Master Thesis

Cap-and-Trade and innovation:
Has EU ETS increased low-carbon patenting and green R&D spending in Norway?

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Abstract

This master thesis estimates the causal effects of EU Emissions Trading System (ETS) on green innovative performance of Norwegian firms. EU ETS is the first and greatest carbon market in the world, but the effects of EU ETS remain debated, due to a generous compensation scheme, low effective quota prices and the high number of free allowances provided to regulated firms. This master thesis contributes some evidence to this debate, with a dataset on innovation activity, EU ETS regulation and firms' characteristics. The main results suggest that regulated firms have increased green intramural R&D spending, where the estimated effects suggest an annual increase of 2,000,000-13,000,000 NOK. Moreover, the estimates suggest that there has been a weak positive effect low-carbon patenting as well, however not at any significant level. Other results suggest the same pattern, where regulated firms have a minor increase in green innovative activity, thus these results are neither statistically significant, nor of substantial degree. The reason for this could be caused by a low effective carbon price for regulated manufacturing industries, due to a generous carbon compensation scheme and low quota prices.

Key words: EU ETS, cap-and-trade, green innovation, manufacturing industries

Content

List of figures

1.Introduction

One of the greatest challenges present globally, is climate change and global warming. The focus on limiting the consequences of climate change has increased and countries are now cooperating on reducing greenhouse gas (GHG) emissions. In the third part of UNFCC's sixth main report it is stated that global greenhouse gas (GHG) emissions continue to increase, and in 2019 the total emissions globally where 54% higher compared to the 1990 level (Norwegian Environmental Agency, 2022). One of the most important tools to reduce GHG emissions are cap-and-trade system (Martin, Muûls and Wagner 2016). To date, cap-and-trade systems are important contributions to set a price on carbon and to, ideally, create incentives to reduce GHG emissions by increasing low-carbon innovations and develop abatement technologies (Stavins 2007)(Calel 2020). It is therefore crucial to discuss the causal effects of the world's first and largest cap-and-trade system, the European Union's Emissions Trading System (EU ETS).

The EU ETS was officially in operation from 2005 and was the first mandatory cap-and-trade system in history *(*Petrick and Wagner 2014). EU ETS is the cornerstone of EU's climate ambitions to reduce GHG emissions and covers around 40% of GHG emission produced in EU. The European Commission intends to achieve climate neutrality in EU by 2050 and reduce the net reduction of GHG emissions with 55% by 2030. To achieve these goals, low-carbon technologies are necessary (European Commission 2022).

Regardless of EU ETS' ambitions, the causal effects are remained debated. One reason for this is the high degree of free allowances and a general low quota price (Klemetsen, Rosendahl and Raknerud 2020). Most of the research on the effects of EU ETS has been on the direct CO2 emissions reduction (Martin, Muûls and Wagner 2016), while the scope of literature on innovation remains limited (Calel 2020). Calel (2020) found in his study that the overall low-carbon patenting and R&D spending for regulated firms in Britain was 20-30% higher than non-regulated firms in phase I and II. Drawing inspiration by Calel, I will contribute some evidence to the debate of EU ETS, by looking at the low-carbon patenting and R&D spending for regulated firms. My research question is

> *"Has EU ETS regulation increased green innovation among regulated Norwegian firms?"*

To measure the causal effect of EU ETS regulation, I conduct a Difference-in-Differences (DiD) analysis, on panel data obtained from the Norwegian Environmental Agency (NEA), the Norwegian Industrial Property Office (NIPO) and Statistics Norway. Similar to Calel, I found

an increase in low-carbon patenting and green intramural R&D spending for regulated firms. However, the estimates of low-carbon patents are somewhat small and insignificant. While for green intramural R&D spending, the estimates suggest an annual increase of 2-13 mill. NOK for regulated firms, depending on the empirical framework. Thus, the significance of these estimates are also dependent on the empirical assumptions.

The structure of this thesis is as follows: chapter 2 contains background information about EU ETS and the Norwegian regulatory context. Chapter 3 contains a theoretical framework for cap-and-trade systems and a definition of innovation followed by a literature review of empirical research in chapter 4. Chapter 5 is a description of my dataset, while chapter 6 presents my empirical approach and its implications. In chapter 7 and 8 I present my results and the robustness checks, respectively. Finally, I discuss my findings in chapter 9 and conclude in chapter 10.

2.Background

2.1 EU ETS

EU ETS is a cap-and-trade system for emission allowances, EU Allowance Units (EUA), which are tradable for all regulated plants in the regulated countries. The legal framework of EU ETS is based on the ETS Directive, where regulation rules for each trading phase are established. To date, all countries in the EU and EEA-EFTA (Iceland, Liechtenstein and Norway) are participating in EU ETS (Directive 2003/87/EC). Regulation takes place at plant-level, where plants that operates in energy-intensive industries, electricity production and aviation are obligated to participate. Moreover, each industry has its own threshold for participation, in terms of capacity abilities and GHG emissions (European Commission 2022). EU ETS puts a cap on how much CO_2 equivalents a plant could produce in a year. Each plant can then trade the excess permits they have or buy permits from other plants, where every quota provides the permission to release one ton of CO_2. The overall goal is to reduce the amount of allowances available in the market, to increase the carbon price over time, thus reduce GHG emissions and increase low-carbon technology. If an installation, or parts of a regulated installation, is used for research and development (R&D) and other innovation activities, the installation will not be regulated by EU ETS (Directive 2003/87/EC)(European Commissions 2022)(Norwegian Environmental Agency 2019).

EU ETS was adopted in 2003 and phase I was a pilot phase (2005-2007), where the main motivation was to prepare and establish the infrastructure of the system prior to 2008 and a

majority of the allowances were provided for free (European Commission 2022). The price for non-compliance were 40 euros. The first phase included regulation of CO_2 emissions from energy-intensive industries and power generations, and the Member states allocated 95% of the allowances for free. In phase II this was reduced to 90% (Directive 2003/87/EC). In phase II (2008-2012) the EFTA-countries joined, and NOx were regulated as well. The penalty for non-compliance increased to 100 euros. Due to the financial crisis in 2008, production in Europe fell drastically, which led to a decrease in GHG emissions and further led to a price drop of EUA and a surplus in permits (European Commission 2022)(Klemetsen, Rosendahl and Jakobsen 2020). In phase III (2013-2020) additional industries and gases were regulated, such as the aluminum production. The share of free allowances are still large and the price on EUA remained low in phase III after 2008, see figure 1.

The Directive aims to encourage the use of more energy-efficient technologies, including heat and power technology, producing less emissions per unit of output. The Directive aims to provide incentives to use more energy-efficient technologies and reduce CO_2 intensity per output produced. The most important stimulation acts in the Directive for green innovation, i.e., CCS, renewable energy and other low-carbon technologies, are the carbon price signal the Directive sets. However, due to high number of allowances in EU ETS, it was established a market stability reserve to stabilize the and reduce the number of allowances. The aim of MRS is to provide credible investment signals to reduce GHG emissions and to increase low-carbon innovation (Directive 2003/87/EC).

Figure 1: Historical price of EUA

Note: the figure illustrates the historical price of EUA, from 2005 to 2022. The graph is collected from *Trading Economics:* https://tradingeconomics.com/commodity/carbon, collected 05.05.2022

Figure 1 illustrates the historical price of EUA, which experienced a drop after the financial crisis in 2008 and remained low until 2018. The Y-axis represents prices in euros. The figure shows that the mean price per quota (per ton of CO2 equivalents emitted) has been 20 euros. After 2018 the price of EUA has increased steadily and experienced a historical high price in 2021. In my analysis I do not include the years after 2018, and the price of EUA remains low for the years covered in my analysis. As stated in the Directive, a robust carbon price is crucial to stimulate low-carbon innovation (European Commission, 2022). The low price of EUA could therefore have some implication on the weak effect of low-carbon patenting among the regulated firms from my estimations.

2.2 The Norwegian regulatory context

Norway has been a part of EU ETS since 2008, but from 2005 firms could voluntarily participate in the system. Firms could buy allowances from other regulated plants in EU, but Norwegian firms could not sell allowances. EU ETS regulates about 50% of Norwegian GHG emissions, mainly from manufacturing industry and the petroleum sector, leaving EU ETS as among the most important policy instruments to reduce GHG emissions (Regjeringen 2020)(Norwegian Environmental Agency 2022). Fossil fuels are the greatest source of CO2 emissions in Norway, and there has been a tax on CO2 emissions from 1991, which regulates emissions from fossil fuels and petroleum (Randen, Slettebø and Grimstad 2021) (Regjeringen 2020). To provide incentives for firms to reduce GHG emissions, it is important to target efficiently, and the EU proposes that emissions from not-regulated firms should be regulated by other means, such as carbon-taxes or other arrangements (Directive 2003/87/EC).

As mentioned, the carbon price is crucial to promote low-carbon innovations. However, the effective marginal carbon price for the regulated manufacturing firms in Norway is low, compared to other industries and economic agents. In figure 2 we can see the overview of the effective marginal carbon price, based on estimates from Randen, Slettebø and Grimstad (2021). The Y-axis represents the effective marginal carbon price, and the X-axis shows the total CO2 emissions from fossil fuels. The effective marginal carbon price for the industries subject to quotas is low. They argue that the price of EUA plays a limited role on the effective marginal carbon price in Norway, since they amount of free allowances are high (Randen, Slettebø and Grimstad 2021).

Effective marginal carbon price on CO_2 emissions from fossil fuels in various industries, accumulated. NOK per ton of CO_2 emission. 2020[1].

Effective marginal carbon price
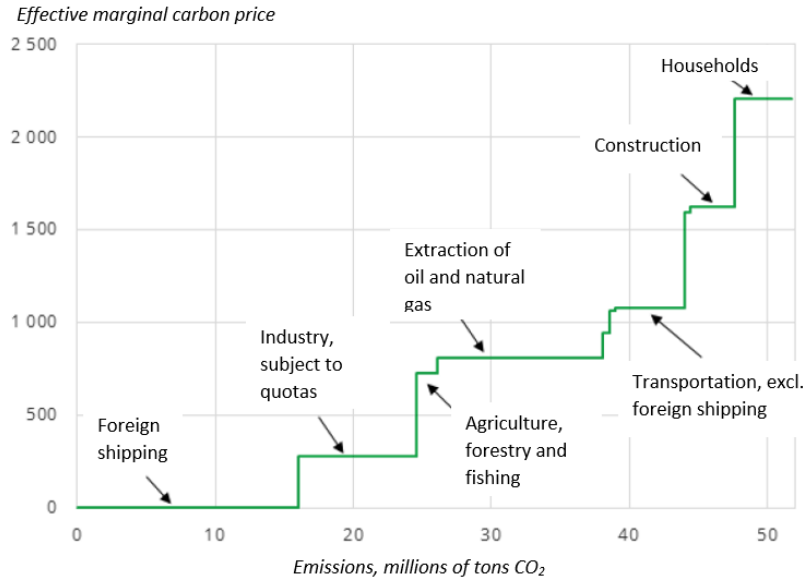
[1]Calculated as a weighted average when consuming different fuels

Source: Environmental accounting (Miljøregnskap), Statistics Norway

Figure 2: Effective carbon price in Norway, 2020

Note: the figure plots the marginal effective carbon price for a various set of Norwegian economic agents and industries. The graph is collected from Statistics Norway (Randen, Slettebø and Grimstad 2021): https://www.ssb.no/natur-og-miljo/miljoregnskap/artikler/stor-variasjon-i-effektive-karbonpriser on 01.05.22. I have translated the text boxes, based on the article in Norwegian.

As we can see from figure 2, the sample of firms in this analysis has the second lowest effective carbon price, while households have the highest effective carbon price. The petroleum sector faces both CO2 tax and EU ETS regulation, which makes the effective carbon price higher for this industry, compared to manufacturing industry. As Randen, Slettebø and Grimstad (2021) points out: the industry subjected to quotas are among the industries that release the most CO2 emissions in Norway, yet at the same time face a low effective carbon price. At the same time, the tax on CO2 is higher than the price of quotas, and over 90% of the effective average carbon price is determined by taxes and fees, while the rest is determined by the quotas. Therefore, the control group could have incentives to innovate in low-carbon technology as well.

In Norway, energy-intensive industry receives CO2 compensation, to reduce the risk of carbon leakage. Carbon leakage is a risk that is discussed in the EU ETS design and is also one of the reasons why there are such a generous amount of free allowances. Carbon leakage means that some industries have a risk of re-allocating their production to other countries which have a less ambitious carbon pricing scheme, where the incentive is to reduce the price of production. If the carbon price is high for industries with a high risk of carbon leakage, the risk of moving

production increases, and the global CO2 emissions are not reduced. The Norwegian CO2 compensation is given to 46 firms in 2020, where 2/3 of these are EU ETS regulated firms. In 2020 2,5 billion NOK was provided to these 46 firms as a CO2 compensation (Slettebø, Randen and Grimstad 2021). In figure 3 we can see the distribution of CO2 compensation for regulated and not regulated firms. The scheme began in 2013, and my dataset is only available up till 2017. The Y-axis represents the CO2 compensations in 1000 NOK over years in the X-axis.
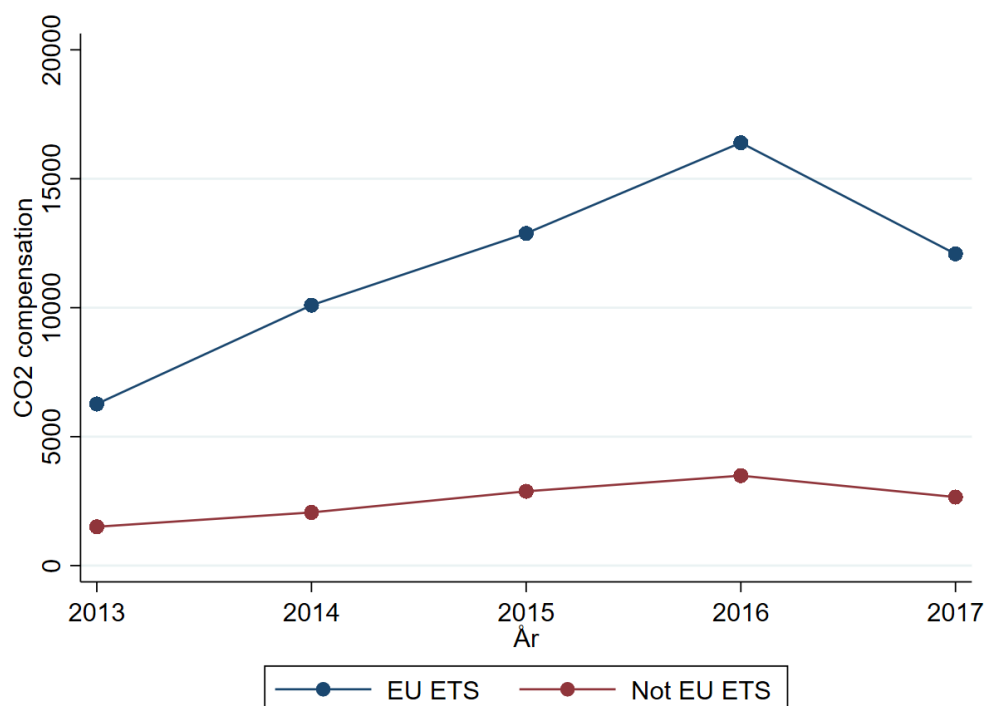
Figure 3: The CO2 compensation scheme for Norwegian firms

Note: the figure plots the yearly CO2 compensation in 1000 NOK received by Norwegian firms. Data source: the Norwegian Environmental Agency.

