Rare Earth Export Restrictions in China: a difference-in-differences analysis

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2016

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A Difference-in-Differences Analysis

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Master Thesis
Vrije Universiteit Amsterdam
MSc Spatial, Transport, and Environmental Economics

VU Supervisor: Dr. Steven Poelhekke
June 2016

Abstract

This thesis has empirically researched what the effect was of China's export restrictions, regarding rare earth elements, on China's domestic refining and downstream production of rare earth elements. This was done by using the difference-in-differences technique, using six different models frequently used in gravity model estimations; OLS, Poisson, negative binomial, zero-inflated Poisson, zero-inflated negative binomial and Poisson pseudo-maximum likelihood. The data that is used are Chinese export values to 85 countries divided into roughly 5,000 commodity classes.

This research indicates that there is evidence that the export restrictions on rare earths in China resulted in 13.8% to 15.8% more exports of rare earths-using commodities. This would mean that as long as domestic consumption of these commodities remained constant or is increased, the downstream production of rare earths-using commodities also increased with at least these percentages.

Acknowledgements

This Master Thesis is written as completion of the Master Spatial, Transport and Environmental Economics at the VU University Amsterdam. I would like to express my gratitude to my VU supervisor Dr. Steven Poelhekke for his useful comments and input during this research.

Jip Claassens

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SECTION I: INTRODUCTION

The World is increasingly dependent on rare earth elements or rare earths. These are 17 elements in the periodic table with unique chemical properties that prove extremely useful in many applications, ranging from glass additives, lighting, metallurgical applications, catalysts, batteries, magnets, medical techniques, lasers, televisions, and much more. However, the production of these rare earth elements is extremely concentrated in one country: China[1]. China knows its position and tries to use this position by reducing the export of these raw materials and thereby increasing the domestic refining and downstream production of commodities that use rare earth elements, which it can consequently export as more value-added commodities. Or is China just restricting production and exports to limit pollution and preserve their resource stock? Does their policy actually work? This thesis will try to find an answer to a question that has not yet been answered: *did the export restriction of rare earths in China result in more domestic refining of rare earths and downstream production of rare earth-using commodities?*

The following sub-questions will contribute in answering the research question:

1. How can export restrictions promote domestic production?
2. What are the effects of export restrictions in other study areas according to other studies? And what methodology did they use?
3. Which sectors use rare earth elements? And at what threshold of rare earth usage does a sector qualify as a rare earth using sector?
4. How much rare earths did China produce and export before and after the imposition of the restrictions?
5. What was China's sectorial composition in terms of rare earths usage before and after the imposition of the restrictions?
6. What are the yearly sectorial trade flows from China to the rest of the world?
7. Details of China's policy: What was exactly treated? How was it imposed? During which time period? What were the motivations for enforcing and lifting the restriction?
8. What econometrical models are most suitable for answering this research question?

The structure of the thesis will be as follows: next, there will be a section in which literature, concerning the economic theory and similar research, will be provided. This will answer sub-questions 1 and 2 (Section II). The following section presents the data with its sources, in which the rare earth applications will be discussed followed by the worldwide production trends, and China's role in it. In the second part of that section will be an extensive overview of the methodology of this thesis. This section will provide the answers to the sub-questions 3 through 8 (Section III). After which the results will be presented and discussed and vulnerabilities of the research will be pointed out (Section IV). And finally, there will be a conclusion summarizing the main findings (Section V).

[1] In 2010, China supplied 97% of all rare earth oxides worldwide (USGS, 2012).

SECTION II: LITERATURE

2.1 Export restrictions

Export restrictions can be defined as "*measures instituted by exporting countries to supervise export flows*" (Goode, 2007) or more elaborate as "*a border measure that takes the form of a government law or regulation which expressly limits the quantity of exports or places explicit conditions on the circumstances under which exports are permitted, or that takes the form of a governmental-imposed fee or tax on exports of the products calculated to limit the quantity of exports*" (United States - Measures treating exports restraints as subsidies, 2001).

There are many reasons why countries would want to impose export restrictions. It could be for economic goals, like raising government revenues, raising the foreign exchange rate, promotion of value-added downstream industries or as support for economic agreements with other countries. There might also be non-economic goals, like maintaining national security or some social objectives (Bonavirra, Koscielski, & Wilson, 2009; Mitra & Josling, 2009; Takacs, 1994).

Many instruments are available for governments to choose from, each of them have different effects on different parts of the economy. Some export-restrictive measures are export prohibitions; export quotas; export licensing; export duties and levies; and minimum export prices. On the other hand, there are also export-incentive measures, like export subsidies; duty and tax drawback; export processing zones; export finance, insurance and guarantees; and other promotion measures (Bonavirra et al., 2009; Kim, 2010).

One of the most used forms of export restrictions are export taxes or duties. They can be an ad valorem tax, which is a percentage of the value of the product. Or a specific tax, which is a specific amount per unit or weight of a product (Kim, 2010). Export taxes are also deemed the least damaging export measure by the WTO compared to other measures. Export taxes generate income for governments, are transparent and easy to implement (Bonavirra et al., 2009; Piermartini, 2004). These export restrictions are relatively often applied to raw industrial materials (Fung & Korinek, 2014).

There is quite some literature on the effects of export restraints. Many try to model its effects using different models. There is a wide consensus that export restrictions are often used as a policy instrument to limit the export of industrial raw materials and promote domestic more value-added industries that generate higher value exports, this is often called the "infant industry argument" (Bonavirra et al., 2009; Melitz, 2005; Mitra & Josling, 2009; Piermartini, 2004; Takacs, 1994). Due to a decreased export quantity as a result of an export restriction, there is a higher supply in the domestic market which will decrease the domestic price and this lower price provides a higher domestic demand. If the product is used as an industrial input, this lower price can provide an implicit subsidy to the domestic processing industry (Bonavirra et al., 2009).

This policy of protecting the “infant” industries, conflicts with the proposition that free trade is always optimal. There are skeptics that question the validity of the infant industry argument, their focus is on two points: 1) are the goals of the infant industry protection actually achieved through the trade regime, and 2) the empirical likelihood of the combination of “dynamic factors” and “externalities” that would need to arise to justify the infant industry protection (Krueger & Tuncer, 1982, p. 1142).

The conditions in which the infant industry argument is valid are: 1) some newly established activities are initially high cost relative to established foreign enterprises and it requires time for them to become competitive. 2) It does not pay any individual entrepreneur to enter an infant industry at free trade prices, but 3) the industry, if developed, would be economic enough to permit a reasonable rate of return on the initial losses; and therefore 4) the industry requires a temporary period of protection or assistance during which its costs will fall enough to permit it to survive international competition without assistance (Krueger & Tuncer, 1982, pp. 1142-1143).

If an exporter has a significant share of world supply, it has market power in the world markets. Consequently, any changes in its export volume will affect world prices, making the country a price setter (Piermartini, 2004). Hence, importers can’t turn to other cheaper suppliers, and are therefore dependent on the lower and more expensive supply. In the short run, this means that there is a net income transfer from the importing countries to the exporting country. In the long run, such an export restriction might result in inefficiencies in the downstream processing industries of the exporting country, due to the artificially low domestic input prices. Foreign producers use a more expensive input and have therefore an incentive to develop new technologies or substitutes, which can reduce their costs (Bonavirra et al., 2009).

The World Trade Organization is the best source on the use of export controls in the world. Through its Trade Policy Review (TPR), it has reviewed 131 countries between 1994 and 2009. Of those 131 countries, 72 imposed export taxes, 71% of those are low-middle or low-income countries. Of these countries 90% tax agricultural products, 44% tax raw materials and 26% tax other commodities (Bonavirra, Koscielski, & Wilson, 2009). In addition to the export taxes, nearly all the countries that have been reviewed by the WTO use some form of a quantitative restriction on the export of certain products. Whereas export taxes are usually used for economic reasons, the quantitative restrictions are often imposed as obligations under international agreements and conventions, but also for environmental or security reasons (Bonavirra et al., 2009).

Governments are often unaware of the economic costs of such a policy, such as the redistribution of economic benefits from the producers of raw materials to the downstream processors. When the export restrictions apply to the agriculture sector this can lead to a greater social inequality between the rural population and the urban population (Bonavirra et al., 2009; Takacs, 1994).

The economic literature on export restrictions is mostly focused on food, other agricultural products, and fossil fuels. A government's motivation for imposing export restrictions on rare earths is likely to be different from food or fossil fuels. Since rare earths are only used as an intermediary input in downstream industry and their production is relatively small, both in monetary and quantity terms (Pothen & Fink, 2015).

In the literature, there are multiple papers of scientists who built models to estimate the effects of different of such export restrictions, while looking at specific variables. Both theoretical and empirical models are used. Bouët (2001) tries to theoretically explain the effect of research and development (R&D) in a duopoly in combination with a Voluntary Export Restriction (VER). In his model, there are two firms: a northern (domestic) and a southern (foreign), who operate with Cournot or Bertrand competition. Both firms produce an identical product with constant marginal costs. However, the northern firm can invest in R&D to increase the probability of lowering its marginal costs. The southern firm can impose a VER to reduce its export and increase the world price. But it depends on the marginal costs of the northern firm. A VER would raise the northern firm's profits in a high-marginal-cost state, investing in R&D has therefore a smaller increase in profits. The reduced investment in R&D leads to a sufficient reduction in the probability of a low-marginal-cost state. Because the northern firm operates at the high marginal cost, the southern firm is still competitive and thus benefits. If the northern firm operates at the low costs, it outcompetes the southern firm regardless of the VER, and the VER would not help the southern firm. In the Cournot case, the game should be repeated for the VER to be credible and in the Bertrand case the two firms will collude (Bouët, 2001).

Takacs (1994) first builds a theoretical model which is in turn empirically tested. She uses a partial equilibrium model to assess the effects of export controls on raw materials to investigate the impact of export restrictions (export licensing) and to estimate the potential magnitude of the transfers between producers, processors and exporters and the net costs of the export-control regimes. Takacs found that the impact of a raw material export restriction on total export earnings is ambiguous; it does encourage domestic processing, but hurts raw material producers and causes economic distortions which will in turn cause net losses to the country. The change in export earnings is the difference between a decrease in the value of raw materials export and an increase in the value of final goods exports, but the decline in raw material exports may outweigh the effects of increased final good exports. But *"the raw material export control is more likely to increase export earnings the greater the value-added in processing, the greater the elasticity of supply of the processing industry, and the smaller the elasticity of supply of the raw material, and the larger the processing industry relative to raw material production"* (Takacs, 1994, p. 8).

Gourdon et al. (2015) investigate China's fiscal policy. They use HS 6-digit sectoral data (Harmonized System codes, as used by the U.S.) over 2002-2012 with average export tax and export VAT costs (VAT minus tax rebate) and perform a regression analysis to identify the main features that characterize products with a high degree of export taxation. They use export tax and export VAT costs as two dependent variables. They use specifications to test statements made by the public authorities, like: "*encouragement of exports from sectors producing high value-added and high-technology products, limitation of exports from polluting sectors, mitigation of the risk of trade disputes and food security*" or "*favoring downstream sectors and improving terms of trade*". Their results support the explanations given by public authorities to justify variations in export taxes and export VAT rebates. It also reveals that both fiscal tools encourage exports of more value-added and high technology products, and it possibly indirectly subsidizes downstream industries. The export VAT rebate seems to specifically limit the export of air polluting sectors, mitigate trade dispute risks and promote food security (Gourdon et al., 2015).

