THE EFFECT OF ANTIDUMPING PROTECTION ON R&D INVESTMENT

BACHELOR THESIS GENERAL ECONOMICS

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Abstract: This thesis studies the effect of antidumping protection measures on R&D investments of firms in the U.S. in the years 2009-2014. Three difference-in-differences models are estimated, using a proxy of R&D investments per product. This proxy consists of U.S. imports and industry level R&D expenditures. Furthermore, the analysis controls for a self-selection bias by only including products that belong to antidumping claim sensitive industries. No significant effect is found in this study.

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TABLE OF CONTENTS

I. INTRODUCTION

Since the mid-19th century, a large number of economists and politicians stand for free world trade. Tariffs, subsidies and other trade barriers have become undesirable and are partly banned in international treaties and agreements. In the discussion about trade barriers, the antidumping debate arises. Academics are arguing that antidumping protection is a disguised import tariff and a broadly misused regulation (Pierce, 2000).

Antidumping protection, as the name says, protects local producers against dumping. Dumping is a practice in which foreign producers export their products against an unacceptably low price. This harms local producers in the importing country. Therefore, this practice is forbidden in the WTO regulation the General Agreement for Tariffs and Trade (GATT). Countries in which local producers feel harmed by dumped products, can file an antidumping claim at the WTO Dispute Settlement Body (WTO, 2017). This authority investigates whether a specific product from a specific country has been dumped. If its finding is affirmative, a minimum price level for the product is set. From that moment on, imports originating from all countries must be priced above that level. To illustrate, in the U.S. in 2017, 85 antidumping protection measures were in force. Thus, imports of 85 different products were subject to a minimum price. Foreign exporters can either choose to raise their price, referred to as undertaking, or pay a fine to the U.S. government, called an antidumping duty. Academics are debating about whether this is not as much a free trade barrier as any other import tariff.

One of the concerns with regards to trade barriers in general, is that competition is reduced and firms are less triggered to work efficiently. This gives rise to the hypothesis that trade barriers might discourage investments in research and development. Several academics support this hypothesis and find a positive relation between innovation and R&D and open international trade (eg. Baldwin & Gu, 2004). Researchers also found that antidumping claims mainly occur in R&D intensive industries such as chemicals, primary metals, electronics and mechanical engineering (Niels, 2000, Gao, 2005). These findings raise a new question: What is the relationship between antidumping protection and R&D investments? Based on free trade theory, a negative correlation is expected. On the other hand, some academics argue that temporary protection can allow local producers to gain enough profits to reinvest in R&D. In 2005, Gao and Miyagiwa published a theoretical framework with which they found a negative effect of antidumping protection on the R&D investment incentive. Besides Gao's framework, no other study of this relationship exists. Therefore, I will empirically study the effect of antidumping protection on R&D investments, using data on R&D investments and antidumping protection measures in the U.S. in the years 2009-2014. By transforming the R&D investments per industry to R&D investments per product using a proxy based on imports, I estimate three difference-in-differences estimators of the relationship between antidumping protection and R&D investments. Model 1 and 2 estimate an effect on the investment level and model 3 estimates an effect on the investment percentage change. The selection of the control and treatment group of this analysis controls for a self-selection bias. In this thesis, the industries in which imports of at least one product were investigated for antidumping protection, will be called the *antidumping industries*. With this is meant, all investigated products make an industry an antidumping industry. Also the ones with a non-affirmative outcome. Only products that belong to an antidumping industry are included in the control group. This controls for the risk that in these antidumping industries, margins were decreasing in the studied years. This is likely because producers that see their margins decrease, might tend to lobby for antidumping protection. Decreasing margins can also have a negative effect on R&D investments. None of the difference-in-differences models prove a significant effect of antidumping protection on R&D investments. Nevertheless, it is important to further study this relationship, due to an important caveat in this thesis. If one is able to calculate a better proxy for product R&D expenditures, the results might be radically different.

In the next section, I describe the relevant literature in the field of antidumping laws, economic effects of antidumping protection, the effect of trade barriers on R&D, and the relationship between antidumping protection and R&D investments. In the data section, I clarify the composition of my dataset. In that section I show with the product *industry import penetration* that industry level analysis is impossible. Furthermore, I describe how the variables *effective antidumping rate* and *R&D per product* are established. In the methodology section, I describe the selection of the control and treatment group and motivate what difference-in-differences models I use in the analysis. In the results section, I discuss the outcomes of the models. Lastly, in the conclusion and discussion, I summarize key findings and suggest how future research in this field can be done effectively.

II. LITERATURE REVIEW

To put the debate about antidumping protection and its effects in context, I will give a brief summary of the history, economic effects and the relationship between innovation and antidumping protection. Furthermore, I discuss literature from related fields of study, like price discrimination, predation and effects of trade barriers in general.

History of antidumping laws

In the early 19th century, the first antidumping laws were established. These laws mainly concerned fear of monopolization: foreign firms predating domestic firms (Viner & Kelley, 1923). After 1921, the aim of antidumping laws shifted towards obtaining 'fairness'. This was about not letting foreign firms obtain market share at the expense of domestic producers. In 1947, antidumping law was internationally recorded in the 1947 GATT, even though it took several decades before most countries implemented the provisions (Finger, 1991). The discussion about the effects of antidumping protection arose during the 1980's. In this period, antidumping laws started to become a substitute for other kinds of trade barriers, which were dismantled in order to liberalize trade. Between 1979 and 1998 the number of countries that had adopted antidumping laws increased from less than 10 to about 60 (Niels, 2000). In this period, the main use shifted from the USA, EU, Canada and Australia towards developing countries.

Theory of antidumping

For determining whether products are dumped, and how severely they are dumped, the *dumping margin* must be calculated. Generally, the dumping margin is the difference between the export price of a certain product and the fair price of that product. The higher the dumping margin, the more harmful the practice is for domestic producers. Dumping margins are key in determining the antidumping duties that the dumpers have to pay. Several methods in the determination of fair prices and therewith dumping margins have emerged in the past decades. Traditionally, the product selling prices in home or third countries were seen as the fair price. Since the 1980's, the *constructed value*-method is of more common use. In this practice, the production costs plus a reasonable profit margin indicate the fair price of a product. Another method for computing dumping margins, is by determining the volume of dumped imports and their effect on domestic prices and quantities. In this method, the fair price is not the main determining factor, but the loss of revenue suffered by domestic producers due to the dumpers. This method is called *material injury determination*.

