

Effects of Trade Barriers on Foreign Direct Investment: Evidence from Chinese Solar Panels

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Abstract

The recent comeback of protectionism and industrial policy will affect the international allocation of resources beyond the short run. Analyzing similar events from the past can help us envision their long-lasting effects. What are some unintended consequences of trade barriers in strategic economic sectors? I study the anti-dumping and countervailing Duties (AD-CVD) implemented by the Obama Administration in 2012 against the imports of solar panels from China. Leveraging the variation given by the policy's discriminatory nature, which assigns differential rates to Chinese firms in the same industry, I develop a difference-in-differences design. I estimate the effect on Foreign Direct Investment (FDI) decisions by Chinese firms using a Poisson Pseudo-Maximum Likelihood method and data on FDI announcements from 2009 to 2015. My findings show that in 2012, targeted firms increase FDI by 145 million dollars per year, from a previous average of 9 million dollars. These results for greenfield investment do not carry over to cross-border mergers and acquisitions. I find a reduction in the number of projects of 50% in 2013 and 2014. I use location choice models to test different hypotheses for FDI location. I find evidence of production fragmentation in Asia after the imposition of the duties, mostly to countries that end up becoming exporters of solar panels to the US, showing support for the export-platform hypothesis. These results document FDI diversion that modifies investment patterns in the short run and eludes the trade barriers in the medium run, weakening the intended effects of the protectionist policy.

Keywords: Foreign Direct Investment, Anti-Dumping, Solar Panels, United States, China.

JEL Codes: F13, F14, F21, F23

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1 Introduction

A return to protectionism involving large economies, important increases in tariffs, and retaliations in a wide range of economic sectors has taken place since 2018 (Fajgelbaum et al. (2020)). On top of that, industrial policy is back on the scene (Aiginger and Rodrik (2020)). Many of the industrial policies implemented by developed nations are in the form of non-tariff barriers, which require granular evidence and a deep institutional context to have an adequate measurement of their effects (Lane (2020)). This paper uses the imposition of non-tariff barriers on Chinese solar panel firms in 2012 to examine the intended and unintended effects of trade barriers in the short and medium term.

The United States put a 30% tariff rate on solar panels and washing machines in 2018, propelling the beginning of what has been labeled the “Trade War” with China. Yet, this was not the first time the US solar panel industry received protection from its Chinese competitors. In 2012, the US imposed anti-dumping and countervailing duties (AD-CVDs) against the import of Chinese solar cells and modules (panels) in what is now known as one of the largest remedy cases in the US and the first one involving the renewable energy sector. This policy achieved its expected immediate result of decreasing US imports of solar cells from China. However, it also motivated different strategies by targeted Chinese multinationals in the solar panel industry that had unintended consequences in the global allocation of resources.

In this paper, I document this previous US experience implementing non-tariff barriers in a strategic economic sector. I examine how these measures impact Foreign Direct Investment (FDI) decisions by multinational firms in a context where a nationalist industrial policy clashes with international climate change commitments. Specifically, I study how the AD-CVDs imposed by the US modified FDI decisions by targeted Chinese firms and test for the economic motives explaining the firms’ reactions that I document.

AD-CVDs are frequently used forms of administered protection. The Anti-Dumping Agreement (Agreement on Implementation of Article VI of the GATT 1994), defines dumping as “the introduction of a product into the commerce of another country at less than its normal value” (World Trade Organization). Meanwhile, the Agreement on Subsidies and Countervailing Measures allows countries to launch their investigation and charge an extra duty (countervailing duty) if they find that subsidized imports are hurting domes-

tic producers (World Trade Organization).¹ Both mechanisms aim at a particular product from a specific exporter. This characteristic makes them a “leaky form of protection” (Irwin (2019)), and creates an interesting setting to analyze differential effects on firms. Most of the literature focuses on the effect of these types of barriers on trade flows. Less is known about their impact on FDI decisions at the firm level.

I fill this gap by examining how AD-CVDs affect foreign direct investment announcements by Chinese solar panel firms. I exploit the fact that the policy targets Chinese companies in the same industry with two different rates to develop a difference-in-differences framework. I compare the changes in investment decisions before and after the policy by targeted firms, granted a specific rate, relative to the non-targeted group assigned a general, PRC-wide, rate. Leveraging this variation given by the policy’s discriminatory nature, and the fact that there is a large presence of zeros in the left-hand-side variable, I use a Poisson Pseudo-Maximum Likelihood method (PPML) to estimate a multiplicative model of FDI. I examine greenfield investment amounts using monthly firm-level data on FDI announcements from 2009 to 2015, considering three years before and after the policy change. I also evaluate if the policy affects the number of projects by firms that announce more than one project per year. Since FDI can represent both greenfield and brownfield investments, I use data on mergers and acquisitions to estimate the effects of the policy on the probability of completing an M&A deal.

I then devise a variety of tests for evaluating several theoretical predictions regarding multinational firms’ location choices for foreign direct investment. These include tariff-jumping, horizontal, vertical, and export platform FDI. Although not mutually exclusive, each hypothesis suggests different location and industry choices for foreign investments. I use linear probability and probit models to test for these motivations by estimating if the likelihood of investing in different regions changes by year as a reaction to the 2012 US policy. I also estimate the impact of industry activities on location choices to find evidence for production fragmentation. To understand if this behavior is specific to targeted firms, I fit a model of location choice using a variation of McFadden’s Conditional Logit model.

Tariff-jumping FDI is described by Blonigen (2002) as multinational firms locating a manufacturing plant in the country that imposes a trade barrier to provide to the domestic market. I test this by estimating the probability of investing in the US by targeted Chinese firms in the industry. The literature defines horizontal FDI as investments in production

¹See more information for [AD](#) and [CVD](#).

facilities to serve the consumers in the foreign market. This is efficient for a multinational firm when the cost of installing and operating a new facility is lower than the trade costs (Helpman et al. (2004)). I test this hypothesis for Europe assuming it could represent a substitute market for the US. Meanwhile, vertical FDI involves cross-country production fragmentation and is driven by differential factor prices between the home and the host country. The affiliate abroad assumes part of the production process and sells to the final market, instead of the parent company. I test for this motivation by estimating the probability of investing in Asia and the impact that different industry activities have in deciding to locate in this region. Finally, export-platform FDI is a decision that depends on the differential costs of exporting and establishing a plant in the desired market. In the context of this paper, exporting costs include the trade barrier. I also test this motivation to the location choice in Asia and use a descriptive analysis of FDI and trade data to find support for this hypothesis.

My results show that targeted firms increase FDI by 145 million dollars in 2012, the year the policy is implemented. This finding is statistically significant and economically relevant since the average FDI announcement before the policy for this group is 9 million dollars per year. These results are robust to considering anticipation by the firms, and to including financial controls for a sub-sample of publicly traded firms. Following this initial reaction to the policy, there is a decrease in the number of projects in the next two years. Targeted firms that announce more than one project per year reduce their projects by 53% in 2013 and 2014. Since these estimations are for greenfield investments, I rely on a different dataset to determine if this result is also salient in the mergers and acquisitions (M&A) of the targeted firms. I find a negative and statistically significant result in 2012 for completed domestic and cross-border deals. This means that after the policy, targeted firms have a lower probability of completing an M&A deal than non-targeted firms, both in the Chinese domestic market and abroad.

I do not find evidence to support the tariff-jumping hypothesis, meaning there is no increase in FDI by targeted firms in the US. I also do not find support for horizontal FDI in Europe, on the contrary, I find that these firms decrease their investment in the region in 2015. I find evidence for vertical FDI in 2015 when targeted firms increase their investment in Asia. I then test if industry activities impact the probability of investing in that region, finding evidence of production fragmentation. Finally, a descriptive analysis of the data shows that Asian countries that receive FDI after the policy end up becoming exporters of

solar cells to the US in the medium run, showing initial support for the export-platform hypothesis.

Since these firms produce solar cells and modules, whether assembled on solar panels or not, my results show how a change in bilateral trade policy can reshape multinational production. This can be motivated by multinational firms' need for efficiency gains after facing a negative external shock, as well as exporting to the desired final market from a different country. Overall, my results document FDI diversion that modifies investment patterns in the short run and eludes the trade barriers in the medium run, weakening the intended effects of the protectionist policy.

My paper contributes to the literature on the response of multinational firms to changes in bilateral trade conditions, specifically anti-dumping duties. I differentiate from previous work that documents trade diversion in that my focus is on FDI. [Flaen et al. \(2020\)](#) use ADDs against South Korea, Mexico, and China to estimate the price effect of US import restrictions on washing machines. Using country-level trade flows and firm-level import data, the authors find small changes in US prices explained by firms' production relocation strategies. They also show that the "country-hopping" behavior of the affected firms prevented the ADDs' objective of reducing imports. I depart from their approach in that I use an empirical strategy to test changes in FDI decisions at the firm level as a response to AD-CVDs and document large and significant increases in greenfield FDI by targeted firms, confirming there is an important investment diversion.

I also contribute to the literature on the effects of temporary trade barriers implemented by the US. A study of US ADDs on Chinese imports by [Bown et al. \(2022\)](#) uses an instrumental variable approach to show the effects on supply chains. They find that this protection decreases imports and raises prices in targeted industries, harming domestic jobs due to the increasing costs for downstream producers. [Bown and Crowley \(2007\)](#) show that the US imposition of ADDs against Japan creates trade deflection, increasing Japanese exports of the same product to a third country; while the imposition of these measures against a third country depresses trade, decreasing Japanese exports of that product to a third country. Meanwhile, [Bown and Crowley \(2010\)](#) find that using the China safeguard by the US and the EU did not result in growing Chinese exports to third markets. [Blonigen and Prusa \(2015\)](#) provide a review of the effects of dumping and anti-dumping literature and find that trade diversion is the most common unintended effect of ADDs. A previous paper analyzing the effects of ADD on FDI is by [Blonigen \(2002\)](#). His results suggest that

only multinational firms from industrialized countries can afford to engage in tariff-jumping FDI.

Similarly, my findings add to the studies of FDI location decisions by multinational firms, in this case as an unintended consequence of a trade barrier, by examining which hypotheses hold for FDI decisions after the imposition of protectionist policies in the United States. My findings support the existence of vertical and export platform FDI in this case. As defined in [Tintelnot \(2017\)](#), firms with export-platform affiliates face fixed costs of foreign investment. My empirical results show that the trade costs and the possibility of losing a relevant market can overcome the presence of the large costs of establishing a foreign affiliate.

My paper also contributes to the growing empirical literature on US-China trade relations. By including non-tariff trade barriers, I show a broader picture of the US trade policy regarding China. As [Bown \(2021\)](#) describes, China has been a target for AD-CVDs from the US for a long time. Before the 2018 trade war, more than 7% of Chinese imports in the US were covered by AD-CVDs. Similar to [Fajgelbaum et al. \(2021\)](#), my findings show a global reallocation of resources and the creation of new investment patterns due to a US-China trade conflict. I provide an in-depth analysis of a strategic economic sector such as the renewable energy industry.

The structure of this paper is the following: Section [2](#) provides background on the Chinese solar panel sector and the 2012 imposition of solar trade barriers by the United States. Section [3](#) describes the data and provides the summary statistics. Section [4](#) presents the empirical framework. Section [5](#) details the results. Section [6](#) provides the robustness checks. Section [7](#) concludes.

2 Background: Chinese Solar Panels & the 2012 US Trade Barriers

In this section, I describe the photovoltaic value chain, the main characteristics of China's solar manufacturing industry, and the US imports of solar cells and modules during the period under analysis. I also provide an overview of the trade barriers enacted by the Obama Administration in 2012. I then argue that this setting presents several advantages for estimating the impact of trade barriers on FDI decisions by multinational firms.

2.1 The Photovoltaic Value Chain

Figure 1 shows the different stages of the Photovoltaic (PV) value chain. The primary raw material in the production process of solar panels is silica sand. This sand goes through a chemical process to obtain the high-purity silicon required for solar energy generation. The purified silicon is melted and formed into cylinders or bricks called ingots, which are then sliced into thin wafers. The process continues by adding metal conductors to the wafers' surface and creating the solar cell. Cells are soldered together and encapsulated in glass sheets to form a module. Combining the modules with equipment such as connectors and batteries constitutes a system.