The key take-away from this chapter is that the effective price on carbon for the regulated firms is low, which can have implications for the incentives to innovate. I will discuss this further in the following chapter, where I present the theoretical framework of this thesis.

3.Theoretical framework

In this chapter I will discuss the framework of cap-and-trade systems, in terms of economic theory, and connect this theory with the implications of the empirical evidence of the EU ETS. In the second part of this chapter, I will discuss a theoretical framework for defining innovation and discuss the implications of these measures.

3.1 Cap-and-trade

EU ETS is a cap-and-trade system. The goal of a cap-and-trade system is to reduce GHG emissions, by indirectly regulate the price of emissions by providing allowances for firms to trade with other firms. The allowances are allocated either by grandfathering (free allocation) or by auctions. However, the price of allowances is determined by the marginal abatement cost of firms, and not by allocation (Requate 2005). The cap in cap-and-trade denotes the amount of allowances available in the market, which ideally should be reduced over time, to generate incentives to further reduce emissions and adopt abatement technologies. In a cap-and-trade system, the number of permits is therefore crucial to obtain efficient outcomes (Weitzman 1974)(European Union 2015). How the emissions are distributed among firms in a cap-and-trade system, is therefore not relevant for the overall GHG reduction, as long as the total level of emissions is reduced. If one firm increases its emissions, another firm has to reduce its emissions. This implies that the number of permits cannot be too generous. Thus, the sum of permits indirectly determines the climate effect (Directive2003/87/EC) (Regjeringen 2020). By having fewer allowances in the market, the equilibrium price for allowances will increase, and over time the investment in green technology will increase (Holtsmark and Midttømme 2021). However, the number of permits has been one of the main criticisms of EU ETS (Klemetsen, Rosendahl and Jakobsen 2020).

As opposed to a cap-and-trade system, a carbon tax regulates the price directly. In economic theory one can distinguish between market-based instruments and command-and-control regulations, where the latter implies direct regulations such as carbon taxes, and EU ETS is a marked-based system (Requate 2005). The European Commission proposed a carbon tax for EU in 1992, however, due to the asymmetric economic structures of EU countries, such a tax scheme was difficult to implement efficiently (European Commission 1992). Instead, with a cap-and-trade system, firms can achieve the lowest marginal cost of abatement to meet the cap. In other words: trading ensures that firms meet the same carbon price and that the emissions are reduced where it is the most cost effective. Over time, the number of allowances will be reduced in EU ETS, which will ensure that the incentives to adapt abatement technologies are strengthened over time (European Union 2015)(Requate 2005).

3.2 Defining innovation

It is crucial to understand the nature of innovation, to set a framework for this thesis, both in terms of selecting the variables of interest, but also to understand the results. There are multiple ways to measure innovation. Schumpeter (1942) argued that the core of any capitalist market

is competition, and competition provides incentives to innovate. However, it is crucial, according to Schumpeter, that the innovation activities are protected by intellectual property rights, such that the firms can achieve a temporarily monopolistic profit. If innovative ideas and improvements are free for everyone, there will not be any incentive to innovate since each firm will not gain by developing new technology (Schumpeter 1942). This argument suggest that the core of innovation is competition and monopolistic profits, due to property rights, i.e., patents. However, patents are rather rare compared to R&D expenditure, and patents could be viewed as successful R&D spending (Cornea and Ornaghi 2014). Leaving both R&D and patents as important measures of innovation, since patents are dependent on R&D expenditure, and, according to Schumpeter, the goal is to obtain a patent, i.e., monopolistic profits.

The definition of innovation is debated, and especially in terms of what is defined as "green" innovation (Elkins 2010). A green innovation could be defined as adoption of technology already used by others (Kemp 2010). Calel rules out low-carbon adoption technology for patents, due to the reason that this is not "new" technology. In my research this is rather infeasible, since the sample size of low-carbon patents is low, and to remove these patents, the estimates could become rather unreliable. Therefore, I include low-carbon adoption technologies in my definition of green innovation. This is consistent with a broad definition of green innovation (Teixido, Verde and Nicolli 2019). In a study by Hagedoorn and Clood (2003) their findings suggest that there is an overlap between R&D and innovations, and they recommend that research could rely on either of these indicators to measure innovative performance of firms. I therefore conduct my analysis with both R&D expenditure and patent that include adoption technologies, to obtain a broader and more nuanced aspect of the innovation activities among regulated firms.

4.Literature review

Several studies have looked at the causal effect of EU ETS on emission as the outcome variable, but few studies have looked at the causal effect on low-carbon innovation. My master thesis contributes to this part of the EU ETS literature. I limit the literature review to contain only empirical research at firm or plant level, to construct an analytical framework for my thesis.

Calel (2020) studied the effect on low-carbon patenting and R&D spending for regulated British firms in 2005-2012. In his study, he found that regulated firms have increased low-carbon patenting and R&D spending by around 20-30%. The paper identifies low-carbon patenting as Cooperative Patent Classification (CPC) codes which are tagged with Y02, which is a general

tagging scheme developed by the European Patent Office (EPO) constructed to classify low-carbon technological developments (Veefkind et.al. 2012). British firms regulated by EU ETS have on average greater annual profits, employees and emissions, therefore, to obtain a suitable control group, Calel construct a control group based on propensity score matching. As this thesis is conceptually inspired by the paper by Calel, I use the Y02 class of CPC codes to identify low-carbon patenting for Norwegian firms. As far as my knowledge goes, this classification of low-carbon patenting has not been applied in Norwegian microdata studies before[1]. Moreover, similar to Calel I divide between general R&D expenditure and green R&D expenditure, but contrary to Calel, I divide between different categories of green R&D expenditure, and I separate extramural and intramural R&D expenditure, to capture some essence of in-house versus outsourced innovation. While the low-carbon R&D expenditure is only available from 2008 in Calel's data, thus infeasible to conduct a DiD where 2005 is the treatment year, I have a rich data from Statistics Norway, with environmental and climate related variables from 2001. Therefore, I can provide some further analysis on R&D expenditure, in addition to patenting behavior.

The results from this master thesis contributes to understanding the causal effects of EU ETS for Norwegian regulated firms for the years 2001-2013. Klemetsen, Rosendahl and Jakobsen (2020) estimate the causal effects on emissions and economic performance for regulated plants in Norway. In their study, they find a negative effect on emission in phase II (2008-2012), but not a significant effect in other phases. To obtain an appropriate control group, they apply propensity score matching using psmatch2 in their DiD analysis. Moreover, they restrict their sample to manufacturing industries, but leave out extraction of crude petroleum and natural gas. Since this master thesis' focus is on green innovation, my dependent variable will not be related to emission or energy-intensity. However, due to the value of comparison for studies done at microlevel in Norway I draw some inspiration by their paper. I restrict my sample to manufacturing industries, and I conduct a robustness check of 1:3 neighbors, similar to Klemetsen, Rosendahl and Jakobsen.

There is an increasing literature that estimates the causal effects of EU ETS regulation on economic performance, however, the literature on green innovation is somewhat limited. In this part I present some recent papers regarded this subject, which I have drawn inspiration, and

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[1] In Klemetsen, Bye and Raknerud (2018) they used International Patent Classification (IPC) codes to classify green patents. In correspondence with Brita Bye, I understood that CPC codes is now more preferred than IPC codes, since IPC codes might target a broader definition of green innovation. See chapter 5 for a more elaborate discussion of IPC and CPC codes.

which have been valuable reads for my analysis. Martin, Muûls and Wagner (2013) studied the effects on low-carbon innovation, in terms of R&D expenditure related to abatement technologies or energy consumption. They used data from interviews with managers from 770 manufacturing firms in 2009, from six different countries in Europe. Their results suggest that most firms have climate-related innovations, while this is more related to process innovation, compared to product innovation. Moreover, they find that there is a negative causal effect of receiving free allocations on low-carbon innovation. This result is of some relevance to my study, since the effective carbon price for regulated firms, as seen in figure 2, is low. Therefore, this could have implications on the findings in my study. Rogge and Hoffmann (2010) did 42 exploratory interviews with experts from the power generation technologies in Germany. Their main results were that EU ETS have an effect on the direction of technological change and technology development for large-scale and coal-based technologies. While this paper is not econometric, its results are crucial to understand the innovation activity from the innovators. Löfgren et. al. (2014) conducted a DiD estimation on whether EU ETS regulation for Swedish firms provided incentives to invest in low-carbon technologies. This study include all regulated sectors, as opposed to my analysis, over the years 2000-2008. Their main analysis suggest that there are no statistically significant estimations of low-carbon investments for regulated firms. Similar to my thesis, and what Calel (2020) suggest, it is somewhat difficult to obtain statistically significant estimates when sample size of innovation activities are low. However, in contrast to Löfgren et. al., I limit the scope of sectors to ensure some similarities within industries and to ensure that the control group is more similar to the treatment group, which is obtained with propensity score matching. My research design is therefore somewhat different from Löfgren et. al.

The interest of understanding the causal effects of EU ETS is increasing, and several papers have done research one estimating the regulatory effect on emission reduction. In the following I will briefly present the evidence on emission reduction from relevant papers. Petrick and Wagner (2014) estimated the effect on emissions, using plant-level data for German manufacturing firms in 2005-2010. Their evidence was not significant for phase I, while a small decrease in emissions in phase II. They conducted a DiD analysis with propensity score matching, which I will elaborate further in chapter 6. Bel and Joseph (2015) estimated emissions level in the EU member states (defined prior to 2007), using a dynamic linear panel data regression, and found that the financial crisis from 2008 was the main reason for the reduction in emissions, for these states. Jaraitė and Di Maria (2016) analyzed a various number

of variables on economic performance, including investment behavior and CO2 intensity. Their results suggest a modest increase in investments in 2010, but not a reduction in CO2 emissions. I draw some inspiration of their methodology, which I discuss in chapter 6.

Klemetsen, Bye and Raknerud (2018) have studied the effect of non-market regulations on green patents for Norwegian firms. Since this paper use the same dataset from the Norwegian Industrial Property Office (NIPO) as me, I have drawn crucial inspiration from this paper, to obtain a better understanding of the dataset on patent applications. They find that there is a significant effect on innovations from implicit regulatory costs obtained from threats of sanctions. However, they analyze the effect of direct environmental regulations on Norwegian patents. In contrast, EU ETS is an indirect regulation, which was discussed in chapter 3. Their sample of patent applications are therefore larger than mine, which makes it infeasible for me differ between granted patents and ungranted patents in their robustness checks, since this could cause unreliable estimates. They classify green-patent applications with IPC codes, which I will discuss in the next chapter.

5. Data

In this thesis I use panel data from Statistics Norway, the Norwegian Industry Property Office (NIPO) and the Norwegian Environmental Agency (NEA), where the key observational variable is organization number at firm-level. The main dataset covers 17 years, from 2001 to 2017. For my analysis, I have four different outcome variables for measuring green innovative activity, but I also examine other outcome variables, such as all patent applications, extramural and intramural R&D expenditure. There are a total of 423 unique firms in my sample, where 344 unregulated firms and 84 regulated firms in my dataset, in the industries of B and C in the Standard Industrial Classification 2007 (SIC 2007), over the two-digit NACE codes from 05-33, which covers industries such as mining and quarrying, manufacturing of textiles, beverages, food, chemicals and metals. I exclude NACE code 06, extraction of crude petroleum and natural gas since the petroleum sector have a different regulatory context. Moreover, due to comparative value, since Klemetsen, Rosendahl and Jakobsen (2020) covers these industries as well.

In the following I will present my method for measuring innovation activity and how I have classified these activities with either green or low-carbon labels. Since I have data on both patent applications and R&D spending, from NIPO and Statistics Norway respectively, I discuss each dataset isolated. I also present and discuss the dataset from the Norwegian

Environmental Agency (Miljødirektoratet, NEA), where I have the overview of regulated firms and emission levels.
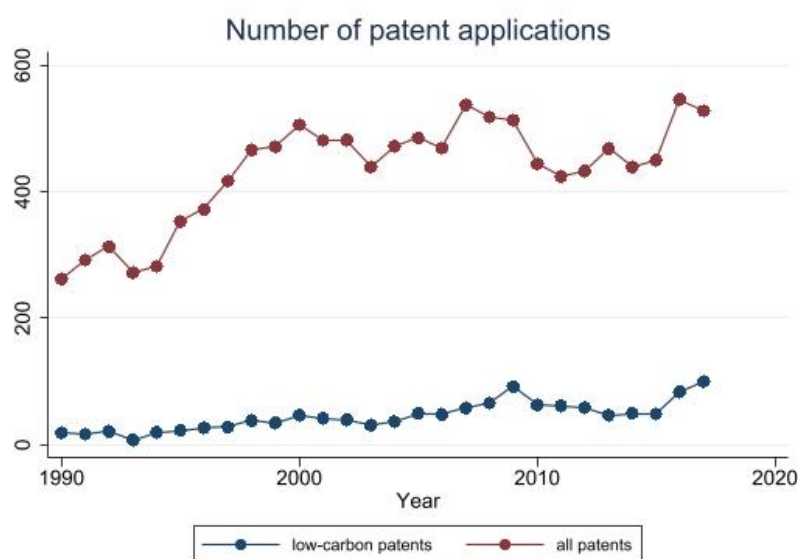
5.1 Patent applications

The dataset from NIPO contains all patent applications from Norwegian firms by the application status at 23.04.18, over the years 1990-2017. There are 12,134 unique patent applications over these years. This dataset is merged with a dataset from Statistics Norway, by the firm organization number, with a complete list of CPC and IPC codes for each patent application. CPC and IPC codes are classification schemes provided by The European Patent Organization (EPO) to identify patents. To classify low-carbon patents using CPC and IPC codes, there are two potential strategies. The IPC Green Inventory classifies patents with environmental technologies, listed in the UNFCCC. This classification covers a range of topics, from transportation to agriculture, and nuclear power generation. The potential problem with this classification strategy, is that it might be too broad and capture more technologies than the ones that directly reduce emissions (World Intellectual Property Organization 2022). Therefore, I use the general tagging scheme Y02 for CPC codes similar to Calel (2020), which identifies new technological developments and low-carbon patents for mitigation and adaption technologies. The classification system is based on the abilities to reduce GHG emissions directly. Additionally, the Y02 class include technologies which aim to improve energy efficiency. The Y02 class by EPO is "the most accurate tagging of climate change mitigation patents available today" (Calel 2020) and has been developed in the framework of the Kyoto Protocol and the Paris Agreement (European Patent Office 2022)(Veefkind et. al. 2012)(Patentstyret 2021).

