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

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Abstract

The return 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 of the 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 on the imports of solar panels from China. Due to their differential exposure to US trade policy, Chinese firms are granted different AD-CVD rates. I leverage this variation to 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 also find a reduction in the number of projects of 53% 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 duties, mostly to countries that become 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, significant 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 industrial policies implemented by developed nations are in the form of non-tariff barriers, which require granular evidence and a deep institutional context to adequately measure their effects (Lane (2020)). This paper uses a US protectionist policy on solar panels from China in 2012 to examine the 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 early 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 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 domestic 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 firms in the solar panel industry. I exploit the fact that the policy targets companies in the same industry with two different rates to develop a difference-in-differences design.

My empirical design has specific characteristics due to China being a non-market economy for the US anti-dumping law. The legal framework assumes that all Chinese firms are under government control unless proven otherwise. Firms that show their independence are granted a specific anti-dumping duty rate. All others in the industry are assigned a general rate (PRC-wide) greater than the specific rate. My analysis of export activity by the two groups of firms shows that those granted a specific rate are the larger exporters and hence have more presence in the US domestic market. Thus, the different AD-CVD rates reflect the differential exposure to the US trade policy, with firms receiving the specific - lower - rate being the most exposed. I leverage this variation given by the policy's discriminatory nature to compare the changes in foreign direct investment decisions before and after the policy by targeted firms, granted a specific rate, relative to the non-targeted group, assigned the PRC-wide rate.

Motivated by 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

[1] See more information for AD and CVD.

of projects by firms that make more than one announcement 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 a cross-border M&A deal.

I devise various 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 locations and industry choices for foreign investments. I use logit and linear probability models (LPM) 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 use LPM to 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 conditional logit.

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

Horizontal FDI is defined as investments in production 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.

Vertical FDI involves cross-country production fragmentation and is driven by differential factor costs between the home and the host country (Alfaro and Charlton (2009)). 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 (Antràs et al. (2024)). In the context of this paper, exporting costs include the trade barrier. I also test this motivation for 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 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. In contrast to previous work documenting trade diversion, I focus on foreign direct investment diversion. Flaaen 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 using 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 an important investment diversion.

Other work in this literature also focuses 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 anti-dumping duties against Japan creates trade deflection, increasing Japanese exports of the same product to a third country. In contrast, 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 safeguardby 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.

This paper speaks to the growing literature on empirical analysis of industrial policy by analyzing the effects of a temporary trade barrier whose main objective is to protect a domestic industry from import competition. Lashkaripour and Lugovskyy (2023) discusses the efficacy of trade and industrial policy in distorted open economies and finds that welfare increases only when they are implemented with international coordination. Identifying the causal effects of these policies is challenging given that, by design, the intervention is non-random and its targets are defined by political economy reasons (Juhász et al. (2023)). My research design carefully addresses these concerns and provides causal estimates with deep institutional background.

My findings add to the studies of FDI location choice by multinational firms. In this case, as a consequence of trade barriers, examining which hypotheses hold for the location choice decision of firms affected by the imposition of protectionist policies. As defined in Tintelnot (2017), firms with export-platform affiliates face fixed costs of foreign investment. My empirical results show that the increase in trade costs and the loss of a relevant market can compensate for the restriction of the high costs of establishing a foreign affiliate. By including cross-border M&A I provide a comprehensive approach to FDI and how multinational firms decide to serve a foreign market. This is highlighted by Nocke and Yeaple (2007) who show that cross-border M&A is done by the most efficient firms in industries where the source of firm heterogeneity is their mobile capabilities. This is not the case in industries where firms differ mostly in non-mobile capabilities, which aligns with my results.

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 presents 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, which show that AD investigations significantly decrease the total export volume (Lu et al. (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. This is captured by some of the firms' quotes mentioned in Section 5.4.1 and Appendix A.7.

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 for 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 manages to recover very rapidly, reflecting different strategies, including the Chinese domestic market playing a new 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 analysis period. 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 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 is 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 show "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 allows for the rest of the process to continue. The scope of the investigation defined by Commerce covers 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 finds 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 investigation shows 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, experienced a decline in many performance indicators, and reported, among other difficulties, the closure of production facilities. The investigation finds a "causal nexus" between subject imports and the poor condition of the domestic industry (United States International Trade Commission (2012)).

The preliminary determinations for the countervailing case are issued on March 26, 2012, and for the anti-dumping case on May 25, 2012. In October, a final determination is issued for the anti-dumping case. On December 7, 2012, the USDOC issues an amended final duty order for the anti-dumping case (United States Department of Commerce (2012a)) and a final determination for the countervailing duty order on crystalline silicon photovoltaic cells, whether or not assembled into modules imported from China (United States Department of Commerce (2012b)). The details for HTSUS codes in the determination are in Appendix Table A1.

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. In this case, the USDOC finds that the revocation of the duties would lead to dumping margins of up to the maximum rate; hence, the orders remain in place (United States Department of Commerce (2018)).

2.4.1 Determination of the Differential Rates

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 relies on information on cost and price structures from a third country. In the case studied in this paper, the surrogate country is 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 demonstrate sufficient independence from the government. If that is the case, the firm is granted a separate rate.[2]

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 the companies' 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, they include a list of the names of these companies. I refer to this group as the targeted firms.

Most of the companies listed by the Department of Commerce were named in the petition. This makes them part of the investigation and allows them to submit the required information. Firms that are active in this process need sufficient resources to afford it. Moreover, those with more interest in the US market, and thus more to lose from not complying, are usually actively participating in the investigation.

Meanwhile, all other Chinese firms 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

[2] In a regular anti-dumping case, firms in the same industry that are not named in the petition are not restrained. The fact that they are in this case is explained by China being an NME.

information. It is the policy of the Department of Commerce in cases in which entities do not 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 (United States Department of Commerce (2012c).

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 covers 31 government programs during the year 2010. The results are CVD rates of 15.4% on average.

In summary, considering both the anti-dumping and the countervailing duties, an average 40% 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. As discussed in Section 3.1.1, firms granted a specific rate are the larger exporters and hence have more presence in the US domestic market. Thus, the different AD-CVD rates reflect the differential exposure to the US trade policy, with firms receiving the specific - lower - rate being the most exposed.

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, modifies 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 are set by the US in response to American solar panel companies' interests. Thus, they are determined outside the realm of commercial relations between Chinese solar panel firms and their FDI destination countries. 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 can restructure after a shock. The solar panel production process has different stages that allow for analyzing cross-country production fragmentation as a response to an external shock.

Given that more than a decade has passed since the imposition of these measures, this setting 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. This time frame contributes to the study of foreign direct investment since these are large projects that generally have a long maturity process.

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).

3 Data

I employ several data sources, greenfield foreign investment announcements being the main one. I also collect data on mergers and acquisitions, financial indicators on Chinese solar panel firms, imports and exports from the US and China, as well as country macroeconomic variables. All of these are used to create my 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 project 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, which 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 for firms that usually have this activity is 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 projects before and after the policy in 2012. The first chart is for the number of projects, and the second is for FDI amounts. Some interesting patterns arise, showing that there is a change in the geography of these investments. Other regions, which group Africa, Latin America and the

Caribbean, and Oceania, receive more FDI from the firms in the sample after the policy. Meanwhile, North America decreases the number of projects received. Europe slightly increases the number of projects and, considering the FDI amounts, the change after the policy is quite large. Interestingly, there is an important rise in the number of projects and FDI amounts in Asia after the policy. These facts motivate 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 during the different stages of the determination process. The list includes the set of firms granted a specific rate of anti-dumping duties, which are exporters and producers of solar cells and modules. The list has 61 targeted (unique) firms, but it is longer because it includes subsidiaries. The published list of firms was the same during the whole investigation process, meaning firms were not entering or exiting the policy. All other Chinese firms in the same industry not included in that list are granted a general duty, the PRC-wide rate.