2.2 China's Policy

Quantitative restrictions are prohibited by the World Trade Organization according to Article XI of the General Agreement on Tariffs and Trade (GATT) of 1994, there is, however, an explicit exception for "duties, taxes or other charges", and they are therefore allowed (Bonavirra et al., 2009; Piermartini, 2004). There are also exceptions to the general prohibition of quantitative restrictions, like in article XX-g: "*relating to the conservation of exhaustible natural resources if such measures are made effective in conjunction with restrictions on domestic production or consumption*" and article XX-I adds: "*involving restrictions on exports of domestic materials necessary to ensure essential quantities of such materials to a domestic processing industry during periods when the domestic price of such materials is held below the world price as part of a governmental stabilization plan*" (World Trade Organization, 1994).

China's official statements justify their policy (export quotas, export taxes, changing export VAT rebates, export licensing) within these WTO rules, however, many other countries dispute this. On June 23, 2009, the United States filed a WTO case against China over its export restraints on raw materials (WT/DS394 - China - Measures Related to the Exportation of Various Raw Materials, 2009). And on February 11, 2015, the United States requested consultations with China with regard to certain measures providing subsidies contingent upon export performance to enterprises in several industries in China (WT/DS489 - China - Measures Related to Demonstration Bases and common Service Platforms Programmes - Request for consultations by the United States, 2015). And on March 13, 2012, the United States again requested consultations with China, this time with regard to measures related to the exportation of rare earths, tungsten, and molybdenum. A week later Japan and the European Union joined the request. In 2014 this and other disputes were aggregated and even though China appealed the WTO panel's report, China informed the WTO in May 2015 that it had removed all restrictions that were mentioned in the complaint (212 eight-digit Chinese Customs Commodity Codes and over 30 measures) (WT/DS431 - China - Measures Related to the Exportation of Rare Earths, Tungsten and Molybdenum, 2015).

If China really did remove all the restrictions has to be seen. A month before that statement, China's Ministry of Industry and Information Technology released a circular with the "first batch of total amount of control planning for rare earth production 2015". This states what the production quotas are and how they are divided among the six large province- or state-owned enterprises[2] (CCM, 2016; Hongpo, 2015; Wang, 2015). These quotas are production quotas, that would mean that supply decreases, both for domestic and foreign consumers. This could really be a measure of preserving reserves for the future, or it is a measure to avoid setting export restrictions. And those export restrictions are not allowed by the WTO and are complained about. However, this measure would not promote the domestic downstream processing industry.

[2] the six giants account for 94% of the mining quota and 93% of the smelting and separation quota

SECTION III: DATA & METHODOLOGY

This thesis will empirically research what the effect was of China's export restrictions, regarding rare earth elements, on China's domestic refining of rare earths and the downstream production of rare earth-using commodities. It does so by using the econometric difference-in-differences technique. This method compares the average change over time in the outcome variable for the treatment group, compared to that of the control group. The treatment group are the commodities that use to a certain extent rare earth elements and the control group are the commodities that do not use rare earth elements. The outcome variable is the export trade value in U.S.D., which is the trade flow from China to the rest of the world, divided into sectorial data. If the trade value positively changes for commodities that use rare earths, after the imposition of the restrictions, this could indicate that the down-stream industry of rare earths is indeed promoted by this policy. This would be measurable effect using trade values, which are freely available. Chinese domestic production data is, however, much less easily available. These trade values are available from and to all countries for many years and divided into many sectors. China's export restrictions started in 2010, so the time periods to consider are three or four years before and after this year. This section is structured as follows, first, the occurrence and applications of rare earth elements are further discussed. After which worldwide trends of production and consumption presented, combined with the obtained Chinese export data. Then the econometric methods that will be used in this thesis are explained and its precise set-up for this research demonstrated.

3.1 Rare Earths

This thesis focusses on a particular group of raw industrial materials: rare earth elements or often shortened to rare earths. Rare earths are a group of 17 elements in the periodic table (Figure 4 in Appendix A), the 15 lanthanides and the metals scandium and yttrium. The lanthanides are commonly divided into two groups: lower atomic weight elements; lanthanum to europium, which are called light rare earth elements (LREE) and heavy rare earth elements (HREE) gandolinium to lutetium and yttrium (Connelly, Damhus, Hartshorn, & Hutton, 2005; Humphries, 2013; Migaszewski & Galuszka, 2015; Pothen & Fink, 2015). Due to lanthanide contraction, a unique structure of electrons within their atoms, all rare earths except scandium have similar ionic radii and thereby similar chemical properties. Because of this similarity, rare earths usually occur together in their deposits, this similarity makes also separating them technically challenging and costly (Pothen & Fink, 2015).

Contrary to what the name rare earth elements suggest, rare earths are neither rare nor earths. They are moderately abundant in the earth's crust, the average concentration in the Earth's upper crust is relatively high with 0.015%. Some rare earths are even more abundant than copper, lead, gold and platinum (Migaszewski & Galuszka, 2015; Pothen & Fink, 2015). The rarest stable rare earth, lutetium, is more abundant than gold or platinum (Pothen & Fink, 2015). However, due to their geochemical properties, they are very dispersed, making it more difficult and costlier to mine than more conventional minerals. There are about 270 minerals that contain substantial amounts of lanthanides and yttrium, fewer than 10% of these minerals are of economic value and have been commercially mined. Bastnäsite deposits in China and the United States are the largest source of rare earths, monazite deposits are the second largest (Humphries, 2013; Mayer Brown, 2014; Migaszewski & Galuszka, 2015). Rare earths often occur along with other elements such as copper, gold, uranium, phosphates and iron, and are often produced as a by-product (Humphries, 2013).

The first rare earth element discovered was gadolinite in 1787, and up until the mid-20-century rare earths were just something for chemists to work with, without any commercial applications. However, since the 1940s its unique chemical properties gave rise to all kinds of technological applications we all use today. Most of the electronic devices we use have to some extent rare earths in them (Mayer Brown, 2014; Migaszewski & Galuszka, 2015). For example, liquid-crystal displays (LCDs) use europium as the red phosphor and there is no substitute for it. Fire-optic cables used for communication use erbium which functions as a laser amplifier. The most abundant rare earth, cerium, is used as a polishing agent for glass and is used in nearly all mirrors and eye glasses to precision lenses (Haxel, Hedrick, & Orris, 2002; Humphries, 2013; Mayer Brown, 2014). Some rare earths have the characteristic of being a permanent magnet; their use revolutionized the computerized world. These high-strength rare earth permanent magnets allowed miniaturization of many electronic components and gave rise to mobile phones, laptop computers, disk drives and much more. Rare earths are also essential as a catalytic converter in the petroleum industry, but also play an important role in the world's transition to more sustainable energy use. Rare earths are used in energy-efficient fluorescent lamps, hybrid vehicles, rechargeable batteries and wind turbines (Haxel et al., 2002; Humphries, 2013; Mayer Brown, 2014; Migaszewski & Galuszka, 2015).

3.2 Rare Earth applications

In 2008, 129,000 metric tons of rare earth oxides (REO) were consumed worldwide, of which 60% in mature[3] applications (catalysts and the glass, lighting, and metallurgical industries), and 40% in developing[4] applications (battery alloys, ceramics, magnets, and other sectors that grow 4 to 10% a year; Table 1; USGS, 2011). A more elaborate table with applications for each rare earth element is shown in Table 13 in Appendix B. Moreover, in Table 14 in Appendix C are all the commodity classes that use rare earths to some extent. For this table, different sources are used to find out what products use rare earths, which are then manually translated into six-digit HS2007 commodity classes. This results in over 200 of the more than 5,000 commodity classes that use rare earths to some extent.

Table 1: Most important applications of rare earths, the last two columns show the amount of rare earth oxides (REO) used per application in tonnes per year (tpa) in 2008 and the share of heavy rare earths used per application (from Pothen & Fink (2015).

APPLICATION	EXEMPLARY PRODUCTS	tpa REO	% HREO
GLASS INDUSTRY	Polishing powders, colorized or decolorized glass	28,444	3
CATALYSTS	Catalysts for fluid cracking, automotive catalysts	27,380	0
MAGNETS	Permanent magnets in hard discs, wind turbines	26,228	7
BATTERY ALLOYS	Nickel-metal hydride (NiMH) batteries	12,098	0
METALLURGY	Steel and aluminum alloys	11,503	0
PHOSPHORS	TV sets, monitors, fluorescent lamps	9,002	81
CERAMICS	Superconductors, ceramic capacitors	7,000	53
OTHER	Paints and pigments, waste water treatment	7,520	21

[3] Sectors that grow at the rate of growth for the general economy

[4] High-growth technologies

3.3 Worldwide trends

There is concern that the distribution of deposits of rare earths and metals is overly concentrated in a few countries, such as China. In the world, there are three main source countries for rare earths: China, the United States, and Australia. In 2010 more than 97% of the world's supply of rare earth oxides (REO) came from China (USGS, 2012), mostly from the Fe-REE-Nb mineral deposit at Bayan Obo in Inner Mongolia. China holds the largest economic reserve of rare earths: about 50% of the world's stock (Humphries, 2013; Migaszewski & Galuszka, 2015; Wang, Lei, Ge, & Wu, 2015). However, this figure is disputed by other sources and they say it should be around 25-35% (Chen, 2011; Mayer Brown, 2014). Moreover, the proven world reserve of the group of heavy rare earths lies almost entirely in China (Mayer Brown, 2014; Wang et al., 2015). However, these percentages are decreasing as more and more exploration efforts result in newly discovered reserves. Moreover, these percentages represent economically proven reserves, what means that if the prices go up, less economic favorable reserves will be included in these world reserves. Because economically proven reserves are reserves that are developed or undeveloped and have a reasonable certainty that it contains the desired natural resources and that it can be mined with today's technology and under existing economic conditions (Owen, Inderwildi, & King, 2010).

From the 1960s to 1980s the United States were the largest producer of rare earths (Figure 1), mainly from the Mountain Pass mine in California. China gradually increased its rare earth production since the 1980s, and taking a world leading position from 1986. This increased world production lowered the prices, cutting profits and in combination with high ecological costs, the Mountain Pass mine was closed down in 2002 (Wang et al., 2015). With China's global supply climbing up to 97% in 2010 it gained significant market power.

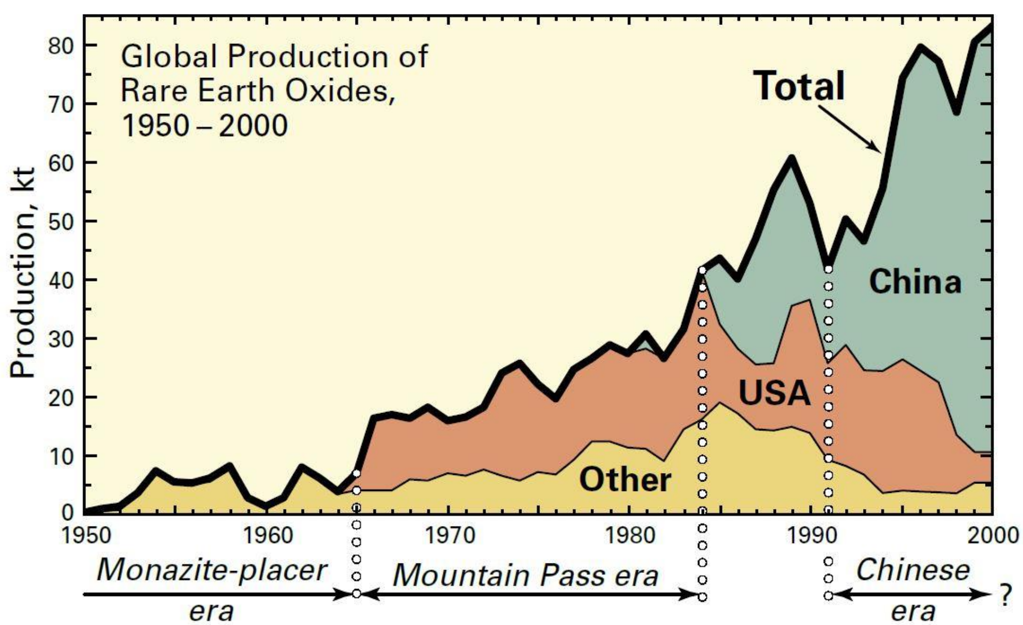

Figure 1: Global production of rare earth oxides (from USGS (2002)

Since 2009 China started to tighten its regulation on exports, limiting export quantities. Moreover, they tightened production quotas. In September 2011, China ceased production at three out of eight of its major mines, reducing 40% of total production, in August 2012 it decreased another 20% (Gourdon, Monjon, & Poncet, 2015; Mayer Brown, 2014). Official reasons are the desire to promote products with high added-value and to reduce the export share of 'undesirable industries' as a means to reduce environmental damages and preserve its natural reserves (Gourdon et al., 2015; WT/DS431 - China - Measures Related to the Exportation of Rare Earths, Tungsten and Molybdenum, 2015).