The WTO adopts the material injury determination concept in the GATT, but does not define injury or a precise dumping margin calculation method. National authorities can therefore implement their own rules and measures to determine the exact dumping margins (Niels, 2000). This freedom leads to disagreements. An example, is a recent debate about whether *zeroing* is a validate manner to compute antidumping margins (Vermulst & Ikenson, 2007). Zeroing is a calculation method which gives relatively high dumping margins. Without the zeroing, prices that are above costs at a certain moment in time, can offset prices that are below costs at another moment in time. With zeroing, this is not possible anymore. Therefore this practice is in favor of a country that wants to protect its domestic producers. In 2007, more than sixty of the 357 disputes in the 12-year activity of the Dispute Settlement Body of the WTO addressed zeroing (Vermulst & Ikenson, 2007). The literature that will be discussed next, is based on several different kinds of dumping margin determination. Overall, the main consequence of antidumping protection is that foreign firms sell for a higher price or a lower quantity than they would do under free trade, in order to avoid paying an antidumping duty.

While analyzing literature about dumping and antidumping, a broader field of study can be taken into notice. The theory of the effects of dumping is closely related to two concepts from the industrial organization literature. Namely, price discrimination and predation. Price discrimination can be profit maximizing for firms with at least some market power, where demand abroad differs from domestic demand. If lower prices abroad are not possible due to antidumping protection, the exporter will reduce its output. This can imply a welfare loss. The theory of predation is closely related to antidumping, because pricing below costs can diminish profits of rivals and make them leave the market (Davies and Mcguinness, 1982). Dumping investigation and predatory pricing investigation are therefore related practices (Niels, 2000). Some findings related to price discrimination and predation will therefore be discussed as well.

Economic effects of antidumping

Currently, a wide range of literature on the economic effects of antidumping laws exist. Niels (2000) derived three broad conclusions from the pre-2000 literature. First, antidumping may be used to protect domestic firms from foreign competitors (Prusa, 1992, Staiger & Wolak, 1992). Second, antidumping laws may facilitate collusion between domestic and foreign firms. Ultimately, this collusion can cause a price increase and a competition decrease in the domestic market. This can be beneficial for both the foreign and the domestic firm, but harmful for firms outside the cartel (Veugelers & Vandenbussche, 1999). Third, output or price decisions of foreign firms can be influenced by the risk of dumping investigations. As a result, behavior is affected even before any measure is applicable (Prusa & Kolev, 1999). Other main outcomes of research in the field of antidumping, are that domestic producers gain in terms of profits and that there is a risk of trade diversion. Trade diversion is a shift of output from efficient to less efficient firms due to the competition decrease. Furthermore, foreign producers typically choose to raise their prices instead of paying a duty. This makes a part of the gains that a government could get from adopting antidumping laws, profit for the exporting firm itself.

Another economic effect of antidumping protection discussed in the literature, is its influence on plant productivity. The empirical study of Pierce (2011), estimates the decrease in US plant productivity of plants that produce products subject to antidumping measures with a difference-in-differences model. Pierce's main explanation for the substantial decrease in productivity, is that production shifts from efficient restrained firms to less efficient protected firms. The methods in this empirical study form the base of this thesis. Konings and Vandenbussche (2008) empirically studied plant productivity responses as well. They found that domestic U.S. manufacturers with a relatively low productivity level gain by the protection, and firms with a high initial productivity level lose.

One of the economic effects of antidumping protection that is essential for this research, is that it decreases imports. Staiger and Wolak (1994) investigated the effect on imports of US antidumping cases with an econometric model, and found that imports were reduced substantially. Furthermore, Bloningen and Prusa (2001) find that antidumping trade policy has negative effects on imports in the pre-investigation, the investigation and the post-investigation phase of the process. They support that the threat that a duty will be imposed can influence the choices of foreign exporters before any measure is applicable. Other studies find that antidumping protection might cause countries to isolate themselves from international trade. Using U.S. import and antidumping data, Bown and Crowley, 2007 find a 50-60 percent reduction in imports due to antidumping duties. Moreover, a recent study empirically proves that the trade isolation can continue if the antidumping measure protection is not applicable anymore (Besedeš & Prusa, 2016).

Effect of trade barriers on R&D

As product imports tend to decrease when antidumping duties are imposed, it is relevant to discuss the relationship between trade or trade barriers and R&D investments and innovation. In 1990, Clemens discussed a possible positive effect of trade protection on R&D. He argued that protection could give the domestic producers time and profit margins to catch up with the foreign technologies. Later, Brander and Spencer (1985) analyzed the effect of trade policy instruments on cost reducing R&D investments. Their model concluded that R&D investments can be influenced by more factors than just profit maximizing behavior. They found an ambiguous effect of trade policy instruments on R&D investments. In 1991, James found that a tariff that restricts prices, can raise R&D expenditure in a Cournot game. This implies a positive effect of trade barriers. With these differing outcomes, no evidential positive or negative effect of trade barriers on R&D investments can be assumed. Grossman and Helpman (1990) investigated the relationship between trade and innovation. Trade can stimulate innovation because other countries will imitate the technology of the first moving country. Furthermore, the expected value of exploiting a new technology can increase by means of international trade. In an empirical study using firm level data, Baldwin and Gu (2004) found that the exporters were generally more innovative, both before and after their entry in the export market. Overall, the literature tends to find a positive relation between trade and innovation. While innovation and R&D investments are not equivalent, this indicates that international trade affects R&D expenditures positively.

Effect of antidumping protection on R&D

The direct relationship between R&D investments and antidumping protection is hardly studied. Miyagiwa and Ohno (2006) analyzed the converse relationship. Namely, how dumping can be a signal of innovation. They drew the conclusion that in R&D intensive industries, with fast changing technologies, an innovative firm may want to export a greater quantity to signal the efficiency of its new technology. This can lead to pricing below average costs. Relevant circumstances for this to be profit maximizing, are that the firm has a relatively poor innovation reputation, a substantive discount factor and a strongly cost-reducing technology.