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). This constitutes my treatment group. 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 the Federal Register did not list, but is as similar as possible to the targeted firms regarding industry and FDI activity.

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

To understand how these two groups compare in terms of FDI, my outcome of interest, Table 4 shows the results for the means differences test in the 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 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 statistically significant difference 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.

I also analyze the share of China's exports to the world in 2011.[3] As a proxy for the subject products in the AD-CVDs, I consider exports for HS code 854140, defined as "Electrical apparatus; photosensitive, including photovoltaic cells, whether or not assembled in modules or made up into panels, light emitting diodes." More than 2800 Chinese companies exported products in this classification to the world in 2011, and 95% of them have shares of Chinese exports below 0.04%. This shows this is a very skewed industry in terms of exports. I consider the firms at or above the 95th percentile in Chinese exports of this product to the world to see how my two groups of firms are represented in the higher exporters sub-sample. I find that firms in the targeted group are nearly all in the 99th percentile of Chinese exports and are significantly larger exporters than the non-targeted firms in my control group. Firms in the non-targeted group are small exporters to the world in this aggregated industry, and I assume that a similar pattern applies to the imports in question.

This analysis of the export activity by the two groups of firms reflects that the targeted group is more exposed to the US trade policy than the non-targeted group. Even though the non-targeted group has the larger AD-CVD rate, they are not

[3] I am grateful to Professor Judith Dean for supplying this export share data. The shares were constructed from China Customs data (firm-level trade at the HS 6-digit level).

affected by it since they are not relevant exporters. Thus, the different AD-CVD rates reflect the differential exposure to the US trade policy, with firms receiving the specific - lower - rate being the most exposed.

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).

Panel A in 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, Panel B in Table 3 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 Markets sample. 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 5 I show the results for the means differences test for the financial data. The left panel in the table shows statistically significant differences at the 10% level between the two groups in ROAA, with non-targeted firms having the larger average. After the policy, there is a statistically significant difference at the 10% level in EBITDA/A, with non-targeted firms having larger values, and DEBTAm, which is larger for targeted firms. I consider some of these variables as controls in my robustness checks.

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 the threats to identification from this approach.

4.1 Estimation Strategy: FDI

Using data on FDI announcements from 2009 to 2015, I leverage the variation given by the policy's discriminatory nature to estimate its 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. The different AD-CVD rates reflect the differential exposure to the US trade policy, with firms receiving the specific rate being more exposed compared to the firms receiving the PRC-wide rate.

Motivated by the large presence of zeros on the left-hand-side variable, my specification is a multiplicative model, and I estimate the coefficients using a Poisson Pseudo-Maximum Likelihood (PPML) method as proposed by Santos Silva and Tenreyro (2006). The authors show that in the presence of heteroskedasticity and zero values, such as FDI data, the results from log-linearized models estimated by OLS are biased estimations of elasticities. Similarly, Chen and Roth (2023) suggest using Poisson regression instead of the log-transformation log(1+Y) when Y can equal zero. Under the correct specification of the conditional mean, the data do not have to be Poisson (count data) for the estimator to be consistent (Wooldridge (2010), Gourieroux et al. (1984)). By the same token, Wooldridge (2023) shows that a difference-in-differences design with nonlinear alternatives only requires the specification of a conditional mean function. For the Poisson regression estimator, it is an exponential mean function.[4] Thus, my multiplicative model of FDI is as follows:

$$Y_{it} = exp[\sum_{s=2009}^{2015} \delta_s (D_{it} \times 1[y = s]) + \beta \boldsymbol{X}_{it} + \gamma_i + \lambda_t]\eta_{it}. \tag{1}$$

Where Y_{it} is the outcome of interest: FDI in levels, aggregation is yearly, for a firm i in period (month-year) t; D_i is the indicator for targeted 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-year); 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. When considering mergers and acquisitions, the left-hand-side variable is the existence of a M&A acquisition deal.

4.1.1 Threats to Identification

The key assumption for the difference-in-differences research design is the parallel trends assumption. This means that the pre-treatment trajectories for treated and control groups are parallel. Another necessary assumption is that the treatment is not endogenous. When this is the case, it is possible to claim that the treatment group would not have changed its trajectory with respect to the control group in the

[4]
$$E[y_i|x] = exp(x_i\beta).$$

absence of treatment (Cunningham (2021)).

My main supports for the parallel trend assumption are the event study plots in Figure 6 for FDI amounts, Figure 7 for the number of projects by firms that make more than one announcement per year, and Figure 8 for cross-border M&A deals. In all cases, the estimated coefficients show no statistically significant effects in the pre-policy period. This implies that the difference-in-differences between both groups of firms had similar trends before 2012.

When the treatment is endogenous its assignment depends on the potential outcomes. In my specification, the potential outcomes are given by the foreign direct investment activity of targeted firms after the policy. The treatment is the specific AD-CVD rate assigned by the Department of Commerce which, by targeting the largest exporters, approximates Chinese solar panel firms' exposure to US trade policy (see discussion in section 3.1.1). An endogenous treatment in this case would mean that the assignment of the specific AD-CVD rate depends on firms' FDI activity. I provide evidence that this is not the case in Table 4, showing that the results for the means difference tests are not statistically significant before the policy. Similarly, the plot of the raw data in Figure A1 reflects the variation in outcomes after the policy.

This evidence contributes to supporting the identification assumption that in the absence of treatment, the mean outcome for firms in the treated group would have evolved parallel to that of the control group. In the context of this paper, the differences in targeted and non-targeted firms' mean FDI amounts, number of projects, and cross-border M&A deals after 2011 can be explained by being granted specific AD-CVDs.

4.2 Estimation Strategy: Location Choice

Motivated by the changes in patterns shown in figure 5, I study the location choice over time. I use a logit model to estimate equation 2 with my fDi Markets sample from 2009 to 2015. A similar approach using linear probability models is shown in Appendix A.4.

$$Pr(y = 1|x) = G(\boldsymbol{x\beta}) \tag{2}$$

Where:

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

$$\boldsymbol{x'_{it}\beta} = \beta_0 + \sum_{s=1}^{7} \beta_s \times \boldsymbol{Year} + \beta_8 X_{it} + \epsilon_{it}.$$

The error term ϵ_{it} has a standard logistic distribution (Wooldridge (2010), hence function $G(\boldsymbol{x\beta})$ in equation 2 is:

$$G(\boldsymbol{x\beta}) = \frac{exp(\boldsymbol{x\beta})}{1 + exp(\boldsymbol{x\beta})}.$$

$I(region)_{it}$ is in 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, or firm. Robust standard errors are clustered at the firm level.

To have a better understanding of firms' location choice decisions, I estimate a conditional logit model as in McFadden (1974). In this model, individuals - firms - choose the option with the greatest utility from a set of alternatives. Firms' choices are at least in part explained by the observable characteristics of the alternatives. In this case, the alternatives are given by the regions in the dataset: j=1,...,6. Following Wooldridge (2010), the specification for the random utility faced by the firms is presented in equation 3:

$$y^*_{ij} = \boldsymbol{z}_j \boldsymbol{\gamma} + \boldsymbol{w}_i \boldsymbol{\delta}_j + a_{ij}. \tag{3}$$

Where y^*_{ij} is the firm's i random utility from choosing to invest in the region j; $\boldsymbol{z}_j$ is a vector of characteristics of the regions that influence FDI location (GDP per capita, inflation rate, rule of law); $\boldsymbol{w}_i$ are firm-specific characteristics (if it is a targeted firm); $\boldsymbol{\delta}_0 = \boldsymbol{0}$ as a normalization; a_{ij} are unobservables that affect the firm's location choice. This error term is assumed to be of independent random variables with a type I extreme-value distribution so the probability of investing in each region is given by:

$$P(y_i = j|\boldsymbol{z}) = \frac{exp(\boldsymbol{z_j\gamma})}{\sum_{h=1}^{J} exp(\boldsymbol{z_h\gamma})}. \tag{4}$$

I modify the original structure of my fDi Markets sample to fit this model and estimate equations 3 and 4. For every month-year, each firm has six options for where to invest: Asia, Europe, North America, Africa, Latin America, or Oceania. In the few cases where 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 with the larger magnitude gives the location choice. Robust standard errors are clustered at the firm level

Finally, 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 5 using a Linear Probability Model.

$$Y_{it} = \delta \textbf{Activity}_{it} + \beta X_{it} + \gamma_i + \upsilon_{it}. \tag{5}$$

Where Y_{it} is the probability of investing in a particular region by firm i in period t; $\textbf{Activity}_{it}$ 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; υ_{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 over time, where the percentage change is given by 100*(exp(δ)-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 6 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, including firm, month, and year fixed effects, and varying 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 2.83,8 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 increased FDI by targeted firms with respect to non-targeted firms in 2012.

