_E. This fixed entry cost prevents firms below a certain level of productivity from operating in the market. We model the firm costs as follows:

$$\mathrm{TC}_i^l = c_i q_i^l + \theta z_i^l q_i^l + \theta (z_i^l)^2 \tag{4}$$

$c_i q_i^l$ marks here the rising marginal cost c with the quantity produced, it is an output-dependent "processing cost". $\theta z_i^l q_i^l$ refers here to the additional cost of producing quality goods and $\theta (z_i^l)^2$ is the design or research cost of upgrading. θ here refers to the "ability" to upgrade, which we set at the country level, for high and low-innovation countries. Finally, the convex cost of increasing in quality limits the possibility for firms to upgrade their products and create product differentiation in the spirit of Shaked and Sutton (1982)[8]. These different elements are firms and market-specific, hence it allows firms to vary in quality and quantity by destination.

Firms ignore their productivity before entering the market; it is revealed when they pick a marginal cost of production c in a distribution $G(c)$. Entering a market comes with a fixed cost of entry f_E, which is considered sunk here since the model is static. If the expected profit π of a firm is revealed to be inferior to f_E then the firm stops producing and exits the market.

In our setup, we are in an open economy, firms make a profit at Home (H) and at Foreign (F).

$$\begin{aligned}
\pi^{ll} &= p^{ll}q^{ll} - c\,q^{ll} - \theta\,z^{ll}q^{ll} - \theta\,(z^{ll})^2 \\
\pi^{l\bar{l}} &= \frac{p^{l\bar{l}}}{\tau^f}q^{l\bar{l}} - \delta c\,q^{l\bar{l}} - \theta\,z^{l\bar{l}}q^{l\bar{l}} - \theta\,(z^{l\bar{l}})^2
\end{aligned} \tag{5}$$

where $l \in \{h, f\}$ and $\bar{l} \neq l$. With p^{ll} and q^{ll} respectively indicating the price and quantity of firms producing at l and selling on the same market. Conversely, firms face trade cost δ when exporting, independent of their quality[9]. The marginal productivity of firms is correlated to their ability to export, possibility to access foreign markets is a source of comparative advantage. Our variable of interest in our case is the pass-through of add-valorem tariff τ^l.

For our case study, we are interested in the effect of Home h imposing tariffs on Foreign exports to its domestic market. Therefore we focus on the profit of home firms at home π^{hh} and foreign firms at home π^{fh}, and more precisely on the pass-through of the tariffs on the tariff-inclusive import price: $\frac{p^{fh}}{\tau^h}$:

$$\begin{aligned}
\pi^{hh} &= p^{hh}q^{hh} - c\,q^{hh} - \theta\,z^{hh}q^{hh} - \theta\,(z^{hh})^2 \\
\pi^{fh} &= \frac{p^{fh}}{\tau^h}q^{fh} - \delta c\,q^{fh} - \theta\,z^{fh}q^{fh} - \theta\,(z^{fh})^2
\end{aligned} \tag{6}$$

Firms choose quality and price to deliver to each market independently to maximize their profits. The optimal quality (see subsection A.2) is defined as :

[8]If there was no convex cost of increasing the production natural monopoly would dominate.

[9]The additive structure of trade cost allows to make appear incomplete pass-through. Since most of the quality differentiation we observe is on the chemical treatment of raw materials or semi-conductor manufacturing (e.g. mono-crystalline, poly-crystalline, thin-film), it is reasonable to assume that high-quality solar panels are not more expensive to trade than low-quality ones. Moreover, there exist empirical evidence that support the importance of additive trade cost in international trade (Hummels and Skiba, 2004).

$$
\begin{aligned}
z^{fh} &= \lambda^{fh}\delta\tau^h(c^{fh} - c) \\
z^{hh} &= \lambda^{hh}(c^{hh} - c)
\end{aligned} \tag{7}
$$

With $\lambda^{fh} = \frac{L^h(1-\theta\tau^h)}{4\gamma\theta\tau^h - L^h(1-\theta\tau^h)^2}$ and $\lambda^{hh} = \frac{L^h(1-\theta)}{4\gamma\theta - L^h(1-\theta)^2}$[10]. λ is defined as the "quality scope" the ladder of quality on which an industry operates. A flat ladder ($\lambda = 1$) would mean that there is not much room for vertical differentiation. In that case, prices are declining with productivity and we are back to Melitz (2003); Melitz and Ottaviano (2008). Conversely, with a steep ladder ($\lambda > 1$), firms with higher productivity can set both higher quality and prices.

More generally, the scope for quality differentiation increases with market size (L) and the degree of substitutability between differentiated goods (γ). In contrast, it decreases with the level of tariffs (τ) and the difficulty of upgrading quality (θ). In essence, a large market with intense competition among differentiated products and a high capacity for innovation—such as a *developed* country—is expected to exhibit greater variation in product quality. A larger market provides more opportunities for firms to recover the fixed costs associated with quality upgrading.

Conversely, the imposition of tariffs (τ) functions as an effective reduction in market size within a two-country framework. This lowers the potential return on quality investments, thereby discouraging upgrading and leading to a less differentiated industry.

From the firm perspective, the choice to deliver a certain quality to a given market is synthesized by this scope for quality (market-based parameter) and their relative marginal cost relative to the market cost-cutoff ($c^{fh} - c$). Since the scope for quality in a given market is set by the market conditions, the quality of the variety delivered to a given market is monotonically increasing with the firm productivity ($1/c$). This relation between cost differential and quality scope is crucial since the tariff will affect firms' optimal quality choice differently depending on their productivity level.

For foreign firms exporting to the domestic markets :

$$
\begin{aligned}
z^{fh} &= \lambda^{fh}\delta\tau^h(c^{fh} - c) \\
p^{fh} &= \frac{1}{2}\delta\tau^h(c^{fh} + c) + \frac{1}{2}(1 + \tau^h\theta)\lambda^{fh}\delta\tau^h(c^{fh} - c) \\
q^{fh} &= \frac{L^h}{2\gamma}\left[\delta\tau^h(c^{fh} - c) + (1 - \tau^h\theta)\lambda^{fh}\delta\tau^h(c^{fh} - c)\right] \\
\pi^{fh} &= \frac{\delta^2 L^h\tau^h}{4\gamma}\left[1 + (1 - \theta\tau^h)\lambda^{fh}\right](c^{fh} - c)^2
\end{aligned} \tag{8}
$$

[10] We assume that $4\theta\gamma > L^l(1-\theta\tau^l)^2$ and $1 > \theta\tau^l$ so that the scope is always positive.

For domestic firms producing for the domestic market we obtain the following functions, we just set $\delta = \tau^h = 1$.

3.3 Market Equilibrium

To close the model we need equilibrium conditions under which a firm can operate in a given market. For that, they must have a positive profit just so to pay the fixed entry cost (f_E) of entering a given market. When a firm draws its marginal cost c if $c > c^{fh}$ then the firm loses money and stops producing. It states that a firm must cover the fixed cost entry by its profit at home or abroad.

$$\begin{aligned} f_E &= \int_0^{c^{fh}} \pi^{fh} dG(c) + \int_0^{c^{ff}} \pi^{ff} dG(c) \text{ for firm in F} \\ f_E &= \int_0^{c^{hf}} \pi^{hf} dG(c) + \int_0^{c^{hh}} \pi^{hh} dG(c) \text{ for firm in H} \end{aligned} \tag{9}$$

From these equations, we can determine the market cost cutoff above which firms cannot operate profitably. As it is standard, we will assume that the marginal cost c is distributed Pareto such that $G(c) = (c/c_M)^k$ with a support $c \in [0, c_M]$ with c_M being the maximum value c can take and k the shape parameter. A higher k implies more concentration of firms on the right tail of the distribution.

After some manipulation (see subsection A.3), we can express the free entry condition :

$$\begin{aligned} c^{fh} &= \frac{\phi^h}{\delta\tau^h}\left(\frac{1-\rho^f}{1-\rho^h\rho^f}\right)^{\frac{1}{k+2}} \\ c^{ff} &= \phi^f\left(\frac{1-\rho^h}{1-\rho^f\rho^h}\right)^{\frac{1}{k+2}} \end{aligned} \tag{10}$$

Note that ϕ^l and ρ^l are such that :

$$\phi^l = \frac{\gamma 2(k+1)(k+2)c_M^k f_E}{L^l[1+(1-\theta)\lambda^{ll}]} \text{ and } \rho^l = (\delta\tau^l)^{-k}\frac{4\gamma\theta - (1-\theta)^2 L^l}{4\gamma\theta\tau^l - (1-\theta\tau^l)^2 L^l}$$

The first expression is the cost cut-off for firms in F exporting to market H, the second is the free entry conditions for firms in F operating in F. The free entry condition of firm in H operating in H can be recovered from the first expression by using this identity: $c^{fh} = \frac{c^{hh}}{\delta\tau^h}$.

These expressions provide closed forms solutions of the model and intuition on what are the dynamics at play. We can see that the import cutoff value (from *home* perspective) is given by c^{fh}. $\frac{\phi^h}{\delta\tau^h L^h}$ give intuition on home market profitability for exporter from F with ϕ^h being the objective measure of market access conditions divided by the trade cost $\delta\tau^h$. L plays its competitive role as in Melitz and Ottaviano (2008), an increase in size leads to a lower cost-cutoff leading less productive firms to exit the market, increasing the productivity. However, the vertical quality differentiation changes the intuition on prices and markups which do not necessarily decrease with market size increases since firms producing high-quality variety can also impose a higher markup (see Equation 8).

We now turn our analysis to the equilibrium import price structure, we can decompose it following Equation 8 as being formed of two components productivity and quality:

$$p^* \equiv \frac{p^{fh}}{\tau^h} \Longrightarrow p^* = \underbrace{\frac{\delta}{2}(c^{fh} + c)}_{\text{Productivity}} + \underbrace{\frac{\delta}{2}\kappa(c^{fh} - c)}_{\text{Quality}} \tag{11}$$

To alleviate the notation we have set $\kappa = (1 + \tau^h\theta)\lambda^{fh}$ which is a proportional measure of the quality scope for differentiation in the market. We now have an expression of import price determined by three key parameters: firm productivity c, market import cost-cutoff c^{fh}, and the quality scope for differentiation κ. Taking the total log derivative we have (full derivation in subsection A.3):

$$d\ln(p^*) = \frac{\delta}{2}\left[\underbrace{\frac{(1+\kappa)c^{fh}d\ln(c^{fh})}{p^*}}_{\text{Market Condition}} - \underbrace{\frac{(1-\kappa)cd\ln(\frac{1}{c})}{p^*}}_{\text{Productivity}} + \underbrace{\frac{(c^{fh}-c)\kappa d\ln(\kappa)}{p^*}}_{\text{Quality}}\right] \tag{12}$$

We can clearly see the different effects at play in the import price equilibrium, while trade cost $\frac{\delta}{2}$ mechanically increases the cost of import, the quality, productivity, and market conditions interplay in non-trivial ways.

First, depending on the value of κ the sign of productivity effect on price can change. If $\kappa < 1$, we are considering a low-quality scope good, then productivity correlates negatively with prices, and more productive/bigger firms will set a lower price than less productive ones (Roberts and Supina, 1996; Foster et al., 2008). This is the classical correlation of Melitz and Ottaviano (2008), bigger firms have higher markups and lower prices. If $\kappa > 1$, we are considering a medium to high-quality scope industry, which is the case we are interested in, then the sign of the productivity effect shift, and the correlation between productivity and prices appears to be positive (Verhoogen, 2008; Kugler and Verhoogen, 2012; Manova and Zhang, 2012).

This result, adds nuance to Melitz and Ottaviano (2008). In the case of $\kappa > 1$, both quality and productivity would push up the prices[11]. The logic is that more productive firms would also produce higher-quality goods (see (8)). Hence, quality adds ambiguity to the correlation between productivity and import/export prices. The sign of the correlation is an empirical question that we will tackle in section 5.

Second, the cost cutoff is always positively correlated to the import prices, an increase in cost cutoff will make this market less competitive by allowing less productive firms to maintain themselves in the market. It will also create the possibility for more productive firms to charge higher markups, making the market more profitable. This situation then would decrease the average productivity and increase the prices and markups. A decrease in the cost cutoff would have the opposite effect.

Third, quality, when it plays, always tends to increase the prices of imports as higher-quality goods are more expensive.

Then the overall effect of tariffs depends on the degree of differentiation implied by the quality scope. A flatter quality would imply a low level of vertical quality differentiation, which would make our case closer to the canonical Melitz and Ottaviano (2008). Conversely, a steep quality ladder would make considerably change our expectation on price change depending on the quality of the good and then productivity of the firm.

3.4 Tariff Elasticity

Now that we have our core setup with the equilibrium import price defined, we can study the elasticity of prices with respect to tariffs, which will give us the level of pass-through onto consumers that we should expect. Given the linear form of the demand, unlike in CES function, the pass-through can vary by firm. These non-constant markups allow for strategic pricing of firms depending on the elasticity of demand they face and then transmission of the pass-through (Parenti et al., 2017; Mrázová and Neary, 2017).

The tariff absorption elasticity is defined as (see derivation in subsection A.4):

$$\varepsilon_{p^*} = \frac{\partial \ln(p^*)}{\partial \ln \tau^h} = \frac{\delta}{2}\left[\frac{(1+\kappa)c^{fh}}{p^*}\varepsilon_{c^{fh}} + \frac{(c^{fh}-c)\kappa}{p^*}\varepsilon_{\kappa}\right] \tag{13}$$

[11]In Melitz and Ottaviano (2008), the price function is $p(c) = \frac{1}{2}(c_D + c)$, high productivity firms sell for a lower price, and markup is $\mu(c) = \frac{1}{2}(c_D - c)$, firms partially absorb their productivity differential into higher markups.

It directly follows from Equation 12 and $\varepsilon_{c^{fh}} = \frac{\partial \ln c^{fh}}{\partial \ln \tau^h}$ represents the elasticity of cost cut-off to import and $\varepsilon_\kappa = \frac{\partial \ln \kappa}{\partial \ln \tau^h}$ the elasticity of quality ladder to import. Then, tariff influence the price through the quality and cost-cutoff channels, so far productivity is left aside as tariffs are not directly impacting firms in our model[12]. It measures the impact of 1% increase in tariff on home price in %.

We have shown in the appendix (subsection A.4) that an increase in tariffs reduces both the cost cut-off for importing ($\varepsilon_{c^{fh}} < 0$) and the quality scope ($\varepsilon_\kappa < 0$). These results stem from the fact that, under higher tariffs, only more productive firms are able to profitably access the market. As a result, the effective market size for foreign firms contracts, and the profitability of offering a wide range of designs diminishes. Consequently, following a tariff hike, we expect the average quality of imported goods to rise, since only firms with higher productivity and quality can remain in the market. Therefore, the price elasticity with respect to tariffs is also negative, which means that exporter in F will decrease their free of board export price to the home market and then partially absorb the tariff increase. This lead to an incomplete pass-through. In the context of solar panels, this implies that prices should rise after a tariff increase, but by less than the increase in tariff.

The relation between tariff pass-through and productivity is however more complex due to the fact that c is present at both the numerator and the denominator. At the numerator the elasticity of prices with respect to tariff varies negatively with the productivity of the firm. A more productive firm will absorb more the tariff, and it comes solely from the quality channel. We can think for instance that a firm selling higher quality solar panels might be able to absorb more the shock due to initial higher prices and markups. Conversely, at denominator we know from Equation 11 that prices can vary positively or negatively with productivity depending on the scope of quality differentiation κ.

Using the linearity of c with respect to the denominator and numerator, and then monotonicity of c with respect to ε_{p^*} we take the endpoints of productivity distribution:

$$\varepsilon_{p^*} = \frac{1+\kappa}{2}\varepsilon_{c^{fh}} \text{ for } c = c^{fh}$$
$$\varepsilon_{p^*} = \varepsilon_{c^{fh}} + \left(\frac{\kappa}{1+\kappa}\right)\varepsilon_\kappa \text{ for } c = 0$$

[12] We implicitly assume that the productivity of firms is unaffected because firms produce in their homeland f or h and are not internationalized or do not choose to invest in another country market (FDI). It comes from the fact that our unique factor of production is labor and is assumed to be immutable.

For the elasticity of tariff absorption to be higher for high-productivity firms it must be that $\kappa < 1$:

$$\frac{1}{2}\varepsilon_{c^{fh}}(\kappa^2 - 1) > \kappa\varepsilon_\kappa$$

Indeed, if $\kappa < 1$, the market is in a low-quality scope setting, high-productivity firms produce and sell for a cheaper price than low-productivity firms, leading them to increase relatively lower prices in case of tariff to conserve an edge on their competitors and can absorb it due to higher productivity and markups.

But, when $\kappa > 1$ then the case is more subtle and depends on the relative magnitude of elasticity of the cost-cutoff and product scope to the tariff.

If $\varepsilon_{c^{fh}} > \varepsilon_\kappa$ then for certain value of κ the inequality hold even with $\kappa > 1$. We calculated that this maximum value is 2.41, it is a medium-quality scope market. This raises an interesting case, in which the lowest-productivity firms still increase prices more than the high-productivity firms for a medium-quality scope. It adds an important nuance to our base setup since this moderately high-quality scope implies that, following Equation 8, high-productivity firms have higher markups than low-productivity firms, explaining that they can absorb a tariff increase.

For higher values of κ, the inequality sign reverses and high-productivity firms, producing high-quality goods, can pass on to their consumer a larger price increase since their product are very differentiated from their competitors.

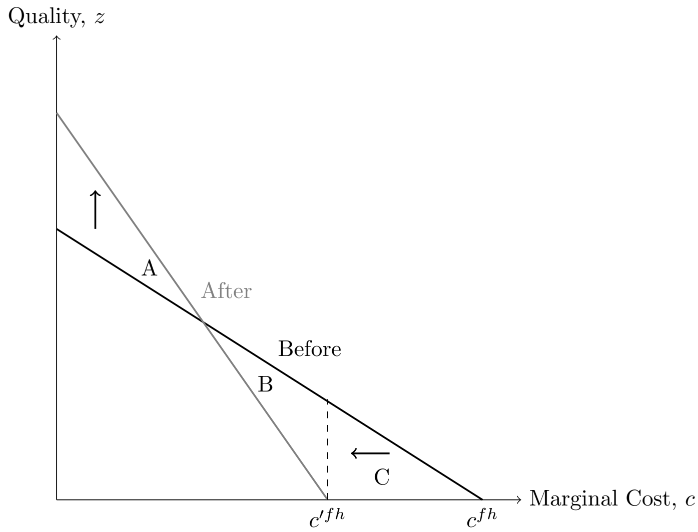
3.5 Tariff Effects on Firms and Quality Scope

In this last theoretical section, we discuss some effects that emerge from the model and should guide our thoughts for the empirical analysis.

The first is the *selection effect*, this effect stems from the fact that due to variable production cost, only firms with the smaller variable cost (i.e. the highest marginal productivity) can select for export. The imposition of tariff from H on F's firms leads the cost cut-off c^{fh} to decrease which in turn reduces the number of firms able to export to H. This effect is crucial as it impacts our perceived outcomes on prices in H in various ways. Everything being equal, the average price level of imported solar panels, following the tariff implementation should increase as cheaper imported varieties are left out of the market, and the quality of imported varieties should increase. This is a compositional effect.

A second and related effect, extensively discussed by Bagwell and Lee (2020), is the *firm-delocation effect*. An increase in tariff in H increases the number of domestic entrants in H. The cost cut-off of domestic firms c^{hh} has

Figure 1: Tariff Effect on Quality Scope



Notes: This graph shows the effect of imposing tariffs on quality along the productivity distribution. It reduces the quality ladder. The cost-cutoff goes from c^{fh} to c'^{fh}, reducing the number of firms able to reach the H market. Firms in C exit, firms in B remain but lower the quality, and firms in A increase the quality.

increased, domestic firms of H are now facing less competitive pressure, and the firms just below the former c^{hh} threshold can now maintain themselves on the domestic market. This increases the variety of goods available, but there are lower-quality goods. An important implication is that this phenomenon generates in trade models a Metzler paradox. Note that this effect emerges in the classical Melitz-Ottaviano type model, with no endogenous quality.

The implementation of endogenous quality slightly modifies the Metzler effect. Instead of having a decrease in average pre-tariff prices in the tariff-imposing country, we have a "*quasi-Metzler paradox*"[13], the quality can fall on average on the tariff imposing market (due to the possibility of lower quality firms to maintain themselves), explaining partly the apparent fall in prices.

A last effect that emerges from the model is a form of the *Alchian-Allen effect*. Due to higher tariff absorption for high-productivity firms in the context of low or medium quality-scope, we can see an Alchian-Allen effect emerges; more likely in the context of medium quality where prices correlate with quality. Figure 1 reflects that quality shift due to tariff, with an increase

[13] The term has been coined by Ludema and Yu (2016).

in tariff lowering the quality ladder, and higher quality firms increasing the quality more than lower quality firms. As shown by Antoniades (2015) this led to an increase in the average quality exported to the Home market. This compositional change of export is a key effect of tariff.

Ultimately, the imposition of a tariff can influence the composition of imports in two ways: first, by selecting only the most productive (and often higher-quality) firms; and second, by altering the product mix exported to the tariff-imposing country in favor of more qualitative goods if the Alchian-Allen effect dominates the quasi-Metzler paradox.[14]. The magnitude of those different effects is discussed is discussed in the empirical sections.

3.6 From Theory to Data

To bring our model to the data, we must adopt additional assumptions. Due to limited access to firm-level data, we adapt our model's predictions accordingly. In the theoretical framework, each firm produces a single variety of a differentiated good. In contrast, our data captures firms that produce multiple solar panel models spanning a range of quality levels.

To bridge this gap, we assume that each product variant is produced by a distinct firm/plant and that these firms are owned by a common upper-level entity that does not engage in strategic interactions—neither across its own product lines nor with competitors. In effect, we model the market as composed of independent producers, each choosing quality in isolation, even if they belong to the same parent firm.

This is a strong assumption. The behavior predicted in a model with a single product per firm may not hold in a setting with multiple products under common ownership, particularly when strategic interactions across varieties or firms are relevant.

In addition to assuming that each solar panel is produced by a distinct manufacturing plant with its own cost structure—reflecting specific production processes—we also assume that these panels are exported and branded by an upper-level firm. Following the model, we posit a positive correlation between productivity and quality: although we do not directly observe the productivity of each sub-manufacturer, we assume that only more productive producers can produce higher-quality solar panels.

Having acknowledged these limitations, a natural extension of our framework would be to allow firms to produce multiple products, as in Mayer et al. (2014), or Chen and Juvenal (2016) with higher quality produce being the core product and more costly to produce.

[14]This last statement is an aside from the pure model logic since each firm produces only one variety and not a bundle.

Despite its simplifying assumptions, we believe our framework retains significant value. First, it offers clear intuition about firm and product-level behavior. Extrapolating these mechanisms to the larger, multi-product firms observed in our data does not contradict the model's core predictions. As such, the framework provides a useful lens through which to analyze the interaction between endogenous quality choice and variable markups.