Each patent application can be tagged with multiple CPC and IPC codes, since the patent can be in multiple sectors and technologies at the same time. To obtain a panel data set, with only one observation per firm per year, I create a dummy variable that is equal to 1 whenever a firm has *at least* one patent application with a Y02 tag. Moreover, some firms have multiple patent applications per year, therefore I created a variable that summarize the total amount of low-carbon patent applications per firm per year. These two variables provide different results in the regression results, since there are in general few patent applications in the data sample, but of the firms that innovate, some innovate heavily, where the range of yearly amount of patent applications is 1-41. Therefore, it is crucial to distinguish between these two effects.

To get an idea of how the patent data looks like, I present two figures of *all* patent applications in Norway, i.e., this is not limited to the firms of my sample. In figure 4 we can see the evolution

of patent applications among Norwegian firms. There are 12,134 patent applications between 1991 and 2017, where 1,261 of the patent applications contains at least one low-carbon classification according to Y02, which is 10,39% of the total patent applications. In figure 4 I present only low-carbon patent applications, to better see the evolution, not related to regular patent applications. As we can see, the number of low-carbon patent applications has in absolute terms increased among Norwegian firms, between 1990 and 2017, which is easier to see in figure 5 than in 4.

Figure 4: Evolution of all patent applications among Norwegian firms

Note: the figure plots the average yearly number of patent applications among all firms in Norway, separated between all types of patent applications and low-carbon patent applications. Dataset: Norwegian Industry Property Office.
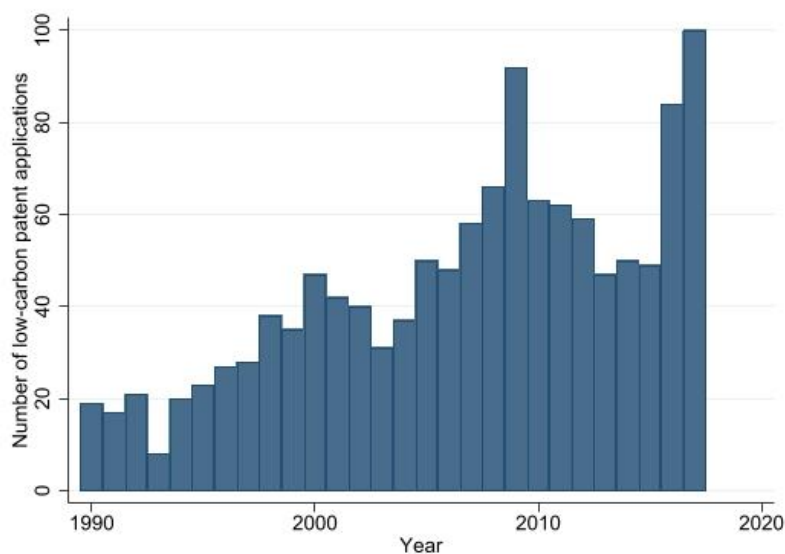
Figure 5: Evolution of low-carbon patent applications among Norwegian firms

In my dataset, I cannot distinguish between patents of great significant and those which are less significant. It could be that some of the patent applications have little value. However, similar to Klemetsen, Bye and Raknerud (2018) I am not interested in the value of the patents, but the innovation activity itself. Therefore, I do not distinguish between the application status for the patents. As patent applications are costly, it is unlikely that a firm would allocate resources to a patent application if it were not realistic (Dechezleprêtre et. al. 2011). Moreover, I cannot control for why the patent application was denied in the first place. Therefore, by controlling for granted patent applications could potentially add more concerns to the interpretation of the results, than what is fruitful for the analysis.

5.2 R&D expenditure

The other dataset to measure innovation activity is a dataset from the R&D-survey (Indikatorrapporten: FoU- og innovasjonsstatistikken for næringslivet) from Statistics Norway. This data is rich and contains a variety of aspects of innovation and contains information about intramural and extramural R&D expenditure, R&D personnel and environmental aspects of R&D, as well as numerous interesting variables that I have not included, such as the female share of R&D personnel, cooperation with other firms, funding sources and the division between process and product innovation. In the original dataset there are 26,886 unique firms over the years 1997-2017. The panel data is unbalanced, since the survey is based on a sample of selected firms (i.e., not obligated for all firms conducting R&D activities) and there are some variables that change over time. This is especially the case for the green variables. In 2001 and 2003 there are two variables of interest, relating to environmental technology (miljøteknologi) and energy usage. These two variables merge in 2005-2006, where there is only variable of interest. This merge could potentially be problematic since energy usage does not necessarily mean renewable energy. However, I find it necessary to include, since I cannot divide this joint variable into subcategories. Therefore, I include the energy variable for 2001+2003 as well. I control for the energy usage when I divide the overall variable into several subcategories. From 2007 there 5 relevant variables, for renewable energy, other environmental related energy aspects (miljørelatert energi), climate research (klimaforskning), CCS-technology (CO2-håndtering) and other environmental research (miljøforskning). These five variables are consistent till 2012, the variable for climate research is changed with "other climate research and technology". These variables are consistent till 2015. In 2015 there are seven relevant variables, where two new are added related to 1) climate technology and other abatement

technologies and 2) climate adjustments. These seven variables are consistent till 2017. All these variables are expressed as the share of intramural R&D expenditure in percent.

In the analysis, I created a variable that is the total share of all these variables, per firm per year, to capture the development of green intramural R&D expenditure expressed in 1000 NOK. I divide this variable further into subcategories for 1) energy related expenditure and 2) research and technology. Moreover, I generated a dummy variable that is equal to 1 if a firm had green intramural R&D expenditure.

Since the variables change over time, the estimates might come with some uncertainty. Similar to Calel, this data is survey-based, and as he suggests, the sampling frame of surveys are not necessarily corresponding with the sample of firms of interest. Moreover, there could be some misunderstandings when firms fill out the survey. There are manuals provided to the firms, however the Research Council suggests that there still might be misunderstandings in the dataset. Needless to say, this can affect the estimates of my analysis, since the data does not necessarily reflect the true R&D spending of the firms in my sample. However, as Calel (2020) also argues, the results can still be read as suggestive, while not definitive.

In the analysis I have four main outcome variables: 1) a dummy variable for low-carbon patenting, which is equal to 1 if a firm had (at least one) low-carbon patents per year 2) a continuous variable of all low-carbon patent applications per year per firm, 3) a dummy variable for green intramural R&D expenditure, which is equal to 1 if a firm had expenditure in green R&D for a given year, and 4) a continuous variable of all green intramural R&D expenditure, which captures the total share of green R&D of the intramural R&D expenditure in 1000 NOK.

5.3 EU ETS dataset and the main sample

In my analysis I am interested in the causal effect of EU ETS regulation on green innovation. Therefore, I will limit the sample to include only EU ETS regulated firms and a control group conducted by the firms that are subject to quotas from a dataset provided by NEA. I discuss the implication of control group in chapter 6. The variables in this dataset include a dummy for EU ETS regulation for all phases and emissions released by firms, for both regulated and not regulated firms. To obtain information about firms' characteristics, I merge this dataset with the plant- and firm dataset (VOF) provided by Statistics Norway. The dataset by NEA has the plant-level organizational number as the key observational variable. Since innovation activity takes place at the firm-level, I must aggregate this data up from plant-level to firm-level. Firms are the judicial unity that collects all plants in one institutional unity. A firm can have multiple plants, for example in different geographic locations or industry areas (Berge and Grini 2014).

EU ETS regulation takes place at plant-level, and each firm can have multiple plants, where one can be regulated and the other can be not-regulated. To solve this issue, I define each firm that has at least one plant which is regulated, as a regulated firm. This is also to solve a potential spillover problem in the regression analysis, which I discuss in chapter 6.
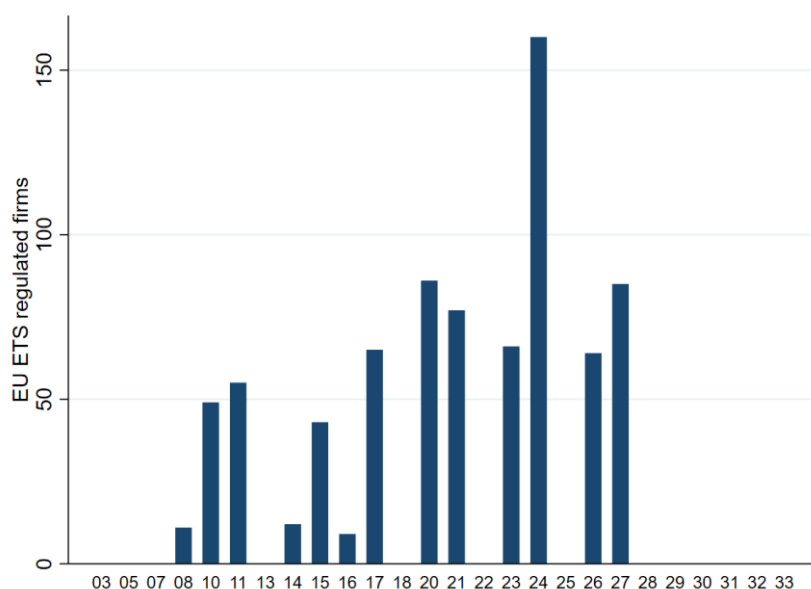
Figure 6: EU ETS regulated firms over two-digit industries

Note: The figure plots the sum of EU ETS regulated firms over the two-digit industry codes in my data sample. Data from the Norwegian Environmental Agency. I have removed observations < 3 due to confidentiality.

In figure 8 we can see the overview of EU ETS regulated firms over the scope of the two-digit industry codes in my analysis. EU ETS regulation is determined by the type of pollution, capacity limit and plant activity, it is crucial to understand which industries the regulated firms are registered in (Directive 2003/87/EC). Industry 24, manufacturing for basic metals, stands out as the industry with the highest share of firms. There are 13 two-digit industries with EU ETS regulated firms in this sample, covering industries as manufacturing of food (10), beverages (11) leather (15) and chemicals (20)[2].

In figure 9 we can see the share of not-regulated firms over two-digit industry codes. Industries 10, 15, 20 and 24 stand out as the industries with the highest share of unregulated firms in the sample, while there are more industries covered for unregulated firms, with a total of 26 two-digit industries. The share of firms in industries is important to keep in mind when conducting the empirical approach, which I will discuss in chapter 6.

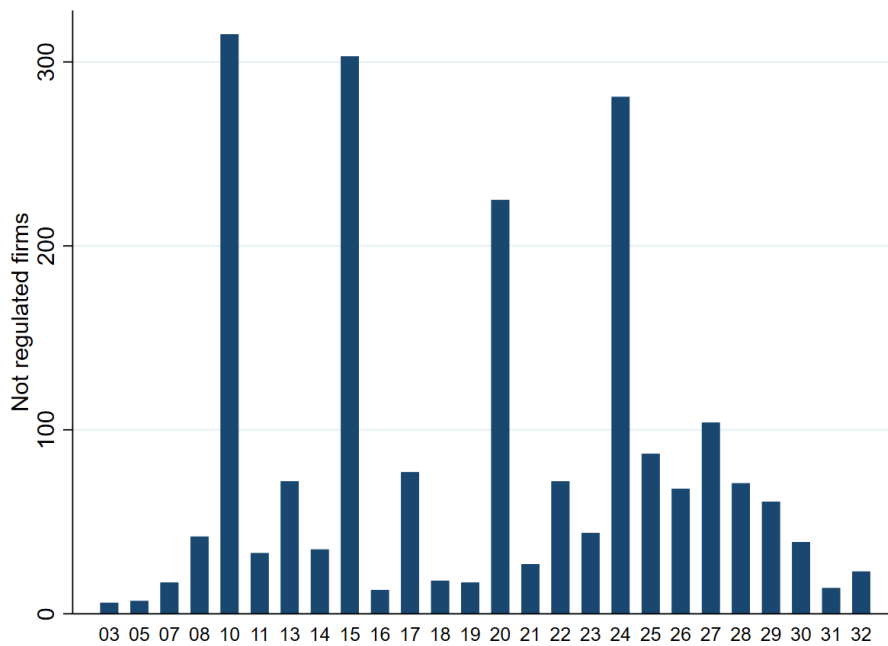[2] See the Standard Industrial Classification 2007 (SIC 2007) for an overview of all NACE codes

Figure 7: Not-regulated firms over two-digit industries

Note: The figure plots the sum of not regulated firms over the two-digit industry codes in my data sample. Data from the Norwegian Environmental Agency. I have removed observations < 3 due to confidentiality.

6.0 Research design

The overall goal in this thesis is to estimate the causal effect of EU ETS regulation on green innovation, where the counterfactual is understood as the absence of EU ETS regulation. Since I want to identify the causal effect, I must exploit the design of EU ETS to find an appropriate empirical approach. I apply a Difference-in-Differences (DiD) estimation to compare the green innovation activity between EU ETS-regulated firms and non-EU ETS regulated firms. DiD is a common research design used to evaluate causal effects of policy interventions, where an important assumption is that in the absence of treatment, the average outcomes for treated and comparisons groups would have followed the same trends over time. The DiD method is an estimation of the changes in a dependent variable over time, between a treatment group and a control group, by comparing the outcomes ex ante and ex post treatment between the groups. Moreover, by conducting a DiD with fixed effects, one can control for time invariant factors, which changes over time, but are constant across groups. Ideally, the research design should be a randomized control trial, where the groups are randomly assigned treatment. Therefore, ideal randomized experiments can estimate the causal effect, due to treatment assignment leads to exchangeability (Angrist and Pischke 2009)(Gertler et. al. 2016)(Hernan and Robins 2020)(Stock and Watson 2014).