In column 2, I show the estimation using the number of jobs created by the project as a control variable, 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 7 shows my estimations of the effects of the policy on 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 the number of jobs created by the project as a control variable. 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 negative 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 M&A deals: Domestic and Cross-Border

In Table 8, 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 that 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 in the year the policy is implemented. 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. Unlike the previous specification, I do not find significant effects at the 5% level. 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, increasing their presence in the Chinese domestic market as a response to the policy, and their brownfield foreign direct 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 choice for foreign direct investment.

Even though FDI location choice decisions in one country are not independent of the other alternatives, this initial test allows me to pin down pattern changes following the policy change. In addition, in the following section, I develop a conditional logit model of location choice that includes all potential alternatives.

5.4.1 Evolution Over Time

Does the location choice of targeted firms change after the policy? I test if each year has a particular effect on the probability of investing in the three relevant regions in the sample: the US, Europe, and Asia. I first approach this question by estimating equation 2. Full estimations for this logit model are presented in Table A2. I also estimate linear probability models and present the results in Table A3 in the Appendix. In Figure 9 I show the conditional marginal effects with 95% confidence intervals for the targeted firms estimated using FDI as a control variable.

The first graph shows the effects of each year in the sample on the probability of investing in the US. I do not find a statistically significant effect in any of the years. This means I cannot support the tariff-jumping hypothesis of targeted firms increasing their foreign direct investment in the US as a consequence of the AD-CVDs. These results align with those from Blonigen (2002) that finds tariff-jumping is only a realistic option for multinational firms from industrialized countries like Japan.

In the second graph, I present the effects of each year in the sample on the probability of investing in Europe. There could be different motivations for this location choice. One of them could also be tariff jumping since the European Union started anti-dumping investigations on Chinese solar panel firms in 2013, a year after the US. Another motivation could be to serve the European market, after having restricted access to the US. However, I do not find support for either of these. My estimations show that from 2013 until the end of the period, there is a statistically significant negative effect on the probability of investing in Europe for targeted firms.

The third graph shows the effects of each year in the sample on the probability of investing in Asia. Here, the estimations show a positive trend after 2013 and statistically significant effects in 2015. After receiving a negative shock like AD-CVDs, there might be different motivations for Chinese firms to increase their presence in other Asian countries. For instance, a necessity for reducing costs and increasing efficiency, thus promoting production fragmentation in the region (vertical FDI); establishing new plants that could later export to the US (export platform FDI); or increasing their presence in China or other domestic Asian markets. Some of these strategies are addressed by the companies in their Annual Reports or other communications, as shown in quotes here and the Appendix A.7:

The company's external affairs department told reporters that at the beginning of the case, the company began to strengthen its "internal skills" practice, and actively explored emerging markets while enhancing product competitiveness. It has reached a number of export contracts and intentions with emerging market countries, making up for the loss of exports to the United States. (CNPV Solar Power)[5]

In the face of Europe and the United States' anti-dumping, the company actively expands emerging markets, deepens the industrial chain, and avoids risks brought about by international trade frictions to the greatest extent. (Zhejiang Sunflower Light)[6]

The company announced plans to expand its solar panel production capacity in Malaysia. This shows that panel manufacturers will deploy new production capacity in a trade-neutral zone to export to the world, while China's production capacity is for domestic consumption (Hanwha Q CELLS).[7]

5.4.2 Location Choice in 2015

The results above show statistically significant results for the year 2015. There are positive effects on the probability of targeted firms investing in Asia and negative effects for Europe. However, the estimated effects are small and close to zero. I take a deeper look into what these initial results suggest to have a better understanding

[5] 2012 website article.

[6] 2012 Annual Report.

[7] 2014 website article.

of the effects of the policy on the location choice decision. I do this by estimating a conditional logit model of location choice for the year 2015.

Table 9 presents the conditional marginal effects for the estimations from equation 4. The control variables are GDP per capita, inflation rate, and a rule of law index. [8] Table A4 in the Appendix does the same without the rule of law as a control variable.

Panel A of the table shows the conditional marginal effects for targeted firms on the predicted probability of choosing from the set of location choices J=1,...,6. These outcomes are shown in each row: Asia, Europe, North America, Africa, Latin America and the Caribbean, and Oceania. The first column gives predicted probabilities of the outcome. The second column shows the standard errors clustered at the firm level. The following columns present the z-statistic, the results for the z-test, and the 95% confidence interval.

The coefficient 0.363 is the expected probability of a targeted firm investing in Asia in 2015 with respect to the non-targeted group. This means that targeted firms have a 36.3% higher probability of locating in Asia than non-targeted firms. This result is statistically significant as shown by the z-statistic and the 95% confidence interval. The coefficient -0.421 is the expected probability of a targeted firm investing in Europe in 2015 with respect to the base outcome. This represents a 42.1% smaller probability of investing in Europe for the firms in the targeted group compared to the non-targeted. This result is also statistically significant, as shown by the respective statistics. The estimated coefficients for the rest of the location choices are not statistically significant or cannot be estimated in the case of Oceania.

Thus, we can conclude that the two groups of firms have different reactions to the policy in terms of location choice in 2015, with targeted firms choosing to locate their investments in Asia.

[8] These variables are extracted from the World Development Indicators.

5.4.3 Industry Activities: Vertical FDI

I move to the vertical FDI hypothesis and estimate equation 5 for Asia in 2015, the region and year where I find statistically significant effects in my previous models. Thus, in Table 10, 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.

After analyzing the estimations for the four columns, I 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, 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: Export Platform FDI

To contribute to understanding whether the export platform hypothesis applies in this case, I take a deeper look at the data. Considering the destination countries in Figure 10, 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 A2 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 11, 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 determine if the new plants become exporters. The numbers in the chart show the quantity imported from each country (in million units) and, in parentheses, 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 over 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 A3. 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 11, 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 that 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 in 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 12, 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 a firm. The main explanatory variables are the interaction between the indicator for targeted firms and the year. I present three specifications, all of which 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 in 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 the total debt percentage of total assets as a control variable. 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.

Column 3 in this table presents the estimations controlling 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 provide insight into the effect heterogeneity. A sub-sample of firms experiences a larger reaction to the policy, reflected in the amounts of their new investments and the effects lasting up to three years after.