The AD-CVDs under study apply to photovoltaic cells “whether or not assembled into modules.” This implies that solar panels made by these cells are also subject to the duties

2.2 Solar Panel Manufacturing in China

To contextualize the Chinese solar panel manufacturing industry in the period under analysis, Figure 2 shows the evolution of different performance indicators. The chart in the top left-hand side shows the evolution of revenue and total assets. This reflects an overall positive economic performance for the industry. The slump in 2012, after the protectionist measures in the US, is followed by a recovery that outperforms previous years. The chart in the top right-hand side reflects the evolution of exports and domestic demand. The pre-policy growth in exports is impressive, as is the decline after 2012. There is a recovery after 2013 but values do not go back to previous levels during this period. This aligns with previous findings on how Chinese exporters respond to U.S. antidumping investigations that show that AD investigations significantly decrease the total export volume (Lu, Tao, Zhang 2013).

Domestic demand, however, grows rapidly in the post-policy period becoming more relevant than exports. This suggests a potential change in the companies' strategies regarding which markets they focus on after being hit by the US barriers.

The two charts at the bottom reflect that the evolution in the number of employees (on the left), slightly decreases after the policy but recovers and continues its ascending path afterward. Similarly, the number of enterprises (on the right) has an overall positive slope that only decreases in 2012 but promptly recovers.

This description shows a few relevant characteristics of the Chinese solar panel industry

in the context of this paper. There is an important growth, especially in the level of exports, in the years leading to the US protectionist measures. In 2012, the Chinese industry is negatively affected but it recovers very rapidly, with the domestic market playing a significant role.

2.3 US Imports of Solar Cells

To provide context to the policy and my findings, I show in Figure 3 the US imports of subject products during the period of analysis. The left-hand side chart shows the quantities in million units, while the right-hand side chart the customs value in billion dollars.

After reaching its highest point in 2011, imported quantities of solar cells in the US decreased and did not reach their previous levels. This shows the motivation for US firms to seek protection, the imported quantities in the domestic market had been rapidly growing. The number of imports from China decreased by 50% from 2011 to 2012, the year the duties were imposed. These quantities remained below half the 2011 peak for the rest of the period. This reflects that the imposition of the AD-CVDs had their intended effect of reducing the quantity of import competition from China.

The value of US imports of solar cells, on the other hand, increased by 260% between 2009 and 2015. Although there was a reduction from 2012 to 2013, values recovered and surpassed previous levels by the end of the period. Since quantities decreased during this time, this suggests an overall increase in the prices of imports. When considering only those from China, values increased until 2011 and declined afterward. Hence, the rise in the overall import prices was due to the imports that substituted Chinese cells.

2.4 The 2012 Solar Trade Barriers in the US

Figure 4 shows the timeline for the policy procedure. On October 19, 2011, SolarWorld Industries America (the petitioner) starts a petition for AD-CVDs on the import of crystalline silicon photovoltaic (CSPV) cells from China. Twenty days later, the US Department of Commerce (USDOC) initiated its investigations to determine the existence of dumping and subsidies (United States Department of Commerce, 2011). This was followed by an examination by the US International Trade Commission (USITC), an independent agency, of whether the domestic industry is materially injured. The results of the USITC's preliminary determination showed "reasonable indication" of injury due to imports from China

of CSPV cells and modules “that are alleged to be sold in the United States at less than fair value and subsidized by the Government of China” (United States International Trade Commission, 2011). This allowed for the rest of the investigation to continue. The scope of the investigation defined by Commerce covered modules, laminates, and panels produced in a third country from solar cells made in China. However, it did not include modules, laminates, and panels produced in China from solar cells made in a third country.

The USITC final determination found that the US industry is “materially injured” because of imports of CSPV cells and modules from China that the USDOC determined were subsidized and sold in the United States at less than fair value. The results of the investigation showed that the US domestic industry faced a decline in market share due to the increasing import competition from China sold at low prices. Furthermore, despite a growth in demand and reductions in costs the domestic industry still did not make a profit, showed a decline in many performance indicators, and reported, among other difficulties, the closure of production facilities. The investigation found a “causal nexus” between subject imports and the poor condition of the domestic industry (United States International Trade Commission, 2012).

The preliminary determinations were issued on March 26, 2012, for the countervailing case, and on May 25, 2012, for the anti-dumping case (United States Department of Commerce, 2012). On December 7, 2012, the USDOC issued the final duty order on crystalline silicon photovoltaic cells whether or not assembled into modules imported from China (see the detail for HTSUS codes detail in Appendix Table ??).

For purposes of the US anti-dumping and countervailing duty laws, the USDOC defines China as a non-market economy (NME). This means that the country does not operate on market principles of cost or pricing structures ([Section 771\(18\) of the Tariff Act of 1930](#)). This has a direct impact on the dumping investigation process. In general, dumping is found when the price of the product in the importing country is less than the price of the same product in the exporting country. Because China is an NME, the US administration has to rely on information on cost and price structures from a third country instead. In the case studied in this paper, the surrogate country was Thailand, as proposed by the petitioners. Chinese firms argued in favor of India, which was the petitioner’s initial proposal.

Another relevant implication of the NME status of China is the determination of the dumping duty rates. For these types of economies, the USDOC presumes that all companies within the country are subject to government control. Hence, they are all assigned a single

rate unless they can demonstrate sufficient independence from the government. If that is the case, the firm can be granted a separate rate.

In the case under study, 61 companies were granted a separate rate. Two of them were the mandatory respondents chosen by the USDOC, Trina Solar and Wuxi Suntech. The rates for these two companies were 18.32% and 29.14% respectively and were estimated based on their own data. Meanwhile, the other 59 companies were granted a rate of 24.48%, calculated as the weighted average of the two mandatory respondents. When the AD-CVD determinations are published in the federal register, it includes a list with the names of these companies. Since most of them were named in the petition and hence forced to be part of the investigation process, I refer to this group as the targeted firms.

Meanwhile, all other Chinese exporters and producers in this industry that are not specifically listed, referred to as the PRC-wide entity, received an anti-dumping duty rate of 249.96%. The determination of this rate was based on what is called "Adverse Facts Available" (AFA) because the PRC-wide entity did not respond to the USDOC requests for information. It is the policy of the Department in cases in which entities fail to cooperate, to establish a rate high enough "that the party does not obtain a more favorable result by failing to cooperate than if it had cooperated fully." The Department selected as AFA the highest margin alleged in the petition by Solar World Americas.

The other investigation started by the petition resulted in the USDOC determining that countervailable subsidies were provided to Chinese producers and exporters of CSPV cells. The investigation covered 31 government programs during the year 2010. The results were CVD rates of 15.4% on average.

In summary, an average 40% AD-CVD rate was charged to the targeted firms, those granted a separate rate, while the PRC-Wide entity had a total of approximately 265%. This differential exposure to the policy is the basis of the research design in this paper.

AD-CVD orders are in place for five years after which the Department of Commerce conducts a sunset review to determine whether the order should remain in effect or not. In this case, the USDOC found that the revocation would lead to dumping margins of up to 249.96%, hence the orders remained in place (United States Department of Commerce, 2018).

2.5 Advantages of this Policy Setting

The evaluation of the causal effects of trade policy faces many methodological challenges, such as measurement of trade policy, endogeneity, and other identification concerns (Goldberg and Pavcnik (2016)).

This policy presents several advantages for the study of FDI decisions by multinational firms. First, the fact that there were specific duties for some firms makes this an ideal setting to study the effect of targeted protectionist policies. The discriminatory (and targeted) nature of the policy allows me to analyze the characteristics of the targeted firms relative to other Chinese firms in the same sector, and to examine whether the former, as a response, modify investment choices in a differentiated way relative to themselves in the past and relative to the control group (the non-targeted group of solar panel firms in China).

Second, changes in AD-CVDs can be interpreted as economically exogenous. These duties were determined by the US responding to the interest of American solar panel companies, thus they were determined outside the realm of commercial relations between Chinese solar panel firms and their FDI destination countries. Furthermore, anti-dumping duties are a very common tool used by most members of the World Trade Organization. A better understanding of its direct and indirect effects helps to have a comprehensive knowledge of trade policy. “In terms of trade policy, AD is where the action is” Blonigen and Prusa (2015).

As I discuss in Section 4.1.1 the trends in FDI of treated (i.e., the targeted) and control firms are not different before the AD-CVDs were imposed. This provides support for the validity of this difference-in-difference research design. This identification strategy helps overcome the endogeneity of trade policy, a key empirical challenge in estimating the causal impacts of trade barriers.

It also helps identify how the geography of production fragmentation can restructure after a shock. The production process of solar panels has differentiated stages that allow for analyzing cross-country production fragmentation as a response to an external shock.

This setting also allows me to estimate the medium and long-term effects of trade barriers, something that the studies of the recent US-China trade war are still unable to assess, given that more than a decade has passed since the imposition of these measures. This contributes to my study of FDI since these large projects generally have a long maturity process.

3 Data

I use four main data sources to construct empirical tests for the effects of AD-CVDs on the investment strategies of Chinese solar panel firms after 2012. The key dependent variable is data on announcements of greenfield investments. I also study if mergers and acquisitions had a significant change after the duties are imposed. Finally, I collect a variety of financial and trade data to create the empirical setting.

3.1 FDI: Greenfield Investments

The source for Foreign Direct Investment information is fDi Markets. This dataset tracks announcements on cross-border greenfield investment, defined as a new physical project or expansion of an existing one that creates jobs and capital investment. It includes monthly data on projects' variables at the firm level across all sectors and countries. These variables are: Project Date, Investing Company, Parent Company, Source Country, Source State, Source City, Destination Country, Destination State, Administrative Region, Destination City, Industry Sector, Sub-Sector, Cluster, Industry Activity, Capital Investment, Capital Investment Estimated (Yes or No), Jobs Created, Jobs Created Estimated (Yes or No), Project Type (New or Expansion). The Capital Investment and Jobs Created variables are estimated when the information is not released by the investing company.

I use announcements from 2009 to 2015 by firms based in China in the solar cell industry as defined in Section 3.1.1 and characterized by Cluster, Industry Sector, and Sub-Sector shown in Table 1. This table reflects that the vast majority of the projects are new, as opposed to expansions of existing plants. It also presents the activities that I use to test the production fragmentation hypothesis. As well as the region where the projects are located that I use in my location choice models.

The original dataset presents an observation for a firm when it makes an investment announcement. I modify this to organize the data as a panel where each firm appears every month of every year. If it does not make an announcement, the FDI variable is set to zero. This is because not making an FDI announcement is also economically relevant and gives information for the estimations. In Table 2 I present the summary statistics for this data arrangement for the variables used in my estimations. I create the variable projects by counting the number of announcements per firm per month.

Figure 5 shows the difference in the number of projects before and after the policy.

Some interesting patterns arise. There is a change in the geographical pattern. Regions like Africa, Latin America and the Caribbean, and Oceania, receive more FDI investment from the firms in the sample after the policy. Meanwhile, North America decreases the number of projects received and Europe slightly increases. Interestingly, there is a very large increase in the number of projects located in Asia after the policy. These facts motivate some of my empirical tests in the location choice section.

3.1.1 Targeted and Non-Targeted Firms

The firms targeted by the Department of Commerce are published in the Federal Register. The list includes a set of firms that are granted a specific rate of anti-dumping duties. All other firms in the same industry not included in that list, are granted a general duty, the PRC-wide rate. These firms are exporters and producers, and the list includes subsidiaries. The list has 61 targeted (unique) firms, but it is longer because it includes multiple subsidiaries of these firms.

I refer to targeted firms as those companies that face specific rates. I find that 25 out of the 61 targeted firms in the fDi Markets database have FDI activity between 2009 and 2015 (i.e., 40% of the firms listed in the Federal Register). Thus, I exclude from my analysis firms that are targeted, but that do not engage in FDI during my period of analysis.

Then I define a set of Chinese solar panel firms as a control group. I look in the fDi Markets database for Chinese firms that operate in the same economic activities as the targeted firms according to the cluster, industry, sub-sector, and industry activity classification (see table 1). This approach yields a control group with 52 companies that were not listed by the Federal Register but that is as similar as possible to the targeted firms when it comes to industry and FDI activity.