The treatment criteria of EU ETS are not randomly assigned, but is based on industry classifications, capacity limits and plant activity (Directive 2003/87/EC). I do not observe the capacity limits the plants in my sample. When the treatment is not randomly assigned, the empirical method is not straightforward, and it is therefore necessary to discuss different methods and their implications to obtain a suitable research design. Other empirical EU ETS studies have applied different econometric approaches to identify the causal treatment effect of regulation (Martin, Muûls and Wagner 2016)(Jaraite and Di Maria 2016), which I will discuss in more detail in this chapter.

6.1 Treatment effect

To understand which method that is the most suitable for the case of EU ETS regulation, it is important to understand how an ideal research design for experiments look like, and where my study deviates from the ideal. The ideal research design conducts a complete randomized assignment, where the treatment and the control group follow the same trend prior to treatment (Angrist and Pischke 2009). The basic DiD equation measures the differences before and after the treatment, for the treatment and the control group. The basic DiD equation measures the differences before and after the treatment, for the treatment and the control group. The DiD estimate is formally expressed:

$$\beta = (\bar{Y}^{t,after} - \bar{Y}^{t,before}) - (\bar{Y}^{c,after} - \bar{Y}^{c,before})$$

$$\beta = \Delta(\bar{Y}^{t,} - \bar{Y}^{c})$$

(6.1)

The notation is formally adopted by Stock and Watson (2015) where $(\bar{Y}^{t,after} - \bar{Y}^{t,before})$ denotes the difference between ex post and ex ante treatment for the treated group in the outcome variable, and $(\bar{Y}^{c,after} - \bar{Y}^{c,before})$ denotes the difference between ex post and ex ante treatment for the control group in the outcome variable, in case both which we observe in a *true* experiment. While these types of experiments are not common for economic studies, economists do quasi-experiments, which implies that the treatment is "as-if randomly assigned." In quasi-experiments randomness conducted by statistical strategies, like propensity score matching (Angrist and Pischke 2009)(Stock and Watson 2015). By naively comparing the outcome between the treated and the control group, one may obtain a misleading estimate

of the treatment effect, due to the omitted variable bias (Angrist and Pischke 2009)(Woolridge 2010). It is therefore more suitable to include a selection bias.

To estimate the average causal effect (ATE):

$$E[Y_i|D_i = 1] - E[Y_i|D_i = 0] = E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 1]$$
$$+ E[Y_{0i}|D_i = 1] - E[Y_{0i}|D_i = 0]$$

(6.2)

This notation is formally adopted by Angrist and Pischke (2009). Where the first expression is the observed differences in the outcome variable, which is the sum of the average treatment effect on the treated (ATT or ATET) and the selection bias. Y_{1i} denotes the treated group, while Y_{0i} denotes the untreated group. This equation implies that when there is a correlation between selection bias and the outcome variable, there will be a selection problem. Ideally, one would overcome the selection bias to ensure that the effect of treatment could be causally linked to the treatment (Angrist and Pischke 2009).

The problem with selection biases is that it could cause to misleading estimates of the causal effects, if there are unobserved differences between the groups that can affect the differences in outcomes after treatment. In the absence of treatment, the treatment group should ideally follow the same trend, which is the counterfactual of the causal treatment effect of the treated group (Angrist and Pischke 2009)(Woolridge 2010). In the following I will elaborate on the potential selection biases and how I can strategically reduce and overcome them.

6.2 Identification strategy

In randomized experiments the treatment and control group are more likely to be similar pre-treatment, while for quasi-experiments it could be misleading to compare outcomes, due to the possibility of having systematically differences in characteristics pre-treatment, which randomization ensures (Angrist and Pischke 2009)(Rosenbaum and Rubin 1983). Since EU ETS regulation is based on emissions, capacity limits and industry affiliation, there will be selection biases if I had conducted a DiD analysis on the original sample. However, there are statistical strategies to cope with the selection bias. The most crucial assumption is the parallel trend assumption, which states that the control group and the treatment group must have the same parallel trends prior to treatment takes place (Hernan and Robins 2020)(Stuart 2010). This does not mean that the treatment and control group must have the same means in the outcome

variable, but that the trend is moving in the same direction in the pre-period. However, this assumption is difficult to fulfill. There is no statistical method to ensure that this assumption holds, and one must therefore visually inspect the observations. The intuition goes as follows: in absence of a treatment effect, the two groups would follow the same trend in outcome. If the outcomes change after the time of treatment, then we could argue that the treatment is the cause of the change in outcomes. Violation of parallel trend assumption will lead to biased estimation of the causal effect (Stuart 2010)(Ryan et. al. 2018). Examining the parallel trend assumption, I will visually inspect the outcome variables pre and post matching controls.

In figure 8 we can see the trend for the binary outcome for low-carbon patent applications. The Y-axis is the average yearly share of firms which had at least one low-carbon patent application over years from the X-axis. In other words: this is not the total amount of low-carbon patents, which is expressed in figure 9. The green line indicates when treatment was officially in operation in Norway, from 2008. Following the movements up till phase II begins, we can see that the average share of firms having at least one low-carbon patent application among unregulated firms are moving more steadily, while for the regulated firms the graph is more fluctuating. A crucial reason for this is that there are few low-carbon patents in the first place. From the graph we can see that for the regulated firms, there are 2-8% of the regulated firms that have had a low-carbon patent, while 1-2% of the regulated firms that have had a low-carbon patent.
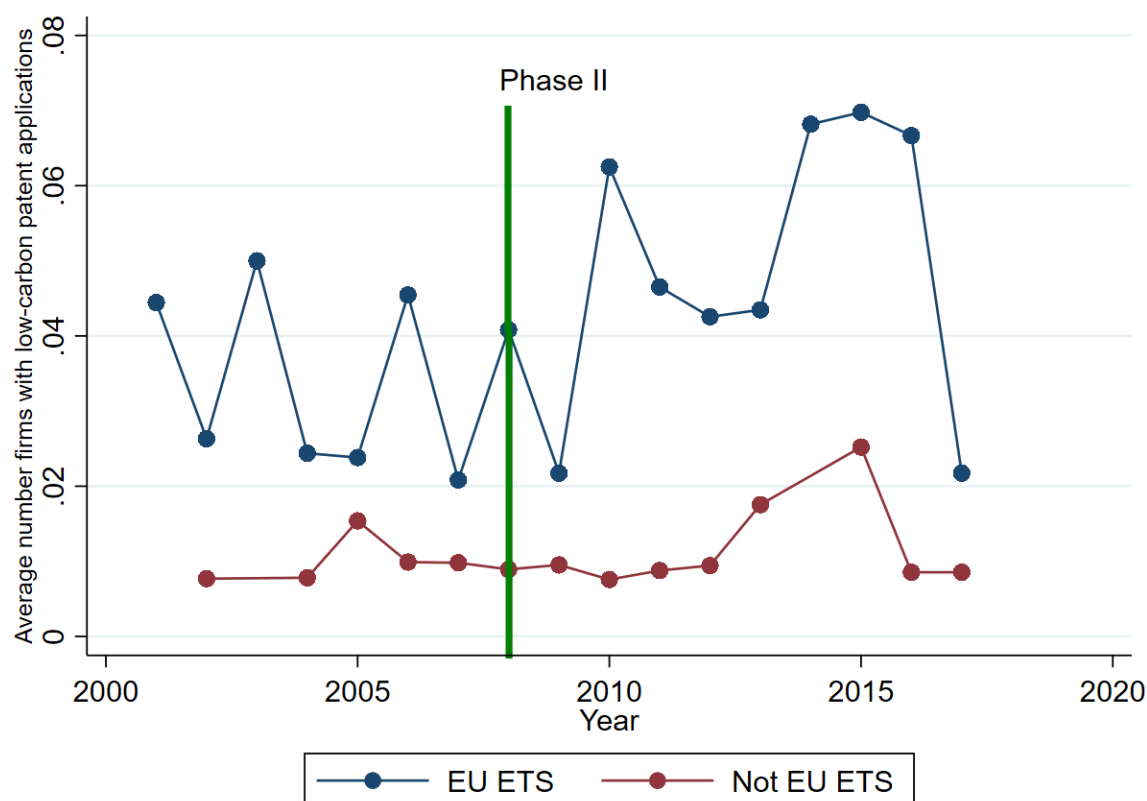
Figure 8: Average number of firms having at least one low-carbon patent

Note: this figure plots the average number of firms with at least one low-carbon patent application over the years, divided between the regulated and not regulated firms in the sample. Data source: Norwegian Industry Property Office and the Norwegian Environmental Agency

Figure 9 measures the annual average number of low-carbon patent applications, where the number of patents are expressed in the Y-axis over years in the X-axis. From the graph we can see that the two top points for an average yearly number of low-carbon patents are in 2010 and 2016 for the EU ETS firms, with an average of 0.25 low-carbon patents in the regulated groups for these two years, while the bottom point for the EU ETS group is in 2005 with ca. 0.025 patents for the firms in this group that year. While for the unregulated firms, the average is more stable, moving from ca. 0.01 to 0.03 in the entire scope of years. The numbers are low on average, since there are few firms that have low-carbon patent applications, as seen in figure 8. As mentioned in chapter 5, the annual range goes from 1 to 7 low-carbon patents per year. While for regular patents the range goes from 1 to 41, meaning that there are some firms that innovate more heavily than others.
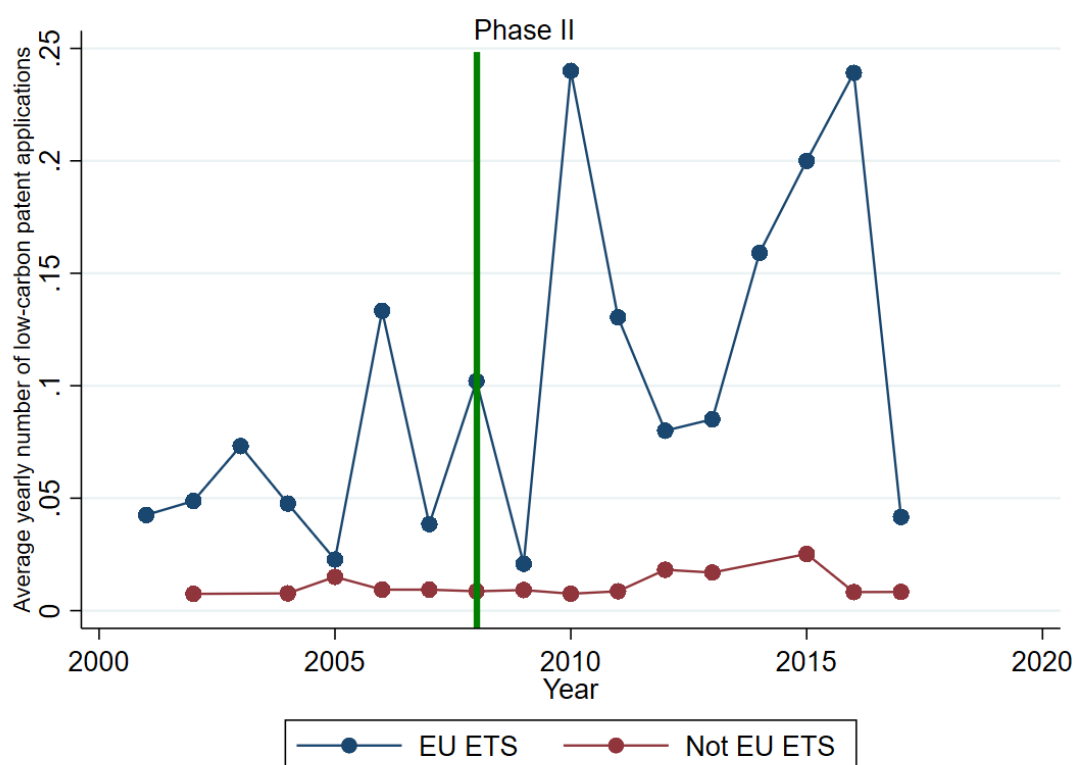
Figure 9: Average annually number of low-carbon patent applications

Note: this figure plots the average number of low-carbon patent applications over the years, divided between the regulated and not regulated firms in the sample. Data source: Norwegian Industry Property Office and the Norwegian Environmental Agency

Both in graph 8 and 9 we can see that the trends between the regulated and not regulated firms are somewhat different prior to 2008. Since the parallel trend assumption is crucial to be fulfilled for a reliable causal regression estimation, however, it might be difficult to obtain a completely parallel trend for the low-carbon patent applications, since the sample size is so low. This problem has also been discussed by Calel (2020). While a propensity score matching can trim the sample to obtain a sample of two groups that are more similar, based on the covariates that is chosen, trimming the sample can come with some loss of sample size of the patents. In other words: by reducing the sample, I might lose some of the patents as well, which will of course affect how the trends move and the reliability on the estimation results, since there are so few patents in the first place. I will discuss this further in chapter 6.3