3.4 Data

The main data source for this thesis is the UN COMTRADE Database[5]. This database contains the most complete dataset of international trade data. Over 170 reporter countries provide their annual trade data detailed by commodities and trade partners (United Nations, 2016). This thesis looks at export patterns from China, however, that data is not readily available. Be that as it may, countries that import from China do report their import data to this UN Comtrade Database. One can assume that the sum of the import from China would be same as the sum of the exports from China.

To exclude small island states and countries that hardly trade with China, only countries that import, for at least one year between 2007 and 2014, for more than one billion US dollars in commodities from China are considered in this research. This results in 85 countries. Then, for each country, for each year between 2007 and 2014, for each HS2007 commodity class their import values are extracted. This results in around one and a half million observations.

There are, however, many observations missing. Not each country imports each commodity class each year, and not each country imports from China each year. To include these zero-flows, in STATA, the fillin command is used to generate these observations, this results in nearly two-million newly generated observations. Then a dummy variable is created, where each commodity class that uses rare earths get the value one.

Figure 2 shows trends from the COMTRADE database. It shows export trends between 2007 and 2014 for commodity classes that use rare earths and classes that do not use it, and both. On the secondary axis, the Chinese GDP is shown. From the trends, one can see that the commodity classes that use rare earths are increasing from 2011. However, the total exports are also increasing, and if the increase comes from a general increase in exports or as a result of policy interventions, is the topic of this thesis. It is interesting to see that while China closed down multiple mines that produced rare earths, this cannot be seen from this dataset. There might be some time-lag present, which is not yet visible.

[5] United Nations Commodity Trade Statistics Database

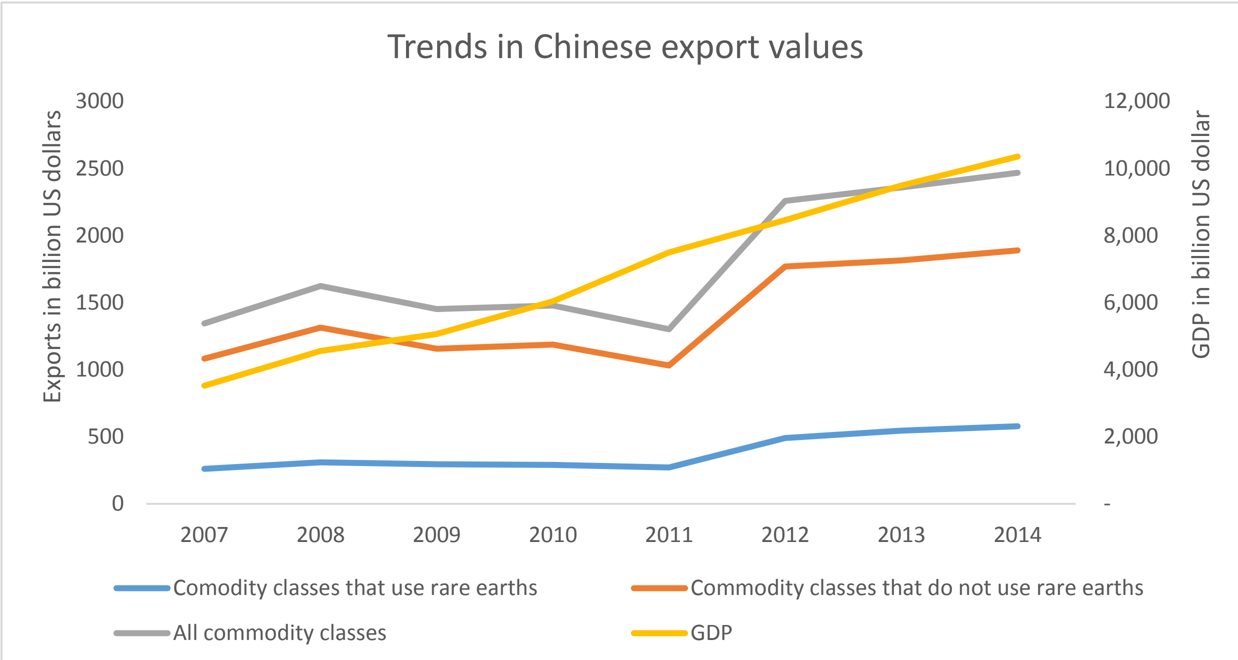

Figure 2: Trends Chinese export data

The HS2007 commodity classes are structured into three levels, resulting in a six-digit code. The first two digits stand for the chapter (which is already a sort of sub-sector), which is consequently subdivided into the next two digits and again into the last two digits. As will be discussed later on there are two groups in the difference-in-difference method; a group of commodity classes that use rare earths (treated group) and a group of commodity classes that do not use rare earths (control group). In the first part, the non-treated commodity classes are not similar industries, but just all the non-rare earths-using commodity classes. This is not what it normally should be when conducting such an analysis. However, there is chosen to do this anyway because of the nature of the treatment. All the countries were treated and everyone was treated at the same period. On the other hand, with this in mind, another approach is offered where only the commodity classes are used that lie in the first two-digit parent commodity class that has rare earth elements in them[6]. This assumes that the commodities that are in the same parent two-digit classes are similar and should act as the control group. The time trend for these last two groups can be seen in Figure 5 in Appendix D, which looks quite similar to the earlier mentioned trends in Figure 2.

The descriptives for the used dataset are shown in Table 2, the first part shows information about the non-aggregated dataset, the second part shows descriptives for the country-aggregated dataset, thereby omitting individual country information. Then the descriptives for the aggregated and non-aggregated are shown where there is the different control group.

[6] These two-digit commodity classes are: 28, 32, 36, 38, 70, 72, 85, 87, 90

Table 2: Descriptives of the used dataset, for the non-aggregated dataset and for the country-aggregated dataset, and for the different control group (same-industry control group)

	VARIABLE	LABEL	OBS	MEAN	STD. DEV.	MIN	MAX
NON-AGGREGATED	year	Year	3430600	2010.5	2.29	2007	2014
	trade	Trade value in US dollar	3430600	4,163,441	104,000,000	0	42,200,000,000
	lntradeori	Ln of trade	1808518	11.96	3.11	0	24.46
	traderesc	Trade divided by 1 million	3430600	4.16	103.91	0	42,164
	time	Dummy for years with export restrictions	3430600	0.63	0.48	0	1
	treated	Dummy for rare earth using commodities	3430600	0.04	0.20	0	1
	did	Interaction time*treated	3430600	0.03	0.16	0	1
AGGREGATED	year	Year	40360	2010.50	2.29	2007	2014
	trade	Trade value in US dollar	40360	354,000,000	2,490,000,000	0	173,000,000,000
	lntrade	Ln of trade	39982	17.24	2.63	1.79	25.87
	traderesc	Trade divided by 1 million	40360	353.89	2485.63	0	172,699
	time	Dummy for years with export restrictions	40360	0.63	0.48	0	1
	treated	Dummy for rare earth using commodities	40360	0.04	0.20	0	1
	did	Interaction time*treated	40360	0.03	0.16	0	1
NON-AGGREGATED SAME-INDUSTRY CONTROL GROUP	year	Year	690200	2010.5	2.29	2007	2014
	trade	Trade value in US dollar	690200	7,991,730	163,000,000	0	42,200,000,000
	lntrade	Ln of trade	407132	12.34	3.13	0	24.46
	traderesc	Trade divided by 1 million	690200	7.99	162.78	0	42,164
	time	Dummy for years with export restrictions	690200	0.63	0.48	0	1
	treated	Dummy for rare earth using commodities	690200	0.20	0.40	0	1
	did	Interaction time*treated	690200	0.13	0.33	0	1
AGGREGATED SAME-INDUSTRY CONTROL GROUP	year	Year	8120	2010.5	2.29	2007	2014
	trade	Trade value in US dollar	8120	679,000,000	4,000,000,000	0	173,000,000,000
	lntrade	Ln of trade	8091	17.99	2.41	3.09	25.87
	traderesc	Trade divided by 1 million	8120	679.30	4000.05	0	172,699
	time	Dummy for years with export restrictions	8120	0.63	0.48	0	1
	treated	Dummy for rare earth using commodities	8120	0.20	0.40	0	1
	did	Interaction time*treated	8120	0.13	0.33	0	1

3.5 Empirical framework

A way to look into the effect of China's trade policy is the difference-in-differences method, this method has become increasingly popular in estimating causal relationships. It can identify a specific intervention or treatment, by comparing the difference in outcomes after and before the intervention for groups affected by the intervention to the same difference for unaffected groups (Bertrand, Duflo, & Mullainathan, 2004). The method is often used because of its simplicity and its potential to circumvent many of the endogeneity problems that typically arise when comparing heterogeneous individuals. However, it only works well if the interventions are as good as random, conditional on time and group fixed effects. As a result, most of the criticism on the method revolves around the possible endogeneity of the interventions themselves (Bertrand, Duflo, & Mullainathan, 2004).

A classic example of using the difference-in-differences method is the research by Card and Krueger (1994). They look at the effect of the minimum wage on employment. On April 1, 1992, New Jersey raised the state minimum wage from $4.25 to $5.05, the researchers collected data from minimum-wage employers, in the states New Jersey and Pennsylvania for February 1992 and November 1992. They then computed difference-in-differences estimates of the effects of the New Jersey minimum wage increase. Thus, they compared the change in employment in New Jersey to the change in employment in Pennsylvania around the time New Jersey raised its minimum. They found that employment in Pennsylvania was slightly higher than New Jersey before, but falls in November while employment in New Jersey increases slightly (see Figure 3). This results in a positive difference-in-differences, employment went up when the minimum wage went up (Card & Krueger (1994) in Angrist & Pischke (2009).

But how convincing is this evidence? The key assumption here, is the common trend assumption. It assumes that the employment trend would be the same in each state without the treatment (Angrist & Pischke, 2009; Bertrand, Duflo, & Mullainathan, 2004). A way to investigate if this assumption is valid is by looking at data from more time periods. Card and Krueger (2000) later found, by looking at more time periods, that Pennsylvania did not provide a good measure of counterfactual employment rates in New Jersey in the absence of a policy change, and vice versa (Angrist & Pischke, 2009, p. 172).