The final dataset contains 185 monthly investment announcements by 77 unique firms. Once I fill in the months in which there are no FDI announcements, the total observations in my sample go to 6468 (i.e., 77 firms x 12 months x 7 years).

To provide a better description of these two groups, Table 5 shows the results for the means differences test in the FDI data: FDI amount, jobs created by the project, and the total number of projects per month. The panel on the left shows the differences in means for the three variables between non-targeted and targeted firms before the policy, as well as the t-statistic for this difference. The results for this test show that the only variable

in which these two groups have a statistically significant difference before the policy is in the number of projects (the absolute value of the t-statistic for this difference is 3.70). The panel on the right shows the differences in the same variables between the two groups after the policy. In this case, all three variables have a difference that is statistically significant at least at the 10% level, with the targeted group having a larger average than the non-targeted group in all cases. This provides evidence for the similar characteristics of the two groups before the policy and how they changed afterward.

3.2 Mergers and Acquisitions

I use data from Thomson and Reuters covering the period from 2009 to 2014 to analyze the impact of the AD-CVDs on mergers and acquisitions. I identify in this dataset 71 deals done by 12 targeted firms and 9 non-targeted firms as defined in the fDi Markets sample. I construct a firm-month-year panel with 1512 observations (i.e., 21 firms x 12 months x 6 years).

Table 3 shows that 68% of the M&A activity by these firms has China as a target country. This means that Chinese multinationals are increasing their domestic presence. When considering cross-country M&A, Hong Kong is the most frequent target country with 10% of the deals, followed by the US with 7%.

To understand if this is horizontal or vertical M&A, table 4 shows the industry activities by acquirer and target company. The most frequent types of deals share the same activity, Electronic and Electrical Equipment, indicating a horizontal integration of firms. The most common vertical integration is done by Investment and Commodity firms that target companies in Electronic and Electric Equipment activities.

3.3 Financial Statements

I use Refinitiv to find the financial summaries for the publicly traded firms in my FDI dataset. To compare the targeted and non-targeted groups of firms, and for some robustness checks, I compile the annual financial data for these firms and call them “financial sub-sample”. The database has financials for 26 targeted firms and 14 non-targeted firms, all obtained from Refinitiv. I collect variables such as Capital Expenditure (CapEx or CapExAs if it is divided by assets); Gross Profit Margin; Earnings before interest, taxes, depreciation, and amortization (EBITDA; or EBITDA/A if it is divided by assets); Return

on Average Total Assets (ROAA); Total Debt Percentage of Total Assets (DEBTA); and Log of Assets.

In Table 6 I show the results for the means differences test for the financial data. The left panel in the table shows that there are statistically significant differences between the two groups for three variables. CapEx, and DEBTA, being the targeted group the one with the larger mean; and ROAA, with non-targeted firms having the larger average. I include some of these variables as controls in my robustness checks. Meanwhile, after the policy, DEBTA remains different and larger for targeted firms. And EBITDA/A becomes different, with non-targeted firms having the larger values.

4 Empirical Framework

In this section, I discuss my empirical strategies to estimate the effect of trade barriers on FDI decisions by firms. I also analyze some threats to identification from this strategy.

4.1 Estimation Strategy: FDI

Using data on FDI announcements from 2009 to 2015, I leverage the variation given by policy’s discriminatory nature to estimate their impact on firms. I develop a difference-in-differences design where the treatment is given by the AD-CVD rate the US imposed on the imports of Chinese solar cells and modules in 2012.

Since FDI data tends to be heteroskedastic and have a large presence of zeros, when these models are log-linearized and estimated by OLS the results are biased estimations of elasticities (Santos-Silva and Silvana (2006)). To overcome this, my specification is a multiplicative model and I estimate the coefficients using a Poisson Pseudo-Maximum Likelihood (PPML) method.

$$Y_{it} = \exp\left[\sum_{s=2009}^{2015} \delta_s(D_{it} \times 1[t = s]) + \beta \mathbf{X}_{it} + \gamma_i + \lambda_t\right] \eta_{it}. \quad (1)$$

Where Y_{it} is the outcome of interest: FDI in levels, aggregation is monthly or yearly; or the existence of a M&A acquisition deal, for a firm i in period t ; D_i is the indicator for specific-rate firms; X_{it} are control variables such as the number of projects, jobs created, or financial variables; γ_i are firm fixed effects; λ_t are time fixed effects (month and year,

or year, depending on the aggregation level); and η_{it} is the error term. Robust standard errors are clustered at the firm level.

To test for a change in announcements, I use the same specification as in equation 1 and modify the dependent variable for the number of yearly projects for firms that make more than one announcement per year.

4.1.1 Threats to Identification

In this section, I analyze if the key assumption for the difference-in-differences research design is met in my setting. This is the parallel trends assumption, i.e. if the pre-treatment trajectories for targeted and non-targeted firms are parallel. For this, I use an OLS estimation method in equation 2 using the Stata did-regress package. This allows for a graphical analysis and a hypothesis test.

$$Y_{it} = \delta d_{it} + \gamma_i + \lambda_t + \varepsilon_{it}. \quad (2)$$

Where Y_{it} is the outcome of interest (FDI amounts), for a firm i in period t ; d_i is the indicator for treatment (equals to one after 2011 for targeted firms); γ_i are firm fixed effects; λ_t are year fixed effects; and ε_{it} is the error term. Robust standard errors are clustered at the firm level.

Figure 7 shows the graphical diagnostics for the parallel trends assumption. The chart on the left shows the observed means and the one on the right the linear trend models. The red parallel line in 2011 shows the last year without the effects of the policy. The blue line reflects the evolution of FDI for the control group and the dark red line for the treatment group. In both charts, we observe that up to the year of the policy, the evolution of the FDI levels for the two groups had a similar behavior.

Table 7 shows the results of a test on the linear-trends model coefficient that captures the differences in the trends between both groups. If the coefficient is zero, there are no differences in the slopes. The estimations for this test do not reject the hypothesis that the linear trends are parallel in the pre-treatment period.

Thus, there is evidence to support the existence of parallel trends in the pre-treatment period. This contributes to the claim that the difference in FDI amounts experienced by the two groups after 2011 is due to the treatment, the AD-CVDs.

4.2 Estimation Strategy: Location Choice

Motivated by the changes in patterns shown in the data in figure 5, I estimate changes in location choice over time. I use Probit models to estimate equation 3 using my fDi Markets sample from 2009 to 2015.

$$Pr(Y = 1|X) = \Phi(\beta X^t) \quad (3)$$

Where:

$$y_{it} = I(region)_{it},$$

$$\beta x'_{it} = \beta Year + \alpha X_{it} + \gamma ID_i + \epsilon_{it}.$$

$I(region)_{it}$ is an indicator for each of the six regions in the data, for a project announced by firm i in period t (month-year); **Year** is a vector of dummy variables from years 2009 to 2015; X_{it} controls for FDI amounts, number of projects, or jobs created; ID_i is a firm control; ϵ_{it} is the error term. Robust standard errors are clustered at the firm level.

To understand if this behavior is specific to targeted firms granted, I estimate a location choice model using a variation of McFadden's Conditional Logit model (McFadden 1973). In this model, individuals choose the option with the greatest utility. I modify the original structure of the fDi Markets data to fit this model. For each month-year, each firm has six options for where to invest: Asia, Europe, North America, Africa, Latin America, or Oceania. If a firm makes more than one investment per month, I order the projects by FDI amount and number of jobs created. The region of the project of the larger magnitude gives the location choice. This creates a set of alternatives is $J=1, \dots, 6$. An indicator y_{ijt} equals one if firm i chooses alternative j in period t , and zero otherwise. There are q case-specific variables (if the firm is granted a specific rate, year, FDI amount, and number of projects per month). The focus of my estimations is to identify location choices by the characteristics of the firms and projects (cases), rather than of the regions (alternatives). I aim to find if targeted firms make a different location choice than non-targeted firms. Hence, I do not include alternative-specific variables since all firms face the same region characteristics when they make their location choice and what is relevant in this case is the difference among the two groups of firms. The specification for this random utility faced

by the firms is presented in equation 4.

$$u_{it} = (z_{it}A)' + v_{it}. \quad (4)$$

Where u_{it} is the utility for firm i in month-year t , $A = (\alpha_1, \dots, \alpha_6)$ is a qxJ matrix of case-specific regression coefficients; the error term v_{it} are independent random variables with a type I extreme-value Gumbel distribution (StataCorp. 2023).

The observed part of the utility is given by the profit function:

$$\pi_{ijt} = (z_{it}A)' * D_i \quad (5)$$

Where $(z_{it}A)'$ are the variables observed at the project level such as the month-year and the FDI amount, and D_i are the firm characteristics given by the treatment indicator.

The probability of investing in each region is given by:

$$P_{ij} = \frac{\exp(\pi_{ijt})}{\sum_{j=1}^6 \exp(\pi_{ijt})} \quad (6)$$

I estimate equation 5 and equation 6 using a conditional logit method and data from my fDi Markets sample from 2009 to 2015.

To investigate if the type of industry activity developed by the new projects impacts the probability of investing in a particular region, I estimate the equation 7 using a Linear Probability Model.

$$Y_{it} = \delta \mathbf{Activity}_{it} + \beta X_{it} + \gamma_i + v_{it}. \quad (7)$$

Where Y_i is the probability of investing in a particular region by firm i in period t ; $\mathbf{Activity}_{it}$ is a vector of dummy variables for the industry activities in the dataset presented in Table 1; and X_{it} controls for FDI amounts or the number of projects; γ_i are firm fixed effects; v_{it} is the error term. Robust standard errors are clustered at the firm level.

5 Results and Discussion: Effects of Trade Barriers on FDI

In this section, I describe my empirical findings using a PPML method for estimating equation 1. In my specification of the exponential model, the dependent variable is measured in levels and the right-hand-side treatment variable D is an indicator taking the value zero or one. In the difference-in-differences interpretation, the first difference is between the two groups of firms in the setting: the targeted firms (those granted a specific AD-CVD rate) and the non-targeted firms (those assigned the PRC-wide rate). The second difference is before and after the duties are applied. Thus, variable D equals one for targeted firms in the year 2012 and after, and zero otherwise. The coefficients δ are the semi-elasticities estimated overtime where the percentage change is given by $100 \cdot (\exp(\delta) - 1)\%$. I normalize the results by excluding the year before the treatment, 2011, as is commonly done in the literature (Sun and Abraham (2021)).

5.1 Increase in FDI amounts

Table 8 presents my main results using the fDi Markets data from 2009 to 2015. The dependent variable is the monthly dollar amount of FDI projects by firm. The main explanatory variables are the interaction between the indicator for targeted firms and the year. I present three specifications which all include firm, month, and year fixed effects and vary in their control variables. In Panel A I show the estimated coefficients using PPML, and in Panel B the economic valuation of the coefficients.

In column 1, I show the estimation of the model without control variables. The coefficient for the targeted firms in 2012 is 2.838 and it is statistically significant at the five percent level. Using the formula for the semi-elasticity, this converts into a 1608% increase in the dependent variable. To provide a more comprehensive meaning for this estimation, I show the dollar amounts in Panel B. I calculate this by multiplying the percentage change by the yearly average FDI in the pre-policy period. I use two benchmarks for this valuation. First, the average amount invested by targeted firms, which is 9 million dollars, and then the average amount invested by all the firms in my sample, which is 13 million dollars. This translates into 145 and 208 million dollars per year respectively of increase in FDI by targeted firms with respect to non-targeted firms in 2012.

In column 2, I show the estimation using as a control variable the number of jobs created by the project, as a way of considering the potential impact of the project. The coefficient for targeted firms in 2012 is 2.464 and it is statistically significant at the five percent level. This semi-elasticity represents a 1075% increase in FDI, meaning 97 million dollars per year when the coefficient is evaluated at the pre-policy average for targeted firms, and 139 million dollars per year using the average for all firms. Hence, the economic value of the change in FDI is smaller in this case than in the specification without any controls.