In figure 10 we can see the average yearly share of firms that have invested in green intramural R&D expenditure on the Y-axis over the years, based on a dummy variable which captures whether a firm invested in green R&D expenditure. In 2017, almost 50% of the regulated firms invested in green R&D, while from 2001 to 2008 around 30% of the regulated firms invested in green R&D. For the unregulated firms, ca 12-15% of the firms invested in green R&D

between 2001 to 2008. In 2017, around 25% of the firms had green R&D expenditure. By visually inspecting figure 18, it could be argued that the parallel trend assumption, to some degree, holds for the pre-period, since the groups move in the same direction up till 2008.
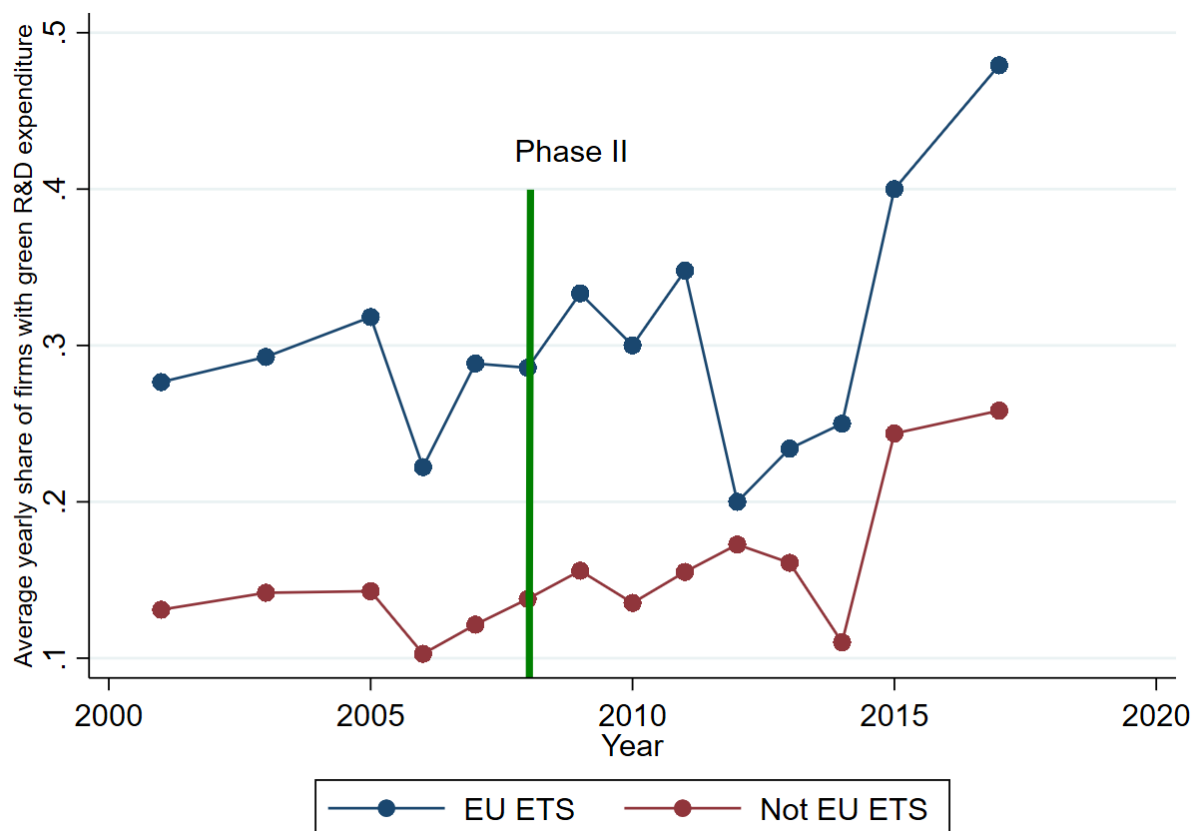
Figure 10: Average yearly share of firms that has green intramural R&D expenditure

Note: this figure plots the average number of firms with green intramural R&D expenditure over the years, divided between the regulated and not regulated firms in the sample. Data source: Statistics Norway and the Norwegian Environmental Agency

In figure 11 we can see the average yearly green intramural R&D expenditure, expressed in 1000 NOK for both groups. The Y-axis represents the total 1000 NOK, while the X-axis represents years. From 2001 to 2008 the average yearly green intramural R&D expenditure for regulated firms is between 2,000,000 and 6,000,000 NOK, while from 2013 to 2015 there is a big increase, up to 15,000,000 NOK, which is mainly driven by one large investment by one firm.
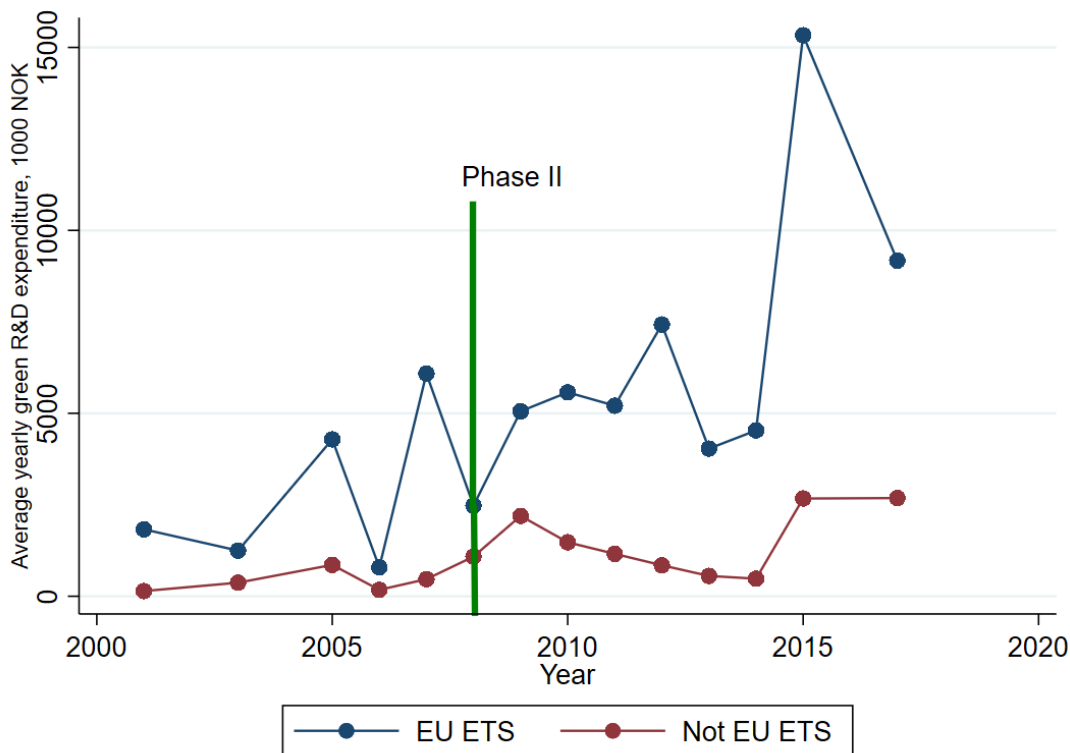
Figure 11: Average yearly green intramural R&D expenditure, 1000 NOK

Note: this figure plots the average amount of green intramural R&D expenditure in 1000 NOK over the years, divided between the regulated and not regulated firms in the sample. Data source: Statistics Norway and the Norwegian Environmental Agency

As mentioned in chapter 5, a potential problem with the variables from the R&D dataset is that the survey is not time-consistent, i.e., some years the survey did not have thematic categories for intramural expenditure and that variables change over time. The implications of this is that it makes it tricky to estimate the parallel trend assumption correctly. The variation could cause to misleading interpretation of the outcome variable.

Based on the inspection of the graph, it could be argued that the parallel trend assumption is violated for figure 11, since the regulated and the unregulated do not follow the same trend prior to 2008. Moreover, figures 8 and 9 also suggest that there potentially could be a violation of the parallel trend, while figure 10 seems to move in the somewhat same direction. I must therefore conduct a statistical strategy to reduce these differences. Since there are so few firms that have either patents or intramural R&D spending, the parallel trend assumption is hard to fulfill completely. However, the parallel trend assumption is crucial to fulfill to be able to identify causal effects (Hernan and Robin 2020). I will discuss how I can estimate the counterfactual outcome, i.e., a suitable control group, by propensity score matching in chapter 6.3.

Another crucial assumption is that there must not be any spillover effect (interference) between the treated and the control group. This is also called the stable unit treatment value assumption (SUTVA) (Angrist, Imbens and Rubin 1996)(Hernan and Robins 2020)(Woolridge 2010). I conduct the analysis on firm level, due to all innovative activities take place at firm-level, but also to internalize some potential spillovers from plants. A firm can have multiple plants, which is the case in my dataset. There could therefore be some potential spillover effects between a regulated plant and a not-regulated plant inside the same firm, which would cause a bias in the estimation (Petrick and Wagner 2014). I have therefore defined all firms that have at least one regulated plant as a regulated firm, to internalize the potential spillover effect. However, there might be some other spillover effects between firms. As mentioned in chapter 2, the effective marginal carbon price has been low for the regulated industries, while higher for other industries which are faced with the Norwegian CO_2 tax. If abatement technological innovations conducted by the regulated firms are available for not-regulated industries, which have high rates of emissions and also face a higher carbon price, this might lead to some spillover effect between regulated and not-regulated firms. I cannot control for this in my analysis, thus, to ensure that SUTVA holds completely might become problematic.

6.3 Propensity score matching

6.3.1 Discussion of method

Abadie (2005) has a proposed solution to when there are differences between the treatment and control group prior to treatment. Propensity score matching is a strategy to remove or minimize biases in quasi-experiments where the treatment is not randomized and is a popular strategy to estimate causal inference in absence of random assignment (Caliendo and Kopeining 2008). The propensity score estimates the probability of a unit (a firm in this analysis) to be assigned treatment based on covariates. To estimate the probability of treatment, it is therefore crucial to understand how the treatment is assigned in the first place. When we understand the selection criteria, we can easier choose the covariates to estimate the probability of treatment, hence obtaining a better estimation of the treatment probability (Stuart 2010)(Austin 2011)(Rosenbaum and Rubin 1983). The results of the propensity score matching estimation is based on the covariates that are chosen, hence the more we know about the selection criteria, the better the estimation will be. There is a trade-off between sample size and biasedness. By including many covariates to approximate the selection criteria as much as possible, it is also more difficult to obtain exact matches (Stuart 2011). There are multiple matching strategies that

I can conduct in my thesis. It is therefore important to get an overview of the potential implications of each strategy, prior to selecting the preferred strategy.

Petrick and Wagner (2014) conduct a 1:1 matching with replacement as their main strategy, which implies that one control firm can be matched with multiple treatment firms. As a robustness test, they estimate a 1:20 matching. The effect of using 1:M matching is not necessarily straightforward, since oversampling of control firms could reduce the estimate variance, i.e., the control group fits the treatment group better per firm in the control group, based on the covariates. However, the potential problem with using many neighbors, may lead to a smaller sample of control firms and the bias can be higher. Petrick and Wagner differs between process-regulated industries, due to the selection criteria of EU ETS regulation. This leads to a potential comparison between paper production and steel production. The covariates for propensity score matching include CO_2 emissions, profits, exports, employees and wage rate. Jaraite and Corrado Di Maria (2016) also conduct a 1:1 matching with replacement, and they argue that there is a trade-off between bias and variance in terms of allowing for replacement. They argue that it is more appropriate to use replacement since there are great differences between regulated and unregulated firms, hence a 1:1 matching without replacement could create a control group that is not that similar to the treatment group. Klemetsen, Rosendahl and Jakobsen (2020) also use propensity score matching to obtain a control group of firms that are not regulated by EU ETS. They conduct matching based on covariates from 2001, and they require exact match on emission source and industry affiliation at a two-digit level. Moreover, they include the level of emissions, profits and number of employees as covariates to approximate the selection criteria, respectively for capacity limit and plant size. In their main analysis they do a 1:10 nearest neighbor matching, and 1:3 nearest neighbor matching as a robustness check.

Following Jaraite and Corrado Di Maria (2016) and Petrick and Wagner (2014) I conduct a propensity score matching with 1:1 and replacement. Similar to Klemetsen, Rosendahl and Jakobsen (2020) I conduct a 1:3 matching as a robustness check, to allow for multiple control firms to be matched with a treatment firm. I choose replacement in the main analysis since matching with replacement generates a higher quality of matching, and a decreased bias, since the algorithm choose the firms from the control group that fit the treatment group the best, based on the covariates chosen. However, the sample of control group could become small, since the control firms could be matched with several treatment firms. This implication is crucial to keep in mind when conducting propensity score matching. The propensity score matching is only as

good as the choice and quality of the covariates, and since the EU ETS regulation already implies that the regulated firms are the biggest emitters, it is with low probability that one will obtain a "perfect" control group after matching. However, the propensity score matching will find the *closest* non-regulated firms. This is a crucial difference and is important to keep in mind when reading the results of this thesis, since there might be some unreliability of the estimates due to differences between the treatment and control group (Jaraite and Corradi Di Maria 2016)(Rosenbaum and Rubin 1983).

To approximate the selection criteria, I follow Klemetsen, Rosendahl and Jakobsen (2020), Calel (2020) and Petrick and Wagner (2014) by choosing variables that imply capacity limits and production activity, i.e., number of employees, profits and CO_2 emissions. Since the selection criteria is based on industry specific thresholds, I choose to run a loop over each two-digit NACE code to match firm based on these covariates. In this way I can match my entire sample and create a control group that is more similar to the treatment group. I obtain two different matching control groups: 1) based on covariates employees, emissions and profits, 2) a loop over each two-digit industry code where there are at least one regulated and one not-regulated firms, on the same covariates. I divide between these two strategies, since running an industry loop might lose some generalizability, since the estimates will only be valid for the relevant industries that is included in the weights. Moreover, I include a regression adjustment with propensity score weighting, which is doubly robust since is sufficient that either the regression model or the propensity score method are correctly specified (Angrist and Pischke 2009). As a robustness check I conduct a 1:3 propensity score matching, with inverse propensity score weighting and common support.

6.3.2 Results from matching
The propensity score matching is conducted by the Stata command psmatch2 by Leuven and Sianesi. I have conducted matching based on the pre-period 2001-2003. There are several reasons why I chose this pre-period for matching. First of all, the allocation of allowances in Norway was based on emission levels in 1998-2001, therefore I want to be as close as possible to approximate the selection criteria appropriately. Second of all, it was signaled by the Norwegian government in 2001 that EU ETS was going to be ratified (Klemetsen, Rosendahl and Jakobsen 2020). To ensure that there has not been a reallocation of production to come below the threshold, it seems appropriate to matching from this year. However, Dechezleprêtre and Calel (2016) argue that firms will have little incentives to reallocate production, to reduce emissions per plant to avoid regulation, since this is relatively more costly than the price of

allowances and regulation. Third of all, since it was voluntary for Norwegian firms to participate in EU ETS from 2005, it is possible that there has been a weak treatment effect prior to 2008 (Klemetsen, Rosendahl and Jakobsen 2020). And lastly, since the variables for profits and employees are sometimes missing or registered with 0 in the dataset, (which I have not changed from the original dataset), I choose to match with multiple years, to obtain more firms based on these covariates. When I match based on covariates that are missing for some firms, these firms will most likely not be in the matched sample. However, if these observations are not supposed to be missing, but in reality are higher, then the results of the matching could lose some reliability.