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 in 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

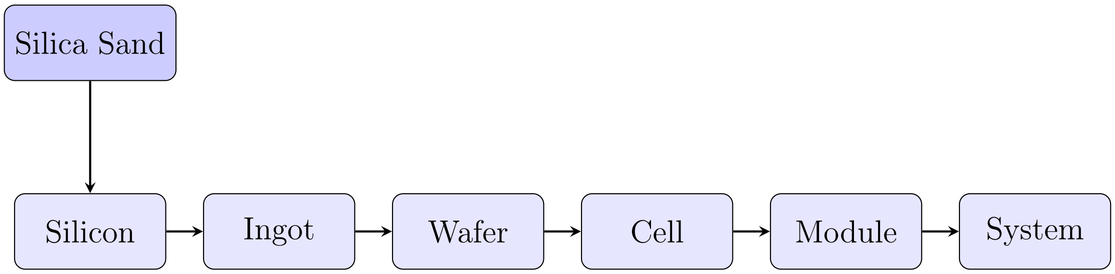
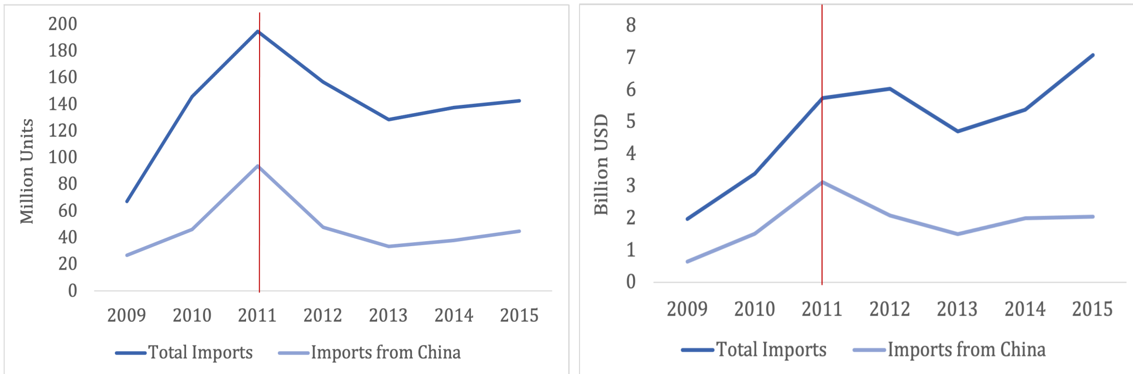


Figure 2. Economic Performance of the Chinese Solar Industry

Source: IBISWorld (2021)

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



Source: USITC (2021)

Figure 4. Policy's Timeline

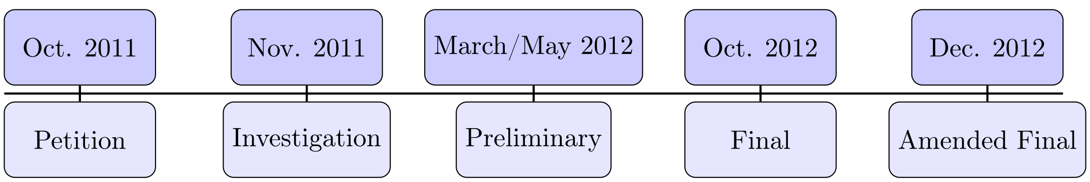


Table 1. fDi Markets Sample Description

Panel A: 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
Panel B: 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

NOTE: This table describes the variables in my fDi markets sample. Panel A shows the percentage of observations within the environmental technology cluster by industry sector, sub-sector, and industry activity. Panel B shows the type of projects and their locations.

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

NOTE: This table presents the summary statistics in my fDi markets sample after expanding the sample as a panel with one observation per firm per month during the period 2009-2015.

Table 3. Characteristics of M&A Deals by Chinese Firms

Panel A: By Country	Target	Percent
	China	68
	Hong Kong	10
	United States	7
	Portugal	2
	Sweden	2
	United Kingdom	2
	Other	6
Panel B: By Industry		
Acquiror	Target	Percent
Horizontal		
Electronic and Electrical Equipment	Electronic and Electrical Equipment	49
Vertical		
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		20

NOTE: This table describes the Thomson and Reuters M&A data from 2009 to 2014. Panel A shows target countries for M&A deals. Panel B shows the Industry of Acquiror and Target companies. When the industry is the same in both companies is a horizontal deal, otherwise, it is a vertical deal.

Table 4. 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	Mean	1.23	0.75	0.48	0.54	3.75	6.72	-2.97	-1.35
(mill.USD)	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		

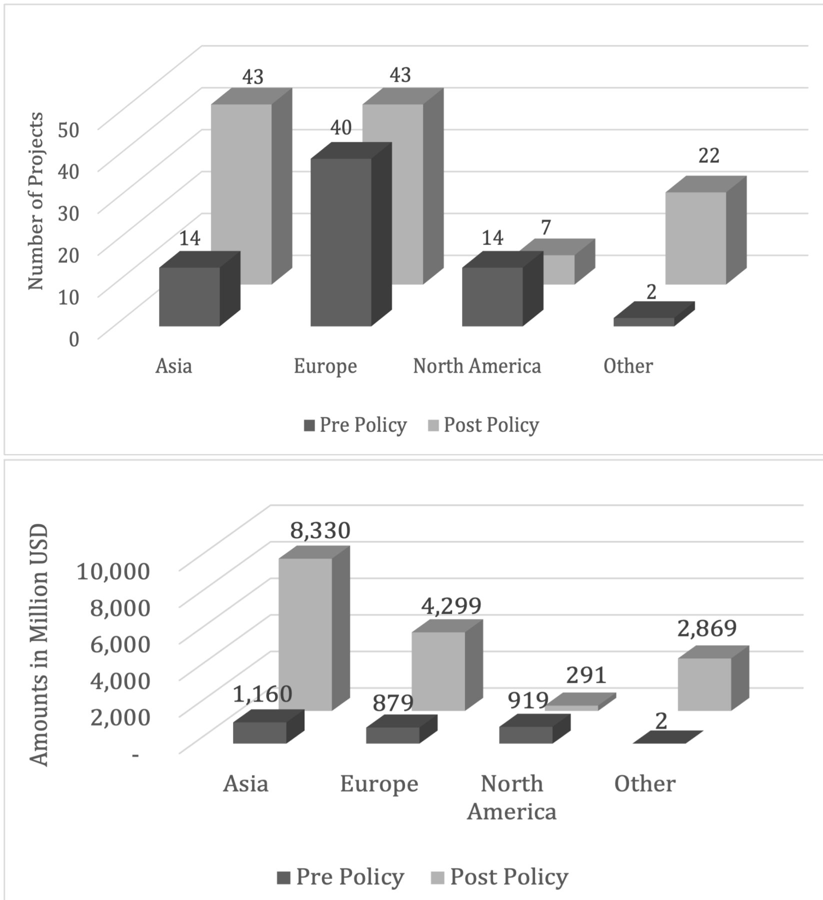
NOTE: This table presents the means differences test for my fDi markets sample. The differences are statistically significant at the 10% level if the t-statistic is greater than 1.645, and at the 5% level if it is larger than 1.96.

Table 5. 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		

NOTE: This table presents the means differences test for my Refinitiv sample. The differences are statistically significant at the 10% level if the t-statistic is greater than 1.645, and at the 5% level is it larger than 1.96. CapEx is Capital Expenditure; Proft Mg is Gross Profit Margin; EBITDA/A is Earnings Before Interest, Taxes, Depreciation, and Amortization divided by assets; ROAA is the Return on Average Total Assets; DEBTA is the Total Debt Percentage of Total Assets; Log of Assets takes the logarithm of Assets.