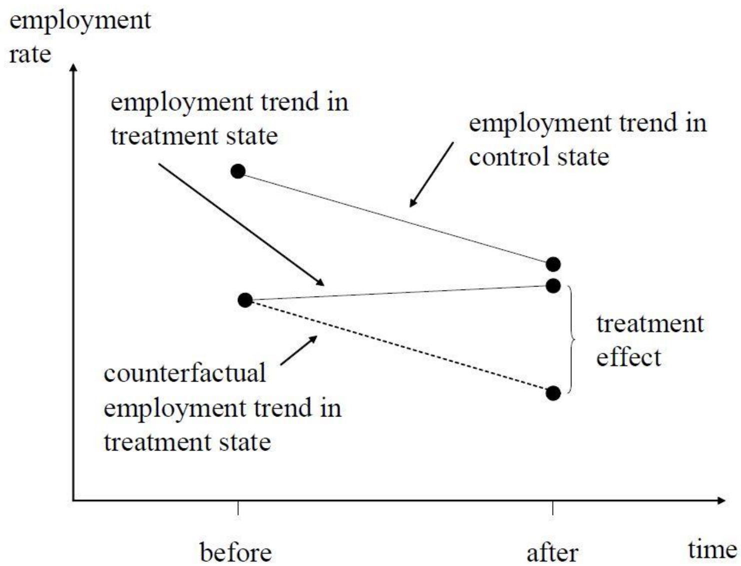

Figure 3: Causal effects in the difference-in-differences model (from Angrist & Pischke, 2009)

To explain how the difference-in-differences model is set-up, the following minimum wage example will be taken from Angrist & Pischke (2009):

Y_{1ist} : fast food employment at restaurant *I* and period t if there is a high state minimum wage
Y_{0ist} : fast food employment at restaurant *I* and period t if there is a low state minimum wage

The heart of the difference-in-differences setup is an additive structure for potential outcomes in the no-treatment state. Specifically, we assume that:

$$E[Y_{0ist}|s,t] = \gamma_s + \lambda_t$$

This equation states that in the absence of a minimum wage change, employment is determined by the sum of a time-invariant state effect and a year effect that is common across states.

D_{st}: dummy for high-minimum-wage states, where states are indexed by *s* and observed in period *t*.

Using the common trend assumption, we assume that $E[Y_{1ist} - Y_{0ist}|s,t]$ is a constant, denoted β, this results in:

$$Y_{ist} = \gamma_s + \lambda_t + \beta D_{st} + \varepsilon_{ist} \qquad (1)$$

Where $E[\varepsilon_{ist}|s,t] = 0$. From there, we get:

$$E[Y_{ist}|s = PA, t = Nov] - E[Y_{ist}|s = PA, t = Feb] = \lambda_{Nov} - \lambda_{Feb}$$

And

$$E[Y_{ist}|s = NJ, t = Nov] - E[Y_{ist}|s = Nj, t = Feb] = \lambda_{Nov} - \lambda_{Feb} + \beta$$

The population difference-in-differences, β, is the causal effect of interest:

$$[E(Y_{ist}|s = PA, t = Nov) - E(Y_{ist}|s = PA, t = Feb)]$$

$$- [E(Y_{ist}|s = NJ, t = Nov) - E(Y_{ist}|s = NJ, t = Feb)] = \beta$$

Regression can be used to estimate equation (1). Let NJ_s be a dummy for restaurants in New Jersey and d_t be a time-dummy that switches on for observations obtained in November (i.e., after the minimum wage change), then:

$$Y_{ist} = \alpha + \gamma NJ_s + \lambda d_t + \beta(NJ_s * d_t) + \varepsilon_{ist} \tag{2}$$

Wherein β is again the difference-in-differences estimator and $NJ_s \cdot d_t = D_{st}$ as in equation (1).

3.5.1 Granger's causality test (lead & lag test)

When there are multiple treatment groups and multiple periods, it becomes difficult to visually inspect the evolution of state-specific trends in periods without treatment. The common trend is still the identifying assumption, and should be properly tested. One way is to allow for leads and lags of the treatment, as first proposed by Granger (1969). His idea was to see whether causes happen before consequences and not the other way around (Angrist & Pischke, 2009; Pischke, 2015). Let *k* denote the time at which the treatment is started in state *s*, then the model is as stated in Pischke (2015):

$$Y_{ist} = \gamma_s + \lambda_t + \sum_{j=-m}^{q} \beta_j D_{st}\,(t = k + j) + X_{ist}\delta + \varepsilon_{ict} \tag{3}$$

Instead of a single treatment effect, we have now also included *m* "leads" and *q* "lags" of the treatment effect[7]. β_j is the coefficient on the j_{th} lead or lag. A test of the difference-in-differences assumption is $\beta_j = 0$

[7] These leads and lags are not actually leads and lags of the treatment indicator in a time-series jargon sense. They are just interactions of the treatment indicator with time dummies.

� $j < 0$, i.e. the coefficients on all leads of the treatment should be zero. Moreover, the β_j, $j \geq 0$ may not be identical. For example, the effect of the treatment could accumulate over time, so that β_j increases in j (Pischke, 2015).

3.5.2 Econometric method for Gravity models

Since this thesis looks at trade flows, one cannot ignore gravity models. However, this thesis is not about explaining trade flows, but about investigating the changes in trade flows as a result of an imposed policy. That being said, elements from the gravity model will be used in this thesis. The variable Y_{ist} discussed in the previous sub-sector is such a trade flow. In this thesis it will denote the export value in USD for commodity class *i*, to destination country *s* from origin country China[8], in period *t* and can be treated in the same way as in a gravity model.

In gravity models, the log-linear formulation is a widely used tool to investigate international bilateral trade flows (Burger, van Oort, & Linders, 2009). However, a major weakness in such a formulation is that it implies trade among all countries in all goods and this is obviously not the case, resulting in many zero-flows[9] (Burger, van Oort, & Linders, 2009; Haveman & Hummels, 2004). The log-linear model cannot deal well with zero-flows since the logarithm of zero is undefined. There are several ways to deal with this problem, one can omit all zero-valued flows or arbitrarily add a small positive number (usually 0.5 or 1) (Linders & de Groot, 2006). However, by omitting the zero-flows important information is left out the model and can lead to biased estimates. Moreover, adding a small positive value can seriously distort the coefficients (Flowerdew & Aitkin, 1982; Linders & de Groot, 2006) and by playing with the size of the value it can generate an estimate to your liking (King, 1988). Another problem of the log-linear formulation and other models arises in the presence of heteroscedasticity. Heteroscedasticity does not affect the estimates, but it does bias the variance of the estimated parameters, consequently the t-values for these coefficients cannot be trusted (Santos Silva & Tenreyro, 2006). This will be discussed later on.

Different methods are being proposed to deal with the zero-flow problem, such as the use of Poisson and modified Poisson models by Santos Silva & Tenreyro (2006). Poisson regression models have several econometric advantages over the log-linear formulation, which results in more reliable estimates (Burger, van Oort, & Linders, 2009). A Poisson model assumes that the model is equidispersed, which means that the conditional variance is equal to the conditional mean. However, this is an assumption that is not likely to hold in trade data, where the conditional variance is often higher than the conditional mean. Violation of this assumption results in overdispersion of the dependent variable. The presence of unobserved heterogeneity, not taken into account by the Poisson model, is often the reason for more variation than expected and thus overdispersion. This unobserved heterogeneity originates from omitted variables. If the model is not corrected for over- or underdispersion it results in the consistent but inefficient estimation of

[8] There is only one origin country in this dataset, therefore it needs no index itself
[9] A country imports or exports nothing of a certain product in a certain period.

the dependent variable (Burger, van Oort, & Linders, 2009). A way to correct for this overdispersion is using modified Poisson models, like a Poisson pseudo-maximum likelihood (PPML) model or a negative binomial regression model. In the negative binomial model, a multiplicative random effect is added to represent the unobserved heterogeneity (Rodriguez, 2013).

The Poisson model as stated in Burger, van Oort, & Linders (2009) is the following:

$$\Pr[I_{ij}] = \frac{\exp(-\mu_{ij})\,\mu_{ij}^{I_{ij}}}{I_{ij}!} \tag{4}$$

$$\mu_{ij} = \exp(\alpha_0 + \beta' X_{ij} + \eta_i + \gamma_j) \tag{5}$$

Where I_{ij} is the trade volume between country *i* and *j* that has a Poisson distribution with a conditional mean (μ) that is function of the independent variables in equation (5). Where α_0 is a proportionality constant, X_{ij} is the 1 x *k* row vector of explanatory variables with corresponding parameter vector β, η_i is an origin-country specific effect, and γ_j is destination-country specific effect (Burger, van Oort, & Linders, 2009).

The negative binomial regression model as stated in Burger, van Oort, & Linders (2009) is:

$$\Pr[I_{ij}] = \frac{\Gamma(I_{ij} + \alpha^{-1})}{I_{ij}!\,\Gamma(\alpha^{-1})}\left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_{ij}}\right)^{\alpha^{-1}}\left(\frac{\mu_{ij}}{\alpha^{-1} + \mu_{ij}}\right)^{I_{ij}} \tag{6}$$

Where μ_{ij} is again equation (5), Γ the gamma function, and α a parameter that determines the degree of dispersion in predictions, thereby allowing the conditional variance to exceed the conditional mean. If α approaches zero, the negative binomial regression model reduces to the Poisson regression model (Burger, van Oort, & Linders, 2009).

A problem with count data models, like Poisson and negative binomial models, is that empirical data often contains more zeros than would be predicted by the Poisson or negative binomial distributions (Burger, van Oort, & Linders, 2009; Rodriguez, 2013). According to Greene (1994), these excess zeros will 'masquerade' as overdispersion, however, it is important to separate the excess-zeros and overdispersion issues into two different processes underlying the deficiencies of the Poisson model. Overdispersion stems from unobserved heterogeneity, whereas excess zeros derive from 'non-Poissonness', or overabundance of zeros (Burger, van Oort, & Linders, 2009). This excess zero problem is addressed in zero-inflated models (Poisson or negative binomial) or a zero-adapted Poisson model, but also in a Poisson pseudo-maximum likelihood (PPML) model.

The zero-inflated Poisson model consists of two parts, first, it uses a logit model to distinguish counts of zero from larger counts (7) and then uses a Poisson model to predict the latter (8):

$$\Pr[I_{ij}] = \psi_{ij} + (1 - \psi_{ij}) \exp(-\mu_{ij}) \tag{7}$$

$$\Pr[I_{ij}] = (1 - \psi_{ij}) \frac{\exp(-\mu_{ij})\mu_{ij}^{I_{ij}}}{I_{ij}!} \tag{8}$$

Where μ_{ij} is again equation (5), and ψ_{ij} is the proportion of observations with a strictly zero count, which is determined by a logit model. If ψ_{ij} is 0, the zero-inflated Poisson model reduces to a Poisson model (Burger, van Oort, & Linders, 2009).

Similar to the zero-inflated Poisson model is the zero-inflated negative binomial model. Where it combines the logit equation with the negative binomial. This model adds again unobserved heterogeneity to the Poisson equation (Rodriguez, 2013). As can be seen in these equations from Burger, van Oort, & Linders (2009):

$$\Pr[I_{ij} = 0] = \psi_{ij} + (1 - \psi_{ij}) \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_{ij}} \right)^{\alpha^{-1}} \tag{9}$$

$$\Pr[I_{ij}] = (1 - \psi_{ij}) \frac{\Gamma(I_{ij} + \alpha^{-1})}{I_{ij}!\,\Gamma(\alpha^{-1})} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_{ij}} \right)^{\alpha^{-1}} \left(\frac{\mu_{ij}}{\alpha^{-1} + \mu_{ij}} \right)^{I_{ij}} \tag{10}$$

The Vuong statistic can be used to test whether to use a zero-inflated over a non-zero inflated model, by examining if there is evidence for excessive zeros (Vuong, 1989). The choice between Poisson and negative binomial should depend on the degree of overdispersion.