In figure 12 we can see the average yearly green intramural R&D expenditure for the matched sample, based on the covariates, but not restricted to industries. The pre-trend is more parallel in this figure, compared to figure 11. However, it is not possible to conclude that the parallel trend assumption holds, but it is possible to argue that based on the trend in this outcome variable, the trend seems to be more parallel than in the original sample from figure 11.
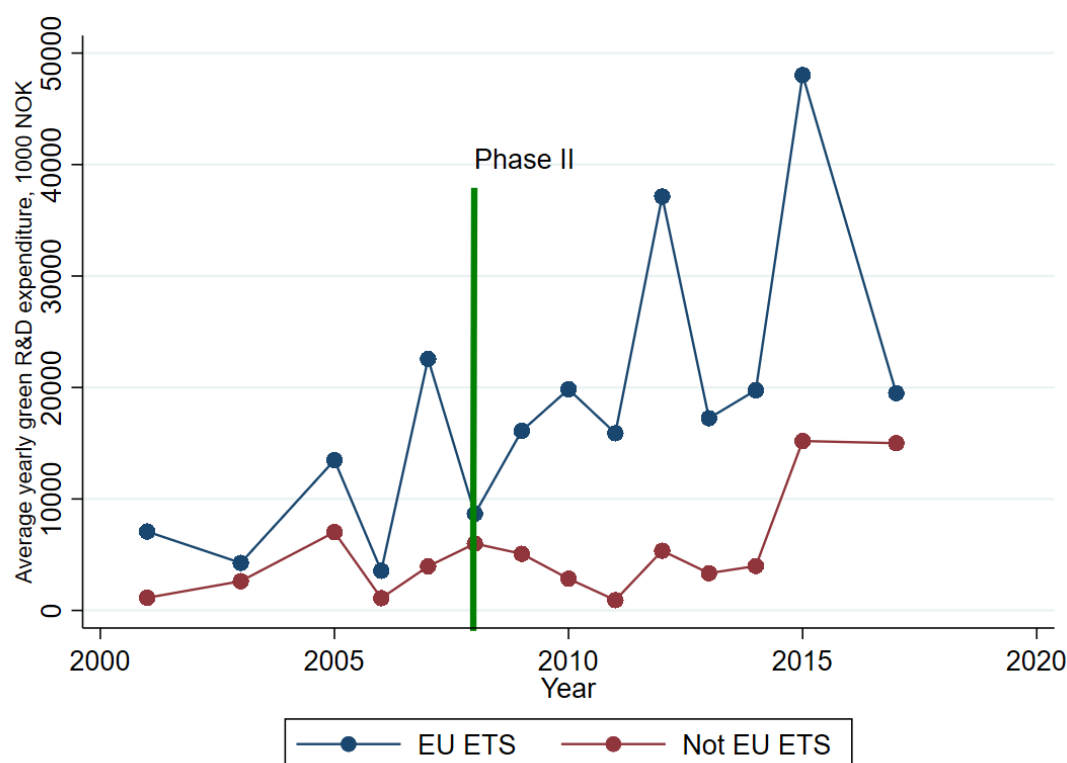
Figure 12: Average yearly green R&D expenditure, 1000 NOK

Note: this figure plots the average amount of green intramural R&D expenditure in 1000 NOK over the years, divided between the regulated and not regulated firms in the sample from propensity score matching based on covariates of profits, employees and CO2 emissions. Data source: Statistics Norway and the Norwegian Environmental Agency

In figure 13 we can see the results for the matched sample with industry affiliation. Here the results have changed, the pre-treatment trend for unregulated firms are more stable, up till 2007. While in figure 12, there was a slight increase in 2005. However, the trend seemed to be more parallel in graph 12, than 13. These two graphs implies that the matched samples might have some different affect on the regression output. This is also exemplified by tables 4 and 5 presented later in this chapter.
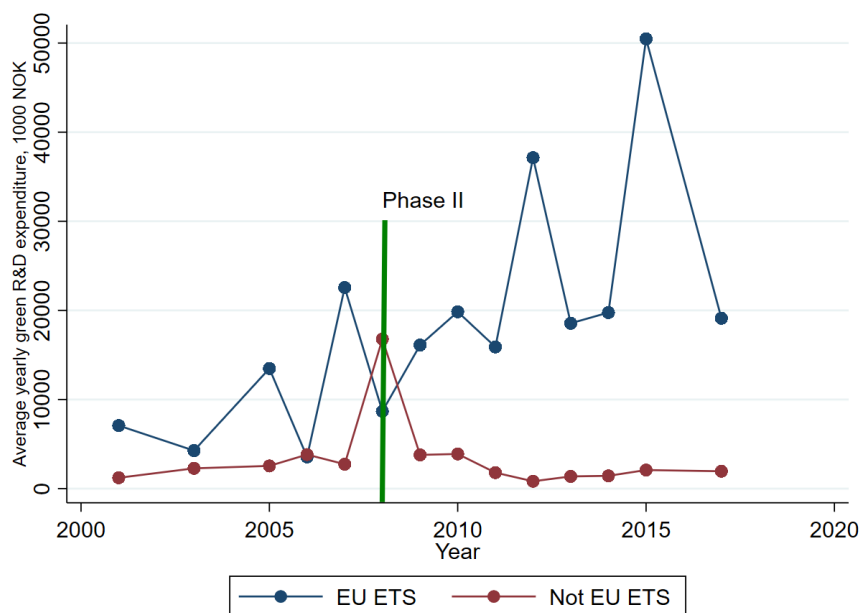
Figure 13: Average yearly green R&D expenditure, 1000 NOK, matched sample within industries

Note: this figure plots the average amount of green intramural R&D expenditure in 1000 NOK over the years, divided between the regulated and not regulated firms in the sample from propensity score matching based on covariates of profits, employees and CO2 emissions within each two-digit industry. Data source: Statistics Norway and the Norwegian Environmental Agency

Since there are so few low-carbon patents, I find it infeasible and unnecessary to visually inspect the parallel trends of this variable, which will be obvious from table 3-5. Table 1 shows the descriptive statistics of firms' characteristics in 2001-2003, before matching. While table 2 shows the descriptive statistics of firm's characteristics in the same period, but for the matched sample based on industry loop. The frequency in both tables is firm-year observations. On average, the regulated firms have a higher number of employees, profits and emissions, compared to the unregulated sample. In both tables, I have chosen to include the mean, median and maximum value for profits, employees and emissions of CO_2, since these are the covariates I use in the propensity score matching to approximate the selection criteria. The means are higher than the median, which implies that the distribution in the sample is positively skewed.

Therefore, I included the maximum value for all of these variables, to obtain some information about how skewed the samples are.

Table 1: descriptive statistics of firm's characteristics in 2001-2003

2001-2003	EU ETS		
	0	1	Total
Frequency	420	129	549
Firms	198	61	259
Mean			
Profits	568,254	4,051,618	1,388,687
Employees	230	584	313.1239
Emissions, CO2	5	289	71.31764
Median			
Profits	162,093	614,979	245996
Employees	109	311	123.5
Emissions, CO2	.21	53	.552
Maximum value			
Profits	1.14e+07	1.86e+08	1.86e+08
Employees	2031	10119	10119
Emissions, CO2	185	10052	10052

Note: Summary statistics for regulated and unregulated firms in 2001-2003, based on the full sample. Data source: Statistics Norway

In table 2 we can see the descriptive statistics of firm's characteristics in 2001-2003, after matching. This matched sample is based on 1:1 with replacement on the covariates employees, profits and CO2 emissions, over a loop for each two-digit industry code. In table 2, the average in employees, profits and emissions are now higher for the unregulated firms, due to the assumptions of the selection criteria. Therefore, the control group is now somewhat more similar to the treatment group, relative to table 1. The absolute difference between the regulated and the unregulated firms are, on average, reduced in the matched sample based on the covariates.

Table 2: descriptive statistics of firm's characteristics in 2001-2003 in matched sample

2001-2003	EU ETS		
	0	1	Total
Frequency	36	118	154
Firms	24	56	80
Mean			
Profits	1,697,510	4,051,618	2320410
Employees	571	585	379.056
Emissions, CO2	84	300	162.5195
Median			
Profits	1,119,285	614,979	298114
Employees	336	311	117
Emissions, CO2	50	52	13.875
Maximum value			
Profits	6169731	1.86e+08	1.86e+08
Employees	1136	10119	10119
Emissions, CO2	185	10052	10052.21

Note: Summary statistics for the regulated and unregulated firms, 2001-2003. Data source: Statistics Norway

Table 3-5 report the summary statistics for the variables that measure innovation activity, for the period 2001-2007. Table 3 reports the statistics for the full sample, table 4 is restricted to the matched sample conducted on matching based on only covariates, while table 5 reports the statistics for the matching on covariates with an industry loop. These three tables provide crucial information before conducting the regression.

Table 3: descriptive statistics of firm's innovation activities in 2001-2007, full sample

Full sample	EU ETS		
	0	1	Total
Mean			
Intramural R&D 1000 NOK	5784	30866	12257
Extramural R&D 1000 NOK	3305	29856	12193
Green R&D 1000 NOK	285	2173	772
Total			
Firms with patent	32	24	56
Firms with low-carbon patents	6	10	16
Patents	62	147	209
Low-carbon patents	6	18	24
Firms with green R&D expenditure	82	64	146

Note: Summary statistics for the regulated and unregulated firms, 2001-2003. Data source: Statistics Norway

In table 3 we can see that regulated firms have on average more intramural, extramural and green R&D expenditure. However, there are more unregulated firms that have patent applications and green R&D expenditures compared to the regulated firms. We can also see that there are not many low-carbon patents in this period, where there are only a total of 16 in the entire sample. In table 4 we can see the statistics for the matched sample on covariates employees, profits and CO2 emissions. The total NOK for intramural and green R&D has increased for both groups. However, the number of firms with low-carbon and regular patents has decreased for the control group. The reduction in the number of patents and low-carbon patents for the regulated firms suggest that these patents (those who are now dropped from the sample) belongs to firms that are not similar to the treatment group, based on the covariates that I used in the propensity score matching. This reduction is even greater in table 5.

Table 4: descriptive statistics of firm's innovation activities in 2001-2007, matched samples, covariates

Matched samples, covariates	EU ETS		
	0	1	Total
Mean			
Intramural R&D 1000 NOK	6748	35113	14543
Extramural R&D 1000 NOK	3237	29329	1241
Green R&D 1000 NOK	335	2468	921
Total			
Firms with patent	27	24	51
Firms with low-carbon patents	5	10	15
Patents	57	147	204
Low-carbon patents	5	18	23
Firms with green R&D expenditure	75	64	137

Note: Summary statistics for the regulated and unregulated firms on matched sample on covariates , 2001-2003. Data source: Statistics Norway

In table 5 we can see that there are no low-carbon patents for the control group. Moreover, the number of regular patents are also reduced for the control group. However, the variables for R&D expenditure has increased, which suggests that the propensity score matching might fit better for the R&D data, than for the patent data. It is important to understand that the matched sample based on the industry loop will lose some generalizability outside of the scope of industries kept in the matched sample. Moreover, since the assumptions I have made may not be true to reality, the sample conducted by matching may not necessarily be reliable estimates of the selection criteria (Gertler et. al. 2016).

Table 5: descriptive statistics of firm's innovation activities in 2001-2007 in matched sample, industry affiliations

Matched sample, covariates	EU ETS		
	0	1	Total
Mean			
Intramural R&D 1000 NOK	15347.06	35113.18	26845.82
Extramural R&D 1000 NOK	3884.218	29329.88	17980.01
Green R&D 1000 NOK	502.9688	2468.18	1646.213
Total			
Firms with patent	2.84264	24	23.3715
Firms with low-carbon patents	0	10	7.30361
Patents	2.84264	147	113.206
Low-carbon patents	0	18	13.1465
Firms with green R&D expenditure	13.8579	62	73.7665

Note: Summary statistics for the regulated and unregulated firms, matched samples on covariates profits, employees and CO2 emissions on two-digit industry loop, 2001-2003. Data source: Statistics Norway

7.0 Results

In this chapter I present the results of EU ETS regulation on innovation activity. I have divided the results into two sub-parts, whereas the first is for patent applications and the second is for R&D expenditure. The main question of this thesis is whether regulation has, causally, led to increased innovation activity. In the R&D dataset, there are multiple variables to measure R&D expenditure, for instance the difference between intramural and extramural expenditure. Moreover, there are multiple variables to measure different aspect of green R&D expenditure, with variables that vary over time and are measured differently in the different survey-periods. This might lead to inconsistency in the results. To control for this variation, I will do the analysis for multiple outcomes and samples obtained from propensity score matching. For patent activity, I differ between low-carbon patents (in accordance with the Y02 tagging scheme) and all patents. Equation (7.1) is the DiD regression model, and is expressed by:

$$E_{it} = \beta_0 + \beta_{1t} + EUETS_i\beta_2 + \beta_3(EUETS_i * \beta_1) + \varepsilon_{it} \qquad (7.1)$$

The dependent variable in equation (7.1) is the outcome variable of green innovation for firm i in year t. β_{1t} is the treatment year, which is 2008 in my analysis. In my analysis I keep the period after 2008 as the entire treatment phase. $EUETS_i$ is a dummy variable which is equal to 1 when a firm is regulated by EU ETS, while β_2 denotes the coefficient for treatment. The interaction term of the treatment group dummy and the timing of treatment is denoted by $\beta_3(EUETS_i * \beta_1)$ and is defined as the DiD estimator. The error term expressed by ε_{it} is assumed to be uncorrelated with treatment.

I run the analysis on three different samples. The first sample, column (1) in the regression output, is the entire sample of firms, where the control group is all other firms that are obligated to report their emissions to NEA, still restricted to the industry codes similar to 05-33, except 06, while the treatment group is the firms that are regulated by EU ETS. The second sample, column (2) is based on 1:1 matching with replacement on the covariates to approximate the selection criteria. However, I do not control for industry affiliation in this sample. In sample 3, column (3) I conduct the same propensity score matching as in 2, but control for industry

affiliation, i.e., the selection is restricted to all industries that have at least one EU ETS regulated and one not-regulated firm. I divide between these two samples to obtain control for the trade-off between precision and unbiasedness which I obtain in sample 3, and sample size and generalizability from sample 2.