Second, by incorporating a quality ladder—defined at the country or industry level—the model captures the nuanced competitive dynamics that emerge across firms. When the quality scope is relatively flat, competition centers on price, and we expect a negative correlation between quality (or productivity) and prices. In contrast, a medium or steep quality scope enables high-quality firms to differentiate themselves more clearly, leading to a positive correlation between quality and prices. This distinction reflects the different modes of competition firms may face depending on the structure of their industry.

With these considerations in mind, we now turn to the empirical analysis.

4 Data

To answer our question about the effect of quality on tariff pass-through and the compositional change following tariff implementation we need detailed data on the solar panel U.S. market, tariff, and control for socio-demographic factors.

4.1 Data On Solar Panel Quality and Prices

Our key dataset is the publicly available Tracking the Sun dataset published yearly by the Lawrence Berkeley National Lab to analyze the evolution of the solar panel market. It is the most comprehensive dataset available for the U.S. solar panel market, it contains detailed information at the installed system level on the flux of installation for non-utility scale installation. That is installation below 1MW, which represents more than 90% of total installation in the U.S. during our period (2010-2018). Installation is reported at the zip code-installation date level. We can observe the module manufacturer of the solar panel, the model, the installer, the type of customer (i.e. residential, commercial), the total installation price, the estimated amount of rebate or grant obtained, and the crucial information about its efficiency rate for converting solar energy into electricity.

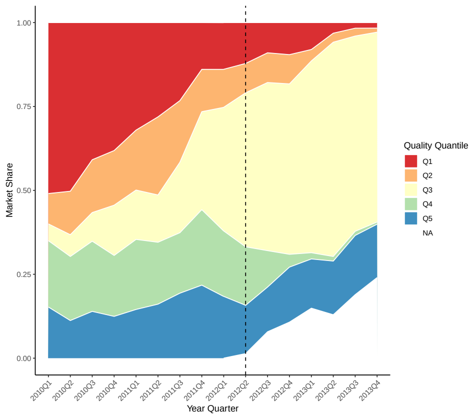
This last information comes from the California Energy Commission and the SolarHub website, a professional website reporting detailed technical information about solar panels. Professional sources estimate the core of the innovative and differentiating characteristics relies on the module efficiency Barbose and Darghouth (2019); Com (2024). Then, to discern the quality differentiation between products we use three main measures of quality.

The first is the efficiency rate, which is a continuous variable defined at the panel model level. This metric is physical characteristics, robust to compositional change, and inter-temporally comparable.

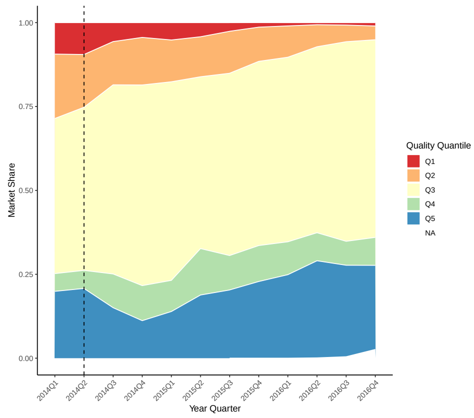
The second metric follows directly the precedent, this is a quintile metric of quality. We used the years before the tariff implementation, respectively 2011, 2013, and 2017, to build our metric. As it will be discussed further in the empirical part, this metric is sensible to compositional change, however, it still provides useful information as it allows to access more precisely the effect for each quantile of efficiency.

Finally, a complementary premium definition is the *premium installation*. We define premium installation, as installations that include premium features such as a built-in micro-inverter which considerably improves the overall efficiency of the installation and requires high manufacturing capabilities. However, this last metric has become more and more common throughout the decade to the point that it represents close to 45% of installed solar panels in 2018.

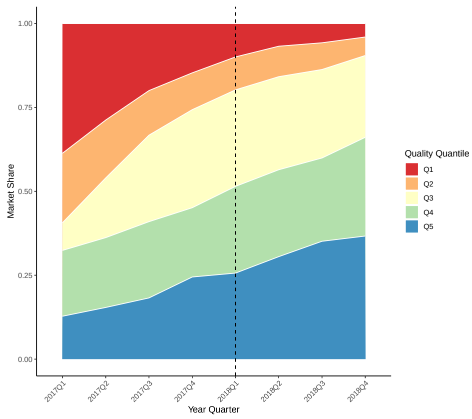
Figure 2: Market Share per Quantile of Quality



(a) 2010-2013



(b) 2014-2016



(c) 2017-2018

Notes: This figure displays the market share defined as the sum of installed solar panels per installation site within each quintile at a quarterly rate. The quintile definition used is the one described in the section 4. The same figures exist in the appendix for the second definition of quantile Figure 16. The vertical black dashed lines represent the tariff date application. The "NA" values in the first graph correspond to the introduction of new panels that are more efficient than the most efficient panel included in our original definition.

Figure 2 shows the evolution of market shares by quality quintile over the subperiod. In particular, Figure 2a highlights a rapid shift in market share during certain years, driven in part by the introduction of new models that fall outside the scope of our predefined metrics. This pattern reflects the fast pace of technological advancement in the industry and confirms significant compositional change in this measure over time.

While this dynamic makes the quintile metric somewhat fragile, it still provides useful and suggestive information that can be interpreted through the lens of our model. Cautiously, and acknowledging the limitations of this metric, we observe that the highest-quality solar panels tend to maintain a relatively stable market share—except during the 2017–2018 period—while medium-quality panels consistently capture a larger portion of the market. This is unsurprising, as these products are generally cheaper to produce and more accessible, and thus likely represent a larger share of the mass of available products.

Table 1: Sampled Firms

Manufacturer	Market Share	Country of Origin
Maxeon - Sunpower	0.1724	USA
LG Electronics inc.	0.1252	South Korea
Hanwha Qcells	0.1195	South Korea
SolarWorld	0.0761	Germany
Canadian Solar	0.0635	China
REC Solar	0.0552	Norway
Jinko Solar	0.0542	China
Trina Solar	0.0537	China
Panasonic	0.0343	Japan
Hyundai Energy Solutions co., ltd.	0.0311	South Korea
Yingli Energy (China)	0.0284	China
Silfab	0.0206	USA
Mission Solar Energy llc	0.0119	USA
Sharp	0.0116	Japan
Suntech Power	0.0116	China

Notes: The market share is calculated as the sum of solar panels installed on the total quantity of solar panels, for each brand, for the entire period of 2010-2018. The Country of Origin columns do not refer to the production site but the head-quarter location or historical origin of the brand. For instance, Maxeon-Sunpower is a historical US brand but the production is based in Malaysia and the Philippines.

Considering the scope of our observations, we delimited our analysis to firms representing 90% of the market share. It reduces the number of firms from more than 269 to 15. All these firms were present over the entire period, and we observed all their commercialized solar panels, hence there is no risk of omitted Chinese firms entering post-anti-dumping tariffs and not being affected.

Moreover, for our analysis, we choose to focus on the period going from 2010 to 2018 and on California to limit the difficulty of assessing the interstate rebate programs also because California represents two-thirds of the observations and then largely predicts the national trend we can observe in the data[15].

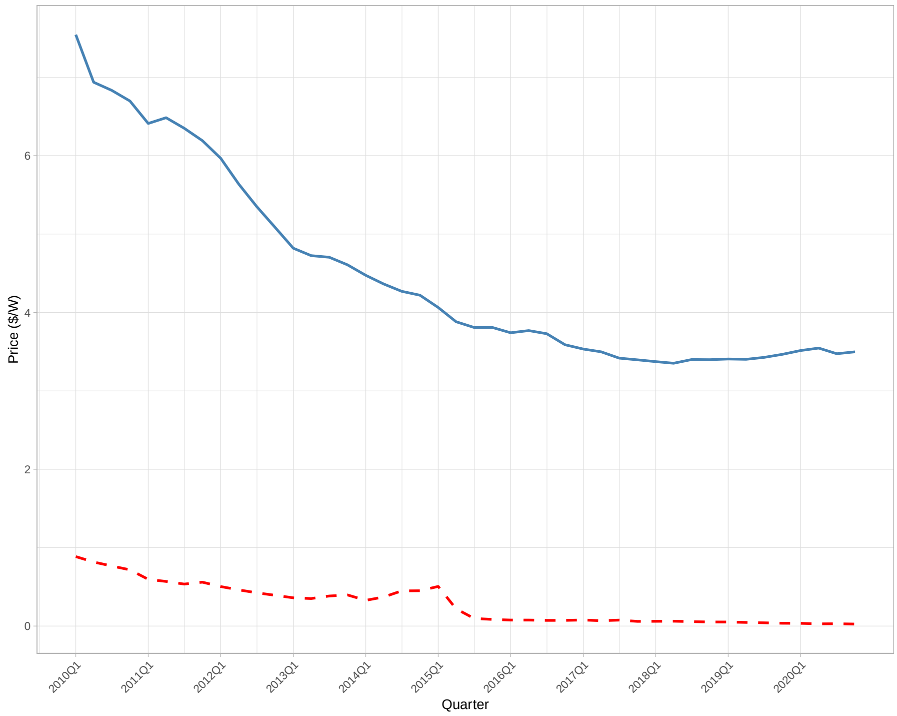


Figure 3: Price and Rebate per $/W

For prices, we observe the total installation prices, which we measure in $\$/W$ to take into account potential differences in installation size. They are deemed to be reliable for Home-Owned systems (i.e. the household by the system and pays an installer to install it), but Third-Party-Owned systems (i.e. a company buys the solar panels, receives the rebate, and leases to the household) are notoriously non-reliable (Trabisch, 2013; Pless and van Benthem, 2019) and then excluded from the scope of our analysis. Note that all prices are deflated using 2010 as the reference year. For the main analysis, we use prices gross of subsidy, as this approach is more conservative and avoids potential biases stemming from misreported rebates. For comparison, we also provide the corresponding estimates using net prices in the appendix

[15]However, note that two important states are missing due to the absence of reporting, Florida and Hawaii, but they are both smaller markets than California due to the important subsidy program of the latter and its larger size.

(Table 18)[16].

The rebate amount, reported by state data providers, is treated as a lump-sum transfer to the household. It does not include the federal Investment Tax Credit (ITC) of 30%, but accounts for all other financial incentives offered at the state level in California. The most significant of these during our period was the California Solar Initiative (CSI), which began in 2008 and effectively ended in 2013,[17] despite its formal closure occurring later.

The CSI rebate was a lump-sum transfer determined by several installation characteristics, including system size, module efficiency, location, and site shading. These attributes were used to compute a "design factor," which served as a proxy for the system's expected electricity output. Households applied for the CSI rebate through their electricity provider, and the rebate amount was then passed on to them directly.

The program was designed to incentivize solar adoption by making upfront costs more affordable. Importantly, the rebate amount declined over time in response to the cumulative installed capacity within each electricity provider's territory. As a result, the rebate varied both across time and geography, offering a potential source of exogenous variation in prices.

Importantly, the subsidy was not tied to local content requirements, and we observed no systematic differences in rebate amounts between Chinese and non-Chinese solar systems. Overall, rebates account for a relatively small share of total installation prices in our data—approximately 2% on average—and are therefore unlikely to constitute a major confounding factor in our analysis of tariff effects on demand.

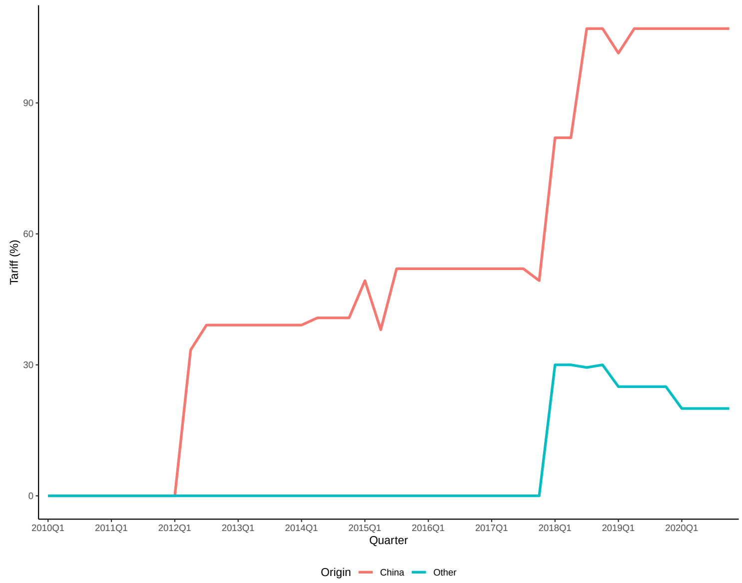
4.2 Solar Panel Dispute and Tariff

We use three tariff episodes in our analysis: two rounds of anti-dumping tariffs targeting Chinese firms and the 2018 Safeguard Tariffs, which applied to imports from all countries.

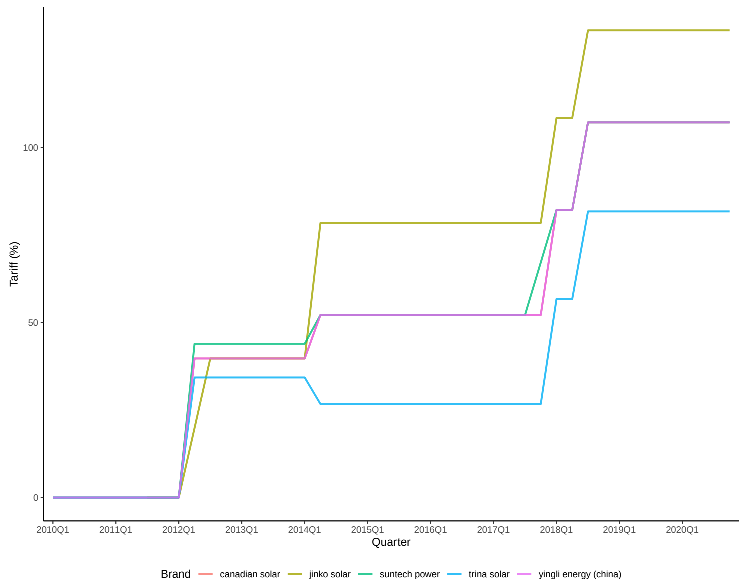
The anti-dumping tariffs stem from legal complaints initiated by the German manufacturer SolarWorld in 2011 and 2013. These complaints, lodged in both Europe and the United States, accused Chinese firms of "unfair pricing." In response, trade authorities in both jurisdictions conducted investigations and, in 2012 and 2013, imposed substantial anti-dumping duties on all Chinese firms.

[16]The results are qualitatively similar when using net prices, except for the first tariff wave, where the effect becomes statistically insignificant. These differences are discussed in more detail in the appendix.

[17]Although the program officially terminated in 2016, most of the funding had been exhausted by 2013.



(a) Origin Level Weighted Tariff



(b) Firm Level Nominal Tariff

Figure 4: Tariff Level by Origin and Brands

Notes: The Figure 4a displays the weighted average tariff by origin, the weight is the firm level market-share for each year. Figure 4b shows firm-level tariffs for the Chinese firms in our sample.

A second round of anti-dumping tariffs occurred only in the United States following SolarWorld's claim that Chinese producers were circumventing the initial duties by routing products through third countries. The U.S. International Trade Commission and Department of Commerce ruled in favor of SolarWorld again, and in 2014 imposed additional duties targeting firms involved in circumvention—most notably intermediaries based in Taiwan and Malaysia.

For these anti-dumping tariffs, we use firm-level data from the U.S. International Trade Commission and the Federal Register, which document both the justification for the tariffs and the corresponding duty rates. While all Chinese firms were subject to these inquiries, the applied tariff rates vary by firm depending on the estimated "dumping margin"—i.e., the degree to which a firm's prices were deemed below fair market value—as well as the firm's level of cooperation during the investigation. In cases of non-compliance, a punitive tariff rate of 250% was applied. However, this rate affected only a small number of low-volume exporters, which we excluded from our analysis.

As shown in Figure 4, the tariff rates applied to firms were relatively homogeneous during the first wave of anti-dumping duties, but became significantly more heterogeneous in the second wave. This divergence reflects both differences in the estimated "dumping margins" and variations in firms' compliance with the investigation process—most notably, Trina Solar exhibited greater cooperation than its peers, which resulted in a lower tariff rate.

We identify the start of each tariff episode using the date of provisional measure validation published in the *Federal Register*. This information was cross-checked with the anti-dumping database maintained by Bown (2016). These dates and rates are considered reliable, as the final and provisional tariff levels were either identical or differed by no more than one percentage point, and were systematically applied to the same set of firms.

The final tariff episode we consider is the 2018 Safeguard Tariff. Our contribution to the literature on this period is to focus on a single industry and to precisely document the tariff rates faced by individual firms. Although the safeguard tariff was set at 30% for all firms, it applied on top of existing anti-dumping duties for Chinese firms. As a result, total tariff exposure for some major Chinese producers—such as Jinko Solar, Yingli Energy China, and Suntech Power—exceeded 100%.

It is important to note that the U.S. solar market is highly dependent on imports. Even American brands such as Maxeon–SunPower—a pioneer in the U.S. solar industry and producers of some of the highest-quality solar panels—have located most of their manufacturing in Southeast Asia and Mexico. As a result, the 2018 Safeguard Tariff affected all brands operating in the U.S. market, although the degree of impact varied across firms depending on their production geography.

4.3 Solar U.S. Market

Turning to the structure of the American solar panel market, it is characterized by a high degree of concentration, with a few large firms supplying the majority of installed systems. While U.S.-based production does exist, it falls outside the scope of our analysis. Notably, although some Chinese firms have established manufacturing facilities within the United States, domestic production remains insufficient to meet demand (Bahar, 2022). As a result, concerns about widespread tariff circumvention through minimal U.S.-based assembly are limited. During the period under study, the U.S. solar market remained heavily dependent on imports to meet installation demand.

An important feature of our dataset is the presence of detailed information on installers. For each system, we observe whether it was installed by a third-party firm and, if so, which one. While a small share of households install systems independently, the vast majority (97%) contract with an installer.

In both our theoretical model and empirical framework, we assume that tariff pass-through is determined independently by the manufacturing firm, rather than by installer-specific markups. This assumption is supported by the distribution of installer activity. As shown in Figure 13, among host-owned systems, a large share of installers install fewer than five systems per year. Moreover, on average, each installer works with six different manufacturers annually. Given this fragmentation, we assume that installers are not systematically correlated to a specific brand. However, because installer-level differences may still affect pricing outcomes, we include installer-fixed effects in our regressions to control for this source of variation, consistent with the evidence in O'Shaughnessy et al. (2018); O'Shaughnessy (2019).

Installed systems do not differ drastically by brand origin. While Chinese manufacturers tend to be less represented in the premium segment—none of their panel models qualify in the top-tier category—they still offer high-quality solar panels (Figure 12). As a result, we do not observe substantial price differences between Chinese and non-Chinese brands.

To complement our installation data, we use detailed socio-demographic information from the U.S. Census Bureau at the Census Tract level.[18] We find that Chinese firms tend to serve systematically less affluent households, whether measured by income, home values, or educational attainment. These patterns suggest a market positioning strategy focused on affordability, with

[18]An intermediate administrative unit between the county and zip code levels, designed to provide consistency in census data across time and space.

Chinese manufacturers primarily targeting middle- and upper-middle-income consumers.

Nonetheless, customers in the solar market overall remain relatively affluent. Solar installations represent a major investment, typically costing several thousand dollars, and while subsidies are available, they are generally insufficient to fully offset the upfront financial burden for most households.

Table 2: Sample Descriptive Statistics

	Mean		Standard Error	
	Non-Chinese	Chinese	Non-Chinese	Chinese
Panel Characteristics				
Price ($/W)	3.83	3.88	1.76	1.66
Rebate ($/W)	0.08	0.08	0.29	0.28
Premium Panel (%)	0.12	0.00	0.33	0.00
Premium Installation (%)	0.49	0.39	0.50	0.49
Efficiency	0.19	0.17	0.02	0.02
Premium Panel Price ($/W)	3.87	NA	1.17	NA
Premium Installation Price ($/W)	3.78	4.18	1.54	2.07
System Size (kW DC)	6.37	6.25	3.04	3.04
Socio-demographics				
Population Density	2,857.78	2,777.72	3,251.80	3,783.74
Median Household Income	$75,817.74	$68,941.48	27059.25	25727.82
Median Home Value	$425,413.42	$364,045.27	217845.33	209479.69
Share with BA Degree (%)	36.04	30.30	22.13	20.95
Sample Composition				
Share of Observations	0.88	0.12		
Num. Observations	369,438	51,724		

Notes: Panel characteristics come from the Tracking the Sun dataset; socio-demographics are from census data at the ZIP code level. All statistics are averaged over the period.

5 Empirical

Our empirical analysis of the impact of tariffs on installation prices proceeds in three parts. First, we estimate the price variation induced by tariffs at the installed system level and examine the heterogeneity of this effect along the quality dimension. Second, we provide suggestive evidence of an Alchian-Allen effect and document an overall upward shift in the quality composition of firms affected by the tariffs. Finally, we estimate demand separately for low- and high-quality goods and find that higher-quality products are slightly less price elastic, consistent with the predictions of our theoretical model.

We document heterogeneous price elasticity along the quality dimension, with lower-quality panels exhibiting relatively larger price increases than their higher-quality counterparts. This greater price increase is also associated with an overall improvement in quality across the entire distribution. Finally, we find suggestive evidence that demand is less elastic for higher-quality panels.

5.1 Tariff Pass-Through

To understand how tariffs are pass-through onto consumers we use the following linear model that allows for quality differentiation:

$$\begin{aligned}\ln p_i =& \beta_0 \ln \text{Tariff} + \beta_1 \ln \text{Tariff} \times \text{QualityMetrics}_i + \beta_2 \text{Premium Installation} \\ &+ \beta_3 \text{QualityMetrics}_i + \beta_4 \text{Premium Installation} + \theta \mathbf{X}_i + \text{FE} + \varepsilon_i\end{aligned} \tag{14}$$

where $\ln p_i$ is the log installation price in $\$/W$ at the system level gross of subsidy[19], and $\ln \text{Tariff}$ is the $1 +$ tariff rate faced by each solar panel manufacturer, and Quality Metrics recover our different notions of quality : *efficiency* and *premium installation.*

To estimate the degree of price variation due to tariff we exploit variation in tariff exposure across solar panel systems in time and space. Our baseline specification includes quarter-year, installer, origin, and county fixed effects. This absorbs the broad time-declining trend in prices, installer-specific pricing behavior that could be influenced by their competitive environment, origin-specific effects such as cost structure or tariff level, and local market heterogeneity at the county level such as solar potential or income differences. The identifying variation of β_0 and β_1 is due to within county, installer, origin, and year variation across the solar installation systems and across firms' exposure to the tariff - due to firm-level exposure to tariffs.

[19]We provided in the appendix (see subsection B.5) the same table for the prices net of rebate, the results are similar.