Another model that is proposed to deal with excess zeros is the Zero-Altered Poisson (Hurdle) model by Mullahy (1986). This model is similar to the zero-inflated Poisson model, however, it uses a zero-truncated Poisson model for the second part, where the zeros are 'hurdled' over. However, by zero-truncating, important information might get lost (Rodriguez, 2013).

The last model to discuss is widely used for the estimation of gravity models: the Poisson pseudo-maximum likelihood model (Anderson & Yotov, 2012; Bahn & Massenburg, 2008; Fally, 2015; Gomez-Herrera & Milgram-Baleix, 2010; Shepherd, 2010). It performs similarly to a Poisson model while it can deal with overdispersion and also performs well in the presence of excess zeros (Santos Silva & Tenreyro, 2006, 2011). However, Martin & Pham (2015) point out that Santos Silva & Tenreyro's (2006) demonstration of the PPML model does not include excess zeros in their used dataset, while the PPML model does perform very well for the analysis of nonlinear relationships in models where zeros are infrequent (Martin & Pham, 2015). However, Santos Silva & Tenreyro (2011) revisited their earlier paper and demonstrated with another dataset that the PPML model does perform well, even with excess zeros.

3.5.3 Heteroscedasticity and serial correlation

It is important to consider heteroscedasticity and serial correlation in the data. Since it is very likely that trade data contains heteroscedasticity[10] and serial correlation[11]. Two tests for heteroscedasticity that are widely used in economics are the White (1980) test and the Lagrangian multiplier test by Breusch & Pagan (1979). If there is heteroscedasticity, the parameter estimates will retain their consistency. However, their standard errors are inefficient and need to be corrected, since they tend to be deflated resulting in large t-values. There are several ways to correct this issue, the easiest way is to use heteroscedastic-robust standard errors (Angrist & Pischke, 2009). However, this only adjusts for heteroscedasticity and in practice in a panel setting it is much more important to correct for serial correlation. It is therefore recommended to use cluster-robust standard errors (Angrist & Pischke, 2009; Cameron & Trivedi, 2005).

3.6 Used estimation techniques

From the previous sub-sections, the methodology for this thesis will be constructed. Wherein equation (2) will be the most important, but should be adapted for this research into:

$$Y_{ict} = \alpha + \gamma S_i + \lambda d_t + \beta(S_i * d_t) + \varepsilon_{it} \tag{11}$$

Let Y_{ict} be the observed trade value, per commodity class *i,* from China to country *c*, in period *t,* α a constant term, γ the treatment group specific effects, S_i a dummy for HS commodity classes that use REE, λ time specific effects, d_t dummy for years in which there are export restrictions, β the treatment effect, and ε_{ict} a random unobserved error term.

As mentioned before, the trade flow is often log transformed, this will be done for specification (1):

$$\ln(Y_{ict}) = \alpha + \gamma S_i + \lambda d_t + \beta(S_i * d_t) + \varepsilon_{it} \tag{12}$$

[10] If the data is homoscedastic, the variance and the expected value of the error term are constant. But in trade data they are often not, where the expected value of the error term is a function of the regressors and is therefore heteroscedastic (Gomez-Herrera, 2013).

[11] Serial correlation, the tendency for one observation to be correlated with those that have gone before (Angrist & Pischke, 2009, p. 236), or in other words, the error terms of individual units are serially correlated. This can also occur due the possible omission of relevant variables (Bhargava, Franzini, & Narendranathan, 1982).

For specification (2) the Poisson model will be estimated.

$$\Pr[Y_{ict}] = \frac{\exp(-\mu_{ict})\,\mu_{ict}^{Y_{ict}}}{Y_{ict}!} \tag{13}$$

$$\mu_{ict} = \exp(\alpha_0 + \gamma S_i + \lambda d_t + \beta(S_i * d_t)) \tag{14}$$

Where Y_{ict} is the export value of commodity class *i* to country *c* in period *t,* and α_0 is a proportionality constant.

The negative binomial regression model is used in specification (3):

$$\Pr[Y_{ict}] = \frac{\Gamma(Y_{ict} + \alpha^{-1})}{Y_{ict}!\,\Gamma(\alpha^{-1})}\left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_{ict}}\right)^{\alpha^{-1}}\left(\frac{\mu_{ict}}{\alpha^{-1} + \mu_{ict}}\right)^{Y_{ict}} \tag{15}$$

Where μ_{ict} is the same as equation (14), Γ the gamma function, and α a parameter that determines the degree of dispersion in predictions.

Zero-inflated Poisson model is used in specification (4):

$$\Pr[Y_{ict}] = \psi_{ict} + (1 - \psi_{ict})\exp(-\mu_{ict}) \tag{16}$$

$$\Pr[Y_{ict}] = (1 - \psi_{ict})\frac{\exp(-\mu_{ict})\mu_{ict}^{Y_{ict}}}{Y_{ict}!} \tag{17}$$

And the zero-inflated negative binomial model in specification (5):

$$\Pr[Y_{ict} = 0] = \psi_{ict} + (1 - \psi_{ict})\left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_{ict}}\right)^{\alpha^{-1}} \tag{18}$$

$$\Pr[Y_{ict}] = (1 - \psi_{ict})\frac{\Gamma(Y_{ict} + \alpha^{-1})}{Y_{ict}!\,\Gamma(\alpha^{-1})}\left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_{ict}}\right)^{\alpha^{-1}}\left(\frac{\mu_{ict}}{\alpha^{-1} + \mu_{ict}}\right)^{Y_{ict}} \tag{19}$$

For both the zero-inflated Poisson and the negative binomial model is μ_{ict} again the same as in equation (14).

The Poisson pseudo-maximum likelihood model is used for specification (6) and (7). Their calculation method slightly differs from each other, the first one uses a generalized linear model (GLM), with a log link and a Poisson distribution and uses iteratively-reweighted least squares (IRLS). While the second one uses the PPML STATA program that was written by Santos Silva & Tenreyro (2006). This one, though, does have some difficulties treating large values in the dependent variable. Therefore, the variable trade is divided by one million (*traderesc*), this does not impact the final result since the estimator is scale-invariant (Shepherd, 2013). This program also does not support including fixed effects, except manual dummies.

SECTION IV: RESULTS & DISCUSSION

In this section, the results of this thesis are presented. The results are divided into two parts, first the results for the dataset where the countries are aggregated, and then for the non-aggregated dataset. In the aggregated dataset all the countries are summed, which means that there are still 8 years left and 5000 6-digit commodity classes, which is just the total of China's exports for each year divided into the 5000 commodity classes.

4.1 Aggregated data results

The regression results for the country-aggregated data are shown in Table 3. Specification (1) uses the log-linear OLS formulation with year fixed effects, wherein the zero-flows are omitted, resulting in biased estimators. Moreover, the White test and the Breusch-Pagan test both indicate heteroscedasticity in the country-aggregated trade values (Table 4). Which means that the already biased estimates of specification (1), also have t-values that cannot be trusted. Therefore, heteroscedastic-robust standard errors are used that are clustered in 2-digit commodity classes[12], which also corrects for possible serial correlation issues.

Table 3: Regression results for the country-aggregated dataset

VARIABLES	(1) OLS lntrade	(2) Poisson trade	(3) NB trade	(4) ZIP trade	(5) ZINB trade	(6) GLM-PPML trade	(7) PPML traderesc
time (λ)	0.764***	0.577***	0.561***	0.579***	-	0.577***	0.577***
	(0.0647)	(0.0507)	(0.0496)	(0.0509)		(0.0507)	(0.0507)
treated (γ)	1.749***	1.746***	1.747***	1.737***	-	1.746***	1.746***
	(0.506)	(0.357)	(0.357)	(0.356)		(0.357)	(0.357)
did (β)	-0.261***	0.147***	0.129***	0.148***	-	0.147***	0.147***
	(0.0929)	(0.0481)	(0.0467)	(0.0486)		(0.0481)	(0.0481)
Constant (α)	16.79***	19.22***	19.23***	19.23***	-	19.22***	5.408***
	(0.188)	(0.198)	(0.199)	(0.196)		(0.198)	(0.198)
Observations	39,982	40,360	40,360	40,360	40,360	40,360	40,360
R-squared	0.024						0.018
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dest. Country FE[13]	No	No	No	No	No	No	No
2-digit Com Clus SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[12] The 2-digit commodity classes are used for clustering because it is expected that the standard errors are correlated within the same industry (the first two digits of the commodity class code).
[13] Since this is the country-aggregated dataset, there is no information left about the destination countries and could therefore not be included as destination country fixed effects.

Table 4: Results from heteroscedasticity tests (aggregated dataset)

DEP. VAR.	TEST	TEST STATISTIC	P-VALUE
LN (TRADE)	White	23.14	0.0812
	Breusch-Pagan	7.42	0.0064
TRADE	White	228.90	0.0000
	Breusch-Pagan	118520.51	0.0000

Specification (2) shows a Poisson model, however, the conditional variance is a billion times larger than the conditional mean[14], which means severe overdispersion. This indicates that while the coefficients are consistent, they are inefficient. Which is also demonstrated by an extremely high Chi^2 when looking at the Poisson goodness of fit[15]. The same goes for the zero-inflated Poisson (ZIP) regression (specification 4).

This overdispersion can be dealt with by using a negative binomial (NB) regression (specification 3), a zero-inflated negative binomial (ZINB) regression (specification 5) or a Poisson pseudo-maximum likelihood (PPML) regression (specification 6 and 7). The zero-inflated negative binomial (ZINB) model failed to converge and estimates could therefore not be calculated. This leaves us with the negative binomial (NB) model and the PPML models. The Vuong test could test if there are excess-zeros issues in the dataset, but STATA could not calculate this test. However, this dataset contains 378 zeros in the 40,360 observations. It is, therefore, likely that there is no excess-zeros issue here. Which would mean that both the negative binomial regression and the PPML regressions could be used. The results both the PPML models are identical except for the constant, this is because of rescaled nature of the dependent variable.

The difference-in-differences coefficient (β) of 0.129 for negative binomial regression (specification 3) and 0.147 for both the Poisson pseudo-maximum likelihood regressions (specification 6 and 7) indicate a 13.8% and 15.8% increase[16] in export value of commodity classes that use rare earths after the export restrictions were imposed.

[14] The variance is 6.18e+18 and the mean is 3.54e+08
[15] Deviance goodness-of-fit = 5.73e+13 with 0.0000 Prob > Chi^2,
Pearson goodness-of-fit = 4.79e+14 with 0.0000 Prob > Chi^2
[16] The coefficient need to interpreted as e^{β} = $e^{0.147}$ = 1.158, meaning a 15.8% increase.

4.1.1 Common trend assumption

However, the common trend assumption for the difference-in-differences method still needs to be validated. The results of Granger causality (lead and lag) test are shown in Table 5. For the assumption to hold the coefficients on all leads should be zero or close to zero, and the lags are not allowed be identical. In specification (1) the leads are close to zero and the lags are not identical and statistically significant. Which indicates that the common trend assumption holds. Specification (2) shows a specification where the dataset is treated as a panel dataset and two leads are included. Again, both leads are close to zero. Specification (3) uses the PPML model to estimate the leads, here the first lead is statistically significant, which means that the treatment was already somewhat anticipated. Specification (4) checks that first lead when the second lead is not included, and its again statistically significant. These results indicate that the common trend assumption is not violated and the difference-in-differences coefficients from Table 3 can be trusted.