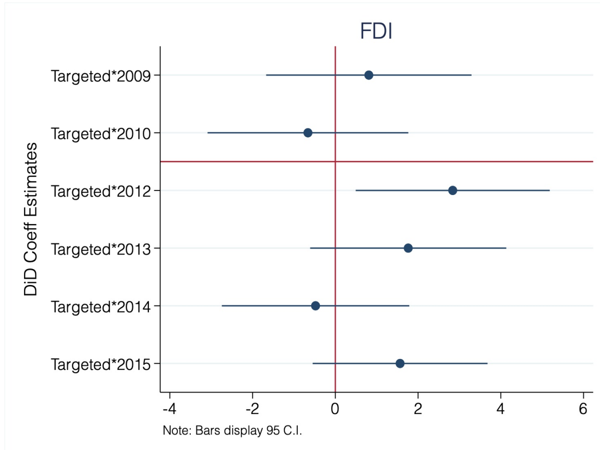
Figure 5. Projects Pre and Post Policy by Location: Number & Amounts



Source: fDi markets

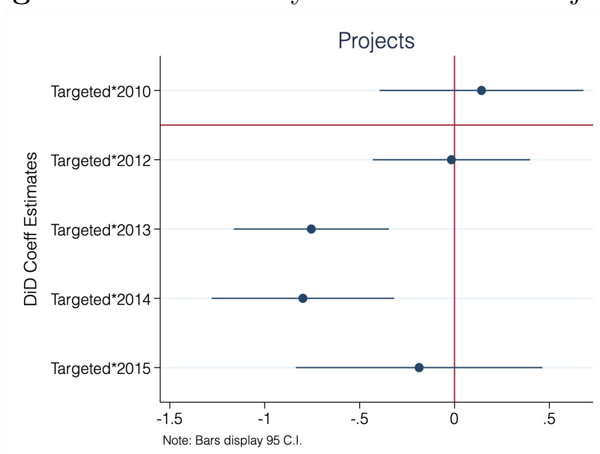
NOTE: The top panel in this figure shows the total number of projects by region announced from 2009 to 2011 (Pre Policy), and from 2012 to 2015 (Post Policy). The bottom panel shows the same information in millions of US dollars.

Figure 6. Event Study for FDI Amounts



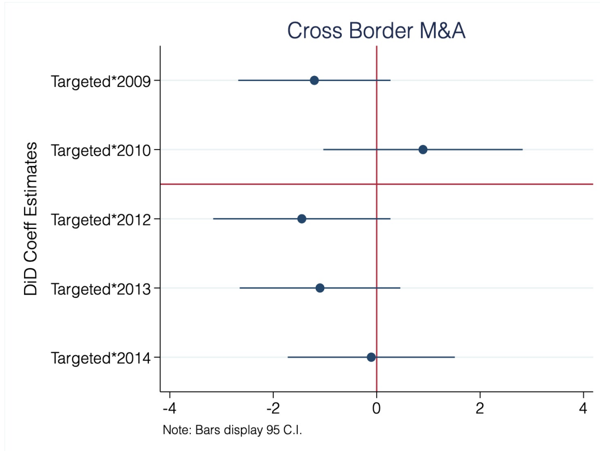
NOTE: This figure shows the estimations based on equation 1 using FDI as a dependent variable with no control variables. The source is fDi Markets data from 2009 to 2015.

Figure 7. Event Study for Number of Projects



NOTE: This figure shows the estimations based on equation 1 using the number of projects per year as a dependent variable with no control variables. The sample is restricted to firms making more than one announcement per year. It does not show results for 2009 due to lack of observations. The source is fDi Markets data from 2009 to 2015.

Figure 8. Event Study for Cross-Border M&A



NOTE: This figure shows the estimations based on equation 1 using the existence of a cross-border merger and acquisition deal as a dependent variable with no control variables. The source is Thompson and Reuters M&A data from 2009 to 2014.

Table 6. Effects of Trade Barriers on FDI

Panel A: Estimation of coefficients (PPML)			
	(1) FDI	(2) FDI	(3) FDI
Targeted*2009	0.810	0.826	-0.321
	(1.267)	(1.258)	(1.249)
Targeted*2010	-0.662	0.223	-0.224
	(1.238)	(1.780)	(1.221)
post-policy			
Targeted*2012	2.838**	2.464**	2.352*
	(1.197)	(1.034)	(1.243)
Targeted*2013	1.762	1.795	2.281
	(1.209)	(1.177)	(1.639)
Targeted*2014	-0.478	-0.303	0.985
	(1.156)	(1.173)	(1.221)
Targeted*2015	1.566	0.983	2.392*
	(1.078)	(1.417)	(1.301)
Fixed effects			
Firm	✓	✓	✓
Month	✓	✓	✓
Year	✓	✓	✓
Controls			
Jobs		✓	
Projects			✓
Observations	6468	6468	6468
PseudoR^2	0.372	0.475	0.762
Panel B: Economic valuation of coefficients (in million dollars)			
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*(exp(δ)-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 7. Effects of Trade Barriers on the Number of Projects

Panel A: Estimation of coefficients (PPML)			
	(1) Projects	(2) Projects	(3) Projects
Targeted*2010	0.142	0.117	0.149
	(0.274)	(0.274)	(0.292)
post-policy			
Targeted*2012	-0.0162	-0.0209	0.0132
	(0.212)	(0.213)	(0.209)
Targeted*2013	-0.755***	-0.708***	-0.827**
	(0.209)	(0.166)	(0.342)
Targeted*2014	-0.799***	-0.800***	-0.839***
	(0.245)	(0.238)	(0.189)
Targeted*2015	-0.186	-0.234	-0.223
	(0.331)	(0.340)	(0.351)
Fixed Effects			
Firm	✓	✓	✓
Year	✓	✓	✓
Controls			
Jobs		✓	
FDI			✓
Observations	552	552	552
PseudoR^2	0.099	0.099	0.101
Panel B: Percentage change in the number of projects			
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

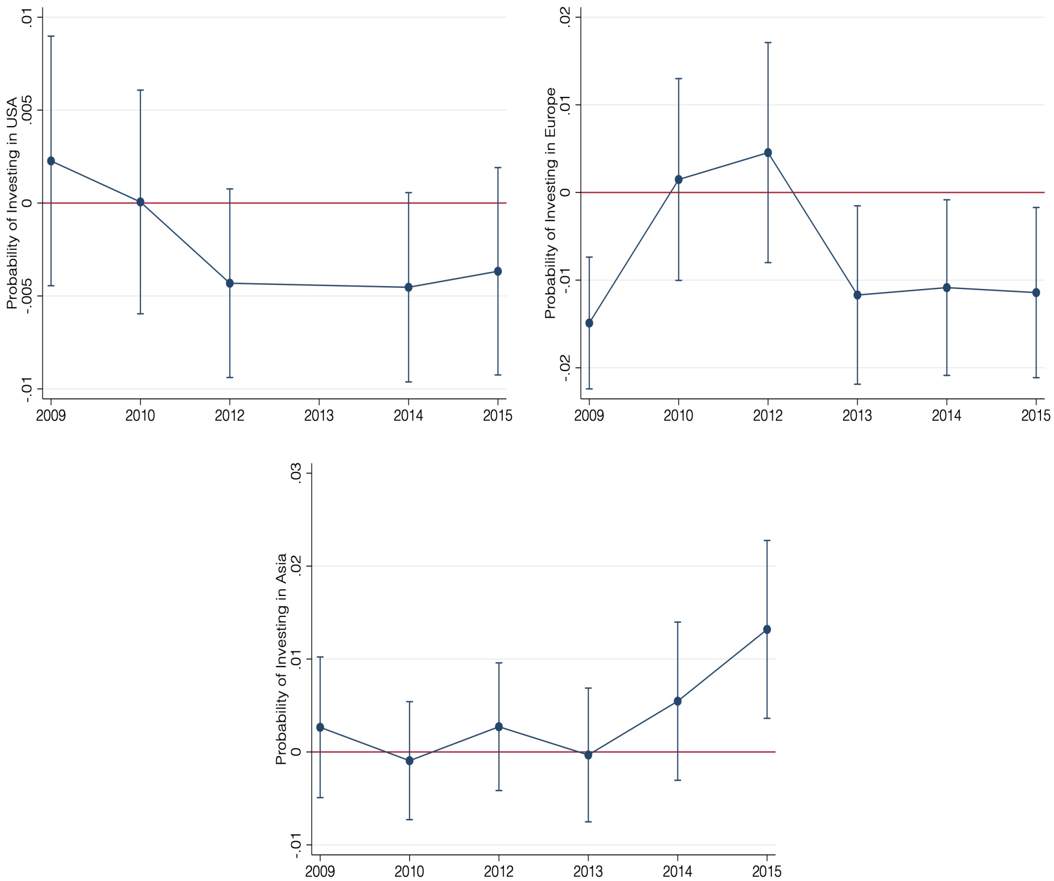
NOTE: Panel A of this table presents the results of the PPML estimations for equation 1 using fDi markets data from 2009 to 2015 for the subsample of firms that make more than one announcement per year. The dependent variable equals the number of announced projects per year. It does not show results for the year 2009 due to lack of observations. The coefficients represent semi-elasticities. The percentage change is calculated as=100*(exp(δ)-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 8. Effects of Trade Barriers on M&A