The closest related study of the effect of antidumping protection on R&D is the theoretical model of Gao and Miyagiwa (2005). They study a type of dumping that is motivated by international price discrimination. The model uses a standard setting with two countries, two price setting firms and two stages. An essential element is that there is a given ad valorem transportation cost for exports. In their model, three effects influence the incentives to invest in cost reducing R&D. The *competition effect*, the *cost reducing effect* and the *antidumping effect*. The first two decrease the investment incentive for both firms. The antidumping effect increases the investment incentive of the restrained firm and is stronger than the other two negative effects for this firm together. Herewith, the overall investment incentive of the restrained firm will go up. This effect is not applicable for the protected firm, so for the protected firm the overall investment incentive will go down. According to Gao and Miyagawa (2005) the aggregate investment incentive will go down because the decreasing effects together are stronger than the increasing effects.

Empirical study

After Gao's theoretical analysis of the effect of antidumping on R&D, an empirical study is in place. The aim of this study is to estimate how R&D investment is affected by antidumping protection. In the existing body of literature, it seems that no such study has been done yet. As described above, some other economic relations of R&D with antidumping are examined. The red line in the existing literature is that antidumping causes several different types of welfare costs. A decrease in R&D expenditure adds another welfare cost. As shown in figure 1, many countries use antidumping protection. Therefore, it is of economic relevance to study the welfare effects of this type of protection.

Another strength of this study compared to Gao's theoretical model is that the latter captures just a small part of the relationship between antidumping and R&D investment. More factors might play a role, e.g. that less international trade decreases the benefits of spillovers, which makes investing in R&D less attractive. This empirical study estimates all effects.

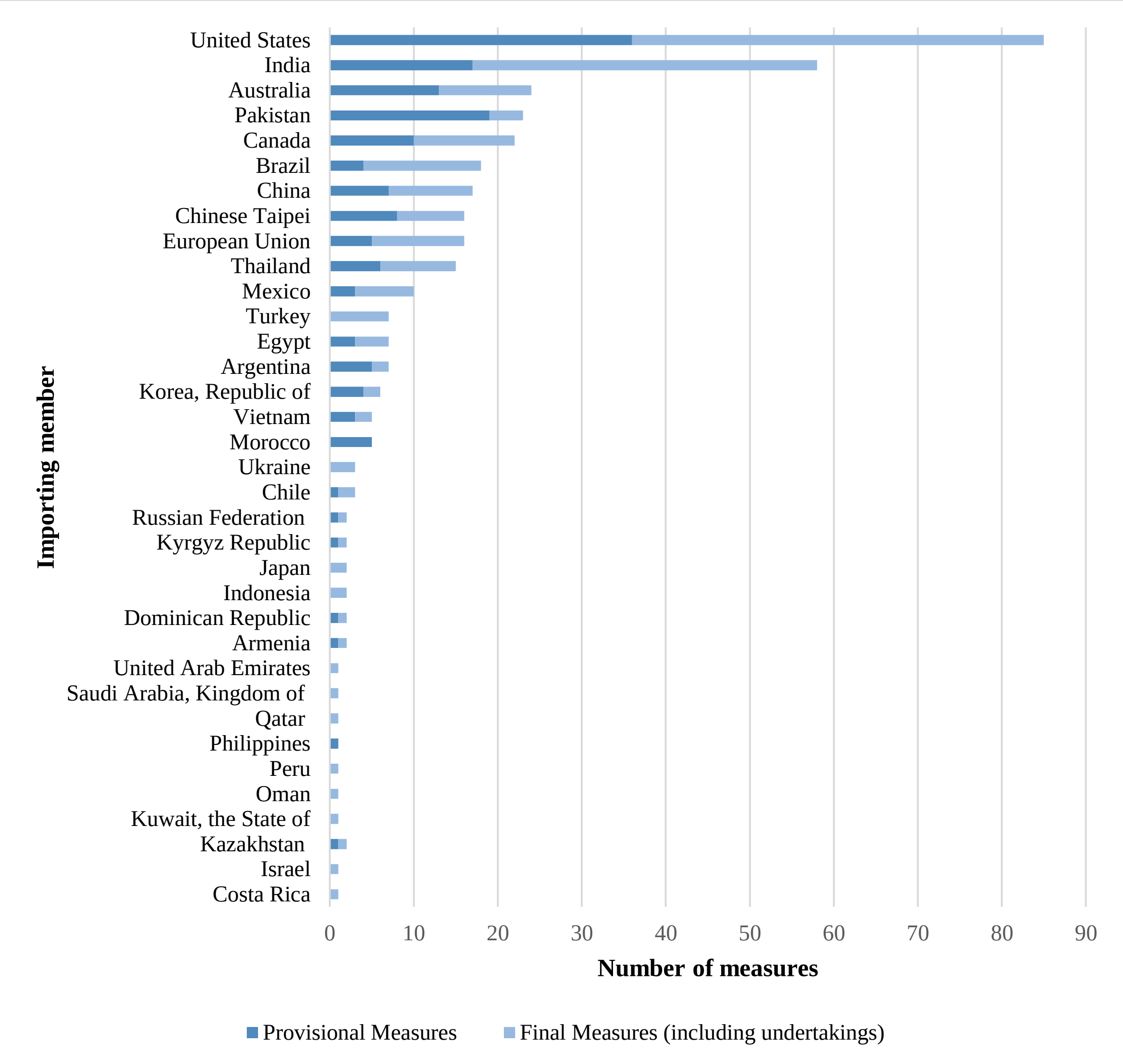

Figure 1: Worldwide antidumping use in 2017

Note: In 2017, 35 states used antidumping protection measures. The European Union counts as one state because it is one legal entity for the WTO Dispute Settlement Body. Including undertakings means that decisions of importers to sell to a higher price instead of paying duties are counted as well (WTO, 2017).