The third and final column in this table presents the estimations controlling by how many projects a firm announces per month. The objective is to take into consideration the frequency of the FDI activity by the firms. In this case, the coefficient for the year 2012 is statistically significant at the 10% level with a value of 2.352 which represents an increase of 952%. This is equivalent to 86 or 123 million dollars per year, depending on which of the two benchmarks is used. In this specification, I also find a statistically significant effect for the year 2015. This means that after taking into account the number of projects, targeted firms increased FDI by 90 to 129 million dollars in 2015 with respect to non-targeted firms. Thus, the number of announcements also impacts the results, making them smaller in magnitude but introducing an effect in other years.

5.2 Decrease in the Number of Projects

Table 9 my estimations of the effects of the policy in the number of projects for the sub-sample of firms that make more than one announcement per year. FDI greenfield investments are large projects and take a long time to materialize. Hence, not all multinational firms that engage in FDI activity announce several projects per year. To analyze if the trade barriers under study might affect the number of announcements, I study the sub-sample of firms that have more FDI activity in the period. I estimate my model for the sub-sample of firms that make more than one announcement per year, which are 23 firms that represent 30% of the original sample. The dependent variable is the count of the number of announcements per year.

I present three specifications which all include firm and year fixed effects and vary in their control variables. In Panel A I show the estimated coefficients using PPML, and in Panel B the percentage change in the number of projects.

In column 1, I present the estimation of the model without control variables. The

coefficient for targeted firms in 2013 is -0.755 and it is statistically significant at the one percent level. Using the formula for the semi-elasticity, Panel B reflects that this converts into a 53% decrease in the number of projects by targeted firms in comparison with firms in the non-targeted group. Similarly, the coefficient for the year 2014 is -0.799 and represents a reduction of 55% in the dependent variable.

In column 2, I show the estimation using as a control variable the number of jobs created by the project. The coefficient for targeted firms in 2013 is -0.708 while for 2014 it is -0.800, both are statistically significant at the one percent level. These semi-elasticities represent a decrease in the number of projects of 51% and 55% respectively.

The third and final column in this table presents the estimations controlling by the FDI amounts. As in the previous two columns, I find positive and statistically significant effects for targeted firms in the years 2013 and 2014. The estimated coefficients imply that these firms reduce their number of projects by 56 and 57% in 2013 and 2014 respectively.

Thus, the results are consistent in showing that after the initial reaction to the policy of increasing FDI amounts in 2012, firms that engage in more FDI activity reduce their number of projects for two years after the policy. This might reflect the necessity to let the new larger projects announced in 2012 mature, as well as a response to the financial setbacks experienced by these companies shown in Table 5, as a consequence of having restricted access to a large market as the US.

5.3 Effects on M&A deals: Domestic and Cross-Border

In Table 10, I show my estimations for mergers and acquisitions using Thomson and Reuters data from 2009 to 2014. These results complement my previous estimates for greenfield investments and help provide a wider picture of the foreign and domestic activity of the firms under analysis. The dependent variable equals one if there is an M&A deal on that month, domestic or cross-border, and zero otherwise. Thus, this specification estimates the probability of having such a deal. As before, the main explanatory variables are the interaction between the indicator for targeted firms and the year. I present two specifications which all include firm, month, and year fixed effects and vary in their control variables. In Panel A I show the estimated coefficients using PPML, and in Panel B how the coefficients convert to percentage changes.

In column 1, I show the estimation of the model controlling for completed deals, which

could be domestic or cross-border. I find a negative and statistically significant coefficient for the year 2012. This means that targeted firms have a lower probability of completing an M&A deal than non-targeted firms the year after the policy. The coefficient is -1.469, statistically significant at the five percent level, and implies that targeted firms have a probability of completing an M&A deal that is 77% lower than non-targeted firms.

In column 2, I show the estimation adding as a control variable if it is a cross-border deal. Hence this complements the FDI activity by these firms including brownfield investments to my previous estimates for greenfield projects. I find a negative coefficient, statistically significant at the 10% level, for the year 2012. This semi-elasticity of -1.448 translates into targeted firms having a -76% probability of completing a cross-border M&A deal that year.

Thus, the two groups show different strategies after the policy. Targeted firms increase their greenfield investment amounts in 2012, as shown by previous estimates. While these results show that non-targeted firms increase their domestic merger and acquisitions, augmenting their presence in the Chinese domestic market as a response to the policy, and their brownfield investment.

5.4 Change in Location Choice

In this section, I describe the results of a variety of tests I devise for evaluating several theoretical predictions regarding multinational firms' location choices for foreign direct investment.

5.4.1 Changes Over Time

Does the location choice change over time? I first approach this question estimating equation 3 to find if there is a particular effect of each year in the probability of investing in the three relevant regions in the sample: the US, Europe, and Asia.

The estimations for the probit model are presented in Table 11, and for the linear probability models in Table A2 in the Appendix. The results show that there is no change in the probability of targeted firms investing in the US by year, showing no evidence of tariff jumping behavior². Meanwhile, investment in Europe decreases after the policy. There is no evidence to support a hypothesis of Chinese firms increasing their investment in Europe to substitute for the loss of the US market. Finally, the probability of investing in Asia

²The year 2013 cannot be estimated due to lack of enough observations.

risers after the policy and is statistically significant in 2015. This leaves space for vertical and export platform FDI.

5.4.2 Targeted and Non-Targeted Firms in 2015

Table 12 presents the marginal effects for the conditional logit model of location choice in 2015 controlling for FDI amounts, and Table 13 does the same controlling for the number of projects per month. In the first panel, we observe a positive and significant effect for Asia in both specifications and a negative effect for Europe. The second panel shows a statistically significant difference between the location choices of the two groups.

5.4.3 Impact of Industry Activities

I move to the vertical FDI hypothesis and estimate equation 7 for Asia in 2015, the region and year where I find statistically significant effects in my previous models. Thus, in Table 14, I show the linear probability estimations using my fDi Markets sample restricted for the year 2015. The coefficients multiplied by 100 are interpreted as the percentage change in the dependent variable when the dummy explanatory variable equals one. I divide the sample for targeted and non-targeted firms and present the results in separate columns for each group. The dependent variable equals one if a firm makes an announcement of a project in Asia in a particular month, and zero otherwise. The main explanatory variables are each of the industry activities defined by fDi Markets. I present two specifications for each group which include firm fixed effects and vary in their control variables.

In column 1, I show the estimation of the model for targeted firms controlling for FDI amounts. I find positive and statistically significant effects (at 1% level) for three industry activities. There is a 78.4% increase in the probability of investing in Asia if the activity in the new project is Electricity; 83% if it is Manufacturing; and 98% for Sales. Meanwhile, the rest of the activities do not have a statistically significant effect on such probability. In column 2 I present the same estimation for the non-targeted group. These results do not show a statistically significant effect of electricity activities. They show an increase in the probability of investing in Asia for manufacturing (56.3%), and sales (49%). Which are similar in sign but smaller in magnitude and statistical significance than the effects for targeted firms. Headquarters and design activities decrease the probability for this group.

In column 2, I present the estimation of the model for targeted firms controlling for the

number of projects. The results in this specification are very similar to those in column one in sign, size, and statistical significance. In column 4 I show the same estimation for the non-targeted group. These results do not show a statistically significant effect for most of the activities. I only find that there is a 58.9% decrease in the probability of investing in Asia for design activities.

Hence, after analyzing the estimations for the four columns I can conclude that electricity, manufacturing, and sales activities have a positive effect on the probability of investing in Asia by targeted firms. Comparing this with the results for the non-targeted group, I see there is a difference in many of the effects, with manufacturing and sales having a small positive impact only in one of the specifications. These results point in the direction of a new structure of cross-border activities for targeted firms and contribute to the vertical FDI hypothesis.

5.4.4 Destination Countries

To contribute to understanding if the export platform hypothesis applies in this case, I take a deeper look into the data. Considering the destination countries in Figure 8 we can see the different countries where the two groups of firms choose to locate their new plants. The most frequent choices for targeted firms are Japan (with 6 projects), Turkey (4 projects), India (3 projects), and Thailand (3 projects). These add up to 70% of the projects in the post-policy period. The rest of the destination countries receive one project. Meanwhile, the preferred locations by firms in the non-targeted group are India (6 projects), Japan (4 projects), and the United Arab Emirates (2 projects). These countries make up 70% of the projects, while the other destinations received one project in this period. The same graph for the pre-policy period is presented in Figure A1 in the Appendix. The comparison between the destination countries in Asia during the two periods shows that firms invest in a larger number of countries post-policy.

I then look into data from the USITC to find imports of solar cells by source country. In Figure 9 I show imports from Japan, Thailand, India, and Turkey, the countries that receive the most number of projects. I divide the data into three periods: pre-policy (2009 to 2011), post-policy (2012 to 2015), and medium-run (2016 to 2018). Because greenfield investments take time to mature after they are announced, it makes sense to consider a longer period after the policy is implemented to capture if the new plants become exporters.

The numbers in the chart show the quantity imported from each country (in million units) and in parenthesis the share they represent from the total US imports in each period.

There is a difference in the relevance of each of these countries as a source of solar cells to the US. There were virtually zero imports from Turkey before the policy. After, it grows their magnitude and relative share, although remaining pretty low at 0.2% of total US imports of solar cells in the medium-run. India also shows an increase in absolute quantity but only grows to 0.3% of the share in the medium run, from 0.2%. Thailand presents a more important change through time, growing to 2.8% in the medium run. Finally, Japan has the most important share of imports through time. It was already a relevant source of solar cells in the US before the policy with 5.6% of imports, it managed to consistently grow up to 8.3% in the medium-run.

Thus, even though the FDI destination countries have different relevance in the US domestic markets, the four of them manage to grow in quantities and share over time, with Thailand and Japan showing the most growth. This is relevant in a context where the overall imported quantities of solar cells in the US diminished from 2009 to 2018, as shown in Figure A2. Although I do not have data on firm-level exports to the US to confirm if the plants installed by the Chinese firms affected by the US trade barriers are the ones exporting through these other countries, the fact that the countries become more relevant sources of import after the policy shows initial support for the export platform hypothesis.

6 Robustness Checks

6.1 Anticipation

A relevant aspect to consider in difference-in-differences settings is anticipation of the agents. Whenever a policy is about to be modified, and if there is a level of public knowledge that this will happen, agents can adapt their behavior to avoid potential negative effects of the policy change. In this case, this would mean that Chinese firms that anticipated the AD-CVDs were to be imposed modified their strategy before being hit by the duties and hence negatively impacted their exports to the US and streams of income. This is indeed considered in the investigation by the US Department of Commerce. In the preliminary determinations of May 2012, the USDOC states that “exporters, producers, and importers of solar cells from the PRC had reason to believe that AD and CVD proceedings were likely

during September 2011” (US Department of Commerce, 2012).

I test for this possible change in firms’ behavior by eliminating from the sample the period from November 2011 to April 2012 (included). This considers the beginning of the investigations and the publication of the preliminary determinations in May 2012. I also consider the period starting in September 2011, following the USDOC statement about firms knowing about this policy change since September.

In Table 15 I present my results for these robustness checks that test for anticipation, using my fDi Markets sample from 2009 to 2015. The dependent variable is the monthly dollar amount of FDI announcements by firm. The main explanatory variables are the interaction between the indicator for targeted firms and the year. I present two specifications which all include firm, month, and year fixed effects, and vary in the period eliminated for the anticipation test. In Panel A I show the estimated coefficients using PPML, and in Panel B the economic valuation of the coefficients. Overall, these estimations confirm my previous results: targeted firms increase their FDI amounts the year of the policy, with one of the specifications showing results three years after.

In column 1, I show the estimation of the model without control variables after removing the months from November 2011 to April 2012 (included). The coefficient for the targeted firms in 2012 is 3.181 and it is statistically significant at the five percent level. Using the formula for the semi-elasticity, this translates into a 2307% increase in FDI. Panel B shows the economic valuation for this estimation which is 208 million dollars per year when considering the pre-policy average FDI for targeted firms, and 298 million dollars considering the average for all the firms. In this specification, I also find effects in the year 2015, though economically and statistically smaller. The coefficient of 1.963, significant at the 10% level, implies an increase of 55 to 79 million dollars per year in FDI by targeted firms.

Column 2 presents the estimation of the model without control variables after removing the months from September 2011 to April 2012 (included). The coefficient for the targeted firms in 2012 is 2.456, statistically significant at the 10% level, implying an increase of 96 or 138 million dollars depending on the benchmark chosen.