Table 5: Lead and lag test for the country-aggregated dataset

VARIABLES	(1) OLS lntrade	(2) OLS lntrade	(3) GLM-PPML trade	(4) GLM-PPML trade
time (λ)	0.797***	0.685***	0.501***	0.533***
	(0.0698)	(0.0593)	(0.0517)	(0.0528)
treated (γ)	-3.802***	1.797***	1.733***	1.722***
	(0.0399)	(0.522)	(0.356)	(0.351)
β_{-3}	0.278***			
	(0.0951)			
β_{-2}	0.210***			
	(0.0724)			
β_{-1}	0.150***			
	(0.0476)			
β_{0}		-0.198***	0.0288	0.0716*
		(0.0664)	(0.0389)	(0.0403)
β_{+1}	-0.0388	-0.0423	0.0814***	0.0721**
	(0.0711)	(0.0754)	(0.0312)	(0.0294)
β_{+2}	-0.0772	-0.0513	-0.0205	
	(0.0982)	(0.0739)	(0.0173)	
β_{+3}	-0.0666			
	(0.0989)			
β_{+4}	-0.172**			
	(0.0810)			
Constant (α)	22.987***	16.78***	19.23***	19.23***
	(0.0518)	(0.187)	(0.199)	(0.199)
Observations	39,982	30,003	30,270	35,315
R-squared	0.9275	0.022		
Year FE	Yes	Yes	Yes	Yes
Commodity-year FE	Yes	No	No	No
2-digit Com Clus SE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.1.2 Same-industry control group

In the previous subsections, the non-treated commodity classes are not similar industries, opposed to what it normally should be when conducting such an analysis. There was chosen to do this anyway because of the nature of the treatment. All the countries were treated and everyone was treated at the same period. With this in mind, another approach is offered where only the commodity classes are used that lie in the first two-digit parent commodity class that has rare earth elements in them[17]. This assumes that the commodities that are in the same parent two-digit classes are similar and should act as the control group. The time trend for these two groups can be seen in Figure 5 in Appendix D, which looks quite similar to the earlier mentioned trends in Figure 2. To this altered dataset, the same specifications as earlier are applied, and those results can be found in Table 7. The zero-inflated negative binomial (ZINB) model failed to converge and estimates for that model could therefore not be calculated.

The heteroscedasticity tests produce different results (Table 6) compared to those for the complete aggregated dataset. For the log-transformed trade values, the tests indicate that there is no evidence for heteroscedasticity. As a consequence, Table 7 shows results for each specification with robust clustered standard errors (a) and without (b). However, specification 2b, 4b, and 6b show each relatively small standard errors, indicating that while there is no evidence for heteroscedasticity, there probably is a serial correlation which also results in inefficient standard errors. Here the standard errors are smaller than the true standard errors, and thereby inflating the t-value. Therefore, should the results from the specifications without robust clustered standard errors be ignored. Moreover, also in this dataset, there is severe overdispersion. Which means that the Poisson (specification 2) and the zero-inflated Poisson (specification 4) should be ignored. Excess zeros are no concern in this dataset since it contains only 29 zeros out of the 8120 observations.

This leaves again only the negative binomial regression (specification 3) and the Poisson pseudo-maximum likelihood regressions (specification 6 and 7), but their difference-in-differences coefficient (β) is not statistically significant. Hence, no inference could be done with these results. Consequently, performing a Granger causality test is unnecessary.

Table 6: Results from heteroscedasticity test (country-aggregated dataset with same-industry control group)

DEP. VAR.	TEST	TEST STATISTIC	P-VALUE
LN (TRADE)	White	5.57	0.9861
	Breusch-Pagan	1.22	0.2702
TRADE	White	66.57	0.0000
	Breusch-Pagan	17182.93	0.0000

[17] These 2-digit commodity classes are: 28, 32, 36, 38, 70, 72, 85, 87, 90. Using the 4-digit commodity classes would be useless since these hardly differ from the 6-digit classes i.e. the 4-digit contains often only two 6-digit classes. While there are 99 2-digit classes that contain similar subclasses.

Table 7: Regression results from the country-aggregated dataset with same-industry control group

VARIABLES	(1a) OLS lntrade	(1b) OLS lntrade	(2a) Poisson trade	(2b) Poisson trade	(3a) NB trade	(3b) NB trade	(4a) ZIP trade	(4b) ZIP trade	(6a) GLM-PPML trade	(6b) GLM-PPML trade	(7a) PPML traderesc	(7b) PPML traderesc
time	0.839***	0.839***	0.695***	0.695***	0.679***	0.679***	0.695***	0.695***	0.695***	0.695***	0.695***	0.695***
	(0.0382)	(0.109)	(0.0357)	(2.02e-06)	(0.0480)	(0.0810)	(0.0351)	(2.02e-06)	(0.0357)	(2.02e-06)	(0.0357)	(0.220)
treated	1.169**	1.169***	1.518***	1.518***	1.524***	1.524***	1.513***	1.513***	1.518***	1.518***	1.518***	1.518***
	(0.446)	(0.107)	(0.189)	(1.58e-06)	(0.193)	(0.0796)	(0.187)	(1.58e-06)	(0.189)	(1.58e-06)	(0.189)	(0.151)
did	-0.336***	-0.336**	0.0774	0.0774***	0.0588	0.0588	0.0811	0.0811***	0.0774	0.0774***	0.0774	0.0774
	(0.0901)	(0.135)	(0.0534)	(1.88e-06)	(0.0541)	(0.101)	(0.0548)	(1.88e-06)	(0.0534)	(1.88e-06)	(0.0534)	(0.217)
Constant	17.37***	17.37***	19.44***	19.44***	19.45***	19.45***	19.45***	19.45***	19.44***	19.44***	5.629***	5.629***
	(0.516)	(0.0776)	(0.516)	(1.67e-06)	(0.519)	(0.0577)	(0.515)	(1.67e-06)	(0.516)	(1.67e-06)	(0.516)	(0.135)
Obs.	8,091	8,091	8,120	8,120	8,120	8,120	8,120	8,120	8,120	8,120	8,120	8,120
R-squared	0.039	0.039									0.027	0.027
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dest. Country FE	No	No	No	No	No	No	No	No	No	No	No	No
2-digit Com Clus SE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No

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

4.2 Non-aggregated data results

Table 8 shows the results for the non-aggregated data set. Just like for the country-aggregated data set, different estimation models are used. Specification (1) uses again the log-linear OLS formulation with year fixed effects and this time also destination country fixed effects, wherein the zero-flows are omitted, resulting in biased estimators. And again, the White test and the Breusch-Pagan test both indicate heteroscedasticity in the non-aggregated trade values (Table 9). Therefore, for each specification, heteroscedastic-robust standard errors are used that are clustered in 2-digit commodity classes. The negative binomial (NB) model and the zero-inflated Poisson (ZIP) model failed to converge and estimates could therefore not be calculated.

Table 8: Regression results for the non-aggregated dataset

VARIABLES	(1) OLS lntrade	(2) Poisson trade	(3) NB trade	(4) ZIP trade	(5) ZINB trade	(6) GLM-PPML trade	(7) PPML traderesc
time	0.394***	0.577***	-	-	0.153***	0.577***	0.577***
	(0.0444)	(0.0507)			(0.0450)	(0.0507)	(0.0507)
treated	0.822	1.746***	-	-	1.470***	1.746***	1.746***
	(0.531)	(0.357)			(0.305)	(0.357)	(0.357)
did	-0.0835	0.147***	-	-	0.194***	0.147***	0.147***
	(0.0595)	(0.0481)			(0.0473)	(0.0481)	(0.0481)
Constant	10.99***	13.26***	-	-	15.70***	13.26***	0.966***
	(0.196)	(0.287)			(0.164)	(0.287)	(0.198)
Observations	1,808,518	3,430,600	3,430,600	3,430,600	3,430,600	3,430,600	3,430,600
R-squared	0.175						0.001
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dest. Country FE	Yes	Yes	Yes	Yes	Yes	Yes	No
2-digit Com Clus SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Specification (2) shows a Poisson model, however, the conditional variance is here 100 million times larger than the conditional mean[18], which means severe overdispersion. This indicates that while the coefficients are consistent, they are inefficient. Which is also demonstrated by an extremely high Chi^2 when looking at the Poisson goodness of fit[19]. Again to deal with this overdispersion, the zero-inflated negative binomial

[18] The variance is 1.08e+16 and the mean is 1.04e+08

[19] Deviance goodness-of-fit = 7.82e+13 with 0.0000 Prob > Chi^2,
Pearson goodness-of-fit = 1.14e+15 with 0.0000 Prob > Chi^2

regression, and the Poisson pseudo maximum likelihood regressions are used (specification 5, 6 and 7). The resulting coefficients from specification (6) and (7) are identical to the country-aggregated results, again only the constant differs. This dataset contains very much (47%) zeros, and excess zeros is here definitely an issue. But as mentioned before, the zero-inflated negative binomial and the PPML model can both handle this issue very well.

The difference-in-differences coefficient (β) of 0.194 for specification (5) and 0.147 for specification (6) and (7) indicate a 21.4% and a 15.8% increase in the export value of commodity classes that use rare earths after the export restrictions were imposed.

Table 9: Results from heteroscedasticity tests (non-aggregated dataset)

DEP. VAR.	TEST	TEST STATISTIC	P-VALUE
LN (TRADE)	White	1579.08	0.0000
	Breusch-Pagan	1526.05	0.0000
TRADE	White	437.44	0.0000
	Breusch-Pagan	8,580,000	0.0000

4.2.1 Common trend assumption

Again, the common trend assumption for the difference-in-differences method still needs to be validated. The results of Granger causality test are shown in Table 10. For the assumption to hold the coefficients on all leads should be zero or close to zero, and the lags are not allowed be identical. In specification (1), (2), and (3) the leads are close to zero and the lags are not identical. Which indicates that the common trend assumption is not violated and the difference-in-differences coefficients from Table 8 can be trusted. However, when the PPML model is used the leads are statistically significant which would suggest that the common trend assumption is violated and consequently that the coefficients from Table 8 cannot be trusted.

Table 10: Lead and lag test for the non-aggregated dataset

VARIABLES	(1) OLS lntrade	(1) OLS lntrade	(2) OLS lntrade	(3) GLM-PPML trade	(4) GLM-PPML trade
time (λ)	0.494***	0.317***	0.401***	0.557***	0.557***
	(0.0586)	(0.0580)	(0.0466)	(0.0498)	(0.0498)
treated (γ)	-2.798***	0.663	0.747	1.750***	1.750***
	(0.3315)	(0.479)	(0.510)	(0.374)	(0.374)
β_{-3}	0.219***	0.154**	0.167**	-0.0166	-0.0166
	(0.0594)	(0.0775)	(0.0790)	(0.0439)	(0.0439)
β_{-2}	0.210**	0.0512	0.0458	-0.0372	-0.0372
	(0.0444)	(0.0420)	(0.0457)	(0.0458)	(0.0458)
β_{-1}	0.0767**	0.0412*	0.0342	0.0442	0.0442
	(0.0335)	(0.0225)	(0.0229)	(0.0315)	(0.0315)
β_{0}					
β_{+1}	-0.0580	-0.0188	-0.0339	0.0668***	0.0668***
	(0.0523)	(0.0383)	(0.0402)	(0.0257)	(0.0257)
β_{+2}	0.0044	0.0419	0.0306	0.123***	0.123***
	(0.0407)	(0.0363)	(0.0301)	(0.0236)	(0.0236)
β_{+3}	-0.0344	0.0101	-0.0105	0.204***	0.204***
	(0.0418)	(0.0489)	(0.0430)	(0.0233)	(0.0233)
β_{+4}	-0.0782*	-0.0200	-0.0404	0.223***	0.223***
	(0.0443)	(0.0596)	(0.0545)	(0.0300)	(0.0300)
Constant (α)	14.416***	11.84***	10.98***	14.78***	13.27***
	(0.326)	(0.110)	(0.195)	(0.199)	(0.286)
Observations	1,808,518	1,808,518	1,808,518	3,430,600	3,430,600
R-squared	0.5404	0.005	0.175		
Year FE	Yes	Yes	Yes	Yes	Yes
Dest. Country FE	Yes	No	Yes	No	Yes
Commodity-year FE	Yes	No	No	No	No
2-digit Com Clus SE	No	Yes	Yes	Yes	Yes
Dest. Country Clus SE	Yes	No	No	No	No

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.2.2 Same-industry control group

Here again the same specification as earlier, but now with the same-industry control group. The zero-inflated Poisson (ZIP) and the zero-inflated negative binomial (ZINB) models failed to converge and estimates for that model could therefore not be calculated. The heteroscedasticity tests (Table 12) indicate that there is evidence for heteroscedasticity. As a consequence, Table 7 shows only results with robust clustered standard errors.