III. DATA

For the analysis I merged several datasets on R&D, antidumping measures and on imports. In this section I will explain which datasets are used, and how these data are processed.

R&D and antidumping data

For studying R&D investments, I merged 2009-2014 U.S. R&D data from the Survey of Industrial Research and Development (National Science Foundation, 2009-2014). The U.S. is an appropriate region due to data availability and their relatively high antidumping protection use (Figure 1). I used survey data of R&D investments *funded by the company and performed by the company and others*. This is the most suitable data, because the antidumping protection will mainly affect the investment decisions of the producers themselves, even though they might outsource their R&D activities. This survey provides the R&D investments per industry and gives one or a group of NAICS codes per industry. In the North American Industry Classification System, every industry has one NAICS code. The granularity of the R&D data differs per industry. For some industries, the investment is given for a superordinate sector, for example *Food*. For others, the data is available on a more detailed level. For example, *Software Publishers*, which is an industry within subindustry *Publishing*. *Publishing* at its turn is a subindustry within the sector *Information*. The more detailed the given industry, the more digits the corresponding NAICS code has. Because the superordinate sector R&D investments are the aggregate of the subindustries, I removed all superordinate sectors of which subindustries are available.

The second dataset is the 2009-2014 Global Antidumping Database (Bown, 2016). This database provides a list of products that were subject to antidumping investigations in the U.S. and covers the years 1995-2015. For each investigation, the database also contains the dates and outcomes of each jurisdictional phase[1] and the final decision. All products are defined with a 10-digit Harmonized Tariff System (HTS) number. With the *concord-long table*, from the R-package *Product Concordance* (Zhu & Kim, 2016), I assigned a NAICS code to all HTS product numbers. These were merged with the corresponding columns in the R&D dataset. By merging on the longest NAICS codes available, I assigned the most detailed available industry R&D data to the products. This resulted in one dataset with R&D investment in 2009-2014 per industry, the matching products that have been subject to antidumping investigations[2] and the

[1] There are two jurisdictional phases: the preliminary phase and the final phase. From the final phase follows the definitive decision (WTO, 2017).

[2] A product is subject to an antidumping investigation if the exports of that product from at least one country were investigated by the WTO Dispute Settlement Body.

outcomes of these investigations. In ten different industries products were investigated for antidumping protection: the antidumping industries. Table 1 shows the R&D investments in the antidumping industries.

Table 1: R&D investments per industry

Industry	2009	2010	2011	2012	2013	2014
Electrical equipment, appliances, and components	4497	4808	5317	4157	5396	5317
Fabricated metal products	2118	1612	1934	1892	2094	1934
Food	5220	5162	5850	5424	6688	5850
Furniture and related products	527	408	353	394	426	353
Nonmetallic mineral products	1405	1687	1617	1781	1724	1617
Paper	1543	1607	1785	870	1032	1785
Plastics and rubber products	3139	2356	2412	4218	4664	2412
Primary metals	758	853	837	888	751	837
Textiles, apparel, and leather products	524	541	670	605	769	670
Wood products	599	263	215	D	223	215

Note: Total R&D investments per industry in the antidumping industries. The R&D investments are measured in millions of U.S. dollars. D means that the investments could not be published, because such a small number of producers was active in the market that publishing the data would reveal too much information about one producer. Coincidently, all antidumping industries were superordinate sectors. Despite, they are not all the same size and therefore not entirely comparable.

Effective antidumping rate

When the WTO Dispute Settlement Body investigates dumping claims, it mostly investigates claims regarding one product, imported from several different exporting countries. For example, in 2009 the U.S. imports of *Polyethylene Retail Carrier Bags* originating from Indonesia, Taiwan and Vietnam were investigated separately. Every importing country can get a differing antidumping decision. This means, the WTO can decide to approve the protection claim on imports from Indonesia, but dismiss the claim with regards the imports coming from Taiwan. Furthermore, the WTO can decide upon a high fine for one country, and a lower fine for another country. The height of the fine is called the rate of the antidumping duty. From the moment that a claim is approved for imports of a product from one country, all five to ten year future U.S. imports of that product will be subject to an antidumping duty. The antidumping rate that is applicable on all U.S. imports, is the weighted average of the rates of all cases that got assigned an antidumping duty (Pierce, 2000). This is called the effective antidumping rate. Like Pierce (2000), I use the shortened name for this effective antidumping rate: *Rate.* The computation of *Rate* is shown in equation 1.

$$(1)\ Rate_p = \sum_C Import\ Share_{cpT-1} \times Antidumping\ Rate_{cp}$$

The effective antidumping rate is the sum of shares of imports of product *p,* from the different countries *c*, multiplied by the antidumping rate of all concerning exporting countries individually. Treatment year *T* is the year that the antidumping measure was imposed. The country import share in the year before the treatment, *T-1,* is used. The imports from a certain country in this year are the most representative for the country share of total imports in the U.S.. This is because import from a certain country can decrease substantially due to an antidumping measure. With respect to the products for which only one country got an affirmative final antidumping decision, the effective antidumping rate is simply the to that country assigned duty. To compute this effective antidumping rates per product, I used data on U.S. imports on product level from the sixteen countries[4] that have been subject to antidumping investigations in the years 2009-2014 (International Trade Administration, 2018). With this extension, every protected product gets assigned one time fixed effective antidumping rate. This is because treatment year T is time-invariant, because for each product, one single antidumping measure was imposed. Because we use the import share in fixed year T, the import share of a country is time-invariant as well. The variable *Antidumping Rate* is also time-invariant: a country has only one antidumping duty per product in the concerning years. Because *Import Share* and *Antidumping Rate* are time-invariant, the variable *Rate* is also time-invariant. A product has one *Rate,* that has the same value over all years. To account for the fact that the antidumping protection is not applicable yet in the years before the duty was set, a treatment dummy is added, as shown in equations 2 and 3.

$$(2)\ Post_{pt} = 0\ if\ t \leq T_p$$

$$(3)\ Post_{pt} = 1\ if\ t > T_p$$

The dummy is 1 in all years after the decision, because most antidumping decisions are effective during five to ten years (Konings and Vandenbussche, 2008). This implies that nearly all duties will be applicable in all studied years after the decision. The interaction effect of *Post* and *Rate* is the actual antidumping protection. This interaction variable will be the variable of interest in the analysis. This variable is product and time specific. Before and during year *T* it is zero, after year T it is equal to the effective antidumping rate.