We implemented a more constraining set of fixed effects, with origin-by-quarter, installer, and county fixed effects to assess the stability of our results. Our objective is to absorb time-varying shock for the country of origin, while still controlling for potential local heterogeneity and tariff differences between installers. This limits potential supply-side induced shock like productivity shocks. The identifying variation of β_0 and β_1 comes from the variation in system cost across differentially exposed panels within the same county, installer, net of origin quarterly shocks.

To control other aspects affecting installation price, and strengthen our causality claim, we also implement a rich set of socio-demographic control variables $\mathbf{X}$ such as median house value, median income household, level of education, as well as demand-side variables potentially affecting the price such as electricity price or rebate perceived. Finally, we cluster our standard errors at the zip code level to account for spatial correlation.

Table 3: Price-to-Tariff Elasticity Estimates

	Overall		Anti-Dumping : 2010 - 2013		Anti-Dumping : 2014 - 2016		Trade War 2018	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln Tariff	0.421***	0.179*	1.089**	1.245*	1.085***	1.473***	0.543***	0.055
	(0.055)	(0.082)	(0.376)	(0.516)	(0.222)	(0.248)	(0.080)	(0.096)
ln Tariff x Efficiency	−1.963***	−0.272	−7.034**	−6.318*	−5.167***	−7.825***	−2.148***	0.670
	(0.280)	(0.438)	(2.527)	(2.907)	(1.226)	(1.387)	(0.404)	(0.489)
ln Tariff x Premium Installation	−0.068***	−0.049***	0.053	0.050	0.002	0.024	−0.079***	−0.055***
	(0.009)	(0.010)	(0.033)	(0.033)	(0.019)	(0.019)	(0.012)	(0.014)
Premium Installation	0.042***	0.034***	0.012*	0.012**	0.036***	0.032***	0.052***	0.048***
	(0.002)	(0.003)	(0.005)	(0.005)	(0.003)	(0.004)	(0.004)	(0.004)
Efficiency	1.653***	1.542***	−0.393	−0.535	0.783***	0.938***	1.927***	1.393***
	(0.084)	(0.106)	(0.443)	(0.463)	(0.152)	(0.166)	(0.124)	(0.134)
Num.Obs	414 762	414 762	34 545	34 545	115 726	115 726	128 111	128 111
R2	0.533	0.540	0.707	0.710	0.503	0.511	0.445	0.452
FE: County	X	X	X	X	X	X	X	X
FE: Year-Quarter	X		X		X		X	
FE: Installer	X	X	X	X	X	X	X	X
FE: Origin	X		X		X		X	
FE: Year-Quarter × Origin		X		X		X		X
Min-Max Efficiency	0.09–0.23	0.09–0.23	0.09–0.21	0.09–0.21	0.10–0.22	0.10–0.22	0.09–0.23	0.09–0.23

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

Table 3 summarizes our findings on price variation induced by tariffs. We consistently find a positive effect of tariffs on system-level prices, with the exception of our most restrictive specification applied to the 2018 Trade War period. This exception may simply reflect limited within-origin-quarter price variation once the trade shock has been absorbed. Notably—and contrary to some popular claims (Wesoff, 2014)—we observe price increases even during the first wave of anti-dumping tariffs.

The interaction term β_1 tells us how the price-tariff elasticity shifts when system efficiency rises by one percentage point. Our negative estimate of β_1

implies that, at higher efficiency levels, tariffs produce smaller relative price increases on the highest-quality solar panels. In an OLS regression, β_1 can be interpreted as a weighted average of the tariff's conditional average treatment effects across the range of system efficiencies.

The baseline price increase for an increase of 1% of tariff for the least efficient solar panel for the first and second anti-dumping tariff was of 0.45% (column 3) and 0.56%[20] (column 5) and for the most efficient of we would find negative estimate under a constant and linear effect hypothesis.

In the 2018 episode, the baseline pass-through for the least efficient panels falls to 0.35%, reflecting the much wider dispersion in applied tariffs (25%–133%) and hence in quality-specific exposure. Overall, the price elasticity declines with module efficiency.

However, under our more restrictive fixed effects specification, we no longer detect significant price variation attributable to tariffs during the Trade War period. This result is driven by the inclusion of origin-by-quarter fixed effects: because the additional tariffs were applied uniformly at the origin and quarter level, little residual variation remains for identification.

It is also important to note that this specification affects our estimate for the overall period. Since the Trade War accounts for the largest share of installations subject to tariff implementation in our sample, estimates from this episode exert substantial influence on the aggregate result, effectively pulling down the overall estimated pass-through.

Consistent with this pattern, we do not find significant heterogeneous price effects along the quality distribution when using the second set of fixed effects. This suggests that heterogeneous pass-through effects likely exist within the quality distribution but are obscured by limited identifying variation under more saturated fixed effects.

To uncover how pass-through varies over the quality distribution, we split the sample into three sub-periods (2010–13, 2014–16, 2017–18). Within each sub-period, we rank installations by panel efficiency for the year before treatment (2011, 2013, 2017) and assign them to quintile $Q_1, \ldots, Q_5$ (with Q_1 as the reference). We then estimate

$$\ln p_i = \beta_0 \ln \mathrm{Tariff}_i + \sum_{q=2}^{5} \beta_q \big(\ln \mathrm{Tariff}_i \times Q_{i,q}\big) + \theta\, \mathbf{X}_i \; + \; \mathrm{FE}_i + \varepsilon_i \tag{15}$$

where

$$Q_{i,q} = \begin{cases} 1, & \text{if observation } i \text{ is in efficiency quintile } q, \\ 0, & \text{otherwise.} \end{cases}$$

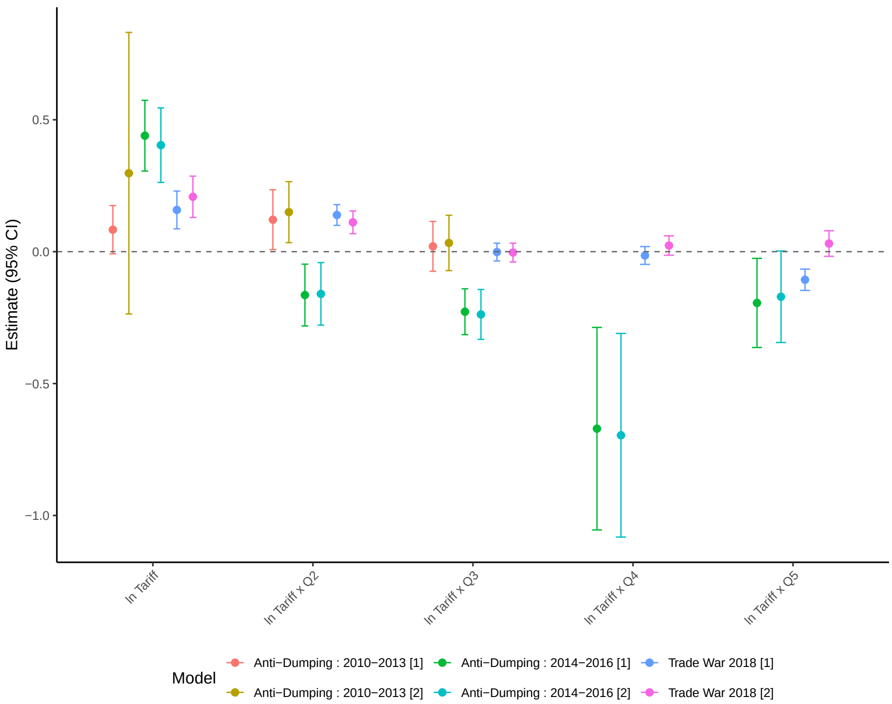
[20] $1.085 - 5.167 \times 0.10 = 0.56$

Here β_0 is the price to tariff elasticity in the lowest-efficiency quintile (Q_1), and each β_q measures the difference in elasticity between decile q and the reference decile Q_1.

This approach has two limitations. First, it implicitly assumes that quality is defined in relative terms within each period, rather than based on an absolute standard over time. That is, it assumes consumers form preferences based on a panel's efficiency relative to other models available at the time, rather than according to fixed efficiency benchmarks. This rules out the possibility that consumers have stable, time-invariant preferences for specific efficiency levels, or that they behave forward-looking by delaying purchases in anticipation of future technological improvements. However, following Gerarden (2023), we assume myopic consumer behavior is a reasonable assumption in this context, given the unexpectedly sharp price declines observed during the period.

Second, the ranking of panel efficiency may shift due to tariff-induced composition effects or instability in product quality over time. This undermines the comparability of quality metrics across periods, or even across years within the same sub-period. To address this concern, we propose a robustness check (Figure 7) using an alternative ranking based on the full sub-period. This approach better accounts for compositional changes caused by tariffs. While it does not eliminate potential selection into quality quantiles due to tariff exposure, it mitigates the concern and yields qualitatively similar results.

Figure 5: Estimate of Price Elasticity per Efficiency Quintile



Notes: This display the estimate of Equation 15. The standard errors are clustered at the zip code level. We voluntarily omit the Overall estimation to alleviate the figure. The entire table is available in the appendix (Table 14).

Figure 5 and Table 3 document substantial heterogeneity in price-to-tariff elasticity across the efficiency distribution. In the first anti-dumping episode (2010–2013), which applied only to Chinese-origin panels, the estimated elasticity is positive and statistically significant in all configurations but relatively stronger for the first and second quintiles than the third. There is no Chinese panel above the third quantile, this explains the absence of point estimates. Note that the 4th and 5th quintile point estimates of the second anti-dumping wave are noisy given the very low number of observations[21]. This mirrors our earlier finding that the highest-efficiency Chinese panels exhibited lower price elasticity than the least-efficient ones, but above all most Chinese solar panels qualify as low quality explaining their relatively higher price increase.

By contrast, during the second anti-dumping wave (2014–2016), the estimated price elasticity was negative and statistically significant across all

[21]See in Appendix the for the number of observations per quintile (Table 12, Table 13). Consistently with quality improvement observed, and caused by tariff, the second definition exhibits a different distribution of observations between quintiles.

efficiency deciles relative to the baseline tariff-induced price increase. This indicates that the price response to the tariff was conditional on panel efficiency, with the first decile showing a larger price increase than the average. These results suggest that, in this period, the price adjustment was either relatively uniform across the quality distribution or disproportionately borne by the lowest-quality panels.

Overall, the results point to a relatively stronger price increase for solar panels in the first quintile of the efficiency distribution during the anti-dumping tariff waves. This pattern is broadly consistent with the findings reported in Table 3. However, the potential endogeneity arising from selection into treatment—namely, the targeting of Chinese firms—remains a concern that we cannot fully address with these episodes alone.

In this regard, the 2018 Trade War provides a useful complementary setting. All countries were subject to the same tariff treatment, and any anticipation effects are believed to be relatively limited (Fajgelbaum et al., 2020). This episode thus offers a cleaner empirical environment to benchmark the effects of tariffs on price and quality dynamics.

For the 2017–2018 Trade War, the baseline effect of the tariff is positive. The estimated price elasticity conditional on efficiency quantile is positive until the second quantile, remains close to the overall mean across the middle of the distribution, and turns significantly negative in the top 20%—indicating lower price variation relative to the baseline tariff effect. Interestingly, this pattern closely mirrors the estimates observed during the first anti-dumping wave, lending additional support to our findings. Without over-interpreting, the data suggest a lower quality threshold around the second quantile and an upper threshold near the fifth.

These findings align with our theoretical model. In a medium-quality scope framework, firms producing mid-range panels benefit from higher markups and prices, which explains the relatively smaller price elasticity observed at the top of the distribution. Conversely, the higher elasticity among lower-quality panels may reflect a stronger quality upgrading effect at the bottom of the available product range. While this would appear to contradict the model—where quality improvements are expected to be concentrated at the top—it is consistent with the suggestive evidence of compositional quality shifts discussed in subsection B.2, where we observe an increase in quality at the lower end and a slight decrease at the upper end of the distribution. Although these results are preliminary, they echo the elasticity patterns documented here.

That said, the negative price elasticity at the top could also reflect compositional shifts in firm exposure. In particular, high-quality manufacturers such as Korean and American brands—previously unaffected by anti-dumping measures—were newly subjected to the 2018 safeguard tariffs. Given their strong presence at the upper end of the quality distribution, the observed negative elasticity may simply reflect their comparatively limited price adjustment in response to the new tariff.

Therefore, our results appear to support the conclusion that higher-quality panels are relatively less affected by tariff increases than their lower-quality counterparts.

One important caveat is that our dependent variable is the total system installation price, rather than the panel-only price, and we do not observe component-level markups. As shown in Table 3, a one-percentage-point increase in panel efficiency is associated with a 1.65% higher installation price, and systems equipped with a built-in micro-inverter command a 4.2% price premium. These estimates likely capture higher underlying markups associated with higher-quality systems.

As a result, the greater relative price variation observed among low-efficiency panels may simply reflect their lower baseline prices: the same absolute price adjustment translates into a larger percentage change at the lower end of the quality distribution.

The price response to tariff seems to be consequent in any case, with a 1% increase in tariff leading to between 0.3% and 0.5% increase in installation prices, even though the transmission is heterogeneous along the quality distribution. This nuance is even more important as our research framework allows for the quality of imported solar panels to vary in response to tariffs. Indeed the elasticity of quality scope to price declines with tariff increase, which can lead to a selection effect of firms (i.e. only the most productive firms stay in the market) and an Alchian-Allen effect. If higher quality solar panel relatively less increase their prices due to tariff implementation, then it can lead to a quality shift of import toward higher solar panel quality.

5.2 Quality Shift

To determine the impact of tariffs on imports we follow our previous strategy and exploit the variation in time and space of tariff at the system level to identify the tariff effects on the efficiency of the installed system :

$$\ln \text{Efficiency}_i = \beta_0 \text{Tariff} + \theta \mathbf{X} + \text{FE} + \varepsilon_i \tag{16}$$

where efficiency is converting solar energy into electricity in percent. Tariff is the firm-level tariff, fixed effects and the set of covariates are the same as in the previous section. In this setup, β_0 identifies the systems across firms' effects of exposure to tariffs on efficiency and can be interpreted as an elasticity of quality change to the tariff variation.

Even though we limit firm exit margin responses by restricting our sample to the largest firms—thereby minimizing firm-level selection effects—our results still provide suggestive evidence of an upward quality shift among tariff-exposed solar systems. On average, systems subject to tariffs are equipped with higher-efficiency panels.

As shown in column 5 of Table 4, a 1% increase in tariff exposure is associated with a 0.325% increase in observed panel efficiency, relative to a counterfactual group with similar characteristics. Importantly, tariffs were imposed at the firm level, not on individual panel models. Therefore, this effect cannot be explained by model-specific tariff differences but rather points to a compositional change in demand for higher-quality products among treated firms. This pattern offers suggestive evidence consistent with an Alchian–Allen effect.

Table 4: Change in Average Efficiency for Tariff Exposed Panels

	Overall		Anti-Dumping : 2010-2013		Anti-Dumping : 2014-2016		Trade War 2018	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln Tariff	0.131***	0.242***	0.043***	0.195***	0.325***	0.323***	0.185***	0.209***
	(0.005)	(0.008)	(0.010)	(0.057)	(0.012)	(0.011)	(0.010)	(0.011)
Num.Obs	269 069	269 069	34 545	34 545	106 413	106 413	128 111	128 111
R2	0.761	0.792	0.799	0.811	0.790	0.800	0.711	0.724
FE: County	X	X	X	X	X	X	X	X
FE: Quarter	X		X		X		X	
FE: Installer	X	X	X	X	X	X	X	X
FE: Origin	X		X		X		X	
FE: Year Quarter × Origin		X		X		X		X
Mean Dep. Var	−1.713	−1.713	−1.822	−1.822	−1.727	−1.727	−1.672	−1.672

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

Nonetheless, given our findings in the previous subsection, we expect the compositional change to have heterogeneous effects across the quality distribution. We therefore ask the following question: how do tariffs influence changes in efficiency across the quality spectrum? More specifically, which quantiles of the distribution experience the greatest upward quality adjustment?

To answer this, we estimate a conditional quantile regression. However, it is important to emphasize that quantile regressions are not linear models, and thus require a specific approach to account for fixed effects. Due to the nonlinearity of quantile estimation, standard demeaning methods used in OLS are not applicable—quantiles are sensitive to the shape and skewness of the distribution, and subtracting means would distort their position. As a result, we adopt an estimation strategy that explicitly accommodates fixed effects in the quantile framework.

Therefore, we follow the method developed by Rios Avila et al. (2024), which builds on the framework introduced by Machado and Santos Silva (2019), to estimate quantile regressions with fixed effects. Their estimator allows for a flexible and interpretable decomposition of conditional quantile effects while accommodating unobserved heterogeneity through fixed effects. Their estimator of the quantile regression which can be decomposed as :

$$\beta(\tau) = \beta + q_\tau \times \gamma$$

where β represents the location component and can be estimated using standard linear methods, and γ captures the scale component, which modulates how quantile coefficients vary across the distribution. The term q_τ is the τ-th unconditional quantile of a standardized error term ε, assumed to be i.i.d. and independent of the covariates. This structure allows for heteroskedasticity while maintaining a tractable and interpretable model for conditional quantiles. Fixed effects are used for the linear estimation part of this regression, and then do not affect the quantile regression.

The first step is to estimate the first moment of the distribution with the following conditions, similar to a linear regression:

$$y_i = x_i'\beta + \nu_i \text{ and } \mathbb{E}[x_i\nu_i] = 0$$

Next, we estimate the scale coefficients by modeling heteroskedasticity as a linear function of characteristics of covariates. We use the absolute value of the errors from the location model ν as the dependent variable, to recover the conditional standard deviation of the errors. Note that it is important that $x_i'\gamma > 0$ otherwise quantile coefficients might cross.

$$|\nu_i| = x_i'\gamma + \omega_i \text{ and } \mathbb{E}[x_i(|\nu_i| - x_i'\gamma)], x_i'\gamma > 0$$

Finally, the quantile position is recovered by normalizing the residuals from the linear regression by the estimated scale component. This approach identifies the position of each observation within the conditional distribution. Formally, if the model is expressed as:

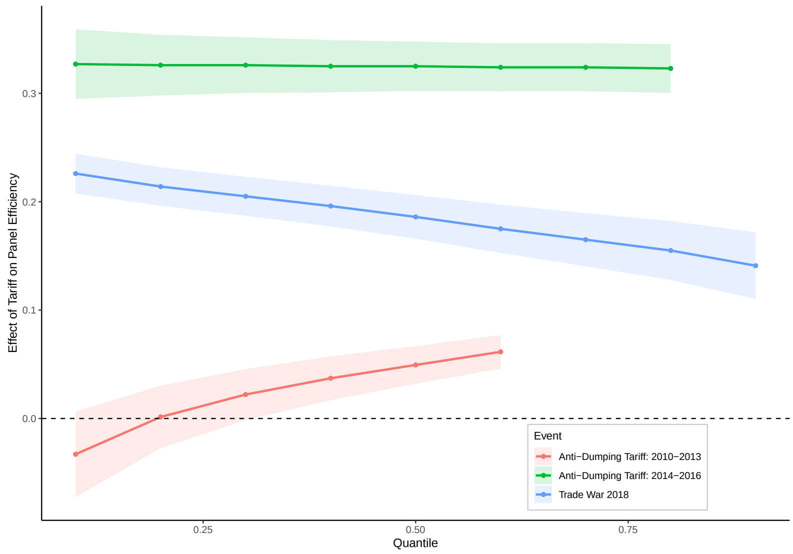
$$\begin{aligned}
\mathbb{E}[1(x_i'(\beta + \gamma q_\tau \geq y_i) - \tau] = 0 \\
\mathbb{E}[1(q_\tau \geq \frac{y_i - x_i'\beta}{x_i'\gamma}) - \tau] = 0
\end{aligned}$$

Adding multiple fixed effects in the data-generating process then leads to :

$$\begin{aligned}
y_i &= x_i'\beta + \delta_1 + \delta_2 + \nu_i \\
\nu_i &= \varepsilon_i \times (x_i'\gamma + \zeta_1 + \zeta_2)
\end{aligned}$$

where we assume that x'_i varies within groups 1 and 2 and δ' and ζ' are the location and scale fixed effects associated with the group fixed effects. In our case, the linear part of the regression is similar to Equation 16, where the dependent variable is the log of efficiency, explained by the log of tariff, with our usual structure of fixed effects and covariates.

Figure 6: Quantile Regression of the Change in Efficiency due to Tariff



Notes: The dependent variable is the log of efficiency of installed solar panels. The regression is binned by decile. The standard errors are clustered at the zip code level. The set of fixed effects is: year-quarter, origin, installer, and county.

For the sake of brevity, we only present our results for the first set of fixed effects in Figure 6 but the tables for the two structures of fixed effects are available in the appendix (Table 15, Table 16) and the results are numerically and qualitatively similar.

Surprisingly, we find a very homogeneous effect across the efficiency distribution for the second anti-dumping tariff wave. Conditional on observables and fixed effects, each quantile shows that solar systems exposed to the tariff increased their efficiency by approximately 0.325%. This stability aligns with the results in Figure 5, where—except for the first quantile, which exhibits a high price elasticity to the tariff—each quantile displays a smaller elasticity relative to the baseline increase in price.

For the other tariff episodes, the results are consistent with previous findings. During the first anti-dumping wave, quality upgrades are not statistically different from zero up to the third quantile at the 5% significance level. However, a clear positive linear trend emerges across the quality distribution, with panels in the upper quantiles—particularly those produced by Chinese firms—showing a statistically significant increase in efficiency of about 0.06%. This coincides with relatively smaller price increases for high-quality panels, suggesting that limited pass-through at the top end of the distribution is associated with upward quality adjustments. These results reinforce the idea that higher-quality solar panels saw smaller relative price increases but responded with quality improvements.

The strongest effects are found during the 2018 Trade War. We observe significant positive effects across the efficiency distribution, with a stronger response among lower-quality panels. For panels in the first quantile, conditional on observables and fixed effects, a 1% increase in tariff exposure leads to a 0.226% increase in efficiency. At the other end of the distribution, the effect is 0.141%. This declining trend may be explained by the fact that improving quality is easier at the bottom of the distribution than at the top. It is also consistent with our theoretical model, where lower-productivity firms are pushed out of the market by the tariff, reinforcing the compositional shift.

It is important to note that these are relative estimates. A smaller percentage increase in efficiency among high-performing panels may still represent a substantial absolute gain, potentially greater than that of lower-efficiency panels.

Unlike in previous tariff episodes, all firms were treated under the 2018 Trade War. This implies that our quantile estimates are more sensitive to variation in tariff intensity across firms. In particular, many high-end manufacturers—such as Maxeon (USA) and LG Electronics (South Korea)—are located at the top of the quality distribution but received relatively smaller tariffs. These firms, which do not produce domestically, were still subject to the safeguard tariff, but their smaller exposure may weigh down the overall estimate in upper quantiles. To test this hypothesis, we re-estimate the model using only Chinese firms (see Table 17). The results reveal a similarly positive and flat trend, consistent with the pattern observed in the second anti-dumping tariff wave.