Panel A: Estimation of coefficients (PPML)		
	(1) M&A	(2) M&A
Targeted*2009	-0.614	-1.205
	(0.614)	(0.751)
Targeted*2010	1.163	0.896
	(0.985)	(0.983)
post-policy		
Targeted*2012	-1.469**	-1.448*
	(0.684)	(0.875)
Targeted*2013	-0.960	-1.096
	(0.729)	(0.792)
Targeted*2014	-0.291	-0.105
	(0.694)	(0.824)
Fixed Effects		
Firm	✓	✓
Month	✓	✓
Year	✓	✓
Controls		
Completed	✓	✓
Cross Border		✓
Observations	1512	1512
PseudoR^2	0.299	0.329
Panel B: Percentage change in M&A		
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*(exp(δ)-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 9. Location Choice by Year for Targeted Firms



NOTE: These figures show the conditional marginal effects with 95% confidence intervals for targeted firms on the predicted probability of investing in the US for the first graph, Europe for the second, and Asia for the third. Estimations are based on equation 2 using FDI as the control variable. Coefficients for the US in 2013 cannot be estimated due to a lack of observations.

Table 9. Location Choice in 2015

Conditional Marginal Effects (delta-method)						
0.Non-targeted	(base outcome)					
1.Targeted	dy/dx	std. err.	z	P>z	[95% conf.	interval]
Outcome:						
Asia	0.363	0.130	2.800	0.005	0.109	0.617
Europe	-0.421	0.122	-3.440	0.001	-0.661	-0.181
North America	-0.085	0.067	-1.260	0.209	-0.217	0.047
Africa	0.084	0.082	1.030	0.303	-0.076	0.244
Latin America & Caribbean	0.075	0.079	0.940	0.345	-0.080	0.229
Oceania	-0.016	0.012	-1.380	0.168	-0.039	0.007

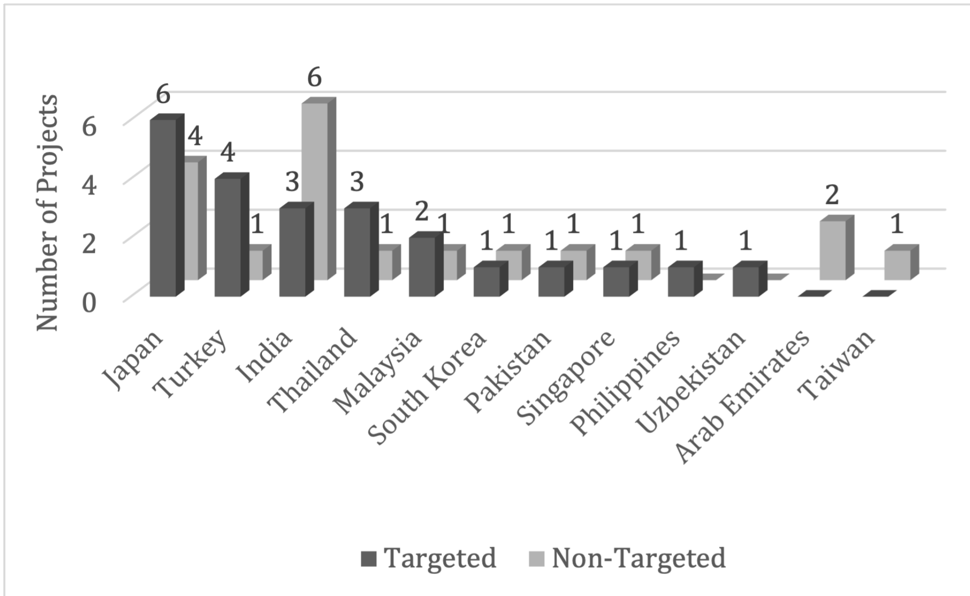
NOTE: This table shows the conditional marginal effects for targeted firms on the predicted probability of choosing from the set of location choices J=1,...,6. Estimations are based on the conditional logit model from equation 4, using as control variables GDP per capita, inflation rate, and an index of the rule of law. dy/dx is the discrete change from the base level.

Table 10. Production Relocation in Asia

Linear Probability Estimation of Investing in Asia in 2015 by Firms:				
Industry	(1)	(2)	(3)	(4)
Activity	Targeted	Non-Targeted	Targeted	Non-Targeted
Electricity	0.784***	0.212	0.757***	-0.162
	(0.146)	(0.154)	(0.149)	(0.278)
Manufacturing	0.830***	0.563**	0.742***	-0.120
	(0.147)	(0.261)	(0.248)	(0.502)
Sales	0.979***	0.494*	0.898***	-0.234
	(0.014)	(0.252)	(0.084)	(0.444)
Headquarters	-0.021	-0.003***	-0.100	-0.589**
	(0.014)	(0.001)	(0.084)	(0.224)
Logistics	-0.002		-0.172	
	(0.001)		(0.165)	
Design		-0.001***		-0.589**
		(0.000)		(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 5 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 a firm investments in Asia in a specific month, and zero otherwise. The coefficients multiplied by 100 represent the percentage change. Some coefficients are not 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.

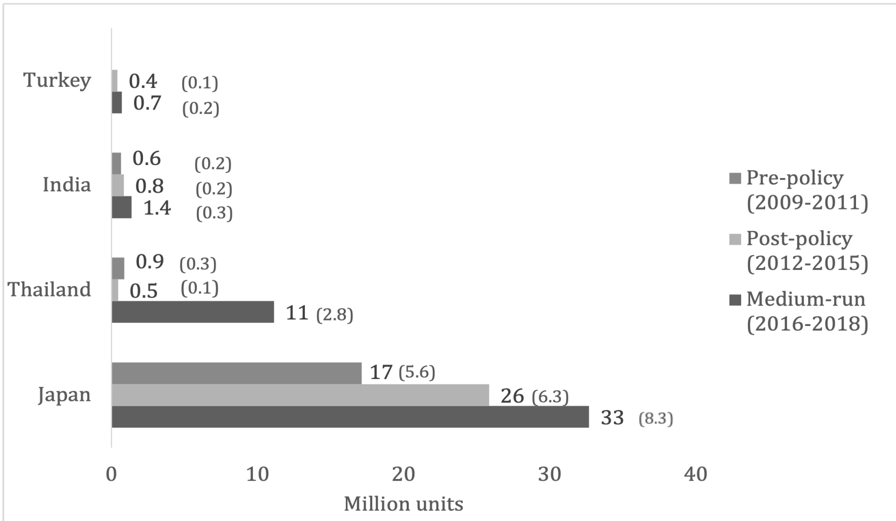
Figure 10. FDI in Asian Countries Post-Policy by Group of Firms



Source: fDi markets

NOTE: This figure shows the number of projects in Asia announced by targeted and non-targeted firms from 2012 to 2015.

Figure 11. US Imports of Solar Cells by Country of Chinese FDI Destination: Million Units & (Percentage of Total)



Source: USITC

NOTE: This figure shows the number of solar cells in million units imported into the US from selected Asian countries from 2009 to 2018 by sub-periods. In parenthesis is the number as a share of total US imports of solar cells in each sub-period.