[4] China, Germany, India, Indonesia, Japan, Malaysia, Mexico, South Korea, Sweden, Taiwan, Turkey, Ukraine and Vietnam.

Industry import penetration

The antidumping data is given on product level and the R&D data is available on industry level. Because the product antidumping data is much more detailed, I analyzed what share of an industry is taken by products that were subject to antidumping protection in the years 2009-2014. To do this, I extended the antidumping and R&D dataset with data on product imports originated from all countries (International Trade Administration, 2018). With the total U.S. imports on product level and the total U.S. imports on industry level in the years 2009-2014, I computed the *industry import penetration* as in equation 4.

$$(4)\ \ Industry\ Import\ Penetration_{pt} = \frac{Product\ Import_{pt}}{Industry\ Import_{It}}$$

Industry import penetration of product *p*, in year *t*, is the share of imports of product *p*, in year *t* within the imports of corresponding industry I in year *t*. Table 2 shows the total industry import penetration per industry, i.e. the sum of the import industry penetration shares of all investigated products that fall within a certain industry.

Table 2: Total industry import penetration per industry

Industry	Products disapproved	Disapproved industry IP	Products approved	Approved industry IP
Electrical equipment	1	7,1%	5	30,1%
Fabricated metal products	2	7,9%	5	14,1%
Food	0	0,0%	2	6,2%
Furniture and related products	0	0,0%	1	53,5%
Nonmetallic mineral products	1	4,6%	1	3,2%
Paper	0	0,0%	2	38,1%
Plastics and rubber products	0	0,0%	1	29,1%
Primary metals	6	11,2%	13	34,1%
Textiles, apparel, and leather products	1	10,5%	1	3,5%
Wood products	1	12,4%	1	12,4%

Note: Number of products which have been subject to antidumping investigations in 2009-2014 per antidumping industry. The industry import penetration (IP) is the sum of the share of imports the investigated products had in the industry. If a final injury decision was affirmative for imports from at least one country, the product belongs to the ‘approved’-group.

R&D per product

Notable in table 2 is, that the approved industry import penetration within the industries is low. Therefore, it is not valid to use product level antidumping data to investigate an effect on industry level R&D investments. The products on which the treatment is applicable, cover at most 53,5 percent of an industry and often less. It is not likely that the effect caused by this treatment is strong enough to measure. Another problem with analysis on industry level, is that the number of observations is too low for a sound analysis. Optimally, we would want to use product level R&D data, which is not publicly available. This is also challenging to measure, because a single R&D investment can contribute to several products. Therefore, I use a proxy of R&D per product as in equation 5.

$$(5)\ R\&D_{pt} = R\&D_{It} \times Industry\ Import\ Penetration_{pt}$$

R&D investment per product is total R&D investment in industry *I*, in which product *p* belongs, divided pro rata the import share of this product in industry *I* at time *t*. In this proxy it is assumed that imports positively correlated with R&D investments. The use of this proxy, has several beneficial effects on this study. First, it is unlikely that an effect on a whole industry can be found when just a few products within an industry are treated. By estimating an effect on product level, the whole treatment group was protected by antidumping measures. Second, this method increases the number of observations from ten industries over six years, to 531 products over six years. This implies a substantial improvement of the reliability of the results. Third, due to this proxy, a more valid control group can be selected. Controlling for a self-selection bias, the control group preferably consists of products that are similar to the ones of the treatment group. Konings and Vandenbussche (2008), selected only products from antidumping industries for their control group. Without the proxy, all antidumping industries would belong to the treatment group. As shown in table 2, in all industries at least one product received antidumping protection. None of these industries would qualify for the control group because they are all in the treatment group. Thus, the proxy for a study on product level makes it possible to control for a self-selection bias in the composition of the control and treatment group. The product R&D proxy also has disadvantages. It is not guaranteed that R&D investments are closely related to the share of imports of products. It is even possible, that the industry import penetration of a product, has more influence on the value of R&D per product than actual R&D expenditures. This concern is illustrated by means of figure 2 , 3 and 4.