Overall, the observed price increase is correlated with a shift toward higher-quality panels within each quantile of the efficiency distribution. This suggests that, alongside tariff-induced price changes, the composition of imported solar panels also evolved. However, because our estimator is conditional on quantiles, covariates, and fixed effects, we cannot infer an unconditional improvement in quality due to the tariffs (Rios-Avila and Maroto, 2024), unless we assume that the rank of panel efficiency remains stable after treatment. Given the rapid pace of technological progress over the decade (see Figure 15), this assumption is unlikely to hold, limiting our ability to make such a claim.

A second and important limitation is that the relatively flat trends in quality variation across quantiles may reflect a downward bias in the scale component of the model. This could result from violations of key assumptions—specifically, negative values of $x_i'\gamma$, which mechanically depress the scale estimate. As a result, we adopt a conservative interpretation and conclude that the evidence points to quality improvements, conditional on quantile position, but we cannot firmly conclude to Alchian-Allen effect.

To address this limitation, we turn in the appendix to unconditional quantile regressions (subsection B.2), as developed by Firpo et al. (2009). This approach allows us to assess how the entire distribution of efficiency shifts with tariff exposure. Preliminary results are broadly consistent with those from the conditional quantile regressions and indicate a general upward shift in quality—particularly concentrated in the lower end of the distribution—supporting our hypothesis of tariff-induced quality upgrading. However, given that these results are preliminary, we prefer to interpret them with caution.

Within our theoretical framework, assuming a medium-quality scope environment, our findings are only mildly consistent with the model's predictions. At the top of the distribution, we observe an increase in the quality of solar panels, which aligns with the model. However, this increase is smaller than that observed among panels at the lower end of the distribution—a result that deviates from the model's implications.

One possible explanation lies in dynamic responses by Chinese firms, which may have introduced higher-quality models specifically to maintain market presence under increasing tariff pressure. It is also worth noting that Chinese firms improved their product quality substantially over the decade, but this innovation was primarily geared toward serving their much larger domestic market. Therefore, while technological upgrading was not necessarily driven by trends in the U.S. market, the specific panels exported to the U.S. appear to reflect strategic adaptation to external demand conditions.

5.3 Demand Estimation

Turning to the shape of demand, and in line with our theoretical framework, we expect the elasticity of demand to be subconvex. Specifically, under a quasi-linear utility function, as characterized by Mrázová and Neary (2017), demand is subconvex—meaning it is more convex at any point than a CES demand function evaluated at the same point. This implies that demand elasticity decreases with sales volume: larger exporters, who correspond to more productive firms (Equation 8), face lower demand elasticity and can thus charge higher markups.

Accordingly, when tariffs reduce sales across the entire firm distribution, they increase demand elasticity for all firms. However, this increase is comparatively larger for lower-quality products, which operate closer to the elastic portion of the demand curve. This asymmetry provides a mechanism for explaining why lower-quality goods may exhibit higher price sensitivity and weaker markup resilience in response to tariff shocks.

To determine the shape of demand along the quality distribution, we implement an instrumental variable strategy to control for price endogeneity — using tariffs as an instrument for price. Tariffs act as a cost shifter at the installation level: prices increase overall, but heterogeneously across the quality distribution. The relevance condition is satisfied, as tariffs are correlated with price variation. The random instrument condition also holds since tariffs are independent of zip code–level demand for solar panels. The exclusion restriction is valid because tariffs may lower demand, but only indirectly through their effect on prices — unlike quotas, which can affect demand more directly. The most challenging assumption is monotonicity. Being exposed to tariffs should not lead to a price decrease. Even though we observe relatively smaller price increases for high-quality solar panels — and in some cases, for all panels during the second anti-dumping tariff — we assume that price changes due to tariff remain positive across all quality levels. In other words, lower price increases do not imply actual price reductions at any point in the quality distribution.

We caveat though that tariff affect prices heterogeneously, and more specifically do not affect certain category of product at all like the highest quality product of the first and second anti-dumping tariff. The 4th and 5th quintile are never considered by the treatment since Chinese do not commercialize panel in those categories. Hence, estimates of those quantile are likely to capture indirect effect of tariff.

Also, given that we are regressing on a count variable, we can relax the linear model assumptions (conditional independence on covariates, normal distribution and constant variance, linear relations), and turn to a Poisson regression to estimate demand semi-elasticity. We instrument it with a tariff as discussed above, following the control function approach.

Control function (Petrin and Train, 2010; Wooldridge, 2015) are a popular alternative instrumental variable approach, compatible with both linear and non-linear regressors. Our approach takes the following form :

$$\ln \text{Price}_i = \beta_0 \ln \text{Tariff}_i + \theta \mathbf{X}_i + \text{FE} + \mu_i \tag{17}$$

where the price function controls for price endogeneity, we instrument prices with a tariff as they generate an exogenous positive price shock at the system level, $\mathbf{X}$ denotes our set of covariates with median income, median household value, the share of the population with a bachelor degree, population density, the population level, fixed effects are county, installer, year quarter, and origin. The residual of this first regression serves as the control function $\hat{\mu}$ to correct for price endogeneity and recover the downward-sloping demand curve.

Table 5: Control Function : Instrumenting Tariff

	Anti-Dumping: 2010-2013	Anti-Dumping: 2014-2016	Trade War
	Poisson	Poisson	Poisson
ln Tariff	0.060*	0.226***	0.171***
	(0.026)	(0.044)	(0.031)
Num.Obs.	35 540	109 120	132 378
R2	0.705	0.492	0.440
R2 Adj.	0.701	0.488	0.436
FE: Year Quarter	X	X	X
FE: Origin	X	X	X
FE: Installer	X	X	X
FE: County	X	X	X

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

Notes: The dependent variable is the log of gross price of solar panels at the installation level. Standard Errors are clustered at the zip code level.

Consistent with our previous findings, we find that tariffs have an overall positive effect on price elasticity. Specifically, a 1% increase in tariff exposure leads to a 0.226% increase in installation price during the second anti-dumping tariff wave. From this regression, we extract the corresponding residuals $\hat{\mu}$, which—by construction—are purged of the endogenous components of price variation. These residuals serve as a clean input for further analysis, particularly in identifying demand-side effects net of tariff-induced pricing shocks.

We now turn to the main equations to recover demand elasticity :

$$\text{Demand}_j = \beta_0 \text{Price}_i + \beta_1 \text{Price}_i^2 + \theta \mathbf{X}_i + \text{FE} + \hat{\mu}_i + \varepsilon_i \tag{18}$$

The specification follows a Poisson regression framework, where the dependent variable, *Demand*, is measured as the total number of installed solar panels at the zip code–year level. The coefficient β_0 captures the demand elasticity with respect to price variation, while β_1 identifies the curvature of the elasticity function.

We follow the approach of Pless and van Benthem (2019), who use this flexible structure to estimate the curvature of the inverse demand function. This initial proxy of inverse demand elasticity is informative for assessing our hypothesis of market power among higher-quality panels, which are more likely to sustain markups.

However, in the absence of detailed data on firm-level markups and pass-through behavior, we are unable to recover the full empirical pricing manifold without imposing additional parametric assumptions.

Moreover, identifying elasticity at the product level would require adopting a richer substitution structure, such as those developed in the industrial organization literature (Berry et al., 1995; Berry and Haile, 2021). Implementing such an approach would constitute a substantial undertaking—potentially a paper in its own right. Consequently, we leave this question for future research.

The residual term $\hat{\mu}$ is assumed to be independently and identically distributed (i.i.d.) and captures the component of price variation that is correlated with the structural error term ε_i. As a result, conditional on $\hat{\mu}$, demand is independent of ε_i, satisfying the exclusion restriction for identification.

We include fixed effects for county, year-quarter, and origin to control for unobserved heterogeneity at these levels. Installer fixed effects are excluded, as demand at the zip code level does not exhibit sufficient variation across installers. The set of covariates $\mathbf{X}$ is consistent with those previously discussed in earlier sections.

While Poisson models relax the assumptions of normality and homoskedasticity of the residuals, it is important to note that the consistency of the Poisson estimator relies on the equidispersion property—namely, that the conditional mean and variance of the dependent variable are equal. In the presence of substantial overdispersion, this assumption may be violated, leading to downward-biased standard errors and misleading inference.

To address this issue, we conduct an overdispersion test and complement our baseline results with a negative binomial regression, which is more robust to overdispersion in count data settings (Bouche et al., 2009).

First, we observe that the inclusion of our control function $\hat{\mu}$ appropriately adjusts the price coefficients and allows us to recover a downward-sloping demand curve, as theoretically expected. We also find strong evidence of overdispersion in our dataset. Specifically, the estimated dispersion parameter θ is low, indicating that the variance of the dependent variable substantially exceeds the mean.[22]

Given this result, we focus our attention on the Negative Binomial regression, which accounts for overdispersion. Since it shares the same log-link functional form as the Poisson model, the estimated coefficients can be

[22]The dispersion parameter θ in the Negative Binomial model governs the variance, which is defined as $\mu + \mu^2/\theta$. As θ becomes large, the second term vanishes and the model converges to the Poisson case where the variance equals the mean.

Table 6: Demand Estimation

	Anti-Dumping: 2010-2013		Anti-Dumping: 2014-2016		Trade War	
	Poisson	NegBin	Poisson	NegBin	Poisson	NegBin
Price	−0.451***	−0.273***	−0.096***	−0.123***	−0.029*	−0.042**
	(0.085)	(0.045)	(0.012)	(0.013)	(0.014)	(0.015)
Price^2	0.016***	0.009***	0.005***	0.006***	0.000	0.001
	(0.004)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
$\hat{\mu}$	1.240***	0.793***	0.209***	0.253***	0.100***	0.109***
	(0.246)	(0.133)	(0.026)	(0.033)	(0.026)	(0.029)
Log-Likelihood	−205 346.330	−119 016.140	−819 493.400	−477 291.170	−1 086 248.730	−579 271.240
AIC	410 854.700	238 194.300	1 639 142.800	954 738.300	2 172 645.500	1 158 690.500
Overdispersion (theta)		2.610		4.400		4.510
Mean Price	6.130	6.130	4.067	4.067	3.580	3.580
FE: Year Quarter	X	X	X	X	X	X
FE: Origin	X	X	X	X	X	X
FE: County	X	X	X	X	X	X

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

interpreted as semi-elasticities.[23]

We first observe a declining pattern in price elasticity[24] over the decade: from –1.56 during the first anti-dumping wave, to –0.45 in the second, and –0.14 during the 2017–2018 Trade War. The first two elasticity estimates are consistent with prior work on solar panel demand during this period (Hughes and Podolefsky, 2015; Gillingham and Tsvetanov, 2019; Pless and van Benthem, 2019; Ros and Sai, 2023). However, the estimated elasticity for the 2017–2018 period is considerably lower than in earlier periods and below most values reported in the literature.

This reduction may reflect both structural and econometric factors. From a structural standpoint, the solar panel market experienced substantial growth over the decade, driven by rapidly declining prices and sustained public subsidies. These developments likely contributed to increased market participation and diluted the average effect of tariff-induced price changes. As the market matured, the marginal consumer may also have become less price-sensitive, contributing to a flattening of the demand curve.

However, we cannot rule out concerns regarding instrument strength during the Trade War period. Specifically, substantial heterogeneity in firms' pass-through behavior—some passing on tariff-induced costs more aggressively than others—may weaken the instrument's relevance for identifying average price effects. This concern is particularly salient given the wide variation in firm-

[23]For example, a \$1 increase in solar panel prices over the 2010–2013 period leads to a 27.3% reduction in demand.

[24]To recover elasticity we do for column 2: $(-0.451 + 2 \times 0.016) \times \text{MeanPrice} = -1.56$ with $\text{MeanPrice} = 6.130$.

specific tariff rates during the Trade War and also applies, albeit to a lesser extent, to the second anti-dumping wave.

Another limitation arises from our static approach. We do not account for dynamic adoption behavior, which may lead to higher effective elasticities, as highlighted in Ros and Sai (2023). For example, installation "bunching" in anticipation of tariff implementation could bias our estimates downward. Nonetheless, in the robustness section, we show that our results are not sensitive to the inclusion of potentially confounding variables such as electricity prices. Since the primary outside option for installation is grid electricity consumption, accounting for retail electricity rates strengthens the credibility of our demand estimates.

Considering the squared price terms, we find that all coefficients are positive, although their magnitudes are generally small. This result supports our hypothesis that demand is convex and that elasticity decreases as prices rise—a relationship we interpret as consistent with lower elasticity for higher-quality goods. However, due to the small size of the estimates and the methodological limitations previously discussed, we refrain from drawing strong conclusions.

Moreover, because we do not estimate markups or pass-through directly—and doing so would require stronger parametric assumptions—we conclude our analysis of demand at this point. It is worth noting that, despite their imprecision, these estimates represent, to the best of our knowledge, the only available elasticity measures for each subperiod of this decade.

6 Conclusion

Tariffs have increasingly reshaped international trade in recent years and are likely to remain a central feature of trade policy moving forward. In this paper, we sought to examine the impact of tariffs on price transmission along quality dimensions, as well as the resulting compositional changes in imports.

We showed that in a setting of incomplete tariff pass-through and differentiated product markets, price elasticity tends to be stronger for lower-quality goods. However, once we consider the role of quality in shaping price responses, we also find that the observed price increases are correlated with an overall improvement in product quality. This appears to stem from both supply-side mechanisms—where lower-quality panels are unable to absorb the additional import costs—and potentially from demand-side effects, although the latter are more difficult to empirically identify.

Looking ahead, future work could usefully explore how income heterogeneity interacts with these dynamics to better assess the welfare implications of tariffs in markets for differentiated goods. Since exposure to price changes likely varies across income groups, and assuming preferences for quality are not uniform, this raises important questions about the distributional consequences of trade policy in contexts where pass-through is incomplete.

A final issue to which our approach could be valuably extended is the trade-off between access to cheaper, though lower-quality, environmental goods through imports, and producing them domestically at higher prices—potentially reducing the adoption of these technologies. This trade-off lies at the heart of the political rationale behind active U.S. trade policies, particularly since the Trump I administration, which emphasized reshoring and strategic autonomy over cost efficiency.

While our current analysis does not directly address this dimension, it offers a promising avenue for future research. Extending our framework to explicitly incorporate this trade-off could provide important insights into the broader implications of tariff policy, especially in sectors like solar energy where environmental and industrial goals intersect.

7 Limitations and Extensions

Throughout this paper, we have presented several pieces of evidence pointing to heterogeneous price elasticities along quality dimensions, shifts in the composition of imported solar panel quality, and demand estimates that are broadly consistent with our theoretical framework. While these early findings are promising, our approach remains subject to several limitations, and we outline potential improvements for future iterations of this work.

The first avenue for improvement, as discussed in the theory section, is to extend the model to explicitly incorporate multi-product firms with heterogeneous quality across products like Chen and Juvenal (2016). Such a framework would allow us to derive richer theoretical predictions regarding compositional change in response to tariff implementation and better mirror the complexity of firm behavior observed in the data.

The second improvement concerns our measure of quality. A promising extension would be to construct a hedonic quality index, following the approach of A. Auer et al. (2018). This method would enable us to account for quality evolution over time and compare how quality is valued across counties. In turn, this would offer a more precise tool for analyzing international price differences and tariff pass-through effects.

The third limitation of our study—and a promising avenue for future improvement—is the lack of direct access to confidential data on import prices of solar panels, which would enable us to estimate the true tariff pass-through rather than relying solely on price elasticity. While our current approach sheds light on how prices respond to tariff exposure, it does not allow us to precisely decompose how much of the tariff is actually passed through to consumers. This distinction is important: price elasticity may reflect large pre-existing price differentials and does not by itself inform us about the degree of pass-through.

For instance, we could observe a scenario where higher-quality panels exhibit complete tariff pass-through yet still display relatively low price elasticity, simply because of a larger baseline price. To address this limitation, one possibility would be to scrape public price data from major online retailers[25], although such platforms typically do not provide historical pricing, which limits their usefulness for policy evaluation over time.

Alternatively, we could adopt a more structural approach, following the methodology proposed by Houde and Wang (2023), to recover pass-through and markups. However, even under this framework, we would remain constrained by data availability, particularly regarding cost structure and product-level margins.

[25]Such as Solar Store.

A fourth potential extension would be to develop the normative implications of the model. In particular, we could formally model the welfare effects of adopting low-cost, lower-quality Chinese solar panels, which nevertheless generate positive environmental externalities. This would enable us to examine the trade-off between protectionist policies—aimed at promoting the adoption of higher-quality, potentially domestically produced panels—and broader adoption driven by lower prices. Our current empirical setup is particularly suited to such an analysis, as it allows for a comparison between the effects of targeted tariffs and those of global tariffs. Extending the model to incorporate a third-country exporter could further enhance our ability to distinguish between country-specific and market-wide trade policy effects.

A last, interesting extension would be to investigate potential spillover effects from the first two anti-dumping tariff waves targeting Chinese firms. Specifically, we could examine whether counties more exposed to Chinese imports prior to the tariffs experienced disproportionate price changes afterward. Such an analysis would help uncover whether substitution or strategic pricing responses occurred in markets where Chinese firms previously had a strong presence.

Finally, despite the limitations of our current framework, we offer a meaningful extension on the core topic of interest: the shift in quality. Specifically, we provide an unconditional quantile regression that seeks to capture changes in the distribution of panel quality associated with tariff exposure. While these results are still preliminary, they offer promising insights into how trade policy may shape the quality composition of imports beyond average effects.

References

(2024, June). Compare 2025's best solar panels by reviews, efficiency & price. https://www.solarreviews.com/solar-panel-reviews.

A. Auer, R., T. Chaney, and P. Sauré (2018, January). Quality pricing-to-market. *Journal of International Economics 110*, 87–102.

Amiti, M. and A. K. Khandelwal (2013, May). Import Competition and Quality Upgrading. *The Review of Economics and Statistics 95*(2), 476–490.

Andres, P. (2024, October). Adapting to Competition: Solar PV Innovation in Europe and the Impact of the 'China Shock'. *Environmental and Resource Economics*.

Antoniades, A. (2015, March). Heterogeneous Firms, Quality, and Trade. *Journal of International Economics 95*(2), 263–273.

Autor, D., D. Dorn, and G. H. Hanson (2021). On the persistence of the China shock. Technical report, National Bureau of Economic Research.

Autor, D. H., D. Dorn, and G. H. Hanson (2013, October). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review 103*(6), 2121–2168.

Aw, B. Y. and M. J. Roberts (1986, August). Measuring quality change in quota-constrained import markets: The Case of U.S. Footwear. *Journal of International Economics 21*(1), 45–60.

Bagwell, K. and S. H. Lee (2020, November). Trade policy under monopolistic competition with firm selection. *Journal of International Economics 127*, 103379.

Bahar, H. (2022, August). Special Report on Solar PV Global Supply Chains. Technical report, IEA.

Baldwin, R. and J. Harrigan (2011). Zeros, Quality, and Space: Trade Theory and Trade Evidence. *American Economic Journal: Microeconomics 3*(2), 60–88.

Barbose, G. and N. Darghouth (2019, October). Tracking the Sun - Pricing and Design Trends for Distributed Photovoltaic Systems in the United States. Technical report, Lawrence Berkeley National Laboratory.

Berry, S., J. Levinsohn, and A. Pakes (1995). Automobile Prices in Market Equilibrium. *Econometrica 63*(4), 841–890.

Berry, S. T. and P. A. Haile (2021, September). Foundations of Demand Estimation.

Bollinger, B. and K. Gillingham (2023, June). Learning-by-Doing in Solar Photovoltaic Installations.

Borenstein, S. (2017, September). Private Net Benefits of Residential Solar PV: The Role of Electricity Tariffs, Tax Incentives, and Rebates. *Journal of the Association of Environmental and Resource Economists 4*(S1), S85–S122.

Bouche, G., B. Lepage, V. Migeot, and P. Ingrand (2009, August). Intérêt de la détection et de la prise en compte d'une surdispersion dans un modèle de Poisson : Illustration à partir d'un exemple. *Revue d'Épidémiologie et de Santé Publique 57*(4), 285–296.

Bown, C. P. (2016). Global Antidumping Database Version 1.0.

Chen, N. and L. Juvenal (2016, May). Quality, trade, and exchange rate pass-through. *Journal of International Economics 100*, 61–80.

Crozet, M., K. Head, and T. Mayer (2012, April). Quality Sorting and Trade: Firm-level Evidence for French Wine. *The Review of Economic Studies 79*(2), 609–644.

de Chaisemartin, C. and X. D'Haultfœuille (2023, June). Credible Answers to Hard Questions: Differences-in-Differences for Natural Experiments.

De Groote, O. and F. Verboven (2019, June). Subsidies and Time Discounting in New Technology Adoption: Evidence from Solar Photovoltaic Systems. *American Economic Review 109*(6), 2137–2172.

Fajgelbaum, P., P. Goldberg, P. Kennedy, A. Khandelwal, and D. Taglioni (2024, June). The US-China Trade War and Global Reallocations. *American Economic Review: Insights 6*(2), 295–312.

Fajgelbaum, P., G. M. Grossman, and E. Helpman (2011, August). Income Distribution, Product Quality, and International Trade. *Journal of Political Economy 119*(4), 721–765.

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

Falvey, R. E. (1979, October). The Composition of Trade within Import-restricted Product Categories. *Journal of Political Economy 87*(5, Part 1), 1105–1114.

Feenstra, R. C. and J. Romalis (2014, May). International Prices and Endogenous Quality *. *The Quarterly Journal of Economics 129*(2), 477–527.

Firpo, S., N. M. Fortin, and T. Lemieux (2009). Unconditional Quantile Regressions. *Econometrica 77*(3), 953–973.

Flaaen, A., A. Hortaçsu, and F. Tintelnot (2020, July). The Production Relocation and Price Effects of US Trade Policy: The Case of Washing Machines. *American Economic Review 110*(7), 2103–2127.

Foster, L., J. Haltiwanger, and C. Syverson (2008, March). Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability? *American Economic Review 98*(1), 394–425.

Gerarden, T. D. (2023). Demanding Innovation: The Impact of Consumer Subsidies on Solar Panel Production Costs. *Management Science 69*(12), 7799–7820.

Gillingham, K., H. Deng, R. Wiser, N. Darghouth, G. Nemet, G. Barbose, V. Rai, and C. Dong (2016, July). Deconstructing Solar Photovoltaic Pricing: The Role of Market Structure, Technology, and Policy. *The Energy Journal 37*(3), 231–250.

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

Hallak, J. C. (2006, January). Product quality and the direction of trade. *Journal of International Economics 68*(1), 238–265.

Helpman, E., M. J. Melitz, and S. R. Yeaple (2004, March). Export Versus FDI with Heterogeneous Firms. *American Economic Review 94*(1), 300–316.

Houde, S. and W. Wang (2023, May). The Incidence of the U.S.-China Solar Trade War.