Table 11: Regression results from the non-aggregated dataset with same-industry control group

VARIABLES	(1a) OLS lntrade	(2a) Poisson trade	(3a) NB trade	(6a) GLM-PPML trade	(7a) PPML traderesc
time	0.444**	0.695***	1.078***	0.695***	0.695***
	(0.136)	(0.0357)	(0.0330)	(0.0357)	(0.0357)
treated	0.511	1.518***	1.328***	1.518***	1.518***
	(0.419)	(0.189)	(0.237)	(0.189)	(0.189)
did	-0.141**	0.0774	-0.0761*	0.0774	0.0774
	(0.0546)	(0.0534)	(0.0444)	(0.0534)	(0.0534)
Constant	11.27***	13.40***	13.35***	13.40***	1.186**
	(0.371)	(0.528)	(0.655)	(0.528)	(0.516)
Observations	407,132	690,200	690,200	690,200	690,200
R-squared	0.196				0.002
Year FE	Yes	Yes	Yes	Yes	Yes
Dest. Country FE	Yes	Yes	Yes	Yes	No
2-digit Com Clus SE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

There is again overdispersion in the dataset, which means the Poisson model cannot be used. Nearly half of the observations contain zeros, indicating evidence for the excess zeros issue. Which means the negative binomial model should not be used. Which leaves only the PPML models, but the difference-in-differences coefficient (β) is not statistically significant. Hence, no inference could be done with these results. Therefore, performing a Granger causality test is unnecessary.

Table 12: Results from heteroscedasticity tests (non-aggregated dataset with same-industry control group)

DEP. VAR.	TEST	TEST STATISTIC	P-VALUE
LN (TRADE)	White	1185.712	0.0000
	Breusch-Pagan	829.35	0.0000
TRADE	White	197.8523	0.0000
	Breusch-Pagan	1.36e+06	0.0000

Section V: Conclusion

This thesis has empirically researched what the effect was of China's export restrictions, regarding rare earth elements, on China's domestic refining of rare earths and the downstream production of rare earths-using commodities. This was done by using the econometric difference-in-differences technique. This method compares the average change over time in the Chinese export value in US dollars of commodity classes that use rare earth elements (treatment group), compared to the average change over time in the Chinese export value of commodity classes that do not use rare earth elements (control group).

But before this analysis, relevant literature about export restrictions was discussed, complemented with a few empirical models. After which context was given about China's trade policies, then the rare earth elements were introduced, what they are, where and how they are mined, where they are exactly used for, and what production and consumption trends are across the world. Next the used dataset was explained, and subsequently the used methodology was extensively discussed, first by looking at the difference-in-differences method and its limitations, which is then extended to be calculated using six different models frequently used in gravity model estimations; OLS, Poisson, negative binomial, zero-inflated Poisson, zero-inflated negative binomial and Poisson pseudo-maximum likelihood. In which attention is given to all kinds of econometric issues that arise using each of those different models, and how the different models deal or cannot deal with these issues.

The results are split into parts, where the first part looked at a dataset where the countries where aggregated, while second part looks at the non-aggregated dataset. From the country-aggregated dataset only the negative binomial regression and the Poisson pseudo-maximum likelihood (PPML) regression could be used and gave statistically significant coefficients, indicating a 13.8% and 15.8% increase in the export value of commodity classes that use rare earths after the export restrictions were imposed. When using a different control group, the coefficients for the usable models are not statistically significant.

When looking at the non-aggregated dataset, the difference-in-differences coefficients indicate a 21.4% and a 15.8% increase in the export value of commodity classes that use rare earths after the export restrictions were imposed. However, the common trend assumption for this dataset is violated and therefore should the coefficients from this dataset not be trusted. When using a different control group, the coefficients for the usable models are again not statistically significant.

This research indicates that there is evidence that the export restrictions on rare earths in China resulted in 13.8% to 15.8% more exports of rare earths-using commodities. This would mean that as long as domestic consumption of these commodities remained constant or is increased, the downstream production of rare earths-using commodities also increased with at least these percentages.

However, one must take note that this research uses export values[20] and when one would use actual domestic data instead of export data, another picture might emerge, also because there might be more and more domestic production of rare earths-using commodities that is domestically consumed. It is therefore suggested that in future research this domestic data should be used to give a more reliable result.

[20] Actually it is import from other countries, but their import is assumed to be equal to China's export.

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Appendix A

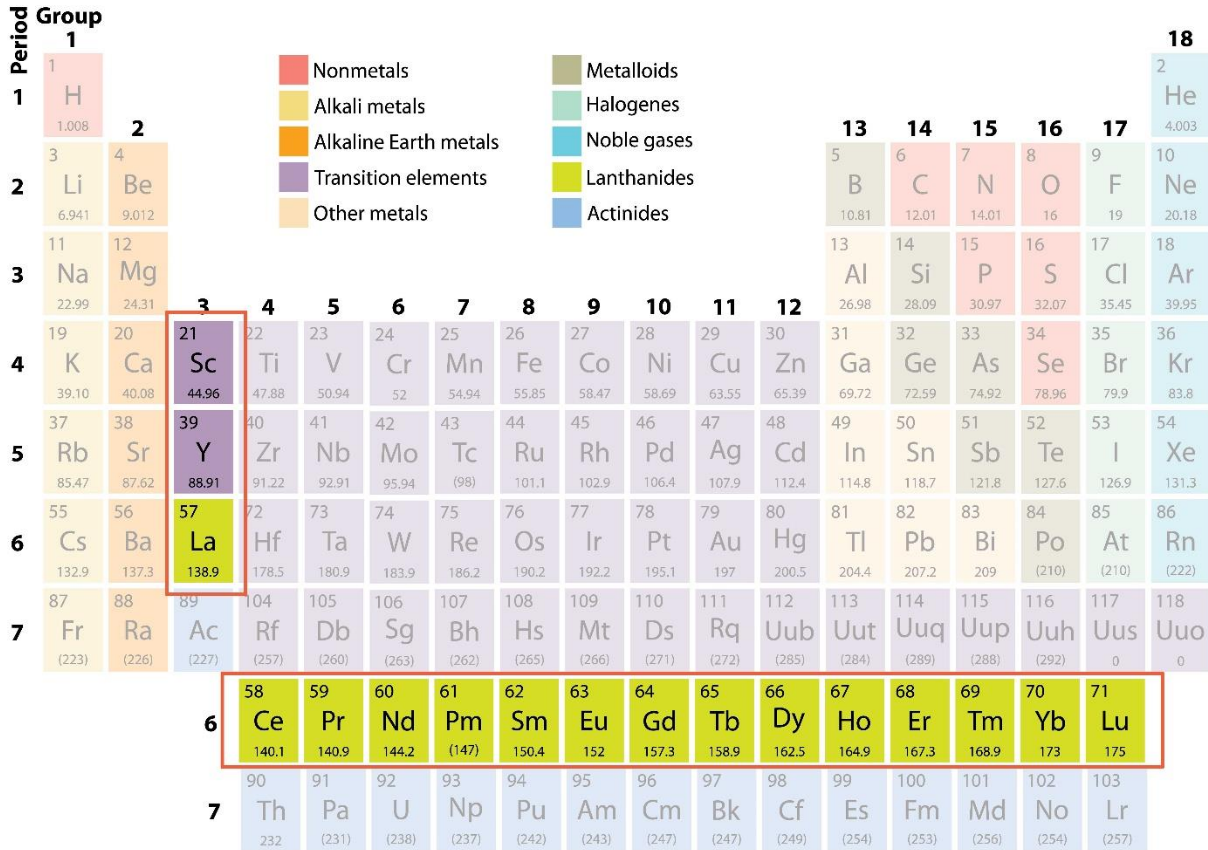

Figure 4: Periodic table with the rare earth elements highlighted with red (from Rare Earth Elements (2015).

Appendix B

Table 13: Industrial and commercial applications for each rare earth element (Bade, 2010; Macheri, Sundaresan, & Chandrashekar, 2013; Schuler, Buchert, Liu, Dittrich, & Merz, 2011; USGS, 2011)

SYMBOL	NAME	USES
SC	Scandium	
		Light aluminum-scandium alloys for aerospace components and sports equipment, titanium alloys are similar and cheaper and more used
		Additive in metal-halide lamps and mercury-vapor lamps
		Radioactive tracing agent in oil refineries
		Lasers for dentists
Y	Yttrium	
		YBCO high-temperature superconductors
		Yttrium aluminum garnet (YAG) near-infrared laser to cut metals, and phosphor to make white LEDs
		Yttrium vanadate (YVO4) as host for europium in television red phosphor for CRT displays and LED
		Yttria-stabilized zirconia (YSZ) used in automobile exhaust systems
		Yttrium iron garnet (YIG) for microwave filters
		Energy-efficient light bulbs
		Spark plugs
		Gas mantles
		Additive to metals
		Used in medical drugs for cancer
LA	Lanthanum	
		Additive to high refractive index and alkali-resistant glass, and camera and telescope lenses
		Ignition elements in lighters and torches, mischmetal a pyrophoric alloy in lighter flints
		Hydrogen storage, hydrogen sponge alloys
		Battery-electrodes, electron cathodes, Nickel-metal hydride (NiMh) batteries
		Additive to steel
		Fluid catalytic cracking catalyst for oil refineries
		Carbon lighting for studio lighting and projection (phased out)
		Scintillators (after glow)
		Gas tungsten arc welding (GTAW) electrodes, as substitute for radioactive thorium
		Hot cathode materials in vacuum tubes
		ZBLAN gas used in fiber-optical communication systems
		Pool products that remove phosphates that feed algae
		Phosphor lamp coatings
CE	Cerium	
		Chemical oxidizing agent in the exhaust gasses from motor vehicles
		Polishing powder

		Yellow colors in glass and ceramics
		Catalyst for self-cleaning ovens
		Fluid catalytic cracking catalyst for oil refineries
		Ferrocerium flints for lighters
		Additive to metals
		Gas tungsten arc welding (GTAW) electrodes
		Permanent magnets
		Carbon lighting for studio lighting and projection (phased out)
PR	Praseodymium	
		Rare-earth magnets
		Lasers
		Carbon lighting for studio lighting and projection (phased out)
		Yellow colorant in glasses and enamels
		Additive in didymium glass used in welding goggles
		Ferrocerium firesteel (flint) products
		Additive in metals for aircraft engines
		Single mode fiber optical amplifier
		Oxidation catalyst
ND	Neodymium	
		Rare-earth magnets
		Lasers
		Violet colors in glass and ceramics
		Didymium glass
		Ceramic capacitors
		Used in cryocoolers
		Fertilizer
PM	Promethium	
		Research purposes
		Atomic batteries
		Luminescent paint
SM	Samarium	
		Samarium-cobalt magnets
		Catalyst assisting decomposition of plastics
		Additive to glass and ceramics to increase absorption of IR
		Treatment for cancer
		Neutron capture in nuclear reactors
		Lasers
		Masers
EU	Europium	
		Red and blue phosphors in TV's
		Lasers
		Mercury-vapor lamps
		Fluorescent lamps