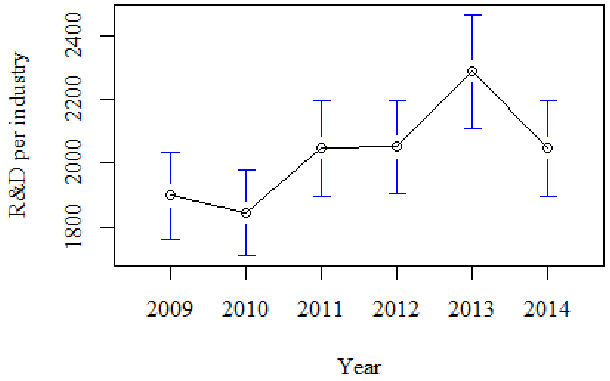

Figure 2: Mean product R&D in U.S. $

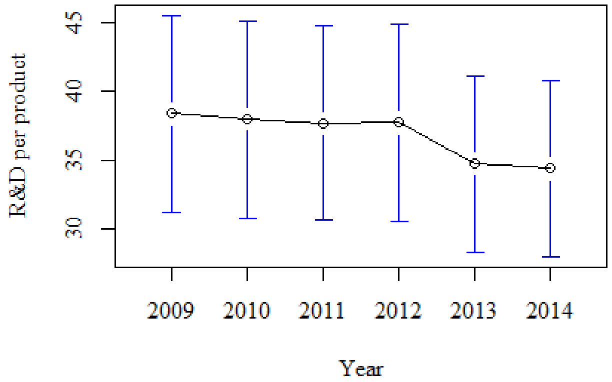

Figure 3: Mean industry R&D in U.S. $

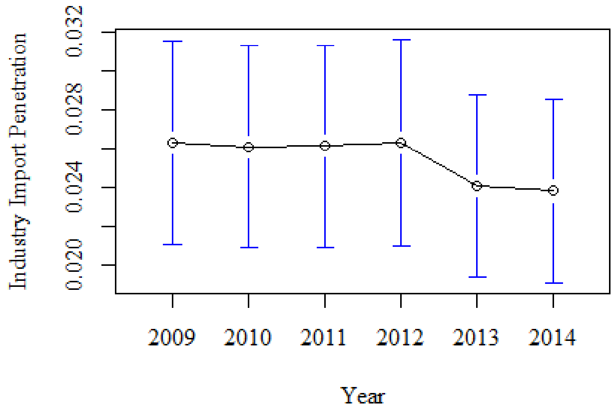

Figure 4: Mean industry import penetration

Note: The development of product R&D and of its components industry R&D and industry import penetration over the years 2009-2014. Important to note is that product R&D might depend more on the industry import penetration than on actual R&D investments. The blue bars show the confidence intervals, twice the standard deviation. Not all U.S. import products are included in the graphs. Only the products that are relevant for this study, the ones in the control and treatment group are included. These are all products in the antidumping industries.

Figure 2 shows that mean R&D per product is decreasing slightly throughout the concerning years. Though, the size of the error bars shows that this conclusion is unsure. R&D per product is composed of the industry import penetration of the products and the total R&D investments in the industry. A decrease in the product R&D can therefore be explained by either a decrease in the R&D investments in the industry or the share of the imports of this product in the industry. If for instance more products are added to the industry, the import penetration will go down and the product R&D will be influenced negatively as well. This decrease would have nothing to do with actual R&D expenditure. In figure 3 and 4 is shown that mean industry R&D is first increasing and later decreasing. These figures also show that mean import penetration is decreasing in the same pattern as R&D per product. This shows that the proxy of product R&D might not be very representative for R&D investments. Because this is the best proxy that can be made with the available data, this variable will be used in the further analysis.

After the described data processing, the panel dataset has, among others, the variables R&D per product, the treatment year and the interaction between the effective antidumping duty and the treatment dummy, over the years 2009-2014.

IV. METHODOLOGY

In this section I will first discuss how the control and treatment group are composed. Thereafter I will set out the models that I will use in the analysis.

Treatment and control group

The treatment group is the group of products that have been protected with an antidumping measure in the years 2009-2014, i.e. for which at least one case has been approved by the WTO Dispute Settlement Body. In composing the control group, there must be controlled for the self-selection bias in a way similar to the one described by Konings and Vandenbussche (2008). This bias is that the applications for antidumping protection can be correlated with factors affecting R&D investments. For example, if there is a negative demand shock for certain products, profits can be low in an industry. This can make producers lobby for protection and decide upon a decrease in investments. Therefore, the control group contains all products in the ten antidumping industries[5] that did not receive protection. Assuming that antidumping industries are in similar economic condition, this is a sound instrument to control for the self-selection bias. This differs slightly from what Konings and Vandenbussche (2008) did, as they only used the products that have been investigated but that did not receive protection. I use all products in the antidumping industries, including the non-investigated. With this method, the treatment group contains 32 products and the control group contains 499 products.

[5] Listed in table 1.

Difference-in-differences

For analyzing whether antidumping protection has an effect on R&D expenditures, a difference-in-differences effect will be measured. With the difference-in-differences estimation, the difference in the differences between R&D investments for the control and treatment group will be measured. Figure 5 shows what will be tested.

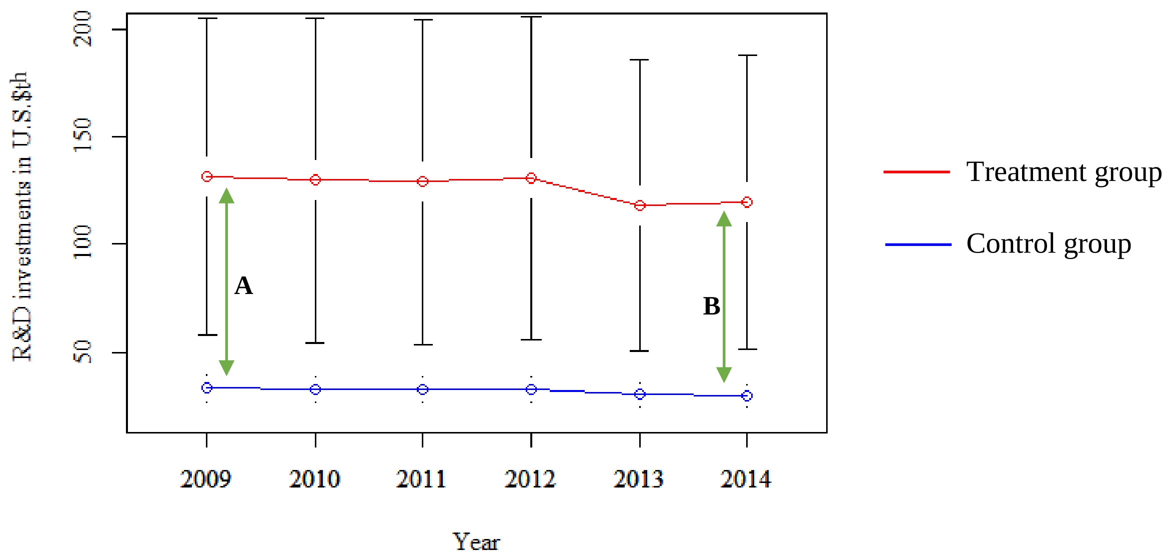

Figure 5: Difference-in-differences product R&D

Note: This figure shows mean product R&D expenditures. The difference-in-differences estimator is the difference between arrow A and B. Arrow A is the difference between the control and treatment group before the protection measure. Arrow B is the difference between the control and the treatment group after the measure. The black bars are the confidence intervals, which are twice the standard deviations. The confidence intervals of the treatment group are wider than the confidence interval of the control group is because the control group contains 499 products and the treatment group 32 products.