Hughes, J. E. and M. Podolefsky (2015, June). Getting Green with Solar Subsidies: Evidence from the California Solar Initiative. *Journal of the Association of Environmental and Resource Economists 2*(2), 235–275.

Hummels, D. and A. Skiba (2004, December). Shipping the Good Apples Out? An Empirical Confirmation of the Alchian-Allen Conjecture. *Journal of Political Economy 112*(6), 1384–1402.

Khandelwal, A. (2010, October). The Long and Short (of) Quality Ladders. *The Review of Economic Studies 77*(4), 1450–1476.

Kugler, M. and E. Verhoogen (2012, January). Prices, Plant Size, and Product Quality. *The Review of Economic Studies 79*(1), 307–339.

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

Machado, J. A. F. and J. M. C. Santos Silva (2019, November). Quantiles via moments. *Journal of Econometrics 213*(1), 145–173.

Manova, K. and Z. Zhang (2012, February). Export Prices Across Firms and Destinations*. *The Quarterly Journal of Economics 127*(1), 379–436.

Mayer, T., M. J. Melitz, and G. I. P. Ottaviano (2014, February). Market Size, Competition, and the Product Mix of Exporters. *American Economic Review 104*(2), 495–536.

Melitz, M. J. (2003). The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica 71*(6), 1695–1725.

Melitz, M. J. and G. I. P. Ottaviano (2008, January). Market Size, Trade, and Productivity. *The Review of Economic Studies 75*(1), 295–316.

Mrázová, M. and J. P. Neary (2017, December). Not So Demanding: Demand Structure and Firm Behavior. *American Economic Review 107*(12), 3835–3874.

Nauze, A. L. (2023, November). Motivation Crowding in Peer Effects: The Effect of Solar Subsidies on Green Power Purchases. *The Review of Economics and Statistics 105*(6), 1465–1480.

O'Shaughnessy, E. (2019, February). Non-monotonic effects of market concentration on prices for residential solar photovoltaics in the United States. *Energy Economics 78*, 182–191.

O'Shaughnessy, E., G. F. Nemet, and N. Darghouth (2018, April). The geography of solar energy in the United States: Market definition, industry structure, and choice in solar PV adoption. *Energy Research & Social Science 38*, 1–8.

Ottaviano, G., T. Tabuchi, and J.-F. Thisse (2002, May). Agglomeration and Trade Revisited. *International Economic Review 43*(2), 409–435.

Parenti, M., P. Ushchev, and J.-F. Thisse (2017, January). Toward a theory of monopolistic competition. *Journal of Economic Theory 167*, 86–115.

Petrin, A. and K. Train (2010, February). A Control Function Approach to Endogeneity in Consumer Choice Models. *Journal of Marketing Research 47*(1), 3–13.

Piveteau, P. and G. Smagghue (2019, May). Estimating firm product quality using trade data. *Journal of International Economics 118*, 217–232.

Pless, J. and A. A. van Benthem (2019, October). Pass-Through as a Test for Market Power: An Application to Solar Subsidies. *American Economic Journal: Applied Economics 11*(4), 367–401.

Rios-Avila, F. and M. L. Maroto (2024, May). Moving Beyond Linear Regression: Implementing and Interpreting Quantile Regression Models With Fixed Effects. *Sociological Methods & Research 53*(2), 639–682.

Rios Avila, F., L. Siles, and G. J. Canavire Bacarreza (2024). Estimating Quantile Regressions with Multiple Fixed Effects Through Method of Moments. *SSRN Electronic Journal*.

Roberts, M. J. and D. Supina (1996, April). Output price, markups, and producer size. *European Economic Review 40*(3), 909–921.

Ros, A. J. and S. S. Sai (2023, February). Residential rooftop solar demand in the U.S. and the impact of net energy metering and electricity prices. *Energy Economics 118*, 106491.

Shaked, A. and J. Sutton (1982, January). Relaxing Price Competition Through Product Differentiation. *The Review of Economic Studies 49*(1), 3–13.

Trabisch, H. (2013, December). Why Treasury Is Investigating SolarCity and Solar Third-Party Funds. https://www.greentechmedia.com/articles/read/why-treasury-is-investigating-solarcity-and-solar-third-party-funds.

Verhoogen, E. A. (2008, May). Trade, Quality Upgrading, and Wage Inequality in the Mexican Manufacturing Sector*. *The Quarterly Journal of Economics 123*(2), 489–530.

Wesoff, E. (2014, January). Breaking: SolarWorld Aims to Close China PV Trade Loophole With New Filing. https://www.greentechmedia.com/articles/read/breaking-solarworld-aims-to-close-loophole-in-new-chinese-pv-trade-filing.

Wooldridge, J. M. (2015). Control Function Methods in Applied Econometrics. *The Journal of Human Resources 50*(2), 420–445.

A Mathematical Appendix

A.1 Consumer Demand

Development of the calculus for (3):

$$
\begin{aligned}
\gamma q_i^c &= \alpha + z_i^l - p_i^l - \eta Q_c^l \\
\iff q_i^c &= \frac{1}{\gamma}\left[\alpha + z_i^l - p_i^l - \eta \int_{i\in\Omega} q_i^c di\right] \\
\iff q_i^c &= \frac{1}{\gamma}\left[\alpha + z_i^l - p_i^l - \eta N^l \bar{q}\right] \\
\iff q_i^c &= \frac{1}{\gamma}\left[\alpha + z_i^l - p_i^l - \eta N^l \left(\frac{1}{\gamma + \eta N^l}[\alpha + \bar{z}^l - \bar{p}]\right)\right] \\
\iff q_i^c &= \frac{1}{\gamma}\frac{\alpha\gamma}{\gamma + \eta N^l} + \frac{1}{\gamma} z_i^l - \frac{1}{\gamma} p_i^l - \frac{1}{\gamma}\frac{N^l\eta}{\gamma + \eta N^l}\bar{z}^l + \frac{1}{\gamma}\frac{N^l\eta}{\gamma + \eta N^l}\bar{p}^l \\
\iff q_i^c &= \frac{\alpha}{\gamma + \eta N} + \frac{1}{\gamma} z_i^l - \frac{1}{\gamma} p_i^l - \frac{1}{\gamma}\frac{N^l\eta}{\gamma + \eta N^l}\bar{z}^l + \frac{1}{\gamma}\frac{N^l\eta}{\gamma + \eta N^l}\bar{p}^l \\
\iff q^c \equiv L^l q_i^c &= \frac{L^l\alpha}{\gamma + \eta N^l} + \frac{L^l}{\gamma} z_i^l - \frac{L^l}{\gamma} p_i^l - \frac{L^l}{\gamma}\frac{N^l\eta}{\gamma + \eta N^l}\bar{z}^l + \frac{L^l}{\gamma}\frac{N^l\eta}{\gamma + \eta N^l}\bar{p}^l
\end{aligned}
$$

with $\bar{q} = \frac{1}{N}\int_{i\in\Omega^*} q_i^c di$, $\bar{p} = \frac{1}{N}\int_{i\in\Omega^*} p_i di$, $\bar{z} = \frac{1}{N}\int_{i\in\Omega^*} z_i di$ and $\Omega^* \subset \Omega$ the subset of consumed differentiated goods.

A.2 Firms

Development of the calculus for (8). We want to derive from the profit function the profit-maximizing equations for quantity, price, and quality.

First we take the derivative of π with respect to p, to obtain the optimal quantity function:

$$
\begin{aligned}
\frac{\partial \pi^{fh}}{\partial p^{fh}} &= q^{fh} + \frac{\partial q^{fh}}{\partial p^{fh}} p^{fh} - \delta\tau^h c \frac{\partial q^{fh}}{\partial p^{fh}} - \tau^h \theta z^{fh} \frac{\partial q^{fh}}{\partial p^{fh}} \\
q^{fh} &= \frac{L^h}{\gamma}\left(p^{fh} - \delta\tau^h c - \tau^h \theta z\right)
\end{aligned}
$$

Then we use (3) when the firm produces at the threshold price p_{max} for which the demand is $q(p_{max}) = 0$ and $z = 0$:

$$
\begin{aligned}
0 &= \frac{L^h\alpha}{\gamma+\eta N^h} - \frac{L^h}{\gamma}p_{max} - \frac{L^h}{\gamma}\frac{N^h\eta}{\gamma+\eta N^h}\bar{z}^h + \frac{L^h}{\gamma}\frac{N^h\eta}{\gamma+\eta N^h}\bar{p}^h \\
\iff \frac{L^h}{\gamma}p_{max} &= \frac{L^h\alpha}{\gamma+\eta N^h} - \frac{L^h}{\gamma}\frac{N^h\eta}{\gamma+\eta N^h}\bar{z}^h + \frac{L^h}{\gamma}\frac{N^h\eta}{\gamma+\eta N^h}\bar{p}^h
\end{aligned}
$$

Then we plug $\frac{L^h}{\gamma}p_{max}$ in (3) and find :

$$
q^{fh} = \underbrace{\frac{L^h\alpha}{\gamma+\eta N^h} - \frac{L^h}{\gamma}\frac{N^h\eta}{\gamma+\eta N^h}\bar{z}^h + \frac{L^h}{\gamma}\frac{N^h\eta}{\gamma+\eta N^h}\bar{p}^h}_{\frac{L^h}{\gamma}p_{max}} + \frac{L^h}{\gamma}z_i^{fh} - \frac{L^h}{\gamma}p_i^{fh}
$$

$$
\iff q^{fh} = \frac{L^h}{\gamma}p_{max} + \frac{L^h}{\gamma}z_i^{fh} - \frac{L^h}{\gamma}p_i^{fh}
$$

Finally we can equate with $q^{fh} = \frac{L^h}{\gamma}\left(p^{fh} - \delta\tau^h c - \tau^h\theta z\right)$:

$$
\begin{aligned}
\frac{L^h}{\gamma}\left(p^{fh} - \delta\tau^h c - \tau^h\theta z^{fh}\right) &= \frac{L^h}{\gamma}p_{max} + \frac{L^h}{\gamma}z^{fh} - \frac{L^h}{\gamma}p^{fh} \\
\iff p^{fh} - \delta\tau^h c - \tau^h\theta z^{fh} &= p_{max} + z^{fh} - p^{fh} \\
\iff p^{fh} &= \frac{1}{2}\Big[\underbrace{p_{max}}_{\delta\tau^h c^{fh}} + \delta\tau^h c + (1+\tau^h\theta)z^{fh}\Big] \\
\iff p^{fh} &= \frac{1}{2}\left[\delta\tau^h(c^{fh}+c) + (1+\tau^h\theta)z^{fh}\right] \\
\iff p^{fh} &= \frac{1}{2}\delta\tau^h(c^{fh}+c) + \frac{1}{2}(1+\tau^h\theta)z^{fh}
\end{aligned}
$$

With c^{fh} the cost cutoff for exporting to the h market above which demand is 0. We deduce p_{max} as the maximum price for which demand is not negative as the transport and tariff inclusive price times the marginal cost of the least productive firm able to pass the cost-cut toff: $p_{max} = \delta\tau^h c^{fh}$. Note that we also drop the i subscript to alleviate the notation.

Hence we can rewrite the profit-maximizing price, quantity and profit functions as:

$$
\begin{aligned}
p^{fh} &= \frac{1}{2}\delta\tau^h(c^{fh}+c) + \frac{1}{2}(1+\tau^h\theta)z^{fh} \\
q^{fh} &= \frac{L^h}{2\gamma}\left[\delta\tau^h(c^{fh}-c) + (1-\tau^h\theta)z^{fh}\right] \\
\pi^{fh} &= \frac{L^h}{4\gamma}\left[\delta\tau^h(c^{fh}-c) + (1-\theta\tau^h)z^{fh}\right]^2 - \theta(z^{fh})^2
\end{aligned}
$$

For the quality function, we just take the derivative of the profit function with respect to z :

$$
\begin{aligned}
\frac{\partial \pi^{fh}}{\partial z^{fh}} &= 0 \\
\Longleftrightarrow L^h\left[\delta\tau^h(c^{fh}-c)+(1-\theta\tau^h)z^{fh}\right](1-\theta\tau^h) &= 4\gamma\theta\tau^h z^{fh} \\
\Longleftrightarrow L^h(1-\theta\tau^h)\delta\tau^h(c^{fh}-c) &= z^{fh}\left[4\gamma\theta\tau^h - L^h(1-\theta\tau^h)^2\right] \\
\Longleftrightarrow \frac{L^h(1-\theta\tau^h)}{4\gamma\theta\tau^h - L^h(1-\theta\tau^h)^2}\delta\tau^h(c^{fh}-c) &= z^{fh} \\
\Longleftrightarrow \lambda^{fh}\delta\tau^h(c^{fh}-c) &= z^{fh}
\end{aligned}
$$

Therefore, the final optimal quality functions are:

$$
\begin{aligned}
z^{fh} &= \lambda^{fh}\delta\tau^h(c^{fh}-c) \\
z^{hh} &= \lambda^{hh}(c^{hh}-c)
\end{aligned}
$$

With $\lambda^{fh} = \frac{L^h(1-\theta\tau^h)}{4\gamma\theta\tau^h - L^h(1-\theta\tau^h)^2}$ and $\lambda^{hh} = \frac{L^h(1-\theta)}{4\gamma\theta - L^h(1-\theta)^2}$ defining the "quality scope" of good exporting from f to h and from home firms h for *Home* markets.

And finally, by plugging this optimal quality choice function in our previous equations we obtain :

$$
\begin{aligned}
p^{fh} &= \frac{1}{2}\delta\tau^h(c^{fh}+c) + \frac{1}{2}(1+\tau^h\theta)\lambda^{fh}\delta\tau^h(c^{fh}-c) \\
q^{fh} &= \frac{L^h}{2\gamma}\left[\delta\tau^h(c^{fh}-c)+(1-\tau^h\theta)\lambda^{fh}\delta\tau^h(c^{fh}-c)\right] \\
\pi^{fh} &= \frac{\delta^2 L^h\tau^h}{4\gamma}\left[1+(1-\theta\tau^h)\lambda^{fh}\right](c^{fh}-c)^2
\end{aligned}
$$

For home firm we just need to set $\delta = \tau = 1$:

$$
\begin{aligned}
p^{hh} &= \frac{1}{2}(c^{hh}+c) + \frac{1}{2}(1+\theta)\lambda^{hh}(c^{hh}-c) \\
q^{hh} &= \frac{L^h}{2\gamma}\left[(c^{hh}-c)+(1-\theta)\lambda^{hh}(c^{hh}-c)\right] \\
\pi^{hh} &= \frac{L^h}{4\gamma}\left[1+(1-\theta)\lambda^{hh}\right](c^{hh}-c)^2
\end{aligned}
$$

A.3 Market Equilibrium

We can rewrite (9) as :

$$f_E = \int_0^{c^{fh}} \frac{\delta^2 L^h \tau^h}{4\gamma} \big[1 + (1-\theta\tau^h)\lambda^{fh}\big](c^{fh} - c)^2 dG(c)$$
$$+ \int_0^{c^{ff}} \frac{L^f}{4\gamma} \big[1 + (1-\theta)\lambda^{ff}\big](c^{ff} - c)^2 dG(c)$$

We only consider the profit made abroad (in Home) by a firm in Foreign since the reasoning is identical for the profit made on the domestic market to the exception of $\tau = \delta = 1$.

We remind that we are considering a Pareto distribution so that $G(c) = (\frac{c}{c_M})^k$ with $c \in [0, c_M]$. To ease the re-expression of our distribution we can derive the value of $G(c)$:

$$\frac{d}{dc}G(c) = g(c) = kc^{k-1}c_M^{-k}$$
$$dG(c) = g(c)dc = kc^{k-1}c_M^{-k}dc$$

We can plug this in our first member (we do not consider the second member yet since it is very similar):

$$f_E = \frac{\delta^2 L^h \tau^h}{4\gamma} \big[1 + (1-\theta\tau^h)\lambda^{fh}\big] \int_0^{c^{fh}} (c^{fh} - c)^2 kc^{k-1}c_M^{-k}dc + ...$$

For the rest of the calculation we set the following variable $u = \frac{c}{c^{fh}}$ such that :

$$u = \frac{c}{c^{fh}} \iff c = c^{fh}u \text{ and } dc = c^{fh}du$$
$$\text{and } c^{fh} - c = (1-u)c^{fh}$$

Now we have all the elements to simplify our cost-cutoff functions:

$$\frac{\delta^2 L^h \tau^h}{4\gamma}\left[1+(1-\theta\tau^h)\lambda^{fh}\right]\int_0^1 (1-u)^2 (c^{fh})^2 k (c^{fh})^{k-1} u^{k-1} c_M^{-k} c^{fh} du + ...$$

$$= \frac{\delta^2 L^h \tau^h}{4\gamma}\left[1+(1-\theta\tau^h)\lambda^{fh}\right](c^{fh})^{k+2} k c_M^{-k} \underbrace{\int_0^1 (1-u)^2 u^{k-1} du}_{B(k,3)=\frac{\Gamma(3)\Gamma(k)}{\Gamma(k+3)}} + ...$$

$$= \frac{\delta^2 L^h \tau^h}{4\gamma}\left[1+(1-\theta\tau^h)\lambda^{fh}\right](c^{fh})^{k+2} k c_M^{-k} \frac{2}{(k+2)(k+1)} + ...$$

$$= \frac{\delta^2 L^h \tau^h}{2\gamma(k+2)(k+1)}\left[1+(1-\theta\tau^h)\lambda^{fh}\right](c^{fh})^{k+2} k c_M^{-k} + ...$$

Symmetrically we have:

$$\frac{L^f}{2\gamma(k+2)(k+1)}\left[1+(1-\theta)\lambda^{ff}\right](c^{ff})^{k+2} k c_M^{-k}$$

Then plugging back in our free entry equation for country f we obtain :

$$\begin{aligned} f_E = & \frac{\delta^2 L^h \tau^h}{2\gamma(k+2)(k+1)}\left[1+(1-\theta\tau^h)\lambda^{fh}\right](c^{fh})^{k+2} k c_M^{-k} \\ & + \frac{L^f}{2\gamma(k+2)(k+1)}\left[1+(1-\theta)\lambda^{ff}\right](c^{ff})^{k+2} k c_M^{-k} \end{aligned}$$

and symmetrically for country h we have :

$$\begin{aligned} f_E = & \frac{\delta^2 L^f \tau^f}{2\gamma(k+2)(k+1)}\left[1+(1-\theta\tau^f)\lambda^{hf}\right](c^{hf})^{k+2} k c_M^{-k} \\ & + \frac{L^h}{2\gamma(k+2)(k+1)}\left[1+(1-\theta)\lambda^{hh}\right](c^{hh})^{k+2} k c_M^{-k} \end{aligned}$$

Hence, we obtain a system of 2 equations:

$$\begin{cases} L^f\,[1+(1-\theta)\lambda^{ff}](c^{ff})^{k+2} + L^h\,\delta^{-k}(\tau^h)^{-k-1}[1+(1-\theta\tau^h)\lambda^{fh}](c^{hh})^{k+2} = D \\ L^h\,[1+(1-\theta)\lambda^{hh}](c^{hh})^{k+2} + L^f\,\delta^{-k}(\tau^f)^{-k-1}[1+(1-\theta\tau^f)\lambda^{hf}](c^{ff})^{k+2} = D \end{cases}$$

with $D = \gamma 2 f_E (k+2)(k+1) c_M^k$, $c^{hf} = \frac{c^{ff}}{\delta\tau^f}$ and $c^{fh} = \frac{c^{hh}}{\delta\tau^h}$.

With this system being set, we can now derive a unique cost cut-off threshold for each country. To simplify a bit the calculation we set the following variable :

$$
\begin{aligned}
&L^h \left[1 + (1-\theta)\,\lambda^{hh}\right] = A^{hh},\\
&L^f \left[1 + (1-\theta)\,\lambda^{ff}\right] = A^{ff},\\
&L^f\,\delta^{-k}\,(\tau^f)^{-k-1}\left[1 + (1-\theta)\,\lambda^{hf}\right] = B^{hf},\\
&L^h\,\delta^{-k}\,(\tau^h)^{-k-1}\left[1 + (1-\theta)\,\lambda^{fh}\right] = B^{fh},\\
&(c^{hh})^{k+2} = X \text{ and } (c^{ff})^{k+2} = Y,\\
&2\gamma\,(k+1)(k+2)\,c_M^k\,f_E = D
\end{aligned}
$$

This brings the following system of equations:

$$
\begin{cases}
A^{ff}Y + B^{fh}X = D\\[2ex]
A^{hh}X + B^{hf}Y = D
\end{cases}
$$

Solving for X and Y, we have:

$$
X = \frac{D\left(A^{ff} - B^{hf}\right)}{A^{hh}A^{ff} - B^{fh}B^{hf}}, \quad Y = \frac{D\left(A^{hh} - B^{fh}\right)}{A^{hh}A^{ff} - B^{hf}B^{fh}}
$$

We factorize by A^{ff} and A^{hh} in the numerators, and by $A^{hh}A^{ff}$ in the denominator:

$$
X = \frac{D\,A^{ff}\left(1 - \frac{B^{hf}}{A^{ff}}\right)}{A^{hh}A^{ff}\left(1 - \frac{B^{fh}B^{hf}}{A^{hh}A^{ff}}\right)}, \quad Y = \frac{D\,A^{hh}\left(1 - \frac{B^{fh}}{A^{hh}}\right)}{A^{hh}A^{ff}\left(1 - \frac{B^{fh}B^{hf}}{A^{hh}A^{ff}}\right)}
$$

We then set:

$$
\phi^\ell = \left(\frac{D}{A^{\ell\ell}}\right)^{1/(k+2)}, \qquad \rho^\ell = \frac{B^{\ell\bar{\ell}}}{A^{\ell\ell}} \quad \text{with } \ell \in \{h, f\}, \text{ and } \bar{l} \neq l
$$

Then we have:

$$
X = \frac{D(1-\rho^f)}{A^{hh}(1-\rho^h\rho^f)} \quad \Rightarrow \quad c^{hh} = \phi^h\left(\frac{1-\rho^f}{1-\rho^h\rho^f}\right)^{1/(k+2)}
$$

$$
Y = \frac{D(1-\rho^h)}{A^{ff}(1-\rho^f\rho^h)} \quad \Rightarrow \quad c^{ff} = \phi^f\left(\frac{1-\rho^h}{1-\rho^f\rho^h}\right)^{1/(k+2)}
$$

Finally, we can re-express c^{hh} to make appear the export to h cost cut-off. For that we recall $c^{fh} = c^{hh}/\delta\tau^h$:

$$c^{fh} = \frac{\phi^h}{\delta\tau^h}\left(\frac{1-\rho^f}{1-\rho^h\rho^f}\right)^{\frac{1}{k+2}}$$

$$c^{ff} = \phi^f\left(\frac{1-\rho^h}{1-\rho^f\rho^h}\right)^{\frac{1}{k+2}}$$

We also develop ρ^l such that :

$$\rho^l = (\delta\tau^l)^{-k}\frac{4\gamma\theta-(1-\theta)^2L^l}{4\gamma\theta\tau^l-(1-\theta\tau^l)^2L^l}$$

Now that we have the cutoff value we can determine a certain number of aggregate values, such as the average quality, prices, and markup with respect to the cutoff value c^{hh}.