Table 11. Effects of Trade Barriers on FDI - Anticipation Test

Panel A: Estimation of coefficients (PPML)		
	(1)	(2)
	FDI	FDI
Targeted*2009	1.208	0.483
	(1.350)	(1.506)
Targeted*2010	-0.264	-0.989
	(1.288)	(1.451)
post-policy		
Targeted*2012	3.181**	2.456*
	(1.274)	(1.437)
Targeted*2013	2.160	1.435
	(1.467)	(1.610)
Targeted*2014	-0.0802	-0.805
	(1.233)	(1.400)
Targeted*2015	1.963*	1.239
	(1.173)	(1.345)
Fixed Effects		
Firm	✓	✓
Month	✓	✓
Year	✓	✓
Period Removed		
Nov.2011-Apr.2012	✓	
Sep.2011-Apr.2012		✓
Observations	5382	5092
PseudoR^2	0.362	0.379
Panel B: Economic valuation of coefficients (in million dollars)		
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*(exp(δ)-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 12. Effects of Trade Barriers on FDI - Financial Sub-Sample

Panel A: Estimation of coefficients (PPML)			
	(1)	(2)	(43)
	FDI	FDI	FDI
Targeted*2009	-0.422	-0.227	-2.400
	(1.604)	(2.089)	(1.853)
post-policy			
Targeted*2012	5.271***	5.285***	6.609***
	(1.768)	(1.668)	(2.027)
Targeted*2013	1.937	1.892	2.378
	(1.860)	(1.845)	(2.139)
Targeted*2014	1.151	0.812	-1.851
	(2.174)	(1.987)	(1.779)
Targeted*2015	3.755*	2.982	3.826**
	(1.941)	(1.984)	(1.913)
Fixed Effects			
Firms	✓	✓	✓
Year	✓	✓	✓
Controls			
CapExAs	✓		✓
DEBTA		✓	✓
Observations	96	89	82
PseudoR^2	0.770	0.783	0.864
Panel B: Economic valuation of coefficients (in million dollars)			
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*(exp(δ)-1)%. Standard errors clustered at the firm level are shown in parentheses. Results for the year 2010 are not estimated due to a lack of observations. 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

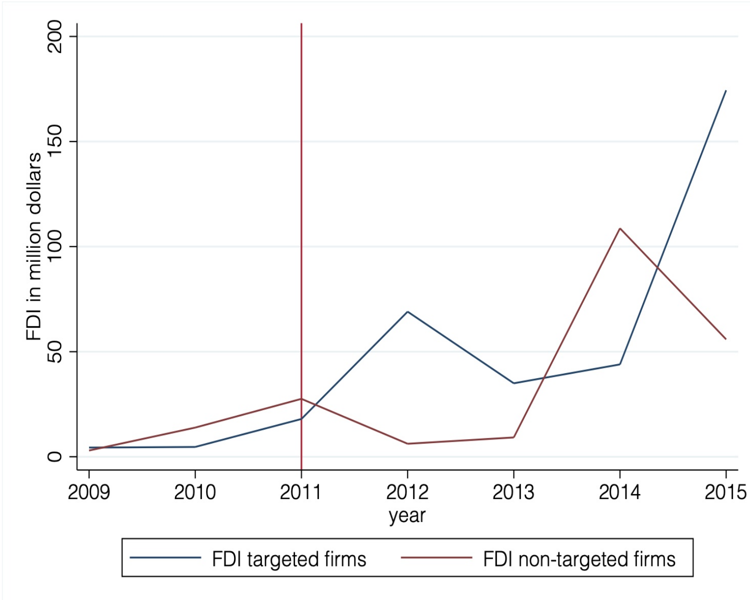
Panel B: Weight of Imports by HTSUS Code (Percent)

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 More on Targeted and Non-Targeted firms

Figure A1. FDI amounts by group of firms



NOTE: This figure plots the raw data for the average FDI amounts per year by groups of firms. The red vertical line shows the last year without the effects of the policy (2011). The source is fDi markets data from 2009 to 2015.

A.3 Logit Models

In Table A2 I show the logit coefficients estimated using equation 2.

Table A2. Location Choice Over Time

	Logit 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	0.353	0.987	0.340	-1.722***	-2.119***	-1.749***	0.519	1.322	0.313
	(0.536)	(0.705)	(0.541)	(0.553)	(0.750)	(0.566)	(0.803)	(1.369)	(0.658)
year=2010	0.0110	-0.114	-0.0463	0.0798	0.217	0.0283	-0.273	-1.804	-1.747
	(0.569)	(0.881)	(0.581)	(0.314)	(0.387)	(0.319)	(0.901)	(2.215)	(1.628)
year=2012	-1.608	-1.501	-1.619	0.228	0.315	0.211	0.529	0.996	0.272
	(1.103)	(1.242)	(1.105)	(0.317)	(0.349)	(0.320)	(0.766)	(1.231)	(0.640)
year=2013				-1.042*	-0.815	-1.055**	-0.0857	0.675	-0.773
				(0.534)	(0.654)	(0.538)	(0.970)	(1.489)	(1.102)
year=2014	-1.834	-5.147	-1.620	-0.919**	-1.741**	-0.770*	0.877	1.560	0.747
	(1.257)	(3.736)	(1.105)	(0.459)	(0.876)	(0.435)	(0.777)	(1.224)	(0.626)
year=2015	-1.143	-1.506	-1.101	-1.000**	-1.422*	-0.896**	1.485**	2.415**	1.071*
	(0.964)	(1.576)	(0.927)	(0.504)	(0.800)	(0.445)	(0.718)	(1.079)	(0.550)
Controls									
Firm ID	✓	✓	✓	✓	✓	✓	✓	✓	✓
Other	FDI	Projects	Jobs	FDI	Projects	Jobs	FDI	Projects	Jobs
Observations	5544	5544	5544	6468	6468	6468	6468	6468	6468
PseudoR^2	0.0533	0.417	0.0475	0.0626	0.516	0.0411	0.168	0.531	0.260

NOTE: This table presents the logit coefficients for the estimations based on equation 2. The dependent variables are all binary indicators and equal to 1 if the firm makes an FDI investment in the US (columns 1, 2, 3); Europe (columns 4, 5, 6); and Asia (columns 7, 8, 9). Some coefficients are not estimated due to a lack of observations. Standard errors clustered at the firm level are shown in parentheses. Statistical significance levels are given by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.4 Linear Probability Models

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

$$Y_{it} = \delta \mathbf{Year} + \beta X_{it} + \gamma_i + \epsilon_{it}. \tag{6}$$

Where is Y_{it} the probability of investing in a particular region for a 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; 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 A3, are in line with the logit estimations presented above. Overall, these results confirm the logit estimations for targeted firms. I do not find support for the tariff-jumping hypothesis that would imply a positive effect of the years after the policy on the probability of investing in the US. I find a negative and statistically significant effect in 2015 on the probability of investing in Europe, and positive, although not significant for all specifications, effects on the probability of investing in Asia in 2015.