In figure 5, the mean R&D expenditure per product is shown for the treatment and for the control group. In one of the intermediate years, an antidumping measure was imposed on the products in the treatment group. The difference-in-differences model will estimate whether the difference arrow A denotes, differs significantly from the difference that arrow B denotes. The alternative hypothesis is that there is a significant difference. As described in the literature review, there is no evidence for an upward or downward effect of antidumping protection on R&D expenditures. Therefore, all models will test two-sided and seek for a negative or positive effect. Interesting to note, is that the mean R&D in the treatment group is much larger than in the control group. This is in line with the findings of Niels (2000). The higher uncertainty in the mean of the treatment group is due to this group containing only 32 products, while the control group contains 499.

The difference-in-differences estimator is used because it has several statistical perks. One is that time specific factors that affect both the control and treatment group, such as economic conjecture developments, do not affect the result. Secondly, effects that are fixed over time do not influence the estimator. For instance, the level of return of R&D investment can be higher in the chemicals industry than in the furniture industry. This level of return on investment will have approximately the same influence on the chemicals industry over the six studied years. This time fixed factor, does not influence the estimator. The former example also illustrates the third strength. The method allows groups to start at different levels of R&D investment. The most important assumption of the difference-in-differences model is the parallel trend assumption. This means that we assume counterfactually that the treatment and control group R&D investments would have developed similarly without antidumping protection. By controlling for the self-selection bias, I attempt to comply with this assumption.

For estimating the difference-in-differences, I will use fixed effects panel data models. The fixed effects model allows the product-specific effects to be correlated with the regressors. For instance, return of R&D investments of a product may be correlated with the effective antidumping rate. Fixed effects models compute the leftover product specific variation α_p in R&D investments per product that is not explained by the regressors. This fixed effects model estimates a difference-in-differences estimator, because time-invariant factors α_t are not taken into account. This is approximately equal to the result of subtracting the R&D investment change in the treatment group from the R&D investment change in the control group. Because α_t is the same for both groups, they eliminate each other in the difference-in-differences model. Following, I will explain which three different models I will use.

Model 1

First, I will use a simple estimation without control variables. Equation 6 estimates the difference-in-differences effect of antidumping protection on product R&D.

$$(6)\ \ R\&D_{pt} = \alpha_p + \beta_1 Rate_p * Post_{pt} + \beta_2 Post_{pt} + \epsilon_{pt}$$

In Model 1, α_p is the product specific effect. α_p differs per product, but not over time. *Rate* is the variable I described at the data section for product *p*, the effective antidumping rate. This variable is time invariant, because a product gets assigned one effective antidumping duty over all years. As described in the former section, treatment dummy *Post* is 1 if time *t* is after the year of the final antidumping decision, treatment year *T*. *Rate* on itself cannot be included because it is very similar to the interaction variable. Both are mostly zero. Just in a few cases, when *Post* equals zero and *Rate* does not equal zero, they differ. Hence, *Rate* individually is not included to avoid multicollinearity. The dependent variable level is R&D investments of product *p*, at time *t*. Coefficient β_1 is the variable of interest that measures the difference-in-differences effect of antidumping on product level R&D investments. ϵ_{pt} is the product and time specific error term.

Model 2

In model 1, time-invariant and group specific effects are filtered out of the difference-in-difference coefficient. Despite, time-variant variables that affect both antidumping protection and R&D investments do influence the estimator. Therefore, another regressor will be estimated with the addition of three control variables. Industry R&D investment, absolute product imports and product R&D investments in the former year. Absolute product imports can influence product R&D investments negatively or positively. Negatively because this might be a sign of either a low production level in the U.S. because it is an import product. Positively because a a product is popular in the U.S.. Product imports influence antidumping protection as well, because the more a product is imported, the more the local producers feel need to file claims against the foreign producers. Lagged R&D product investment is added because the investments in this year can depend on the investments in the former year. Possibly negatively, if companies tend to invest less in a product in which they invested more a year earlier. Lagged R&D product investment can correlate with antidumping protection as well. This is the case if a product in which is highly invested earlier, is more likely to receive protection. This is plausible because investors have more lobby-interests for those products. With the control variables, equation 7 results.

$$(7)\ R\&D_{pt} = \alpha_p + \beta_1 Rate_p * Post_{pt} + \beta_2 Post_{pt} + \beta_3 R\&D_{It} + \beta_4 Imports_{pt} + \beta_5 R\&D_{pt-1} + \epsilon_{pt}$$

In model 2, industry R&D investment, absolute product imports and product R&D investments in *t-1* are added. The basis of the equation and the tested hypothesis is the same as in model 1.

Model 3

As shown in figure 5, the mean product R&D of the treatment group is much higher than that of the control group. This can be caused by a higher industry R&D or a higher import share in the industry. If one of those is relatively high, the absolute change in product R&D might not give a good image of the effect of antidumping protection on R&D. Absolute changes in product R&D might be larger in the treatment group than in the control group. This would violate the parallel trend assumption. Therefore a difference-in-differences model on relative changes in product R&D will be tested. Important to note, is that I will now test a different hypothesis. In model 1 and 2, the difference in the level of R&D investments is tested. In model 3, the percentage change is the dependent variable. Now, the alternative hypothesis is that there is an effect of antidumping protection on the change in R&D investments. Thus, that product R&D investments will rise or decline faster than without the protection. This will be tested with the model in equation 8.

$$(8)\ \%\Delta R\&D_{pt} = \alpha + \beta_1 Rate_p * Post_{pt} + \beta_2 Post_{pt} + \beta_3 Imports_{pt} + \beta_4 R\&D_{It} + \beta_5 R\&D_{pt} + \beta_6 R\&D_{pt-1} + \epsilon_{pt}$$

In model 3, the independent variables are similar to model 2, but the dependent variable is the relative change in product R&D in year *t* compared to year *t-1*. Table 3 gives the summary statistics on the variables used in the models.

Table 3: Summary statistics

	Product R&D	Effective AD Duty * Post	Product imports	Industry R&D	Change product R&D
Minimum	0	0	0	215	-97,8
1st quartile	1.401	0	30 650	670	-11,5
Median	6.640	0	152 800	888	-2,0
Mean	36.816	0.707	868 800	2 029	2,0
3rd quartile	32.815	0	691 600	2 118	7,9
Maximum	1 028.528	220	20 320 000	6 688	1968,3
Number of obs.	3 186	3 186	3 186	3 186	2 576

Note: Product R&D, product imports and industry R&D are given in millions of U.S. $. Change in product R&D is given in %.