In this section, we develop the calculation of the tariff absorption mechanisms of our model. We develop here the total log derivative of (11).

First, we rewrite (11) such that we have it expressed in function of the cost-cutoff and firm productivity separately:

$$p^* = \frac{\delta}{2}[c^{fh}(1+\kappa)+c(1-\kappa)]$$

We differentiate with respect to each key elements: c, c^{fh}, κ

$$\begin{aligned} dp^* &= \frac{\delta}{2}[(1+\kappa)dc^{fh}+c^{fh}d(1+\kappa)+(1-\kappa)dc+cd(1-\kappa)] \\ \iff dp^* &= \frac{\delta}{2}[(1+\kappa)dc^{fh}+c^{fh}d\kappa+(1-\kappa)dc-cd\kappa] \\ \iff dp^* &= \frac{\delta}{2}[(1+\kappa)dc^{fh}+(1-\kappa)dc+(c^{fh}-c)d\kappa] \end{aligned}$$

And the log derivation :

$$
\begin{aligned}
d\ln(p^*) &= \frac{dp^*}{p^*} \\
\iff d\ln(p^*) &= \frac{\frac{\delta}{2}[(1+\kappa)dc^{fh} + (1-\kappa)dc + (c^{fh}-c)d\kappa]}{p^*} \\
\iff d\ln(p^*) &= \frac{\delta}{2}\frac{[(1+\kappa)c^{fh}d\ln(c^{fh}) + (1-\kappa)cd\ln(c) + (c^{fh}-c)\kappa d\ln(\kappa)]}{p^*} \\
\iff d\ln(p^*) &= \frac{\delta}{2}\frac{[(1+\kappa)c^{fh}d\ln(c^{fh}) - (1-\kappa)cd\ln(\frac{1}{c}) + (c^{fh}-c)\kappa d\ln(\kappa)]}{p^*} \\
\iff d\ln(p^*) &= \frac{\delta}{2}\Bigg[\underbrace{\frac{(1+\kappa)c^{fh}d\ln(c^{fh})}{p^*}}_{\text{Market Condition}} - \underbrace{\frac{(1-\kappa)cd\ln(\frac{1}{c})}{p^*}}_{\text{Productivity}} + \underbrace{\frac{(c^{fh}-c)\kappa d\ln(\kappa)}{p^*}}_{\text{Quality}}\Bigg]
\end{aligned}
$$

A.4 Tariffs Absorption

In this section, we develop the proof of derivation for the elasticity of prices with respect to tariffs (13).

$$
\frac{\partial \ln p^*}{\partial \ln \tau^h} = \frac{\partial p^*}{\partial \tau^h} \times \frac{\tau^h}{p^*} = \frac{\partial}{\partial \ln \tau^h}\frac{\delta}{2}\left[\frac{(1+\kappa)c^{fh}\ln(c^{fh})}{p^*} - \frac{(1-\kappa)c\ln(\frac{1}{c})}{p^*} + \frac{(c^{fh}-c)\kappa\ln(\kappa)}{p^*}\right]
$$

c is invariant with tariff, then its derivative is 0. We are left with :

$$
\frac{\partial p^*}{\partial \tau^h} \times \frac{\tau^h}{p^*} = \frac{\delta}{2}\left[\frac{(1+\kappa)c^{fh}}{p^*}\frac{\partial \ln c^{fh}}{\partial \ln \tau^h} + \frac{(c^{fh}-c)\kappa}{p^*}\frac{\partial \ln \kappa}{\partial \ln \tau^h}\right]
$$

We derive separately $\frac{\partial \ln(c^{fh})}{\partial \ln \tau^h} = \varepsilon_{c^{fh}}$ and $\frac{\partial \ln \kappa}{\partial \ln \tau^h} = \varepsilon_{\kappa}$.

$$
\frac{\partial \ln c^{fh}}{\partial \ln \tau^h} = \frac{\partial}{\partial \ln \tau^h}\ln\left(\frac{\phi^h}{\delta\tau^h}\right) + \left(\frac{1}{k+2}\right)\frac{\partial}{\partial \ln \tau^h}\ln\left(\frac{1-\rho^f}{1-\rho^h\rho^f}\right)
$$

Decomposing :

$$
\frac{\partial}{\partial \ln \tau^h}\ln\left(\frac{\phi^h}{\delta\tau^h}\right) = -1
$$

We compute the derivative:

$$\frac{\partial}{\partial \ln(\tau^h)} \ln\left(\frac{1-\rho^f}{1-\rho^h\rho^f}\right) = -\frac{\partial}{\partial \ln(\tau^h)} \ln(1-\rho^f\rho^h)$$

Using the chain rule:

$$= \frac{\rho^f \dfrac{\partial \rho^h}{\partial \tau^h} \cdot \tau^h}{1-\rho^f\rho^h}$$

Rewriting this expression:

$$= \frac{\rho^f\rho^h}{1-\rho^f\rho^h} \cdot \frac{\dfrac{\partial \rho^h}{\partial \tau^h} \cdot \tau^h}{\rho^h}$$

So the final expression is:

$$\frac{\partial}{\partial \ln(\tau^f)} \ln\left(\frac{1-\rho^h}{1-\rho^h\rho^f}\right) = \frac{\rho^h\rho^f}{1-\rho^h\rho^f} \cdot \frac{\partial \rho^f}{\partial \tau^f} \cdot \frac{\tau^f}{\rho^f}$$

Assembling, we have :

$$\frac{\partial c^{fh}}{\partial \tau^h} \cdot \frac{\tau^h}{c^{fh}} = \left[\frac{1}{k+2}\right] \left(\frac{\rho^f\rho^h}{1-\rho^f\rho^h} \cdot \frac{\partial \rho^h}{\partial \tau^h}\frac{\tau^h}{\rho^h}\right) - 1$$

Now we are left with $\frac{\partial \rho^h}{\partial \tau^h}\frac{\tau^h}{\rho^h}$:

$$\frac{\partial \rho^f}{\partial \tau^h}\frac{\tau^h}{\rho^h} = \frac{\partial \ln \rho^h}{\partial \ln \tau^h} = \frac{\partial}{\partial \tau^h}\left[-k\ln(\delta\tau^h) + \ln(4\gamma\theta - (1-\theta)^2 L^h) - \ln(4\gamma\theta\tau^h - (1-\theta\tau^h)^2 L^h)\right]$$

$$\frac{\partial \rho^f}{\partial \tau^h}\frac{\tau^h}{\rho^h} = -(k+1+\kappa)$$

Combining everything we obtain the following elasticity of cost-cutoff to tariff :

$$\varepsilon_{c^{fh}} = -\left[\frac{k+1+\kappa}{k+2}\right]\left(\frac{\rho^f\rho^h}{1-\rho^f\rho^h}\right) - 1 < 0$$

The elasticity of the cost cutoff to the tariff is negative. It implies that an increase of 1% of the tariff decreases the cost cutoff of 1%, making it more complex for foreign firms to enter the market.

The elasticity of quality scope to tariff is given by :

$$
\begin{aligned}
\frac{\partial \ln \kappa}{\partial \ln \tau^h} &= \frac{\partial}{\partial \tau^h} \ln \left[\frac{L^h(1-\theta\tau^h)^2}{4\gamma\theta\tau^h - L^h(1-\theta\tau^h)^2} \right] \\
&= \frac{\partial}{\partial \ln \tau^h} \left[\ln(L^h) + 2\ln(1-\theta\tau^h) - \ln(4\gamma\theta\tau^h - L^h(1-\theta\tau^h)^2) \right] \\
&= 2\frac{\partial(1-\theta\tau^h)}{\partial \tau^h} \cdot \frac{\tau^h}{(1-\theta\tau^h)} - \frac{\partial(4\gamma\theta\tau^h - L^h(1-\theta\tau^h)^2)}{\partial \tau^h} \cdot \frac{\tau^h}{4\gamma\theta\tau^h - L^h(1-\theta\tau^h)^2} \\
&= \frac{-2\theta\tau^h}{(1-\theta\tau^h)} - \frac{4\gamma\theta\tau^h + 2\theta L^h\tau^h(1-\theta\tau^h)}{4\gamma\theta\tau^h - L^h(1-\theta\tau^h)^2} < 0
\end{aligned}
$$

Hence, we find logically that an increase in tariff reduces the quality scope.

The tariff absorption elasticity varies along the productivity of firms, however, c being present at both the numerator of Equation 13 and denominator (recall that p^* is defined as Equation 8), it makes our analysis more complicated. However, the linearity of the relationship between the numerator and denominator allows us to take the highest and lowest productivity points and compare them.

Hence for the highest productivity $c = 0$:

$$
\begin{aligned}
p^* &= \frac{\delta}{2} c^{fh}(1+\kappa) \text{ plugging in} \\
\varepsilon_{p^*} &= \frac{\delta}{2} \left[\frac{(1+\kappa)c^{fh}}{\frac{\delta}{2}(1+\kappa)c^{fh}} \varepsilon_{c^{fh}} \right] + \frac{\delta}{2} \left[\frac{c^{fh}\kappa}{\frac{\delta}{2}(1+\kappa)c^{fh}} \varepsilon_{\kappa} \right] \\
&= \varepsilon_{c^{fh}} + \frac{\kappa}{1+\kappa} \varepsilon_{\kappa}
\end{aligned}
$$

And for the lowest $c = c^{fh}$:

$$
\begin{aligned}
p^* &= \delta c^{fh} \text{ plugging in} \\
\varepsilon_{p^*} &= \frac{\delta}{2} \left[\frac{(1+\kappa)c^{fh}}{\delta c^{fh}} \varepsilon_{c^{fh}} \right] \\
&= \frac{1+\kappa}{2} \varepsilon_{c^{fh}}
\end{aligned}
$$

We now have our price elasticity of tariff for both low and high-productivity firms. It is immediate that the relative pass-through of a tariff depends on κ. For high productivity firms to have a lower price elasticity to tariff (it means to relatively absorb more tariff, to increase less prices) :

$$
\begin{aligned}
\frac{1+\kappa}{2}\varepsilon_{cfh} &> \varepsilon_{cfh} + \frac{\kappa}{1+\kappa}\varepsilon_{\kappa} \\
\frac{1+\kappa}{2}\varepsilon_{cfh} - \varepsilon_{cfh} &> \frac{\kappa}{1+\kappa}\varepsilon_{\kappa} \\
\varepsilon_{cfh}\left(\frac{\kappa-1}{2}\right) &> \frac{\kappa}{1+\kappa}\varepsilon_{\kappa} \\
\varepsilon_{cfh}\left(\frac{(\kappa-1)(\kappa+1)}{2}\right) &> \kappa\varepsilon_{\kappa} \\
\varepsilon_{cfh}\left(\frac{\kappa^2-1}{2}\right) &> \kappa\varepsilon_{\kappa}
\end{aligned}
$$

First Case :

Note that both ε_{cfh} and ε_{κ} are negative as shown above. Then, if $0 < \kappa < 1$:

$$
\underbrace{\varepsilon_{cfh}\left(\frac{\kappa^2-1}{2}\right)}_{>0} > \underbrace{\kappa\varepsilon_{\kappa}}_{<0}
$$

However, if $\kappa > 1$ then the case is more subtle:

$$
\underbrace{\varepsilon_{cfh}\left(\frac{\kappa^2-1}{2}\right)}_{<0} \gtreqless \underbrace{\kappa\varepsilon_{\kappa}}_{<0}
$$

Second and Third Case :

A first is for $\kappa > 1$:

$$
\begin{aligned}
\frac{\varepsilon_{cfh}}{\varepsilon_{\kappa}} &< \frac{2\kappa}{\kappa^2-1} \\
\Longrightarrow 1 < \frac{\varepsilon_{cfh}}{\varepsilon_{\kappa}} &< \frac{2\kappa}{\kappa^2-1}
\end{aligned}
$$

To have that the magnitude of $\varepsilon_{cfh} > \varepsilon_{\kappa} \Longrightarrow \frac{\varepsilon_{cfh}}{\varepsilon_{\kappa}} > 1$. It leads to solve the case for which :

$$
\begin{aligned}
&1 < \frac{\varepsilon_{cfh}}{\varepsilon_\kappa} < \frac{2\kappa}{\kappa^2 - 1}\\
\Longrightarrow &1 < \frac{2\kappa}{\kappa^2 - 1}\\
\Longrightarrow &\kappa^2 - 1 < 2\kappa\\
\Longrightarrow &0 < 2\kappa - \kappa^2 + 1
\end{aligned}
$$

We solve for the determinant of this quadratic function and find $\Delta = 8$, then it admits two real roots for which it is superior or equal to 0.

$$x_1 = \frac{-b + \sqrt{\Delta}}{2a} \approx -0.41 \text{ and } x_2 = \frac{-b - \sqrt{\Delta}}{2a} \approx 2.41$$

The first root is impossible to reach by definition ($\kappa > 0$), then the equation solves for $\kappa = 2.41$. For any value of $\kappa \in]0, 2.41[\Longrightarrow \varepsilon_{cfh} > \varepsilon_\kappa \Longrightarrow \frac{1}{2}(\kappa^2 - 1)\varepsilon_{cfh} > \kappa\varepsilon_\kappa$. And conversely for $\kappa > 2.41$.

B Data Appendix

In this section, we present robustness checks for our main results and offer an extension by estimating the unconditional quantile regression of tariff exposure on panel efficiency. We then detail the data preparation steps undertaken to clean the dataset, construct our primary variables, address data-related challenges, and justify the methodological choices made throughout the process (see subsection B.3). In addition, we provide supplementary tables and figures that support our empirical strategy and findings in subsection B.5. The full code used to generate our results is publicly available on our GitHub repository: JonathanGarson/solar_panel.

B.1 Robustness

To complement our main analysis of the effect of tariffs on prices, we conduct two robustness checks. The first addresses a key concern identified by de Chaisemartin and D'Haultfœuille (2023), namely that a necessary (though weak) condition for causal inference under OLS is that the treatment variable be uncorrelated with the error term. We test this condition directly. More broadly, we argue that our extended set of controls and fixed effects supports the stronger Conditional Independence Assumption, under which our OLS estimates can be interpreted causally.

Table 7: Test of Independence between Treatment and Errors

	Overall	AD 2010–2013	AD 2014–2016	Trade War 2017–2018
ln Tariff	0.000	0.000	0.000	0.000
	(0.004)	(0.018)	(0.008)	(0.005)
Num.Obs.	414 762	34 545	106 413	128 111
R2	0.000	0.000	0.000	0.000

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The dependent variable is the residual error from the column 1, 3, 5, 7 of Table 3. Standard Errors are clustered at the zip code level. Fixed effects are county, year-quarter, installer, and origin.

Reassuringly, we do not find evidence of a correlation between the treatment variable and the regression residuals, which reinforces the credibility of a causal interpretation of the link between tariffs and price variation.

To further strengthen our claim that price variation is not mechanically driven by covariates or the fixed effects structure, we conduct a placebo test

by randomly assigning tariff exposure across firms. Specifically, we randomly shuffle the observed tariff rates with replacement, without stratification, and re-estimate our baseline regressions. Standard errors are clustered at the ZIP code level.
Our regression is identical to our main specification :

$$\begin{aligned}\ln p_i =&\beta_0 \ln \text{Tariff} + \beta_1 \ln \text{Tariff} \times \text{QualityMetrics}_i + \beta_2 \text{Premium Installation} \\ &+ \beta_3 \text{QualityMetrics}_i + \beta_4 \text{Premium Installation} + \theta \mathbf{X}_i + \text{FE} + \varepsilon_i\end{aligned}$$

Table 8: Placebo Tariff Effect on Prices

	Overall		Anti-Dumping : 2010 - 2013		Anti-Dumping : 2014 - 2016		Trade War 2018	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln Placebo Tariff	−0.009	−0.012	−0.006	−0.008	−0.017	−0.022	0.011	0.004
	(0.019)	(0.019)	(0.045)	(0.045)	(0.036)	(0.036)	(0.041)	(0.040)
ln Placebo Tariff x Efficiency	0.080	0.096	0.018	0.032	0.106	0.129	−0.044	−0.011
	(0.101)	(0.099)	(0.254)	(0.253)	(0.197)	(0.195)	(0.214)	(0.213)
ln Placebo Tariff x Premium Installation	−0.002	−0.002	0.009	0.009	0.007	0.007	0.001	0.002
	(0.004)	(0.004)	(0.012)	(0.012)	(0.007)	(0.007)	(0.007)	(0.007)
Efficiency	1.354***	1.509***	−0.480	−0.625	0.705***	0.762***	1.643***	1.575***
	(0.073)	(0.077)	(0.422)	(0.437)	(0.153)	(0.161)	(0.107)	(0.106)
Premium Installation	0.031***	0.027***	0.014**	0.014**	0.036***	0.033***	0.036***	0.037***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)
Num.Obs	414 762	414 762	34 545	34 545	115 726	115 726	128 111	128 111
R2	0.532	0.540	0.706	0.709	0.502	0.511	0.444	0.451
FE: County	X	X	X	X	X	X	X	X
FE: Year-Quarter	X		X		X		X	
FE: Installer	X	X	X	X	X	X	X	X
FE: Origin	X		X		X		X	
FE: Year-Quarter × Origin		X		X		X		X

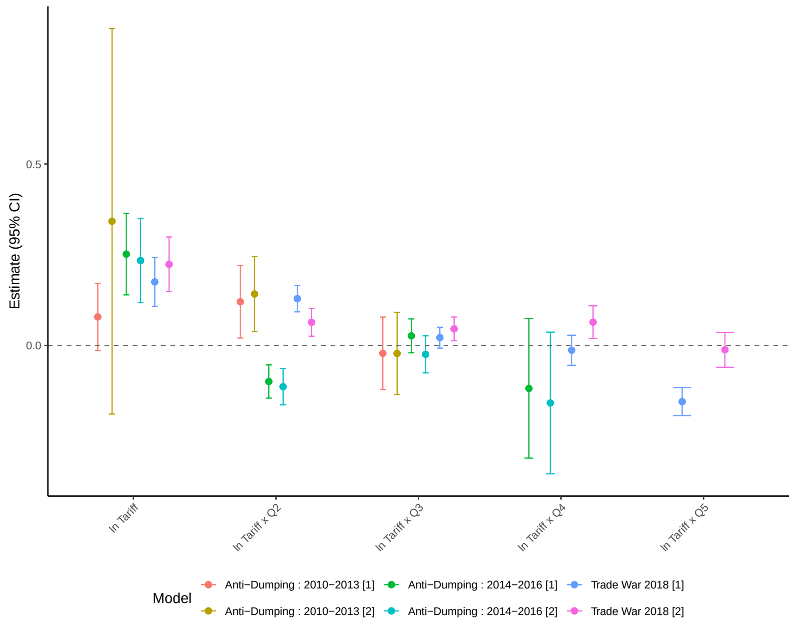
+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

Across specifications, we find no significant price effects associated with these artificially assigned tariffs. This does not imply that non-treated firms did not raise their prices during the period, but rather that such price changes cannot be attributed to the tariff exposure of the Chinese firms. These results support our interpretation that the observed price effects are indeed driven by actual tariff implementation rather than underlying trends or noise in the data.

We use the same regression Equation 15 (see below) as in our empirical part but we change the definition of quantile. Now, quantiles are defined over the entire subperiods, and then less fragile to compositional change.

$$\ln p_i = \beta_0 \ln \text{Tariff}_i + \sum_{q=2}^{5} \beta_q \big(\ln \text{Tariff}_i \times Q_{i,q}\big) + \theta \ \mathbf{X}_i \ + \ \text{FE}_i + \varepsilon_i$$

Figure 7: Estimate of price Elasticity per Efficiency Quintile (2nd definition)



Our price elasticity results are coherent with our previous findings. Widening the definition scope does not change qualitatively our results. We still find higher price elasticity for lower-efficiency panels. This is consistent with our results of the quality shift in both the empirical part and our extension in the appendix subsection B.2.

B.2 Extension: Unconditional Quantile Effect of Tariff

Unconditonal quantile regression allow us to explore the following question : how would the observed distribution of quality (across county, origin, installer and time) change, measured by the change in the τ_{ith} quantile, if all solar panel had, on average, 1%, more exposure everything else being constant?

To answer this question, we use the estimator developed by Firpo et al. (2009), which relies on the Recentered Influence Function (RIF). The core idea of this method is to estimate the marginal effect of a small change in a covariate—such as a 1% increase in the tariff—on a specific unconditional quantile of the outcome variable's distribution (e.g., the 25th, 50th, or 75th percentile of price).

The RIF transforms the original outcome variable into a new variable whose expected value equals the quantile of interest. This transformation allows us to apply standard linear regression techniques to estimate the effect of covariates on that quantile—despite quantiles being inherently nonlinear. In this way, we can recover the Unconditional Quantile Partial Effects (UQPE), which reflect how a marginal increase in a covariate shifts the entire distribution of the outcome, rather than its conditional expectation.

We define the RIF as :

$$\text{RIF}(y_i, Q_\tau(.), F_y) = Q_\tau(y) + \frac{\tau - \Delta(y_i \leq Q_\tau(y))}{f_y(Q_\tau(y))}$$

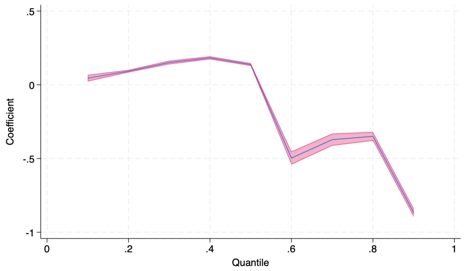
where $Q_\tau(.)$ is the unconditional quantile, τ is the rank of percentile of interest, $\Delta(.)$ is an indicator function for whether observation y_i is below $Q_\tau(y)$, and $f_y(Q_\tau(y))$ is the density function of distribution of y evaluated at the $Q_\tau(y)$.

Therefore, we can now use standard OLS approach on our RIF, including fixed effects and covariates is therefore not an issue since only standard linear regression assumptions are required :

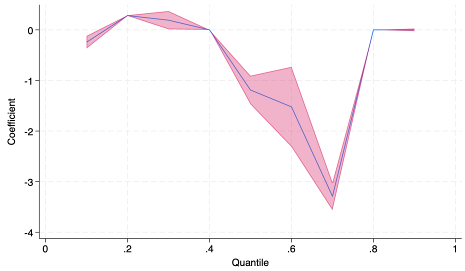
$$\mathrm{RIF}(\ln \mathrm{Efficiency_i}, \mathrm{Q}_\tau(.), \mathrm{F_y}) = \beta_0(\tau) \ln \mathrm{Tariff} + \theta(\tau)\mathbf{X} + \delta(\tau)\mathrm{FE} + \varepsilon_i$$

where the dependent variable is the RIF of log efficiency at the installed solar system level, $\beta_0(\tau)$ captures the τ quantile of effect of being exposed to a marginal (1%) increase in tariff on installed panel efficiency, $\theta(\tau)$ captures the effect of our usual set of covariates for each quantile, and finaly the fixed effects are origin, year-quarter, installer and county. The standard errors are bootstrap 100 times. This regression is ran for our usual 3 subperiods.