The overall estimates of the DiD suggest that EU ETS has encouraged green intramural R&D spending for regulated firms, depending on the empirical assumptions. For low-carbon patenting, the estimations are weaker and not statistically significant, however, they are positive. The main drawback of the estimations is the lack of significant estimations. In panel data estimations, the p-value could be artificially low, and it is therefore crucial to cluster the standard errors. I cluster at firm-level, to control for firm-fixed effects, similar to Klemetsen, Rosendahl and Jakobsen (2020). Moreover, I apply regression adjustment with propensity score weighting in all output tables to obtain doubly robust results. This estimation is doubly robust, since it combines both the propensity score method and the regression method, such that only one of these methods need to be correctly specified (Funk et. al. 2011). All estimations are dependent on that the assumptions of chapter 6 must hold. I will discuss the limitations of the results in chapter 9.

7.1 Regression output, patent applications

Table 6 reports the regression output estimated by (7.1) on low-carbon patents. Panel A estimates the effect based on the full sample, while panel B restricts the sample to whether the firm had a regular patent, i.e., these estimates for low-carbon patents are conditional on that a firm must have a regular patent. The latter therefore estimates the probability of having a low-carbon patent if the firm has a regular patent. d. in row (1) and (3) denotes that the outcome variable is a dummy variable, while rows (2) and (4) are continuous variables that captures the sum of all low-carbon patents.

The estimations on the full sample indicates an annual increase of 1-6% regulated firms that apply for low-carbon patents, depending on the different empirical assumptions. While for row (2) the estimations indicates a small positive effect, just above zero, on the annual rate of low-carbon patent applications for regulated firms, with an annual increase of ca. 0.1 low-carbon patent per year from 2008-2017. However, for the restricted sample in panel B, the estimated effect is ca. 1 low-carbon patent per year. This result is not generalizable for firms that do not have patent applications. By examining the signs and the doubly robust estimations, the overall results suggest that there is a positive, but weak, effect of EU ETS regulation on low-carbon patenting for regulated firms. However, these outcomes are not statistically significant and

neither results have a p-value lower than 0.05. From table 3-5 we know that there are few low-carbon patents in the samples and the effective sample size is therefore small. Moreover, in the matched sample in column (3) does not contain any low-carbon patent for the control group, which provides some unreliability to this estimate. One should therefore read the results in this column with caution.

Table 6: DiD estimations for low-carbon patenting

	Full sample	Matched sample	Industry	Doubly robust
Panel A: Full sample				
Low-carbon patent, d.	0.011	0.022 *	0.023 *	0.064 *
	(0.014)	(0.012)	(0.01)	(0.019)
All low-carbon patents	0.067	0.09 *	0.1 *	0.16 *
	(0.045)	(0.06)	(0.06)	(0.1)
Panel B: firms with at least one patent application				
Low-carbon pat, d.	0.057	0.140	0.064	0.99
	(0.164)	(0.11)	(0.013)	(0.13)
All low-carbon patents	0.73 *	0.89 *	0.34	1.022*
	(0.35)	(0.40)	(0.2)	(0.48)

*** p<.01", "** p<.05, "* p<.1

Note: Difference-in-Difference estimation for low-carbon patent applications. The regression output is the interaction term (DiD) outlined from equation (7.1). Column (1) are results on the full sample, column (2) are results restricted to the matched sample from 1:1 matching on covariates profits, CO_2 emissions and employees and column (3) are restricted to matching similar to column (2) but with matching conducted for two-digit industry codes. Panel A: regression on the full sample. Panel B: Restricted to firms that have had at least one patent application in the time period, 2001-2017. St. errors clustered at firm-level.

To estimate the overall innovation activity in terms of patent applications, I ran a regression for regular patent applications as well. The regression output can be seen in table 7. d. denotes dummy, and row (2) and (3) are continuous variables that summarize all patents per year. We can see that for the dummy variable for patents, the effect is between 0-2%, meaning that there is a small increase in the number of regulated firms that apply for patents, however these estimates are not significant. There is an annual increase of 0.23-0.49 patents for regulated firms in the treatment period in panel A. However, in the restricted sample, the estimates are higher, which might not come as a surprise, since there are few firms that innovate. These estimates implies that for firms that already have patent applications, there is an annual increase of 2-3

patents in the treatment period per year for the treatment group. The dummy variable is dropped due to multicollinearity in panel B. As we know from tables 3-5 column (3) must be read with some cautions for patent applications as well, since the number of patent applications for the control group fell in this sample. However, all signs are positive, but weak and not with p-value below 0.05.

Table 7: DiD estimations for all patent applications

	Full sample	Matched sample	Industry	Doubly robust
Panel A: full sample				
Patent, d.	0.0043	0.015	0.053 *	0.032
	(0.015)	(0.014)	(0.028)	(0.013)
All patents	0.23	0.49	0.41	0.37
	(0.23)	(0.34)	(0.33)	(0.31)
Panel B: restricted sample, to whether a firm has had a patent at least one year				
All patents	1.93 *	3.26 *	3.35 *	3.21
	(1.02)	(0.69)	(1.08)	(1.03)

** p<.01", "* p<.05, "* p<.1

Note: Difference-in-Difference estimation for patent applications. The regression output is the interaction term (DiD) outlined from equation (7.1). Column (1) are results on the full sample, column (2) are results restricted to the matched sample from 1:1 matching on covariates profits, CO2 emissions and employees and column (3) are restricted to matching similar to column (2) but with matching conducted for two-digit industry codes. Panel A: regression on the full sample. Panel B: Restricted to firms that have had at least one patent application in the time period, 2001-2017. St. errors clustered at firm-level.

7.2 R&D spending

To estimate the causal effect on R&D expenditure, the main variable of interests is green intramural R&D expenditure, both as a dummy and expressed in 1000 NOK. The green intramural R&D expenditure is the total share of all green variables in the R&D survey, as expressed in chapter 5. To obtain some nuances of this variable, I divide it into two subcategories: green energy and environmental research and technology. Additionally, I run a DiD regression on the extramural R&D expenditure and intramural R&D expenditure.

Table 8 represents the regression output for green intramural R&D expenditure. Row (1) and (3) estimates the effect on the dummy variable of green intramural R&D expenditure, which is equal to 1 whenever a firm has green intramural R&D expenditure. Row (2) and (4) estimates the effect on the continuous variable of green intramural R&D expenditure in 1000 NOK. For both variables the effect is stronger in panel B, which is restricted to whether a firm has had intramural R&D expenditure. On average, the estimated effect from table 8 indicates that there

is an annual increase of 2,600,000-4,300,000 NOK in the full sample, while an annual increase of 4,600,000-13,600,000 NOK if the firm has had intramural R&D expenditure in at least one year. The latter is therefore an estimate that loose some generalizability for the rest of the EU ETS firms, since it implies intramural R&D expenditure. The dummy variable estimates the probability of a firm investing in green R&D expenditure, where the magnitude of the effect is somewhat fluctuating. The results are not statistically significant, but for dummy variable in panel B, the estimates suggests that there are 10% more regulated firms that have green intramural R&D expenditure, at an annual rate, as long as the firm has had intramural R&D expenditure as well. All results suggest a positive effect, however, neither of these results have a p-value which is lower than 0.05.

Table 8: all green intramural R&D expenditure

	Unweighted	Matched sample	Industry	Doubly robust
Panel A: full sample				
Green R&D, d.	0.017	0.010	0.16	0.016
	(0.04)	(0.05)	(0.10)	(0.07)
Green R&D, 1000 NOK	2661	3654	3787	6715
	(1589)	(1495)	(1512)	(5057)
Panel B: restricted to whether the firm had intramural R&D expenditure				
Green R&D, d.	0.108 *	0.091	0.06	0.05
	(0.068)	(0.075)	(0.016)	(0.089)
Green R&D, 1000 NOK	4604	8249	9284	13660 *
	(7346)	(5752)	(5839)	(8668)

*** p<.01", "** p<.05, "* p<.1

Note: Difference-in-Difference estimation for green intramural R&D expenditure. The regression output is the interaction term (DiD) outlined from equation (7.1). Column (1) are results on the full sample, column (2) are results restricted to the matched sample from 1:1 matching on covariates profits, CO2 emissions and employees and column (3) are restricted to matching similar to column (2) but with matching conducted for two-digit industry codes. Panel A: regression on the full sample. Panel B: Restricted to firms that have had at intramural R&D expenditure at least once in the time period, 2001-2017. St. errors clustered at firm-level.

Table 9 reports the regression output for the divided green intramural R&D expenditure, between green energy and climate/environmental research and technology development. The estimates from Panel A are obtained from the full sample, while the estimates from panel B are conditional on that the firm must have had intramural R&D expenditure at least once. For both

variables, the strongest effect is from panel B, which is consistent for the other variables as well in the previous tables: if a firm already innovates, EU ETS have a stronger causal effect (as long as the assumptions hold, and the estimates are reliable). Table 9 indicates that there has been an annual increase for both variables, however the effect on climate and technology is somewhat smaller than the variable for energy. The annual increase in R&D expenditure on green energy, is estimated to be between 2,000,000-7,000,000 NOK for the regulated firms, depending on the empirical approach. For climate and environmental technology and research, the annual increase is between 200,000 and 2,500,000 NOK, also depending on the empirical framework. However, the signs are consistent in all outcomes, also for the doubly robust. The estimates for green energy is higher than for climate and environmental related research and technology, which could be caused by an overestimation of the "green" aspect of energy, which was discussed in chapter 5. Therefore, this estimate should be read with some caution.

Table 9: Green intramural R&D expenditure, energy, and climate and research

	Full sample	Matched sample	Industry	Doubly robust
Panel A: full sample				
Energy, 1000 NOK	1966	3536	2859	3721 *
	(1899)	(2785)	(1333)	(2843)
Tech and research, 1000 NOK	694	786	214	589
	(352)	(572)	(218)	(378)
Panel B: restricted to whether the firm had intramural R&D expenditure				
Energy, 1000 NOK	5136	7514*	6232 *	6828
	(2377)	(5060)	(5204)	(5381)
Tech and research, 1000 NOK	2505*	2033*	1594*	2304 *
	(1670)	(1830)	(2621)	(1759)

*** p<.01", "** p<.05, "* p<.1

Note: Difference-in-Difference estimation for green energy and climate/environmental research/technology intramural R&D expenditure, all variables expressed in 1000 NOK. The regression output is the interaction term (DiD) outlined from equation (7.1). Column (1) are results on the full sample, column (2) are results restricted to the matched sample from 1:1 matching on covariates profits, CO2 emissions and employees and column (3) are restricted to matching similar to column (2) but with matching conducted for two-digit industry codes. Row 1: regression on the full sample. Row 2: Restricted to firms that have had intramural R&D expenditure, 2001-2017. St. errors clustered at firm-level.

To obtain a more nuanced understanding of the R&D activity among regulated firms, I have included table 10, which shows the estimation results for both the intramural and extramural

R&D expenditure. The signs in table 10 are negative for three out of six estimates for intramural R&D expenditure. As seen in tables 3-5, the intramural R&D is more similar among the control and the treatment firms when conducting propensity score matching, which provides some reliability to these estimates. However, as I have mentioned throughout this chapter: every estimate must be understood within its own empirical framework. Neither the intramural nor extramural R&D expenditure differ between categories, which makes the reading of these estimates rather unnuanced. However, the sample size of these variables are the largest among the variables on innovation activity and are the innovation activities that are the most common among firms in the sample. For extramural R&D expenditure, the estimates are divergent in signs and magnitude. All estimates in panel A suggest a negative sign for extramural R&D spending for the regulated firms. When restricting the sample to panel B, the estimates are positive for both variables (excluded one sign for intramural). These estimates implies that for regulated firms that have either intramural or extramural R&D expenditure, the effect is positive. If the firms does not have intramural or extramural R&D expenditure, the causal effect is negative. However, neither results are statistically significant.

Table 11: intramural and extramural R&D expenditure

	Unweighted	Matched sample	Industry	Doubly robust
Panel A: full sample				
Intramural	-8678	-8311	3256	-5577
	(7123)	(9672)	(12262)	(11632)
Extramural	-2667	-973	-4039	-2273
	(4391)	(5774)	(5694)	(10026)
Panel B: restricted to whether the firms had R&D activity based on the dependent variable				
Intramural	-5574	5001	15150	7395
	(14960)	(18170)	(19747)	(22411)
Extramural	3305	8581	5900	7200
	(626)	(15193)	(17151)	(12943)

*** p<.01", "** p<.05, "* p<.1

Note: Difference-in-Difference estimation for patent applications. The regression output is the interaction term (DiD) outlined from equation (7.1). Column (1) are results on the full sample, column (2) are results restricted to the matched sample from 1:1 matching on covariates profits, CO2 emissions and employees and column (3) are restricted to matching similar to column (2) but with matching conducted for two-digit industry codes. Panel A: regression on the full sample.

The overall findings presented in this chapter indicates that there is an increase green intramural R&D spending for regulated firms, as long as the assumptions discussed in chapter 6 holds. Moreover, the effect on low-carbon patents is positive, however weak and insignificant. The magnitude of the estimate are higher when I restrict the regression to be based on whether the firm had conducted innovation activities, which might not come as a surprise, since the number of firms that conduct innovation activities are rare in my sample, and as mentioned before: there are some firms that innovate heavily. Therefore, these restricted estimates loose some generalizability outside the scope of innovative firms.

8.0 Robustness checks

Robustness checks are measures to provide analytical strength to one's results, and it can be based on the research design and measurements (Angrist and Pischke 2009). In the robustness check I will conduct DiD estimation based on new samples obtained from propensity score matching. It is crucial to do a robustness check in this thesis, since outcomes could potentially be unreliable, due to the pre-period trends of the outcome variables estimated, small sample sizes and the lack of generalizability from some of the estimates in the main analysis. In this chapter, I will focus on the four main outcome variables that measure green innovation, i.e., low-carbon patents and green intramural R&D expenditure. In my main analysis, I did a propensity score matching with 1:1 and replacement and included industry affiliation. As a robustness test, I conduct a propensity score matching using 1-3 neighbors (similar to Klemetsen, Rosendahl and Jakobsen 2020). The choice of the covariates and methods of propensity score matching, can have crucial implications for the results, as we have seen in chapter 6. This robustness check is therefore conducted to provide some more evidence, with a different empirical approach. If the results from the robustness check deviates heavily from the main analysis, this suggest that either of the methods are misspecified. Similar to the main analysis, the propensity score matching is on the covariates profits, employees and CO_2 emissions, as well as industry affiliation, to approximate the selection criteria of EU ETS, where the inverse probability weights provides higher weights to the control firms that match the treatment firm the best, based on these covariates (Austin 2011)(Stuart 2010). I do not run a loop over the industries, as I did in the main analysis, but I restrict the sample to consist of two-digit industry codes with at least one regulated and unregulated firms. There are therefore only 15 two-digit industry codes in this sample.