		NMR relaxation agent
		Fluorescent glass
GD	Gadolinium	
		High refractive index glass or garnets
		Lasers
		X-ray tubes
		Computer memories
		Scintillator in PET-scans
		MRI contrast agent
		NMR relaxation agent
		Magnetostrictive alloys such as Galfenol
		Steel additive
		Treatment for cancer
		Neutron capture in nuclear reactors
		Green phosphor in color TV tubes
		Gadolinium gallium garnet is used for imitation diamonds for computer bubble memory
TB	Terbium	
		Additive in Neodymium based magnets
		Green phosphors in fluorescent lamps and TV tubes
		Lasers
		Solid state devices
		Magnetostrictive alloys such as Terfenol-D, in actuators, naval sonar, sensors and other magneto-mechanical devices
DY	Dysprosium	
		Additive in Neodymium based magnets
		Lasers
		Magnetostrictive alloys such as Terfenol-D, in actuators, naval sonar, sensors and other magneto-mechanical devices
		Neutron capture in nuclear reactors
		Data-storage applications, such as in hard disks
		Additive in metal-halide lamps
HO	Holmium	
		Lasers in microwave equipment in medical, dental, and fiber-optical applications
		Wavelength calibration standards for optical spectrophotometers
		Magnets
		Neutron capture in nuclear reactors as burnable poison
		Yellow or red colorant in glass and cubic zirconia
ER	Erbium	
		Infrared lasers
		Additive in vanadium steel
		Amplifier in fiber-optic technology
		Neutron capture in nuclear reactors as burnable poison

		Pink colorant in glass, cubic zirconia, and porcelain. Often used in sunglasses and cheap jewelry
		Used in cryocoolers
TM	Thulium	
		Portable X-ray machines
		Metal-halide lamps
		Lasers used in laser-based surgery, military, medicine and meteorology applications
		Euro banknotes
		Microwave equipment
		Arc lighting
YB	Ytterbium	
		Infrared lasers
		Chemical reducing agent
		Decoy flares
		Additive to stainless steel
		Stress gauges
		Nuclear medicine
		Atomic clock
		Portable X-ray machines
LU	Lutetium	
		Positron emission tomography – PET scan detectors
		High-refractive-index glass
		Lutetium tantalate hosts for phosphors
		Fluid catalytic cracking catalyst for oil refineries
		Phosphor in LED light bulbs
		Host for X-ray phosphors

Appendix C

Table 14: HS2007 Commodity classes that use to some extent rare earth elements. A (*) indicates that entire subclass (EUROSTAT, 2016)

HS2007	COMMODITY DESCRIPTION
280530	Rare-earth metals, scandium, and yttrium, whether or not intermixed or inter alloyed
2835*	Phosphinates (hypophosphites), phosphonates (phosphites) and phosphates; polyphosphates, whether or not chemically defined
320420	Synthetic organic products of a kind used as fluorescent brightening agents
320650	Inorganic products of a kind used as luminophores
3207*	Prepared pigments, prepared opacifiers and prepared colors, vitrifiable enamels and glazes, engobes (slips), liquid lustres and similar preparations, of a kind used in the ceramic, enameling or glass industry; glass frit and other glass, in the form of powder, granules or flakes
3208*	Paints and varnishes (including enamels and lacquers) based on synthetic polymers or chemically modified natural polymers, dispersed or dissolved in a non-aqueous medium; solutions as defined in note 4 to this chapter
3209*	Paints and varnishes (including enamels and lacquers) based on synthetic polymers or chemically modified natural polymers, dispersed or dissolved in an aqueous medium
360500	Matches, other than pyrotechnic articles of heading 3604
360690	Ferro-cerium and other pyrophoric alloys in all forms; articles of combustible materials as specified in note 2 to this chapter - Other
3815*	Reaction initiators, reaction accelerators, and catalytic preparations, not elsewhere specified or included
381800	Chemical elements doped for use in electronics, in the form of discs, wafers or similar forms; chemical compounds doped for use in electronics
7005*	Float glass and surface ground or polished glass, in sheets, whether or not having an absorbent, reflecting or non-reflecting layer, but not otherwise worked
7017*	Laboratory, hygienic or pharmaceutical glassware, whether or not graduated or calibrated
7202	Ferro-alloys
8505*	Electromagnets; permanent magnets and articles intended to become permanent magnets after magnetization; electromagnetic or permanent magnet chucks, clamps and similar holding devices; electromagnetic couplings, clutches, and brakes; electromagnetic lifting heads
8506*	Primary cells and primary batteries
850740	Electric accumulators, including separators therefor, whether or not rectangular (including square) - Nickel-iron
851110	Sparking plugs
851220	Other lighting or visual signaling equipment
8515*	Electric (including electrically heated gas), laser or other light or photon beam, ultrasonic, electron beam, magnetic pulse or plasma arc soldering, brazing or welding machines and apparatus, whether or not capable of cutting; electric machines and apparatus for hot spraying of metals or cermets
8517*	Telephone sets, including telephones for cellular networks or for other wireless networks; other apparatus for the transmission or reception of voice, images or other data, including apparatus for communication in a wired or wireless network (such as a local or wide area

	network), other than transmission or reception apparatus of heading 84.43, 85.25, 85.27 or 85.28
8518*	Microphones and stands therefor; loudspeakers, whether or not mounted in their enclosures; headphones and earphones, whether or not combined with a microphone, and sets consisting of a microphone and one or more loudspeakers; audio-frequency electric amplifiers; electric sound amplifier sets
8519*	Sound recording or sound reproducing apparatus
8521*	Video recording or reproducing apparatus, whether or not incorporating a video tuner
8523*	Discs, tapes, solid-state non-volatile storage devices, 'smart cards' and other media for the recording of sound or of other phenomena, whether or not recorded, including matrices and masters for the production of discs, but excluding products of Chapter 37
8525*	Transmission apparatus for radio-broadcasting or television, whether or not incorporating reception apparatus or sound recording or reproducing apparatus; television cameras, digital cameras and video camera recorders
8527*	Reception apparatus for radio-broadcasting, whether or not combined, in the same housing, with sound recording or reproducing apparatus or a clock
8528*	Monitors and projectors, not incorporating television reception apparatus; reception apparatus for television, whether or not incorporating radio-broadcast receivers or sound or video recording or reproducing apparatus
853223	Electrical capacitors, fixed, variable or adjustable (pre-set) - Ceramic dielectric, single layer
853224	Electrical capacitors, fixed, variable or adjustable (pre-set) - Ceramic dielectric, multilayer
8539*	Electric filament or discharge lamps, including sealed beam lamp units and ultraviolet or infra-red lamps; arc lamps
8540*	Thermionic, cold cathode or photo-cathode valves and tubes (for example, vacuum or vapor or gas filled valves and tubes, mercury arc rectifying valves and tubes, cathode-ray tubes, television camera tubes)
8541*	Diodes, transistors, and similar semiconductor devices; photosensitive semiconductor devices, including photovoltaic cells whether or not assembled in modules or made up into panels; light-emitting diodes; mounted piezoelectric crystals
8542*	Electronic integrated circuits
870892	Silencers (mufflers) and exhaust pipes; parts thereof
9001*	Optical fibers and optical fiber bundles; optical fiber cables other than those of heading 85.44; sheets and plates of polarizing material; lenses (including contact lenses), prisms, mirrors and other optical elements, of any material, unmounted, other than such elements of glass not optically worked
9002*	Lenses, prisms, mirrors and other optical elements, of any material, mounted, being parts of or fittings for instruments or apparatus, other than such elements of glass not optically worked
900490	Spectacles, goggles and the like, corrective, protective or other - Other
900510	Binoculars
900580	Binoculars, monoculars, other optical telescopes, and mountings therefor; other astronomical instruments and mountings therefor, but not including instruments for radio-astronomy - Other instruments
9006*	Photographic (other than cinematographic) cameras; photographic flashlight apparatus and flashbulbs other than discharge lamps of heading 85.39
9007*	Cinematographic cameras and projectors, whether or not incorporating sound recording or reproducing apparatus

9011*	Compound optical microscopes, including those for photomicrography, cinephotomicrography or micro projection
9012*	Microscopes other than optical microscopes; diffraction apparatus
9013*	Liquid crystal devices not constituting articles provided for more specifically in other headings; lasers, other than laser diodes; other optical appliances and instruments, not specified or included elsewhere in this chapter
9022*	Apparatus based on the use of X-rays or of alpha, beta or gamma radiations, whether or not for medical, surgical, dental or veterinary uses, including radiography or radiotherapy apparatus, X-ray tubes and other X-ray generators, high tension generators, control panels and desks, screens, examination or treatment tables, chairs and the like

Appendix D

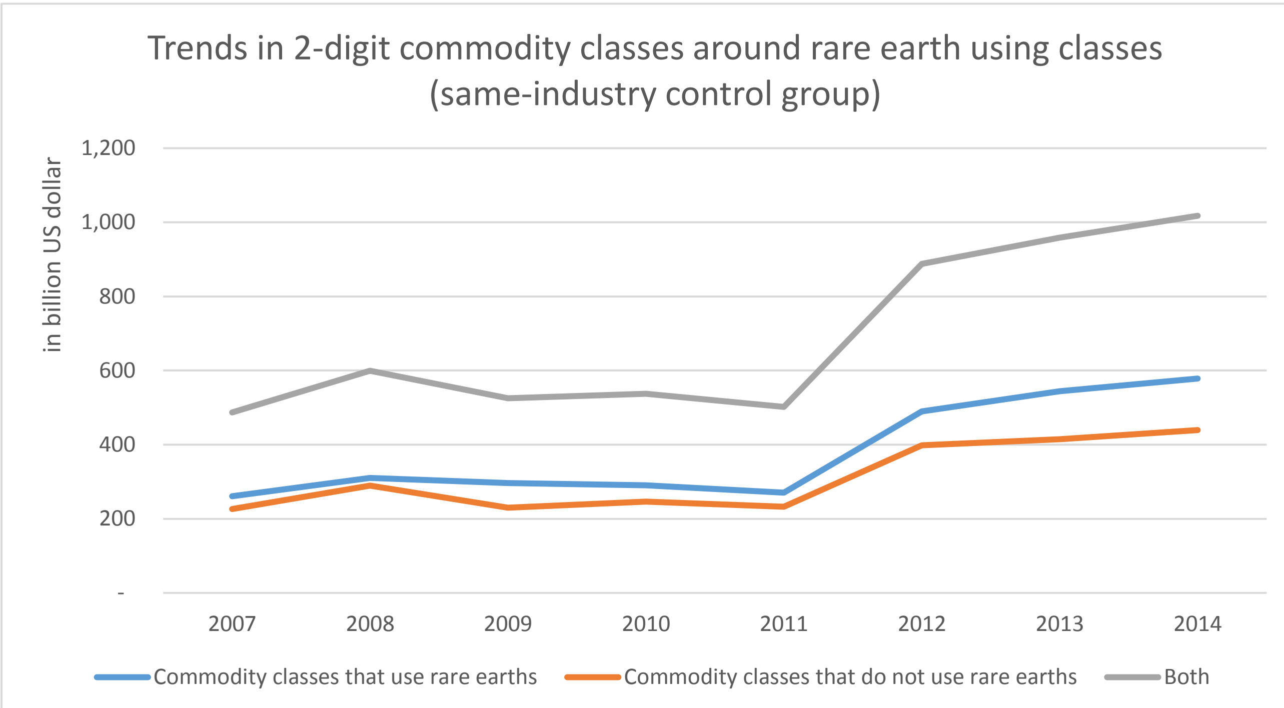

Figure 5: Trends in 2-digit commodity classes around rare earth using classes