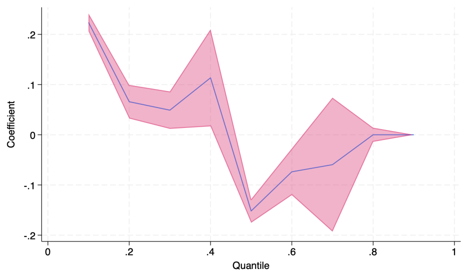
Figure 8: Unconditional Quantile Effect of Tariff on Efficiency



(a) 2010-2013



(b) 2014-2016



(c) 2017-2018

Notes: The dependent variable is log efficiency, and the independent variable is log tariff. Standard errors are bootstrap 100 times.

We observe that the positive effects of tariffs on log efficiency are concentrated in the lower part of the distribution—specifically in the bottom 4 deciles—for both the first anti-dumping tariff and the Trade War. For example, in the 2017–2018 sample, a 1% increase in tariff exposure is associated with a 0.1% increase in log efficiency at the 4th decile but a 0.1% decline at the 6 decile.

This pattern aligns with the segments of the market that exhibit the strongest price increases and supports the hypothesis that the higher price elasticity observed in those deciles may be partly driven by quality upgrading among lower-efficiency panels. The adjustment appears to be stronger at the bottom of the quality distribution. Note that this contradicts our model prediction that average quality should increase but mostly by the top of the distribution.

Interestingly, we also find negative or null effects above the 5th decile, particularly under the Trade War, where effects vanish or turn negative after the 7th decile. This may reflect the crowding-out of middle-efficiency panels, which could have been squeezed by both quality upgrading at the bottom and the increased cost burden from tariffs, leading them to exit the market.

For the second anti-dumping tariff, the results are more ambiguous. While we still observe positive effects at the lower end, we also find negative impacts between the 4th and 8th deciles. These findings are broadly consistent with the relatively muted price elasticity across the distribution in that period and may indicate a downgrading in panel quality rather than an upgrade.

However, these results should be interpreted with caution. As shown in Figure 8, the standard errors are large, reflecting high variability likely driven by heterogeneous tariff rates. Additionally, for both Figure 8a and Figure 8b, no solar panels above the 6th decile were directly exposed to tariffs. In the case of the Trade War, Chinese panels are nearly absent beyond the 6th decile, implying that the highest-quality panels were relatively less affected by tariff increases. This pattern likely explains the smaller variation in tariff exposure and weaker effects observed in the upper deciles. As a result, the estimated coefficients for the top 4 deciles should be interpreted either as reflecting indirect spillover effects or as linear extrapolations beyond the range of directly treated observations.

B.3 Data Construction

B.3.1 Tracking The Sun

Our main dataset is *Tracking the Sun* (hereafter TTS), published by the Lawrence Berkeley National Laboratory, which compiles publicly collected data on solar panel installations across the United States. TTS is an extensive database that captures nearly the entire universe of non-utility-scale solar systems installed in the U.S., providing detailed information on location, system size, total installation cost, rebates[26], module manufacturer, installer, presence of integrated micro-inverters, technology type, efficiency, and battery integration.

This comprehensive dataset covers approximately 95% of all installed systems during our study period and represents 56% of total U.S. installed capacity (Houde and Wang, 2023). It includes only grid-connected systems—whether rooftop or ground-mounted—for residential, community, or small-scale commercial use. Large utility-scale systems (those above 1 MW of capacity) are excluded. For reference, a typical residential installation is around 6 kW.

The data are primarily sourced from state agencies and utilities that manage photovoltaic (PV) incentive programs, solar renewable energy credit registration systems, or interconnection processes.

[26] Excluding the federal Investment Tax Credit (ITC).

Before our own cleaning procedure, the data had already undergone preliminary standardization. Duplicates, entries with missing installation dates or system sizes, and other incomplete records were removed. Each row in the dataset thus corresponds to a unique solar installation. Manufacturer, model, and installer names were standardized in spelling but not corrected in cases of misattribution.

Cleaning Procedure and Choices The raw dataset contains approximately 3 million observations spanning 27 U.S. states up to and including 2023, with the largest share concentrated in California. Each observation corresponds to an individual solar system installation and its associated characteristics.

Because our analysis focuses on manufacturers, it was crucial to recover all potentially misattributed entries. As a first step, we cleaned the dataset for misspelled module manufacturer names. The most frequently misspelled—and also among the most prominent—brands included Hanwha Qcells, Canadian Solar, Panasonic, and Solar Power[27]. This correction allowed us to recover thousands of installations that would otherwise have been excluded.

We then removed all observations with missing data for any of the following variables: *installation_date*, *zip_code*, *installer_name*, *module_manufacturer_1–3*, *module_model_1–3*, *technology_module_1–3*, *efficiency_module_1–3*, *module_quantity_1–3*, *PV_system_size_DC*, *total_installed_price*, *nameplate_capacity_module_1–3*.

Next, we deflated both the installation prices and rebates using the Consumer Price Index (CPI) from the U.S. Bureau of Labor Statistics, setting 2010 as the base year. At this stage, we created two key variables: the installation price and rebate expressed in dollars per watt ($/W).

To restrict our analysis to comparable systems, we limited the sample to residential installations and excluded cases where the reported price was lower than the value of the rebate. This filtering step was particularly important, as we observed significant data issues around 2013 in California—coinciding with the end of the California Solar Initiative (CSI). We also removed systems equipped with batteries to avoid confounding the price variable, and kept only systems where a single module brand was used (e.g., excluding installations combining LG and Trina Solar) to ensure price attribution is brand-specific.

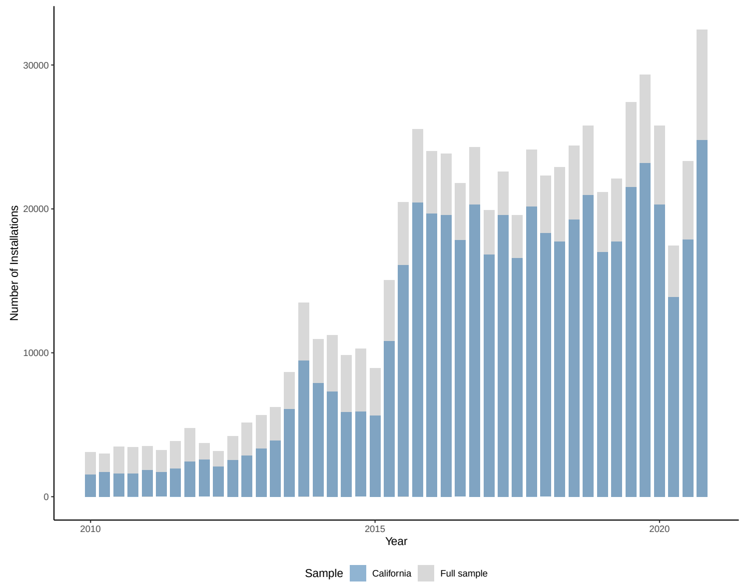
We further excluded installations associated with Tesla and SolarCity (renamed Tesla), as these entities are known for frequent misreporting and for being mistakenly recorded as both manufacturer and installer—when in fact they only operate as installers. While Tesla accounts for a large share of U.S. installations, removing these entries increased the reliability of our dataset.

[27] Respectively South Korean, Chinese, Japanese, and Chinese manufacturers.

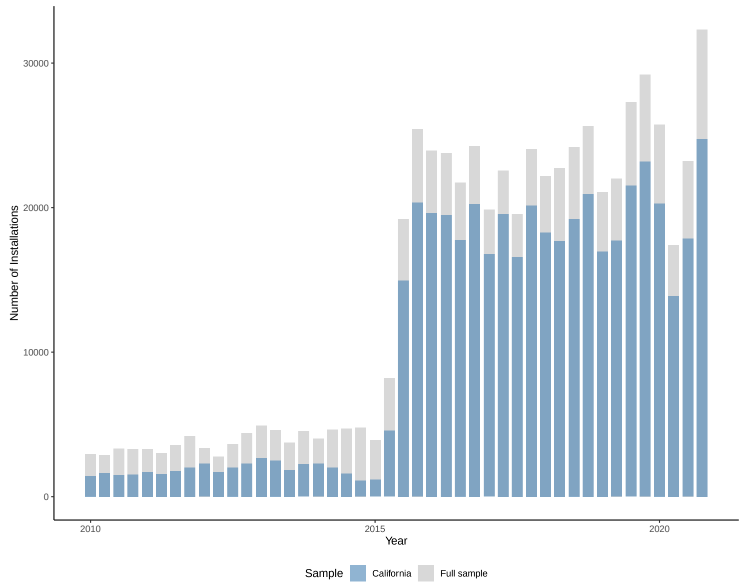
Lastly, we excluded systems above 20 kW, which are more likely to represent small neighborhood-scale projects rather than individual households. We also trimmed outliers by removing price observations above \$15/W and below \$1/W. These extremes are implausible, as \$15/W in 2010 would be more than \$4/W above typical prices a decade earlier and over five times the average price observed by 2018. We then merged our data with the *zipcode* which matches zip code to county, and provided information on the real estate market from the 2010 American Community Survey conducted by the Census Bureau.

Regarding the selection process for our analytical sample, we chose to focus on the largest firms, which together account for approximately 90% of the observations. While this excludes smaller firms and those that may have entered or exited the market during the study period, we consider evolving market shares among the included firms as a proxy for these dynamics. Many smaller brands exhibit limited market presence, often with only a few hundred models sold over the entire period. To ensure tractability and consistency, we restrict our analysis to the most prominent manufacturers.

Another important choice was to limit the sample to installations in California, for three main reasons. First, California accounts for more than two-thirds of all observations in the dataset, and therefore largely drives national trends. Second, restricting the sample to a single state reduces potential confounding from variation in state-level subsidy programs. Third, California is the most consistent state in terms of data reporting across the study period. In contrast, other key solar states such as Texas, Utah, Maine, and Florida report data for fewer than 4% of installed systems (Barbose and Darghouth, 2019), which could introduce measurement error and inconsistency.



(a) Before Cleaning



(b) After Cleaning

Figure 9: California Share of Sample Before and After Cleaning

We observe a relative jump in installation in 2016 in Figure 9a, but it is mainly due to two data cleaning choices.

The first important exclusion concerns systems installed by Tesla and SolarCity. Following a conservative approach and the precedent set by Barbose and Darghouth (2019), we removed all installations associated with these companies[28]. These firms are known for misreporting installation prices, leading to significant measurement errors (see subsection B.3 for details). Furthermore, Tesla is frequently misclassified in the dataset as a module manufacturer, although it does not manufacture panels but instead sources them from a range of Chinese and non-Chinese suppliers. This makes tracking exposure to tariffs particularly difficult. As Tesla is the largest installer in the U.S., excluding it naturally leads to a notable reduction in the number of observations.

This drop in coverage is further accentuated by the relatively low number of reported installations during the 2014–2015 period. Many of these entries were affected by rebate misreporting—specifically, cases where the reported rebate exceeded the total installation cost—which led to their removal. Since this period follows the effective end of the California Solar Initiative, we are not concerned about the exclusion introducing systematic bias.

B.3.2 Tariff Data

In this section, we rely on the work of Bown (2016) and his team to identify the legal references (juridical identifiers) of the relevant trade inquiries. Based on these references, we retrieved and reviewed the official inquiry documents and decisions, from which we manually extracted and encoded the list of affected firms. As the starting point for each tariff, we use the date of the provisional measures. This is not problematic, as the list of affected firms and the tariff rates are identical between the provisional and final measures.

We define the tariff as the sum of the countervailing and anti-dumping duties, which are imposed simultaneously but differ in magnitude. The original database provides both components separately; however, for our analysis, we use the combined rate since both duties must be paid together—ad valorem—at the point of importation.

B.3.3 Census Data and Other Small Datasets

We also incorporate data from the U.S. Census Bureau at the census tract level. Census tracts are stable statistical units used by the American Community Survey (ACS) since 2010 and are more consistent over time than ZIP codes, which are based on postal delivery routes and can change frequently. In our dataset, we work with 1,695 ZIP codes, 938 census tracts, and 54 counties. Census tracts serve as the linking geographic identifier between our solar installation data and socio-demographic information.

We rely on two waves of the ACS, from 2010 and 2015, to extract socio-demographic characteristics at the tract level. Specifically, we use the share of

[28]SolarCity, originally founded by Elon Musk's cousins, was acquired by Tesla in 2016.

the population with a bachelor's degree, median house value, median household income, total population, and population density.

More anecdotally, we also collected data on electricians' wages at the county-year level from the Bureau of Labor Statistics, as well as annual electricity rates from the U.S. Department of Energy. These variables were considered as potential instruments for estimating the demand for solar panels. Specifically, electricity prices serve as a proxy for the price of the outside good—that is, grid-supplied electricity—and are thus likely to increase demand for solar panels when high. Electricians' wages, by contrast, act as a potential cost shifter, influencing the installation cost component of system prices.

B.4 Software Considerations and Contributions

Most of the data analysis was conducted using R, with the exception of the conditional and unconditional quantile regressions with fixed effects, which were initially implemented in Stata. Given our preference for R, we developed a custom implementation of conditional quantile regression with fixed effects directly in R. To our knowledge, this is the first implementation of this method in R. It was constructed using the `demean` function from the `fixest` package along with standard R functions.

For consistency and benchmarking purposes, we used the output from Stata in the final analysis, though the results obtained from our R implementation were qualitatively similar. Notably, while implementing the conditional quantile regression (CQR), we identified that the non-negativity assumption of $x_i'\gamma$ was violated for a small subset of observations—highlighting an important empirical limitation.

B.5 Complementary Tables and Figures

Table 9: Market Share of Top 15 Manufacturers (2010-2020)

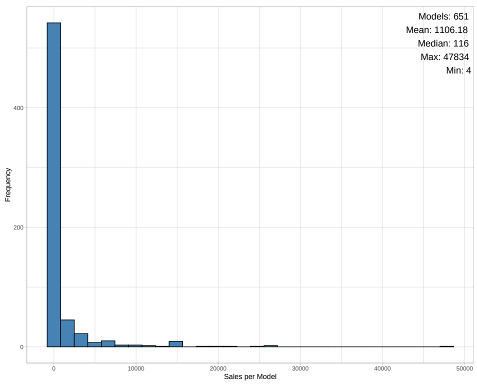
Manufacturer	Market Share	Country of Origin
Maxeon - Sunpower	0.1485	USA
Hanwha QCells	0.1176	South Korea
LG Electronics inc.	0.1095	South Korea
Trina solar	0.0854	China
REC solar	0.0767	Norway
SolarWorld	0.0663	Germany
Canadian Solar	0.0661	China
Jinko Solar	0.0469	China
Kyocera Solar	0.0363	Japan
Yingli Energy (China)	0.0360	China
Panasonic	0.0274	Japan
Hyundai Energy Solutions co., ltd.	0.0270	South Korea
Longi Green Energy Technology co., ltd.	0.0194	China
Silfab	0.0169	USA
Sharp	0.0106	Japan

Notes: The column represents the market share over the period 2010-2020 operating in the United States. Cumulated, these companies represent 90% of the market.
Data: Calculated from Tracking the Sun.

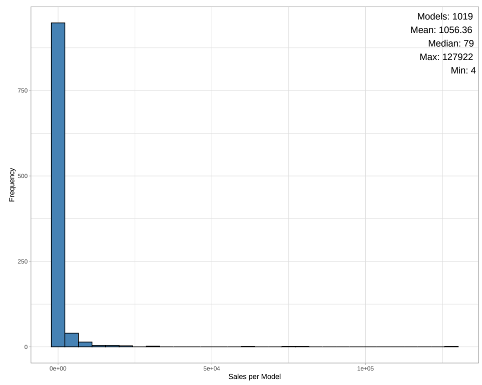
Year	Share Chinese Firms	Top 5 Chinese Firms
2010	0.2639446	0.8935308
2011	0.3643031	0.8885062
2012	0.4417768	0.8653154
2013	0.5036724	0.8216040
2014	0.5344476	0.8258260
2015	0.3688959	0.9308563
2016	0.3484012	0.9196815
2017	0.3212119	0.9619895
2018	0.2693011	0.9298735
2019	0.2347731	0.8192657
2020	0.2331878	0.8955562

Notes: The second column represents the share of installed solar panels by year sourced from a Chinese firm. The third column represents the ratio of those Chinese solar panels coming from one of the top 5 Chinese firms in the period (all affected by AD).

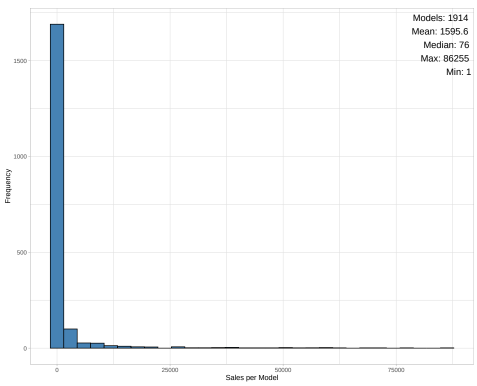
Table 10: Share of Chinese Solar Panels installed each year



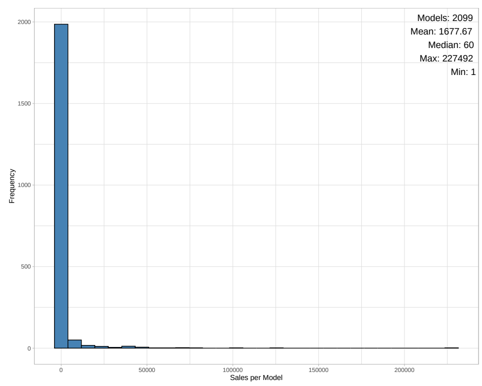
(a) 2011



(b) 2013

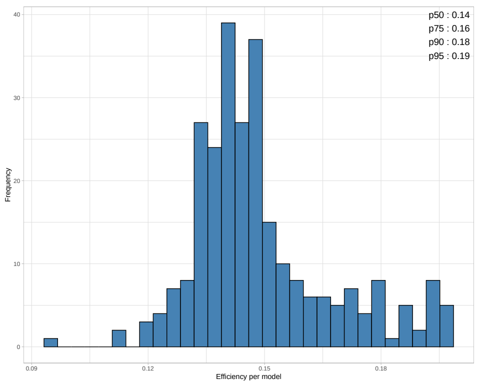


(c) 2017

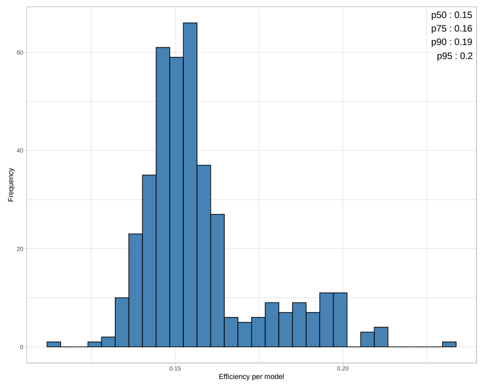


(d) 2019

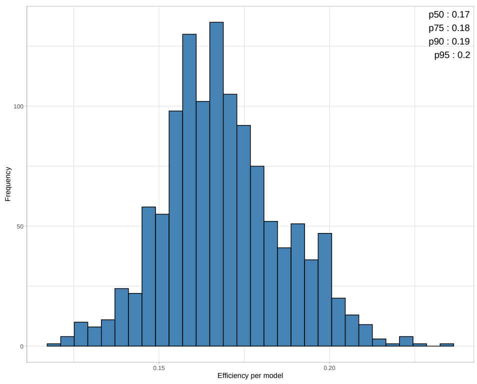
Figure 10: Model Sales Distribution



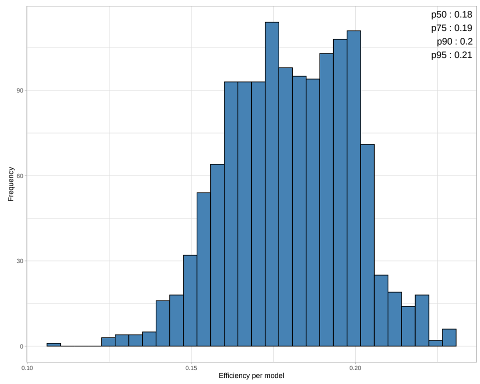
(a) 2011



(b) 2013

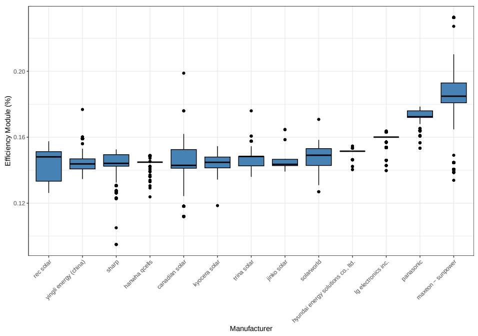


(c) 2017

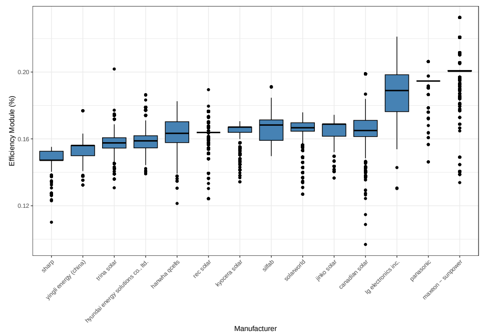


(d) 2019

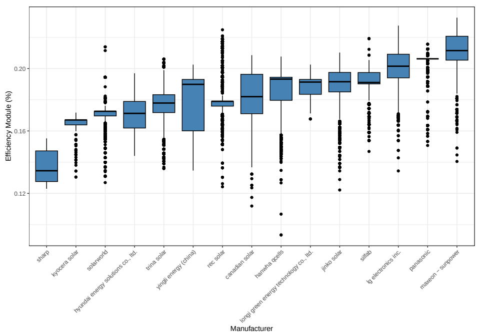
Figure 11: Model Efficiency Distribution



(a) 2010-2012



(b) 2013-2016



(c) 2017-2020

Figure 12: Within firms distribution of solar panels quality.