Table 12 reports the summary statistics for the sample after matching. Since this is a robustness check, it is of value to compare this table with tables 1-2. Table 12 suggest that the control group and the treatment group are now more similar, compared to table 1, which is the original sample. The absolute difference between the means in covariates are now smaller.

Table 12: summary statistics for the sample with 1:3 matching

2001-2003	EU ETS		
	0	1	Total
Frequency	90	117	207
Mean			
Profits	1,111,043	4,083,166	2,786,505
Employees	275	594	455
Emissions, CO2	14	295	173
Median			
Profits	458095	635261	526563
Employees	175	322	240
Emissions, CO2	1.5135	52	16
Maximum value			
Profits	1.14e+07	1.86e+08	1.86e+08
Employees	1136	10119	10119
Emissions, CO2	185	10052	10052

Note: Summary statistics for the regulated and unregulated firms, 2001-2003. Data source: Statistics Norway

Table 13 reports the summary statistics for the innovation variables in the pre-period 2001-2007. Compared to the full sample in table 3, the average of intramural R&D expenditure and green intramural R&D expenditure has increased for both firms. While the number of patents and low-carbon patents has been reduced for the control group, leaving only 1 low-carbon patent in this sample. This indicates that the patent applications vanishes when conducting the propensity score matching based on these covariates. However, the estimates for the R&D variables are now more similar between the treatment and control groups, compared to the full sample. I am interested in the similarities, to obtain better understanding of how the variables are affected by the propensity score matching.

Table 13: summary statistics for the sample with 1:3 matching

	EU ETS		
2001-2007	0	1	Total
Mean			
Intramural R&D 1000 NOK	13019	57900	30028
Extramural R&D 1000 NOK	3272	29310	14193
Green R&D 1000 NOK	1464	11082	6394
Total			
Firms with patent	15	24	39
Firms with low-carbon patent	1	10	11
Patents	19	147	166
Low-carbon patents	1	18	19
Firms with green R&D	58	61	119

Note: Summary statistics of innovation measures for the regulated and unregulated firms, 2001-2003. Data source: Statistics Norway

In figure 14 we can see the plotted trend of average yearly green intramural R&D expenditure for both firms, in the weighted sample from 1:3 matching. Compared to the figure 11, the trends pre-treatment is moving in a more similar way, relatively speaking. Thus, the matched sample could be a better fit to estimate the R&D expenditure in this sample as well, as opposed to patent applications. However, I do not conclude with that the parallel trend assumption holds, I just suggest that this pre-treatment is more similar than the one for the full sample.
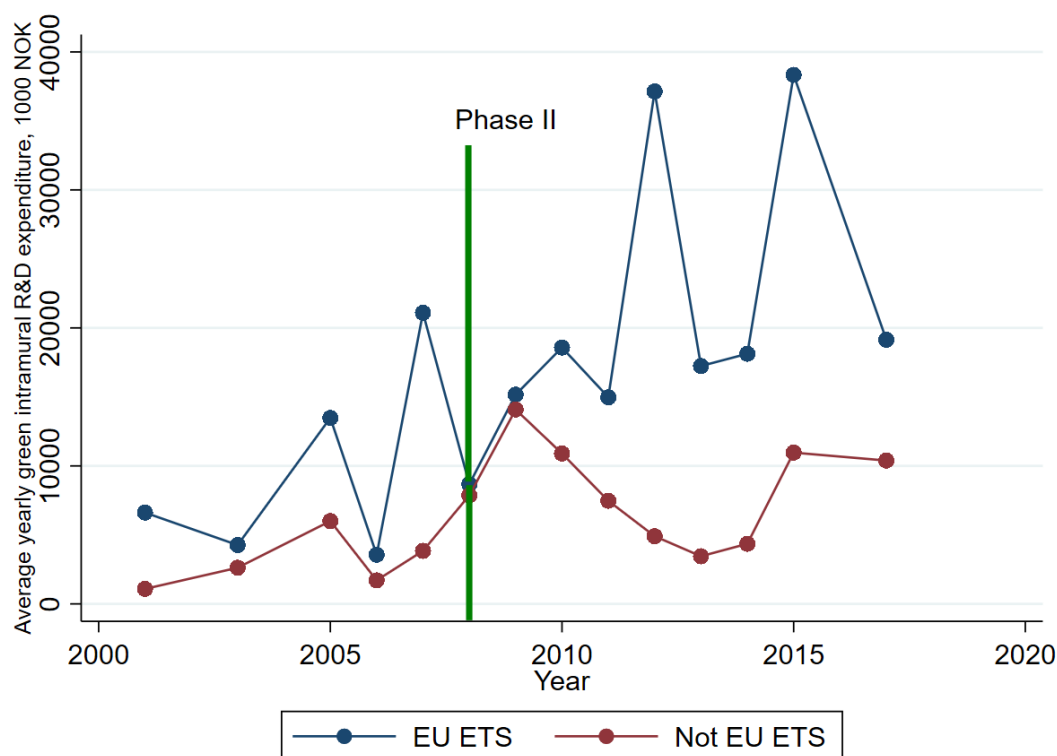
Figure 14: Average yearly green intramural R&D expenditure, 1000 NOK

Note: This figure plots the average yearly green intramural R&D expenditure in 1000 NOK on the Y-axis, over the years on the X-axis, for the treatment and the control group. Data source: Statistics Norway and the Norwegian Environmental Agency.

In table 14 we can see the regression output for low-carbon patents. As we already know, these results must be examined with some caution, due to the low number of low-carbon patents in the control group. The estimates suggest that there is a weak, but positive, effect on the regulated firms. Which suggests the same trend and sign as the regression output in chapter 7. However, it is rather difficult to claim that these estimates are of great reliability since that the parallel trend assumption is most likely violated for these outcomes.

Table 14: low-carbon patents

	Common support	Inverse-probability weights	Doubly robust
Low-carbon patent, d.	0.023	0.018	0.029
	(0.018)	(0.020)	(0.014)
All low-carbon patents	0.101	0.103	0.104
	(0.06)	(0.06)	(0.08)
Low-carbon pat, d.	0.029	0.04	0.06
	(0.167)	(0.161)	(0.18)
All low-carbon patents	0.98	0.97	0.96
	(0.56)	(0.57)	(0.54)

** p<.01", "* p<.05"* p<.1

Note: Difference-in-Difference estimation for low-patent applications. The regression output is the interaction term (DiD) outlined from equation (7.1). Column (1) are results restricted to the matched sample from 1:3 matching on covariates profits, CO_2 emissions and employees, on common support and column (2) are restricted to the inverse-probability weights. Panel A: regression on the full sample. Panel B: Restricted to firms that have had intramural R&D expenditure in the time period, 2001-2017. St. errors clustered at firm-level.

Table 15 represents the regression output for green intramural R&D expenditure. Similar to the results in chapter 7, the effect is positive, and in this case, also statistically significant with a p-value lower than 0.05 for 3 out of 6 estimates on the continuous variable. These results indicates an increase of 3-9 mill. NOK annually, depending on whether the firm has intramural R&D expenditure or not. However, these results are not generalizable outside the scope of the 15 two-digit industries from the propensity score matching since the other industries are not represented in this regression outputs. Which is crucial to keep in mind, when reading the results.

Table 15: green R&D expenditure

	Common support	Inverse-probability weights	Doubly robust
Green R&D, d.	0.019	0.032	0.031
	(0.048)	(0.074)	(0.043)
Green R&D, NOK	4194 **	3086 *	3892*
	(1587)	(1710)	(1492)
			8402*
			(3871)
Green R&D, NOK	8252 **	9522 **	
	(3277)	(2849)	

*** p<.01", "** p<.05 "* p<.1

Note: Difference-in-Difference estimation for green intramural R&D expenditure. The regression output is the interaction term (DiD) outlined from equation (7.1). Column (1) are results restricted to the matched sample from 1:3 matching on covariates profits, CO_2 emissions and employees, on common support and column (2) are restricted to the inverse-probability weights. Panel A: regression on the full sample. Panel B: Restricted to firms that have had intramural R&D expenditure in the time period, 2001-2017. St. errors clustered at firm-level.

9.0 Discussion

The results from chapter 7 and 8 indicates a positive effect on green R&D spending for EU ETS regulated firms, and a weak, yet positive, effect on low-carbon patenting. The magnitude of the estimation is determined by the assumptions and restrictions presented from chapter 6 and onwards. The estimations which are restricted to firms which already have conducted innovation activities, are of the greatest magnitude. This result may not come as a surprise, since there are few firms that have innovative activities in my sample. This result loose some generalizability outside the scope of innovative firms since these results are conditional on that the firm must already innovate. Nevertheless, the estimates on the full samples are still positive, yet not with the same magnitude. Since innovation activity is rare for firms in my sample, the estimates must be read with some caution. According to the law of large numbers, the results would get close to the expected value of the population in large samples (Sydsæter 2010). However, in my dataset, the sample size of those firms who have conducted innovation activity is relatively small, and one should therefore interpret the estimates of this analysis with some caution. Needless to say, the estimation is therefore more suggestive, than definitive. In the following I provide some discussions to my thesis.

An important element to discuss is the propensity score matched samples. Since I have conducted propensity score matching based to approximate industry affiliation, some results are not generalizable outside the scope of these industries. However, the most crucial aspect to discuss is the reduction of the total amount of low-carbon and regular patents when I conduct a propensity score matching. Aside to the 1:1 with replacement and 1:3 matchings, I have examined a various amount of different strategies, for example 1:10 with only CO_2 emissions as the covariate to determine treatment. Even in this case, there are only 3 low-carbon patents remained in the weighted dataset. This suggest that the firms that have most of the low-carbon patents in the group of unregulated firms, are not similar to the treatment group based on the covariates I used to approximate the selection criteria of EU ETS, i.e., not on the high rates of emission level, profits and employees. However, it would be problematic to change the covariates just to obtain more patents in my analysis. Since I am mainly interested in the causal effect of EU ETS, it is crucial to approximate the selection criteria as much as possible, to limit the selection bias, to obtain more reliable estimates and hence obtain something I could have claimed to be a causality. However, these patents will not cooperate on these terms. Therefore, it is a trade-off between obtaining reliability and sample size.

In contrast, the estimations on the R&D variables might have a higher degree of reliability, at least compared to the estimates on low-carbon patent application. In chapter 7 and 8 I plotted the trends in the outcome variable of green intramural R&D expenditure, and the trend in the pre-treatment phase are more parallel in the matched samples (both for 1:1 and 1:3), compared to the full sample. The parallel trend assumption is crucial to fulfill to obtain reliable estimates, as discussed. However, this is difficult to complete and verify completely. Therefore, I suggest that the matched samples could be better estimates on the R&D sample, while the matched samples are "worse" estimates for the patent sample. The problem of selection bias and obtaining a suitable control group, are present in this thesis, and I will not claim that I have overcome this problem completely. However, the problem of selection bias is common for EU ETS literature, since it is somewhat difficult to obtain an appropriate control group, based on the assumptions presented in chapter 6, when the treatment assignment is not randomized, and the characteristics are so different between the unregulated firms and the regulated firms.

The main contribution of this thesis is, however, that the findings lend some support to the results presented by Calel (2020) and the increasing research on the causal effects of EU ETS on firm's behavior. Similar to Calel, I find a positive effect on green R&D expenditure, but a weakly positive, yet insignificant effect on low-carbon patenting. The estimated effects in Calel's paper on low-carbon patents is larger than mine, which could be caused by country-fixed differences in terms of innovative culture or other features that determines innovation somehow, or the fact that there are more patents available in Calel's dataset. Calel argues that it is difficult to obtain low p-values when the sample size are so small as they are. Moreover, since I wanted to control for firm-fixed effects, I clustered at firm-level. This increased the p-value substantially from when I ran the regressions without clustered errors. However, it is rather difficult to claim that there is a causal effect on low-carbon patenting by EU ETS regulation, due to the violation of the parallel trend assumption, and the fact that I cannot measure the causal effect without an appropriate control group. There are too large differences between the regulated and the unregulated firms in the full sample, to claim that this effect is causal for low-carbon patents. However, I suggest that the estimates on green R&D are more reliable, since the parallel trend assumption holds to some degree in the matched sample, but also for the green dummy variable in the full sample.

Another important aspect that could cause the limited amount of low-carbon patenting, is due to the low effective carbon price and the high amount of free allowances, which I discussed in chapter 2-3. Klemetsen, Rosendahl and Jakobsen (2020) also point out the low price on EUA

as a potential reason for why the reduction in CO2 emissions are low for Norwegian firms. I did not control for CO2 emissions as an outcome variable, but as discussed in chapter 2-3, one of the most important aims of EU ETS is to stimulate low-carbon innovation by obtaining an effective carbon price. For future research, I suggest estimating the effects on more recent data, since the carbon price has increased in the period after my data.

10.0 Conclusion

In this thesis my motivation was to estimate the causal effect of EU ETS regulation on green innovation for Norwegian manufacturing firms, from 2008 till 2017. The aim of EU ETS is to reduce the overall GHG emissions in Europe and to provide incentives for firms to innovate in low-carbon technologies. The main findings in this thesis suggest that EU ETS regulation has had a positive effect on green intramural R&D expenditure, and a weak, yet insignificant, effect on low-carbon patenting. Similar to Calel (2020) my estimates are consistent throughout studies for green intramural R&D expenditure. Depending on the econometric assumptions, the overall increase in green intramural R&D expenditure has a positive increase of 2-13 mill. NOK annually. However, the question regarding causality remains conflicted when it comes to the effects obtained in this thesis. While the results for green intramural R&D expenditure are of great magnitude, and the matched sample to some degree satisfies the parallel trend assumption, this is not the case for the results of low-carbon patents, since most of the low-carbon patents vanishes in the matching process.

One of the main issues with estimating the causal effects of EU ETS, is to obtain an appropriate research design to overcome the selection bias caused by the treatment assignment. In my thesis, I contribute with some discussion of the implications of propensity score matching on EU ETS. However, the propensity score matching is not a perfect solution to overcome the selection bias. The main caveat in this thesis is that I cannot generalize the estimates outside the scope of the samples. However, this is a common problem in the EU ETS literature.

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