Table A3. Location Choice Over Time

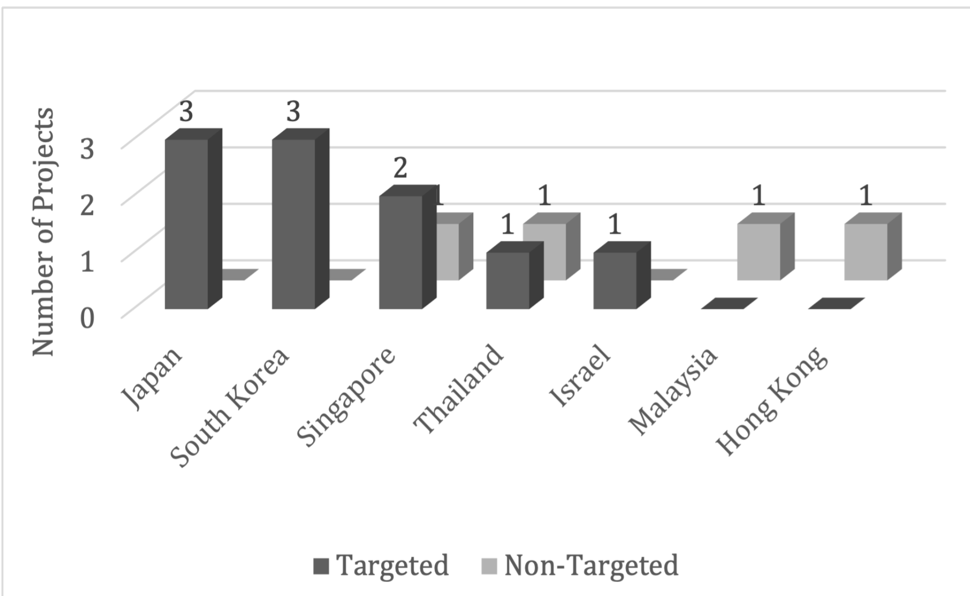
	Linear Probability Estimation of Targeted Firms Investing in:								
	(1) USA	(2) USA	(3) USA	(4) Europe	(5) Europe	(6) Europe	(7) Asia	(8) Asia	(9) Asia
year=2009	0.007	0.008	0.007	-0.010	-0.006	-0.010	-0.002	0.000	-0.003
	(0.008)	(0.008)	(0.008)	(0.007)	(0.006)	(0.007)	(0.011)	(0.009)	(0.011)
year=2010	0.007	0.007	0.007	0.007	0.008	0.007	-0.012	-0.012*	-0.013
	(0.008)	(0.007)	(0.008)	(0.012)	(0.009)	(0.012)	(0.009)	(0.006)	(0.009)
year=2012	-0.007	-0.008	-0.007	0.012	0.010	0.013	-0.004	-0.004	-0.002
	(0.007)	(0.007)	(0.007)	(0.012)	(0.010)	(0.012)	(0.009)	(0.010)	(0.010)
year=2013	-0.010*	-0.006	-0.010*	-0.007	0.002	-0.007	-0.011	-0.002	-0.010
	(0.006)	(0.005)	(0.006)	(0.011)	(0.010)	(0.012)	(0.010)	(0.008)	(0.009)
year=2014	-0.010*	-0.009*	-0.010*	-0.011	-0.008	-0.010	-0.009	-0.005	-0.007
	(0.006)	(0.005)	(0.006)	(0.010)	(0.009)	(0.010)	(0.008)	(0.008)	(0.009)
year=2015	-0.010*	-0.011**	-0.011*	-0.021***	-0.019***	-0.018***	0.014	0.024**	0.012
	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.013)	(0.010)	(0.013)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	FDI	Projects	Jobs	FDI	Projects	Jobs	FDI	Projects	Jobs
Observations	2100	2100	2100	2100	2100	2100	2100	2100	2100
Within R^2	0.008	0.162	0.010	0.025	0.311	0.007	0.169	0.311	0.187

NOTE: This table shows the results for the Linear Probability Model estimations based on equation 6. The sample is restricted to targeted firms. The dependent variables are all binary indicators and equal to 1 if the firm makes an FDI investment in the US (columns 1, 2, 3); Europe (columns 4, 5, 6); and Asia (columns 7, 8, 9). The coefficients multiplied by 100 represent the percentage change. Standard errors clustered at the firm level are shown in parentheses. Statistical significance levels are given by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.5 Destination Countries in Asia Pre-Policy

In Figure A2, 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 10. 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.

Figure A2. FDI in Asian Countries Pre-Policy by Group of Firms



Source: fDi markets

NOTE: This figure shows the number of projects in Asia announced by targeted and non-targeted firms from 2009 to 2011.

A.6 Marginal Effects of Conditional Logit Model

In this section, I present the estimations for the conditional logit model of location choice using as a control variable the number of jobs created.

Table A4. Location Choice in 2015

Conditional Marginal Effects (delta-method)						
0.Non-targeted	(base outcome)					
1.Targeted	dy/dx	std. err.	z	P>z	[95% conf.	interval]
Outcome:						
Asia	0.524	0.096	5.470	0.000	0.336	0.712
Europe	-0.513	0.092	-5.550	0.000	-0.694	-0.332
North America	-0.079	0.048	-1.640	0.101	-0.173	0.015
Africa	0.050	0.086	0.590	0.558	-0.118	0.219
Latin America & Caribbean	0.069	0.076	0.900	0.366	-0.081	0.219
Oceania	-0.052	0.029	-1.810	0.070	-0.108	0.004

NOTE: This table shows the conditional marginal effects for targeted firms on the predicted probability of choosing from the set of location choices J=1,...,6. Estimations are based on the conditional logit model from equation 4 using as control variables GDP per capita and the inflation rate the number of jobs created as a control variable. dy/dx is the discrete change from the base level.

A.7 Selected Firms' Quotes on Their Reaction to the Policy

Some of the company's products are sold overseas, and the trade protection policies of importing countries will have a certain impact on the company's overseas sales... In this regard, the company will increase its efforts in emerging markets including the domestic market development, actively demonstrate corresponding measures, etc. (Risen Energy)[9]

In order to effectively avoid the potential risks brought by dumping and anti-dumping, Phono Solar reached a cooperation with a Vietnamese partner last year and established a local module manufacturing base. It is a powerful measure to further enhance its ability to supply to the world, and thus achieve smooth shipments to Europe the United States, and other regions. (Phono Solar)[10]

According to Wang Yiyu, chief financial officer of Yingli Green Energy, recently, the past pattern of relying solely on European and American markets has been broken, and Yingli will focus on developing emerging markets such as Southeast Asia in the next step. Yingli began to vigorously develop emerging markets such as China, Southeast Asia, and Africa. (Yingli)

[9] 2014 Annual Report.
[10] 2017 website article.

Table A5. Change in US Imports of Solar Cells by Sub-Period

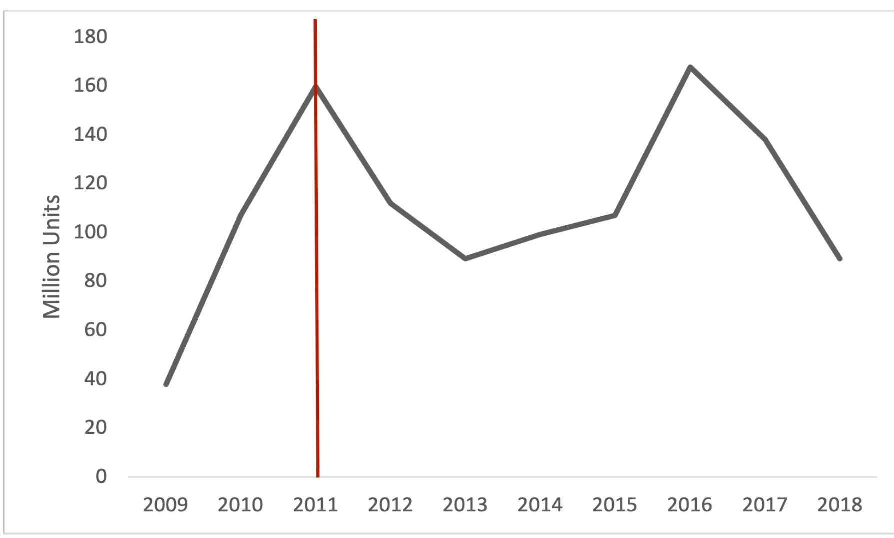
Percent	Sub-Period
320	2009 to 2011
-4	2012 to 2015
-20	2012 to 2018
135	2009 to 2018

Source: USITC

A.8 US Imports of Solar Cells 2009 to 2018

Figure A3 shows the evolution in a 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. A decrease follows the recovery from 2013 to 2016 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 A5, where we observe that the years after the policy show a decrease in the number of imports.

Figure A3. US Imports of Solar Cells from 2009 to 2018



Source: USITC (2021)

NOTE: This figure shows imported solar cells in million units in the US from 2009 to 2018.