(a) Full Sample

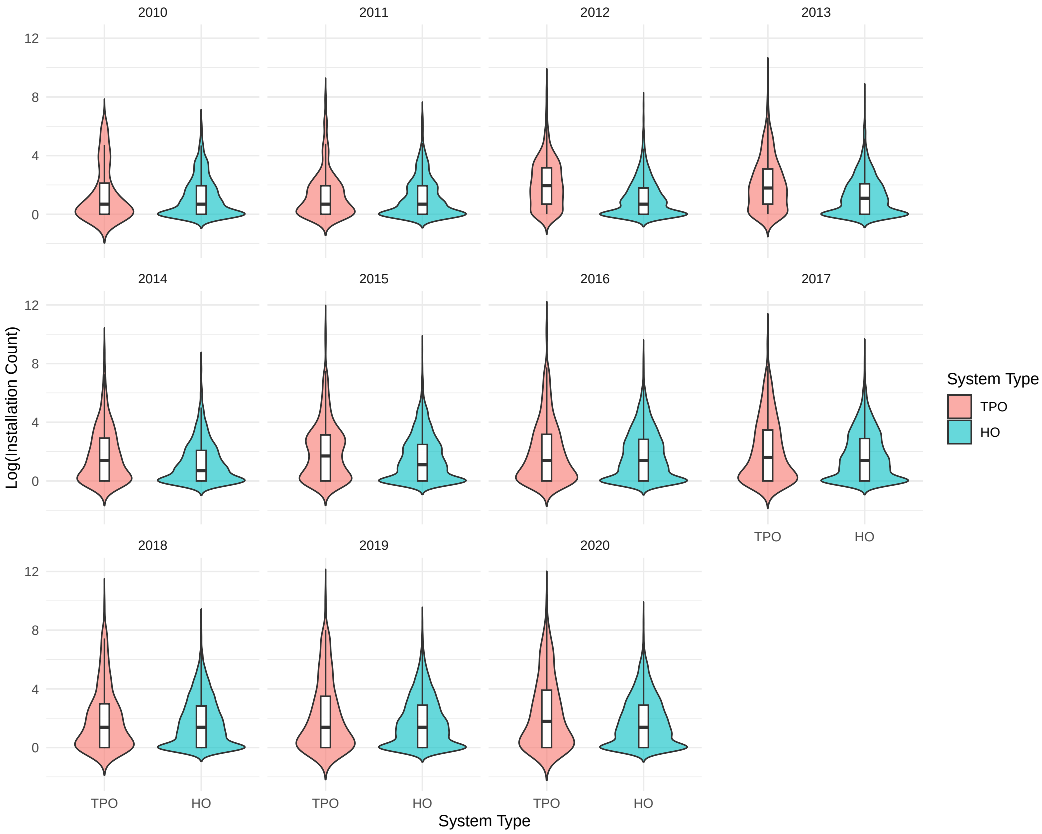
	Decile	2010-2013	2014-2016	2018
	D1	4062	11559	14533
	D2	3257	10931	12220
	D3	3492	14326	14306
	D4	3782	13069	12029
	D5	3401	5013	14218
	D6	3508	10975	12702
	D7	5120	11919	13096
	D8	4603	13809	14068
	D9	1360	7180	14097
	D10	3061	10621	11451
Total	—	35,646	109,402	132,720

(b) Chinese Firms

	Decile	2010-2013	2014-2016	2017-2018
	D1	1209	3532	4303
	D2	1490	3376	5001
	D3	1454	1206	1175
	D4	881	2646	686
	D5	1286	2819	3796
	D6	1219	369	3435
	D7	NA	51	173
	D8	NA	1	1
Total	—	7,539	14,000	18,570

Table 11: Number of Observations per Decile of Efficiency

Figure 13: Distribution of installations by installer for HO and TPO systems



Notes: The figures display the log installation by the installer for HO and TPO systems before joining the installers that together represented less than 5% of installed systems.

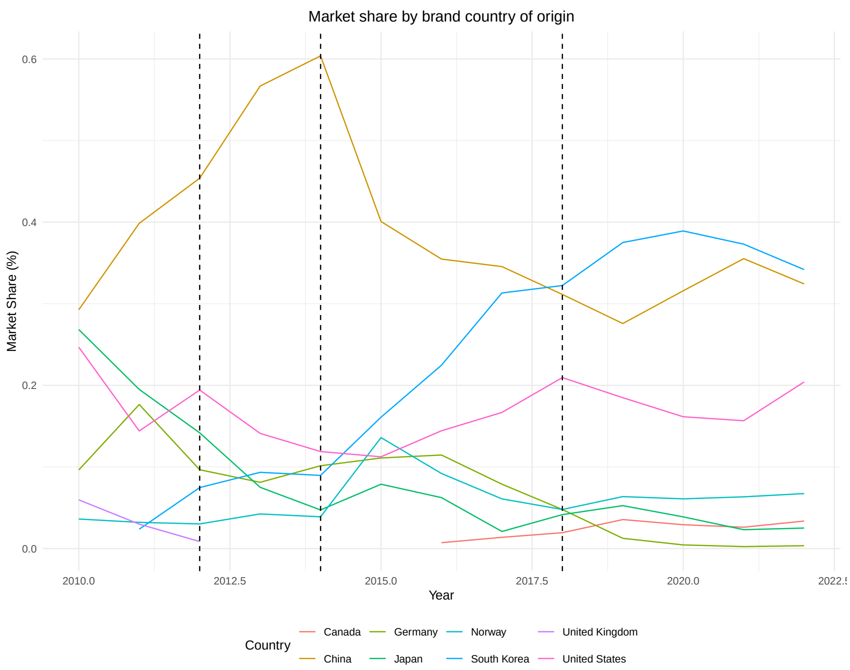


Figure 14: Market Share by Origin

(a) Full Sample

	Quintile	2010-2013	2014-2016	2018
	Q1	7061	1791	19994
	Q2	3770	9051	15752
	Q3	10671	60996	30416
	Q4	5120	9455	30935
	Q5	6558	27520	35622
Total	—	33,180	108,813	132,719

(b) China Only

	Quintile	2010-2013	2014-2016	2018
	Q1	2674	1010	5253
	Q2	1499	2516	4297
	Q3	3366	10469	5396
	Q4	NA	2	3623
	Q5	NA	1	1
Total	—	7,539	13,998	18,570

Table 12: Number of Observations per Quintile (1st Definition)

(a) Full Sample

	Quintile	2010-2013	2014-2016	2018
	Q1	7319	22490	26753
	Q2	7274	27395	26335
	Q3	6909	15988	26920
	Q4	9723	25728	27164
	Q5	4421	17801	25548
Total	—	35,646	109,402	132,720

(b) China Only

	Quintile	2010-2013	2014-2016	2018
	Q1	2699	6908	9304
	Q2	2335	3852	1861
	Q3	2505	3188	7231
	Q4	NA	52	174
	NA	NA	NA	NA
Total	—	7,539	14,000	18,570

Table 13: Number of Observations per Quintile (2nd Definition)

	Overall		Anti-Dumping : 2010-2013		Anti-Dumping : 2014-2016		Trade War 2018	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln Tariff	0.103***	0.225***	0.083+	0.297	0.440***	0.404***	0.158***	0.208***
	(0.020)	(0.034)	(0.047)	(0.272)	(0.068)	(0.072)	(0.037)	(0.040)
ln Tariff x Quintile Q2	0.128***	0.129***	0.121*	0.150*	−0.164**	−0.160**	0.139***	0.111***
	(0.017)	(0.018)	(0.058)	(0.059)	(0.060)	(0.060)	(0.020)	(0.022)
ln Tariff x Quintile Q3	0.034**	0.035*	0.020	0.033	−0.228***	−0.238***	−0.001	−0.003
	(0.013)	(0.016)	(0.048)	(0.054)	(0.044)	(0.048)	(0.017)	(0.018)
ln Tariff x Quintile Q4	0.037*	0.044*			−0.671***	−0.696***	−0.014	0.023
	(0.016)	(0.019)			(0.196)	(0.197)	(0.017)	(0.019)
ln Tariff x Quintile Q5	0.063**	0.159***			−0.194*	−0.171+	−0.106***	0.031
	(0.021)	(0.027)			(0.086)	(0.088)	(0.021)	(0.025)
Num.Obs	266 053	266 053	32 097	32 097	105 846	105 846	128 110	128 110
R2	0.588	0.597	0.714	0.717	0.494	0.502	0.445	0.452
R2-Adj.	0.587	0.595	0.710	0.712	0.490	0.498	0.442	0.448
FE: County	X	X	X	X	X	X	X	X
FE: Year-Quarter	X		X		X		X	
FE: Installer	X	X	X	X	X	X	X	X
FE: Origin	X		X		X		X	
FE: Year-Quarter × Origin		X		X		X		X

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

Table 14: Estimate of Price Elasticity to Tariff for Decile of Installed Quality Solar Panel

(a) 2010–2013

	(1)	(2)	(3)	(4)	(5)	(6)
	log_efficiency	log_efficiency	log_efficiency	log_efficiency	log_efficiency	log_efficiency
location						
Log Tariff Rate	0.0429^{***}	0.0429^{***}	0.0429^{***}	0.0429^{***}	0.0429^{***}	0.0429^{***}
	(0.00972)	(0.00972)	(0.00972)	(0.00972)	(0.00972)	(0.00972)
scale						
Log Tariff Rate	0.0460^{***}	0.0460^{***}	0.0460^{***}	0.0460^{***}	0.0460^{***}	0.0460^{***}
	(0.00725)	(0.00725)	(0.00725)	(0.00725)	(0.00725)	(0.00725)
qtile						
Log Tariff Rate	-0.0330	0.00140	0.0221^{*}	0.0371^{***}	0.0494^{***}	0.0615^{***}
	(0.0201)	(0.0147)	(0.0120)	(0.0103)	(0.00885)	(0.00789)
Observations	34545	34545	34545	34545	34545	34545

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

(b) 2014–2016

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log_efficiency	log_efficiency	log_efficiency	log_efficiency	log_efficiency	log_efficiency	log_efficiency	log_efficiency
location								
Log Tariff Rate	0.325^{***}	0.325^{***}	0.325^{***}	0.325^{***}	0.325^{***}	0.325^{***}	0.325^{***}	0.325^{***}
	(0.0117)	(0.0117)	(0.0117)	(0.0117)	(0.0117)	(0.0117)	(0.0117)	(0.0117)
scale								
Log Tariff Rate	-0.00156	-0.00156	-0.00156	-0.00156	-0.00156	-0.00156	-0.00156	-0.00156
	(0.00540)	(0.00540)	(0.00540)	(0.00540)	(0.00540)	(0.00540)	(0.00540)	(0.00540)
qtile								
Log Tariff Rate	0.327^{***}	0.326^{***}	0.326^{***}	0.325^{***}	0.325^{***}	0.324^{***}	0.324^{***}	0.323^{***}
	(0.0164)	(0.0143)	(0.0131)	(0.0123)	(0.0116)	(0.0113)	(0.0113)	(0.0115)
Observations	106413	106413	106413	106413	106413	106413	106413	106413

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

(c) 2017–2018

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	log_efficiency	log_efficiency	log_efficiency	log_efficiency	log_efficiency	log_efficiency	log_efficiency	log_efficiency	log_efficiency
location									
Log Tariff Rate	0.185^{***}	0.185^{***}	0.185^{***}	0.185^{***}	0.185^{***}	0.185^{***}	0.185^{***}	0.185^{***}	0.185^{***}
	(0.0104)	(0.0104)	(0.0104)	(0.0104)	(0.0104)	(0.0104)	(0.0104)	(0.0104)	(0.0104)
scale									
Log Tariff Rate	-0.0287^{***}	-0.0287^{***}	-0.0287^{***}	-0.0287^{***}	-0.0287^{***}	-0.0287^{***}	-0.0287^{***}	-0.0287^{***}	-0.0287^{***}
	(0.00506)	(0.00506)	(0.00506)	(0.00506)	(0.00506)	(0.00506)	(0.00506)	(0.00506)	(0.00506)
qtile									
Log Tariff Rate	0.226^{***}	0.214^{***}	0.205^{***}	0.196^{***}	0.186^{***}	0.175^{***}	0.165^{***}	0.155^{***}	0.141^{***}
	(0.00934)	(0.00907)	(0.00919)	(0.00957)	(0.0103)	(0.0114)	(0.0125)	(0.0139)	(0.0157)
Observations	128111	128111	128111	128111	128111	128111	128111	128111	128111

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Quantile Regression of Tariff on Efficiency Across Periods

(a) 2010–2013

	(1) log_efficiency	(2) log_efficiency	(3) log_efficiency	(4) log_efficiency	(5) log_efficiency	(6) log_efficiency
location						
Log Tariff Rate	0.195***	0.195***	0.195***	0.195***	0.195***	0.195***
	(0.0562)	(0.0562)	(0.0562)	(0.0562)	(0.0562)	(0.0562)
scale						
Log Tariff Rate	0.103**	0.103**	0.103**	0.103**	0.103**	0.103**
	(0.0468)	(0.0468)	(0.0468)	(0.0468)	(0.0468)	(0.0468)
qtile						
Log Tariff Rate	0.0235	0.101	0.144**	0.178***	0.210***	0.238***
	(0.120)	(0.0878)	(0.0718)	(0.0610)	(0.0530)	(0.0484)
Observations	34545	34545	34545	34545	34545	34545

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

(b) 2014–2016

	(1) log_efficiency	(2) log_efficiency	(3) log_efficiency	(4) log_efficiency	(5) log_efficiency	(6) log_efficiency	(7) log_efficiency	(8) log_efficiency
location								
Log Tariff Rate	0.324***	0.324***	0.324***	0.324***	0.324***	0.324***	0.324***	0.324***
	(0.0114)	(0.0114)	(0.0114)	(0.0114)	(0.0114)	(0.0114)	(0.0114)	(0.0114)
scale								
Log Tariff Rate	-0.00368	-0.00368	-0.00368	-0.00368	-0.00368	-0.00368	-0.00368	-0.00368
	(0.00533)	(0.00533)	(0.00533)	(0.00533)	(0.00533)	(0.00533)	(0.00533)	(0.00533)
qtile								
Log Tariff Rate	0.330***	0.328***	0.327***	0.325***	0.324***	0.323***	0.322***	0.321***
	(0.0162)	(0.0142)	(0.0130)	(0.0121)	(0.0113)	(0.0109)	(0.0108)	(0.0110)
Observations	106413	106413	106413	106413	106413	106413	106413	106413

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

(c) 2017–2018

	(1) log_efficiency	(2) log_efficiency	(3) log_efficiency	(4) log_efficiency	(5) log_efficiency	(6) log_efficiency	(7) log_efficiency	(8) log_efficiency	(9) log_efficiency
location									
Log Tariff Rate	0.185***	0.185***	0.185***	0.185***	0.185***	0.185***	0.185***	0.185***	0.185***
	(0.0104)	(0.0104)	(0.0104)	(0.0104)	(0.0104)	(0.0104)	(0.0104)	(0.0104)	(0.0104)
scale									
Log Tariff Rate	-0.0287***	-0.0287***	-0.0287***	-0.0287***	-0.0287***	-0.0287***	-0.0287***	-0.0287***	-0.0287***
	(0.00506)	(0.00506)	(0.00506)	(0.00506)	(0.00506)	(0.00506)	(0.00506)	(0.00506)	(0.00506)
qtile									
Log Tariff Rate	0.226***	0.214***	0.205***	0.196***	0.186***	0.175***	0.165***	0.155***	0.141***
	(0.00934)	(0.00907)	(0.00919)	(0.00957)	(0.0103)	(0.0114)	(0.0125)	(0.0139)	(0.0157)
Observations	128111	128111	128111	128111	128111	128111	128111	128111	128111

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Quantile Regression of Tariff on Efficiency Across Periods with the second FE structure

	(1) log_efficiency	(2) log_efficiency	(3) log_efficiency	(4) log_efficiency	(5) log_efficiency	(6) log_efficiency	(7) log_efficiency	(8) log_efficiency	(9) log_efficiency
location									
Log Tariff Rate	0.225***	0.225***	0.225***	0.225***	0.225***	0.225***	0.225***	0.225***	0.225***
	(0.0108)	(0.0108)	(0.0108)	(0.0108)	(0.0108)	(0.0108)	(0.0108)	(0.0108)	(0.0108)
scale									
Log Tariff Rate	-0.0115*	-0.0115*	-0.0115*	-0.0115*	-0.0115*	-0.0115*	-0.0115*	-0.0115*	-0.0115*
	(0.00655)	(0.00655)	(0.00655)	(0.00655)	(0.00655)	(0.00655)	(0.00655)	(0.00655)	(0.00655)
qtile									
Log Tariff Rate	0.242***	0.236***	0.233***	0.229***	0.224***	0.220***	0.217***	0.214***	0.209***
	(0.0170)	(0.0144)	(0.0129)	(0.0116)	(0.0106)	(0.0100)	(0.00999)	(0.0103)	(0.0113)
Observations	17480	17480	17480	17480	17480	17480	17480	17480	17480

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Quantile Regression with Fixed Effects, Trade War, China only

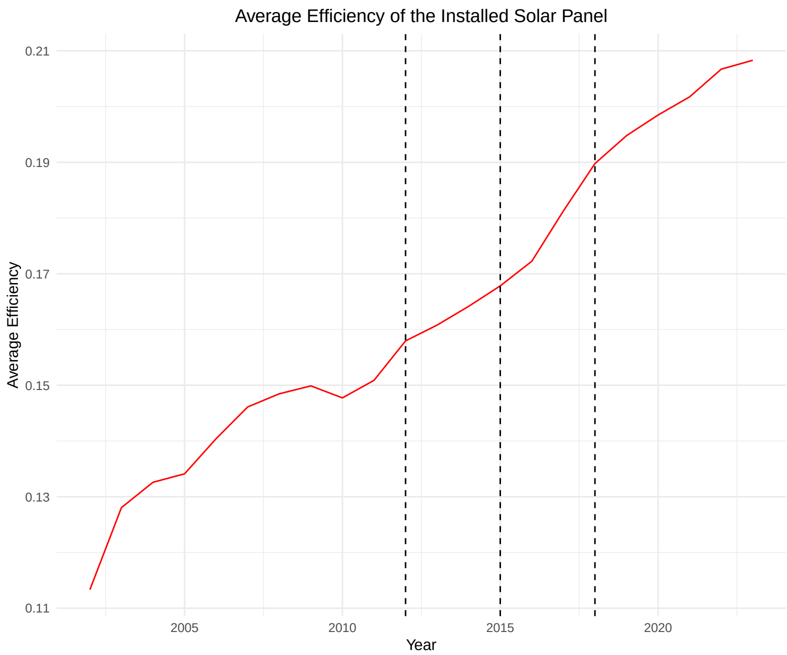
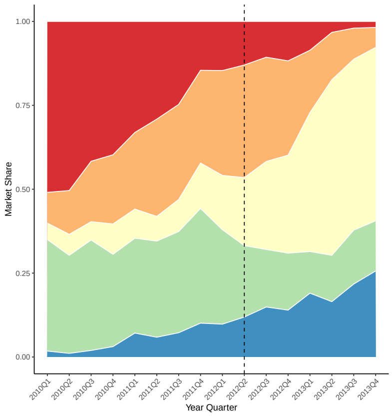
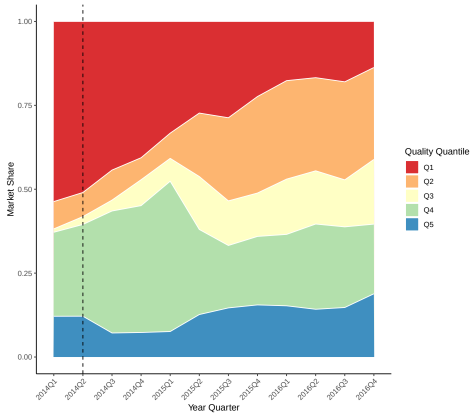


Figure 15: Average Efficiency of Installed Solar System per Year

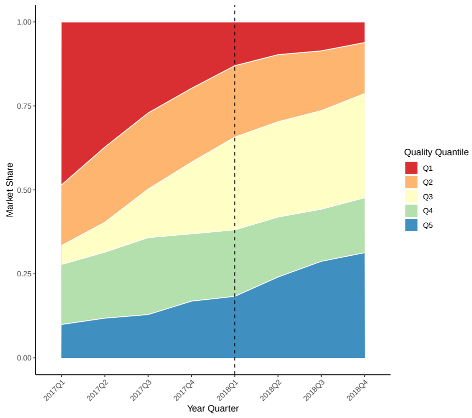
Figure 16: Market Share per Quantile of Quality (2nd Definition)



(a) 2010-2013



(b) 2014-2016



(c) 2017-2018

Notes: This figures displays the market share defined as the sum of installed solar panel per installation sites within for each quintile at a quarterly rate. The quintile definition used is the one described in the section 5, that is quintile of efficiency are assess over the entire sub-period considered. The vertical black dashed lines represent the tariff date application.

Interestingly, we find that the first wave of anti-dumping tariffs had no discernible effect on prices. This is the only notable divergence observed in our data. However, we remain cautious in interpreting this result, as it may be influenced by reporting issues in rebate data during the early period around 2013, as discussed in the appendix (section 4). Moreover, this finding aligns with our main specification when we consider the weighted conditional average effect of the tariff for the first wave, which is positive but very small—an estimated 0.06% increase in installation price for a 1% increase in tariff (Table 5).

Table 18: Price-to-Tariff Elasticity Estimate (net price)

	Overall		Anti-Dumping : 2010 - 2013		Anti-Dumping : 2014 - 2016		Trade War 2018	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln Tariff	0.393***	0.046	0.432	0.251	1.056***	0.618*	0.562***	0.365***
	(0.061)	(0.110)	(0.458)	(0.666)	(0.238)	(0.270)	(0.082)	(0.108)
ln Tariff x Efficiency	−1.870***	0.226	−1.923	1.793	−5.450***	−3.005*	−2.270***	−0.882
	(0.296)	(0.573)	(3.118)	(4.045)	(1.313)	(1.526)	(0.413)	(0.539)
ln Tariff x Premium Installation	−0.097***	−0.029**	0.002	0.010	−0.011	−0.007	−0.079***	−0.037*
	(0.009)	(0.011)	(0.039)	(0.046)	(0.022)	(0.021)	(0.013)	(0.015)
Premium Installation	0.067***	0.028***	0.024**	0.022*	0.049***	0.040***	0.054***	0.042***
	(0.003)	(0.003)	(0.008)	(0.010)	(0.004)	(0.005)	(0.004)	(0.005)
Efficiency	1.559***	1.290***	−0.945	−0.702	0.838***	0.863***	2.045***	1.807***
	(0.100)	(0.167)	(0.628)	(0.741)	(0.185)	(0.243)	(0.127)	(0.141)
Num.Obs	414 762	414 762	34 545	34 545	115 726	115 726	128 111	128 111
R2	0.471	0.580	0.710	0.760	0.461	0.544	0.435	0.509
FE: County	X	X	X	X	X	X	X	X
FE: Year-Quarter	X		X		X		X	
FE: Installer	X		X		X		X	
FE: Origin	X		X		X		X	
FE: Year-Quarter × Origin		X		X		X		X
FE: Year-Quarter × Installer		X		X		X		X
Min-Max Efficiency	0.09–0.23	0.09–0.23	0.09–0.21	0.09–0.21	0.10–0.22	0.10–0.22	0.09–0.23	0.09–0.23

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

Notes: The dependent variable is the log of net price. The standard errors are clustered at the zip code level.