Hence, even after considering the possibility of firms modifying their behavior as a response to the policy before the policy is in place, my results remain robust.

6.2 Financial Sub-Sample

In Table 16 I present my first robustness checks. I use a financial sub-sample that results from merging my fDi Markets sample from 2009 to 2015 with variables averaged at the year level, with the Refinitiv data I collected with financial information for publicly traded firms. Hence, this is a yearly sub-sample that contains financial performance indicators, as well as the FDI variables. The dependent variable is the yearly dollar amount of FDI announcements by firm. The main explanatory variables are the interaction between the indicator for targeted firms and the year. I present three specifications which all include firm and year fixed effects, and vary in their control variables. In Panel A I show the estimated coefficients using PPML, and in Panel B the economic valuation of the coefficients. Overall, these estimations confirm my previous results: targeted firms increase their FDI amounts the year of the policy, with some specifications showing results three years after. Given the characteristics of this sub-sample, which is biased towards larger firms that can manage to be public, the dollar amounts are larger than in my previous estimates.

In column 1, I show the estimation of the model controlling for the ratio of capital expenditure over assets. The coefficient for the targeted firms in 2012 is 5.271 and it is statistically significant at the one percent level. Using the formula for the semi-elasticity, this converts into a 19361% increase in the dependent variable. To provide a more comprehensive meaning for this estimation, I show the dollar amounts in Panel B. I calculate this by multiplying the percentage change by the average FDI in the pre-policy period using two benchmarks for this valuation. First, the average amount invested by targeted firms in the sub-sample, which is 12 million dollars, and then by all the firms in the sub-sample, which is 16 million dollars. This implies that in 2012, for the sub-sample of publicly traded companies, targeted firms increased their FDI amounts by 2406 or 3086 million dollars per year respectively, with respect to the non-targeted group. I also find a positive effect in 2015, though economically and statistically smaller. The coefficient of 3.755 represents an increase in FDI by targeted firms of 519 or 665 million dollars, depending on the benchmark used.

In column 2, I show the estimation using as a control variable the total debt percentage of total assets. I find a positive and statistically significant effect for the interaction of targeted firms and the year 2012, which is very similar in magnitude and significance to the coefficient in column 1.

Finally, column 3 in this table presents the estimations controlling both by capital expenditure over assets and the total debt percentage of total assets. The effects I find in this specification are larger than in the two previous ones. The coefficient for the targeted firms in 2012 is 6.609, statistically significant at the one percent level, which means an increase of 9207 or 11808 million dollars. I also find a positive statistically significant effect in 2015, with a coefficient of 3.826 that converts into an increase of 558 or 715 million dollars.

These estimations confirm my previous results and show that there is a sub-sample of firms that have an even larger reaction to the policy in terms of the dollar amounts they invest and that have effects up to three years after the AD-CVDs are imposed by the US.

7 Summary and Concluding Remarks

I analyze the case of the anti-dumping and countervailing duties implemented by the Obama administration in 2012 against imports of Chinese solar panels. Leveraging the variation given by the policy's discriminatory nature, I test for the change in Foreign Direct Investment decisions by targeted firms.

My findings show that in 2012, targeted firms increase FDI by 145 million dollars per year, from a previous average of 9 million dollars. The estimations are robust to considering anticipation by the firms, and to including financial controls for the sub-sample of publicly traded firms. These results are for greenfield investment and not mergers and acquisitions. On the contrary, targeted firms have a lower probability of completing an M&A deal, either domestically or cross-border, than non-targeted firms. Furthermore, targeted firms that make more than one announcement per year reduce their number of projects by half for two years after the policy. This reflects a re-adaptation of the firms' strategies after the initial reaction of increasing the FDI amounts the year of the policy.

I use a variety of tests to identify the different hypotheses behind the location choice decisions by targeted Chinese multinational firms in the solar panel industry. I show that the increase in investments does not correspond to tariff-jumping or horizontal FDI as it does not reflect a preference for locating in the US or Europe respectively. I find a rise in investments in Asia in 2015 and estimate that after the policy, manufacturing, and electricity industry activities have a positive impact on the probability of investing in that region. A detailed analysis of FDI and trade data shows that these countries end up

becoming exporters of solar panels to the US, showing support for the export-platform hypothesis in the medium run.

Since these firms produce solar cells and modules, whether assembled on solar panels or not, my results show how a change in bilateral trade policy can reshape multinational production. This can be motivated by multinational firms' need for efficiency gains after facing a negative external shock, as well as exporting to the desired final market from a different country. Overall, my results document FDI diversion that modifies investment patterns in the short run and eludes the trade barriers in the medium run, weakening the intended effects of the protectionist policy.

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Figure 1. Photo Voltaic Value Chain

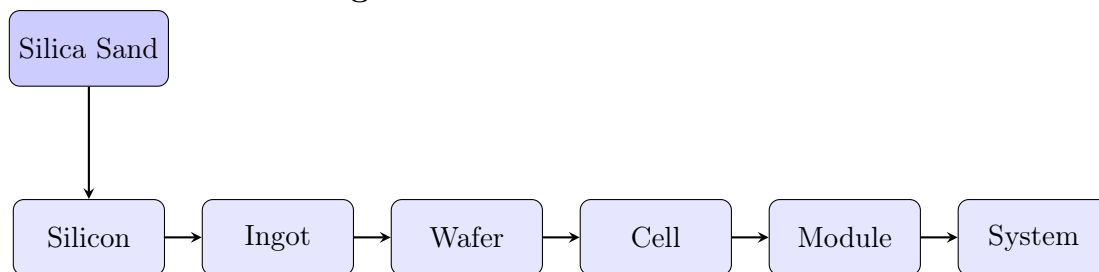
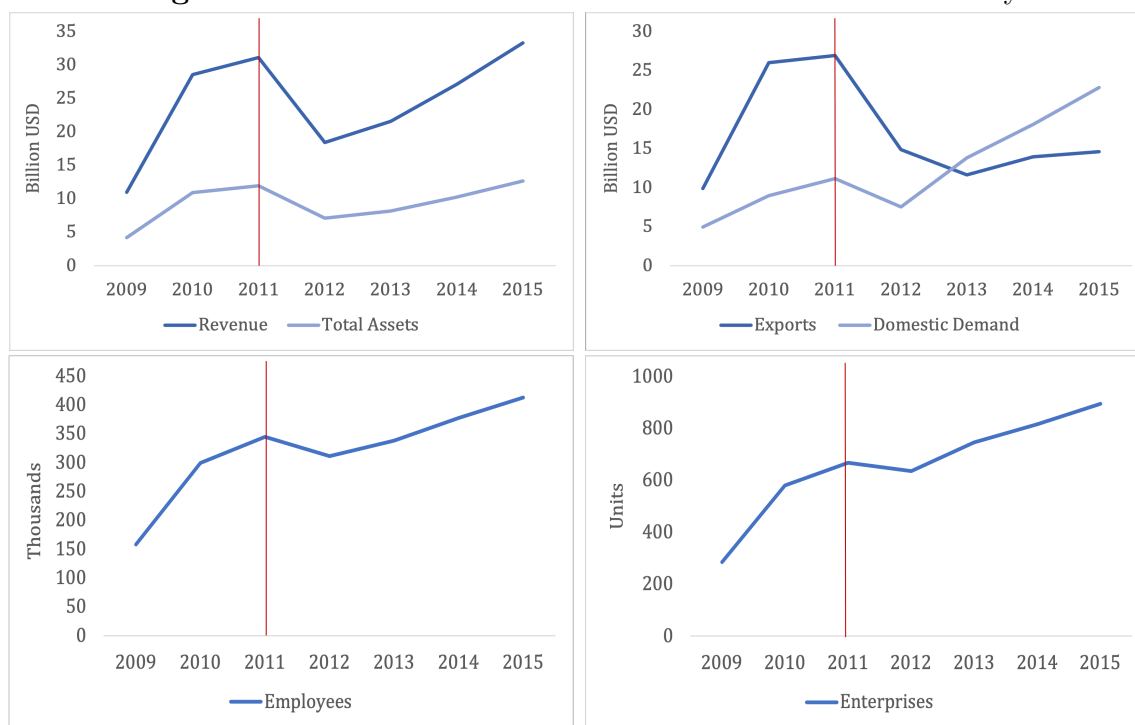
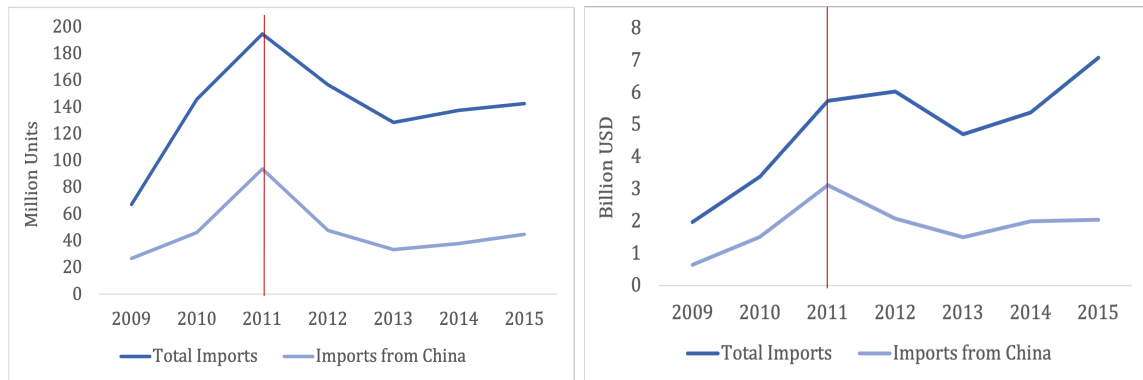


Figure 2. Economic Performance of the Chinese Solar Industry



Source: IBISWorld

Figure 3. US Imports of Solar Cells: Quantity & Value



Source: USITC

Figure 4. Policy's Timeline

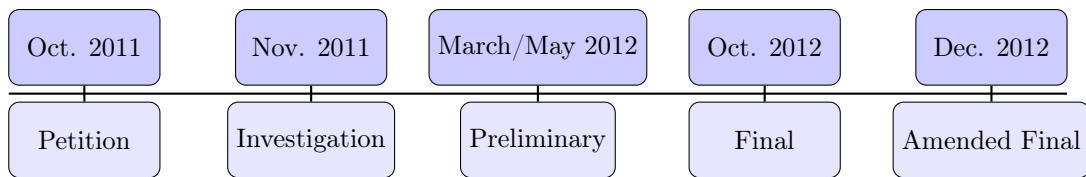


Table 1. fDi Markets Sample Description

FDI announcements within the cluster of environmental technology		Percent
Industry Sector		
Electronic components		75
Renewable energy		24
Other		1
Sub-Sector		
All other electrical equipment & comp..		75
Solar electric power		24
Other		1
Industry Activity		
Sales, Marketing & Support		43
Electricity		21
Manufacturing		15
Headquarters		14
Design, Development & Testing		4
Logistics, Distribution & Transportat..		4
FDI announcements by project type and location		
ProjectType		
New		96
Expansion		4
Location		
Europe		43
Asia		31
North America		11
Africa		8
Oceania		4
Latin America & Caribbean		3

Table 2. Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
FDI	6,468	3.15	49.4	0	2,000
Jobs	6,468	3.91	71.0	0	3,000
Projects	6,468	0.03	0.2	0	4

Table 3. Target country in M&A deals

Target country	Percent
China	68
Hong Kong	10
United States	7
Portugal	2
Sweden	2
United Kingdom	2
Other	6

Table 4. Type of M&A by Industry

Acquiror	Target	Percent
<i>Horizontal</i>		
Electronic and Electrical Equipment	Electronic and Electrical Equipment	49
<i>Vertical</i>		
Invest. & Commodity Firms, Dealers, Exch.	Electronic and Electrical Equipment	10
Electronic and Electrical Equipment	Invest. & Commodity Firms, Dealers, Exch.	7
Electronic and Electrical Equipment	Wholesale Trade-Durable Goods	5
Electric, Gas, and Water Distribution	Electronic and Electrical Equipment	5
Metal and Metal Products	Electric, Gas, and Water Distribution	5
Other vertical	Electronic and Electrical Equipment	20