I will discuss the statistics in table 3 shortly. The number of observations of all variables except for product R&D percentage change is 3 186. This number consists of 531 products in six years. Product R&D percentage change has less observations because I did not add 2008 R&D data, therefore the 2008-2009 change cannot be computed. Furthermore, if the product R&D in a former year is zero, mainly because there were negligible imports of that product in that year, the percentage change cannot be computed. These datapoints are omitted as well. The minimum product import is zero, because some products were not imported in some years. Therewith, the minimum product R&D is zero as well. The fact that the means are higher than the medians of the variables indicates that all distributions are right skewed.

V. RESULTS

The results of the three difference-in-differences models are shown in table 4 Table 4 displays the outcomes of the models for the variable of interest, the interaction effect of *Rate* and *Post*. The full results are included in the attachment.

Table 4: Results models

Model	Estimate	Std. error	T-statistic	P-value
(1) No control variables	0.036	0.096	0.373	0.710
(2) With control variables	0.006	0.068	0.088	0.930
(3) Relative change	4.067	166.198	0.024	0.981

Note: This table only shows the results of the variable Rate * Post. None of the P-values is significant.

The parameter of the variable of interest is not significant for any of the models. The P-value is above the in the literature commonly required five percent confidence level. For model 1 and 2 the alternative hypothesis is that the difference between the level of product R&D investments of the control and treatment group after the protection, is either bigger or smaller than the difference before the protection. With P-values 0.710 and 0.930, the alternative hypothesis is not accepted. With regards model 3, the alternative hypothesis is that the difference between the change of product R&D investments of the control and treatment group after the protection is bigger or smaller than the difference before the protection. With a P-value of 0.981, this alternative hypothesis is also not accepted.

VI. CONCLUSION AND DISCUSSION

This thesis investigated the effect of antidumping protection on a proxy of product level R&D investments with three difference-in-differences models. By only using products that belong to antidumping industries, was controlled for a self-selection bias. Based on data from the years 2009-2014, I did not find a significant effect of antidumping protection on the level or the change of R&D investments in the U.S. There are a few caveats in this study, that could have influenced the results.

First, there is likely to be omitted variable bias. If there are time-variant factors, that influence both R&D and antidumping protection, the estimator is biased. An important example is product prices in the U.S.. If prices of a product are high, profit margins are high and it would be more attractive to invest in R&D. Furthermore, if local prices are relatively high, dumping and therefore claims for antidumping protection will be more likely. This will cause a positive bias in the estimator. Thus, the estimator will be higher than it is supposed to be. This would not change the non-significant finding. Another omitted variable could be employment in the production process. There can be a positive or a negative relationship between number of employees and R&D investments. R&D expenditure might increase because the product is produced in the U.S. in large quantities, or it might decrease because it is a labour intensive industry where automatization is not profitable. If the number of people involved in the industry is high, lobbying practices for antidumping protection are more likely. This can cause both an upward and a downward bias. Another important variable to add in future research, is production data of U.S. producers. The more is produced in the U.S., the more R&D investments and the more antidumping protection claims there will be. Consequently, this omitted variable causes an upward bias. To solve these problems in future research, more data must be added to the models.

Another bias that is not accounted for, is the government selection bias (Konings and Vandenbussche, 2008). This is a bias in the selection of the treatment and control group. The government selection bias implies that products with certain characteristics are more likely to receive antidumping protection. For example employment. As described above, lobbying practices will be more likely when a lot of people are involved in the industry. Konings and Vandenbusche account for this sample selection bias by limiting their treatment and control group to products which are similar based on a set of characteristics. In further studies one can select the control group on characteristics like employment, product prices, output or exports similar to the treatment group.

Another caveat is reverse causality. Possibly, R&D investments influence antidumping protection as well. If an industry requires relatively large innovation investments, producers might feel more need for trade protection. This will cause them to lobby for antidumping measures. This positive reverse effect can cause an overestimation of the causal effect.

Furthermore, the nature of R&D investments might not be suitable for a test that analyses an effect that follows shortly after a treatment. Maybe R&D investments are decided upon years ahead, because the investments are project based. To solve this, more years can be analysed in future research.

The most important criticism on this study, is that there is probably a non-random measurement error. The proxy that is used for the computation of R&D per product is most obviously not accurate. There is no empirical prove that R&D investments correlate positively with import shares. The correlation can just as well be negative for certain products. For example, for a product that is hardly produced locally, and therefore imported. Eliminating this non-random measurement error can cause radically different results. The measurement error can be reduced by using data on production in the U.S., instead of on imports. Even though R&D investments do not have to develop proportionally with production, this will most likely give a better proxy. Another solution would be to gather R&D data on a product level. However, this might incur product classifying problems and would be costly. Improving this proxy is my main recommendation for future research, because this might turn the outcome of the study.

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VIII. ATTACHMENT

Difference-in-differences results

Table 6: Full results model 1

Term	Estimate	Std. error	T-statistic	P-value
Rate*Post	0.036	0.096	0.373	0.710
Post	-9.630	4.250	-2.266	0.025

Table 7: Full results model 2

Term	Estimate	Std. error	T-statistic	P-value
Rate * Post	0,006	0,068	0,088	0,930
Post	2,929	3,732	0,785	0,434
Product Import	0,000	0,000	-0,824	0,411
Industry R&D	-0,021	0,004	-5,682	0,000
Lag R&D per product	0,543	0,065	8,412	0,000

Table 8: Full results model 3

Term	Estimate	Std. error	T-statistic	P-value
Rate * Post	4.067	166.198	0.024	0.981
Post	1369.211	12976.009	-0.106	0.916
Product Import	0.000	0.000	0.945	0.348
Industry R&D	-1.471	9.037	-0.163	0.871
Lag R&D per product	92.918	213.065	0.436	0.664