Table 5. Mean Differences Test: FDI data

		PRE-POLICY				POST-POLICY			
		Non-targeted	Targeted	Diff.	t-stat	Non-targeted	Targeted	Diff.	t-stat
Obs.		1,872	900			2,496	1,200		
FDI (mill.USD)	Mean	1.23	0.75	0.48	0.54	3.75	6.72	-2.97	-1.35
	Std. dev.	26.12	8.36			58.07	70.79		
Jobs	Mean	2.32	2.10	0.22	0.10	2.35	11.01	-8.66	-3.00
	Std. Dev.	62.03	18.07			30.45	137.55		
Projects	Mean	0.02	0.05	-0.03	-3.70	0.03	0.05	-0.02	-3.14
	Std. Dev.	0.18	0.25			0.21	0.26		

Table 6. Mean Difference Test: Financial Data

		PRE-POLICY				POST-POLICY			
		Non-Targeted	Targeted	Diff.	t-stat	Non-Targeted	Targeted	Diff.	t-stat
CapEx	Mean	115.87	200.15	-84.27	-1.50	79.5	70.5	9.0	0.4
	Std. Dev.	136.02	282.94			95.2	113.4		
	Obs.	32	33			49	32		
Profit Mg	Mean	27.65	25.20	2.46	0.41	7.9	17.3	-9.4	-0.8
	Std. Dev.	17.11	29.95			57.9	36.6		
	Obs.	32	34			50	33		
EBITDA/A.	Mean	0.09	0.05	0.03	0.99	0.05	0.003	0.04	2.2
	Std. Dev.	0.17	0.07			0.1	0.1		
	Obs.	33	31			50	32		
ROAA	Mean	8.99	0.76	8.23	1.76	-2.0	-40.4	38.4	1.1
	Std. Dev.	25.20	16.06			14.8	252.9		
	Obs.	32	46			48	51		
DEBTA.	Mean	25.35	31.98	-6.64	-1.32	25.5	44.0	-18.6	-3.4
	Std. Dev.	22.01	16.96			18.2	29.7		
	Obs.	31	30			47	29		
Log Assets	Mean	6.32	6.07	0.25	0.69	6.73	6.57	0.16	0.53
	Std. Dev.	1.87	1.52			1.66	1.39		
	Obs.	34	54			50	50		

Figure 5. Projects Pre and Post-policy by Location Region: Number & Amounts

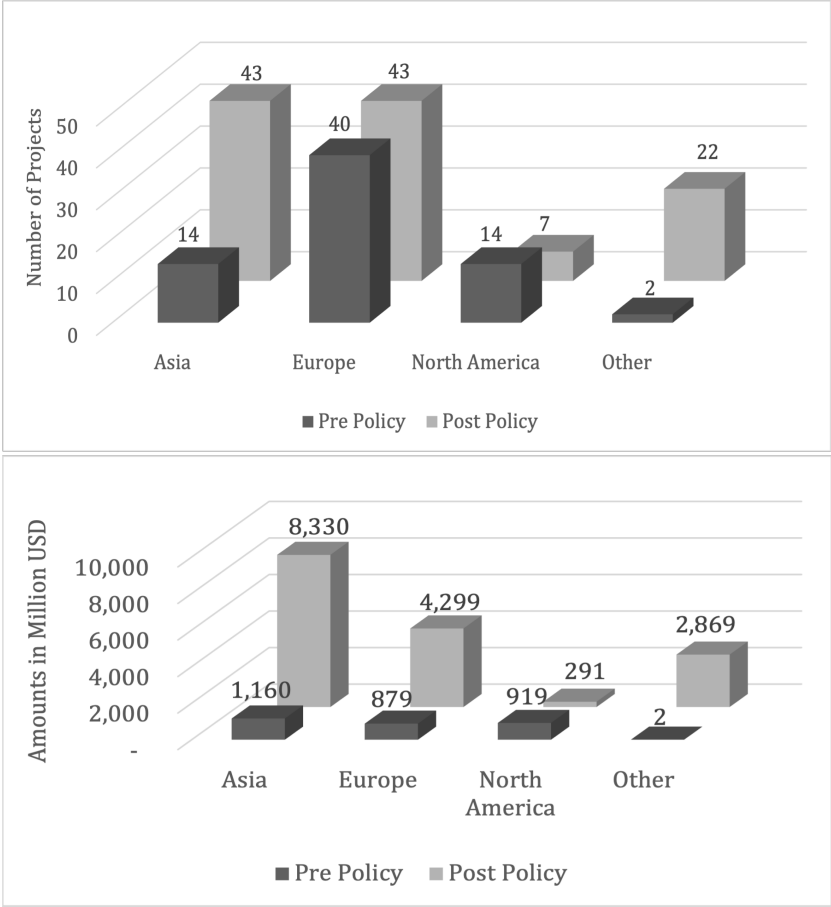


Figure 6. Pre-trends for FDI amounts

Table 7. Parallel-trends test
(pre-treatment period)

H0: Linear trends are parallel	
	FDI
$F(1, 77) =$	0.25
$\text{Prob}>F$	0.62

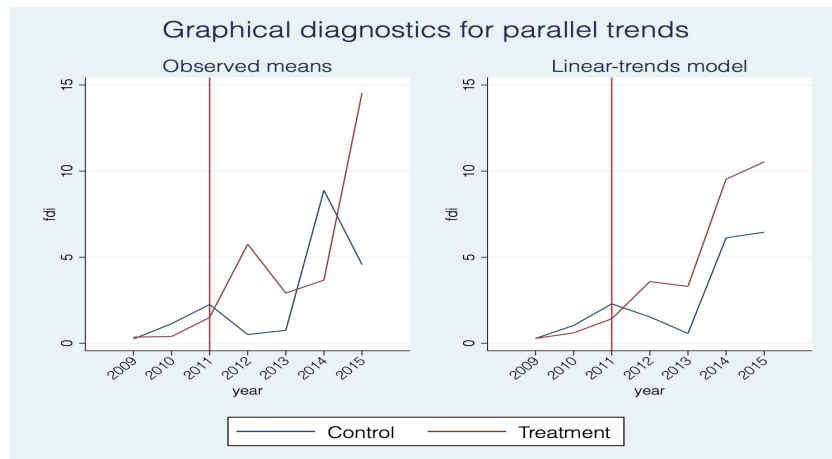


Table 8. Effects of Trade Barriers on FDI

<i>Panel A: Estimation of coefficients (PPML)</i>			
	(1) FDI	(2) FDI	(3) FDI
Targeted*2009	0.810 (1.267)	0.826 (1.258)	-0.321 (1.249)
Targeted*2010	-0.662 (1.238)	0.223 (1.780)	-0.224 (1.221)
<i>post-policy</i>			
Targeted*2012	2.838** (1.197)	2.464** (1.034)	2.352* (1.243)
Targeted*2013	1.762 (1.209)	1.795 (1.177)	2.281 (1.639)
Targeted*2014	-0.478 (1.156)	-0.303 (1.173)	0.985 (1.221)
Targeted*2015	1.566 (1.078)	0.983 (1.417)	2.392* (1.301)
<i>Fixed effects</i>			
Firm	✓	✓	✓
Month	✓	✓	✓
Year	✓	✓	✓
<i>Controls</i>			
Jobs		✓	
Projects			✓
Observations	6468	6468	6468
PseudoR ²	0.372	0.475	0.762
<i>Panel B: Economic valuation of coefficients (in million dollars)</i>			
Targeted*2012	145	97	86
Targeted*2015			90
Mean FDI pre-policy for targeted firms:			9
Targeted*2012	208	139	123
Targeted*2015			129
Mean FDI pre-policy for all firms:			13

NOTE: Panel A of this table presents the results of the PPML estimations for equation 1 using fDi markets data from 2009 to 2015. The dependent variable is FDI in million dollars per month per project. The coefficients represent semi-elasticities. The percentage change is calculated as $100 \cdot (\exp(\delta) - 1)\%$. Standard errors clustered at the firm level are shown in parentheses. Statistical significance levels are given by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Panel B presents the economic valuation. For each statistically significant coefficient, I estimate the percentage change and then multiply it by the yearly values in the pre-policy period of the mean dependent variable both for targeted and all firms.

Table 9. Effects of Trade Barriers on the Number of Projects

<i>Panel A: Estimation of coefficients (PPML)</i>			
	(1) Projects	(2) Projects	(3) Projects
Targeted*2010	0.142 (0.274)	0.117 (0.274)	0.149 (0.292)
<i>post-policy</i>			
Targeted*2012	-0.0162 (0.212)	-0.0209 (0.213)	0.0132 (0.209)
Targeted*2013	-0.755*** (0.209)	-0.708*** (0.166)	-0.827** (0.342)
Targeted*2014	-0.799*** (0.245)	-0.800*** (0.238)	-0.839*** (0.189)
Targeted*2015	-0.186 (0.331)	-0.234 (0.340)	-0.223 (0.351)
<i>Fixed Effects</i>			
Firm	✓	✓	✓
Year	✓	✓	✓
<i>Controls</i>			
Jobs		✓	
FDI			✓
Observations	552	552	552
PseudoR ²	0.0994	0.0998	0.101
<i>Panel B: Percentage change in the number of projects</i>			
Targeted*2013	-53	-51	-56
Targeted*2014	-55	-55	-57
Projects pre-policy for firms in the subsample:			
	Mean	Std. Dev	Max
Targeted	2.5	0.6	4
All firms	2.9	1.2	7

NOTE: Panel A of this table presents the results of the PPML estimations for equation 1 using fDi markets data from 2009 to 2015 for the subsample of firms that make more than one announcement per year. The dependent variable equals the number of announced projects per year. It does not show results for the year 2009 due to lack of observations. The coefficients represent semi-elasticities. The percentage change is calculated as $100 * (\exp(\delta) - 1)\%$. Standard errors clustered at the firm level are shown in parentheses. Statistical significance levels are given by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Panel B presents the equivalence in the percentage change for the projects for each statistically significant coefficient.

Table 10. Effects of Trade Barriers on M&A

<i>Panel A: Estimation of coefficients (PPML)</i>		
	(1) M&A	(2) M&A
Targeted*2009	-0.614 (0.614)	-1.205 (0.751)
Targeted*2010	1.163 (0.985)	0.896 (0.983)
<i>post-policy</i>		
Targeted*2012	-1.469** (0.684)	-1.448* (0.875)
Targeted*2013	-0.960 (0.729)	-1.096 (0.792)
Targeted*2014	-0.291 (0.694)	-0.105 (0.824)
<i>Fixed Effects</i>		
Firm	✓	✓
Month	✓	✓
Year	✓	✓
<i>Controls</i>		
Completed	✓	✓
Cross Border		✓
Observations	1512	1512
PseudoR ²	0.299	0.329
<i>Panel B: Percentage change in M&A</i>		
Targeted*2012	-77	-76

NOTE: Panel A of this table presents the results of the PPML estimations for equation 1 using Thomson and Reuters M&A data from 2009 to 2014. The dependent variable equals to one the month there is an M&A deal and zero otherwise. The coefficients represent semi-elasticities. The percentage change is calculated as $100 \times (\exp(\delta) - 1)\%$. Standard errors clustered at the firm level are shown in parentheses. Statistical significance levels are given by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Panel B presents the percentage change in the probability of having an M&A deal for each statistically significant coefficient.

Figure 7. Probability of Investing in the US, Europe, and Asia.

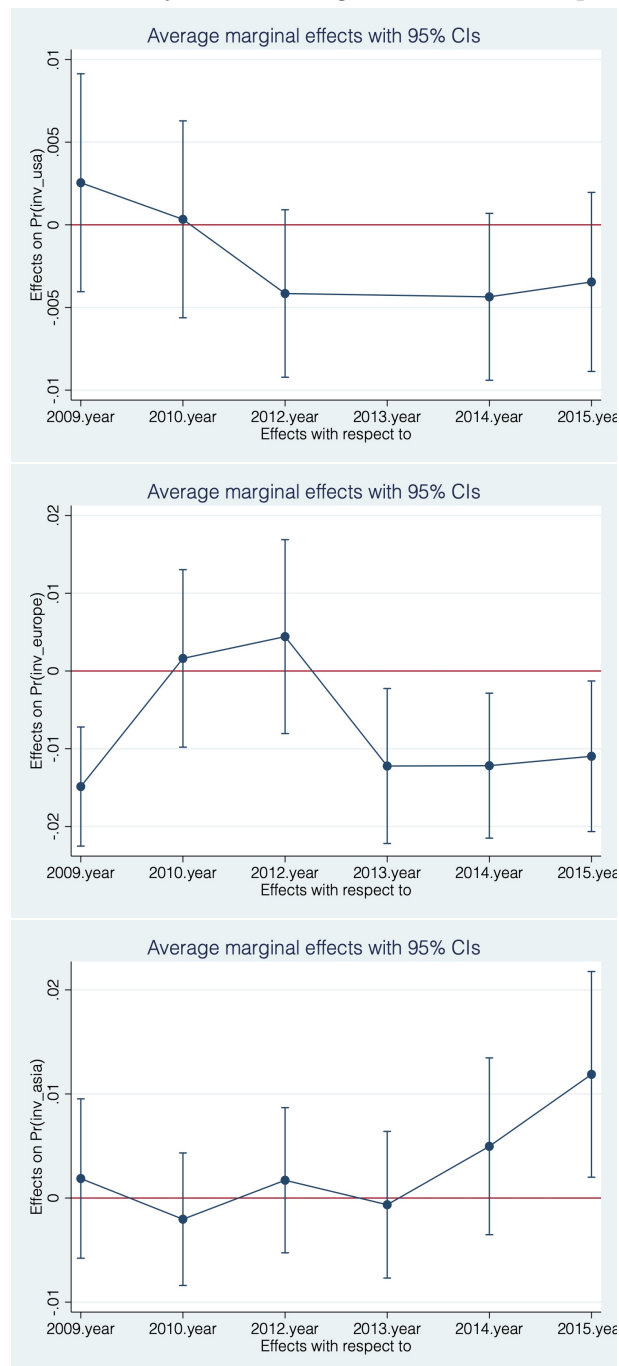


Table 11. Location Choice Over Time

Probit Estimation of the Probability of Investing in:									
	(1) USA	(2) USA	(3) USA	(4) Europe	(5) Europe	(6) Europe	(7) Asia	(8) Asia	(9) Asia
year=2009	0.086 (0.190)	0.235 (0.231)	0.066 (0.193)	-0.619*** (0.187)	-0.637*** (0.241)	-0.634*** (0.190)	0.116 (0.242)	0.654 (0.563)	0.146 (0.246)
year=2010	-0.056 (0.202)	-0.108 (0.277)	-0.094 (0.208)	0.035 (0.125)	0.113 (0.150)	0.008 (0.128)	-0.179 (0.275)	-0.188 (0.759)	-0.474 (0.411)
year=2012	-0.497 (0.339)	-0.547 (0.432)	-0.515 (0.339)	0.091 (0.128)	0.188 (0.151)	0.085 (0.129)	0.107 (0.229)	0.534 (0.555)	0.0822 (0.238)
year=2013				-0.421** (0.198)	-0.427 (0.318)	-0.398** (0.196)	-0.0479 (0.268)	0.437 (0.588)	-0.193 (0.311)
year=2014	-0.552 (0.374)	-1.314 (1.120)	-0.518 (0.338)	-0.419** (0.165)	-0.603* (0.332)	-0.319** (0.162)	0.255 (0.230)	0.751 (0.545)	0.306 (0.240)
year=2015	-0.350 (0.293)	-0.414 (0.430)	-0.367 (0.300)	-0.353** (0.172)	-0.448 (0.282)	-0.335** (0.165)	0.437** (0.211)	1.047** (0.493)	0.405* (0.215)
Firm ID	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	FDI	Projects	Jobs	FDI	Projects	Jobs	FDI	Projects	Jobs
Observations	5616	5616	5616	6552	6552	6552	6552	6552	6552
Pseudo R^2	0.053	0.416	0.047	0.074	0.526	0.046	0.169	0.548	0.284

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

NOTE: This table shows the results for the Probit estimations based on equation 3. Coefficients show the marginal effects for treated firms. Robust standard errors are clustered at the firm level.

Table 12. Location Choice in 2015: Conditional Marginal Effects

0.specific-rate	(base outcome)					
1.specific-rate _outcome	dy/dx	std. err.	z	P>z	[95% conf. interval]	
Asia	0.398	0.150	2.650	0.008	0.104	0.692
Europe	-0.404	0.118	-3.430	0.001	-0.635	-0.174
North America	-0.117	0.078	-1.490	0.135	-0.270	0.036
Africa	0.058	0.097	0.600	0.549	-0.132	0.248
Latin America & Caribbean	0.065	0.064	1.020	0.309	-0.060	0.190
Oceania	0.000	0.000	0.000	1.000	0.000	0.000
Delta-method						
	Contrast	std. err.	z	P>z	[95% conf. interval]	
Outcome: Asia specific-rate (1 vs 0)	0.348	0.150	2.320	0.020	0.054	0.641
Outcome: Europe specific-rate (1 vs 0)	-0.405	0.115	-3.520	0.000	-0.630	-0.179
Control variable: FDI amounts						

Figure 8. FDI in Asian Countries Post-Policy by Group of Firms

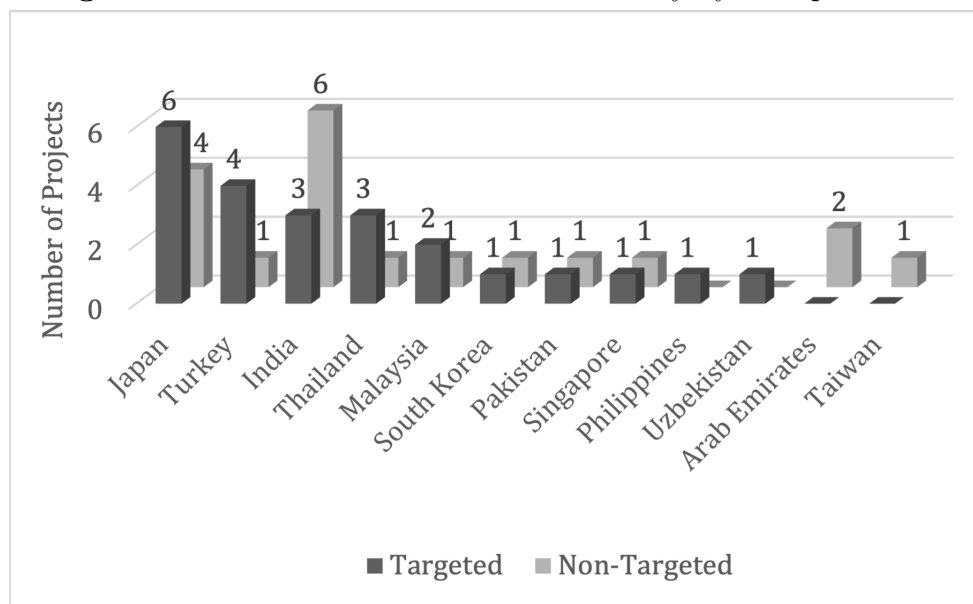
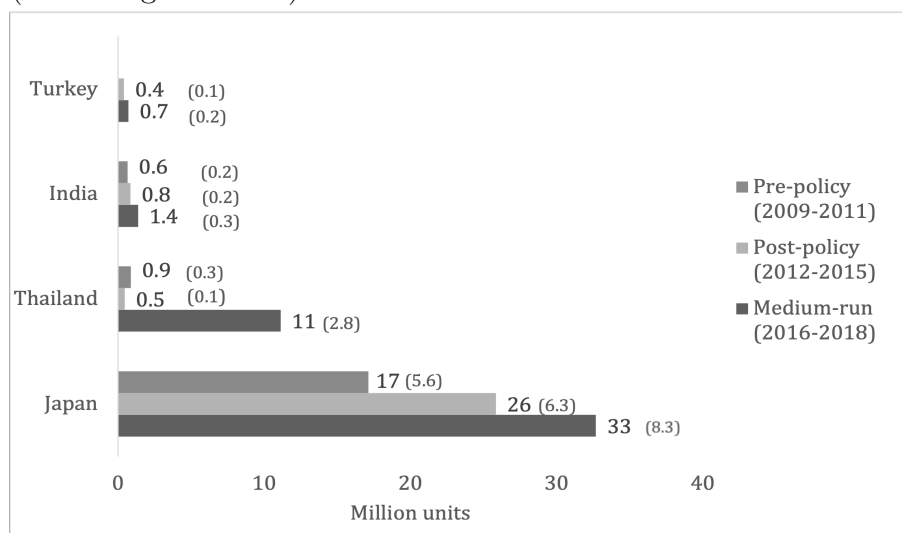


Table 13. Location Choice in 2015: Conditional Marginal Effects

0.specific-rate	(base outcome)					
1.specific-rate _outcome	dy/dx	std. err.	z	P>z	[95% conf. interval]	
Asia	0.367	0.150	2.440	0.015	0.073	0.661
Europe	-0.405	0.117	-3.460	0.001	-0.635	-0.175
North America	-0.119	0.079	-1.510	0.130	-0.274	0.035
Africa	0.050	0.092	0.540	0.586	-0.130	0.230
Latin America & Caribbean	0.107	0.072	1.480	0.138	-0.035	0.249
Oceania	0.000	0.000	0.000	1.000	0.000	0.000
Delta-method						
	Contrast	std. err.	z	P>z	[95% conf. interval]	
Outcome: Asia specific-rate (1 vs 0)	0.361	0.148	2.440	0.015	0.071	0.650
Outcome: Europe specific-rate (1 vs 0)	-0.406	0.114	-3.560	0.000	-0.630	-0.182
Control variable: number of projects per month						

Figure 9. US Imports of Solar Cells by Country of Chinese FDI Destination: Million Units & (Percentage of Total)



Source: USITC

Table 14. Production Fragmentation in Asia

Linear Probability Estimation of Investing in Asia in 2015 by Firms:				
Industry Activity	(1) Targeted	(2) Non-Targeted	(3) Targeted	(4) Non-Targeted
Electricity	0.784*** (0.146)	0.212 (0.154)	0.757*** (0.149)	-0.162 (0.278)
Manufacturing	0.830*** (0.147)	0.563** (0.261)	0.742*** (0.248)	-0.120 (0.502)
Sales	0.979*** (0.014)	0.494* (0.252)	0.898*** (0.084)	-0.234 (0.444)
Headquarters	-0.021 (0.014)	-0.003*** (0.001)	-0.100 (0.084)	-0.589** (0.224)
Logistics	-0.002 (0.001)		-0.172 (0.165)	
Design		-0.001*** (0.000)		-0.589** (0.224)
Firm FE Controls	✓ FDI	✓ FDI	✓ Projects	✓ Projects
Observations	300	624	300	624
R^2	0.864	0.591	0.863	0.569

NOTE: This table presents the results of the OLS estimations for equation 7 using fDi markets data for the year 2015. Columns 1 and 3 show the results for the sample restricted to targeted firms, while columns 2 and 4 show the results for the sample restricted to non-targeted firms. The dependent variable equals one if there is a firm makes an investment in Asia in a specific month, and zero otherwise. The coefficients multiplied by 100 represent the percentage change. Some coefficients might not be estimated due to a lack of observations. Standard errors clustered at the firm level are shown in parentheses. Statistical significance levels are given by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Panel B presents the economic valuation. For each statistically significant coefficient, I estimate the percentage change and then multiply it by the yearly values in the pre-policy period of the mean dependent variable both for targeted and all firms.

Table 15. Effects of Trade Barriers on FDI
Anticipation Test

<i>Panel A: Estimation of coefficients (PPML)</i>		
	(1) FDI	(2) FDI
Targeted*2009	1.208 (1.350)	0.483 (1.506)
Targeted*2010	-0.264 (1.288)	-0.989 (1.451)
<i>post-policy</i>		
Targeted*2012	3.181** (1.274)	2.456* (1.437)
Targeted*2013	2.160 (1.467)	1.435 (1.610)
Targeted*2014	-0.0802 (1.233)	-0.805 (1.400)
Targeted*2015	1.963* (1.173)	1.239 (1.345)
<i>Fixed Effects</i>		
Firm	✓	✓
Month	✓	✓
Year	✓	✓
<i>Period Removed</i>		
Nov.2011-Apr.2012	✓	
Sep.2011-Apr.2012		✓
Observations	5382	5092
PseudoR ²	0.362	0.379
<i>Panel B: Economic valuation of coefficients (in million dollars)</i>		
Targeted*2012	208	96
Targeted*2015	55	
Mean FDI pre-policy for targeted firms:		9
Targeted*2012	298	138
Targeted*2015	79	
Mean FDI pre-policy for all firms:		13

NOTE: Panel A of this table presents the results of the PPML estimations for equation 1 using fDi markets data from 2009 to 2015. In the first column, the months from November 2011 to April 2012 are removed; in the second column the months from September 2011 to April 2012. The dependent variable is FDI in million dollars per month per project. The coefficients represent semi-elasticities. The percentage change is calculated as $100 \cdot (\exp(\delta) - 1)\%$. Standard errors clustered at the firm level are shown in parentheses. Statistical significance levels are given by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Panel B presents the economic valuation. For each statistically significant coefficient, I estimate the percentage change and then multiply it by the yearly values in the pre-policy period of the mean dependent variable both for targeted and all firms.

Table 16. Effects of Trade Barriers on FDI
Financial Sub-Sample

<i>Panel A: Estimation of coefficients (PPML)</i>			
	(1) FDI	(2) FDI	(43) FDI
Targeted*2009	-0.422 (1.604)	-0.227 (2.089)	-2.400 (1.853)
<i>post-policy</i>			
Targeted*2012	5.271*** (1.768)	5.285*** (1.668)	6.609*** (2.027)
Targeted*2013	1.937 (1.860)	1.892 (1.845)	2.378 (2.139)
Targeted*2014	1.151 (2.174)	0.812 (1.987)	-1.851 (1.779)
Targeted*2015	3.755* (1.941)	2.982 (1.984)	3.826** (1.913)
<i>Fixed Effects</i>			
Firms	✓	✓	✓
Year	✓	✓	✓
<i>Controls</i>			
CapExAs	✓		✓
DEBTA		✓	✓
Observations	96	89	82
PseudoR ²	0.770	0.783	0.864
<i>Panel B: Economic valuation of coefficients (in million dollars)</i>			
Targeted*2012	2406	2440	9207
Targeted*2015	519		558
Mean FDI pre-policy targeted firms, sub-sample:			12
Targeted*2012	3086	3130	11808
Targeted*2015	665		715
Mean FDI pre-policy all firms, sub-sample:			16

NOTE: Panel A of this table presents the results of the PPML estimations for equation 1 using fDi markets data from 2009 to 2015 merged with Refinitiv data. These are sub-samples that contain financial information from publicly traded firms. The dependent variable is FDI in million dollars per year per firm. The variable CapExAs is the ratio of capital expenditure over assets. The variable DEBTA is the total debt percentage of total assets. The coefficients represent semi-elasticities. The percentage change is calculated as $100 \cdot (\exp(\delta) - 1)\%$. Standard errors clustered at the firm level are shown in parentheses. Statistical significance levels are given by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Panel B presents the economic valuation. For each statistically significant coefficient, I estimate the percentage change and then multiply it by the pre-policy period mean dependent variable in the sub-sample both for targeted and all firms.

A Appendix

A.1 HTSUS Codes

The most important product treated by the ADD is 8541.40.6020: Solar cells assembled into modules or panels. It represents the majority of the treated imports and experienced important growth during the period (from 43% to more than 90%)

Table A1. HTSUS Codes and Description

Panel A: Description of HTSUS Codes					
8501.61.0000	AC generators (alternators) of an output not exceeding 75 kVA				
8507.20.20	Other				
8541.40.6020	Solar cells assembled into modules or panels				
8541.40.6030	Solar cells, not assembled into modules or made up into panels				
8501.31.8000	Generators				
Panel B: Weight of Imports by HTSUS Code (Percent)					
Year/Code	8501.31.8000	8501.61.0000	8507.20.80	8541.40.6020	8541.40.6030
2009	0.9	5.2	28.5	63.8	1.7
2010	0.5	1.9	18.3	76.9	2.3
2011	0.2	1.2	8.1	86.4	4.1
2012	0.2	1.5	11.2	85.9	1.2
2013	0.6	1.6	13.1	84.5	0.2
2014	0.7	1.3	14.1	82.0	1.9
2015	0.5	0.9	10.5	87.7	0.4
2016	0.3	0.5	6.5	92.1	0.6

Note: Panel A of this table shows the HTSUS codes defined by the US Department of Commerce for the imposition of the AD-CVDs. Panel B shows the weight of imports by HTS code, the source is the US International Trade Commission.

A.2 Linear Probability Models

Here, I present a different specification for estimating the models of location choice changes over time using a linear probability model.

$$Y_{it} = \delta \mathbf{Year} + \beta X_{it} + \gamma_i + \epsilon_{it}. \quad (8)$$

Where is Y_{it} the probability of investing in a particular region for a firm i in period t (month-year); \mathbf{Year} is a vector of dummy variables from years 2009 to 2015; X_{it} controls for FDI amounts, number of projects, or jobs created; γ_i are firm fixed effects; ϵ_{it} is the error term. Robust standard errors are clustered at the firm level. Detailed results shown in Table A2, are in line with the Probit estimations presented above.

A.3 Destination Countries in Asia

In this chart, we observe that before the policy both groups of firms invested in a smaller range of Asian countries compared to post-policy seen in Figure 8. In terms of which countries receive more investments by targeted firms, Japan is the most frequent destination though with a smaller number of projects than after the policy. South Korea and Singapore follow in relevance for this group of firms. On the other hand, the non-targeted firms make fewer investments in this region overall in a variety of countries with only one project.

Table A2. Location Choice Over Time

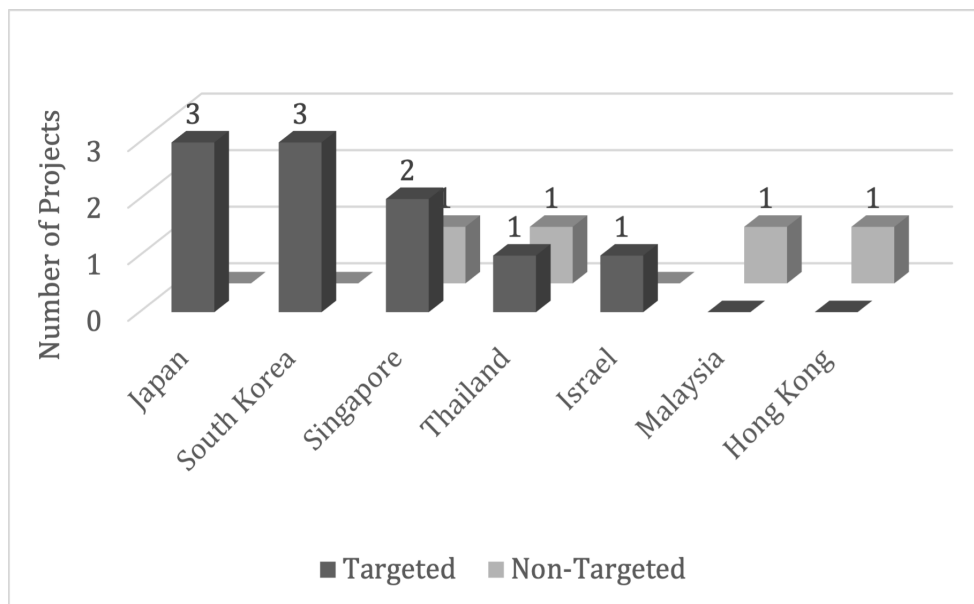
Linear Probability Estimation of Investing in:									
	(1) USA	(2) USA	(3) USA	(4) Europe	(5) Europe	(6) Europe	(7) Asia	(8) Asia	(9) Asia
year=2009	0.003 (0.007)	0.004 (0.007)	0.003 (0.007)	-0.009 (0.007)	-0.006 (0.006)	-0.010 (0.007)	-0.002 (0.011)	0.000 (0.009)	-0.003 (0.011)
year=2010	0.003 (0.007)	0.004 (0.007)	0.003 (0.007)	0.007 (0.011)	0.007 (0.009)	0.006 (0.011)	-0.012 (0.009)	-0.012* (0.006)	-0.013 (0.009)
year=2012	-0.007 (0.006)	-0.008 (0.006)	-0.007 (0.007)	0.011 (0.012)	0.009 (0.009)	0.013 (0.012)	-0.004 (0.009)	-0.003 (0.010)	-0.002 (0.010)
year=2013	-0.010* (0.005)	-0.007 (0.005)	-0.010* (0.005)	-0.007 (0.011)	0.002 (0.009)	-0.006 (0.011)	-0.011 (0.010)	-0.002 (0.007)	-0.010 (0.009)
year=2014	-0.010* (0.005)	-0.009* (0.005)	-0.010* (0.005)	-0.010 (0.009)	-0.008 (0.008)	-0.010 (0.010)	-0.008 (0.008)	-0.005 (0.007)	-0.006 (0.009)
year=2015	-0.010* (0.005)	-0.011* (0.005)	-0.011* (0.006)	-0.020*** (0.007)	-0.019*** (0.006)	-0.017*** (0.007)	0.014 (0.013)	0.023** (0.010)	0.012 (0.013)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	FDI	Projects	Jobs	FDI	Projects	Jobs	FDI	Projects	Jobs
Observations	2184	2184	2184	2184	2184	2184	2184	2184	2184
Within R^2	0.006	0.113	0.008	0.024	0.311	0.006	0.169	0.312	0.187

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

NOTE: This table shows the results for the Linear Probability Model estimations based on equation 8. The sample is restricted to treated firms. Robust standard errors are clustered at the firm level.

Figure A1. FDI in Asian Countries Pre-Policy by Group of Firms

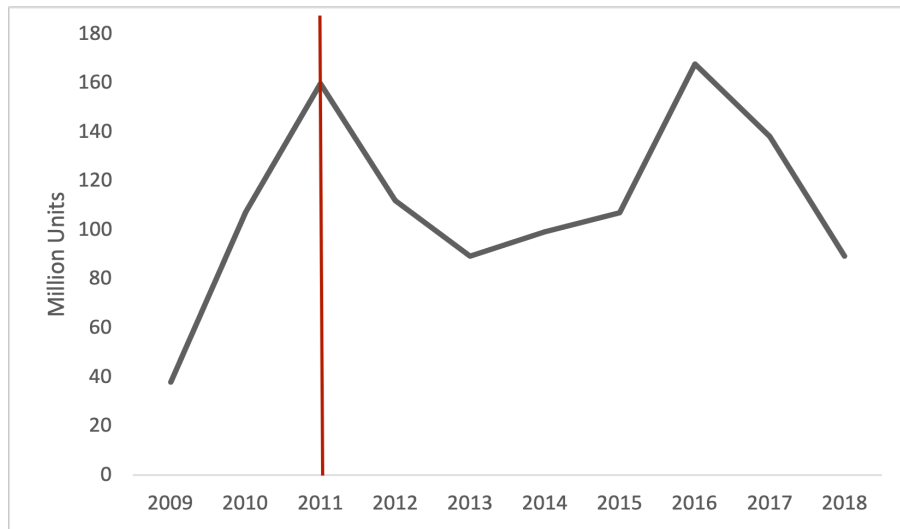


A.4 US Imports of Solar Cells 2009 to 2018

This graph shows the evolution in the million units of solar cells imported into the US from 2009 to 2018. There is a rapid increase up to 2011 and a reduction after the policy is implemented in 2012. The recovery from 2013 to 2016 is again followed by a decrease in the next two years. Overall, even though the quantities imported at the end of the period are larger than at the beginning, there were important fluctuations.

This evolution in percentage change by sub-periods is shown in Table A3, where we observe that the years after the policy show a decrease in the number of imports.

Figure A2. US Imports of Solar Cells 2009 to 2018



Source: USITC

Table A3. Change in Total US Imports of Solar Cells by Period

Percent	Period
320	2009 to 2011
-4	2012 to 2015
-20	2012 to 2018
135	2009 to 2018